Documentation for the nGraph Library and Compiler Stack

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Version 0.29

nGraph Compiler Stack Documentation¶

Introduction¶

Future developments in Artificial Intelligence will increasingly rely on better methods to accelerate the performance of deep learning workloads. As Deep Learning models become more complex, and as the volume of data those models are expected to handle increases rapidly, the deployment of scalable AI solutions becomes a greater challenge.

Today, two standard approaches to accelerate deep learning performance are:

1. **Design hardware solutions dedicated to deep learning computation –** Many companies, ranging from startups to established manufacturers such as Intel, are actively developing Application Specific Integrated Circuits to accelerate the performance of deep learning for both training and inference.
2. **Optimize software to accelerate performance –** nGraph Compiler, an open-source deep learning compiler, is Intel's solution to deliver performance via software optimization. nGraph provides developers with a way to accelerate workloads via software and to provide a significant increase in performance for standard hardware targets such as CPUs and GPUs. For deploying scalable AI solutions, nGraph uses kernel libraries, a popular and effective method to improve deep learning performance. Where kernel libraries are available and perform well, we use them.

Motivations¶

The current State-of-the-Art software solution for deep learning computation is to integrate kernel libraries such as Intel® Math Kernel Library for Deep Neural Networks and Nvidia's CuDNN into deep learning frameworks. These kernel libraries offer a performance boost during runtime on specific hardware targets through highly-optimized kernels and other operator-level optimizations.

However, kernel libraries have three main problems:

1. Kernel libraries do not support graph-level optimizations.
2. Framework integration of kernel libraries does not scale.
3. The number of required kernels keeps growing.

nGraph Compiler addresses the first two problems, and nGraph Compiler combined with PlaidML addresses the third problem. nGraph applies graph-level optimizations by taking the computational graph from a deep learning framework such as TensorFlow and reconstructing it with nGraph's :abbr: IR (Intermediate Representation). nGraph IR centralizes computational graphs from various frameworks and provides a unified way to connect backends for targeted hardware. To address the third problem, nGraph is integrated with PlaidML, a tensor compiler, which generates code in LLVM, OpenCL, OpenGL, and Metal. Low-level optimizations are automatically applied to the generated code, resulting in a more efficient execution that does not require manual kernel integration for most hardware targets.

The following three sections explore the main problems of kernel libraries in more detail and describe how nGraph addresses them.

Problem 1: Kernel libraries do not support graph-level optimizations¶

The example diagrams below show how a deep learning framework, when integrated with a kernel library, can optimally run each operation in a computational graph, but the choice of operations in the graph may not be optimal.

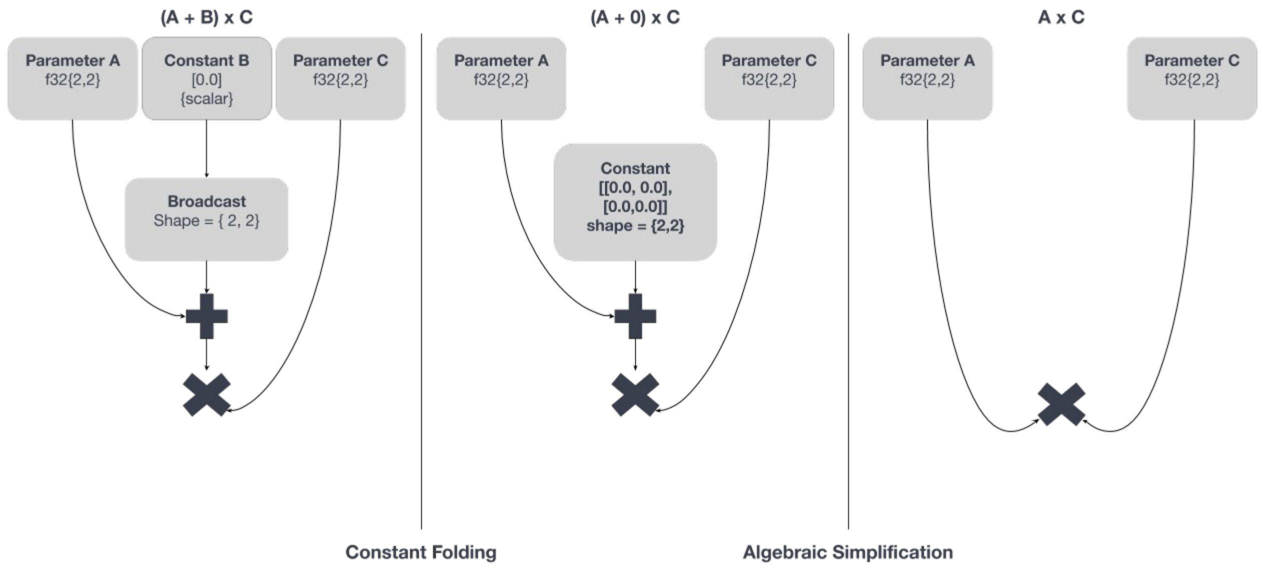


Figure A: The mathematical operations in a Deep Learning stack can be simplified significantly with a graph compiler

The computation is constructed to execute `(A+B)*C`. With nGraph, we can further optimize the graph to be represented as `A*C`. From the first graph shown on the left, the operation on the constant `B` can be computed at compile time (an optimization known as *constant folding*). The graph can be further simplified to the one on the right because the constant has a value of zero (known as *algebraic simplification*). Without such graph-level optimizations, a deep learning framework with a kernel library will compute all operations, resulting in suboptimal execution.

Problem 2: Framework integration of kernel libraries does not scale¶

Due to the growing number of new deep learning accelerators, integrating kernel libraries with frameworks has become increasingly more difficult. For each new deep learning accelerator, a custom kernel library integration must be implemented by a team of experts. This labor-intensive work is further complicated by the number of frameworks, as illustrated in the following diagram.

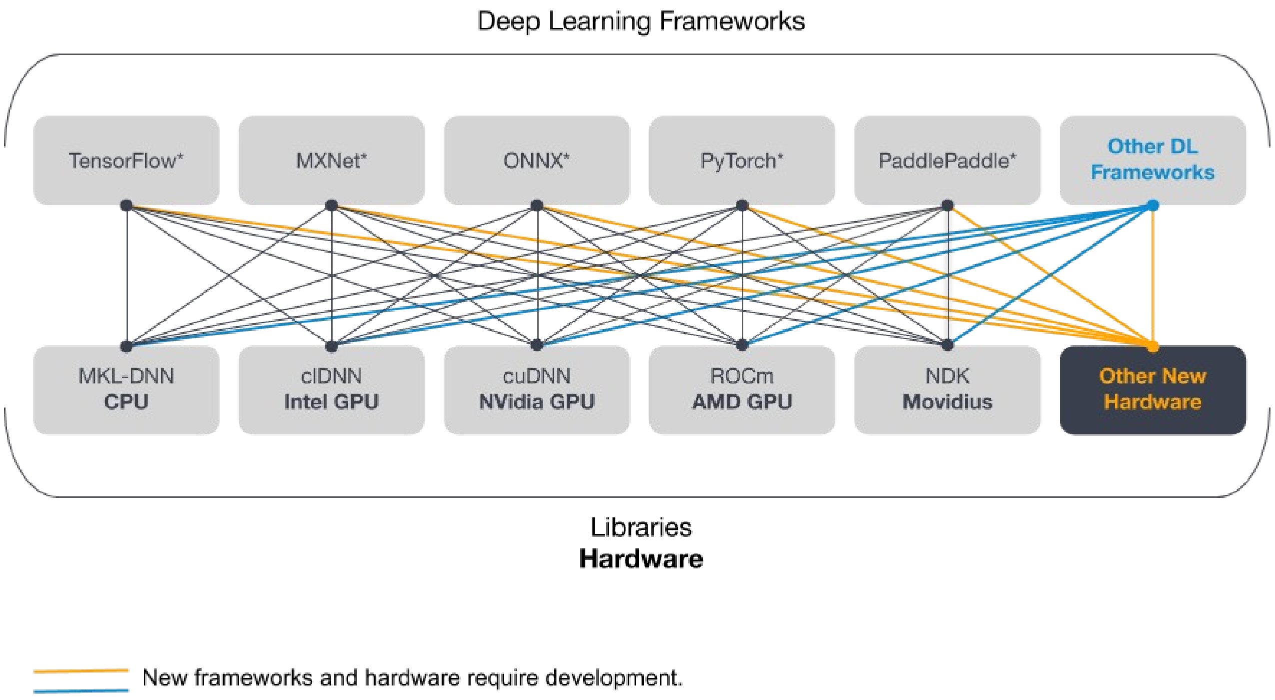


Figure B: A many-to-many problem

Each framework must be manually integrated with each hardware-specific kernel library. Additionally, each integration is unique to the framework and its set of deep learning operators, view on memory layout, feature set, etc. Each connection that needs to be made increases the amount of work, resulting in a fragile setup that is costly to maintain.

nGraph solves this problem with bridges. A bridge takes a computational graph or similar structure and reconstructs it in the nGraph IR along with a few primitive nGraph operations. With a unified computational graph, kernel libraries no longer need to be separately integrated into each deep learning framework. Instead, the libraries only need to support nGraph primitive operations, and this approach streamlines the integration process for the backend.

Problem 3: The number of required kernels keeps growing¶

Integrating kernel libraries with multiple deep learning frameworks is a difficult task that becomes more complex with the growing number of kernels needed to achieve optimal performance. Past deep learning research has been built on a small set of standard computational primitives (convolution, GEMM, etc.). But as AI research advances and industrial deep learning applications continue to develop, the number of required kernels continues to increase exponentially. The number of required kernels is based on the number of chip designs, data types, operations, and the cardinality of each parameter per operation. Each connection in the following diagram represents significant work for what will ultimately be a fragile setup that is costly to maintain.

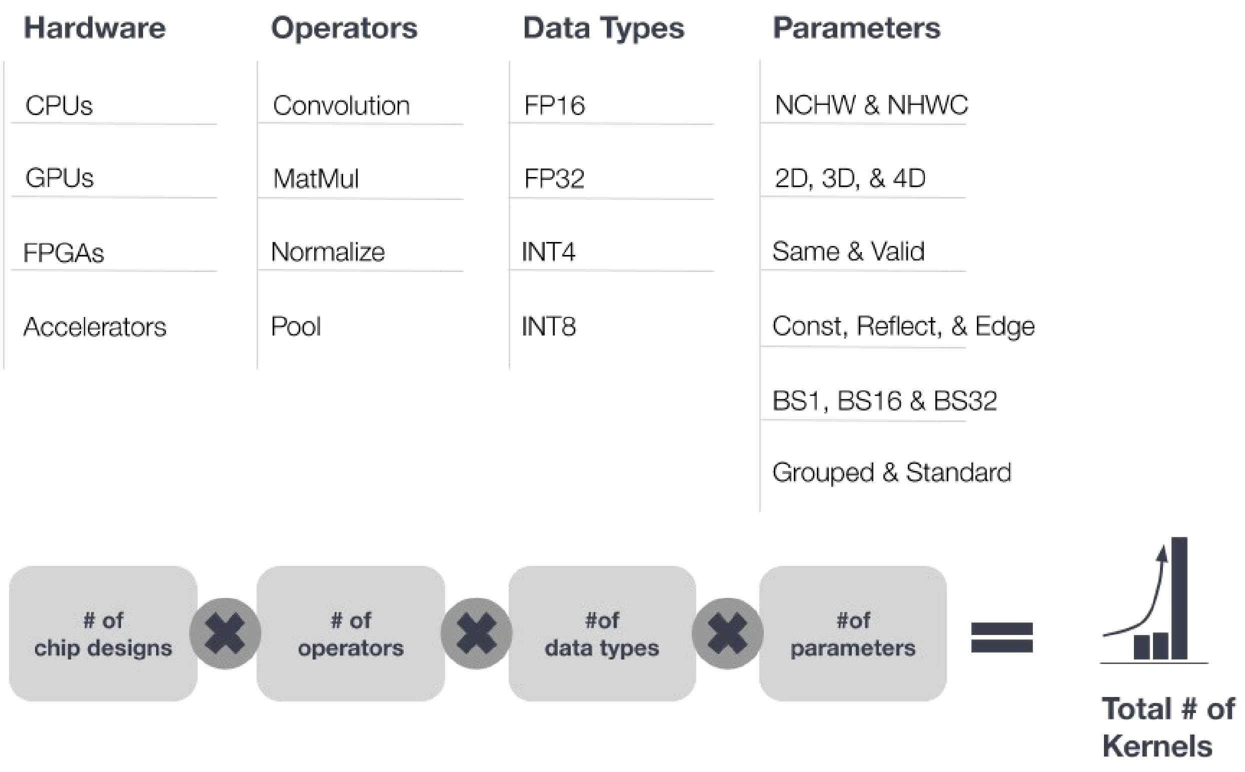


Figure C: Inevitable scaling problem

Integrating PlaidML with nGraph provides flexibility to support the latest deep learning models in the absence of hand-optimized kernels for new operations. PlaidML works together with nGraph to address the exponential growth of kernels.

PlaidML takes two inputs: the operation defined by the user and the machine description of the hardware target. It then automatically generates kernels that are iteratively optimized through an IR known as Stripe. Integration of PlaidML with nGraph allows users to choose the hardware and framework that suits their needs, resulting in freedom from kernel libraries.

Solution: nGraph and PlaidML¶

We developed nGraph and integrated it with PlaidML to allow developers to accelerate deep learning performance and address the problem of scalable kernel libraries. To address the problem of scaling backends, nGraph applies graph-level optimizations to deep learning computations and unifies computational graphs from deep learning frameworks with nGraph IR.

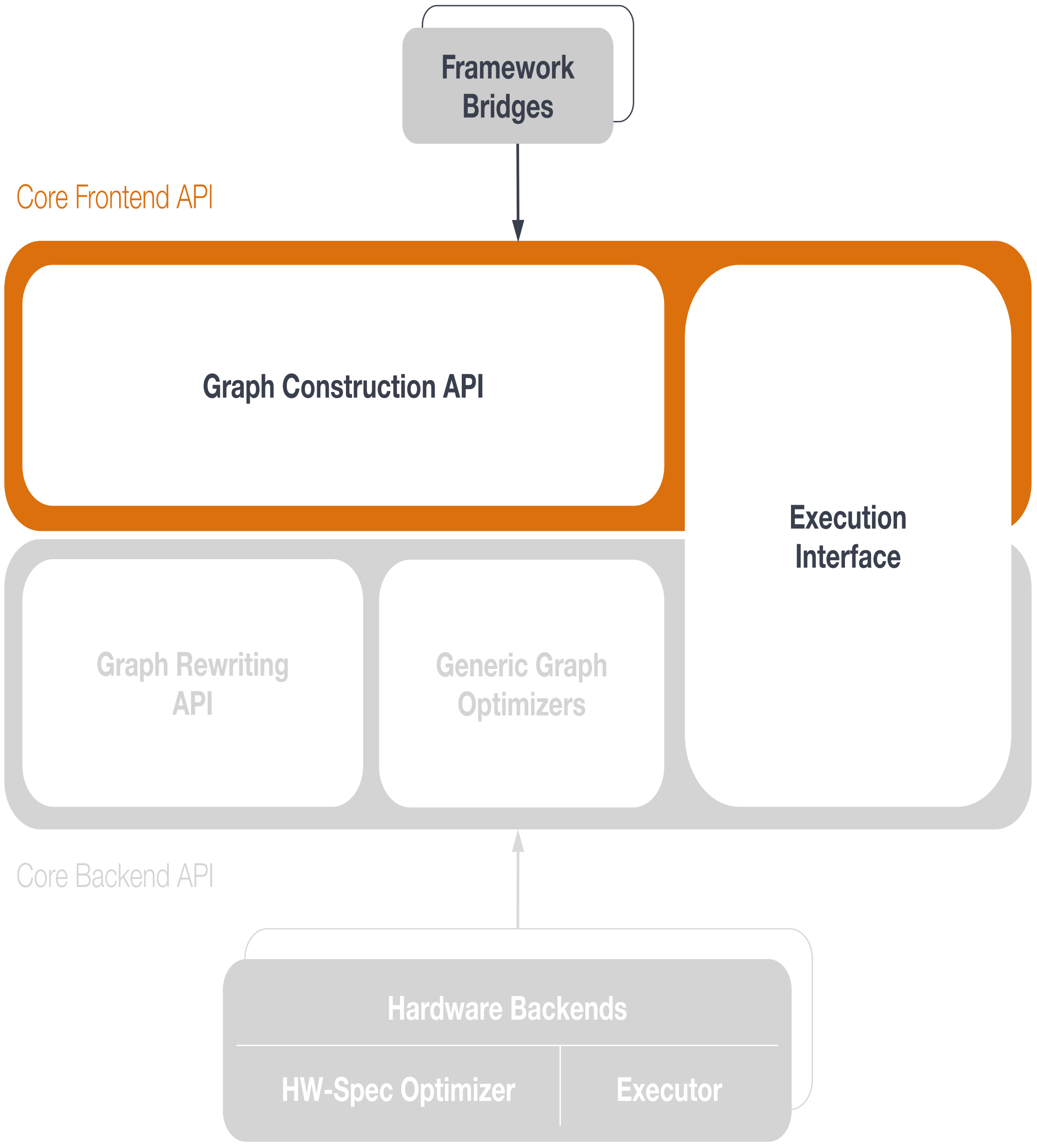
In conjunction with nGraph's graph-level optimizations, PlaidML automatically applies low-level optimizations to improve deep learning performance. Additionally, PlaidML offers extensive support for various hardware targets due to its ability to generate code in LLVM, OpenCL, OpenGL, and Metal.

Given a backend with existing kernel libraries, nGraph can readily support the target hardware because the backend only needs to support a few primitive operations. If the hardware supports one of the coding languages supported by PlaidML, developers must specify the machine description to support the hardware. Together, nGraph and PlaidML provide the best of both worlds.

This documentation provides technical details of nGraph's core functionality as well as framework and backend integrations. Creating a compiler stack like nGraph and PlaidML requires expert knowledge, and we're confident that nGraph and PlaidML will make life easier for many kinds of developers:

1. Framework owners looking to support new hardware and custom chips.
2. Data scientists and ML developers wishing to accelerate deep learning performance.
3. New DL accelerator developers creating an end-to-end software stack from a deep learning framework to their silicon.

Basic concepts¶



A framework bridge connects to the nGraph graph construction API

To understand how a data science framework (TensorFlow, PyTorch, PaddlePaddle*, and others) can unlock acceleration available in the nGraph Compiler, it helps to familiarize yourself with some basic concepts.

We use the term bridge to describe code that connects to any nGraph device backend(s) while maintaining the framework's programmatic or user interface. We have a bridge for the TensorFlow framework. We also have a PaddlePaddle* bridge. Intel previously contributed work to an MXNet bridge; however, support for the MXNet bridge is no longer active.

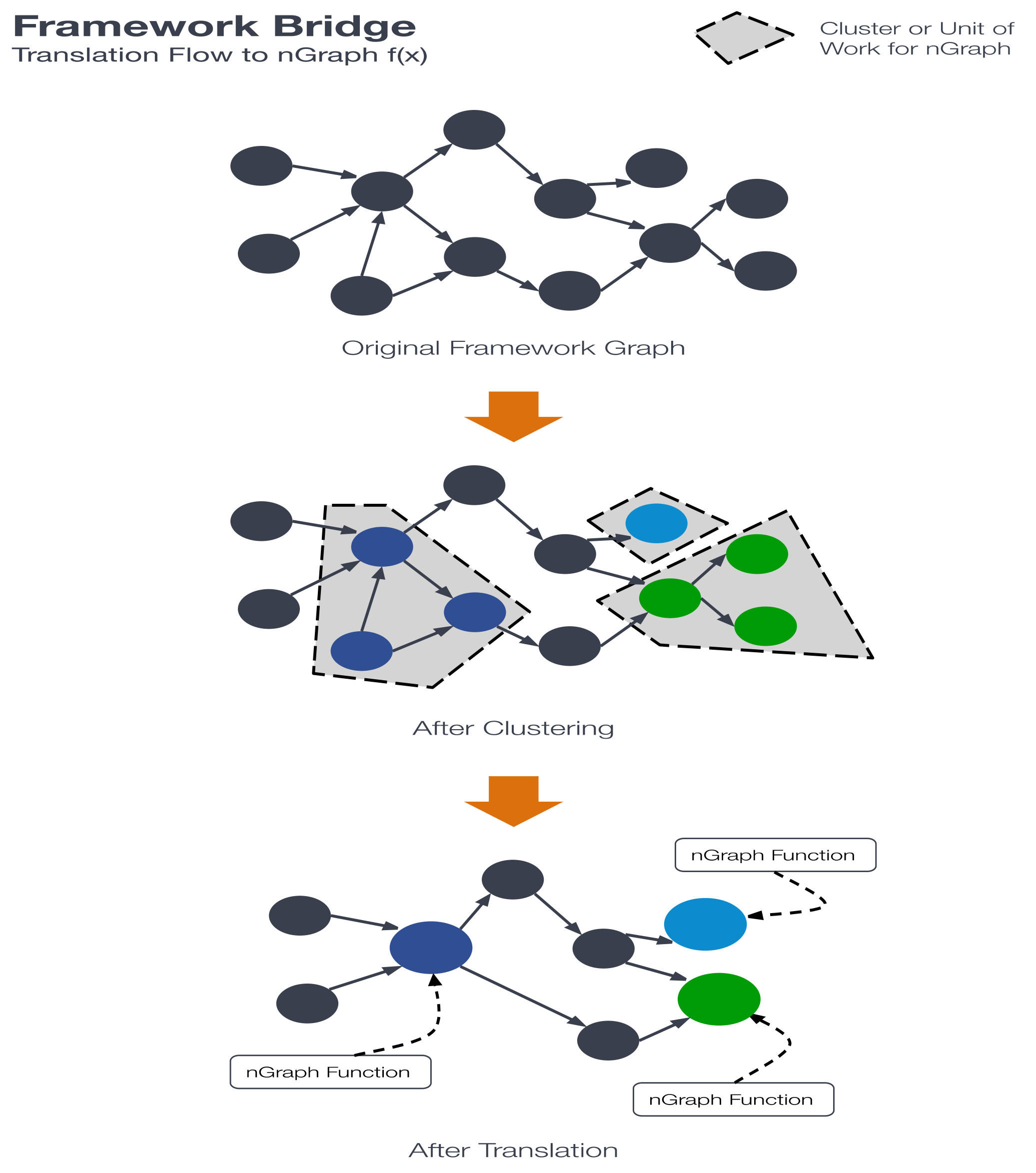
ONNX on its own is not a framework; it can be used with nGraph's Python API to import and execute ONNX models.

Because it is framework agnostic (providing opportunities to optimize at the graph level), nGraph can do the heavy lifting required by many popular workloads without any additional effort of the framework user. Optimizations that were previously available only after careful integration of a kernel or hardware-specific library are exposed via the Core graph construction API

The illustration above shows how this works.

While a Deep Learning framework is ultimately meant for end-use by data scientists, or for deployment in cloud container environments, nGraph's Core ops are designed for framework builders themselves. We invite anyone working on new and novel frameworks or neural network designs to explore our highly-modularized stack of components.

Please read the other/index section for other framework-agnostic configurations available to users of the nGraph Compiler stack.



TensorFlow¶

See the README on the ngraph_bridge repo for the many ways to connect Tensorflow to nGraph, enabling a DSO backend that can speed up your TensorFlow training and inference workloads.

ONNX¶

nGraph is able to import and execute ONNX models. Models are converted to nGraph's Intermediate Representation and converted to `Function` objects, which can be compiled and executed with nGraph backends.

You can use nGraph's Python API to run an ONNX model and nGraph can be used as a backend to ONNX with the add-on package nGraph ONNX.

Note: In order to support ONNX, nGraph must be built with the `NGRAPH_ONNX_IMPORT_ENABLE` flag. See Building nGraph-ONNX for more information. All nGraph packages published on PyPI are built with ONNX support.

Importing an ONNX model¶

You can download models from the ONNX Model Zoo. For example, ResNet-50:

```
$ wget https://s3.amazonaws.com/download.onnx/models/opset_9/resnet50.tar.gz
$ tar -xzvf resnet50.tar.gz
```

Use the following Python commands to convert the downloaded model to an nGraph `Function`:

```
# Import ONNX and load an ONNX file from disk
>>> import onnx
>>> onnx_protobuf = onnx.load('resnet50/model.onnx')

# Convert ONNX model to an ngraph model
>>> from ngraph.impl.onnx_import import import_onnx_model
>>> ng_function = import_onnx_model(onnx_protobuf.SerializeToString())

# The importer returns a list of ngraph models for every ONNX graph output:
>>> print(ng_function)
<Function: 'resnet50' ([1, 1000])>
```

This creates an nGraph `Function` object, which can be used to execute a computation on a chosen backend.

Running a computation¶

You can now create an nGraph `Runtime` backend and use it to compile your `Function` to a backend-specific `Computation` object. Finally, you can execute your model by calling the created `Computation` object with input data:

```
# Using an nGraph runtime (CPU backend) create a callable computation object
>>> import ngraph as ng
>>> runtime = ng.runtime(backend_name='CPU')
>>> resnet_on_cpu = runtime.computation(ng_function)
>>> print(resnet_on_cpu)
<Computation: resnet50(Parameter_269)>

# Load an image (or create a mock as in this example)
>>> import numpy as np
>>> picture = np.ones([1, 3, 224, 224], dtype=np.float32)

# Run computation on the picture:
>>> resnet_on_cpu(picture)
```

```
[array([[2.16105007e-04, 5.58412226e-04, 9.70510227e-05, 5.76671446e-05,
         7.45318757e-05, 4.80892748e-04, 5.67404088e-04, 9.48728994e-05,
         ...
```
Find more information about nGraph and ONNX in the nGraph ONNX GitHub repository.

PaddlePaddle¶*

PaddlePaddle is an open source deep learning framework developed by Baidu. It aims to enable performant large-scale distributed computation for deep learning. The nGraph Compiler stack's integration to PaddlePaddle respects PaddlePaddle's design philosophy to minimize switching cost for users. To access nGraph from PaddlePaddle, we've added three modules to PaddlePaddle:

- nGraph engine operator (op),
- nGraph engine, and
- nGraph bridge.

The nGraph engine op inherits the PaddlePaddle operator class to allow nGraph engine op to be called using methods consistent with other PaddlePaddle operators. When the nGraph engine is called by the aforementioned op, the nGraph bridge converts PaddlePaddle operators into nGraph operators. nGraph will then build a computational graph based on the converted ops according to the input topology.

Integration design¶

Key design criteria for nGraph-PaddlePaddle integration includes:

1. Minimal intermediate links between nGraph and PaddlePaddle, to reduce latency and improve performance.
2. Close to no switching cost for end users of PaddlePaddle framework.
3. Ease of maintenance.

To satisfy the first design criteria, nGraph designed its operator to match PaddlePaddle's implementation. nGraph is triggered by the PaddlePaddle executor by one line of code.

After nGraph engine is called, it and the nGraph C++ backend manage all the heavy lifting for performance optimization. The Python frontend on PaddlePaddle remains the same, and end users need **no changes** in the code they write to be able to benefit from the increased performance. This design fulfills the second criteria.

Lastly, the code contributed by nGraph to PaddlePaddle repository mainly resides in the `fluid/operator/ngraph` directory, and having most of the nGraph code in one place allows for easy maintenance.

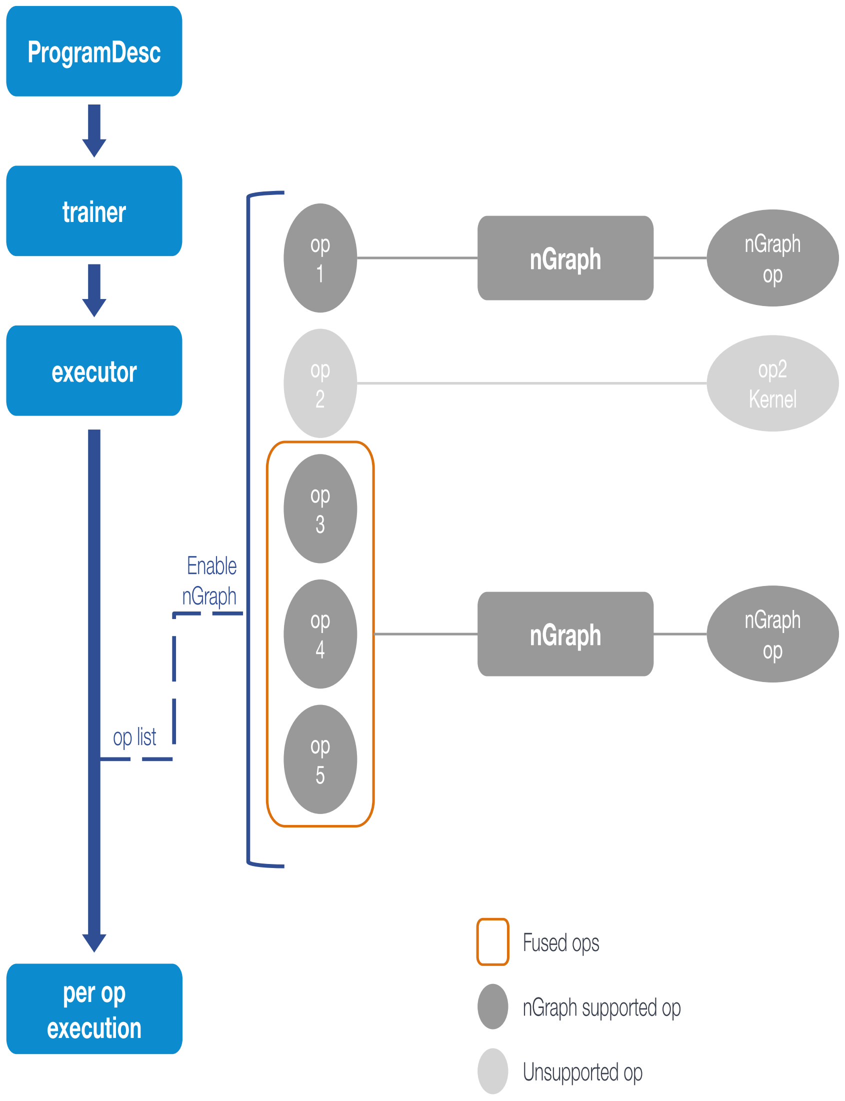
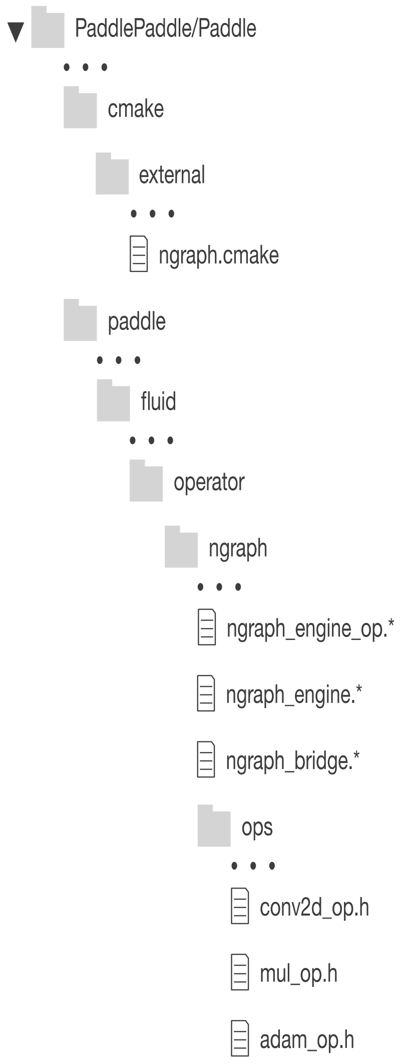


Figure A above depicts nGraph access from PaddlePaddle. The PaddlePaddle executor generates an executable operator according to the program description (ProgramDesc). nGraph scans the operator sequence before execution, and replaces the supported operators (or subgraphs) with nGraph operators. PaddlePaddle can then execute the nGraph operators and the unreplaced PaddlePaddle operators with a uniform interface. The unreplaced operators are executed by PaddlePaddle native implementation.

nGraph's current integration reflected on PaddlePaddle's github repository is organized in the following file structure:



Compilation of nGraph is handled by the `ngraph.cmake` file in the `cmake/external directory`. Other newly-introduced files are located primarily in the paddle/fluid/operator/ngraph directory. The nGraph operators replacing PaddlePaddle operators as described in the previous section can be found in the `ngraph/ops` directory.

Integration details¶

More details on implementation of nGraph engine op, nGraph engine, and nGraph bridges are provided below:

1. **nGraph engine op**: Triggers subgraphs to be executed by nGraph.
   - Input: Input variable set

- Output: Output variable set
- Attribute :
  - Graph: Serialized subgraph. The protobuffer described by PaddlePaddle is serialized and passed to nGraph **as a string**.
  - Interval: The interval of ops in operator list that will be executed by nGraph.
- Related code :
  - `Paddle/fluid/operators/ngraph/ngraph_engine_op.h` link to ngraph_engine_op header code
  - `Paddle/fluid/operators/ngraph/ngraph_engine_op.cc` link to ngraph_engine_op cpp code

2. **nGraph engine**: calls the nGraph Library to perform calculations.

   The nGraph engine class includes the input and output required to build a nGraph function graph from the nGraph engine kernel, the execution function, and the data exchange between nGraph and PaddlePaddle. The primary methods are:

   - `BuildNgIO`: gets input and output variables.
   - `GetNgFunction`: obtains the nGraph function used in the calculation. It matches entire pattern of the input to the output and saves functions that need to be called repeatedly.
   - `BuildNgFunction`: builds nGraph functions.
   - `Run`: calls backend execution and exchange data with the paddle.

- Related code :
  - `Paddle/fluid/operators/ngraph/ngraph_engine.h` link to ngraph_engine header code
  - `Paddle/fluid/operators/ngraph/ngraph_engine.cc` link to ngraph_engine cpp code

3. **nGraph bridge**: converts PaddlePaddle operators to nGraph operators.

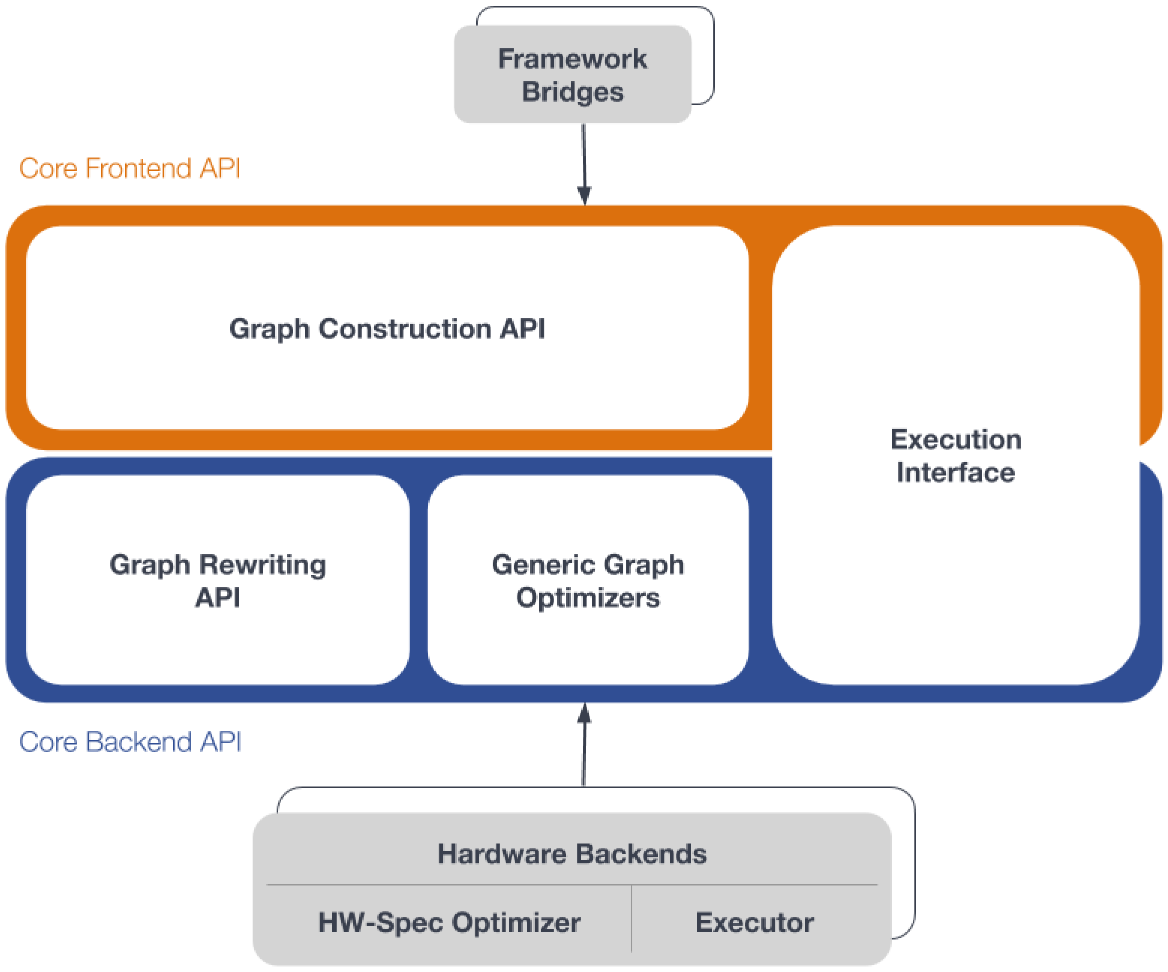
   The nGraph bridge converts supported PaddlePaddle operators to nGraph operators, which results in a reconstruction of the subgraph with nGraph's intermediate representation. The convertable operators are located in the ngraph ops directory, and each operator has its own files for easy management. For the conversion of operators. There is a common unified interface to facilitate code development and operator transformation. The relevant interfaces are:

- GetInputNode: obtains input node for the conversion operator. The nodes are managed through a map.
- SetOutputNode: sets the constructed node to the map.
- Related code :
  - `Paddle/fluid/operators/ngraph/ngraph_bridge.h` link to ngraph_bridge header code
  - `Paddle/fluid/operators/ngraph/ngraph_bridge.cc` link to ngraph_bridge cpp code

nGraph compilation control and trigger method¶

1. **Compile Control** – The compilation of nGraph is controlled with the `WITH_NGRAPH` option. If compiled using `WITH_NGRAPH=ON`, the nGraph Library will be downloaded and compiled. This option has a corresponding `PADDLE_WITH_NGRAPH` flag. If compiled `WITH_NGRAPH=OFF`, the relevant code will not be compiled.
2. **Trigger Control** – `FLAGS_use_ngraph` triggers nGraph. If this option is set to `true`, nGraph will be triggered by the PaddlePaddle executor to convert and execute the supported subgraph. Demos are provided under `paddle/benchmark/fluid/train/demo` (link train_demo) and `paddle/benchmark/fluid/train/imdb_demo` (link imdb_demo)

Basic Concepts¶

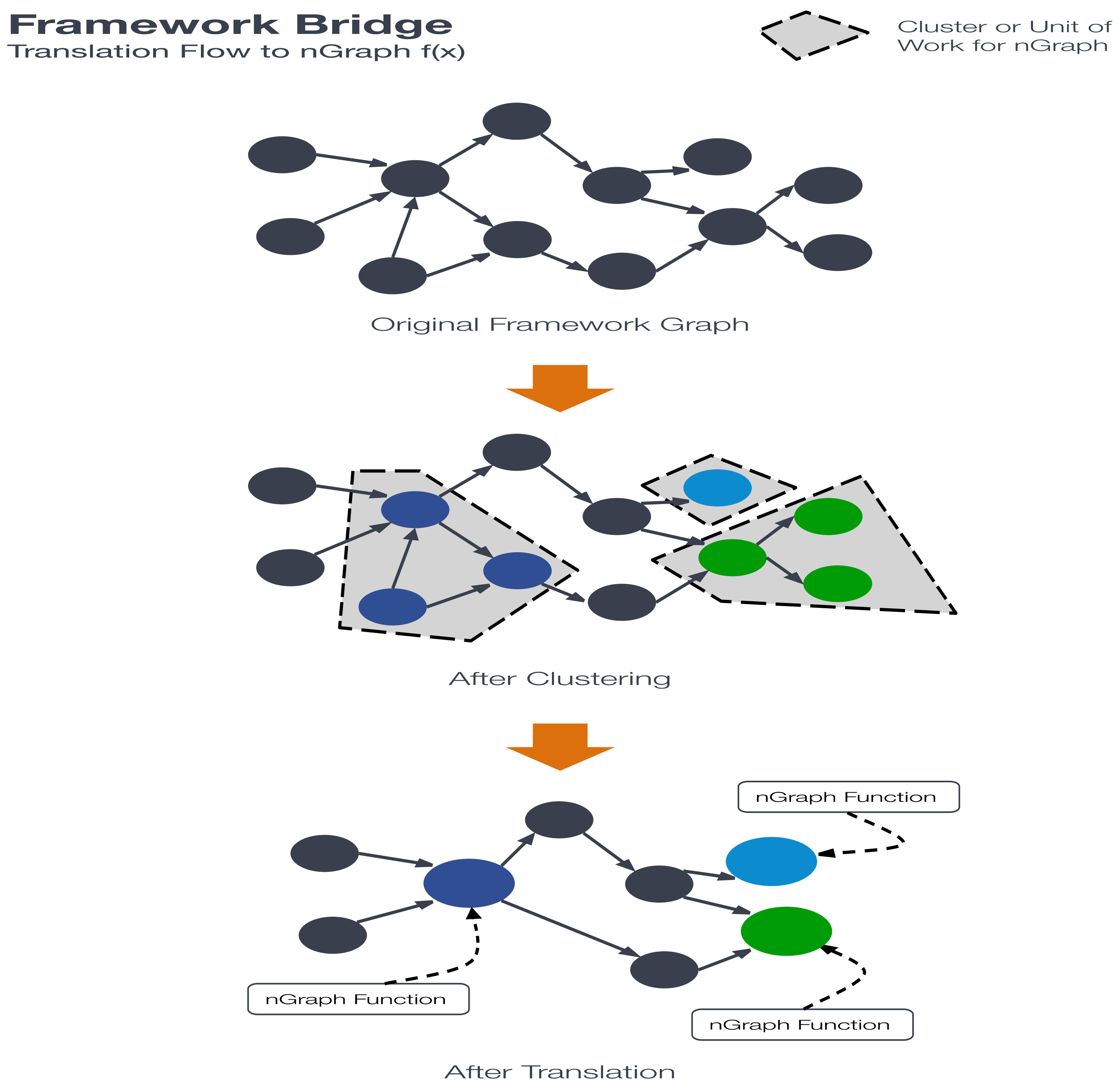


The whole nGraph Compiler stack

The nGraph Compiler stack consists of bridges, core, and backends. We’ll examine each of these briefly to get started.

A framework bridge interfaces with the “frontend” Core API. A framework bridge is a component that sits between a framework like TensorFlow or PaddlePaddle, and the nGraph Core frontend API. A framework bridge does two things: first, it translates a framework’s operations into graphs in nGraph’s in-memory Intermediary Representation. Second, it executes the nGraph IR graphs via the backend execution interface.

The details of bridge implementation vary from framework to framework, but there are some common patterns: a fairly typical example for a graph-based framework is illustrated here, and consists of basically two phases: a **clustering** phase and a **translation** phase.



Translation flow to an nGraph function

The clustering phase operates on the original framework's graph. During this stage, we look for maximal subgraphs containing nodes that can be translated to data flow functions in nGraph. The ability to capture subgraphs of the original graph means that we maintain interoperability with the native framework runtime. Any node that is not placed in a cluster can still by handled by the native framework. On the other hand, identifying maximal subgraphs means that we can avoid unnecessary handoffs between the native framework runtime and nGraph; minimizing this is good for performance.

In the second phase, called translation, we cut out each cluster subgraph, translate it into an nGraph Function, and replace the cluster subgraph with a stand-in node called an "encapsulation node" that holds a pointer to the nGraph `Function`. Later, at runtime, those functions will be invoked when the framework asks us to execute the encapsulation node.

It's worth noting that backends have total freedom to rewrite the nGraph Functions: they can do it for the sake of structural or algorithmic optimization of the graph, for easy integration with kernel libraries, or for any or no reason at all.

Namespaces in nGraph¶

What follows here is a table of all documented namespaces with brief descriptions:

Namespace	**Description**	**Location in Repo**	**Docs**
`ngraph`	The Intel nGraph C++ API	ngraph	Implicit namespace omitted from most API documentation
`builder`	Convenience functions that create additional graph nodes to implement commonly-used recipes; for example, auto-broadcast	builder	Coming Soon
`descriptor`	Descriptors are compile-time representations of objects that will appear at run-time	descriptor	Coming Soon
`op`	Ops used in graph construction	op	List of Core ops
`runtime`	The objects and methods used for executing the graph	runtime	Backend APIs

Build and Test¶

- Building nGraph from source
- Building nGraph-PlaidML from source

There are a few common paths to take when manually building the nGraph Compiler stack from source code. Today nGraph supports various developers working on all parts of the Deep Learning stack, and the way you decide to build or install components ought to depend on the capabilities of your hardware, and how you intend to use it.

A "from scratch" source-code build of the nGraph Library enables the CPU, `Interpreter`, and unit tests by default. See Building nGraph from source for more detail.

A “from scratch” source-code build that defaults to the PlaidML backend contains rich algorithm libraries akin to those that were previously available only to developers willing to spend extensive time writing, testing, and customizing kernels. An `NGRAPH_PLAIDML` dist can function like a framework that lets developers compose, train, and even deploy DL models in their preferred language on neural networks of any size. This is a good option if, for example, you are working on a laptop with a high-end GPU that you want to use for compute. See Building nGraph-PlaidML from source for instructions on how to build.

In either case, there are some prerequisites that your system will need to build from sources.

Prerequisites¶

Operating System	Compiler	Build System	Status	Additional Packages
CentOS 7.4 64-bit	GCC 4.8	CMake 3.9.0	supported	`wget zlib-devel ncurses-libs ncurses-devel patch diffutils gcc-c++ make git perl-Data-Dumper`
Ubuntu 16.04 or 18.04 (LTS) 64-bit	Clang 6	CMake 3.5.1 + GNU Make	supported	`build-essential cmake clang-format-6.0 clang-tidy-6.0 clang-6.0 git curl zlib1g zlib1g-dev libtinfo-dev unzip autoconf automake libtool`
Clear Linux* OS for Intel® Architecture version 28880+	Clang 8.0	CMake 3.14.2	experimental	bundles `machine-learning-basic c-basic python-basic python-basic-dev dev-utils`

Building nGraph from source¶

Important

The default **cmake** procedure (no build flags) will install `ngraph_dist` to an OS-level location like `/usr/bin/ngraph_dist` or `/usr/lib/ngraph_dist`. Here we specify how to build locally to the location of `~/ngraph_dist` with the cmake target `-DCMAKE_INSTALL_PREFIX=~/ngraph_dist`.

All of the nGraph Library documentation presumes that `ngraph_dist` gets installed locally. The system location can be used just as easily by customizing paths on that system. See the `ngraph/CMakeLists.txt` file to change or customize the default CMake procedure.

- Ubuntu LTS build steps
- CentOS 7.4 build steps

Ubuntu LTS build steps¶

The process documented here will work on Ubuntu* 16.04 (LTS) or on Ubuntu 18.04 (LTS).

1. Ensure you have installed the Prerequisites for Ubuntu*.
2. Clone the NervanaSystems `ngraph` repo:

   ```
   $ git clone https://github.com/NervanaSystems/ngraph.git
   $ cd ngraph
   ```

3. Create a build directory outside of the `ngraph/src` directory tree; somewhere like `ngraph/build`, for example:

   ```
   $ mkdir build && cd build
   ```

4. Generate the GNU Makefiles in the customary manner (from within the `build` directory). This command enables ONNX support in the library and sets the target build location at `~/ngraph_dist`, where it can be found easily.

   ```
   $ cmake .. -DNGRAPH_ONNX_IMPORT_ENABLE=ON
   -DCMAKE_INSTALL_PREFIX=~/ngraph_dist
   ```

   Other optional build flags – If running `gcc-5.4.0` or `clang-3.9`, remember that you can also append `cmake` with the prebuilt LLVM option to speed-up the build. Another option if your deployment system has Intel® Advanced Vector Extensions (Intel® AVX) is to target the accelerations available directly by compiling the build as follows during the cmake step: `-DNGRAPH_TARGET_ARCH=skylake-avx512`.

   ```
   $ cmake .. [-DNGRAPH_TARGET_ARCH=skylake-avx512]
   ```

5. Run `$ make` and `make install` to install `libngraph.so` and the header files to `~/ngraph_dist`:

   ```
   $ make   # note: make -j <N> may work, but sometimes results in out-of-
   memory errors if too many compilation processes are used
   $ make install
   ```

6. (Optional, requires doxygen, Sphinx, and breathe). Run `make html` inside the `doc/sphinx` directory of the cloned source to build a copy of the website docs locally. The low-level API docs with inheritance and collaboration diagrams can be found inside the `/docs/doxygen/` directory. See the Contributing to documentation for more details about how to build documentation for nGraph.

CentOS 7.4 build steps¶

The process documented here will work on CentOS 7.4.

1. Ensure you have installed the Prerequisites for CentOS*, and update the system with **yum**.

```
$ sudo yum update
```

2. Install Cmake 3.4:

   ```
   $ wget https://cmake.org/files/v3.4/cmake-3.5.0.tar.gz
   $ tar -xzvf cmake-3.5.0.tar.gz
   $ cd cmake-3.5.0
   $ ./bootstrap --system-curl --prefix=~/cmake
   $ make && make install
   ```

3. Clone the NervanaSystems `ngraph` repo via HTTPS and use Cmake 3.5.0 to build nGraph Libraries to `~/ngraph_dist`. This command enables ONNX support in the library (optional).

   ```
   $ cd /opt/libraries
   $ git clone https://github.com/NervanaSystems/ngraph.git
   $ cd ngraph && mkdir build && cd build
   $ ~/cmake/bin/cmake .. -DCMAKE_INSTALL_PREFIX=~/ngraph_dist -
   DNGRAPH_ONNX_IMPORT_ENABLE=ON
   $ make && sudo make install
   ```

Building nGraph-PlaidML from source¶

The following instructions will create the `~/ngraph_plaidml_dist` locally:

1. Ensure you have installed the Prerequisites for your OS.

2. Install the prerequisites for the backend. Our hybrid `NGRAPH_PLAIDML` backend works best with Python3 versions. We recommend that you use a virtual environment, due to some of the difficulties that users have seen when trying to install outside of a venv.

   ```
   $ sudo apt install python3-pip
   $ pip install plaidml
   $ plaidml-setup
   ```

3. Clone the source code, create and enter your build directory:

   ```
   $ git clone https://github.com/NervanaSystems/ngraph.git
   $ cd ngraph && mkdir build && cd build
   ```

4. Prepare the CMake files as follows:

   ```
   $ cmake .. -DCMAKE_INSTALL_PREFIX=~/ngraph_plaidml_dist -
   DNGRAPH_CPU_ENABLE=OFF -DNGRAPH_PLAIDML_ENABLE=ON
   ```

5. Run **make** and `make install`. Note that if you are building outside a local or user path, you may need to run `make install` as the root user.

   ```
   $ make
   $ make install
   ```

   This should create the shared library `libplaidml_backend.so` and nbench. Note that if you built in a virtual environment and run `make check` from it, the Google Test may report failures. Full tests can be run when PlaidML devices are available at the machine level.

For more about working with the PlaidML backend from nGraph, see our API documentation PlaidML from nGraph.

macOS* development¶

Note: Although we do not currently offer full support for the macOS platform, some configurations and features may work.

The repository includes two scripts (`maint/check-code-format.sh` and `maint/apply-code-format.sh`) that are used respectively to check adherence to `libngraph` code formatting conventions, and to automatically reformat code according to those conventions. These scripts require the command `clang-format-3.9` to be in your `PATH`. Run the following commands (you will need to adjust them if you are not using bash):

```
$ brew install llvm@3.9 automake
$ mkdir -p $HOME/bin
$ ln -s /usr/local/opt/llvm@3.9/bin/clang-format $HOME/bin/clang-format-3.9
$ echo 'export PATH=$HOME/bin:$PATH' >> $HOME/.bash_profile
```

Testing the build¶

We use the googletest framework from Google for unit tests. The `cmake` command automatically downloaded a copy of the needed `gtest` files when it configured the build directory.

To perform unit tests on the install:

1. Create and configure the build directory as described in our Build and Test guide.
2. Enter the build directory and run `make check`:

   ```
   $ cd build/
   $ make check
   ```

Constructing Graphs¶

Execute a computation¶

This section explains how to manually perform the steps that would normally be performed by a framework bridge to execute a computation. nGraph graphs are targeted toward automatic construction; it is far easier for a processor (a CPU, GPU, or purpose-built silicon) to execute a computation than it is for a human to map out how that computation happens. Unfortunately, things that make by-hand graph construction simpler tend to make automatic construction more difficult, and vice versa.

Nevertheless, it can be helpful to break down what is happening during graph construction. The documetation that follows explains two approaches frameworks can use to compile with nGraph operations:

- Using complete shapes
- Using partial shapes

The nGraph Intermediate Representation uses a strong, dynamic type system, including static shapes. This means that at compilation, every tensor (or, equivalently, every node output) in the graph is assigned **complete shape information**; that is, one and only one shape. The static process by which this assignment takes place is called shape propagation.

In the first scenario, the model description walk-through is based on the `abc.cpp` code in the `/doc/examples/abc` directory, and it deconstructs the steps that must happen (either programmatically or manually) in order to successfully execute a computation given complete shape information.

Scenario One: Using Complete Shapes¶

A step-by-step example of how a framework might execute with complete shape information is provided here. For a step-by-step example using dynamic shapes, see Scenario Two: Known Partial Shape.

- Define the computation
- Specify the backend upon which to run the computation
- Compile the computation
- Allocate backend storage for the inputs and outputs
- Initialize the inputs
- Invoke the computation
- Access the outputs

Define the computation¶

To a framework, a computation is simply a transformation of inputs to outputs. While a bridge can programmatically construct the graph from a framework's representation of the computation, graph construction can be somewhat more tedious when done manually. For anyone interested in specific nodes (vertices) or edges of a computation that reveal "what is happening where", it can be helpful to think of a computation as a zoomed-out and *stateless* data-flow graph where all of the nodes are well-defined tensor operations and all of the edges denote use of an output from one operation as an input for another operation.

Most of the public portion of the nGraph API is in the `ngraph` namespace, so we will omit the namespace. Use of namespaces other than `std` will be namespaces in `ngraph`. For example, the `op::Add` is assumed to refer to `ngraph::op::Add`. A computation's graph is constructed from ops; each is a member of a subclass of `op::Op`, which, in turn, is a subclass of `Node`. Not all graphs are computation, but all graphs are composed entirely of instances of `Node`. Computation graphs contain only `op::Op` nodes.

We mostly use shared pointers for nodes, i.e. `std::shared_ptr<Node>`, so that they will be automatically deallocated when they are no longer needed. More detail on shared pointers is given in the glossary.

Every node has zero or more *inputs*, zero or more *outputs*, and zero or more *attributes*.

The specifics for each `type` permitted on a core `Op`-specific basis can be discovered in our List of Core ops docs. For our purpose to define a computation, nodes should be thought of as essentially immutable; that is, when constructing a node, we need to supply all of its inputs. We get this process started with ops that have no inputs, since any op with no inputs is going to first need some inputs.

`op::Parameter` specifes the tensors that will be passed to the computation. They receive their values from outside of the graph, so they have no inputs. They have attributes for the element type and the shape of the tensor that will be passed to them.

```
// Build the graph
Shape s{2, 3};
auto a = std::make_shared<op::Parameter>(element::f32, s);
auto b = std::make_shared<op::Parameter>(element::f32, s);
auto c = std::make_shared<op::Parameter>(element::f32, s);
```

The above code makes three parameter nodes where each is a 32-bit float of shape `(2, 3)` and a row-major element layout.

To create a graph for `(a + b) * c`, first make an `op::Add` node with inputs from `a` and `b`, and an `op::Multiply` node from the add node and `c`:

```
auto t0 = std::make_shared<op::Add>(a, b);
auto t1 = std::make_shared<op::Multiply>(t0, c);
```

When the `op::Add` op is constructed, it will check that the element types and shapes of its inputs match; to support multiple frameworks, ngraph does not do automatic type conversion or broadcasting. In this case, they match, and the shape of the unique output of `t0` will be a 32-bit float with shape `(2, 3)`. Similarly, `op::Multiply` checks that its inputs match and sets the element type and shape of its unique output.

Once the graph is built, we need to package it in a `Function`:

```
auto f = std::make_shared<Function>(OutputVector{t1},
                                    ParameterVector{a, b, c});
```

The first argument to the constuctor specifies the nodes that the function will return; in this case, the product. An `OutputVector` is a vector of references to outputs of `op::Node`. The second argument specifies the parameters of the function, in the order they are to be passed to the compiled function. A `ParameterVector` is a vector of shared pointers to `op::Parameter`.

Important

The parameter vector must include **every** parameter used in the computation of the results.

Specify the backend upon which to run the computation¶

For a framework bridge, a *backend* is the environment that can perform the computations; it can be done with a CPU, GPU, or purpose-built silicon. A *transformer* can compile computations for a backend, allocate and deallocate tensors, and invoke computations.

Factory-like managers for classes of backend managers can compile a `Function` and allocate backends. A backend is somewhat analogous to a multi-threaded process.

There are two backends for the CPU: the optimized `"CPU"` backend, which uses the DNNL, and the `"INTERPRETER"` backend, which runs reference versions of kernels that favor implementation clarity over speed. The `"INTERPRETER"` backend can be slow, and is primarily intended for testing. See the documentation on runtime options for various backends for additional details.

To continue with our original example and select the `"CPU_Backend"`:

```
// Create the backend
auto backend = runtime::Backend::create("CPU");
```

Compile the computation¶

Compilation triggers something that can be used as a factory for producing a `CallFrame` which is a *function* and its associated *state* that can run in a single thread at a time. A `CallFrame` may be reused, but any particular `CallFrame` must only be running in one thread at any time. If more than one thread needs to execute the function at the same time, create multiple `CallFrame` objects from the `ExternalFunction`.

Allocate backend storage for the inputs and outputs¶

At the graph level, functions are stateless. They do have internal state related to execution, but there is no user-visible state. Variables must be passed as arguments. If the function updates variables, it must return the updated variables.

To invoke a function, tensors must be provided for every input and every output. At this time, a tensor used as an input cannot also be used as an output. If variables are being updated, you should use a double-buffering approach where you switch between odd/even generations of variables on each update.

Backends are responsible for managing storage. If the storage is off-CPU, caches are used to minimize copying between device and CPU. We can allocate storage for the three parameters and the return value.

```
// Allocate tensors for arguments a, b, c
auto t_a = backend->create_tensor(element::f32, s);
auto t_b = backend->create_tensor(element::f32, s);
auto t_c = backend->create_tensor(element::f32, s);
// Allocate tensor for the result
auto t_result = backend->create_tensor(element::f32, s);
```

Each tensor is a shared pointer to a Tensorview, which is the interface backends implement for tensor use. When there are no more references to the tensor view, it will be freed when convenient for the backend. See the Backend APIs documentation for details on how to work with `Tensor`.

Initialize the inputs¶

Next we need to copy some data into the tensors.

```
    // Initialize tensors
    float v_a[2][3] = {{1, 2, 3}, {4, 5, 6}};
    float v_b[2][3] = {{7, 8, 9}, {10, 11, 12}};
    float v_c[2][3] = {{1, 0, -1}, {-1, 1, 2}};

    t_a->write(&v_a, sizeof(v_a));
    t_b->write(&v_b, sizeof(v_b));
    t_c->write(&v_c, sizeof(v_c));
```

The `runtime::Tensor` interface has `write` and `read` methods for copying data to/from the tensor.

Invoke the computation¶

To invoke the function, we simply pass argument and resultant tensors to the call frame:

```
    // Invoke the function
    auto exec = backend->compile(f);
```

Access the outputs¶

We can use the `read` method to access the result:

```
    // Get the result
    float r[2][3];
    t_result->read(&r, sizeof(r));

    std::cout << "[" << std::endl;
    for (size_t i = 0; i < s[0]; ++i)
    {
        std::cout << " [";
        for (size_t j = 0; j < s[1]; ++j)
        {
            std::cout << r[i][j] << ' ';
        }
        std::cout << ']' << std::endl;
    }
    std::cout << ']' << std::endl;

    return 0;
```

Compiling with Complete Shape Information¶

“The (a + b) * c example for executing a computation on nGraph”¶

```
//
***************************************************************************
**
// Copyright 2017-2020 Intel Corporation
//
// Licensed under the Apache License, Version 2.0 (the "License");
// you may not use this file except in compliance with the License.
// You may obtain a copy of the License at
//
//     http://www.apache.org/licenses/LICENSE-2.0
//
// Unless required by applicable law or agreed to in writing, software
// distributed under the License is distributed on an "AS IS" BASIS,
// WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
// See the License for the specific language governing permissions and
// limitations under the License.
//
***************************************************************************
**

#include <iostream>

#include <ngraph/ngraph.hpp>

using namespace ngraph;

int main()
{
    // Build the graph
    Shape s{2, 3};
    auto a = std::make_shared<op::Parameter>(element::f32, s);
    auto b = std::make_shared<op::Parameter>(element::f32, s);
    auto c = std::make_shared<op::Parameter>(element::f32, s);

    auto t0 = std::make_shared<op::Add>(a, b);
    auto t1 = std::make_shared<op::Multiply>(t0, c);

    // Make the function
    auto f = std::make_shared<Function>(OutputVector{t1},
                                        ParameterVector{a, b, c});

    // Create the backend
    auto backend = runtime::Backend::create("CPU");

    // Allocate tensors for arguments a, b, c
    auto t_a = backend->create_tensor(element::f32, s);
    auto t_b = backend->create_tensor(element::f32, s);
    auto t_c = backend->create_tensor(element::f32, s);
    // Allocate tensor for the result
    auto t_result = backend->create_tensor(element::f32, s);

    // Initialize tensors
    float v_a[2][3] = {{1, 2, 3}, {4, 5, 6}};
    float v_b[2][3] = {{7, 8, 9}, {10, 11, 12}};
    float v_c[2][3] = {{1, 0, -1}, {-1, 1, 2}};

    t_a->write(&v_a, sizeof(v_a));
    t_b->write(&v_b, sizeof(v_b));
    t_c->write(&v_c, sizeof(v_c));

    // Invoke the function
    auto exec = backend->compile(f);
    exec->call({t_result}, {t_a, t_b, t_c});

    // Get the result
    float r[2][3];
    t_result->read(&r, sizeof(r));

    std::cout << "[" << std::endl;
    for (size_t i = 0; i < s[0]; ++i)
    {
        std::cout << " [";
        for (size_t j = 0; j < s[1]; ++j)
        {
            std::cout << r[i][j] << ' ';
        }
        std::cout << ']' << std::endl;
    }
    std::cout << ']' << std::endl;

    return 0;
}
```

Scenario Two: Known Partial Shape¶

The second scenario involves the use of dynamic tensors. A dynamic tensor is a tensor whose shape can change from one “iteration” to the next. When a dynamic tensor is created, a framework bridge might supply only *partial* shape information: it might be **all** the tensor dimensions, **some** of the tensor dimensions, or **none** of the tensor dimensions; furthermore, the rank of the tensor may be left unspecified. The “actual” shape of the tensor is not specified until some function writes some value to it. The actual shape can change when the value of the tensor is overwritten. It is the backend’s responsibility to set the actual shape. The model description for the second scenario based on the `partial_shape.cpp` code in the `/doc/examples/dynamic_tensor` directory, and it deconstructs the steps that must happen (either programmatically or manually) in order to successfully retreive shape data.

- Create a dynamic tensor
- Initialize input of shape
- Get the result
- Compiling with Known Partial Shape

Create and compile a graph where the provided info of shape `x` is `(2,?)`:

```
    auto x_shape_info = PartialShape{2, Dimension::dynamic()};
    auto x = make_shared<op::Parameter>(element::i32, x_shape_info);
    auto a = x + x;
    auto f = make_shared<Function>(OutputVector{a}, ParameterVector{x});
    auto be = runtime::Backend::create("CPU", true);
    auto ex = be->compile(f);
```

Create a dynamic tensor¶

Create a dynamic tensor of shape `(2,?)`

```
    auto t_out = be->create_dynamic_tensor(element::i32, x_shape_info);
    execute(be, ex, t_out, 3);
    execute(be, ex, t_out, 11);
    execute(be, ex, t_out, 20);
```

At this point, `t_out->get_shape()` would throw an exception, while `t_out->get_partial_shape()` would return "`(2,?)`".

Initialize input of shape¶

```
    auto t_in = be->create_tensor(element::i32, Shape{2, n});
    {
        vector<int32_t> t_val(2 * n);
        iota(t_val.begin(), t_val.end(), 0);
        t_in->write(&t_val[0], t_val.size() * sizeof(t_val[0]));
    }
```

At this point, `t_out->get_shape()` would return `Shape{2,3}`, while `t_out->get_partial_shape()` would return "`(2,?)`".

Get the result¶

```
    ex->call({t_out}, {t_in});

    auto s = t_out->get_shape();
    vector<int32_t> r(s[0] * s[1]);
    t_out->read(&r[0], r.size() * sizeof(r[0]));
    cout << "[" << endl;
    for (size_t i = 0; i < s[0]; ++i)
    {
        cout << " [";
        for (size_t j = 0; j < s[1]; ++j)
        {
            cout << r[i * s[1] + j] << ' ';
        }
        cout << ']' << endl;
    }
    cout << ']' << endl;
}
```

At this point, `t_out->get_shape()` would return `Shape{2,20}`, while `t_out->get_partial_shape()` would return "`(2,?)`".

Compiling with Known Partial Shape¶

“Full code for compiling with dynamic tensors and partial shape”¶

```
//
*************************************************************************
**
// Copyright 2017-2020 Intel Corporation
//
// Licensed under the Apache License, Version 2.0 (the "License");
// you may not use this file except in compliance with the License.
// You may obtain a copy of the License at
//
//     http://www.apache.org/licenses/LICENSE-2.0
//
// Unless required by applicable law or agreed to in writing, software
// distributed under the License is distributed on an "AS IS" BASIS,
// WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
// See the License for the specific language governing permissions and
// limitations under the License.
//
*************************************************************************
**

#include <iostream>
#include <numeric>
#include <vector>

#include <ngraph/ngraph.hpp>

using namespace std;
using namespace ngraph;

void execute(shared_ptr<runtime::Backend> be,
             shared_ptr<runtime::Executable> ex,
             shared_ptr<runtime::Tensor> t_out,
             uint32_t n);

int main()
{
    // Create and compile a graph where the provided info of shape of x is
    // (2,?)
    auto x_shape_info = PartialShape{2, Dimension::dynamic()};
    auto x = make_shared<op::Parameter>(element::i32, x_shape_info);
    auto a = x + x;
    auto f = make_shared<Function>(OutputVector{a}, ParameterVector{x});
    auto be = runtime::Backend::create("CPU", true);
    auto ex = be->compile(f);

    // Create a dynamic tensor of shape (2,?)
    auto t_out = be->create_dynamic_tensor(element::i32, x_shape_info);
    execute(be, ex, t_out, 3);
    execute(be, ex, t_out, 11);
    execute(be, ex, t_out, 20);

    return 0;
}

void execute(shared_ptr<runtime::Backend> be,
             shared_ptr<runtime::Executable> ex,
             shared_ptr<runtime::Tensor> t_out,
             uint32_t n)
{
    // Initialize input of shape (2, n)
    auto t_in = be->create_tensor(element::i32, Shape{2, n});
    {
        vector<int32_t> t_val(2 * n);
        iota(t_val.begin(), t_val.end(), 0);
        t_in->write(&t_val[0], t_val.size() * sizeof(t_val[0]));
    }
    // Get the result
    ex->call({t_out}, {t_in});

    auto s = t_out->get_shape();
    vector<int32_t> r(s[0] * s[1]);
    t_out->read(&r[0], r.size() * sizeof(r[0]));
    cout << "[" << endl;
    for (size_t i = 0; i < s[0]; ++i)
    {
        cout << " [";
        for (size_t j = 0; j < s[1]; ++j)
        {
            cout << r[i * s[1] + j] << ' ';
        }
        cout << ']' << endl;
    }
    cout << ']' << endl;
}
```

Build a graph with operators¶

This section illustrates the use of C++ operators to simplify the building of graphs.

Several C++ operators are overloaded to simplify graph construction. For example, the following:

```
auto t1 = std::make_shared<op::Multiply>(t0, c);
```

can be simplified to:

```
auto t1 = (a + b) * c;
```

The expression `a + b` is equivalent to `std::make_shared<op::Add>(a, b)` and the `*` operator similarly returns `std::make_shared<op::Multiply>` to its arguments.

Make a stateful computation¶

In this section, we show how to make a stateful computation from nGraph's stateless operations.

The basic idea is that any computation with side-effects can be factored into a stateless function that transforms the old state into the new state.

An example from C++¶

Let's start with a simple C++ example, a function `count` that returns how many times it has already been called:

update.cpp¶

```
int count()
{
    static int counter = 0;
    return counter++;
}
```

The static variable `counter` provides state for this function. The state is initialized to 0. Every time `count` is called, the current value of `counter` is returned and `counter` is incremented. To convert this to use a stateless function, define a function that takes the current value of `counter` as an argument and returns the updated value.

```
std::tuple<int, int> stateless_count(int counter)
{
    return std::tuple<int, int>(counter, counter + 1);
}
```

To use this version of counting,

```
    int counter = 0;
    {
        auto r(stateless_count(counter));
        counter = std::get<1>(r);
        std::cout << std::get<0>(r);
    }
    std::cout << ", ";
    {
        auto r(stateless_count(counter));
        counter = std::get<1>(r);
        std::cout << std::get<0>(r);
    }
    std::cout << std::endl;
```

Update in nGraph¶

In working with nGraph-based construction of graphs, updating takes the same approach. During training, we include all the weights as arguments to the training function and return the updated weights along with any other results. For more complex forms of training, such as those using momentum, we would add the momentum tensors as additional arguments and include their updated values as additional results. A simple case is illustrated in the documentation for how to Derive a trainable model.

Derive a trainable model¶

Documentation in this section describes one of the possible ways to turn a DL model for inference into one that can be used for training.

Additionally, and to provide a more complete walk-through that *also* trains the model, our example includes the use of a simple data loader for uncompressed MNIST data.

Automating graph construction¶

In a Machine Learning ecosystem, it makes sense to use automation and abstraction where possible. nGraph was designed to automatically use the “ops” of tensors provided by a framework when constructing graphs. However, nGraph’s graph-construction API operates at a fundamentally lower level than a typical framework’s API, and writing a model directly in nGraph would be somewhat akin to programming in assembly language: not impossible, but not the easiest thing for humans to do.

To make the task easier for developers who need to customize the “automatic”, construction of graphs, we’ve provided some demonstration code for how this could be done. We know, for example, that a trainable model can be derived from any graph that has been constructed with weight-based updates.

The following example named `mnist_mlp.cpp` represents a hand-designed inference model being converted to a model that can be trained with nGraph.

Model overview¶

Due to the lower-level nature of the graph-construction API, the example we’ve selected to document here is a relatively simple model: a fully-connected topology with one hidden layer followed by `Softmax`.

Remember that in nGraph, the graph is stateless; values for the weights must be provided as parameters along with the normal inputs. Starting with the graph for inference, we will use it to create a graph for training. The training function will return tensors for the updated weights.

Note

This example illustrates how to convert an inference model into one that can be trained. Depending on the framework, bridge code may do something similar, or the framework might do this operation itself. Here we do the conversion with nGraph because the computation for training a model is significantly larger than for inference, and doing the conversion manually is tedious and error-prone.

Code structure¶

Inference¶

We begin by building the graph, starting with the input parameter `X`. We also define a fully-connected layer, including parameters for weights and bias:

```
    auto X = std::make_shared<op::Parameter>(
        element::f32, Shape{batch_size, input_size});

    // Layer 0
    auto W0 = std::make_shared<op::Parameter>(element::f32,
                                              Shape{input_size, l0_size});
    auto b0 =
        std::make_shared<op::Parameter>(element::f32, Shape{l0_size});
    auto l0_dot = std::make_shared<op::Dot>(X, W0, 1);
    auto b0_broadcast = std::make_shared<op::Broadcast>(
        b0, Shape{batch_size, l0_size}, AxisSet{0});
    auto l0 = std::make_shared<op::Relu>(l0_dot + b0_broadcast);
```

Repeat the process for the next layer,

```
    auto W1 = std::make_shared<op::Parameter>(element::f32,
                                              Shape{l0_size, l1_size});
    auto b1 =
        std::make_shared<op::Parameter>(element::f32, Shape{l1_size});
    auto l1_dot = std::make_shared<op::Dot>(l0, W1, 1);
    auto b1_broadcast = std::make_shared<op::Broadcast>(
        b1, Shape{batch_size, l1_size}, AxisSet{0});
    auto l1 = l1_dot + b1_broadcast;
```

and normalize everything with a `softmax`.

```
    // Softmax
    auto softmax = std::make_shared<op::Softmax>(l1, AxisSet{1});
```

Loss¶

We use cross-entropy to compute the loss. nGraph does not currenty have a core op for cross-entropy, so we implement it directly, adding clipping to prevent underflow.

```
    auto Y =
        std::make_shared<op::Parameter>(element::f32, Shape{batch_size});
    auto labels =
        std::make_shared<op::OneHot>(Y, Shape{batch_size, output_size}, 1);
    auto softmax_clip_value = std::make_shared<op::Constant>(
        element::f32, Shape{}, std::vector<float>{log_min});
    auto softmax_clip_broadcast = std::make_shared<op::Broadcast>(
        softmax_clip_value, Shape{batch_size, output_size}, AxisSet{0, 1});
    auto softmax_clip =
        std::make_shared<op::Maximum>(softmax, softmax_clip_broadcast);
    auto softmax_log = std::make_shared<op::Log>(softmax_clip);
    auto prod = std::make_shared<op::Multiply>(softmax_log, labels);
    auto N = std::make_shared<op::Parameter>(element::f32, Shape{});
    auto loss = std::make_shared<op::Divide>(
        std::make_shared<op::Sum>(prod, AxisSet{0, 1}), N);
```

Backprop¶

We want to reduce the loss by adjusting the weights. We compute the adjustments using the reverse-mode autodiff algorithm, commonly referred to as "backprop" because of the way it is implemented in interpreted frameworks. In nGraph, we augment the loss computation with computations for the weight adjustments. This allows the calculations for the adjustments to be further optimized.

```
    // Each of W0, b0, W1, and b1
    auto learning_rate =
        std::make_shared<op::Parameter>(element::f32, Shape{});
    auto delta = -learning_rate * loss;
```

For any node `N`, if the update for `loss` is `delta`, the update computation for `N` will be given by the node

```
auto update = loss->backprop_node(N, delta);
    auto W1_next = W1 + adjoints.backprop_output(W1);
    auto b1_next = b1 + adjoints.backprop_output(b1);
```

The different update nodes will share intermediate computations. So to get the updated values for the weights as computed with the specified backend:

```
    auto t_W0 = make_output_tensor(backend, W0, 0);
    auto t_b0 = make_output_tensor(backend, b0, 0);
    auto t_W1 = make_output_tensor(backend, W1, 0);
    auto t_b1 = make_output_tensor(backend, b1, 0);

    std::function<float()> rand(
        std::bind(std::uniform_real_distribution<float>(-1.0f, 1.0f),
                  std::default_random_engine(0)));
    randomize(rand, t_W0);
    randomize(rand, t_b0);
    randomize(rand, t_W1);
    randomize(rand, t_b1);

    // Allocate inputs
    auto t_X = make_output_tensor(backend, X, 0);
    auto t_Y = make_output_tensor(backend, Y, 0);

    auto t_learning_rate = make_output_tensor(backend, learning_rate, 0);
    auto t_N = make_output_tensor(backend, N, 0);
    set_scalar(t_N, static_cast<float>(batch_size), 0);

    // Allocate updated variables
    auto t_W0_next = make_output_tensor(backend, W0_next, 0);
    auto t_b0_next = make_output_tensor(backend, b0_next, 0);
    auto t_W1_next = make_output_tensor(backend, W1_next, 0);
    auto t_b1_next = make_output_tensor(backend, b1_next, 0);

    auto t_loss = make_output_tensor(backend, loss, 0);
    auto t_softmax = make_output_tensor(backend, softmax, 0);
```

Update¶

Since nGraph is stateless, we train by making a function that has the original weights among its inputs and the updated weights among the results. For training, we'll also need the labeled training data as inputs, and we'll return the loss as an additional result. We'll also want to track how well we are doing; this is a function that returns the loss and has the labeled testing data as input. Although we can use the same nodes in different functions, nGraph currently does not allow the same nodes to be compiled in different functions, so we compile clones of the nodes.

```
    NodeMap train_node_map;
    auto train_function = clone_function(
        Function(
            OutputVector{
                loss, softmax, W0_next, b0_next, W1_next, b1_next},
            ParameterVector{X, Y, N, learning_rate, W0, b0, W1, b1}),
        train_node_map);
    auto train_exec = backend->compile(train_function);
```

Distribute training across multiple nGraph backends¶

Important

Distributed training is not officially supported in version 0.29; however, the following configuration options have worked for nGraph devices with mixed or limited success in testing.

In the previous section, we described the steps needed to create a "trainable" nGraph model. Here we demonstrate how to train a data parallel model by distributing the graph to more than one device.

Frameworks can implement distributed training with nGraph versions prior to 0.13:

- Use `-DNGRAPH_DISTRIBUTED_ENABLE=OMPI` to enable distributed training with OpenMPI. Use of this flag requires that OpenMPI be a pre-existing library in the system. If it's not present on the system, install OpenMPI version `2.1.1` or later before running the compile.
- Use `-DNGRAPH_DISTRIBUTED_ENABLE=MLSL` to enable the option for Intel® Machine Learning Scaling Library for Linux* OS:

  Note

  The Intel® MLSL option applies to Intel® Architecture CPUs (`CPU`) and `Interpreter` backends only. For all other backends, `OpenMPI` is presently the only supported option. We recommend the use of Intel MLSL for CPU backends to avoid an extra download step.

Finally, to run the training using two nGraph devices, invoke `mpirun`.

To deploy data-parallel training, the `AllReduce` op should be added after the steps needed to complete the backpropagation; the new code is highlighted below:

```
    ngraph::autodiff::Adjoints adjoints(OutputVector{loss},
                                        OutputVector{delta});
    auto grad_W0 = adjoints.backprop_output(W0);
    auto grad_b0 = adjoints.backprop_output(b0);
    auto grad_W1 = adjoints.backprop_output(W1);
    auto grad_b1 = adjoints.backprop_output(b1);

    auto avg_grad_W0 = std::make_shared<op::AllReduce>(grad_W0);
    auto avg_grad_b0 = std::make_shared<op::AllReduce>(grad_b0);
    auto avg_grad_W1 = std::make_shared<op::AllReduce>(grad_W1);
    auto avg_grad_b1 = std::make_shared<op::AllReduce>(grad_b1);

    auto W0_next = W0 + avg_grad_W0;
    auto b0_next = b0 + avg_grad_b0;
    auto W1_next = W1 + avg_grad_W1;
    auto b1_next = b1 + avg_grad_b1;
```

See the full code in the `examples` folder `/doc/examples/mnist_mlp/dist_mnist_mlp.cpp`.

```
mpirun -np 2 dist_mnist_mlp
```

Import a model¶

Importing a model from ONNX

nGraph APIs can be used to run inference on a model that has been *exported* from a Deep Learning framework. An export produces a file with a serialized model that can be loaded and passed to one of the nGraph backends.

Importing a model from ONNX¶

The most-widely supported export format available today is ONNX. Models that have been serialized to ONNX are easy to identify; they are usually named `<some_model>.onnx` or `<some_model>.onnx.pb`. These tutorials from ONNX describe how to turn trained models into an `.onnx` export.

Important

If you landed on this page and you already have an `.onnx` or an `.onnx.pb` formatted file, you should be able to run the inference without needing to dig into anything from the “Frameworks” sections. You will, however, need to have completed the steps outlined in our Build and Test guide.

To demonstrate functionality, we’ll use an already-serialized CIFAR10 model trained via ResNet20. Remember that this model has already been trained and exported from a framework such as Caffe2, PyTorch or CNTK; we are simply going to build an nGraph representation of the model, execute it, and produce some outputs.

Installing `ngraph_onnx` with nGraph from scratch¶

See the documentation on: building nGraph and nGraph-ONNX for the latest instructions.

Importing a serialized model¶

After building and installing `ngraph_onnx`, we can import a model that has been serialized by ONNX, interact locally with the model by running Python code, create and load objects, and run inference.

This section assumes that you have your own ONNX model. With this example model from Microsoft*'s Deep Learning framework, CNTK, we can outline the procedure to show how to run ResNet on model that has been trained on the CIFAR10 data set and serialized with ONNX.

(Optional) Localize your export to the virtual environment¶

For this example, let's say that our serialized file was output under our $HOME directory, say at `~/onnx_conversions/trained_model.onnx`. To make loading this file easier, you can run the example below from your Venv in that directory. If you invoke your python interpreter in a different directory, you will need to specify the relative path to the location of the `.onnx` file.

Important

If you invoke your Python interpreter in directory other than where you outputted your trained model, you will need to specify the **relative** path to the location of the `.onnx` file.

```
(onnx) $ cd ~/onnx_conversions
(onnx) $ python3
```

Enable ONNX and load an ONNX file from disk¶

```
import onnx

onnx_protobuf = onnx.load('/path/to/model/cntk_ResNet20_CIFAR10/model.onnx')
```

Convert an ONNX model to an ngraph model¶

```
from ngraph_onnx.onnx_importer.importer import import_onnx_model
ng_model = import_onnx_model(onnx_protobuf)[0]
```

The importer returns a list of ngraph models for every ONNX graph output:

```
print(ng_models)
[{
    'name': 'Plus5475_Output_0',
    'output': <Add: 'Add_1972' ([1, 10])>,
    'inputs': [<Parameter: 'Parameter_1104' ([1, 3, 32, 32], float)>]
 }]
```

The `output` field contains the ngraph node corrsponding to the output node in the imported ONNX computational graph. The `inputs` list contains all input parameters for the computation which generates the output.

Using ngraph_api, create a callable computation object¶

```
import ngraph as ng
runtime = ng.runtime(backend_name='CPU')
resnet = runtime.computation(ng_model['output'], *ng_model['inputs'])
```

Load or create an image¶

```
import numpy as np
picture = np.ones([1, 3, 32, 32])
```

Run ResNet inference on picture¶

```
resnet(picture)
```

Put it all together¶

“Demo sample code to run inference with nGraph”¶

```
import onnx

onnx_protobuf = onnx.load('/path/to/model/cntk_ResNet20_CIFAR10/model.onnx')

# Convert a serialized ONNX model to an ngraph model
from ngraph_onnx.onnx_importer.importer import import_onnx_model
ng_model = import_onnx_model(onnx_protobuf)[0]


# Using an ngraph runtime (CPU backend), create a callable computation
import ngraph as ng
runtime = ng.runtime(backend_name='CPU')
resnet = runtime.computation(ng_model['output'], *ng_model['inputs'])

# Load or create an image
import numpy as np
picture = np.ones([1, 3, 32, 32])

# Run ResNet inference on picture
resnet(picture)
```

Outputs will vary greatly, depending on your model; for demonstration purposes, the code will look something like:

```
array([[ 1.312082 , -1.6729496,  4.2079577,  1.4012241, -3.5463796,
      2.3433776,  1.7799224, -1.6155214,  0.0777044, -4.2944093]],
   dtype=float32)
```

Python API¶

This section contains the Python API component of the nGraph Compiler stack. The Python API exposes nGraph™ C++ operations to Python users. For quick-start you can find an example of the API usage below.

Note that the output at `print(model)` may vary; it varies according to the number of nodes or variety of step used to compute the printed solution. Various NNs configured in different ways should produce the same result for simple calculations or accountings. More complex computations may have minor variations with respect to how precise they ought to be. For example, a more efficient graph `<Multiply: 'Multiply_12' ([2, 2])>` can also be achieved with some configurations.

“Basic example”¶

```
import numpy as np
import ngraph as ng

A = ng.parameter(shape=[2, 2], name='A', dtype=np.float32)
B = ng.parameter(shape=[2, 2], name='B')
C = ng.parameter(shape=[2, 2], name='C')
# >>> print(A)
# <Parameter: 'A' ([2, 2], float)>

model = (A + B) * C
# >>> print(model)
# <Multiply: 'Multiply_14' ([2, 2])>

runtime = ng.runtime(backend_name='CPU')
# >>> print(runtime)
# <Runtime: Backend='CPU'>

computation = runtime.computation(model, A, B, C)
# >>> print(computation)
# <Computation: Multiply_14(A, B, C)>

value_a = np.array([[1, 2], [3, 4]], dtype=np.float32)
value_b = np.array([[5, 6], [7, 8]], dtype=np.float32)
value_c = np.array([[9, 10], [11, 12]], dtype=np.float32)

result = computation(value_a, value_b, value_c)
# >>> print(result)
# [[ 54.  80.]
#  [110. 144.]]
```

nGraph Python APIs¶

`ngraph`	ngraph module namespace, exposing factory functions for all ops and other classes.
`ngraph.exceptions`	ngraph exceptions hierarchy.
`ngraph.ops`	Factory functions for all ngraph ops.
`ngraph.runtime`	Create a Runtime object (helper factory).

The “How to” articles in this section explain how to build or construct graphs with nGraph components. The recipes are all framework agnostic; in other words, if an entity (framework or user) wishes to make use of target-based computational resources, it can either:

- Do the tasks programatically through a framework, or
- Provide a serialized model that can be imported to run on one of the nGraph backends.

Note

This section is aimed at intermediate-level developers. It assumes an understanding of the concepts in the previous sections. It does not assume knowledge of any particular frontend framework.

Compiler Passes¶

List of passes¶

The kinds of compiler passes available can be broken down into different buckets:

Graph Optimization Passes¶

Graph Optimization Passes	More Detail
`AlgebraicSimplification`	Algebraic Simplification
`CommonSubexpressionElimination`	Common Subexpression Elimination
`ConstantFolding`	Constant Folding
`CoreFusion`	Core Fusion
`ReshapeElimination`	Reshape Elimination
`ReshapeSinking`	Reshape Sinking

Node Optimization Passes¶

Node Optimization Passes	More Detail
`NopElimination`	
`ZeroDimTensorElimination`	

Memory Assignment Passes¶

Memory Assignment Passes	More Detail
`AssignLayout`	
`Liveness`	
`MemoryLayout`	
`PropagateCacheability`	

Codegen Passes¶

Important

Codegen is currently experimental only.

Codegen Passes	More Detail
`CommonFunctionCollection`	Experimental Only

Debug Passes¶

Debug Passes	More Detail
`DumpSorted`	
`MemoryVisualize`	

Debug Passes	More Detail
`Serialization`	
`VisualizeTree`	

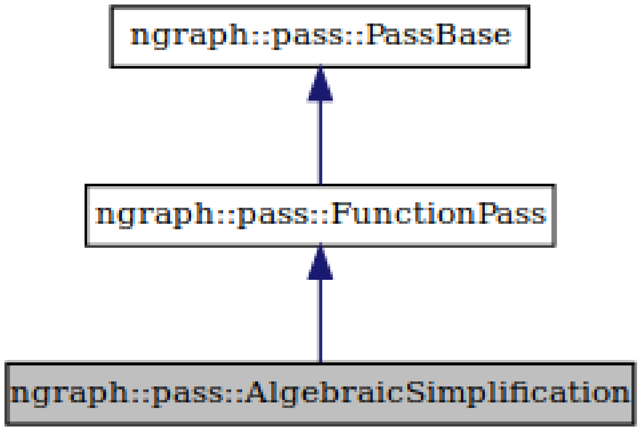
Maintenance Passes¶

Maintenance Passes	More Detail
`GetOutputElementElimination`	
`LikeReplacement`	
`ValidateGraph`	

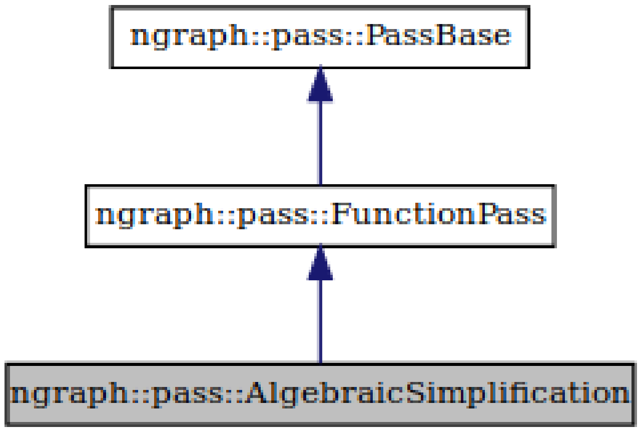
Important

All of the above passes are currently implementable; more detailed documentation for each pass may be a Work In Progress (WIP).

Algebraic Simplification¶


ngraph::pass::PassBase
ngraph::pass::FunctionPass
ngraph::pass::AlgebraicSimplification

[legend]


ngraph::pass::PassBase
ngraph::pass::FunctionPass
ngraph::pass::AlgebraicSimplification

Algebraic simplification

The **Algebraic Simplification** pass implements what amounts to a “grab bag” of algebraic simplification rules. It does some basic things like rewrite “zero times x” to simply “zero”, or “zero plus x” to plain “x”.

It can also do a number of tricks more specific to deep learning. For example, if we discover that a tensor is being sliced up by adjacent segments, only to have those slices concatenated back together again, we can skip the slicing and concatting altogether. Or, if a tensor is being padded, but the actual width of the padding is zero all around, we can skip the padding step entirely.

Several other transformations like this are implemented in the algebraic simplification pass. And while none of these transformations might seem particularly impressive on their own, when everything comes together the results of this pass often yield improvement even on the initial graph straight out of the bridge. This pass is also quite important as a “glue” pass that can be used to clean up and/or re-simplify after other passes have done their own tricks. See the example on Compiler Passes for an example of how effective this can be.

`Common Subexpression Elimination`¶

`Constant Folding`¶

`Core Fusion`¶

`Reshape Elimination`¶

The pass also called **Reshape/Transpose Elimination** will find and optimize where we can “push” two `Transpose` ops through a matrix multiplication. For example, if you have two matrices (say, *foo* and *bar*), both of these matrices will be transposed (to produce *foo.t* and *bar.t*, respectively), after which *foo.t* and *bar.t* get multiplied together.

Often a more efficient way to implement this is to switch the order of the arguments *foo* and *bar*, multiply them together, and then transpose the output of the matmul. Effectively, this cuts two Transpose operations down to just one, where the **Reshape/Transpose** elimination will do that rewrite for you.

Another common pattern that can be optimized via nGraph is the case where two transpositions cancel each other out. One example of this is taking the “Transpose” of the transpose of a matrix, though actually a more common case is when the graph is translating among different batch formats. We can often move these operations around through a process called **Reshape sinking/swimming**, and in cases where two transposes wind up canceling each other out, we can cut them both out of the graph.

`Reshape Sinking`¶

`Zero-Element Tensor Elimination`¶

Passes that use Matcher¶

- CPUFusion (GraphRewrite)

- CoreFusion (GraphRewrite)
- ReshapeElimination (GraphRewrite)
- AlgebraicSimplification
- CPUPostLayoutOptimizations (GraphRewrite)
- CPURnnMatFusion
- and many more…

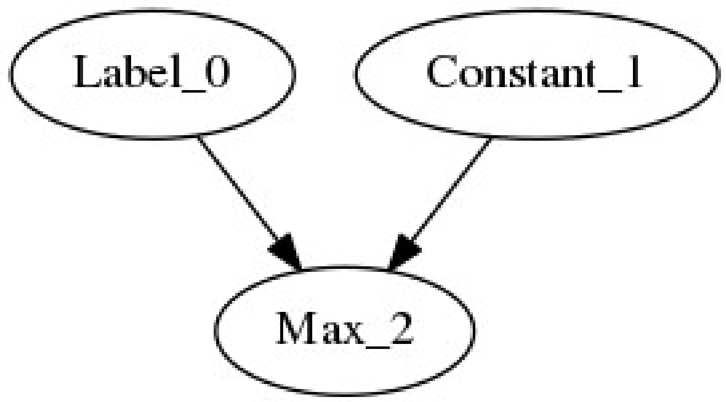
Register `simplify_neg` handler¶

```
static std::unordered_map<std::type_index,
std::function<bool(std::shared_ptr<Node>)>>
         initialize_const_values_to_ops()
     {
         return std::unordered_map<std::type_index,
std::function<bool(std::shared_ptr<Node>)>>({
             {TI(op::Add), simplify_add},
             {TI(op::Multiply), simplify_multiply},
             {TI(op::Sum), simplify_sum},
             {TI(op::Negative), simplify_neg}
         });
     }
```

Add a fusion¶

```
max(0, A) = Relu(A)
```

Pattern for capturing¶



```
max(0, A) = Relu(A)
```

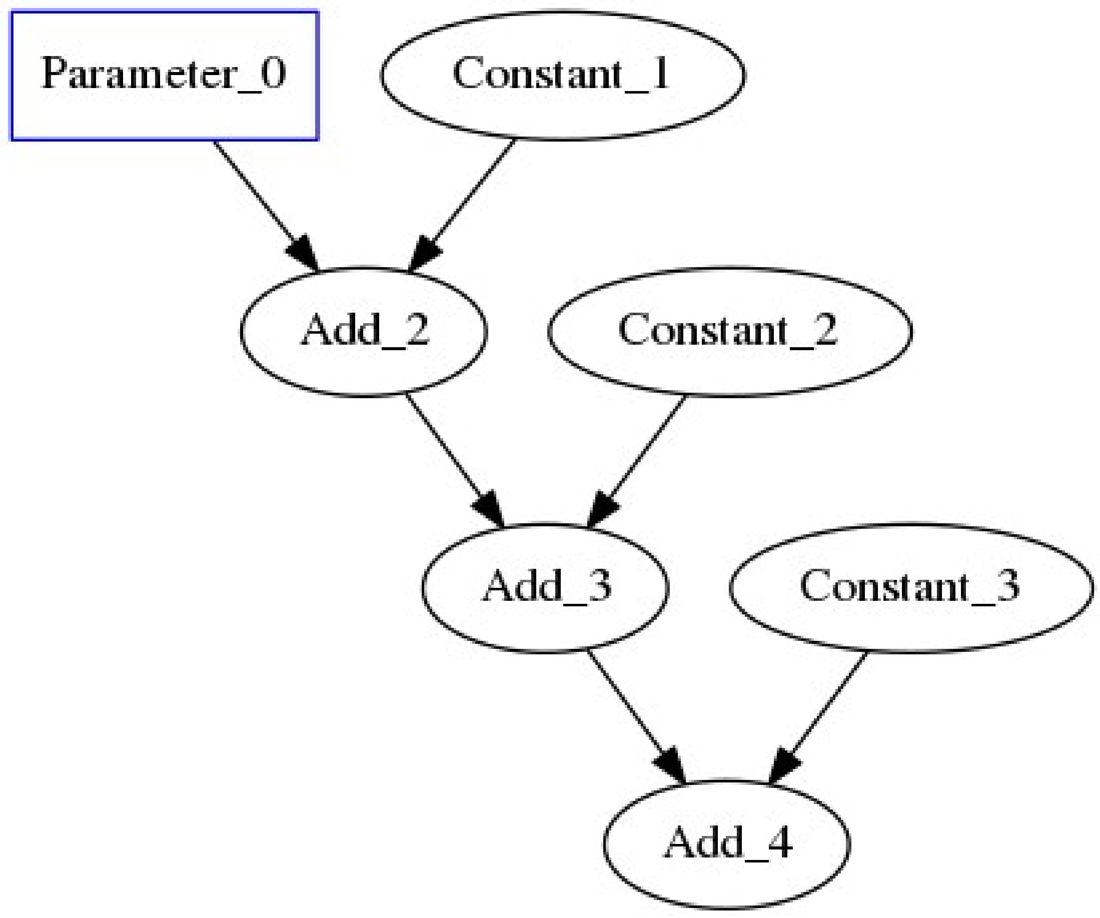
```
namespace ngraph
 {
     namespace pass
     {
         class CoreFusion;
     }
 }

 class ngraph::pass::CoreFusion : public ngraph::pass::GraphRewrite
 {
```

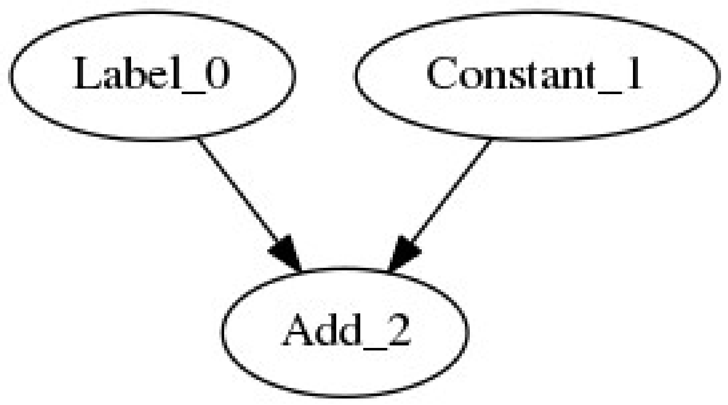
```
 public:
     CoreFusion()
         : GraphRewrite()
     {
         construct_relu_pattern();
     }

     //this should go in a cpp file.
     void construct_relu_pattern()
     {
         auto iconst0 = ngraph::make_zero(element::i32, Shape{});
         auto val = make_shared(iconst0);
         auto zero = make_shared(iconst0, nullptr, NodeVector{iconst0});

         auto broadcast_pred = [](std::shared_ptr n) {
             return static_cast(std::dynamic_pointer_cast(n));
         };
         auto skip_broadcast = std::make_shared(zero, broadcast_pred);
         auto max = make_shared(skip_broadcast, val);

     pattern::graph_rewrite_callback callback = [val, zero](pattern::Matcher&
m) {
             NGRAPH_DEBUG << "In a callback for construct_relu_pattern against
"
                          << m.get_match_root()->get_name();

             auto pattern_map = m.get_pattern_map();
             auto mzero = m.get_pattern_map()[zero];
             if (!ngraph::is_zero(mzero))
             {
                 NGRAPH_DEBUG << "zero constant = " << mzero->get_name() << "
not equal to 0n";
                 return false;
             }
             auto mpattern = m.get_match_root();

             auto cg = shared_ptr(new op::Relu(pattern_map[val]));
             ngraph::replace_node(m.get_match_root(), cg);
             return true;
         };

         auto m = make_shared(max, callback);
         this->add_matcher(m);
     }
 };
```

Recurrent patterns¶

Equivalent to "`A(BC)+A`" in regexes

```
(((A + 0) + 0) + 0) = A
```





```
Shape shape{};
 auto a = make_shared<op::Parameter>(element::i32, shape);
 auto b = make_shared<op::Parameter>(element::i32, shape);
 auto rpattern = std::make_shared<pattern::op::Label>(b);
 auto iconst0 = ngraph::make_zero(element::i32, shape);
 auto abs = make_shared<op::Abs>(a);
 auto add1 = iconst0 + b;
 auto add2 = iconst0 + add1;
 auto add3 = iconst0 + add2;
 auto padd = iconst0 + rpattern;
 std::set<std::shared_ptr<pattern::op::Label>> empty_correlated_matches;
 RecurrentMatcher rm(padd, rpattern, empty_correlated_matches, nullptr);
 ASSERT_TRUE(rm.match(add3));
```

Basic concepts¶

Generic graph optimization passes

This section discusses how to use nGraph to create a Pass Manager for your backend, and provides both a simple and a complex example to follow.

The pass manager infrastructure in nGraph makes it easy to reuse and mix the generic optimization passes. It also permits you to roll your own device-specific optimizations; that is, the same unified interface and APIs may be used to cover both things.

Invoking these passes is fairly straightforward, illustrated by the following steps and the code below.

1. Create a “pass manager” object (line 1)
2. Populate it with the desired pass or passes (lines 2-4)
3. Invoke the pass manager with a pointer to your unoptimized graph, and it will return a pointer to an optimized graph (lines 5-8)

```
1                                           pass::Manager pass_manager;
2
3                                       pass_manager.register_pass<pass::Livene
4                                       ss>();
5
6                                       pass_manager.register_pass<pass::Memory
7                                       Layout>();
8
9                                           Shape shape{1};
                                            auto c =
                                        op::Constant::create(element::i32,
                                        shape, {5});
                                            auto f =
                                        make_shared<Function>(make_shared<op::N
                                        egative>(c), ParameterVector{});

                                            pass_manager.run_passes(f);
```

nGraph Core includes a large library of hardware-agnostic passes useful for almost any kind of hardware backend. Some of these passes are likely familiar to people who are comfortable with classical compiler designs. Others, like the reshape/transpose elimination and sinking passes, are quite specific to deep learning.

A simple example¶

Here’s a fairly straightforward function graph: it has 4 ops: Convolution, Broadcast, Add, and Relu. With nGraph, backends have the ability to rewrite the graph in ways that are specific to the underlying device/hardware’s capabilities.

When, for example, the device is an Intel® Architecture IA CPU, it can support a fused

`ConvolutionBiasReLU` kernel. The backend is able to rewrite the graph into its own custom ops that more closely match the hardware-specific primitives; here they get matched via Intel® MKL-DNN.

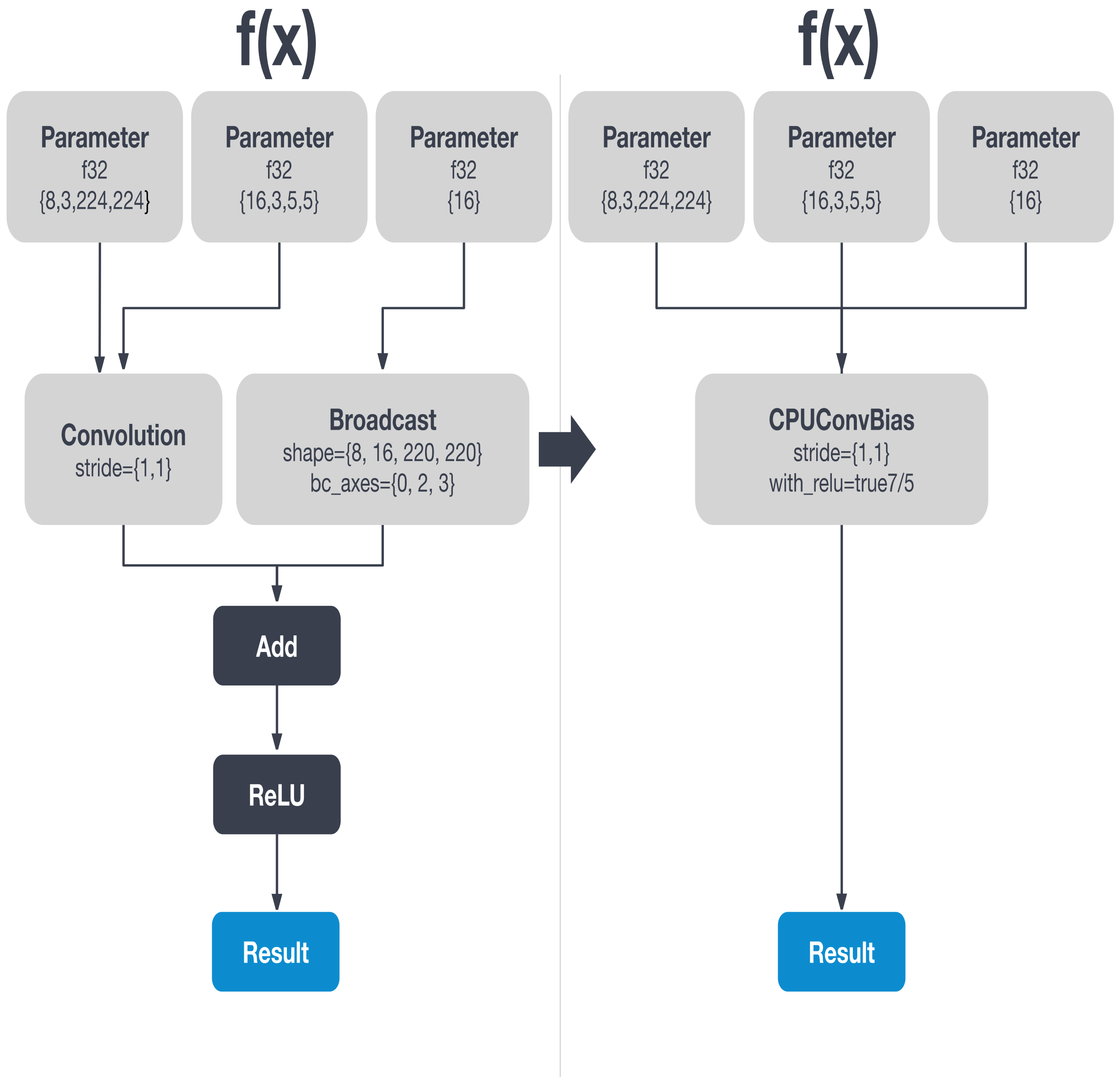

f(x)
Parameter f32 {8,3,224,224}
Parameter f32 {16,3,5,5}
Parameter f32 {16}
Convolution stride={1,1}
Broadcast shape={8, 16, 220, 220} bc_axes={0, 2, 3}
Add
ReLU
Result
f(x)
Parameter f32 {8,3,224,224}
Parameter f32 {16,3,5,5}
Parameter f32 {16}
CPUConvBias stride={1,1} with_relu=true7/5
Result

Figure A: On the left side of *Figure A* is a fully-formed function graph prior to fusion. After graph rewrite, the CPU implements a number of custom fusions.

A complex example¶

The effectiveness of graph-level optimization with nGraph is more striking to look at in terms of an actual input graph, such as one from the framework bridge. Here is slightly more complicated example drawn from a topology called MobileNet which makes heavy use of group convolution.

In group convolution, sometimes called depthwise convolution, a batch's different feature channels get divided into groups that are processed independently, rather than every convolution kernel seeing all of the input feature channels.

With "Group Convolution Fusion", it is possible to optimize a subgraph that has implemented group convolution by many instances of "ordinary" convolution.

Figure B shows an excerpt from `MobileNet v1`, a topology which makes heavy use of group convolution. Here, an image batch and a filter batch first undergo a "preprocessing" phase where segments along the channel axis are sliced out: one per channel group. Next, there are separate convolutions on each channel group before finally concatenating the result back together.

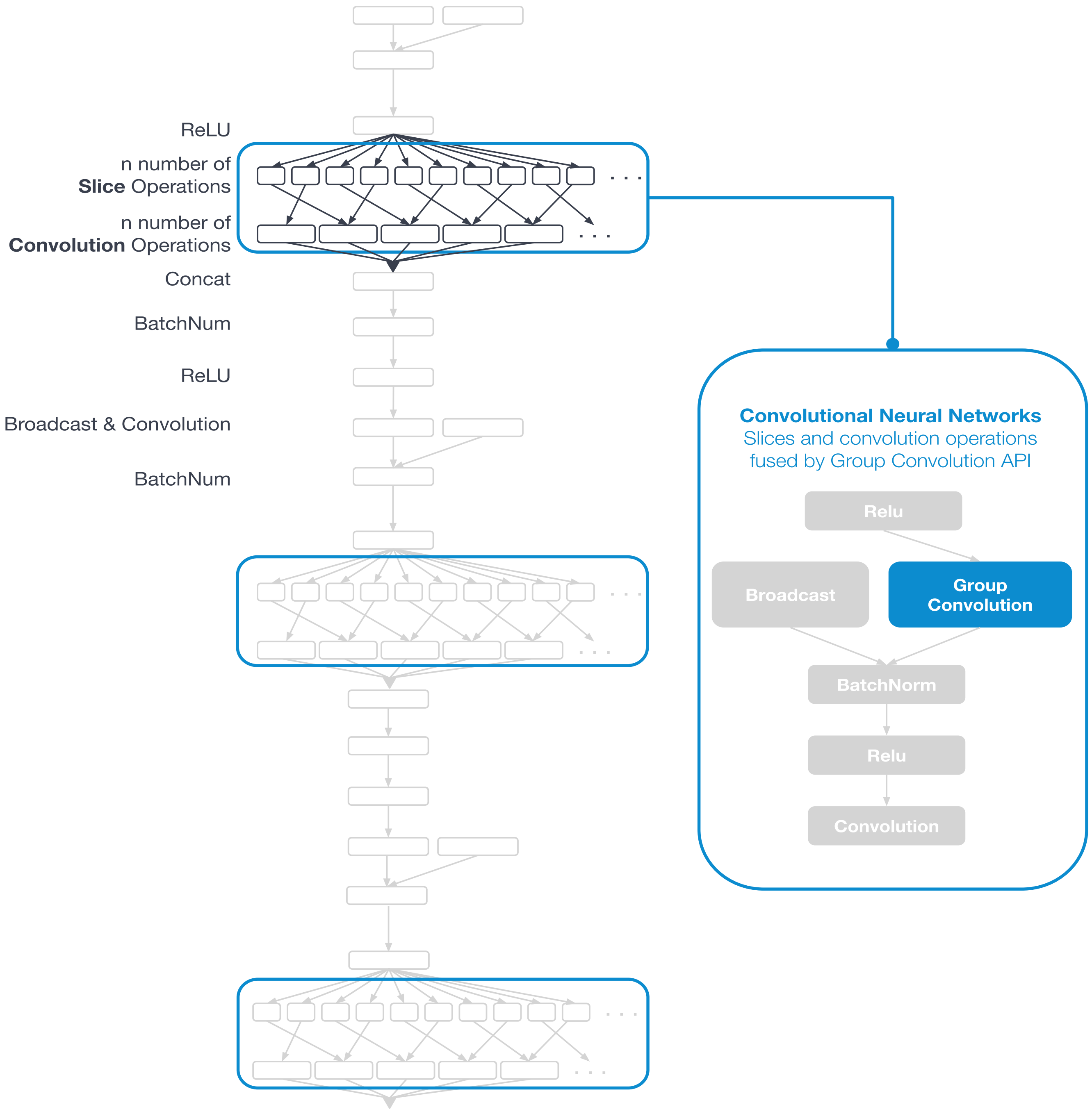


Figure B: Each of these grouped convolution complexes – the operations within the rectangles on the left – is very wide; each is too wide to fit legibly on the illustration.

The group convolution fusion is able to replace each of those giant subgraphs with a single CPU group convolution node. This ends up being beneficial in several ways:

- Reduces sheer node count,

- Provides mappability to MKL-DNN, which has an accelerated group convolution implementation, and
- Eliminates unnecessary temporary nodes.

Pattern Matcher¶

Overview: Optimize graphs with nGraph Compiler fusions¶

The nGraph Compiler is an optimizing compiler. As such, it provides a way to capture a given function graph and perform a series of optimization passes over that graph. The result is a semantically-equivalent graph that, when executed using any backend, has hardware-agnostic *and* hardware-specific optimizations, providing superior runtime characteristics to increase training performance or reduce inference latency.

There are several ways to describe what happens when we capture and translate the framework's output of ops into an nGraph graph. Fusion is the term we shall use in our documentation; the action also can be described as: *combining*, *folding*, *squashing*, *collapsing*, or *merging* of graph functions.

Optimization passes may include algebraic simplifications, domain-specific simplifications, and fusion. Most passes share the same mode of operation (or the same operational structure) and consist of various stages (each one a step) where a developer can experiment with the intercepted or dynamic graph. These steps may be cycled or recycled as needed:

1. Locate a list of potentially-transformable subgraphs in the given graph.
2. Transform the selected candidates into semantically-equivalent subgraphs that execute faster, or with less memory (or both).
3. Verify that the optimization pass performs correctly, with any or all expected transformations, with the `NGRAPH_SERIALIZE_TRACING` option, which serializes a graph in the json format after a pass.
4. Measure and evaluate your performance improvements with `NGRAPH_CPU_TRACING`, which produces timelines compatible with `chrome://tracing`.

Optimizations can be experimented upon without using any backend by registering a pass with pass manager (`Manager`), calling `run_passes` on a function, and then inspecting the transformed graph.

Optimization passes can be programmed ahead of time if you know or can predict what your graph will look like when it's ready to be executed (in other words: which ops can be automatically translated into nGraph Core ops).

The `Interpreter` is simply a backend providing reference implementations of ngraph ops in C++, with the focus on simplicity over performance.

Example¶

Let us first consider a simple example. A user would like to execute a graph that describes the following arithmetic expression:

\(a + b * 1\) or \(Add(a, Mul(b, 1))\)

In the above expressions, 1 is an identity element; any element multiplied by the identity element is equal to itself. This is the same as saying:

\(b * 1 = b\)

The writer of an optimization pass which uses algebraic simplification would probably want to first `locate` all multiplication expressions where multiplicands are multiplied by 1 (for stage 1) and to then `transform`, `simplify`, or `replace` those expressions with just their multiplicands (for stage 2).

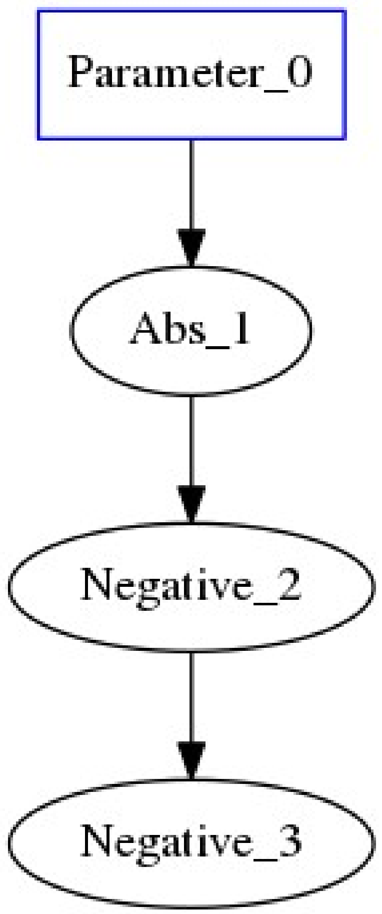
To make the work of an optimization pass writer easier, the nGraph Library includes facilities that enable the *finding* of relevant candidates using pattern matching (via `pattern/matcher.hpp`), and the *transforming* of the original graph into a condensed version (via `pass/graph_rewrite.hpp`).

Using `GraphRewrite` to fuse ops¶

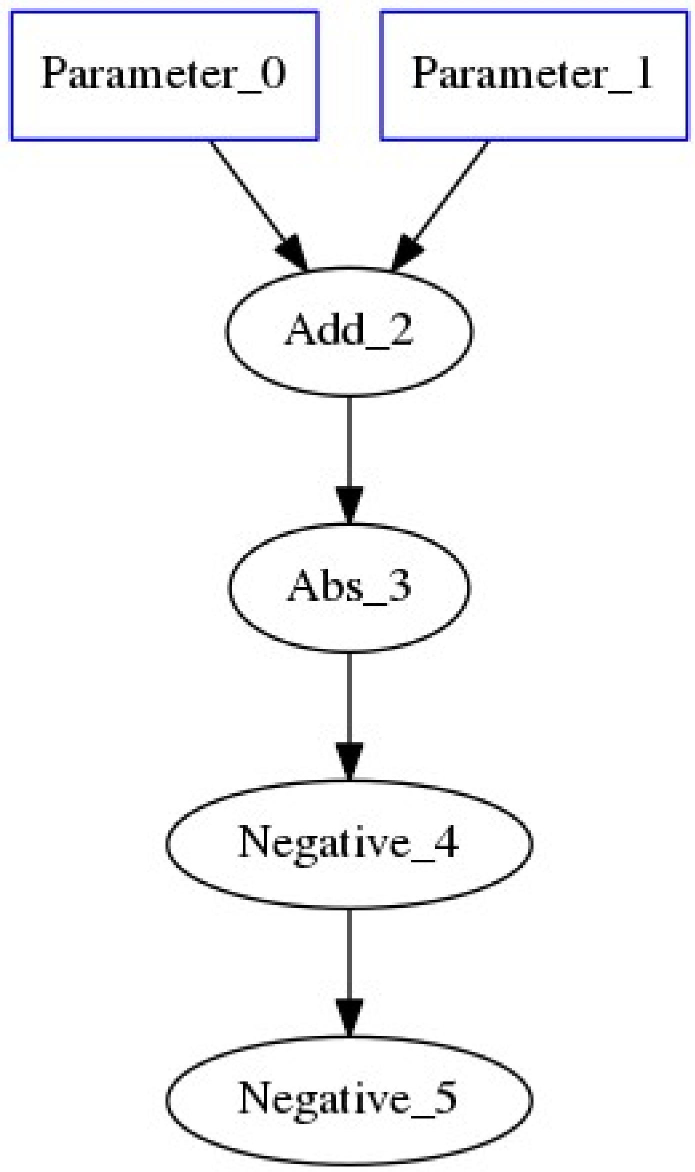
- Exact pattern matching
- Constructing labels from existing nodes

Exact pattern matching¶

For the example of `-(-A) = A`, various graphs of varying complexity can be created and overwritten with recipes for pattern-matching + graph-rewrite. To get started, a simple example for a trivial graph, followed by more complex examples:

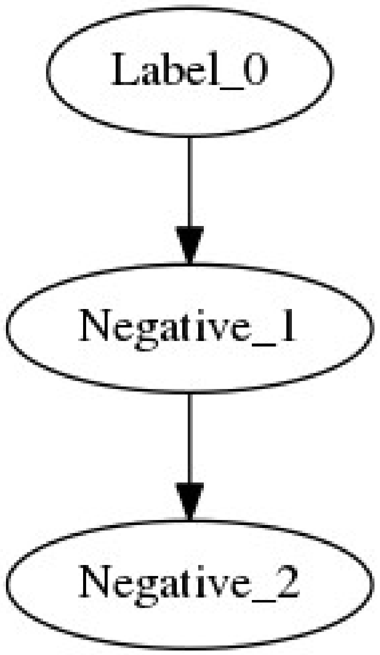


```
auto a = make_shared<op::Parameter>(element::i32, shape);
auto absn = make_shared<op::Abs>(a);
auto neg1 = make_shared<op::Negative>(absn);
auto neg2 = make_shared<op::Negative>(neg1);
```



```
auto a = make_shared<op::Parameter>(element::i32, shape);
auto b = make_shared<op::Parameter>(element::i32, shape);
auto c = a + b;
auto absn = make_shared<op::Abs>(c);
auto neg1 = make_shared<op::Negative>(absn);
auto neg2 = make_shared<op::Negative>(neg1);
```

Label AKA `.` in regexes¶

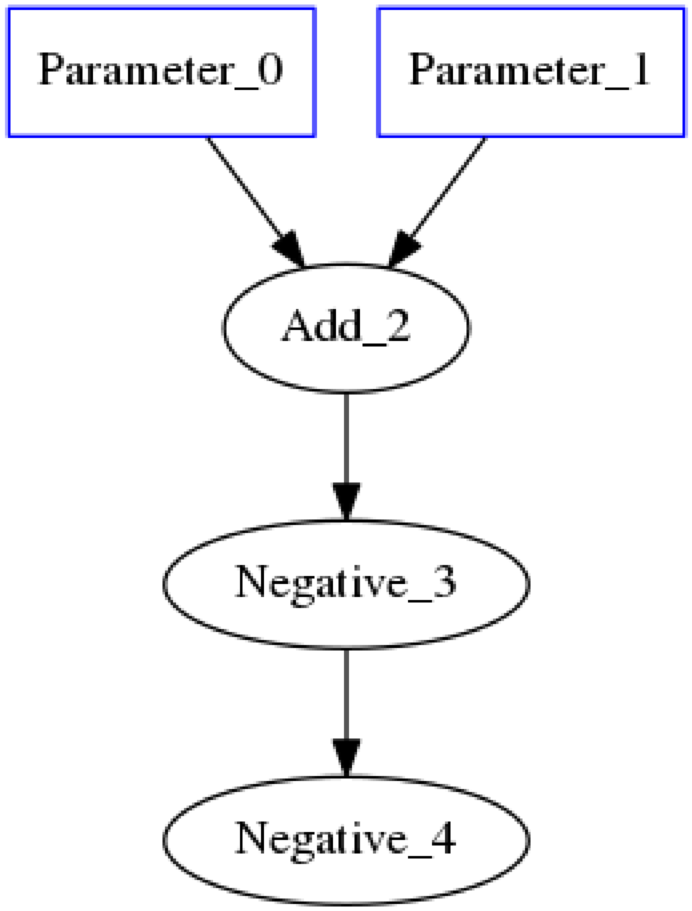


For the code below, `element::f32` will still match integer Graph1 and Graph2

```
//note element::f32, will still match integer Graph1 and Graph2
auto lbl = std::make_shared<pattern::op::Label>(element::f32, Shape{});
auto neg1 = make_shared<op::Negative>(lbl);
auto neg2 = make_shared<op::Negative>(neg1);
```

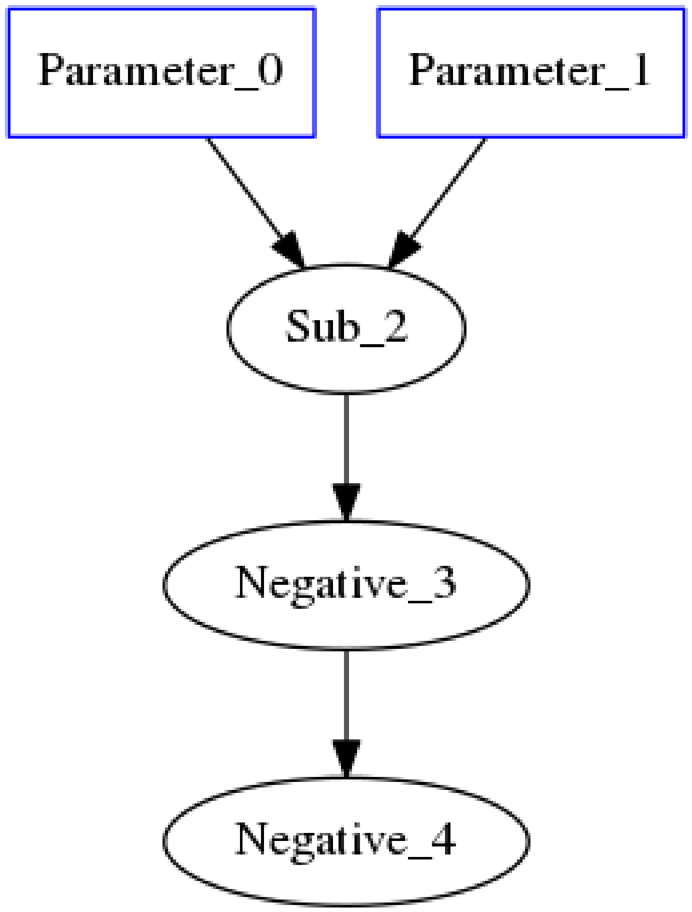
Constructing labels from existing nodes¶

Double Negative w/ Addition¶



```
auto a = make_shared<op::Parameter>(element::i32, shape);
//`lbl` borrows the type and shape information from `a`
auto lbl = std::make_shared<pattern::op::Label>(a);
auto neg1 = make_shared<op::Negative>(a);
auto neg2 = make_shared<op::Negative>(neg1);
```

Double Negative w/ Subtraction¶



Predicates are of type `std::function<bool(std::shared_ptr<Node>)>`

```
//predicates are of type std::function<bool(std::shared_ptr<Node>)>
auto add_or_sub = [](std::shared_ptr<Node> n) {
    return std::dynamic_pointer_cast<op::Add>(n) != nullptr ||
        std::dynamic_pointer_cast<op::Sub>(n) != nullptr
};

auto lbl = std::make_shared<pattern::op::Label>(
    element::f32,
    Shape{},
    add_or_sub
);
auto neg1 = make_shared<op::Negative>(a);
auto neg2 = make_shared<op::Negative>(neg1);
```

The nGraph Compiler is an optimizing compiler. As such, it provides a way to capture a given function graph and perform a series of optimization passes over that graph. The result is a semantically-equivalent graph that, when executed using any backend, has optimizations inherent at the hardware level: superior runtime characteristics to increase training performance or reduce inference latency.

class `Matcher`¶

Matcher looks for node patterns in a computation graph. The patterns are described by an automaton that is described by an extended computation graph. The matcher executes by attempting to match the start node of the pattern to a computation graph value (output of a Node). In addition to determing if a match occurs, a pattern node may add graph nodes to a list of matched nodes, associate nodes with graph values, and start submatches. Submatches add match state changes to the enclosing match if the submatch succeeds; otherwise the state is reverted.
The default match behavior of a pattern node with a graph nodes is that the computation graph value is added to the end of the matched value list and the match succeeds if the node/pattern types match and the input values match. In the case of a commutative node, the inputs can match in any order. If the matcher is in strict mode, the graph value element type and shape must also match.
Pattern nodes that have different match behavior are in ngraph::pattern::op and have descriptions of their match behavior.

Public Functions

`Matcher`(*const* Output<Node> &*pattern_node*, *const* std::string &*name*, bool *strict_mode*)¶

Constructs a Matcher object.

Parameters

- `pattern_node`: is a pattern sub graph that will be matched against input graphs
- `name`: is a string which is used for logging and disabling a matcher
- `strict_mode`: forces a matcher to consider shapes and ET of nodes

bool `match`(*const* Output<Node> &*graph_value*)¶

Matches a pattern to `graph_node`.

Parameters

- `graph_value`: is an input graph to be matched against

bool `match`(*const* Output<Node> &*graph_value*, *const* PatternMap &*previous_matches*)¶

Matches a pattern to `graph_node`.

Parameters

- `graph_value`: is an input graph to be matched against
- `previous_matches`: contains previous mappings from labels to nodes to use

size_t `add_node`(Output<Node> *node*)¶

Low-level helper to match recurring patterns.

Parameters

- `graph`: is a graph to be matched against
- `pattern`: is a recurring pattern
- `rpattern`: specifies a node to recur from next
- `patterns`: a map from labels to matches

MatcherState `start_match()`¶

Try a match.

Fusion¶

There are several ways to describe what happens when we capture and translate the framework's output of ops into an nGraph graph. Fusion is the term we shall use in our documentation; the action also can be described as: *combining*, *folding*, *squashing*, *collapsing*, or *merging* of graph functions.

Optimization passes may include algebraic simplifications, domain-specific simplifications, and fusion. Most passes share the same mode of operation (or the same operational structure) and consist of various stages (each one a step) where a developer can experiment with the intercepted or dynamic graph. These steps may be cycled or recycled as needed:

1. Locate a list of potentially-transformable subgraphs in the given graph.
2. Transform the selected candidates into semantically-equivalent subgraphs that execute faster, or with less memory (or both).
3. Verify that the optimization pass performs correctly, with any or all expected transformations, with the `NGRAPH_SERIALIZE_TRACING` option, which serializes a graph in the json format after a pass.
4. Measure and evaluate your performance improvements with `NGRAPH_CPU_TRACING`, which produces timelines compatible with `chrome://tracing`.

Optimizations can be experimented upon without using any backend by registering a pass with pass manager (`Manager`), calling `run_passes` on a function, and then inspecting the transformed graph.

Optimization passes can be programmed ahead of time if you know or can predict what your graph will look like when it's ready to be executed (in other words: which ops can be automatically translated into nGraph Core ops).

The `Interpreter` is simply a backend providing reference implementations of ngraph ops in C++, with the focus on simplicity over performance.

Example¶

Let us first consider a simple example. A user would like to execute a graph that describes the following arithmetic expression:

\(a + b * 1\) or \(Add(a, Mul(b, 1))\)

In the above expressions, 1 is an identity element; any element multiplied by the identity element is equal to itself. In other words, the original expression \(a + b * 1\) is exactly equivalent to the expression \(a + b\), so we can eliminate this extra multiplication step.

The writer of an optimization pass which uses algebraic simplification would probably want to first `locate` all multiplication expressions where multiplicands are multiplied by 1 (for stage 1) and to then `replace`, those expressions with just their multiplicands (for stage 2).

To make the work of an optimization pass writer easier, the nGraph Library includes facilities that enable the *finding* of relevant candidates using pattern matching (via `pattern/matcher.hpp`), and the *transforming* of the original graph into an optimized version (via `pass/graph_rewrite.hpp`).

List of Core ops¶

Some operations are experimental.

More about Core Ops

- Abs
- Acos
- Add
- All
- AllReduce
- And
- Any
- Asin
- Atan
- AvgPool
- AvgPoolBackprop
- BatchNormInference
- BatchNormTraining
- BatchNormTrainingBackprop
- Broadcast
- BroadcastDistributed
- Ceiling
- Concat
- Constant
- Convert
- Convolution
- Cos
- Cosh
- Dequantize
- Divide
- Dot
- DropOut
- Equal
- Exp
- Floor
- GetOutputElement
- GreaterEq
- Greater
- LessEq
- Less
- Log
- Max
- Maximum
- MaxPool
- Min
- Minimum
- Multiply
- Negative
- NotEqual
- Not
- OneHot
- Or
- Pad
- Parameter
- Power
- Product
- Quantize
- RandomUniform
- Relu
- Result
- ShapeOf
- Sigmoid
- Sign
- Sin
- Sinh
- Slice
- Softmax
- Sqrt
- Subtract
- Tan
- Tanh
- Transpose
- Xor

Abs¶

```
Abs  // Elementwise absolute value operation
```

Description¶

Produces a single output tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the absolute value of the value at each `arg` coordinate.

Inputs¶

Name	**Element Type**	**Shape**
`arg`	Any	Any

Outputs¶

Name	**Element Type**	**Shape**
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \left|\mathtt{arg}_{i_0, \ldots, i_{n-1}}\right|\]

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow \Delta\ \mathrm{sgn}(\mathtt{arg})\]

C++ Interface¶

class `Abs` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise absolute value operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Abs`()¶

Constructs an absolute value operation.

`Abs`(*const* Output<Node> &*arg*)¶

Constructs an absolute value operation.

Output `[d1, ...]`

Parameters

- `arg`: Output that produces the input tensor.`[d1, ...]`

Acos¶

```
Acos  // Elementwise acos operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the inverse cosine of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \cos^{-1}(\mathtt{arg}_{i_0, \ldots, i_{n-1}})\]

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow -\frac{\Delta}{\sqrt{1-\mathtt{arg}^2}}\]

C++ Interface¶

class `Acos` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise inverse cosine (arccos) operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Acos`()¶

Constructs an arccos operation.

`Acos`(*const* Output<Node> &*arg*)¶

Constructs an arccos operation.
Output `[d1, ...]`

Parameters

- `arg`: Output that produces the input tensor.`[d1, ...]`

Add¶

```
Add  // Elementwise add operation
```

Description¶

Elementwise add operation.

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is the sum of the values at the corresponding input coordinates.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	same as `arg0`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} + \mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

Backprop¶

\[\begin{split}\overline{\mathtt{arg0}} &\leftarrow \Delta \\ \overline{\mathtt{arg1}} &\leftarrow \Delta\end{split}\]

C++ Interface¶

class `Add` : *public* ngraph::op::util::BinaryElementwiseArithmetic¶

Elementwise addition operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Add`()¶

Constructs an uninitialized addition operation.

`Add`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs an addition operation.
Output `[d0, ...]`

Parameters

- `arg0`: Output that produces the first input tensor.`[d0, ...]`
- `arg1`: Output that produces the second input tensor.`[d0, ...]`
- `auto_broadcast`: Auto broadcast specification

All¶

`All // Boolean "all" reduction operation.`

Description¶

Reduces a tensor of booleans, eliminating the specified reduction axes by taking the logical conjunction (i.e., “AND-reduce”).

Inputs¶

Name	Element Type	Shape
`arg`	`ngraph::element::boolean`	Any

Attributes¶

Name	Description
`reduction_axes`	The axis positions (0-based) on which to calculate the conjunction

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`, with `reduction_axes` removed.

C++ Interface¶

class `All` : *public* ngraph::op::util::LogicalReduction¶

Logical “all” reduction operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`All`()¶

Constructs an “all” reduction operation.

`All`(*const* Output<Node> &*arg*, *const* AxisSet &*reduction_axes*)¶

Constructs an “all” reduction operation.

Parameters

- `arg`: The tensor to be reduced.
- `reduction_axes`: The axis positions (0-based) to be eliminated.

`All`(*const* Output<Node> &*arg*, *const* Output<Node> &*reduction_axes*)¶

Constructs an “all” reduction operation.

Parameters

- `arg`: The tensor to be reduced.
- `reduction_axes`: The axis positions (0-based) to be eliminated.

virtual std::shared_ptr<Node> `get_default_value`() *const*¶

Return

The default value for All.

AllReduce¶

```
AllReduce // Collective operation
```

Description¶

Combines values from all processes or devices and distributes the result back to all processes or devices.

Inputs¶

Name	Element Type	Shape
`arg`	`element::f32` `element::f64`	Any

Outputs¶

Name	Element Type	Shape
`output`	`element::f32` `element::f64`	Same as `arg`

C++ Interface¶

class `AllReduce` : *public* ngraph::op::Op¶

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

And¶

```
And  // Elementwise logical-and operation
```

Description¶

Produces tensor with boolean element type and shape as the two inputs, which must themselves have boolean element type, where the value at each coordinate of `output` is `1` (true) if `arg0` and `arg1` are both nonzero, `0` otherwise.

Inputs¶

Name	Element Type	Shape
`arg0`	`ngraph::element::boolean`	any
`arg1`	`ngraph::element::boolean`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}}\, \mathtt{\&\&}\, \mathtt{arg1}_{i_0, \ldots, i_{n-1}}$$

C++ Interface¶

class `And` : *public* ngraph::op::util::BinaryElementwiseLogical¶

Elementwise logical-and operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`And`()¶

Constructs a logical-and operation.

`And`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a logical-and operation.
Output `[d0, ...]`

Parameters

- `arg0`: Output that produces the first input tensor.`[d0, ...]`
- `arg1`: Output that produces the second input tensor.`[d0, ...]`
- `auto_broadcast`: Auto broadcast specification

Any¶

`Any // Boolean "any" reduction operation.`

Description¶

Reduces a tensor of booleans, eliminating the specified reduction axes by taking the logical disjunction (i.e., “OR-reduce”).

Inputs¶

Name	Element Type	Shape
`arg`	`ngraph::element::boolean`	Any

Attributes¶

Name	Description
`reduction_axes`	The axis positions (0-based) on which to calculate the disjunction

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`, with `reduction_axes` removed.

C++ Interface¶

class `Any` : *public* ngraph::op::util::LogicalReduction¶

Logical “any” reduction operation.
Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a

dummy type_info for Node if the class has not been updated yet.

`Any()`¶

Constructs an “any” reduction operation.

`Any`(*const* Output<Node> &*arg*, *const* AxisSet &*reduction_axes*)¶

Constructs an “any” reduction operation.

Parameters

- `arg`: The tensor to be reduced.
- `reduction_axes`: The axis positions (0-based) to be eliminated.

`Any`(*const* Output<Node> &*arg*, *const* Output<Node> &*reduction_axes*)¶

Constructs an “any” reduction operation.

Parameters

- `arg`: The tensor to be reduced.
- `reduction_axes`: The axis positions (0-based) to be eliminated.

shared_ptr<Node> `get_default_value`() *const*¶

Return

The default value for Any.

Asin¶

```
Asin  // Elementwise asin operation
```

Description¶

Produces a tensor of the same element type and shape as `arg`, where the value at each coordinate of `output` is the inverse sine of the value at the corresponding coordinate of `arg`.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`.

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \sin^{-1}(\mathtt{arg}_{i_0, \ldots, i_{n-1}})$$

Backprop¶

$$\overline{\mathtt{arg}} \leftarrow \frac{\Delta}{\sqrt{1-\mathtt{arg}^2}}$$

C++ Interface¶

class `Asin` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise inverse sine (arcsin) operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Asin`()¶

Constructs an arcsin operation.

`Asin`(*const* Output<Node> &*arg*)¶

Constructs an arcsin operation.
Output `[d1, ...]`

Parameters

- `arg`: Output that produces the input tensor.`[d1, ...]`

Atan¶

```
Atan // Elementwise atan operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the inverse tangent of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	**Element Type**	**Shape**
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \tan^{-1}(\mathtt{arg}_{i_0, \ldots, i_{n-1}})$$

Backprop¶

$$\overline{\mathtt{arg}} \leftarrow \frac{\Delta}{1+\mathtt{arg}^2}$$

C++ Interface¶

class `Atan` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise inverse tangent (arctan) operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Atan`()¶

Constructs an arctan operation.

`Atan`(*const* Output<Node> &*arg*)¶

Constructs an arctan operation.

Output `[d1, ...]`

Parameters

- `arg`: Output that produces the input tensor.`[d1, ...]`

AvgPool¶

```
AvgPool  // Average Pooling operation
```

Description¶

Average pooling windows its input and produces an average for each window.

Inputs¶

Name	Element Type	Shape	Notes
`data`	Any	$(N,C,d_1,\ldots,d_n)$	$n>0, d_i>0$

Attributes¶

Name	Type	Notes
`w`	`Shape[n]`	Window shape. $w_i\le d_i$
`s`	`Strides[n]`	Window strides.
`p`	`Shape[n]`	Padding below.
`q`	`Shape[n]`	Padding above.
`i`	`Boolean`	Include padding in average.

Outputs¶

Name	Element Type	Shape
`output`	Any	$(N,C,d'_1,\ldots,d'_n)$

Average pooling takes as its input, a batch tensor data of shape $(N,C,d_1,\ldots,d_n)$, where where N is the batch size, and $C > 0$ is the number of channels (sometimes called features). The dimensions $(d_1,\ldots,d_n)$ correspond to the shape of an n-dimensional data item in a batch. For example, where $n=2$, the data may represent a two-dimensional image. It also takes four attributes:

1. *window shape*,
2. *window movement strides*, (optional)
3. *padding below*, (optional)
4. *padding above*, (optional)
5. *include padding in average*

The shape of output is $(N,C,d'_1,\ldots,d'_n)$, where $d'_n = \lceil \frac{p_i + d_i + q_i - w_i + 1}{s_i} \rceil$.

Informal definition: If $\textit{i}$ is $\textit{true}$, then averages are computed as though the padding region contained regular elements of value zero. If $\textit{i}$ is $\textit{false}$, then averages are computed using only the non-padding tensor elements that are present in each window.

Example: Consider two instances of this operator with the following attributes: $\textit{w} = (2,2)$, $\textit{s} = (1,1)$, $\textit{p} = (1,1)$, and (in one instance) $\textit{i} = false$ or (in the other instance) $\textit{i} = true$.

Consider how those two operator instances would handle this input tensor:

$$\begin{split}T_\textit{in} = \begin{bmatrix} 1 & 3 & 5 & \ldots \\ 7 & 11 & 13 & \ldots \\ 17 & 19 & 23 & \ldots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}\end{split}$$

Applying the padding indicated by the value of $\textit{p}$, we have the padded image of $T_\textit{in}$ as follows:

$$\begin{split}T_\textit{in,padded} = \begin{bmatrix} (0) & (0) & (0) & (0) & \ldots \\ (0) & 1 & 3 & 5 & \ldots \\ (0) & 7 & 11 & 13 & \ldots \\ (0) & 17 & 19 & 23 & \ldots \\ (0) & \vdots & \vdots & \vdots & \ddots \end{bmatrix}\end{split}$$

Now consider how the two variations of this example's *AvgPool* operator will compute the "average" value of the top-left window, which contains exactly the elements:

\[\begin{split}\begin{bmatrix} (0) & (0) \\ (0) & 1 \end{bmatrix}\end{split}\]

If \(\textit{i} = false\), then the operator simply ignores the padding elements. It therefore computes the average of the single-element set \(\{ 1 \}\), yielding \(1.0\).

If \(\textit{i} = true\), then the operator computes the average of the set \(\{ 0, 0, 0, 1\}\), yielding 0.25.

Note: This operator is ill-defined when *both* of the following conditions hold: (1) \(\textit{i} = false\), and (2) the operator's other attribute values indicate that at least one window will contain only padding elements.

Formal definition: *In the absence of padding*, given an input data batch tensor \(T_\textit{in}\), the output tensor is defined by the equation

\[T_\textit{out}[a,c,i_1,\ldots,i_n] = \frac{\sum_{j_1 = s_1 i_1, \ldots, j_n = s_n i_n}^{j_1 = s_1 i_1 + w_1 - 1, \ldots, j_n = s_n i_n + w_n - 1} T_\textit{in}[a,c,j_1,\ldots,j_n]}{\prod_{i=1}^n{w_n}}\]

In the presence of padding, we do not always want to divide by a reciprocal equal to the number of elements in the window, since some of the output points are determined by a window that is partly hanging beyond the edge of the tensor. In this case we can define the output

In this case we can define the output via a few intermediate steps.

First define the *sum tensor* \(T_\textit{sum}\), with shape \((N,C,d'_1,\ldots,d'_n)\), as follows.

\[T_\textit{sum}[a,c,i_1,\ldots,i_n] = \frac{\sum_{j_1 = s_1 i_1, \ldots, j_n = s_n i_n}^{j_1 = s_1 i_1 + w_1 - 1, \ldots, j_n = s_n i_n + w_n - 1} \textit{val}[a,c,j_1,\ldots,j_n]}{\prod_{i=1}^n{w_n}}\]

where

\[\begin{split}\textit{val}[a,c,j_1,\ldots,j_n] = \begin{cases} T_\textit{in}[a,c,j_1,\ldots,j_n]&\text{if for all } k, p_k \le j_k < p_k + d_k\\ 0&\text{otherwise}. \end{cases}\end{split}\]

Second, define the *divisor tensor* \(T_\textit{div}\), with shape \((N,C,d'_1,\ldots,d'_n)\), as follows.

\[T_\textit{div}[a,c,i_1,\ldots,i_n] = \frac{\sum_{j_1 = s_1 i_1, \ldots, j_n = s_n i_n}^{j_1 = s_1 i_1 + w_1 - 1, \ldots, j_n = s_n i_n + w_n - 1} \textit{val}[a,c,j_1,\ldots,j_n]}{\prod_{i=1}^n{w_n}}\]

where

\[\begin{split}\textit{val}[a,c,j_1,\ldots,j_n] = \begin{cases} 1&\text{if for all }k, p_k \le j_k < p_k + d_k\\ 0&\text{otherwise}. \end{cases}\end{split}\]

Finally, define \(T_\textit{out}\) as the result of elementwise dividing \(T_\textit{sum}\) by \(T_\textit{div}\). Note that at positions where \(T_\textit{div}\) is zero, values may be infinity or nan. (This corresponds to a condition where the pooling window is completely out of bounds, encompassing no valid values.)

Backprop¶

C++ Interface¶

class `AvgPool` : *public* ngraph::op::Op¶

Batched average pooling operation, with optional padding and window stride.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`AvgPool`()¶

Constructs a batched average pooling operation.

`AvgPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*, *const* Strides &*window_movement_strides*, *const* Shape &*padding_below*, *const* Shape &*padding_above*, bool *include_padding_in_avg_computation*, *const* PadType &*pad_type*, bool *ceil_mode*)¶

Constructs a batched average pooling operation.

Parameters

- `arg`: The output producing the input data batch tensor.`[d1, dn]`
- `window_shape`: The window shape.`[n]`
- `window_movement_strides`: The window movement strides.`[n]`
- `padding_below`: The below-padding shape.`[n]`
- `padding_above`: The above-padding shape.`[n]`
- `include_padding_in_avg_computation`: If true then averages include padding elements, each treated as the number zero. If false, padding elements are entirely ignored when computing averages.
- `pad_type`: Padding type to use for additional padded dimensions
- `ceil_mode`: Whether to use ceiling while computing output shape.

`AvgPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*, *const* Strides &*window_movement_strides*, *const* Shape &*padding_below*, *const* Shape &*padding_above*, bool *include_padding_in_avg_computation*, *const* PadType &*pad_type*)¶

Constructs a batched average pooling operation.

Parameters

- `arg`: The output producing the input data batch tensor.`[d1, dn]`
- `window_shape`: The window shape.`[n]`
- `window_movement_strides`: The window movement strides.`[n]`
- `padding_below`: The below-padding shape.`[n]`
- `padding_above`: The above-padding shape.`[n]`
- `include_padding_in_avg_computation`: If true then averages include padding elements, each treated as the number zero. If false, padding elements are entirely ignored when computing averages.
- `pad_type`: Padding type to use for additional padded dimensions

`AvgPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*, *const* Strides &*window_movement_strides*, *const* Shape &*padding_below*, *const* Shape &*padding_above*, bool *include_padding_in_avg_computation* = false)¶

Constructs a batched average pooling operation.

Parameters

- `arg`: The output producing the input data batch tensor.`[d1, dn]`
- `window_shape`: The window shape.`[n]`
- `window_movement_strides`: The window movement strides.`[n]`
- `padding_below`: The below-padding shape.`[n]`
- `padding_above`: The above-padding shape.`[n]`
- `include_padding_in_avg_computation`: If true then averages include padding elements, each treated as the number zero. If false, padding elements are entirely ignored when computing averages.

`AvgPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*, *const* Strides &*window_movement_strides*)¶

Constructs a batched, unpadded average pooling operation (i.e., all padding shapes are set to 0).

Parameters

- `arg`: The output producing the input data batch tensor.`[d1, ..., dn]`
- `window_shape`: The window shape.`[n]`
- `window_movement_strides`: The window movement strides.`[n]`

`AvgPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*)¶

Constructs an unstrided batched convolution operation (i.e., all window movement strides are 1 and all padding shapes are set to 0).

Parameters

- `arg`: The output producing the input data batch tensor.`[d1, ..., dn]`
- `window_shape`: The window shape.`[n]`

void `validate_and_infer_types`()¶

Throws if the node is invalid.

const Shape &`get_window_shape`() *const*¶

Return

The window shape.

const Strides &`get_window_movement_strides`() *const*¶

Return

The window movement strides.

const Shape &`get_padding_below`() *const*¶

Return

The below-padding shape.

const Shape &`get_padding_above`() *const*¶

Return

The above-padding shape.

const op::PadType &`get_pad_type`() *const*¶

Return

The pad type for pooling.

shared_ptr<Node> `get_default_value`() *const*¶

Return

The default value for AvgPool.

AvgPoolBackprop¶

```
AvgPoolBackprop // Average Pooling backprop operation.
```

Description¶

C++ Interface¶

class `AvgPoolBackprop` : *public* ngraph::op::Op¶

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

> Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

void `validate_and_infer_types`()¶

> Throws if the node is invalid.

Python Interface¶

BatchNormInference¶

```
BatchNormInference  // Adjust input for mean and variance
```

Description¶

Inputs¶

Name	**Element Type**	**Shape**
`input`	real	\((\bullet, C, \ldots)\)
`gamma`	same as `input`	\((C)\)
`beta`	same as `input`	\((C)\)
`mean`	same as `input`	\((C)\)
`variances`	same as `input`	\((C)\)

Attributes¶

Name	**Type**	**Notes**
`epsilon`	`double`	Small bias added to variance to avoid division by 0.

Outputs¶

Name	**Element Type**	**Shape**
`normalized`	same as `gamma`	Same as `input`

Mathematical Definition¶

The axes of the input fall into two categories: positional and channel, with channel being axis 1. For each position, there are \(C\) channel values, each normalized independently.

Normalization of a channel sample is controlled by two values:

- the mean \(\mu\), and
- the variance \(\sigma^2\);

and by two scaling attributes: \(\gamma\) and \(\beta\).

\[\mathtt{normalized}_{\bullet, c, \ldots} = \frac{\mathtt{input}_{\bullet, c, \ldots}-\mu_c}{\sqrt{\sigma^2_c+\epsilon}}\gamma_c+\beta_c\]

C++ Interface¶

class `BatchNormInference` : *public* ngraph::op::Op¶

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

> Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`BatchNormInference`(*const* Output<Node> &*input*, *const* Output<Node> &*gamma*, *const* Output<Node> &*beta*, *const* Output<Node> &*mean*, *const* Output<Node> &*variance*, double *epsilon*)¶

Parameters

- `input`: [., C, …]
- `gamma`: gamma scaling for normalized value. [C]
- `beta`: bias added to the scaled normalized value [C]
- `mean`: value for mean normalization [C]
- `variance`: value for variance normalization [C]
- `epsilon`: Avoids divsion by 0 if input has 0 variance

NGRAPH_DEPRECATED_DOC `BatchNormInference`(double *eps*, *const* Output<Node> &*gamma*, *const* Output<Node> &*beta*, *const* Output<Node> &*input*, *const* Output<Node> &*mean*, *const* Output<Node> &*variance*)¶

> In this version of BatchNorm:
> MEAN AND VARIANCE: provided by the 'mean' and 'variance' parameters.
> OUTPUT VALUE: a single tensor with the normalized value of 'input'.
> AUTODIFF SUPPORT:
> - 'generate_adjoints(…) may throw an exception.
>
> SHAPE DETAILS: gamma: must have rank 1, with the same span as input's channel

axis. beta: must have rank 1, with the same span as input’s channel axis. input: must have rank >= 2. The second dimension represents the channel axis and must have a span of at least 1. mean: must have rank 1, with the same span as input’s channel axis. variance: must have rank 1, with the same span as input’s channel axis. output: shall have the same shape as ‘input’.

void `validate_and_infer_types()`¶

Throws if the node is invalid.

BatchNormTraining¶

```
BatchNormTraining  // Compute mean and variance from the input.
```

Description¶

Inputs¶

Name	**Element Type**	**Shape**
`input`	real	$(\bullet, C, \ldots)$
`gamma`	same as `input`	(C)
`beta`	same as `input`	(C)

Attributes¶

Name	**Type**	**Notes**
`epsilon`	`double`	Small bias added to variance to avoid division by 0.

Outputs¶

Name	**Element Type**	**Shape**
`normalized`	same as `gamma`	Same as `input`
`batch_mean`	same as `gamma`	(C)
`batch_variance`	same as `gamma`	(C)

The `batch_mean` and `batch_variance` outputs are computed per-channel from `input`.

Mathematical Definition¶

The axes of the input fall into two categories: positional and channel, with channel being axis 1. For each position, there are C channel values, each normalized independently.

Normalization of a channel sample is controlled by two values:

- the batch_mean μ, and
- the batch_variance σ^2;

and by two scaling attributes: γ and β.

The values for μ and σ^2 come from computing the mean and variance of `input`.

\[\begin{split}\mu_c &= \mathop{\mathbb{E}}\left(\mathtt{input}_{\bullet, c, \ldots}\right)\\ \sigma^2_c &= \mathop{\mathtt{Var}}\left(\mathtt{input}_{\bullet, c, \ldots}\right)\\ \mathtt{normlized}_{\bullet, c, \ldots} &= \frac{\mathtt{input}_{\bullet, c, \ldots}-\mu_c}{\sqrt{\sigma^2_c+\epsilon}}\gamma_c+\beta_c\end{split}\]

Backprop¶

\[\begin{split}[\overline{\texttt{input}}, \overline{\texttt{gamma}}, \overline{\texttt{beta}}]=\\ \mathop{\texttt{BatchNormTrainingBackprop}}(\texttt{input},\texttt{gamma},\texttt{beta},\texttt{mean},\texttt{variance},\overline{\texttt{normed_input}}).\end{split}\]

C++ Interface¶

class `BatchNormTraining` : *public* ngraph::op::Op¶

Batchnorm for training operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`BatchNormTraining`(*const* Output<Node> &*input*, *const* Output<Node> &*gamma*, *const* Output<Node> &*beta*, double *epsilon*)¶

Parameters

- `input`: Must have rank >= 2, [., C, …]
- `gamma`: gamma scaling for normalized value. [C]
- `beta`: bias added to the scaled normalized value [C]
- `epsilon`: Avoids divsion by 0 if input has 0 variance

NGRAPH_DEPRECATED_DOC `BatchNormTraining`(double *eps*, *const* Output<Node> &*gamma*, *const* Output<Node> &*beta*, *const* Output<Node> &*input*)¶

In this version of BatchNorm:
MEAN AND VARIANCE: computed directly from the content of ‘input’.
OUTPUT VALUE: A tuple with the following structure: [0] - The normalization of ‘input’. [1] - The per-channel means of (pre-normalized) ‘input’. [2] - The per-channel variances of (pre-normalized) ‘input’.
AUTODIFF SUPPORT: yes: ‘generate_adjoints(…)’ works as expected.
SHAPE DETAILS: gamma: must have rank 1, with the same span as input’s channel axis. beta: must have rank 1, with the same span as input’s channel axis. input: must have rank >= 2. The second dimension represents the channel axis and must have a span of at

least 1. output[0]: shall have the same shape as ‘input’. output[1]: shall have rank 1, with the same span as input’s channel axis. output[2]: shall have rank 1, with the same span as input’s channel axis.

void `validate_and_infer_types()`¶

Throws if the node is invalid.

BatchNormTrainingBackprop¶

```
BatchNormTrainingBackprop  // Compute mean and variance backprop from the
input.
```

Description¶

Computes the `input`, `gamma` and `beta` backprop increments.

Inputs¶

Name	Element Type	Shape
`input`	real	$(\bullet, C, \ldots)$
`gamma`	same as `input`	(C)
`beta`	same as `input`	(C)
`mean`	same as `input`	(C)
`variance`	same as `input`	(C)
`normalized_delta`	same as `input`	same as `input`

Attributes¶

Name	Type	Notes
`epsilon`	`double`	Small bias added to variance to avoid division by 0.

Outputs¶

Name	Element Type	Shape
`input_delta`	same as `input`	Same as `input`
`gamma_delta`	same as `gamma`	(C)
`beta_delta`	same as `beta`	(C)

Mathematical Definition¶

It is easiest to simplify by looking at a single channel and flattening the remaining axes into a vector; so `gamma` and `beta` are scalars, and `input` is an N-element vector.

The step by step forward training computation is

\[\begin{split}\mathtt{mean} &= \frac{\sum{\mathtt{input}_i}}{N}\\ \mathtt{centered}_i &= \mathtt{input}_i - \mathtt{mean}\\ \mathtt{square}_i &= \mathtt{centered}_i^2\\ \mathtt{variance} &= \frac{\sum \mathtt{square}_i}{N}\\ \mathtt{invsqrt} &= \frac{1}{\sqrt{\

mathtt{variance}+\epsilon}}\\ \mathtt{gmul} &= \texttt{gamma}\cdot \mathtt{invsqrt}\\ \ mathtt{normed}_i &= \mathtt{centered}_i\mathtt{gmul}+\texttt{beta}\end{split}\]

Using the notation \(\overline{\texttt{name}}\) for \(\texttt{name_delta}\) and \(\overline{x} \ leftarrow y\) to mean the backprop value for \(\texttt{x_delta}\) is a sum that includes \(y\).

We work backwards

\[\begin{split}\overline{\texttt{beta}}&\leftarrow \overline{\texttt{normed}}\\ \overline{\ texttt{gmul}}&\leftarrow \sum \overline{\texttt{normed}}_i\\ \overline{\texttt{centered}}_i&\ leftarrow\overline{\texttt{normed}}_i\texttt{gmul}\\ \overline{\texttt{gamma}}&\leftarrow \ overline{\texttt{gmul}}\cdot\texttt{invsqrt}\\ \overline{\texttt{invsqrt}}&\leftarrow\ texttt{gamma}\cdot\overline{\texttt{gmul}}\\ \overline{\texttt{variance}}&\leftarrow -\frac{\ overline{\texttt{invsqrt}}\cdot\texttt{invsqrt}}{2\cdot(\texttt{variance}+\epsilon)}\\ \overline{\ texttt{square}}_i&\leftarrow\frac{\overline{\texttt{variance}}}{N}\\ \overline{\ texttt{centered}}_i&\leftarrow 2\cdot\texttt{centered}_i\cdot\overline{\texttt{square}}_i\\ \ overline{\texttt{input}}_i&\leftarrow\overline{\texttt{centered}}_i\\ \overline{\texttt{mean}}&\ leftarrow\sum\overline{\texttt{centered}}_i\\ \overline{\texttt{input}}_i&\leftarrow\frac{\ overline{\texttt{mean}}}{N}\end{split}\]

C++ Interface¶

class `BatchNormTrainingBackprop` : *public* ngraph::op::Op¶

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

> Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

void `validate_and_infer_types`()¶

> Throws if the node is invalid.

Broadcast¶

```
Broadcast  // Operation that produces a tensor based on arg's axes
```

Description¶

Operation whose `output` tensor ignores axes not in the `arg` tensor.

Inputs¶

Name	**Element Type**	**Shape**
`arg`	Any	Any

Attributes¶

Name	Type	Notes
`shape`	`Shape`	The shape of the output.
`broadcast_axes`	`AxisSet`	Axis positions in `shape` that are broadcast.

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `shape`

The shape of `arg` must match `shape` with elements in `broadcast_axes` removed.

For example, if `arg` is \([a, b, c]\) then

\[\begin{split}\mathtt{Broadcast(arg, Shape{2, 3}, AxisSet{0})} &= \begin{bmatrix} a & b & c\\ a & b & c \end{bmatrix}\\ \mathtt{Broadcast(arg, Shape{3, 2}, AxisSet{1})} &= \begin{bmatrix} a & a\\ b & b\\ c & c \end{bmatrix}\end{split}\]

Mathematical Definition¶

For a coordinate \(C\), let \(p(C)\) be a coordinate with the axes in `broadcast_axes` removed. For example, if \(\mathtt{broadcast_axes}=\{1,3\}\) then \(p([d_0, d_1, d_2, d_3, d_4]) = [d_0, d_2, d_4]\). Then

\[\mathtt{output}_C = \mathtt{arg}_{p(C)}.\]

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow \mathtt{Sum}(\Delta, \mathtt{broadcast_axes}).\]

C++ Interface¶

class `Broadcast` : *public* ngraph::op::Op¶

> Operation which "adds" axes to an input tensor, replicating elements from the input as needed along the new axes.
> Subclassed by ngraph::op::v0::BroadcastLike

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

> Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Broadcast`()¶

> Constructs a broadcast operation.

`Broadcast`(*const* Output<Node> &*arg*, *const* Shape &*shape*, *const* AxisSet &*broadcast_axes*)¶

Constructs a broadcast operation.

Parameters

- `arg`: The input tensor to be broadcast.
- `shape`: The shape of the output tensor.
- `broadcast_axes`: The axis positions (0-based) in the result that are being broadcast. The remaining axes in shape must be the same as the shape of arg.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

const AxisSet &`get_broadcast_axes`() *const*¶

Return

A set containing the indices of the broadcast axes (0-based).

BroadcastDistributed¶

```
BroadcastDistributed // Collective operation
```

Description¶

Broadcast values from a primary root process or device to other processes or devices within the op communicator.

Inputs¶

Name	Element Type	Shape
`arg`	`element::f32` `element::f64`	Any

Outputs (in place)¶

Name	Element Type	Shape
`arg`	`element::f32` `element::f64`	Same as `arg`

C++ Interface¶

class `BroadcastDistributed` : *public* ngraph::op::Op¶

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

void `validate_and_infer_types`()¶

> Throws if the node is invalid.

Ceiling¶

```
Ceiling  // Elementwise ceiling operation
```

Description¶

Produces a single output tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the ceiling of the value at each `arg` coordinate.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \lceil \mathtt{arg}_{i_0, \ldots, i_{n-1}}\rceil$$

Backprop¶

Not defined by nGraph.

The backprop would be zero for non-integer input and undefined for integer input; a zero backprop would have no effect on the backprop to `arg`, so there is no need for `Ceiling` to define a backprop.

C++ Interface¶

class `Ceiling` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

> Elementwise ceiling operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

> Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Ceiling`()¶

Constructs a ceiling operation.

`Ceiling`(*const* Output<Node> &*arg*)¶

Constructs a ceiling operation.

Parameters

- `arg`: Node that produces the input tensor.

Concat¶

```
Concat  // Concatenation operation
```

Description¶

Produce from `Nodes` of `args` some outputs with the same attributes

Inputs¶

Name	Type	Notes
`args`	`Nodes`	All element types the same. All shapes the same except on `concatenation_axis`

Attributes¶

Name	Notes
`concatenation_axis`	Less than the rank of the shape

Outputs¶

Name

Element Type

Shape

`output`

Same as `args` | Same as `arg` on non-`concatenation_axis`

Sum of `concatenation_axis` lengths of `args`

Mathematical Definition¶

We map each tensor in `args` to a segment of `output` based on the coordinate at `coordinate_axis`.

Let

\[\begin{split}s(i) &= \sum_{j<i} \mathtt{args}[i].\mathtt{shape}\left[\ mathtt{concatenation_axis}\right]\\ t(i) &= \text{The greatest }j\text{ such that }i \ge s(j)\\ p(C)_i &= \begin{cases} C_i-s(t(i))&\text{if }i==\mathtt{concatenation_axis}\\ C_i&\

text{otherwise} \end{cases}\\ \mathtt{output}_C&=\mathtt{args}[t(C_i)]_{p(C)}\end{split}\]

Backprop¶

We slice the backprop value into the backprops associated with the inputs.

C++ Interface¶

class `Concat` : *public* ngraph::op::Op¶

Concatenation operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Concat`()¶

Constructs a concatenation operation.

`Concat`(*const* OutputVector &*args*, int64_t *axis*)¶

Constructs a concatenation operation.

Parameters

- `args`: The outputs producing the input tensors.
- `axis`: The axis along which to concatenate the input tensors.

`Concat`(*const* NodeVector &*args*, int64_t *axis*)¶

Constructs a concatenation operation.

Parameters

- `args`: The nodes producing the input tensors.
- `axis`: The axis along which to concatenate the input tensors.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

int64_t `get_concatenation_axis`() *const*¶

Return

The concatenation axis.

int64_t `get_axis`() *const*¶

Return

The concatenation axis.

Constant¶

```
Constant // Literal constant tensor
```

Description¶

The output is a tensor initialized from the `values` attribute.

Attributes¶

Name	**Type**	**Notes**
`type`	`ngraph::element::type`	The element type of the value in the computation
`shape`	`ngraph::Shape`	The shape of the constant
`values`	`const std::vector<T>&`	Constant elements in row-major order. T must be compatible with the element type

Outputs¶

Name	**Element Type**	**Shape**
`output`	`type`	`shape`

C++ Interface¶

class `Constant` : *public* ngraph::op::Op¶

Class for constants.
Subclassed by ngraph::op::v0::ScalarConstantLike

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

template <*typename* T>
`Constant`(*const* element::Type &*type*, Shape *shape*, *const* std::vector<T> &*values*)¶

Constructs a tensor constant.

Parameters

- `type`: The element type of the tensor constant.
- `shape`: The shape of the tensor constant.
- `values`: A vector of literals for initializing the tensor constant. The size of values must match the size of the shape.

`Constant`(*const* element::Type &*type*, Shape *shape*, *const* std::vector<std::string> &*values*)¶

Constructs a tensor constant This constructor is mainly to support deserialization of constants.

Parameters

- `type`: The element type of the tensor constant.
- `shape`: The shape of the tensor constant.
- `values`: A list of string values to use as the constant data.

`Constant`(*const* element::Type &*type*, *const* Shape &*shape*, *const* void **data*)¶

Constructs a tensor constant with the supplied data.

Parameters

- `type`: The element type of the tensor constant.
- `shape`: The shape of the tensor constant.
- `data`: A void* to constant data.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

Shape `get_shape_val`() *const*¶

Returns the value of the constant node as a Shape object Can only be used on element::i64 nodes and interprets negative values as zeros.

Strides `get_strides_val`() *const*¶

Returns the value of the constant node as a Strides object Can only be used on element::i64 nodes and interprets negative values as zeros.

Coordinate `get_coordinate_val`() *const*¶

Returns the value of the constant node as a Coordinate object Can only be used on element::i64 nodes and interprets negative values as zeros.

CoordinateDiff `get_coordinate_diff_val`() *const*¶

Returns the value of the constant node as a CoordinateDiff object Can only be used on element::i64 nodes.

AxisVector `get_axis_vector_val`() *const*¶

Returns the value of the constant node as an AxisVector object Can only be used on element::i64 nodes and interprets negative values as zeros.

AxisSet `get_axis_set_val`() *const*¶

Returns the value of the constant node as an AxisSet object Can only be used on element::i64 nodes and interprets negative values as zeros. Repeated values are allowed.

std::vector<std::string> `get_value_strings`() *const*¶

Return

The initialization literals for the tensor constant.

template <*typename* T>
std::vector<T> `cast_vector`() *const*¶

Return the Constant's value as a vector cast to type T.

Return

Constant's data vector.

Template Parameters

- `T`: Type to which data vector's entries will be cast.

Public Static Functions

template <*typename* T>
static std::shared_ptr<op::v0::Constant> `create`(*const* element::Type &*type*, Shape *shape*, *const* std::vector<T> *values*)¶

Wrapper around constructing a shared_ptr of a Constant.

Parameters

- `type`: The element type of the tensor constant.
- `shape`: The shape of the tensor constant.
- `values`: A vector of values to use as the constant data.

template <*typename* T>
static std::shared_ptr<op::v0::Constant> `create`(*const* element::Type &*type*, Shape *shape*, std::initializer_list<T> *values*)¶

Wrapper around constructing a shared_ptr of a Constant.

Parameters

- `type`: The element type of the tensor constant.

- `shape`: The shape of the tensor constant.
- `values`: An initializer_list of values to use as the constant data.

Convert¶

```
Convert // Convert a tensor from one element type to another
```

Description¶

Long description

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Attributes¶

Name	Type	Notes
`element_type`	`ngraph::element::type`	The element type of the result

Outputs¶

Name	Element Type	Shape
`output`	`element_type`	Same as `arg`

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow \mathtt{Convert}(\Delta,\mathtt{arg->get_element_type()})\]

C++ Interface¶

class `Convert` : *public* ngraph::op::Op¶

Elementwise type conversion operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Convert`()¶

Constructs a conversion operation.

`Convert`(*const* Output<Node> &*arg*, *const* ngraph::element::Type &*destination_type*)¶

Constructs a conversion operation.

Parameters

- `arg`: Node that produces the input tensor.
- `destination_type`: Element type for the output tensor.

void `validate_and_infer_types()`¶

Throws if the node is invalid.

Convolution¶

```
Convolution  // A batched convolution operation
```

Description¶

Long description

Inputs¶

Name	Element Type	Shape
`image_batch`	Any	`(N, C_in, d_1, ..., d_n)`
`filters`	Same as `image_batch`	`(N, C_in, df_1, ..., df_n)`

Attributes¶

Name	Type	Notes
`window_movement_strides`	`Strides[n]`	How far to slide the window along each axis at each step
`window_dilation_strides`	`Strides[n]`	Per-axis dilation to apply to the filters
`padding_below`	`Shape[n]`	How many padding elements to add below the 0-coordinate on each axis
`padding_above`	`Shape[n]`	How many padding elements to add above the max-coordinate on each axis
`image_dilation_strides`	`Strides[n]`	Per-axis dilation to apply to the image batch

Outputs¶

Name	Element Type	Shape
`features_out`	Same as `image_batch`	`(N, C_in, d_1 - df_1 + 1, ..., d_n - df_n + 1)`

It must be the case that after dilation and padding are applied, the filter fits within the image.

Mathematical Definition¶

Padding¶

Let p (the padding below) and q (the padding above) be a sequence of n integers, and T be a tensor of shape $(d_1,\dots,d_n)$, such that for all i, $p_i + d_i + q_i \ge 0$. Then $\mathit{Pad}[p,q](T)$ is the tensor of shape $(p_1 + d_1 + q_1,\dots,p_n + d_n + q_n)$ such that

$$\begin{split}\mathit{Pad}[p,q](T)_{i_1,\dots,i_n} \triangleq \begin{cases} T_{i_1 - p_1,\dots,i_n - p_n} &\mbox{if for all }j, i_j \ge p_j\mbox{ and }i_j < p_j + d_j \\ 0 &\mbox{otherwise.} \end{cases}\end{split}$$

Dilation¶

Let l (the dilation strides) be a sequence of n positive integers, and T be a tensor of shape $(d_1,\dots,d_n)$. Then $\mathit{Dilate}[l](T)$ is the tensor of shape $(d'_1,\dots,d'_n)$ where $d'_i = \mathit{max}(0,l_i(d_i - 1) + 1)$ such that

$$\begin{split}\mathit{Dilate}[l](T)_{i_1,\dots,i_n} \triangleq \begin{cases} T_{i_1/l_1,\dots,i_n/l_n} &\mbox{if for all }j, i_j\mbox{ is a multiple of }l_j \\ 0 &\mbox{otherwise.} \end{cases}\end{split}$$

Striding¶

Let s (the strides) be a sequence of n positive integers, and T be a tensor of shape $(d_1,\dots,d_n)$. Then $\mathit{Stride}[s](T)$ is the tensor of shape $(d'_1,\dots,d'_n)$ where $d'_i = \left\lceil \frac{d_i}{s_i} \right\rceil$ such that

$$\mathit{Stride}[s](T)_{i_1,\dots,i_n} \triangleq T_{s_1i_1,\dots,s_ni_n}$$

s is the how far, not the unit of farness.

Convolution¶

Padded, Dilated, Strided Convolution¶

$$\mathit{PDSConv}[g,p,q,l,s](T_\mathit{image},T_\mathit{filter} \triangleq \mathit{Stride}[s](\mathit{Conv}(\mathit{Pad}[p,q](\mathit{Dilate}[g](T_\mathit{batch})),\mathit{Dilate}[l](T_\mathit{filter})))$$

Batched, Padded, Dilated, Strided Convolution¶

C++ Interface¶

class `Convolution` : *public* ngraph::op::Op¶

Batched convolution operation, with optional window dilation and stride.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Convolution`()¶

Constructs a batched convolution operation.

`Convolution`(*const* Output<Node> &*data_batch*, *const* Output<Node> &*filters*, *const* Strides &*window_movement_strides*, *const* Strides &*window_dilation_strides*, *const* CoordinateDiff &*padding_below*, *const* CoordinateDiff &*padding_above*, *const* Strides &*data_dilation_strides*, *const* PadType &*pad_type* = PadType::EXPLICIT)¶

Constructs a batched convolution operation.
Output `[N, C_OUT, R1, ... Rf]`

Parameters

- `data_batch`: The node producing the input data batch tensor.`[N, C_IN, D1, ... Df]`
- `filters`: The node producing the filters tensor.`[C_OUT, C_IN, F1, ... Ff]`
- `window_movement_strides`: The window movement strides.`[f]`
- `window_dilation_strides`: The window dilation strides.`[f]`
- `padding_below`: The padding-below sizes.`[f]`
- `padding_above`: The padding-above sizes.`[f]`
- `data_dilation_strides`: The data dilation strides.`[f]`
- `pad_type`: The pad type for automatically computing padding sizes.`[f]`

`Convolution`(*const* Output<Node> &*data_batch*, *const* Output<Node> &*filters*, *const* Strides &*window_movement_strides*, *const* Strides &*window_dilation_strides*, *const* CoordinateDiff &*padding_below*, *const* CoordinateDiff &*padding_above*)¶

Constructs a batched convolution operation with no data dilation (i.e., all data dilation strides are 1).
Output `[N, C_OUT, R1, ... Rf]`

Parameters

- `data_batch`: The node producing the input data batch tensor.`[N, C_IN, D1, ... Df]`
- `filters`: The node producing the filters tensor.`[C_OUT, C_IN, F1, ... Ff]`
- `window_movement_strides`: The window movement strides.`[f]`
- `window_dilation_strides`: The window dilation strides.`[f]`
- `padding_below`: The padding-below sizes.`[f]`
- `padding_above`: The padding-above sizes.`[f]`

`Convolution`(*const* Output<Node> &*data_batch*, *const* Output<Node> &*filters*, *const* Strides &*window_movement_strides*, *const* Strides &*window_dilation_strides*)¶

Constructs a batched convolution operation with no padding or data dilation (i.e., padding above and below are 0 everywhere, and all data dilation strides are 1).
Output `[N, C_OUT, R1, ... Rf]`

Parameters

- `data_batch`: The node producing the input data batch tensor.`[N, C_IN, D1, ... Df]`
- `filters`: The node producing the filters tensor.`[C_OUT, C_IN, F1, ... Ff]`
- `window_movement_strides`: The window movement strides.`[f]`
- `window_dilation_strides`: The window dilation strides.`[f]`

`Convolution`(*const* Output<Node> &*data_batch*, *const* Output<Node> &*filters*, *const* Strides &*window_movement_strides*)¶

Constructs a batched convolution operation with no window dilation, padding, or data dilation (i.e., padding above and below are 0 everywhere, and all window/data dilation strides are 1).
Output `[N, C_OUT, R1, ... Rf]`

Parameters

- `data_batch`: The node producing the input data batch tensor.`[N, C_IN, D1, ... Df]`
- `filters`: The node producing the filters tensor.`[C_OUT, C_IN, F1, ... Ff]`
- `window_movement_strides`: The window movement strides.`[f]`

`Convolution`(*const* Output<Node> &*data_batch*, *const* Output<Node> &*filters*)¶

Constructs a batched convolution operation with no window dilation or movement stride (i.e., padding above and below are 0 everywhere, and all window/data dilation strides and window movement strides are 1).
Output `[N, C_OUT, R1, ... Rf]`

Parameters

- `data_batch`: The node producing the input data batch tensor.`[N, C_IN, D1, ... Df]`
- `filters`: The node producing the filters tensor.`[C_OUT, C_IN, F1, ... Ff]`

void `validate_and_infer_types`()¶

Throws if the node is invalid.

const Strides &`get_window_movement_strides`() *const*¶

Return

The window movement strides.

const Strides &`get_window_dilation_strides`() *const*¶

Return

The window dilation strides.

const CoordinateDiff &`get_padding_below`() *const*¶

Return

The padding-below sizes (possibly negative).

const CoordinateDiff &`get_padding_above`() *const*¶

Return

The padding-above sizes (possibly negative).

const Strides &`get_data_dilation_strides`() *const*¶

Return

The input data dilation strides.

const PadType &`get_pad_type`() *const*¶

Return

The pad type for convolution.

shared_ptr<Node> `get_default_value`() *const*¶

Return

The default value for Convolution.

Cos¶

```
Cos  //  Elementwise cosine operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the cosine of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \cos(\mathtt{arg}_{i_0, \ldots, i_{n-1}})$$

Backprop¶

$$\overline{\mathtt{arg}} \leftarrow -\Delta\ \sin(\mathtt{arg})$$

C++ Interface¶

class `Cos` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise cosine operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Cos`()¶

Constructs a cosine operation.

`Cos`(*const* Output<Node> &*arg*)¶

Constructs a cosine operation.

Parameters

- `arg`: Node that produces the input tensor.

Cosh¶

```
Cosh  //  Elementwise hyperbolic cosine operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the hyperbolic cosine of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \cosh(\mathtt{arg}_{i_0, \ldots, i_{n-1}})\]

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow \Delta\ \sinh(\mathtt{arg})\]

C++ Interface¶

class `Cosh` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise hyperbolic cosine (cosh) operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Cosh`()¶

Constructs a hyperbolic cosine operation.

`Cosh`(*const* Output<Node> &*arg*)¶

Constructs a hyperbolic cosine operation.

Parameters

- `arg`: Node that produces the input tensor.

Dequantize¶

```
Dequantize // Maps quantized input to real output
```

Description¶

Produces a tensor of element type `type` and the same shape as `input` where the value of each coordinate \(i\) of `output` is the corresponding coordinate of `input` minus `zero_point` quantity multiplied by `scale`. The coordinate j of `scale` and `zero_point` is the coordinate of `output` projected onto `axes`.

Inputs¶

Name

Element Type

Shape

`input`

Any quantized type

Any

`scale`

Same as `output`

`input` shape projected onto `axes`

`zero_point` | Same as `input` | `input` shape projected onto `axes`

Attributes¶

Name	Description
`type`	`output` element type; any real type
`axes`	Axis positions on which `scale` and `zero_point` are specified

Outputs¶

Name	Element Type	Shape
`output`	`type`	Same as `input`

***Mathematical Definition*¶**

$$\mathtt{output}_{i,j} = (\mathtt{input}_{i,j} - \mathtt{zero\_point}_{j}) \mathtt{scale}_{j}$$

***C++ Interface*¶**

class `Dequantize` : *public* ngraph::op::Op¶

> Dequantize operation Maps quantized input (q) to real output (r) using scale (s) and zero point (z): r = (q - o) * s.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

> Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a

dummy type_info for Node if the class has not been updated yet.

`Dequantize()`¶

Constructs a Dequantize operation.

`Dequantize`(*const* Output<Node> &*input*, *const* Output<Node> &*scale*, *const* Output<Node> &*zero_point*, *const* element::Type &*type*, *const* AxisSet &*axes*)¶

Constructs a Dequantize operation.

Parameters

- `input`: quantized input
- `scale`: scale used for mapping
- `zero_point`: zero point used for mapping
- `type`: output element type
- `axes`: axis positions on which `scale` and `zero_point` are specified

void `validate_and_infer_types()`¶

Throws if the node is invalid.

Divide¶

```
Divide  //  Elementwise divide operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is the quotient of the values at the corresponding input coordinates.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	same as `arg0`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \frac{\mathtt{arg0}_{i_0, \ldots, i_{n-1}}}{\mathtt{arg1}_{i_0, \ldots, i_{n-1}}}\]

Backprop¶

\[\begin{split}\overline{\mathtt{arg0}} &\leftarrow \frac{\Delta}{\mathtt{arg1}}\\ \overline{\mathtt{arg1}} &\leftarrow -\Delta \frac{\mathtt{Output}}{\mathtt{arg1}}\end{split}\]

C++ Interface¶

class `Divide` : *public* ngraph::op::util::BinaryElementwiseArithmetic¶

Elementwise division operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Divide`()¶

Constructs a division operation.

`Divide`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, bool *pythondiv*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a division operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `pythondiv`: Use Python style rounding for integral type
- `auto_broadcast`: Auto broadcast specification

`Divide`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a division operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Dot¶

```
Dot  //  Generalized dot product operation
```

Description¶

Generalized dot product operation, including scalar-tensor product, matrix-vector product, and matrix multiplication.

A few common cases are as follows:

- If $m = 0$ and $n = 1$ or $p = 1$, the operation is a scalar-tensor product.
- If $m = 1$, $n = 2$, and $p = 1$, the operation is a matrix-vector product.
- If $m = 1$ and $n = p = 2$, the operation is a matrix multiplication.

Inputs¶

Name	Element Type	Shape
`arg0`	any	$(i_1,\dots,i_n,j_1,\dots,j_m)$
`arg1`	same as `arg0`	$(j_1,\ldots,j_m,k_1,\dots,k_p)$

Attributes¶

Name		
reduction_axes_count	`size_t`	The number of axes to reduce through dot-product (corresponds to m in the formulas above)

Outputs¶

Name	Element Type	Shape
`output`	same as `arg0`	$(i_1,\ldots,i_n,k_1,\dots,k_p)$

Mathematical Definition¶

$$\begin{split}\mathtt{output}_{i_1,\dots,i_n,k_1,\ldots,k_p} = \begin{cases} \mathtt{arg0}_{i_1,\dots,i_n} \cdot \mathtt{arg1}_{k_1,\dots,k_p}&\text{if }m=0,\\ \sum_{j_1, \ldots, j_m} \mathtt{arg0}_{i_1,\dots,i_n,j_1,\dots,j_m} \cdot \mathtt{arg1}_{j_1,\ldots,j_m,k_1,\ldots,k_p} &\text{otherwise}. \end{cases}\end{split}$$

Backprop¶

To be documented.

C++ Interface¶

class `Dot` : *public* ngraph::op::Op¶

Generalized dot product operation, including scalar-tensor product, matrix-vector product, and matrix multiplication.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a

dummy type_info for Node if the class has not been updated yet.

`Dot`()¶

Constructs a dot product operation.

`Dot`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, size_t *reduction_axes_count*, bool *has_reduction_axes_count* = true)¶

Constructs a dot product operation.

Parameters

- `arg0`: The node producing the first argument.
- `arg1`: The node producing the second argument.
- `reduction_axes_count`: The number of axes to dot.

`Dot`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*)¶

Constructs a dot product operation with default dot-axis selection depending on the inputs.
If `arg0` or `arg1` is a scalar, there are no dot-axes. Else, there is one dot-axis.
(Note that in particular, this results in scalar-tensor products where one or the other argument is a scalar, a matrix-vector products where `arg0` is a matrix and `arg1` is a vector, and a matrix multiplication where `arg0` and `arg1` are both matrices.)

Parameters

- `arg0`: The node producing the first argument.
- `arg1`: The node producing the second argument.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

DropOut¶

```
DropOut  // DropOut
```

Description¶

Inputs¶

Attributes¶

Name	Description

Outputs¶

Name	Element Type	Shape
`output`		

Mathematical Definition¶

C++ Interface¶

Equal¶

```
Equal  // Elementwise equal operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is `1` (true) if `arg0` is equal to `arg1`, `0` otherwise.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} == \mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

C++ Interface¶

class `Equal` : *public* ngraph::op::util::BinaryElementwiseComparison¶

Elementwise is-equal operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Equal`()¶

Constructs an equal operation.

`Equal`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs an equal operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Exp¶

```
Exp  // Elementwise expine operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the expine of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \exp(\mathtt{arg}_{i_0, \ldots, i_{n-1}})\]

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow \Delta\ \mathtt{output}\]

C++ Interface¶

class `Exp` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise natural exponential (exp) operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Exp`()¶

Constructs an exponential operation.

`Exp`(*const* Output<Node> &*arg*)¶

Constructs an exponential operation.

Parameters

- `arg`: Node that produces the input tensor.

Floor¶

```
Floor  // Elementwise floor operation
```

Description¶

Produces a single output tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the floor of the value at each `arg` coordinate.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \lfloor \mathtt{arg}_{i_0, \ldots, i_{n-1}}\rfloor\]

Backprop¶

Not defined by nGraph.

The backprop would be zero for non-integer input and undefined for integer input; a zero backprop would have no effect on the backprop to `arg`, so there is no need for `Floor` to define a backprop.

C++ Interface¶

class `Floor` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise floor operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Floor`()¶

Constructs a floor operation.

`Floor`(*const* Output<Node> &*arg*)¶

Constructs a floor operation.

Parameters

- `arg`: Node that produces the input tensor.

GetOutputElement¶

```
GetOutputElement  // Operation to select a unique output from an op
```

Description¶

Accesses an output of a node.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Attributes¶

Name	Description
`n`	The output number from the node `arg`

Outputs¶

Name	Element Type	Shape
`output`	Depends on arg	Depends on arg

C++ Interface¶

class `GetOutputElement` : *public* ngraph::op::Op¶

Operation to get an output from a node.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`GetOutputElement`(*const* std::shared_ptr<Node> &*arg*, size_t *n*)¶

Constructs a get-tuple-element operation.

Parameters

- `arg`: The input tuple.
- `n`: The index of the tuple element to get.

Output<Node> `get_as_output`() *const*¶

Return the equilent Output<Node>

void `validate_and_infer_types`()¶

Throws if the node is invalid.

size_t `get_n`() *const*¶

Return

The index of the tuple element to get.

GreaterEq¶

```
GreaterEq  // Elementwise greater or equal operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is true (1) if `arg0` is greater than or equal to `arg1`, 0 otherwise.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} \ge \mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

C++ Interface¶

class `GreaterEq` : *public* ngraph::op::util::BinaryElementwiseComparison¶

Elementwise greater-than-or-equal operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`GreaterEq`()¶

Constructs a greater-than-or-equal operation.

`GreaterEq`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a greater-than-or-equal operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Greater¶

```
Greater  // Elementwise greater operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is true (1) if `arg0` is greater than `arg1`, 0 otherwise.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} > \mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

C++ Interface¶

class `Greater` : *public* ngraph::op::util::BinaryElementwiseComparison¶

Elementwise greater-than operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Greater`()¶

Constructs a greater-than operation.

`Greater`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a greater-than operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

LessEq¶

```
LessEq  // Elementwise less or equal operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is true (1) if `arg0` is less than or equal to `arg1`, 0 otherwise.

Inputs¶

Name	**Element Type**	**Shape**
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	**Element Type**	**Shape**
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} \le \mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

C++ Interface¶

class `LessEq` : *public* ngraph::op::util::BinaryElementwiseComparison¶

Elementwise less-than-or-equal operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`LessEq`()¶

Constructs a less-than-or-equal operation.

`LessEq`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a less-than-or-equal operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Less¶

```
Less  // Elementwise less operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is true (1) if `arg0` is less than `arg1`, 0 otherwise.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} < \mathtt{arg1}_{i_0, \ldots, i_{n-1}}$$

C++ Interface¶

class `Less` : *public* ngraph::op::util::BinaryElementwiseComparison¶

Elementwise less-than operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Less`()¶

Constructs a less-than operation.

`Less`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a less-than operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.

- `auto_broadcast`: Auto broadcast specification

Log¶

```
Log  // Elementwise logine operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the logine of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	**Element Type**	**Shape**
`arg`	Any	Any

Outputs¶

Name	**Element Type**	**Shape**
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \log(\mathtt{arg}_{i_0, \ldots, i_{n-1}})$$

Backprop¶

$$\overline{\mathtt{arg}} \leftarrow \frac{\Delta}{\mathtt{input}}$$

C++ Interface¶

class `Log` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

> Elementwise natural log operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

> Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Log`()¶

> Constructs a natural log operation.

`Log`(*const* Output<Node> &*arg*)¶

> Constructs a natural log operation.

Parameters

- `arg`: Node that produces the input tensor.

Max¶

```
Max  // Max reduction
```

Description¶

Reduces the tensor, eliminating the specified reduction axes by taking the maximum element.

Inputs¶

Name	**Element Type**	**Shape**
`arg`	Any	\((d_1,\dots,d_n)~(n \geq 0)\)

Attributes¶

Name	**Description**
`reduction_axes`	The axis positions (0-based) on which to calculate the max

Outputs¶

Name	**Element Type**	**Shape**
`output`	Same as `arg`	\((d_i:i\not\in \mathtt{reduction_axes})\)

C++ Interface¶

class `Max` : *public* ngraph::op::util::ArithmeticReduction¶

Max-reduction operation.

Maximum¶

```
Maximum  // Elementwise maximum operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is the maximum of the values at the corresponding input coordinates.

Inputs¶

Name	**Element Type**	**Shape**
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	same as `arg0`	same as `arg0`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \max(\mathtt{arg0}_{i_0, \ldots, i_{n-1}}, \ \mathtt{arg1}_{i_0, \ldots, i_{n-1}})$$

Backprop¶

$$\begin{split}\overline{\mathtt{arg0}} &\leftarrow \mathtt{Greater}(\mathtt{arg0}, \ \mathtt{arg1})\ \Delta \\ \overline{\mathtt{arg1}} &\leftarrow \mathtt{Greater}(\mathtt{arg1}, \ \mathtt{arg0})\ \Delta\end{split}$$

C++ Interface¶

class `Maximum` : *public* ngraph::op::util::BinaryElementwiseArithmetic¶

Elementwise maximum operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Maximum`()¶

Constructs a maximum operation.

`Maximum`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a maximum operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

MaxPool¶

```
MaxPool  // MaxPool operations
```

Description¶

Batched max pooling operation, with optional padding and window stride.

Inputs¶

Name	Element Type	Shape
`arg`	any	$(N, C, d_1, \ldots, d_n)$

Attributes¶

Name	Description
`window_shape`	The window shape.
`window_movement_strides`	The window movement strides. (defaults to 1s)
`padding_below`	The below-padding shape. (defaults to 0s)
`padding_above`	The above-padding shape. (defaults to 0s)

Outputs¶

Name	Element Type	Shape
`output`	same as `arg`	$(N,C,d'_1,\ldots,d'_n)$

The input for max pooling is a data batch tensor of shape $(N,C,d_1,\dots,d_n)$ where $n > 0$, every $d_i > 0$, and where N is the batch size, and $C > 0$ is the number of channels (sometimes called features). The dimensions $(d_1,\dots,d_n)$ correspond to the shape of an n-dimensional data item in a batch. For example, where $n=2$, the data may represent a two-dimensional image. It also has two attributes:

1. *the window shape* a size vector $(w_1,\ldots,w_n)$ where every $w_i \le d_i$; and
2. *the window movement strides, optional* a vector of positive integers $(s_1,\dots,s_n)$.

The output has the shape $(N,C,d'_1,\ldots,d'_n)$, where $d'_n = \lceil \frac{d_i - w_i + 1}{s_i} \rceil$.

Mathematical Definition¶

Given an input data batch tensor T_{in}, the output tensor is defined by the equation

$$T_{out}[a,c,i_1,\dots,i_n] = \max_{j_1 = s_1 i_1, \dots, j_n = s_n i_n}^{j_1 = s_1 i_1 + w_1 - 1, \dots, j_n = s_n i_n + w_n - 1} (T_{in}[a,c,j_1,\dots,j_n])$$

C++ Interface¶

class `MaxPool` : *public* ngraph::op::Op¶

Batched max pooling operation, with optional padding and window stride.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`MaxPool`()¶

Constructs a batched max pooling operation.

`MaxPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*, *const* Strides &*window_movement_strides*, *const* Shape &*padding_below*, *const* Shape &*padding_above*, *const* PadType &*pad_type*, bool *ceil_mode*)¶

Constructs a batched max pooling operation.

Parameters

- `arg`: The node producing the input data batch tensor.
- `window_shape`: The window shape.
- `window_movement_strides`: The window movement strides.
- `padding_below`: The below-padding shape.
- `padding_above`: The above-padding shape.
- `pad_type`: The pad type for automatically computing padding sizes
- `ceil_mode`: Whether to use ceiling while computing output shape.

`MaxPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*, *const* Strides &*window_movement_strides*, *const* Shape &*padding_below*, *const* Shape &*padding_above*, *const* PadType &*pad_type*)¶

Constructs a batched max pooling operation.

Parameters

- `arg`: The node producing the input data batch tensor.
- `window_shape`: The window shape.
- `window_movement_strides`: The window movement strides.
- `padding_below`: The below-padding shape.
- `padding_above`: The above-padding shape.
- `pad_type`: The pad type for automatically computing padding sizes

`MaxPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*, *const* Strides &*window_movement_strides*, *const* Shape &*padding_below*, *const* Shape &*padding_above*)¶

Constructs a batched max pooling operation.

Parameters

- `arg`: The node producing the input data batch tensor.
- `window_shape`: The window shape.
- `window_movement_strides`: The window movement strides.
- `padding_below`: The below-padding shape.
- `padding_above`: The above-padding shape.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

`MaxPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*, *const* Strides &*window_movement_strides*)¶

Constructs a batched, unpadded max pooling operation (i.e., all padding shapes are set to 0).

Parameters

- `arg`: The node producing the input data batch tensor.
- `window_shape`: The window shape.
- `window_movement_strides`: The window movement strides.

`MaxPool`(*const* Output<Node> &*arg*, *const* Shape &*window_shape*)¶

Constructs an unstrided batched max pooling operation (i.e., all window movement strides are 1 and all padding shapes are set to 0).

Parameters

- `arg`: The node producing the input data batch tensor.
- `window_shape`: The window shape.

const Shape &`get_window_shape`() *const*¶

Return

The window shape.

const Strides &`get_window_movement_strides`() *const*¶

Return

The window movement strides.

const Shape &`get_padding_below`() *const*¶

Return

The below-padding shape.

const Shape &`get_padding_above`() *const*¶

Return

The above-padding shape.

const PadType &`get_pad_type`() *const*¶

Return

The pad type for pooling.

bool `get_ceil_mode`() *const*¶

Return

The ceiling mode being used for output shape computations

shared_ptr<Node> `get_default_value`() *const*¶

Return

The default value for MaxPool.

Min¶

```
Min  // Min reduction
```

Description¶

Reduces the tensor, eliminating the specified reduction axes by taking the minimum element.

Inputs¶

Name	Element Type	Shape
`arg`	Any	\((d_1,\dots,d_n)~(n \geq 0)\)

Attributes¶

Name	Description
`reduction_axes`	The axis positions (0-based) on which to calculate the max

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	\((d_i:i\not\in \mathtt{reduction_axes})\)

C++ Interface¶

class `Min` : *public* ngraph::op::util::ArithmeticReduction¶

Min-reduction operation.

Minimum¶

```
Minimum  // Short description.
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is the minimum of the values at the corresponding input coordinates.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	same as `arg0`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \min(\mathtt{arg0}_{i_0, \ldots, i_{n-1}}, \mathtt{arg1}_{i_0, \ldots, i_{n-1}})\]

Backprop¶

\[\begin{split}\overline{\mathtt{arg0}} &\leftarrow \mathtt{Less}(\mathtt{arg0}, \mathtt{arg1})\ \Delta \\ \overline{\mathtt{arg1}} &\leftarrow \mathtt{Less}(\mathtt{arg1}, \mathtt{arg0})\ \Delta\end{split}\]

C++ Interface¶

class `Minimum` : *public* ngraph::op::util::BinaryElementwiseArithmetic¶

Elementwise minimum operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Minimum`()¶

Constructs a minimum operation.

`Minimum`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a minimum operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Multiply¶

```
Multiply  //  Elementwise multiply operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is the product of the values at the corresponding input coordinates.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	same as `arg0`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} \ mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

Backprop¶

\[\begin{split}\overline{\mathtt{arg0}} &\leftarrow \Delta\ \mathtt{arg1}\\ \overline{\ mathtt{arg1}} &\leftarrow \Delta\ \mathtt{arg0}\end{split}\]

C++ Interface¶

class `Multiply` : *public* ngraph::op::util::BinaryElementwiseArithmetic¶

Elementwise multiplication operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Multiply`()¶

Constructs a multiplication operation.

`Multiply`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a multiplication operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Negative¶

```
Negative  //  Elementwise negative operation
```

Description¶

Produces a single output tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the negative of the value at each `arg` coordinate.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = -\mathtt{arg}_{i_0, \ldots, i_{n-1}}\]

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow -\Delta\]

C++ Interface¶

class `Negative` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise negative operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a

dummy type_info for Node if the class has not been updated yet.

`Negative`()¶

Constructs a negative operation.

`Negative`(*const* Output<Node> &*arg*)¶

Constructs a negative operation.

Parameters

- `arg`: Node that produces the input tensor.

NotEqual¶

```
NotEqual  // Elementwise "not equal" operation
```

Description¶

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is `1` (true) if `arg0` is not equal to `arg1`, `0` otherwise.

Inputs¶

Name	**Element Type**	**Shape**
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	**Element Type**	**Shape**
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} \neq \mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

C++ Interface¶

class `NotEqual` : *public* ngraph::op::util::BinaryElementwiseComparison¶

Elementwise not-equal operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a

dummy type_info for Node if the class has not been updated yet.

`NotEqual`()¶

Constructs a not-equal operation.

`NotEqual`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a not-equal operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Not¶

```
Not // Elementwise negation operation
```

Description¶

Produces a single output tensor of boolean type and the same shape as `arg,` where the value at each coordinate of `output` is the negation of the value at each `arg` coordinate.

Inputs¶

Name	Element Type	Shape
`arg`	`element::boolean`	Any

Outputs¶

Name	Element Type	Shape
`output`	`element::boolean`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \neg\mathtt{arg}_{i_0, \ldots, i_{n-1}}\]

C++ Interface¶

class `Not` : *public* ngraph::op::Op¶

Elementwise logical negation operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Not()`¶

Constructs a logical negation operation.

`Not`(*const* Output<Node> &*arg*)¶

Constructs a logical negation operation.

Parameters

- `arg`: Node that produces the input tensor.

void `validate_and_infer_types()`¶

Throws if the node is invalid.

OneHot¶

```
OneHot  // One-hot expansion
```

Description¶

Inputs¶

Name	Element Type	Shape
`arg`	Any integral type	$(d_1,\dots,d_{m-1},d_{m+1},\dots,d_n)~(n \geq 0)$

Attributes¶

Name	Description
`shape`	The desired output shape, including the new one-hot axis.
`one_hot_axis`	The index within the output shape of the new one-hot axis.

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	`shape`

Mathematical Definition¶

$$\begin{split}\mathtt{output}_{i_0, \ldots, i_{n-1}} = \begin{cases} 1&\text{if }i_{\mathtt{one\_hot\_axis}} = \mathtt{arg}_{(i : i\ne \mathtt{one\_hot\_axis})}\\ 0&\text{otherwise} \end{cases}\end{split}$$

C++ Interface¶

class `OneHot` : *public* ngraph::op::Op¶

One-hot operator.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`OneHot`()¶

Constructs a one-hot operation.

`OneHot`(*const* Output<Node> &*arg*, *const* PartialShape &*shape*, size_t *one_hot_axis*)¶

Constructs a one-hot operation.

Parameters

- `arg`: Node that produces the input tensor to be one-hot encoded.
- `shape`: The shape of the output tensor, including the new one-hot axis.
- `one_hot_axis`: The index within the output shape of the new one-hot axis.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

size_t `get_one_hot_axis`() *const*¶

Return

The index of the one-hot axis.

Or¶

```
Or  // Elementwise logical-or operation
```

Description¶

Produces tensor with boolean element type and shape as the two inputs, which must themselves have boolean element type, where the value at each coordinate of `output` is `1` (true) if `arg0` or `arg1` is nonzero, `0` otherwise.

Inputs¶

Name	Element Type	Shape
`arg0`	`ngraph::element::boolean`	any
`arg1`	`ngraph::element::boolean`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}}\, \mathtt{||}\, \mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

C++ Interface¶

class `Or` : *public* ngraph::op::util::BinaryElementwiseLogical¶

Elementwise logical-or operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Or`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a logical-or operation.

Output `[d0, ...]`

Parameters

- `arg0`: Node that produces the first input tensor.`[d0, ...]`
- `arg1`: Node that produces the second input tensor.`[d0, ...]`
- `auto_broadcast`: Auto broadcast specification

Pad¶

```
Pad // General padding operation
```

Description¶

Adds edge padding.

Inputs¶

Name	Element Type	Shape
`arg`	Any	$(d_1, \ldots, d_n)$
`arg_pad_value`	Same as `arg`	Scalar

Attributes¶

Name	Description
`padding_below`	Padding added before `arg`. May be negative.
`padding_above`	Padding added after `arg`. May be negative.
`pad_mode`	Padding mode: `CONSTANT(default)`, `EDGE` or `REFLECT`.

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	$(d'_1, \ldots, d'_n)$

$$d'_i = \mathtt{padding\_below}_i+d_i\cdot(\mathtt{padding\_interior}_i)+\mathtt{padding\_above}_i$$

Takes an input tensor of shape $(d_1,\dots,d_n)$ and pads by inserting a scalar x supplied as input, in three possible ways:

1. *exterior padding* inserts copies of x *below or above* the bounds of existing rows, columns, etc.,
2. *interior padding* inserts copies of x *between* rows, columns, etc., or
3. both of the above.

The number and position of elements to be inserted along a given axis is determined by three attributes:

1. *the padding-below* `CoordinateDiff` $(p_1,\ldots,p_n)$,
2. *the padding-above* `CoordinateDiff` $(q_1,\ldots,q_n)$, and
3. *the interior padding* `Shape` $(r_1,\ldots,r_n)$.

The output tensor will have the shape $(d'_1,\dots,d'_n)$ where $d'_i = p_i + (d_i - 1)(r_i + 1) + 1 + q_i$ if $d_i > 0$, and $d'_i = p_i + q_i$ if $d_i = 0$.

Example: given a 3×3 tensor, with interior-padding sizes of $(1,2)$, padding-below of $(1,2)$, padding-above of $(1,0)$, and a pad-value of 42, we obtain:

```
          42 42 42 42 42 42 42 42 42
          42 42  1 42 42  2 42 42  3
1 2 3     42 42 42 42 42 42 42 42 42
4 5 6 --> 42 42  4 42 42  5 42 42  6
7 8 9     42 42 42 42 42 42 42 42 42
          42 42  7 42 42  8 42 42  9
          42 42 42 42 42 42 42 42 42
```

In other words we have inserted one new row between each pair of adjacent rows, two new columns between each pair of adjacent columns, one new row at the top and two new columns on the left, and one new row at the bottom and zero new columns on the right; then filled the new rows and columns with 42.

Note

The terms below and above here refer respectively to lower- or higher-numbered coordinate indices, and numbering starts at the upper-left corner; thus inserting a row “below” actually inserts it at the “top” of the matrix.

C++ Interface¶

class `Pad` : *public* ngraph::op::Op¶

Generic padding operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Pad`()¶

Constructs a generic padding operation.

`Pad`(*const* Output<Node> &*arg*, *const* Output<Node> &*arg_pad_value*, *const* CoordinateDiff &*padding_below*, *const* CoordinateDiff &*padding_above*, PadMode *pad_mode* = PadMode::CONSTANT)¶

Constructs a padding operation. Padding embeds the values of the input tensor into a larger tensor initialized to arg_pad_value.

Parameters

- `arg`: The node producing the input tensor to be padded.
- `arg_pad_value`: The node producing the scalar value to be used outside the are initialized by arg when pad_mode is CONSTANT.
- `padding_below`: How many elements to add on each axis before index 0 of arg. Rank must match arg.
- `padding_above`: How many elements to add on each axis after the last element of arg. Rank must match arg.
- `pad_mode`: The padding mode: CONSTANT(default), EDGE, REFLECT or SYMMETRIC. CONSTANT initializes new elements with arg_pad_value, EDGE uses the nearest value from arg. REFLECT and SYMMETRIC tile the background by flipping arg at the edge (SYMMETRIC) or on the last row/column/etc. (REFLECT).

void `validate_and_infer_types`()¶

Throws if the node is invalid.

const CoordinateDiff &`get_padding_below`() *const*¶

Return

The padding-below sizes.

const CoordinateDiff &`get_padding_above`() *const*¶

Return

The padding-above sizes.

const Shape &`get_padding_interior`() *const*¶

DEPRECATED. This is just a stub for backends that used to implement the interior padding feature, which is no longer supported.

Return

Returns a shape full of zeros, with the same rank as get_padding_below().

PadMode `get_pad_mode`() *const*¶

Return

The padding mode.

virtual std::shared_ptr<Node> `get_default_value`() *const*¶

Return

The default value for Pad.

Parameter¶

```
Parameter // A function parameter.
```

Description¶

Parameters are nodes that represent the arguments that will be passed to user-defined functions. Function creation requires a sequence of parameters.

Attributes¶

Name	Description
`element_type`	The `element::Type` of the parameter.
`shape`	The `Shape` of the parameter.
`cacheable`	True if the parameter is not expected to be frequently updated.

Outputs¶

Name	Element type	Shape
`output`	`element_type`	`shape`

A `Parameter` produces the value of the tensor passed to the function in the position of the parameter in the function's arguments. The passed tensor must have the element type and shape specified by the parameter.

Backprop¶

\[\leftarrow \Delta\]

C++ Interface¶

class `Parameter` : *public* ngraph::op::Op¶

A function parameter.

Parameters are nodes that represent the arguments that will be passed to user-defined functions. Function creation requires a sequence of parameters. Basic graph operations do not need parameters attached to a function.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Parameter`()¶

Constructions a tensor-typed parameter node.

`Parameter`(*const* ngraph::element::Type &*element_type*, *const* PartialShape &*pshape*, *const* bool *cacheable* = false)¶

Constructions a tensor-typed parameter node.

Parameters

- `element_type`: The element type of the parameter.
- `pshape`: The partial shape of the parameter.
- `cacheable`: True if the parameter is not expected to be frequently updated.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

Power¶

```
Power  // Elementwise exponentiation operation
```

Description¶

Elementwise exponentiation operation.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	same as `arg0`	same as `arg0`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} ^ {\mathtt{arg1}_{i_0, \ldots, i_{n-1}}}$$

Backprop¶

$$\begin{split}\overline{\mathtt{arg0}} &\leftarrow \frac{\Delta \cdot \mathtt{arg1}}{\mathtt{arg0}} \\ \overline{\mathtt{arg1}} &\leftarrow \Delta \cdot \mathtt{output} \cdot \log(\mathtt{arg1})\end{split}$$

C++ Interface¶

class `Power` : *public* ngraph::op::util::BinaryElementwiseArithmetic¶

Elementwise exponentiation operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Power`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs an exponentiation operation.

Parameters

- `arg0`: Node that produces the first input tensor.

- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Product¶

`Product // Product reduction operation.`

Description¶

Reduces the tensor, eliminating the specified reduction axes by taking the product.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Attributes¶

Name	Description
`reduction_axes`	The axis positions (0-based) on which to calculate the product

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`, with `reduction_axes` removed.

Mathematical Definition¶

\[\begin{split}\mathit{product}\left(\{0\}, \left[\begin{array}{ccc} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{array} \right]\right) &= \left[(1 * 3 * 5), (2 * 4 * 6) \right] = \left[15, 48 \right]&\text{ dimension 0 (rows) is eliminated} \\ \mathit{product}\left(\{1\}, \left[\begin{array}{ccc} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{array} \right]\right) &= \left[(1 * 2), (3 * 4), (5 * 6) \right] = \left[2, 12, 30 \right]&\text{ dimension 1 (columns) is eliminated}\\ \mathit{product}\left(\{0,1\}, \left[\begin{array}{ccc} 1 & 2 \\ 3 & 4 \\ 5 & 6 \end{array} \right]\right) &= (1 * 2) * (3 * 4) * (5 * 6) = 720&\text{ both dimensions (rows and columns) are eliminated}\end{split}\]

C++ Interface¶

class `Product` : *public* ngraph::op::util::ArithmeticReduction¶

> Product reduction operation.
> Reduces the tensor, eliminating the specified reduction axes by taking the product.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

> Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Product()`¶

Constructs a product reduction operation.

`Product`(*const* Output<Node> &*arg*, *const* AxisSet &*reduction_axes*)¶

Constructs a product reduction operation.

Parameters

- `arg`: The tensor to be reduced.
- `reduction_axes`: The axis positions (0-based) to be eliminated.

`Product`(*const* Output<Node> &*arg*, *const* Output<Node> &*reduction_axes*)¶

Constructs a product reduction operation.

Parameters

- `arg`: The tensor to be reduced.
- `reduction_axes`: The axis positions (0-based) to be eliminated.

shared_ptr<Node> `get_default_value`() *const*¶

Return

The default value for Product.

Quantize¶

```
Quantize // Maps real input to quantized output
```

Description¶

Produces a tensor of element type `type` and the same shape as `input` where the value of each coordinate \(i\) of `output` is the corresponding coordinate of `input` divided by `scale` rounded as specified by `round_mode` plus `zero_point`. The coordinate \(j\) of `scale` and `zero_point` is the coordinate of `output` projected onto `axes`.

Inputs¶

Name	Element Type	Shape
`input`	Any real type	Any
`scale`	Same as `input`	`input` shape projected onto `axes`
`zero_point`	Same as `output`	`input` shape projected onto `axes`

Attributes¶

Name	Description
`type`	`output` element type; any quantized type
`axes`	Axis positions on which `scale` and `zero_point` are specified
`round_mode`	*ROUND_NEAREST_TOWARD_INFINITY:* round to nearest integer in case of two equidistant integers round away from zero e.g. 2.5 -> 3 -3.5 -> -4 *ROUND_NEAREST_TOWARD_ZERO:* round to nearest integer in case of two equidistant integers round toward zero e.g. 2.5 -> 2 -3.5 to -3 *ROUND_NEAREST_UPWARD:* round to nearest integer in case of two equidistant integers round up e.g. 2.5 to 3 -3.5 to -3 *ROUND_NEAREST_DOWNWARD:* round to nearest integer in case of two equidistant integers round down e.g. 2.5 to 2 -3.5 to -4 *ROUND_NEAREST_TOWARD_EVEN:* round to nearest integer in case of two equidistant integers round to even e.g. 2.5 to 2 -3.5 to -4 *ROUND_TOWARD_INFINITY:* round to nearest integer away from zero *ROUND_TOWARD_ZERO:* round to nearest integer toward zero *ROUND_UP:* round to nearest integer toward infinity (ceiling) *ROUND_DOWN:* round to nearest integer toward negative infinity (floor)

Outputs¶

Name	Element Type	Shape
`output`	`type`	Same as `input`

Mathematical Definition¶

\[\mathtt{output}_{i,j} = \mathtt{round}\left(\frac{\mathtt{input}_{i,j}}{\mathtt{scale}_{j}}\right) + \mathtt{zero_point}_{j}\]

C++ Interface¶

class `Quantize` : *public* ngraph::op::Op¶

Quantize operation Maps real input (r) to quantized output (q) using scale (s), zero point (z) and round mode: q = ROUND(r / s) + o.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a

dummy type_info for Node if the class has not been updated yet.

`Quantize`(*const* Output<Node> &*input*, *const* Output<Node> &*scale*, *const* Output<Node> &*zero_point*, *const* ngraph::element::Type &*type*, *const* ngraph::AxisSet &*axes*, RoundMode *round_mode*)¶

Constructs a Quantize operation.

Parameters

- `input`: real input
- `scale`: scale used for mapping
- `zero_point`: zero point used for mapping
- `type`: output element type
- `axes`: axis positions on which `scale` and `zero_point` are specified
- `round_mode`: describes how to perform ROUND function (see above)

void `validate_and_infer_types`()¶

Throws if the node is invalid.

RandomUniform¶

```
RandomUniform  // Operation that generates a tensor populated with random
               // values of a uniform distribution.
```

Description¶

Warning

This op is experimental and subject to change without notice.

Inputs¶

Name

Element Type

Shape | Notes

`min_value`

Any floating point type

Scalar | Minimum value for the random distribution

`max_value`

Same as `max_value`

Scalar

Maximum value for the random distribution

`result_shape`

`element::i64`

Vector of any size

Shape of the output tensor

`use_fixed_seed`

`element::boolean`

Scalar

Flag indicating whether to use the fixed seed value `fixed_seed` (useful for testing)

Attributes¶

Name	Type	Notes
`fixed_seed`	`uint64_t`	Fixed seed value to use if `use_fixed_seed` flag is set to `1`. This should be used only for testing; if `use_fixed_seed` is `1`, `RandomUniform` will produce the _same_ values at each iteration.

Outputs¶

Name	Element Type	Shape
`output`	Same as `min_value`	`result_shape`

Mathematical Definition¶

\[\mathtt{output}_i = \mathtt{uniform_rand}(\mathtt{min}=\mathtt{min_value}, \mathtt{max}=\mathtt{max_value})\]

C++ Interface¶

class `RandomUniform` : *public* ngraph::op::Op¶

Generates a tensor populated with random values of a uniform distribution.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`RandomUniform`()¶

Constructs an uninitialized RandomUniform node.

`RandomUniform`(*const* Output<Node> &*min_value*, *const* Output<Node> &*max_value*, *const* Output<Node> &*result_shape*, *const* Output<Node> &*use_fixed_seed*, uint64_t *fixed_seed*)¶

Constructs a RandomUniform node.

Parameters

- `min_value`: Output producing the minimum value (inclusive) for the random uniform distribution. Must return a scalar of floating point type, and the type must match that of `max_value`.
- `max_value`: Output producing the maximum value (inclusive) for the random uniform distribution. Must return a scalar of floating point type, and the type must match that of `min_value`.
- `result_shape`: Output producing the shape of the output tensor. Must return a vector of type `element::i64`.
- `use_fixed_seed`: Output producing a boolean scalar Flag indicating whether to use the value supplied in `fixed_seed` to re-seed the random number generator at this iteration. Note that whenever `use_fixed_seed` is `true`, the same values will be generated in the output tensor. This flag is primarily used for debugging. If `use_fixed_seed` is `false`, the value in `fixed_seed` is ignored.
- `fixed_seed`: Fixed seed value to be supplied to the random number generator if `use_fixed_seed` is `true`. If `use_fixed_seed` is `false`, this value is ignored.

uint64_t `get_fixed_seed`() *const*¶

Returns the fixed seed value to be supplied to the random number generator if `use_fixed_seed` is `true`. If `use_fixed_seed` is `false`, this value is ignored.

void `set_fixed_seed`(uint64_t *fixed_seed*)¶

Sets the fixed seed value to be supplied to the random number generator if `use_fixed_seed` is `true`. If `use_fixed_seed` is `false`, this value is ignored.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

Relu¶

```
Relu  // Elementwise relu operation
```

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\begin{split}\mathtt{output}_{i_0, \ldots, i_{n-1}} = \begin{cases} 0&\text{if }\mathtt{arg}_{i_0, \ldots, i_{n-1}} \le 0 \\ \mathtt{arg}_{i_0, \ldots, i_{n-1}}&\text{otherwise} \end{cases}\end{split}\]

C++ Interface¶

class `Relu` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise Relu operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Relu`(*const* Output<ngraph::Node> &*arg*)¶

Constructs a Relu operation.

Parameters

- `arg`: Node that produces the input tensor.

Result¶

```
Result  // Allow a value to be a result
```

Description¶

Captures a value for use as a function result. The output of the op is the same as the input.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output} = \mathtt{arg}\]

C++ Interface¶

class `Result` : *public* ngraph::op::Op¶

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Result`()¶

Allows a value to be used as a function result.

`Result`(*const* Output<Node> &*arg*, bool *needs_default_layout* = false)¶

Allows a value to be used as a function result.

Parameters

- `arg`: Node that produces the input tensor.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

ShapeOf¶

```
ShapeOf  // Operation that returns the shape of its input tensor
```

Description¶

Warning

This op is experimental and subject to change without notice.

Returns the shape of its input argument as a tensor of element type `u64`.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	`element::u64`	`{r}` where `r` is the rank of `arg`’s shape.

Mathematical Definition¶

\[\mathtt{output} = \mathtt{shapeof}(\mathtt{arg})\]

C++ Interface¶

class `ShapeOf` : *public* ngraph::op::Op¶

Operation that returns the shape of its input argument as a tensor.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`ShapeOf`(*const* Output<Node> &*arg*)¶

Constructs a shape-of operation.

void `validate_and_infer_types`()¶

Throws if the node is invalid.

Sigmoid¶

```
Sigmoid  // Elementwise sigmoid operation
```

Description¶

Produces a single output tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the sigmoid of `arg` at the same coordinate.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \frac{1}{1+\exp(-\mathtt{arg}_{i_0, \ldots, i_{n-1}})}\]

C++ Interface¶

class `Sigmoid` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

Sign¶

```
Sign  //  Elementwise sign operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the sign (-1, 0, 1) of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	**Element Type**	**Shape**
`arg`	Any	Any

Outputs¶

Name	**Element Type**	**Shape**
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{sgn}(\mathtt{arg}_{i_0, \ldots, i_{n-1}})\]

C++ Interface¶

class `Sign` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise sign operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Sign`(*const* Output<Node> &*arg*)¶

Constructs an elementwise sign operation.

Parameters

- `arg`: Node that produces the input tensor.

Sin¶

```
Sin  //  Elementwise sine operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the sine of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	**Element Type**	**Shape**
`arg`	Any	Any

Outputs¶

Name	**Element Type**	**Shape**
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \sin(\mathtt{arg}_{i_0, \ldots, i_{n-1}})\]

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow \Delta\ \cos(\mathtt{arg})\]

C++ Interface¶

class `Sin` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise sine operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Sin`(*const* Output<Node> &*arg*)¶

Constructs a sine operation.

Parameters

- `arg`: Node that produces the input tensor.

Sinh¶

```
Sinh  //  Elementwise hyperbolic sine operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the hyperbolic sine of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \sinh(\mathtt{arg}_{i_0, \ldots, i_{n-1}})$$

Backprop¶

$$\overline{\mathtt{arg}} \leftarrow \Delta\ \cosh(\mathtt{arg})$$

C++ Interface¶

class `Sinh` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise hyperbolic sine (sinh) operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Sinh`(*const* Output<Node> &*arg*)¶

Constructs a hyperbolic sine operation.

Parameters

- `arg`: Node that produces the input tensor.

Slice¶

```
Slice  // Produces a sub-tensor of its input.
```

Description¶

Takes a slice of an input tensor, i.e., the sub-tensor that resides within a bounding box, optionally with a stride.

Inputs¶

Name	Element Type	Shape
arg	Any	$D=D_1, D_2, \ldots, D_n$.

Attributes¶

Name	Description
lower_bounds	The (inclusive) lower-bound coordinates $L=L_1, L_2, \ldots, L_n.$
upper_bounds	The (exclusive) upper-bound coordinates $U=U_1, U_2, \ldots, U_n.$
strides	The strides $S=S_1, S_2, \ldots, S_n$ for the slices. Defaults to 1s.

Outputs¶

Name	Element Type	Shape
`output`	Same as arg	$D'_i=\lceil\frac{U_i-L_i}{S_i}\rceil$.

Mathematical Definition¶

$$\mathtt{output}_I = \mathtt{arg}_{L+I*S}$$

where $I=I_1, I_2, \ldots, I_n$ is a coordinate of the output.

C++ Interface¶

class `Slice` : *public* ngraph::op::Op¶

Takes a slice of an input tensor, i.e., the sub-tensor that resides within a bounding box, optionally with stride.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Slice`()¶

Constructs a tensor slice operation.

`Slice`(*const* Output<Node> &*arg*, *const* Coordinate &*lower_bounds*, *const* Coordinate &*upper_bounds*, *const* Strides &*strides*)¶

Constructs a tensor slice operation.

Parameters

- `arg`: The tensor to be sliced.
- `lower_bounds`: The axiswise lower bounds of the slice (inclusive).
- `upper_bounds`: The axiswise upper bounds of the slice (exclusive).
- `strides`: The slicing strides; for example, strides of `{n,m}` means to take every nth row and every mth column of the input matrix.

`Slice`(*const* Output<Node> &*arg*, *const* Coordinate &*lower_bounds*, *const* Coordinate &*upper_bounds*)¶

Constructs a tensor slice operation with unit strides; i.e., every element inside the bounding box will be copied to the output slice.

Parameters

- `arg`: The tensor to be sliced.
- `lower_bounds`: The axiswise lower bounds of the slice (inclusive).
- `upper_bounds`: The axiswise upper bounds of the slice (exclusive).

void `validate_and_infer_types`()¶

Throws if the node is invalid.

const Coordinate &`get_lower_bounds`() *const*¶

Return

The inclusive lower-bound coordinates.

const Coordinate &`get_upper_bounds`() *const*¶

Return

The exclusive upper-bound coordinates.

const Strides &`get_strides`() *const*¶

Return

The slicing strides.

Softmax¶

```
Softmax  // Softmax operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the expine of the value of the corresponding coordinate of `arg` divided by the sum of the expine of all coordinates of `arg` in the specified `axes.`

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Attributes¶

Name	Description
`axes`	The axis positions (0-based) on which to calculate the softmax

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

$$\mathtt{output}_{i} = \frac{\exp(\mathtt{arg}_{i})}{\sum_{j} \exp(\mathtt{arg}_{j})}$$

C++ Interface¶

class `Softmax` : *public* ngraph::op::Op¶

Softmax operation.

Sqrt¶

```
Sqrt  //  Elementwise square root operation
```

Description¶

Produces a tensor of the same element type and shape as `arg,` where the value at each coordinate of `output` is the square root of the value at the corresponding coordinate of `arg.`

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \sqrt{\mathtt{arg}_{i_0, \ldots, i_{n-1}}}$$

Backprop¶

$$\overline{\mathtt{arg}} \leftarrow \frac{\Delta}{2\cdot \mathtt{output}}$$

C++ Interface¶

class `Sqrt` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise square root operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Sqrt`(*const* Output<Node> &*arg*)¶

Constructs a square operation.

Parameters

- `arg`: Node that produces the input tensor.

Subtract¶

```
Subtract  // Elementwise subtract operation
```

Description¶

Elementwise subtract operation.

Produces tensor of the same element type and shape as the two inputs, where the value at each coordinate of `output` is the difference of the values at the corresponding input coordinates.

Inputs¶

Name	Element Type	Shape
`arg0`	any	any
`arg1`	same as `arg0`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	same as `arg0`	same as `arg0`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}} - \mathtt{arg1}_{i_0, \ldots, i_{n-1}}$$

Backprop¶

$$\begin{split}\overline{\mathtt{arg0}} &\leftarrow \Delta \\ \overline{\mathtt{arg1}} &\leftarrow -\Delta\end{split}$$

C++ Interface¶

class `Subtract` : *public* ngraph::op::util::BinaryElementwiseArithmetic¶

Elementwise subtraction operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Subtract`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a subtraction operation.

Parameters

- `arg0`: Node that produces the first input tensor.
- `arg1`: Node that produces the second input tensor.
- `auto_broadcast`: Auto broadcast specification

Tan¶

```
Tan  //  Elementwise tangent operation
```

Description¶

Produces a tensor of the same element type and shape as `arg`, where the value at each coordinate of `output` is the tangent of the value at the corresponding coordinate of `arg`.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

$$\mathtt{output}_{i_0, \ldots, i_{n-1}} = \tan(\mathtt{arg}_{i_0, \ldots, i_{n-1}})$$

Backprop¶

$$\overline{\mathtt{arg}} \leftarrow \frac{\Delta}{\cos^2(\mathtt{arg})}$$

C++ Interface¶

class `Tan` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise tangent operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Tan`(*const* Output<Node> &*arg*)¶

Constructs a tangent operation.

Parameters

- `arg`: Node that produces the input tensor.

Tanh¶

```
Tanh  // Elementwise hyperbolic tangent operation.
```

Description¶

Produce a tensor with the same shape and element typye as `arg,` where the value at each coordinate of `output` is the hyperbolic tangent of the value of `arg` at the same coordinate.

Inputs¶

Name	**Element Type**	**Shape**
`arg`	Any	Any

Outputs¶

Name	**Element Type**	**Shape**
`output`	Same as `arg`	Same as `arg`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \tanh(\mathtt{arg}_{i_0, \ldots, i_{n-1}})\]

Backprop¶

\[\overline{\mathtt{arg}} \leftarrow \Delta\ (1 - \mathtt{output}^2)\]

C++ Interface¶

class `Tanh` : *public* ngraph::op::util::UnaryElementwiseArithmetic¶

Elementwise hyperbolic tangent operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node’s class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Tanh`(*const* Output<Node> &*arg*)¶

Constructs a hyperbolic tangent operation.

Parameters

- `arg`: Node that produces the input tensor.

Transpose¶

```
Transpose  // Operation that transposes axes of a tensor
```

Description¶

Warning

This op is not yet implemented in any backend.

Warning

This op is experimental and subject to change without notice.

Operation that transposes axes of an input tensor. This operation covers matrix transposition, and also more general cases on higher-rank tensors.

Inputs¶

Name	Element Type	Shape
`arg`	Any	Any
`input_order`	`element::i64`	`[n]`, where `n` is the rank of `arg`.

Outputs¶

Name	Element Type	Shape
`output`	Same as `arg`	`P(ShapeOf(arg))`, where *P* is the permutation supplied for `input_order`.

The input `input_order` must be a vector of shape [n], where `n` is the rank of `arg`, and must contain every integer in the range `[0,n-1]`. This vector represents a permutation of `arg`'s dimensions. For example,

`arg` Shape	**`input_order` Value**	**`output` Shape**	**Comment**
`[3,4]`	`[1,0]`	`[4,3]`	Transposes the `arg` matrix.
`[3,3]`	`[1,0]`	`[3,3]`	Transposes the `arg` matrix.
`[3,3]`	`[1,0]`	`[3,3]`	Transposes the `arg` matrix.
`[3,4,8]`	`[2,0,1]`	`[8,3,4]`	Moves the “last” dimension to the “first” position.

Mathematical Definition¶

\[\mathtt{output}_{i_0,i_1,...,i_n} = \mathtt{arg}_{i_{\mathtt{input_order}[0]},i_\mathtt{input_order}[1],...,i_\mathtt{input_order}[n]}.\]

Backprop¶

Not yet implemented.

C++ Interface¶

class `Transpose` : *public* ngraph::op::Op¶

Tensor transpose operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Transpose`(*const* Output<Node> &*arg*, *const* Output<Node> &*input_order*)¶

Constructs a transpose operation.

Parameters

- `arg`: Node producing the tensor to be transposed.
- `input_order`: Node producing the permutation to apply to the axes of the input shape. Must be a vector of element type element::i64, with shape [n], where n is the rank of arg. The tensor's value must contain every integer in the range [0,n-1].

void `validate_and_infer_types`()¶

Throws if the node is invalid.

Xor¶

```
Xor  // Elementwise logical-xor operation
```

Description¶

Produces tensor with boolean element type and shape as the two inputs, which must themselves have boolean element type, where the value at each coordinate of `output` is `0` (true) if `arg0` or `arg1` both zero or both nonzero, or `1` otherwise.

Inputs¶

Name	Element Type	Shape
`arg0`	`ngraph::element::boolean`	any
`arg1`	`ngraph::element::boolean`	same as `arg0`

Outputs¶

Name	Element Type	Shape
`output`	`ngraph::element::boolean`	same as `arg0`

Mathematical Definition¶

\[\mathtt{output}_{i_0, \ldots, i_{n-1}} = \mathtt{arg0}_{i_0, \ldots, i_{n-1}}\, \mathtt{XOR}\, \mathtt{arg1}_{i_0, \ldots, i_{n-1}}\]

C++ Interface¶

class `Xor` : *public* ngraph::op::util::BinaryElementwiseLogical¶

Elementwise logical-xor operation.

Public Functions

const NodeTypeInfo &`get_type_info`() *const*¶

Returns the NodeTypeInfo for the node's class. During transition to type_info, returns a dummy type_info for Node if the class has not been updated yet.

`Xor`(*const* Output<Node> &*arg0*, *const* Output<Node> &*arg1*, *const* AutoBroadcastSpec &*auto_broadcast* = AutoBroadcastSpec())¶

Constructs a logical-xor operation.
Output `[d0, ...]`

Parameters

- `arg0`: Node that produces the first input tensor.`[d0, ...]`
- `arg1`: Node that produces the second input tensor.`[d0, ...]`
- `auto_broadcast`: Auto broadcast specification

More about Core Ops¶

An `Op`'s primary role is to function as a node in a directed acyclic computation graph.

Core ops are ops that are available and generally useful to all framework bridges and that can be compiled by all transformers. A framework bridge may define framework-specific ops to simplify graph construction, provided that the bridge can enable every transformer to replace all such ops with equivalent clusters or subgraphs composed of core ops. In a similar manner, transformers may define transformer-specific ops to represent kernels or other intermediate operations.

The input and output ports of ops are any of the functions which work with `Output<Node>/Input<Node>`. Previous functions that worked at the level of ops are deprecated, like:
`Node::get_element_type()`
as it does not take any input. This function has been replaced with new functions like:
`Node::get_output_element_type(index)`
where there is no ambiguity.

If a framework supports extending the set of ops it offers, a bridge may even expose transformer-specific ops to the framework user.

Important

Our design philosophy is that the graph is not a script for running kernels; rather, our compilation will match `ops` to appropriate kernels for the backend(s) in use. Thus, we expect that adding of new Core ops should be infrequent and that most functionality instead gets added with new functions that build sub-graphs from existing core ops.

It is easiest to define a new op by adapting an existing op. Some of the tasks that must be performed are:

- Op constructor:
    - Checking type-consistency of arguments
    - Specifying the result type for a call
- Serializer/Deserializer
- Transformer handlers:
    - Interpreter (reference) implementation of behavior. The implementation should favor clarity over efficiency.

Provenance¶

Basic concepts¶

The term provenance refers to the matching of device code to framework subgraphs; it is analogous to source code locators in conventional compilers, which associate regions of object code with source files and line numbers. Provenance is *extensible* in that it may also include the chain of passes that lead from the framework graph to the executing code.

It can associate device code with specific tags added by a framework bridge which correspond to the framework ops that create the nGraph nodes. This works only for those transformations that take place in nGraph: the information stored in the nodes can include additional details about how the device code was chosen. For example, whenever a graph transformation is performed with one of the nGraph core Ops, a lower level of abstraction can record information about the transformation that may be useful to anyone wondering why a kernel was "chosen"; a complete description of the steps leading to the device kernels being used, as well as all of the framework nodes that led to the kernel, can be obtained.

Existing use cases¶

Currently, every node nGraph touches can optionally have a set of provenance tags, which are strings set by a framework bridge. When a set of nodes is replaced by a new set of nodes, a combination of heuristics and special casing is used to set the tags on the new nodes based on the tags from the old nodes.

A builder is a function that creates a sub-graph and returns a root node to the bridge. The bridge is not necessarily aware of the subgraph, only of the returned node, where it sets tags. The remaining nodes' tags are set by associating a set of nodes, called a *provenance group*, with the node. Any tags added to the node are also added to the nodes in the provenance group.

An updated implementation of the functionality of builders is the *fused op*, a node that can replace itself with a subgraph. When the node is expanded into a subgraph, a vector of values is returned, corresponding to outputs of the original fused op; the tags of the fused op are added to all nodes in the values in reverse dataflow direction, up to (though not including) the input values of the fused op.

Quantization¶

Quantization refers the process of reducing the number of bits that represent a number. In a DL context, weights and activations can be represented using 8-bit integers (INT8) to compress the model size of a trained neural network without any significant loss in model accuracy. INT8 is one kind of quantization. Compared with 32-bit floating point (FP32), using arithmetic with lower precision, such as INT8, to calculate weights and activation requires less memory.

Implementing a quantized model with nGraph¶

To implement a quantized model with nGraph, provide a partially (or fully) quantized model (where the convolution layer in the model is replaced with a quantized convolution, for example) to the nGraph Library along with quantized parameters: weights, activations, scale, and zero point.

Note

As of version 0.29, only quantization for inference is supported.

nGraph Quantized Operators (Ops)¶

nGraph uses scale and zero point (also used by ONNX) to map real values to quantized values. All quantized ops use scale and zero point and can be used just like any other nGraph op.

Scale: the quantization scale of the tensor

Zero point: the zero point of the tensor

Round mode: used in combination with scale and zero point to round real values to quantized values

Op	**Description**
Quantize	Maps real values (r) to quantized values (q) using scale (s), zero point (z), and round mode; produces a quantized tensor.
Dequantize	Maps quantized values (q) to real values (r) using scale (s) and zero point (z); converts a quantized tensor to a floating-point tensor.
`FakeQuantize`	Performs element-wise linear quantization.
`QuantizedConvolution`	Performs 8-bit convolution.
`QuantizedDot`	Performs 8-bit dot.

Quantization Ops¶

Some frameworks such as TensorFlow* have fused ops. nGraph provides optional operations to help users easily translate (map) any quantized model created from frameworks with fused ops to nGraph. Unlike builders, experimental ops take scale and zero point instead of min and max.

Operator	Description
QuantizedConvolutionBias	This experimental op can be fused with a ReLU op.
QuantizedConvolutionBiasAdd	This experimental op constructs a quantized convolution with bias and optional ReLU. And then takes input for the add operation.
QuantizedConvolutionBiasSignedAdd	Same as QuantizedConvolutionBiasAdd but with signed add.
QuantizedConvolutionRelu	This experimental op is designed for a particular use case that would require convolution and ReLU to be combined.
QuantizedDotBias	This experimental op can be fused with a ReLU op.

Experimental Quantized Ops (optional)¶

nGraph Quantization Design¶

The goal of nGraph quantization is to flexibly support a wide variety of frameworks and users. The use of scale and zero point as well as quantized builders in the nGraph design helps to achieve this goal.

Scale and Zero Point¶

Using scale and zero point allows nGraph to be framework agnostic (i.e., it can equally support all deep learning frameworks). nGraph Bridges will automatically convert min and max (provided by a DL framework) to scale and zero point as needed. Quantized builders are available to help the bridges perform this calculation. However, if users are directly using nGraph (and not using a bridge), they are required to provide scale and zero point for quantized ops.

Another advantage of using scale and zero point to express quantization parameters is that users can flexibly implement quantized ops into various nGraph backends. When implementing quantized ops, all current nGraph backends will directly use scale and zero point (and not min and max) to perform the quantized computation.

Quantized Builders¶

Quantized builders are helper utilities to assist framework integrators to enable quantized models with nGraph. They serve as an API (interface) between framework bridges and nGraph, allowing framework bridges to directly construct ops in the nGraph Abstraction Layer.

Quantized builders help nGraph framework bridges by:

- Breaking down a fused quantized operator in the framework to a subgraph (of quantized and non-quantized operators) in the nGraph core IR
- Converting from min and max to scale and zero point based on the quantization mode described by the DL framework

Note: Fused ops and quantized builders serve the same purpose. In the future, fused ops will replace quantized builders.

nGraph Quantized Builders¶

Category	Builder	Description
Scaled Mode Min / Max Builders		
	ScaledQuantize	Converts min and max to scale and zero point using a scaled mode calculation and then constructs and returns an nGraph Quantize operator.
	ScaledDequantize	Converts min and max to scale and zero point using a scaled mode calculation and then constructs and returns an nGraph Dequantize operator.
Quantized Convolution and Variants		
	ScaledQuantizedConvolution	Constructs a quantized convolution with an optional ReLU.
	ScaledQuantizedConvolutionBias	Constructs a quantized convolution with bias and an optional ReLU.
	ScaledQuantizedConvolutionBiasAdd	Constructs a quantized convolution with bias and an optional ReLU, where the output is added to the output of another convolution (sum_input).
Quantized Dot (Matmul) and Variants		
	ScaledQuantizedDot	Constructs a quantized dot (Matmul) with an optional ReLU.
	ScaledQuantizedDotBias	Constructs a quantized dot (Matmul) with bias and an optional ReLU.
Quantized Concat		
	ScaledQuantizedConcat	Constructs a quantized concatenation.

Dynamic Shapes¶

For an example on how to use dynamic shapes, see the Scenario Two: Known Partial Shape documentation.

Runtime Error Checking¶

Static type-checking in the presence of dynamic shapes will make optimistic assumptions about things like shape mismatches. For example, if an elementwise op is provided inputs of shapes `(2,?)` and `(?,5)`, the type checker will proceed under the assumption that the user is not going to pass tensors with inconsistent shape at runtime, and therefore infer an output shape of `(2,5)`. That means that shape mismatches can now occur at runtime.

PartialShape, Dimension, and Rank Classes¶

Partial shape information is expressed via the `PartialShape`, `Dimension`, and `Rank` classes.

Note

`Rank` is an alias for `Dimension`, used when the value represents the number of axes in a shape, rather than the size of one dimension in a shape.

class `PartialShape`¶

Class representing a shape that may be partially or totally dynamic.

A PartialShape may have:

- Dynamic rank. (Informal notation: `?`)
- Static rank, but dynamic dimensions on some or all axes. (Informal notation examples: `{1,2,?,4}`, `{?,?,?}`)
- Static rank, and static dimensions on all axes. (Informal notation examples: `{1,2,3,4}`, `{6}`, `{}`)

Public Functions

`PartialShape`(std::initializer_list<Dimension> *init*)¶

Constructs a shape with static rank from an initializer list of Dimension.
Examples:

Parameters

- `init`: The Dimension values for the constructed shape.

```
PartialShape s{2,3,4};                     // rank=3, all dimensions static
PartialShape s{};                          // rank=0
PartialShape s{2,Dimension::dynamic(),3};  // rank=3, dimension 1 dynamic
```

`PartialShape`(*const* std::vector<Dimension> &*dimensions*)¶

Constructs a PartialShape with static rank from a vector of Dimension.

Parameters

- `dimensions`: The Dimension values for the constructed shape.

`PartialShape`()¶

Constructs a static PartialShape with zero rank (the shape of a scalar).

`PartialShape`(*const* Shape &*shape*)¶

Constructs a static PartialShape from a Shape.

Parameters

- `shape`: The Shape to convert into PartialShape.

bool `is_static`() *const*¶

Check if this shape is static.
A shape is considered static if it has static rank, and all dimensions of the shape are static.

Return

`true` if this shape is static, else `false`.

bool `is_dynamic`() *const*¶

Check if this shape is dynamic.
A shape is considered static if it has static rank, and all dimensions of the shape are static.

Return

`false` if this shape is static, else `true`.

Rank `rank`() *const*¶

Get the rank of the shape.

Return

The rank of the shape. This will be Rank::dynamic() if the rank of the shape is dynamic.

bool `compatible`(*const* PartialShape &*s*) *const*¶

Check whether this shape is compatible with the argument, i.e., whether it is possible to merge them.
Two shapes are compatible if

- one or both of them has dynamic rank, or
- both shapes have dynamic and equal rank, and their dimensions are elementwise compatible (see Dimension::compatible()).

Return

`true` if this shape is compatible with `s`, else `false`.

Parameters

- `s`: The shape to be checked for compatibility with this shape.

bool `same_scheme`(*const* PartialShape &*s*) *const*¶

Check whether this shape represents the same scheme as the argument.
Two shapes
`s1` and `s2` represent the same scheme if

- they both have dynamic rank, or
- they both have static and equal rank `r`, and for every `i` from `0` to `r-1`, `s1[i]` represents the same scheme as `s2[i]` (see Dimension::same_scheme()).

Return

`true` if this shape represents the same scheme as `s`, else `false`.

Parameters

- `s`: The shape whose scheme is being compared with this shape.

bool `relaxes`(*const* PartialShape &*s*) *const*¶

Check whether this shape is a relaxation of the argument.
Intuitively, a
PartialShape `s1` is said to *relax* `s2` (or *is a relaxation* of `s2`) if it is "more permissive" than `s2`. In other words, `s1` is a relaxation of `s2` if anything you can form by plugging things into the dynamic dimensions of `s2` is also something you can form by plugging things into the dynamic dimensions of `s1`, but not necessarily the other way around.

Return

`true` if this shape relaxes `s`, else `false`.

Parameters

- `s`: The shape which is being compared against this shape.

`s1.relaxes(s2)` is equivalent to `s2.refines(s1)`.
Formally, PartialShape `s1` is said to *relax* PartialShape `s2` if:

- `s1` has dynamic rank, or
- `s1` and `s2` both have static rank `r`, and for every `i` from `0` to `r-1`, either `s1[i]` is dynamic, or `s1[i]` == `s2[i]`.

bool `refines`(*const* PartialShape &*s*) *const*¶

Check whether this shape is a refinement of the argument.
Intuitively, a
PartialShape `s1` is said to *relax* `s2` (or *is a relaxation* of `s2`) if it is "less permissive" than

`s2`. In other words, `s1` is a relaxation of `s2` if anything you can form by plugging things into the dynamic dimensions of `s1` is also something you can form by plugging things into the dynamic dimensions of `s2`, but not necessarily the other way around.

Return

`true` if this shape refines `s`, else `false`.

Parameters

- `s`: The shape which is being compared against this shape.

`s1.refines(s2)` is equivalent to `s2.relaxes(s1)`.

Formally, PartialShape `s1` is said to *refine* PartialShape `s2` if:

- `s2` has dynamic rank, or
- `s1` and `s2` both have static rank `r`, and for every `i` from `0` to `r-1`, either `s2[i]` is dynamic, or `s1[i]` == `s2[i]`.

bool `merge_rank`(Rank *r*)¶

Checks that this shape's rank is compatible with `r`, and, if this shape's rank is dynamic and `r` is static, updates this shape to have a rank of `r` with dimensions all dynamic.

Return

`true` if this shape's rank is compatible with `r`, else `false`.

Shape `to_shape`() *const*¶

Convert a static PartialShape to a Shape.

Return

A new Shape `s` where `s[i] = size_t((*this)[i])`.

Exceptions

- `std::invalid_argument`: If this PartialShape is dynamic.

bool `all_non_negative`() *const*¶

Returns `true` if all static dimensions of the tensor are non-negative, else `false`.

const Dimension &`operator[]`(size_t *i*) *const*¶

Index operator for PartialShape.

Return

A reference to the `i`th Dimension of this shape.

Parameters

- `i`: The index of the dimension being selected.

Dimension &`operator[]`(size_t *i*)¶

Index operator for PartialShape.

Return

A reference to the `i`th Dimension of this shape.

Parameters

- `i`: The index of the dimension being selected.

`operator std::vector<Dimension>`() *const*¶

Returns a vector of the dimensions. This has no meaning if dynamic.

Public Static Functions

PartialShape `dynamic`(Rank *r* = Rank::dynamic())¶

Construct a PartialShape with the given rank and all dimensions (if any) dynamic.

Return

A PartialShape with the given rank, and all dimensions (if any) dynamic.

bool `merge_into`(PartialShape &*dst*, *const* PartialShape &*src*)¶

Try to merge one shape into another.
Merges
`src` into `dst`, returning `true` on success and `false` on failure. If `false` is returned, the effect on `dst` is unspecified.

Return

`true` if merging succeeds, else `false`.

Parameters

- `dst`: The shape that `src` will be merged into.
- `src`: The shape that will be merged into `dst`.

To merge two partial shapes `s1` and `s2` is to find the most permissive partial shape `s` that is no more permissive than `s1` or `s2`, if `s` exists. For example:

```
merge(?,?) -> ?
merge(?,{?,?}) -> {?,?}
merge({?,?},{?,?}) -> {?,?}
merge({1,2,3,4},?) -> {1,2,3,4}
merge({1,2},{1,?}) -> {1,2}
merge({1,2,?,?},{1,?,3,?}) -> {1,2,3,?}
merge({1,2,3},{1,2,3}) -> {1,2,3}

merge({1,?},{2,?}) fails [dimension 0 constraints are inconsistent]
merge({?,?},{?,?,?}) fails [ranks are inconsistent]
```

This function (merge_into) performs the “merge” operation described above on `dst` and `src`, but overwrites `dst` with the result and returns `true` if merging is successful; if merging is unsuccessful, the function returns `false` and may make unspecified changes to `dst`.

bool `broadcast_merge_into`(PartialShape &*dst*, *const* PartialShape &*src*, *const* op::AutoBroadcastSpec &*autob*)¶

Try to merge one shape into another along with implicit broadcasting.

class `Dimension`¶

Class representing a dimension, which may be dynamic (undetermined until runtime), in a shape or shape-like object.
Static dimensions may be implicitly converted from int64_t. A dynamic dimension is constructed with Dimension() or Dimension::dynamic().
XXX: THIS CLASS IS NOT IN USE YET AND THE ENTIRE DESIGN IS SUBJECT TO CHANGE.

Public Functions

`Dimension`(int64_t *dimension*)¶

Construct a static dimension.

Parameters

- `dimension`: Value of the dimension. Must not be equal to Dimension::s_dynamic_val.

Exceptions

- `std::invalid_argument`: If `dimension` == Dimension::s_dynamic_val.

`Dimension`()¶

Construct a dynamic dimension.

bool `is_static`() *const*¶

Check whether this dimension is static.

Return

`true` if the dimension is static, else `false`.

bool `is_dynamic`() *const*¶

Check whether this dimension is dynamic.

Return

`false` if the dimension is static, else `true`.

`operator int64_t`() *const*¶

Convert this dimension to `int64_t`. This dimension must be static.

Exceptions

- `std::invalid_argument`: If this dimension is dynamic.

`operator size_t`() *const*¶

Convert this dimension to `size_t`. This dimension must be static and non-negative.

Exceptions

- `std::invalid_argument`: If this dimension is dynamic or negative.

bool `same_scheme`(*const* Dimension &*dim*) *const*¶

Check whether this dimension represents the same scheme as the argument (both dynamic, or equal).

Return

`true` if this dimension and `dim` are both dynamic, or if they are both static and equal; otherwise, `false`.

Parameters

- `dim`: The other dimension to compare this dimension to.

bool `compatible`(*const* Dimension &*d*) *const*¶

Check whether this dimension is capable of being merged with the argument dimension. Two dimensions are considered compatible if it is possible to merge them. (See Dimension::merge.)

Return

`true` if this dimension is compatible with `d`, else `false`.

Parameters

- `d`: The dimension to compare this dimension with.

bool `relaxes`(*const* Dimension &*d*) *const*¶

Check whether this dimension is a relaxation of the argument.
A dimension
`d1` *relaxes* (or *is a relaxation of*) `d2` if `d1` and `d2` are static and equal, or `d1` is dynamic.

Return

`true` if this dimension relaxes `d`, else `false`.

Parameters

- `d`: The dimension to compare this dimension with.

`d1.relaxes(d2)` is equivalent to `d2.refines(d1)`.

bool `refines`(*const* Dimension &*d*) *const*¶

Check whether this dimension is a refinement of the argument.
A dimension
`d2` *refines* (or *is a refinement of*) `d1` if `d1` and `d2` are static and equal, or `d2` is dynamic.

Return

`true` if this dimension relaxes `d`, else `false`.

Parameters

- `d`: The dimension to compare this dimension with.

`d1.refines(d2)` is equivalent to `d2.relaxes(d1)`.

Dimension `operator+`(*const* Dimension &*dim*) *const*¶

Addition operator for Dimension.

Return

Dimension::dynamic() if either of `*this` or `dim` is dynamic; else, a static dimension with value `int64_t(*this)+in64_t(dim)`.

Parameters

- `dim`: Right operand for addition.

Dimension `operator-`(*const* Dimension &*dim*) *const*¶

Subtraction operator for Dimension.

Return

Dimension::dynamic() if either of `*this` or `dim` is dynamic; else, a static dimension with value `int64_t(*this)-int64_t(dim)`.

Parameters

- `dim`: Right operand for subtraction.

Dimension `operator*`(*const* Dimension &*dim*) *const*¶

Multiplication operator for Dimension.

Return

0 if either of `*this` or `dim` is static and 0; else, Dimension::dynamic() if either of `*this` or `dim` is dynamic; else, a static dimension with value `int64_t(*this)*int64_t(dim)`.

Parameters

- `dim`: Right operand for multiplicaiton.

Dimension &`operator+=`(*const* Dimension &*dim*)¶

Add-into operator for Dimension.

Return

A reference to `*this`, after updating `*this` to the value `*this + dim`.

Parameters

- `dim`: Right operand for addition.

Dimension &`operator*=`(*const* Dimension &*dim*)¶

Multiply-into operator for Dimension.

Return

A reference to `*this`, after updating `*this` to the value `*this * dim`.

Parameters

- `dim`: Right operand for multiplication.

Public Static Functions

bool `merge`(Dimension &*dst*, *const* Dimension *d1*, *const* Dimension *d2*)¶

Try to merge two Dimension objects together.

- If `d1` is dynamic, writes `d2` to `dst` and returns `true`.
- If `d2` is dynamic, writes `d1` to `dst` and returns `true`.
- If `d1` and `d2` are static and equal, writes `d1` to `dst` and returns `true`.
- If `d1` and `d2` are both static and unequal, leaves `dst` unchanged and returns `false`.

Return

`true` if merging succeeds, else `false`.

Parameters

- `dst`: Reference to write the merged Dimension into.
- `d1`: First dimension to merge.
- `d2`: Second dimension to merge.

bool `broadcast_merge`(Dimension &*dst*, *const* Dimension *d1*, *const* Dimension *d2*)¶

Try to merge two Dimension objects together with implicit broadcasting of unit-sized dimension to non unit-sized dimension.

static Dimension `dynamic`()¶

Create a dynamic dimension.

Return

A dynamic dimension.

Public Static Attributes

const int64_t `s_dynamic_val` = {(std::numeric_limits<int64_t>::max())}¶

Constant for the value used internally to represent a dynamic dimension.

Working with Backends¶

- What is a backend?
- How to use?
- nGraph bridge
- OpenCL

What is a backend?¶

In the nGraph Compiler stack, what we call a *backend* is responsible for function execution and value allocation. A backend can be used to carry out computations from a framework on a CPU, GPU, or ASIC; it can also be used with an *Interpreter* mode, which is primarily intended for testing, to analyze a program, or to help a framework developer customize targeted solutions.

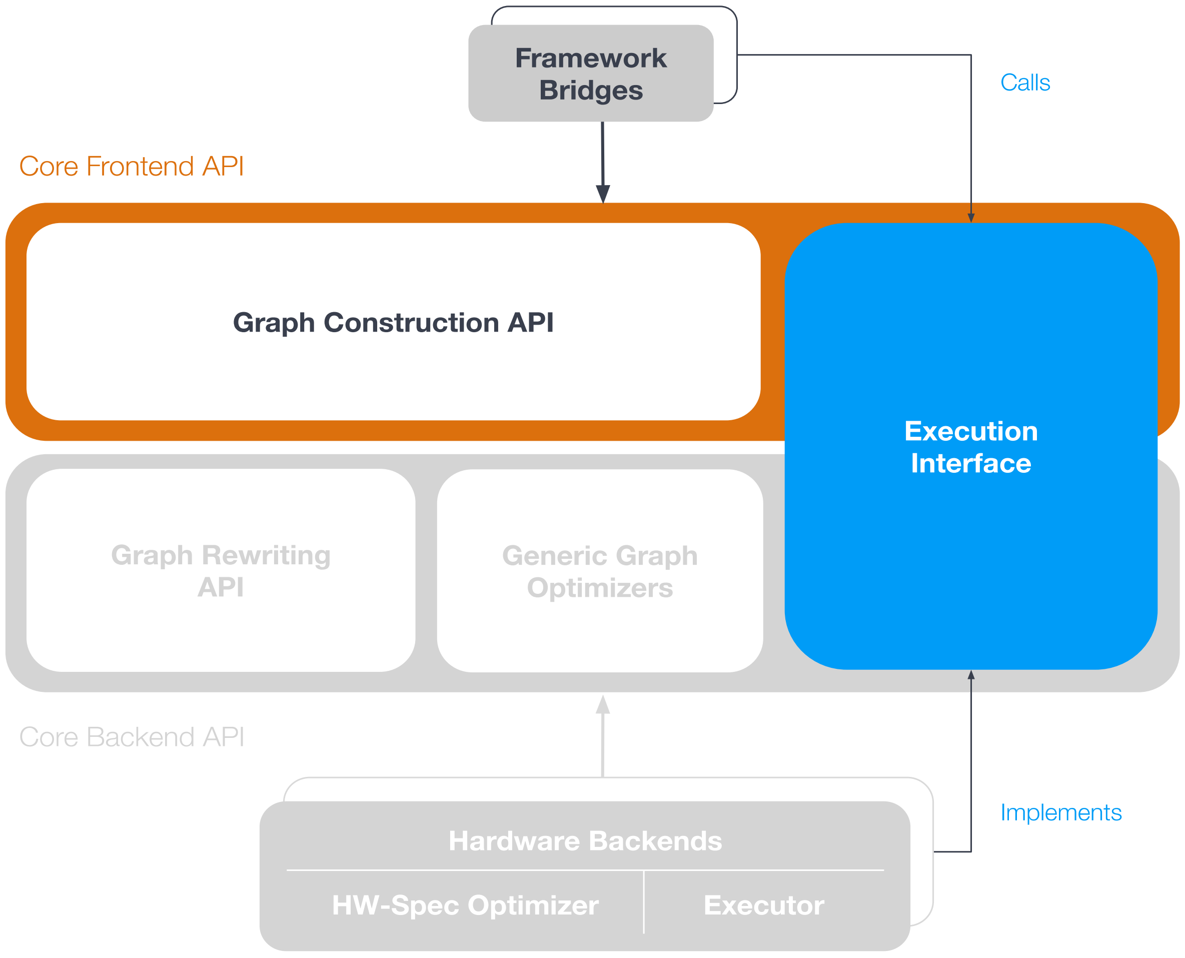
nGraph also provides a way to use the advanced tensor compiler PlaidML as a backend; you can learn more about this backend and how to build it from source in our documentation: Building nGraph-PlaidML from source.

Backend	**Current nGraph support**	**Future nGraph support**
Intel® Architecture Processors (CPUs)	Yes	Yes
Intel® Nervana™ Neural Network Processor™ (NNPs)	Yes	Yes
AMD* GPUs	Yes	Some

Each backend must define a function `ngraph_register_${backend}_backend` that registers a backend constructor function and ensures that initializations are performed. An example that includes initializations can be found in the `ngraph/src/runtime/cpu/cpu_backend.cpp` file. See also: Backend APIs.

How to use?¶

1. Create a `Backend`; think of it as a compiler.
2. A `Backend` can then produce an `Executable` by calling `compile`.
3. A single iteration of the executable is executed by calling the `call` method on the `Executable` object.



Execution API
A Simple Interface
~10 Virtual Functions

- Tensor creation
- Data transfer to/from device
- Precompilation of graphs
- Execution of graphs

The API is **called** by framework bridges.

Functions are **implemented** by each backend.

The execution interface for nGraph

The nGraph execution API for `Executable` objects is a simple, five-method interface; each backend implements the following five functions:

- The `create_tensor()` method allows the bridge to create tensor objects in host memory or an accelerator's memory.
- The `write()` and `read()` methods are used to transfer raw data into and out of tensors that reside in off-host memory.
- The `compile()` method instructs the backend to prepare an nGraph function for later

execution.

- And, finally, the `call()` method is used to invoke an nGraph function against a particular set of tensors.

How to display ngraph-related passes executed during runtime?¶

One easy way to get info about passes is to set the environment variable `NGRAPH_PROFILE_PASS_ENABLE=1`. With this set, the pass manager will dump the name and execution time of each pass.

nGraph bridge¶

When specified as the generic backend – either manually or automatically from a framework – `NGRAPH` defaults to CPU, and it also allows for additional device configuration or selection.

Because nGraph can select backends, specifying the `INTELGPU` backend as a runtime environment variable also works if one is present in your system:

```
NGRAPH_TF_BACKEND="INTELGPU"
```

An axpy.py example is optionally available to test; outputs will vary depending on the parameters specified.

```
NGRAPH_TF_BACKEND="INTELGPU" python3 axpy.py
```

- `NGRAPH_INTELGPU_DUMP_FUNCTION` – dumps nGraph's functions in dot format.

OpenCL¶

OpenCL is only needed for the PlaidML from nGraph; if you have only a CPU backend, it is not needed.

1. Install the latest Linux driver for your system. You can find a list of drivers at https://software.intel.com/en-us/articles/opencl-drivers; You may need to install OpenCL SDK in case of an `libOpenCL.so` absence.

2. Any user added to "video" group:

   ```
   sudo usermod –a –G video <user_id>
   ```

   may, for example, be able to find details at the `/sys/module/[system]/parameters/` location.

Backend APIs¶

Backend APIs¶

Each backend `BACKEND` needs to define the macro `${BACKEND}_API` appropriately to import symbols referenced from outside the library, and to export them from within the library. See any of the `${backend}_backend_visibility` header files for an example; see also What is a backend?

DynamicBackend¶

class `DynamicBackend` : *public* Backend¶

Wrapper class used to provide dynamic tensor support on backends that otherwise do not support dynamic tensors.
The main function of this class is to intercept `create_dynamic_tensor` and `compile`:

- `create_dynamic_tensor` will return a special `DynamicTensor` object whose shape can be updated after creation. Internally, `DynamicTensor` wraps static tensors managed by the wrapped backend.
- `compile` will return a special `DynamicExecutable` object, which allows dynamic shapes to be supported via graph cloning.

This class is instantiated by `ngraph::runtime::Backend::create`.

PlaidML from nGraph¶

class `PlaidML_Backend` : *public* Backend¶

As of version `0.15`, there is a new backend API to work with functions that can be compiled as a runtime `Executable`. Where previously `Backend` used a `shared_ptr<Function>` as the handle passed to the `call` method to execute a compiled object, the addition of the `shared_ptr<Executable>` object has more direct methods to actions such as `validate`, `call`, `get_performance_data`, and so on. This new API permits any executable to be saved or loaded *into* or *out of* storage and makes it easier to distinguish when a Function is compiled, thus making the internals of the `Backend` and `Executable` easier to implement.

Distributed Training¶

TBD WIP

Quantization-Aware Training¶

Quantization-Aware Training is a technique used to quantize models during the training process. The main idea is that the quantization is emulated in the forward path by inserting some "Quantization" and "De-Quantization" nodes (Q-DQ) several places in the network to emulate the inference quantization noise. The expectation is the backward propagation will alter the weights so that they will adapt to this noise, and the result loss will be much better than traditional Post-Training Quantization.

For the weights, it is also common to take different quantization functions that cut off outliers. Some examples are available in the Distiller guide. Distiller is an open-source Python package for neural network compression research. Network compression can reduce the footprint of a neural network, increase its inference speed, and save energy. Additionally, a framework for pruning, regularization and quantization algorithms is provided. A set of tools for analyzing and evaluating compression performance on previously-known State-of-the-Art (SotA) algorithms

When using QAT techniques, the position in which the Q-DQ ops are placed needs to align with the fusions hardware does for inference.

Validated Workloads¶

We have validated performance [1] for the following workloads:

- CPU Tensorflow
- CPU ONNX
- GPU TensorFlow
- GPU ONNX

CPU Tensorflow¶

TensorFlow Workload	**Genre of Deep learning**
Resnet50 v1	Image recognition
Resnet50 v2	Image recognition
Inception V3	Image recognition
Inception V4	Image recognition
Inception-ResNetv2	Image recognition
MobileNet v1	Image recognition
Faster RCNN	Object detection
VGG16	Image recognition
SSD-VGG16	Object detection
SSD-MobileNetv1	Object detection
R-FCN	Object detection
Yolo v2	Object detection

TensorFlow Workload	**Genre of Deep learning**
Transformer-LT	Language translation
Wide & Deep	Recommender system
NCF	Recommender system
U-Net	Image segmentation
DCGAN	Generative adversarial network
DRAW	Image generation
A3C	Reinforcement learning

CPU ONNX¶

Additionally, we validated the following workloads are functional through nGraph ONNX importer. ONNX models can be downloaded from the ONNX Model Zoo.

ONNX Workload	**Genre of Deep Learning**
DenseNet-121	Image recognition
Inception-v1	Image recognition
Inception-v2	Image recognition
ResNet-50	Image recognition
Mobilenet	Image recognition
Shufflenet	Image recognition
SqueezeNet	Image recognition
VGG-16	Image recognition
ZFNet-512	Image recognition
MNIST	Image recognition
Emotion-FERPlus	Image recognition
BVLC AlexNet	Image recognition
BVLC GoogleNet	Image recognition
BVLC CaffeNet	Image recognition
BVLC R-CNN ILSVRC13	Object detection
ArcFace	Face Detection and Recognition

GPU TensorFlow¶

TensorFlow Workload	**Genre of Deep Learning**
Resnet50 v2	Image recognition
Inception V3	Image recognition
Inception V4	Image recognition
Inception-ResNetv2	Image recognition
VGG-16	Image recognition

GPU ONNX¶

ONNX Workload	Genre of Deep Learning
Inception V1	Image recognition
Inception V2	Image recognition
ResNet-50	Image recognition
SqueezeNet	Image recognition

Important

Please see Intel’s Optimization Notice for details on disclaimers.

Footnotes

[1]	Benchmarking performance of DL systems is a young discipline; it is a good idea to be vigilant for results based on atypical distortions in the configuration parameters. Every topology is different, and performance changes can be attributed to multiple causes. Also watch out for the word “theoretical” in comparisons; actual performance should not be compared to theoretical performance.

Contents

Diagnostics¶

Important

Many of the following flags may be experimental only and subject to change.

Build nGraph with various compile flags and environment variables to diagnose performance and memory issues. See also Performance testing with nbench.

Compile Flags¶

Compile Flag	Description	Default Value
`NGRAPH_CODE_COVERAGE_ENABLE`	Enable code coverage data collection	`FALSE`
`NGRAPH_DEBUG_ENABLE`	Enable output for `NGRAPH_DEBUG` statements	`FALSE`
`NGRAPH_DEPRECATED_ENABLE`	Enable compiler deprecation pragmas for	`FALSE`

Compile Flag	Description	Default Value
	deprecated APIs (recommended only for development use)	
`NGRAPH_DEX_ONLY`	Build CPU DEX without codegen	`FALSE`
`NGRAPH_DISTRIBUTED_ENABLE`	Enable distributed training using MLSL/OpenMPI	`OFF`
`NGRAPH_DISTRIBUTED_MLSL_ENABLE`	Use MLSL	`OFF`
`NGRAPH_DOC_BUILD_ENABLE`	Automatically build documentation	`OFF`
`NGRAPH_FAST_MATH_ENABLE`	Enable fast math	`ON`
`NGRAPH_HALIDE`		`OFF`
`NGRAPH_INTERPRETER_ENABLE`	Control the building of the `INTERPRETER` backend	`TRUE`
`NGRAPH_INTERPRETER_STATIC_LIB_ENABLE`	Enable build INTERPRETER backend static library	`FALSE`
`NGRAPH_JSON_ENABLE`	Enable JSON based serialization and tracing features	`TRUE`
`NGRAPH_LIB_VERSIONING_ENABLE`	Enable shared library versioning	`FALSE`
`NGRAPH_MLIR_ENABLE`	Control the building of MLIR backend	`FALSE`
`NGRAPH_NOP_ENABLE`	Control the building of the NOP backend	`TRUE`
`NGRAPH_ONNX_IMPORT_ENABLE`	Enable ONNX importer	`FALSE`
`NGRAPH_PLAIDML_ENABLE`	Enable the PlaidML backend	`${PLAIDML_FOUND}`
`NGRAPH_PYTHON_BUILD_ENABLE`	Enable build of `NGRAPH` python package wheel	`FALSE`
`NGRAPH_STATIC_LIB_ENABLE`	Enable build `NGRAPH` static library	`FALSE`
`NGRAPH_TBB_ENABLE`	Only if (`NGRAPH_CPU_ENABLE`) Control usage of TBB for CPU backend	`TRUE`
`NGRAPH_TOOLS_ENABLE`	Control the building of tools	`TRUE`
`NGRAPH_UNIT_TEST_ENABLE`	Control the building of unit tests	`TRUE`
`NGRAPH_USE_PREBUILT_LLVM`	Use a precompiled LLVM	`FALSE`
`NGRAPH_USE_PREBUILT_MLIR`	Use the precompiled MLIR	`FALSE`

Environment Variables¶

Important

Many of the following flags may be experimental only and subject to change.

Environment Variable	Description
`NGRAPH_DISABLE_LOGGING`	Disable printing all logs irrespective of build type
`NGRAPH_DISABLED_FUSIONS`	Disable specified fusions. Specified as ; separated list and supports regex
`NGRAPH_ENABLE_REPLACE_CHECK`	Enables strict type checking in copy constructor copy_with_new_args
`NGRAPH_ENABLE_SERIALIZE_TRA`	generates 1 `json` file per pass to run with `nbench` for

Environment Variable	Description
`CING`	localized execution rather than whole stack execution
`NGRAPH_ENABLE_TRACING`	Enables creating graph execution timelines to be viewed in `chrome://tracing` see also General Visualization Tools.
`NGRAPH_ENABLE_VISUALIZE_TRACING`	Enables creating visual graph for each pass `.svg` files by default; see also General Visualization Tools
`NGRAPH_FAIL_MATCH_AT`	Allows one to specify node name patterns to abort pattern matching at particular nodes. Helps debug an offending fusion
`NGRAPH_GTEST_INFO`	Enables printing info about a specific test
`NGRAPH_INTER_OP_PARALLELISM`	See Intra-op and inter-op parallelism
`NGRAPH_INTRA_OP_PARALLELISM`	See Intra-op and inter-op parallelism
`NGRAPH_PASS_ATTRIBUTES`	Specify pass-specific attributes as a semi-colon separated list to be enabled or disabled. Naming of pass attributes is up to the backends and see also pass config
`NGRAPH_PASS_ENABLES`	Specify a semi-colon separated list to enable or disable a pass on core or backend. This will override the default enable/disable values
`NGRAPH_PROFILE_PASS_ENABLE`	Dump the name and execution time of each pass; shows per-pass time taken to compile
`NGRAPH_PROVENANCE_ENABLE`	Enable adding provenance info to nodes. This will also be added to serialized files.
`NGRAPH_SERIALIZER_OUTPUT_SHAPES`	Enable adding output shapes in the serialized graph
`NGRAPH_VISUALIZE_EDGE_JUMP_DISTANCE`	Calculated in code; helps prevent *long* edges between two nodes very far apart
`NGRAPH_VISUALIZE_EDGE_LABELS`	Set it to 1 in `/.bashrc`; adds label to a graph edge when NGRAPH_ENABLE_VISUALIZE_TRACING=1
`NGRAPH_VISUALIZE_TREE_OUTPUT_SHAPES`	Set it to 1 in `/.bashrc`; adds output shape of a node when NGRAPH_ENABLE_VISUALIZE_TRACING=1
`NGRAPH_VISUALIZE_TREE_OUTPUT_TYPES`	Set it to 1 in `/.bashrc`; adds output type of a node when NGRAPH_ENABLE_VISUALIZE_TRACING=1
`NGRAPH_VISUALIZE_TRACING_FORMAT`	Default format is `.svg`. See also General Visualization Tools
`OMP_NUM_THREADS`	See: OpenMPI Runtime Library Documentation

Debug Tracer¶

Another diagnostic configuration option is to activate `NGRAPH_CPU_DEBUG_TRACER`, a runtime environment variable that supports extra logging and debug detail.

This is a useful tool for data scientists interested in outputs from logtrace files that can, for example, help in tracking down model convergences. It can also help engineers who might want to add their new `Backend` to an existing framework to compare intermediate tensors/values to references from a CPU backend.

To activate this tool, set the `env` var `NGRAPH_CPU_DEBUG_TRACER=1`. It will dump `trace_meta.log` and `trace_bin_data.log`. The names of the logfiles can be customized.

To specify the names of logs with those flags:

```
NGRAPH_TRACER_LOG = "meta.log"
NGRAPH_BIN_TRACER_LOG = "bin.log"
```

Intra-op and inter-op parallelism¶

- `intra_op_parallelism_threads`
- `inter_op_parallelism_threads`

Some frameworks, like TensorFlow*, use these settings to improve performance; however, they are often not sufficient for optimal performance. Framework-based adjustments cannot access the underlying NUMA configuration in multi-socket Intel® Xeon® processor-based platforms, which is a key requirement for many kinds of inference-engine computations.

The meta_log contains:

```
kernel_name, serial_number_of_op, tensor_id, symbol_of_in_out, num_elements,
shape, binary_data_offset, mean_of_tensor, variance_of_tensor
```

A line example from a unit-test might look like:

```
K=Add S=0 TID=0_0 >> size=4 Shape{2, 2} bin_data_offset=8 mean=1.5 var=1.25
```

The binary_log line contains:

```
tensor_id, binary data (tensor data)
```

A reference for the implementation of parsing these logfiles can also be found in the unit test for this feature.

Looking at graph objects¶

A number of nGraph objects can print themselves on streams. For example,``cerr << a + b`` produces `v0::Add Add_2(Parameter_0[0]:f32{2,3}, Parameter_1[0]:f32{2,3}):(f32{2,3})` indicating the specific version of the op, its name, arguments, and outputs.

Debug TensorFlow*¶

Note

These flags are all disabled by default

For profiling with TensorFlow* and `nbench`, see Use nbench to ease end-to-end debugging for TensorFlow*.

Flag	Description
`NGRAPH_ENABLE_SERIALIZE=1`	Generate nGraph-level serialized graphs
`NGRAPH_TF_VLOG_LEVEL=5`	Generate ngraph-tf logging info for different passes
`NGRAPH_TF_LOG_PLACEMENT=1`	Generate op placement log at stdout
`NGRAPH_TF_DUMP_CLUSTERS=1`	Dump Encapsulated TF Graphs formatted as

Flag	Description
	`NGRAPH_cluster_<cluster_num>`
`NGRAPH_TF_DUMP_GRAPHS=1`	Dump TF graphs for different passes: precapture, capture, unmarked, marked, clustered, declustered, encapsulated
`TF_CPP_MIN_VLOG_LEVEL=1`	Enable TF CPP logs
`NGRAPH_TF_DUMP_DECLUSTERED_GRAPHS=1`	Dump graphs with final clusters assigned. Use this to view TF computation graph with colored nodes indicating clusters
`NGRAPH_TF_USE_LEGACY_EXECUTOR`	This flag will be obsolete soon.

Debug ONNX¶

Note

These flags are all disabled by default

Flag	Description
`ONNXRUNTIME_NGRAPH_DUMP_OPS`	Dumps ONNX ops
`ONNXRUNTIME_NGRAPH_LRU_CACHE_SIZE`	Modify LRU cache size (`NGRAPH_EP_LRU_CACHE_DEFAULT_SIZE 500`)

*Debug PaddlePaddle**¶

PaddlePaddle has its own env vars.

General Visualization Tools¶

nGraph provides serialization and deserialization facilities, along with the ability to create image formats or a PDF.

`NGRAPH_ENABLE_VISUALIZE_TRACING=1` enables visualization and generates graph visualization files.

Note

Using `NGRAPH_ENABLE_VISUALIZE_TRACING=1` will affect performance.

When visualization is enabled, `svg` files for your graph get generated. The default format can be adjusted by setting the `NGRAPH_VISUALIZE_TRACING_FORMAT` flag to another format, like PNG or PDF.

Note

Large graphs are usually not legible with formats like PDF.

Large graphs may require additional work to get into a human-readable format. On the back end, very long edges will need to be cut to make (for example) a hard-to-render training graph tractable. This can be a tedious process, so incorporating the help of a rendering engine or third-party tool like one listed below may be useful.

1. Gephi
2. Cytoscape
3. Netron

Performance testing with nbench¶

The nGraph Compiler stack includes the `nbench` tool which provides additional methods of assessing or debugging performance issues.

If you follow the build process under Build and Test, the `NGRAPH_TOOLS_ENABLE` flag defaults to `ON` and automatically builds `nbench`. As its name suggests, `nbench` can be used to benchmark any nGraph-serialized model with a given backend.

To benchmark an already-serialized nGraph `.json` model with, for example, a `CPU` backend, run `nbench` as follows.

```
$ cd ngraph/build/src/tools
$ nbench/nbench -b CPU - i 1 -f <serialized_json file>
```

Samples for testing can be found under `ngraph/test/models`.

nbench¶

```
Benchmark and nGraph JSON model with a given backend.

SYNOPSIS
    nbench [-f <filename>] [-b <backend>] [-i <iterations>]
OPTIONS
    -f|--file                   Serialized model file
    -b|--backend                Backend to use (default: CPU)
    -d|--directory              Directory to scan for models. All models are
benchmarked.
    -i|--iterations             Iterations (default: 10)
    -s|--statistics             Display op statistics
    -v|--visualize              Visualize a model (WARNING: requires Graphviz
installed)
    --timing_detail             Gather detailed timing
    -w|--warmup_iterations      Number of warm-up iterations
    --no_copy_data              Disable copy of input/result data every
iteration
    --dot                       Generate Graphviz dot file
    --double_buffer           Double buffer inputs and outputs
```

*Use `nbench` to ease end-to-end debugging for TensorFlow**¶

Rather than run a TensorFlow* model “end-to-end” all the time, developers who notice a problem with performance or memory usage can generate a unique serialized model for debugging by using `NGRAPH_ENABLE_SERIALIZE=1`. This serialized model can then be run and re-run with `nbench` to efficiently experiment with any changes in `ngraph` space; developers can make changes and test changes without the overhead of a complete end-to-end compilation for each change.

Find or display version¶

If you’re working with the Python API, the following command may be useful:
```
python3 -c "import ngraph as ng; print('nGraph version: ',ng.__version__)";
```
To manually build a newer version than is available from the latest PyPI (Python Package Index), see our nGraph Python API BUILDING.md documentation.

Contribution Guide¶

Contents

License¶

All contributed code must be compatible with the Apache 2 license, preferably by being contributed under the Apache 2 license. Code contributed with another license will need the license reviewed by Intel before it can be accepted.

Code formatting¶

All C/C++ source code in the repository, including the test code, must adhere to the source-code formatting and style guidelines described here. The coding style described here applies to the nGraph repository. Related repositories may make adjustments to better match the coding styles of libraries they are using.

Adding ops to nGraph Core¶

Our design philosophy is that the graph is not a script for running optimized kernels; rather, the graph is a specification for a computation composed of basic building blocks which we call `ops`. Compilation should match groups of `ops` to appropriate optimal semantically equivalent groups of kernels for the backend(s) in use. Thus, we expect that adding of new Core ops should be infrequent and that most functionality instead gets added with new functions that build sub-graphs from existing core ops.

Coding style¶

We have a coding standard to help us to get development done. If part of the standard is impeding progress, we either adjust that part or remove it. To this end, we employ coding standards that facilitate understanding of *what nGraph components are doing*. Programs are easiest to understand when they can be understood locally; if most local changes have local impact, you do not need to dig through multiple files to understand what something does and if it is safe to modify.

Names¶

Names should *briefly* describe the thing being named and follow these casing standards:

- Define C++ class or type names with `CamelCase`.
- Assign template parameters with `UPPER_SNAKE_CASE`.
- Case variable and function names with `lower_snake_case`.

Method names for basic accessors are prefixed by `get_`, `is_`, or `set_` and should have simple \(\mathcal{O}(1)\) implementations:

- A `get_` method should be externally idempotent. It may perform some simple initialization and cache the result for later use. Trivial `get_` methods can be defined in a header file. If a method is non-trivial, that is often a sign that it is not a basic accessor.
- An `is_` may be used instead of `get_` for boolean accessors.
- A `set_` method should change the value returned by the corresponding `get_` method.
  - Use `set_is_` if using `is_` to get a value.
  - Trivial `set_` methods may be defined in a header file.
- Names of variables should indicate the use of the variable.
  - Member variables should be prefixed with `m_`.
  - Static member variables should be rare and be prefixed with `s_`.
- Do not use `using` to define a type alias at top-level in header file. If the abstraction is useful, give it a class.
  - C++ does not enforce the abstraction. For example if `X` and `Y` are aliases for the same type, you can pass an `X` to something expecting a `Y`.
  - If one of the aliases were later changed, or turned into a real type, many callers could require changes.

Namespaces¶

- `ngraph` is for the public API, although this is not currently enforced.
  - Use a nested namespace for implementation classes.
  - Use an unnamed namespace or `static` for file-local names. This helps prevent unintended name collisions during linking and when using shared and dynamically-loaded libraries.
  - Never use `using` at top-level in a header file.
    - Doing so leaks the alias into users of the header, including headers that follow.
    - It is okay to use `using` with local scope, such as inside a class definiton.
  - Be careful of C++'s implicit namespace inclusions. For example, if a parameter's type is from another namespace, that namespace can be visible in the body.
  - Only use `using std` and/or `using ngraph` in `.cpp` files. `using` a nested namespace has can result in unexpected behavior.

File Names¶

- Do not use the same file name in multiple directories. At least one IDE/debugger ignores the directory name when setting breakpoints.

- Use `.hpp` for headers and `.cpp` for implementation.
- Reflect the namespace nesting in the directory hierarchy.
- Unit test files are in the `tests` directory.
  - Transformer-dependent tests are tests running on the default transformer or specifying a transformer. For these, use the form
    ```
    TEST(file_name, test_name)
    ```
  - Transformer-independent tests:
    - File name is `file_name.in.cpp`
    - Add `#include "test_control.hpp"` to the file's includes
    - Add the line `static std::string s_manifest = "${MANIFEST}";` to the top of the file.
    - Use
      ```
      NGRAPH_TEST(${BACKEND_NAME}, test_name)
      ```
      for each test. Files are generated for each transformer and the `${BACKEND_NAME}` is replaced with the transformer name.

      Individual unit tests may be disabled by adding the name of the test to the `unit_test.manifest` file found in the transformer's source file directory.

Formatting¶

Things that look different should look different because they are different. We use **clang format** to enforce certain formatting. Although not always ideal, it is automatically enforced and reduces merge conflicts.

- The `.clang-format` file located in the root of the project specifies our format. Simply run:
  ```
  $ make style-check
  $ make style-apply
  ```
- Formatting with `#include` files:
  - Put headers in groups separated by a blank line. Logically order the groups downward from system-level to 3rd-party to `ngraph`.
  - Formatting will keep the files in each group in alphabetic order.
  - Use this syntax for files that **do not change during nGraph development**; they will not be checked for changes during builds. Normally this will be everything but the ngraph files:
    ```
    #include <file>
    ```
  - Use this syntax for files that **are changing during nGraph development**; they will be checked for changes during builds. Normally this will be ngraph headers:

```
#include "file"
```

  - Use this syntax for system C headers with C++ wrappers:

    ```
    #include <c...>
    ```

- To guard against multiple inclusion, use:

  ```
  #pragma once
  ```

  - The syntax is a compiler extension that has been adopted by all supported compilers.

- The initialization

  ```
  Foo x{4, 5};
  ```

  is preferred over

  ```
  Foo x(4, 5);
  ```

- Indentation should be accompanied by braces; this includes single-line bodies for conditionals and loops.

- Exception checking:

  - Throw an exception to report a problem.
  - Nothing that calls `abort`, `exit` or `terminate` should be used. Remember that ngraph is a guest of the framework.
  - Do not use exclamation points in messages!
  - Be as specific as practical. Keep in mind that the person who sees the error is likely to be on the other side of the framework and the message might be the only information they see about the problem.

- If you use `auto`, know what you are doing. `auto` uses the same type-stripping rules as template parameters. If something returns a reference, `auto` will strip the reference unless you use `auto&`:

  - Don't do things like

    ```
    auto s = Shape{2,3};
    ```

    Instead, use

    ```
    Shape s{2, 3};
    ```

  - Indicate the type in the variable name.

- One variable declaration/definition per line

  - Don't use the C-style

    ```
    int x, y, *z;
    ```

    Instead, use:

    ```
    int x;
    int y;
    int* z;
    ```

To contribute documentation for your code, please see the Contributing to documentation.
orphan:

Contributing to documentation¶

Note

Tips for contributors who are new to the highly-dynamic environment of documentation in AI software:

- A good place to start is "document something you figured out how to get working". Content changes and additions should be targeted at something more specific than "developers". If you don't understand how varied and wide the audience is, you'll inadvertently break or block things.
- There are experts who work on all parts of the stack; try asking how documentation changes ought to be made in their respective sections.
- Start with something small. It is okay to add a "patch" to fix a typo or suggest a word change; larger changes to files or structure require research and testing first, as well as some logic for why you think something needs changed.
- Most documentation should wrap at about `80`. We do our best to help authors source-link and maintain their own code and contributions; overwriting something already documented doesn't always improve it.
- Be careful editing files with links already present in them; deleting links to papers, citations, or sources is discouraged.
- Please do not submit Jupyter* notebook code to the nGraph Library or core repos; best practice is to maintain any project-specific examples, tests, or walk-throughs in a separate repository and to link back to the stable `op` or Ops that you use in your project.

For updates within the nGraph Library `/doc` repo, please submit a PR with any changes or ideas you'd like integrated. This helps us maintain trackability with respect to changes made, additions, deletions, and feature requests.

If you prefer to use a containerized application, like Jupyter* notebooks, Google Docs*, the GitHub* GUI, or MS Word* to explain, write, or share documentation contributions, you can convert the `doc/sphinx/source/*.rst` files to another format with a tool like `pypandoc` and share a link to your efforts on our wiki.

Another option is to fork the ngraph repo, essentially snapshotting it at that point in time, and to build a Jupyter* notebook or other set of docs around it for a specific use case. Add a note on our wiki to show us what you did; new and novel applications may have their projects highlighted on an upcoming ngraph.ai release.

Note

Please do not submit Jupyter* notebook code to the nGraph Library or core repos; best practice is to maintain any project-specific examples, tests, or walk-throughs in a separate repository.

Documenting source code examples¶

When **verbosely** documenting functionality of specific sections of code – whether they are entire code blocks within a file, or code strings that are **outside** the nGraph Library's documentation repo, here is an example of best practice:

Say a file has some interesting functionality that could benefit from more explanation about one or more of the pieces in context. To keep the "in context" navigable, write something like the following in your `.rst` documentation source file:

```
.. literalinclude:: ../../../examples/abc/abc.cpp
   :language: cpp
   :lines: 20-31
```

And the raw code will render as follows

```
using namespace ngraph;

int main()
{
    // Build the graph
    Shape s{2, 3};
    auto a = std::make_shared<op::Parameter>(element::f32, s);
    auto b = std::make_shared<op::Parameter>(element::f32, s);
    auto c = std::make_shared<op::Parameter>(element::f32, s);

    auto t0 = std::make_shared<op::Add>(a, b);
```

You can now verbosely explain the code block without worrying about breaking the code. The trick here is to add the file you want to reference relative to the folder where the `Makefile` is that generates the documentation you're writing.

See the **note** at the bottom of this page for more detail about how this works in the current 0.29 version of nGraph Library documentation.

Adding captions to code blocks¶

One more trick to helping users understand exactly what you mean with a section of code is to add a caption with content that describes your parsing logic. To build on the previous example, let's take a bigger chunk of code, add some line numbers, and add a caption:

```
.. literalinclude:: ../../../examples/abc/abc.cpp
   :language: cpp
   :lines: 48-56
   :caption: "caption for a block of code that initializes tensors"
```

and the generated output will show readers of your helpful documentation

"caption for a block of code that initializes tensors"¶

```
    // Initialize tensors
    float v_a[2][3] = {{1, 2, 3}, {4, 5, 6}};
    float v_b[2][3] = {{7, 8, 9}, {10, 11, 12}};
    float v_c[2][3] = {{1, 0, -1}, {-1, 1, 2}};

    t_a->write(&v_a, sizeof(v_a));
    t_b->write(&v_b, sizeof(v_b));
    t_c->write(&v_c, sizeof(v_c));
```

Our documentation practices are designed around "write once, reuse" that we can use to prevent code bloat. See the Contribution Guide for our code style guide.

How to build the documentation¶

Note

Stuck on how to generate the html? Run these commands; they assume you start at a command line running within a clone (or a cloned fork) of the `ngraph` repo. You do **not** need to run a virtual environment to create documentation if you don't want; running `$ make clean` in the `doc/sphinx` folder removes any generated files.

Right now the minimal version of Sphinx needed to build the documentation is Sphinx v. 1.7.5. This can be installed with **pip3**, either to a virtual environment, or to your base system if you plan to contribute much core code or documentation. For C++ API docs that contain inheritance diagrams and collaboration diagrams which are helpful for framework integratons, building bridge code, or creating a backend UI for your own custom framework, be sure you have a system capable of running doxygen.

To build documentation locally, run:

```
$ sudo apt-get install python3-sphinx
$ pip3 install Sphinx==1.7.5
$ pip3 install breathe numpy
$ cd doc/sphinx/
$ make html
$ cd build/html
$ python3 -m http.server 8000
```

Then point your browser at `localhost:8000`.

To build documentation in a python3 virtualenv, try:

```
$ python3 -m venv py3doc
$ . py3doc/bin/activate
(py3doc)$ pip install Sphinx breathe numpy
(py3doc)$ cd doc/sphinx
(py3doc)$ make html
(py3doc)$ cd build/html
(py3doc)$ python -m http.server 8000
```

Then point your browser at `localhost:8000`.

Note

For docs built in a virtual env, Sphinx latest changes may break documentation; try building with a specific version of Sphinx.

For tips on writing reStructuredText-formatted documentation, see the sphinx stable reST documentation.

Glossary¶

ANN

Artificial Neural Network, often abbreviated as NN.

backend

A component that can execute computations.

bridge

A component of nGraph that acts as a backend for a framework, allowing the framework to define and execute computations.

builder

A builder is a function that creates a sub-graph and returns a root node to the bridge. Fused ops are preferred over builders See also: Basic concepts.

data-flow graph

Data-flow graphs are used to implement deep learning models. In a data-flow graph, nodes represent operations on data and edges represent data flowing between those operations.

dynamic tensor

A tensor whose shape can change from one “iteration” to the next. When created, a framework bridge might supply only *partial* shape information: it might be **all** the tensor dimensions, **some** of the tensor dimensions, or **none** of the tensor dimensions; furthermore, the rank of the tensor may be left unspecified.

export

The serialized version of a trained model that can be passed to one of the nGraph backends for computation.

framework

Frameworks provide expressive user-facing APIs for constructing, training, validating, and deploying DL/ML models: TensorFlow*, PaddlePaddle*, MXNet*, PyTorch*, and Caffe* are all examples of well-known frameworks.

function graph

The nGraph Library uses a function graph to represent an `op`’s parameters and results.

fusion

Fusion is the fusing, combining, merging, collapsing, or refactoring of a graph’s functional operations (`ops`) into one or more of nGraph’s core ops.

ISA

An acronym for “Instruction Set Architecture,” an ISA is machine code that is compatible with the underlying silicon architecture. A realization of an ISA is called an *implementation*. An ISA permits multiple implementations that may vary in performance, physical size, memory use or reuse, and monetary cost among other things. An ISA defines everything a machine-language programmer needs to know in order to program a particular backend device. What an ISA defines will differ among ISAs; in general, it defines things like:

- supported *data types*;
- physical *states* available, such as the main memory and registers;
- *semantics*, such as the memory consistency and addressing modes;
- *low-level machine instructions* that comprise a machine language;
- and the *input/output model*.

Be careful to not confuse ISAs with microarchitectures.

LSTM

LSTM is an acronym for “Long Short-Term Memory”. LSTMs extend on the traditional RNN by providing a number of ways to “forget” the memory of the previous time step via a set of learnable gates. These gates help avoid the problem of exploding or vanishing gradients that occur in the traditional RNN.

model description

A description of a program’s fundamental operations that are used by a framework to generate inputs for computation.

NN

NN is an acronym for “Neural Network”. NN models are used to simulate possible combinations of binary logic processing and multi-layer (multi-dimensional) paths through which a data-flow graph may be mapped or computed. A NN does not have centralized storage; rather, a NN manifests as information stored as patterns throughout the network structure. NNs may be **Recurrent** (feedback loop) or **Nonrecurrent** (feed-forward) with regard to the network vector.

op

An op represents an operation. Ops are stateless and have zero or more inputs and zero or more outputs. Some ops have additional constant attributes. Every output of an op corresponds to a tensor and has an element type and a shape. The element types and shapes of the outputs of an op are determined by the inputs and attributes of the op.

parameter

In the context of a function graph, a “parameter” refers to what “stands in” for an argument in an op definition.

provenance

The term provenance refers to the matching of device code to framework sub-graphs; it is analogous to source code locators in conventional compilers, which associate regions of object code with source files and line numbers.

quantization

Quantization refers to the conversion of numerical data into a lower-precision representation. Quantization is often used in deep learning to reduce the time and energy needed to perform computations by reducing the size of data transfers and the number of steps needed to perform a computation. This improvement in speed and energy usage comes at a cost in terms of numerical accuracy, but deep learning models are often able to function well in spite of this reduced accuracy.

RANN

Recurrent Artificial Neural Network, often abbreviated as RNN.

result

In the context of a function graph, the term “result” refers to what stands in for the returned value.

RNN

A Recurrent Neural Network is a variety of NN where output nodes from a layer on a data-flow graph have loopback to nodes that comprise an earlier layer. Since the RNN has no “centralized” storage, this loopback is the means by which the ANN can “learn” or be trained. There are several sub-categories of RNNs. The traditional RNN looks like:
\(s_t = tanh(dot(W,x_{t-1}) + dot(U, s_{t-1})\)
where \(x\) is the input data, \(s\) is the memory, and output is \(o_t = softmax(dot(V, s_t))\). Tanh, Dot, and Softmax are all nGraph core Ops.

SGD

Stochastic Gradient Descent, also known as incremental gradient descent, is an iterative method for optimizing a differentiable objective function.

shape

The shape of a tensor is a tuple of non-negative integers that represents an exclusive upper bound for coordinate values.

shape propagation

The static process by which assignment of every tensor (or, equivalently, every node output) in the graph is assigned **complete shape information**.

shared pointer

The C++ standard template library has the template `std::shared_ptr<X>`. A shared pointer is used like an `X*` pointer, but maintains a reference count to the underlying object. Each new shared pointer to the object increases the count. When a shared pointer goes out of scope, the reference count is decremented, and, when the count reaches 0, the underlying object is deleted. The function template `std::make_shared<X>(...)` can be used similarly to `new X(...)`, except it returns a `std::shared_ptr<X>` instead of an `X*`. If there is a chain of shared pointers from an object back to itself, every object in the chain is referenced, so the reference counts will never reach 0 and the objects will never

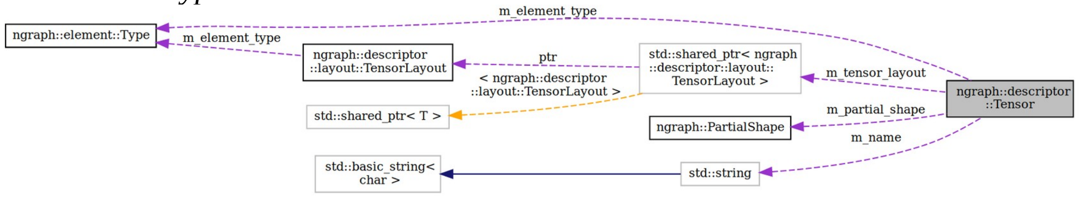
be deleted.
If a referenced `b` and `b` wanted to track all references to itself and shared pointers were used both directions, there would be a chain of pointers form `a` to itself. We avoid this by using shared pointers in only one direction, and raw pointers for the inverse direction. `std::enabled_shared_from_this` is a class template that defines a method `shared_from_this` that provides a shared pointer from a raw pointer.
nGraph makes use of shared pointers for objects whose lifetime is hard to determine when they are allocated.

step

An abstract "action" that produces zero or more tensor outputs from zero or more tensor inputs. Steps correspond to *ops* that connect *nodes*.

tensors

Tensors are maps from *coordinates* to scalar values, all of the same type, called the *element type* of the tensor.


m_element_type
ngraph::element::Type
m_element_type
ngraph::descriptor ::layout::TensorLayout
ptr
std::shared_ptr< ngraph ::descriptor::layout:: TensorLayout >
< ngraph::descriptor ::layout::TensorLayout >
std::shared_ptr< T >
m_tensor_layout
ngraph::descriptor ::Tensor
m_partial_shape
ngraph::PartialShape
m_name
std::basic_string< char >
std::string

Tensorview

The interface backends implement for tensor use. When there are no more references to the tensor view, it will be freed when convenient for the backend.

validated

To provide optimizations with nGraph, we first confirm that a given workload is "validated" as being functional; that is, we can successfully load its serialized graph as an nGraph function graph

Release Notes¶

nGraph is provided as source code, APIs, build scripts, and some binary formats for various Compiler stack configurations and use cases.

For downloads formatted as `.zip` and `tar.gz`, see https://github.com/NervanaSystems/ngraph/releases.

This page includes additional documentation updates.

We are pleased to announce the release of version 0.29.

Core updates for 0.29¶

- Constant folding improvements
- Pattern refactoring
- Serialization bug-fixes
- Build improvements

Latest documentation updates¶

- Improved documentation on Pad op

Important

Pre-releases (`-rc-0.*`) have newer features, and are less stable.

Changelog on Previous Releases¶

0.28¶

- Better debugging documentation
- Dynamic Shapes and APIs
- Provenance
- Add linkages and overview for quantization APIs
- New ngraph.ai themed illustrations

0.27.1¶

- Fixes broken serializer for Sum and Product
- New ops
- Provenance improvements from 0.25.1
- More dynamic shape ops
- More informative errors
- Additional details on quantization
- Index updates
- API updates
- All ops support `Output<Node>` arguments

- Additional ops
- ONNX handling unknown domains
- Provenance works with builders and fused ops
- `RPATH` for finding openmpi
- Negative indices/axes fixes
- Migrate some `get_argument` removals
- Negative indices/axes fixes
- Better support for MKL-DNN 1.0 (DNNL)
- Additional constant element types
- Add new Sphinx-friendly theme (can be built natively for an alternative to ngraph.ai docs).
- Update PaddlePaddle documentation to reflect demo directories instead of example directory.
- Update doc regarding the validation of `Sum` op.

0.26.1¶

- Performance increase for `ConstantFolding` pass

0.25.1¶

- Allow DLLs that link nGraph statically to load backends
- Add rank id to trace file name
- Allow provenance merging to be disabled
- Remove some white-listed compiler warnings
- Provenance, builders, ops that make ops, and fused op expansions
- Note the only support for nGPU is now through PlaidML; nGraph support for nGPU (via cuDNN) has been deprecated.
- iGPU works only with nGraph version 0.24.

0.25.0¶

- Better PlaidML support
- Double-buffering support
- Constant folding
- Support for static linking
- Additional ops
- Preliminary static linking support
- Known issue: No PlaidML training support
- Doc: Add instructions how to build NGRAPH_PLAIDML backend
- Published interim version of doc navigation for updates at ngraph.ai
- GPU validations: added 5 functional TensorFlow workloads and 4 functional ONNX workloads

0.24¶

- Fixes reshape sink/swim issue

- More ONNX ops
- Elementwise divide defaults to Python semantics
- GenerateMask seed optional
- Graph visualization improvements
- Preserve control dependencies in more places
- GetOutputElement has single input

0.23¶

- More ONNX ops
- Elementwise divide defaults to Python semantics
- GenerateMask seed optional
- Document new debug tool
- Graph visualization improvements
- Note deprecation of MXNet's `ngraph-mxnet` PyPI
- Note default change to svg files for graphs and visualization
- Add more prominent tips for contributors who find the doc-contributor-README
- Better GSG / Install Guide structure.
- Added group edits and new illustrations from PR 2994 to introduction.rst.
- Ensure ngraph-bridge link in README goes to right place.
- Make project extras their own subdirectory with index to help organize them.
- **Known Issues**
  - When using TensorFlow* v1.14.0 with `` `ngraph-bridge `` v0.16.0rc0 and CPU backend, we saw notable to severe decreases in throughput in many models.

0.22¶

- More ONNX ops
- Optimizations
- Don't reseed RNG on each use
- Initial doc and API for IntelGPU backend
- DynamicBackend API

0.21¶

- The offset argument in tensor reads and writes has been removed
- Save/load API
- More ONNX ops
- Better tensor creation
- More shape support
- Provenance improvements
- offset arg for tensor creation is deprecated
- static linking support
- Initial test of 0.21-doc
- Updated `doc-contributor-README` for new community-based contributions.
- Added instructions on how to test or display the installed nGraph version.

- Added instructions on building nGraph bridge (ngraph-bridge).
- Updated Backend Developer Guides and ToC structure.
- Tested documentation build on Clear Linux OS; it works.
- Fixed a few links and redirs affected by filename changes.
- Some coding adjustments for options to render math symbols, so they can be documented more clearly and without excessive JS (see replacements.txt).
- Consistent filenaming on all BE indexes.
- Removed deprecated TensorAPI.

0.20¶

- Save/load API
- More ONNX ops
- Better tensor creation
- More shape support
- Provenance improvements

pre-0.20¶

- More dynamic shape preparation
- Distributed interface factored out
- fp16 and bfloat16 types
- codegen execution parameterized by context
- NodeMap, NodeVector, ParameterVector, ResultVector now vectors
  - `node_vector.hpp` replaced by `node.hpp`
  - `op/parameter_vector.hpp` replaced by `op/parameter.hpp`
  - `op/result_vector.hpp` replaced by `op/result.hpp`
- Additional ONNX ops
- Add graph visualization tools to doc
- Update doxygen to be friendlier to frontends
- Python formatting issue
- mkl-dnn work-around
- Event tracing improvements
- Gaussian error function
- Begin tracking framework node names
- ONNX quantization
- More fusions
- Allow negative padding in more places
- Add code generation for some quantized ops
- Preliminary dynamic shape support
- initial distributed ops
- Pad op takes CoordinateDiff instead of Shape pad values to allow for negative padding.
- NodeInput and NodeOutput classes prepare for simplifications of Node
- Test improvements
- Additional quantization ops

- Performance improvements
- Fix memory leak
- Concat optimization
- Doc updates

The Intel Homomorphic Encryption (HE) transformer for nGraph enables deep learning on encrypted data using homomorphic encryption.

Distributed training with nGraph¶

Important

Distributed training is not officially supported as of version 0.29; however, some configuration options have worked for nGraph devices in testing environments.

How? (Generic frameworks)¶

See also: [Distribute training across multiple nGraph backends]()

To synchronize gradients across all workers, the essential operation for data parallel training, due to its simplicity and scalability over parameter servers, is `allreduce`. The AllReduce op is one of the nGraph Library's core ops. To enable gradient synchronization for a network, we simply inject the AllReduce op into the computation graph, connecting the graph for the autodiff computation and optimizer update (which then becomes part of the nGraph graph). The nGraph Backend will handle the rest.

Data scientists with locally-scalable rack or cloud-based resources will likely find it worthwhile to experiment with different modes or variations of distributed training. Deployments using nGraph Library with supported backends can be configured to train with data parallelism and will soon work with model parallelism. Distributing workloads is increasingly important, as more data and bigger models mean the ability to [Distribute training across multiple nGraph backends]() work with larger and larger datasets, or to work with models having many layers that aren't designed to fit to a single device.

Distributed training with data parallelism splits the data and each worker node has the same model; during each iteration, the gradients are aggregated across all workers with an op that performs "allreduce", and applied to update the weights.

Using multiple machines helps to scale and speed up deep learning. With large mini-batch training, one could train ResNet-50 with Imagenet-1k data to the *Top 5* classifier in minutes using thousands of CPU nodes. See [arxiv.org/abs/1709.05011]().

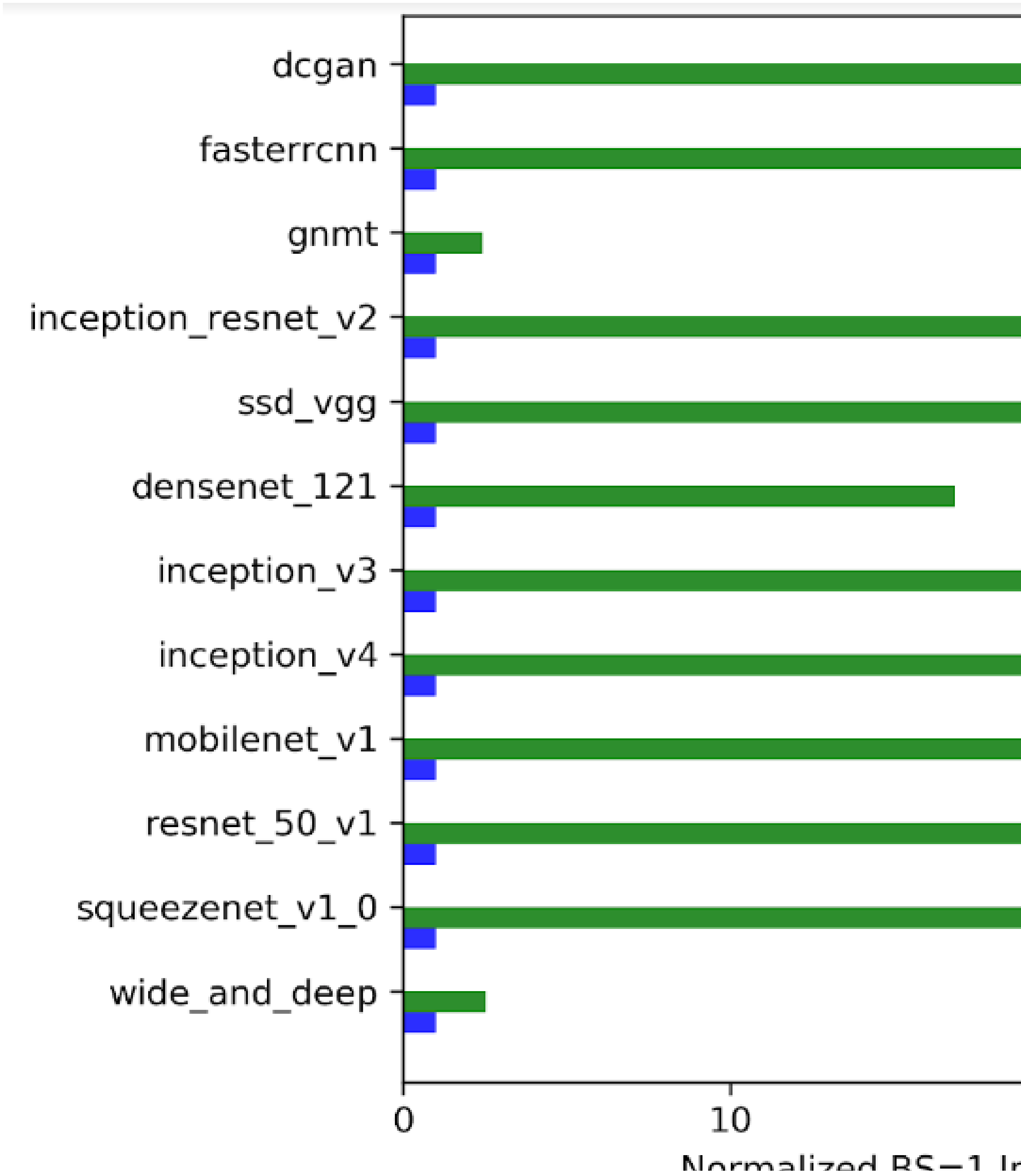
Testing latency¶

Important

This tutorial was tested using previous versions. While it is not currently or officially supported in the latest nGraph Compiler stack 0.29, some configuration options may still work.

Many open-source DL frameworks provide a layer where experts in data science can make use of optimizations contributed by machine learning engineers. Having a common API benefits both: it simplifies deployment and makes it easier for ML engineers working on advanced deep learning hardware to bring highly-optimized performance to a wide range of models, especially in inference.

One DL framework with advancing efforts on graph optimizations is Apache MXNet*, where Intel has contributed efforts showing how to work with our nGraph Compiler stack as an experimental backend. Our approach provides **more opportunities** to start working with different kinds of graph optimizations **than would be available to the MXNet framework alone**, for reasons outlined in our introduction documentation. Note that the MXNet bridge requires trained models only; it does not support distributed training.


dcgan
fasterrcnn
gnmt
inception_resnet_v2
ssd_vgg
densenet_121
inception_v3
inception_v4
mobilenet_v1
resnet_50_v1
squeezenet_v1_0
wide_and_deep
0
10
Normalized BS=1 In

Up to 45X faster compilation with nGraph backend

Tutorial: Testing inference latency of ResNet-50-V2 with MXNet¶

This tutorial supports compiling MXNet with nGraph's CPU backend.

Begin by cloning MXNet from GitHub:

```
git clone --recursive https://github.com/apache/incubator-mxnet
```

To compile run:

```
cd incubator-mxnet
make -j USE_NGRAPH=1
```

MXNet's build system will automatically download, configure, and build the nGraph library, then link it into `libmxnet.so`. Once this is complete, we recommend building a python3 virtual environment for testing, and then install MXNet to the virtual environment:

```
python3 -m venv .venv
. .venv/bin/activate
cd python
pip install -e .
cd ../
```

Now we're ready to use nGraph to run any model on a CPU backend. Building MXNet with nGraph automatically enabled nGraph on your model scripts, and you shouldn't need to do anything special. If you run into trouble, you can disable nGraph by setting

```
MXNET_SUBGRAPH_BACKEND=
```

If you do see trouble, please report it and we'll address it as soon as possible.

Running ResNet-50-V2 Inference¶

To show a working example, we'll demonstrate how MXNet may be used to run ResNet-50 Inference. For ease, we'll consider the standard MXNet ResNet-50-V2 model from the gluon model zoo, and we'll test with `batch_size=1`. Note that the nGraph-MXNet bridge supports static graphs only (dynamic graphs are in the works); so for this example, we begin by converting the gluon model into a static graph. Also note that any model with a saved checkpoint can be considered a "static graph" in nGraph. For this example, we'll presume that the model is pre-trained.

```
import mxnet as mx

# Convert gluon model to a static model
from mxnet.gluon.model_zoo import vision
import time

batch_shape = (1, 3, 224, 224)

input_data = mx.nd.zeros(batch_shape)

resnet_gluon = vision.resnet50_v2(pretrained=True)
resnet_gluon.hybridize()
resnet_gluon.forward(input_data)
resnet_gluon.export('resnet50_v2')
resnet_sym, arg_params, aux_params = mx.model.load_checkpoint('resnet50_v2', 
0)
```

To load the model into nGraph, we simply bind the symbol into an Executor.

```
model = resnet_sym.simple_bind(ctx=mx.cpu(), data=batch_shape,
grad_req='null')
model.copy_params_from(arg_params, aux_params)
```

At binding, the MXNet Subgraph API finds nGraph, determines how to partition the graph, and in the case of Resnet, sends the entire graph to nGraph for compilation. This produces a single call to an NNVM `NGraphSubgraphOp` embedded with the compiled model. At this point, we can test the model's performance.

```
dry_run = 5
num_batches = 100
for i in range(dry_run + num_batches):
   if i == dry_run:
       start_time = time.time()
   outputs = model.forward(data=input_data, is_train=False)
   for output in outputs:
       output.wait_to_read()
print("Average Latency = ", (time.time() - start_time)/num_batches * 1000,
"ms")
```

Indices and tables¶

- Search Page
- Index