Machine Learning

Pytorch Tutorial

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Outline

- Background: Prerequisites & What is Pytorch?
- Training & Testing Neural Networks in Pytorch
- Dataset & Dataloader
- Tensors
- torch.nn: Models, Loss Functions
- torch.optim: Optimization
- Save/load models

Prerequisites

- We assume you are already familiar with…

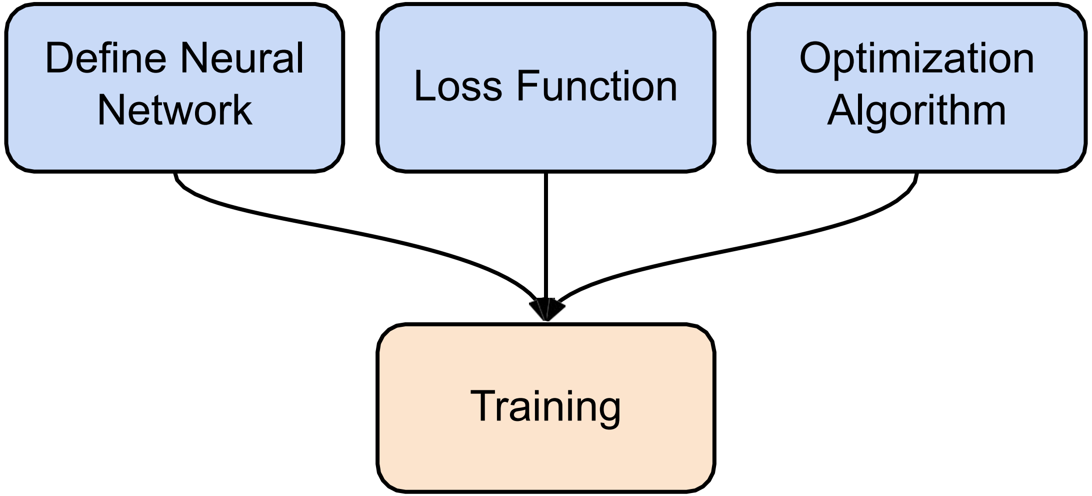
1. **Python3**
    - `if-else, loop, function, file IO, class, ...`
    - refs: link1, link2, link3
2. **Deep Learning Basics**
    - Prof. Lee’s 1st & 2nd lecture videos from last year
    - ref: link1, link2

Some knowledge of **NumPy** will also be useful!

What is PyTorch?

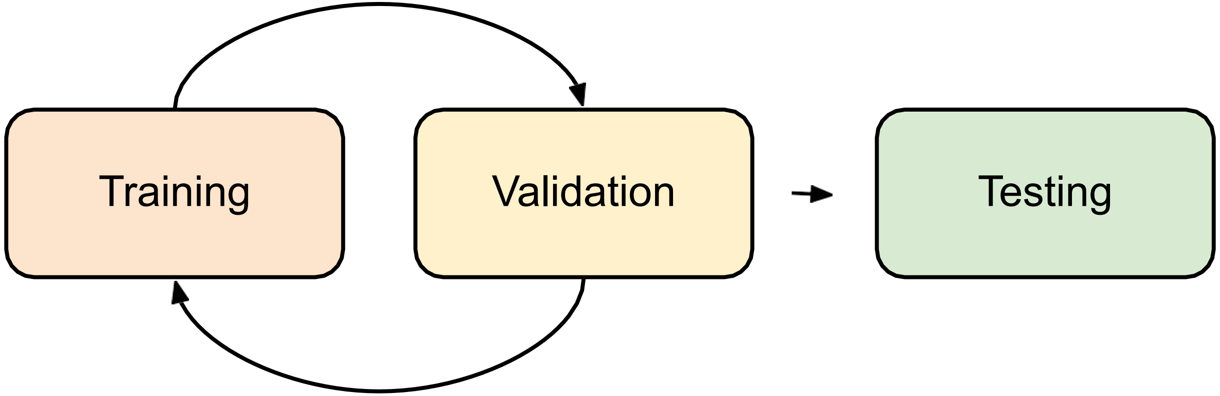
- An **machine learning framework** in Python.
- Two main features:
    - N-dimensional **Tensor** computation (like NumPy) on **GPUs**
    - **Automatic differentiation** for training deep neural networks

Training Neural Networks



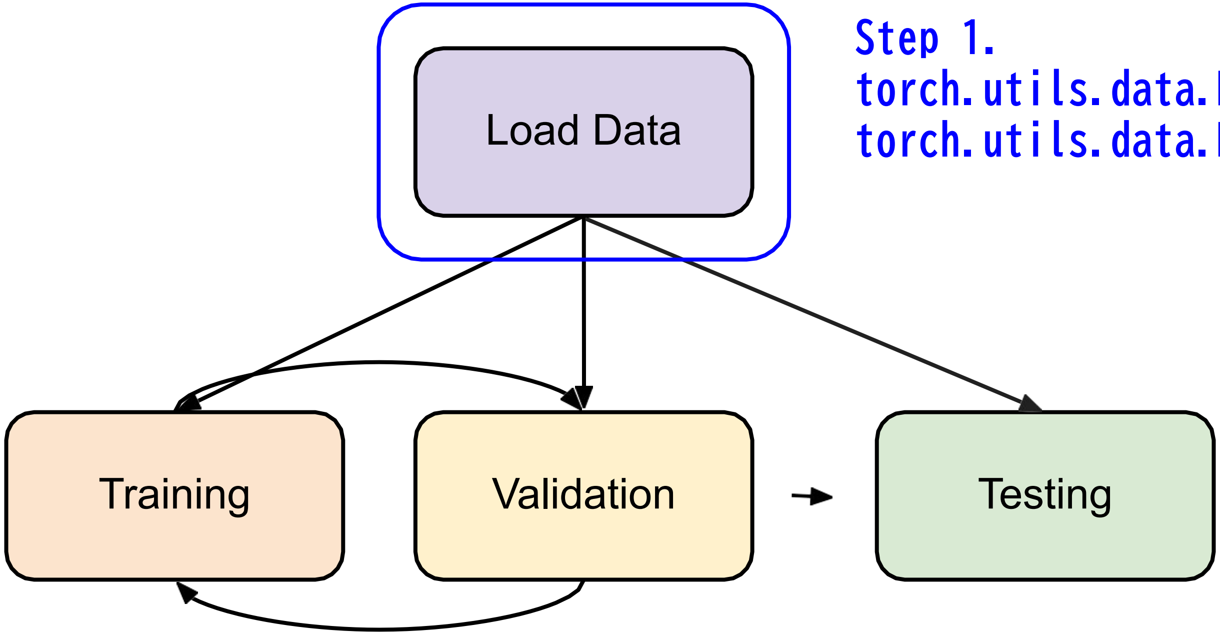
More info about the training process in [last year's lecture video](#).

Training & Testing Neural Networks



Guide for training/validation/testing can be found here.

Training & Testing Neural Networks - in Pytorch



Step 1.
torch.utils.data.Dataset &
torch.utils.data.DataLoader

Dataset & Dataloader

- `Dataset`: stores data samples and expected values
- `Dataloader`: groups data in batches, enables multiprocessing

- `dataset = MyDataset(file)`
- `dataloader = DataLoader(dataset, batch_size, shuffle=True)`

Training: True
Testing: False

More info about batches and shuffling here.

Dataset & Dataloader

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

class MyDataset(Dataset):
    def init (self, file):
        self.data = ...

    def __getitem__(self, index):
        return self.data[index]

    def __len__(self):
        return len(self.data)
```

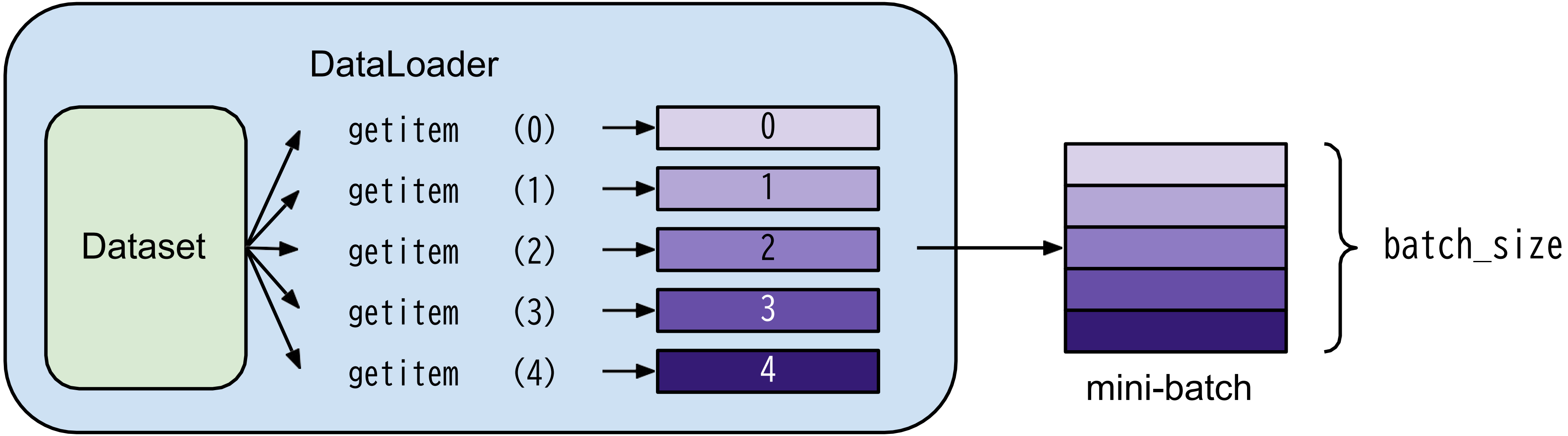
Read data & preprocess

Returns one sample at a time

Returns the size of the dataset

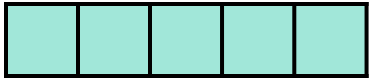
Dataset & Dataloader

```
dataset = MyDataset(file)

dataloader = DataLoader(dataset, batch_size=5, shuffle=False)
```

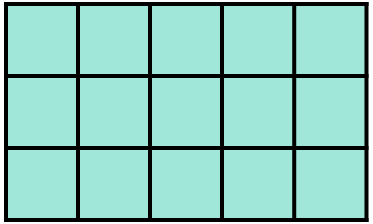


Tensors

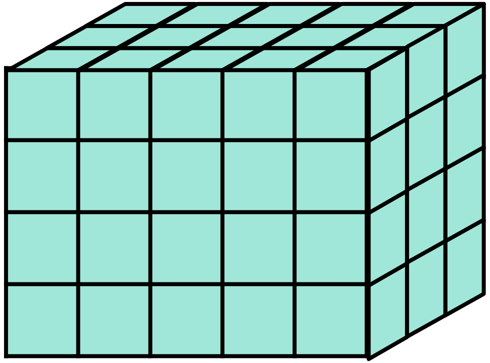
- High-dimensional matrices (arrays)



1-D tensor
e.g. audio



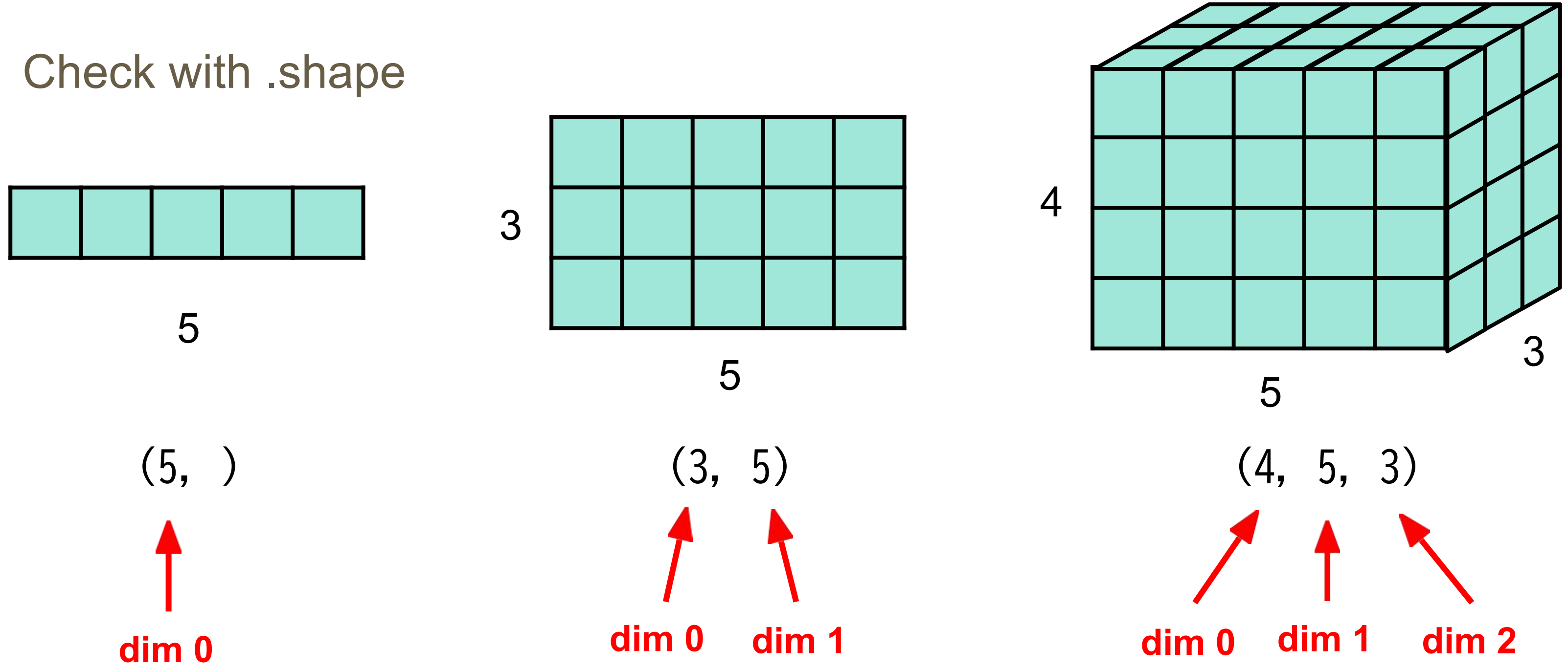
2-D tensor
e.g. black&white images



3-D tensor
e.g. RGB images

Tensors – Shape of Tensors

- Check with .shape



Note: `dim` in PyTorch == `axis` in NumPy

Tensors – Creating Tensors

- Directly from data (list or numpy.ndarray)

```
x = torch.tensor([[1, -1], [-1, 1]])

x = torch.from_numpy(np.array([[1, -1], [-1, 1]]))
```

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

- Tensor of constant zeros & ones

```
x = torch.zeros([2, 2])

x = torch.ones([1, 2, 5])
```

shape

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

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

Tensors – Common Operations

Common arithmetic functions are supported, such as:

- Addition

```
z = x + y
```

- Subtraction

```
z = x - y
```

- Power

```
y = x.pow(2)
```

- Summation

```
y = x.sum()
```

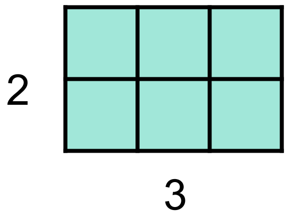
- Mean

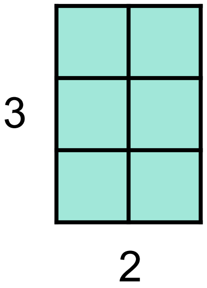
```
y = x.mean()
```

Tensors – Common Operations

- **Transpose**: transpose two specified dimensions

```
>>> x = torch.zeros([2, 3])

>>> x.shape
torch.Size([2, 3])

>>> x = x.transpose(0, 1)

>>> x.shape

torch.Size([3, 2])
```





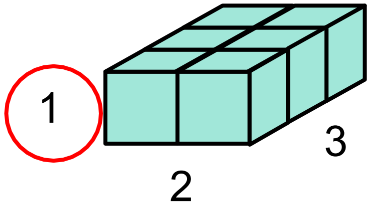
Tensors – Common Operations

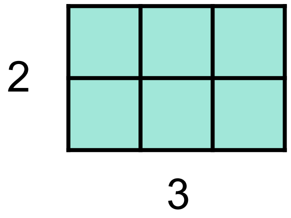
- **Squeeze**: remove the specified dimension with length = 1

```
>>> x = torch.zeros([1, 2, 3])
>>> x.shape
torch.Size([1, 2, 3])
>>> x = x.squeeze(0)
```

(dim = 0)

```
>>> x.shape
torch.Size([2, 3])
```



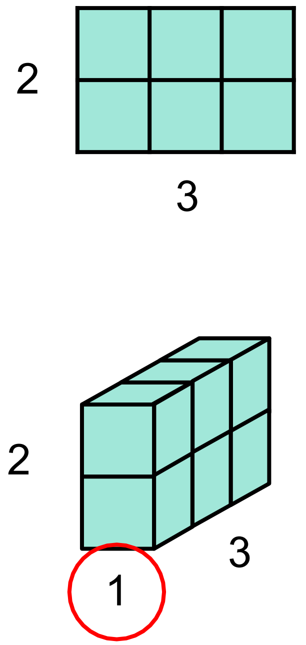


Tensors – Common Operations

- **Unsqueeze**: expand a new dimension

```
>>> x = torch.zeros([2, 3])
>>> x.shape
torch.Size([2, 3])
>>> x = x.unsqueeze(1)
>>> x.shape
torch.Size([2, 1, 3])
```

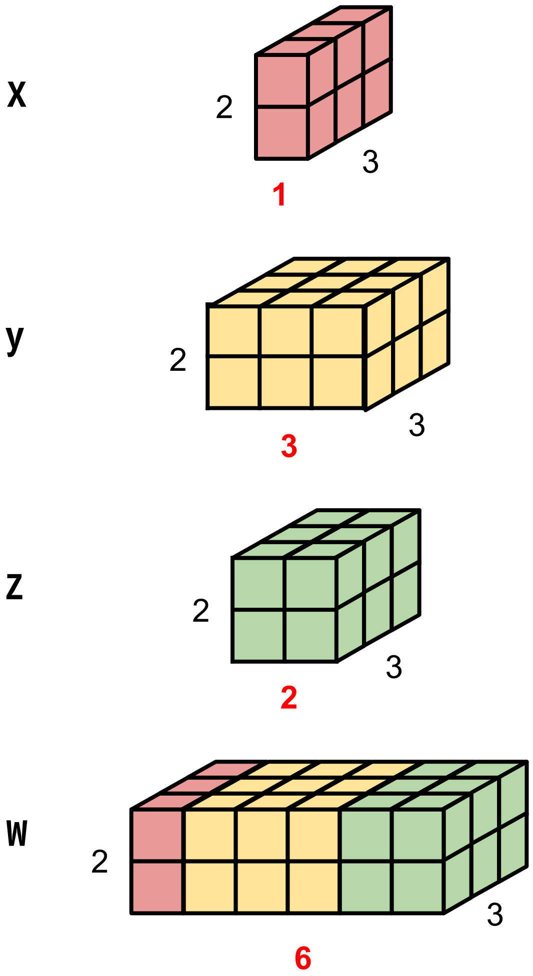
(dim = 1)



Tensors – Common Operations

- **Cat**: concatenate multiple tensors

```
>>> x = torch.zeros([2, 1, 3])
>>> y = torch.zeros([2, 3, 3])
>>> z = torch.zeros([2, 2, 3])
>>> w = torch.cat([x, y, z], dim=1)
>>> w.shape
torch.Size([2, 6, 3])
```



more operators: https://pytorch.org/docs/stable/tensors.html

Tensors – Data Type

- Using different data types for model and data will cause errors.

Data type	dtype	tensor
32-bit floating point	`torch.float`	`torch.FloatTensor`
64-bit integer (signed)	`torch.long`	`torch.LongTensor`

see official documentation for more information on data types.

Tensors – PyTorch v.s. NumPy

- Similar attributes

PyTorch	NumPy
x.shape	x.shape
x.dtype	x.dtype

see official documentation for more information on data types.

ref: https://github.com/wkentaro/pytorch-for-numpy-users

Tensors – PyTorch v.s. NumPy

- Many functions have the same names as well

PyTorch	NumPy
x.reshape / x.view	x.reshape
x.squeeze()	x.squeeze()
x.unsqueeze(1)	np.expand_dims(x, 1)

ref: https://github.com/wkentaro/pytorch-for-numpy-users

Tensors – Device

- Tensors & modules will be computed with **CPU** by default

  Use **.to()** to move tensors to appropriate devices.
- CPU

```
x = x.to('cpu')
```

- GPU

```
x = x.to('cuda')
```

Tensors – Device (GPU)

- Check if your computer has NVIDIA GPU

  `torch.cuda.is_available()`

- Multiple GPUs: specify `'cuda:0'`, `'cuda:1'`, `'cuda:2'`, ...

- Why use GPUs?
  - Parallel computing with more cores for arithmetic calculations
  - See [What is a GPU and do you need one in deep learning?]

Tensors – Gradient Calculation

```
1 >>> x = torch.tensor([[1., 0.], [-1., 1.]], requires_grad=True)
2 >>> z = x.pow(2).sum()
3 >>> z.backward()
4 >>> x.grad
  tensor([[ 2.,   0.],
          [-2.,   2.]])
```

1 $x = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix}$

2 $z = \sum_i \sum_j x_{i,j}^2$

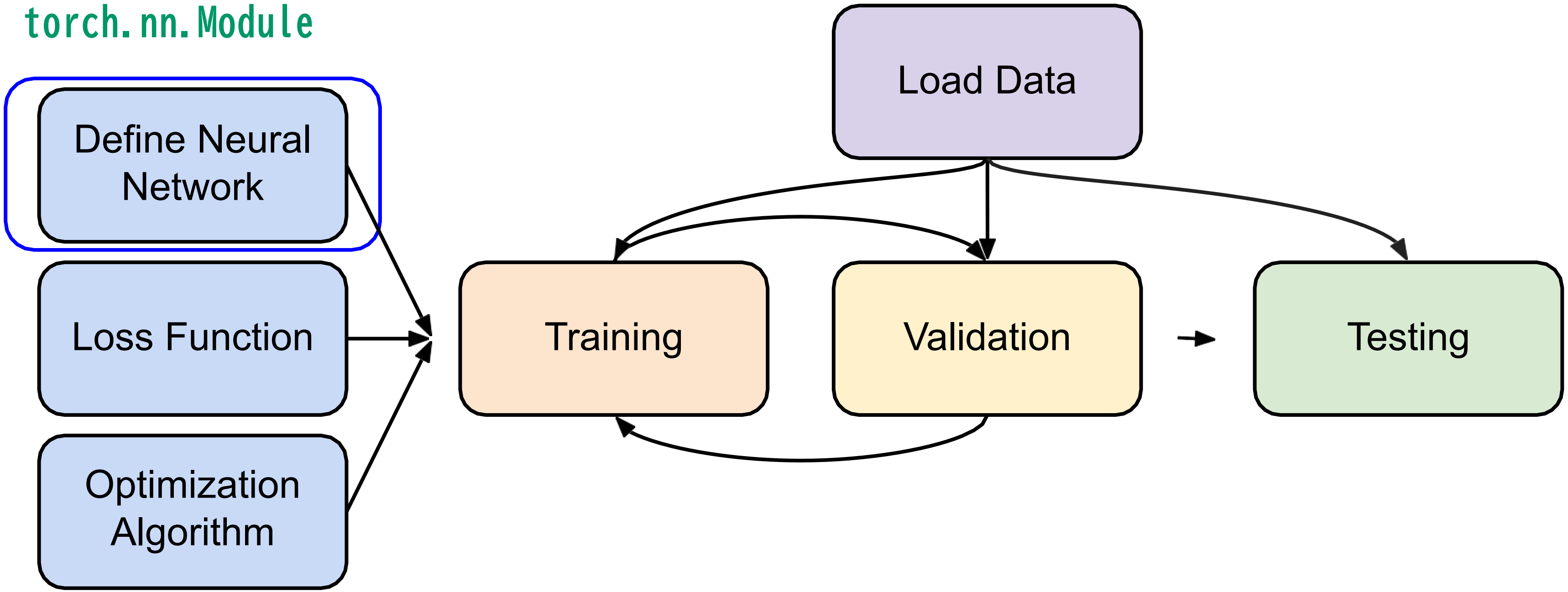
3 $\frac{\partial z}{\partial x_{i,j}} = 2x_{i,j}$

4 $\frac{\partial z}{\partial x} = \begin{bmatrix} 2 & 0 \\ -2 & 2 \end{bmatrix}$

See here to learn about gradient calculation.

Training & Testing Neural Networks – in Pytorch

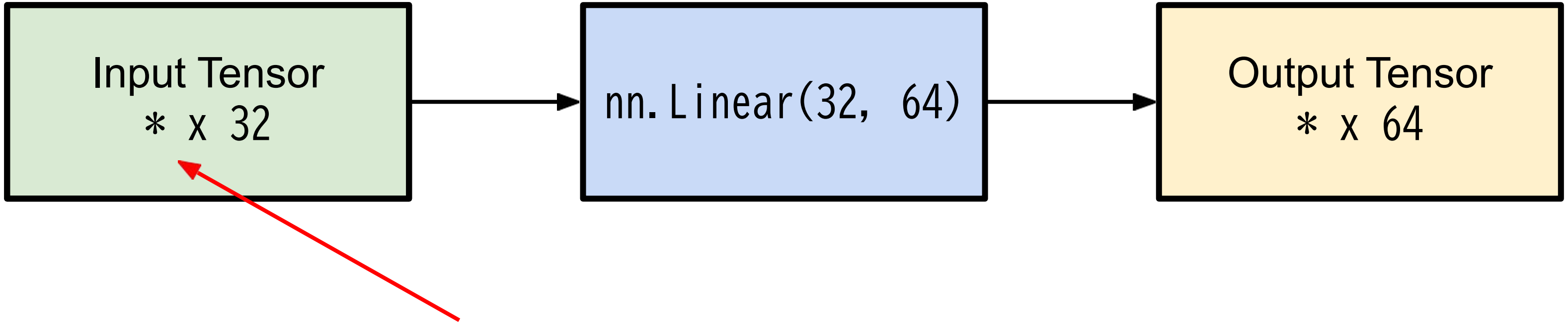
`Step 2.`
`torch.nn.Module`



torch.nn – Network Layers

- Linear Layer (**Fully-connected** Layer)

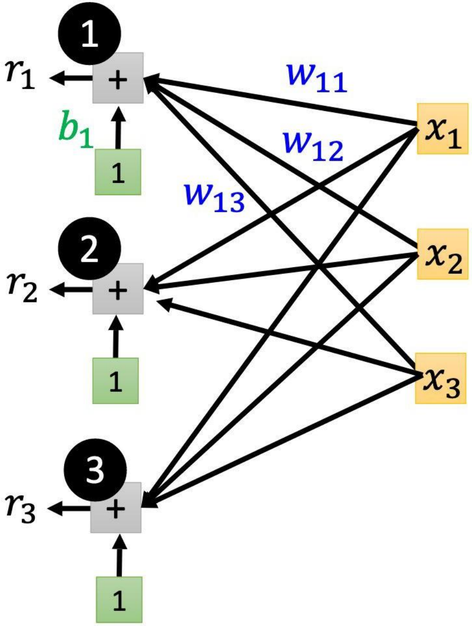
  `nn.Linear(in_features, out_features)`

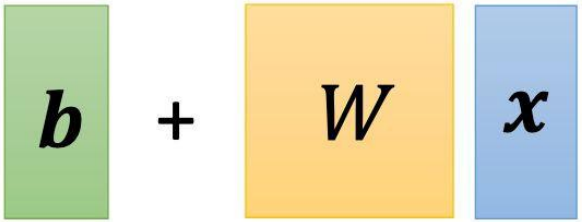


can be any shape (but last dimension must be 32)
e.g. (10, 32), (10, 5, 32), (1, 1, 3, 32), ...

torch.nn – Network Layers

- Linear Layer (**Fully-connected** Layer)

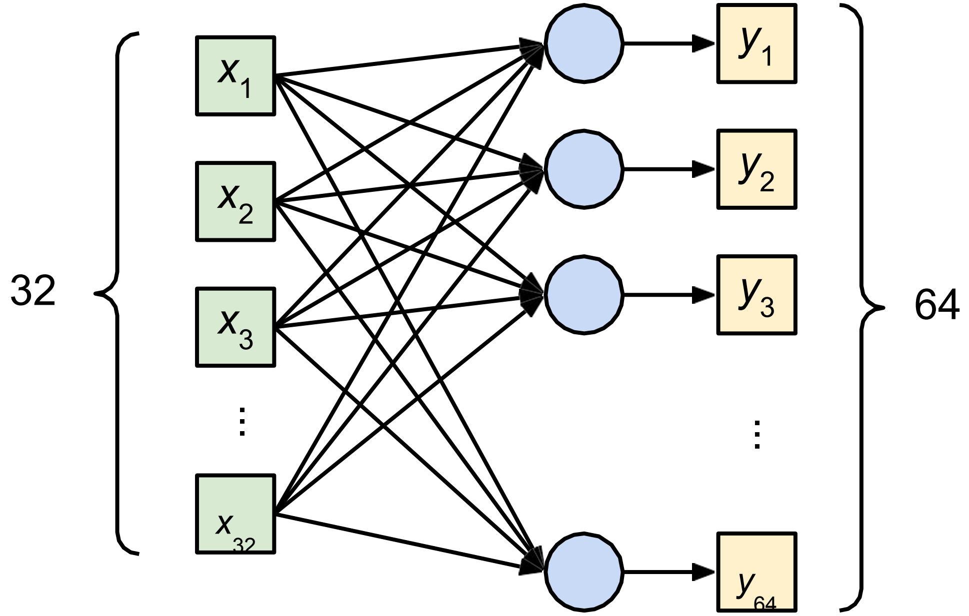


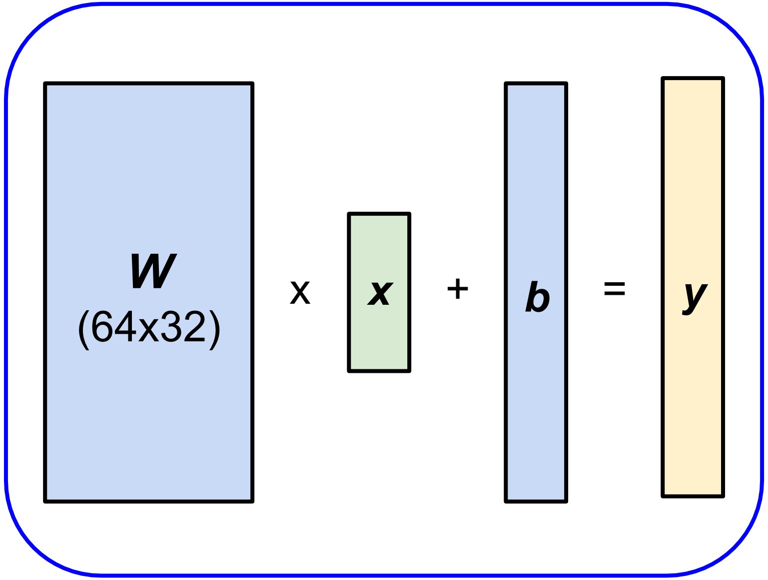


ref: [last year's lecture video]

torch.nn – Neural Network Layers

- Linear Layer (**Fully-connected** Layer)

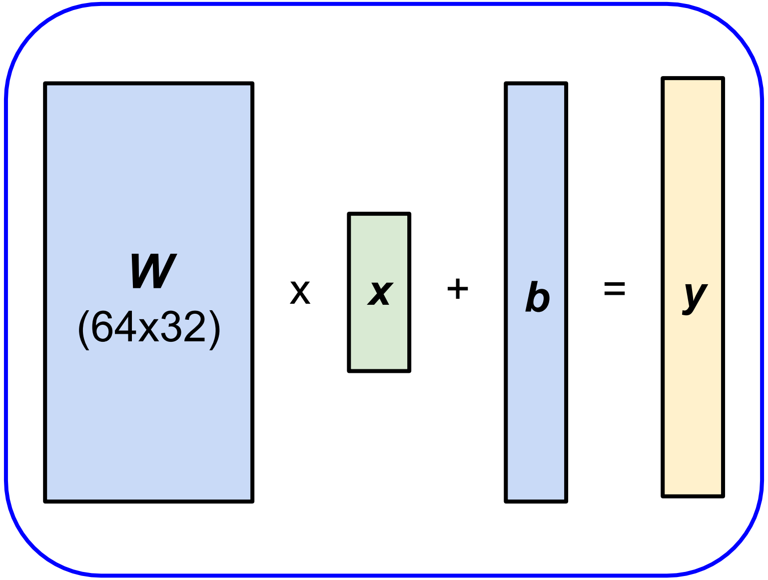




torch.nn – Network Parameters

- Linear Layer (**Fully-connected** Layer)

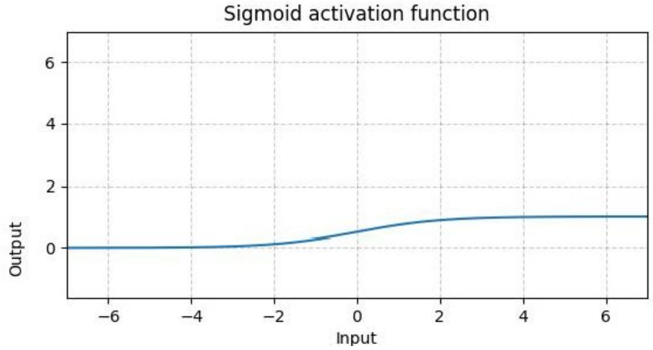
```
>>> layer = torch.nn.Linear(32, 64)
>>> layer.weight.shape
torch.Size([64, 32])
>>> layer.bias.shape
torch.Size([64])
```



torch.nn – Non-Linear Activation Functions

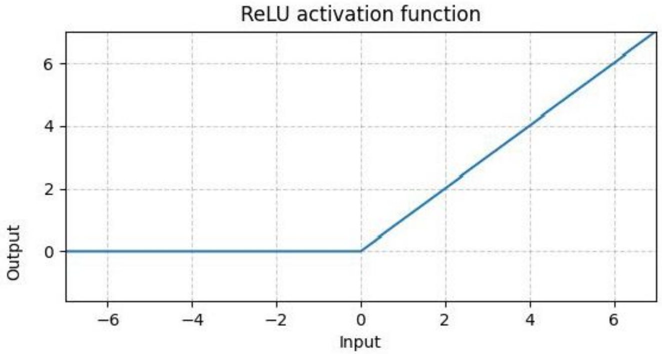
- Sigmoid Activation

```
nn.Sigmoid()
```



- ReLU Activation

```
nn.ReLU()
```



See here to learn about why we need activation functions.

torch.nn – Build your own neural network

```
import torch.nn as nn

class MyModel(nn.Module):
    def init(self):
        super(MyModel, self).init ()
        self.net = nn.Sequential(
            nn.Linear(10, 32),
            nn.Sigmoid(),
            nn.Linear(32, 1)
        )

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

Initialize your model & define layers

Compute output of your NN

torch.nn – Build your own neural network

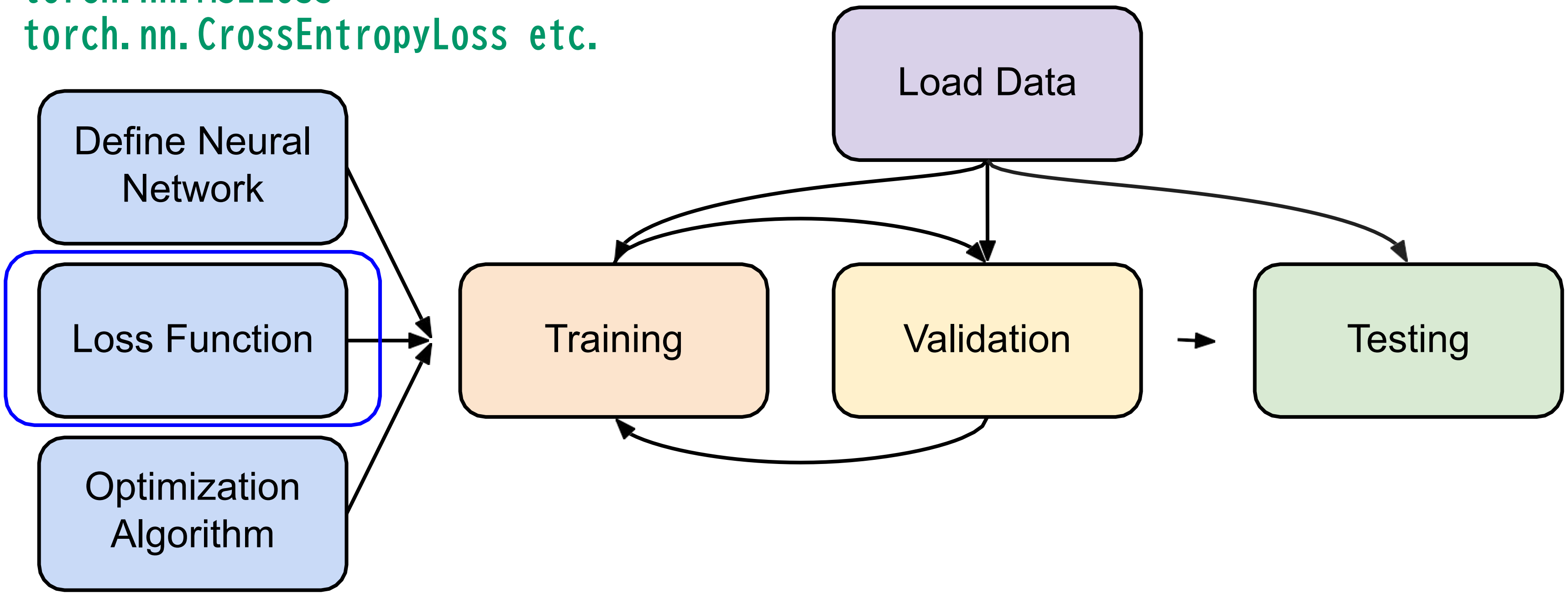
```
import torch.nn as nn

class MyModel(nn.Module):
    def init(self):
        super(MyModel, self).init ()
        self.net = nn.Sequential(
            nn.Linear(10, 32),
            nn.Sigmoid(),
            nn.Linear(32, 1)
        )

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

=

```
import torch.nn as nn

class MyModel(nn.Module):
    def _init_(self):
        super(MyModel, self).__init__()
        self.layer1 = nn.Linear(10, 32)
        self.layer2 = nn.Sigmoid()
        self.layer3 = nn.Linear(32,1)

    def  forward(self,  x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = self.layer3(out)
        return out
```

Training & Testing Neural Networks – in Pytorch

```
Step 3.
torch.nn.MSELoss
torch.nn.CrossEntropyLoss etc.
```



torch.nn – Loss Functions

- Mean Squared Error (for regression tasks)

  ```
  criterion = nn.MSELoss()
  ```

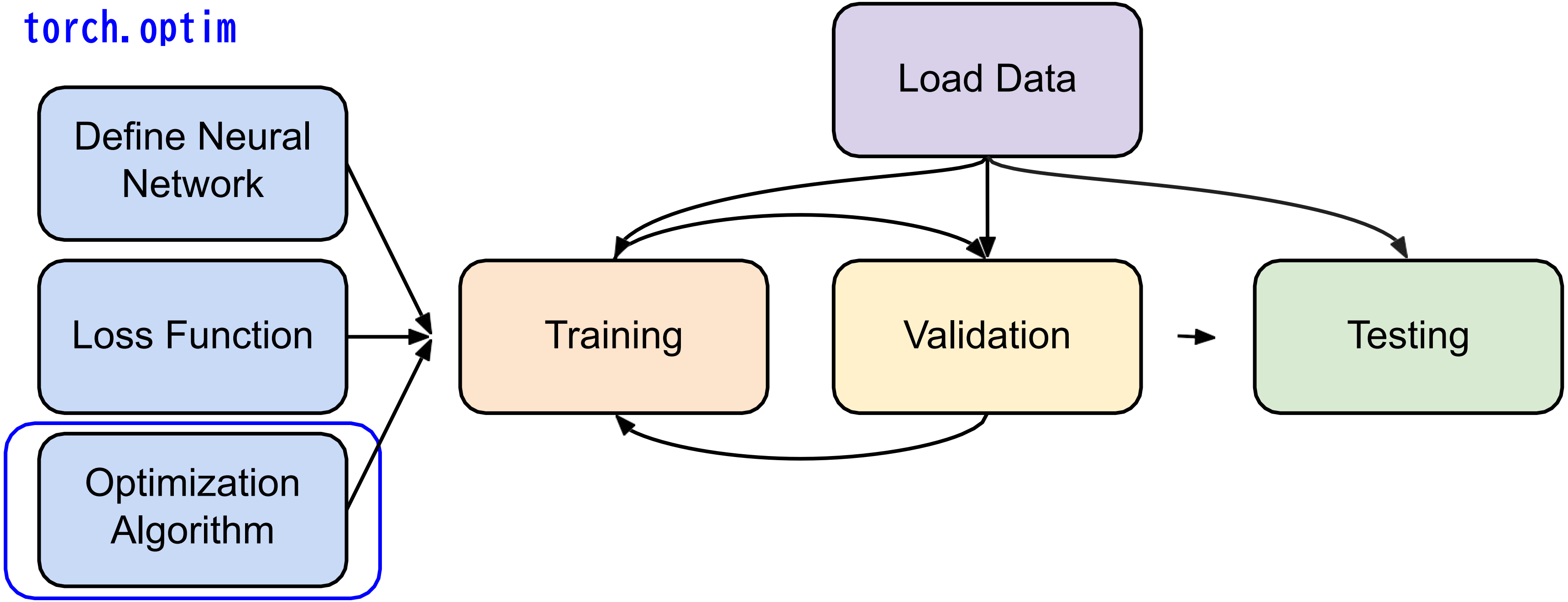
- Cross Entropy (for classification tasks)

  ```
  criterion = nn.CrossEntropyLoss()
  ```

- `loss = criterion(model_output, expected_value)`

Training & Testing Neural Networks – in Pytorch

Step 4.
`torch.optim`



torch.optim

- Gradient-based **optimization algorithms** that adjust network parameters to reduce error. (See Adaptive Learning Rate lecture video)

- E.g. Stochastic Gradient Descent (SGD)

```
torch.optim.SGD(model.parameters(), lr, momentum = 0)
```

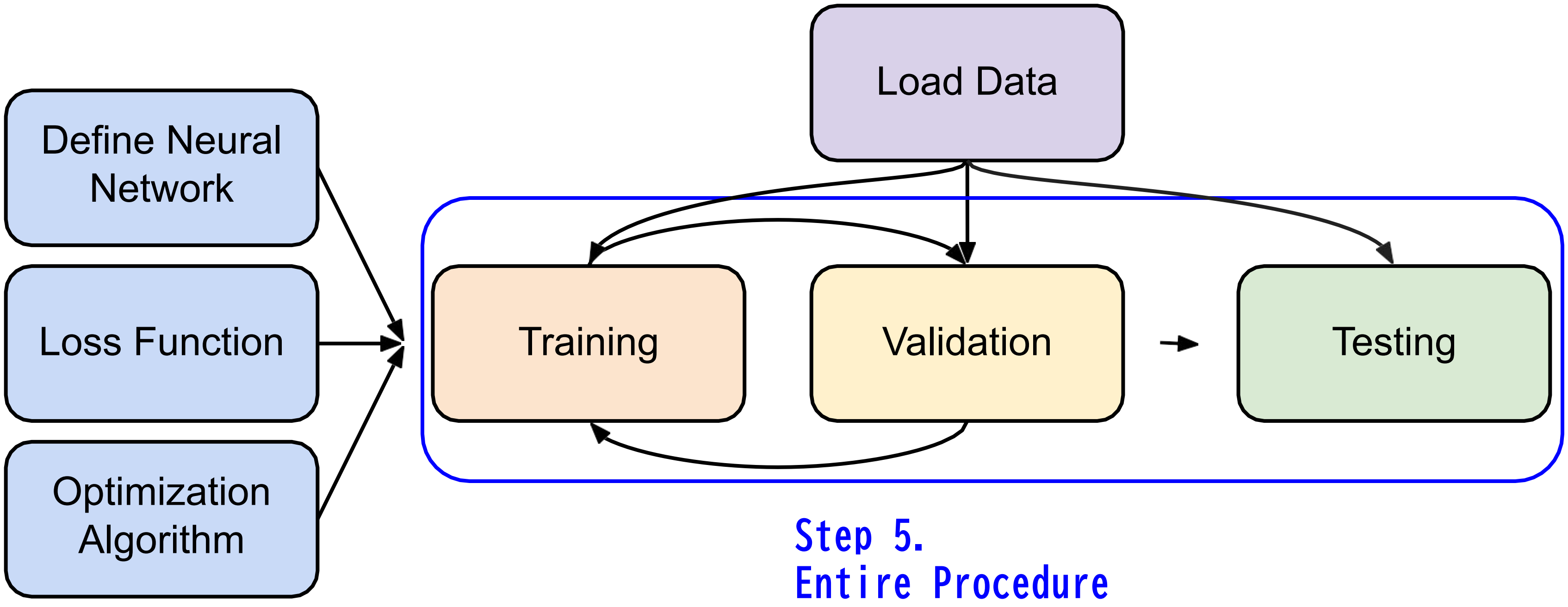
torch.optim

```
optimizer = torch.optim.SGD(model.parameters(), lr, momentum = 0)
```

- For every batch of data:
  1. Call `optimizer.zero_grad()` to reset gradients of model parameters.
  2. Call `loss.backward()` to backpropagate gradients of prediction loss.
  3. Call `optimizer.step()` to adjust model parameters.

See official documentation for more optimization algorithms.

Training & Testing Neural Networks – in Pytorch



Neural Network Training Setup

`dataset = MyDataset(file)`	read data via MyDataset
`tr_set = DataLoader(dataset, 16, shuffle=True)`	put dataset into Dataloader
`model = MyModel().to(device)`	construct model and move to device (cpu/cuda)
`criterion = nn.MSELoss()`	set loss function
`optimizer = torch.optim.SGD(model.parameters(), 0.1)`	set optimizer

Neural Network Training Loop

`for epoch in range(n_epochs):`	iterate n_epochs
`    model.train()`	set model to train mode
`    for x, y in tr_set:`	iterate through the dataloader
`        optimizer.zero_grad()`	set gradient to zero
`        x, y = x.to(device), y.to(device)`	move data to device (cpu/cuda)
`        pred = model(x)`	forward pass (compute output)
`        loss = criterion(pred, y)`	compute loss
`        loss.backward()`	compute gradient (backpropagation)
`        optimizer.step()`	update model with optimizer

Neural Network Validation Loop

```
model.eval()                                          set model to evaluation mode
total_loss = 0
for x, y in dv_set:                                   iterate through the dataloader
    x, y = x.to(device), y.to(device)                 move data to device (cpu/cuda)
    with torch.no_grad():                             disable gradient calculation
        pred = model(x)                               forward pass (compute output)
        loss = criterion(pred, y)                     compute loss
    total_loss += loss.cpu().item() * len(x)          accumulate loss
    avg_loss = total_loss / len(dv_set.dataset)       compute averaged loss
```

Neural Network Testing Loop

```
model.eval()                              set model to evaluation mode
preds = []
for x in tt_set:                          iterate through the dataloader
    x = x.to(device)                      move data to device (cpu/cuda)
    with torch.no_grad():                 disable gradient calculation
        pred = model(x)                   forward pass (compute output)
        preds.append(pred.cpu())          collect prediction
```

Notice - model.eval(), torch.no_grad()

- `model.eval()`
  Changes behaviour of some model layers, such as dropout and batch normalization.

- `with torch.no_grad()`
  Prevents calculations from being added into gradient computation graph.
  Usually used to prevent accidental training on validation/testing data.

Save/Load Trained Models

- Save

```
torch.save(model.state_dict(), path)
```

- Load

```
ckpt = torch.load(path)
model.load_state_dict(ckpt)
```

More About PyTorch

- torchaudio
  - speech/audio processing
- torchtext
  - natural language processing
- torchvision
  - computer vision
- skorch
  - scikit-learn + pyTorch

More About PyTorch

- Useful github repositories using PyTorch
  - Huggingface Transformers (transformer models: BERT, GPT, ...)
  - Fairseq (sequence modeling for NLP & speech)
  - ESPnet (speech recognition, translation, synthesis, ...)
  - Most implementations of recent deep learning papers
  - ...

References

- Machine Learning 2022 Spring Pytorch Tutorial
- Official Pytorch Tutorials
- https://numpy.org/

Any questions?