

Agenda

☐ What is ONNX

☐ ONNX @ Microsoft

- ☐ What is ONNX Runtime
- ☐ How to create ONNX models

Open and Interoperable Al





Open Neural Network Exchange

Open format for ML models

github.com/onnx































































Key Design Principles

- Support DNN but also allow for traditional ML
- Flexible enough to keep up with rapid advances
- Compact and cross-platform representation for serialization
- Standardized list of well defined operators informed by real world usage

ONNX Spec

- File format
- Operators



File format

Model

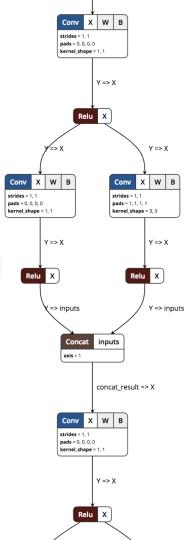
- Version info
- Metadata
- Acyclic computation dataflow graph

Graph

- Inputs and outputs
- List of computation nodes
- Graph name

Computation Node

- Zero or more inputs of defined types
- One or more outputs of defined types
- Operator
- Operator parameters



Data types

Tensor type

- Element types supported:
 - int8, int16, int32, int64
 - uint8, uint16, uint32, uint64
 - float16, float, double
 - bool
 - string
 - complex64, complex128

Non-tensor types:

- Sequence
- Map

```
message TypeProto {
 message Tensor {
    optional TensorProto.DataType elem type = 1;
    optional TensorShapeProto shape = 2;
  // repeated T
 message Sequence {
    optional TypeProto elem type = 1;
    map<K,V>
 message Map {
    optional TensorProto.DataType key type = 1;
    optional TypeProto value type = 2;
  oneof value {
    Tensor tensor type = 1;
    Sequence sequence type = 4;
    Map map type = 5;
```

Operators

An operator is identified by < <u>name</u>, <u>domain</u>, <u>version</u>>

Core ops (ONNX and ONNX-ML)

- Should be supported by ONNX-compatible products
- Generally cannot be meaningfully further decomposed
- Currently 124 ops in ai.onnx domain and 18 in ai.onnx.ml
- Supports many scenarios/problem areas including image classification, recommendation, natural language processing, etc.

Custom ops

- Ops specific to framework or runtime
- Indicated by a custom domain name
- Primarily meant to be a safety-valve

Relu

Relu takes one input data (Tensor) and produces one output data (Tensor) where the rectified linear function, y = max(0, x), is applied to the tensor elementwise.

Version

This version of the operator has been available since version 6 of the default ONNX operator set. Other versions of this operator: Relu-1

Inputs

```
x:T
Input tensor
```

Outputs

```
Y:T
Output tensor
```

Type Constraints

tensor(float16), tensor(float), tensor(double)
 Constrain input and output types to float tensors.

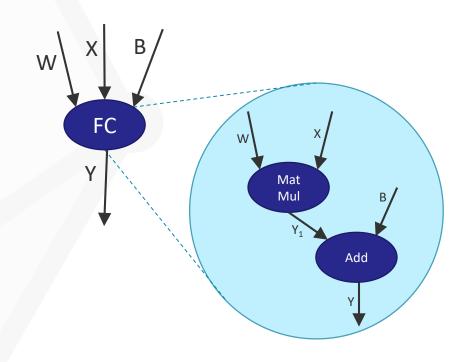
Examples

▼ relu

Functions

 Compound ops built with existing primitive ops

 Runtimes/frameworks/tools can either have an optimized implementation or fallback to using the primitive ops



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- ☐ What is ONNX Runtime

☐ How to create ONNX models

ML @ Microsoft

- LOTS of internal teams and external customers
- LOTS of models from LOTS of different frameworks









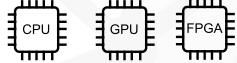


Different teams/customers deploy to different targets











ONNX @ Microsoft

PLATFORMS



PRODUCTS















Up to 14.6x

Performance gains seen by Microsoft services

100s of Millions

of devices where ONNX Runtime is running

Billions

of requests handled by ONNX Runtime across Microsoft services

ONNX @ Microsoft

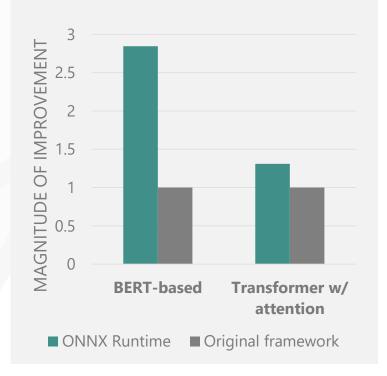
Bing QnA - List QnA and Segment QnA

- Two models used for generating answers
- Up to 2.8x perf improvement with ONNX Runtime



PERFORMANCE

Up to <u>**2.8x**</u> perf improvement with ONNX Runtime



ONNX @ Microsoft

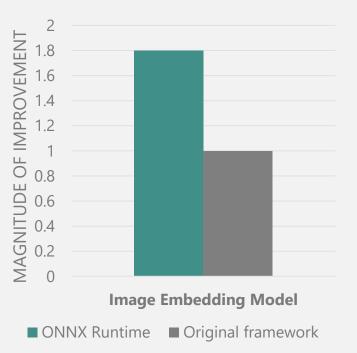
Bing Multimedia - Semantic Precise Image Search

- Image Embedding Model Project image contents into feature vectors for image semantic understanding
- 1.8x perf gain by using ONNX and ONNX Runtime



PERFORMANCE

1.8x perf improvement with ONNX Runtime



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☐ How to create ONNX models



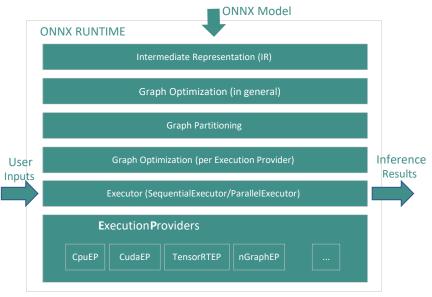
github.com/microsoft/onnxruntime

- High performance
- Cross platform
- Lightweight & modular
- **Extensible**

ONNX Runtime

- High performance runtime for ONNX models
- Extensible architecture to plug-in optimizers and hardware accelerators
- Supports full ONNX-ML spec (v1.2 and higher, currently up to 1.5)
- Works on Mac, Windows, Linux (ARM too)
- CPU, GPU, Intel edge devices, Nvidia Jeston Nano, ...
- Python, C#, and C APIs
- Code Generation
- Training

ONNX Runtime – Architecture



Graph Optimization

- · Node elimination (dropout, identity, etc.)
- Node fusion, constant folding, etc.

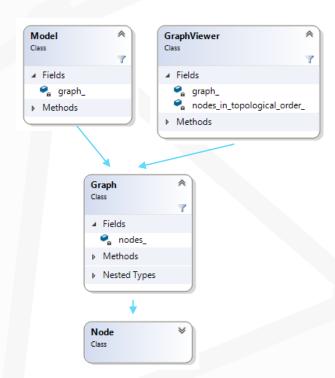
Graph Partitioning

- Graph partitioning based on execution providers' capability
- Greedy algo based on user preferences

Execution Provider

- · Plug-in hardware accelerator
- · Key APIs
 - GetCapability given a graph, return a collection of sub-graphs it can run
 - Compile given a sub-graph (node), return function pointers to run the sub-graph

ONNX Runtime - IR



Model/Graph/Node

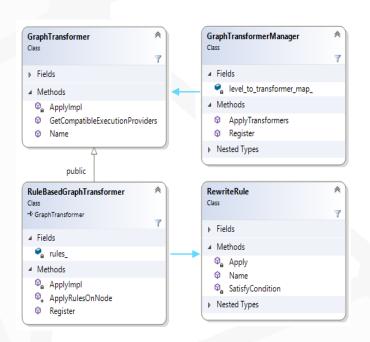
- In-memory object mapping to ONNX model file format design.
- Offering APIs to read/write a computational graph.

GraphViewer

Read-only view of a computational graph. Used in:

- IExecutionProvider (API between Runtime and hardware accelerator)
- Model evaluation (after model optimization and partitioning)

ONNX Runtime – Graph Optimization



RewriteRule

An interface created for finding patterns (with specific nodes) and applying rewriting rules against a sub-graph.

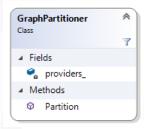
GraphTransformer

 An interface created for applying graph transformation with full graph editing capability.

TransformerLevel

- Level 0: Transformers anyway will be applied after graph partitioning (e.g. cast insertion, mem copy insertion)
- Level 1: General transformers not specific to any specific execution provider (e.g. drop out elimination)
- Level 2: Execution provider specific transformers

ONNX Runtime – Graph Partitioning



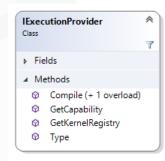
<u>GraphPartitioner</u>

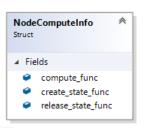
- Given a mutable graph, graph partitioner assigns graph nodes to each execution provider per their capability and idea goal is to reach best performance in a heterogeneous environment.
- ONNX RUNTIME uses a "greedy" node assignment mechanism
- Users specify a preferred execution provider list in order
- ONNX RUNTIME will go thru the list in order to check each provider's capability and assign nodes to it if it can run the nodes.

FUTURE:

- Profiling based partitioning
- ML based partitioning

ONNX Runtime – Execution Provider





IExecutionProvider

A hardware accelerator interface to query its capability and get corresponding executables.

- Kernel based execution providers
 These execution providers provides implementations of operators defined in ONNX (e.g. CPUExecutionProvider, CudaExecutionProvider, MKLDNNExecutionProvider, etc.)
- 2) Runtime based execution providers

 These execution providers may not have implementations with the
 granularity of ONNX ops, but it can run whole or partial ONNX graph. Say, it
 can run several ONNX ops (a sub-graph) together with one function it has
 (e.g. TensorRTExecutionProvider, nGraphExecutionProvider, etc.)

NodeComputeInfo

A data structure carries executables returned by runtime-based execution providers.

ONNX Runtime – API Example

```
import onnxruntime
session = onnxruntime.InferenceSession("mymodel.onnx")
results = session.run([], {"input": input_data})
```



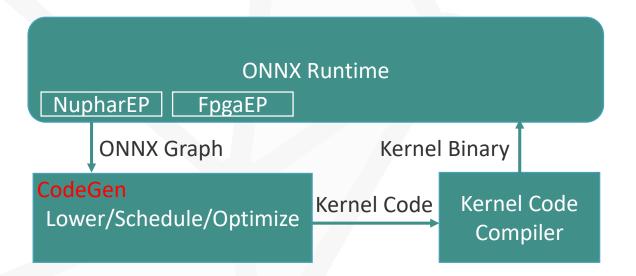
```
using Microsoft.ML.OnnxRuntime;
var session = new InferenceSession("model.onnx");
var results = session.Run(input);
```

C#

..... also available for C

ONNX Runtime – CodeGen

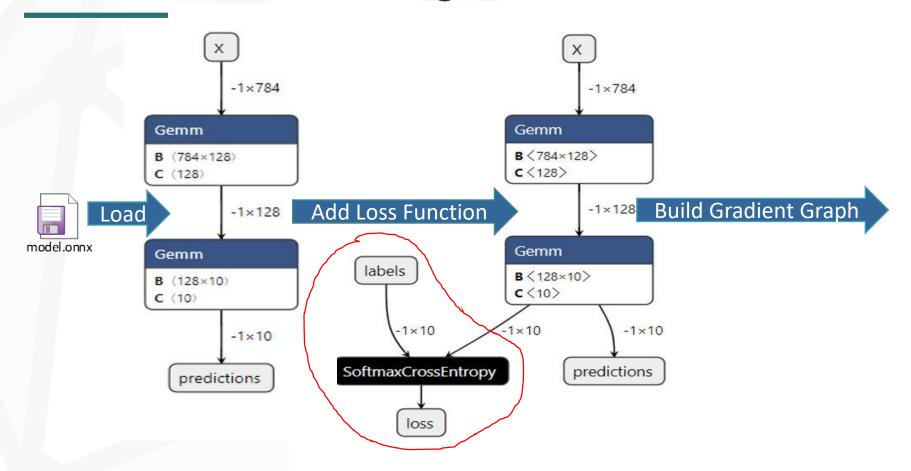
- TVM/Halide Based
- Used by NupharEP and FpgaEP
- NupharEP is open source

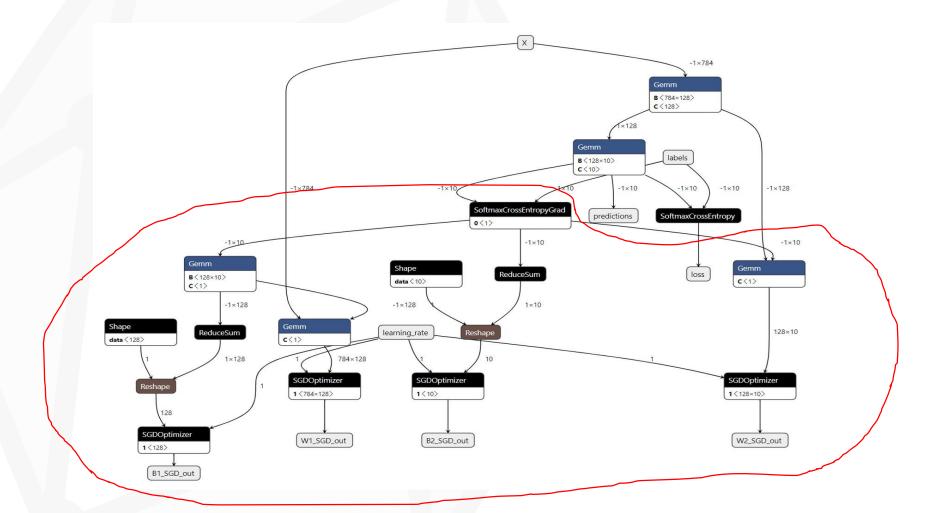


ONNX Runtime – Training

- Enables training on Device
 - Helps reinforcement learning, quantized retraining, ...
 - A fast, light-weight runtime with both training and inferencing capability
 - ONNX RT is 3MB binary size, ONNX + Training about 5MB
- Enables large-scale training for multiple frontends and backends
 - A single, unified software stack that
 - Supports multiple training framework frontends (TensorFlow, PyTorch,...)
 - Supports multiple accelerator backends (GPU, ...)
 - A combined SW and HW stack

ONNX Runtime – Training





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4 ways to get an ONNX model



ONNX Model Zoo



Services like Azure Custom Vision



Convert existing models



Train models in systems like Azure Machine Learning service

ONNX Model Zoo: github.com/onnx/models

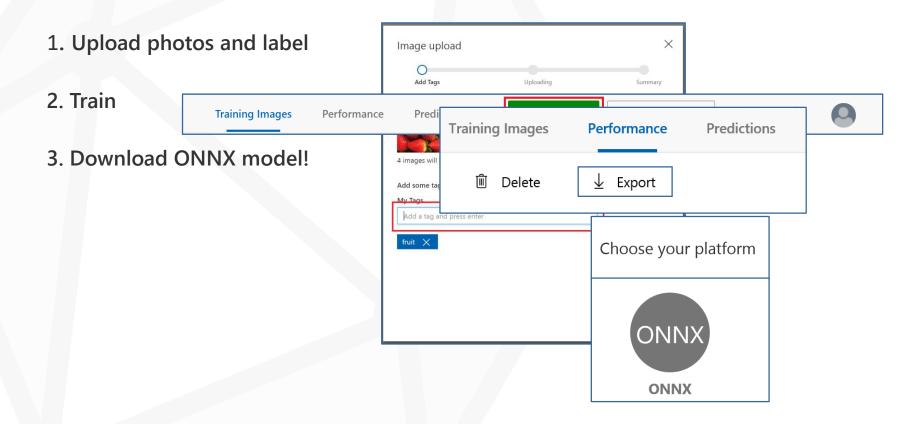
Image Classification

This collection of models take images as input, then classifies the major objects in the images into a set of predefined classes.

Model Class	Reference	Description							
MobileNet	Sandler et al.	Efficient CNN model for mobile and embedded vision applications. Top-5 error from paper - ~10%							
ResNet	He et al., He et	Very deep CNN model (up to 152 layers), won the ImageNet							
Sauce and Note	landola et al. Simonyan et al.	Top-5	Model	Download	Checksum	Download (with sample test data)			
SqueezeNet		fewer Top-5	ResNet-	44.6 MB	MD5	42.9 MB			
VGG		Deep Challe Top-5	ResNet-	83.2 MB	MD5	78.6 MB			

	Model	Download	Checksum	Download (with sample test data)	ONNX version	Opset version	Top-1 accuracy (%)	Top-5 accuracy (%)
	ResNet- 18	44.6 MB	MD5	42.9 MB	1.2.1	7	69.70	89.49
•	ResNet- 34	83.2 MB	MD5	78.6 MB	1.2.1	7	73.36	91.43
	ResNet- 50	97.7 MB	MD5	92.0 MB	1.2.1	7	75.81	92.82
	ResNet- 101	170.4 MB	MD5	159.4 MB	1.2.1	7	77.42	93.61
	ResNet- 152	230.3 MB	MD5	216.0 MB	1.2.1	7	78.20	94.21

Custom Vision Service: customvision.ai



Convert models

- **Tensorflow:** onnx/tensorflow-onnx
- **Keras:** onnx/keras-onnx
- **Scikit-learn:** onnx/sklearn-onnx
- **CoreML:** onnx/onnxmltools
- **LightGBM:** onnx/onnxmltools
- **LibSVM:** onnx/onnxmltools
- **XGBoost:** onnx/onnxmltools
- **SparkML** (alpha): onnx/onnxmltools

Native export

- **Pytorch**
- **CNTK**









LightGBM











Convert models: Examples

torch.onnx.export(model, sample_input, "model.onnx")

```
python -m tf2onnx.convert
                                                                            -- input frozen model.pb
        from keras.models import load model
                                                                            --inputs input batch:0,
        import keras2onnx
                                                                lengths:0
        import onnx
                                                                            --outputs top k:1
                                                                            --fold const
        keras_model = load_model("model.h5")
                                                                            --opset 8
                                                                            -- output deepcc.onnx
        onnx model = keras2onnx.convert keras(keras model,
        keras model.name)
                                                            serializers
        onnx.save model(onnx model, 'model.onnx')
                                       serializers.<mark>load</mark> npz("my.model", model)
import torch
                    O PyTorch
import torch.onnx
                                       sample_input = np.zeros((1, 3, 224, 224), dtype=np.float32)
                                       chainer.config.train = False
model = torch.load("model.pt")
sample_input = torch.randn(1, 3, 224, onnx_chainer.export(model, sample_input, filename="my.onnx")
```

ONNX & ONNX Runtime - Community Projects

Get Involved

Discuss

Participate in discussions for advancing the ONNX spec.

gitter.im/onnx

Contribute

Make an impact by contributing feedback, ideas, and code.

github.com/onnx

github.com/microsoft/onnxruntime

Q&A