Neural Network Exchange Format

Deploying Trained Networks to Inference Engines

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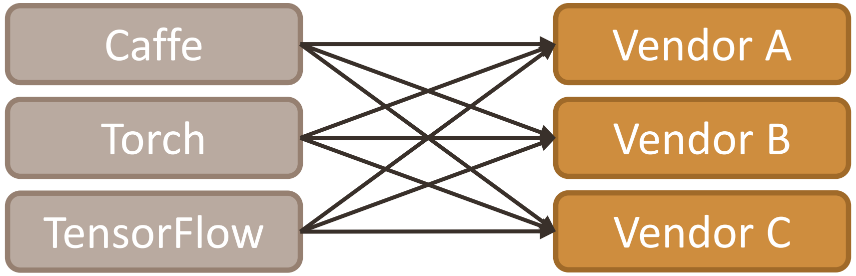
AIMOTIVE

Outlook

- The NN deployment problem and its resolution
- About the NNEF working group, AIMOTIVE
- NNEF design philosophy
- NNEF components and usage
- Future directions and contribution

NNEF In a Nutshell - The problem

- **There is a wide range of open-source deep learning frameworks available**
  - Caffe, Torch, Theano, TensorFlow, Chainer, CNTK, MXNet, Caffe2, PyTorch
  - Each framework has its own model format to store trained networks
- **Various chip vendors have released or are planning to release deep learning inference kits / engines**
  - Nvidia, Intel, AMD, ARM, Apple, Qualcomm, …
- **Inference engines need to be compatible with many deep learning frameworks**
- **Network descriptions have no clear semantics (ambiguities)**



NNEF In a Nutshell - The solution

- **Create a unified network description format to facilitate deployment of networks from frameworks to inference engines**
  - Describe network structure and data with clear semantics
- **Provide tools to convert from frameworks to the exchange format**
- **Provide tools for inference engines to import the exchange format**
  - No need to worry about where the network was trained
- **Focus on Edge devices in production environments**
  - Low power, low cost
  - Safety critical

About the NNEF group

- **Neural Network Exchange Format Working Group was founded in September 2016**
  - Initiated by AImotive
  - After an exploratory phase earlier to investigate industry requirements
  - The standardization idea was also circulated among framework developers
- **NNEF group is in collaboration with the OpenVX Working Group**
  - OpenVX provides an execution model for running computational graphs on embedded HW for vision
  - Has a neural network extension, incorporates NNEF import
- **Provisional specification was released in December 2017**
- **Version 1.0 was released in November 2018, revision 1.0.1 in April 2019**
- **Open for new companies to join!!**

About AImotive

- **AImotive is a software company delivering artificial intelligence based software stack for self-driving cars**
  - Software components for recognition, localization, control
    - Relying primarily on camera inputs
  - Hardware IP for custom chip to accelerate neural networks in a low power budget with high efficiency
- **Solutions heavily build on neural networks**
  - We use various deep learning frameworks to train networks
  - We use GPUs and FPGAs for prototyping, custom chips for production
  - We experience the NN exchange problem in-house and in relation with partners

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Deep Learning Frameworks - Similarities and Differences

- **We work with and examined various frameworks**
  - Torch, Caffe, TensorFlow, PyTorch (examined Theano, Chainer, Caffe2)
- **They vary in the way they build networks, but the underlying operations are very similar**
  - Most of the core ops are powered by the same implementation (cuDNN)
  - They build a computational graph that is similar on the lower level
    - The high level interface is different
- **However, there are critical differences in the operations**
  - Differences in parameterizations of computations (mathematical formulas)
  - Differences in output shape computations (asymmetric padding)
  - Differences in output value computations (border handling, image resizing)

NNEF Design Philosophy

- **Convey all relevant information from DL frameworks to inference engines**
- **Platform independence**
  - No hardware specification, no hardware specific data formats, etc.
- **Flexible, extensible description (rapidly changing field)**
  - By vendor specific operations
  - By future use cases and operations
- **Easy to consume by compiler/optimization tools**
- **Implementable and optimizable on various hardware platforms**
  - Hierarchical description, multiple levels of granularity
- **Support for quantization techniques**

NNEF Design Philosophy - Supported Network Architectures

- **Support the following learning tasks**
  - Image classification
  - Semantic segmentation
  - Object detection, instance segmentation
  - Video processing (action classification)
- **Support at least the following network architectures**
  - Fully connected networks (MLPs, auto-encoders)
  - Convolutional networks (feedforward, encoder-decoder)
  - Recurrent networks (LSTMs, GRUs)
- **Support inference mainly, but training graphs are also possible**
  - Needs extra operations for gradients/optimizer

NNEF Design Philosophy - Validation of Network Description

- **Ensure that a network description can be easily validated**
  - Syntactic/semantic validity of a document
  - Validity of the resulting graph
    - Implementation independent aspects
      - Graph connectivity, declaration of used identifiers
    - For example well defined tensor shapes and proper initialization
- **Possibility to check that an inference engine can execute a network**
  - Without loading the whole network
    - Structure is separated out from the data
  - Whether all operations/parameterizations are supported

What is included in the standard

- **NNEF aims to abstract out the network description from frameworks**
  - Only the network structure and data (no data feeding or training logic)
- **A distilled set of frequently used operations**
  - Well defined input-output mapping (output shape and value)
  - Well defined parameterization (math formulas)
- **A simple syntax for describing networks on a medium level**
  - Functional description, functional language-like
- **Data format (binary) for storing network parameters (weights)**
- **Support for describing quantization info**

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NNEF Components - Structure description

- **Devised a simple language to describe network structure**
  - Describe a computational graph on tensor objects
  - Simple syntax, limited set of features
  - Strictly typed, single-static assignment, easier to analyze/validate
- **Supports the hierarchical description of graph fragments**
  - Similar to functions in scripting languages for graph building
  - Define larger fragments (compound ops) from smaller ones (primitives)
    - Instantly extensible with new compounds that can be built from primitives
    - Vendors don't need to implement all primitives, can optimize compounds
- **A predefined set of primitive and compound operations for building networks**
  - Element-wise, activation, linear, pooling, normalization

NNEF Components - Data storage

- **The structure description has data parameters (network weights)**
- **Parameter tensors are stored in a separate format**
  - Simple data-format to store tensor data in floating point or quantized representation
- **All the data and structure description is wrapped around with a container**
  - Optionally compressed/encrypted tar file
  - Results in a single data-stream

NNEF Components - Quantization info

- **Quantization is a crucial element of executing networks efficiently on embedded hardware**
- **Quantization information needs to be stored in the network description**
  - In a platform independent manner
    - No reference to underlying data representations, like bit widths, arithmetic precision, etc.
  - Approach: ‘pseudo’ quantization, conceptually on real-valued data
- **Quantization algorithms are various**
  - Describe them as compounds built from primitives
    - Rounding and clamping operations
- **Quantization algorithm for activations and for stored parameters**
  - The data itself may be stored in the quantized format
  - Along with quantization algorithm

NNEF Generation and Consumption

- **It is possible to write third party converters for DL frameworks**
  - We have done that for Caffe, TensorFlow, PyTorch
  - Starting from proprietary formats of frameworks
  - Map operations to NNEF operations
  - Reverse conversion is also possible
  - Only for operations supported by both the framework and NNEF
- **NNEF can be consumed by compiler stacks / proprietary inference engines**
  - APIs may implement a subset of NNEF operations
  - NNEF operations may be lowered before consumption
    - The recipe for lowering can be defined in NNEF syntax
  - Compilation may happen online of offline

NNEF Tools

- **Continuously developing a library of tools to support the usage of NNEF**
  - github.com/KhronosGroup/NNEF-Tools
- **File format parser (C++ and Python)**
  - Easy to use, load/validate model in one line, return simple model structure
- **Converter tools (Python)**
  - Simple library to support writing of converters with a common logic
  - Available for TensorFlow, Caffe, ONNX, bidirectional conversion
- **Model zoo: collection of models converted to NNEF for reference**
- **Future possibilities (contributions are welcome)**
  - Quantization helpers
  - Graph optimization/visualization
  - Front ends for compiler stacks

Future Directions - Conformance

- **NNEF is a file format which may be input to a compilation process**
  - Compiler verification is well developed in practice
  - The file itself describes an executable graph
- **Define NNEF conformance tests like compiler verification tests**
  - Test cases separated by *domain* (image processing) and *task* (classification)
  - Test cases described by source files and input data
    - Source files are NNEF models
    - Input/expected output data represented as tensor binaries
  - Test cases cover a subset of operations
    - Subset of possible parameter combinations
  - Test cases for complete networks
    - Define task dependent metrics for evaluation, leave room for approximations

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NNEF vs ONNX

- In our view, there are no clear *conceptual* advantages/disadvantages of one or the other
- Technical differences
  - ONNX uses binary format (protobuf)
  - NNEF uses text format for describing network structure for transparency
- Difference in development
  - ONNX is more rapidly changing, good for R&D
    - Developed by open source community
  - NNEF is a slower changing, more stable standard, better for industry
    - Developed by a consortium of industry players with a well established governance model
    - Member companies can have a vote on development decisions

NNEF Advisory Panel

- Anyone who wishes to review the NNEF specification draft can join an Advisory Panel
  - After signing and NDA with Khronos Group
- Provides early access to specification drafts
- Share feedback on mailing list

Thank you!

Contact Info

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Hands-on Demo

- **Clone NNEF-Tools repository from GitHub**
  - Install nnef python module
  - Few words about the organization of the repo (parser, io, converters)
- **Show validator.py and sample.py**
  - Turn on shape inference, compression
  - Change something in the examples to make it fail
- **Show the model zoo**
  - Download some ONNX or TF models and convert them to NNEF
  - Convert back to NNEF
- **Show conversion from TF python code**
  - Show the mapping of ops from TF to NNEF