Introduction to PyTorch

CPEN 455 Tutorial 3

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Acknowledgment: Muchen Li, Qi Yan

Outline

- Introduction
- Tensor & Tensor Operations
- Dataset & Dataloaders
- Build the model
- Model Optimization

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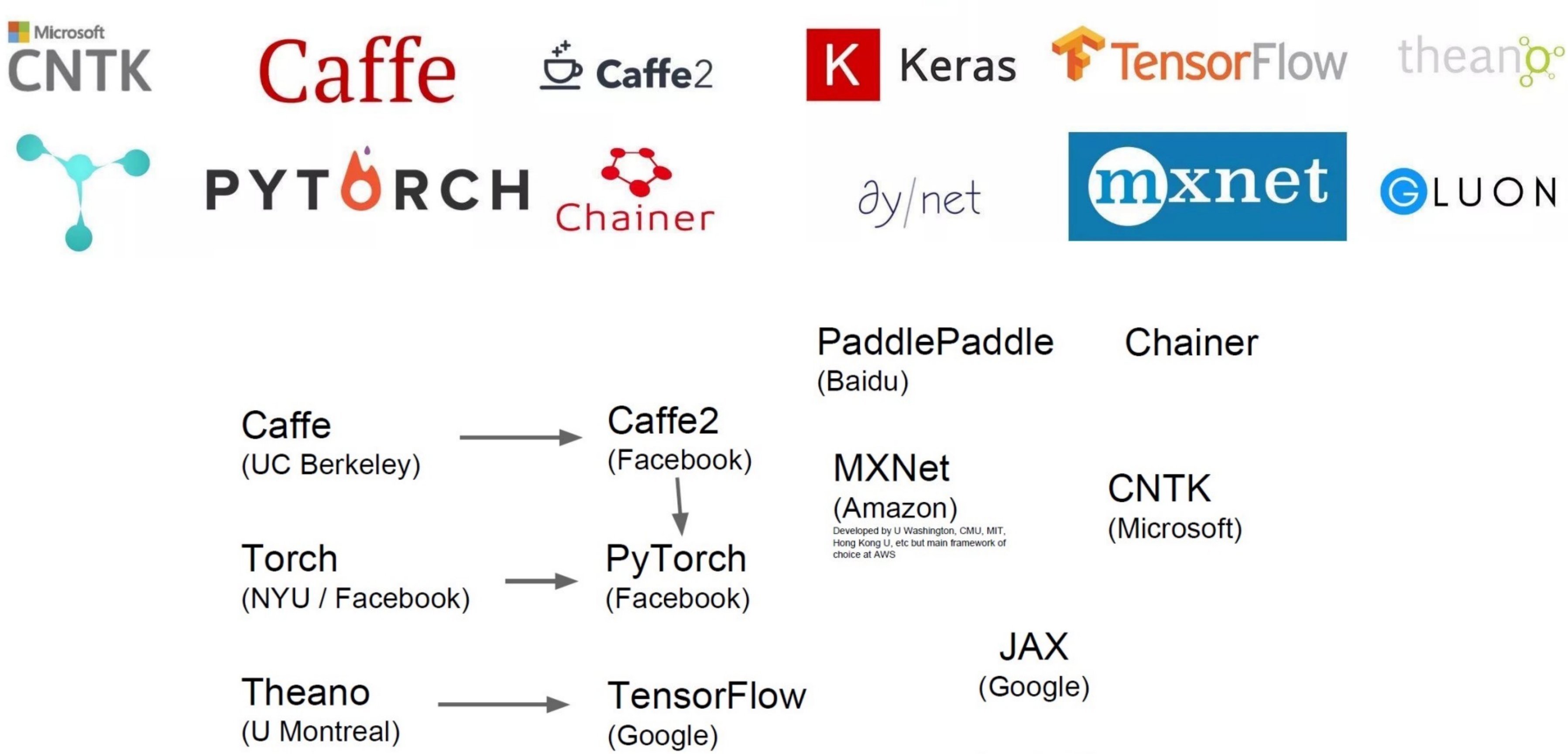
DL Frameworks

DL Frameworks



[2] Image Credit: https://www.cs.princeton.edu/courses/archive/fall19/cos484/lectures/pytorch.pdf

DL Frameworks Bring Peace of Mind

- GPU Acceleration

[4] Image Credit: https://developer.nvidia.com/blog/cuda-refresher-cuda-programming-model/

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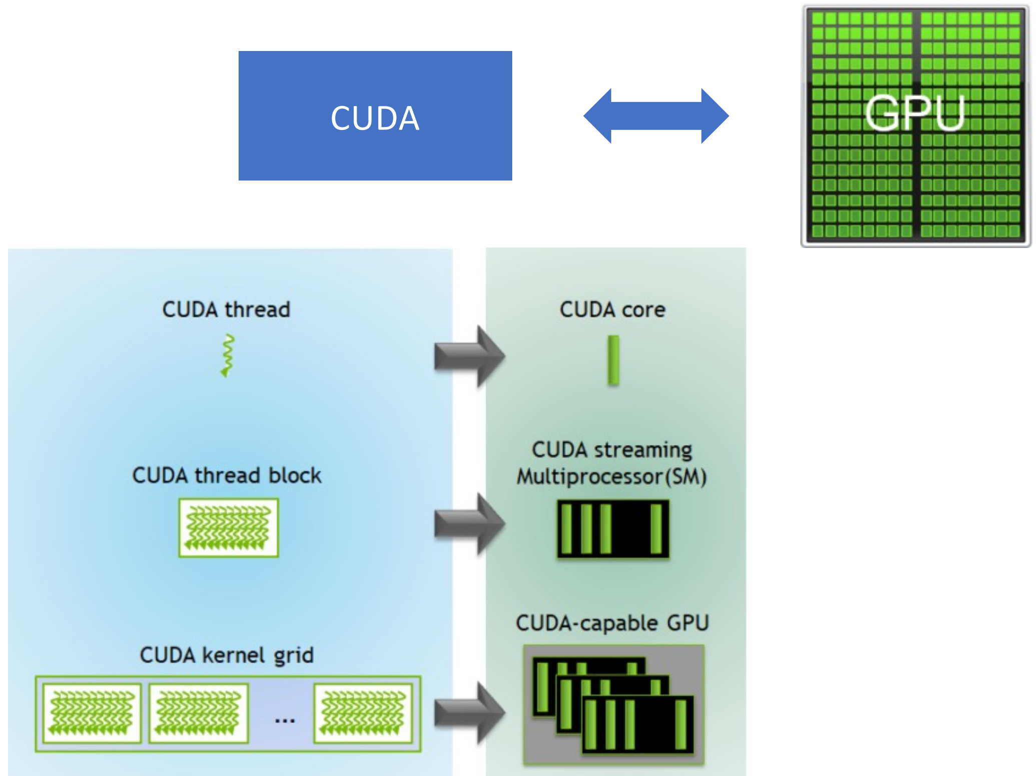

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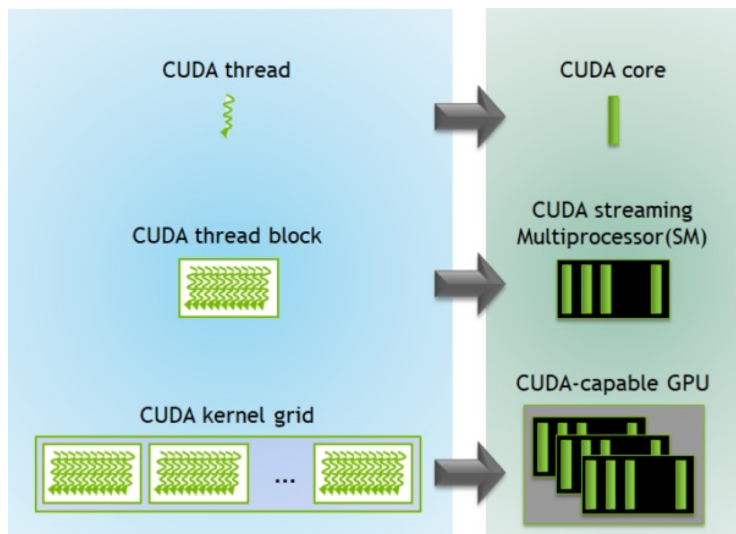

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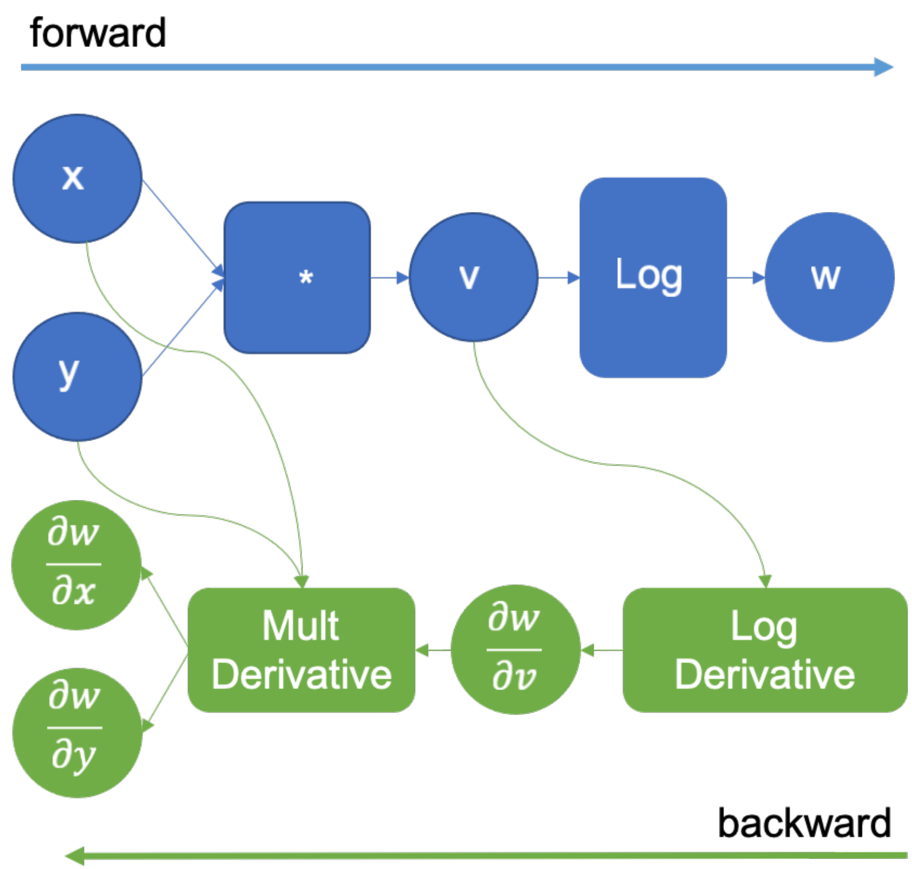
DL Frameworks Bring Peace of Mind

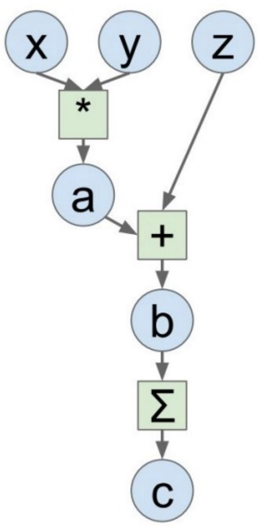
- Autograd: A reverse automatic differentiation system.



[5] Image Credit: https://pytorch.org/blog/overview-of-pytorch-autograd-engine/

DL Frameworks

Computation Graph



Numpy

```python
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```

Tensorflow

```python
import numpy as np
np.random.seed(0)
import tensorflow as tf

N, D = 3, 4

with tf.device('/gpu:0'):
    x = tf.placeholder(tf.float32)
    y = tf.placeholder(tf.float32)
    z = tf.placeholder(tf.float32)

    a = x * y
    b = a + z
    c = tf.reduce_sum(b)

grad_x, grad_y, grad_z = tf.gradients(c, [x, y, z])

with tf.Session() as sess:
    values = {
        x: np.random.randn(N, D),
        y: np.random.randn(N, D),
        z: np.random.randn(N, D),
    }
    out = sess.run([c, grad_x, grad_y, grad_z],
                   feed_dict=values)
    c_val, grad_x_val, grad_y_val, grad_z_val = out
```

PyTorch

```python
import torch

N, D = 3, 4

x = torch.rand((N, D),requires_grad=True)
y = torch.rand((N, D),requires_grad=True)
z = torch.rand((N, D),requires_grad=True)

a =x * y
b =a + z
c=torch.sum(b)

c.backward()
```

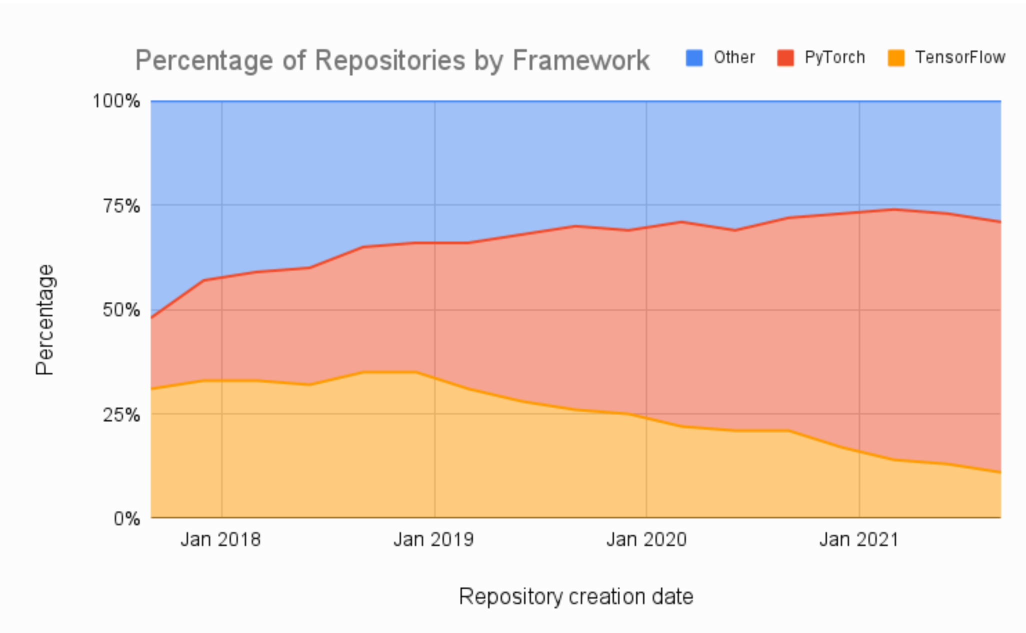
[3] Image Credit: https://hackernoon.com/pytorch-vs-tensorflow-who-has-more-pre-trained-deep-learning-models

PyTorch

PyTorch [1] is a deep learning framework (free and open-sourced under the modified BSD license) based on the Torch library, originally developed by Meta AI and now part of the Linux Foundation umbrella.

Many pieces of deep learning software are built on top of PyTorch, including Tesla Autopilot, Uber's Pyro, Hugging Face's Transformers, PyTorch Lightning, and Catalyst etc.

Pytorch is getting Popular



[1] Image Credit: https://hackernoon.com/pytorch-vs-tensorflow-who-has-more-pre-trained-deep-learning-models

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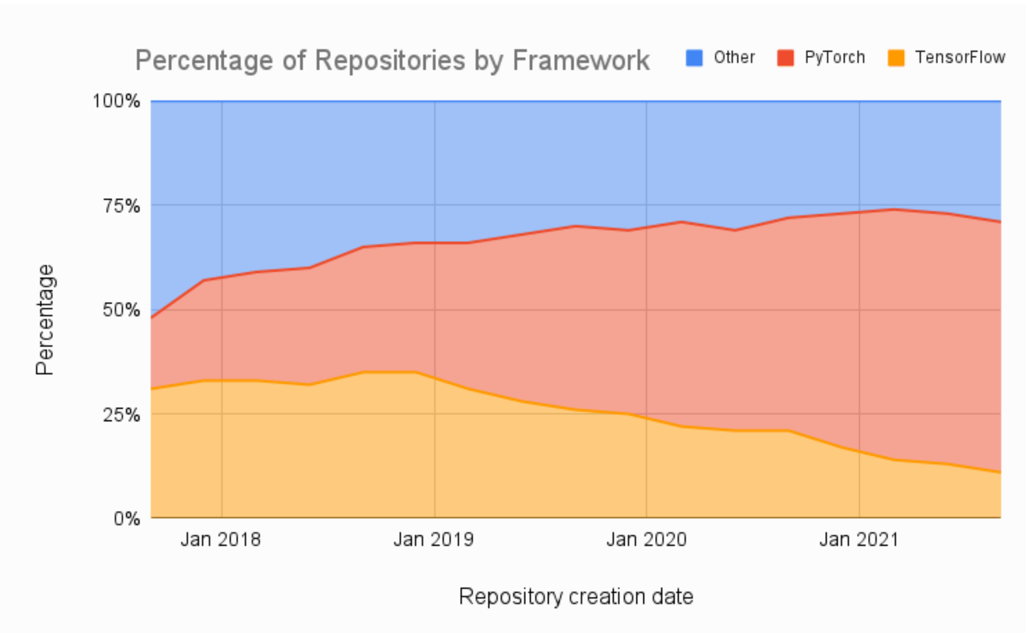

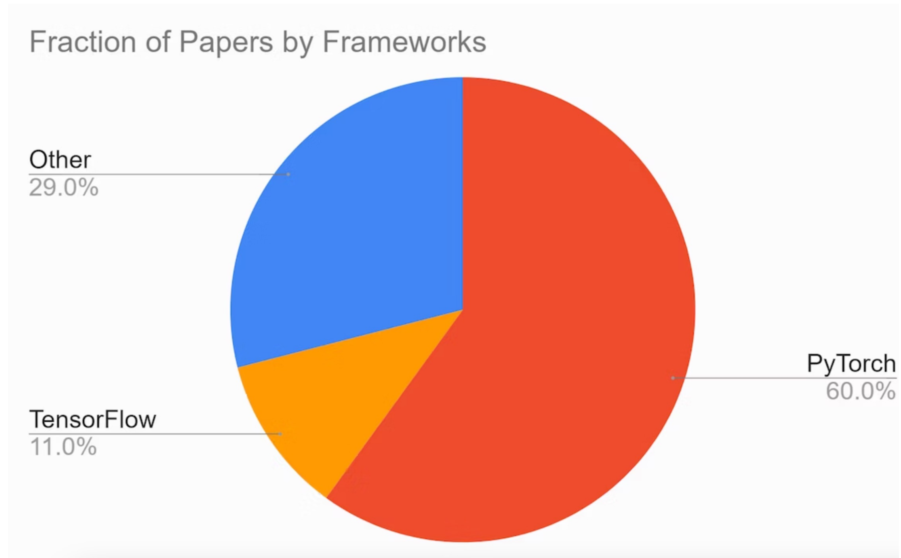

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Why Pytorch?

- It’s easy to use.
- It’s Pythonic and flexible (easy to customize and extend).
- It’s your best friend in deep learning projects.

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- It’s easy to use.
- It’s Pythonic and flexible (easy to customize and extend).
- It’s your best friend in deep learning projects.
- And you’ll need it in your assignment anyway ;)

Installing Pytorch

- On your own device:
  - Use Anconda/MiniConda to manage
  - *conda install pytorch -c pytorch*
  - https://docs.conda.io/projects/miniconda/en/latest/

- Google Colab:
  - Jupyter notebook Management
  - *!pip3 install torch*
  - https://colab.google/

Write Code

- Use Whatever Editor you like

- Jupyter Lab/Jupyter NoteBook
  - Interactive coding session
  - Install: pip/conda install jupyter
  - Run: jupyter notebook –port 8888
  - Visit at localhost:8888

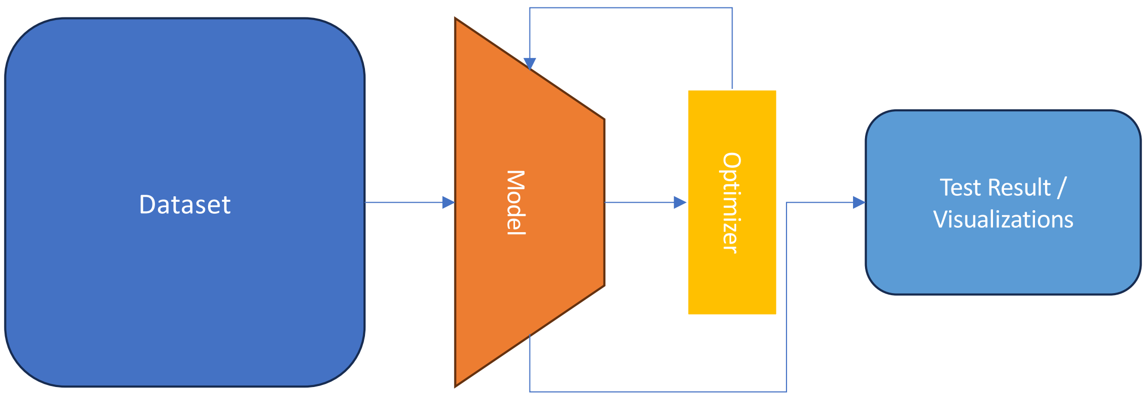
- Debug Pytorch code just like debugging any python code

[4] Image credit: https://www.devopsschool.com/blog/best-most-popular-code-editor-for-delphi-programming-language/

Overview

Fundamental Concepts of PyTorch:

- Tensors
- Autograd
- Modular structure
  - Models / Layers
  - Datasets & Dataloader



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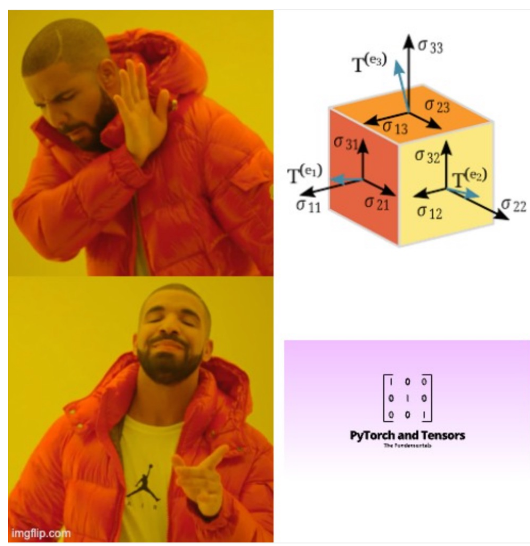
- Tensor & Tensor Operations
- Dataset & Dataloaders
- Build the model
- Model Optimization

1. Tensors

- Tensors are a specialized data structure that are very similar to arrays and matrices. In PyTorch, we use tensors to encode the inputs and outputs of a model, as well as the model's parameter

- Tensors are similar to NumPy's ndarrays, except that tensors can run on GPUs or other hardware accelerators.



1. Tensors

1.1 Creating a Tensor

1.2 Attribute of Tensors

- Shape, Device and datatype

1.3 Operation on Tensors

- Move between devices
- Indexing & Slicing
- Stack & Concatenation
- Algorithmic operations (Tensor products)

1. Creating a Tensor

- Directly from Data

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

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

[5] Code Credit: https://pytorch.org/tutorials/beginner/basics/tensorqs_tutorial.html

1. Creating a Tensor

- Directly from Data

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data = [[1, 2],[3, 4]]
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```
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x_np = torch.from_numpy(np_array)
```

- With Random / Constant Value

```
shape = (2,3,)
rand_tensor = torch.rand(shape)
ones_tensor = torch.ones(shape)
zeros_tensor = torch.zeros(shape)

print(f"Random Tensor: \n {rand_tensor} \n")
print(f"Ones Tensor: \n {ones_tensor} \n")
print(f"Zeros Tensor: \n {zeros_tensor}")
```

```
Random Tensor:
 tensor([[0.5771, 0.5705, 0.3618],
        [0.9053, 0.1620, 0.2274]])

Ones Tensor:
 tensor([[1., 1., 1.],
        [1., 1., 1.]])

Zeros Tensor:
 tensor([[0., 0., 0.],
        [0., 0., 0.]])
```

[5] Code Credit: https://pytorch.org/tutorials/beginner/basics/tensorqs_tutorial.html

1.2 Attribute of Tensors

- Data type, Shape and Device

```
tensor = torch.rand(3,4)

print(f"Shape of tensor: {tensor.shape}")
print(f"Datatype of tensor: {tensor.dtype}")
print(f"Device tensor is stored on: {tensor.device}")
```

```
Shape of tensor: torch.Size([3, 4])
Datatype of tensor: torch.float32
Device tensor is stored on: cpu
```

[5] Code Credit: https://pytorch.org/tutorials/beginner/basics/tensorqs_tutorial.html

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```

```
Shape of tensor: torch.Size([3, 4])
Datatype of tensor: torch.float32
Device tensor is stored on: cpu
```

requires_grad: a flag for whether the tensor is a parameter to be updated

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1.3 Operations

- There are over 100 tensor operations, including arithmetic, linear algebra (e.g. matrix manipulation transposing, indexing, slicing), sampling).

1.3 Operations: Move between devices

- By default tensors are created on CPU, one can move tensor explicitly to GPU for future operations:

```
# We move our tensor to the GPU if available
if torch.cuda.is_available():
    tensor = tensor.to("cuda")
```

- In the case of multiple GPUs, you should specify the CUDA id like “cuda:1”, otherwise, “cuda” default to GPU 0.

[5] Code Credit: https://pytorch.org/tutorials/beginner/basics/tensorqs_tutorial.html

1.3 Operations: Index & Slicing

- Pytorch support a lot of APIs available in Numpy. E.g. You can index and slice tensor exactly like numpy arrays:

```python
tensor = torch.ones(4, 4)
print(f"First row: {tensor[0]}")
print(f"First column: {tensor[:, 0]}")
print(f"Last column: {tensor[..., -1]}")
tensor[:,1] = 0
print(tensor)
```

```
First row: tensor([1., 1., 1., 1.])
First column: tensor([1., 1., 1., 1.])
Last column: tensor([1., 1., 1., 1.])
tensor([[1., 0., 1., 1.],
        [1., 0., 1., 1.],
        [1., 0., 1., 1.],
        [1., 0., 1., 1.]])
```

[5] Code Credit: https://pytorch.org/tutorials/beginner/basics/tensorqs_tutorial.html

Tips 1.1 Mastering Indexing

- Basic Indexing
  - Single element indexing
  - Dimensional indexing tools: ’:’, ’…’
  - Slicing and striding: x[start:end:stride]

- Advance Indexing
  - Integer array indexing
  - Boolean array indexing

- Demo

[6] https://numpy.org/doc/stable/user/basics.indexing.html

Tips 1.2: Master the Shape of your Tensor

- Mastering the shape of your tensor can be the most crucial to get your code right. In practice, we need to get tensor into right shape before we can apply certain functions on it.

- .view() .reshape() .contiguous()
- .permute() .transpose() .repeat()
- .squeeze() .unsqueeze()

- Demo

1.3 Operations: Concatenation

- You can use torch.cat to concatenate a sequence of tensors along a given dimension. See also torch.stack

```
t1 = torch.cat([tensor, tensor, tensor], dim=1)
print(t1)
```

```
In [3]: t1 = torch.cat([tensor, tensor, tensor], dim=1)
   ...: print(t1)
tensor([[1., 0., 1., 1., 1., 0., 1., 1., 1., 0., 1., 1.],
        [1., 0., 1., 1., 1., 0., 1., 1., 1., 0., 1., 1.],
        [1., 0., 1., 1., 1., 0., 1., 1., 1., 0., 1., 1.],
        [1., 0., 1., 1., 1., 0., 1., 1., 1., 0., 1., 1.]])
```

[5] Code Credit: https://pytorch.org/tutorials/beginner/basics/tensorqs_tutorial.html

1.3 Operations: Arithmetic operations

```
# This computes the matrix multiplication between two tensors. y1, y2, y3
will have the same value
# ``tensor.T`` returns the transpose of a tensor
y1 = tensor @ tensor.T
y2 = tensor.matmul(tensor.T)

y3 = torch.rand_like(y1)
torch.matmul(tensor, tensor.T, out=y3)


# This computes the element-wise product. z1, z2, z3 will have the same
value
z1 = tensor * tensor
z2 = tensor.mul(tensor)

z3 = torch.rand_like(tensor)
torch.mul(tensor, tensor, out=z3)
```

```
tensor([[3., 3., 3., 3.],
        [3., 3., 3., 3.],
        [3., 3., 3., 3.],
        [3., 3., 3., 3.]])
```

[5] Code Credit: https://pytorch.org/tutorials/beginner/basics/tensorqs_tutorial.html

1.3 Operations: Arithmetic operations

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value
z1 = tensor * tensor
z2 = tensor.mul(tensor)

z3 = torch.rand_like(tensor)
torch.mul(tensor, tensor, out=z3)
```

```
tensor([[1., 0., 1., 1.],
        [1., 0., 1., 1.],
        [1., 0., 1., 1.],
        [1., 0., 1., 1.]])
```

[5] Code Credit: https://pytorch.org/tutorials/beginner/basics/tensorqs_tutorial.html

Tips 1.3 Avoid Loops

- Loops can be easy to implement but is very inefficient.
- You should avoid using loops as much as you can and try to use pytorch provided API to get around. Let the optimized backend library plays its role.

[7] Vectorization in numpy https://www.scaler.com/topics/np-vectorize/

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- Vectorization:

  Example 1: To calculate a dot product between Vector X and Vector Y

  Use torch.dot(X, Y) instead of a for loop.

  Example 2: Batch Matrix Multiplication A: k*m*n. B: k*n*l

  Use torch.bmm(A, B) instead of doing torch.mm() k times.

[7] Vectorization in numpy https://www.scaler.com/topics/np-vectorize/

1.3 Operations

Check out more operations at https://pytorch.org/docs/stable/torch.html

Indexing, Slicing, Joining, Mutating Ops

`adjoint`	Returns a view of the tensor conjugated and with the last two dimensions transposed.
`argwhere`	Returns a tensor containing the indices of all non-zero elements of `input`.
`cat`	Concatenates the given sequence of tensors in `tensors` in the given dimension.
`concat`	Alias of `torch.cat()`.
`concatenate`	Alias of `torch.cat()`.
`conj`	Returns a view of `input` with a flipped conjugate bit.
`chunk`	Attempts to split a tensor into the specified number of chunks.
`dsplit`	Splits `input`, a tensor with three or more dimensions, into multiple tensors depthwise according to `indices_or_sections`.
`column_stack`	Creates a new tensor by horizontally stacking the tensors in `tensors`.
`dstack`	Stack tensors in sequence depthwise (along third axis).
`gather`	Gathers values along an axis specified by *dim*.
`hsplit`	Splits `input`, a tensor with one or more dimensions, into multiple tensors horizontally according to `indices_or_sections`.

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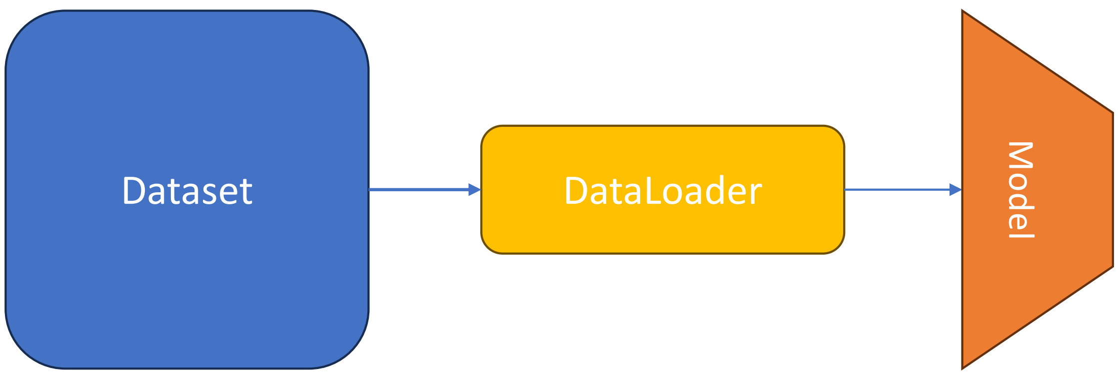
2. Dataset & Dataloaders

- Data is of crucial importance in deep learning. We want to handle it well and reduce the overhead of the DL system.
  - **torch.utils.data.DataLoader**
  - **torch.utils.data.Dataset**



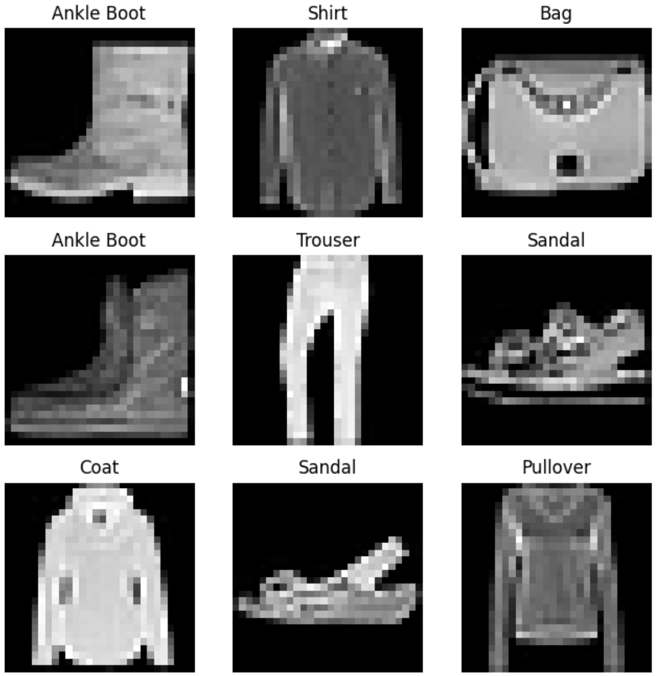
2.1 Dataset: A Example

- Image Dataset: FashionMNIST

annotations_file

```
tshirt1.jpg, 0
tshirt2.jpg, 0
......
ankleboot999.jpg, 9
```

```
labels_map = {
    0: "T-Shirt",
    1: "Trouser",
    2: "Pullover",
    3: "Dress",
    4: "Coat",
    5: "Sandal",
    6: "Shirt",
    7: "Sneaker",
    8: "Bag",
    9: "Ankle Boot",
}
```



[8] Image Credit: https://pytorch.org/tutorials/beginner/basics/data_tutorial.html

2.1 Dataset: A Example

```
from torch.utils.data import Dataset
```

Store data
Meta data as
attributed

```
class CustomImageDataset(Dataset):
    def __init__(self, annotations_file, img_dir, transform=None, target_transform=None):
        self.img_labels = pd.read_csv(annotations_file)
        self.img_dir = img_dir
        self.transform = transform
        self.target_transform = target_transform

    def __len__(self):
        return len(self.img_labels)

    def __getitem__(self, idx):
        img_path = os.path.join(self.img_dir, self.img_labels.iloc[idx, 0])
        image = read_image(img_path)
        label = self.img_labels.iloc[idx, 1]
        if self.transform:
            image = self.transform(image)
        if self.target_transform:
            label = self.target_transform(label)
        return image, label
```

[8] Image Credit: https://pytorch.org/tutorials/beginner/basics/data_tutorial.html

2.1 Dataset: A Example

Returns number of samples

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        if self.target_transform:
            label = self.target_transform(label)
        return image, label
```

Get the idx th sample

Read Image data and label

[8] Image Credit: https://pytorch.org/tutorials/beginner/basics/data_tutorial.html

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        image = read_image(img_path)
        label = self.img_labels.iloc[idx, 1]
        if self.transform:
            image = self.transform(image)
        if self.target_transform:
            label = self.target_transform(label)
        return image, label
```

Apply transform to data. E.g. Normalization/ Augmentation

[8] Image Credit: https://pytorch.org/tutorials/beginner/basics/data_tutorial.html

2.1 Dataset: A Example

- The Dataset retrieves our dataset's features and labels one sample at a time.
- While training a model, we typically want to pass samples in "minibatches", reshuffle the data at every epoch to reduce model overfitting, and use Python's multiprocessing to speed up data retrieval.
- DataLoader is an iterable that abstracts this complexity for us in an easy API.

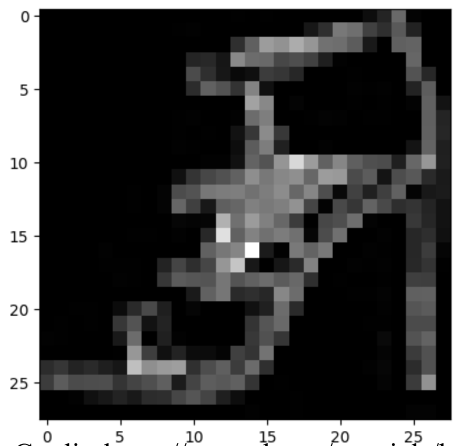
```
from torch.utils.data import DataLoader

train_dataloader = DataLoader(training_data, batch_size=64, shuffle=True)
test_dataloader = DataLoader(test_data, batch_size=64, shuffle=True)
```

[8] Image Credit: https://pytorch.org/tutorials/beginner/basics/data_tutorial.html

2.1 Dataset: A Example

```python
# Display image and label.
train_features, train_labels = next(iter(train_dataloader))
print(f"Feature batch shape: {train_features.size()}")
print(f"Labels batch shape: {train_labels.size()}")
img = train_features[0].squeeze()
label = train_labels[0]
plt.imshow(img, cmap="gray")
plt.show()
print(f"Label: {label}")
```




```
Feature batch shape: torch.Size([64, 1, 28, 28])
Labels batch shape: torch.Size([64])
Label: 5
```

[8] Image Credit: https://pytorch.org/tutorials/beginner/basics/data_tutorial.html

Tips 2.1 What's happening in dataloader

Wait, what exactly do dataloader do?

- Data Loading Order:
  - Determine the order to sample data. (e.g. shuffling given a particular seed.) In the multi-gpu distributed training case. It also coordinate to avoid repeat samples between different process.

- Parallel Sampling:
  - Reading data sequentially can be a bad idea. Dataloader fork num_worker of subprocesses to enable parallel sampling

```
CLASS torch.utils.data.DataLoader(dataset, batch_size=1, shuffle=None, sampler=None,
      batch_sampler=None, num_workers=0, collate_fn=None, pin_memory=False, drop_last=False,
      timeout=0, worker_init_fn=None, multiprocessing_context=None, generator=None, *,
      prefetch_factor=None, persistent_workers=False, pin_memory_device='')  [SOURCE]
```

[8] Image Credit: https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader

Tips 2.1 What's happening in dataloader

- Batching data:
  - This is done by the collate_fn (collate function), which 1. collate tensor memory for sampled data and 2. concatenate the tensors to be a single batch data. You can create your own collate_fn to handle different structure of data.

- Accelerate data loading:
  - This can be done by pin_memory and prefetch_factor

CLASS torch.utils.data.DataLoader(*dataset*, *batch_size=1*, *shuffle=None*, *sampler=None*, *batch_sampler=None*, *num_workers=0*, *collate_fn=None*, *pin_memory=False*, *drop_last=False*, *timeout=0*, *worker_init_fn=None*, *multiprocessing_context=None*, *generator=None*, ***, *prefetch_factor=None*, *persistent_workers=False*, *pin_memory_device=''*) [SOURCE]

[8] Image Credit: https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader

Recap

- Tensor operations
  - Index, Slice, Stride, Concatenate, reshape
- Dataset and DataLoader Module
  - Examples and tips

Next Time

- Build the model
- Model Optimization
- Automatic Gradient
- Build Training and Testing Loop