Deep Learning Frameworks Portability Survey: Post-K Perspective

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Why This Report?

What is the path forward, and effort, required to qualify Post-K for supporting DL software stacks?

Fundamental Conditions:
• Post-K MUST support training DNNs, not just inference
• No branching/custom versions of DL frameworks
Summary

- The issue is not just a low-level primitive library
  - How to interface it with a DL framework?
- Different DL frameworks are designed differently
  - Different tradeoffs WRT supporting new hardware
- TensorFlow (TF) is modular
  - Defining and interfacing a new backend is relatively straightforward
- Chainer does not provide separation of concerns
  - Yet codebase is small: support could be added
- Model exchange formats (ONNX and NNEF)
  - Might support training in the future
Survey Methodology

- We investigate DL software solutions
  - At different abstraction levels of DL domains

- Automated approach
  - Use basic DNN primitives (eg: activation func, dense layer)
  - Trace execution paths and call stacks
  - Collecting code fragments
    - At which GPU/CPU take different execution paths
Scope of Survey

- Objective of survey is ARM CPU platform

- Focus on x86 CPUs, not GPU
  - However, frameworks not thoroughly optimized for CPU
  - For some frameworks not optimized at all
  - So we focus heavily on studying GPU backends
Overview of DL Software Stacks

- DL frameworks include the following layers of abs:
  - User interface
    - API
    - Import/export formats
  - Intermediate representation / graph-level optimizations
  - Tensor computation backend
    - Hard-coded
    - Code generation
    - DL Primitives library
    - BLAS libraries
Model Exchange Formats

- Allows moving between frameworks
- **ONNX (Open Neural Network eXchange)**
  - Extensible graph computation model
  - Built-in operators and data types
  - Limitations:
    - No cycles allowed
    - Must adhere to SSA
    - Only NCHW layout supported
    - No backprob

- **NNEF (Neural Network Exchange Format)**
  - Not a graph engine: can not be executed

<table>
<thead>
<tr>
<th>Framework</th>
<th>Exporting</th>
<th>Importing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caffe2</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>PyTorch</td>
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<td></td>
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<tr>
<td>CNTK</td>
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<td>MXNet</td>
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<td>✓</td>
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<tr>
<td>Chainer</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>TensorFlow</td>
<td>✓</td>
<td>(✓)</td>
</tr>
</tbody>
</table>
DL Libraries for Performance Primitives

- Most computations in DNN can use BLAS primitives

- However, more efficient and specialized algo. Used

- Algorithms are common to DL frameworks
  - Implementation is HW specific
  - Lib. typically developed/maintained by HW vendors
cuDNN (Nvidia)

- Closed source

- Provides primitives of DNNs (including backprob):
  - N-dim convolution || Pooling || softmax || Activation
  - Tensor transformations || Normalization || RNN

- Includes up to eight different convolution algorithms

- cuDNN is evolving to allow fusing operators
  - ex: fusing batchnorm with add and Relu operations
MKL-DNN (Intel)

- Open source
  - Yet relies heavily on MKL (closed source)

- Support many primitives
  - For both x86 and Xeon Phi
  - Most primitives in fp32 (some also in int8)
  - No mention of reduced precision training

- MKL-DDN is a rough proxy for the effort required
  - ~81k lines of code
  - Supports only fp32, for a range of x86 processors
ARM NN SDK (ARM)

- Open source
  - Current support is for Caffee and TF (not complete)
- Supports ARM Cortex CPUs and Mali GPUs
- Forward propagation only
  - No means to derive backwards computation
  - Models are read from prototxt format
  - prototxt presents the computation graph
- ~21k lines of code using C++ templating
Chainer (1 of 2)

- A Python-based framework widely used in Japan
  - Heavy geared towards GPUs
  - Define-by-run approach (AKA dynamic comp. graph)

- Not modular: separate implementations hardcoded
  - Think #if #def style programming
- Uses NumPy as containers for Tensors
- Distributed training uses MPI (and NCCL)
Chainer (2 of 2)

- ChainerX is a new variant that is modular
- Not clear if it will replace Chainer or not
TensorFlow (1 of 2)

- A symbolic math library for tensor computation
  - Different frontends and backends
  - Current uses Keras as official Python frontend
  - Includes a compiler for linear algebra (XLA)
TensorFlow (2 of 2)

- Extending the frontend
  - One can define and add “operators”
  - TF can then a graph with the new “operators”
  - Relatively easy
    - Requires some knowledge of internal C++ code used

- Extending the backend
  - The programmer has to define how the graph is exec.
    - ex: Fujitsu A64FX has four CMGs to split the graph to

- Distributed training
  - Google’s gRPC (and MPI version also exists)
    - Scaling issues, still remains commonly used
    - Mesh-TensorFlow (model-parallelism)
A detailed look at TensorFlow
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int n, c, c__, h, h__, p, s, d, ws; // Layer parameters
half *x, *y, *w, *ws; // Tensors
int wsLimit = 64 * 1024 * 1024;
cudnnConvolutionFwdAlgo_t algo;

// Create cuDNN handle/descriptors
cudnnHandle_t handle;
cudnnTensorDescriptor_t xDesc, yDesc;
cudnnFilterDescriptor_t wDesc;
cudnnConvolutionDescriptor_t convDesc;
cudnnCreateTensorDescriptor(&xDesc);
cudnnCreateTensorDescriptor(&yDesc);
cudnnCreateFilterDescriptor(&wDesc);
cudnnCreateConvolutionDescriptor(&convDesc);
cudnnCreate(&handle);

// Initialize descriptors
cudnnSetTensor4dDescriptorEx(xDesc, CUDNN_DATA_HALF,
   n, c, h, h__ * h__, 1, h__, c__);
cudnnSetTensor4dDescriptorEx(yDesc, CUDNN_DATA_HALF,
   n, c__, h__, h__ * h__, 1, h__, c__);
cudnnSetFilter4dDescriptor(wDesc, CUDNN_DATA_HALF, wFormat,
   c__, c_, h, k);
cudnnSetConvolution2dDescriptor(convDesc,
   p, p, s, s, d, d,
   CUDNN_CROSS_CORRELATION, CUDNN_DATA_HALF);
cudnnSetConvolutionMathType(convDesc, CUDNN_TENSOR_OP_MATH);

// Get a convolution algorithm
cudnnGetConvolutionForwardAlgorithm(handle,
   xDesc, wDesc, convDesc, yDesc,
   CUDNN_CONVOLUTION_FWD_SPECIFY_WORKSPACE_LIMIT,
   &algo);

// Perform convolution: \( Y = \alpha (X \ast W) + \beta Y \)
const float alpha = 1.0, beta = 0.0;
cudnnConvolutionForward(handle,
   &alpha,
   xDesc, x,
   wDesc, w,
   convDesc,
   algo,
   ws,
   wsLimit,
   &beta,
   yDesc, y);
Using MKL-DNN by DL Frameworks

```c++
auto relu_desc = eltwise_forward::desc(prop_kind::forward,
                        algorithm::eltwise_relu, conv_pd.dst_primitive_desc().desc(),
                        negative_slope);
auto relu_pd = eltwise_forward::primitive_desc(relu_desc, cpu_engine);
auto relu_dst_memory = memory(relu_pd.dst_primitive_desc());
auto relu = eltwise_forward(relu_pd, conv_dst_memory, relu_dst_memory);
net_fwd.push_back(relu);

/* Backward */
auto relu_diff_dst_md = lrn_diff_src_memory.get_primitive_desc().desc();
auto relu_src_md = conv_pd.dst_primitive_desc().desc();

relu_diff_dst_md, relu_src_md, negative_slope);
relu_diff_dst_md, relu_src_md, negative_slope);
auto relu_bwd_pd = eltwise_backward::primitive_desc(relu_bwd_desc, cpu_engine, relu_pd);
auto relu_diff_src_memory = memory(relu_bwd_pd.diff_srcPrimitive_desc());
auto relu_bwd = eltwise_backward(relu_bwd_pd, conv_dst_memory,
                                            lrn_diff_src_memory, relu_diff_src_memory);
net_bwd.push_back(relu_bwd);
```