



# Deep Learning with PyTorch

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NSF Workshop: Deep Learning on GPU

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# Agenda for today (July 24)

1. PyTorch
2. MLP
3. CNN

Lunch break (12:30-1:30PM)

4. Transfer Learning
5. Save/Load models
6. PINN

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# PyTorch Tutorial

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# Outline

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

# What is PyTorch?

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



# PyTorch Installation

Python / Conda

CUDA (if applicable): <https://developer.nvidia.com/cuda-downloads>

Create virtual environment (if needed) and activate it

**conda create -n pytorch python=3.11**

**conda activate pytorch**

PyTorch

(pytorch) \$ *<installation command here>*

# Verification

```
(pytorch) $ python
```

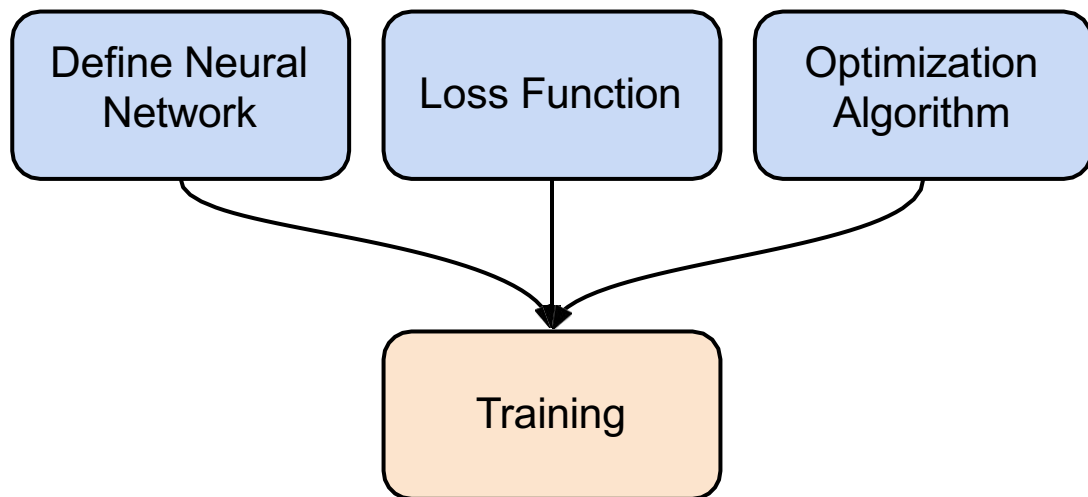
```
>>> import torch
```

```
>>> x = torch.rand(5, 3)
```

```
>>> print(x)
```

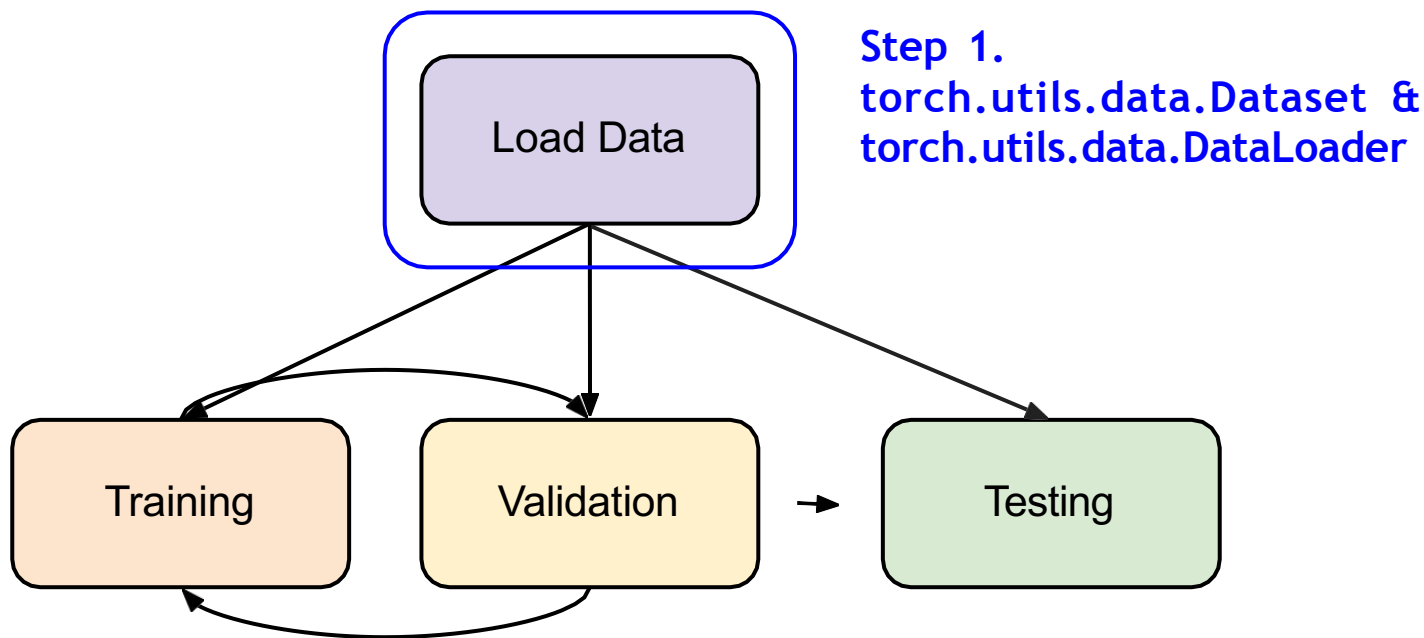
```
>>> torch.cuda.is_available()
```

# Training Neural Networks





# Training & Testing Neural Networks - in Pytorch



# 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

# Dataset & Dataloader

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

```
class MyDataset(Dataset):
```

```
    def __init__(self, file):
```

```
        self.data = ...
```



Read data & preprocess

```
    def __getitem__(self, index):
```

```
        return self.data[index]
```



Returns one sample at a time

```
    def __len__(self):
```

```
        return len(self.data)
```

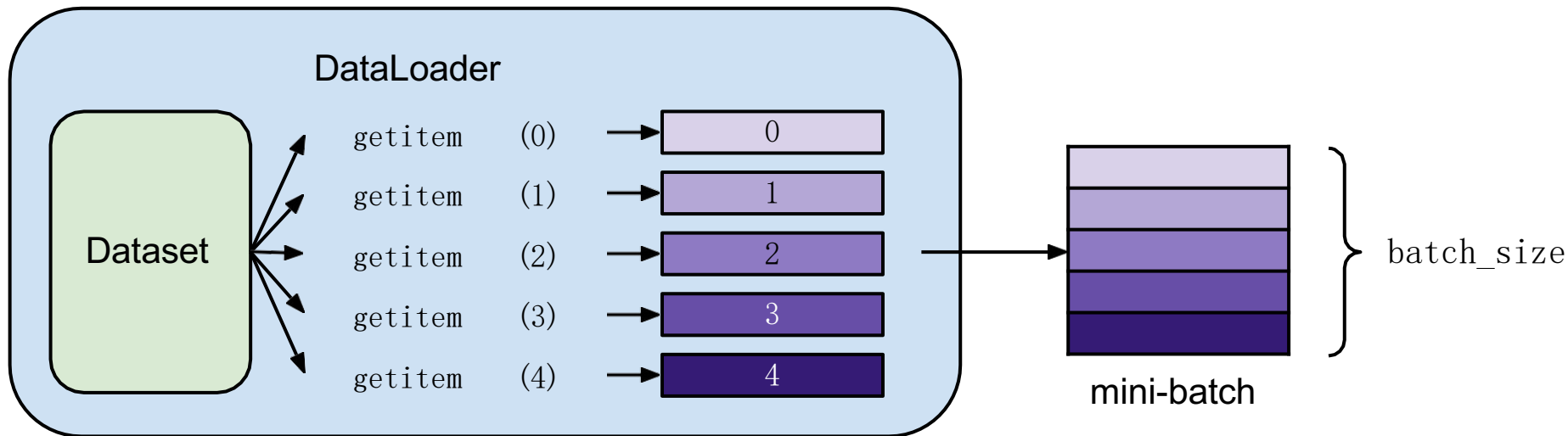


Returns the size of the dataset

# Dataset & Dataloader

```
dataset = MyDataset(file)
```

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

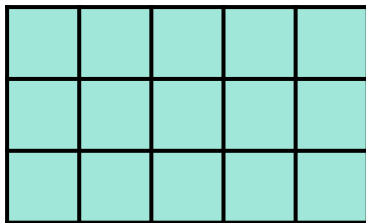


# Tensors

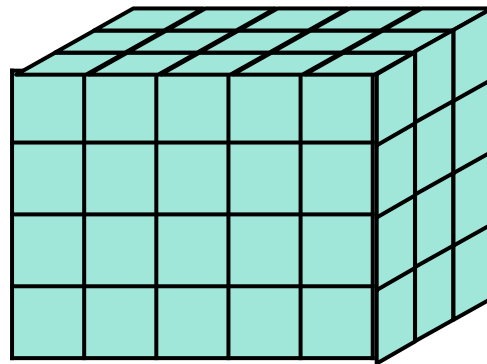
- High-dimensional matrices (arrays)



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`

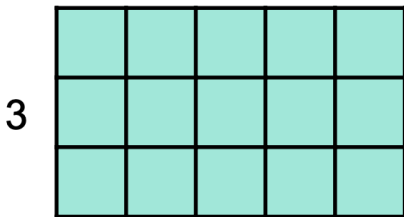


5

(5, )



dim 0



3

5

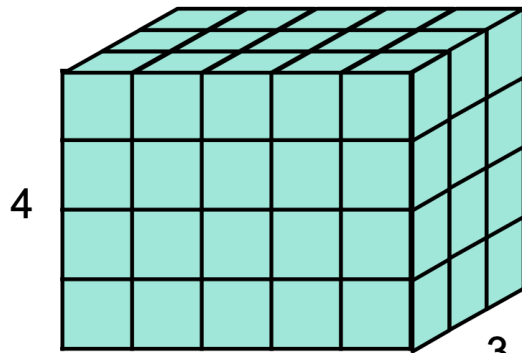
(3, 5)



dim 0



dim 1



4

5

3

(4, 5, 3)



dim 0



dim 1



dim 2

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

$$z = x + y$$

- Summation

$$y = x.\text{sum}()$$

- Subtraction

$$z = x - y$$

- Mean

$$y = x.\text{mean}()$$

- Power

$$y = x.\text{pow}(2)$$



# Tensors — Common Operations

- **Transpose:** transpose two specified dimensions

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

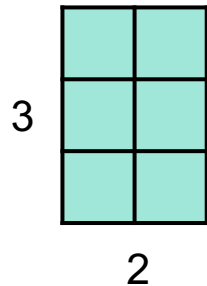
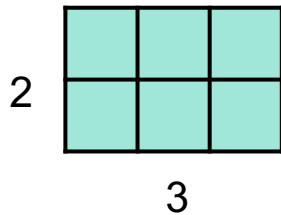
```
>>> x.shape
```

```
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

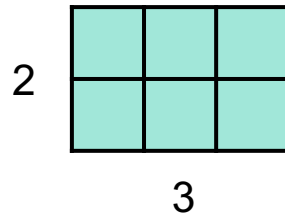
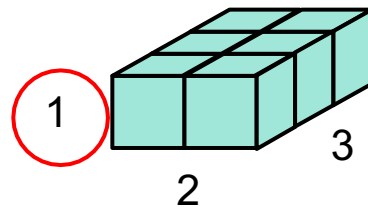
```
>>> x = torch.zeros([1, 2, 3])
```

```
>>> 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])
```

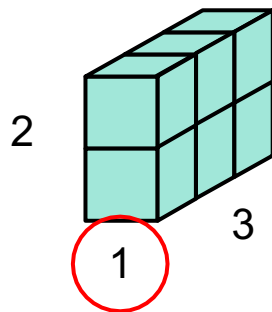
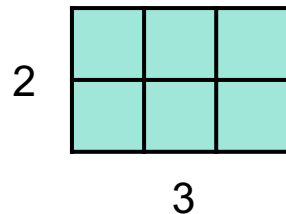
```
>>> x.shape
```

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

```
>>> x = x.unsqueeze(1)      (dim = 1)
```

```
>>> x.shape
```

```
torch.Size([2, 1, 3])
```



# Tensors — Common Operations

- **Cat:** concatenate multiple tensors

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

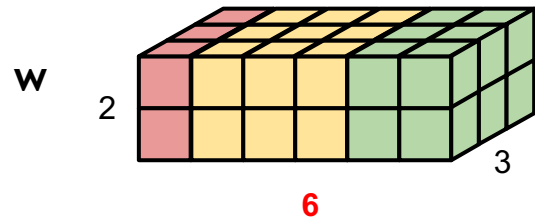
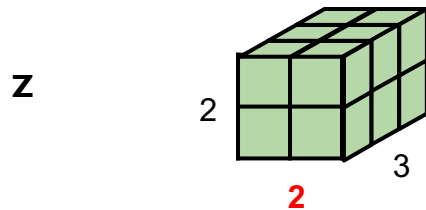
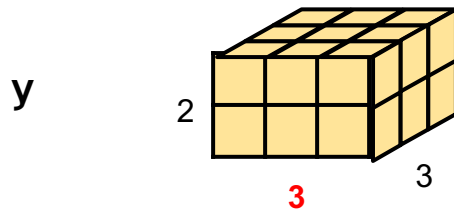
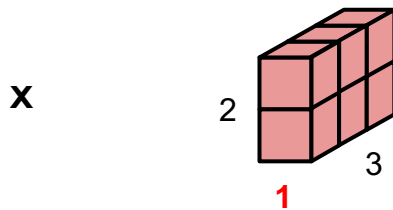
```
>>> y = torch.zeros([2, 3, 3])
```

```
>>> 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	<code>torch.float</code>	<code>torch.FloatTensor</code>
64-bit integer (signed)	<code>torch.long</code>	<code>torch.LongTensor</code>

see [official documentation](#) for more information on data types.

# Tensors — PyTorch v.s. NumPy

- Similar attributes

PyTorch	NumPy
<code>x.shape</code>	<code>x.shape</code>
<code>x.dtype</code>	<code>x.dtype</code>

see [official documentation](#) for more information on data types.

# Tensors — PyTorch v.s. NumPy

- Many functions have the same names as well

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

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

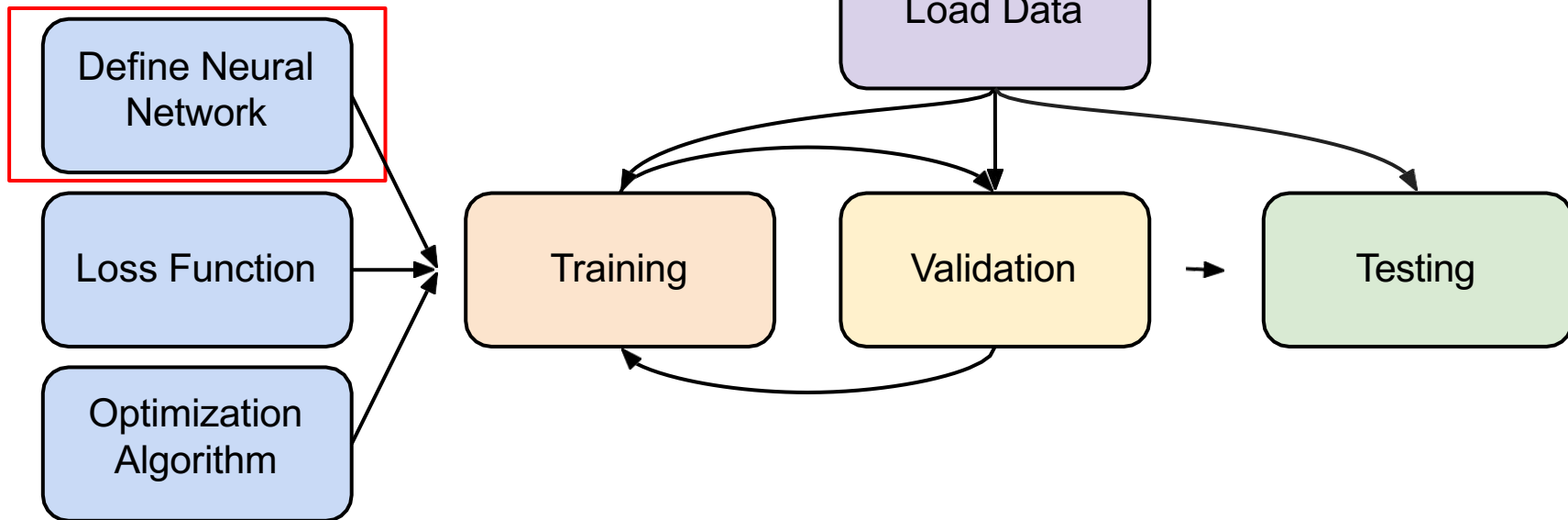
2  $z = \sum_i \sum_j x_{i,j}^2$

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

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

# Training & Testing Neural Networks — in Pytorch

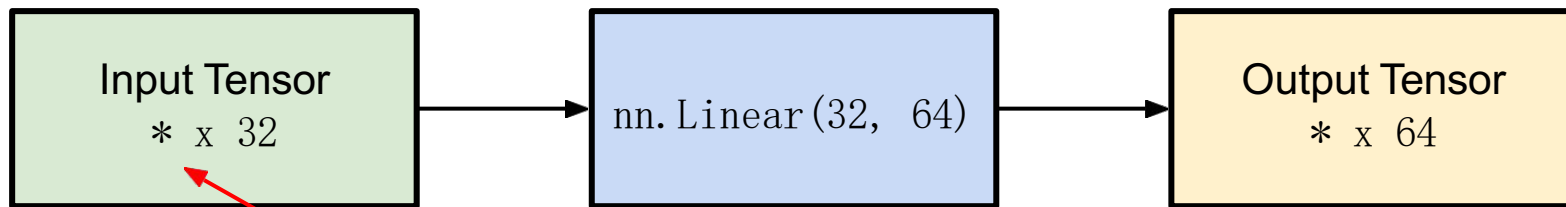
Step 2.  
`torch.nn.Module`



# 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)

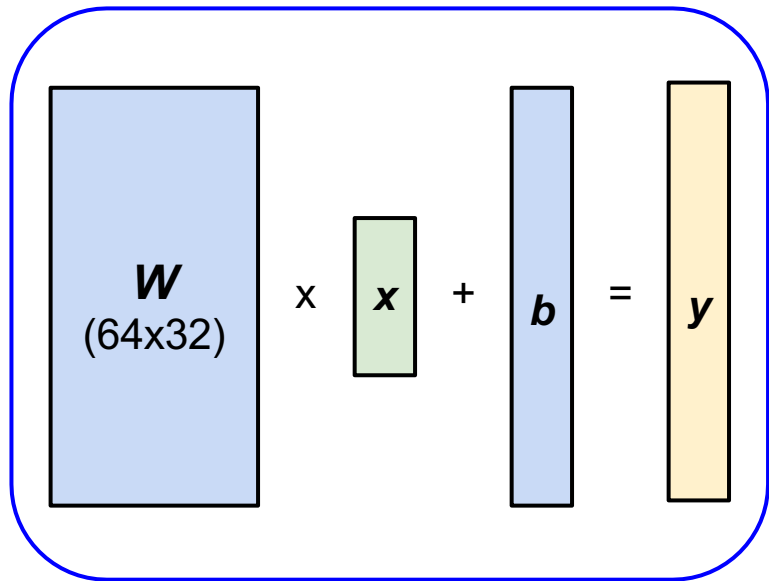
```
>>> layer = torch.nn.Linear(32, 64)
```

```
>>> layer.weight.shape
```

```
torch.Size([64, 32])
```

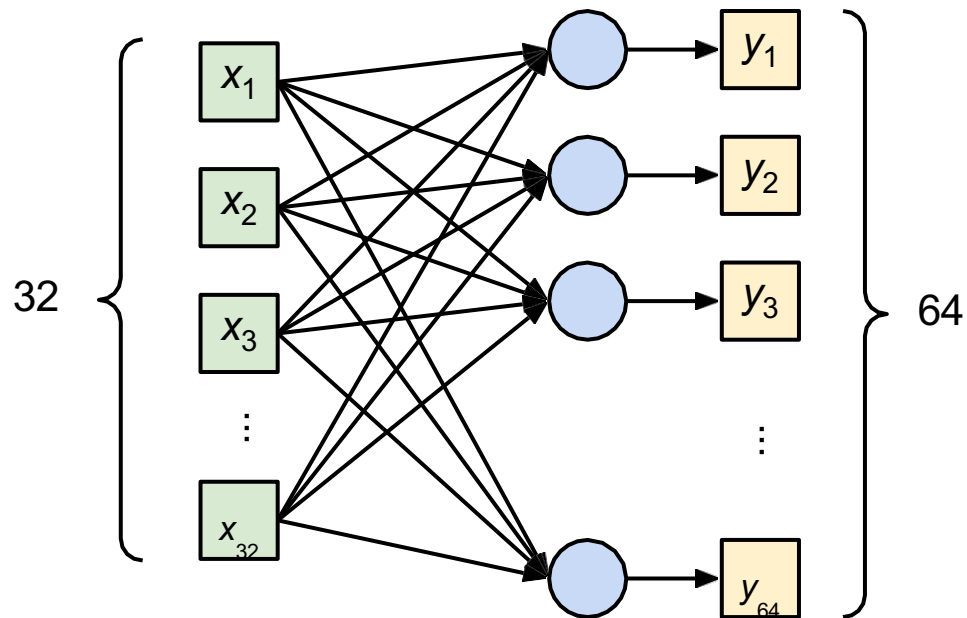
```
>>> layer.bias.shape
```

```
torch.Size([64])
```



# torch.nn — Network Layers

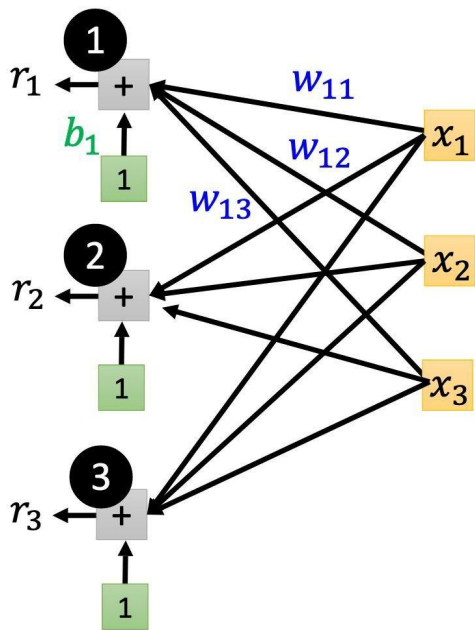
- Linear Layer (**Fully-connected** Layer)



$$\begin{matrix} \text{64x32} \\ W \end{matrix} \times \begin{matrix} x \end{matrix} + \begin{matrix} b \end{matrix} = \begin{matrix} y \end{matrix}$$

# torch.nn — Network Layers

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

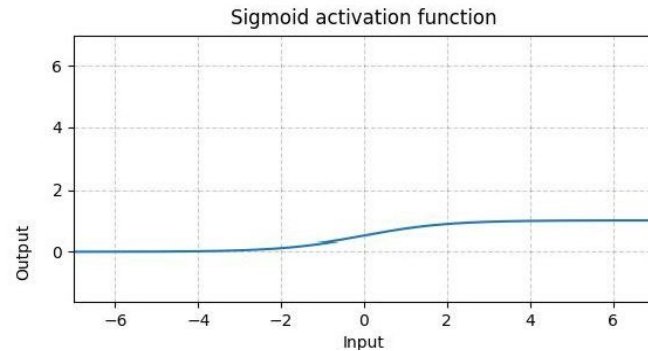


$$b + Wx$$

# torch.nn — Non-Linear Activation Functions

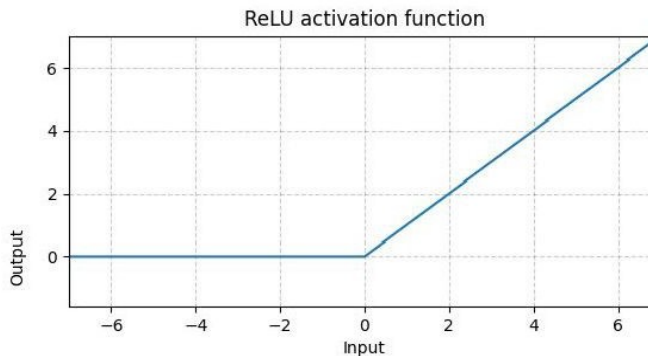
- Sigmoid Activation

```
nn.Sigmoid()
```



- ReLU Activation

```
nn.ReLU()
```





# 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
```

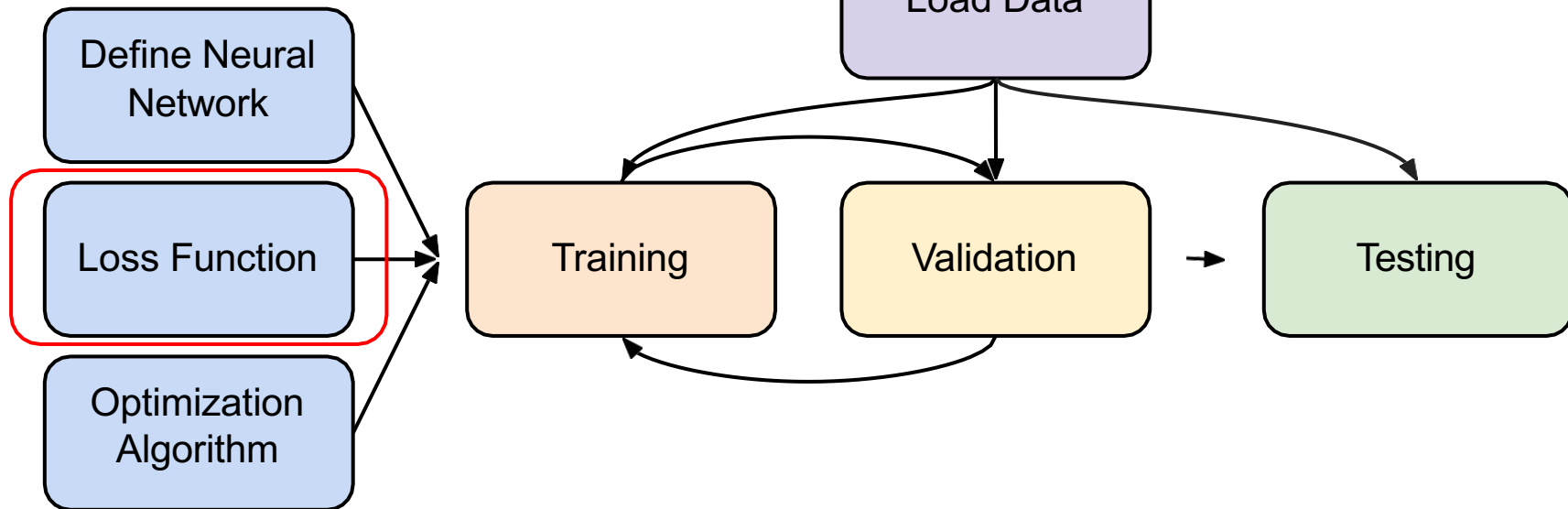
=

# 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()
```

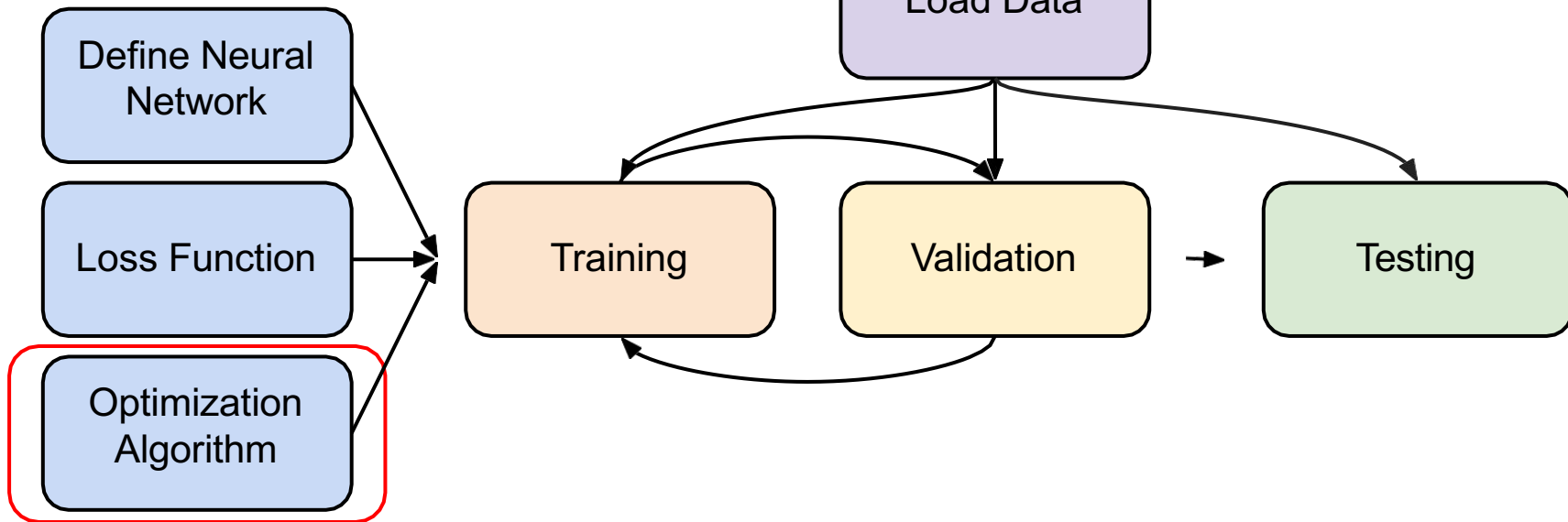
- Cross Entropy (for classification tasks)

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

- `loss = criterion(predicted_value, 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.

- E.g. Stochastic Gradient Descent (SGD)

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

# torch.optim

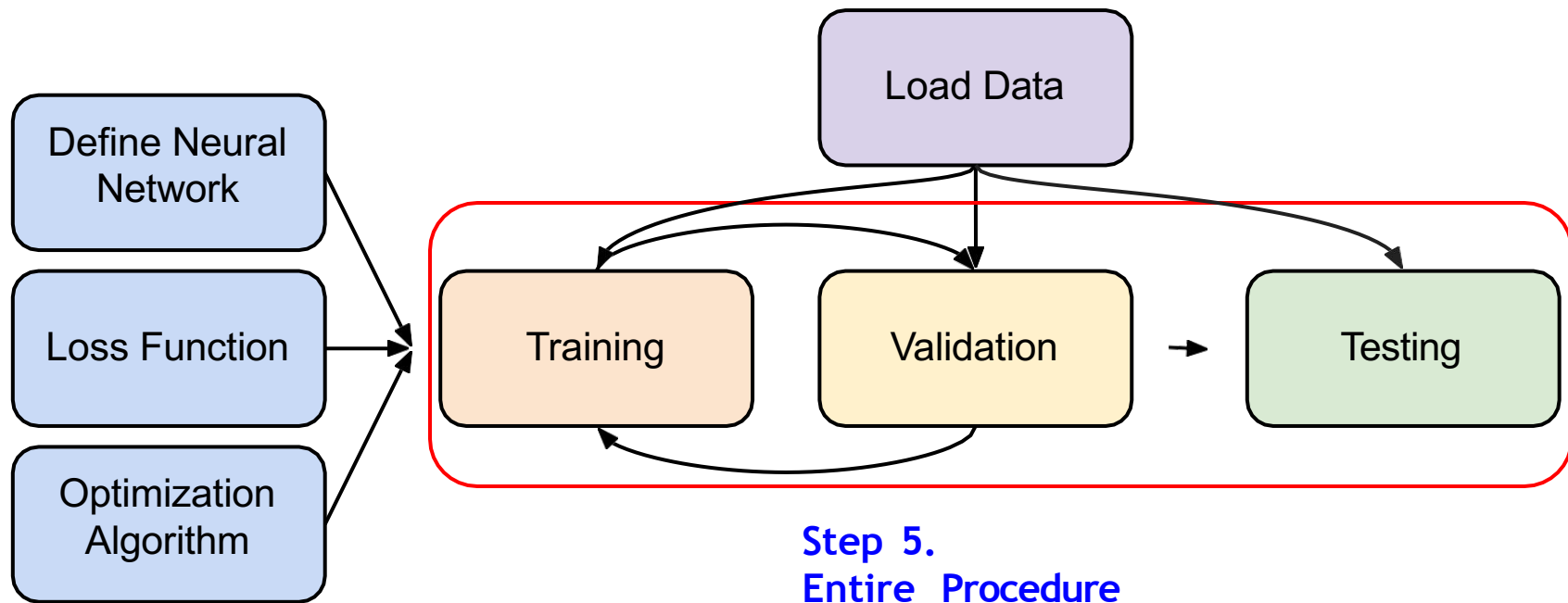
```
optimizer = torch.optim.SGD(model.parameters(), lr)
```

- 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

```
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):
```

```
    model.train()
```

```
    for x, y in tr_set:
```

```
        optimizer.zero_grad()
```

```
        x, y = x.to(device), y.to(device)
```

```
        pred = model(x)
```

```
        loss = criterion(pred, y)
```

```
        loss.backward()
```

```
        optimizer.step()
```

iterate n\_epochs

set model to train mode

iterate over data

set gradient to zero

move data to device (cpu/cuda)

forward pass (compute output)

compute loss

compute gradient (backpropagation)

update model with optimizer

# Neural Network Validation Loop

```
model.eval()
```

set model to evaluation mode

```
total_loss = 0
```

```
for x, y in val_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(val_set.dataset)
```

compute averaged loss

# Neural Network Testing Loop

```
model.eval()
```

set model to evaluation mode

```
preds = []
```

```
for x in test_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

## Note: `model.eval()`, `torch.no_grad()`

- **`model.eval()`**  
Changes behaviour of some model layers, such as dropout and batch normalization.
- **`with torch.no_grad()`**  
Prevents calculation of gradients. Set during validation/testing.

# Save/Load Trained Models

- Save

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

- Load

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

# More About PyTorch

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

# References

- [Official Pytorch Tutorials](#)
- <https://numpy.org/>



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# PyTorch Tutorial (2)

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## Common Errors

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# Common Errors — Tensor on Different Devices

```
model = torch.nn.Linear(5,1).to("cuda:0")
```

```
x = torch.randn(5)
```

```
y = model(x)
```

Error: Tensor ... is on CPU, but expected to be on GPU

=> send the tensor to GPU

```
x = torch.randn(5).to("cuda:0")
```

```
y = model(x)
```

```
print(y.shape)
```

# Common Errors – Mismatched Dimensions

```
x = torch.randn(4,5)
```

```
y = torch.randn(5,4)
```

```
z = x + y
```

The size of tensor x (5) must match the size of tensor y (4) at non-singleton dimension 1

the shape of a tensor is incorrect

=> use **transpose, squeeze, unsqueeze** to align the dimensions

```
y = y.transpose(0,1)
```

```
z = x + y
```

```
print(z.shape)
```

# Common Errors - Cuda Out of Memory

```
import torch
import torchvision.models as models
resnet18 = models.resnet18().to( "cuda:0" ) # Neural Networks for Image
data = torch.randn( 512,3,244,244) # Create fake data (512
out = resnet18(data.to( "cuda:0" )) # Use Data as Input and Feed to
print(out.shape)
```

**CUDA out of memory. Tried to allocate 350.00 MiB (GPU 0; 14.76 GiB total capacity; 11.94 GiB already allocated; 123.75 MiB free; 13.71 GiB reserved in total by PyTorch)**

- => The batch size of data is too large to fit in the GPU. Reduce the batch size.
- ⇒ If even batch size=1 still has this error, reduce model size
- ⇒ If error persists, consider buying a better GPU 😊

# Common Errors – Mismatched Tensor Type

```
import torch.nn as nn
L = nn.CrossEntropyLoss()
preds = torch.randn(5,5)
labels = torch.Tensor([1,2,3,4,0])
lossval = L(preds, labels) # Calculate CrossEntropyLoss between preds and labels
```

**expected scalar type Long but found Float**

=> labels must be long tensors, cast it to type “Long” to fix this issue

```
labels = labels.long()
lossval = L(preds, labels)
print(lossval)
```



## Coding Demo:

[1\\_mlp\\_Day1.ipynb](#)

2\_cnn\_Day1.ipynb

3\_transfer\_Day1.ipynb

4\_save\_load\_Day1.ipynb

5\_PINNs\_Day1.ipynb