An Introduction to Practical 1

Lecture 3 for Advanced Deep Learning Systems

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Introduction

Introduction

Two labs are in Practical 1

- Lab 1: Experiment training of a JSC network
- Lab 2: Write a quantization transformation pass

Deliverable

- A Markdown file: with all answers (plots, tables ...) of the questions and optional questions.
- Corresponding code in your forked repository.

Examination (15%)

- Submission requires the Markdown files only.
- Lab oral to check on your code and Q&A.

Lab 1: Training and evaluating a network using MASE

Using Google Colab

If you do not have a powerful enough work station with a GPU, it is likely you will have to use Google Colab for this course.

There is a quick introduction on how to set it up correctly and use it. The department will reimburse the cost of using Colab Pro.

Suggested and tested usage is through the command line interface in Colab: treat it as a serer not a notebook!

Accessing MASE

MASE has two modes to be accessed

- Direct usage through the command line interface, use it as a tool.
- Interactive usage, import it as a package

In the first lab, we are dealing with the command line interface.

Training a network

The train command

```
# You will need to run this command
./ch train jsc-tiny jsc --max-epochs 10 --batch-size 256
```

- ‘./ch’ to execute
- ‘train’ is the action
- ‘jsc-tiny’ is the target network
- ‘jsc’ is the target dataset
- ‘–parameter’ gives values to parameters through the command line interface

Test and evlaute a network

The test command

```
./ch test jsc-tiny jsc --load your_ckpt
```

You will need to test the trained network (load its trained weights),

Training a network

The train command

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Some training parameters you might use

- ‘batch_size’ how many inputs to proceed concurrently
- ‘learning_rate’ the critical parameter for your optimizer
- ‘max_epochs’ maximum number of epochs to train
- ‘accelerator’ choose to use GPU or not

The underlying system

You have to have a rough idea of what is happening in the underlying hardware system.

- Data: is your data on the disk or on the device? If it is on the device, is it in CPU RAM or GPU VRAM?
- Data pre-processing: is this on CPU or GPU?
- Actual Training: is this on CPU or GPU? If it is on GPU, how much data do you need to ship from CPU to avoid idling GPUs?

MASE automatically handles some of these things, but you need to have an idea of what is going on.

Use 'nvidia-smi' to inspect the system while running your stuff!

Dataset definition

```
@add_dataset_info(
    ...
)
class JetSubstructureDataset(Dataset):
    def __len__(self):
        return len(self.X)

    def __getitem__(self, idx):
        return self.X[idx], self.Y[idx]

    def prepare_data(self) -> None:
        ...

    def setup(self) -> None:

        ...
```

Dataset definition

- If you haven't seen @ in python, go search and learn what is a Python decrorater.
- '__len__' defines the size of the dataset
- '__getitem__' defines how elements in a dataset is accessed

You can almost tell that X and Ys are prepared when instantiating this class, from the '__getitem__' function you can tell elements are accessed through an internal list (CPU RAM or GPU VRAM).

Model definition

```
class JSC_Tiny(nn.Module):
    def __init__(self, info):
        super(JSC_Tiny, self).__init__()
        self.seq_blocks = nn.Sequential(
            # 1st LogicNets Layer
            nn.BatchNorm1d(16),  #  batch norm layer
            nn.Linear(16, 5),  # linear layer
        )

    def forward(self, x):
        return self.seq_blocks(x)
```

Model definition

This is standard Pytorch semantics

- Model must inherit from 'nn.Module'
- Define the network components or layers in '__init__'
- At inference and training, the 'forward' method is executed

```
# runs init
model = JSC_Tiny(nn.Module)
# runs forward
y = model(x)
```

Lab 2: Applying a MASE transformation

Interactive usage

In the interactive usage mode, you are including various modules in MASE.

You will need to figure out the correct path for doing that.

```
# figure out the correct path
machop_path = Path(".").resolve().parent.parent /"machop"
assert machop_path.exists(), "Failed to find machop at:
↪  {}".format(machop_path)
sys.path.append(str(machop_path))
```

Interactive usage: instantiate the same dataset

```
batch_size = 8
model_name = "jsc-tiny"
dataset_name = "jsc"

data_module = MaseDataModule(
    name=dataset_name,
    batch_size=batch_size,
    model_name=model_name,
    num_workers=0,
)
data_module.prepare_data()
data_module.setup()
```

Interactive usage: instantiate the same model

```
model_info = get_model_info(model_name)
model = get_model(
    model_name,
    task="cls",
    dataset_info=data_module.dataset_info,
    pretrained=False)
```

Note: You can also use a Pytorch native model in MASE, but you might have to wrap it with the decrorater.

Generate a MaseGraph and apply passes

```
mg = MaseGraph(model=model)

# analysis pass
mg = init_metadata_analysis_pass(mg, None)
mg = add_common_metadata_analysis_pass(mg, dummy_in)
mg = add_software_metadata_analysis_pass(mg, None)

# transofrm
mg = quantize_transform_pass(mg, pass_args)
```

Polymorphism of Passes

A pass, no matters whether it is an analysis pass or a transform pass, takes the following format

```
# pass_args is a dict
def pass(mg, pass_args):
    ...
# info a a dict
return mg, info
```