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Introduction to Deep Learning

Profiling with DLProf

PyTorch Catalyst

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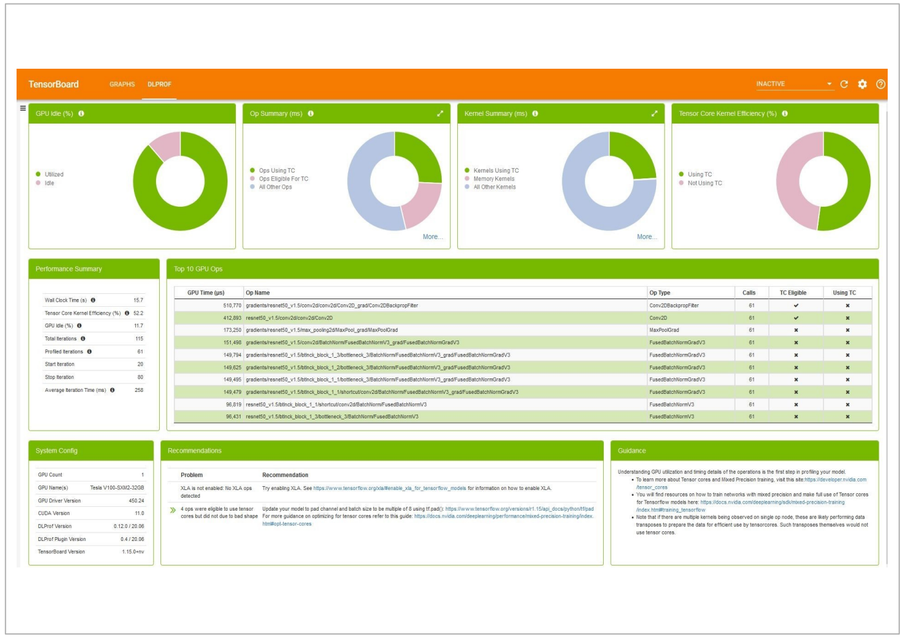
FW Support: TF, PyT, and TRT Lib Support: DALI, NCCL



Visualize Analysis and Recommendations

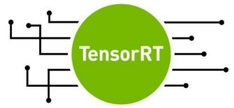
Credit: NVIDIA

Deep Learning Profiler

- **DLProf (CLI & Viewer)**
  - Helps data scientists understand and improve performance of their DL models by analyzing text reports or visualizing the profiling data
- **DLProf CLI**
  - Uses Nsight Systems profiler under the hood
  - Aggregates and correlates CPU and GPU profiling data from a training run to DL model
  - Provides accurate Tensor Core usage detection for operations and kernels
  - Identifies performance issues and provides recommendations via Expert Systems
- **DLProf Viewer**
  - Uses the results from DLProf CLI and provides visualization of the data
  - Currently exists as a TensorBoard plugin

Credit: NVIDIA

GETTING STARTED



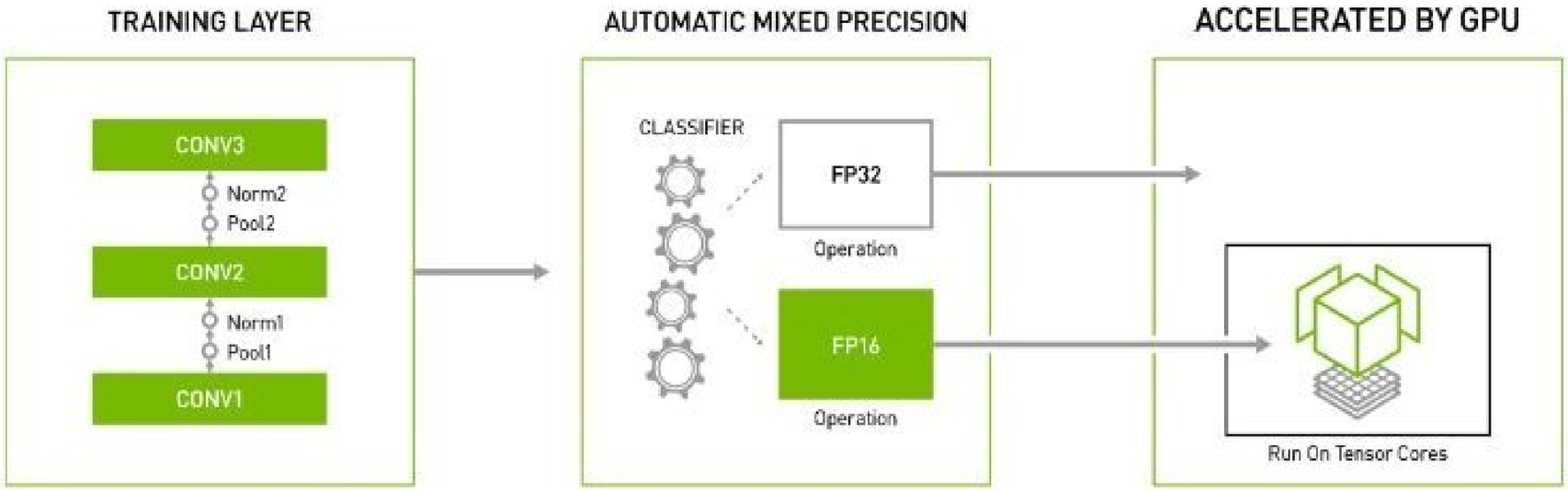
1. TensorFlow and TRT require no additional code modification
2. Profile using DLProf CLI - prepend with ***dlprof***
3. Visualize results with DLProf Viewer

1. Add few lines of code to your training script to enable **nvidia_dlprof_pytorch_nvtx** module
2. Profile using DLProf CLI - prepend with ***dlprof***
3. Visualize with DLProf Viewer

Credit: NVIDIA

AUTOMATIC MIXED PRECISION

AMP



Credit: NVIDIA

BEFORE YOU PROFILE

Do:

- make sure your code runs without an issue
- make a habit of using profiler when you make changes to your code
- Observe if changes you made improve the training performance
- get familiar with the optional arguments DLProf provides
- Iteration range, delay, duration and etc,,

Don’t:

- profile for extended periods of time. It will take very long to profile
- DL training is repetitive and you only need a couple minutes to profile to learn
- try to open DLProf database with your TensorBoard
- You need NVIDIA TB GPU plugin to visualize DLProf event files

Credit: NVIDIA

DEMO

CATALYST

INTRODUCTION

- Catalyst — A Framework for Accelerated Deep Learning R&D based on Pytorch
- Write code with PyTorch, accelerate it with Catalyst!

TRAINING LOOP

```
dl_run = ...
for stage in dl_run.stages:
    for epoch in stage.epochs:
        for loader in epoch.loaders:
            for batch in loader.batches:
                dl_run.handle_batch(batch)
```

SUPPORTED FEATURES

- Universal train/inference loop.
- Training Stages Support
- Provision for ‘callbacks’
- Configuration files for model and data hyperparameters.
- Reproducibility – all source code and environment variables are saved.
- Deep Learning best practices: SWA, AdamW, Ranger optimizer, OneCycle, and more.
- Workflow best practices: fp16 support, distributed training, slurm support, DALI loaders.
- Any hardware backend supported: AMP, Apex, DeepSpeed, FairScale, XLA.

UNIVERSAL TRAIN/INFERENCE LOOP

- This is achieved with the help of Runner Abstraction.
- Runner is an abstraction that takes all the logic of your deep learning experiment:
  - the data you are using,
  - the model you are training,
  - the batch handling logic, and
  - everything about the used metrics and monitoring systems.
- It can be used as a for – loop wrapper.

PYTORCH

```
for epoch in range(num_epochs):
        for train_batch in train_loader:
            x, y = train_batch
            x = x.view(len(x), -1)
            logits = model(x)
            loss = criterion(logits, y)
            print("train loss: ", loss.item())
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()
```

#CATALYST

```
runner = dl.SupervisedRunner()
runner.train(
    model=model,
    criterion=criterion,
    optimizer=optimizer,
    loaders={"train": train_loader,
    "valid": valid_loader},
    num_epochs=1, logdir="./logs", verbose=True
    )
```

```
class CustomRunner(dl.Runner):

    def predict_batch(self, batch):
        # model inference step
        return self.model(batch[0].to(self.device).view(batch[0].size(0), -1))

    def handle_batch(self, batch):
        x, y = batch
        x = x.view(len(x), -1)
        logits = self.model(x)
        loss = self.criterion(logits, y)
        self.batch_metrics["loss"] = loss

        if self.is_train_loader:
            loss.backward()
            self.optimizer.step()
            self.optimizer.zero_grad()
runner = CustomRunner()
# model training
runner.train(
    loaders={"train": train_loader, "valid": valid_loader},
    model=model, criterion=criterion, optimizer=optimizer,
    num_epochs=1, logdir="./logs", verbose=True,
)
```

TRAINING STAGES SUPPORT

- Provides features such as:

  ✓Logging

  ✓Model checkpointing

  ✓Evaluation metrics

```
# CATALYST

runner = dl.SupervisedRunner()
runner.train(
    model=model,
    criterion=criterion,
    optimizer=optimizer,
    loaders={"train": train_loader,
    "valid": valid_loader},
    callbacks=[dl.CheckpointCallback(logdir = '/content/
    logs/checkpoints’,
    resume = '/content/logs/checkpoints/best_full.pth')],
    num_epochs=1, logdir="./logs", verbose=True
)
```

PROVISION FOR ‘CALLBACKS’

- The Callback is an abstraction that helps you to customize the logic during your run.
- Once again, you could do anything natively with PyTorch and Catalyst as a for-loop wrapper.
- Provides reusability.

#CATALYST

```
runner = dl.SupervisedRunner()
runner.train(
    model=model, criterion=criterion,
    optimizer=optimizer, loaders=loaders,
    logdir="./logdir", num_epochs=100,
    callbacks=[
        dl.EarlyStoppingCallback(
            loader_key="valid",
            metric_key="loss",
            minimize=True,
            patience=3,
            min_delta=1e-2)])
```

DEMO

https://colab.research.google.com/drive/1YALTZg0w3CU4Nk44PfFOK77Vsr3kejZq?usp=sharing#scrollTo=mWiJrcv07HeM

https://colab.research.google.com/drive/1HbZgL33mk8NFJummKdcPLOYVKcQBmHDH?usp=sharing

CONCLUSION

- An Accelerated Framework based on Pytorch.
- Create and Research something new rather than write yet another train loop.
- Rapid experimentation, reproducibility, and codebase reuse.

"Write code with PyTorch, accelerate it with Catalyst!"

REFERENCES

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Thank You