PyTorch Tutorial

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Outline

- Introduction
- Autograd
- Network
  - nn Package
  - Optimizer
- Dataset and DataLoader
- Tips to write codes for NLP research?

Introduction

PYTORCH

- It’s a python-based scientific computing package
- A replacement for NumPy to use the power of GPUs
- A deep learning research platform that provides maximum flexibility and speed

Installation

- Follow instructions in https://pytorch.org/get-started/locally/
-

PyTorch Build	Stable (1.9.0)	Preview (Nightly)	LTS (1.8.2)	
Your OS	Linux	Mac	Windows	
Package	Conda	Pip	LibTorch	Source
Language	Python	C++ / Java		
Compute Platform	CUDA 10.2	CUDA 11.1	ROCm 4.2 (beta)	CPU
Run this Command:	`conda install pytorch torchvision torchaudio cudatoolkit=10.2 -c pytorch`			

PyTorch

Three Levels of Abstraction

- Tensor: Imperative ndarray but runs on GPU or other hardware accelerators.
- (Trainable) Tensor: Node in a computational graph; stores data and gradient
- Module: A neural network layer; may store state or learnable weights

Tensors

PyTorch Tensors are just like numpy arrays, but they can run on GPU.

Here we fit a two-layer net using PyTorch Tensors.

```
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

lr = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred-y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred-y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= lr*grad_w1
    w2 -= lr*grad_w2
```

Tensors

Create random tensor for data and weight

Tensor can also be loaded by:

1. Load from data (list)

```
data = [[1, 2],[3, 4]]
x_data = torch.tensor(data)
```

2. From Numpy array

```
np_array = np.array(data)
x_np = torch.from_numpy(np_array)
```

3. From another tensor

```
np_array = np.array(data)
x_np = torch.from_numpy(np_array)
```

```
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

lr = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred-y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred-y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= lr*grad_w1
    w2 -= lr*grad_w2
```

Tensors

Forward pass: compute predictions and loss

```
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

lr = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred-y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred-y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= lr*grad_w1
    w2 -= lr*grad_w2
```

Tensors

Backward pass: manually compute gradients ***if you don't have autograd***.

```
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

lr = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred-y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred-y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= lr*grad_w1
    w2 -= lr*grad_w2
```

Tensors

Optimization: Gradient descent step on weights

```
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

lr = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred-y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred-y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= lr*grad_w1
    w2 -= lr*grad_w2
```

Tensors

To run on GPU, just cast tensors to a cuda datatype.

```
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

lr = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred-y).pow(2).sum()

    grad_y_pred = 2.0 * (y_pred-y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= lr*grad_w1
    w2 -= lr*grad_w2
```

Autograd

Autograd

The previous process:

- Slow
- Gradient is hard to compute when model becomes more complex

=> That’s why we need PyTorch

Key:

Set “required_grad” to True to enable torch.autograd

Autograd

We set the weights' "requires_grad" to be True

```
dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

w3 = w1.detach().clone()
w3.requires_grad=True
# To initialize, you can use:
# w3 = torch.randn(D_in, H, requires_grad=True).type(dtype)

w4 = w2.detach().clone()
w4.requires_grad=True
```

Autograd

Forward pass looks exactly the same as the Tensor/Numpy version.

```
lr = 1e-6
for t in range(500):
    y_pred2 = x.mm(w3).clamp(min=0).mm(w4)
    loss = (y_pred2-y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w3 -= lr * w3.grad
        w4 -= lr * w4.grad

    w3.grad.zero_()
    w4.grad.zero_()
```

Autograd

But the gradient of loss with respect to w3 and w4 can be done by a simple one-line code.

```
lr = 1e-6
for t in range(500):
    y_pred2 = x.mm(w3).clamp(min=0).mm(w4)
    loss = (y_pred2-y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w3 -= lr * w3.grad
        w4 -= lr * w4.grad

    w3.grad.zero_()
    w4.grad.zero_()
```

Autograd

Make gradient step on weights.

```
lr = 1e-6
for t in range(500):
    y_pred2 = x.mm(w3).clamp(min=0).mm(w4)
    loss = (y_pred2-y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w3 -= lr * w3.grad
        w4 -= lr * w4.grad

    w3.grad.zero_()
    w4.grad.zero_()
```

What's torch.no_grad()?

- We need to use NO_GRAD to keep the update out of the gradient computation
- Why is that? It boils down to the DYNAMIC GRAPH that PyTorch uses.

New Autograd Functions

We can define our own autograd functions by writing forward and backward for Tensors

```python
class ReLU(torch.autograd.Function):

    @staticmethod
    def forward(ctx, x):
        ctx.save_for_backward(x)
        return x.clamp(min=0)

    @staticmethod
    def backward(ctx, grad_y):
        x, = ctx.saved_tensors
        grad_input = grad_y.clone()
        grad_input[x < 0] = 0
        return grad_input
```

New Autograd Functions

```
class ReLU(torch.autograd.Function):

    @staticmethod
    def forward(ctx, x):
        ctx.save_for_backward(x)
        return x.clamp(min=0)

    @staticmethod
    def backward(ctx, grad_y):
        x, = ctx.saved_tensors
        grad_input = grad_y.clone()
        grad_input[x < 0] = 0
        return grad_input
```

We then apply our new function in the forward pass.

```
lr = 1e-6
for t in range(500):
    y_pred3 = ReLU.apply(x.mm(w5)).mm(w6)
    loss = (y_pred3-y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w5 -= lr * w5.grad
        w6 -= lr * w6.grad

    w5.grad.zero_()
    w6.grad.zero_()
```

Network

torch.nn

- Higher-level wrapper for working with neural nets
- The most commonly used in my own research

```python
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out)
)
model.cuda()

loss_fn = torch.nn.MSELoss(reduction='sum')

def weights_init(m):
    if isinstance(m, torch.nn.Linear):
        torch.nn.init.zeros_(m.weight)
        torch.nn.init.ones_(m.bias)

model.apply(weights_init)
print(model)

lr = 1e-6

for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param.data -= lr * param.grad.data
```

torch.nn

Define our model as a sequence of layers

Nn also defines common loss functions

```python
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out)
)
model.cuda()

loss_fn = torch.nn.MSELoss(reduction='sum')

def weights_init(m):
    if isinstance(m, torch.nn.Linear):
        torch.nn.init.zeros_(m.weight)
        torch.nn.init.ones_(m.bias)

model.apply(weights_init)
print(model)

lr = 1e-6

for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param.data -= lr * param.grad.data
```

torch.nn

Forward pass:

- Feed data to model
- Use prediction to and ground truth to get loss function

```python
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out)
)
model.cuda()

loss_fn = torch.nn.MSELoss(reduction='sum')

def weights_init(m):
    if isinstance(m, torch.nn.Linear):
        torch.nn.init.zeros_(m.weight)
        torch.nn.init.ones_(m.bias)

model.apply(weights_init)
print(model)

lr = 1e-6

for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param.data -= lr * param.grad.data
```

torch.nn

Pytorch handles autograd for us!

And now, we can simply use model.zero_grad() to clear all gradients for the parameters in the model

```python
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out)
)
model.cuda()

loss_fn = torch.nn.MSELoss(reduction='sum')

def weights_init(m):
    if isinstance(m, torch.nn.Linear):
        torch.nn.init.zeros_(m.weight)
        torch.nn.init.ones_(m.bias)

model.apply(weights_init)
print(model)

lr = 1e-6

for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param.data -= lr * param.grad.data
```

Optimizer

Make gradient step on each model parameter.

Question:

- How can we apply more advanced rules for updating
- Easier way?

```python
import torch

dtype = torch.cuda.FloatTensor
N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)

model = torch.nn.Sequential(
    torch.nn.Linear(D_in, H),
    torch.nn.ReLU(),
    torch.nn.Linear(H, D_out)
)
model.cuda()

loss_fn = torch.nn.MSELoss(reduction='sum')

def weights_init(m):
    if isinstance(m, torch.nn.Linear):
        torch.nn.init.zeros_(m.weight)
        torch.nn.init.ones_(m.bias)

model.apply(weights_init)
print(model)

lr = 1e-6

for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param.data -= lr * param.grad.data
```

Optimizer

Call nn.optim package, which contains various advanced optimizer other than SGD.

Now, all the parameters can be updated via one-line code.

```
optimizer = torch.optim.Adam(model.parameters(), lr=lr)
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    #model.zero_grad()
    optimizer.zero_grad()
    loss.backward()

    optimizer.step()
#     with torch.no_grad():
#         for param in model.parameters():
#             param.data -= lr * param.grad.data
```

Define new modules

Pytorch **Module** is ***a neural network layer***, it can contain weights or other modules.

It provides a more systematic way to structure our code.

```
class TwoLayerMLP(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super().__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)
        self.weight_init()

    def weight_init(self):
        torch.nn.init.zeros_(self.linear1.weight)
        torch.nn.init.zeros_(self.linear2.weight)
        torch.nn.init.ones_(self.linear1.bias)
        torch.nn.init.ones_(self.linear2.bias)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

model = TwoLayerMLP(D_in, H, D_out)
model.cuda()
print(model)
loss_fn = torch.nn.MSELoss(reduction='sum')
lr = 1e-6

optimizer = torch.optim.Adam(model.parameters(), lr=lr)
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Dataset & DataLoaders

DataLoaders

A **DataLoader** wraps a **Dataset** and provides minibatching, shuffling, multithreading, for you

When you need to load custom data, just **write your own Dataset class**

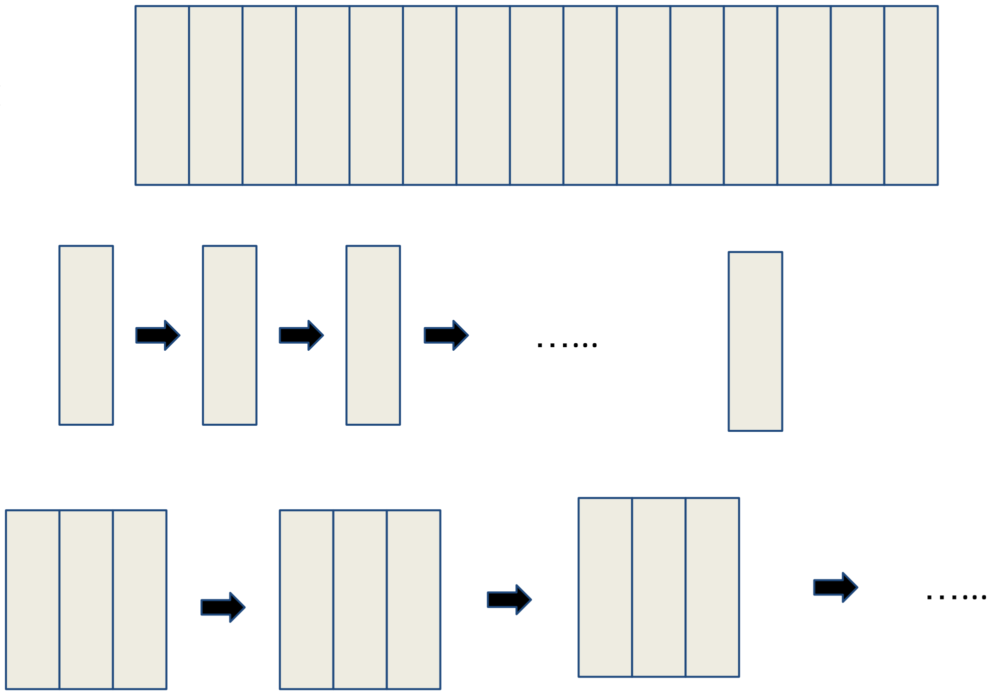
```python
import torch
from torch.utils import data

class Dataset(data.Dataset):
  'Characterizes a dataset for PyTorch'
  def __init__(self, list_IDs, labels):
        'Initialization'
        self.labels = labels
        self.list_IDs = list_IDs

  def __len__(self):
        'Denotes the total number of samples'
        return len(self.list_IDs)

  def __getitem__(self, index):
        'Generates one sample of data'
        # Select sample
        ID = self.list_IDs[index]

        # Load data and get label
        X = torch.load('data/' + ID + '.pt')
        y = self.labels[ID]

        return X, y
```

What is (mini)batching?

All your training data:

Standard for loop:

(Mini) batching:



Adapt Dataset to DataLoaders

```
# Parameters
params = {'batch_size': 64,
          'shuffle': True,
          'num_workers': 6}
max_epochs = 100

# Datasets
partition = # IDs
labels = # Labels

# Generators
training_set = Dataset(partition['train'], labels)
training_generator = data.DataLoader(training_set, **params)

validation_set = Dataset(partition['validation'], labels)
validation_generator = data.DataLoader(validation_set, **params)

# Loop over epochs
for epoch in range(max_epochs):
    # Training
    for local_batch, local_labels in training_generator:
        # Transfer to GPU
        local_batch, local_labels = local_batch.to(device), local_labels.to(device)

        # Model computations
        [...]
```

Adapt Dataset to DataLoaders

```python
# Parameters
params = {'batch_size': 64,
          'shuffle': True,
          'num_workers': 6}
max_epochs = 100

# Datasets
partition = # IDs
labels = # Labels

# Generators
training_set = Dataset(partition['train'], labels)
training_generator = data.DataLoader(training_set, **params)

validation_set = Dataset(partition['validation'], labels)
validation_generator = data.DataLoader(validation_set, **params)

# Loop over epochs
for epoch in range(max_epochs):
    # Training
    for local_batch, local_labels in training_generator:
        # Transfer to GPU
        local_batch, local_labels = local_batch.to(device), local_labels.to(device)

        # Model computations
        [...]
```

DataLoader perform batching automatically

```python
import torch
from torch.utils import data

class Dataset(data.Dataset):
  'Characterizes a dataset for PyTorch'
  def __init__(self, list_IDs, labels):
        'Initialization'
        self.labels = labels
        self.list_IDs = list_IDs

  def __len__(self):
        'Denotes the total number of samples'
        return len(self.list_IDs)

  def __getitem__(self, index):
        'Generates one sample of data'
        # Select sample
        ID = self.list_IDs[index]

        # Load data and get label
        X = torch.load('data/' + ID + '.pt')
        y = self.labels[ID]

        return X, y
```

However, what if your data structure is more complex?

```
data = {
    'tokens': ["This", "is", "a", "scientific", "book", "."],
    'pieces': ["This", "is", "a", "sci", "enti", "fic", "book", "."],
    'triggers': ['is'],
    ...
}
```

- The automatic batching for DataLoader will only concatenate all "data" in the batch into a list.
- But, a list of data structure is not a tensor model can directly use.

=> collate_fn

DataLoader

Several parameters that can be adjusted, for data that are structured in extremely complex case, collate_fn is suggested to be use.

- You can organize your data in a map/dict style
- Given a batch, we reorganize and repack them.

Parameters

- **dataset** (*Dataset*) – dataset from which to load the data.
- **batch_size** (*int, optional*) – how many samples per batch to load (default: `1`).
- **shuffle** (*bool, optional*) – set to `True` to have the data reshuffled at every epoch (default: `False`).
- **sampler** (*Sampler or Iterable, optional*) – defines the strategy to draw samples from the dataset. Can be any `Iterable` with `__len__` implemented. If specified, `shuffle` must not be specified.
- **batch_sampler** (*Sampler or Iterable, optional*) – like `sampler`, but returns a batch of indices at a time. Mutually exclusive with `batch_size`, `shuffle`, `sampler`, and `drop_last`.
- **num_workers** (*int, optional*) – how many subprocesses to use for data loading. `0` means that the data will be loaded in the main process. (default: `0`)
- **collate_fn** (*callable, optional*) – merges a list of samples to form a mini-batch of Tensor(s). Used when using batched loading from a map-style dataset.

```
def collate_fn(self, batch):
    tokens = [inst.tokens for inst in batch]
    pieces = [inst.pieces for inst in batch]
    piece_idxs = [inst.piece_idxs for inst in batch]
    token_lens = [inst.token_lens for inst in batch]
    token_start_idxs = [inst.token_start_idxs for inst in batch]
    triggers = [inst.triggers for inst in batch]
    roles = [inst.roles for inst in batch]
    wnd_ids = [inst.wnd_id for inst in batch]

    return EEBatch(
        tokens=tokens,
        pieces=pieces,
        piece_idxs=piece_idxs,
        token_lens=token_lens,
        token_start_idxs=token_start_idxs,
        triggers=triggers,
        roles=roles,
        wnd_ids=wnd_ids,
    )
```

Summary

1. Prepare you data
    a. Write your own Dataset (inherit torch.nn.util.dataset)
    b. (Write collate_fn)
2. Create your model
    a. A sequential module if your model is super easy and will not be reused.
    b. A nn.Module module
3. Write the loop (how many epoch/steps) to train your model:
    a. Create a DataLoader that wraps the Dataset you provide
    b. Set an optimizer
    c. Set a loss for optimization
    d. For loop….
        i. Forward pass
        ii. Zero-grad
        iii. Backward pass => Get gradient
        iv. Optimizer step to update your models' weight.

Other Tips

Prepare Different Version of Data

- Tiny-size: for debugging syntactic bug (especially for dynamic language, such as python)
- Small-size: check the behavior of the model
- Mid-size: for understanding model behavior and fast development
- Full-size: conduct final experiments

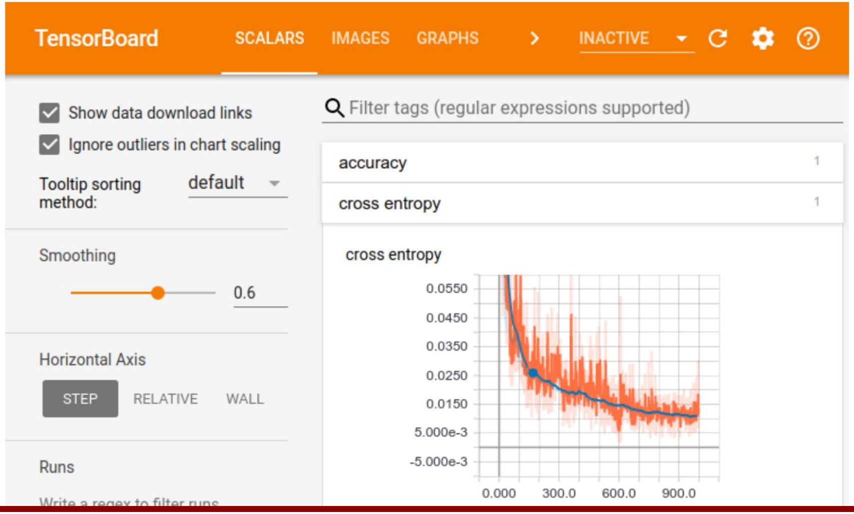
Tensorboard

- Installation: https://pytorch.org/tutorials/recipes/recipes/tensorboard_with_pytorch.html
- Create a Summary Writer

```
from torch.utils.tensorboard import SummaryWriter
writer = SummaryWriter()
```

- During Training/Dev/Test

```
writer.add_scalar("Loss/train", loss, epoch)
```



Padding

- In NLP, we usually need to face cases that requires "padding" so as to batch your data
- Useful tool: `torch.nn.utils.rnn.pad_sequence`

```
>>> from torch.nn.utils.rnn import pad_sequence
>>> a = torch.ones(25, 300)
>>> b = torch.ones(22, 300)
>>> c = torch.ones(15, 300)
>>> pad_sequence([a, b, c]).size()
torch.Size([25, 3, 300])
```

- For unpack, use: `torch.nn.utils.rnn.pack_padded_sequence`

Parameters

- **input** (*Tensor*) – padded batch of variable length sequences.
- **lengths** (*Tensor* or *list*(*int*)) – list of sequence lengths of each batch element (must be on the CPU if provided as a tensor).
- **batch_first** (*bool, optional*) – if `True`, the input is expected in `B x T x *` format.
- **enforce_sorted** (*bool, optional*) – if `True`, the input is expected to contain sequences sorted by length in a decreasing order. If `False`, the input will get sorted unconditionally. Default: `True`.

Extension -- End to end Examples

- https://www.analyticsvidhya.com/blog/2020/01/first-text-classification-in-pytorch/
- https://towardsdatascience.com/lstm-text-classification-using-pytorch-2c6c657f8fc0
-

Acknowledgement

- Several materials from Pytorch Official Materials: https://pytorch.org/tutorials/
- An easy to read blog: https://towardsdatascience.com/understanding-pytorch-with-an-example-a-step-by-step-tutorial-81fc5f8c4e8e#ea0d
- Special thanks to the materials shared from the friends in UCLA NLP group.