modeci-mdf

ModECI project

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CONTENTS

MDF is an open source, community-supported standard and associated library of tools for expressing computational models in a form that allows them to be exchanged between diverse programming languages and execution environments. The overarching aim is to provide a common format for models across **computational neuroscience, cognitive science and machine learning**.

It consists of a specification for expressing models in serialized form (currently JSON, YAML or BSON representations, though others such as HDF5 are planned) and a set of Python tools for implementing a model described using MDF. The serialized formats can be used when importing a model into a supported target environment to execute it; and, conversely, when exporting a model built in a supported environment so that it can be re-used in other environments.

CHAPTER

ONE

MODECI MODEL DESCRIPTION FORMAT (MDF)

Click here for the full MDF documentation

Note: MDF is still in development! See the open issues related to the specification or go here to get in contact regarding MDF. *The MDF format was first proposed following a meeting organised at Princeton in July 2019 by Russ Poldrack of the Center for Reproducible Neuroscience (CRN) at Stanford and the Brain Imaging Data Standard (BIDS) initiative. For more on the previous work in this area, see here.*

1.1 Overview

MDF is an open source, community-supported standard and associated library of tools for expressing computational models in a form that allows them to be exchanged between diverse programming languages and execution environments. The overarching aim is to provide a common format for models across computational neuroscience, cognitive science and machine learning.

It consists of a specification for expressing models in serialized formats (currently JSON, YAML and BSON representations are supported, though others such as HDF5 are planned) and a set of Python tools for implementing a model described using MDF. The serialized formats can be used when importing a model into a supported target environment to execute it; and, conversely, when exporting a model built in a supported environment so that it can be re-used in other environments.

The MDF Python API can be used to create or load an MDF model for inspection and validation. It also includes a basic execution engine for simulating models in the format. However, this is not intended to provide a efficient, general-purpose simulation environment, nor is MDF intended as a programming language. Rather, the primary purpose of the Python API is to facilitate and validate the exchange of models between existing environments that serve different communities. Accordingly, these Python tools include bi-directional support for importing to and exporting from widely-used programming environments in a range of disciplines, and for easily extending these to other environments.

1.2 Development

The implementation and dissemination of the MDF language and associated tools is being carried out by the Model Exchange and Convergence Initiative (ModECI), which has been supported by the NSF Convergence Accelerator Program (Track D: AI-Driven Innovation via Data and Model Sharing), as a publicly accessible open-source project. The initial design has been informed by a series of workshops involving developers of key software environments and other stakeholders in machine learning, cognitive science and neuroscience. Future workshops will address broadening of support to other domains in basic and applied science and technology development (e.g., population biology, medical informatics, structural and environmental monitoring, and complex systems control). Environments for which support is currently being developed include PyTorch, ONNX, WebGME, NeuroML, PsyNeuLink, and ACT-R.

Successful interfacing of MDF to existing disciplinary standards (such as ONNX in machine learning, and NeuroML in neuroscience) as well as general-purpose simulation environments (such as WebGME) will permit bridging between these environments, and translation to the broader set of environments supported by those standards (such as Tensorflow & Keras in the case of ONNX, and The Virtual Brain and SONATA in the case of NeuroML). Initial investigations have also taken place, in collaboration with projects in the NSF Accelerator Track C (Quantum Technology), to use MDF for facilitating the implementation of computational models on quantum hardware.

1.2.1 The core elements of the MDF standard

Models The highest level construct in MDF is a model that consists of one or more **graphs** and model attributes. The former describe the operational features of the model (its structure and execution), while the latter provide additional information (metadata) useful for executing, evaluating, testing or visualizing it.

Graphs A graph specifies the structure and process flow of a **model**. The most fundamental element of a graph is a **node**, which specifies some unit of computation in terms of its **parameters** and **functions**. Nodes are connected to other nodes via directed **edges**, which, in the absence of additional **conditions**, define the computational flow of the model.

Nodes These define the core elements of computation in a **graph**, that receive and transmit information via their **input and output ports**. In general, ports represent points of contact between a **node** and the **edges**that connect it to other nodes.

Output Ports An output port is the starting point of the data transmission process. After processing the information in a **node**, an output port is used to begin the transmission of information to the next **node** through **edges**.

Edges These transmit information from the **output port** of one **node** to the **input port** of another, collectively defining a **graph's** topography. Edges may contain weights that can operate on the information they carry.

Input Ports An input port is the endpoint of the data transmission process. It receives the information transmitted through an **edge** and inputs it to the next **node** for further processing.

Conditions These are a core and distinctive element of the MDF specification, that complement other computational graph-based formats by providing a high-level set of descriptors for specifying conditional execution of **nodes**. This allows models with relatively complex execution requirements (e.g., containing cycles, branches, and/or temporal dependencies) to be expressed as **graphs** in a sufficiently abstract form that facilities exchange among high-level modeling environments without requiring that they be "lowered" to and then recovered from more elaborated procedural descriptions.

Parameters Attributes that determine the configuration and operation of **nodes** and **edges**, can be defined in the MDF using parameters. In the case of parameters specifying large data structures (e.g., weight-matrices), arrays in widely used formats (e.g. numpy arrays, TensorFlow tensors) can be used, and serialisation in portable binary formats (e.g. BSON) is supported. Parameters can either be fixed values, which don't change when the **node** is executed, or can change over time (stateful parameters).

Functions A single value which is evaluated as a function of values on **input ports** and other functions and **parameters**. A key distinction with **parameters** is that a function is always stateless.

Model metadata There is the ability to add "metadata" to the **model**, **graph**, **nodes** and many of their sub elements which provide additional information about that element. While the metadata should not be essential to the mathematical description of the behavior/structure of the element, it could be useful for human interpretability of its function/purpose, or used when it is mapped to a specific application for simulation/visualization. Metadata can be added to the top level model to specify contact information, citations, acknowledgements, pointers to sample data and benchmark results, and environments in which the specified model was originally implemented and any that have been validated to support its execution.

1.3 Installation

1.3.1 Requirements

Requires Python >= 3.7

1.3.2 Quick start

```
pip install modeci-mdf
```

For more detailed installation instructions see here.

For guidelines on contributing to the development of MDF, see here.

1.4 Examples

To get started, follow the simple example in a Jupyter notebook here

Multiple examples of serialized MDF files, the Python scripts used to generate them, as well as mappings to target environments can be found here.

CHAPTER

TWO

INSTALLATION

2.1 Requirements

Python (>=3.7)

2.2 Quick start

```
pip install modeci_mdf
```

2.3 Installation from source

To install the MDF package from source and run it locally:

2.3.1 1) Create a virtual environment (e.g. called `mdf-env`)

```
pip install virtualenv
virtualenv mdf-env
```

2.3.2 2) Activate the virtual environment

```
source mdf-env/bin/activate
```

2.3.3 3) Clone this repository

```
git clone https://github.com/ModECI/MDF.git
```

2.3.4 4) Change to the directory

```
cd MDF
```

2.3.5 5) Install the package

```
pip install .
```

Hello world

Alternatively, to install MDF plus all of the modules required for the export/import interfaces (e.g. PsyNeuLink, NeuroML):

```
pip install .[all]
```

2.4 Additional dependencies

To generate generate Graph images in MDF you require Graphviz which uses dot.

```
pip install graphviz
```

To render the generated DOT source code, you also need to install Graphviz (download page, installation procedure for Windows.

Make sure that the directory containing the dot executable is on your system's PATH (sometimes done by the installer; setting PATH on Linux, Mac, and Windows.

2.5 Generating ModECI MDF documentation offline

The ModECI MDF Documentation can be found online here. If you are working on MDF documentation or you make changes to the documentation, it is good practice to see if it is working as expected before pushing to the Github repository. Here is a walkthrough on how to generate the ModECI MDF documentation offline

2.6 Requirements

Python (3.10)

Make library

Python version-3.10 is ideally used for generating MDF documentation offline but if not working, use python version-3.9. The steps are the same except in creating a virtual environment.

See Installation for python here

Ensure the python version you are using is added to path

For **windows** installation of Make, see here

for **mac** installation of Make, see here

2.6.1 1). Create a virtual environment with python

```
# install virtual environment

pip install virtualenv

# create virtual environment for python 3.9

python3.9 -m virtualenv venv39

or

# create virtual environment for python 3.10

python3.10 -m virtualenv venv310

# Activate virtual environment for python3.9

venv39\Scripts\activate

# Activate virtual environment for python3.10

venv310\Scripts\activate
```

2.6.2 2). Clone MDF repository from Github into your local machine

```
git clone https://github.com/ModECI/MDF.git
```

2.6.3 3). Change into the MDF directory

```
cd MDF
```

2.6.4 4). Install all MDF package into the virtual environment

```
pip install .[all]
```

2.6.5 5). Change directory into sphinx folder

```
# for windows
cd docs\sphinx

# for mac
cd docs/sphinx
```

2.6.6 6). Create offline documentation in sphinx folder

```
# To allow fresh start when making the documentation
make clean

# To make the documentation
make html
```

2.6.7 7). change directory into html folder and run the documentation offline

```
# for windows
Go into build\html folder and double click on the index.html file.
or
cd build\html
index.html

# for mac
Go into build/html folder and double click on the index.html file
```

The documentation will open up in your browser automatically or right click on the file and open in any browser of your choice

CHAPTER

THREE

MODECI CONTRIBUTORS

This page list names and Github profiles of contributors to the various ModECI repositories, listed in no particular order. This file is generated periodically, the most recent was on 2022-12-16.

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- (@vidhya-metacell)
- (@nicholwkprinceton)
- Matteo Cantarelli (@tarelli)
- Brian Broll (@brollb)

3.1 Repositories

- MDF
- Website
- MDFTests
- modelspec
- PsyNeuLink

CHAPTER

FOUR

SPECIFICATION OF MODECI V0.4

Note: the ModECI MDF specification is still in development! See here for ongoing discussions.

CHAPTER

FIVE

MODEL

The top level construct in MDF is Model, which may contain multiple *Graph* objects and model attribute(s)

Allowed parameters

Allowed field	Data Type	Description
metadata	Union[Any, NoneType]	Optional metadata field, an arbitrary dictionary of string keys and JSON serializable values.
id	str	A unique identifier for this Model
format	str	Information on the version of MDF used in this file
generating_application	str	Information on what application generated/saved this file
onnx_opset_version	Union[str, NoneType]	The ONNX opset used for any ONNX functions in this model.

Allowed children

Allowed child	Data Type	Description
graphs	*Graph*	The collection of graphs that make up the MDF model.

CHAPTER

SIX

GRAPH

A directed graph consisting of *Nodes* (with *Parameters* and *Functions* evaluated internally) connected via *Edges*.

Allowed parameters

Allowed field	Data Type	Description
metadata	Union[Any, NoneType]	Optional metadata field, an arbitrary dictionary of string keys and JSON serializable values.
id	str	A unique identifier for this Graph
parameters	Union[Any, NoneType]	Dictionary of global parameters for the Graph
conditions	Union[ConditionSet, NoneType]	The ConditionSet stored as dictionary for scheduling of the Graph

Allowed children

Allowed child	Data Type	Description
nodes	*Node*	One or more *Node(s)* present in the graph
edges	*Edge*	Zero or more *Edge(s)* present in the graph

CHAPTER

SEVEN

NODE

A self contained unit of evaluation receiving input from other nodes on *InputPort(s)*. The values from these are processed via a number of *Function(s)* and one or more final values are calculated on the *OutputPort(s)*

Allowed parameters

Allowed field	Data Type	Description
metadata	Union[Any, NoneType]	Optional metadata field, an arbitrary dictionary of string keys and JSON serializable values.
id	str	A unique identifier for the node.

Allowed children

Allowed child	Data Type	Description
input_ports	*InputPort*	Dictionary of the *InputPort* objects in the Node
functions	*Function*	The *Function(s)* for computation the node
parameters	*Parameter*	Dictionary of *Parameter(s)* for the node
output_ports	*OutputPort*	The *OutputPort(s)* containing evaluated quantities from the node

CHAPTER

EIGHT

INPUTPORT

The *InputPort* is an attribute of a Node which allows external information to be input to the Node

Allowed parameters

Allowed field	Data Type	Description
metadata	Union[Any, NoneType]	Optional metadata field, an arbitrary dictionary of string keys and JSON serializable values.
id	str	The unique (for this Node) id of the input port,
shape	Union[Tuple[int, ...], NoneType]	The shape of the input port. This uses the same syntax as numpy ndarray shapes (e.g., **numpy.zeros(shape)** would produce an array with the correct shape
type	Union[str, NoneType]	The data type of the input received at a port.

CHAPTER

NINE

FUNCTION

A single value which is evaluated as a function of values on *InputPort(s)* and other Functions

Allowed parameters

Allowed field	Data Type	Description
metadata	Union[Any, NoneType]	Optional metadata field, an arbitrary dictionary of string keys and JSON serializable values.
id	str	The unique (for this Node) id of the function, which will be used in other *Functions* and the *OutputPorts* for its value
function	Union[str, NoneType]	Which of the in-build MDF functions (**linear**, etc.). See supported functions: https://mdf.readthedocs.io/en/latest/api/MDF_function_specifications.html
args	Union[Any, NoneType]	Dictionary of values for each of the arguments for the Function, e.g. if the in-built function is linear(slope),the args here could be {"slope":3} or {"slope":"input_port_0 + 2"}
value	Union[EvaluableExpression, List, Dict, ndarray, int, float, str, NoneType]	If the function is a value expression, this attribute will contain the expression and the function and args attributes will be None.

CHAPTER

TEN

PARAMETER

A parameter of the *Node*, which can be: 1) a specific fixed **value** (a constant (int/float) or an array) 2) a string expression for the **value** referencing other named *Parameter(s)*. which may be stateful (i.e. can change value over multiple executions of the *Node*); 3) be evaluated by an inbuilt **function** with **args**; 4) or change from a **default_initial_value** with a **time_derivative**.

Allowed parameters

Allowed field	Data Type	Description
metadata	Union[Any, NoneType]	Optional metadata field, an arbitrary dictionary of string keys and JSON serializable values.
id	str	
value	Union[EvaluableExpression, List, Dict, ndarray, int, float, str, NoneType]	The next value of the parameter, in terms of the inputs, functions and PREVIOUS parameter values
default_initial_value	Union[EvaluableExpression, List, Dict, ndarray, int, float, str, NoneType]	The initial value of the parameter, only used when parameter is stateful.
time_derivative	Union[str, NoneType]	How the parameter changes with time, i.e. ds/dt. Units of time are seconds.
function	Union[str, NoneType]	Which of the in-build MDF functions (linear etc.) this uses, See
args	Union[Any, NoneType]	Dictionary of values for each of the arguments for the function of the parameter, e.g. if the in-build function is **linear(slope)**, the args here could be **{"slope": 3}** or **{"slope": "input_port_0 + 2"}**

Allowed children

Allowed child	Data Type	Description
conditions	*ParameterCondition*	Parameter specific conditions

CHAPTER

ELEVEN

PARAMETERCONDITION

A condition to test on a Node's parameters, which if true, sets the value of this Parameter

Allowed parameters

Allowed field	Data Type	Description
id	str	A unique identifier for the ParameterCondition
test	Union[EvaluableExpression, List, Dict, ndarray, int, float, str, NoneType]	The boolean expression to evaluate
value	Union[EvaluableExpression, List, Dict, ndarray, int, float, str, NoneType]	The new value of the Parameter if the test is true

CHAPTER

TWELVE

OUTPUTPORT

The *OutputPort* is an attribute of a *Node* which exports information to another *Node* connected by an *Edge*

Allowed parameters

Allowed field	Data Type	Description
metadata	Union[Any, NoneType]	Optional metadata field, an arbitrary dictionary of string keys and JSON serializable values.
id	str	Unique identifier for the output port.
value	Union[str, NoneType]	The value of the *OutputPort* in terms of the *InputPort*, *Function* values, and *Parameter* values.
shape	Union[Tuple[int, ...], NoneType]	The shape of the output port. This uses the same syntax as numpy ndarray shapes (e.g., **numpy.zeros(shape)** would produce an array with the correct shape
type	Union[str, NoneType]	The data type of the output sent by a port.

CHAPTER

THIRTEEN

EDGE

An *Edge* is an attribute of a *Graph* that transmits computational results from a sender's *OutputPort* to a receiver's *InputPort*.

Allowed parameters

Allowed field	Data Type	Description
metadata	Union[Any, NoneType]	Optional metadata field, an arbitrary dictionary of string keys and JSON serializable values.
id	str	A unique string identifier for this edge.
sender	str	The **id** of the *Node* which is the source of the edge.
receiver	str	The **id** of the *Node* which is the target of the edge.
sender_port	str	The id of the *OutputPort* on the sender *Node*, whose value should be sent to the **receiver_port**
receiver_port	str	The id of the InputPort on the receiver *Node*
parameters	Union[Any, NoneType]	Dictionary of parameters for the edge.

CHAPTER

FOURTEEN

MDF EXAMPLES

Examples of Python, JSON and YAML files to illustrate the structure and usage of MDF.

Simple | ABCD | Arrays | States | Conditions | Parameters and Functions

14.1 Simple example

Python Source | JSON | YAML

A simple example with 2 Nodes connected by an Edge:

With more detail on Nodes (showing Input Ports (green), Parameters (blue) and Output Ports) (red) and Edges:

14.2 ABCD

Python Source | JSON | YAML

Another simple example with more Nodes.

14.3 Arrays

Python Source | JSON | YAML

An example using arrays for Parameters and weights on Edges.

14.4 States

Python Source | JSON | YAML

An example with Nodes containing persistent States.

14.5 Conditions

Python Source | JSON | YAML

A simple 3 Nodes graph with scheduling Conditions. For more examples of conditions see here.

14.6 Parameters and Functions

Python Source | JSON | YAML

A simple Node with a number of different types of Parameters (in blue; fixed and **stateful**) and Functions (in purple; can be built in or ONNX based).

14.7 More examples

There are further examples under development, including of a Recurrent Neural Network (RNN), and an Integrate and Fire (IaF) neuron model in this directory.

CHAPTER

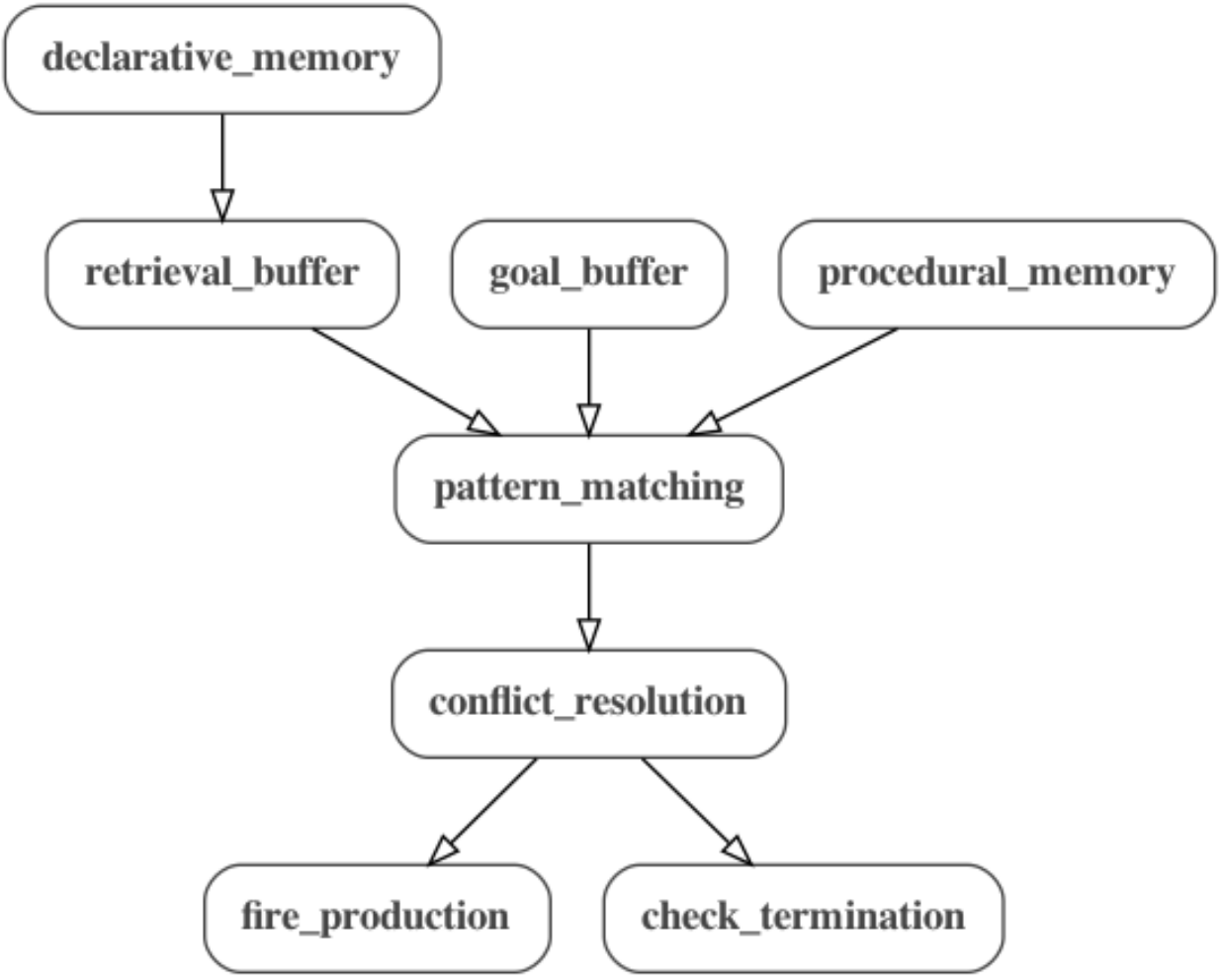
FIFTEEN

INTERACTIONS BETWEEN MDF AND ACT-R

This directory contains examples of ACT-R models converted to MDF. The ACT-R models count.lisp and addition.lisp are based on the ACT-R tutorial.

The scripts count.py and addition.py can be run to create the MDF .json and .yaml files for the given example and execute it using the MDF scheduler.

The below graph represents the basic structure of all ACT-R models in MDF:



There are also more detailed graphs count.png and addition.png for each example.

15.1 Count Model

ACT-R | JSON | YAML | Python Script | Graph

The count model counts from a start value to an end value. The script count.py first reads the original ACT-R model file count.lisp, generates an MDF representation using the MDF ACT-R interface, and outputs the JSON and YAML files. It then executes the MDF model using the MDF scheduler and outputs the final goal set by the model once execution is finished. The final goal has the form:

```
{'name': 'first-goal', 'ISA': 'count-from', 'start': 'two', 'end': 'four',
'count': 'four'}
```

In this example, the start value is two, the end value is four, and the final value of count is four, indicating that the model counted from two to four. The start and end values can be modified in line 17 of count.lisp, which sets the initial goal of the model:

```
(first-goal ISA count-from start two end four)
```

The script can use any values specified in count.lisp, so the model can be modified and run multiple times in order to test different values. The count graph represents this example.

15.2 Addition Model

ACT-R | JSON | YAML | Python Script | Graph

The addition model computes the sum of two numbers. The script addition.py functions identically to the previous example, but uses the addition model instead. The final goal has the form:

```
{'name': 'second-goal', 'ISA': 'add', 'arg1': 'five', 'arg2': 'two', 'sum':
'seven', 'count': 'nil'}
```

In this case, the first argument is five, the second argument is two, and the model has calculated the sum, seven. Like the previous example, the arguments can be modified in line 23 of addition.lisp in order to test different values:

```
(second-goal ISA add arg1 five arg2 two)
```

The addition graph represents this example.

CHAPTER

SIXTEEN

INTERACTIONS BETWEEN NEUROML AND MDF

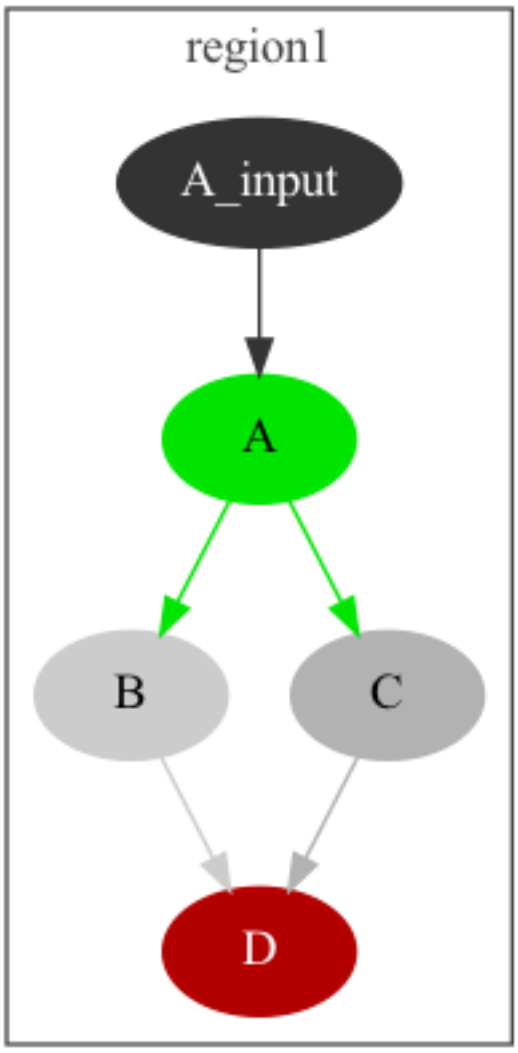
16.1 1) Converting NeuroML to MDF

16.2 1.1) Simple ABCD model

Summary: A model is created in NeuroML (using cell dynamics specified in LEMS and a network in NeuroMLlite) and converted to the equivalent model in MDF, which runs with the reference MDF execution engine.

16.2.1 1.1.1) ABCD - NeuroMLlite version

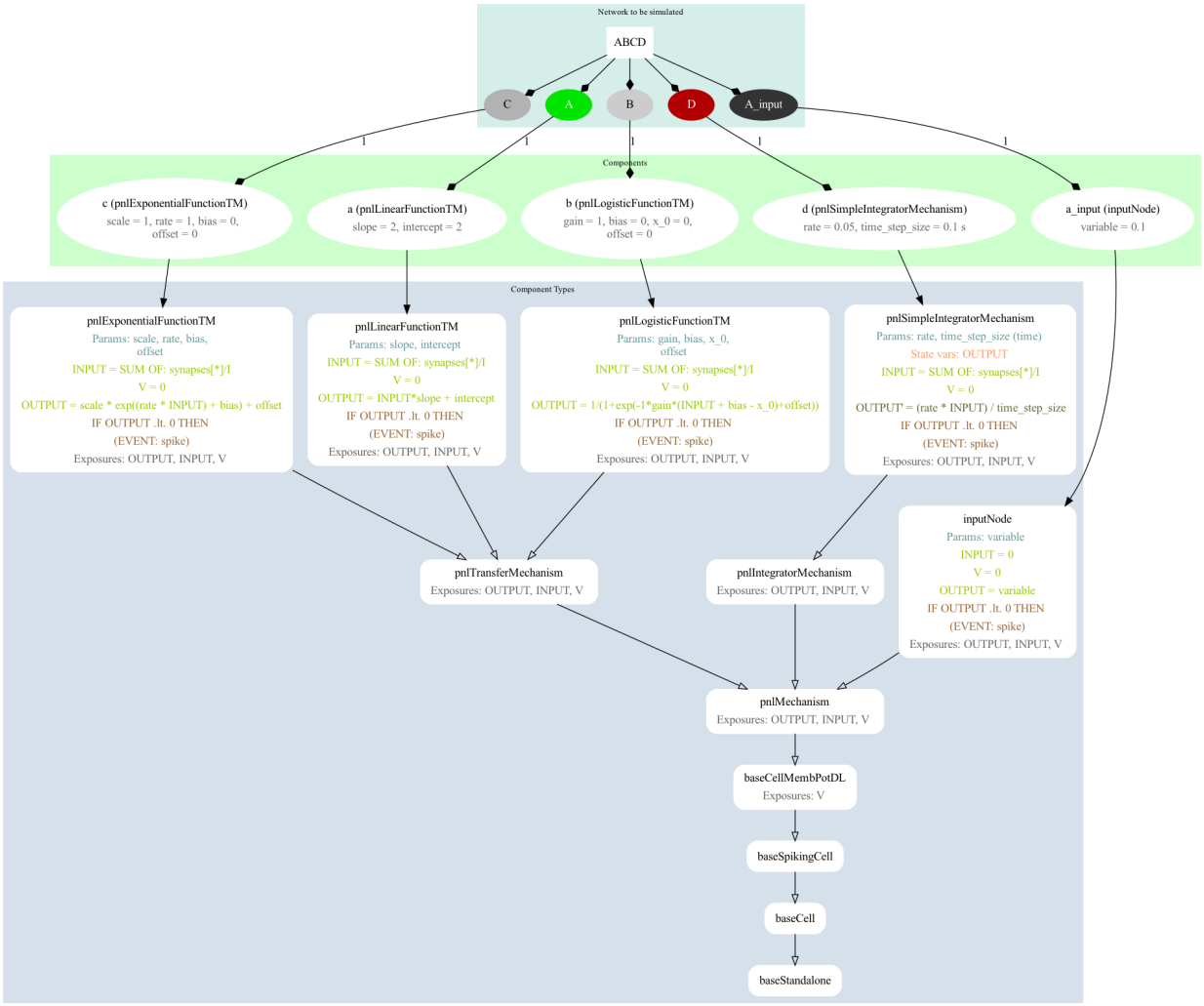
ABCD.py is a script using the NeuroMLlite package to create a simple network with 4 connected elements. The network built can be seen below (this can be generated with `python ABCD.py -graph2`):



16.2.2 1.1.2) ABCD - NeuroML2 version

A version of the network in NeuroML 2 can be generated with `python ABCD.py -nml`, or generated and executed with jNeuroML with `python ABCD.py -nml`. This will produce the NeuroML file: ABCD.net.nml (note though this is not valid, as not all the elements included are pure NeuroML). A LEMS Simulation file is generated for running the model in jNeuroML or pyNeuroML: LEMS_SimABCD.xml

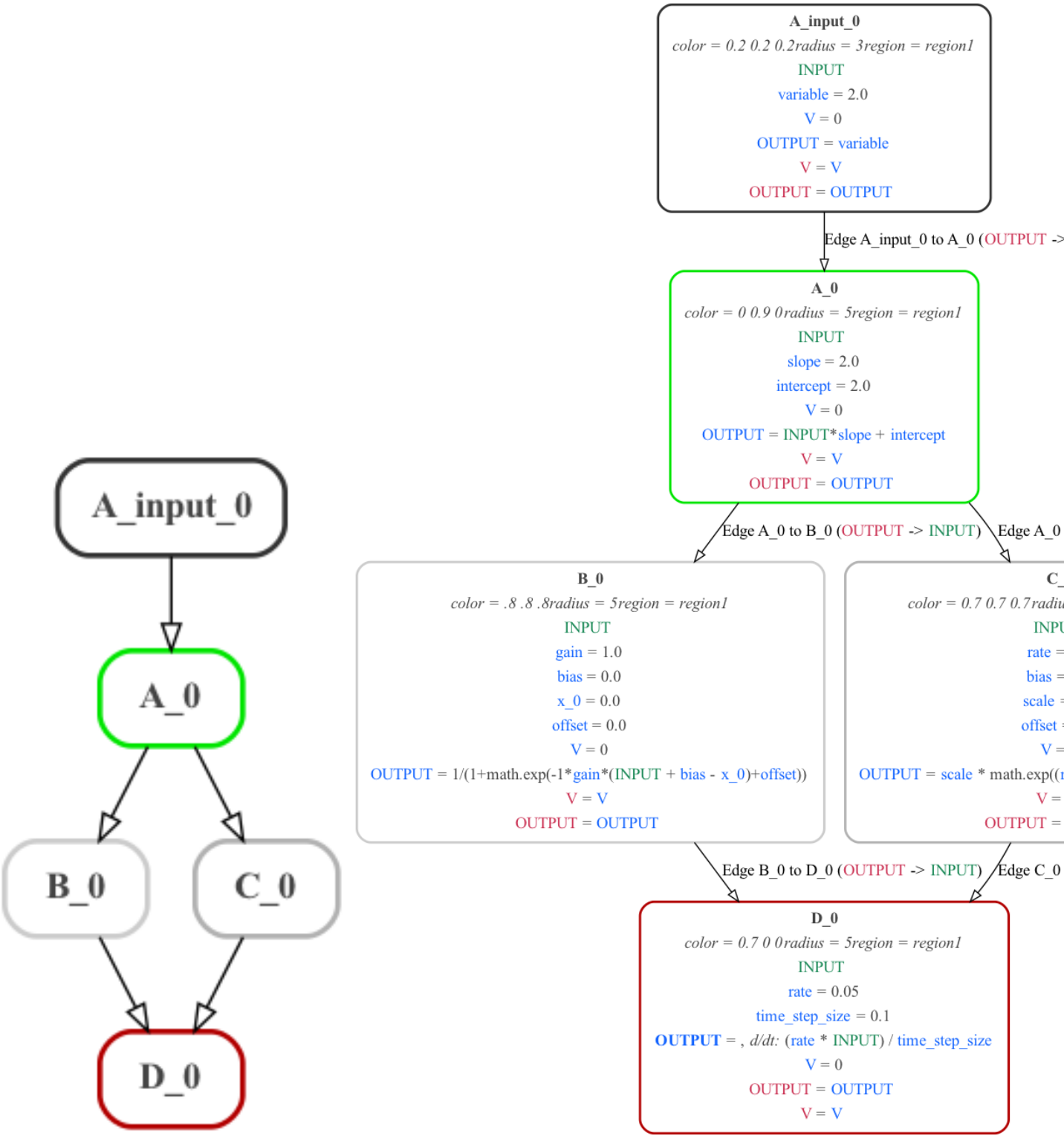
The definitions of the components used for A, B, etc. can be found in PNL.xml. This is a set of definitions of component types based on those present in PsyNeuLink. A graph depicting the definitions of the network elements can be generated with `pynml LEMS_SimABCD.xml -lems-graph`:



16.2.3 1.1.3) ABCD - MDF version

A version of the network in MDF can be generated from NeuroMLlite definition with: `python ABCD.py -mdf` producing ABCD.mdf.yaml and ABCD.mdf.json.

A graph of the structure of the MDF model can be generated with: `python -m modeci_mdf.interfaces.graphviz.exporter ABCD.mdf.yaml 1` (left below), or with more detail: `python -m modeci_mdf.interfaces.graphviz.exporter ABCD.mdf.yaml 3` (right below.)

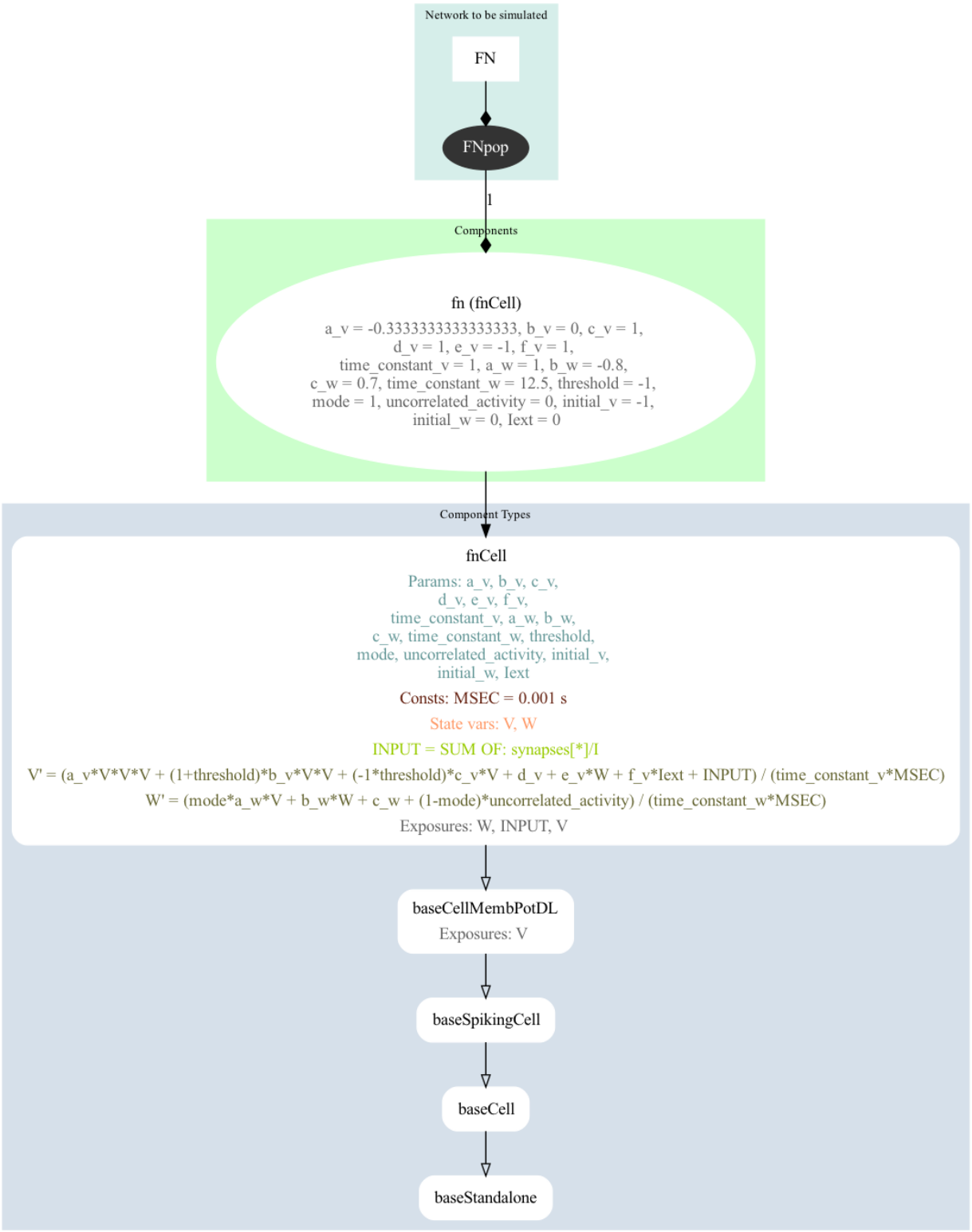

A_input_0
A_0
B_0
C_0
D_0
A_input_0
color = 0.2 0.2 0.2radius = 3region = region1
INPUT
variable = 2.0
V = 0
OUTPUT = variable
V = V
OUTPUT = OUTPUT
Edge A_input_0 to A_0 (OUTPUT ->
A_0
color = 0 0.9 0radius = 5region = region1
INPUT
slope = 2.0
intercept = 2.0
V = 0
OUTPUT = INPUT*slope + intercept
V = V
OUTPUT = OUTPUT
Edge A_0 to B_0 (OUTPUT -> INPUT)
Edge A_0
B_0
color = .8 .8 .8radius = 5region = region1
INPUT
gain = 1.0
bias = 0.0
x_0 = 0.0
offset = 0.0
V = 0
OUTPUT = 1/(1+math.exp(-1*gain*(INPUT + bias - x_0)+offset))
V = V
OUTPUT = OUTPUT
Edge B_0 to D_0 (OUTPUT -> INPUT)
Edge C_0
D_0
color = 0.7 0 0radius = 5region = region1
INPUT
rate = 0.05
time_step_size = 0.1
OUTPUT = , d/dt: (rate * INPUT) / time_step_size
V = 0
OUTPUT = OUTPUT
V = V

16.3 1.2) FitzHugh Nagumo cell models

16.3.1 1.2.1) FN - NeuroML version

A version of the FitzHugh Nagumo neuron model has been created using NeuroMLlite (FN.py) which generated LEMS (LEMS_SimFN.xml) which can simulate the NeuroML model (FN.net.nml).

A graphical representation of the LEMS is below:



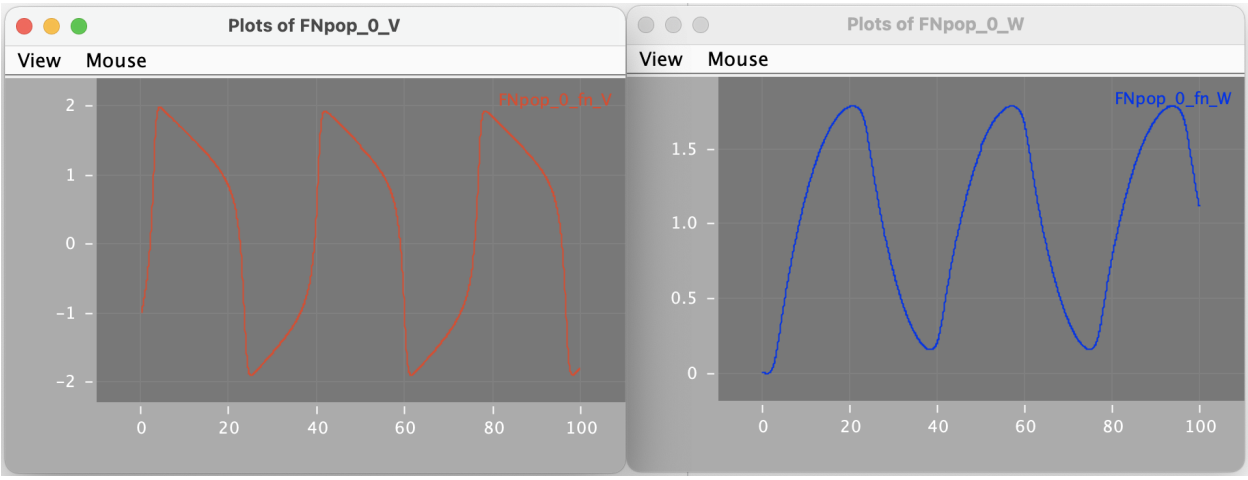
It can be run with:

```
python FN.py -jnml      # Generate and run the LEMS file from the NeuroMLlite␣
↪description
```

(continues on next page)

(continued from previous page)

```
pynml LEMS_SimFN.xml     # Run the LEMS file using pyNeuroML
```



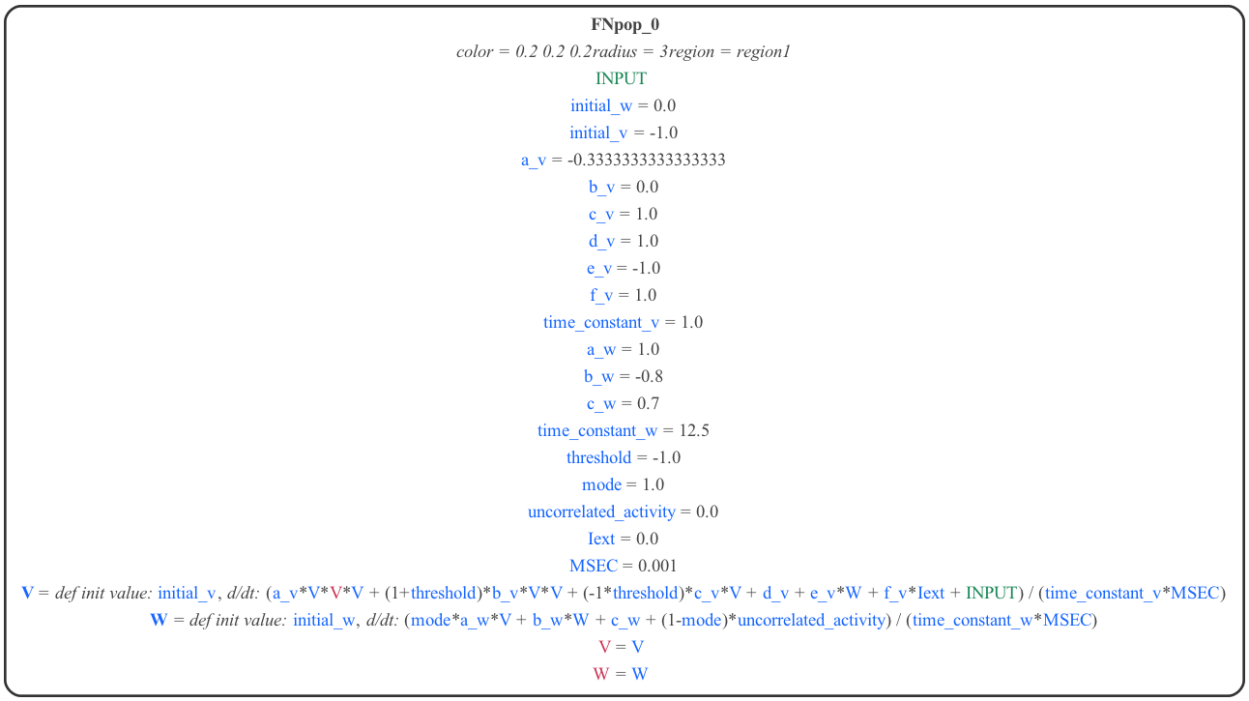
16.3.2 1.2.2) FN - MDF version

The NeuroMLlite version can also be used to generate MDF for the model:

```
python FN.py -mdf       # Generate the MDF serializations (JSON and YAML) from the␣
↪NeuroMLlite description
```

These can be seen here: FN.mdf.json, FN.mdf.yaml, and a graphical version generated with:

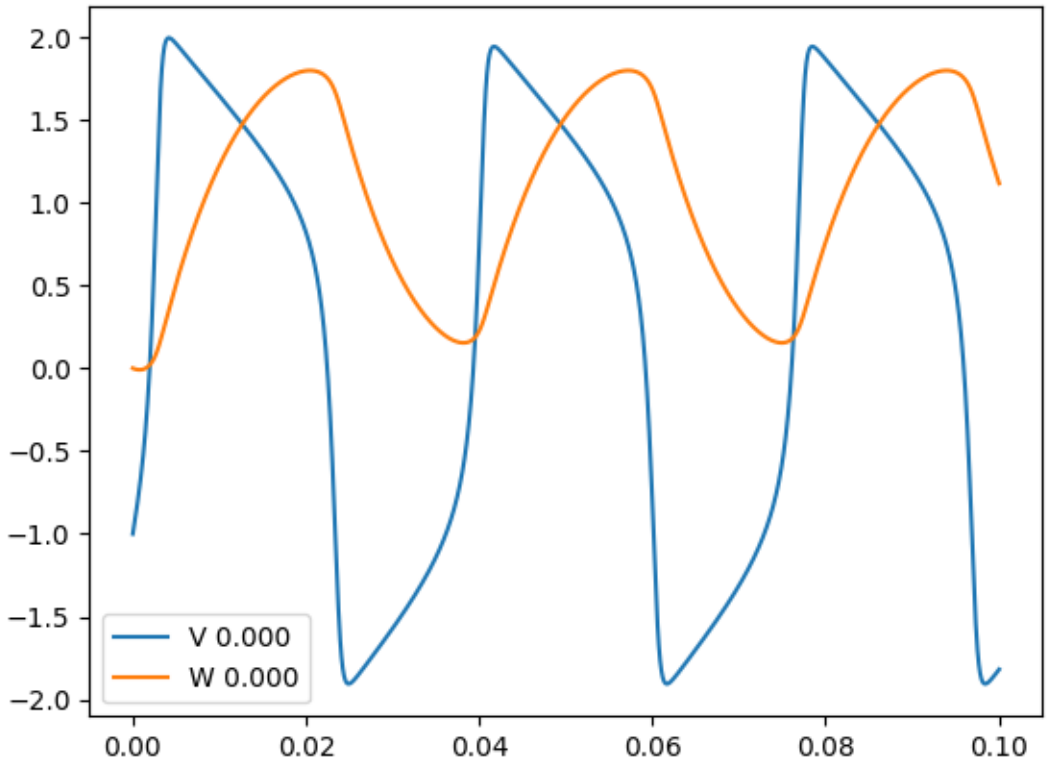
```
python -m modeci_mdf.interfaces.graphviz.importer FN.mdf.yaml 3     #  Generate graph␣
↪from MDF version
```



16.3.3 1.2.3) FN - Execute model using MDF

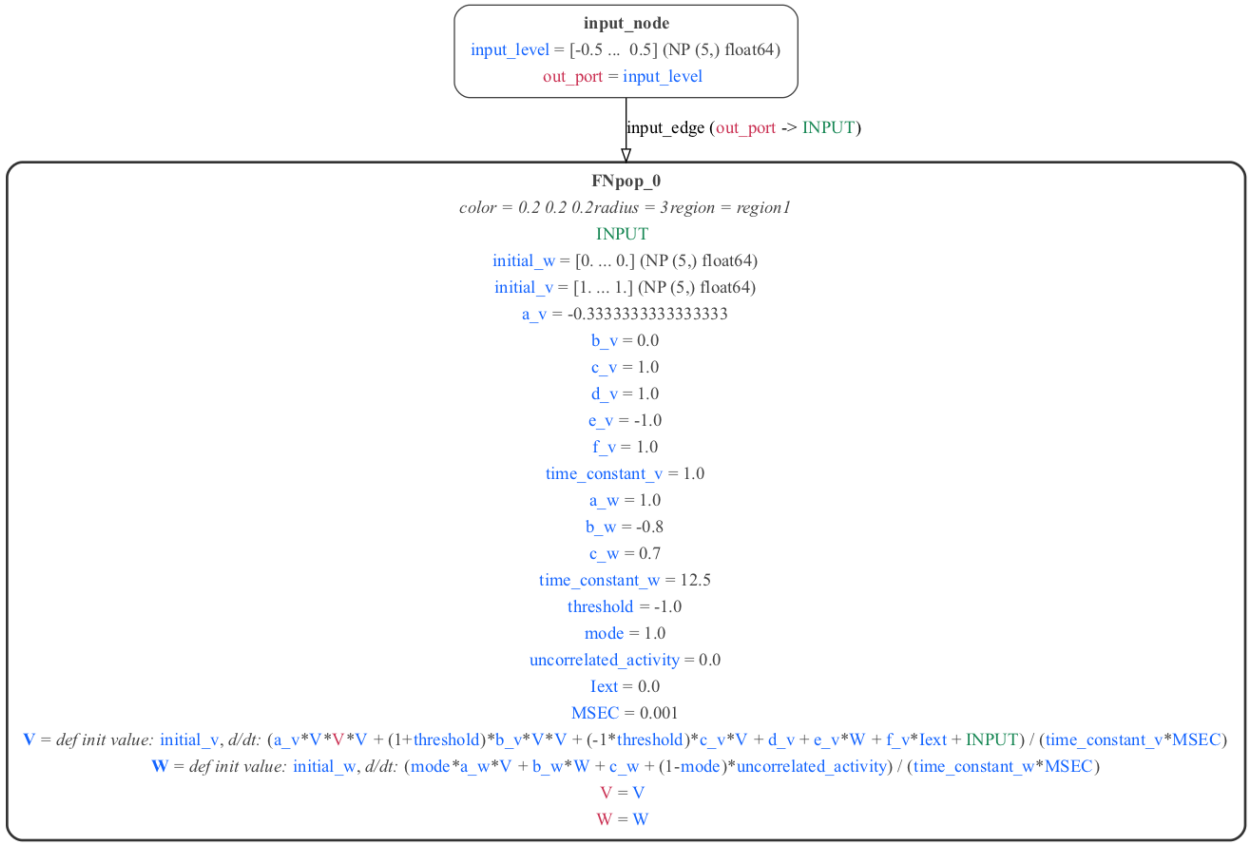
A script has been created (FNrun.py) where the model is loaded, run using the standard MDF execution engine, and plotted:

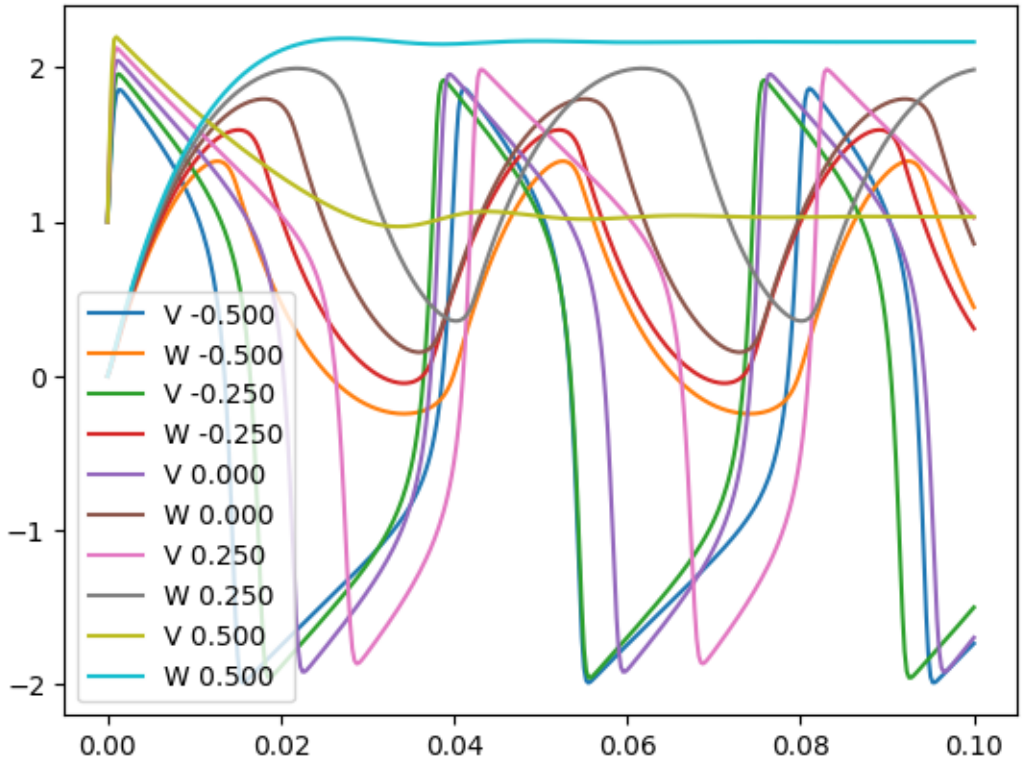
```
python FNrun.py     # Load FN model and run with MDF scheduler
```



Adding the option `-multi` to the Python script for running the FN example, modifies the graph to add an input node with an array of values, meaning multiple instances of the FN neuron will be simulated:

```
python FN.py -multi
```


input_node
input_level = [-0.5 ... 0.5] (NP (5,) float64)
out_port = input_level
input_edge (out_port -> INPUT)
FNpop_0
color = 0.2 0.2 0.2radius = 3region = region1
INPUT
initial_w = [0. ... 0.] (NP (5,) float64)
initial_v = [1. ... 1.] (NP (5,) float64)
a_v = -0.3333333333333333
b_v = 0.0
c_v = 1.0
d_v = 1.0
e_v = -1.0
f_v = 1.0
time_constant_v = 1.0
a_w = 1.0
b_w = -0.8
c_w = 0.7
time_constant_w = 12.5
threshold = -1.0
mode = 1.0
uncorrelated_activity = 0.0
Iext = 0.0
MSEC = 0.001
V = def init value: initial_v, d/dt: (a_v*V*V*V + (1+threshold)*b_v*V*V + (-1*threshold)*c_v*V + d_v + e_v*W + f_v*Iext + INPUT) / (time_constant_v*MSEC)
W = def init value: initial_w, d/dt: (mode*a_w*V + b_w*W + c_w + (1-mode)*uncorrelated_activity) / (time_constant_w*MSEC)
V = V
W = W


2
1
0
−1
−2
0.00
0.02
0.04
0.06
0.08
0.10
V -0.500
W -0.500
V -0.250
W -0.250
V 0.000
W 0.000
V 0.250
W 0.250
V 0.500
W 0.500

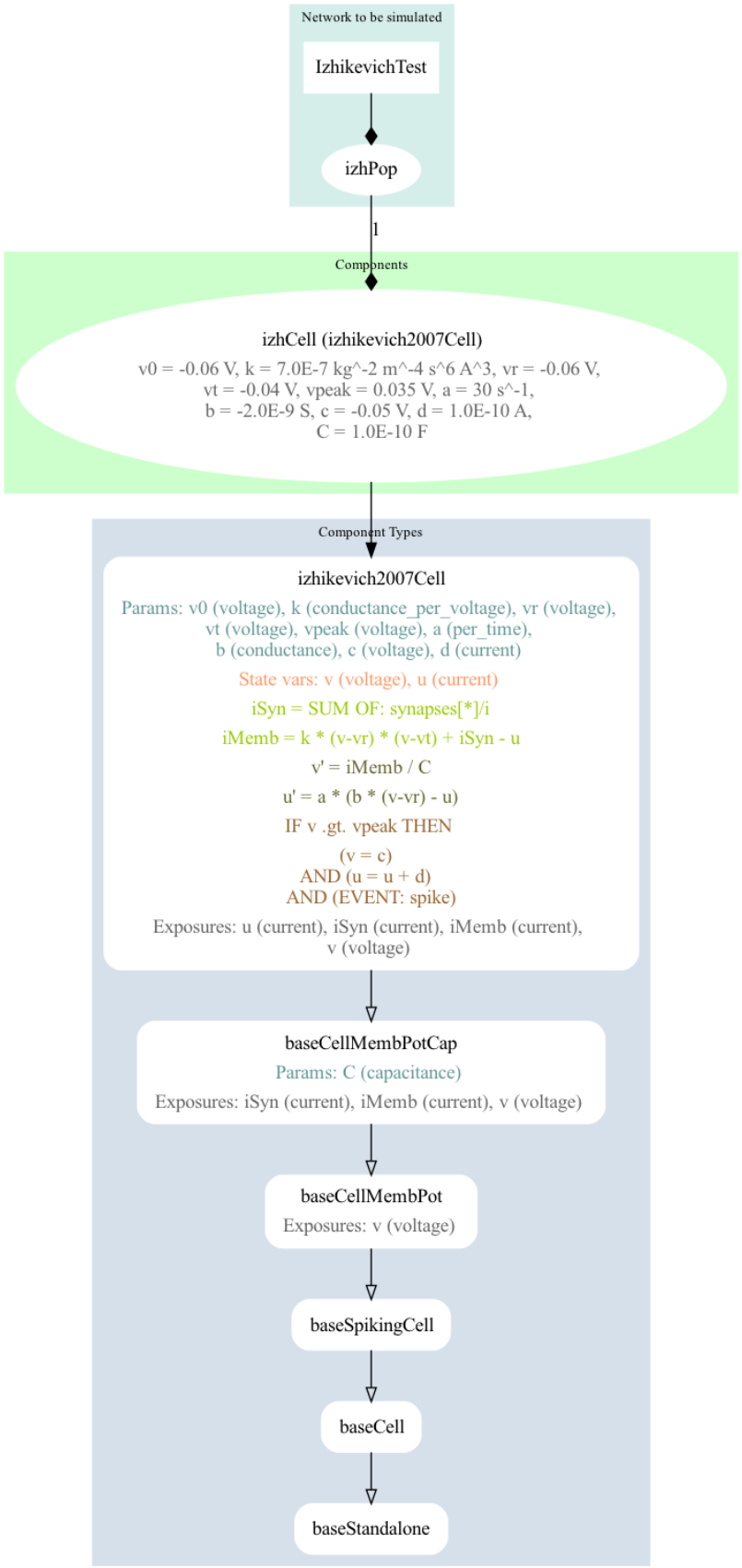
16.4 1.3) Izhikevich cell models

A version of the Izhikevich spiking neuron model has been created in NeuroML and can be exported to MDF and executed with the standard execution engine.

16.4.1 1.3.1) Izhikevich - NeuroML version

The single cell model has been created using NeuroMLlite (Izhikevich.py) which generated LEMS (LEMS_SimIzhikevichTest.xml) which can simulate the NeuroML model (IzhikevichTest.net.nml).

A graphical representation of the LEMS is below:


Network to be simulated
IzhikevichTest
izhPop
1
Components
izhCell (izhikevich2007Cell)
v0 = -0.06 V, k = 7.0E-7 kg^-2 m^-4 s^6 A^3, vr = -0.06 V,
vt = -0.04 V, vpeak = 0.035 V, a = 30 s^-1,
b = -2.0E-9 S, c = -0.05 V, d = 1.0E-10 A,
C = 1.0E-10 F
Component Types
izhikevich2007Cell
Params: v0 (voltage), k (conductance_per_voltage), vr (voltage),
vt (voltage), vpeak (voltage), a (per_time),
b (conductance), c (voltage), d (current)
State vars: v (voltage), u (current)
iSyn = SUM OF: synapses[*]/i
iMemb = k * (v-vr) * (v-vt) + iSyn - u
v' = iMemb / C
u' = a * (b * (v-vr) - u)
IF v .gt. vpeak THEN
(v = c)
AND (u = u + d)
AND (EVENT: spike)
Exposures: u (current), iSyn (current), iMemb (current),
v (voltage)
baseCellMembPotCap
Params: C (capacitance)
Exposures: iSyn (current), iMemb (current), v (voltage)
baseCellMembPot
Exposures: v (voltage)
baseSpikingCell
baseCell
baseStandalone

It can be run with:

```
python Izhikevich.py -jnml      # Generate and run the LEMS file from the NeuroMLlite␣
↪description
pynml LEMS_SimIzhikevichTest.xml    # Run the LEMS file using pyNeuroML
```

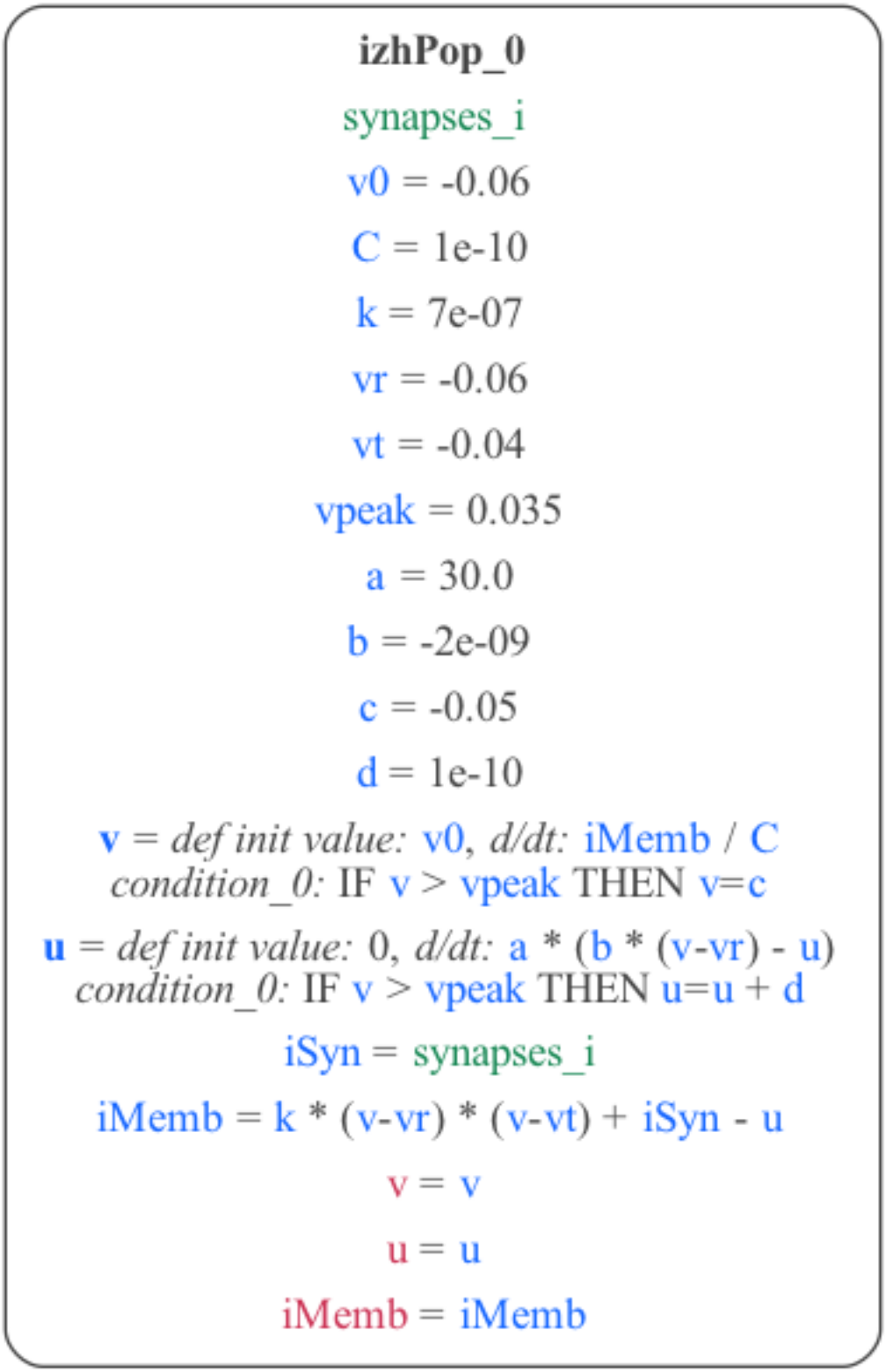
16.4.2 1.3.2) Izhikevich - MDF version

The NeuroMLlite version can also be used to generate MDF for the model:

```
python Izhikevich.py -mdf      # Generate the MDF serializations (JSON and YAML) from␣
↪the NeuroMLlite description
```

These can be seen here: IzhikevichTest.mdf.json, IzhikevichTest.mdf.yaml, and a graphical version generated with:

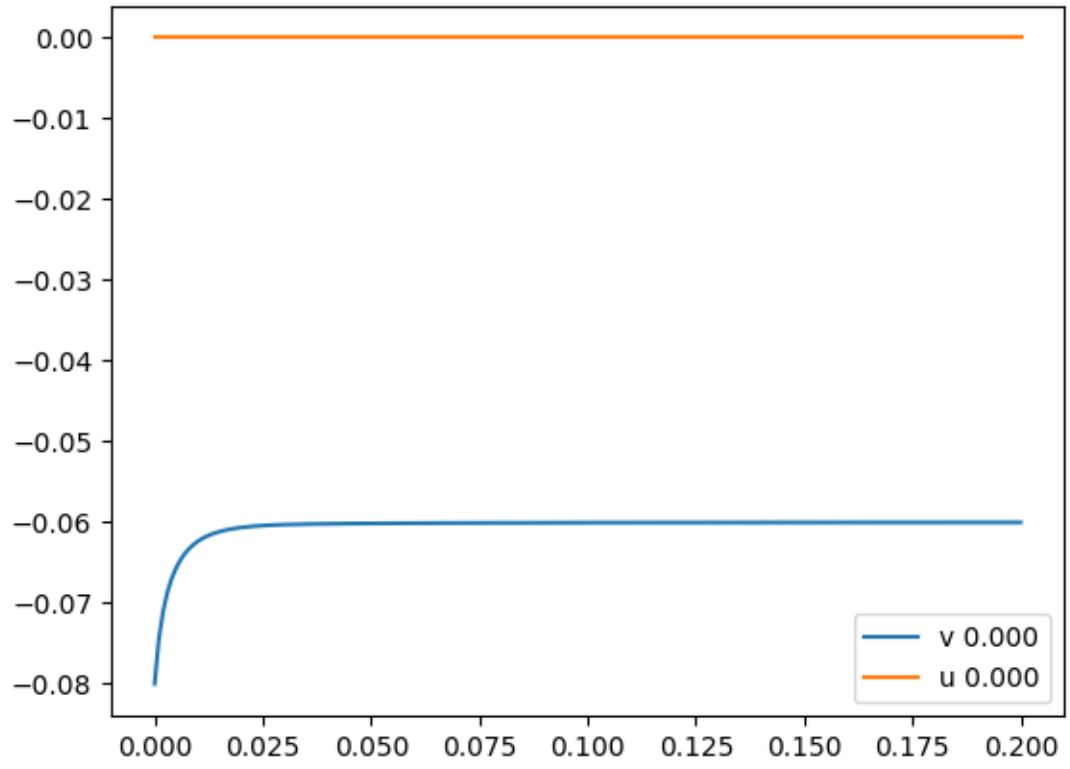
```
python -m modeci_mdf.interfaces.graphviz.importer IzhikevichTest.mdf.yaml 3    # ␣
↪Generate graph from MDF version
```


izhPop_0
synapses_i
v0 = -0.06
C = 1e-10
k = 7e-07
vr = -0.06
vt = -0.04
vpeak = 0.035
a = 30.0
b = -2e-09
c = -0.05
d = 1e-10
v = def init value: v0, d/dt: iMemb / C
condition_0: IF v > vpeak THEN v=c
u = def init value: 0, d/dt: a * (b * (v-vr) - u)
condition_0: IF v > vpeak THEN u=u + d
iSyn = synapses_i
iMemb = k * (v-vr) * (v-vt) + iSyn - u
v = v
u = u
iMemb = iMemb

16.4.3 1.3.3) Izhikevich - Execute model using MDF

A script has been created (Izh_run.py) where the model is loaded, run using the standard MDF execution engine, and plotted:

```
python Izh_run.py    # Load Izh model and run with MDF scheduler
```



16.5 2) Converting MDF to NeuroML/LEMS

It is also possible to convert MDF models into equivalents in NeuroML/LEMS:

```
cd ../MDF  # convert some of the examples in the examples/MDF directory

python -m modeci_mdf.interfaces.neuroml.exporter Simple.json -run
python -m modeci_mdf.interfaces.neuroml.exporter ABCD.json -run
python -m modeci_mdf.interfaces.neuroml.exporter States.json -run
```

CHAPTER

SEVENTEEN

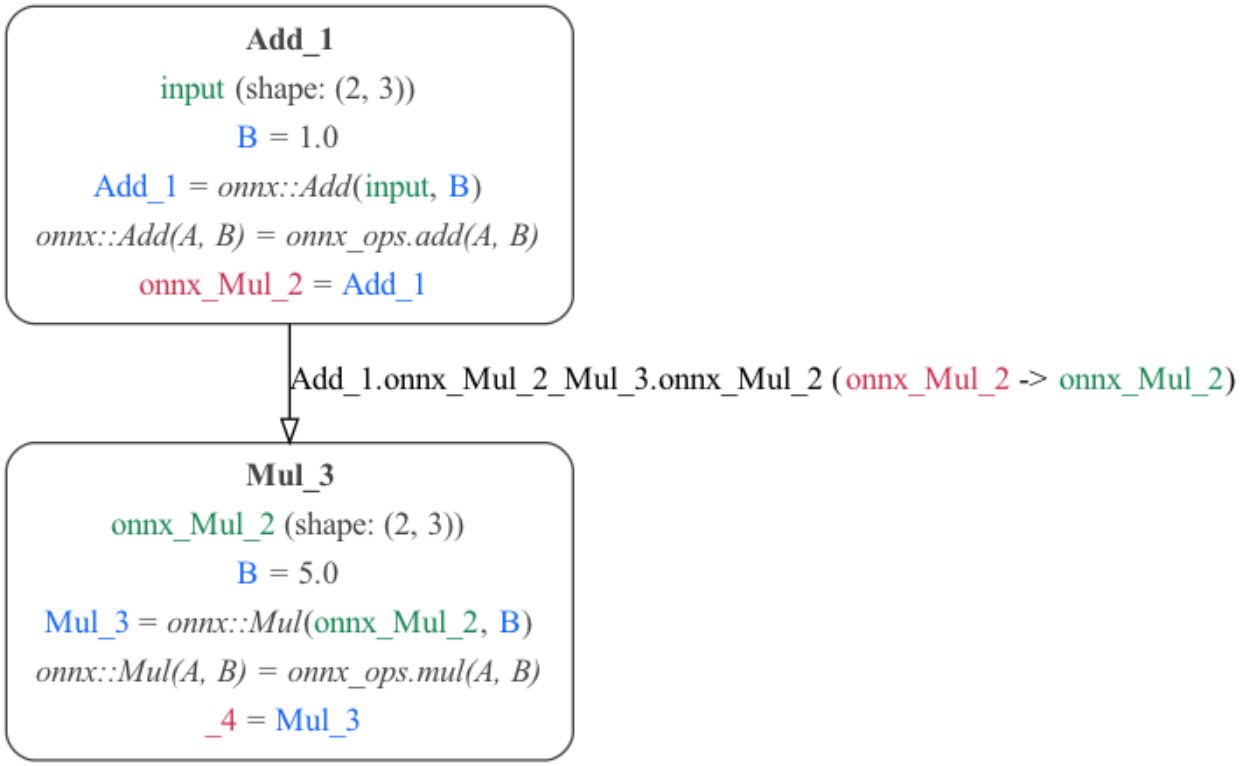
ONNX MDF CONVERTER

17.1 ONNX to MDF

17.1.1 AB Sequential Model - 2 nodes

Python source | JSON | YAML

This is an example of a PyTorch model with 2 nodes. First, the script saves the PyTorch model as ONNX and then converts this to MDF. The graphical view of the generated MDF is shown below.



17.1.2 ABC Sequential Model with Loop

Python source | JSON | YAML

Note: Example still in development!

This is an example of a PyTorch model that is implemented in `onnx_mdf/examples/simple_abc.py`. The model code is very simple:

```
import torch

class A(torch.nn.Module):
    def forward(self, x):
        return x + 1

@torch.jit.script
def loop_b(x, y):
    for i in range(int(y)):
        x = x / 10
    return x

class B(torch.nn.Module):
    def forward(self, x, y):
        return loop_b(x, y)

class C(torch.nn.Module):
    def forward(self, x):
        return x * 100

class ABC(torch.nn.Module):
    def __init__(self):
        super(ABC, self).__init__()
        self.A = A()
        self.B = B()
        self.C = C()

    def forward(self, x, B_loop_count):
        return self.C(self.B(self.A(x), B_loop_count))
```

This implements a PyTorch model with three modules. The modules process the input sequentially, and the inner `B` module has a loop construct.

It is exported to ONNX via a combination of tracing and scripting.

17.1.3 ABCD Branching Conditional Model

Python source | JSON | YAML

Note: Example still in development!

This is an example of a PyTorch model that have four components (A, B, C, D). We loop over the whole model 10 iterations. A is executed only on the first iteration, B is executed every iteration, C is executed every 5 times B is executed, and D is executed every 10 times B is executed. A, B, C, and D are each simple stateless linear functions. This type of conditional execution specification is common in PsyNeuLink. The PyTorch code for the model is fairly straightforward:

```
class Linear(torch.nn.Module):
    def __init__(self, slope=1.0, intercept=0.0):
        super(Linear, self).__init__()
        self.slope = slope
        self.intercept = intercept

    def forward(self, x):
        return self.slope*x + self.intercept


class ABCD(torch.nn.Module):
    def __init__(self, A, B, C, D):
        super(ABCD, self).__init__()
        self.A = A
        self.B = B
        self.C = C
        self.D = D

    def forward(self, x):

        # Since we are implementing conditions that reference the number of calls
        # to A and B, we need to keep track of this.
        num_A_calls = 0
        num_B_calls = 0

        # We need to initialize outputs, torchscript jit complains if c and d
        # are not defined in the FALSE branches of our conditionals.
        a = torch.zeros_like(x)
        b = torch.zeros_like(x)
        c = torch.zeros_like(x)
        d = torch.zeros_like(x)

        for i in range(10):

            # A: pnl.AtNCalls(A, 0),
            if num_A_calls == 0:
                a = self.A(x)
                num_A_calls = num_A_calls + 1

            # B: pnl.Always()
            b = self.B(a)
            num_B_calls = num_B_calls + 1

            # C: pnl.EveryNCalls(B, 5),
            if num_B_calls % 5 == 0:
                c = self.C(b)
```

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```
            # D: pnl.EveryNCalls(B, 10)
            if num_B_calls % 10 == 0:
                d = self.D(b)

        return c, d
```

The ONNX IR representation of this model is shown below. The small computation sub-graphs contained in the if and else body attributes are not shown. These are either a simple multiplication and addition or an identity.

CHAPTER

EIGHTEEN

INTERACTIONS BETWEEN PSYNEULINK AND MDF

18.1 Simple

18.1.1 ABCD

Python source | JSON | Reconstructed source

An example with four Nodes, as in other environments.

18.1.2 SimpleLinear

SimpleLinear-conditional

Python source | JSON | Reconstructed source

A three-Node example with Conditions.

SimpleLinear-timing

Python source | JSON | Reconstructed source

The same model as in SimpleLinear-conditional with Conditions for timeline scheduling. Note: these conditions are still not fully implemented by the scheduler.

18.2 Nested

18.2.1 Nested without scheduling

Python source | JSON | Reconstructed source

A model with several Nodes in two Graphs, one of which contains the other.

18.2.2 Nested with scheduling

Python source | JSON | Reconstructed source

A similar model as in Nested without scheduling with Conditions.

18.3 SimpleFN

Python source | JSON | Reconstructed source

An example with a single Node using the PsyNeuLink implementation of the FitzHugh–Nagumo model.

18.3.1 SimpleFN-timing

Python source | JSON | Reconstructed source

The same model as in SimpleFN with Conditions for timeline scheduling. Note: these conditions are still not fully implemented by the scheduler.

18.3.2 SimpleFN-conditional

Python source | JSON | Reconstructed source

The same model in SimpleFN with scheduling Conditions that mimic the behavior in SimpleFN-timing.

18.4 Stroop

Python source | JSON | Reconstructed source

A model representing the Stroop effect with conflict monitoring that uses Conditions.

CHAPTER

NINETEEN

PYTORCH AND MDF

1. MDF to Pytorch
2. Pytorch to MDF

19.1 MDF to PyTorch

To export an MDF model to PyTorch, provide an MDF model as an input to the mdf_to_pytorch() function.

The output of `mdf_to_pytorch` is a PyTorch model.

```
mdf_to_pytorch(
      mdf_model: model in MDF format
      eval_models: Set Evaluation of model to True or False
      version: MDF version
      model_input: input file name
)
```

It returns a dictionary where `key` = `model name` and `value` = `PyTorch model object`.

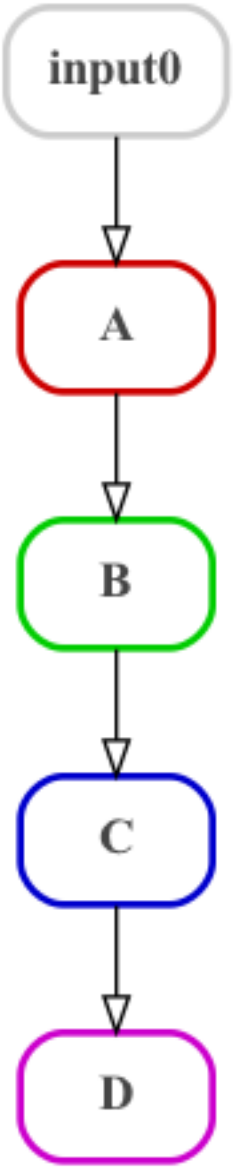
A test script demonstrating conversion of MDF model to PyTorch is at MDF_to_PyTorch.py. This converts multiple MDF models to their respective PyTorch models. The converted models are available in folder: MDF_PyTorch.

19.1.1 Examples

Below are some working examples of this functionality.

1) Simple ABCD example

We convert one of the sample MDF examples ABCD.json:



This is converted to PyTorch and can be seen here: ABCD_pytorch.py.

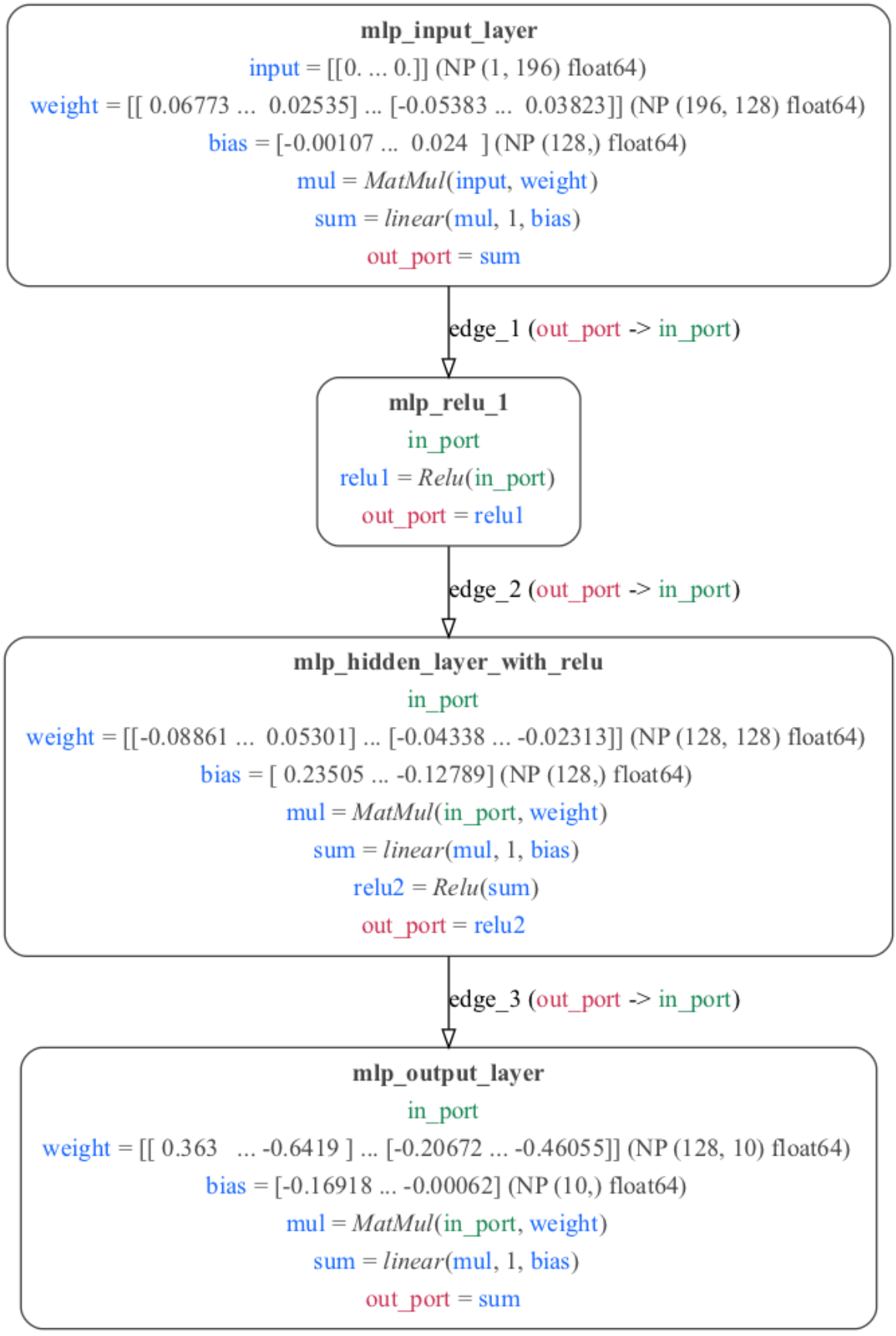
The PyTorch model is further converted to ONNX ABCD.onnx. An image of the contents of the ONNX model (visualized using NETRON) is below.

2) Multi-Layer Perceptron MDF to PyTorch Conversion:

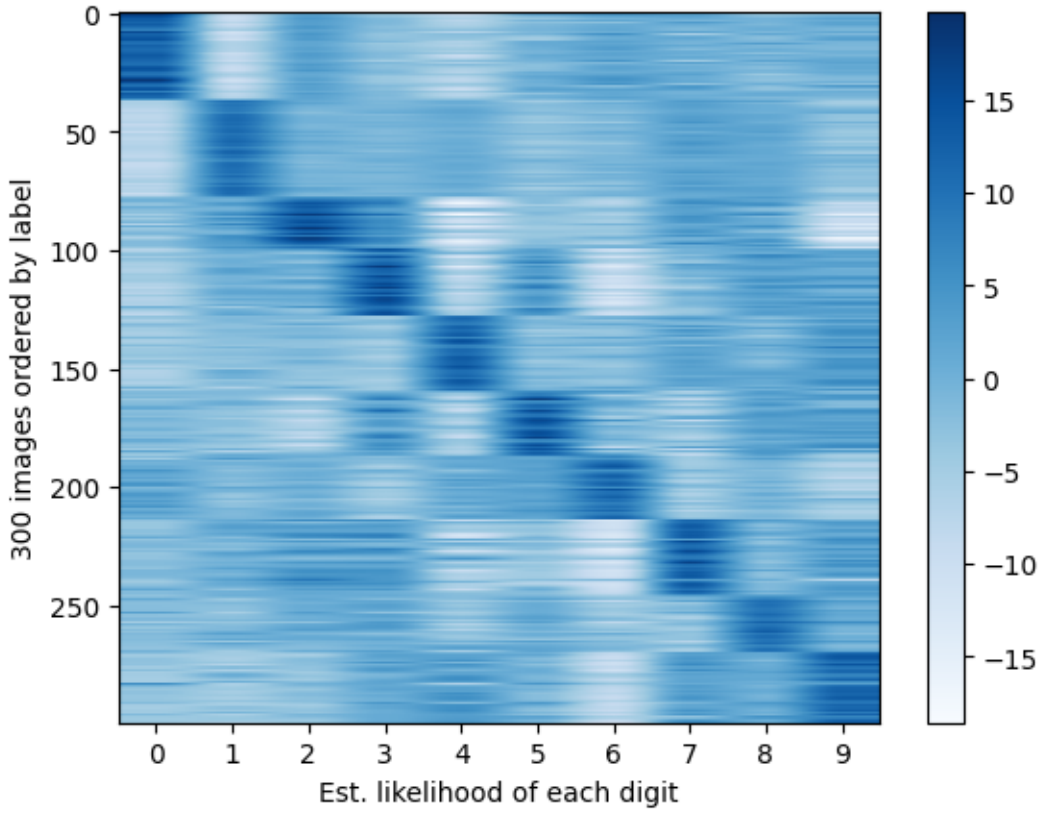
To run an example where a simple Multi-Layer Perceptron (MLP) created using the MDF specification and executed using sample digit-recognition data, run:

```
python mlp_pure_mdf.py
```

A graph of the network can be created with `python mlp_pure_mdf.py -graph`:


mlp_input_layer
input = [[0. ... 0.]] (NP (1, 196) float64)
weight = [[0.06773 ... 0.02535] ... [-0.05383 ... 0.03823]] (NP (196, 128) float64)
bias = [-0.00107 ... 0.024] (NP (128,) float64)
mul = MatMul(input, weight)
sum = linear(mul, 1, bias)
out_port = sum
edge_1 (out_port -> in_port)
mlp_relu_1
in_port
relu1 = Relu(in_port)
out_port = relu1
edge_2 (out_port -> in_port)
mlp_hidden_layer_with_relu
in_port
weight = [[-0.08861 ... 0.05301] ... [-0.04338 ... -0.02313]] (NP (128, 128) float64)
bias = [0.23505 ... -0.12789] (NP (128,) float64)
mul = MatMul(in_port, weight)
sum = linear(mul, 1, bias)
relu2 = Relu(sum)
out_port = relu2
edge_3 (out_port -> in_port)
mlp_output_layer
in_port
weight = [[0.363 ... -0.6419] ... [-0.20672 ... -0.46055]] (NP (128, 10) float64)
bias = [-0.16918 ... -0.00062] (NP (10,) float64)
mul = MatMul(in_port, weight)
sum = linear(mul, 1, bias)
out_port = sum

The network can be run against images from the MNIST database with: `python mlp_pure_mdf.py -run`, and produce 98% accuracy. The image below shows the results of 300 images:



19.2 PyTorch to MDF

The current implementation of our PyTorch to MDF conversion functionality is built on top of the TorchScript infrastructure provided by PyTorch. PyTorch models that can be translated to TorchScript (via `torch.jit.script` or `torch.jit.trace`) should then be able to be converted to their MDF representation automatically. Below are several working examples of this functionality.

To perform an PyTorch to MDF conversion, provide a PyTorch model as an input to the pytorch_to_mdf() function which is available in importer.py. The output of `pytorch_to_mdf()` is an MDF model.

```
pytorch_to_mdf(
      model: The model to translate into MDF.
      args: The input arguments for this model. If a nn.Module is passed then the␣
↪model will be traced with these
          inputs. If a ScriptModule is passed, they are still needed to deterimine␣
↪input shapes.
      trace: Force the use of tracing to compile the model. The default is to use␣
↪torch.jit.script
      use_onnx_ops: Use ONNX ops when possible, fallback to ATEN ops when not␣
↪available. Default is True. If False,
          use only ATEN ops.
)
```

Returns a translated MDF model.

19.2.1 Examples of usage

1) Simple PyTorch To MDF

This is a simple fully-connected neural network model example consisting of input image of 224 * 224 * 3 and resulting in two classes as the output To run an example of converting a PyTorch model written in PyTorch to its MDF representation simply run:

```
python simple_pytorch_to_mdf.py
```

Code is present in simple_pytorch_to_mdf.py The graph representation of the ONNX model can be generated with:

```
python simple_pytorch_to_mdf.py -graph-onnx
```

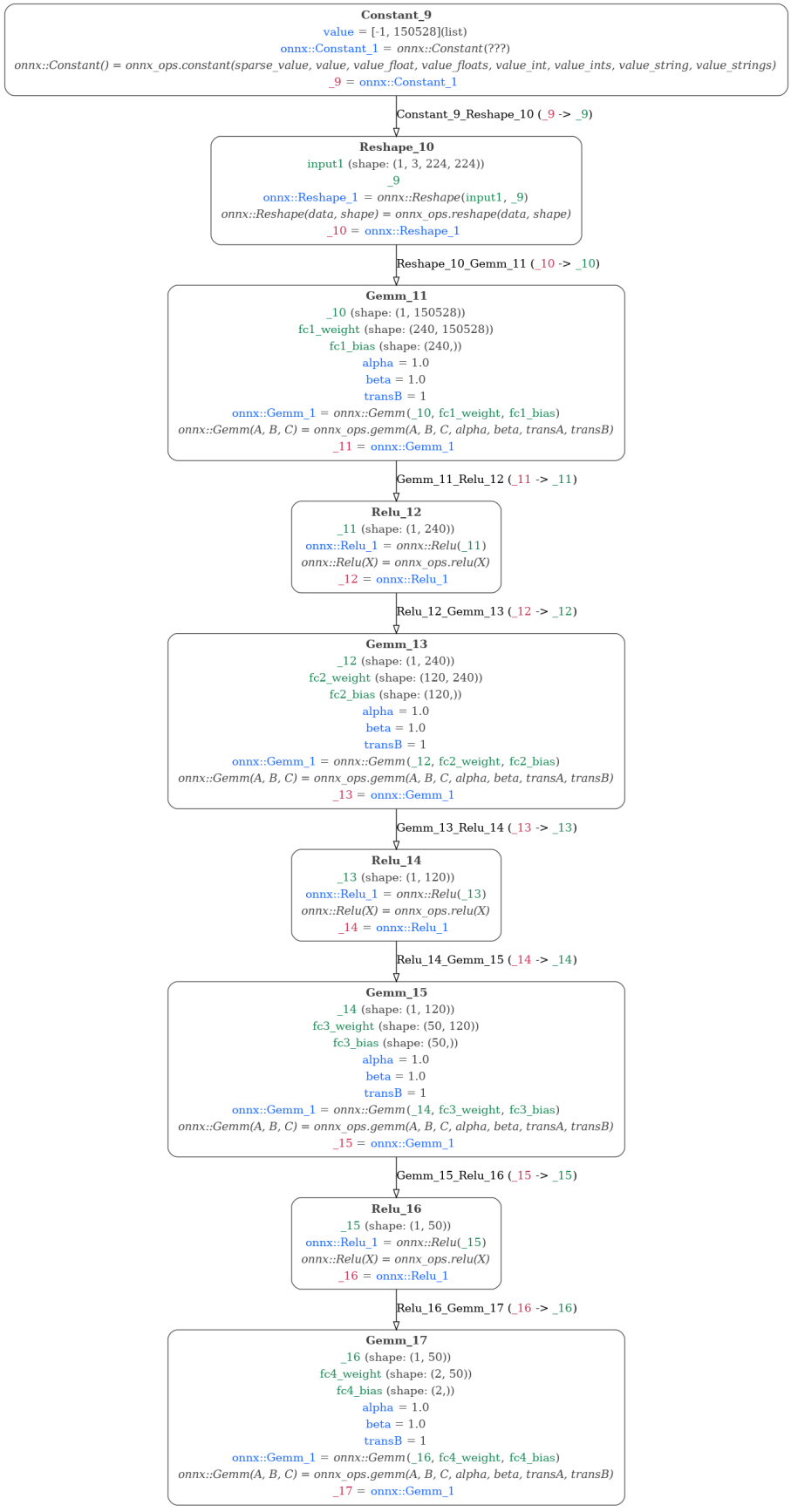
NOTE: This command will run the NETRON python server on the local host where we can export the graph as svg/png

The graph representation of the MDF model can be generated with:

```
python simple_pytorch_to_mdf.py -graph
```

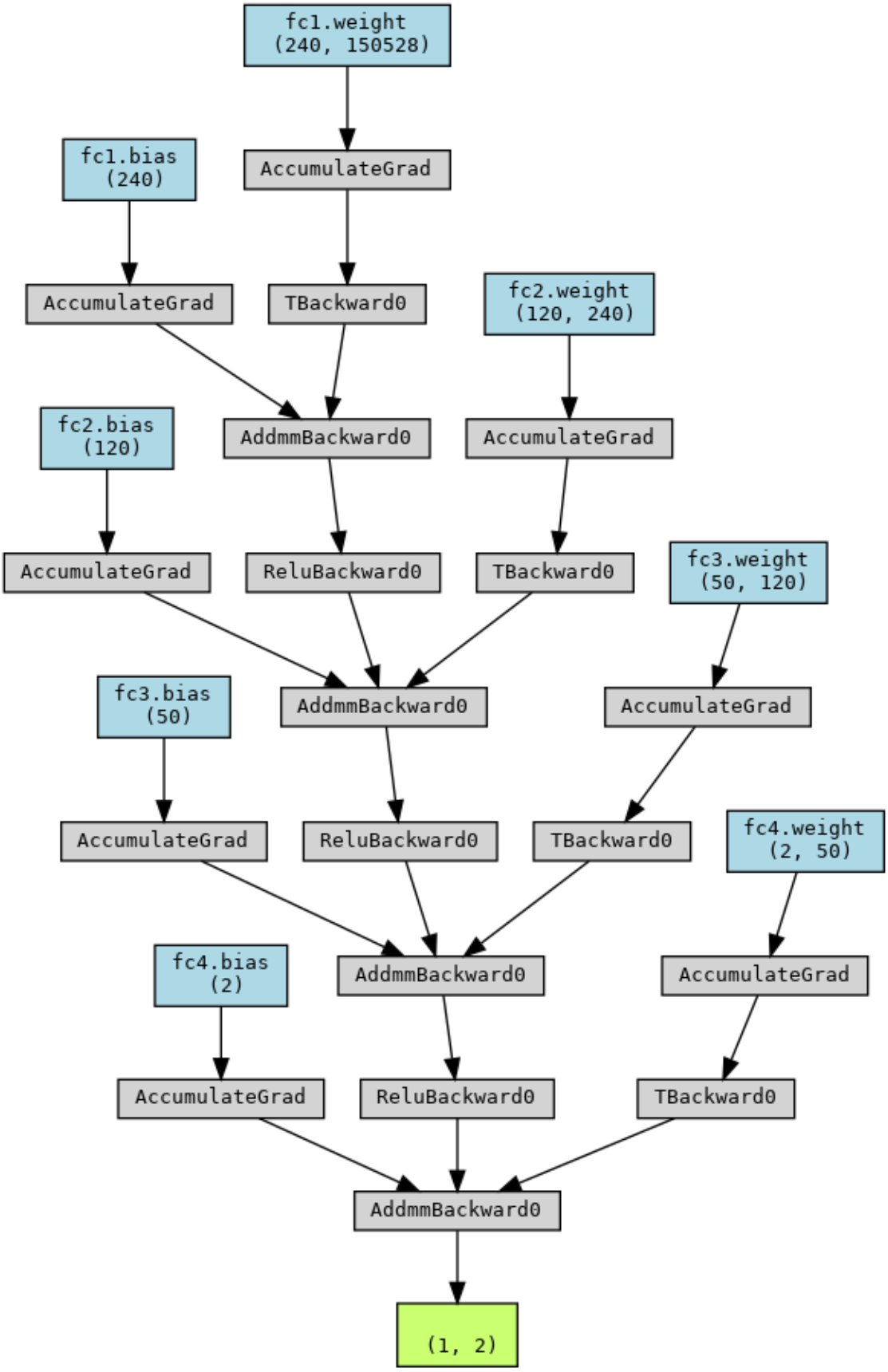
Graphical export from MDF level 1:

Graphical export from MDF level 3:


Constant_9
value = [-1, 150528](list)
onnx::Constant_1 = onnx::Constant(???)
onnx::Constant() = onnx_ops.constant(sparse_value, value, value_float, value_floats, value_int, value_ints, value_string, value_strings)
_9 = onnx::Constant_1
Constant_9_Reshape_10 (_9 -> _9)
Reshape_10
input1 (shape: (1, 3, 224, 224))
_9
onnx::Reshape_1 = onnx::Reshape(input1, _9)
onnx::Reshape(data, shape) = onnx_ops.reshape(data, shape)
_10 = onnx::Reshape_1
Reshape_10_Gemm_11 (_10 -> _10)
Gemm_11
_10 (shape: (1, 150528))
fc1_weight (shape: (240, 150528))
fc1_bias (shape: (240,))
alpha = 1.0
beta = 1.0
transB = 1
onnx::Gemm_1 = onnx::Gemm(_10, fc1_weight, fc1_bias)
onnx::Gemm(A, B, C) = onnx_ops.gemm(A, B, C, alpha, beta, transA, transB)
_11 = onnx::Gemm_1
Gemm_11_Relu_12 (_11 -> _11)
Relu_12
_11 (shape: (1, 240))
onnx::Relu_1 = onnx::Relu(_11)
onnx::Relu(X) = onnx_ops.relu(X)
_12 = onnx::Relu_1
Relu_12_Gemm_13 (_12 -> _12)
Gemm_13
_12 (shape: (1, 240))
fc2_weight (shape: (120, 240))
fc2_bias (shape: (120,))
alpha = 1.0
beta = 1.0
transB = 1
onnx::Gemm_1 = onnx::Gemm(_12, fc2_weight, fc2_bias)
onnx::Gemm(A, B, C) = onnx_ops.gemm(A, B, C, alpha, beta, transA, transB)
_13 = onnx::Gemm_1
Gemm_13_Relu_14 (_13 -> _13)
Relu_14
_13 (shape: (1, 120))
onnx::Relu_1 = onnx::Relu(_13)
onnx::Relu(X) = onnx_ops.relu(X)
_14 = onnx::Relu_1
Relu_14_Gemm_15 (_14 -> _14)
Gemm_15
_14 (shape: (1, 120))
fc3_weight (shape: (50, 120))
fc3_bias (shape: (50,))
alpha = 1.0
beta = 1.0
transB = 1
onnx::Gemm_1 = onnx::Gemm(_14, fc3_weight, fc3_bias)
onnx::Gemm(A, B, C) = onnx_ops.gemm(A, B, C, alpha, beta, transA, transB)
_15 = onnx::Gemm_1
Gemm_15_Relu_16 (_15 -> _15)
Relu_16
_15 (shape: (1, 50))
onnx::Relu_1 = onnx::Relu(_15)
onnx::Relu(X) = onnx_ops.relu(X)
_16 = onnx::Relu_1
Relu_16_Gemm_17 (_16 -> _16)
Gemm_17
_16 (shape: (1, 50))
fc4_weight (shape: (2, 50))
fc4_bias (shape: (2,))
alpha = 1.0
beta = 1.0
transB = 1
onnx::Gemm_1 = onnx::Gemm(_16, fc4_weight, fc4_bias)
onnx::Gemm(A, B, C) = onnx_ops.gemm(A, B, C, alpha, beta, transA, transB)
_17 = onnx::Gemm_1

To visualize the PyTorch model:

```
python simple_pytorch_to_mdf.py -graph-torch
```


fc1.weight
(240, 150528)
fc1.bias
(240)
AccumulateGrad
AccumulateGrad
TBackward0
fc2.weight
(120, 240)
fc2.bias
(120)
AddmmBackward0
AccumulateGrad
AccumulateGrad
ReluBackward0
TBackward0
fc3.weight
(50, 120)
fc3.bias
(50)
AddmmBackward0
AccumulateGrad
AccumulateGrad
ReluBackward0
TBackward0
fc4.weight
(2, 50)
fc4.bias
(2)
AddmmBackward0
AccumulateGrad
AccumulateGrad
ReluBackward0
TBackward0
AddmmBackward0
(1, 2)

The MDF for this model is the written to simple_pytorch_to_mdf.json. The model is then executed via the MDF scheduler and the results are compared to the native execution in PyTorch.

2) Inception Blocks Model

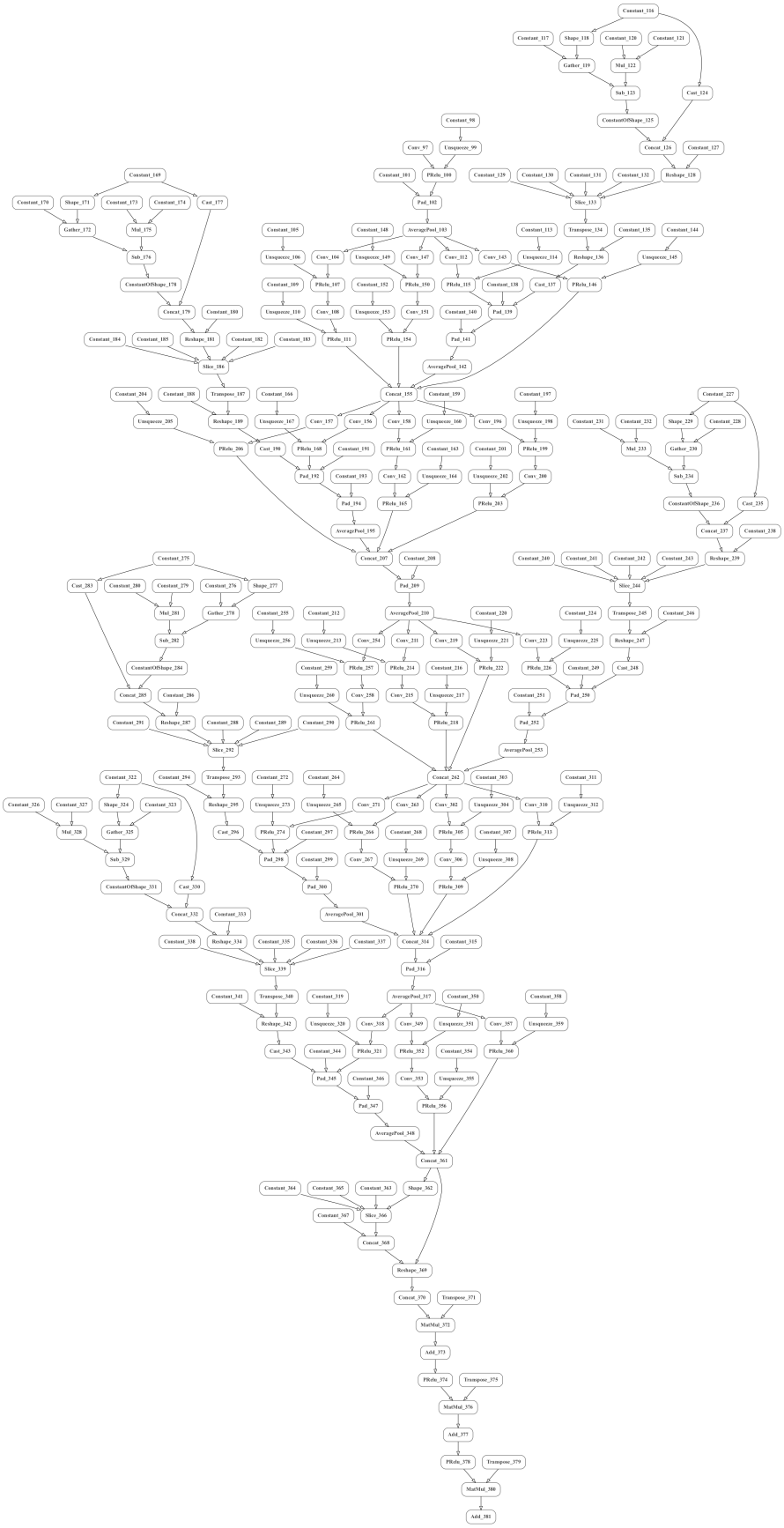
To run an example of converting a PyTorch InceptionV3 like model written in PyTorch to its MDF representation simply run:

```
python inception.py
```

Code is present in inception.py This will define the model in PyTorch, invoke the TorchScript tracing compiler, convert the underlying IR representation of the model to MDF. The MDF for this model is the written to inception.json. The model is then executed via the MDF scheduler and the results are compared to the native execution in PyTorch.

The graph representation of the MDF model can be generated with:

```
python inception.py -graph
```


Constant_116
Constant_117
Shape_118
Constant_120
Constant_121
Gather_119
Mul_122
Sub_123
Cast_124
ConstantOfShape_125
Concat_126
Constant_127
Constant_99
Conv_97
Unsqueeze_99
Constant_101
PRelu_100
Constant_129
Constant_130
Constant_131
Constant_132
Reshape_128
Pad_102
Slice_133
Constant_169
Constant_170
Shape_171
Constant_173
Constant_174
Cast_177
Gather_172
Mul_175
Sub_176
ConstantOfShape_178
Concat_179
Constant_180
Constant_105
Unsqueeze_106
Conv_104
Constant_148
AveragePool_183
Unsqueeze_149
Conv_147
Conv_112
Conv_143
Constant_113
Transpose_134
Constant_135
Constant_144
Unsqueeze_114
Reshape_136
Unsqueeze_145
Constant_109
PRelu_107
Constant_152
PRelu_150
PRelu_115
Constant_138
Cast_137
PRelu_146
Unsqueeze_110
Conv_108
Unsqueeze_153
Conv_151
Constant_140
Pad_139
Constant_184
Constant_185
Reshape_181
Constant_182
Constant_183
PRelu_111
PRelu_154
Pad_141
Slice_186
AveragePool_142
Constant_204
Constant_188
Transpose_187
Constant_166
Concat_155
Constant_159
Constant_197
Constant_227
Unsqueeze_205
Reshape_189
Unsqueeze_167
Conv_157
Conv_156
Conv_158
Unsqueeze_160
Conv_196
Unsqueeze_198
Constant_231
Constant_232
Shape_229
Constant_228
PRelu_206
Cast_198
PRelu_168
Constant_191
PRelu_161
Constant_163
Constant_201
PRelu_199
Mul_233
Gather_230
Pad_192
Constant_193
Conv_162
Unsqueeze_164
Unsqueeze_202
Conv_200
Sub_234
Pad_194
PRelu_165
PRelu_203
ConstantOfShape_236
Cast_235
AveragePool_195
Concat_237
Constant_238
Constant_375
Concat_207
Constant_208
Constant_240
Constant_241
Constant_242
Constant_243
Reshape_239
Cast_283
Constant_280
Constant_279
Constant_276
Shape_277
Pad_289
Slice_244
Mul_281
Gather_278
Constant_255
Constant_212
AveragePool_210
Constant_220
Constant_224
Transpose_245
Constant_246
Sub_282
Unsqueeze_256
Unsqueeze_213
Conv_254
Conv_211
Conv_219
Unsqueeze_221
Conv_223
Unsqueeze_225
Reshape_247
ConstantOfShape_284
Constant_259
PRelu_257
PRelu_214
Constant_216
PRelu_222
PRelu_226
Constant_249
Cast_248
Concat_285
Constant_286
Unsqueeze_260
Conv_258
Conv_225
Unsqueeze_217
Constant_251
Pad_250
Constant_291
Reshape_287
Constant_288
Constant_289
Constant_290
PRelu_261
PRelu_218
Pad_252
Slice_292
AveragePool_253
Constant_322
Constant_294
Transpose_295
Constant_272
Constant_264
Concat_262
Constant_303
Constant_311
Constant_326
Constant_327
Shape_324
Constant_323
Reshape_295
Unsqueeze_273
Unsqueeze_265
Conv_271
Conv_263
Conv_302
Unsqueeze_304
Conv_310
Unsqueeze_312
Mul_328
Gather_325
Cast_296
PRelu_274
Constant_297
PRelu_266
Constant_268
PRelu_305
Constant_307
PRelu_313
Sub_329
Pad_298
Constant_299
Conv_267
Unsqueeze_269
Conv_306
Unsqueeze_308
ConstantOfShape_331
Cast_330
Pad_360
PRelu_270
PRelu_309
Concat_332
Constant_333
AveragePool_301
Constant_338
Reshape_334
Constant_335
Constant_336
Constant_337
Concat_314
Constant_315
Slice_339
Pad_316
Constant_341
Transpose_340
Constant_319
AveragePool_317
Constant_350
Constant_358
Reshape_342
Unsqueeze_320
Conv_318
Conv_349
Unsqueeze_351
Conv_357
Unsqueeze_359
Cast_343
Constant_344
PRelu_321
PRelu_352
Constant_354
PRelu_360
Pad_345
Constant_346
Conv_353
Unsqueeze_355
Pad_347
PRelu_356
AveragePool_348
Concat_361
Constant_364
Constant_365
Constant_363
Shape_362
Constant_367
Slice_366
Concat_368
Reshape_369
Concat_370
Transpose_371
MatMul_372
Add_373
PRelu_374
Transpose_375
MatMul_376
Add_377
PRelu_378
Transpose_379
MatMul_380
Add_381

CHAPTER

TWENTY

INTERACTIONS BETWEEN MDF AND QUANTUM COMPUTING TECHNOLOGIES

Starting summer 2021, we will develop tools for interfacing between MDF and quantum computers. This interface is motivated by expectations that quantum hardware will provide speedups for solving Ising-type MDF problems. We will address both gate- and annealing- based quantum computers:

- for gate-based quantum computers, we will bridge from MDF to OpenQASM, the leading quantum Intermediate Representation.
- for annealing-based quantum computers, we will target platforms such as D-Wave Ocean.

Our work will be agnostic to the exact quantum algorithm/solver used, though we will provide sample implementations using Variational Quantum Eigensolver (VQE) and Quantum Approximate Optimization Algorithm.

As a first step, we have begun developing implementations targeting quantum hardware for the key computations in several cognitive models as listed below. Next, we will extend MDF so that quantum implementations such as the ones we develop, can be expressed in it.

CHAPTER

TWENTYONE

MDF IN WEBGME

This contains a tool for converting the MDF specification into JSON compatible with JSON importer. This allows us to programmatically create a metamodel and, as a result, use WebGME as a design environment for MDF.

21.1 Quick Start

21.1.1 Starting WebGME app

First, install the mdf_gme following:

- NodeJS (LTS recommended)
- MongoDB

Second, start mongodb locally by running the `mongod` executable in your mongodb installation (you may need to create a `data` directory or set `--dbpath`).

Then, run `webgme start` from the project root to start . Finally, navigate to `http://localhost:8888` to start using mdf_gme!

21.1.2 Loading the spec into WebGME

First, install dependencies with `npm install`. Then convert the MDF specification using

```
node spec_to_gme.js path/to/MDF/spec.json
```

Finally, import the JSON into WebGME just like the examples (suffixed with "_meta")!

21.1.3 Loading instances to and from WebGME importable JSON and MDF

```
node bin/instance_converter path/to/MDForGME/instance.json
```

CHAPTER

TWENTYTWO

SPECIFICATION OF STANDARD FUNCTIONS IN MODECI V0.4

Note: the ModECI MDF specification is still in development! See here for ongoing discussions. These functions are defined in https://github.com/ModECI/MDF/blob/main/src/modeci_mdf/standard_functions.py

22.1 All functions:

| MatMul | Relu | change_goal | check_termination | conflict_resolution_function | cos | cosh | exponential | linear | logistic | onnx::Abs | onnx::Acos | onnx::Acosh | onnx::Add | onnx::And | onnx::ArgMax | onnx::ArgMin | onnx::Asin | onnx::Asinh | onnx::Atan | onnx::Atanh | onnx::AveragePool | onnx::BatchNormalization | onnx::Bernoulli | onnx::BitShift | onnx::Cast | onnx::CastLike | onnx::Ceil | onnx::Celu | onnx::Clip | onnx::Compress | onnx::Concat | onnx::ConcatFromSequence | onnx::Constant | onnx::ConstantOfShape | onnx::Conv | onnx::ConvInteger | onnx::ConvTranspose | onnx::Cos | onnx::Cosh | onnx::CumSum | onnx::DepthToSpace | onnx::DequantizeLinear | onnx::Det | onnx::Div | onnx::Dropout | onnx::DynamicQuantizeLinear | onnx::Einsum | onnx::Elu | onnx::Equal | onnx::Erf | onnx::Exp | onnx::Expand | onnx::EyeLike | onnx::Flatten | onnx::Floor | onnx::GRU | onnx::Gather | onnx::GatherElements | onnx::GatherND | onnx::Gemm | onnx::GlobalAveragePool | onnx::GlobalLpPool | onnx::GlobalMaxPool | onnx::Greater | onnx::GreaterOrEqual | onnx::HardSigmoid | onnx::HardSwish | onnx::Hardmax | onnx::Identity | onnx::If | onnx::InstanceNormalization | onnx::IsInf | onnx::IsNaN | onnx::LRN | onnx::LSTM | onnx::LeakyRelu | onnx::Less | onnx::LessOrEqual | onnx::Log | onnx::LogSoftmax | onnx::Loop | onnx::LpNormalization | onnx::LpPool | onnx::MatMul | onnx::MatMulInteger | onnx::Max | onnx::MaxPool | onnx::MaxRoiPool | onnx::MaxUnpool | onnx::Mean | onnx::MeanVarianceNormalization | onnx::Min | onnx::Mod | onnx::Mul | onnx::Multinomial | onnx::Neg | onnx::NegativeLogLikelihoodLoss | onnx::NonMaxSuppression | onnx::NonZero | onnx::Not | onnx::OneHot | onnx::Optional | onnx::OptionalGetElement | onnx::OptionalHasElement | onnx::Or | onnx::PRelu | onnx::Pad | onnx::Pow | onnx::QLinearConv | onnx::QLinearMatMul | onnx::QuantizeLinear | onnx::RNN | onnx::RandomNormal | onnx::RandomNormalLike | onnx::RandomUniform | onnx::RandomUniformLike | onnx::Range | onnx::Reciprocal | onnx::ReduceL1 | onnx::ReduceL2 | onnx::ReduceLogSum | onnx::ReduceLogSumExp | onnx::ReduceMax | onnx::ReduceMean | onnx::ReduceMin | onnx::ReduceProd | onnx::ReduceSum | onnx::ReduceSumSquare | onnx::Relu | onnx::Reshape | onnx::Resize | onnx::ReverseSequence | onnx::RoiAlign | onnx::Round | onnx::Scan | onnx::Scatter | onnx::ScatterElements | onnx::ScatterND | onnx::Selu | onnx::SequenceAt | onnx::SequenceConstruct | onnx::SequenceEmpty | onnx::SequenceErase | onnx::SequenceInsert | onnx::SequenceLength | onnx::Shape | onnx::Shrink | onnx::Sigmoid | onnx::Sign | onnx::Sin | onnx::Sinh | onnx::Size | onnx::Slice | onnx::Softmax | onnx::SoftmaxCrossEntropyLoss | onnx::Softplus | onnx::Softsign | onnx::SpaceToDepth | onnx::Split | onnx::SplitToSequence | onnx::Sqrt | onnx::Squeeze | onnx::StringNormalizer | onnx::Sub | onnx::Sum | onnx::Tan | onnx::Tanh | onnx::TfIdfVectorizer | onnx::ThresholdedRelu | onnx::Tile | onnx::TopK | onnx::Transpose | onnx::Trilu | onnx::Unique | onnx::Unsqueeze | onnx::Upsample | onnx::Where | onnx::Xor | pattern_matching_function | retrieve_chunk | sin | sinh | tan | tanh | update_goal | update_retrieval |

22.2 linear

22.3 logistic

22.4 exponential

22.5 sin

22.6 cos

22.7 tan

22.8 sinh

22.9 cosh

22.10 tanh

22.11 MatMul

22.12 Relu

22.13 onnx::LSTM

Notations:

`X` - input tensor

`i` - input gate

`o` - output gate

`f` - forget gate

`c` - cell gate

`t` - time step (t-1 means previous time step)

`W[iofc]` - W parameter weight matrix for input, output, forget, and cell gates

`R[iofc]` - R recurrence weight matrix for input, output, forget, and cell gates

`Wb[iofc]` - W bias vectors for input, output, forget, and cell gates

`Rb[iofc]` - R bias vectors for input, output, forget, and cell gates

`P[iof]` - P peephole weight vector for input, output, and forget gates

`WB[iofc]` - W parameter weight matrix for backward input, output, forget, and cell gates

`RB[iofc]` - R recurrence weight matrix for backward input, output, forget, and cell gates

`WBb[iofc]` - W bias vectors for backward input, output, forget, and cell gates

`RBb[iofc]` - R bias vectors for backward input, output, forget, and cell gates

`PB[iof]` - P peephole weight vector for backward input, output, and forget gates

`H` - Hidden state

`num_directions` - 2 if direction == bidirectional else 1

Activation functions:

Relu(x) - max(0, x)

Tanh(x) - (1 - e^{-2x})/(1 + e^{-2x})

Sigmoid(x) - 1/(1 + e^{-x})

(NOTE: Below are optional)

Affine(x) - alpha*x + beta

LeakyRelu(x) - x if x >= 0 else alpha * x

ThresholdedRelu(x) - x if x >= alpha else 0

ScaledTanh(x) - alpha*Tanh(beta*x)

HardSigmoid(x) - min(max(alpha*x + beta, 0), 1)

Elu(x) - x if x >= 0 else alpha*(e^x - 1)

Softsign(x) - x/(1 + |x|)

Softplus(x) - log(1 + e^x)

Equations (Default: f=Sigmoid, g=Tanh, h=Tanh):

- it = f(Xt*(Wi^T) + Ht-1*(Ri^T) + Pi (.) Ct-1 + Wbi + Rbi)
- ft = f(Xt*(Wf^T) + Ht-1*(Rf^T) + Pf (.) Ct-1 + Wbf + Rbf)
- ct = g(Xt*(Wc^T) + Ht-1*(Rc^T) + Wbc + Rbc)
- Ct = ft (.) Ct-1 + it (.) ct
- ot = f(Xt*(Wo^T) + Ht-1*(Ro^T) + Po (.) Ct + Wbo + Rbo)
- Ht = ot (.) h(Ct) This operator has **optional** inputs/outputs. See the doc for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

22.14 onnx::Identity

22.15 onnx::Abs

22.16 onnx::BatchNormalization

Output case #1: Y, running_mean, running_var (training_mode=True) Output case #2: Y (training_mode=False)

When training_mode=False, extra outputs are invalid. The outputs are updated as follows when training_mode=True:

```
running_mean = input_mean * momentum + current_mean * (1 - momentum)
running_var = input_var * momentum + current_var * (1 - momentum)

Y = (X - current_mean) / sqrt(current_var + epsilon) * scale + B

where:

current_mean = ReduceMean(X, axis=all_except_channel_index)
current_var =  ReduceVar(X, axis=all_except_channel_index)

Notice that ReduceVar refers to the population variance, and it equals to
sum(sqrd(x_i - x_avg)) / N
where N is the population size (this formula does not use sample size N - 1).
```

The computation of ReduceMean and ReduceVar uses float to avoid overflow for float16 inputs.

When training_mode=False:

```
Y = (X - input_mean) / sqrt(input_var + epsilon) * scale + B
```

For previous (depreciated) non-spatial cases, implementors are suggested to flatten the input shape to (N x C * D1 * D2 * ... * Dn) before a BatchNormalization Op. This operator has **optional** inputs/outputs. See the doc for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

22.17 onnx::Mean

22.18 onnx::Add

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

(Opset 14 change): Extend supported types to include uint8, int8, uint16, and int16.

22.19 onnx::GlobalMaxPool

22.20 onnx::Cast

Casting from string tensor in plain (e.g., "3.14" and "1000") and scientific numeric representations (e.g., "1e-5" and "1E8") to float types is supported. For example, converting string "100.5" to an integer may result 100. There are some string literals reserved for special floating-point values; "+INF" (and "INF"), "-INF", and "NaN" are positive infinity, negative infinity, and not-a-number, respectively. Any string which can exactly match "+INF" in a case-insensitive way would be mapped to positive infinite. Similarly, this case-insensitive rule is applied to "INF" and "NaN". When casting from numeric tensors to string tensors, plain floating-point representation (such as "314.15926") would be used. Converting non-numerical-literal string such as "Hello World!" is an undefined behavior. Cases of converting string representing floating-point arithmetic value, such as "2.718", to INT is an undefined behavior.

Conversion from a numerical type to any numerical type is always allowed. User must be aware of precision loss and value change caused by range difference between two types. For example, a 64-bit float 3.1415926459 may be round

to a 32-bit float 3.141592. Similarly, converting an integer 36 to Boolean may produce 1 because we truncate bits which can't be stored in the targeted type.

In more detail, the conversion among numerical types should follow these rules:

- Casting from floating point to:
  - floating point: +/- infinity if OOR (out of range).
  - fixed point: undefined if OOR.
  - bool: +/- 0.0 to False; all else to True.
- Casting from fixed point to:
  - floating point: +/- infinity if OOR. (+ infinity in the case of uint)
  - fixed point: when OOR, discard higher bits and reinterpret (with respect to two's complement representation for signed types). For example, 200 (int16) -> -56 (int8).
  - bool: zero to False; nonzero to True.
- Casting from bool to:
  - floating point: `{1.0, 0.0}`.
  - fixed point: `{1, 0}`.
  - bool: no change.

22.21 onnx::AveragePool

```
* pad_shape[i] is sum of pads along axis i
```

`auto_pad` is a DEPRECATED attribute. If you are using them currently, the output spatial shape will be following:

```
VALID: output_spatial_shape[i] = ceil((input_spatial_shape[i] - kernel_spatial_
↪shape[i] + 1) / strides_spatial_shape[i])
SAME_UPPER or SAME_LOWER: output_spatial_shape[i] = ceil(input_spatial_shape[i] /␣
↪strides_spatial_shape[i])
```

And pad shape will be following if `SAME_UPPER` or `SAME_LOWER`:

```
pad_shape[i] = (output_spatial_shape[i] - 1) * strides_spatial_shape[i] + kernel_
↪spatial_shape[i] - input_spatial_shape[i]
```

The output of each pooling window is divided by the number of elements (exclude pad when attribute count_include_pad is zero).

22.22 onnx::And

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.23 onnx::LRN

square_sum[n, c, d1, . . . , dk] = sum(X[n, i, d1, . . . , dk] ^ 2), where max(0, c - floor((size - 1) / 2)) <= i <= min(C - 1, c + ceil((size - 1) / 2)).

Y[n, c, d1, . . . , dk] = X[n, c, d1, . . . , dk] / (bias + alpha / size * square_sum[n, c, d1, . . . , dk]) ^ beta

22.24 onnx::ArgMax

22.25 onnx::Resize

22.26 onnx::Expand

22.27 onnx::Neg

22.28 onnx::Mul

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

(Opset 14 change): Extend supported types to include uint8, int8, uint16, and int16.

22.29 onnx::ArgMin

22.30 onnx::Exp

22.31 onnx::Div

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

(Opset 14 change): Extend supported types to include uint8, int8, uint16, and int16.

22.32 onnx::ReverseSequence

For each slice i iterating on batch axis, the operator reverses the first sequence_lens[i] elements on time axis, and copies elements whose index's beyond sequence_lens[i] to the output. So the output slice i contains reversed sequences on the first sequence_lens[i] elements, then have original values copied for the other elements.

Example 1: input = [[0.0, 4.0, 8.0, 12.0], [1.0, 5.0, 9.0, 13.0], [2.0, 6.0, 10.0, 14.0], [3.0, 7.0, 11.0, 15.0]] sequence_lens = [4, 3, 2, 1] time_axis = 0 batch_axis = 1

output = [[3.0, 6.0, 9.0, 12.0], [2.0, 5.0, 8.0, 13.0], [1.0, 4.0, 10.0, 14.0], [0.0, 7.0, 11.0, 15.0]]

Example 2: input = [[0.0, 1.0, 2.0, 3.0], [4.0, 5.0, 6.0, 7.0], [8.0, 9.0, 10.0, 11.0], [12.0, 13.0, 14.0, 15.0]] sequence_lens = [1, 2, 3, 4] time_axis = 1 batch_axis = 0

output = [[0.0, 1.0, 2.0, 3.0], [5.0, 4.0, 6.0, 7.0], [10.0, 9.0, 8.0, 11.0], [15.0, 14.0, 13.0, 12.0]]

22.33 onnx::Ceil

22.34 onnx::DepthToSpace

b, c, h, w = x.shape

tmp = np.reshape(x, [b, blocksize, blocksize, c // (blocksize**2), h, w])

tmp = np.transpose(tmp, [0, 3, 4, 1, 5, 2])

y = np.reshape(tmp, [b, c // (blocksize**2), h * blocksize, w * blocksize])

In the CRD mode, elements along the depth dimension from the input tensor are rearranged in the following order: column, row, and the depth. The output y is computed from the input x as below:

b, c, h, w = x.shape

tmp = np.reshape(x, [b, c // (blocksize ** 2), blocksize, blocksize, h, w])

tmp = np.transpose(tmp, [0, 1, 4, 2, 5, 3])

y = np.reshape(tmp, [b, c // (blocksize ** 2), h * blocksize, w * blocksize])

22.35 onnx::Clip

22.36 onnx::RNN

Notations:

`X` - input tensor

`i` - input gate

`t` - time step (t-1 means previous time step)

`Wi` - W parameter weight matrix for input gate

`Ri` - R recurrence weight matrix for input gate

`Wbi` - W parameter bias vector for input gate

`Rbi` - R parameter bias vector for input gate

`WBi` - W parameter weight matrix for backward input gate

`RBi` - R recurrence weight matrix for backward input gate

`WBbi` - WR bias vectors for backward input gate

`RBbi` - RR bias vectors for backward input gate

`H` - Hidden state

`num_directions` - 2 if direction == bidirectional else 1

Activation functions:

Relu(x) - max(0, x)

Tanh(x) - (1 - e^{-2x})/(1 + e^{-2x})

Sigmoid(x) - 1/(1 + e^{-x})

(NOTE: Below are optional)

Affine(x) - alpha*x + beta

LeakyRelu(x) - x if x >= 0 else alpha * x

ThresholdedRelu(x) - x if x >= alpha else 0

ScaledTanh(x) - alpha*Tanh(beta*x)

HardSigmoid(x) - min(max(alpha*x + beta, 0), 1)

Elu(x) - x if x >= 0 else alpha*(e^x - 1)

Softsign(x) - x/(1 + |x|)

Softplus(x) - log(1 + e^x)

Equations (Default: f=Tanh):

- Ht = f(Xt*(Wi^T) + Ht-1*(Ri^T) + Wbi + Rbi) This operator has **optional** inputs/outputs. See the doc for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

22.37 onnx::Concat

22.38 onnx::Constant

22.39 onnx::LpPool

22.40 onnx::Conv

22.41 onnx::Not

22.42 onnx::Gather

axis = 0 :

Let k = indices[i_{0}, ..., i_{q-1}] Then output[i_{0}, ..., i_{q-1}, j_{0}, ..., j_{r-2}] = input[k , j_{0}, ..., j_{r-2}]

```
data = [
    [1.0, 1.2],
    [2.3, 3.4],
    [4.5, 5.7],
]
indices = [
    [0, 1],
    [1, 2],
]
output = [
    [
```

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```
            [1.0, 1.2],
            [2.3, 3.4],
        ],
        [
            [2.3, 3.4],
            [4.5, 5.7],
        ],
    ]
```

axis = 1 :

Let k = indices[i_{0}, …, i_{q-1}] Then output[j_{0}, i_{0}, …, i_{q-1}, j_{1}, …, j_{r-2}] = input[j_{0}, k, j_{1}, …, j_{r-2}]

```
    data = [
        [1.0, 1.2, 1.9],
        [2.3, 3.4, 3.9],
        [4.5, 5.7, 5.9],
    ]
    indices = [
        [0, 2],
    ]
    axis = 1,
    output = [
            [[1.0, 1.9]],
            [[2.3, 3.9]],
            [[4.5, 5.9]],
    ]
```

22.43 onnx::ConvTranspose

If the pads parameter is provided the shape of the output is calculated via the following equation:

output_shape[i] = stride[i] * (input_size[i] - 1) + output_padding[i] + ((kernel_shape[i] - 1) * dilations[i] + 1) - pads[start_i] - pads[end_i]

output_shape can also be explicitly specified in which case pads values are auto generated using these equations:

total_padding[i] = stride[i] * (input_size[i] - 1) + output_padding[i] + ((kernel_shape[i] - 1) * dilations[i] + 1) - output_shape[i] If (auto_pads == SAME_UPPER): pads[start_i] = total_padding[i]/2; pads[end_i] = total_padding[i] - (total_padding[i]/2) Else: pads[start_i] = total_padding[i] - (total_padding[i]/2); pads[end_i] = (total_padding[i]/2).

```
</i></p>
```

22.44 onnx::Dropout

22.45 onnx::LeakyRelu

22.46 onnx::Elu

22.47 onnx::GlobalAveragePool

22.48 onnx::GatherElements

GatherElements takes two inputs `data` and `indices` of the same rank r >= 1 and an optional attribute `axis` that identifies an axis of `data` (by default, the outer-most axis, that is axis 0). It is an indexing operation that produces its output by indexing into the input data tensor at index positions determined by elements of the `indices` tensor. Its output shape is the same as the shape of `indices` and consists of one value (gathered from the `data`) for each element in `indices`.

For instance, in the 3-D case (r = 3), the output produced is determined by the following equations:

```
out[i][j][k] = input[index[i][j][k]][j][k] if axis = 0,
out[i][j][k] = input[i][index[i][j][k]][k] if axis = 1,
out[i][j][k] = input[i][j][index[i][j][k]] if axis = 2,
```

This operator is also the inverse of ScatterElements. It is similar to Torch's gather operation.

Example 1:

```
data = [
    [1, 2],
    [3, 4],
]
indices = [
    [0, 0],
    [1, 0],
]
axis = 1
output = [
    [1, 1],
    [4, 3],
]
```

Example 2:

```
data = [
    [1, 2, 3],
    [4, 5, 6],
    [7, 8, 9],
]
indices = [
    [1, 2, 0],
    [2, 0, 0],
```

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```
]
axis = 0
output = [
    [4, 8, 3],
    [7, 2, 3],
]
```

22.49 onnx::Gemm

A' = transpose(A) if transA else A

B' = transpose(B) if transB else B

Compute Y = alpha * A' * B' + beta * C, where input tensor A has shape (M, K) or (K, M), input tensor B has shape (K, N) or (N, K), input tensor C is broadcastable to shape (M, N), and output tensor Y has shape (M, N). A will be transposed before doing the computation if attribute transA is non-zero, same for B and transB. This operator supports **unidirectional broadcasting** (tensor C should be unidirectional broadcastable to tensor A * B); for more details please check the doc. This operator has **optional** inputs/outputs. See the doc for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

22.50 onnx::MaxPool

```
* pad_shape[i] is sum of pads along axis i
```

`auto_pad` is a DEPRECATED attribute. If you are using them currently, the output spatial shape will be following:

```
VALID: output_spatial_shape[i] = ceil((input_spatial_shape[i] - ((kernel_spatial_
↪shape[i] - 1) * dilations[i] + 1) + 1) / strides_spatial_shape[i])
SAME_UPPER or SAME_LOWER: output_spatial_shape[i] = ceil(input_spatial_shape[i] /␣
↪strides_spatial_shape[i])
```

And pad shape will be following if `SAME_UPPER` or `SAME_LOWER`:

```
pad_shape[i] = (output_spatial_shape[i] - 1) * strides_spatial_shape[i] + ((kernel_
↪spatial_shape[i] - 1) * dilations[i] + 1) - input_spatial_shape[i]
```

The output of each pooling window is maximum number of elements exclude pad.

22.51 onnx::Equal

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.52 onnx::Tile

22.53 onnx::Flatten

22.54 onnx::Floor

22.55 onnx::GRU

Notations:

`X` - input tensor

`z` - update gate

`r` - reset gate

`h` - hidden gate

`t` - time step (t-1 means previous time step)

`W[zrh]` - W parameter weight matrix for update, reset, and hidden gates

`R[zrh]` - R recurrence weight matrix for update, reset, and hidden gates

`Wb[zrh]` - W bias vectors for update, reset, and hidden gates

`Rb[zrh]` - R bias vectors for update, reset, and hidden gates

`WB[zrh]` - W parameter weight matrix for backward update, reset, and hidden gates

`RB[zrh]` - R recurrence weight matrix for backward update, reset, and hidden gates

`WBb[zrh]` - W bias vectors for backward update, reset, and hidden gates

`RBb[zrh]` - R bias vectors for backward update, reset, and hidden gates

`H` - Hidden state

`num_directions` - 2 if direction == bidirectional else 1

Activation functions:

Relu(x) - max(0, x)

Tanh(x) - (1 - e^{-2x})/(1 + e^{-2x})

Sigmoid(x) - 1/(1 + e^{-x})

(NOTE: Below are optional)

Affine(x) - alpha*x + beta

LeakyRelu(x) - x if x >= 0 else alpha * x

ThresholdedRelu(x) - x if x >= alpha else 0

ScaledTanh(x) - alpha*Tanh(beta*x)

HardSigmoid(x) - min(max(alpha*x + beta, 0), 1)

Elu(x) - x if x >= 0 else alpha*(e^x - 1)

Softsign(x) - x/(1 + |x|)

Softplus(x) - log(1 + e^x)

Equations (Default: f=Sigmoid, g=Tanh):

- zt = f(Xt*(Wz^T) + Ht-1*(Rz^T) + Wbz + Rbz)
- rt = f(Xt*(Wr^T) + Ht-1*(Rr^T) + Wbr + Rbr)
- ht = g(Xt*(Wh^T) + (rt (.) Ht-1)*(Rh^T) + Rbh + Wbh) # default, when linear_before_reset = 0
- ht = g(Xt*(Wh^T) + (rt (.) (Ht-1*(Rh^T) + Rbh)) + Wbh) # when linear_before_reset != 0
- Ht = (1 - zt) (.) ht + zt (.) Ht-1 This operator has **optional** inputs/outputs. See the doc for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

22.56 onnx::ScatterElements

For each entry in `updates`, the target index in `data` is obtained by combining the corresponding entry in `indices` with the index of the entry itself: the index-value for dimension = axis is obtained from the value of the corresponding entry in `indices` and the index-value for dimension != axis is obtained from the index of the entry itself.

For instance, in a 2-D tensor case, the update corresponding to the [i][j] entry is performed as below:

```
output[indices[i][j]][j] = updates[i][j] if axis = 0,
output[i][indices[i][j]] = updates[i][j] if axis = 1,
```

This operator is the inverse of GatherElements. It is similar to Torch's Scatter operation.

Example 1:

```
data = [
    [0.0, 0.0, 0.0],
    [0.0, 0.0, 0.0],
    [0.0, 0.0, 0.0],
]
indices = [
    [1, 0, 2],
    [0, 2, 1],
]
updates = [
    [1.0, 1.1, 1.2],
    [2.0, 2.1, 2.2],
]
output = [
    [2.0, 1.1, 0.0]
    [1.0, 0.0, 2.2]
    [0.0, 2.1, 1.2]
]
```

Example 2:

```
data = [[1.0, 2.0, 3.0, 4.0, 5.0]]
indices = [[1, 3]]
updates = [[1.1, 2.1]]
axis = 1
output = [[1.0, 1.1, 3.0, 2.1, 5.0]]
```

22.57 onnx::GlobalLpPool

22.58 onnx::Greater

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.59 onnx::HardSigmoid

22.60 onnx::Selu

22.61 onnx::Hardmax

Hardmax(element in input, axis) = 1 if the element is the first maximum value along the specified axis, 0 otherwise

The "axis" attribute indicates the dimension along which Hardmax will be performed. The output tensor has the same shape and contains the Hardmax values of the corresponding input.

22.62 onnx::If

22.63 onnx::Min

22.64 onnx::InstanceNormalization

y = scale * (x - mean) / sqrt(variance + epsilon) + B, where mean and variance are computed per instance per channel.

22.65 onnx::Less

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.66 onnx::EyeLike

22.67 onnx::RandomNormal

The data type is specified by the 'dtype' argument. The 'dtype' argument must be one of the data types specified in the 'DataType' enum field in the TensorProto message.

22.68 onnx::Slice

Slice uses the `starts`, `ends`, `axes` and `steps` inputs to select a sub-tensor of its input `data` tensor.

An effective `start[i]`, `end[i]`, and `step[i]` must be computed for each `i` in `[0, ... r-1]` where `r = rank(input)` as follows:

If `axes` are omitted, they are set to `[0, ..., r-1]`. If `steps` are omitted, they are set to `[1, ..., 1]` of length `len(starts)`

The effective values are initialized as `start[i] = 0`, `end[i] = dims[i]` where `dims` are the dimensions of `input` and `step[i] = 1`.

All negative elements of `axes` are made non-negatve by adding `r` to them, where `r =rank(input)`.

All negative values in `starts[i]` and `ends[i]` have `dims[axes[i]]` added to them, where `dims` are the dimensions of `input`. Then `start[axes[i]]` is the adjusted `starts[i]` is clamped into the range `[0, dims[axes[i]]]` for positive stepping and `[0, dims[axes[i]]-1]` for negative stepping.

The clamping for the adjusted `ends[i]` depends on the sign of `steps[i]` and must accommodate copying 0 through `dims[axes[i]]` elements, so for positive stepping `end[axes[i]]` is clamped to `[0, dims[axes[i]]]`, while for negative stepping it is clamped to `[-1, dims[axes[i]]-1]`.

Finally, `step[axes[i]] = steps[i]`.

For slicing to the end of a dimension with unknown size, it is recommended to pass in `INT_MAX` when slicing forward and 'INT_MIN' when slicing backward.

Example 1: data = [[1, 2, 3, 4], [5, 6, 7, 8],] axes = [0, 1] starts = [1, 0] ends = [2, 3] steps = [1, 2] result = [[5, 7],]
Example 2: data = [[1, 2, 3, 4], [5, 6, 7, 8],] starts = [0, 1] ends = [-1, 1000] result = [[2, 3, 4],]

22.69 onnx::PRelu

22.70 onnx::Log

22.71 onnx::LogSoftmax

LogSoftmax(input, axis) = Log(Softmax(input, axis=axis))

The "axis" attribute indicates the dimension along which LogSoftmax will be performed. The output tensor has the same shape and contains the LogSoftmax values of the corresponding input.

22.72 onnx::Loop

1) Trip count. Iteration count specified at runtime. Set by specifying the input M. Optional. Set to empty string to omit. Note that a static trip count (specified at graph construction time) can be specified by passing in a constant node for input M.
2) Loop termination condition. This is an input to the op that determines whether to run the first iteration and also a loop-carried dependency for the body graph. The body graph must yield a value for the condition variable, whether this input is provided or not.

This table summarizes the operating modes of this operator with equivalent C-style code:

```
Operator inputs defined as (max_trip_count, condition_var).

input ("", ""):
    for (int i=0; ; ++i) {
      cond = ... // Note this value is ignored, but is required in the body
    }

input ("", cond) // Note this is analogous to a while loop
    bool cond = ...;
    for (int i=0; cond; ++i) {
      cond = ...;
    }

input ("", 1) // Note this is analogous to a do-while loop
    bool cond = true
    for (int i=0; cond; ++i) {
      cond = ...;
    }

input (trip_count, "") // Note this is analogous to a for loop
    int trip_count = ...
    for (int i=0; i < trip_count; ++i) {
      cond = ...; // ignored
    }

input (trip_count, cond)
    int trip_count = ...;
    bool cond = ...;
    for (int i=0; i < trip_count && cond; ++i) {
      cond = ...;
    }
```

Sample usage - cond as well as trip count

```
graph predict-net {
  %a = Constant[value = <Scalar Tensor [3]>]()
  %b = Constant[value = <Scalar Tensor [6]>]()
  %keepgoing = Constant[value = <Scalar Tensor [1]>]()
  %max_trip_count = Constant[value = <Scalar Tensor [10]>]()
  %keepgoing_out, %b_out, %user_defined_vals = Loop[body = <graph body-net>](%max_
↪trip_count, %keepgoing, %b)
  return
}

graph body-net (
  %i[INT32, scalar]           // iteration number
  %keepgoing_in[BOOL, scalar] // incoming loop-termination-condition; not used
  %b_in[INT32, scalar]        // incoming value of loop-carried-dependency b
) {
  %my_local = Add(%a, %b_in)
  %b_out = Sub(%a, %b_in) // outgoing value of loop-carried-dependency b
  %keepgoing_out = Greater(%my_local, %b_out) // outgoing loop-termination-condition
  %user_defined_val = Add(%b_in, %b_in) // scan-output value to be accumulated
  return %keepgoing_out, %b_out, %user_defined_val
}
```

Sample equivalent C code

```
{
  /* User-defined code (enclosing scope) */
  int a = 3, b = 6;
  bool keepgoing = true; // Analogous to input cond
  /* End user-defined code */

  /* Implicitly-defined code */
  const int max_trip_count = 10; // Analogous to input M
  int user_defined_vals[]; // Imagine this is resizable
  /* End implicitly-defined code */
  /* initialize loop-carried variables and scan-output variables */
  bool keepgoing_out = keepgoing
  int b_out = b

  for (int i=0; i < max_trip_count && keepgoing_out; ++i) {
    /* Implicitly-defined code: bind actual parameter values
       to formal parameter variables of loop-body */
    bool keepgoing_in = keepgoing_out;
    bool b_in = b_out;

    /* User-defined code (loop body) */
    int my_local = a + b_in; // Reading value "a" from the enclosing scope is fine
    b_out = a - b_in;
    keepgoing_out = my_local > b_out;
    user_defined_val = b_in + b_in; // b_in and b_out are different variables
    /* End user-defined code */

    /* Implicitly defined-code */
    user_defined_vals[i] = user_defined_val // accumulate scan-output values
  }
  // int t = my_local; // Can't do this. my_local is not accessible here.

  // The values below are bound to the output variables of the loop and therefore␣
↪accessible
  // b_out; user_defined_vals; keepgoing_out;
}
```

There are several things of note in this code snippet:

1) Values from the enclosing scope (i.e. variable "a" here) are in scope and can be referenced in the inputs of the loop.

2) Any values computed in the loop body that needs to be used in a subsequent iteration or after the loop are modelled using a pair of variables in the loop-body, consisting of an input variable (eg., b_in) and an output variable (eg., b_out). These are referred to as loop-carried dependences. The loop operation node supplies the input value of the input variable for the first iteration, and returns the output value of the output variable produced by the final iteration.

3) Scan_output variables are used to implicitly concatenate values computed across all the iterations. In the above example, the value of user_defined_val computed over all iterations are concatenated and returned as the value of user_defined_vals after the loop.

4) Values created in the body cannot be accessed in the enclosing scope, except using the mechanism described above.

Note that the semantics of this op support "diagonal" or "wavefront" execution. (See Step 3 here for an example: https://devblogs.nvidia.com/optimizing-recurrent-neural-networks-cudnn-5/). Frontends should emit multi-layer RNNs as a series of While operators (with time being the inner looping dimension), with each successive layer consuming the scan_outputs from the previous layer, possibly going through several point-wise operators (e.g. dropout,

residual connections, linear layer).

The input/output of subgraph (produced by loop node) matching is based on order instead of name. The implementation will figure out the names based on this order.

22.73 onnx::LpNormalization

22.74 onnx::MatMul

22.75 onnx::Optional

22.76 onnx::ReduceL2

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.77 onnx::Max

22.78 onnx::MaxRoiPool

22.79 onnx::Or

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.80 onnx::Pad

The three supported `modes` are (similar to corresponding modes supported by `numpy.pad`):

1) `constant`(default) - pads with a given constant value as specified by `constant_value` (which defaults to 0, empty string, or False)

2) `reflect` - pads with the reflection of the vector mirrored on the first and last values of the vector along each axis

3) `edge` - pads with the edge values of array

Example 1 (`constant` mode): Insert 0 pads to the beginning of the second dimension.

data = [[1.0, 1.2], [2.3, 3.4], [4.5, 5.7],]

pads = [0, 2, 0, 0]

mode = 'constant'

constant_value = 0.0

output = [[0.0, 0.0, 1.0, 1.2], [0.0, 0.0, 2.3, 3.4], [0.0, 0.0, 4.5, 5.7],]

Example 2 (`reflect` mode): data = [[1.0, 1.2], [2.3, 3.4], [4.5, 5.7],]

pads = [0, 2, 0, 0]

mode = ‘reflect’

output = [[1.0, 1.2, 1.0, 1.2], [2.3, 3.4, 2.3, 3.4], [4.5, 5.7, 4.5, 5.7],]

Example 3 (`edge` mode): data = [[1.0, 1.2], [2.3, 3.4], [4.5, 5.7],]

pads = [0, 2, 0, 0]

mode = ‘edge’

output = [[1.0, 1.0, 1.0, 1.2], [2.3, 2.3, 2.3, 3.4], [4.5, 4.5, 4.5, 5.7],]

22.81 onnx::RandomUniformLike

The data type is specified by the ‘dtype’ argument, or copied from the input tensor if not provided. The ‘dtype’ argument must be one of the data types specified in the ‘DataType’ enum field in the TensorProto message and be valid as an output type.

22.82 onnx::Reciprocal

22.83 onnx::Pow

22.84 onnx::RandomNormalLike

The data type is specified by the ‘dtype’ argument, or copied from the input tensor if not provided. The ‘dtype’ argument must be one of the data types specified in the ‘DataType’ enum field in the TensorProto message, and be valid as an output type.

22.85 onnx::OneHot

```
when axis = 0:
output[input[i, j, k], i, j, k] = 1 for all i, j, k and 0 otherwise.

when axis = -1:
output[i, j, k, input[i, j, k]] = 1 for all i, j, k and 0 otherwise.
```

22.86 onnx::RandomUniform

The data type is specified by the ‘dtype’ argument. The ‘dtype’ argument must be one of the data types specified in the ‘DataType’ enum field in the TensorProto message.

22.87 onnx::ConcatFromSequence

22.88 onnx::ReduceL1

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.89 onnx::ReduceLogSum

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.90 onnx::ReduceLogSumExp

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.91 onnx::ReduceMax

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.92 onnx::IsNaN

22.93 onnx::ReduceMean

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.94 onnx::ReduceMin

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.95 onnx::ReduceProd

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.96 onnx::ReduceSum

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.97 onnx::ReduceSumSquare

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

22.98 onnx::Relu

22.99 onnx::Reshape

If the attribute 'allowzero' is set, it is invalid for the specified shape to contain both a zero value and -1, as the value of the dimension corresponding to -1 cannot be determined uniquely.

22.100 onnx::Shape

For example: Input tensor with shape: [2, 3, 4] No attributes specified. Output: [2, 3, 4]

Input tensor with shape: [2, 3, 4] start: -1 Output: [4]

Input tensor with shape: [2, 3, 4] end: -1 Output: [2, 3]

Input tensor with shape: [2, 3, 4] start: 1 end: 2 Output: [3]

22.101 onnx::SoftmaxCrossEntropyLoss

shape(scores): (N, C) where C is the number of classes, or (N, C, D1, D2,..., Dk), with K >= 1 in case of K-dimensional loss. shape(labels): (N) where each value is 0 <= labels[i] <= C-1, or (N, D1, D2,..., Dk), with K >= 1 in case of K-dimensional loss.

The loss for one sample, l_i, can caculated as follows: l[i][d1][d2]...[dk] = -y[i][c][d1][d2]..[dk], where i is the index of classes. or l[i][d1][d2]...[dk] = -y[i][c][d1][d2]..[dk] * weights[c], if 'weights' is provided.

loss is zero for the case when label-value equals ignore_index. l[i][d1][d2]...[dk] = 0, when labels[n][d1][d2]...[dk] = ignore_index

where: p = Softmax(scores) y = Log(p) c = labels[i][d1][d2]...[dk]

Finally, L is optionally reduced: If reduction = 'none', the output is L with shape (N, D1, D2, ..., Dk). If reduction = 'sum', the output is scalar: Sum(L). If reduction = 'mean', the output is scalar: ReduceMean(L), or if weight is provided: ReduceSum(L) / ReduceSum(W), where tensor W is of shape (N, D1, D2, ..., Dk) and W[n][d1][d2]...[dk] = weights[labels[i][d1][d2]...[dk]].

22.102 onnx::Sigmoid

22.103 onnx::Size

22.104 onnx::Softmax

Softmax(input, axis) = Exp(input) / ReduceSum(Exp(input), axis=axis, keepdims=1)

The "axis" attribute indicates the dimension along which Softmax will be performed. The output tensor has the same shape and contains the Softmax values of the corresponding input.

22.105 onnx::Softplus

22.106 onnx::Softsign

22.107 onnx::SpaceToDepth

22.108 onnx::TfIdfVectorizer

In contrast to standard n-gram extraction, here, the indexes of extracting an n-gram from the original sequence are not necessarily consecutive numbers. The discontinuity between indexes are controlled by the number of skips. If the number of skips is 2, we should skip two tokens when scanning through the original sequence. Let's consider an example. Assume that input sequence is [94, 17, 36, 12, 28] and the number of skips is 2. The associated 2-grams are [94, 12] and [17, 28] respectively indexed by [0, 3] and [1, 4]. If the number of skips becomes 0, the 2-grams generated are [94, 17], [17, 36], [36, 12], [12, 28] indexed by [0, 1], [1, 2], [2, 3], [3, 4], respectively.

The output vector (denoted by Y) stores the count of each n-gram; Y[ngram_indexes[i]] indicates the times that the i-th n-gram is found. The attribute ngram_indexes is used to determine the mapping between index i and the corresponding n-gram's output coordinate. If pool_int64s is [94, 17, 17, 36], ngram_indexes is [1, 0], ngram_counts=[0, 0], then the Y[0] (first element in Y) and Y[1] (second element in Y) are the counts of [17, 36] and [94, 17], respectively. An n-gram which cannot be found in pool_strings/pool_int64s should be ignored and has no effect on the output. Note that we may consider all skips up to S when generating the n-grams.

The examples used above are true if mode is "TF". If mode is "IDF", all the counts larger than 1 would be truncated to 1 and the i-th element in weights would be used to scale (by multiplication) the count of the i-th n-gram in pool. If mode is "TFIDF", this operator first computes the counts of all n-grams and then scale them by the associated values in the weights attribute.

Only one of pool_strings and pool_int64s can be set. If pool_int64s is set, the input should be an integer tensor. If pool_strings is set, the input must be a string tensor.

22.109 onnx::Split

22.110 onnx::Sqrt

22.111 onnx::Squeeze

22.112 onnx::TopK

If "largest" is 1 (the default value) then the k largest elements are returned. If "sorted" is 1 (the default value) then the resulting k elements will be sorted. If "sorted" is 0, order of returned 'Values' and 'Indices' are undefined.

Given two equivalent values, this operator uses the indices along the axis as a tiebreaker. That is, the element with the lower index will appear first.

22.113 onnx::Sub

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

(Opset 14 change): Extend supported types to include uint8, int8, uint16, and int16.

22.114 onnx::Sum

22.115 onnx::Shrink

22.116 onnx::Tanh

22.117 onnx::Transpose

22.118 onnx::Unsqueeze

For example: Given an input tensor (`data`) of shape [3, 4, 5], then Unsqueeze(data, axes=[0, 4]) outputs a tensor (`expanded`) containing same data as `data` but with shape [1, 3, 4, 5, 1].

The input `axes` should not contain any duplicate entries. It is an error if it contains duplicates. The rank of the output tensor (`output_rank`) is the rank of the input tensor (`data`) plus the number of values in `axes`. Each value in `axes` should be within the (inclusive) range [-output_rank , output_rank - 1]. The order of values in `axes` does not matter and can come in any order.

22.119 onnx::Upsample

22.120 onnx::Xor

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.121 onnx::Acos

22.122 onnx::Asin

22.123 onnx::Atan

22.124 onnx::Cos

22.125 onnx::Sin

22.126 onnx::Tan

22.127 onnx::Multinomial

22.128 onnx::Scan

The attribute body must be a graph, specifying the computation to be performed in every iteration. It takes as input the current values of the state_variables and the current iterated element of the scan_inputs. It must return the (updated) values of the state_variables and zero or more scan_output_element tensors. The values of the scan_output_element tensors are concatenated over all the iterations to produce the scan_output values of the scan construct (similar to the concatenated intermediate hidden-state values of RNN-like constructs). All the output tensors (state_variables as well as scan_output_element tensors) are required to have the same shape in each iteration of the loop (a restriction imposed to enable efficient memory allocation).

Note that the iterated element passed to the body subgraph does not have a sequence axis. It will have a rank one less than the rank of the corresponding scan_input.

The scan operation returns the final values of the state_variables as well as the scan_outputs.

The optional attribute scan_input_directions specifies the direction (forward or backward) for each scan input. If this attribute is omitted, all sequences are scanned in the forward direction. A bidirectional scan may be performed by specifying the same tensor input twice in the scan_inputs, once with a forward direction, and once with a backward direction.

The scan_output of the operation is produced by concatenating the scan_output_element values produced by the body in each iteration. The optional attribute scan_output_directions specifies the direction in which scan_output is constructed (by appending or prepending the scan_output_element to scan_output in each iteration) for each scan_output. If this attribute is omitted, the scan_output_element is appended to the scan_output in each iteration.

The optional attribute scan_input_axes specifies the axis to be scanned for each scan_input. If omitted, every scan_input will be scanned in axis 0. For example, if axis 0 is the batch axis and axis 1 is the time axis (to be scanned), specify an axis value of 1. Note that scanning a non-zero axis may be less efficient than scanning axis zero.

The optional attribute scan_output_axes specifies the axis along which the scan_outputs are accumulated for each scan_output. For example, if axis 1 is the time axis (to be scanned) for both inputs and outputs, specify a scan_input axis and scan_output axis value of 1.

Note that because of the ONNX restriction that only the last parameter of an operator can be variadic, the initial-states and scan-inputs are listed together as one input parameter. Similarly, the final-states and scan-outputs are listed together as one output parameter. The attribute num_scan_inputs indicates the number M of scan-inputs.

The behavior of

```
Scan <
    num_scan_inputs = m,
    body = loop-body,
    scan_input_axes = [axis_1, ..., axis_m]
> (init_1, ..., init_n, scan_1, ..., scan_m)
```

is equivalent to the following pseudo-code:

```
// scan_i.shape[axis_i] denotes the (max) sequence-length of scan_i
// scan_i.shape[axis_i] is required to be equal to scan_j.shape[axis_j] for all i,j.
sequence_length = scan_1.shape[axis_1];

// initialize state-variables
st_1 = init_1; ... st_n = init_n;
// initialize scan-output variables: [] denotes an empty tensor
scan_out_1 = []; ...; scan_out_k = [];
// identify number of iterations:

// execute loop
for (int t = 0; t < sequence_length; ++t) {
    // generate the scan-input elements: the notation T<axis=k>[t] indicates the sub-
↪tensor
    // of rank one less than T obtained by indexing T at position t along axis k.
    si_1 = scan_1<axis=axis_1>[t];
    ... ;
    si_m = scan_m<axis=axis_m>[t];
    // execute loop-body
    st_1, ..., st_n, so_1, ..., so_k = loop-body(st_1, ..., st_n, si_1, ..., si_m)
    // accumulate the scan-output elements
    scan_out_1 = Concat<axis=0>(scan_out_1, so_1); ... ; scan_out_k = Concat<axis=0>
↪(scan_out_k, so_k);
}

return st_1, ..., st_n, scan_out_1, ..., scan_out_k;
```

Sample usage: Encoding RNN using a Scan

The following example shows how a simple RNN over an input tensor %X, with weight tensor %Wi, recurrence weight tensor %Ri, bias tensors %Wbi and %Rbi, and initial hidden-state %H_0 can be encoded as a ScanLoop. Note that the loop-body is a nested graph, and it directly computes

values are computed in the outer graph, they need to be passed in as extra state_variables.

```
graph rnn-encoding {
  %H_0 = ...
  %X = ...
  %Y_h, %Y = Scan[body = <graph rnn-cell-1>, num_scan_inputs=1](%H_0, %X)
  return %Y, %Y_h
}
```

(continues on next page)

(continued from previous page)

```
graph rnn-cell-1 (
  %H_tminus1[FLOAT, tensor]
  %X_t[FLOAT, tensor]
) {
  %Wi = ...
  %Ri = ...
  %Wbi = ...
  %Rbi = ...
  %t1 = X_t * (Wi^T)
  %t2 = H_tminus1*(Ri^T)
  %t3 = Add(%t1, %t2)
  %t4 = Add(%t3, %Wbi)
  %t5 = Add(%t4, %Rbi)
  %Ht = Tanh(%t5)
  %Accumulate = Identity(%Ht)
  return %Ht, %Accumulate
}
```

22.129 onnx::Compress

22.130 onnx::ConstantOfShape

22.131 onnx::MaxUnpool

MaxUnpool is intended to do 'partial' inverse of the MaxPool op. 'Partial' because all the non-maximal values from the original input to MaxPool are set to zero in the output of the MaxUnpool op. Pooling the result of an unpooling operation should give back the original input to the unpooling op.

MaxUnpool can produce the same output size for several input sizes, which makes unpooling op ambiguous. The third input argument, output_size, is meant to disambiguate the op and produce output tensor of known/predictable size.

In addition to the inputs, MaxUnpool takes three attributes, namely kernel_shape, strides, and pads, which define the exact unpooling op. The attributes typically have the same values as the corrsponding pooling op that the unpooling op is trying to invert.

22.132 onnx::Scatter

Scatter takes three inputs `data`, `updates`, and `indices` of the same rank r >= 1 and an optional attribute axis that identifies an axis of `data` (by default, the outer-most axis, that is axis 0). The output of the operation is produced by creating a copy of the input `data`, and then updating its value to values specified by `updates` at specific index positions specified by `indices`. Its output shape is the same as the shape of `data`.

For each entry in `updates`, the target index in `data` is obtained by combining the corresponding entry in `indices` with the index of the entry itself: the index-value for dimension = axis is obtained from the value of the corresponding entry in `indices` and the index-value for dimension != axis is obtained from the index of the entry itself.

For instance, in a 2-D tensor case, the update corresponding to the [i][j] entry is performed as below:

```
output[indices[i][j]][j] = updates[i][j] if axis = 0,
output[i][indices[i][j]] = updates[i][j] if axis = 1,
```

This operator is the inverse of GatherElements. It is similar to Torch's Scatter operation.

Example 1:

```
data = [
    [0.0, 0.0, 0.0],
    [0.0, 0.0, 0.0],
    [0.0, 0.0, 0.0],
]
indices = [
    [1, 0, 2],
    [0, 2, 1],
]
updates = [
    [1.0, 1.1, 1.2],
    [2.0, 2.1, 2.2],
]
output = [
    [2.0, 1.1, 0.0]
    [1.0, 0.0, 2.2]
    [0.0, 2.1, 1.2]
]
```

Example 2:

```
data = [[1.0, 2.0, 3.0, 4.0, 5.0]]
indices = [[1, 3]]
updates = [[1.1, 2.1]]
axis = 1
output = [[1.0, 1.1, 3.0, 2.1, 5.0]]
```

22.133 onnx::Sinh

22.134 onnx::Cosh

22.135 onnx::Asinh

22.136 onnx::Acosh

22.137 onnx::NonMaxSuppression

22.138 onnx::Atanh

22.139 onnx::Sign

22.140 onnx::Erf

22.141 onnx::Where

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.142 onnx::NonZero

22.143 onnx::MeanVarianceNormalization

22.144 onnx::StringNormalizer

22.145 onnx::Mod

```
Mod operator can also behave like C fmod() or numpy.fmod. In this case, the sign of␣
↪the remainder however, will be the same as the Dividend
(in contrast to integer mod). To force a behavior like numpy.fmod() an 'fmod'␣
↪Attribute is provided.
This attribute is set to 0 by default causing the behavior to be like integer mod.
Setting this attribute to 1 causes the remainder to be calculated similar to that of␣
↪numpy.fmod().

If the input type is floating point, then `fmod` attribute must be set to 1.

In case of dividend being zero, the results will be platform dependent.
```

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.146 onnx::ThresholdedRelu

22.147 onnx::MatMulInteger

22.148 onnx::QLinearMatMul

22.149 onnx::ConvInteger

22.150 onnx::QLinearConv

22.151 onnx::QuantizeLinear

22.152 onnx::GatherND

`indices` is an q-dimensional integer tensor, best thought of as a `(q-1)`-dimensional tensor of index-tuples into `data`, where each element defines a slice of `data`

`batch_dims` (denoted as `b`) is an integer indicating the number of batch dimensions, i.e the leading `b` number of dimensions of `data` tensor and `indices` are representing the batches, and the gather starts from the `b+1` dimension.

Some salient points about the inputs' rank and shape:

1) r >= 1 and q >= 1 are to be honored. There is no dependency condition to be met between ranks `r` and `q`
2) The first `b` dimensions of the shape of `indices` tensor and `data` tensor must be equal.
3) b < min(q, r) is to be honored.
4) The `indices_shape[-1]` should have a value between 1 (inclusive) and rank `r-b` (inclusive)
5) All values in `indices` are expected to be within bounds [-s, s-1] along axis of size `s` (i.e.) `-data_shape[i] <= indices[...,i] <= data_shape[i] - 1`. It is an error if any of the index values are out of bounds.

The output is computed as follows:

The output tensor is obtained by mapping each index-tuple in the `indices` tensor to the corresponding slice of the input `data`.

1) If `indices_shape[-1] > r-b` => error condition
2) If `indices_shape[-1] == r-b`, since the rank of `indices` is `q`, `indices` can be thought of as `N (q-b-1)`-dimensional tensors containing 1-D tensors of dimension `r-b`, where `N` is an integer equals to the product of 1 and all the elements in the batch dimensions of the indices_shape. Let us think of each such `r-b` ranked tensor as `indices_slice`. Each *scalar value* corresponding to `data[0:b-1,indices_slice]` is filled into the corresponding location of the `(q-b-1)`-dimensional tensor to form the `output` tensor (Example 1 below)
3) If `indices_shape[-1] < r-b`, since the rank of `indices` is `q`, `indices` can be thought of as `N (q-b-1)`-dimensional tensor containing 1-D tensors of dimension `< r-b`. Let us think of each such tensors as `indices_slice`. Each *tensor slice* corresponding to `data[0:b-1, indices_slice , :]` is filled into the corresponding location of the `(q-b-1)`-dimensional tensor to form the `output` tensor (Examples 2, 3, 4 and 5 below)

This operator is the inverse of `ScatterND`.

`Example 1`

batch_dims = 0

data = [[0,1],[2,3]] # data_shape = [2, 2]

indices = [[0,0],[1,1]] # indices_shape = [2, 2]

output = [0,3] # output_shape = [2]

`Example 2`

batch_dims = 0

data = [[0,1],[2,3]] # data_shape = [2, 2]

indices = [[1],[0]] # indices_shape = [2, 1]

output = [[2,3],[0,1]] # output_shape = [2, 2]

`Example 3`

batch_dims = 0

data = [[[0,1],[2,3]],[[4,5],[6,7]]] # data_shape = [2, 2, 2]

indices = [[0,1],[1,0]] # indices_shape = [2, 2]

output = [[2,3],[4,5]] # output_shape = [2, 2]

`Example 4`

batch_dims = 0

data = [[[0,1],[2,3]],[[4,5],[6,7]]] # data_shape = [2, 2, 2]

indices = [[[0,1]],[[1,0]]] # indices_shape = [2, 1, 2]

output = [[[2,3]],[[4,5]]] # output_shape = [2, 1, 2]

`Example 5`

batch_dims = 1

data = [[[0,1],[2,3]],[[4,5],[6,7]]] # data_shape = [2, 2, 2]

indices = [[1],[0]] # indices_shape = [2, 1]

output = [[2,3],[4,5]] # output_shape = [2, 2]

22.153 onnx::DequantizeLinear

22.154 onnx::IsInf

22.155 onnx::RoiAlign

RoiAlign is proposed to avoid the misalignment by removing quantizations while converting from original image into feature map and from feature map into RoI feature; in each ROI bin, the value of the sampled locations are computed directly through bilinear interpolation.

22.156 onnx::SequenceLength

22.157 onnx::BitShift

Because this operator supports Numpy-style broadcasting, X's and Y's shapes are not necessarily identical. This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.158 onnx::Unique

This operator returns the unique values or sliced unique subtensors of the input tensor and three optional outputs. The first output tensor 'Y' contains all unique values or subtensors of the input. The second optional output tensor 'indices' contains indices of 'Y' elements' first occurance in 'X'.. The third optional output tensor 'inverse_indices' contains, for elements of 'X', its corresponding indices in 'Y'. ". The fourth optional output tensor 'counts' contains the count of each element of 'Y' in the input.

Outputs are either sorted in ascending order or optionally in the order of the first occurrence of the values in the input.

https://docs.scipy.org/doc/numpy/reference/generated/numpy.unique.html

Example 1: input_X = [2, 1, 1, 3, 4, 3] attribute_sorted = 0 attribute_axis = None output_Y = [2, 1, 3, 4] output_indices = [0, 1, 3, 4] output_inverse_indices = [0, 1, 1, 2, 3, 2] output_counts = [1, 2, 2, 1]

Example 2: input_X = [[1, 3], [2, 3]] attribute_sorted = 1 attribute_axis = None output_Y = [1, 2, 3] output_indices = [0, 2, 1] output_inverse_indices = [0, 2, 1, 2] output_counts = [1, 1, 2]

Example 3: input_X = [[1, 0, 0], [1, 0, 0], [2, 3, 4]] attribute_sorted = 1 attribute_axis = 0 output_Y = [[1, 0, 0], [2, 3, 4]] output_indices = [0, 2] output_inverse_indices = [0, 0, 1] output_counts = [2, 1]

Example 4: input_x = [[[1., 1.], [0., 1.], [2., 1.], [0., 1.]], [[1., 1.], [0., 1.], [2., 1.], [0., 1.]]] attribute_sorted = 1 attribute_axis = 1

intermediate data are presented below for better understanding:

there are 4 subtensors sliced along axis 1 of input_x (shape = (2, 4, 2)): A: [[1, 1], [1, 1]], [[0, 1], [0, 1]], [[2, 1], [2, 1]], [[0, 1], [0, 1]].

there are 3 unique subtensors: [[1, 1], [1, 1]], [[0, 1], [0, 1]], [[2, 1], [2, 1]].

sorted unique subtensors: B: [[0, 1], [0, 1]], [[1, 1], [1, 1]], [[2, 1], [2, 1]].

output_Y is constructed from B: [[[0. 1.], [1. 1.], [2. 1.]], [[0. 1.], [1. 1.], [2. 1.]]]

output_indices is to map from B to A: [1, 0, 2]

output_inverse_indices is to map from A to B: [1, 0, 2, 0]

output_counts = [2 1 1]

22.159 onnx::Bernoulli

This operator is non-deterministic and may not produce the same values in different implementations (even if a seed is specified).

22.160 onnx::CumSum

Example:

```
input_x = [1, 2, 3]
axis=0
output = [1, 3, 6]
exclusive=1
output = [0, 1, 3]
exclusive=0
reverse=1
output = [6, 5, 3]
exclusive=1
reverse=1
output = [5, 3, 0]
```

22.161 onnx::Round

Examples:

```
round([0.9]) = [1.0]
round([2.5]) = [2.0]
round([2.3]) = [2.0]
round([1.5]) = [2.0]
round([-4.5]) = [-4.0]
```

22.162 onnx::DynamicQuantizeLinear

22.163 onnx::Range

The number of elements in the output of range is computed as below-

```
number_of_elements = max( ceil( (limit - start) / delta ) , 0 )
```

The pseudocode determining the contents of the output is shown below-

```
for(int i=0; i<number_of_elements; ++i)
{
 output[i] = start + (i * delta);
}
```

`Example 1` Inputs: start = 3, limit = 9, delta = 3 Output: [3, 6]

`Example 2` Inputs: start = 10, limit = 4, delta = -2 Output: [10, 8, 6]

22.164 onnx::Det

22.165 onnx::ScatterND

`indices` is an integer tensor. Let k denote indices.shape[-1], the last dimension in the shape of `indices`. `indices` is treated as a (q-1)-dimensional tensor of k-tuples, where each k-tuple is a partial-index into `data`. Hence, k can be a value at most the rank of `data`. When k equals rank(data), each update entry specifies an update to a single element of the tensor. When k is less than rank(data) each update entry specifies an update to a slice of the tensor. Index values are allowed to be negative, as per the usual convention for counting backwards from the end, but are expected in the valid range.

`updates` is treated as a (q-1)-dimensional tensor of replacement-slice-values. Thus, the first (q-1) dimensions of updates.shape must match the first (q-1) dimensions of indices.shape. The remaining dimensions of `updates` correspond to the dimensions of the replacement-slice-values. Each replacement-slice-value is a (r-k) dimensional tensor, corresponding to the trailing (r-k) dimensions of `data`. Thus, the shape of `updates` must equal indices.shape[0:q-1] ++ data.shape[k:r-1], where ++ denotes the concatenation of shapes.

The `output` is calculated via the following equation:

```
output = np.copy(data)
update_indices = indices.shape[:-1]
for idx in np.ndindex(update_indices):
    output[indices[idx]] = updates[idx]
```

The order of iteration in the above loop is not specified. In particular, indices should not have duplicate entries: that is, if idx1 != idx2, then indices[idx1] != indices[idx2]. This ensures that the output value does not depend on the iteration order.

This operator is the inverse of GatherND.

Example 1:

```
  data    = [1, 2, 3, 4, 5, 6, 7, 8]
  indices = [[4], [3], [1], [7]]
  updates = [9, 10, 11, 12]
  output  = [1, 11, 3, 10, 9, 6, 7, 12]
```

Example 2:

```
  data    = [[[1, 2, 3, 4], [5, 6, 7, 8], [8, 7, 6, 5], [4, 3, 2, 1]],
             [[1, 2, 3, 4], [5, 6, 7, 8], [8, 7, 6, 5], [4, 3, 2, 1]],
             [[8, 7, 6, 5], [4, 3, 2, 1], [1, 2, 3, 4], [5, 6, 7, 8]],
             [[8, 7, 6, 5], [4, 3, 2, 1], [1, 2, 3, 4], [5, 6, 7, 8]]]
  indices = [[0], [2]]
  updates = [[[5, 5, 5, 5], [6, 6, 6, 6], [7, 7, 7, 7], [8, 8, 8, 8]],
             [[1, 1, 1, 1], [2, 2, 2, 2], [3, 3, 3, 3], [4, 4, 4, 4]]]
  output  = [[[5, 5, 5, 5], [6, 6, 6, 6], [7, 7, 7, 7], [8, 8, 8, 8]],
             [[1, 2, 3, 4], [5, 6, 7, 8], [8, 7, 6, 5], [4, 3, 2, 1]],
             [[1, 1, 1, 1], [2, 2, 2, 2], [3, 3, 3, 3], [4, 4, 4, 4]],
             [[8, 7, 6, 5], [4, 3, 2, 1], [1, 2, 3, 4], [5, 6, 7, 8]]]
```

22.166 onnx::SequenceEmpty

22.167 onnx::SequenceConstruct

22.168 onnx::SequenceInsert

22.169 onnx::SequenceAt

22.170 onnx::SequenceErase

22.171 onnx::SplitToSequence

22.172 onnx::Einsum

```
output[output-term] = reduce-sum( input1[term1] * input2[term] )
```

where the reduce-sum performs a summation over all the indices occurring in the input terms (term1, term2) that do not occur in the output-term.

The Einsum operator evaluates algebraic tensor operations on a sequence of tensors, using the Einstein summation convention. The equation string contains a comma-separated sequence of lower case letters. Each term corresponds to an operand tensor, and the characters within the terms correspond to operands dimensions.

This sequence may be followed by "->" to separate the left and right hand side of the equation. If the equation contains "->" followed by the right-hand side, the explicit (not classical) form of the Einstein summation is performed, and the right-hand side indices indicate output tensor dimensions. In other cases, output indices are (implicitly) set to the alphabetically sorted sequence of indices appearing exactly once in the equation.

When a dimension character is repeated in the left-hand side, it represents summation along the dimension.

The equation may contain ellipsis ("...") to enable broadcasting. Ellipsis must indicate a fixed number of dimensions. Specifically, every occurrence of ellipsis in the equation must represent the same number of dimensions. The right-hand side may contain exactly one ellipsis. In implicit mode, the ellipsis dimensions are set to the beginning of the output. The equation string may contain space (U+0020) character.

22.173 onnx::NegativeLogLikelihoodLoss

```
loss[n][d_1][d_2]...[d_k] = -input[n][c][d_1][d_2]...[d_k].
```

When an optional "weight" is provided, the sample loss is calculated as:

```
loss[n][d_1][d_2]...[d_k] = -input[n][c][d_1][d_2]...[d_k] * weight[c].
```

loss is zero for the case when target-value equals ignore_index.

```
loss[n][d_1][d_2]...[d_k] = 0, when target[n][d_1][d_2]...[d_k] = ignore_index
```

If “reduction” attribute is set to “none”, the operator’s output will be the above loss with shape (N, d1, d2, . . . , dk). If “reduction” attribute is set to “mean” (the default attribute value), the output loss is (weight) averaged:

```
mean(loss), if "weight" is not provided,
```

or if weight is provided,

```
sum(loss) / sum(weight[target[n][d_1][d_2]...[d_k]]]), for all samples.
```

If “reduction” attribute is set to “sum”, the output is a scalar: sum(loss).

See also https://pytorch.org/docs/stable/nn.html#torch.nn.NLLLoss.

Example 1:

```
// negative log likelihood loss, "none" reduction
N, C, d1 = 2, 3, 2
input = [[[1.0, 2.0], [2.0, 2.0], [3.0, 2.0]],
         [[0.0, 1.0], [2.0, 2.0], [1.0, 2]]]
target = [[2, 1], [0, 2]]

loss = np.zeros((N, d1))
for n in range(N):
    for d_1 in range(d1):
        c = target[n][d_1]
        loss[n][d_1] = -input[n][c][d_1]

// print(loss)
// [[-3. -2.]
//  [-0. -2.]]
```

Example 2:

```
// weighted negative log likelihood loss, sum reduction
N, C, d1 = 2, 3, 2
input = [[[1.0, 2.0], [2.0, 2.0], [3.0, 2.0]],
        [[0.0, 1.0], [2.0, 2.0], [1.0, 2]]]
target = [[2, 1], [0, 2]]
weight = [0.2, 0.3, 0.1]
loss = np.zeros((N, d1))
for n in range(N):
    for d_1 in range(d1):
        c = target[n][d_1]
        loss[n][d_1] = -input[n][c][d_1] * weight[c]

loss = np.sum(loss)
// print(loss)
// -1.1
```

Example 3:

```
// weighted negative log likelihood loss, mean reduction
N, C, d1 = 2, 3, 2
input = [[[1.0, 2.0], [2.0, 2.0], [3.0, 2.0]],
        [[0.0, 1.0], [2.0, 2.0], [1.0, 2]]]
target = [[2, 1], [0, 2]]
weight = [0.2, 0.3, 0.1]
loss = np.zeros((N, d1))
```

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```
weight_total = 0
for n in range(N):
    for d_1 in range(d1):
        c = target[n][d_1]
        loss[n][d_1] = -input[n][c][d_1] * weight[c]
        weight_total = weight_total + weight[c]

loss = np.sum(loss) / weight_total
// print(loss)
// -1.57
```

22.174 onnx::Celu

```
max(0,x) + min(0,alpha*(exp(x/alpha)-1))
```

22.175 onnx::LessOrEqual

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.176 onnx::GreaterOrEqual

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check the doc.

22.177 onnx::Trilu

22.178 onnx::HardSwish

22.179 onnx::OptionalHasElement

22.180 onnx::OptionalGetElement

22.181 onnx::CastLike

22.182 change_goal

22.183 retrieve_chunk

22.184 pattern_matching_function

22.185 conflict_resolution_function

22.186 update_goal

22.187 update_retrieval

22.188 check_termination

CHAPTER

TWENTYTHREE

MODECI_MDF

MDF is intended to be an open source, community-supported standard and associated library of tools for expressing computational models in a form that allows them to be exchanged between diverse programming languages and execution environments. The MDF Python API can be used to create or load an MDF model for inspection and validation. It also includes a basic execution engine for simulating models in the format. However, this is not intended as a general purpose simulation environment, nor is MDF intended as a programming language. Rather, the primary purpose of the Python API is to facilitate and validate the exchange of models between existing environments that serve different communities. Accordingly, these Python tools include bi-directional support for importing to and exporting from widely-used programming environments in a range of disciplines, and for easily extending these to other environments.

modeci_mdf.execution_engine	The reference implementation of the MDF execution engine; allows for executing `Graph` objects in Python.
modeci_mdf.full_translator	
modeci_mdf.functions	Specifies and implements the MDF the function ontology; a collection of builtin functions that can be used in MDF `Function` and `Parameter` objects.
modeci_mdf.interfaces	Implementations of importers and exporters for supported environments; fulfilling the hub and spoke model of MDF by allowing exchange between different modeling environments via MDF.
modeci_mdf.mdf	The main object-oriented implementation of the MDF schema, with each core component of the MDF specification implemented as a `class`.
modeci_mdf.utils	Useful utility functions for dealing with MDF objects.

23.1 modeci_mdf.execution_engine

The reference implementation of the MDF execution engine; allows for executing `Graph` objects in Python.

This module implements a set of classes for executing loaded MDF models in Python. The implementation is organized such that each class present in *mdf* has a corresponding `Evaluable` version of the class. Each of these classes implements the execution of these components and tracks their state during execution. The organization of the entire execution of the model is implemented at the top-level *evaluate()* method of the *EvaluableGraph* class. The external library graph-scheduler is used to implement the scheduling of nodes under declarative conditional constraints.

Functions

evaluate_expr([expr, func_params, ...])	Evaluates an expression given in string format and a `dict` of parameters.
evaluate_onnx_expr(expr, base_parameters, ...)	Evaluates a simple expression in string format representing an ONNX function call
get_required_variables_from_expression(expr)	Produces a list containing variable symbols in **expr**
main(example_file[, array_format, verbose])	Main entry point for execution engine.

23.1.1 modeci_mdf.execution_engine.evaluate_expr

modeci_mdf.execution_engine.**evaluate_expr**(*expr: Union[str, List[str], numpy.ndarray, tf.tensor] = None*, *func_params: Dict[str, Any] = None*, *array_format: str = 'numpy'*, *allow_strings_returned: Optional[bool] = False*, *verbose: Optional[bool] = False*) → numpy.ndarray

Evaluates an expression given in string format and a `dict` of parameters.

Parameters

- **expr** – Expression or list of expressions to be evaluated
- **func_params** – A dict of parameters (e.g. `{'weight': 2}`)
- **array_format** – It can be a n-dimensional array or a tensor
- **allow_strings_returned** – Don't throw an error if the expression evaluates to a string
- **verbose** – If set to True provides in-depth information else verbose message is not displayed

Returns n-dimensional array

23.1.2 modeci_mdf.execution_engine.evaluate_onnx_expr

modeci_mdf.execution_engine.**evaluate_onnx_expr**(*expr: str*, *base_parameters: Dict[str, Any]*, *evaluated_parameters: Dict*, *verbose: bool = False*) → Any

Evaluates a simple expression in string format representing an ONNX function call

Parameters

- **expr** (*str*) – Expression to be evaluated
- **base_parameters** (*Dict[str, Any]*) – A dict of parameters that may contain variables
- **evaluated_parameters** (*Dict*) – A dict mapping variables used in **base_parameters** to actual values
- **verbose** (*bool, optional*) – If set to True provides in-depth information else verbose message is not displayed. Defaults to False.

Returns the return value of **expr**

Return type Any

23.1.3 modeci_mdf.execution_engine.get_required_variables_from_expression

modeci_mdf.execution_engine.**get_required_variables_from_expression**(*expr: str*) → List[str]

Produces a list containing variable symbols in **expr**

23.1.4 modeci_mdf.execution_engine.main

modeci_mdf.execution_engine.**main**(*example_file: str*, *array_format: str = 'numpy'*, *verbose: bool = False*)

Main entry point for execution engine.

Parameters

- **example_file** – The MDF file to execute.
- **array_format** – The format of arrays to use. Allowed values: 'numpy' or 'tensorflow'.
- **verbose** – Whether to print output to standard out during execution.

Classes

EvaluableFunction(function, verbose)	Evaluates a *Function* value during MDF graph execution.
EvaluableGraph(graph, verbose)	Evaluates a *Graph* with the MDF execution engine.
EvaluableInput(input_port, verbose)	Evaluates input value at the *InputPort* of the node during MDF graph execution.
EvaluableNode(node, verbose)	Evaluates a *Node* during MDF graph execution.
EvaluableOutput(output_port, verbose)	Evaluates the current value of an *OutputPort* during MDF graph execution.
EvaluableParameter(parameter, verbose)	Evaluates the current value of a *Parameter* during the MDF graph execution.

23.1.5 modeci_mdf.execution_engine.EvaluableFunction

class modeci_mdf.execution_engine.**EvaluableFunction**(*function: modeci_mdf.mdf.Function = False*, *verbose: Optional[bool] = False*)

Bases: object

Evaluates a *Function* value during MDF graph execution.

Parameters

- **function** – *Function()* to be evaluated e.g. mdf standard function
- **verbose** – If set to True Provides in-depth information else verbose message is not displayed

Methods

evaluate([parameters, array_format])	Performs evaluation on the basis of given parameters and array_format

evaluate(*parameters: Optional[Dict[str, Any]] = None*, *array_format: str = 'numpy'*) → Dict[str, Any]
Performs evaluation on the basis of given parameters and array_format

Parameters

- **parameters** – A dictionary of function parameters,e.g.logistic, parameters={'gain': 2,"bias": 3,"offset": 1}
- **array_format** – It can be a n-dimensional array or a tensor

Returns value of function after evaluation in Dictionary

23.1.6 modeci_mdf.execution_engine.EvaluableGraph

class modeci_mdf.execution_engine.**EvaluableGraph**(*graph:* modeci_mdf.mdf.Graph, *verbose: Optional[bool] = False*)

Bases: object

Evaluates a *Graph* with the MDF execution engine. This is the top-level interface to the execution engine.

Parameters

- **graph** – A directed graph consisting of *Node*(s) connected via *Edge*(s)
- **verbose** – If set to True Provides in-depth information else verbose message is not displayed

Methods

evaluate([time_increment, array_format, ...])	Evaluates a *Graph*.
evaluate_edge(edge[, time_increment, ...])	Evaluates edges in graph
parse_condition(condition)	Convert the condition in a specific format

evaluate(*time_increment: Optional[Union[int, float]] = None*, *array_format: str = 'numpy'*, *initializer: Optional[Dict[str, Any]] = None*)
Evaluates a *Graph*. This is the top-level interface to the execution engine.

Parameters

- **time_increment** – Time step for next execution
- **array_format** – A n-dimensional array
- **initializer** – sets the initial value of parameters of the node

evaluate_edge(*edge:* modeci_mdf.mdf.Edge, *time_increment: Optional[Union[int, float]] = None*, *array_format: str = 'numpy'*)
Evaluates edges in graph

Parameters

- **time_increment** – Time step for next execution

- **array_format** – A n-dimensional array

parse_condition(*condition: Union[modeci_mdf.mdf.Condition, Dict]*) → graph_scheduler.condition.Condition

Convert the condition in a specific format

Parameters **condition** – Specify the condition under which a Component should be allowed to execute

Returns Condition in specific format

23.1.7 modeci_mdf.execution_engine.EvaluableInput

class modeci_mdf.execution_engine.**EvaluableInput**(*input_port: modeci_mdf.mdf.InputPort, verbose: Optional[bool] = False*)

Bases: object

Evaluates input value at the *InputPort* of the node during MDF graph execution.

Parameters

- **input_port** – The *InputPort* is an attribute of a Node which imports information to the *Node*
- **verbose** – If set to True Provides in-depth information else verbose message is not displayed

Methods

evaluate([parameters, array_format])	Evaluates value at Input port based on parameters and array_format
set_input_value(value)	Set a new value at input port

set_input_value(*value: Union[str, int, numpy.ndarray]*)

Set a new value at input port

Parameters **value** – Value to be set at Input Port

evaluate(*parameters: Optional[Dict[str, Any]] = None*, *array_format: str = 'numpy'*) → Union[int, numpy.ndarray]

Evaluates value at Input port based on parameters and array_format

Parameters

- **parameters** – Dictionary of parameters
- **array_format** – It is a n-dimensional array

Returns value at Input port

23.1.8 modeci_mdf.execution_engine.EvaluableNode

class modeci_mdf.execution_engine.**EvaluableNode**(*node: modeci_mdf.mdf.Node*, *verbose: Optional[bool] = False*)

Bases: object

Evaluates a *Node* during MDF graph execution.

Parameters

- **node** – A self contained unit of evaluation receiving input from other *Node*(s) on *InputPort*(s).
- **verbose** – If set to True Provides in-depth information else verbose message is not displayed

Methods

evaluate([time_increment, array_format])	Evaluate the Node for one time-step
get_output([id])	Get value at output port for given output port's id

evaluate(*time_increment: Optional[Union[int, float]] = None*, *array_format: str = 'numpy'*)
Evaluate the Node for one time-step

Parameters

- **time_increment** – The time-increment to use for this evaluation.
- **array_format** – The format to use for arrays.

get_output(*id: Optional[str] = None*) → Union[int, numpy.ndarray, Tuple]
Get value at output port for given output port's id

Parameters **id** – Unique identifier of the output port. If None, return a tuple for all output ports.

Returns value at the output port. If id is None, return all outputs as a tuple. If there is only one output, return just its value.

23.1.9 modeci_mdf.execution_engine.EvaluableOutput

class modeci_mdf.execution_engine.**EvaluableOutput**(*output_port: modeci_mdf.mdf.OutputPort*, *verbose: Optional[bool] = False*)

Bases: object

Evaluates the current value of an *OutputPort* during MDF graph execution.

Parameters

- **output_port** – Attribute of a Node which exports information to the dependent Node object
- **verbose** – If set to True Provides in-depth information else verbose message is not displayed

Methods

evaluate([parameters, array_format])	Evaluate the value at the output port on the basis of parameters and array_format

evaluate (*parameters: Optional[Dict[str, Any]] = None*, *array_format: str = 'numpy'*) → Union[int, numpy.ndarray]
Evaluate the value at the output port on the basis of parameters and array_format

Parameters

- **parameters** – Dictionary of global parameters of the Output Port
- **array_format** – It is a n-dimensional array

Returns value at output port

23.1.10 modeci_mdf.execution_engine.EvaluableParameter

class modeci_mdf.execution_engine.**EvaluableParameter**(*parameter: modeci_mdf.mdf.Parameter*, *verbose: bool = False*)

Bases: object

Evaluates the current value of a *Parameter* during the MDF graph execution.

Parameters

- **parameter** – The parameter to evaluate during execution.
- **verbose** – Whether to print output of parameter calculations.

Methods

evaluate(parameters[, time_increment, ...])	Evaluate the parameter and store the result in the curr_value attribute.
get_current_value(parameters[, array_format])	Get the current value of the parameter; evaluates the expression if the current value has not yet been set.

get_current_value (*parameters: Dict[str, Any]*, *array_format: str = 'numpy'*) → Any
Get the current value of the parameter; evaluates the expression if the current value has not yet been set. Note: this is different from 'evaluate', as calling that method multiple times can change the state of the parameter, but calling this should not reevaluate the parameter if it has a current value.

Parameters

- **parameters** – a dictionary of parameters and their values that may or may not be needed to evaluate this parameter.
- **array_format** – The array format to use (either 'numpy' or 'tensorflow').

Returns The evaluated value of the parameter.

evaluate (*parameters: Dict[str, Any]*, *time_increment: Optional[float] = None*, *array_format: str = 'numpy'*) → Any
Evaluate the parameter and store the result in the curr_value attribute.

Parameters

- **parameters** – a dictionary of parameters and their values that may or may not be needed to evaluate this parameter.
- **time_increment** – a floating point value specifying the timestep size, only used for `time_derivative` parameters
- **array_format** – The array format to use (either `'numpy'` or `tensorflow'`).

Returns The current value of the parameter.

23.2 modeci_mdf.full_translator

Functions

convert_states_to_stateful_parameters([...])	Translates json file if with states to json file with stateful_parameters, otherwise unchanged :param file_path: File in Json Format

23.2.1 modeci_mdf.full_translator.convert_states_to_stateful_parameters

modeci_mdf.full_translator.**convert_states_to_stateful_parameters**(*file_path: Optional[str] = None*, *dt=5e-05*)

Translates json file if with states to json file with stateful_parameters, otherwise unchanged :param file_path: File in Json Format

Returns file in json format

23.3 modeci_mdf.functions

Specifies and implements the MDF the function ontology; a collection of builtin functions that can be used in MDF `Function` and `Parameter` objects. Code for registering standard functions are with the ontology is implemented in *standard*. If you want to add functions to the ontology that can be used during execution see how this has been done for ONNX (*onnx*) and ACT-R (*actr*)

modeci_mdf.functions.actr	Contains implementations of ACT-R functions using the ccm library.
modeci_mdf.functions.onnx	Programmatically defines every ONNX operation as a python callable function.
modeci_mdf.functions.standard	Implementation of core MDF function ontology.

23.3.1 modeci_mdf.functions.actr

Contains implementations of ACT-R functions using the ccm library.

Functions

change_goal(pattern, curr_goal)	Modifies the current goal buffer using the given pattern.
check_termination(production)	Function used to check if no production was selected.
chunk_to_string(chunk)	Converts a chunk dictionary to a string format.
conflict_resolution_function(productions)	ACT-R conflict resolution function.
get_actr_functions()	Creates a list of all the ACT-R functions as MDF specifications.
match_production(production, context)	Returns True if the production's left hand side matches the given context and adds the matching bindings to the production.
pattern_matching_function(productions, goal, . . .)	Returns the productions that match the given goal and retrieval buffers.
pattern_to_string(pattern)	Converts a pattern dictionary to a string format.
retrieve_chunk(pattern, dm_chunks, types)	Retrieve a chunk from declarative memory given a pattern.
update_buffer(production, buffer)	Returns a pattern to update the given buffer with.
update_goal(production)	Returns a pattern to update the goal buffer with.
update_retrieval(production)	Returns a pattern to update the retrieval buffer with.

modeci_mdf.functions.actr.change_goal

modeci_mdf.functions.actr.**change_goal**(*pattern: Dict[str, str]*, *curr_goal: Dict[str, str]*)

Modifies the current goal buffer using the given pattern.

Parameters

- **pattern** – A dict representing a pattern.
- **curr_goal** – A dict representing the current goal pattern.

Returns The current goal updated with the data in pattern.

modeci_mdf.functions.actr.check_termination

modeci_mdf.functions.actr.**check_termination**(*production: Dict[str, Any]*)

Function used to check if no production was selected.

Parameters **production** – A production dict that was selected.

Returns True if the production is empty.

modeci_mdf.functions.actr.chunk_to_string

modeci_mdf.functions.actr.**chunk_to_string**(*chunk: Dict[str, str]*) → str

Converts a chunk dictionary to a string format.

Parameters **chunk** – A dict representing a chunk.

Returns A string representation of the chunk.

modeci_mdf.functions.actr.conflict_resolution_function

modeci_mdf.functions.actr.**conflict_resolution_function**(*productions: List[Dict[str, Any]]*) → Dict[str, Any]

ACT-R conflict resolution function. Currently selects a production at random from the already matched productions, since utility values and learning are not implemented yet.

Parameters **productions** – A list of productions as dicts.

Returns The selected production from the list.

modeci_mdf.functions.actr.get_actr_functions

modeci_mdf.functions.actr.**get_actr_functions**() → List[Dict[str, Any]]

Creates a list of all the ACT-R functions as MDF specifications.

Returns A list of MDF function specifications.

modeci_mdf.functions.actr.match_production

modeci_mdf.functions.actr.**match_production**(*production: Dict[str, Any]*, *context: Dict[str, Dict[str, str]]*) → bool

Returns True if the production's left hand side matches the given context and adds the matching bindings to the production.

Parameters

- **production** – A dict representing a production.
- **context** – A dict with the contents of the goal and retrieval buffers.

Returns True if the production's left hand side matches the context.

modeci_mdf.functions.actr.pattern_matching_function

modeci_mdf.functions.actr.**pattern_matching_function**(*productions: List[Dict[str, Any]]*, *goal: Dict[str, str]*, *retrieval: Dict[str, str]*) → List[Dict[str, Any]]

Returns the productions that match the given goal and retrieval buffers.

Parameters

- **productions** – A list of all productions as dicts.
- **goal** – The current value of the goal buffer as a dict.
- **retrieval** – The chunk dict retrieved from declarative memory.

Returns A list of productions that match the buffers.

modeci_mdf.functions.actr.pattern_to_string

modeci_mdf.functions.actr.**pattern_to_string**(*pattern: Dict[str, str]*) → str
Converts a pattern dictionary to a string format.

Parameters **chunk** – A dict representing a pattern.

Returns A string representation of the pattern.

modeci_mdf.functions.actr.retrieve_chunk

modeci_mdf.functions.actr.**retrieve_chunk**(*pattern: Dict[str, str]*, *dm_chunks: List[Dict[str, str]]*, *types: Dict[str, List[str]]*) → Dict[str, str]
Retrieve a chunk from declarative memory given a pattern.

Parameters

- **pattern** – A dict representing the pattern to match.
- **dm_chunks** – A list of dicts, each representing a chunk in declarative memory.
- **types** – A dict containing each possible chunk type.

Returns The chunk in declarative memory that matches the pattern.

modeci_mdf.functions.actr.update_buffer

modeci_mdf.functions.actr.**update_buffer**(*production: Dict[str, Any]*, *buffer: str*) → Dict[str, str]
Returns a pattern to update the given buffer with.

Parameters

- **production** – The production dict that specifies the buffer update.
- **buffer** – The name of the buffer to update.

Returns A pattern that the buffer will be updated with.

modeci_mdf.functions.actr.update_goal

modeci_mdf.functions.actr.**update_goal**(*production: Dict[str, Any]*) → Dict[str, str]
Returns a pattern to update the goal buffer with.

Parameters **production** – The production dict that specifies the goal buffer update.

Returns A pattern that the goal buffer will be updated with.

modeci_mdf.functions.actr.update_retrieval

modeci_mdf.functions.actr.**update_retrieval**(*production: Dict[str, Any]*) → Dict[str, str]
Returns a pattern to update the retrieval buffer with.

Parameters **production** – The production dict that specifies the retrieval buffer update.

Returns A pattern that the retrieval buffer will be updated with.

modeci_mdf.functions.actr.ccm

modeci_mdf.functions.actr.ccm

modeci_mdf.functions.actr.ccm.buffer
modeci_mdf.functions.actr.ccm.dm
modeci_mdf.functions.actr.ccm.logger
modeci_mdf.functions.actr.ccm.model
modeci_mdf.functions.actr.ccm.pattern
modeci_mdf.functions.actr.ccm.scheduler

modeci_mdf.functions.actr.ccm.buffer

Classes

Buffer()
Chunk(contents[, bound])

modeci_mdf.functions.actr.ccm.buffer.Buffer

class modeci_mdf.functions.actr.ccm.buffer.**Buffer**
Bases: *modeci_mdf.functions.actr.ccm.model.Model*

Methods

clear()
isEmpty()
modify(**args)
set(chunk)

modeci_mdf.functions.actr.ccm.buffer.Chunk

class modeci_mdf.functions.actr.ccm.buffer.**Chunk**(*contents*, *bound=None*)
Bases: collections.UserDict

Methods

—

modeci_mdf.functions.actr.ccm.dm

Classes

Associated(a, b)
BlendingMemory(buffer[, latency, threshold, ...])
DMAssociate(memory, buffer[, weight, decay, ...])
DMBaseLevel(memory[, decay, limit])
DMFixed(memory[, default])
DMInhibition(memory[, decayScale, timeScale])
DMNoise(memory[, noise, baseNoise])
DMSalience(memory)
DMSpacing(memory[, decayScale, decayIntercept])
DMSpreading(memory, *buffers)
Finst(parent[, size, time])
Memory(buffer[, latency, threshold, ...])
MemorySubModule(parent)
Partial(memory[, strength, limit])

modeci_mdf.functions.actr.ccm.dm.Associated

class modeci_mdf.functions.actr.ccm.dm.**Associated**(*a*, *b*)
Bases: object

Methods

—

modeci_mdf.functions.actr.ccm.dm.BlendingMemory

class modeci_mdf.functions.actr.ccm.dm.**BlendingMemory**(*buffer*, *latency=0.05*, *threshold=0*, *maximum_time=10.0*, *finst_size=4*, *finst_time=3.0*)
Bases: *modeci_mdf.functions.actr.ccm.dm.Memory*

Methods

recall(chunk, matches, request_number)

modeci_mdf.functions.actr.ccm.dm.DMAssociate

class modeci_mdf.functions.actr.ccm.dm.**DMAssociate**(*memory*, *buffer*, *weight=1*, *decay=0.5*, *limit=None*)
Bases: *modeci_mdf.functions.actr.ccm.dm.MemorySubModule*

Methods

activation(chunk)
recalled(chunk)
set_association(pre, post, baselevel)

modeci_mdf.functions.actr.ccm.dm.DMBaseLevel

class modeci_mdf.functions.actr.ccm.dm.**DMBaseLevel**(*memory*, *decay=0.5*, *limit=None*)
Bases: *modeci_mdf.functions.actr.ccm.dm.MemorySubModule*

Methods

activation(chunk)
create(chunk[, time, baselevel])
merge(chunk[, time, baselevel])

modeci_mdf.functions.actr.ccm.dm.DMFixed

class modeci_mdf.functions.actr.ccm.dm.**DMFixed**(*memory*, *default=0*)
Bases: *modeci_mdf.functions.actr.ccm.dm.MemorySubModule*

Methods

activation(chunk)
create(chunk[, fixed])
merge(chunk[, fixed])

modeci_mdf.functions.actr.ccm.dm.DMInhibition

class modeci_mdf.functions.actr.ccm.dm.**DMInhibition**(*memory*, *decayScale=1.0*, *timeScale=5.0*)
Bases: *modeci_mdf.functions.actr.ccm.dm.MemorySubModule*

Methods

activation(chunk)
create(chunk[, time])
merge(chunk[, time])

modeci_mdf.functions.actr.ccm.dm.DMNoise

class modeci_mdf.functions.actr.ccm.dm.**DMNoise**(*memory*, *noise=0.3*, *baseNoise=0.0*)
Bases: *modeci_mdf.functions.actr.ccm.dm.MemorySubModule*

Methods

activation(chunk)
create(chunk, **keys)
logisticNoise(s)

modeci_mdf.functions.actr.ccm.dm.DMSalience

class modeci_mdf.functions.actr.ccm.dm.**DMSalience**(*memory*)
Bases: *modeci_mdf.functions.actr.ccm.dm.MemorySubModule*

Methods

activation(chunk)
context(pattern)
weights(**weights)

modeci_mdf.functions.actr.ccm.dm.DMSpacing

class modeci_mdf.functions.actr.ccm.dm.**DMSpacing**(*memory*, *decayScale=0.0*, *decayIntercept=0.5*)
Bases: *modeci_mdf.functions.actr.ccm.dm.MemorySubModule*

Methods

activation(chunk)
create(chunk[, time])
merge(chunk[, time])

modeci_mdf.functions.actr.ccm.dm.DMSpreading

class modeci_mdf.functions.actr.ccm.dm.**DMSpreading**(*memory*, **buffers*)
Bases: *modeci_mdf.functions.actr.ccm.dm.MemorySubModule*

Methods

activation(chunk)
create(chunk, **keys)

modeci_mdf.functions.actr.ccm.dm.Finst

class modeci_mdf.functions.actr.ccm.dm.**Finst**(*parent*, *size=4*, *time=3.0*)
Bases: object

Methods

add(o)
contains(o)
remove(o)

modeci_mdf.functions.actr.ccm.dm.Memory

class modeci_mdf.functions.actr.ccm.dm.**Memory**(*buffer*, *latency=0.05*, *threshold=0*, *maximum_time=10.0*, *finst_size=4*, *finst_time=3.0*)
Bases: *modeci_mdf.functions.actr.ccm.model.Model*

Methods

add(chunk[, record])
add_adaptor(a)
clear()
fail(request_number)
find_matching_chunks(pattern[, threshold])

continues on next page

Table 30 – continued from previous page

get_activation(chunk)
recall(chunk, matches, request_number)
request(pattern[, partial, require_new])

modeci_mdf.functions.actr.ccm.dm.MemorySubModule

class modeci_mdf.functions.actr.ccm.dm.**MemorySubModule**(*parent*)

Bases: object

Methods

activation(chunk)
create(chunk, **keys)
matched(chunks)
merge(chunk, **keys)
now()
recalled(chunk)

modeci_mdf.functions.actr.ccm.dm.Partial

class modeci_mdf.functions.actr.ccm.dm.**Partial**(*memory*, *strength=1.0*, *limit=- 1.0*)

Bases: object

Methods

match(key, a, b)
request(pattern)
similarity(a, b, value)

modeci_mdf.functions.actr.ccm.logger

Functions

file_exists(filename)	
finished([flush])	
log([screen, html, data, summary, directory])	

modeci_mdf.functions.actr.ccm.logger.file_exists

modeci_mdf.functions.actr.ccm.logger.**file_exists**(*filename*)

modeci_mdf.functions.actr.ccm.logger.finished

modeci_mdf.functions.actr.ccm.logger.**finished**(*flush=True*)

modeci_mdf.functions.actr.ccm.logger.log

modeci_mdf.functions.actr.ccm.logger.**log**(*screen=None*, *html=None*, *data=None*, *summary=None*, *directory=None*)

Classes

DummyLog()	
Log()	
LogProxy(log[, prefix])	
Trace()	

modeci_mdf.functions.actr.ccm.logger.DummyLog

class modeci_mdf.functions.actr.ccm.logger.**DummyLog**
Bases: object

Methods

set(key, value)

modeci_mdf.functions.actr.ccm.logger.Log

class modeci_mdf.functions.actr.ccm.logger.**Log**
Bases: object

Methods

display_all()
display_value(key, value)
ensure_directory_exists()
get_time_code()
reset()
set(key, value)
use_directory(dir)

modeci_mdf.functions.actr.ccm.logger.LogProxy

class modeci_mdf.functions.actr.ccm.logger.**LogProxy**(*log*, *prefix=''*)
Bases: object

Methods

—

modeci_mdf.functions.actr.ccm.logger.Trace

class modeci_mdf.functions.actr.ccm.logger.**Trace**
Bases: object

Methods

add(key, value)
fixed_keys()
get_at(name, time)
get_final(key)
get_pts(vars)
group_pts(pts, key)
keys()
merge_pts(pts, key)

modeci_mdf.functions.actr.ccm.model

Functions

log_everything(model[, log])

modeci_mdf.functions.actr.ccm.model.log_everything

modeci_mdf.functions.actr.ccm.model.**log_everything**(*model*, *log=None*)

Classes

MethodGeneratorWrapper(obj, func, name)
MethodWrapper(obj, func, name)
Model([log])

modeci_mdf.functions.actr.ccm.model.MethodGeneratorWrapper

class modeci_mdf.functions.actr.ccm.model.**MethodGeneratorWrapper**(*obj*, *func*, *name*)

Bases: *modeci_mdf.functions.actr.ccm.model.MethodWrapper*

Methods

__

__call__(**args*, ***keys*)
Call self as a function.

modeci_mdf.functions.actr.ccm.model.MethodWrapper

class modeci_mdf.functions.actr.ccm.model.**MethodWrapper**(*obj*, *func*, *name*)

Bases: object

Methods

__

__call__(**args*, ***keys*)
Call self as a function.

modeci_mdf.functions.actr.ccm.model.Model

class modeci_mdf.functions.actr.ccm.model.**Model**(*log=None*, ***keys*)

Bases: object

Methods

get_children()
now()
run([limit, func])
start()
stop()

modeci_mdf.functions.actr.ccm.pattern

Functions

get(obj, name, key)
parse(patterns[, bound])
partialmatch(obj, name, key, b, value)

modeci_mdf.functions.actr.ccm.pattern.get

modeci_mdf.functions.actr.ccm.pattern.**get**(*obj*, *name*, *key*)

modeci_mdf.functions.actr.ccm.pattern.parse

modeci_mdf.functions.actr.ccm.pattern.**parse**(*patterns*, *bound=None*)

modeci_mdf.functions.actr.ccm.pattern.partialmatch

modeci_mdf.functions.actr.ccm.pattern.**partialmatch**(*obj*, *name*, *key*, *b*, *value*)

Classes

Pattern(patterns[, bound, partial])

modeci_mdf.functions.actr.ccm.pattern.Pattern

class modeci_mdf.functions.actr.ccm.pattern.**Pattern**(*patterns*, *bound=None*, *partial=None*)

Bases: object

Methods

match(obj)

Exceptions

PatternException

modeci_mdf.functions.actr.ccm.pattern.PatternException

exception modeci_mdf.functions.actr.ccm.pattern.**PatternException**

modeci_mdf.functions.actr.ccm.scheduler

Classes

Event(func, time[, args, keys, priority])
Scheduler()
Trigger([name])

modeci_mdf.functions.actr.ccm.scheduler.Event

class modeci_mdf.functions.actr.ccm.scheduler.**Event**(*func*, *time*, *args=[]*, *keys={}*, *priority=0*)

Bases: object

Methods

—

modeci_mdf.functions.actr.ccm.scheduler.Scheduler

class modeci_mdf.functions.actr.ccm.scheduler.**Scheduler**

Bases: object

Methods

add(func[, delay, args, keys, priority, ...])
add_event(event)
do_event(event)
extend(other)

continues on next page

Table 50 – continued from previous page

handle_result(result, event)	
run()	
stop()	
trigger(key[, priority])	

modeci_mdf.functions.actr.ccm.scheduler.Trigger

class modeci_mdf.functions.actr.ccm.scheduler.**Trigger**(*name=''*)
Bases: object

Methods

—

Exceptions

SchedulerError	

modeci_mdf.functions.actr.ccm.scheduler.SchedulerError

exception modeci_mdf.functions.actr.ccm.scheduler.**SchedulerError**

23.3.2 modeci_mdf.functions.onnx

Programmatically defines every ONNX operation as a python callable function. Executing ONNX graphs in this way somewhat defeats the performance purposes of ONNX since the overhead for each operation will be high. However, this allows us to test the MDF scheduler (which invokes Python functions) on any MDF model defined over ONNX operations. In the future, the MDF should probably just compile to ONNX (or some other IR) for execution.

Functions

abs(*args, **kwargs)	Absolute takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the absolute is, y = abs(x), is applied to the tensor elementwise.
acos(*args, **kwargs)	Calculates the arccosine (inverse of cosine) of the given input tensor, element-wise.
acosh(*args, **kwargs)	Calculates the hyperbolic arccosine of the given input tensor element-wise.
add(*args, **kwargs)	Performs element-wise binary addition (with Numpy-style broadcasting support).

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Table 53 – continued from previous page

and(*args, **kwargs)	Returns the tensor resulted from performing the *and* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).
argmax(*args, **kwargs)	Computes the indices of the max elements of the input tensor's element along the provided axis.
argmin(*args, **kwargs)	Computes the indices of the min elements of the input tensor's element along the provided axis.
asin(*args, **kwargs)	Calculates the arcsine (inverse of sine) of the given input tensor, element-wise.
asinh(*args, **kwargs)	Calculates the hyperbolic arcsine of the given input tensor element-wise.
atan(*args, **kwargs)	Calculates the arctangent (inverse of tangent) of the given input tensor, element-wise.
atanh(*args, **kwargs)	Calculates the hyperbolic arctangent of the given input tensor element-wise.
averagepool(*args, **kwargs)	AveragePool consumes an input tensor X and applies average pooling across the tensor according to kernel sizes, stride sizes, and pad lengths.
batchnormalization(*args, **kwargs)	Carries out batch normalization as described in the paper https://arxiv.org/abs/1502.03167.
bernoulli(*args, **kwargs)	Draws binary random numbers (0 or 1) from a Bernoulli distribution.
bitshift(*args, **kwargs)	Bitwise shift operator performs element-wise operation. For each input element, if the
cast(*args, **kwargs)	The operator casts the elements of a given input tensor to a data type specified by the 'to' argument and returns an output tensor of the same size in the converted type.
castlike(*args, **kwargs)	The operator casts the elements of a given input tensor (the first input) to the same data type as the elements of the second input tensor.
ceil(*args, **kwargs)	Ceil takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the ceil is, y = ceil(x), is applied to the tensor elementwise.
celu(*args, **kwargs)	Continuously Differentiable Exponential Linear Units: Perform the linear unit element-wise on the input tensor X using formula:
clip(*args, **kwargs)	Clip operator limits the given input within an interval.
compress(*args, **kwargs)	Selects slices from an input tensor along a given axis where condition evaluates to True for each axis index.
concat(*args, **kwargs)	Concatenate a list of tensors into a single tensor.
concatfromsequence(*args, **kwargs)	Concatenate a sequence of tensors into a single tensor.
constant(*args, **kwargs)	This operator produces a constant tensor.
constantofshape(*args, **kwargs)	Generate a tensor with given value and shape.
conv(*args, **kwargs)	The convolution operator consumes an input tensor and a filter, and computes the output.
convert_type(v)	Helper function to convert types to ONNX compatible types.
convinteger(*args, **kwargs)	The integer convolution operator consumes an input tensor, its zero-point, a filter, and its zero-point, and computes the output.

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Table 53 – continued from previous page

convtranspose(*args, **kwargs)	The convolution transpose operator consumes an input tensor and a filter, and computes the output.
cos(*args, **kwargs)	Calculates the cosine of the given input tensor, element-wise.
cosh(*args, **kwargs)	Calculates the hyperbolic cosine of the given input tensor element-wise.
cumsum(*args, **kwargs)	Performs cumulative sum of the input elements along the given axis.
depthtospace(*args, **kwargs)	DepthToSpace rearranges (permutes) data from depth into blocks of spatial data.
dequantizelinear(*args, **kwargs)	The linear dequantization operator.
det(*args, **kwargs)	Det calculates determinant of a square matrix or batches of square matrices.
div(*args, **kwargs)	Performs element-wise binary division (with Numpy-style broadcasting support).
dropout(*args, **kwargs)	Dropout takes an input floating-point tensor, an optional input ratio (floating-point scalar) and an optional input training_mode (boolean scalar).
dynamicquantizelinear(*args, **kwargs)	A Function to fuse calculation for Scale, Zero Point and FP32->8Bit convertion of FP32 Input data. Outputs Scale, ZeroPoint and Quantized Input for a given FP32 Input. Scale is calculated as: ` y_scale = (max(x) - min(x))/(qmax - qmin) * where qmax and qmin are max and min values for quantization range .i.e [0, 255] in case of uint8 * data range is adjusted to include 0. ` Zero point is calculated as: ` intermediate_zero_point = qmin - min(x)/y_scale y_zero_point = cast(round(saturate(itermediate_zero_point))) * where qmax and qmin are max and min values for quantization range .i.e [0, 255] in case of uint8 * for saturation, it saturates to [0, 255] if it's uint8, or [-127, 127] if it's int8. Right now only uint8 is supported. * rounding to nearest ties to even. ` Data quantization formula is: ` y = saturate (round (x / y_scale) + y_zero_point) * for saturation, it saturates to [0, 255] if it's uint8, or [-127, 127] if it's int8. Right now only uint8 is supported. * rounding to nearest ties to even. `.
einsum(*args, **kwargs)	An einsum of the form `term1, term2 -> output-term` produces an output tensor using the following equation
elu(*args, **kwargs)	Elu takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the function *f(x) = alpha * (exp(x) - 1.) for x < 0, f(x) = x for x >= 0.*, is applied to the tensor elementwise.

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Table 53 – continued from previous page

equal(*args, **kwargs)	Returns the tensor resulted from performing the *equal* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).
erf(*args, **kwargs)	Computes the error function of the given input tensor element-wise.
exp(*args, **kwargs)	Calculates the exponential of the given input tensor, element-wise.
expand(*args, **kwargs)	Broadcast the input tensor following the given shape and the broadcast rule.
eyelike(*args, **kwargs)	Generate a 2D tensor (matrix) with ones on the diagonal and zeros everywhere else.
flatten(*args, **kwargs)	Flattens the input tensor into a 2D matrix.
floor(*args, **kwargs)	Floor takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the floor is, y = floor(x), is applied to the tensor elementwise.
gather(*args, **kwargs)	Given *data* tensor of rank r >= 1, and *indices* tensor of rank q, gather entries of the axis dimension of *data* (by default outer-most one as axis=0) indexed by *indices*, and concatenates them in an output tensor of rank q + (r - 1).
gatherelements(*args, **kwargs)	GatherElements takes two inputs *data* and *indices* of the same rank r >= 1 and an optional attribute *axis* that identifies an axis of *data* (by default, the outer-most axis, that is axis 0).
gathernd(*args, **kwargs)	Given *data* tensor of rank *r* >= 1, *indices* tensor of rank *q* >= 1, and *batch_dims* integer *b*, this operator gathers slices of *data* into an output tensor of rank *q* + *r* - *indices_shape[-1]* - 1 - *b*.
gemm(*args, **kwargs)	General Matrix multiplication: https://en.wikipedia.org/wiki/Basic_Linear_Algebra_Subprograms#Level_3
get_all_schemas_version(max_version)	Enumerate all the OpSchemas available from ONNX.
get_onnx_ops([opset_version])	Enumerate all available ONNX operations and generate MDF function specifications for each one.
get_onnx_schema(func_name[, opset_version])	Return the ONNX schema corresponding to a generated ONNX python function with name **func_name**
globalaveragepool(*args, **kwargs)	GlobalAveragePool consumes an input tensor X and applies average pooling across the values in the same channel.
globallppool(*args, **kwargs)	GlobalLpPool consumes an input tensor X and applies lp pool pooling across the values in the same channel.
globalmaxpool(*args, **kwargs)	GlobalMaxPool consumes an input tensor X and applies max pooling across the values in the same channel.
greater(*args, **kwargs)	Returns the tensor resulted from performing the *greater* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).
greaterorequal(*args, **kwargs)	Returns the tensor resulted from performing the *greater_equal* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).
gru(*args, **kwargs)	Computes an one-layer GRU.

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Table 53 – continued from previous page

hardmax(*args, **kwargs)	The operator computes the hardmax values for the given input:
hardsigmoid(*args, **kwargs)	HardSigmoid takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the HardSigmoid function, y = max(0, min(1, alpha * x + beta)), is applied to the tensor elementwise.
hardswish(*args, **kwargs)	HardSwish takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the HardSwish function, y = x * max(0, min(1, alpha * x + beta)) = x * HardSigmoid<alpha, beta>(x), where alpha = 1/6 and beta = 0.5, is applied to the tensor elementwise.
identity(*args, **kwargs)	Identity operator
if(*args, **kwargs)	If conditional
import_class(name)	Import from a module specified by a string
instancenormalization(*args, **kwargs)	Carries out instance normalization as described in the paper https://arxiv.org/abs/1607.08022.
isinf(*args, **kwargs)	Map infinity to true and other values to false.
isnan(*args, **kwargs)	Returns which elements of the input are NaN.
leakyrelu(*args, **kwargs)	LeakyRelu takes input data (Tensor<T>) and an argument alpha, and produces one output data (Tensor<T>) where the function *f(x) = alpha * x for x < 0, f(x) = x for x >= 0*, is applied to the data tensor elementwise.
less(*args, **kwargs)	Returns the tensor resulted from performing the *less* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).
lessorequal(*args, **kwargs)	Returns the tensor resulted from performing the *less_equal* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).
log(*args, **kwargs)	Calculates the natural log of the given input tensor, element-wise.
logsoftmax(*args, **kwargs)	The operator computes the log of softmax values for the given input:
loop(*args, **kwargs)	Generic Looping construct.
lpnormalization(*args, **kwargs)	Given a matrix, apply Lp-normalization along the provided axis.
lppool(*args, **kwargs)	LpPool consumes an input tensor X and applies Lp pooling across the tensor according to kernel sizes, stride sizes, and pad lengths.
lrn(*args, **kwargs)	Local Response Normalization proposed in the [AlexNet paper](https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf).
lstm(*args, **kwargs)	Computes an one-layer LSTM.
matmul(*args, **kwargs)	Matrix product that behaves like numpy.matmul: https://docs.scipy.org/doc/numpy-1.13.0/reference/generated/numpy.matmul.html
matmulinteger(*args, **kwargs)	Matrix product that behaves like numpy.matmul: https://docs.scipy.org/doc/numpy-1.13.0/reference/generated/numpy.matmul.html.

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Table 53 – continued from previous page

max(*args, **kwargs)	Element-wise max of each of the input tensors (with Numpy-style broadcasting support).
maxpool(*args, **kwargs)	MaxPool consumes an input tensor X and applies max pooling across the tensor according to kernel sizes, stride sizes, and pad lengths.
maxroipool(*args, **kwargs)	ROI max pool consumes an input tensor X and region of interests (RoIs) to apply max pooling across each RoI, to produce output 4-D tensor of shape (num_rois, channels, pooled_shape[0], pooled_shape[1]).
maxunpool(*args, **kwargs)	MaxUnpool essentially computes the partial inverse of the MaxPool op.
mean(*args, **kwargs)	Element-wise mean of each of the input tensors (with Numpy-style broadcasting support).
meanvariancenormalization(*args, **kwargs)	A MeanVarianceNormalization Function: Perform mean variance normalization on the input tensor X using formula: ` (X-EX)/sqrt(E(X-EX)^2) `
min(*args, **kwargs)	Element-wise min of each of the input tensors (with Numpy-style broadcasting support).
mod(*args, **kwargs)	Performs element-wise binary modulus (with Numpy-style broadcasting support).
mul(*args, **kwargs)	Performs element-wise binary multiplication (with Numpy-style broadcasting support).
multinomial(*args, **kwargs)	Generate a tensor of samples from a multinomial distribution according to the probabilities of each of the possible outcomes.
neg(*args, **kwargs)	Neg takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where each element flipped sign, y = -x, is applied to the tensor elementwise.
negativeloglikelihoodloss(*args, **kwargs)	A NegativeLogLikelihoodLoss operator computes (weighted) negative log likelihood loss.
nonmaxsuppression(*args, **kwargs)	Filter out boxes that have high intersection-over-union (IOU) overlap with previously selected boxes.
nonzero(*args, **kwargs)	Returns the indices of the elements that are non-zero (in row-major order - by dimension).
not(*args, **kwargs)	Returns the negation of the input tensor element-wise.
onehot(*args, **kwargs)	Produces a one-hot tensor based on inputs.
optional(*args, **kwargs)	Constructs an optional-type value containing either an empty optional of a certain type specified by the attribute, or a non-empty value containing the input element.
optionalgetelement(*args, **kwargs)	Outputs the element in the optional-type input.
optionalhaselement(*args, **kwargs)	Returns true if the optional-type input contains an element.
or(*args, **kwargs)	Returns the tensor resulted from performing the *or* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).
pad(*args, **kwargs)	Given a tensor containing the data to be padded (*data*), a tensor containing the number of start and end pad values for axis (*pads*), (optionally) a *mode*, and (optionally) *constant_value*, a padded tensor (*output*) is generated.

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Table 53 – continued from previous page

pow(*args, **kwargs)	Pow takes input data (Tensor<T>) and exponent Tensor, and produces one output data (Tensor<T>) where the function *f(x) = x^exponent*, is applied to the data tensor elementwise.
predict_with_onnxruntime(model_def, *inputs)	Simple helper to run an ONNX model with a set of inputs.
prelu(*args, **kwargs)	PRelu takes input data (Tensor<T>) and slope tensor as input, and produces one output data (Tensor<T>) where the function *f(x) = slope * x for x < 0, f(x) = x for x >= 0.*, is applied to the data tensor elementwise.
qlinearconv(*args, **kwargs)	The convolution operator consumes a quantized input tensor, its scale and zero point, a quantized filter, its scale and zero point, and output's scale and zero point, and computes the quantized output.
qlinearmatmul(*args, **kwargs)	Matrix product that behaves like numpy.matmul: https://docs.scipy.org/doc/numpy-1.13.0/reference/generated/numpy.matmul.html.
quantizelinear(*args, **kwargs)	The linear quantization operator.
randomnormal(*args, **kwargs)	Generate a tensor with random values drawn from a normal distribution.
randomnormallike(*args, **kwargs)	Generate a tensor with random values drawn from a normal distribution.
randomuniform(*args, **kwargs)	Generate a tensor with random values drawn from a uniform distribution.
randomuniformlike(*args, **kwargs)	Generate a tensor with random values drawn from a uniform distribution.
range(*args, **kwargs)	Generate a tensor containing a sequence of numbers that begin at *start* and extends by increments of *delta* up to *limit* (exclusive).
reciprocal(*args, **kwargs)	Reciprocal takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the reciprocal is, y = 1/x, is applied to the tensor elementwise.
reducel1(*args, **kwargs)	Computes the L1 norm of the input tensor's element along the provided axes.
reducel2(*args, **kwargs)	Computes the L2 norm of the input tensor's element along the provided axes.
reducelogsum(*args, **kwargs)	Computes the log sum of the input tensor's element along the provided axes.
reducelogsumexp(*args, **kwargs)	Computes the log sum exponent of the input tensor's element along the provided axes.
reducemax(*args, **kwargs)	Computes the max of the input tensor's element along the provided axes.
reducemean(*args, **kwargs)	Computes the mean of the input tensor's element along the provided axes.
reducemin(*args, **kwargs)	Computes the min of the input tensor's element along the provided axes.
reduceprod(*args, **kwargs)	Computes the product of the input tensor's element along the provided axes.
reducesum(*args, **kwargs)	Computes the sum of the input tensor's element along the provided axes.

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Table 53 – continued from previous page

reducesumsquare(*args, **kwargs)	Computes the sum square of the input tensor's element along the provided axes.
relu(*args, **kwargs)	Relu takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the rectified linear function, y = max(0, x), is applied to the tensor elementwise.
reshape(*args, **kwargs)	Reshape the input tensor similar to numpy.reshape.
resize(*args, **kwargs)	Resize the input tensor. In general, it calculates every value in the output tensor as a weighted average of neighborhood (a.k.a. sampling locations) in the input tensor. Each dimension value of the output tensor is: output_dimension = floor(input_dimension * (roi_end - roi_start) * scale) if input "sizes" is not specified.
reversesequence(*args, **kwargs)	Reverse batch of sequences having different lengths specified by *sequence_lens*.
rnn(*args, **kwargs)	Computes an one-layer simple RNN.
roialign(*args, **kwargs)	Region of Interest (RoI) align operation described in the [Mask R-CNN paper](https://arxiv.org/abs/1703.06870).
round(*args, **kwargs)	Round takes one input Tensor and rounds the values, element-wise, meaning it finds the nearest integer for each value.
run_onnx_op(op_name, inputs, output_names[, ...])	Simple helper function that invokes a single ONNX operator with inputs and attibutes and returns the results.
scan(*args, **kwargs)	Scan can be used to iterate over one or more scan_input tensors, constructing zero or more scan_output tensors.
scatter(*args, **kwargs)	This operator is deprecated.
scatterelements(*args, **kwargs)	ScatterElements takes three inputs *data*, *updates*, and *indices* of the same rank r >= 1 and an optional attribute axis that identifies an axis of *data* (by default, the outermost axis, that is axis 0).
scatternd(*args, **kwargs)	ScatterND takes three inputs *data* tensor of rank r >= 1, *indices* tensor of rank q >= 1, and *updates* tensor of rank q + r - indices.shape[-1] - 1.
selu(*args, **kwargs)	Selu takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the scaled exponential linear unit function, *y = gamma * (alpha * e^x - alpha) for x <= 0*, *y = gamma * x for x > 0*, is applied to the tensor elementwise.
sequenceat(*args, **kwargs)	Outputs a tensor copy from the tensor at 'position' in 'input_sequence'.
sequenceconstruct(*args, **kwargs)	Construct a tensor sequence containing 'inputs' tensors.
sequenceempty(*args, **kwargs)	Construct an empty tensor sequence, with given data type.
sequenceerase(*args, **kwargs)	Outputs a tensor sequence that removes the tensor at 'position' from 'input_sequence'.
sequenceinsert(*args, **kwargs)	Outputs a tensor sequence that inserts 'tensor' into 'input_sequence' at 'position'.
sequencelength(*args, **kwargs)	Produces a scalar(tensor of empty shape) containing the number of tensors in 'input_sequence'.

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Table 53 – continued from previous page

shape(*args, **kwargs)	Takes a tensor as input and outputs an 1D int64 tensor containing the shape of the input tensor.
shrink(*args, **kwargs)	Shrink takes one input data (Tensor<numeric>) and produces one Tensor output, having same datatype and shape with input.
sigmoid(*args, **kwargs)	Sigmoid takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the sigmoid function, y = 1 / (1 + exp(-x)), is applied to the tensor elementwise.
sign(*args, **kwargs)	Calculate the sign of the given input tensor element-wise.
sin(*args, **kwargs)	Calculates the sine of the given input tensor, element-wise.
sinh(*args, **kwargs)	Calculates the hyperbolic sine of the given input tensor element-wise.
size(*args, **kwargs)	Takes a tensor as input and outputs a int64 scalar that equals to the total number of elements of the input tensor.
slice(*args, **kwargs)	Produces a slice of the input tensor along multiple axes.
softmax(*args, **kwargs)	The operator computes the normalized exponential values for the given input:
softmaxcrossentropyloss(*args, **kwargs)	Loss function that measures the softmax cross entropy between 'scores' and 'labels'.
softplus(*args, **kwargs)	Softplus takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the softplus function, y = ln(exp(x) + 1), is applied to the tensor elementwise.
softsign(*args, **kwargs)	Calculates the softsign (x/(1+|x|)) of the given input tensor element-wise.
spacetodepth(*args, **kwargs)	SpaceToDepth rearranges blocks of spatial data into depth.
split(*args, **kwargs)	Split a tensor into a list of tensors, along the specified 'axis'.
splittosequence(*args, **kwargs)	Split a tensor into a sequence of tensors, along the specified 'axis'.
sqrt(*args, **kwargs)	Square root takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the square root is, y = x^0.5, is applied to the tensor elementwise.
squeeze(*args, **kwargs)	Remove single-dimensional entries from the shape of a tensor.
stringnormalizer(*args, **kwargs)	StringNormalization performs string operations for basic cleaning.
sub(*args, **kwargs)	Performs element-wise binary subtraction (with Numpy-style broadcasting support).
sum(*args, **kwargs)	Element-wise sum of each of the input tensors (with Numpy-style broadcasting support).
tan(*args, **kwargs)	Calculates the tangent of the given input tensor, element-wise.
tanh(*args, **kwargs)	Calculates the hyperbolic tangent of the given input tensor element-wise.

continues on next page

Table 53 – continued from previous page

tfidfvectorizer(*args, **kwargs)	This transform extracts n-grams from the input sequence and save them as a vector.
thresholdedrelu(*args, **kwargs)	ThresholdedRelu takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the rectified linear function, y = x for x > alpha, y = 0 otherwise, is applied to the tensor elementwise.
tile(*args, **kwargs)	Constructs a tensor by tiling a given tensor.
topk(*args, **kwargs)	Retrieve the top-K largest or smallest elements along a specified axis. Given an input tensor of shape [a_1, a_2, ..., a_n, r] and integer argument k, return two outputs: -Value tensor of shape [a_1, a_2, ..., a_{axis-1}, k, a_{axis+1}, ... a_n] which contains the values of the top k elements along the specified axis -Index tensor of shape [a_1, a_2, ..., a_{axis-1}, k, a_{axis+1}, ... a_n] which contains the indices of the top k elements (original indices from the input tensor).
transpose(*args, **kwargs)	Transpose the input tensor similar to numpy.transpose.
trilu(*args, **kwargs)	Given a 2-D matrix or batches of 2-D matrices, returns the upper or lower triangular part of the tensor(s). The attribute "upper" determines whether the upper or lower part is retained. If set to true, the upper triangular matrix is retained. Lower triangular matrix is retained otherwise. Default value for the "upper" attribute is true. Trilu takes one input tensor of shape [*, N, M], where * is zero or more batch dimensions. The upper triangular part consists of the elements on and above the given diagonal (k). The lower triangular part consists of elements on and below the diagonal. All other elements in the matrix are set to zero. If k = 0, the triangular part on and above/below the main diagonal is retained. If upper is set to true, a positive k retains the upper triangular matrix excluding the main diagonal and (k-1) diagonals above it. A negative k value retains the main diagonal and |k| diagonals below it. If upper is set to false, a positive k retains the lower triangular matrix including the main diagonal and k diagonals above it. A negative k value excludes the main diagonal and (|k|-1) diagonals below it.
unique(*args, **kwargs)	Find the unique elements of a tensor.
unsqueeze(*args, **kwargs)	Insert single-dimensional entries to the shape of an input tensor (*data*).
upsample(*args, **kwargs)	Upsample the input tensor. Each dimension value of the output tensor is: output_dimension = floor(input_dimension * scale).
where(*args, **kwargs)	Return elements, either from X or Y, depending on condition.
xor(*args, **kwargs)	Returns the tensor resulted from performing the *xor* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

modeci_mdf.functions.onnx.abs

modeci_mdf.functions.onnx.**abs**(**args*, ***kwargs*)

Absolute takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the absolute is, y = abs(x), is applied to the tensor elementwise.

modeci_mdf.functions.onnx.acos

modeci_mdf.functions.onnx.**acos**(**args*, ***kwargs*)

Calculates the arccosine (inverse of cosine) of the given input tensor, element-wise.

modeci_mdf.functions.onnx.acosh

modeci_mdf.functions.onnx.**acosh**(**args*, ***kwargs*)

Calculates the hyperbolic arccosine of the given input tensor element-wise.

modeci_mdf.functions.onnx.add

modeci_mdf.functions.onnx.**add**(**args*, ***kwargs*)

Performs element-wise binary addition (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

(Opset 14 change): Extend supported types to include uint8, int8, uint16, and int16.

modeci_mdf.functions.onnx.and

modeci_mdf.functions.onnx.**and**(**args*, ***kwargs*)

Returns the tensor resulted from performing the *and* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.argmax

modeci_mdf.functions.onnx.**argmax**(**args*, ***kwargs*)

Computes the indices of the max elements of the input tensor's element along the provided axis. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned. If select_last_index is True (default False), the index of the last occurrence of the max is selected if the max appears more than once in the input. Otherwise the index of the first occurrence is selected. The type of the output tensor is integer.

modeci_mdf.functions.onnx.argmin

modeci_mdf.functions.onnx.**argmin**(**args*, ***kwargs*)

Computes the indices of the min elements of the input tensor's element along the provided axis. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned. If select_last_index is True (default False), the index of the last occurrence of the min is selected if the min appears more than once in the input. Otherwise the index of the first occurrence is selected. The type of the output tensor is integer.

modeci_mdf.functions.onnx.asin

modeci_mdf.functions.onnx.**asin**(**args*, ***kwargs*)

Calculates the arcsine (inverse of sine) of the given input tensor, element-wise.

modeci_mdf.functions.onnx.asinh

modeci_mdf.functions.onnx.**asinh**(**args*, ***kwargs*)

Calculates the hyperbolic arcsine of the given input tensor element-wise.

modeci_mdf.functions.onnx.atan

modeci_mdf.functions.onnx.**atan**(**args*, ***kwargs*)

Calculates the arctangent (inverse of tangent) of the given input tensor, element-wise.

modeci_mdf.functions.onnx.atanh

modeci_mdf.functions.onnx.**atanh**(**args*, ***kwargs*)

Calculates the hyperbolic arctangent of the given input tensor element-wise.

modeci_mdf.functions.onnx.averagepool

modeci_mdf.functions.onnx.**averagepool**(**args*, ***kwargs*)

AveragePool consumes an input tensor X and applies average pooling across the tensor according to kernel sizes, stride sizes, and pad lengths. average pooling consisting of computing the average on all values of a subset of the input tensor according to the kernel size and downsampling the data into the output tensor Y for further processing. The output spatial shape will be following: ` output_spatial_shape[i] = floor((input_spatial_shape[i] + pad_shape[i] - kernel_spatial_shape[i]) / strides_spatial_shape[i] + 1) ` or ` output_spatial_shape[i] = ceil((input_spatial_shape[i] + pad_shape[i] - kernel_spatial_shape[i]) / strides_spatial_shape[i] + 1) ` if ceil_mode is enabled

` * pad_shape[i] is sum of pads along axis i `

auto_pad is a DEPRECATED attribute. If you are using them currently, the output spatial shape will be following: ` VALID: output_spatial_shape[i] = ceil((input_spatial_shape[i] - kernel_spatial_shape[i] + 1) / strides_spatial_shape[i]) SAME_UPPER or SAME_LOWER: output_spatial_shape[i] = ceil(input_spatial_shape[i] / strides_spatial_shape[i]) ` And pad shape will be following if *SAME_UPPER* or *SAME_LOWER*: ` pad_shape[i] = (output_spatial_shape[i] - 1) * strides_spatial_shape[i] + kernel_spatial_shape[i] - input_spatial_shape[i] ` The output of each pooling window is divided by the number of elements (exclude pad when attribute count_include_pad is zero).

modeci_mdf.functions.onnx.batchnormalization

modeci_mdf.functions.onnx.**batchnormalization**(**args*, ***kwargs*)

Carries out batch normalization as described in the paper https://arxiv.org/abs/1502.03167. Depending on the mode it is being run, There are five required inputs 'X', 'scale', 'B', 'input_mean' and 'input_var'. Note that 'input_mean' and 'input_var' are expected to be the estimated statistics in inference mode (training_mode=False, default), and the running statistics in training mode (training_mode=True). There are multiple cases for the number of outputs, which we list below:

Output case #1: Y, running_mean, running_var (training_mode=True) Output case #2: Y (training_mode=False)

When training_mode=False, extra outputs are invalid. The outputs are updated as follows when training_mode=True: ``` running_mean = input_mean * momentum + current_mean * (1 - momentum) running_var = input_var * momentum + current_var * (1 - momentum)

Y = (X - current_mean) / sqrt(current_var + epsilon) * scale + B

where:

current_mean = ReduceMean(X, axis=all_except_channel_index) current_var = ReduceVar(X, axis=all_except_channel_index)

Notice that ReduceVar refers to the population variance, and it equals to sum(sqrd(x_i - x_avg)) / N where N is the population size (this formula does not use sample size N - 1).

```

The computation of ReduceMean and ReduceVar uses float to avoid overflow for float16 inputs.

When training_mode=False: ` Y = (X - input_mean) / sqrt(input_var + epsilon) * scale + B `

For previous (depreciated) non-spatial cases, implementors are suggested to flatten the input shape to (N x C * D1 * D2 * ... * Dn) before a BatchNormalization Op. This operator has **optional** inputs/outputs. See [the doc](IR.md) for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

### modeci_mdf.functions.onnx.bernoulli

modeci_mdf.functions.onnx.**bernoulli**(*\*args*, *\*\*kwargs*)

Draws binary random numbers (0 or 1) from a Bernoulli distribution. The input tensor should be a tensor containing probabilities p (a value in the range [0,1]) to be used for drawing the binary random number, where an output of 1 is produced with probability p and an output of 0 is produced with probability (1-p).

This operator is non-deterministic and may not produce the same values in different implementations (even if a seed is specified).

### modeci_mdf.functions.onnx.bitshift

modeci_mdf.functions.onnx.**bitshift**(*\*args*, *\*\*kwargs*)

**Bitwise shift operator performs element-wise operation. For each input element, if the** attribute "direction" is "RIGHT", this operator moves its binary representation toward the right side so that the input value is effectively decreased. If the attribute "direction" is "LEFT", bits of binary representation moves toward the left side, which results the increase of its actual value. The input X is the tensor to be shifted and another input Y specifies the amounts of shifting. For example, if "direction" is "Right", X is [1, 4],
```

and S is [1, 1], the corresponding output Z would be [0, 2]. If "direction" is "LEFT" with X=[1, 2] and S=[1, 2], the corresponding output Y would be [2, 8].

Because this operator supports Numpy-style broadcasting, X's and Y's shapes are not necessarily identical.

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.cast

modeci_mdf.functions.onnx.**cast**(**args*, ***kwargs*)

The operator casts the elements of a given input tensor to a data type specified by the 'to' argument and returns an output tensor of the same size in the converted type. The 'to' argument must be one of the data types specified in the 'DataType' enum field in the TensorProto message.

Casting from string tensor in plain (e.g., "3.14" and "1000") and scientific numeric representations (e.g., "1e-5" and "1E8") to float types is supported. For example, converting string "100.5" to an integer may result 100. There are some string literals reserved for special floating-point values; "+INF" (and "INF"), "-INF", and "NaN" are positive infinity, negative infinity, and not-a-number, respectively. Any string which can exactly match "+INF" in a case-insensitive way would be mapped to positive infinite. Similarly, this case-insensitive rule is applied to "INF" and "NaN". When casting from numeric tensors to string tensors, plain floating-point representation (such as "314.15926") would be used. Converting non-numerical-literal string such as "Hello World!" is an undefined behavior. Cases of converting string representing floating-point arithmetic value, such as "2.718", to INT is an undefined behavior.

Conversion from a numerical type to any numerical type is always allowed. User must be aware of precision loss and value change caused by range difference between two types. For example, a 64-bit float 3.1415926459 may be round to a 32-bit float 3.141592. Similarly, converting an integer 36 to Boolean may produce 1 because we truncate bits which can't be stored in the targeted type.

In more detail, the conversion among numerical types should follow these rules:

- Casting from floating point to: * floating point: +/- infinity if OOR (out of range). * fixed point: undefined if OOR. * bool: +/- 0.0 to False; all else to True.
- Casting from fixed point to: * floating point: +/- infinity if OOR. (+ infinity in the case of uint) * fixed point: when OOR, discard higher bits and reinterpret (with respect to two's complement representation for

signed types). For example, 200 (int16) -> -56 (int8).

  - bool: zero to False; nonzero to True.

- Casting from bool to: * floating point: *{1.0, 0.0}*. * fixed point: *{1, 0}*. * bool: no change.

modeci_mdf.functions.onnx.castlike

modeci_mdf.functions.onnx.**castlike**(**args*, ***kwargs*)

The operator casts the elements of a given input tensor (the first input) to the same data type as the elements of the second input tensor. See documentation of the Cast operator for further details.

modeci_mdf.functions.onnx.ceil

modeci_mdf.functions.onnx.**ceil**(**args*, ***kwargs*)

Ceil takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the ceil is, y = ceil(x), is applied to the tensor elementwise.

modeci_mdf.functions.onnx.celu

modeci_mdf.functions.onnx.**celu**(**args*, ***kwargs*)

Continuously Differentiable Exponential Linear Units: Perform the linear unit element-wise on the input tensor X using formula:

```
` max(0,x) + min(0,alpha*(exp(x/alpha)-1)) `
```

modeci_mdf.functions.onnx.clip

modeci_mdf.functions.onnx.**clip**(**args*, ***kwargs*)

Clip operator limits the given input within an interval. The interval is specified by the inputs 'min' and 'max'. They default to numeric_limits::lowest() and numeric_limits::max(), respectively.

modeci_mdf.functions.onnx.compress

modeci_mdf.functions.onnx.**compress**(**args*, ***kwargs*)

Selects slices from an input tensor along a given axis where condition evaluates to True for each axis index. In case axis is not provided, input is flattened before elements are selected. Compress behaves like numpy.compress: https://docs.scipy.org/doc/numpy/reference/generated/numpy.compress.html

modeci_mdf.functions.onnx.concat

modeci_mdf.functions.onnx.**concat**(**args*, ***kwargs*)

Concatenate a list of tensors into a single tensor. All input tensors must have the same shape, except for the dimension size of the axis to concatenate on.

modeci_mdf.functions.onnx.concatfromsequence

modeci_mdf.functions.onnx.**concatfromsequence**(**args*, ***kwargs*)

Concatenate a sequence of tensors into a single tensor. All input tensors must have the same shape, except for the dimension size of the axis to concatenate on. By default 'new_axis' is 0, the behavior is similar to numpy.concatenate. When 'new_axis' is 1, the behavior is similar to numpy.stack.

modeci_mdf.functions.onnx.constant

modeci_mdf.functions.onnx.**constant**(**args*, ***kwargs*)

This operator produces a constant tensor. Exactly one of the provided attributes, either value, sparse_value, or value_* must be specified.

modeci_mdf.functions.onnx.constantofshape

modeci_mdf.functions.onnx.**constantofshape**(**args*, ***kwargs*)
Generate a tensor with given value and shape.

modeci_mdf.functions.onnx.conv

modeci_mdf.functions.onnx.**conv**(**args*, ***kwargs*)
The convolution operator consumes an input tensor and a filter, and computes the output.

modeci_mdf.functions.onnx.convert_type

modeci_mdf.functions.onnx.**convert_type**(*v*)
Helper function to convert types to ONNX compatible types.

modeci_mdf.functions.onnx.convinteger

modeci_mdf.functions.onnx.**convinteger**(**args*, ***kwargs*)
The integer convolution operator consumes an input tensor, its zero-point, a filter, and its zero-point, and computes the output. The production MUST never overflow. The accumulation may overflow if and only if in 32 bits.

modeci_mdf.functions.onnx.convtranspose

modeci_mdf.functions.onnx.**convtranspose**(**args*, ***kwargs*)
The convolution transpose operator consumes an input tensor and a filter, and computes the output.

If the pads parameter is provided the shape of the output is calculated via the following equation:

output_shape[i] = stride[i] * (input_size[i] - 1) + output_padding[i] + ((kernel_shape[i] - 1) * dilations[i] + 1) - pads[start_i] - pads[end_i]

output_shape can also be explicitly specified in which case pads values are auto generated using these equations:

total_padding[i] = stride[i] * (input_size[i] - 1) + output_padding[i] + ((kernel_shape[i] - 1) * dilations[i] + 1) - output_shape[i] If (auto_pads == SAME_UPPER): pads[start_i] = total_padding[i]/2; pads[end_i] = total_padding[i] - (total_padding[i]/2) Else: pads[start_i] = total_padding[i] - (total_padding[i]/2); pads[end_i] = (total_padding[i]/2).

modeci_mdf.functions.onnx.cos

modeci_mdf.functions.onnx.**cos**(**args*, ***kwargs*)
Calculates the cosine of the given input tensor, element-wise.

modeci_mdf.functions.onnx.cosh

modeci_mdf.functions.onnx.**cosh**(**args*, ***kwargs*)

Calculates the hyperbolic cosine of the given input tensor element-wise.

modeci_mdf.functions.onnx.cumsum

modeci_mdf.functions.onnx.**cumsum**(**args*, ***kwargs*)

Performs cumulative sum of the input elements along the given axis. By default, it will do the sum inclusively meaning the first element is copied as is. Through an *exclusive* attribute, this behavior can change to exclude the first element. It can also perform summation in the opposite direction of the axis. For that, set *reverse* attribute to 1.

Example: ` input_x = [1, 2, 3] axis=0 output = [1, 3, 6] exclusive=1 output = [0, 1, 3] exclusive=0 reverse=1 output = [6, 5, 3] exclusive=1 reverse=1 output = [5, 3, 0] `

modeci_mdf.functions.onnx.depthtospace

modeci_mdf.functions.onnx.**depthtospace**(**args*, ***kwargs*)

DepthToSpace rearranges (permutes) data from depth into blocks of spatial data. This is the reverse transformation of SpaceToDepth. More specifically, this op outputs a copy of the input tensor where values from the depth dimension are moved in spatial blocks to the height and width dimensions. By default, *mode* = *DCR*. In the DCR mode, elements along the depth dimension from the input tensor are rearranged in the following order: depth, column, and then row. The output y is computed from the input x as below:

b, c, h, w = x.shape

tmp = np.reshape(x, [b, blocksize, blocksize, c // (blocksize**2), h, w])

tmp = np.transpose(tmp, [0, 3, 4, 1, 5, 2])

y = np.reshape(tmp, [b, c // (blocksize**2), h * blocksize, w * blocksize])

In the CRD mode, elements along the depth dimension from the input tensor are rearranged in the following order: column, row, and the depth. The output y is computed from the input x as below:

b, c, h, w = x.shape

tmp = np.reshape(x, [b, c // (blocksize ** 2), blocksize, blocksize, h, w])

tmp = np.transpose(tmp, [0, 1, 4, 2, 5, 3])

y = np.reshape(tmp, [b, c // (blocksize ** 2), h * blocksize, w * blocksize])

modeci_mdf.functions.onnx.dequantizelinear

modeci_mdf.functions.onnx.**dequantizelinear**(**args*, ***kwargs*)

The linear dequantization operator. It consumes a quantized tensor, a scale, and a zero point to compute the full precision tensor. The dequantization formula is y = (x - x_zero_point) * x_scale. ‘x_scale’ and ‘x_zero_point’ must have same shape, and can be either a scalar for per-tensor / per layer quantization, or a 1-D tensor for per-axis quantization. ‘x_zero_point’ and ‘x’ must have same type. ‘x’ and ‘y’ must have same shape. In the case of dequantizing int32, there’s no zero point (zero point is supposed to be 0).

modeci_mdf.functions.onnx.det

modeci_mdf.functions.onnx.**det**(**args*, ***kwargs*)

Det calculates determinant of a square matrix or batches of square matrices. Det takes one input tensor of shape *[*, M, M]*, where * is zero or more batch dimensions, and the inner-most 2 dimensions form square matrices. The output is a tensor of shape *[*]*, containing the determinants of all input submatrices. e.g., When the input is 2-D, the output is a scalar(shape is empty: *[]*).

modeci_mdf.functions.onnx.div

modeci_mdf.functions.onnx.**div**(**args*, ***kwargs*)

Performs element-wise binary division (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

(Opset 14 change): Extend supported types to include uint8, int8, uint16, and int16.

modeci_mdf.functions.onnx.dropout

modeci_mdf.functions.onnx.**dropout**(**args*, ***kwargs*)

Dropout takes an input floating-point tensor, an optional input ratio (floating-point scalar) and an optional input training_mode (boolean scalar). It produces two tensor outputs, output (floating-point tensor) and mask (optional *Tensor<bool>*). If *training_mode* is true then the output Y will be a random dropout; Note that this Dropout scales the masked input data by the following equation, so to convert the trained model into inference mode, the user can simply not pass *training_mode* input or set it to false. ` output = scale * data * mask, ` where ` scale = 1. / (1. - ratio). ` This operator has **optional** inputs/outputs. See [the doc](IR.md) for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

modeci_mdf.functions.onnx.dynamicquantizelinear

modeci_mdf.functions.onnx.**dynamicquantizelinear**(**args*, ***kwargs*)

A Function to fuse calculation for Scale, Zero Point and FP32->8Bit convertion of FP32 Input data. Outputs Scale, ZeroPoint and Quantized Input for a given FP32 Input. Scale is calculated as: ```

y_scale = (max(x) - min(x))/(qmax - qmin) * where qmax and qmin are max and min values for quantization range .i.e [0, 255] in case of uint8 * data range is adjusted to include 0.

` Zero point is calculated as: ` intermediate_zero_point = qmin - min(x)/y_scale y_zero_point = cast(round(saturate(itermediate_zero_point))) * where qmax and qmin are max and min values for quantization range .i.e [0, 255] in case of uint8 * for saturation, it saturates to [0, 255] if it's uint8, or [-127, 127] if it's int8. Right now only uint8 is supported. * rounding to nearest ties to even. ` Data quantization formula is: ` y = saturate (round (x / y_scale) + y_zero_point) * for saturation, it saturates to [0, 255] if it's uint8, or [-127, 127] if it's int8. Right now only uint8 is supported. * rounding to nearest ties to even. ```

modeci_mdf.functions.onnx.einsum

modeci_mdf.functions.onnx.**einsum**(**args*, ***kwargs*)

An einsum of the form `term1, term2 -> output-term` produces an output tensor using the following equation

`output[output-term] = reduce-sum( input1[term1] * input2[term] )`

where the reduce-sum performs a summation over all the indices occurring in the input terms (term1, term2) that do not occur in the output-term.

The Einsum operator evaluates algebraic tensor operations on a sequence of tensors, using the Einstein summation convention. The equation string contains a comma-separated sequence of lower case letters. Each term corresponds to an operand tensor, and the characters within the terms correspond to operands dimensions.

This sequence may be followed by "->" to separate the left and right hand side of the equation. If the equation contains "->" followed by the right-hand side, the explicit (not classical) form of the Einstein summation is performed, and the right-hand side indices indicate output tensor dimensions. In other cases, output indices are (implicitly) set to the alphabetically sorted sequence of indices appearing exactly once in the equation.

When a dimension character is repeated in the left-hand side, it represents summation along the dimension.

The equation may contain ellipsis ("...") to enable broadcasting. Ellipsis must indicate a fixed number of dimensions. Specifically, every occurrence of ellipsis in the equation must represent the same number of dimensions. The right-hand side may contain exactly one ellipsis. In implicit mode, the ellipsis dimensions are set to the beginning of the output. The equation string may contain space (U+0020) character.

modeci_mdf.functions.onnx.elu

modeci_mdf.functions.onnx.**elu**(**args*, ***kwargs*)

Elu takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the function *f(x) = alpha * (exp(x) - 1.) for x < 0, f(x) = x for x >= 0.*, is applied to the tensor elementwise.

modeci_mdf.functions.onnx.equal

modeci_mdf.functions.onnx.**equal**(**args*, ***kwargs*)

Returns the tensor resulted from performing the *equal* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.erf

modeci_mdf.functions.onnx.**erf**(**args*, ***kwargs*)

Computes the error function of the given input tensor element-wise.

modeci_mdf.functions.onnx.exp

modeci_mdf.functions.onnx.**exp**(**args*, ***kwargs*)
Calculates the exponential of the given input tensor, element-wise.

modeci_mdf.functions.onnx.expand

modeci_mdf.functions.onnx.**expand**(**args*, ***kwargs*)
Broadcast the input tensor following the given shape and the broadcast rule. The broadcast rule is similar to numpy.array(input) * numpy.ones(shape): Dimensions are right alignment; Two corresponding dimensions must have the same value, or one of them is equal to 1. Also, this operator is similar to numpy.broadcast_to(input, shape), but the major difference is numpy.broadcast_to() does not allow shape to be smaller than input.size(). It is possible that the output.shape is not equal to shape, when some dimensions in shape is equal to 1, or the shape.ndim < input.shape.ndim.

modeci_mdf.functions.onnx.eyelike

modeci_mdf.functions.onnx.**eyelike**(**args*, ***kwargs*)
Generate a 2D tensor (matrix) with ones on the diagonal and zeros everywhere else. Only 2D tensors are supported, i.e. input T1 must be of rank 2. The shape of the output tensor is the same as the input tensor. The data type can be specified by the 'dtype' argument. If 'dtype' is not specified, then the type of input tensor is used. By default, the main diagonal is populated with ones, but attribute 'k' can be used to populate upper or lower diagonals. The 'dtype' argument must be one of the data types specified in the 'DataType' enum field in the TensorProto message and be valid as an output type.

modeci_mdf.functions.onnx.flatten

modeci_mdf.functions.onnx.**flatten**(**args*, ***kwargs*)
Flattens the input tensor into a 2D matrix. If input tensor has shape (d_0, d_1, … d_n) then the output will have shape (d_0 X d_1 … d_(axis-1), d_axis X d_(axis+1) … X dn).

modeci_mdf.functions.onnx.floor

modeci_mdf.functions.onnx.**floor**(**args*, ***kwargs*)
Floor takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the floor is, y = floor(x), is applied to the tensor elementwise.

modeci_mdf.functions.onnx.gather

modeci_mdf.functions.onnx.**gather**(**args*, ***kwargs*)
Given *data* tensor of rank r >= 1, and *indices* tensor of rank q, gather entries of the axis dimension of *data* (by default outer-most one as axis=0) indexed by *indices*, and concatenates them in an output tensor of rank q + (r - 1).

axis = 0 :

Let k = indices[i_{0}, …, i_{q-1}] Then output[i_{0}, …, i_{q-1}, j_{0}, …, j_{r-2}] = input[k , j_{0}, …, j_{r-2}]

```

**data = [** [1.0, 1.2], [2.3, 3.4], [4.5, 5.7],
```

] indices = [

[0, 1], [1, 2],

] output = [

[[1.0, 1.2], [2.3, 3.4],

], [

[2.3, 3.4], [4.5, 5.7],

],

]

``` axis = 1 :

Let k = indices[i_{0}, …, i_{q-1}] Then output[j_{0}, i_{0}, …, i_{q-1}, j_{1}, …, j_{r-2}] = input[j_{0}, k, j_{1}, …, j_{r-2}]

```

data = [[1.0, 1.2, 1.9], [2.3, 3.4, 3.9], [4.5, 5.7, 5.9],

] indices = [

[0, 2],

] axis = 1, output = [

[[1.0, 1.9]], [[2.3, 3.9]], [[4.5, 5.9]],

]

```

### modeci_mdf.functions.onnx.gatherelements

modeci_mdf.functions.onnx.**gatherelements**(*\*args*, *\*\*kwargs*)

GatherElements takes two inputs *data* and *indices* of the same rank r >= 1 and an optional attribute *axis* that identifies an axis of *data* (by default, the outer-most axis, that is axis 0). It is an indexing operation that produces its output by indexing into the input data tensor at index positions determined by elements of the *indices* tensor. Its output shape is the same as the shape of *indices* and consists of one value (gathered from the *data*) for each element in *indices*.

For instance, in the 3-D case (r = 3), the output produced is determined by the following equations: ```

out[i][j][k] = input[index[i][j][k]][j][k] if axis = 0, out[i][j][k] = input[i][index[i][j][k]][k] if axis = 1, out[i][j][k] = input[i][j][index[i][j][k]] if axis = 2,

```

This operator is also the inverse of ScatterElements. It is similar to Torch's gather operation.

Example 1: ```

data = [[1, 2], [3, 4],

] indices = [

[0, 0], [1, 0],

] axis = 1 output = [

[1, 1], [4, 3],

]

` Example 2: `

data = [[1, 2, 3], [4, 5, 6], [7, 8, 9],

] indices = [

[1, 2, 0], [2, 0, 0],

] axis = 0 output = [

[4, 8, 3], [7, 2, 3],

]

```

### modeci_mdf.functions.onnx.gathernd

modeci_mdf.functions.onnx.**gathernd**(*\*args*, *\*\*kwargs*)

Given *data* tensor of rank *r* >= 1, *indices* tensor of rank *q* >= 1, and *batch_dims* integer *b*, this operator gathers slices of *data* into an output tensor of rank *q + r - indices_shape[-1] - 1 - b*.

*indices* is an q-dimensional integer tensor, best thought of as a *(q-1)*-dimensional tensor of index-tuples into *data*, where each element defines a slice of *data*

*batch_dims* (denoted as *b*) is an integer indicating the number of batch dimensions, i.e the leading *b* number of dimensions of *data* tensor and *indices* are representing the batches, and the gather starts from the *b+1* dimension.

Some salient points about the inputs' rank and shape:

1) r >= 1 and q >= 1 are to be honored. There is no dependency condition to be met between ranks *r* and *q*
2) The first *b* dimensions of the shape of *indices* tensor and *data* tensor must be equal.
3) b < min(q, r) is to be honored.
4) The *indices_shape[-1]* should have a value between 1 (inclusive) and rank *r-b* (inclusive)
5) All values in *indices* are expected to be within bounds [-s, s-1] along axis of size *s* (i.e.) *-data_shape[i] <= indices[...,i] <= data_shape[i] - 1*. It is an error if any of the index values are out of bounds.

The output is computed as follows:

The output tensor is obtained by mapping each index-tuple in the *indices* tensor to the corresponding slice of the input *data*.

1) If *indices_shape[-1] > r-b* => error condition
2) If *indices_shape[-1] == r-b*, since the rank of *indices* is *q*, *indices* can be thought of as *N (q-b-1)*-dimensional tensors containing 1-D tensors of dimension *r-b*, where *N* is an integer equals to the product of 1 and all the elements in the batch dimensions of the indices_shape. Let us think of each such *r-b* ranked tensor as *indices_slice*. Each *scalar value* corresponding to *data[0:b-1,indices_slice]* is filled into the corresponding location of the *(q-b-1)*-dimensional tensor to form the *output* tensor (Example 1 below)
3) If *indices_shape[-1] < r-b*, since the rank of *indices* is *q*, *indices* can be thought of as *N (q-b-1)*-dimensional tensor containing 1-D tensors of dimension < *r-b*. Let us think of each such tensors as *indices_slice*. Each *tensor slice* corresponding to *data[0:b-1, indices_slice , :]* is filled into the corresponding location of the *(q-b-1)*-dimensional tensor to form the *output* tensor (Examples 2, 3, 4 and 5 below)

This operator is the inverse of *ScatterND*.

*Example 1*
```

batch_dims = 0

data = [[0,1],[2,3]] # data_shape = [2, 2]

indices = [[0,0],[1,1]] # indices_shape = [2, 2]

output = [0,3] # output_shape = [2]

Example 2

batch_dims = 0

data = [[0,1],[2,3]] # data_shape = [2, 2]

indices = [[1],[0]] # indices_shape = [2, 1]

output = [[2,3],[0,1]] # output_shape = [2, 2]

Example 3

batch_dims = 0

data = [[[0,1],[2,3]],[[4,5],[6,7]]] # data_shape = [2, 2, 2]

indices = [[0,1],[1,0]] # indices_shape = [2, 2]

output = [[2,3],[4,5]] # output_shape = [2, 2]

Example 4

batch_dims = 0

data = [[[0,1],[2,3]],[[4,5],[6,7]]] # data_shape = [2, 2, 2]

indices = [[[0,1]],[[1,0]]] # indices_shape = [2, 1, 2]

output = [[[2,3]],[[4,5]]] # output_shape = [2, 1, 2]

Example 5

batch_dims = 1

data = [[[0,1],[2,3]],[[4,5],[6,7]]] # data_shape = [2, 2, 2]

indices = [[1],[0]] # indices_shape = [2, 1]

output = [[2,3],[4,5]] # output_shape = [2, 2]

modeci_mdf.functions.onnx.gemm

modeci_mdf.functions.onnx.**gemm**(**args*, ***kwargs*)

General Matrix multiplication: https://en.wikipedia.org/wiki/Basic_Linear_Algebra_Subprograms#Level_3

A' = transpose(A) if transA else A

B' = transpose(B) if transB else B

Compute Y = alpha * A' * B' + beta * C, where input tensor A has shape (M, K) or (K, M), input tensor B has shape (K, N) or (N, K), input tensor C is broadcastable to shape (M, N), and output tensor Y has shape (M, N). A will be transposed before doing the computation if attribute transA is non-zero, same for B and transB. This operator supports **unidirectional broadcasting** (tensor C should be unidirectional broadcastable to tensor A * B); for more details please check [the doc](Broadcasting.md). This operator has **optional** inputs/outputs. See [the doc](IR.md) for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

modeci_mdf.functions.onnx.get_all_schemas_version

modeci_mdf.functions.onnx.**get_all_schemas_version**(*max_version: int*) → List[onnx.onnx_cpp2py_export.defs.OpSchema]

Enumerate all the OpSchemas available from ONNX.

Parameters **max_version** – Only include up to max_version.

Returns A list of all OpSchemas

modeci_mdf.functions.onnx.get_onnx_ops

modeci_mdf.functions.onnx.**get_onnx_ops**(*opset_version: int = 15*) → List[Dict]

Enumerate all available ONNX operations and generate MDF function specifications for each one.

Parameters **opset_version** – The opset version to use.

Returns

A list of MDF function specifications. Each entry is a Dict that is feed directly to add_mdf_function.

modeci_mdf.functions.onnx.get_onnx_schema

modeci_mdf.functions.onnx.**get_onnx_schema**(*func_name: str*, *opset_version: int = 15*) → onnx.onnx_cpp2py_export.defs.OpSchema

Return the ONNX schema corresponding to a generated ONNX python function with name **func_name**

Parameters

- **func_name** (*str*) – the name of the ONNX python function
- **opset_version** (*int, optional*) – The opset version to use. Defaults to onnx_opset_version.

Raises **ValueError** – **func_name** does not correspond to a generated ONNX python function

Returns The ONNX schema corresponding to function **func_name**

Return type onnx.defs.OpSchema

modeci_mdf.functions.onnx.globalaveragepool

modeci_mdf.functions.onnx.**globalaveragepool**(**args*, ***kwargs*)

GlobalAveragePool consumes an input tensor X and applies average pooling across the values in the same channel. This is equivalent to AveragePool with kernel size equal to the spatial dimension of input tensor.

modeci_mdf.functions.onnx.globallppool

modeci_mdf.functions.onnx.**globallppool**(**args*, ***kwargs*)

GlobalLpPool consumes an input tensor X and applies lp pool pooling across the values in the same channel. This is equivalent to LpPool with kernel size equal to the spatial dimension of input tensor.

modeci_mdf.functions.onnx.globalmaxpool

modeci_mdf.functions.onnx.**globalmaxpool**(**args*, ***kwargs*)

GlobalMaxPool consumes an input tensor X and applies max pooling across the values in the same channel. This is equivalent to MaxPool with kernel size equal to the spatial dimension of input tensor.

modeci_mdf.functions.onnx.greater

modeci_mdf.functions.onnx.**greater**(**args*, ***kwargs*)

Returns the tensor resulted from performing the *greater* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.greaterorequal

modeci_mdf.functions.onnx.**greaterorequal**(**args*, ***kwargs*)

Returns the tensor resulted from performing the *greater_equal* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.gru

modeci_mdf.functions.onnx.**gru**(**args*, ***kwargs*)

Computes an one-layer GRU. This operator is usually supported via some custom implementation such as CuDNN.

Notations:

X - input tensor

z - update gate

r - reset gate

h - hidden gate

t - time step (t-1 means previous time step)

W[zrh] - W parameter weight matrix for update, reset, and hidden gates

R[zrh] - R recurrence weight matrix for update, reset, and hidden gates

Wb[zrh] - W bias vectors for update, reset, and hidden gates

Rb[zrh] - R bias vectors for update, reset, and hidden gates

WB[zrh] - W parameter weight matrix for backward update, reset, and hidden gates

RB[zrh] - R recurrence weight matrix for backward update, reset, and hidden gates

WBb[zrh] - W bias vectors for backward update, reset, and hidden gates

RBb[zrh] - R bias vectors for backward update, reset, and hidden gates

H - Hidden state

num_directions - 2 if direction == bidirectional else 1

Activation functions:

Relu(x) - max(0, x)

Tanh(x) - (1 - e^{-2x})/(1 + e^{-2x})

Sigmoid(x) - 1/(1 + e^{-x})

(NOTE: Below are optional)

Affine(x) - alpha*x + beta

LeakyRelu(x) - x if x >= 0 else alpha * x

ThresholdedRelu(x) - x if x >= alpha else 0

ScaledTanh(x) - alpha*Tanh(beta*x)

HardSigmoid(x) - min(max(alpha*x + beta, 0), 1)

Elu(x) - x if x >= 0 else alpha*(e^x - 1)

Softsign(x) - x/(1 + |x|)

Softplus(x) - log(1 + e^x)

Equations (Default: f=Sigmoid, g=Tanh):

- zt = f(Xt*(Wz^T) + Ht-1*(Rz^T) + Wbz + Rbz)
- rt = f(Xt*(Wr^T) + Ht-1*(Rr^T) + Wbr + Rbr)
- ht = g(Xt*(Wh^T) + (rt (.) Ht-1)*(Rh^T) + Rbh + Wbh) # default, when linear_before_reset = 0
- ht = g(Xt*(Wh^T) + (rt (.) (Ht-1*(Rh^T) + Rbh)) + Wbh) # when linear_before_reset != 0
- Ht = (1 - zt) (.) ht + zt (.) Ht-1

This operator has **optional** inputs/outputs. See [the doc](IR.md) for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

modeci_mdf.functions.onnx.hardmax

modeci_mdf.functions.onnx.**hardmax**(**args*, ***kwargs*)

The operator computes the hardmax values for the given input:

Hardmax(element in input, axis) = 1 if the element is the first maximum value along the specified axis, 0 otherwise

The "axis" attribute indicates the dimension along which Hardmax will be performed. The output tensor has the same shape and contains the Hardmax values of the corresponding input.

modeci_mdf.functions.onnx.hardsigmoid

modeci_mdf.functions.onnx.**hardsigmoid**(**args*, ***kwargs*)

HardSigmoid takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the HardSigmoid function, y = max(0, min(1, alpha * x + beta)), is applied to the tensor elementwise.

modeci_mdf.functions.onnx.hardswish

modeci_mdf.functions.onnx.**hardswish**(**args*, ***kwargs*)

HardSwish takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the HardSwish function, y = x * max(0, min(1, alpha * x + beta)) = x * HardSigmoid<alpha, beta>(x), where alpha = 1/6 and beta = 0.5, is applied to the tensor elementwise.

modeci_mdf.functions.onnx.identity

modeci_mdf.functions.onnx.**identity**(**args*, ***kwargs*)

Identity operator

modeci_mdf.functions.onnx.if

modeci_mdf.functions.onnx.**if**(**args*, ***kwargs*)

If conditional

modeci_mdf.functions.onnx.import_class

modeci_mdf.functions.onnx.**import_class**(*name: str*) → Any

Import from a module specified by a string

modeci_mdf.functions.onnx.instancenormalization

modeci_mdf.functions.onnx.**instancenormalization**(**args*, ***kwargs*)

Carries out instance normalization as described in the paper https://arxiv.org/abs/1607.08022.

y = scale * (x - mean) / sqrt(variance + epsilon) + B, where mean and variance are computed per instance per channel.

modeci_mdf.functions.onnx.isinf

modeci_mdf.functions.onnx.**isinf**(**args*, ***kwargs*)

Map infinity to true and other values to false.

modeci_mdf.functions.onnx.isnan

modeci_mdf.functions.onnx.**isnan**(**args*, ***kwargs*)
Returns which elements of the input are NaN.

modeci_mdf.functions.onnx.leakyrelu

modeci_mdf.functions.onnx.**leakyrelu**(**args*, ***kwargs*)
LeakyRelu takes input data (Tensor<T>) and an argument alpha, and produces one output data (Tensor<T>) where the function *f(x) = alpha * x for x < 0*, *f(x) = x for x >= 0*, is applied to the data tensor elementwise.

modeci_mdf.functions.onnx.less

modeci_mdf.functions.onnx.**less**(**args*, ***kwargs*)
Returns the tensor resulted from performing the *less* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.lessorequal

modeci_mdf.functions.onnx.**lessorequal**(**args*, ***kwargs*)
Returns the tensor resulted from performing the *less_equal* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.log

modeci_mdf.functions.onnx.**log**(**args*, ***kwargs*)
Calculates the natural log of the given input tensor, element-wise.

modeci_mdf.functions.onnx.logsoftmax

modeci_mdf.functions.onnx.**logsoftmax**(**args*, ***kwargs*)
The operator computes the log of softmax values for the given input:

LogSoftmax(input, axis) = Log(Softmax(input, axis=axis))

The “axis” attribute indicates the dimension along which LogSoftmax will be performed. The output tensor has the same shape and contains the LogSoftmax values of the corresponding input.

modeci_mdf.functions.onnx.loop

modeci_mdf.functions.onnx.**loop**(**args*, ***kwargs*)

Generic Looping construct. This loop has multiple termination conditions:

1) Trip count. Iteration count specified at runtime. Set by specifying the input M. Optional. Set to empty string to omit. Note that a static trip count (specified at graph construction time) can be specified by passing in a constant node for input M.

2) Loop termination condition. This is an input to the op that determines whether to run the first iteration and also a loop-carried dependency for the body graph. The body graph must yield a value for the condition variable, whether this input is provided or not.

This table summarizes the operating modes of this operator with equivalent C-style code:

Operator inputs defined as (max_trip_count, condition_var).

input (“”, “”):

for (int i=0; ; ++i) { cond = ... // Note this value is ignored, but is required in the body

}

input (“”, cond) // Note this is analogous to a while loop bool cond = ...; for (int i=0; cond; ++i) {

cond = ...;

}

input (“”, 1) // Note this is analogous to a do-while loop bool cond = true for (int i=0; cond; ++i) {

cond = ...;

}

input (trip_count, “”) // Note this is analogous to a for loop int trip_count = ... for (int i=0; i < trip_count; ++i) {

cond = ...; // ignored

}

input (trip_count, cond) int trip_count = ...; bool cond = ...; for (int i=0; i < trip_count && cond; ++i) {

cond = ...;

}

Sample usage - cond as well as trip count

graph predict-net { %a = Constant[value = <Scalar Tensor [3]>]() %b = Constant[value = <Scalar Tensor [6]>]() %keepgoing = Constant[value = <Scalar Tensor [1]>]() %max_trip_count = Constant[value = <Scalar Tensor [10]>]() %keepgoing_out, %b_out, %user_defined_vals = Loop[body = <graph body-net>](%max_trip_count, %keepgoing, %b) return

}

graph body-net (%i[INT32, scalar] // iteration number %keepgoing_in[BOOL, scalar] // incoming loop-termination-condition; not used %b_in[INT32, scalar] // incoming value of loop-carried-dependency b

) { %my_local = Add(%a, %b_in) %b_out = Sub(%a, %b_in) // outgoing value of loop-carried-dependency b %keepgoing_out = Greater(%my_local, %b_out) // outgoing loop-termination-condition %user_defined_val = Add(%b_in, %b_in) // scan-output value to be accumulated return %keepgoing_out, %b_out, %user_defined_val

}

Sample equivalent C code

{ /* User-defined code (enclosing scope) */ *int a = 3, b = 6; bool keepgoing = true; // Analogous to input cond* */* End user-defined code */*

/* Implicitly-defined code */ *const int max_trip_count = 10; // Analogous to input M int user_defined_vals[]; // Imagine this is resizable* */* End implicitly-defined code */* initialize loop-carried variables and scan-output variables */* bool keepgoing_out = keepgoing int b_out = b

for (int i=0; i < max_trip_count && keepgoing_out; ++i) {

/* Implicitly-defined code: bind actual parameter values to formal parameter variables of loop-body */*

bool keepgoing_in = keepgoing_out; bool b_in = b_out;

/* User-defined code (loop body) */ *int my_local = a + b_in; // Reading value "a" from the enclosing scope is fine b_out = a - b_in; keepgoing_out = my_local > b_out; user_defined_val = b_in + b_in; // b_in and b_out are different variables* */* End user-defined code */*

/* Implicitly defined-code */ user_defined_vals[i] = user_defined_val // accumulate scan-output values

} // int t = my_local; // Can't do this. my_local is not accessible here.

// The values below are bound to the output variables of the loop and therefore accessible // b_out; user_defined_vals; keepgoing_out;

}

There are several things of note in this code snippet:

1) Values from the enclosing scope (i.e. variable "a" here) are in scope and can be referenced in the inputs of the loop.
2) Any values computed in the loop body that needs to be used in a subsequent iteration or after the loop are modelled using a pair of variables in the loop-body, consisting of an input variable (eg., b_in) and an output variable (eg., b_out). These are referred to as loop-carried dependences. The loop operation node supplies the input value of the input variable for the first iteration, and returns the output value of the output variable produced by the final iteration.
3) Scan_output variables are used to implicitly concatenate values computed across all the iterations. In the above example, the value of user_defined_val computed over all iterations are concatenated and returned as the value of user_defined_vals after the loop.
4) Values created in the body cannot be accessed in the enclosing scope, except using the mechanism described above.

Note that the semantics of this op support "diagonal" or "wavefront" execution. (See Step 3 here for an example: https://devblogs.nvidia.com/optimizing-recurrent-neural-networks-cudnn-5/). Frontends should emit multi-layer RNNs as a series of While operators (with time being the inner looping dimension), with each successive layer consuming the scan_outputs from the previous layer, possibly going through several point-wise operators (e.g. dropout, residual connections, linear layer).

The input/output of subgraph (produced by loop node) matching is based on order instead of name. The implementation will figure out the names based on this order.

modeci_mdf.functions.onnx.lpnormalization

modeci_mdf.functions.onnx.**lpnormalization**(**args*, ***kwargs*)

Given a matrix, apply Lp-normalization along the provided axis.

modeci_mdf.functions.onnx.lppool

modeci_mdf.functions.onnx.**lppool**(**args*, ***kwargs*)

LpPool consumes an input tensor X and applies Lp pooling across the tensor according to kernel sizes, stride sizes, and pad lengths. Lp pooling consisting of computing the Lp norm on all values of a subset of the input tensor according to the kernel size and downsampling the data into the output tensor Y for further processing.

modeci_mdf.functions.onnx.lrn

modeci_mdf.functions.onnx.**lrn**(**args*, ***kwargs*)

Local Response Normalization proposed in the [AlexNet paper](https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf). It normalizes over local input regions. The local region is defined across the channels. For an element X[n, c, d1, ..., dk] in a tensor of shape (N x C x D1 x D2, ..., Dk), its region is {X[n, i, d1, ..., dk] | max(0, c - floor((size - 1) / 2)) <= i <= min(C - 1, c + ceil((size - 1) / 2))}.

square_sum[n, c, d1, ..., dk] = sum(X[n, i, d1, ..., dk] ^ 2), where max(0, c - floor((size - 1) / 2)) <= i <= min(C - 1, c + ceil((size - 1) / 2)).

Y[n, c, d1, ..., dk] = X[n, c, d1, ..., dk] / (bias + alpha / size * square_sum[n, c, d1, ..., dk]) ^ beta

modeci_mdf.functions.onnx.lstm

modeci_mdf.functions.onnx.**lstm**(**args*, ***kwargs*)

Computes an one-layer LSTM. This operator is usually supported via some custom implementation such as CuDNN.

Notations:

X - input tensor

i - input gate

o - output gate

f - forget gate

c - cell gate

t - time step (t-1 means previous time step)

W[iofc] - W parameter weight matrix for input, output, forget, and cell gates

R[iofc] - R recurrence weight matrix for input, output, forget, and cell gates

Wb[iofc] - W bias vectors for input, output, forget, and cell gates

Rb[iofc] - R bias vectors for input, output, forget, and cell gates

P[iof] - P peephole weight vector for input, output, and forget gates

WB[iofc] - W parameter weight matrix for backward input, output, forget, and cell gates

RB[iofc] - R recurrence weight matrix for backward input, output, forget, and cell gates

WBb[iofc] - W bias vectors for backward input, output, forget, and cell gates

RBb[iofc] - R bias vectors for backward input, output, forget, and cell gates

PB[iof] - P peephole weight vector for backward input, output, and forget gates

H - Hidden state

num_directions - 2 if direction == bidirectional else 1

Activation functions:

Relu(x) - max(0, x)

Tanh(x) - (1 - e^{-2x})/(1 + e^{-2x})

Sigmoid(x) - 1/(1 + e^{-x})

(NOTE: Below are optional)

Affine(x) - alpha*x + beta

LeakyRelu(x) - x if x >= 0 else alpha * x

ThresholdedRelu(x) - x if x >= alpha else 0

ScaledTanh(x) - alpha*Tanh(beta*x)

HardSigmoid(x) - min(max(alpha*x + beta, 0), 1)

Elu(x) - x if x >= 0 else alpha*(e^x - 1)

Softsign(x) - x/(1 + |x|)

Softplus(x) - log(1 + e^x)

Equations (Default: f=Sigmoid, g=Tanh, h=Tanh):

- it = f(Xt*(Wi^T) + Ht-1*(Ri^T) + Pi (.) Ct-1 + Wbi + Rbi)
- ft = f(Xt*(Wf^T) + Ht-1*(Rf^T) + Pf (.) Ct-1 + Wbf + Rbf)
- ct = g(Xt*(Wc^T) + Ht-1*(Rc^T) + Wbc + Rbc)
- Ct = ft (.) Ct-1 + it (.) ct
- ot = f(Xt*(Wo^T) + Ht-1*(Ro^T) + Po (.) Ct + Wbo + Rbo)
- Ht = ot (.) h(Ct)

This operator has **optional** inputs/outputs. See [the doc](IR.md) for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

modeci_mdf.functions.onnx.matmul

modeci_mdf.functions.onnx.**matmul**(**args*, ***kwargs*)

Matrix product that behaves like numpy.matmul: https://docs.scipy.org/doc/numpy-1.13.0/reference/generated/numpy.matmul.html

modeci_mdf.functions.onnx.matmulinteger

modeci_mdf.functions.onnx.**matmulinteger**(**args*, ***kwargs*)

Matrix product that behaves like numpy.matmul: https://docs.scipy.org/doc/numpy-1.13.0/reference/generated/numpy.matmul.html. The production MUST never overflow. The accumulation may overflow if and only if in 32 bits.

modeci_mdf.functions.onnx.max

modeci_mdf.functions.onnx.**max**(**args*, ***kwargs*)

Element-wise max of each of the input tensors (with Numpy-style broadcasting support). All inputs and outputs must have the same data type. This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.maxpool

modeci_mdf.functions.onnx.**maxpool**(**args*, ***kwargs*)

MaxPool consumes an input tensor X and applies max pooling across the tensor according to kernel sizes, stride sizes, and pad lengths. max pooling consisting of computing the max on all values of a subset of the input tensor according to the kernel size and downsampling the data into the output tensor Y for further processing. The output spatial shape will be following: ` output_spatial_shape[i] = floor((input_spatial_shape[i] + pad_shape[i] - ((kernel_spatial_shape[i] - 1) * dilations[i] + 1)) / strides_spatial_shape[i] + 1) ` or ` output_spatial_shape[i] = ceil((input_spatial_shape[i] + pad_shape[i] - ((kernel_spatial_shape[i] - 1) * dilations[i] + 1)) / strides_spatial_shape[i] + 1) ` if ceil_mode is enabled

` * pad_shape[i] is sum of pads along axis i `

auto_pad is a DEPRECATED attribute. If you are using them currently, the output spatial shape will be following: ` VALID: output_spatial_shape[i] = ceil((input_spatial_shape[i] - ((kernel_spatial_shape[i] - 1) * dilations[i] + 1) + 1) / strides_spatial_shape[i]) SAME_UPPER or SAME_LOWER: output_spatial_shape[i] = ceil(input_spatial_shape[i] / strides_spatial_shape[i]) ` And pad shape will be following if *SAME_UPPER* or *SAME_LOWER*: ` pad_shape[i] = (output_spatial_shape[i] - 1) * strides_spatial_shape[i] + ((kernel_spatial_shape[i] - 1) * dilations[i] + 1) - input_spatial_shape[i] ` The output of each pooling window is maximum number of elements exclude pad.

modeci_mdf.functions.onnx.maxroipool

modeci_mdf.functions.onnx.**maxroipool**(**args*, ***kwargs*)

ROI max pool consumes an input tensor X and region of interests (RoIs) to apply max pooling across each RoI, to produce output 4-D tensor of shape (num_rois, channels, pooled_shape[0], pooled_shape[1]).

modeci_mdf.functions.onnx.maxunpool

modeci_mdf.functions.onnx.**maxunpool**(**args*, ***kwargs*)

MaxUnpool essentially computes the partial inverse of the MaxPool op. The input information to this op is typically the output information from a MaxPool op. The first input tensor X is the tensor that needs to be unpooled, which is typically the pooled tensor (first output) from MaxPool. The second input tensor, I, contains the indices to the (locally maximal) elements corrsponding to the elements in the first input tensor X. Input tensor I is typically the second output of the MaxPool op. The third (optional) input is a tensor that specifies the output size of the unpooling operation.

MaxUnpool is intended to do 'partial' inverse of the MaxPool op. 'Partial' because all the non-maximal values from the original input to MaxPool are set to zero in the output of the MaxUnpool op. Pooling the result of an unpooling operation should give back the original input to the unpooling op.

MaxUnpool can produce the same output size for several input sizes, which makes unpooling op ambiguous. The third input argument, output_size, is meant to disambiguate the op and produce output tensor of known/predictable size.

In addition to the inputs, MaxUnpool takes three attributes, namely kernel_shape, strides, and pads, which define the exact unpooling op. The attributes typically have the same values as the corrsponding pooling op that the unpooling op is trying to invert.

modeci_mdf.functions.onnx.mean

modeci_mdf.functions.onnx.**mean**(**args*, ***kwargs*)

Element-wise mean of each of the input tensors (with Numpy-style broadcasting support). All inputs and outputs must have the same data type. This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.meanvariancenormalization

modeci_mdf.functions.onnx.**meanvariancenormalization**(**args*, ***kwargs*)

A MeanVarianceNormalization Function: Perform mean variance normalization on the input tensor X using formula:
 ` (X-EX)/sqrt(E(X-EX)^2) `

modeci_mdf.functions.onnx.min

modeci_mdf.functions.onnx.**min**(**args*, ***kwargs*)

Element-wise min of each of the input tensors (with Numpy-style broadcasting support). All inputs and outputs must have the same data type. This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.mod

modeci_mdf.functions.onnx.**mod**(**args*, ***kwargs*)

Performs element-wise binary modulus (with Numpy-style broadcasting support). The sign of the remainder is the same as that of the Divisor.

Mod operator can also behave like C fmod() or numpy.fmod. In this case, the sign of the remainder however, will be the same as the Dividend (in contrast to integer mod). To force a behavior like numpy.fmod() an 'fmod' Attribute is provided. This attribute is set to 0 by default causing the behavior to be like integer mod. Setting this attribute to 1 causes the remainder to be calculated similar to that of numpy.fmod().

If the input type is floating point, then *fmod* attribute must be set to 1.

In case of dividend being zero, the results will be platform dependent.

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.mul

modeci_mdf.functions.onnx.**mul**(**args*, ***kwargs*)

Performs element-wise binary multiplication (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

(Opset 14 change): Extend supported types to include uint8, int8, uint16, and int16.

modeci_mdf.functions.onnx.multinomial

modeci_mdf.functions.onnx.**multinomial**(**args*, ***kwargs*)

Generate a tensor of samples from a multinomial distribution according to the probabilities of each of the possible outcomes.

modeci_mdf.functions.onnx.neg

modeci_mdf.functions.onnx.**neg**(**args*, ***kwargs*)

Neg takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where each element flipped sign, y = -x, is applied to the tensor elementwise.

modeci_mdf.functions.onnx.negativeloglikelihoodloss

modeci_mdf.functions.onnx.**negativeloglikelihoodloss**(**args*, ***kwargs*)

A NegativeLogLikelihoodLoss operator computes (weighted) negative log likelihood loss. Its "input" tensor has the shape of (N, C, d1, d2, . . . , dk) where k >= 0. The "input" tensor contains log-probabilities for input[n, :, d_1, d_2,. . . , d_k] being in a class of [0, C). The operator's "target" input tensor has the shape of (N, d1, d2, . . . , dk). It encodes class labels (one of C classes) or it may contain a special value (indicated by an attribute ignore_index) for N x d1 x d2 x . . . x dk samples. The loss value for input[n, :, d_1, d_2,. . . d_k] being classified as class c = target[n][d_1][d_2]. . . [d_k] is computed as:

loss[n][d_1][d_2]. . . [d_k] = -input[n][c][d_1][d_2]. . . [d_k].

When an optional "weight" is provided, the sample loss is calculated as:

loss[n][d_1][d_2]. . . [d_k] = -input[n][c][d_1][d_2]. . . [d_k] * weight[c].

loss is zero for the case when target-value equals ignore_index.

loss[n][d_1][d_2]...[d_k] = 0, when target[n][d_1][d_2]...[d_k] = ignore_index

If "reduction" attribute is set to "none", the operator's output will be the above loss with shape (N, d1, d2, ..., dk). If "reduction" attribute is set to "mean" (the default attribute value), the output loss is (weight) averaged:

mean(loss), if "weight" is not provided,

or if weight is provided,

sum(loss) / sum(weight[target[n][d_1][d_2]...[d_k]]), for all samples.

If "reduction" attribute is set to "sum", the output is a scalar: sum(loss).

See also https://pytorch.org/docs/stable/nn.html#torch.nn.NLLLoss.

Example 1:

// negative log likelihood loss, "none" reduction N, C, d1 = 2, 3, 2 input = [[[1.0, 2.0], [2.0, 2.0], [3.0, 2.0]],

[[0.0, 1.0], [2.0, 2.0], [1.0, 2]]]

target = [[2, 1], [0, 2]]

loss = np.zeros((N, d1)) for n in range(N):

for d_1 in range(d1): c = target[n][d_1] loss[n][d_1] = -input[n][c][d_1]

// print(loss) // [[-3. -2.] // [-0. -2.]]

Example 2:

// weighted negative log likelihood loss, sum reduction N, C, d1 = 2, 3, 2 input = [[[1.0, 2.0], [2.0, 2.0], [3.0, 2.0]],

[[0.0, 1.0], [2.0, 2.0], [1.0, 2]]]

target = [[2, 1], [0, 2]] weight = [0.2, 0.3, 0.1] loss = np.zeros((N, d1)) for n in range(N):

for d_1 in range(d1): c = target[n][d_1] loss[n][d_1] = -input[n][c][d_1] * weight[c]

loss = np.sum(loss) // print(loss) // -1.1

Example 3:

// weighted negative log likelihood loss, mean reduction N, C, d1 = 2, 3, 2 input = [[[1.0, 2.0], [2.0, 2.0], [3.0, 2.0]],

[[0.0, 1.0], [2.0, 2.0], [1.0, 2]]]

target = [[2, 1], [0, 2]] weight = [0.2, 0.3, 0.1] loss = np.zeros((N, d1)) weight_total = 0 for n in range(N):

for d_1 in range(d1): c = target[n][d_1] loss[n][d_1] = -input[n][c][d_1] * weight[c] weight_total = weight_total + weight[c]

loss = np.sum(loss) / weight_total // print(loss) // -1.57

modeci_mdf.functions.onnx.nonmaxsuppression

modeci_mdf.functions.onnx.**nonmaxsuppression**(**args*, ***kwargs*)

Filter out boxes that have high intersection-over-union (IOU) overlap with previously selected boxes. Bounding boxes with score less than score_threshold are removed. Bounding box format is indicated by attribute center_point_box. Note that this algorithm is agnostic to where the origin is in the coordinate system and more generally is invariant to orthogonal transformations and translations of the coordinate system; thus translating or reflections of the coordinate system result in the same boxes being selected by the algorithm. The selected_indices output is a set of integers indexing into the input collection of bounding boxes representing the selected boxes. The bounding box coordinates corresponding to the selected indices can then be obtained using the Gather or GatherND operation.

modeci_mdf.functions.onnx.nonzero

modeci_mdf.functions.onnx.**nonzero**(**args*, ***kwargs*)

Returns the indices of the elements that are non-zero (in row-major order - by dimension). NonZero behaves similar to numpy.nonzero: https://docs.scipy.org/doc/numpy/reference/generated/numpy.nonzero.html, but for scalar input, NonZero produces output shape (0, N) instead of (1, N), which is different from Numpy's behavior.

modeci_mdf.functions.onnx.not

modeci_mdf.functions.onnx.**not**(**args*, ***kwargs*)

Returns the negation of the input tensor element-wise.

modeci_mdf.functions.onnx.onehot

modeci_mdf.functions.onnx.**onehot**(**args*, ***kwargs*)

Produces a one-hot tensor based on inputs. The locations represented by the index values in the 'indices' input tensor will have 'on_value' and the other locations will have 'off_value' in the output tensor, where 'on_value' and 'off_value' are specified as part of required input argument 'values', which is a two-element tensor of format [off_value, on_value]. The rank of the output tensor will be one greater than the rank of the input tensor. The additional dimension is for one-hot representation. The additional dimension will be inserted at the position specified by 'axis'. If 'axis' is not specified then then additional dimension will be inserted as the innermost dimension, i.e. axis=-1. The size of the additional dimension is specified by required scalar input 'depth'. The type of the output tensor is the same as the type of the 'values' input. Any entries in the 'indices' input tensor with values outside the range [-depth, depth-1] will result in one-hot representation with all 'off_value' values in the output tensor.

when axis = 0: output[input[i, j, k], i, j, k] = 1 for all i, j, k and 0 otherwise.

when axis = -1: output[i, j, k, input[i, j, k]] = 1 for all i, j, k and 0 otherwise.

modeci_mdf.functions.onnx.optional

modeci_mdf.functions.onnx.**optional**(**args*, ***kwargs*)

Constructs an optional-type value containing either an empty optional of a certain type specified by the attribute, or a non-empty value containing the input element.

modeci_mdf.functions.onnx.optionalgetelement

modeci_mdf.functions.onnx.**optionalgetelement**(**args*, ***kwargs*)

Outputs the element in the optional-type input. It is an error if the input value does not have an element and the behavior is undefined in this case.

modeci_mdf.functions.onnx.optionalhaselement

modeci_mdf.functions.onnx.**optionalhaselement**(**args*, ***kwargs*)

Returns true if the optional-type input contains an element. If it is an empty optional-type, this op returns false.

modeci_mdf.functions.onnx.or

modeci_mdf.functions.onnx.**or**(**args*, ***kwargs*)

Returns the tensor resulted from performing the *or* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.pad

modeci_mdf.functions.onnx.**pad**(**args*, ***kwargs*)

Given a tensor containing the data to be padded (*data*), a tensor containing the number of start and end pad values for axis (*pads*), (optionally) a *mode*, and (optionally) *constant_value*, a padded tensor (*output*) is generated.

The three supported *modes* are (similar to corresponding modes supported by *numpy.pad*):

1) *constant`(default) - pads with a given constant value as specified by `constant_value* (which defaults to 0, empty string, or False)
2) *reflect* - pads with the reflection of the vector mirrored on the first and last values of the vector along each axis
3) *edge* - pads with the edge values of array

Example 1 (*constant* mode): Insert 0 pads to the beginning of the second dimension.

data = [

[1.0, 1.2], [2.3, 3.4], [4.5, 5.7],

]

pads = [0, 2, 0, 0]

mode = 'constant'

constant_value = 0.0

output = [

[0.0, 0.0, 1.0, 1.2], [0.0, 0.0, 2.3, 3.4], [0.0, 0.0, 4.5, 5.7],

]

Example 2 (*reflect* mode): data = [

[1.0, 1.2], [2.3, 3.4], [4.5, 5.7],

]

pads = [0, 2, 0, 0]

mode = 'reflect'

output = [

[1.0, 1.2, 1.0, 1.2], [2.3, 3.4, 2.3, 3.4], [4.5, 5.7, 4.5, 5.7],

]

Example 3 (*edge* mode): data = [

[1.0, 1.2], [2.3, 3.4], [4.5, 5.7],

]

pads = [0, 2, 0, 0]

mode = 'edge'

output = [

[1.0, 1.0, 1.0, 1.2], [2.3, 2.3, 2.3, 3.4], [4.5, 4.5, 4.5, 5.7],

]

modeci_mdf.functions.onnx.pow

modeci_mdf.functions.onnx.**pow**(**args*, ***kwargs*)

Pow takes input data (Tensor<T>) and exponent Tensor, and produces one output data (Tensor<T>) where the function *f(x) = x^exponent*, is applied to the data tensor elementwise. This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.predict_with_onnxruntime

modeci_mdf.functions.onnx.**predict_with_onnxruntime**(*model_def*, **inputs*) → Dict[str, numpy.array]

Simple helper to run an ONNX model with a set of inputs.

Parameters

- **model_def** – The ONNX model to run.
- ***inputs** – Input values to pass to the model.

Returns A dict of output values, keys are output names for the model. Values are the output values of the model.

modeci_mdf.functions.onnx.prelu

modeci_mdf.functions.onnx.**prelu**(**args*, ***kwargs*)

PRelu takes input data (Tensor<T>) and slope tensor as input, and produces one output data (Tensor<T>) where the function *f(x) = slope * x for x < 0*, *f(x) = x for x >= 0.*, is applied to the data tensor elementwise. This operator supports **unidirectional broadcasting** (tensor slope should be unidirectional broadcastable to input tensor X); for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.qlinearconv

modeci_mdf.functions.onnx.**qlinearconv**(**args*, ***kwargs*)

The convolution operator consumes a quantized input tensor, its scale and zero point, a quantized filter, its scale and zero point, and output's scale and zero point, and computes the quantized output. Each scale and zero-point pair must have same shape. It means they must be either scalars (per tensor) or 1-D tensors (per output channel). Each input or output and its related zero point must have same type. When bias is present it must be quantized using scale = input scale * weight scale and zero point as 0.

modeci_mdf.functions.onnx.qlinearmatmul

modeci_mdf.functions.onnx.**qlinearmatmul**(**args*, ***kwargs*)

Matrix product that behaves like numpy.matmul: https://docs.scipy.org/doc/numpy-1.13.0/reference/generated/numpy.matmul.html. It consumes two quantized input tensors, their scales and zero points, scale and zero point of output, and computes the quantized output. The quantization formula is y = saturate((x / y_scale) + y_zero_point). For (x / y_scale), it is rounding to nearest ties to even. Refer to https://en.wikipedia.org/wiki/Rounding for details. Scale and zero point must have same shape. They must be either scalar (per tensor) or N-D tensor (per row for 'a' and per column for 'b'). Scalar refers to per tensor quantization whereas N-D refers to per row or per column quantization. If the input is 2D of shape [M, K] then zero point and scale tensor may be an M element vector [v_1, v_2, ..., v_M] for per row quantization and K element vector of shape [v_1, v_2, ..., v_K] for per column quantization. If the input is N-D tensor with shape [D1, D2, M, K] then zero point and scale tensor may have shape [D1, D2, M, 1] for per row quantization and shape [D1, D2, 1, K] for per column quantization. Production must never overflow, and accumulation may overflow if and only if in 32 bits.

modeci_mdf.functions.onnx.quantizelinear

modeci_mdf.functions.onnx.**quantizelinear**(**args*, ***kwargs*)

The linear quantization operator. It consumes a high precision tensor, a scale, and a zero point to compute the low precision / quantized tensor. The scale factor and zero point must have same shape, and can be either a scalar for per-tensor / per layer quantization, or a 1-D tensor for per-axis quantization. The quantization formula is y = saturate ((x / y_scale) + y_zero_point). For saturation, it saturates to [0, 255] if it's uint8, or [-128, 127] if it's int8. For (x / y_scale), it's rounding to nearest ties to even. Refer to https://en.wikipedia.org/wiki/Rounding for details. 'y_zero_point' and 'y' must have same type.

modeci_mdf.functions.onnx.randomnormal

modeci_mdf.functions.onnx.**randomnormal**(**args*, ***kwargs*)

Generate a tensor with random values drawn from a normal distribution. The shape of the tensor is specified by the *shape* argument and the parameter of the normal distribution specified by *mean* and *scale*.

The data type is specified by the 'dtype' argument. The 'dtype' argument must be one of the data types specified in the 'DataType' enum field in the TensorProto message.

modeci_mdf.functions.onnx.randomnormallike

modeci_mdf.functions.onnx.**randomnormallike**(**args*, ***kwargs*)

Generate a tensor with random values drawn from a normal distribution. The shape of the output tensor is copied from the shape of the input tensor, and the parameters of the normal distribution are specified by *mean* and *scale*.

The data type is specified by the 'dtype' argument, or copied from the input tensor if not provided. The 'dtype' argument must be one of the data types specified in the 'DataType' enum field in the TensorProto message, and be valid as an output type.

modeci_mdf.functions.onnx.randomuniform

modeci_mdf.functions.onnx.**randomuniform**(**args*, ***kwargs*)

Generate a tensor with random values drawn from a uniform distribution. The shape of the tensor is specified by the *shape* argument and the range by *low* and *high*.

The data type is specified by the 'dtype' argument. The 'dtype' argument must be one of the data types specified in the 'DataType' enum field in the TensorProto message.

modeci_mdf.functions.onnx.randomuniformlike

modeci_mdf.functions.onnx.**randomuniformlike**(**args*, ***kwargs*)

Generate a tensor with random values drawn from a uniform distribution. The shape of the output tensor is copied from the shape of the input tensor, and the parameters of the uniform distribution are specified by *low* and *high*.

The data type is specified by the 'dtype' argument, or copied from the input tensor if not provided. The 'dtype' argument must be one of the data types specified in the 'DataType' enum field in the TensorProto message and be valid as an output type.

modeci_mdf.functions.onnx.range

modeci_mdf.functions.onnx.**range**(**args*, ***kwargs*)

Generate a tensor containing a sequence of numbers that begin at *start* and extends by increments of *delta* up to *limit* (exclusive).

The number of elements in the output of range is computed as below-

number_of_elements = max(ceil((limit - start) / delta) , 0)

The pseudocode determining the contents of the output is shown below-

for(int i=0; i<number_of_elements; ++i)

{

` output[i] = start + (i * delta); `

}

Example 1 Inputs: start = 3, limit = 9, delta = 3 Output: [3, 6]

Example 2 Inputs: start = 10, limit = 4, delta = -2 Output: [10, 8, 6]

modeci_mdf.functions.onnx.reciprocal

modeci_mdf.functions.onnx.**reciprocal**(**args*, ***kwargs*)

Reciprocal takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the reciprocal is, y = 1/x, is applied to the tensor elementwise.

modeci_mdf.functions.onnx.reducel1

modeci_mdf.functions.onnx.**reducel1**(**args*, ***kwargs*)

Computes the L1 norm of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reducel2

modeci_mdf.functions.onnx.**reducel2**(**args*, ***kwargs*)

Computes the L2 norm of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reducelogsum

modeci_mdf.functions.onnx.**reducelogsum**(**args*, ***kwargs*)

Computes the log sum of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reducelogsumexp

modeci_mdf.functions.onnx.**reducelogsumexp**(**args*, ***kwargs*)

Computes the log sum exponent of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reducemax

modeci_mdf.functions.onnx.**reducemax**(**args*, ***kwargs*)

Computes the max of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reducemean

modeci_mdf.functions.onnx.**reducemean**(**args*, ***kwargs*)

Computes the mean of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reducemin

modeci_mdf.functions.onnx.**reducemin**(**args*, ***kwargs*)

Computes the min of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reduceprod

modeci_mdf.functions.onnx.**reduceprod**(**args*, ***kwargs*)

Computes the product of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reducesum

modeci_mdf.functions.onnx.**reducesum**(**args*, ***kwargs*)

Computes the sum of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.reducesumsquare

modeci_mdf.functions.onnx.**reducesumsquare**(**args*, ***kwargs*)

Computes the sum square of the input tensor's element along the provided axes. The resulting tensor has the same rank as the input if keepdims equals 1. If keepdims equals 0, then the resulting tensor has the reduced dimension pruned.

The above behavior is similar to numpy, with the exception that numpy defaults keepdims to False instead of True.

modeci_mdf.functions.onnx.relu

modeci_mdf.functions.onnx.**relu**(**args*, ***kwargs*)

Relu takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the rectified linear function, y = max(0, x), is applied to the tensor elementwise.

modeci_mdf.functions.onnx.reshape

modeci_mdf.functions.onnx.**reshape**(**args*, ***kwargs*)

Reshape the input tensor similar to numpy.reshape. First input is the data tensor, second input is a shape tensor which specifies the output shape. It outputs the reshaped tensor. At most one dimension of the new shape can be -1. In this case, the value is inferred from the size of the tensor and the remaining dimensions. A dimension could also be 0, in which case the actual dimension value is unchanged (i.e. taken from the input tensor). If 'allowzero' is set, and the new shape includes 0, the dimension will be set explicitly to zero (i.e. not taken from input tensor). Shape (second input) could be an empty shape, which means converting to a scalar. The input tensor's shape and the output tensor's shape are required to have the same number of elements.

If the attribute 'allowzero' is set, it is invalid for the specified shape to contain both a zero value and -1, as the value of the dimension corresponding to -1 cannot be determined uniquely.

modeci_mdf.functions.onnx.resize

modeci_mdf.functions.onnx.**resize**(**args*, ***kwargs*)

Resize the input tensor. In general, it calculates every value in the output tensor as a weighted average of neighborhood (a.k.a. sampling locations) in the input tensor. Each dimension value of the output tensor is:

> output_dimension = floor(input_dimension * (roi_end - roi_start) * scale) if input "sizes" is not specified.

modeci_mdf.functions.onnx.reversesequence

modeci_mdf.functions.onnx.**reversesequence**(**args*, ***kwargs*)

Reverse batch of sequences having different lengths specified by *sequence_lens*.

For each slice i iterating on batch axis, the operator reverses the first sequence_lens[i] elements on time axis, and copies elements whose index's beyond sequence_lens[i] to the output. So the output slice i contains reversed sequences on the first sequence_lens[i] elements, then have original values copied for the other elements.

Example 1:

> **input = [[0.0, 4.0, 8.0, 12.0],** [1.0, 5.0, 9.0, 13.0], [2.0, 6.0, 10.0, 14.0], [3.0, 7.0, 11.0, 15.0]]
>
> sequence_lens = [4, 3, 2, 1] time_axis = 0 batch_axis = 1
>
> **output = [[3.0, 6.0, 9.0, 12.0],** [2.0, 5.0, 8.0, 13.0], [1.0, 4.0, 10.0, 14.0], [0.0, 7.0, 11.0, 15.0]]

Example 2:

input = [[0.0, 1.0, 2.0, 3.0], [4.0, 5.0, 6.0, 7.0], [8.0, 9.0, 10.0, 11.0], [12.0, 13.0, 14.0, 15.0]]

sequence_lens = [1, 2, 3, 4] time_axis = 1 batch_axis = 0

output = [[0.0, 1.0, 2.0, 3.0], [5.0, 4.0, 6.0, 7.0], [10.0, 9.0, 8.0, 11.0], [15.0, 14.0, 13.0, 12.0]]

modeci_mdf.functions.onnx.rnn

`modeci_mdf.functions.onnx.rnn(*args, **kwargs)`

Computes an one-layer simple RNN. This operator is usually supported via some custom implementation such as CuDNN.

Notations:

X - input tensor

i - input gate

t - time step (t-1 means previous time step)

Wi - W parameter weight matrix for input gate

Ri - R recurrence weight matrix for input gate

Wbi - W parameter bias vector for input gate

Rbi - R parameter bias vector for input gate

WBi - W parameter weight matrix for backward input gate

RBi - R recurrence weight matrix for backward input gate

WBbi - WR bias vectors for backward input gate

RBbi - RR bias vectors for backward input gate

H - Hidden state

num_directions - 2 if direction == bidirectional else 1

Activation functions:

Relu(x) - max(0, x)

Tanh(x) - (1 - e^{-2x})/(1 + e^{-2x})

Sigmoid(x) - 1/(1 + e^{-x})

(NOTE: Below are optional)

Affine(x) - alpha*x + beta

LeakyRelu(x) - x if x >= 0 else alpha * x

ThresholdedRelu(x) - x if x >= alpha else 0

ScaledTanh(x) - alpha*Tanh(beta*x)

HardSigmoid(x) - min(max(alpha*x + beta, 0), 1)

Elu(x) - x if x >= 0 else alpha*(e^x - 1)

Softsign(x) - x/(1 + |x|)

Softplus(x) - log(1 + e^x)

Equations (Default: f=Tanh):

- Ht = f(Xt*(Wi^T) + Ht-1*(Ri^T) + Wbi + Rbi)

This operator has **optional** inputs/outputs. See [the doc](IR.md) for more details about the representation of optional arguments. An empty string may be used in the place of an actual argument's name to indicate a missing argument. Trailing optional arguments (those not followed by an argument that is present) may also be simply omitted.

modeci_mdf.functions.onnx.roialign

modeci_mdf.functions.onnx.**roialign**(**args*, ***kwargs*)

Region of Interest (RoI) align operation described in the [Mask R-CNN paper](https://arxiv.org/abs/1703.06870). RoiAlign consumes an input tensor X and region of interests (rois) to apply pooling across each RoI; it produces a 4-D tensor of shape (num_rois, C, output_height, output_width).

RoiAlign is proposed to avoid the misalignment by removing quantizations while converting from original image into feature map and from feature map into RoI feature; in each ROI bin, the value of the sampled locations are computed directly through bilinear interpolation.

modeci_mdf.functions.onnx.round

modeci_mdf.functions.onnx.**round**(**args*, ***kwargs*)

Round takes one input Tensor and rounds the values, element-wise, meaning it finds the nearest integer for each value. In case of halfs, the rule is to round them to the nearest even integer. The output tensor has the same shape and type as the input.

Examples: ` round([0.9]) = [1.0] round([2.5]) = [2.0] round([2.3]) = [2.0] round([1.5]) = [2.0] round([-4.5]) = [-4.0] `

modeci_mdf.functions.onnx.run_onnx_op

modeci_mdf.functions.onnx.**run_onnx_op**(*op_name: str*, *inputs: Dict[str, numpy.array]*, *output_names: List[str]*, *opset_version: int = 15*, ***attributes*)

Simple helper function that invokes a single ONNX operator with inputs and attibutes and returns the results. This isn't typically done in ONNX because graphs usually consist of more than one operation. This wrapper probably creates a significant amount of overhead for but if we want to execute and ONNX graph op by op it is the easiest thing to do.

Parameters

- **op_name** – The name of the operation to run, (Conv, Pad, etc.)
- **inputs** – A dict keyed by input name where the values are the input values to pass to the operation.
- **output_names** – The names to use for the output values.
- ****attributes** – Any additional attributes for the ONNX operation.

Returns A dict of output values, keys are output_names. Values are the output values of the operation.

modeci_mdf.functions.onnx.scan

modeci_mdf.functions.onnx.**scan**(**args*, ***kwargs*)

Scan can be used to iterate over one or more scan_input tensors, constructing zero or more scan_output tensors. It combines ideas from general recurrences, functional programming constructs such as scan, fold, map, and zip, and is intended to enable generalizations of RNN-like constructs for sequence-to-sequence processing. Other tensors (referred to as state_variables here) can be used to carry a state when iterating from one element to another (similar to hidden-state in RNNs, also referred to as loop-carried dependences in the context of loops). Many common usages involve a single scan_input tensor (where functionality similar to scan, fold and map can be obtained). When more than one scan_input is used, a behavior similar to zip is obtained.

The attribute body must be a graph, specifying the computation to be performed in every iteration. It takes as input the current values of the state_variables and the current iterated element of the scan_inputs. It must return the (updated) values of the state_variables and zero or more scan_output_element tensors. The values of the scan_output_element tensors are concatenated over all the iterations to produce the scan_output values of the scan construct (similar to the concatenated intermediate hidden-state values of RNN-like constructs). All the output tensors (state_variables as well as scan_output_element tensors) are required to have the same shape in each iteration of the loop (a restriction imposed to enable efficient memory allocation).

Note that the iterated element passed to the body subgraph does not have a sequence axis. It will have a rank one less than the rank of the corresponding scan_input.

The scan operation returns the final values of the state_variables as well as the scan_outputs.

The optional attribute scan_input_directions specifies the direction (forward or backward) for each scan input. If this attribute is omitted, all sequences are scanned in the forward direction. A bidirectional scan may be performed by specifying the same tensor input twice in the scan_inputs, once with a forward direction, and once with a backward direction.

The scan_output of the operation is produced by concatenating the scan_output_element values produced by the body in each iteration. The optional attribute scan_output_directions specifies the direction in which scan_output is constructed (by appending or prepending the scan_output_element to scan_output in each iteration) for each scan_output. If this attribute is omitted, the scan_output_element is appended to the scan_output in each iteration.

The optional attribute scan_input_axes specifies the axis to be scanned for each scan_input. If omitted, every scan_input will be scanned in axis 0. For example, if axis 0 is the batch axis and axis 1 is the time axis (to be scanned), specify an axis value of 1. Note that scanning a non-zero axis may be less efficient than scanning axis zero.

The optional attribute scan_output_axes specifies the axis along which the scan_outputs are accumulated for each scan_output. For example, if axis 1 is the time axis (to be scanned) for both inputs and outputs, specify a scan_input axis and scan_output axis value of 1.

Note that because of the ONNX restriction that only the last parameter of an operator can be variadic, the initial-states and scan-inputs are listed together as one input parameter. Similarly, the final-states and scan-outputs are listed together as one output parameter. The attribute num_scan_inputs indicates the number M of scan-inputs.

The behavior of

Scan < num_scan_inputs = m, body = loop-body, scan_input_axes = [axis_1, . . . , axis_m]

> (init_1, . . . , init_n, scan_1, . . . , scan_m)

is equivalent to the following pseudo-code:

// scan_i.shape[axis_i] denotes the (max) sequence-length of scan_i // scan_i.shape[axis_i] is required to be equal to scan_j.shape[axis_j] for all i,j. sequence_length = scan_1.shape[axis_1];

// initialize state-variables st_1 = init_1; . . . st_n = init_n; // initialize scan-output variables: [] denotes an empty tensor scan_out_1 = []; . . . ; scan_out_k = []; // identify number of iterations:

// execute loop for (int t = 0; t < sequence_length; ++t) {

// generate the scan-input elements: the notation T<axis=k>[t] indicates the sub-tensor // of rank one less than T obtained by indexing T at position t along axis k. si_1 = scan_1<axis=axis_1>[t]; … ; si_m = scan_m<axis=axis_m>[t]; // execute loop-body st_1, …, st_n, so_1, …, so_k = loop-body(st_1, …, st_n, si_1, …, si_m) // accumulate the scan-output elements scan_out_1 = Concat<axis=0>(scan_out_1, so_1); … ; scan_out_k = Concat<axis=0>(scan_out_k, so_k);

}

return st_1, …, st_n, scan_out_1, …, scan_out_k;

Sample usage: Encoding RNN using a Scan

The following example shows how a simple RNN over an input tensor %X, with weight tensor %Wi, recurrence weight tensor %Ri, bias tensors %Wbi and %Rbi, and initial hidden-state %H_0 can be encoded as a ScanLoop. Note that the loop-body is a nested graph, and it directly computes %Wi, %Ri, %Wbi, and %Rbi (typically constants or initializers in the body graph). If these values are computed in the outer graph, they need to be passed in as extra state_variables.

graph rnn-encoding { %H_0 = … %X = … %Y_h, %Y = Scan[body = <graph rnn-cell-1>, num_scan_inputs=1](%H_0, %X) return %Y, %Y_h

}

graph rnn-cell-1 (%H_tminus1[FLOAT, tensor] %X_t[FLOAT, tensor]

) { %Wi = … %Ri = … %Wbi = … %Rbi = … %t1 = X_t * (Wi^T) %t2 = H_tminus1*(Ri^T) %t3 = Add(%t1, %t2) %t4 = Add(%t3, %Wbi) %t5 = Add(%t4, %Rbi) %Ht = Tanh(%t5) %Accumulate = Identity(%Ht) return %Ht, %Accumulate

}

modeci_mdf.functions.onnx.scatter

`modeci_mdf.functions.onnx.`**`scatter`**`(*args, **kwargs)`

This operator is deprecated. Please use ScatterElements, which provides the same functionality.

Scatter takes three inputs *data*, *updates*, and *indices* of the same rank r >= 1 and an optional attribute axis that identifies an axis of *data* (by default, the outer-most axis, that is axis 0). The output of the operation is produced by creating a copy of the input *data*, and then updating its value to values specified by *updates* at specific index positions specified by *indices*. Its output shape is the same as the shape of *data*.

For each entry in *updates*, the target index in *data* is obtained by combining the corresponding entry in *indices* with the index of the entry itself: the index-value for dimension = axis is obtained from the value of the corresponding entry in *indices* and the index-value for dimension != axis is obtained from the index of the entry itself.

For instance, in a 2-D tensor case, the update corresponding to the [i][j] entry is performed as below: ```

output[indices[i][j]][j] = updates[i][j] if axis = 0, output[i][indices[i][j]] = updates[i][j] if axis = 1,

```

This operator is the inverse of GatherElements. It is similar to Torch's Scatter operation.

Example 1: ```

**data = [** [0.0, 0.0, 0.0], [0.0, 0.0, 0.0], [0.0, 0.0, 0.0],

] indices = [
```

[1, 0, 2], [0, 2, 1],

] updates = [

[1.0, 1.1, 1.2], [2.0, 2.1, 2.2],

] output = [

[2.0, 1.1, 0.0] [1.0, 0.0, 2.2] [0.0, 2.1, 1.2]

]

` Example 2: `

data = [[1.0, 2.0, 3.0, 4.0, 5.0]] indices = [[1, 3]] updates = [[1.1, 2.1]] axis = 1 output = [[1.0, 1.1, 3.0, 2.1, 5.0]]

```

### modeci_mdf.functions.onnx.scatterelements

modeci_mdf.functions.onnx.**scatterelements**(*\*args*, *\*\*kwargs*)

ScatterElements takes three inputs *data*, *updates*, and *indices* of the same rank r >= 1 and an optional attribute axis that identifies an axis of *data* (by default, the outer-most axis, that is axis 0). The output of the operation is produced by creating a copy of the input *data*, and then updating its value to values specified by *updates* at specific index positions specified by *indices*. Its output shape is the same as the shape of *data*.

For each entry in *updates*, the target index in *data* is obtained by combining the corresponding entry in *indices* with the index of the entry itself: the index-value for dimension = axis is obtained from the value of the corresponding entry in *indices* and the index-value for dimension != axis is obtained from the index of the entry itself.

For instance, in a 2-D tensor case, the update corresponding to the [i][j] entry is performed as below: ```

output[indices[i][j]][j] = updates[i][j] if axis = 0, output[i][indices[i][j]] = updates[i][j] if axis = 1,

```

This operator is the inverse of GatherElements. It is similar to Torch's Scatter operation.

Example 1: ```

data = [[0.0, 0.0, 0.0], [0.0, 0.0, 0.0], [0.0, 0.0, 0.0],

] indices = [

[1, 0, 2], [0, 2, 1],

] updates = [

[1.0, 1.1, 1.2], [2.0, 2.1, 2.2],

] output = [

[2.0, 1.1, 0.0] [1.0, 0.0, 2.2] [0.0, 2.1, 1.2]

]

` Example 2: `

data = [[1.0, 2.0, 3.0, 4.0, 5.0]] indices = [[1, 3]] updates = [[1.1, 2.1]] axis = 1 output = [[1.0, 1.1, 3.0, 2.1, 5.0]]

```
```

modeci_mdf.functions.onnx.scatternd

modeci_mdf.functions.onnx.**scatternd**(**args*, ***kwargs*)

ScatterND takes three inputs *data* tensor of rank r >= 1, *indices* tensor of rank q >= 1, and *updates* tensor of rank q + r - indices.shape[-1] - 1. The output of the operation is produced by creating a copy of the input *data*, and then updating its value to values specified by *updates* at specific index positions specified by *indices*. Its output shape is the same as the shape of *data*. Note that *indices* should not have duplicate entries. That is, two or more *updates* for the same index-location is not supported.

***indices* is an integer tensor. Let k denote indices.shape[-1], the last dimension in the shape of *indices*.**

indices is treated as a (q-1)-dimensional tensor of k-tuples, where each k-tuple is a partial-index into *data*.

Hence, k can be a value at most the rank of *data*. When k equals rank(data), each update entry specifies an update to a single element of the tensor. When k is less than rank(data) each update entry specifies an update to a slice of the tensor. Index values are allowed to be negative, as per the usual convention for counting backwards from the end, but are expected in the valid range.

updates is treated as a (q-1)-dimensional tensor of replacement-slice-values. Thus, the first (q-1) dimensions of updates.shape must match the first (q-1) dimensions of indices.shape. The remaining dimensions of *updates* correspond to the dimensions of the replacement-slice-values. Each replacement-slice-value is a (r-k) dimensional tensor, corresponding to the trailing (r-k) dimensions of *data*. Thus, the shape of *updates* must equal indices.shape[0:q-1] ++ data.shape[k:r-1], where ++ denotes the concatenation of shapes.

The *output* is calculated via the following equation:

output = np.copy(data) update_indices = indices.shape[:-1] for idx in np.ndindex(update_indices):

output[indices[idx]] = updates[idx]

The order of iteration in the above loop is not specified. In particular, indices should not have duplicate entries: that is, if idx1 != idx2, then indices[idx1] != indices[idx2]. This ensures that the output value does not depend on the iteration order.

This operator is the inverse of GatherND.

Example 1: ```

data = [1, 2, 3, 4, 5, 6, 7, 8] indices = [[4], [3], [1], [7]] updates = [9, 10, 11, 12] output = [1, 11, 3, 10, 9, 6, 7, 12]

```

Example 2: ```

**data = [[[1, 2, 3, 4], [5, 6, 7, 8], [8, 7, 6, 5], [4, 3, 2, 1]],** [[1, 2, 3, 4], [5, 6, 7, 8], [8, 7, 6, 5], [4, 3, 2, 1]], [[8, 7, 6, 5], [4, 3, 2, 1], [1, 2, 3, 4], [5, 6, 7, 8]], [[8, 7, 6, 5], [4, 3, 2, 1], [1, 2, 3, 4], [5, 6, 7, 8]]]

indices = [[0], [2]] updates = [[[5, 5, 5, 5], [6, 6, 6, 6], [7, 7, 7, 7], [8, 8, 8, 8]],

[[1, 1, 1, 1], [2, 2, 2, 2], [3, 3, 3, 3], [4, 4, 4, 4]]]

**output = [[[5, 5, 5, 5], [6, 6, 6, 6], [7, 7, 7, 7], [8, 8, 8, 8]],** [[1, 2, 3, 4], [5, 6, 7, 8], [8, 7, 6, 5], [4, 3, 2, 1]], [[1, 1, 1, 1], [2, 2, 2, 2], [3, 3, 3, 3], [4, 4, 4, 4]], [[8, 7, 6, 5], [4, 3, 2, 1], [1, 2, 3, 4], [5, 6, 7, 8]]]

```

modeci_mdf.functions.onnx.selu

modeci_mdf.functions.onnx.**selu**(**args*, ***kwargs*)

Selu takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the scaled exponential linear unit function, *y = gamma * (alpha * e^x - alpha) for x <= 0*, *y = gamma * x for x > 0*, is applied to the tensor elementwise.

modeci_mdf.functions.onnx.sequenceat

modeci_mdf.functions.onnx.**sequenceat**(**args*, ***kwargs*)

Outputs a tensor copy from the tensor at 'position' in 'input_sequence'. Accepted range for 'position' is in *[-n, n - 1]*, where *n* is the number of tensors in 'input_sequence'. Negative value means counting positions from the back.

modeci_mdf.functions.onnx.sequenceconstruct

modeci_mdf.functions.onnx.**sequenceconstruct**(**args*, ***kwargs*)

Construct a tensor sequence containing 'inputs' tensors. All tensors in 'inputs' must have the same data type.

modeci_mdf.functions.onnx.sequenceempty

modeci_mdf.functions.onnx.**sequenceempty**(**args*, ***kwargs*)

Construct an empty tensor sequence, with given data type.

modeci_mdf.functions.onnx.sequenceerase

modeci_mdf.functions.onnx.**sequenceerase**(**args*, ***kwargs*)

Outputs a tensor sequence that removes the tensor at 'position' from 'input_sequence'. Accepted range for 'position' is in *[-n, n - 1]*, where *n* is the number of tensors in 'input_sequence'. Negative value means counting positions from the back. 'position' is optional, by default it erases the last tensor from 'input_sequence'.

modeci_mdf.functions.onnx.sequenceinsert

modeci_mdf.functions.onnx.**sequenceinsert**(**args*, ***kwargs*)

Outputs a tensor sequence that inserts 'tensor' into 'input_sequence' at 'position'. 'tensor' must have the same data type as 'input_sequence'. Accepted range for 'position' is in *[-n, n]*, where *n* is the number of tensors in 'input_sequence'. Negative value means counting positions from the back. 'position' is optional, by default it inserts 'tensor' to the back of 'input_sequence'.

modeci_mdf.functions.onnx.sequencelength

modeci_mdf.functions.onnx.**sequencelength**(**args*, ***kwargs*)

Produces a scalar(tensor of empty shape) containing the number of tensors in 'input_sequence'.

modeci_mdf.functions.onnx.shape

modeci_mdf.functions.onnx.**shape**(**args*, ***kwargs*)

Takes a tensor as input and outputs an 1D int64 tensor containing the shape of the input tensor. Optional attributes start and end can be used to compute a slice of the input tensor's shape. If start axis is omitted, the slice starts from axis 0. The end axis, if specified, is exclusive (and the returned value will not include the size of that axis). If the end axis is omitted, the axes upto the last one will be included. Negative axes indicate counting back from the last axis. Note that axes will be clamped to the range [0, r-1], where r is the rank of the input tensor if they are out-of-range (after adding r in the case of negative axis). Thus, specifying any end value > r is equivalent to specifying an end value of r, and specifying any start value < -r is equivalent to specifying a start value of 0.

For example: Input tensor with shape: [2, 3, 4] No attributes specified. Output: [2, 3, 4]

Input tensor with shape: [2, 3, 4] start: -1 Output: [4]

Input tensor with shape: [2, 3, 4] end: -1 Output: [2, 3]

Input tensor with shape: [2, 3, 4] start: 1 end: 2 Output: [3]

modeci_mdf.functions.onnx.shrink

modeci_mdf.functions.onnx.**shrink**(**args*, ***kwargs*)

Shrink takes one input data (Tensor<numeric>) and produces one Tensor output, having same datatype and shape with input. It has two attributes, lambd and bias. The formula of this operator is: If x < -lambd, y = x + bias; If x > lambd, y = x - bias; Otherwise, y = 0.

modeci_mdf.functions.onnx.sigmoid

modeci_mdf.functions.onnx.**sigmoid**(**args*, ***kwargs*)

Sigmoid takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the sigmoid function, y = 1 / (1 + exp(-x)), is applied to the tensor elementwise.

modeci_mdf.functions.onnx.sign

modeci_mdf.functions.onnx.**sign**(**args*, ***kwargs*)

Calculate the sign of the given input tensor element-wise. If input > 0, output 1. if input < 0, output -1. if input == 0, output 0.

modeci_mdf.functions.onnx.sin

modeci_mdf.functions.onnx.**sin**(**args*, ***kwargs*)

Calculates the sine of the given input tensor, element-wise.

modeci_mdf.functions.onnx.sinh

modeci_mdf.functions.onnx.**sinh**(**args*, ***kwargs*)
Calculates the hyperbolic sine of the given input tensor element-wise.

modeci_mdf.functions.onnx.size

modeci_mdf.functions.onnx.**size**(**args*, ***kwargs*)
Takes a tensor as input and outputs a int64 scalar that equals to the total number of elements of the input tensor.

modeci_mdf.functions.onnx.slice

modeci_mdf.functions.onnx.**slice**(**args*, ***kwargs*)
Produces a slice of the input tensor along multiple axes. Similar to numpy: https://numpy.org/doc/stable/user/basics.indexing.html?highlight=slice#slicing-and-striding

Slice uses the *starts*, *ends*, *axes* and *steps* inputs to select a sub-tensor of its input *data* tensor.

An effective *start[i]*, *end[i]*, and *step[i]* must be computed for each *i* in *[0, ... r-1]* where *r = rank(input)* as follows:

If *axes* are omitted, they are set to *[0, ..., r-1]*. If *steps* are omitted, they are set to *[1, ..., 1]* of length *len(starts)*

The effective values are initialized as *start[i] = 0*, *end[i] = dims[i]* where *dims* are the dimensions of *input* and `step[i] = `1.

All negative elements of *axes* are made non-negatve by adding *r* to them, where *r =rank(input)*.

All negative values in *starts[i]* and *ends[i]* have *dims[axes[i]]* added to them, where *dims* are the dimensions of *input*. Then *start[axes[i]]* is the adjusted *starts[i]* is clamped into the range *[0, dims[axes[i]]]* for positive stepping and *[0, dims[axes[i]]-1]* for negative stepping.

The clamping for the adjusted *ends[i]* depends on the sign of *steps[i]* and must accommodate copying 0 through *dims[axes[i]]* elements, so for positive stepping *end[axes[i]]* is clamped to *[0, dims[axes[i]]]*, while for negative stepping it is clamped to *[-1, dims[axes[i]]-1]*.

Finally, *step[axes[i]] = steps[i]*.

For slicing to the end of a dimension with unknown size, it is recommended to pass in *INT_MAX* when slicing forward and 'INT_MIN' when slicing backward.

Example 1:

data = [[1, 2, 3, 4], [5, 6, 7, 8],

] axes = [0, 1] starts = [1, 0] ends = [2, 3] steps = [1, 2] result = [

[5, 7],

]

Example 2:

data = [[1, 2, 3, 4], [5, 6, 7, 8],

] starts = [0, 1] ends = [-1, 1000] result = [

[2, 3, 4],

]

modeci_mdf.functions.onnx.softmax

modeci_mdf.functions.onnx.**softmax**(**args*, ***kwargs*)

The operator computes the normalized exponential values for the given input:

Softmax(input, axis) = Exp(input) / ReduceSum(Exp(input), axis=axis, keepdims=1)

The "axis" attribute indicates the dimension along which Softmax will be performed. The output tensor has the same shape and contains the Softmax values of the corresponding input.

modeci_mdf.functions.onnx.softmaxcrossentropyloss

modeci_mdf.functions.onnx.**softmaxcrossentropyloss**(**args*, ***kwargs*)

Loss function that measures the softmax cross entropy between 'scores' and 'labels'. This operator first computes a loss tensor whose shape is identical to the labels input. If the input is 2-D with shape (N, C), the loss tensor may be a N-element vector L = (l_1, l_2, ..., l_N). If the input is N-D tensor with shape (N, C, D1, D2, ..., Dk), the loss tensor L may have (N, D1, D2, ..., Dk) as its shape and L[i,][j_1][j_2]...[j_k] denotes a scalar element in L. After L is available, this operator can optionally do a reduction operator.

shape(scores): (N, C) where C is the number of classes, or (N, C, D1, D2,..., Dk), with K >= 1 in case of K-dimensional loss.

shape(labels): (N) where each value is 0 <= labels[i] <= C-1, or (N, D1, D2,..., Dk), with K >= 1 in case of K-dimensional loss.

The loss for one sample, l_i, can caculated as follows: l[i][d1][d2]...[dk] = -y[i][c][d1][d2]..[dk], where i is the index of classes.

or l[i][d1][d2]...[dk] = -y[i][c][d1][d2]..[dk] * weights[c], if 'weights' is provided.

loss is zero for the case when label-value equals ignore_index. l[i][d1][d2]...[dk] = 0, when labels[n][d1][d2]...[dk] = ignore_index

where: p = Softmax(scores) y = Log(p) c = labels[i][d1][d2]...[dk]

Finally, L is optionally reduced: If reduction = 'none', the output is L with shape (N, D1, D2, ..., Dk). If reduction = 'sum', the output is scalar: Sum(L). If reduction = 'mean', the output is scalar: ReduceMean(L), or if weight is provided: ReduceSum(L) / ReduceSum(W), where tensor W is of shape (N, D1, D2, ..., Dk) and W[n][d1][d2]...[dk] = weights[labels[i][d1][d2]...[dk]].

modeci_mdf.functions.onnx.softplus

modeci_mdf.functions.onnx.**softplus**(**args*, ***kwargs*)

Softplus takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the softplus function, y = ln(exp(x) + 1), is applied to the tensor elementwise.

modeci_mdf.functions.onnx.softsign

modeci_mdf.functions.onnx.**softsign**(**args*, ***kwargs*)

Calculates the softsign (x/(1+|x|)) of the given input tensor element-wise.

modeci_mdf.functions.onnx.spacetodepth

modeci_mdf.functions.onnx.**spacetodepth**(**args*, ***kwargs*)

SpaceToDepth rearranges blocks of spatial data into depth. More specifically, this op outputs a copy of the input tensor where values from the height and width dimensions are moved to the depth dimension.

modeci_mdf.functions.onnx.split

modeci_mdf.functions.onnx.**split**(**args*, ***kwargs*)

Split a tensor into a list of tensors, along the specified 'axis'. Lengths of the parts can be specified using input 'split'. Otherwise, the tensor is split to equal sized parts.

modeci_mdf.functions.onnx.splittosequence

modeci_mdf.functions.onnx.**splittosequence**(**args*, ***kwargs*)

Split a tensor into a sequence of tensors, along the specified 'axis'. Lengths of the parts can be specified using argument 'split'. 'split' must contain only positive numbers. 'split' is either a scalar (tensor of empty shape), or a 1-D tensor. If 'split' is a scalar, then 'input' will be split into equally sized chunks(if possible). Last chunk will be smaller if the 'input' size along the given axis 'axis' is not divisible by 'split'. Otherwise, the tensor is split into 'size(split)' chunks, with lengths of the parts on 'axis' specified in 'split'. In this scenario, the sum of entries in 'split' must be equal to the dimension size of input tensor on 'axis'.

modeci_mdf.functions.onnx.sqrt

modeci_mdf.functions.onnx.**sqrt**(**args*, ***kwargs*)

Square root takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the square root is, y = x^0.5, is applied to the tensor elementwise. If x is negative, then it will return NaN.

modeci_mdf.functions.onnx.squeeze

modeci_mdf.functions.onnx.**squeeze**(**args*, ***kwargs*)

Remove single-dimensional entries from the shape of a tensor. Takes an input *axes* with a list of axes to squeeze. If *axes* is not provided, all the single dimensions will be removed from the shape. If an axis is selected with shape entry not equal to one, an error is raised.

modeci_mdf.functions.onnx.stringnormalizer

modeci_mdf.functions.onnx.**stringnormalizer**(**args*, ***kwargs*)

StringNormalization performs string operations for basic cleaning. This operator has only one input (denoted by X) and only one output (denoted by Y). This operator first examines the elements in the X, and removes elements specified in "stopwords" attribute. After removing stop words, the intermediate result can be further lowercased, uppercased, or just returned depending the "case_change_action" attribute. This operator only accepts [C]- and [1, C]-tensor. If all elements in X are dropped, the output will be the empty value of string tensor with shape [1] if input shape is [C] and shape [1, 1] if input shape is [1, C].

modeci_mdf.functions.onnx.sub

modeci_mdf.functions.onnx.**sub**(**args*, ***kwargs*)

Performs element-wise binary subtraction (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

(Opset 14 change): Extend supported types to include uint8, int8, uint16, and int16.

modeci_mdf.functions.onnx.sum

modeci_mdf.functions.onnx.**sum**(**args*, ***kwargs*)

Element-wise sum of each of the input tensors (with Numpy-style broadcasting support). All inputs and outputs must have the same data type. This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.tan

modeci_mdf.functions.onnx.**tan**(**args*, ***kwargs*)

Calculates the tangent of the given input tensor, element-wise.

modeci_mdf.functions.onnx.tanh

modeci_mdf.functions.onnx.**tanh**(**args*, ***kwargs*)

Calculates the hyperbolic tangent of the given input tensor element-wise.

modeci_mdf.functions.onnx.tfidfvectorizer

modeci_mdf.functions.onnx.**tfidfvectorizer**(**args*, ***kwargs*)

This transform extracts n-grams from the input sequence and save them as a vector. Input can be either a 1-D or 2-D tensor. For 1-D input, output is the n-gram representation of that input. For 2-D input, the output is also a 2-D tensor whose i-th row is the n-gram representation of the i-th input row. More specifically, if input shape is [C], the corresponding output shape would be [max(ngram_indexes) + 1]. If input shape is [N, C], this operator produces a [N, max(ngram_indexes) + 1]-tensor.

In contrast to standard n-gram extraction, here, the indexes of extracting an n-gram from the original sequence are not necessarily consecutive numbers. The discontinuity between indexes are controlled by the number of skips. If the number of skips is 2, we should skip two tokens when scanning through the original sequence. Let's consider an example. Assume that input sequence is [94, 17, 36, 12, 28] and the number of skips is 2. The associated 2-grams are [94, 12] and [17, 28] respectively indexed by [0, 3] and [1, 4]. If the number of skips becomes 0, the 2-grams generated are [94, 17], [17, 36], [36, 12], [12, 28] indexed by [0, 1], [1, 2], [2, 3], [3, 4], respectively.

The output vector (denoted by Y) stores the count of each n-gram; Y[ngram_indexes[i]] indicates the times that the i-th n-gram is found. The attribute ngram_indexes is used to determine the mapping between index i and the corresponding n-gram's output coordinate. If pool_int64s is [94, 17, 17, 36], ngram_indexes is [1, 0], ngram_counts=[0, 0], then the Y[0] (first element in Y) and Y[1] (second element in Y) are the counts of [17, 36] and [94, 17], respectively. An n-gram which cannot be found in pool_strings/pool_int64s should be ignored and has no effect on the output. Note that we may consider all skips up to S when generating the n-grams.

The examples used above are true if mode is "TF". If mode is "IDF", all the counts larger than 1 would be truncated to 1 and the i-th element in weights would be used to scale (by multiplication) the count of the i-th

n-gram in pool. If mode is "TFIDF", this operator first computes the counts of all n-grams and then scale them by the associated values in the weights attribute.

Only one of pool_strings and pool_int64s can be set. If pool_int64s is set, the input should be an integer tensor. If pool_strings is set, the input must be a string tensor.

modeci_mdf.functions.onnx.thresholdedrelu

modeci_mdf.functions.onnx.**thresholdedrelu**(**args*, ***kwargs*)

ThresholdedRelu takes one input data (Tensor<T>) and produces one output data (Tensor<T>) where the rectified linear function, y = x for x > alpha, y = 0 otherwise, is applied to the tensor elementwise.

modeci_mdf.functions.onnx.tile

modeci_mdf.functions.onnx.**tile**(**args*, ***kwargs*)

Constructs a tensor by tiling a given tensor. This is the same as function *tile* in Numpy, but no broadcast. For example A = [[1, 2], [3, 4]], B = [1, 2], tile(A, B) = [[1, 2, 1, 2], [3, 4, 3, 4]]

modeci_mdf.functions.onnx.topk

modeci_mdf.functions.onnx.**topk**(**args*, ***kwargs*)

Retrieve the top-K largest or smallest elements along a specified axis. Given an input tensor of shape [a_1, a_2, . . . , a_n, r] and integer argument k, return two outputs:

-Value tensor of shape [a_1, a_2, . . . , a_{axis-1}, k, a_{axis+1}, . . . a_n] which contains the values of the top k elements along the specified axis

-Index tensor of shape [a_1, a_2, . . . , a_{axis-1}, k, a_{axis+1}, . . . a_n] which contains the indices of the top k elements (original indices from the input tensor).

If "largest" is 1 (the default value) then the k largest elements are returned. If "sorted" is 1 (the default value) then the resulting k elements will be sorted. If "sorted" is 0, order of returned 'Values' and 'Indices' are undefined.

Given two equivalent values, this operator uses the indices along the axis as a tiebreaker. That is, the element with the lower index will appear first.

modeci_mdf.functions.onnx.transpose

modeci_mdf.functions.onnx.**transpose**(**args*, ***kwargs*)

Transpose the input tensor similar to numpy.transpose. For example, when perm=(1, 0, 2), given an input tensor of shape (1, 2, 3), the output shape will be (2, 1, 3).

modeci_mdf.functions.onnx.trilu

modeci_mdf.functions.onnx.**trilu**(**args*, ***kwargs*)

Given a 2-D matrix or batches of 2-D matrices, returns the upper or lower triangular part of the tensor(s). The attribute "upper" determines whether the upper or lower part is retained. If set to true, the upper triangular matrix is retained. Lower triangular matrix is retained otherwise. Default value for the "upper" attribute is true. Trilu takes one input tensor of shape [*, N, M], where * is zero or more batch dimensions. The upper triangular part consists of the elements on and above the given diagonal (k). The lower triangular part consists of elements on and below the diagonal. All other elements in the matrix are set to zero. If k = 0, the triangular part on and above/below the main diagonal is retained. If upper is set to true, a positive k retains the upper triangular matrix excluding the main diagonal and (k-1) diagonals above it. A negative k value retains the main diagonal and |k|

diagonals below it. If upper is set to false, a positive k retains the lower triangular matrix including the main diagonal and k diagonals above it. A negative k value excludes the main diagonal and (|k|-1) diagonals below it.

modeci_mdf.functions.onnx.unique

modeci_mdf.functions.onnx.**unique**(**args*, ***kwargs*)

Find the unique elements of a tensor. When an optional attribute 'axis' is provided, unique subtensors sliced along the 'axis' are returned. Otherwise the input tensor is flattened and unique values of the flattened tensor are returned.

This operator returns the unique values or sliced unique subtensors of the input tensor and three optional outputs. The first output tensor 'Y' contains all unique values or subtensors of the input. The second optional output tensor 'indices' contains indices of 'Y' elements' first occurance in 'X'.. The third optional output tensor 'inverse_indices' contains, for elements of 'X', its corresponding indices in 'Y'. ". The fourth optional output tensor 'counts' contains the count of each element of 'Y' in the input.

Outputs are either sorted in ascending order or optionally in the order of the first occurrence of the values in the input.

https://docs.scipy.org/doc/numpy/reference/generated/numpy.unique.html

Example 1: input_X = [2, 1, 1, 3, 4, 3] attribute_sorted = 0 attribute_axis = None output_Y = [2, 1, 3, 4] output_indices = [0, 1, 3, 4] output_inverse_indices = [0, 1, 1, 2, 3, 2] output_counts = [1, 2, 2, 1]

Example 2: input_X = [[1, 3], [2, 3]] attribute_sorted = 1 attribute_axis = None output_Y = [1, 2, 3] output_indices = [0, 2, 1] output_inverse_indices = [0, 2, 1, 2] output_counts = [1, 1, 2]

Example 3: input_X = [[1, 0, 0], [1, 0, 0], [2, 3, 4]] attribute_sorted = 1 attribute_axis = 0 output_Y = [[1, 0, 0], [2, 3, 4]] output_indices = [0, 2] output_inverse_indices = [0, 0, 1] output_counts = [2, 1]

Example 4:

input_x = [[[1., 1.], [0., 1.], [2., 1.], [0., 1.]], [[1., 1.], [0., 1.], [2., 1.], [0., 1.]]]

attribute_sorted = 1 attribute_axis = 1

intermediate data are presented below for better understanding:

there are 4 subtensors sliced along axis 1 of input_x (shape = (2, 4, 2)): A: [[1, 1], [1, 1]],

[[0, 1], [0, 1]], [[2, 1], [2, 1]], [[0, 1], [0, 1]].

there are 3 unique subtensors: [[1, 1], [1, 1]], [[0, 1], [0, 1]], [[2, 1], [2, 1]].

sorted unique subtensors: B: [[0, 1], [0, 1]],

[[1, 1], [1, 1]], [[2, 1], [2, 1]].

output_Y is constructed from B: [[[0. 1.], [1. 1.], [2. 1.]],

[[0. 1.], [1. 1.], [2. 1.]]]

output_indices is to map from B to A: [1, 0, 2]

output_inverse_indices is to map from A to B: [1, 0, 2, 0]

output_counts = [2 1 1]

modeci_mdf.functions.onnx.unsqueeze

modeci_mdf.functions.onnx.**unsqueeze**(**args*, ***kwargs*)

Insert single-dimensional entries to the shape of an input tensor (*data*). Takes one required input *axes* - which contains a list of dimension indices and this operator will insert a dimension of value *1* into the corresponding index of the output tensor (*expanded*).

For example: Given an input tensor (*data*) of shape [3, 4, 5], then Unsqueeze(data, axes=[0, 4]) outputs a tensor (*expanded*) containing same data as *data* but with shape [1, 3, 4, 5, 1].

The input *axes* should not contain any duplicate entries. It is an error if it contains duplicates. The rank of the output tensor (*output_rank*) is the rank of the input tensor (*data*) plus the number of values in *axes*. Each value in *axes* should be within the (inclusive) range [-output_rank , output_rank - 1]. The order of values in *axes* does not matter and can come in any order.

modeci_mdf.functions.onnx.upsample

modeci_mdf.functions.onnx.**upsample**(**args*, ***kwargs*)

Upsample the input tensor. Each dimension value of the output tensor is:

output_dimension = floor(input_dimension * scale).

modeci_mdf.functions.onnx.where

modeci_mdf.functions.onnx.**where**(**args*, ***kwargs*)

Return elements, either from X or Y, depending on condition. Where behaves like [numpy.where](https://docs.scipy.org/doc/numpy/reference/generated/numpy.where.html) with three parameters.

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

modeci_mdf.functions.onnx.xor

modeci_mdf.functions.onnx.**xor**(**args*, ***kwargs*)

Returns the tensor resulted from performing the *xor* logical operation elementwise on the input tensors *A* and *B* (with Numpy-style broadcasting support).

This operator supports **multidirectional (i.e., Numpy-style) broadcasting**; for more details please check [the doc](Broadcasting.md).

23.3.3 modeci_mdf.functions.standard

Implementation of core MDF function ontology.

This module implements and registers all builtin MDF functions.

Functions

add_mdf_function([name, description, ...])	Register a function with MDF function ontology.
create_python_expression([expression_string])	Converts the mathematical representation of function into function expression in python
create_python_function([name, ...])	Create a Python function e.g.
substitute_args([expression_string, args])	Substitute arg with the value in args dict

modeci_mdf.functions.standard.add_mdf_function

modeci_mdf.functions.standard.**add_mdf_function**(*name: Optional[str] = None*, *description: Optional[str] = None*, *arguments: Optional[List[str]] = None*, *expression_string: Optional[str] = None*)

Register a function with MDF function ontology.

Adds a function to the registered list of available MDF functions.

Parameters

- **name** – name of the function e.g.'sin','cos','linear'
- **description** – Information about the function
- **arguments** – Inputs provided to obtain the result of function
- **expression_string** – Function expression in string format

Returns Updates mdf_functions

modeci_mdf.functions.standard.create_python_expression

modeci_mdf.functions.standard.**create_python_expression**(*expression_string: Optional[str] = None*) → str

Converts the mathematical representation of function into function expression in python

Parameters **expression_string** – Mathematical expression of function in string format

Returns function expression in python

modeci_mdf.functions.standard.create_python_function

modeci_mdf.functions.standard.**create_python_function**(*name: str = None*, *expression_string: str = None*, *arguments: List[str] = None*) → types.FunctionType

Create a Python function e.g. linear, exponential, sin, cos, ReLu

Parameters

- **name** – name of the function e.g.'sin','cos','linear'
- **expression_string** – Function expression in string format
- **arguments** – list of inputs provided to obtain result from the function

Returns A function object

modeci_mdf.functions.standard.substitute_args

modeci_mdf.functions.standard.**substitute_args**(*expression_string: Optional[str] = None*, *args: Optional[Dict[str, str]] = None*) → str

Substitute arg with the value in args dict

Parameters

- **expression_string** – function expression
- **args** – Dictionary of arguments

Returns modified expression string after substitution

23.4 modeci_mdf.interfaces

Implementations of importers and exporters for supported environments; fulfilling the hub and spoke model of MDF by allowing exchange between different modeling environments via MDF.

Most of these exporters and importers are currently a work and progress.

modeci_mdf.interfaces.actr	Import and export code for ACT-R models
modeci_mdf.interfaces.graphviz	Import and export code for GraphViz models
modeci_mdf.interfaces.onnx	Import and export code for ONNX models
modeci_mdf.interfaces.pytorch	Import and export code for PyTorch models

23.4.1 modeci_mdf.interfaces.actr

Import and export code for ACT-R models

modeci_mdf.interfaces.actr.importer	Code for importing ACT-R models into MDF.

modeci_mdf.interfaces.actr.importer

Code for importing ACT-R models into MDF.

Functions

actr_to_mdf(file_name)	Parses an ACT-R .lisp model file and outputs MDF .json and .yaml files.
build_model()	Builds the base model of the ACT-R production system without any chunks, goals, or productions specified.

modeci_mdf.interfaces.actr.importer.actr_to_mdf

modeci_mdf.interfaces.actr.importer.**actr_to_mdf**(*file_name: str*)
Parses an ACT-R .lisp model file and outputs MDF .json and .yaml files.

Parameters **file_name** – The name of the ACT-R model file ending in .lisp.

modeci_mdf.interfaces.actr.importer.build_model

modeci_mdf.interfaces.actr.importer.**build_model**() → *modeci_mdf.mdf.Model*
Builds the base model of the ACT-R production system without any chunks, goals, or productions specified.

Returns An MDF model object representing the core ACT-R production system.

23.4.2 modeci_mdf.interfaces.graphviz

Import and export code for GraphViz models

modeci_mdf.interfaces.graphviz.exporter	Simple export of MDF to GraphViz for generating graphics.

modeci_mdf.interfaces.graphviz.exporter

Simple export of MDF to GraphViz for generating graphics.

Work in progress...

Functions

format_bold(s[, use_bold])	
format_condition(s)	
format_function(s)	
format_input(s)	
format_label(s)	
format_num(s)	
format_output(s)	
format_param(s)	
format_standard_func(s)	
format_standard_func_long(s)	

continues on next page

Table 59 – continued from previous page

format_term_condition(s)
match_in_expr(expr, node)
mdf_to_graphviz(mdf_graph[, engine, ...])
safe_comparitor(comp)

modeci_mdf.interfaces.graphviz.exporter.format_bold

modeci_mdf.interfaces.graphviz.exporter.**format_bold**(*s*, *use_bold=True*)

modeci_mdf.interfaces.graphviz.exporter.format_condition

modeci_mdf.interfaces.graphviz.exporter.**format_condition**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_function

modeci_mdf.interfaces.graphviz.exporter.**format_function**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_input

modeci_mdf.interfaces.graphviz.exporter.**format_input**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_label

modeci_mdf.interfaces.graphviz.exporter.**format_label**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_num

modeci_mdf.interfaces.graphviz.exporter.**format_num**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_output

modeci_mdf.interfaces.graphviz.exporter.**format_output**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_param

modeci_mdf.interfaces.graphviz.exporter.**format_param**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_standard_func

modeci_mdf.interfaces.graphviz.exporter.**format_standard_func**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_standard_func_long

modeci_mdf.interfaces.graphviz.exporter.**format_standard_func_long**(*s*)

modeci_mdf.interfaces.graphviz.exporter.format_term_condition

modeci_mdf.interfaces.graphviz.exporter.**format_term_condition**(*s*)

modeci_mdf.interfaces.graphviz.exporter.match_in_expr

modeci_mdf.interfaces.graphviz.exporter.**match_in_expr**(*expr*, *node*)

modeci_mdf.interfaces.graphviz.exporter.mdf_to_graphviz

modeci_mdf.interfaces.graphviz.exporter.**mdf_to_graphviz**(*mdf_graph*, *engine='dot'*, *output_format='png'*, *view_on_render=False*, *level=2*, *filename_root=None*, *is_horizontal=False*)

modeci_mdf.interfaces.graphviz.exporter.safe_comparitor

modeci_mdf.interfaces.graphviz.exporter.**safe_comparitor**(*comp*)

23.4.3 modeci_mdf.interfaces.onnx

Import and export code for ONNX models

modeci_mdf.interfaces.onnx.exporter	Code for exporting MDF models to ONNX.
modeci_mdf.interfaces.onnx.importer	Code for importing ONNX models into MDF.

modeci_mdf.interfaces.onnx.exporter

Code for exporting MDF models to ONNX.

Functions

convert_mdf_file_to_onnx(input_file)	Converter from MDF to ONNX.
generate_onnx_graph(graph, ...)	
generate_onnx_node(node, graph)	Convert an MDF node into an ONNX node.
main()	
mdf_to_onnx(mdf_model)	Takes an MDF model object and returns a list of ONNX models for each graph in the model.

modeci_mdf.interfaces.onnx.exporter.convert_mdf_file_to_onnx

modeci_mdf.interfaces.onnx.exporter.**convert_mdf_file_to_onnx**(*input_file: str*)

Converter from MDF to ONNX. Takes in a JSON/ONNX file and generates ONNX files.

Parameters **input_file** – The input file path to the MDF file. Output files are generated in same directory with -m2o.onnx extensions.

Returns NoneType

modeci_mdf.interfaces.onnx.exporter.generate_onnx_graph

modeci_mdf.interfaces.onnx.exporter.**generate_onnx_graph**(*graph*, *node-names_in_execution_order*)

modeci_mdf.interfaces.onnx.exporter.generate_onnx_node

modeci_mdf.interfaces.onnx.exporter.**generate_onnx_node**(*node*, *graph*)

Convert an MDF node into an ONNX node. Takes an MDF node, MDF graph and returns the ONNX node, any inputs to the node coming from outside the graph, any outputs from the node going outside the graph, and an initializer for constants

modeci_mdf.interfaces.onnx.exporter.main

modeci_mdf.interfaces.onnx.exporter.**main**()

modeci_mdf.interfaces.onnx.exporter.mdf_to_onnx

modeci_mdf.interfaces.onnx.exporter.**mdf_to_onnx**(*mdf_model*)

Takes an MDF model object and returns a list of ONNX models for each graph in the model.

modeci_mdf.interfaces.onnx.importer

Code for importing ONNX models into MDF.

Functions

convert_file(input_file)	Simple converter from ONNX to MDF.
find_subgraphs(graph[, graph_dict])	Recurse through an ONNX graph and find all subgraphs.
get_onnx_attribute(a)	
get_shape_params(shape)	Small helper function to extract a tuple from the TensorShapeProto.
id_to_port(id)	Turn unique ONNX output and input value names into valid MDF input and outport names
main()	
onnx_node_to_mdf(node, onnx_initializer)	Construct an MDF node (and function) from an ONNX NodeProto or ValueInfoProto
onnx_to_mdf(onnx_model[, onnx_initializer])	Convert a loaded ONNX model into a MDF model.

modeci_mdf.interfaces.onnx.importer.convert_file

modeci_mdf.interfaces.onnx.importer.**convert_file**(*input_file: str*)

Simple converter from ONNX to MDF. Takes in ONNX files and generates MDF JSON/YAML files.

Parameters **input_file** – The input file path to the ONNX file. Output files are generated in same directory with -mdf.json and -mdf.yml extensions.

Returns MoneType

modeci_mdf.interfaces.onnx.importer.find_subgraphs

modeci_mdf.interfaces.onnx.importer.**find_subgraphs**(*graph: onnx.onnx_ml_pb2.GraphProto*, *graph_dict: Optional[Dict[str, onnx.onnx_ml_pb2.GraphProto]] = None*) → Dict[str, onnx.onnx_ml_pb2.GraphProto]

Recurse through an ONNX graph and find all subgraphs.

Parameters

- **graph** – The graph to search.

- **graph_list** – Insert graphs we find into this dict. Use the parent node name as a key. If None, intitialize to empty dict.

Returns All the subgraphs in the for the graph.

modeci_mdf.interfaces.onnx.importer.get_onnx_attribute

modeci_mdf.interfaces.onnx.importer.**get_onnx_attribute**(*a*)

modeci_mdf.interfaces.onnx.importer.get_shape_params

modeci_mdf.interfaces.onnx.importer.**get_shape_params**(*shape: onnx.onnx_ml_pb2.TensorShapeProto*) → Tuple

Small helper function to extract a tuple from the TensorShapeProto. These objects can contain both integer dimensions and parameter dimensions that are variable, like 'batch_size'.

Parameters **shape** – The ONNX shape proto to process.

Returns A tuple that can contain both integers and strings for parameter dimensions.

modeci_mdf.interfaces.onnx.importer.id_to_port

modeci_mdf.interfaces.onnx.importer.**id_to_port**(*id: str*)

Turn unique ONNX output and input value names into valid MDF input and outport names

modeci_mdf.interfaces.onnx.importer.main

modeci_mdf.interfaces.onnx.importer.**main**()

modeci_mdf.interfaces.onnx.importer.onnx_node_to_mdf

modeci_mdf.interfaces.onnx.importer.**onnx_node_to_mdf**(*node: Union[onnx.onnx_ml_pb2.NodeProto, onnx.onnx_ml_pb2.ValueInfoProto], onnx_initializer: Dict[str, Dict[str, Any]]*) → *modeci_mdf.mdf.Node*

Construct an MDF node (and function) from an ONNX NodeProto or ValueInfoProto

Parameters

- **node** – The ONNX node to use to form the MDF node. Can be a node from the model or a ValueInfoProto specifying an input or output.
- **onnx_initializer** – A specification of values in the graph that ONNX has marked as initializer's. This dict is keyed on the name of the parameter, the value is another dict with three entries; shape, type, and value.

Returns The equivalent MDF node for the ONNX node passed in as argument.

modeci_mdf.interfaces.onnx.importer.onnx_to_mdf

modeci_mdf.interfaces.onnx.importer.**onnx_to_mdf**(*onnx_model: Union[onnx.onnx_ml_pb2.ModelProto, onnx.onnx_ml_pb2.GraphProto]*, *onnx_initializer: Optional[Dict[str, Dict[str, Any]]] = None*)

Convert a loaded ONNX model into a MDF model.

Parameters

- **onnx_model** – The ONNX model to convert. Typically, this is the result of a call to onnx.load()
- **onnx_initializer** – A specification of values in the graph that ONNX has marked as initializer's. This dict is keyed on the name of the parameter, the value is another dict with three entries; shape, type, and value.

Returns An MDF description of the ONNX model.

23.4.4 modeci_mdf.interfaces.pytorch

Import and export code for PyTorch models

modeci_mdf.interfaces.pytorch.exporter	Functions for converting from MDF models to PyTorch
modeci_mdf.interfaces.pytorch.importer	Functions for converting from PyTorch TorchScript to MDF models.

modeci_mdf.interfaces.pytorch.exporter

Functions for converting from MDF models to PyTorch

Functions

build_script(nodes, execution_order, ...)	Helper function to create and assemble text components necessary to specify module.py importable model script.
func_args(exp, arg_dict)	
generate_main_forward(nodes, ...)	Helper function to generate the main forward method that will specify the execution of the pytorch model.
get_module_declaration_text(name, node_dict, ...)	Helper function to generate string in module.py.
mdf_to_pytorch(mdf_model, model_input, ...)	Function loads and returns a pytorch model for all models specified in an mdf file.
sym(value)	

modeci_mdf.interfaces.pytorch.exporter.build_script

modeci_mdf.interfaces.pytorch.exporter.**build_script**(*nodes: List[node], execution_order: List[str], model_id1: str, d_e: Dict[str, Any], conditions*, *version: str*)

Helper function to create and assemble text components necessary to specify module.py importable model script. These include:

- **Module declarations**
  - Initialization of functions
  - Definition of forward function
- **Model main call declaration:**
  - Initialization of subcomponents
  - Forward function logic

Parameters

- **nodes** – list of nodes in the graph
- **execution_order** – List of nodes in the order of execution
- **d_e** – Weights on edges stored in dict format
- **model_id1** – id of the model to be converted
- **conditions** –

Returns: complete module.py script as a formatted string

modeci_mdf.interfaces.pytorch.exporter.func_args

modeci_mdf.interfaces.pytorch.exporter.**func_args**(*exp*, *arg_dict*)

modeci_mdf.interfaces.pytorch.exporter.generate_main_forward

modeci_mdf.interfaces.pytorch.exporter.**generate_main_forward**(*nodes: List[node], execution_order: List[str], d_e: Dict[str, Any]*)

Helper function to generate the main forward method that will specify the execution of the pytorch model. This requires proper ordering of module calls as well as preservation of variables.

Parameters

- **nodes** – list of nodes in the graph
- **execution_order** – List of nodes in the order of execution
- **d_e** – Weights on edges stored in dict format

Returns: Function returns the main forward call that will be used to define pytorch model

modeci_mdf.interfaces.pytorch.exporter.get_module_declaration_text

modeci_mdf.interfaces.pytorch.exporter.**get_module_declaration_text**(*name: str*, *node_dict: Dict[Any, Any]*, *execution_order: List[str]*, *version: str*)

Helper function to generate string in module.py. String will create an instance of the torch object corresponding to the node and function at node as method Generated text specifies the definition of class that will form the pytorch model, including __init__method and forward method. Returns string of the class definition with parameters and arguments assigned.

Parameters

- **name** – Name of the node
- **node_dict** – dictionary with attributes of the node such as Input Ports, functions, parameters and
- **execution_order** – List of nodes in the order of execution

Returns: Script in PyTorch schema

modeci_mdf.interfaces.pytorch.exporter.mdf_to_pytorch

modeci_mdf.interfaces.pytorch.exporter.**mdf_to_pytorch**(*mdf_model: Model*, *model_input: str*, *eval_models: bool*, *version: str*)

Function loads and returns a pytorch model for all models specified in an mdf file.

Parameters

- **mdf_model** – model in MDF format
- **eval_models** – Set Evaluation of model to True or False
- **version** – MDF version
- **model_input** – input file name

Returns: Returns a dictionary where key = model name, value = pytorch model object

modeci_mdf.interfaces.pytorch.exporter.sym

modeci_mdf.interfaces.pytorch.exporter.**sym**(*value*)

modeci_mdf.interfaces.pytorch.importer

Functions for converting from PyTorch TorchScript to MDF models.

This code was originally inspired by the following blog post:

> Mike He, "From Models to Computation Graphs (Part I)", https://ad1024.space/articles/22

Functions

convert_to_serializable(value)	Helper function that converts some common unserializable types to JSON seriralizable types
get_graph_constants(graph)	Find all constant nodes in the graph and extract their values as a proper JSON serializable value.
make_func_id(node)	Helper function to get a unique name (used in MDF as id) for a TorchScript node's op/function.
make_model_graph_name(model)	Helper function that generates a clean graph and model name from a TorchScript model
make_node_id(node)	Helper function to get a unique name (used in MDF as id) from a TorchScript Node object
process_onnx_schema(node, consts, port_mapper)	Retrieve the argument names and attributes (parameters in MDF) for this Operation.
process_torch_schema(node, consts, port_mapper)	Parse a TorchScript node schema into argument names and constant attributes (parameters in MDF)
pytorch_to_mdf(model[, args, trace, ...])	Convert a PyTorch model to an MDF model.
torchnode_to_mdfnode(node, graph, consts, ...)	Convert a TorchScript node to an MDF node.
translate_graph(graph, mdf_graph, consts, ...)	Go through a `Graph` or `Block` and translate the nodes and edges to MDF nodes and edges.

modeci_mdf.interfaces.pytorch.importer.convert_to_serializable

modeci_mdf.interfaces.pytorch.importer.**convert_to_serializable**(*value*)

Helper function that converts some common unserializable types to JSON seriralizable types

modeci_mdf.interfaces.pytorch.importer.get_graph_constants

modeci_mdf.interfaces.pytorch.importer.**get_graph_constants**(*graph: torch.Graph*) → Dict[str, Any]

Find all constant nodes in the graph and extract their values as a proper JSON serializable value.

Parameters **graph** – The graph to extract constants from.

Returns A Dict that maps the constant nodes unique TorchScript node ID string to its value.

modeci_mdf.interfaces.pytorch.importer.make_func_id

modeci_mdf.interfaces.pytorch.importer.**make_func_id**(*node: torch.Node*) → str

Helper function to get a unique name (used in MDF as id) for a TorchScript node's op/function.

modeci_mdf.interfaces.pytorch.importer.make_model_graph_name

modeci_mdf.interfaces.pytorch.importer.**make_model_graph_name**(*model: Union[torch.ScriptModule, torch.jit.ScriptFunction]*) → Tuple[str, str]

Helper function that generates a clean graph and model name from a TorchScript model

modeci_mdf.interfaces.pytorch.importer.make_node_id

modeci_mdf.interfaces.pytorch.importer.**make_node_id**(*node: torch.Node*) → str

Helper function to get a unique name (used in MDF as id) from a TorchScript Node object

modeci_mdf.interfaces.pytorch.importer.process_onnx_schema

modeci_mdf.interfaces.pytorch.importer.**process_onnx_schema**(*node: torch.Node*, *consts: Dict*, *port_mapper: modeci_mdf.interfaces.pytorch.importer.PortMappe* → Tuple[Dict[str, str], Dict[str, Any]]

Retrieve the argument names and attributes (parameters in MDF) for this Operation.

Parameters

- **op** – The TorchScript node containing the ONNX operation.
- **port_mapper** – The utitlity class for assigning TorchScript input output ids to Input Output Port ids.

Returns

- A dict representing argument names mapping to input port ids
- A dict mapping parameters (ONNX attributes) names mapping to values

Return type A two element tuple

modeci_mdf.interfaces.pytorch.importer.process_torch_schema

modeci_mdf.interfaces.pytorch.importer.**process_torch_schema**(*node: torch.Node*, *consts: Dict*, *port_mapper: modeci_mdf.interfaces.pytorch.importer.PortMapp* → Tuple[List[str], Dict[str, Any]]

Parse a TorchScript node schema into argument names and constant attributes (parameters in MDF)

Parameters

- **node** – The TorchScript node to retrieve the schema from.
- **consts** – The constant nodes Dict for the graph we are working with.

Returns A tuple containing a list of argument names and Dict of parameter names and values.

modeci_mdf.interfaces.pytorch.importer.pytorch_to_mdf

modeci_mdf.interfaces.pytorch.importer.**pytorch_to_mdf**(*model: Union[Callable, torch.nn.modules.module.Module, torch.jit.ScriptFunction, torch.ScriptModule]*, *args: Union[None, torch.Tensor, Tuple[torch.Tensor]] = None*, *trace: bool = False*, *use_onnx_ops: bool = True*) → Union[*modeci_mdf.mdf.Model*, *modeci_mdf.mdf.Graph*]

Convert a PyTorch model to an MDF model. By default, this function will invoke *torch.jit.script* on the model to compile it down to TorchScript IR and simplify the graph before exporting the MDF. The default is to use ONNX operations when possible and fallback to ATENTorch ops when ONNX support is not available (*torch._C._onnx.OperatorExportTypes.ONNX_ATEN_FALLBACK* mode). To use allATENTorch ops, set use_onnx_ops to False.

Parameters

- **model** – The model to translate into MDF.
- **args** – The input arguments for this model. If a nn.Module is passed then the model will be traced with these inputs. If a ScriptModule is passed, they are still needed to determine input shapes.
- **trace** – Force the use of tracing to compile the model. The default is to use torch.jit.script
- **use_onnx_ops** – Use ONNX ops when possible, fallback to ATEN ops when not available. Default is True. If False, use only ATEN ops.

Returns The translated MDF model

modeci_mdf.interfaces.pytorch.importer.torchnode_to_mdfnode

modeci_mdf.interfaces.pytorch.importer.**torchnode_to_mdfnode**(*node: torch.Node*, *graph: torch.Graph*, *consts: Dict[str, Any]*, *port_mapper: modeci_mdf.interfaces.pytorch.importer.PortMapp* → Optional[*modeci_mdf.mdf.Node*]

Convert a TorchScript node to an MDF node.

Parameters

- **node** – The node to convert.
- **graph** – The graph that this node is a member.

- **consts** – A dict containing any constants in the graph.

Returns The MDF node for this TorchScript node. prim::Constant nodes are excluded from the MDF graph and are instead placed as parameters. In this case, return None.

modeci_mdf.interfaces.pytorch.importer.translate_graph

modeci_mdf.interfaces.pytorch.importer.**translate_graph**(*graph: Union[torch.Graph, torch.Block]*, *mdf_graph:* modeci_mdf.mdf.Graph, *consts: Dict[str, Any]*, *port_mapper:* modeci_mdf.interfaces.pytorch.importer.PortMapper)

Go through a `Graph` or `Block` and translate the nodes and edges to MDF nodes and edges.

Parameters

- **graph** – The graph to translate.
- **mdf_graph** – The MDF graph to store the translation into.
- **consts** – Constant to use for parameters of nodes.
- **port_mapper** – A port mapper instance to handle translating names.

Returns:

Classes

PortMapper(graph, args)	A simple class that handles mapping TorchScript inputouput ids to MDF InputPortOutputPort ids.

modeci_mdf.interfaces.pytorch.importer.PortMapper

class modeci_mdf.interfaces.pytorch.importer.**PortMapper**(*graph: torch.Graph*, *args: Tuple*)

Bases: `object`

A simple class that handles mapping TorchScript inputouput ids to MDF InputPortOutputPort ids. It keeps track of annoying details like graph level inputs and stuff.

Methods

id_to_port(id)	Turn unique TorchScript output and input value names into valid MDF input and outport names
port_to_id(name)	Transform a port name back to is TorchScript ID

id_to_port(*id: str*)

Turn unique TorchScript output and input value names into valid MDF input and outport names

port_to_id(*name: str*)

Transform a port name back to is TorchScript ID

23.5 modeci_mdf.mdf

The main object-oriented implementation of the MDF schema, with each core component of the MDF specification implemented as a `class`. Instances of these objects can be composed to create a representation of an MDF model as Python objects. These models can then be serialized and deserialized to and from JSON or YAML, executed via the *execution_engine* module, or imported and exported to supported external environments using the *interfaces* module.

Functions

parsed_structure_factory(cl)	
parsed_unstructure_factory(cl)	
v(cl)	

23.5.1 modeci_mdf.mdf.parsed_structure_factory

modeci_mdf.mdf.**parsed_structure_factory**(*cl*)

23.5.2 modeci_mdf.mdf.parsed_unstructure_factory

modeci_mdf.mdf.**parsed_unstructure_factory**(*cl*)

23.5.3 modeci_mdf.mdf.v

modeci_mdf.mdf.**v**(*cl*)

Classes

Condition(type, **kwargs, Any]])	A set of descriptors which specifies conditional execution of Nodes to meet complex execution requirements.
ConditionSet(node_specific, ...)	Specifies the non-default pattern of execution of Nodes
Edge(id, sender, receiver, sender_port, ...)	An *Edge* is an attribute of a *Graph* that transmits computational results from a sender's *OutputPort* to a receiver's *InputPort*.
Function(id, function, args, Any]] = None, ...)	A single value which is evaluated as a function of values on :class:`InputPort`(s) and other Functions
Graph(id, nodes, edges, parameters, ...)	A directed graph consisting of :class:`~Node`s (with :class:`~Parameter`s and :class:`~Function`s evaluated internally) connected via :class:`~Edge`s.
InputPort(id[, shape])	The *InputPort* is an attribute of a Node which allows external information to be input to the Node
Model(id, graphs, format, ...)	The top level construct in MDF is Model, which may contain multiple *Graph* objects and model attribute(s)

continues on next page

Table 69 – continued from previous page

Node(id, input_ports, functions, parameters, ...)	A self contained unit of evaluation receiving input from other nodes on :class:`InputPort`(s). The values from these are processed via a number of :class:`Function`(s) and one or more final values are calculated on the :class:`OutputPort`(s).
OutputPort(id, value[, shape])	The *OutputPort* is an attribute of a *Node* which exports information to another *Node* connected by an *Edge*
Parameter(id, value, List, Dict, ...)	A parameter of the *Node*, which can be: 1) a specific fixed `value` (a constant (int/float) or an array) 2) a string expression for the `value` referencing other named :class:`Parameter`(s).
ParameterCondition(id, test, List, Dict, ...)	A condition to test on a Node's parameters, which if true, sets the value of this Parameter

23.5.4 modeci_mdf.mdf.Condition

class modeci_mdf.mdf.**Condition**(*type: Optional[str] = None*, ***kwargs: Optional[Dict[str, Any]]*)

Bases: modeci_mdf.mdf.MdfBase

A set of descriptors which specifies conditional execution of Nodes to meet complex execution requirements.

Variables

- **type** (*str*) – The type of *Condition* from the library
- **kwargs** (*Optional[Dict[str, Any]]*) – The dictionary of keyword arguments needed to evaluate the *Condition*

Method generated by attrs for class MdfBase.

Methods

23.5.5 modeci_mdf.mdf.ConditionSet

class modeci_mdf.mdf.**ConditionSet**(*node_specific: Optional[Dict[str, modeci_mdf.mdf.Condition]] = None*, *termination: Optional[Dict[str, modeci_mdf.mdf.Condition]] = None*, ***, *metadata: Optional[Dict[str, Any]] = None*)

Bases: modeci_mdf.mdf.MdfBase

Specifies the non-default pattern of execution of Nodes

Variables

- **node_specific** (*Optional[Dict[str, modeci_mdf.mdf.Condition]]*) – A dictionary mapping nodes to any non-default run conditions
- **termination** (*Optional[Dict[str, modeci_mdf.mdf.Condition]]*) – A dictionary mapping time scales of model execution to conditions indicating when they end

Method generated by attrs for class ConditionSet.

Methods

—

23.5.6 modeci_mdf.mdf.Edge

class modeci_mdf.mdf.**Edge**(*id: str, sender: str, receiver: str, sender_port: str, receiver_port: str, parameters: Optional[Dict[str, Any]] = None, *, metadata: Optional[Dict[str, Any]] = None*)

Bases: modeci_mdf.mdf.MdfBase

An *Edge* is an attribute of a *Graph* that transmits computational results from a sender's *OutputPort* to a receiver's *InputPort*.

Variables

- **id** (*str*) – A unique string identifier for this edge.
- **sender** (*str*) – The id of the *Node* which is the source of the edge.
- **receiver** (*str*) – The id of the *Node* which is the target of the edge.
- **sender_port** (*str*) – The id of the *OutputPort* on the sender *Node*, whose value should be sent to the receiver_port
- **receiver_port** (*str*) – The id of the InputPort on the receiver *Node*
- **parameters** (*Optional[Dict[str, Any]]*) – Dictionary of parameters for the edge.

Method generated by attrs for class Edge.

Methods

—

23.5.7 modeci_mdf.mdf.Function

class modeci_mdf.mdf.**Function**(*id: str, function: Optional[str] = None, args: Optional[Dict[str, Any]] = None, value: Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]] = None, *, metadata: Optional[Dict[str, Any]] = None*)

Bases: modeci_mdf.mdf.MdfBase

A single value which is evaluated as a function of values on :class:`InputPort`(s) and other Functions

Variables

- **id** (*str*) – The unique (for this Node) id of the function, which will be used in other :class:`~Function`s and the :class:`~OutputPort`s for its value
- **function** (*Optional[str]*) – Which of the in-build MDF functions (linear, etc.). See supported functions: https://mdf.readthedocs.io/en/latest/api/MDF_function_specifications.html
- **args** (*Optional[Dict[str, Any]]*) – Dictionary of values for each of the arguments for the Function, e.g. if the in-built function is linear(slope),the args here could be {"slope":3} or {"slope":"input_port_0 + 2"}

- **value** (*Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]]*) – If the function is a value expression, this attribute will contain the expression and the function and args attributes will be None.

Method generated by attrs for class Function.

Methods

23.5.8 modeci_mdf.mdf.Graph

class modeci_mdf.mdf.**Graph**(*id: str*, *nodes: List[modeci_mdf.mdf.Node] = NOTHING*, *edges: List[modeci_mdf.mdf.Edge] = NOTHING*, *parameters: Optional[Dict[str, Any]] = None*, *conditions: Optional[modeci_mdf.mdf.ConditionSet] = None*, *, *metadata: Optional[Dict[str, Any]] = None*)

Bases: modeci_mdf.mdf.MdfBase

A directed graph consisting of :class:`~Node`s (with :class:`~Parameter`s and :class:`~Function`s evaluated internally) connected via :class:`~Edge`s.

Variables

- **id** (*str*) – A unique identifier for this Graph
- **nodes** (*List[modeci_mdf.mdf.Node]*) – One or more :class:`Node`(s) present in the graph
- **edges** (*List[modeci_mdf.mdf.Edge]*) – Zero or more :class:`Edge`(s) present in the graph
- **parameters** (*Optional[Dict[str, Any]]*) – Dictionary of global parameters for the Graph
- **conditions** (*Optional[modeci_mdf.mdf.ConditionSet]*) – The ConditionSet stored as dictionary for scheduling of the Graph

Method generated by attrs for class Graph.

Methods

get_node(id)	Retrieve Node object corresponding to the given id

get_node(*id: str*) → Optional[*modeci_mdf.mdf.Node*]

Retrieve Node object corresponding to the given id

Parameters **id** – Unique identifier of Node object

Returns *Node* object if the entered `id` matches with the `id` of node present in the *Graph*. `None` if a node is not found with that id .

property dependency_dict

Returns the dependency among nodes as dictionary

Key: receiver, Value: Set of senders imparting information to the receiver

Returns Returns the dependency dictionary

property inputs

Enumerate all Node-InputPort pairs that specify no incoming edge. These are input ports for the graph itself and must be provided values to evaluate

Returns A list of Node, InputPort tuples

23.5.9 modeci_mdf.mdf.InputPort

class modeci_mdf.mdf.**InputPort**(*id: str, shape=None, type: Optional[str] = None, *, metadata: Optional[Dict[str, Any]] = None*)

Bases: modeci_mdf.mdf.MdfBase

The *InputPort* is an attribute of a Node which allows external information to be input to the Node

Variables

- **id** (*str*) – The unique (for this Node) id of the input port,
- **shape** (*Optional[Tuple[int, ..]]*) – The shape of the input port. This uses the same syntax as numpy ndarray shapes (e.g., `numpy.zeros(shape)` would produce an array with the correct shape
- **type** (*Optional[str]*) – The data type of the input received at a port.

Method generated by attrs for class InputPort.

Methods

—

23.5.10 modeci_mdf.mdf.Model

class modeci_mdf.mdf.**Model**(*id: str, graphs: List[modeci_mdf.mdf.Graph] = NOTHING, format: str = 'ModECI MDF v0.4', generating_application: str = 'Python modeci-mdf v0.4.4', onnx_opset_version: Optional[str] = None, *, metadata: Optional[Dict[str, Any]] = None*)

Bases: modeci_mdf.mdf.MdfBase

The top level construct in MDF is Model, which may contain multiple *Graph* objects and model attribute(s)

Variables

- **id** (*str*) – A unique identifier for this Model
- **graphs** (*List[modeci_mdf.mdf.Graph]*) – The collection of graphs that make up the MDF model.
- **format** (*str*) – Information on the version of MDF used in this file
- **generating_application** (*str*) – Information on what application generated/saved this file
- **onnx_opset_version** (*Optional[str]*) – The ONNX opset used for any ONNX functions in this model.

Method generated by attrs for class Model.

Methods

to_graph_image([engine, output_format, ...])	Convert MDF graph to an image (png or svg) using the Graphviz export

to_graph_image(*engine: str = 'dot'*, *output_format: str = 'png'*, *view_on_render: bool = False*, *level: int = 2*, *filename_root: Optional[str] = None*, *only_warn_on_fail: bool = False*, *is_horizontal: bool = False*)

Convert MDF graph to an image (png or svg) using the Graphviz export

Parameters

- **engine** – dot or other Graphviz formats
- **output_format** – e.g. png (default) or svg
- **view_on_render** – if True, will open generated image in system viewer
- **level** – 1,2,3, depending on how much detail to include
- **filename_root** – will change name of file generated to filename_root.png, etc.
- **only_warn_on_fail** – just give a warning if this fails, e.g. no dot executable. Useful for preventing errors in automated tests

23.5.11 modeci_mdf.mdf.Node

class modeci_mdf.mdf.**Node**(*id: str*, *input_ports: List[modeci_mdf.mdf.InputPort] = NOTHING*, *functions: List[modeci_mdf.mdf.Function] = NOTHING*, *parameters: List[modeci_mdf.mdf.Parameter] = NOTHING*, *output_ports: List[modeci_mdf.mdf.OutputPort] = NOTHING*, ***, *metadata: Optional[Dict[str, Any]] = None*)

Bases: modeci_mdf.mdf.MdfBase

A self contained unit of evaluation receiving input from other nodes on :class:`InputPort`(s). The values from these are processed via a number of :class:`Function`(s) and one or more final values are calculated on the :class:`OutputPort`(s)

Variables

- **id** (*str*) – A unique identifier for the node.
- **input_ports** (*List[modeci_mdf.mdf.InputPort]*) – Dictionary of the *InputPort* objects in the Node
- **parameters** (*List[modeci_mdf.mdf.Parameter]*) – Dictionary of :class:`Parameter`(s) for the node
- **functions** (*List[modeci_mdf.mdf.Function]*) – The :class:`Function`(s) for computation the node
- **output_ports** (*List[modeci_mdf.mdf.OutputPort]*) – The :class:`OutputPort`(s) containing evaluated quantities from the node

Method generated by attrs for class Node.

Methods

get_input_port(id)	Retrieve *InputPort* object corresponding to the given id :param id: Unique identifier of class:*InputPort* object
get_output_port(id)	Retrieve *OutputPort* object corresponding to the given id :param id: Unique identifier of class:*OutputPort* object
get_parameter(id)	Get a parameter by its string `id`

get_parameter(*id: str*) → Optional[*modeci_mdf.mdf.Parameter*]
Get a parameter by its string `id`

Parameters **id** – The unique string id of the *Parameter*

Returns The *Parameter* object stored on this node. `None` if not found.

get_input_port(*id: str*) → *modeci_mdf.mdf.InputPort*
Retrieve *InputPort* object corresponding to the given id :param id: Unique identifier of class:*InputPort* object

Returns *InputPort* object if the entered id matches with the id of class:*InputPort* present in the class:*Node*

Return type class

get_output_port(*id: str*) → *modeci_mdf.mdf.OutputPort*
Retrieve *OutputPort* object corresponding to the given id :param id: Unique identifier of class:*OutputPort* object

Returns *OutputPort* object if the entered id matches with the id of class:*OutputPort* present in the class:*Node*

Return type class

23.5.12 modeci_mdf.mdf.OutputPort

class modeci_mdf.mdf.**OutputPort**(*id: str*, *value: Optional[str] = None*, *shape=None*, *type: Optional[str] = None*, ***, *metadata: Optional[Dict[str, Any]] = None*)
Bases: `modeci_mdf.mdf.MdfBase`

The *OutputPort* is an attribute of a *Node* which exports information to another *Node* connected by an *Edge*

Variables

- **id** (*str*) – Unique identifier for the output port.
- **value** (*Optional[str]*) – The value of the *OutputPort* in terms of the *InputPort*, *Function* values, and *Parameter* values.
- **shape** (*Optional[Tuple[int, ..]]*) – The shape of the output port. This uses the same syntax as numpy ndarray shapes (e.g., `numpy.zeros(shape)` would produce an array with the correct shape
- **type** (*Optional[str]*) – The data type of the output sent by a port.

Method generated by attrs for class OutputPort.

Methods

—

23.5.13 modeci_mdf.mdf.Parameter

class modeci_mdf.mdf.**Parameter**(*id: str*, *value: Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]] = None*, *default_initial_value: Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]] = None*, *time_derivative: Optional[str] = None*, *function: Optional[str] = None*, *args: Optional[Dict[str, Any]] = None*, *conditions: List[modeci_mdf.mdf.ParameterCondition] = NOTHING*, **, metadata: Optional[Dict[str, Any]] = None*)

Bases: modeci_mdf.mdf.MdfBase

A parameter of the *Node*, which can be: 1) a specific fixed `value` (a constant (int/float) or an array) 2) a string expression for the `value` referencing other named `Parameter`(s). which may be stateful (i.e. can change value over multiple executions of the :class:`Node`); 3) be evaluated by an inbuilt `function` with `args`; 4) or change from a `default_initial_value` with a `time_derivative`.

Variables

- **value** (*Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]]*) – The next value of the parameter, in terms of the inputs, functions and PREVIOUS parameter values
- **default_initial_value** (*Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]]*) – The initial value of the parameter, only used when parameter is stateful.
- **time_derivative** (*Optional[str]*) – How the parameter changes with time, i.e. ds/dt. Units of time are seconds.
- **function** (*Optional[str]*) – Which of the in-build MDF functions (linear etc.) this uses, See
- **https** – //mdf.readthedocs.io/en/latest/api/MDF_function_specifications.html
- **args** (*Optional[Dict[str, Any]]*) – Dictionary of values for each of the arguments for the function of the parameter, e.g. if the in-build function is `linear(slope)`, the args here could be `{"slope": 3}` or `{"slope": "input_port_0 + 2"}`
- **conditions** (*List[modeci_mdf.mdf.ParameterCondition]*) – Parameter specific conditions

Method generated by attrs for class Parameter.

Methods

is_stateful()	Is the parameter stateful?
summary()	Short summary of Parameter...

summary()
Short summary of Parameter...

is_stateful() → bool
Is the parameter stateful?

A parameter is considered stateful if it has a `time_derivative`, `default_initial_value`, or its id is referenced in its value expression.

Returns `True` if stateful, *False* if not.

23.5.14 modeci_mdf.mdf.ParameterCondition

class modeci_mdf.mdf.**ParameterCondition**(*id: str, test: Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]] = None, value: Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]] = None*)

Bases: `modelspec.base_types.Base`

A condition to test on a Node's parameters, which if true, sets the value of this Parameter

Variables

- **id** (*str*) – A unique identifier for the ParameterCondition
- **test** (*Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]]*) – The boolean expression to evaluate
- **value** (*Optional[Union[modelspec.base_types.EvaluableExpression, List, Dict, numpy.ndarray, int, float, str]]*) – The new value of the Parameter if the test is true

Method generated by attrs for class ParameterCondition.

Methods

—

23.6 modeci_mdf.utils

Useful utility functions for dealing with MDF objects.

Functions

color_rgb_to_hex(rgb)	Convert a rgb color to hexadecimal format.
create_example_node(node_id, graph)	Create a simple example node with Input inside a graph
is_number(s)	Return `True` if cast to `float` does not throw ValueError, `False` otherwise.
load_mdf(filename)	Load an MDF file from JSON or YAML.
load_mdf_json(filename)	Load an MDF JSON file
load_mdf_yaml(filename)	Load an MDF YAML file
print_summary(graph)	Print a summary of a graph to standard out.
simple_connect(pre_node, post_node, graph)	Create an edge connecting two nodes in a graph.

23.6.1 modeci_mdf.utils.color_rgb_to_hex

modeci_mdf.utils.**color_rgb_to_hex**(*rgb*)

Convert a rgb color to hexadecimal format.

23.6.2 modeci_mdf.utils.create_example_node

modeci_mdf.utils.**create_example_node**(*node_id: str*, *graph:* modeci_mdf.mdf.Graph) → *modeci_mdf.mdf.Node*

Create a simple example node with Input inside a graph

Parameters

- **node_id** – The unique id for the first node in the graph.
- **graph** – The graph to add the example node.

Returns The node (with id=node_id) created in the graph.

23.6.3 modeci_mdf.utils.is_number

modeci_mdf.utils.**is_number**(*s*)

Return `True` if cast to `float` does not throw ValueError, `False` otherwise.

23.6.4 modeci_mdf.utils.load_mdf

modeci_mdf.utils.**load_mdf**(*filename: str*) → *modeci_mdf.mdf.Model*

Load an MDF file from JSON or YAML. File type is detected automatically based on extension.

23.6.5 modeci_mdf.utils.load_mdf_json

modeci_mdf.utils.**load_mdf_json**(*filename: str*) → *modeci_mdf.mdf.Model*
Load an MDF JSON file

23.6.6 modeci_mdf.utils.load_mdf_yaml

modeci_mdf.utils.**load_mdf_yaml**(*filename: str*) → *modeci_mdf.mdf.Model*
Load an MDF YAML file

23.6.7 modeci_mdf.utils.print_summary

modeci_mdf.utils.**print_summary**(*graph:* modeci_mdf.mdf.Graph)
Print a summary of a graph to standard out.

23.6.8 modeci_mdf.utils.simple_connect

modeci_mdf.utils.**simple_connect**(*pre_node*, *post_node*, *graph*) → *modeci_mdf.mdf.Edge*
Create an edge connecting two nodes in a graph.

Parameters

- **pre_node** – The source node.
- **post_node** – The destination node.
- **graph** – The graph to and the edge.

Returns The edge that has been added to the graph.

CHAPTER

TWENTYFOUR

INDICES AND TABLES

- genindex
- modindex
- search

PYTHON MODULE INDEX

m

INDEX

Symbols

A

B

C

D

E

F

G

H

I

L

M

N

O

P

Q

R

S

T

U

V

W

X