SOL: Reducing the Maintenance Overhead for Integrating Hardware Support into AI Frameworks

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ABSTRACT
The increased interest in Artificial Intelligence (AI) raised the need for highly optimized and sophisticated AI frameworks. Starting with the Lua-based Torch many frameworks have emerged over time, such as Theano [16], Caffe [8], Chainer [17], CNTK [14], MxNet [2], PyTorch [13], DL4J, or TensorFlow [1].

All of these provide a high level scripting API that allows users to easily design neural networks and run these on various kinds of hardware. What the user usually does not see is the high effort put into these frameworks to provide peak execution performance.

While mainstream CPUs and GPUs have the “luxury” to have a wide spread user base in the open source community, less mainstream CPU, GPU or accelerator vendors need to put in a high effort to get their hardware supported by these frameworks. This includes not only the development of highly efficient compute libraries such as CUDNN, OneDNN or VEDNN but also supporting an ever growing number of simpler compute operations such as summation and multiplications. Each of these frameworks, nowadays, supports several hundred of unique operations, with tensors of various sizes, shapes and data types, which end up in thousands of compute kernels required for each device type. And the number of operations keeps increasing.

That is why NEC Laboratories Europe started developing the SOL\(^2\) AI Optimization project already years ago, to deliver optimal performance to users while keeping the maintenance burden minimal.

1 AI FRAMEWORK EXECUTION PHASES
The key insight of SOL is based on understanding the execution phases of AI frameworks which are outlined in the following code example Listing 1.

The first phase is the “Model Initialization”. In this phase the neural network structure gets defined and model weights either get loaded from a pre-trained dataset or randomly initialized. Depending on the framework, the model either gets directly initialized on the target device or it needs to be manually transferred.

In the second phase, the inference or training datasets get processed. This often is done by the Numpy, SciKit Learn or Pandas libraries.

Last, the model gets executed either in a simple inference task or in a training loop. Let’s take a closer look at a training loop (Listing 2).

First, we build up an optimizer that takes care of updating our model weights during training and a loss function. We then have multiple nested loops that iterate over the batches of our dataset and multiple epochs. Within our loop we execute the forward execution of our model, compute the loss and execute the backward pass, which computes the gradients. Last, we call the optimizer to update our weights.

2 SOL PRINCIPLE
What hardware vendors so far have been doing was to port all low level function calls of AI frameworks to their own compute libraries, which then directly can be executed by the AI framework. This is a huge effort and requires lots of workforce to implement and maintain all of these functions (Figure 1).

When looking at the training loop (Listing 1), we see that we have four atomic steps.

(1) the forward pass of the model
(2) the execution of the loss function

Listing 1: Simplistic PyTorch code that initializes a model, generates input data and runs it in inference mode.

import torch
import torchvision

# 1. Model Initialization Phase
model = torchvision.resnet50()
model = model.to(device)

# 2. Data Preparation Phase
input = torch.rand(1, 2, 3)

# 3. Model Execution Phase
output = model(input)

Listing 2: Simple example of a PyTorch training loop.

optimizer = torch.optim.sgd(model.parameters())
loss_function = torch.nn.functional.l1_loss

for epoch in range(epochs):
    for input, target in dataset:
        output = model(input)
        loss = loss_function(output, target)
        loss.backward()
        optimizer.step()
Figure 1: State-of-the-art device support in AI frameworks. Hardware vendors upstream the entire device support into the codebase of the AI framework and only share external compute libraries for compute heavy kernels, i.e., Convolution or GEMM.

(3) the backward pass of the model
(4) the update of the model weights

Independently from the used AI framework these four steps get triggered within training loops. Which means that it does not matter if the framework calls a single compute kernel within these steps, or hundreds of these. The framework expects the output after the step, but how this output is computed is not defined.

Therefore, within SOL we replace the 1st and 3rd step with our neural network compiler engine. For the user this just means to run a single command which returns a new instance of the neural network, that is fully compatible with the AI framework, but whose computations do rely on SOL instead of the AI framework’s execution engine. With this trick, a hardware vendor does not need to support over 90% of the AI framework’s compute kernels, as for this we use our unified compiler engine that can be utilized in any AI frameworks with little effort. So, instead of constantly maintaining compute kernels for each AI framework separately, and keep up with the fast development cycles and API changes, SOL only requires a single unified device support and abstracts the entire integration into the AI framework (Figure 2).

This leaves us with the loss functions and the weight update, which are mainly based on very simple computations and are little effort to be integrated into each of these frameworks.

```python
import sol
sol_model = sol.optimize(model, ...)
```

Listing 3: Minimal steps to apply SOL optimizations.

To add this minimal necessary device support of the NEC SX-Aurora TSUBASA to TensorFlow and PyTorch, we developed the veda-tensorflow [10] and veda-pytorch [9] Python modules. These only contain these minimal required compute kernels and necessary callbacks for the AI frameworks. veda-tensorflow is based on the TensorFlow PluggableDevice API [15] that has been introduced in TensorFlow v2.6. For PyTorch we use their function registry to side-load our compute kernels into PyTorch’s execution engine and added the ‘VE’ device type in PyTorch v1.10. This allows to add the entire SX-Aurora device support without any code changes to TensorFlow or PyTorch.

Frameworks that don’t have the option to register device support at runtime (i.e. DL4J) still can be used with SOL through our transparent offloading [18] mechanism. With transparent offloading, SOL is able to use a model that is stored in the host memory and execute it on any target device. For this, SOL maintains a copy of the model on the device and transparently synchronizes changes to the weights between the host and the device memory. However, this method can have performance penalties due to memory synchronization and should not be used when native hardware integration is available.

3 SOL ARCHITECTURE

SOL uses an extensible plugin infrastructure. Heart of SOL is the so called “core” that contains most of it’s functionality, graph representation and transformations. Further, SOL consists of:

**JITs**: plugins that enable to compile generated source code using external compilers such as GCC, LLVM or ISPC.
Frameworks: plugins that serve three purposes:
1. parsing the AI framework specific neural network format and translate them to SOL’s own “High Level Intermediate Representation” (HLIR)
2. generating wrappers that allow to integrate SOL optimized neural network’s into the AI frameworks
3. connect SOL’s runtime to the AI framework’s memory allocation system

Devices: plugins providing basic device functionality like enumeration, memory management, etc.

Backends: plugins that translate parts of the HLIR graph to device specific and optimized implementations.

When sol.optimize(...) is called, SOL performs the following steps.
1. the framework plugin parses the neural network structure and translates it into SOL’s HLIR format.
2. SOL applies generic optimizations and transformations, i.e., removing layers that do not contribute to any output of the neural networks, are mathematically irrelevant, or can be statically evaluated because their input is constant.
3. generates/compiles framework specific wrappers that integrate the optimized model into the AI framework
4. return an instance of this optimized model to the user.

When the model gets executed the very first time, SOL generates three versions of the neural network.
1. an inference version
2. a training forward version
3. a training backward version

Each of these versions get optimized individually. During the optimization procedure, SOL performs a layer-by-layer auto-tuning and selects the backends that perform best. SOL allows that multiple backends (i.e., different BLAS libraries) implement the same layers, and the best performing gets chosen. In contrast to tools like TVM [3] that perform an exhaustive and very long auto-tuning (up to several hours), SOL relies on a layer-by-layer auto-tuning, that is usually completed within seconds.

After determining the best backend for each layer, SOL groups connected layers that have the same backend assigned to enable layer merging. All of the grouped layers get compiled by the respective backends and finally get linked to a single library that contains the entire execution pipeline and compute kernels for the respective neural network.

Since SOL v0.4.1 we support to extend SOL through its SDK. SOL’s plugin-infrastructure makes it easy extendable. All parts of SOL can be extended, the backends, jits, frameworks and devices. Further, entirely new layers and transformation passes can be added. Please refer to the SDK\footnote{sol.neclab.eu/docs/v0.5.0/sdk.html} for more information.

4 SOL BENEFITS

So far we mainly discussed how the concept behind SOL can reduce the maintenance effort for hardware vendors to support new hardware within AI frameworks with little effort. But SOL also provides many benefits to AI users through its unique design principles.

Figure 3: Inference performance comparison of SOL of the TorchVision Resnet50, executed in vanilla PyTorch v1.11.0, PyTorch + SOL and cross-executing the PyTorch defined model in TensorFlow v2.8.0 + SOL (see next section for details). You can see that on Intel Xeon 6126 SOL is 15% faster than vanilla PyTorch. Further, TensorFlow has a higher execution overhead compared to PyTorch when running the identical SOL model. When using the NEC SX-Aurora TSUBASA VE10B, we achieve more than 50% speedup compared to vanilla PyTorch on the Intel Xeon. As previously mentioned transparent offloading inherits a small performance penalty compared to native execution because of the memory transfer to the accelerator.

4.1 Performance

Performance is a key aspect in AI training as due to the high computational demands the costs of training models can be extreme, i.e., 12MS for training GPT-3 [19].

Therefore, a lot of work is invested in making the AI frameworks as efficient as possible. But still, depending on which neural network you are running, the one or other AI framework might be faster.

With SOL this problem does not exist, as it compiles hardware specialized implementations of the neural networks, which not only outperform the AI framework’s execution engines but also provides equivalent performance independent of which AI framework is used (Figure 3). This relieves users from evaluating which AI framework performs fastest for them and allows them to use the framework they personally prefer.

4.2 Cross-Framework Execution

A common problem for AI developers is that neural networks are written in a specific framework and it’s tedious to convert it to other frameworks. ONNX [12] has established itself as “THE” neural network storage format. However, as of today all major AI frameworks can only export ONNX models and not load them. Projects like...
ONNX-TF [6] or ONNX-Pytorch [4] try to add this missing functionality but they often hit limitations of the frameworks themselves, as can be seen at the list of supported layers4. This is caused by the fact that not all layers, hyper-parameters and data types supported by PyTorch are available in TensorFlow and vice versa. For example PyTorch’s AdaptiveAvgPooling allows arbitrary output shapes, while TensorFlow’s GlobalAvgPooling only supports to entirely reduce the pixel dimensions. Or Tensorflow’s CumSum allows inclusive/exclusive and reversed modes, while PyTorch only supports inclusive CumSums.

This requires teams to agree on a common AI framework to be used and even manually port (or even adjust) neural networks if they are only available in foreign formats.

As SOL does not use the AI framework’s execution engines, it does not have these limitations. Therefore SOL can directly execute a PyTorch model within TensorFlow or vice versa, even for operations that are not natively supported within TensorFlow.

For users, this only requires to add a single keyword.

```python
sol_model = sol.optimize(pytorch_model, ..., framework='tensorflow')
```

Listing 4: Minimal changes needed to run any PyTorch model in TensorFlow.

So far SOL supports loading any Python based neural networks (PyTorch, TensorFlow or ONNX) and run these in PyTorch, TensorFlow (as tf.Module or tf.keras.model.Model) or as a plain Python function that uses NumPy arrays as input. When executing with NumPy arrays the user can use transparent offloading to execute the neural network on any device and is not bound to the host CPU.

### 4.3 Dynamic Dimensions

Dynamic dimensions in executing neural networks is a two sided blade. From a user perspective it allows more flexibility. From the framework perspective it can decrease the performance as it requires to handle more runtime information and prevents the application of certain compile-time optimizations. However, as the users demand it today, all AI frameworks support them.

In all AI frameworks, the user needs to manually identify which dimensions should be dynamic. Further, using dynamic dimensions in AI frameworks can easily hit implementation limitations. For example the torch.jit.trace(...) function for jit compiling a neural network does not allow to use any dynamic dimensions at all.

Instead SOL uses a new unique dynamic dimensions system. SOL automatically determines which dimensions can be dynamic based on the structure of the neural network. For example, if a layers uses a bias with 128 channels, this dimension is fixed by the structure of the neural network and cannot be dynamically set. This method does not require any user input. After analyzing the neural network, SOL reports the possible input and output shapes as in the following example (Listing 5).

In this example, SOL has identified four dynamic dimensions (#0-#3). However, by default SOL uses the fixed dimensions and requires the user to explicitly enable dynamic dimensions manually. This guarantees that SOL can optimize all dimensions that don’t need to be dynamic. To enable a dynamic dimension the sol.optimize(..., vdims=[...]) keyword can be used. SOL allows to enable (True), disable (False) or overwrite (integer > 0) the values used.

```python
Listing 5: Input and output shapes inferred by SOL after parsing a network. SOL identified four (#0-#3) dynamic dimensions.
```

```python
Inputs: in_0 [#0, 5, #1, #2, #3]
Outputs: out_0 {
    "A": [#0, 5, #1, #2, #3],
    "B": [#0, 5, #1, 3, 3],
    "C": [#0, 5, #1, 5, 7],
}
```

Listing 5: Input and output shapes inferred by SOL after parsing a network. SOL identified four (#0-#3) dynamic dimensions.

### 4.4 Memory Consumption Estimation

Most users of AI frameworks have already encountered the situation where their training died with the message: out of memory, which can be troublesome if it occurs after several days of training. The main reason is that while the number of model parameters is easy to identify, i.e. by TensorFlows model.summary() method (Listing 6) it is not possible to get a good estimate of peak memory consumption from any AI framework without running the model at least once.

For example PyTorch’s torch.cuda.max_memory_allocated() can be used to get a rough estimate of the memory consumption. This is because of two main issues. First, dynamic graphs (as used by PyTorch) get evaluated at runtime, which does not allow to take a grasp of the neural network structure before executing. And second, during training of neural networks intermediate results need to be stored between forward and backward pass, which increases the peak memory consumption during training.

As SOL compiles the neural network and employs a static schedule during this procedure, it knows exactly when it allocates memory and when it frees it. This allows SOL to give an estimation of the peak memory consumption before running for the first time.

```python
Listing 7: Peak memory estimated by SOL.
```

```python
Estimated Peak Memory Consumption:
Inference: ~15MB
Training: ~25MB
```

Listing 7: Peak memory estimated by SOL.

SOL only reports an estimate, as due to memory alignment and fragmentation it’s impossible to give a more accurate number. SOL can also generate more detailed reports which show the development of the memory consumption over time and which kind of data (parameters, inputs, outputs or intermediate) are causing the memory consumption.

### 5 NEURAL NETWORK DEPLOYMENT

After a neural network has been trained, it needs to be deployed in its final application where it is undesirable to ship the entire AI
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| Model: "model"
| Layer (type) | Output Shape | Param # |
|--------------|--------------|---------|
| input_1 (InputLayer) | [(None, 224, 224, 3)] | 0 |
| conv2d (Conv2D) | (None, 56, 56, 64) | 23296 |
| max_pooling2d (MaxPooling2D) | (None, 27, 27, 64) | 0 |
| conv2d_1 (Conv2D) | (None, 27, 27, 192) | 307392 |
| max_pooling2d_1 (MaxPooling2D) | (None, 13, 13, 192) | 0 |
| conv2d_2 (Conv2D) | (None, 13, 13, 384) | 663936 |
| conv2d_3 (Conv2D) | (None, 13, 13, 256) | 884992 |
| conv2d_4 (Conv2D) | (None, 13, 13, 256) | 590080 |
| max_pooling2d_2 (MaxPooling2D) | (None, 6, 6, 256) | 0 |
| flatten (Flatten) | (None, 9216) | 0 |
| dense (Dense) | (None, 4096) | 37752832 |
| dense_1 (Dense) | (None, 4096) | 16781312 |
| dense_2 (Dense) | (None, 1000) | 4097000 |

Total params: 61,100,840
Trainable params: 61,100,840
Non-trainable params: 0

Listing 6: Output of model.summary() of Alexnet in Keras.

framework with the application. There are two types of deployment options available: Runtime Engines and Compilers.

- **Neural Network Runtime Engines:**
  - PyTorch provides libtorch which is a C++ API enabling to run PyTorch models. However, libtorch with CUDA support is 1.5GB which is undesirable to be shipped with most applications.
  - TensorFlow provides TensorFlow-lite which is much more lightweight but still consumes several hundreds of megabytes.
  - ONNXRuntime [5] is a lightweight execution engine for ONNX models that supports vendor specific backends.

- **Neural Network Compilers:**
  - NVIDIA’s TensorRT [11] allows to deploy neural networks for their own hardware.
  - Intel’s OpenVINO [7] allows deploying neural networks on all kinds of Intel hardware (CPUs, FPGA, IPU, ...).
  - TVM is a widely used inference compiler that supports a huge variety of target platforms.

This is only a small list of tools available for deploying neural networks. As can be seen, especially the compilers (except TVM) are vendor specific and limit the user to their respective hardware. So if the user needs to support multiple vendors, it’s easier to stick to runtime engines to ease the effort required to maintain multiple implementations, with the drawback of higher storage consumption and lower performance compared to compiled neural networks.

Another aspect is the compatibility, especially with the compiler support. When training your neural network in an AI framework it is not guaranteed that the compiler you choose is able to compile the given neural networks with the chosen layers and hyper-parameters.

SOL overcomes these issues as it is not only multi-vendor, but it also guarantees that if you have trained your neural network with SOL, the exact same network can also be compiled to an optimized library. As of now, SOL supports deployment of neural networks in device specific libraries, with minimal storage footprint, for static and shared linux libraries. In case you need special adjustments for your system or application, you can also directly use the optimized source code for your neural network and adjust it to your specific needs.

6 SUMMARY

In this article we presented the SOL AI Optimization project⁶. SOL enhances the usability and performance of AI frameworks, independently from the used hardware and to enable vendors to add hardware support easily to any AI framework, with minimal maintenance effort.

If you are interested in using SOL, please apply for SOL’s closed beta⁷.

REFERENCES

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⁶sol.neclab.eu
⁷sysml.neclab.eu/projects/sol/closed_beta/
Figure 4: Advanced SOL memory consumption report for forward pass of training. Each bar does not correspond to a single layer, but to a group of merged layers.