AI VIETNAM
All-in-One Course

Multi-layer Perception

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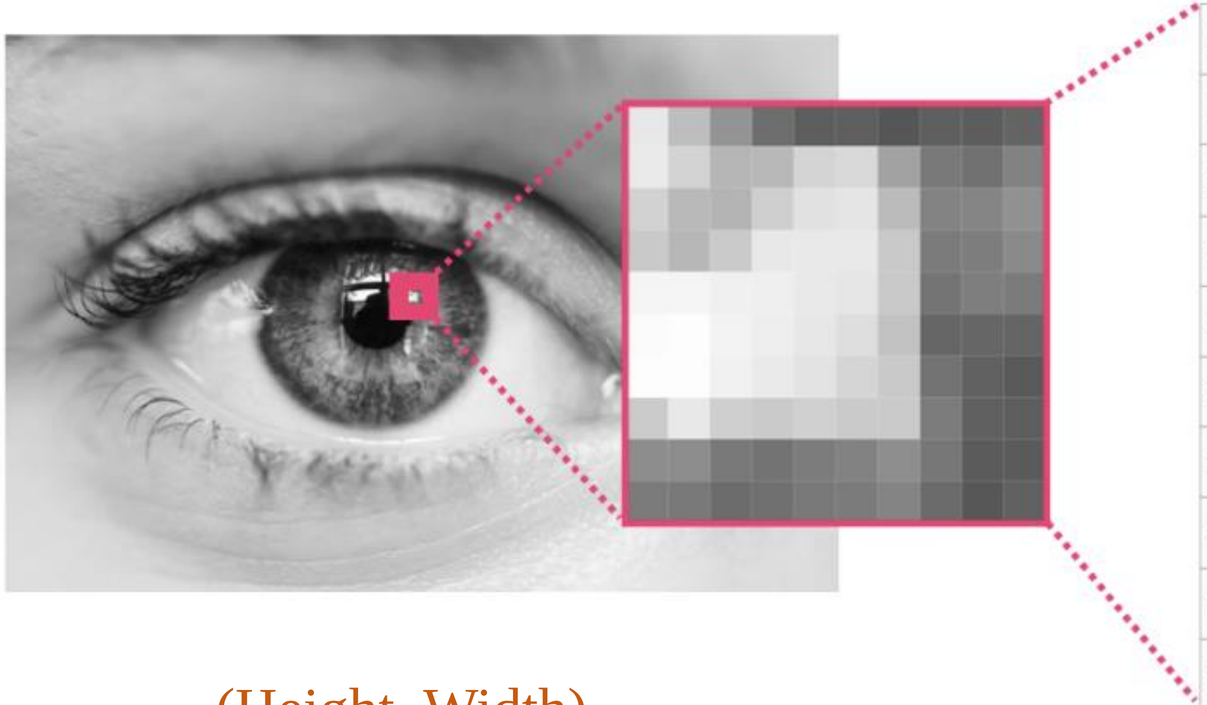
Ph.D. in Computer Science

Outline

- Image Data Loading Using Numpy&PyTorch
- Softmax+Normalization for Fashion-MNIST
- MLP and Examples
- Step-by-Step Implementation
- Training Strategy (optional)

Image Classification: Image Data

❖ Grayscale images



230	194	147	108	90	98	84	96	91	101
237	206	188	195	207	213	163	123	116	128
210	183	180	205	224	234	188	122	134	147
198	189	201	227	229	232	200	125	127	135
249	241	237	244	232	226	202	116	125	126
251	254	241	239	230	217	196	102	103	99
243	255	240	231	227	214	203	116	95	91
204	231	208	200	207	201	200	121	95	95
144	140	120	115	125	127	143	118	92	91
121	121	108	109	122	121	134	106	86	97

(Height, Width)

Pixel p = scalar

$0 \leq p \leq 255$

Resolution: #pixels
Resolution = HeightxWidth

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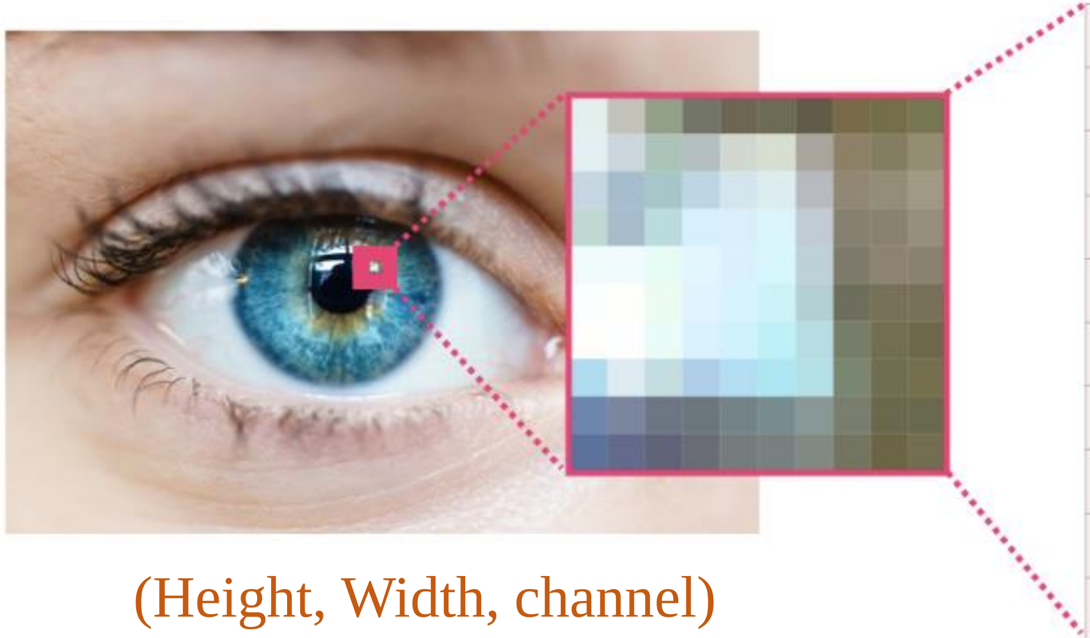
Image Classification: Image Data

❖ Color images



233	188	137	96	90	95	63	73	73	82
									109
									131
									122
									115
									87
									74
									74
									74
									82

237	202	159	120	105	110	88	107	112	121
									142
									155
									140
									133
									111
									107
									113
									105
									113

226	191	147	110	101	112	98	123	110	119
221	191	176	182	203	214	169	144	133	145
185	160	161	184	205	223	186	137	147	161
181	174	189	207	206	215	194	136	142	151
246	237	237	231	208	206	192	122	143	144
254	254	241	224	199	192	181	99	122	117
239	248	232	207	187	182	184	110	114	110
193	215	193	167	158	164	181	114	112	111
113	119	110	111	113	123	135	120	108	106
93	97	91	103	107	111	122	112	104	114

(Height, Width, channel)

RGB color image

Pixel $p=\begin{bmatrix} r \\ g \\ b \end{bmatrix}$

$0 \leq r,g,b \leq 255$

Resolution: #pixels

Resolution = HeightxWidth

Important Packages

❖ Some functions

To download a file

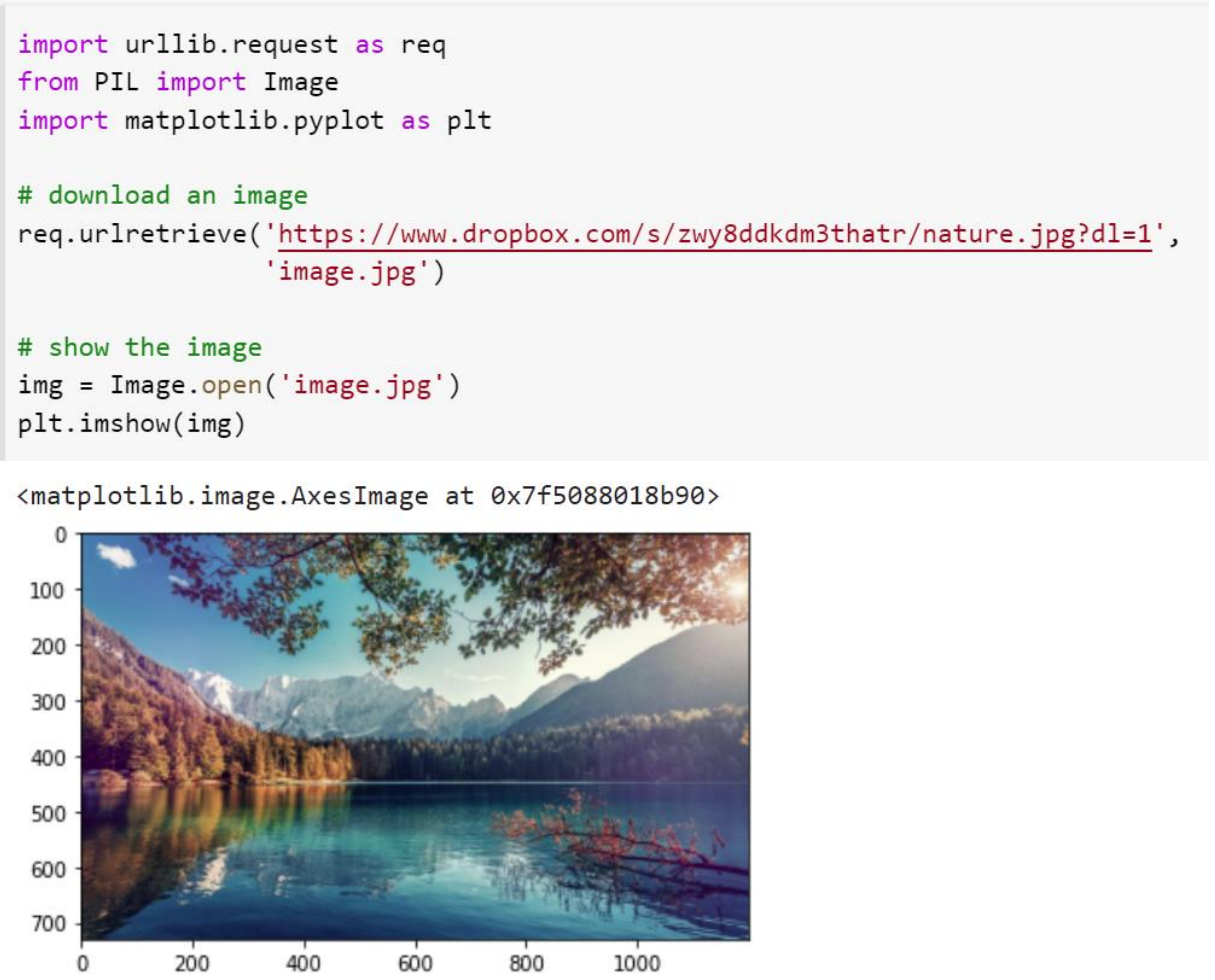
import urllib.request as req
req.urlretrieve(url, name)

To open an image

from PIL import Image
img = Image.open(name)

To show an image

import matplotlib.pyplot as plt
plt.imshow(img)



```
import urllib.request as req
from PIL import Image
import matplotlib.pyplot as plt

# download an image
req.urlretrieve('https://www.dropbox.com/s/zwy8ddkdm3thatr/nature.jpg?dl=1',
                'image.jpg')

# show the image
img = Image.open('image.jpg')
plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x7f5088018b90>
```

Image Data

MNIST dataset

Grayscale images

Resolution=28x28

Training set: 60000 samples

Testing set: 10000 samples

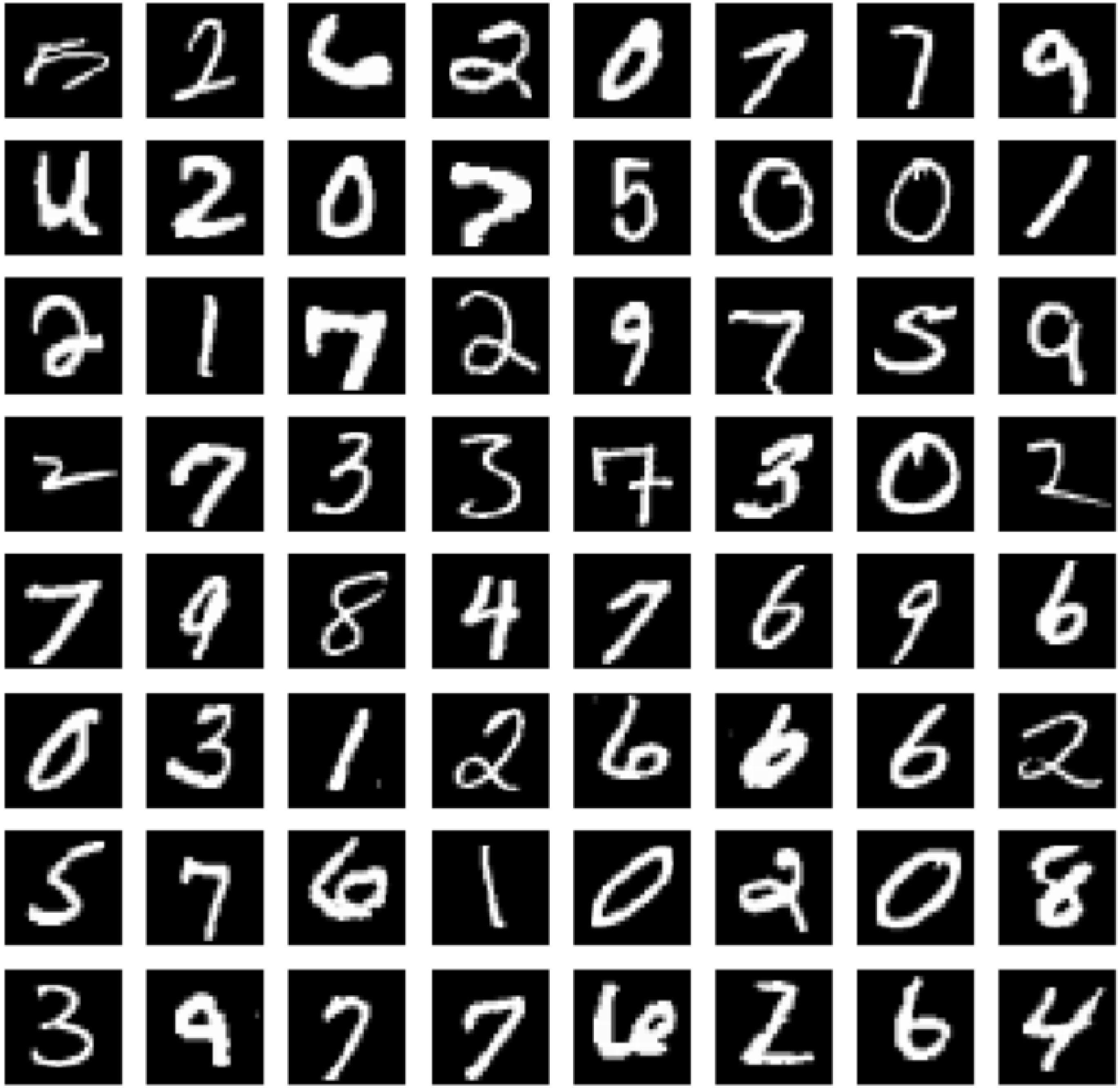


Image Data

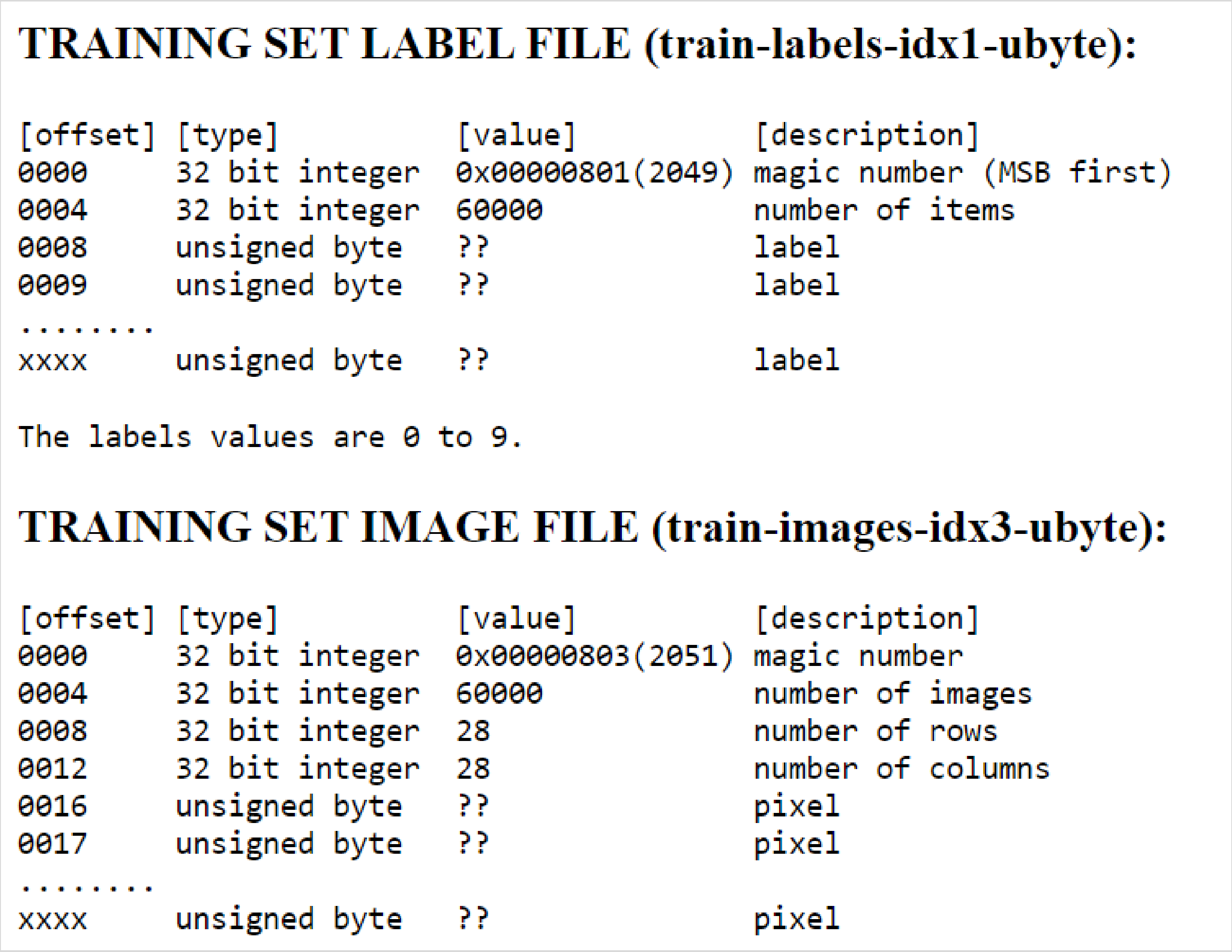
MNIST dataset

Grayscale images

Resolution=28x28

Training set: 60000 samples

Testing set: 10000 samples



TRAINING SET LABEL FILE (train-labels-idx1-ubyte):

```
[offset] [type]          [value]          [description]
0000     32 bit integer  0x00000801(2049) magic number (MSB first)
0004     32 bit integer  60000            number of items
0008     unsigned byte   ??               label
0009     unsigned byte   ??               label
........
xxxx     unsigned byte   ??               label

The labels values are 0 to 9.
```

TRAINING SET IMAGE FILE (train-images-idx3-ubyte):

```
[offset] [type]          [value]          [description]
0000     32 bit integer  0x00000803(2051) magic number
0004     32 bit integer  60000            number of images
0008     32 bit integer  28               number of rows
0012     32 bit integer  28               number of columns
0016     unsigned byte   ??               pixel
0017     unsigned byte   ??               pixel
........
xxxx     unsigned byte   ??               pixel
```

http://yann.lecun.com/exdb/mnist/

Image Data

Fashion-MNIST dataset

Grayscale images

Resolution=28x28

Training set: 60000 samples

Testing set: 10000 samples

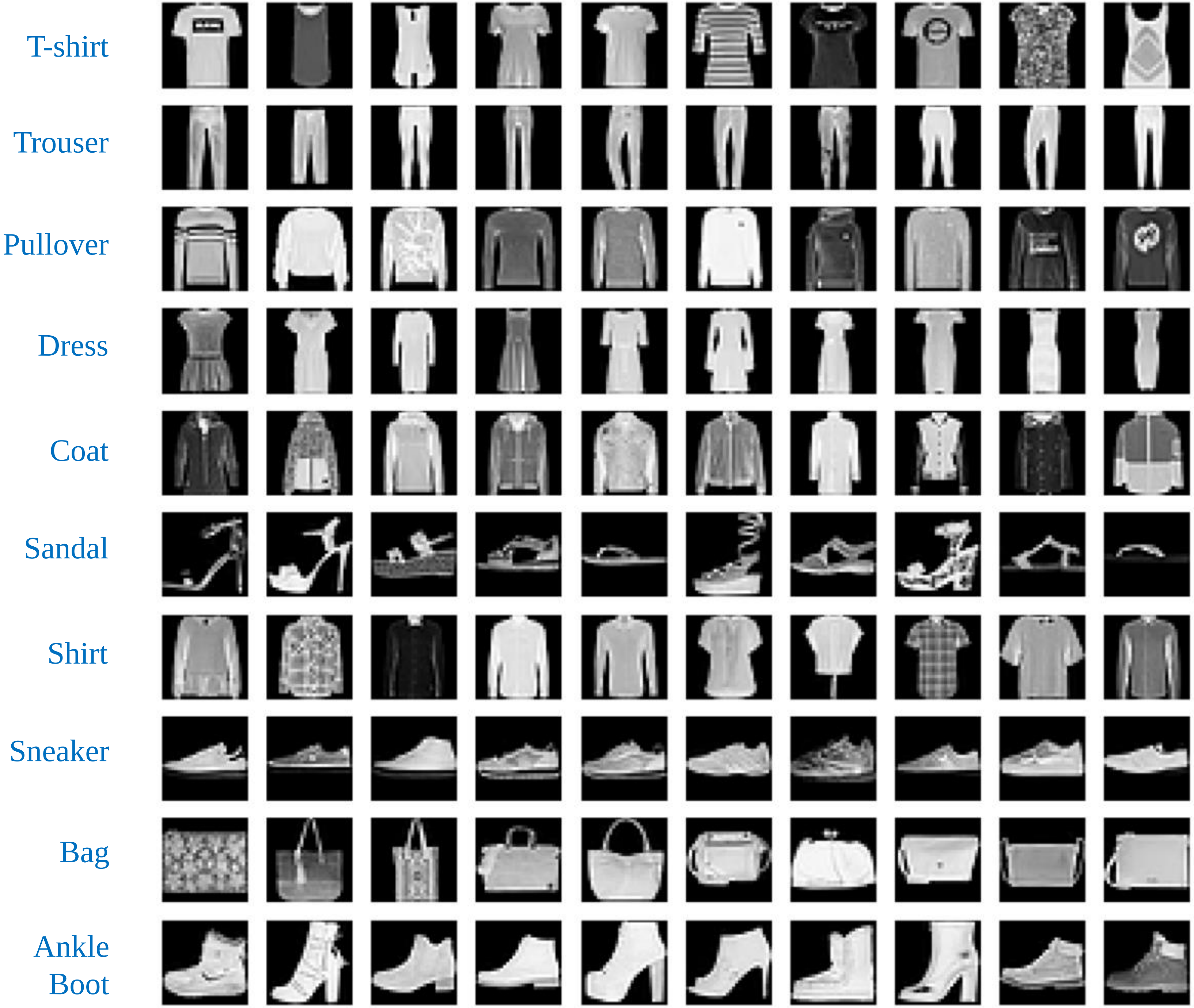
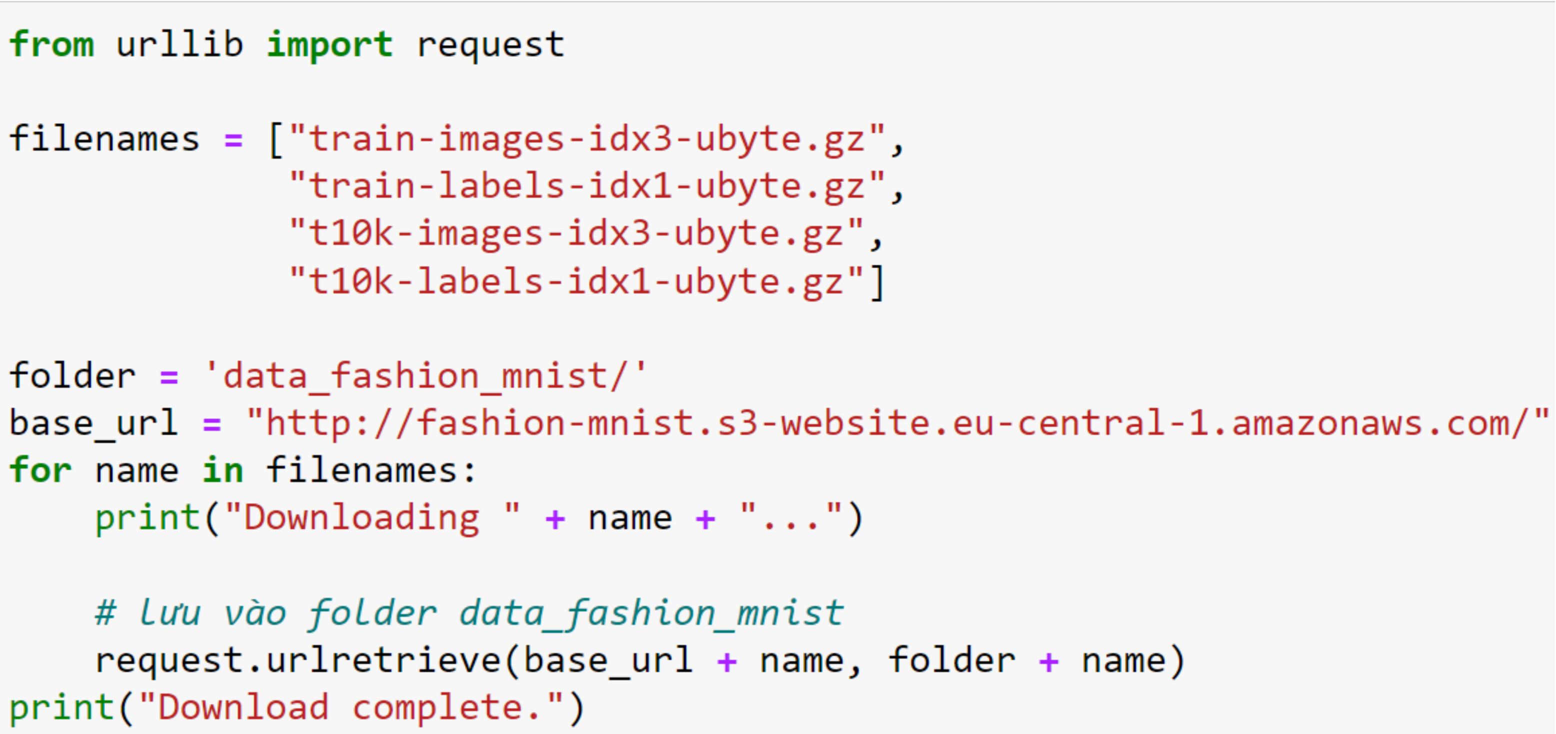


Image Classification

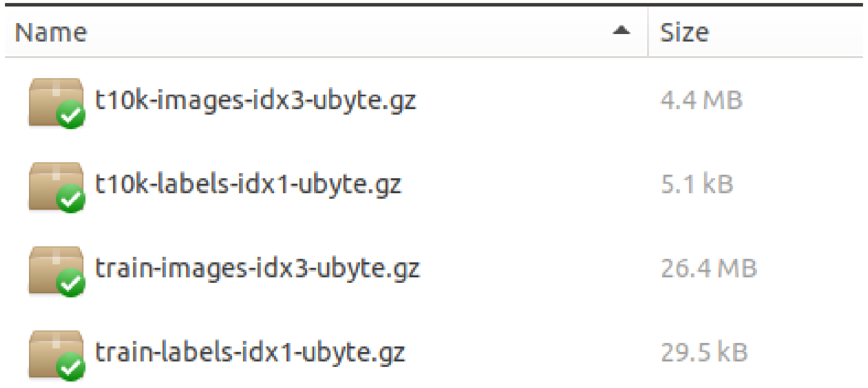
Fashion-MNIST dataset

- Grayscale images
- Resolution=28x28
- Training set: 60000 samples
- Testing set: 10000 samples



```python
from urllib import request

filenames = ["train-images-idx3-ubyte.gz",
             "train-labels-idx1-ubyte.gz",
             "t10k-images-idx3-ubyte.gz",
             "t10k-labels-idx1-ubyte.gz"]

folder = 'data_fashion_mnist/'
base_url = "http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/"
for name in filenames:
    print("Downloading " + name + "...")

    # lưu vào folder data_fashion_mnist
    request.urlretrieve(base_url + name, folder + name)
print("Download complete.")
```

Download data



Name	Size
t10k-images-idx3-ubyte.gz	4.4 MB
t10k-labels-idx1-ubyte.gz	5.1 kB
train-images-idx3-ubyte.gz	26.4 MB
train-labels-idx1-ubyte.gz	29.5 kB

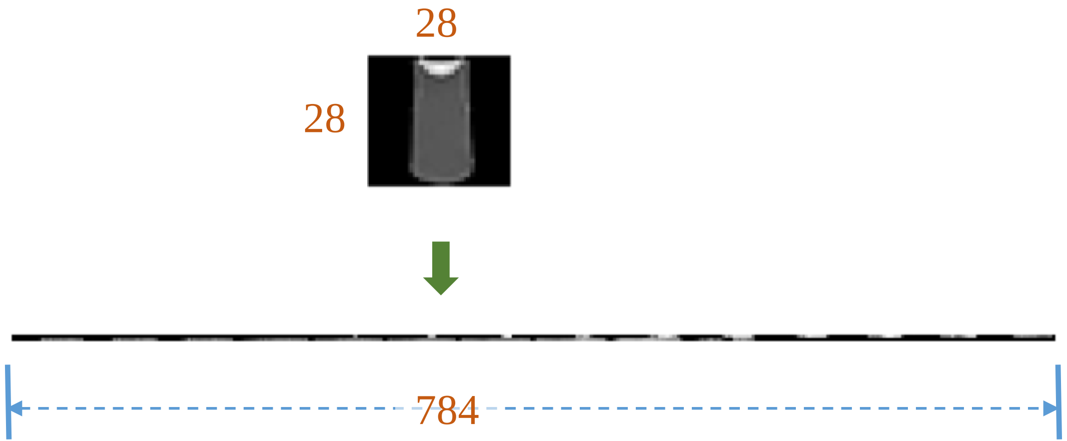
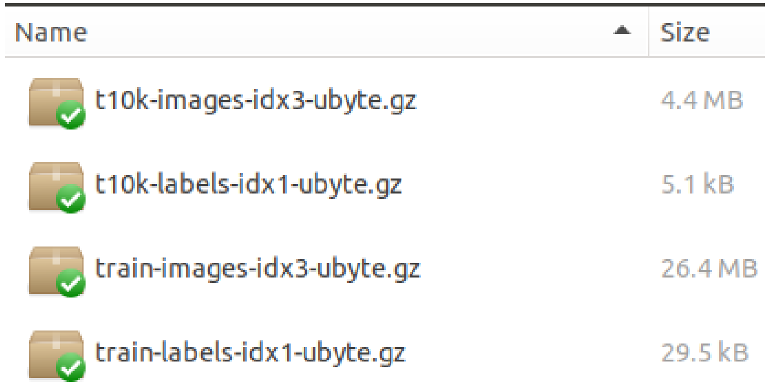


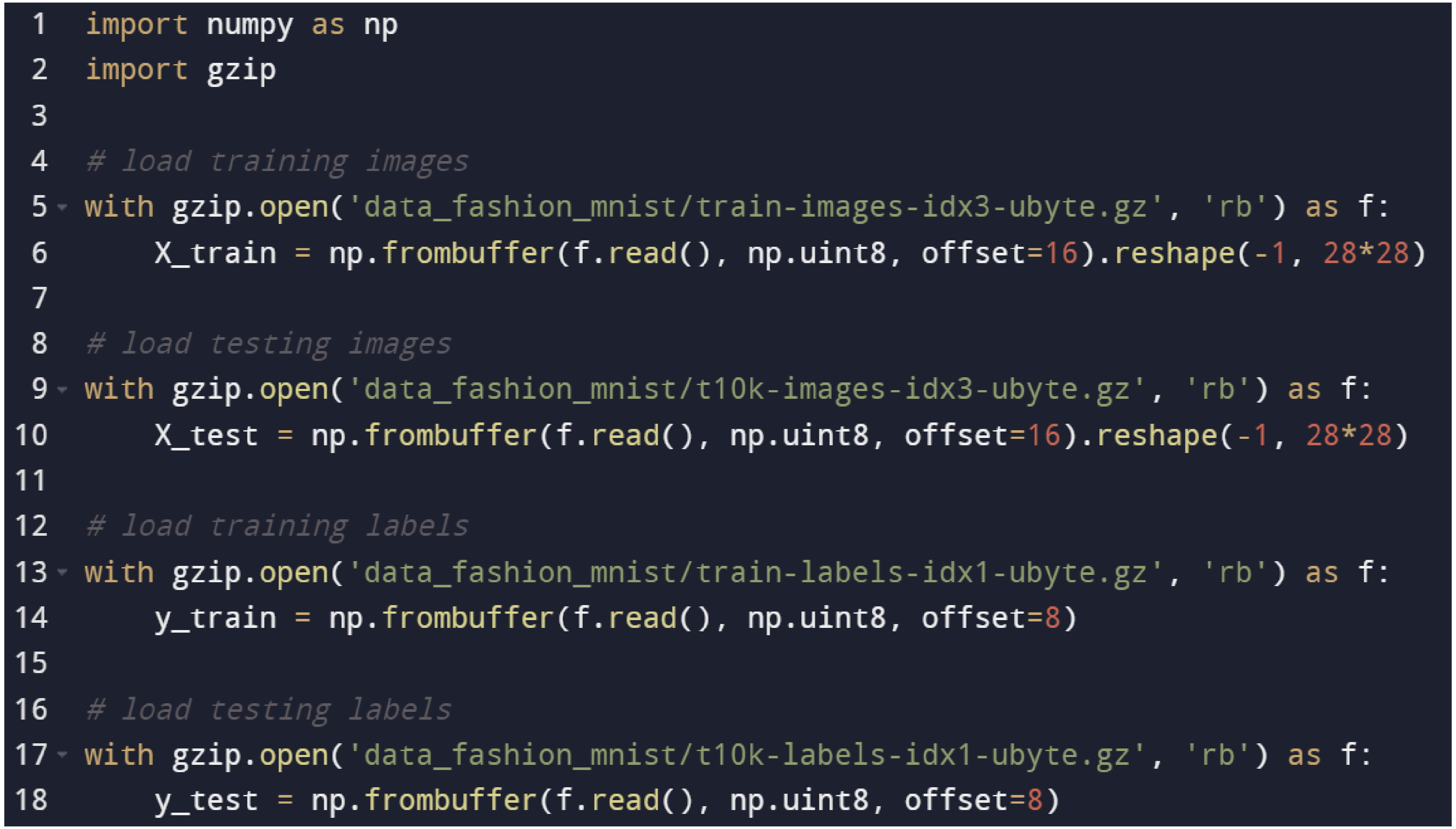
Image Data

Fashion-MNIST data

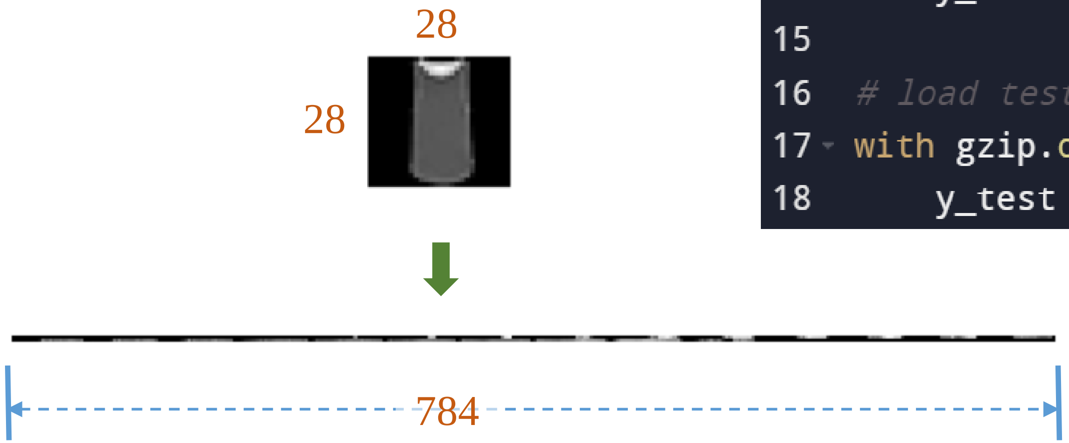
Download data

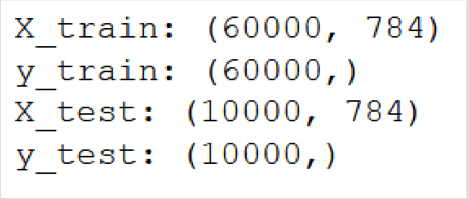


Name	Size
t10k-images-idx3-ubyte.gz	4.4 MB
t10k-labels-idx1-ubyte.gz	5.1 kB
train-images-idx3-ubyte.gz	26.4 MB
train-labels-idx1-ubyte.gz	29.5 kB



```python
import numpy as np
import gzip

# load training images
with gzip.open('data_fashion_mnist/train-images-idx3-ubyte.gz', 'rb') as f:
    X_train = np.frombuffer(f.read(), np.uint8, offset=16).reshape(-1, 28*28)

# load testing images
with gzip.open('data_fashion_mnist/t10k-images-idx3-ubyte.gz', 'rb') as f:
    X_test = np.frombuffer(f.read(), np.uint8, offset=16).reshape(-1, 28*28)

# load training labels
with gzip.open('data_fashion_mnist/train-labels-idx1-ubyte.gz', 'rb') as f:
    y_train = np.frombuffer(f.read(), np.uint8, offset=8)

# load testing labels
with gzip.open('data_fashion_mnist/t10k-labels-idx1-ubyte.gz', 'rb') as f:
    y_test = np.frombuffer(f.read(), np.uint8, offset=8)
```



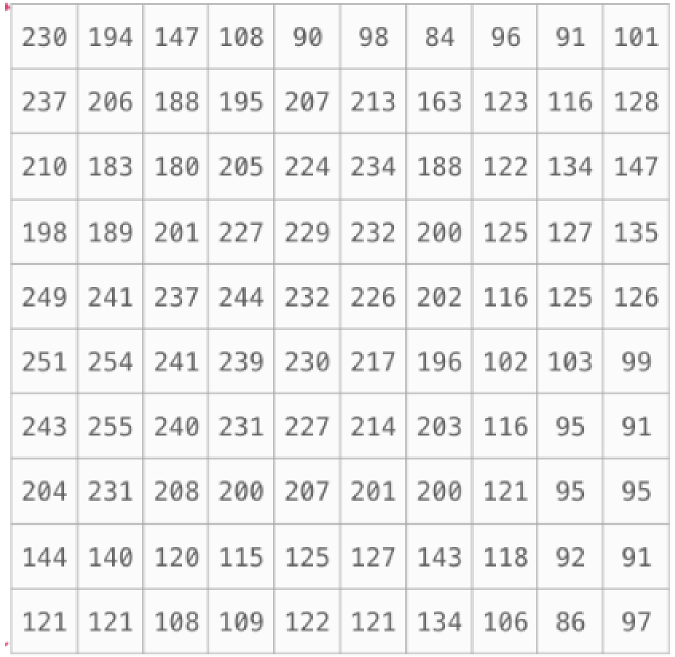


```
X_train: (60000, 784)
y_train: (60000,)
X_test: (10000, 784)
y_test: (10000,)
```

Demo

Image Data

❖ Using Pytorch



230	194	147	108	90	98	84	96	91	101
237	206	188	195	207	213	163	123	116	128
210	183	180	205	224	234	188	122	134	147
198	189	201	227	229	232	200	125	127	135
249	241	237	244	232	226	202	116	125	126
251	254	241	239	230	217	196	102	103	99
243	255	240	231	227	214	203	116	95	91
204	231	208	200	207	201	200	121	95	95
144	140	120	115	125	127	143	118	92	91
121	121	108	109	122	121	134	106	86	97

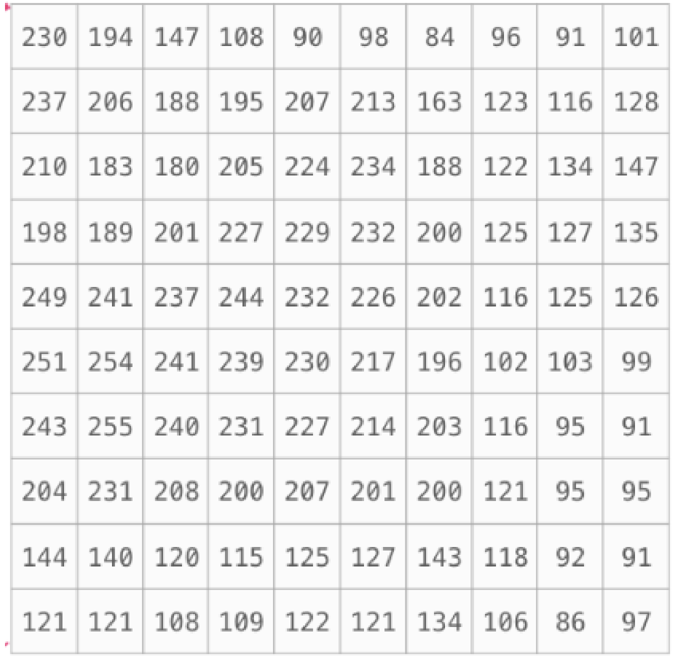
data
(ndarray, tensor)

Size

…

Mode

…



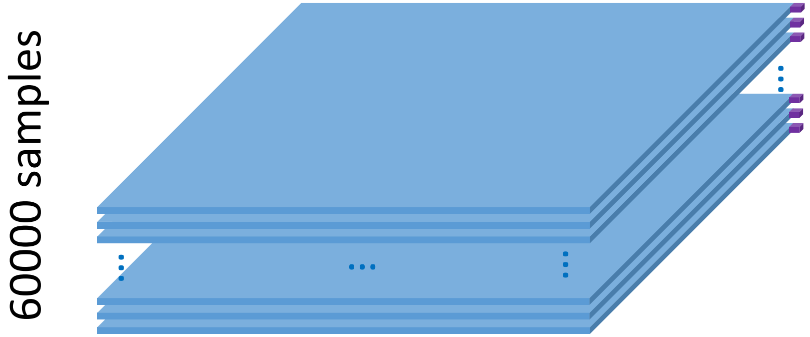
230	194	147	108	90	98	84	96	91	101
237	206	188	195	207	213	163	123	116	128
210	183	180	205	224	234	188	122	134	147
198	189	201	227	229	232	200	125	127	135
249	241	237	244	232	226	202	116	125	126
251	254	241	239	230	217	196	102	103	99
243	255	240	231	227	214	203	116	95	91
204	231	208	200	207	201	200	121	95	95
144	140	120	115	125	127	143	118	92	91
121	121	108	109	122	121	134	106	86	97

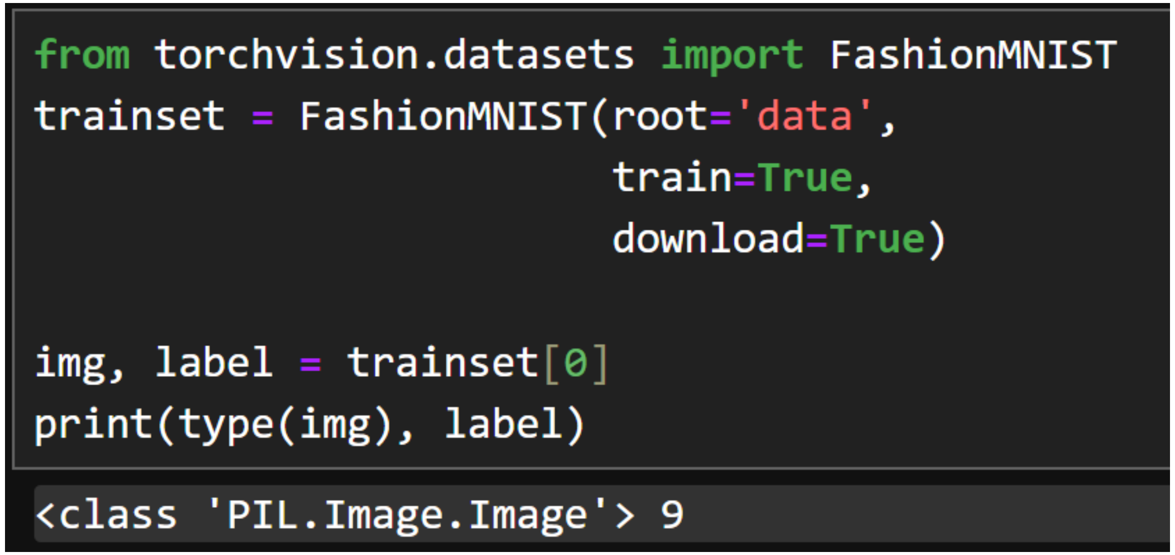
data
(ndarray, tensor)

Fashion MNIST

❖ Using Pytorch

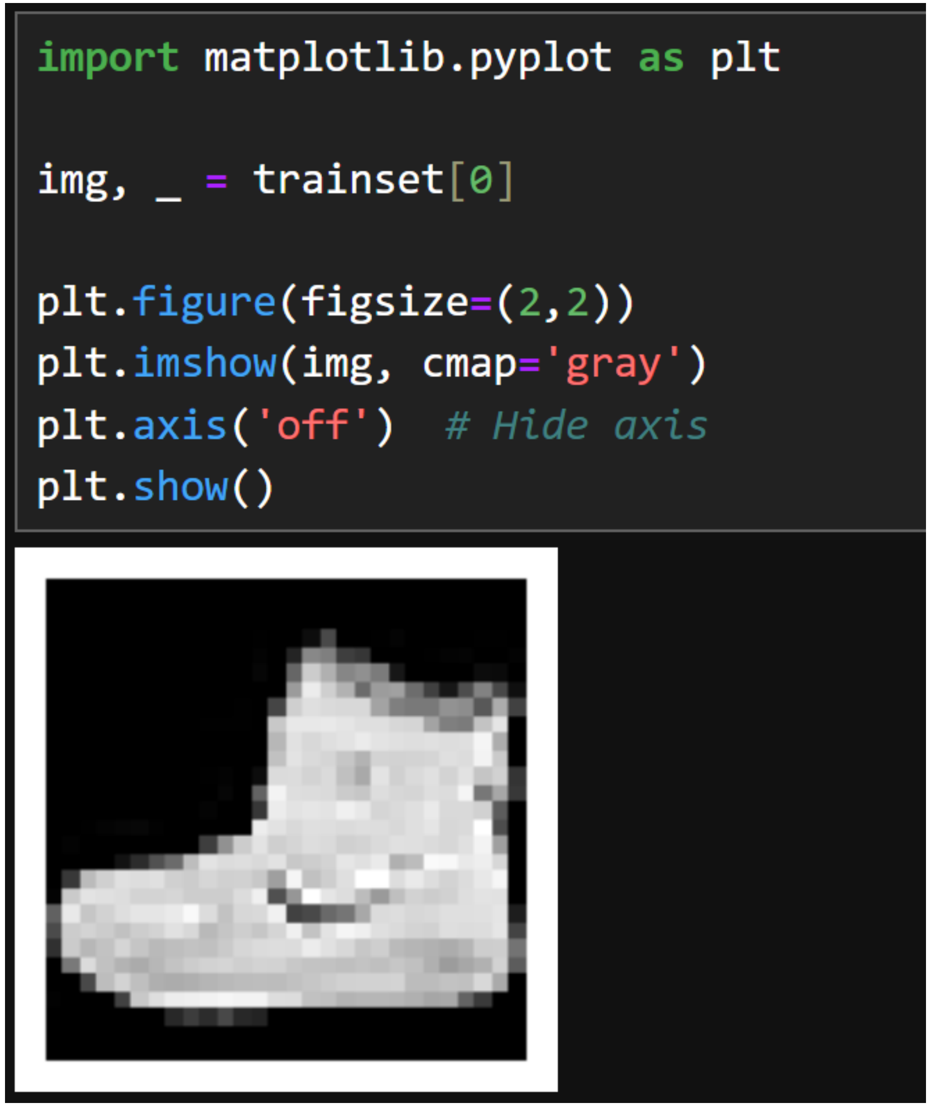
Each sample is a tuple (PIL image, label)





```python
from torchvision.datasets import FashionMNIST
trainset = FashionMNIST(root='data',
                        train=True,
                        download=True)


img, label = trainset[0]
print(type(img), label)
```

```
<class 'PIL.Image.Image'> 9
```

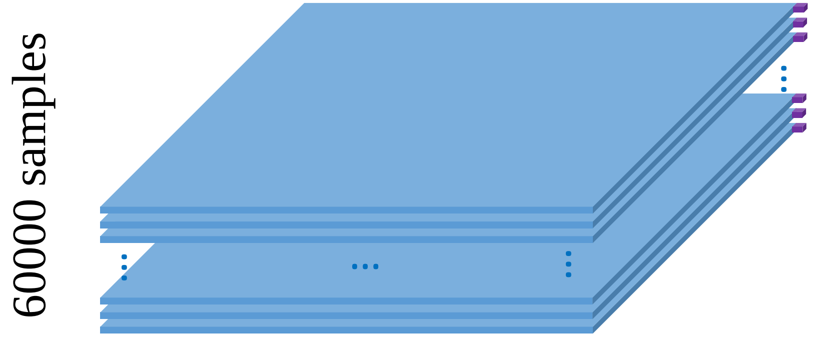


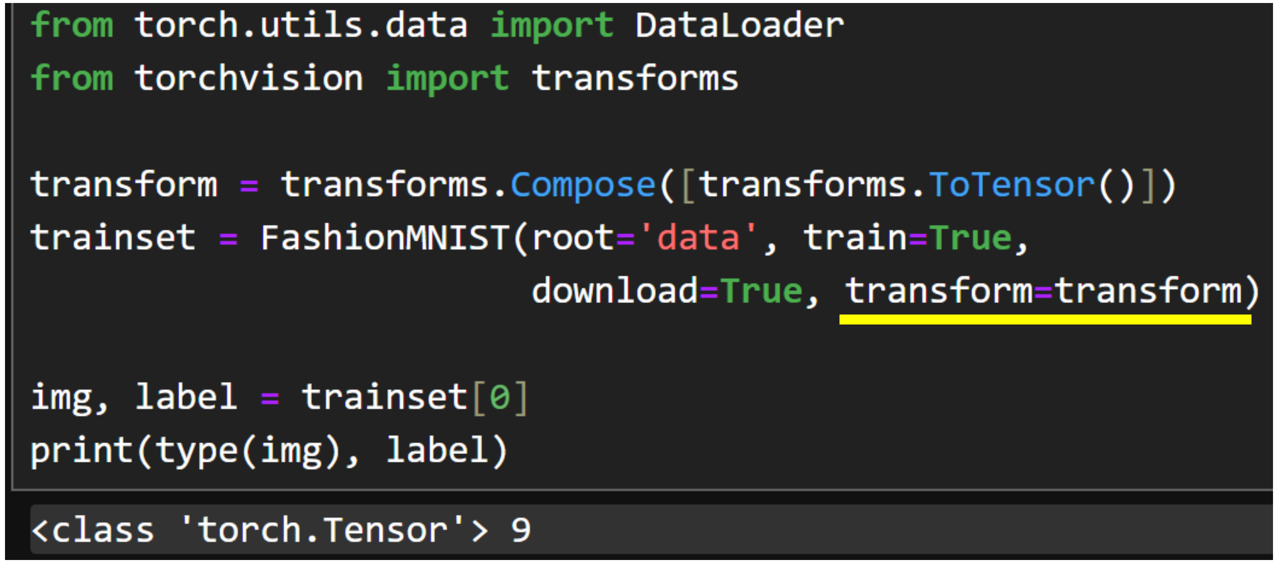
```python
import matplotlib.pyplot as plt

img, _ = trainset[0]

plt.figure(figsize=(2,2))
plt.imshow(img, cmap='gray')
plt.axis('off')  # Hide axis
plt.show()
```

Fashion MNIST

❖ Using Pytorch

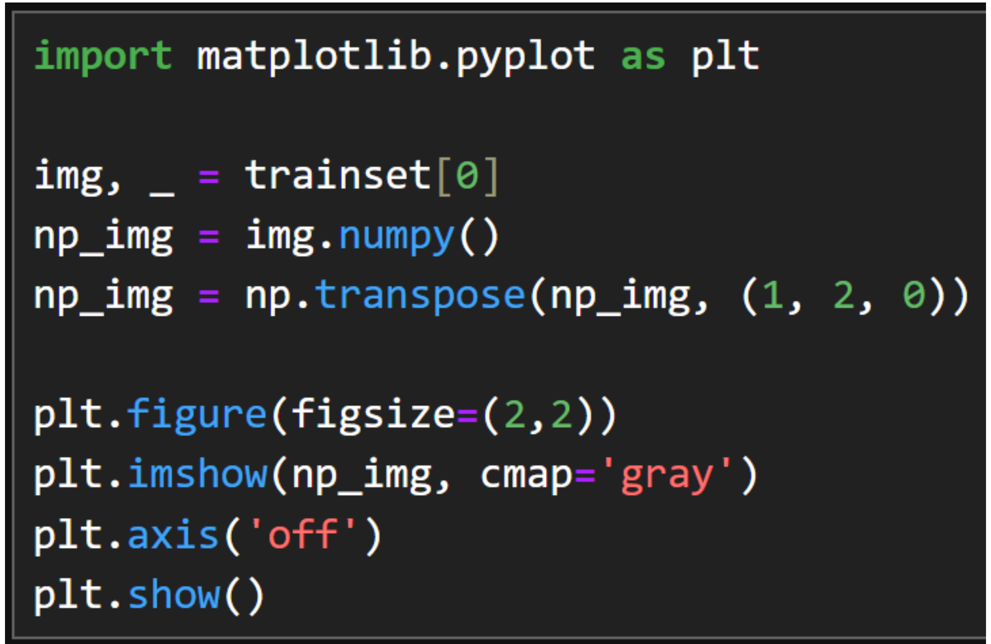
Each sample is a tuple (image tensor, label)



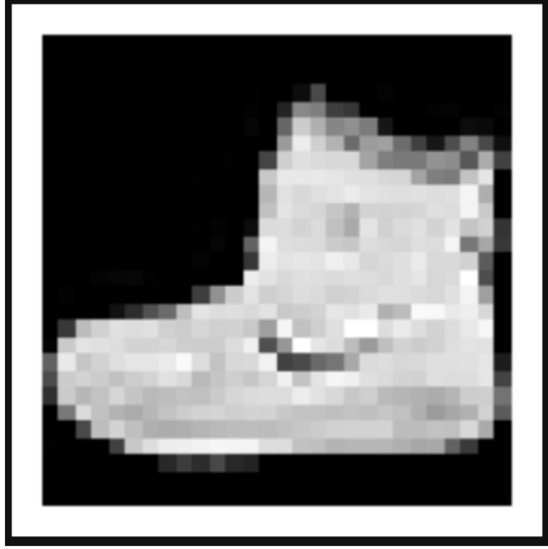


```
from torch.utils.data import DataLoader
from torchvision import transforms

transform = transforms.Compose([transforms.ToTensor()])
trainset = FashionMNIST(root='data', train=True,
                        download=True, transform=transform)

img, label = trainset[0]
print(type(img), label)
```

```
<class 'torch.Tensor'> 9
```



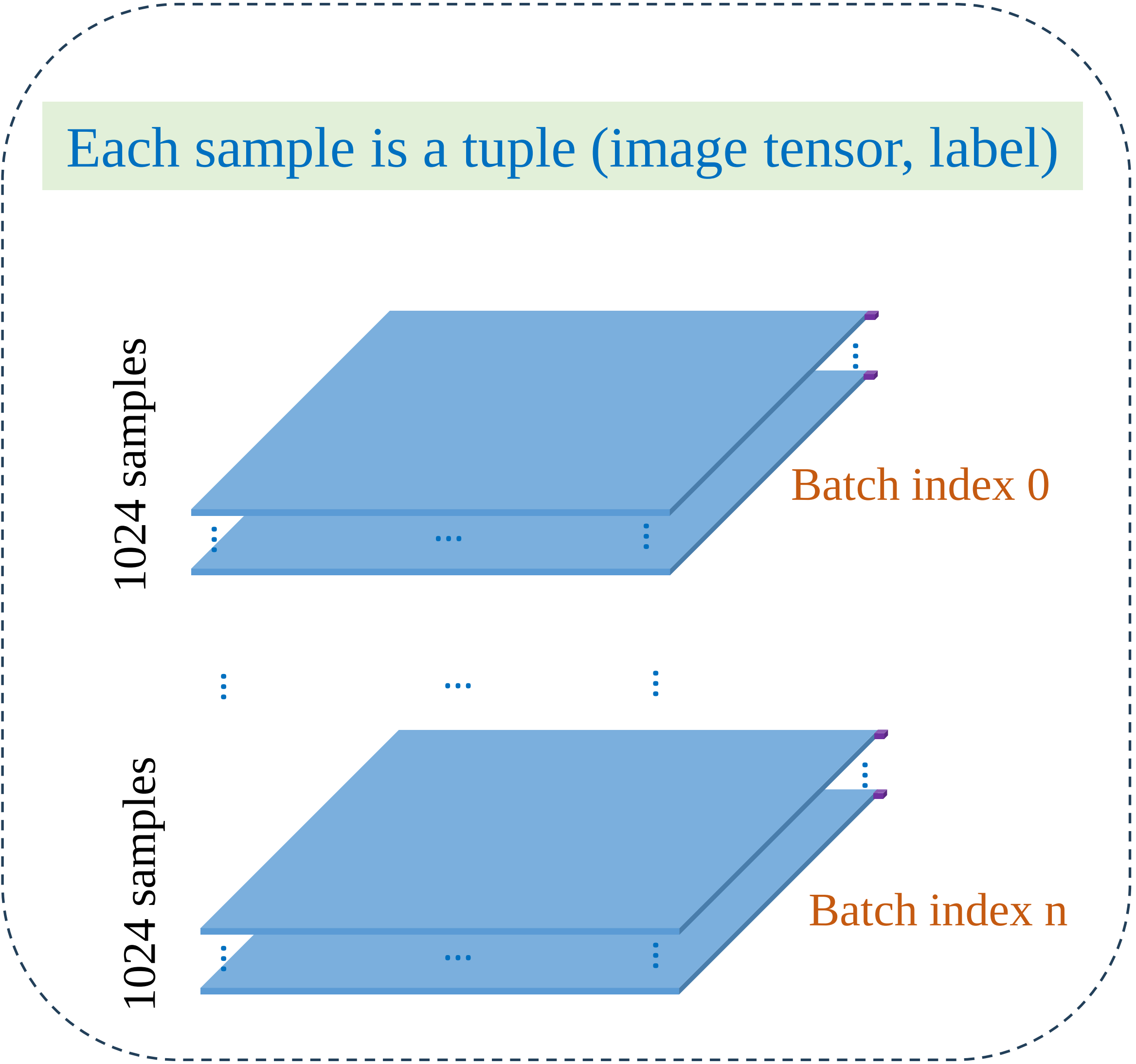
```
import matplotlib.pyplot as plt

img, _ = trainset[0]
np_img = img.numpy()
np_img = np.transpose(np_img, (1, 2, 0))

plt.figure(figsize=(2,2))
plt.imshow(np_img, cmap='gray')
plt.axis('off')
plt.show()
```



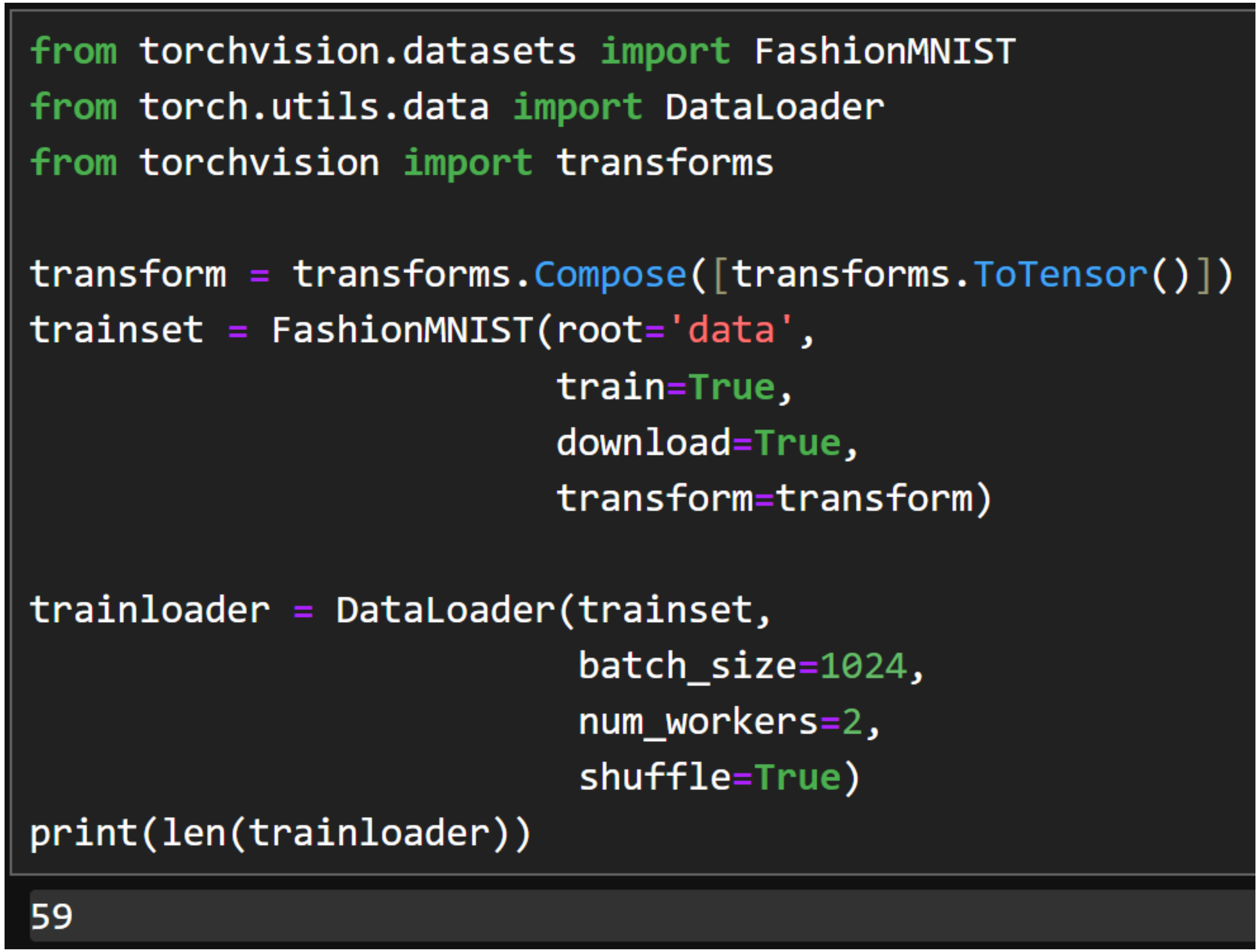
Fashion MNIST

approximately

❖ Using Pytorch



Each sample is a tuple (image tensor, label)

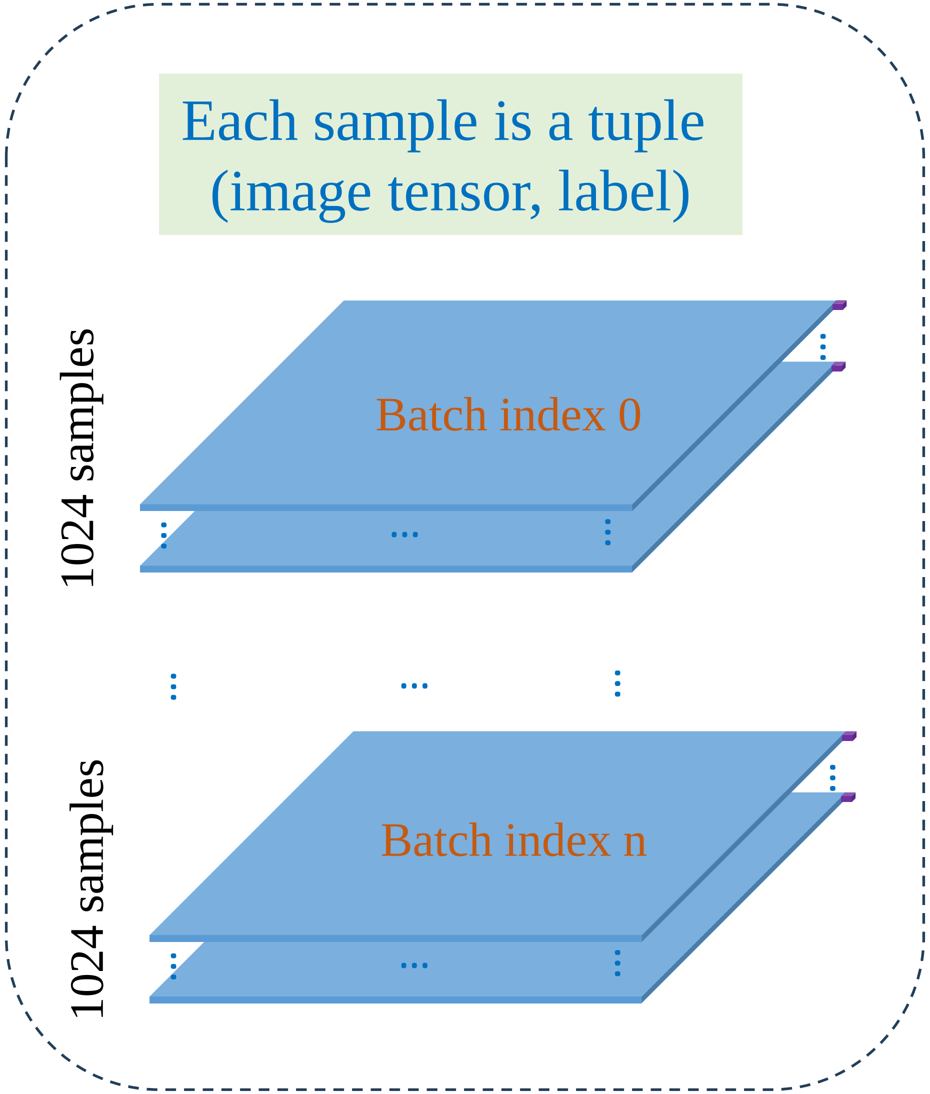


```python
from torchvision.datasets import FashionMNIST
from torch.utils.data import DataLoader
from torchvision import transforms

transform = transforms.Compose([transforms.ToTensor()])
trainset = FashionMNIST(root='data',
                        train=True,
                        download=True,
                        transform=transform)

trainloader = DataLoader(trainset,
                         batch_size=1024,
                         num_workers=2,
                         shuffle=True)
print(len(trainloader))
```

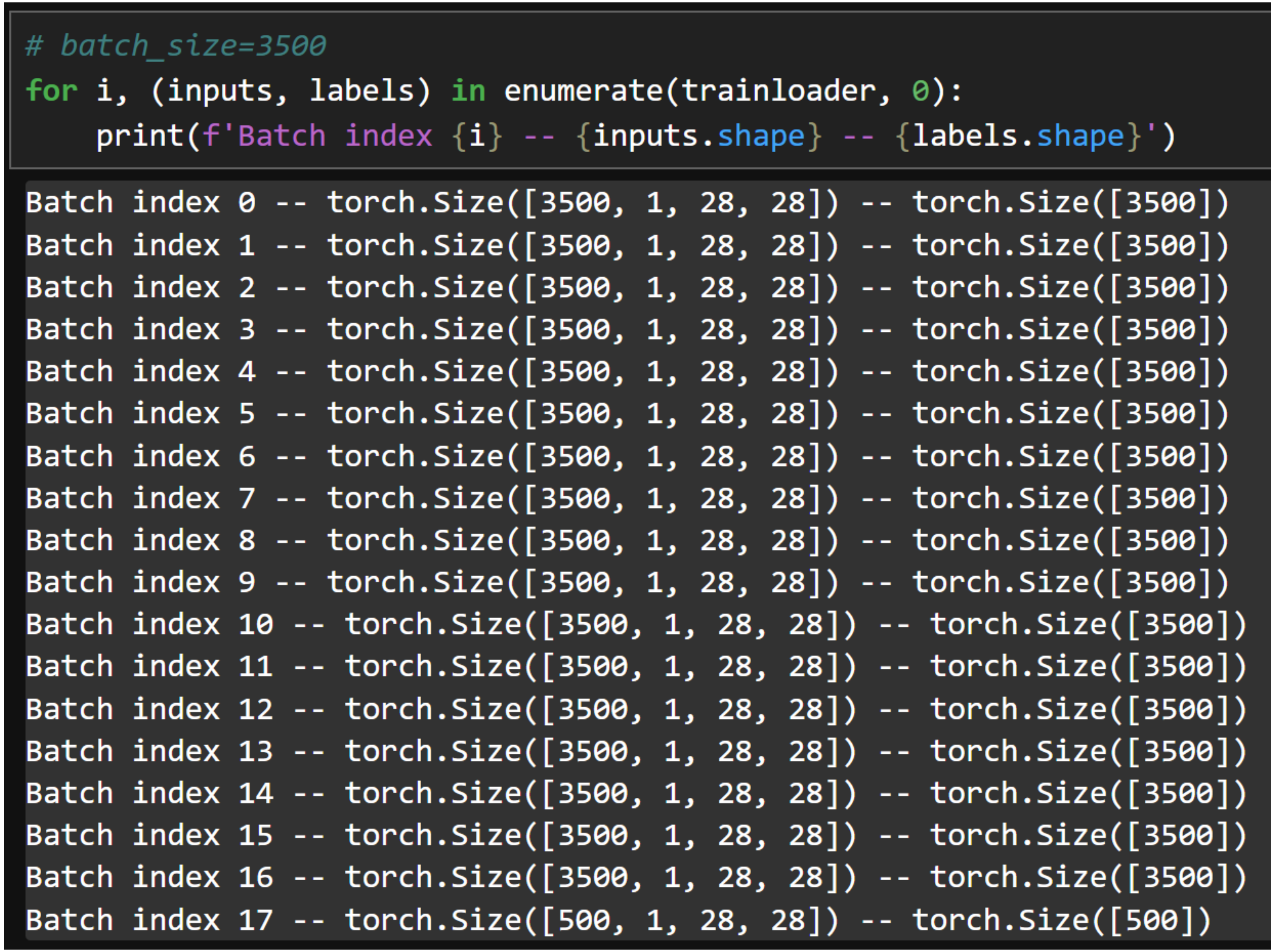
```
59
```

Fashion MNIST

❖ Using Pytorch



Each sample is a tuple (image tensor, label)



```python
# batch_size=3500
for i, (inputs, labels) in enumerate(trainloader, 0):
    print(f'Batch index {i} -- {inputs.shape} -- {labels.shape}')
```

```
Batch index 0 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 1 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 2 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 3 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 4 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 5 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 6 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 7 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 8 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 9 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 10 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 11 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 12 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 13 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 14 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 15 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 16 -- torch.Size([3500, 1, 28, 28]) -- torch.Size([3500])
Batch index 17 -- torch.Size([500, 1, 28, 28]) -- torch.Size([500])
```

Outline

- Image Data Loading Using Numpy&PyTorch
- Softmax+Normalization for Fashion-MNIST
- MLP and Examples
- Step-by-Step Implementation
- Training Strategy (optional)

Softmax Regression

Petal_Length	Label
1.4	0
1.3	0
1.5	0
4.5	1
4.1	1
4.6	1

$$\boldsymbol{x} = \begin{bmatrix} 1 \\ x \end{bmatrix}$$

$$\boldsymbol{\theta} = \begin{bmatrix} b_0 & b_1 \\ w_0 & w_1 \end{bmatrix}$$

One-hot encoding for label

$$\begin{array}{l} \phantom{y = 0 \rightarrow \boldsymbol{y}^T = [}\, y_0 \;\;\; y_1 \\ y = 0 \rightarrow \boldsymbol{y}^T = [1 \;\;\; 0] \\ y = 1 \rightarrow \boldsymbol{y}^T = [0 \;\;\; 1] \end{array}$$

scalar

vector

$$z_0 = xw_0 + b_0$$

$$z_1 = xw_1 + b_1$$

$$\hat{y}_0 = \frac{e^{z_0}}{\sum_{j=0}^{1} e^{z_j}}$$

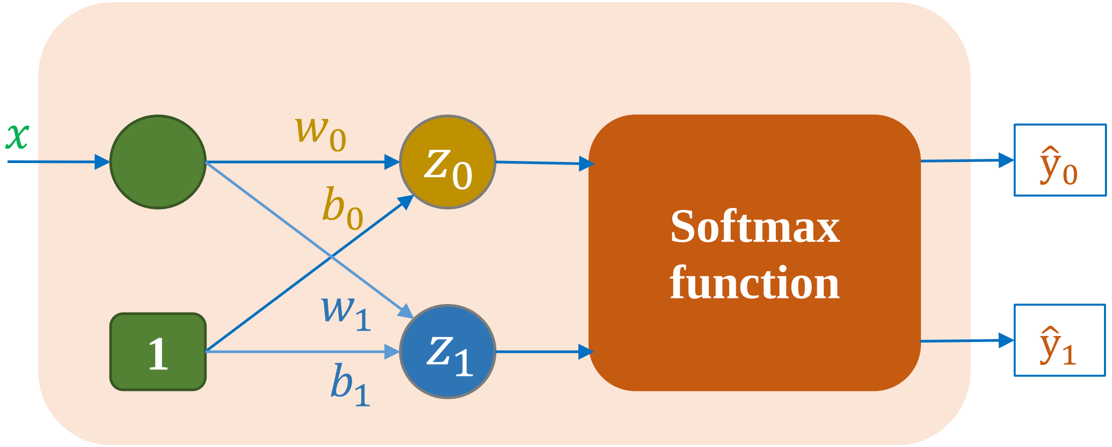
$$\hat{y}_1 = \frac{e^{z_1}}{\sum_{j=0}^{1} e^{z_j}}$$

$$\boldsymbol{z} = \begin{bmatrix} z_0 \\ z_1 \end{bmatrix} = \begin{bmatrix} b_0 & w_0 \\ b_1 & w_1 \end{bmatrix} \begin{bmatrix} 1 \\ x \end{bmatrix} = \begin{bmatrix} \boldsymbol{\theta}_0^T \\ \boldsymbol{\theta}_1^T \end{bmatrix} \begin{bmatrix} 1 \\ x \end{bmatrix} = \boldsymbol{\theta}^T \boldsymbol{x}$$

$$\hat{\mathbf{y}} = \begin{bmatrix} \hat{y}_0 \\ \hat{y}_1 \end{bmatrix} = \frac{1}{\sum_{j=0}^{1} e^{z_j}} \begin{bmatrix} e^{z_0} \\ e^{z_1} \end{bmatrix} = \frac{e^{\boldsymbol{z}}}{\sum_{j=0}^{1} e^{z_j}}$$

$$L(\boldsymbol{\theta}) = -\sum_{i=0}^{1} y_i \log \hat{y}_i = -\boldsymbol{y}^T log \hat{\mathbf{y}}$$

Model



Derivative

$$\frac{\partial L}{\partial \hat{y}_i} = -\frac{y_i}{\hat{y}_i}$$

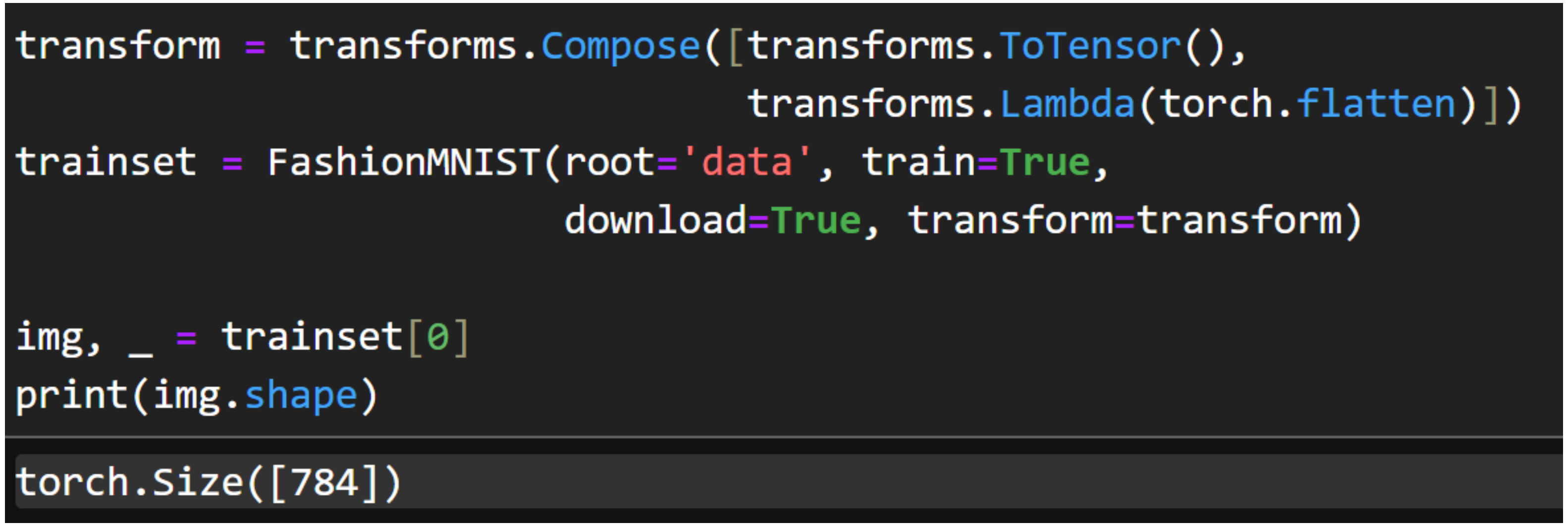
$$\frac{\partial \hat{y}_i}{\partial z_j} = \begin{cases} \hat{y}_i(1 - \hat{y}_i) & if\ i = j \\ -\hat{y}_i \hat{y}_j & if\ i \neq j \end{cases}$$

$$\frac{\partial L}{\partial z_i} = \hat{y}_i - y_i$$

$$\frac{\partial L}{\partial w_i} = x(\hat{y}_i - y_i)$$

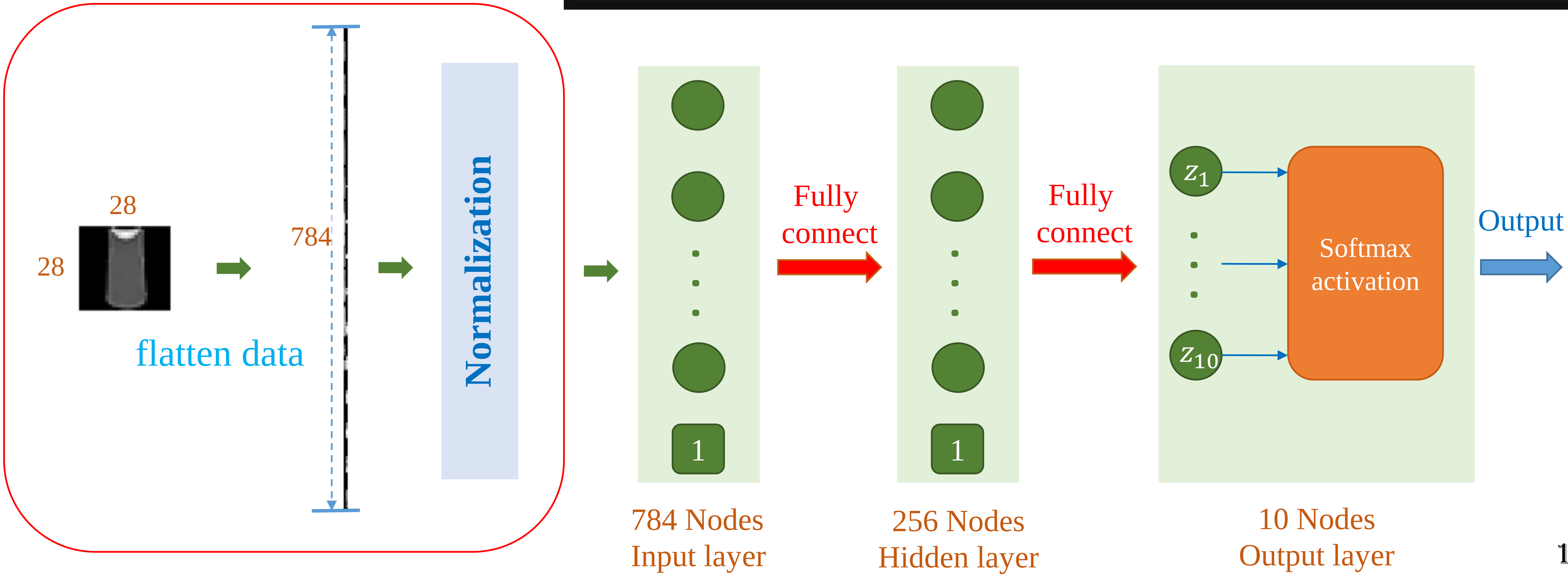
$$\frac{\partial L}{\partial b_i} = \hat{y}_i - y_i$$

Where to put Flatten

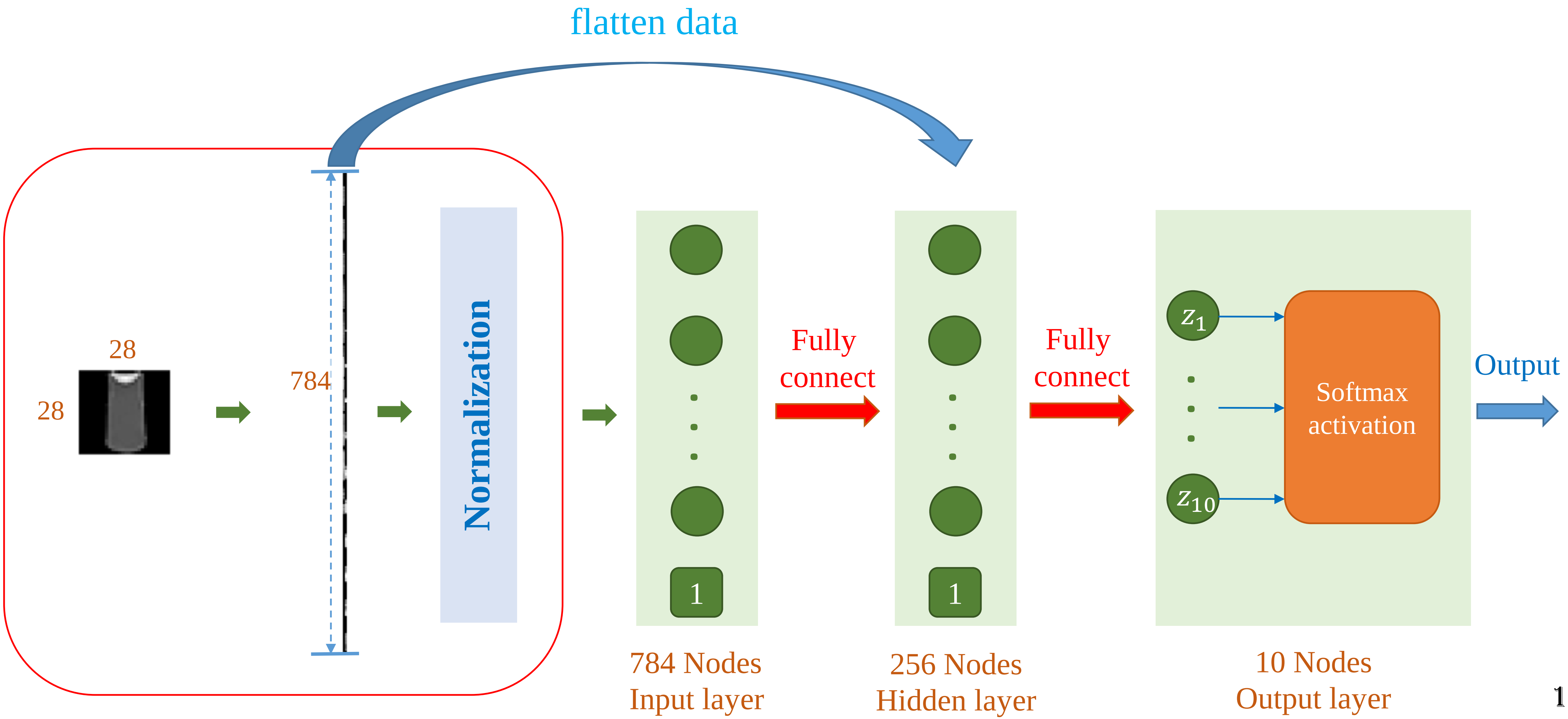


```
transform = transforms.Compose([transforms.ToTensor(),
                                transforms.Lambda(torch.flatten)])
trainset = FashionMNIST(root='data', train=True,
                        download=True, transform=transform)

img, _ = trainset[0]
print(img.shape)
```

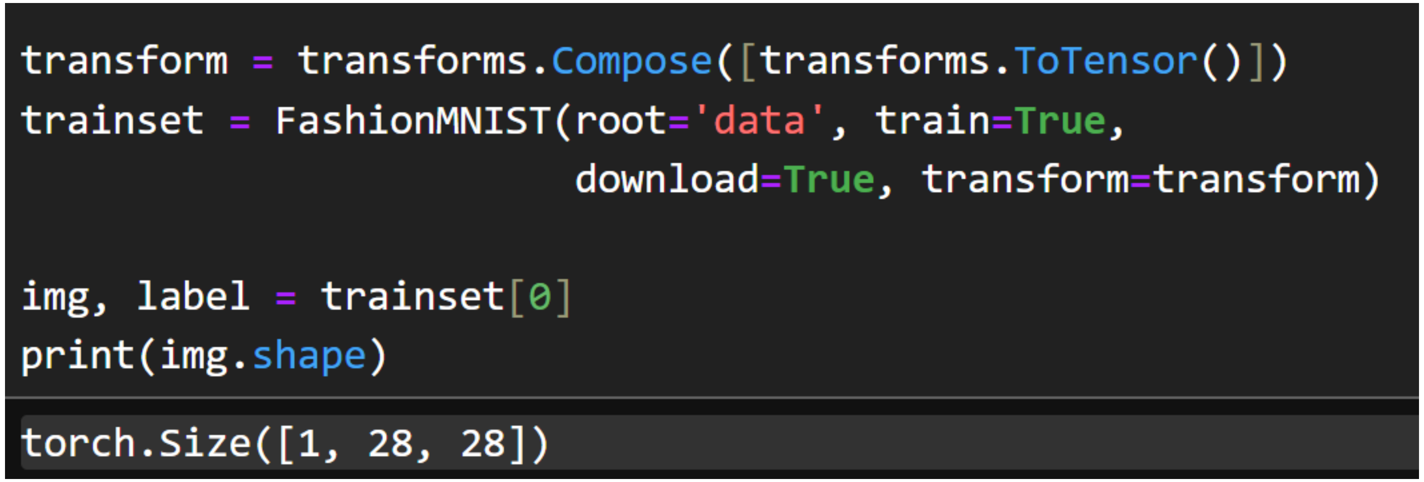
```
torch.Size([784])
```



Where to put Flatten

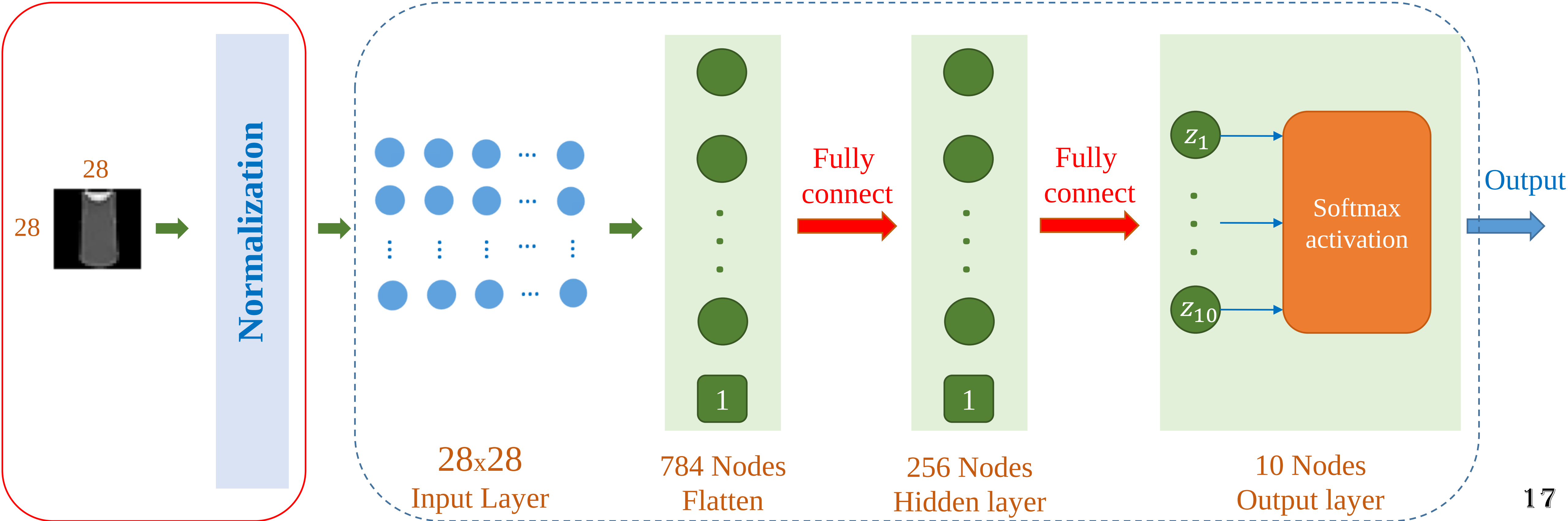


Where to put Flatten



```
transform = transforms.Compose([transforms.ToTensor()])
trainset = FashionMNIST(root='data', train=True,
                        download=True, transform=transform)

img, label = trainset[0]
print(img.shape)
```

```
torch.Size([1, 28, 28])
```

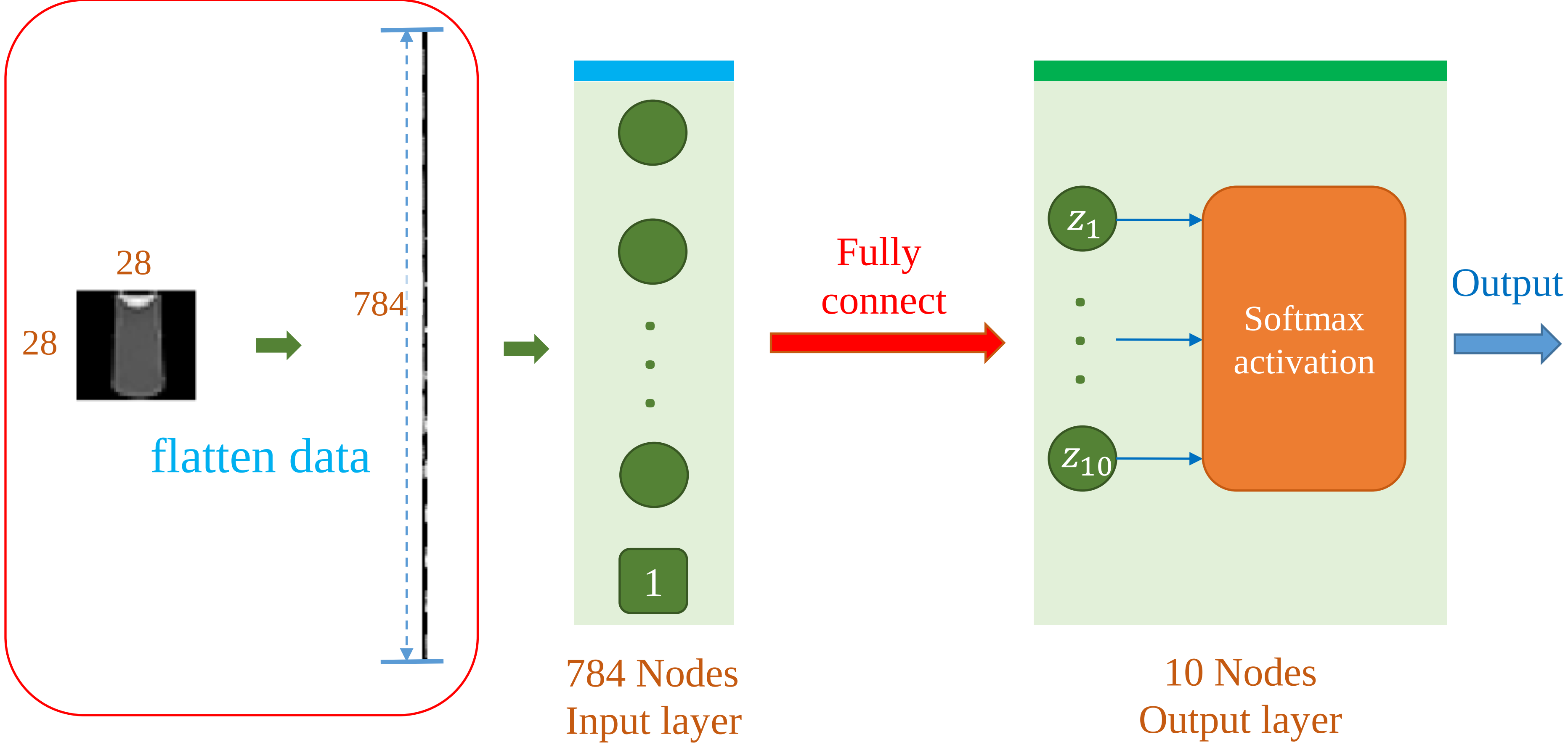


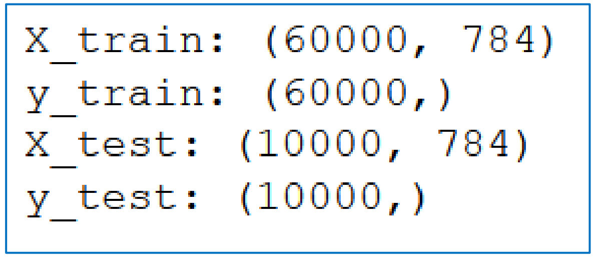
Case 1

Softmax Regression

without normalization

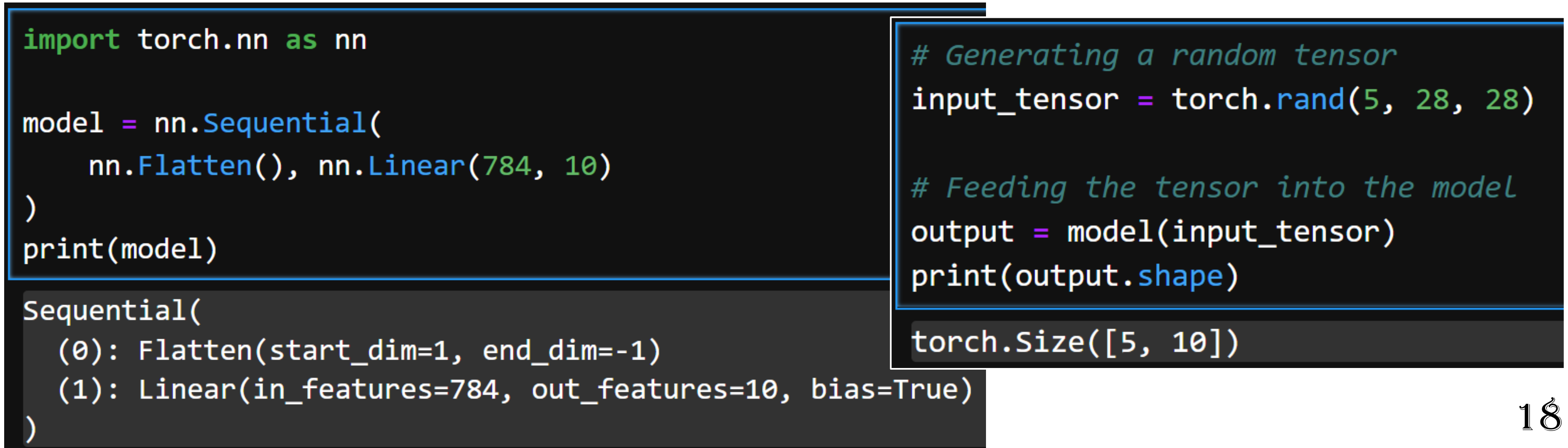
learning rate = 0.01





```
X_train: (60000, 784)
y_train: (60000,)
X_test: (10000, 784)
y_test: (10000,)
```

Data Sets

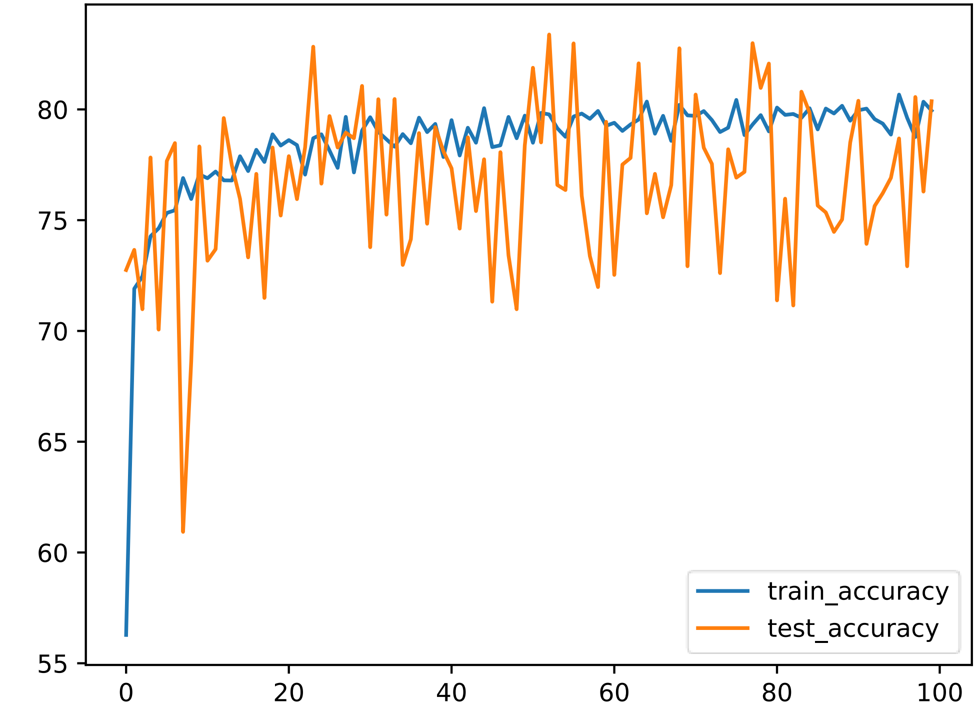


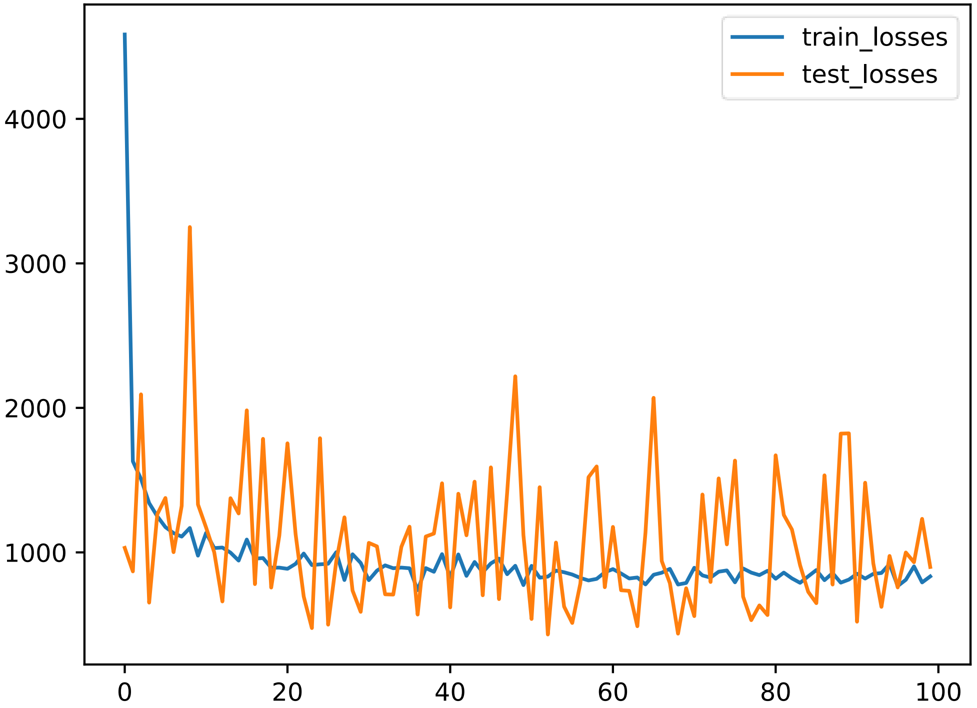
```
import torch.nn as nn

model = nn.Sequential(
    nn.Flatten(), nn.Linear(784, 10)
)
print(model)
```

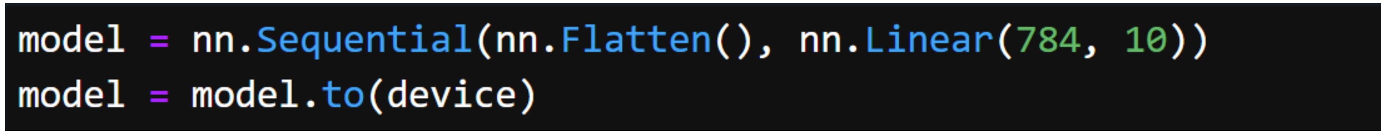
```
Sequential(
  (0): Flatten(start_dim=1, end_dim=-1)
  (1): Linear(in_features=784, out_features=10, bias=True)
)
```

```
# Generating a random tensor
input_tensor = torch.rand(5, 28, 28)

# Feeding the tensor into the model
output = model(input_tensor)
print(output.shape)
```

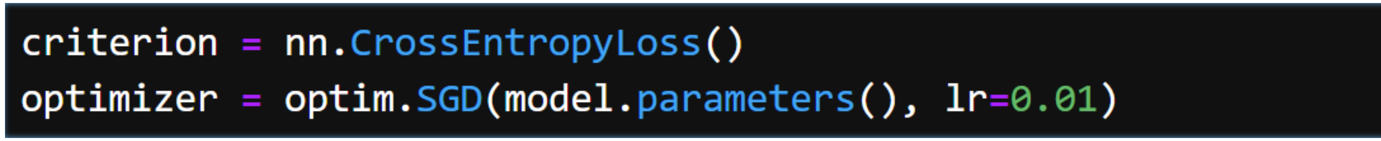
```
torch.Size([5, 10])
```



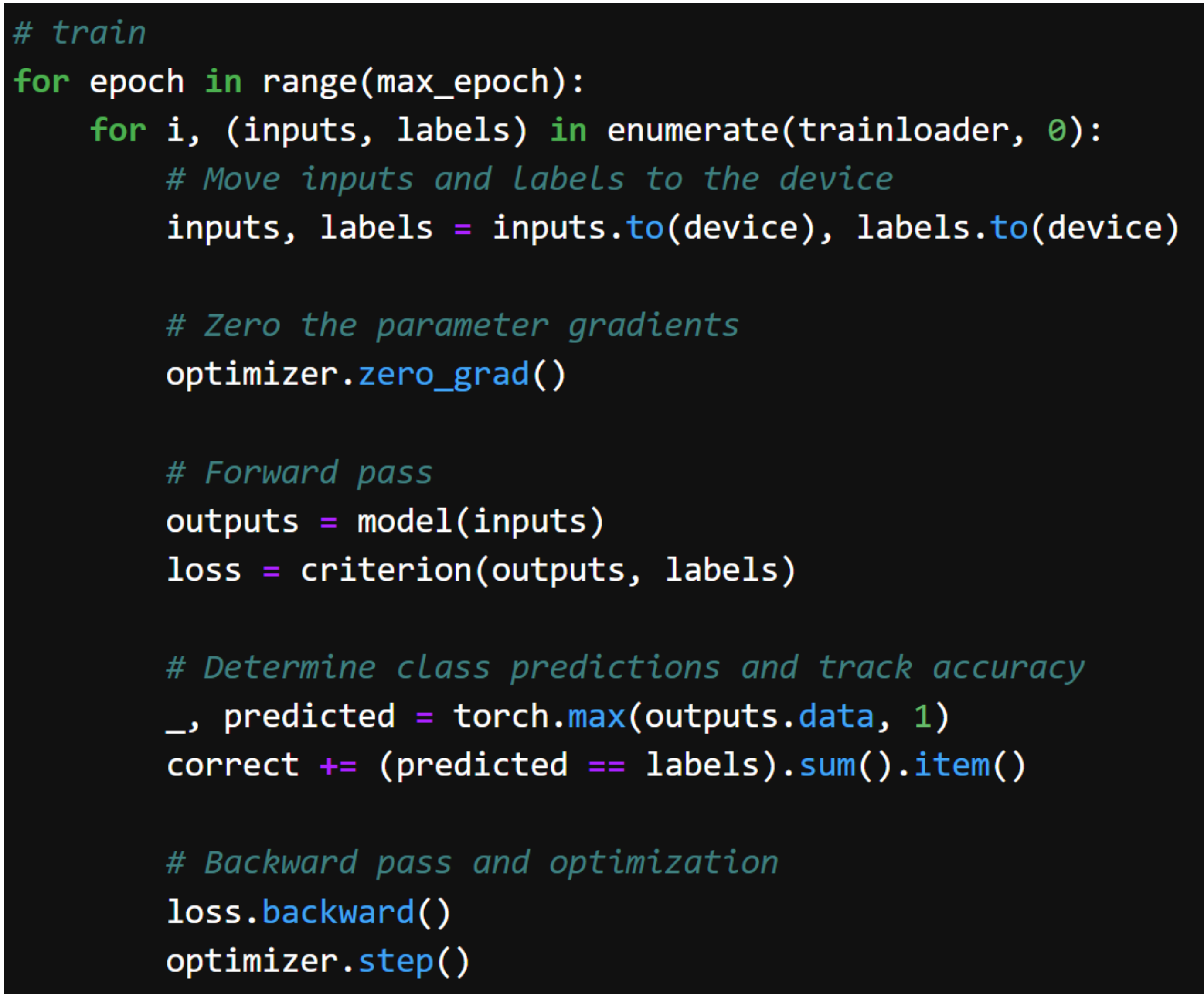




```
model = nn.Sequential(nn.Flatten(), nn.Linear(784, 10))
model = model.to(device)
```



```
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)
```



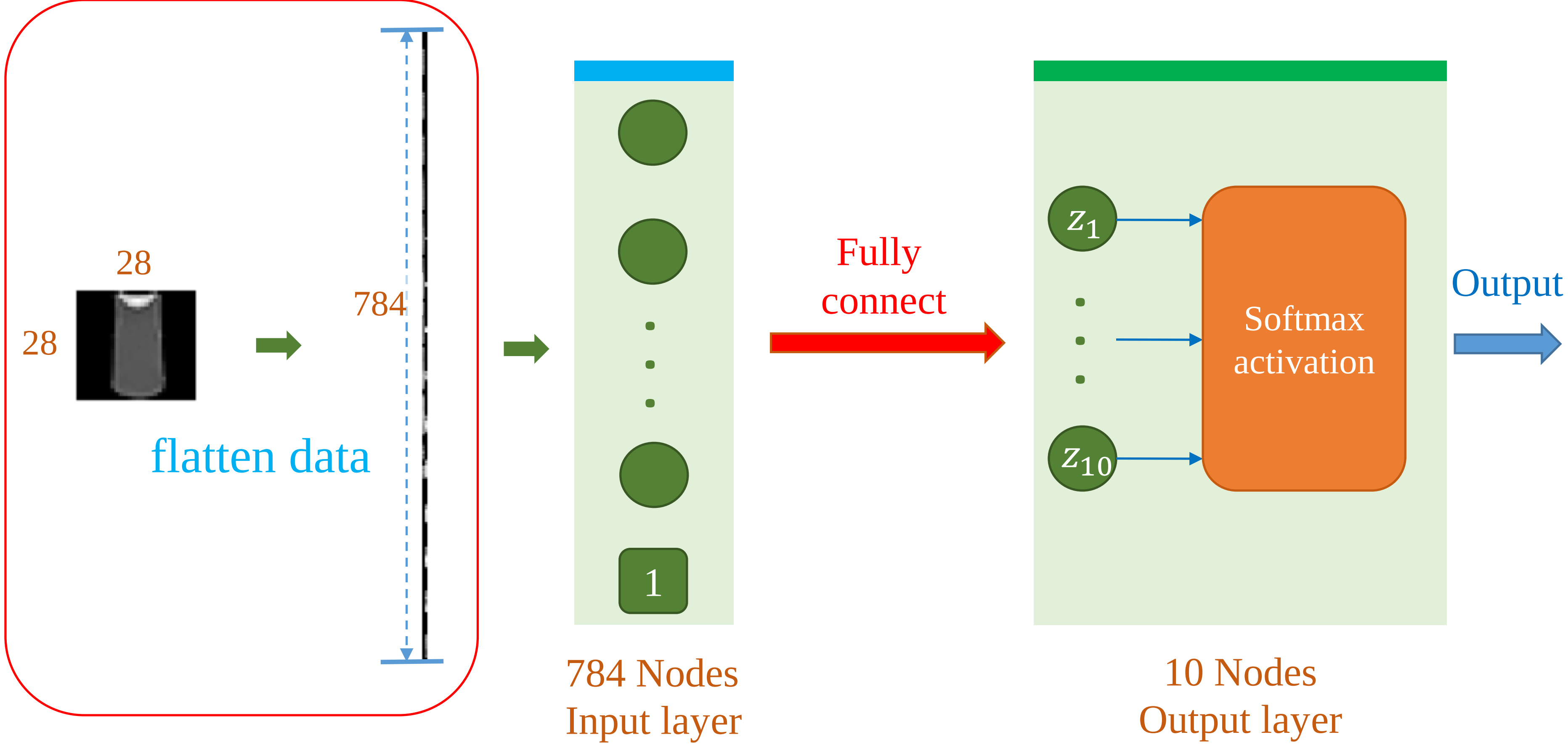
```
# train
for epoch in range(max_epoch):
    for i, (inputs, labels) in enumerate(trainloader, 0):
        # Move inputs and labels to the device
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Determine class predictions and track accuracy
        _, predicted = torch.max(outputs.data, 1)
        correct += (predicted == labels).sum().item()

        # Backward pass and optimization
        loss.backward()
        optimizer.step()
```

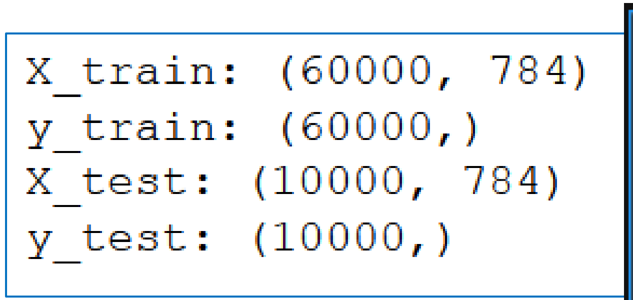
Case 2

Softmax Regression

without normalization

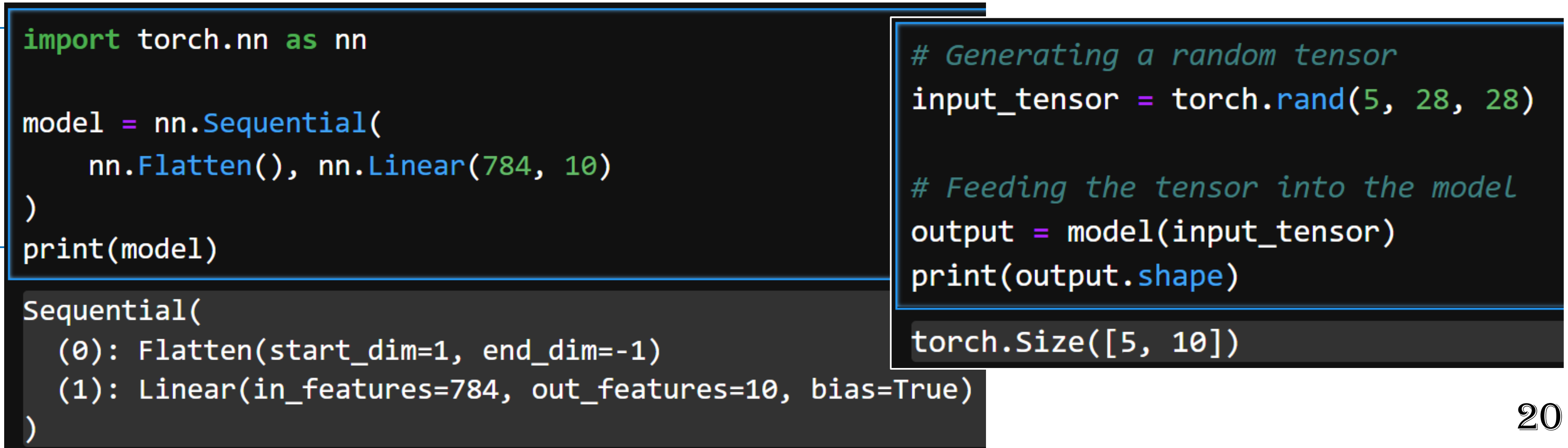
learning rate = 0.00001





```
X_train: (60000, 784)
y_train: (60000,)
X_test: (10000, 784)
y_test: (10000,)
```

Data Sets

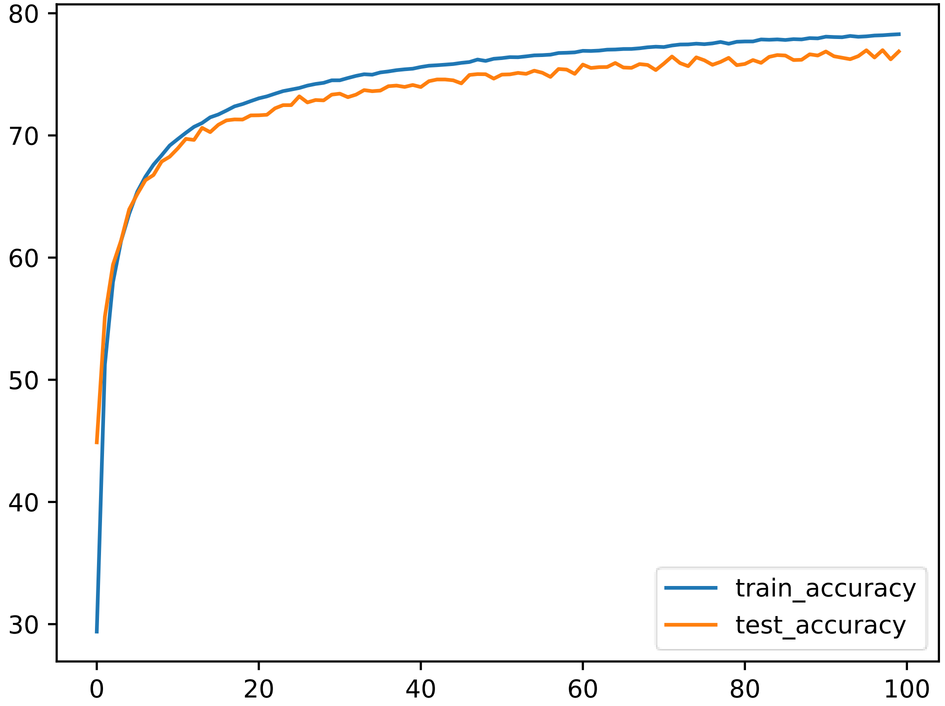


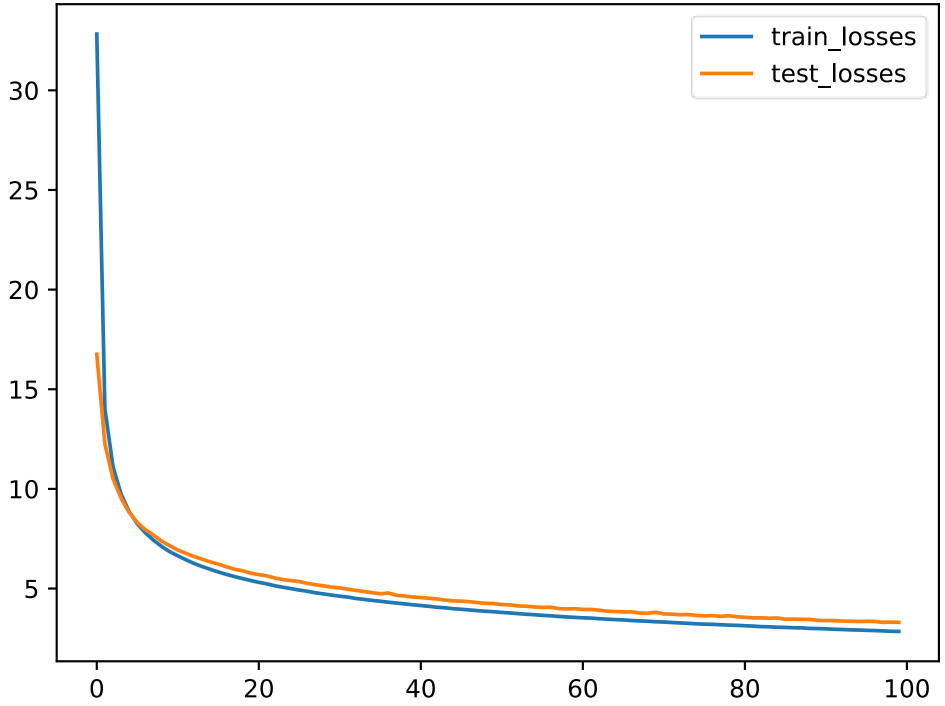
```
import torch.nn as nn

model = nn.Sequential(
    nn.Flatten(), nn.Linear(784, 10)
)
print(model)
```

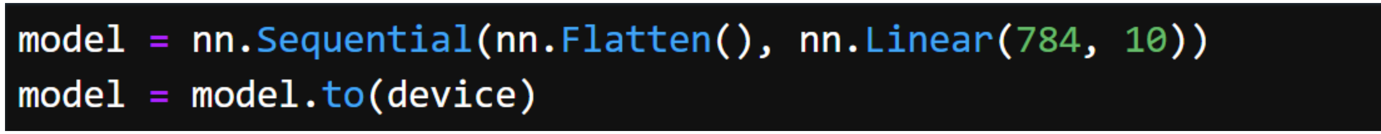
```
Sequential(
  (0): Flatten(start_dim=1, end_dim=-1)
  (1): Linear(in_features=784, out_features=10, bias=True)
)
```

```
# Generating a random tensor
input_tensor = torch.rand(5, 28, 28)

# Feeding the tensor into the model
output = model(input_tensor)
print(output.shape)
```

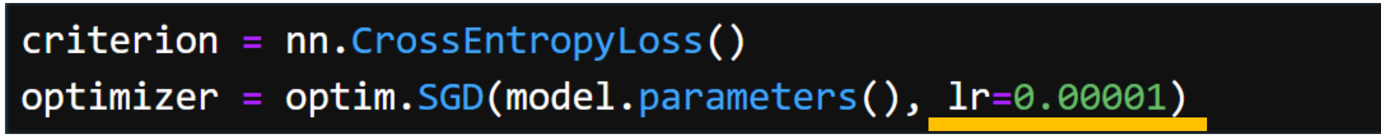
```
torch.Size([5, 10])
```



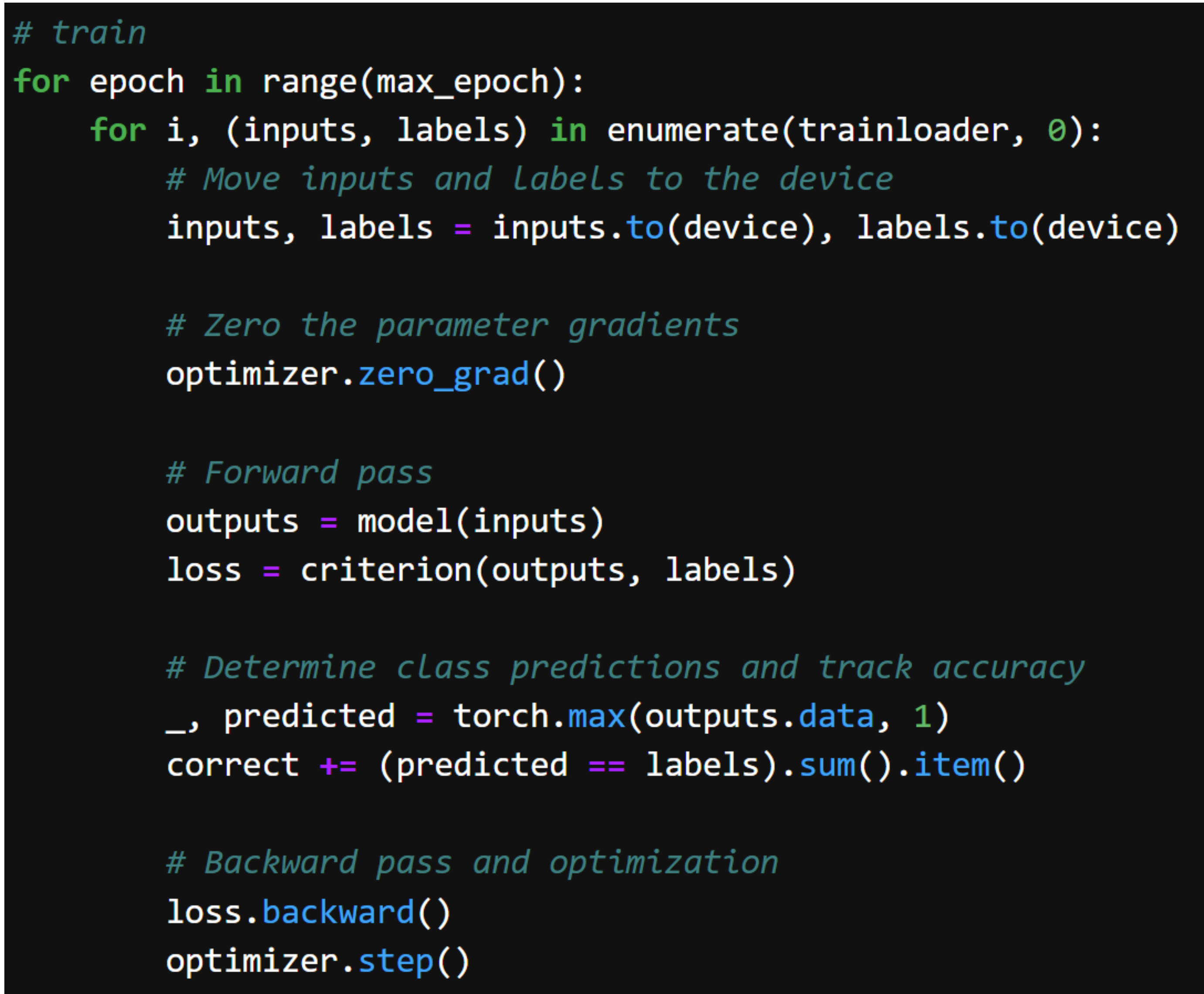




```
model = nn.Sequential(nn.Flatten(), nn.Linear(784, 10))
model = model.to(device)
```



```
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.00001)
```

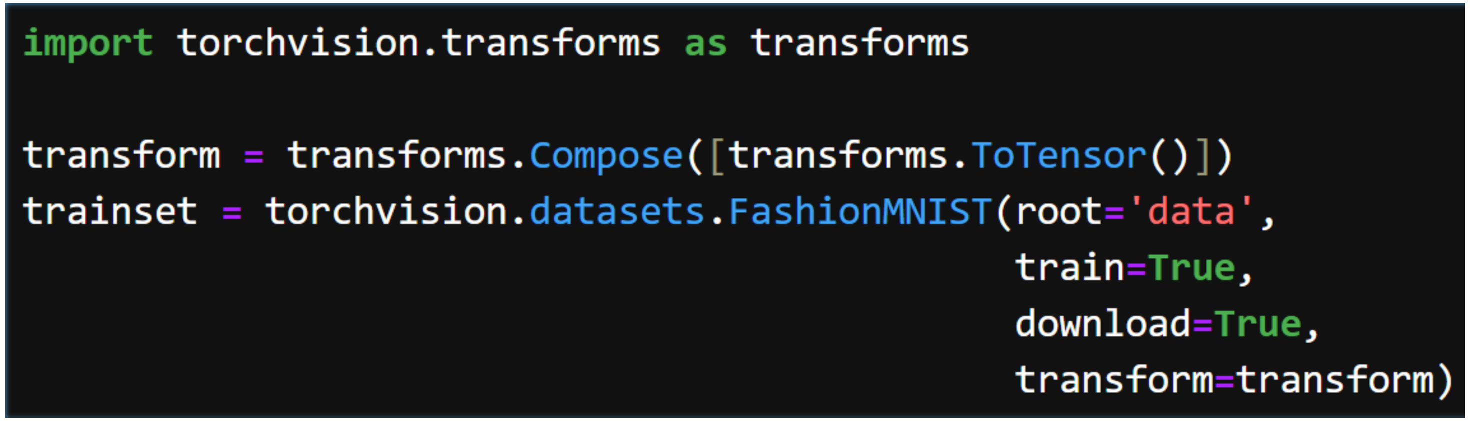


```
# train
for epoch in range(max_epoch):
    for i, (inputs, labels) in enumerate(trainloader, 0):
        # Move inputs and labels to the device
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Determine class predictions and track accuracy
        _, predicted = torch.max(outputs.data, 1)
        correct += (predicted == labels).sum().item()

        # Backward pass and optimization
        loss.backward()
        optimizer.step()
```

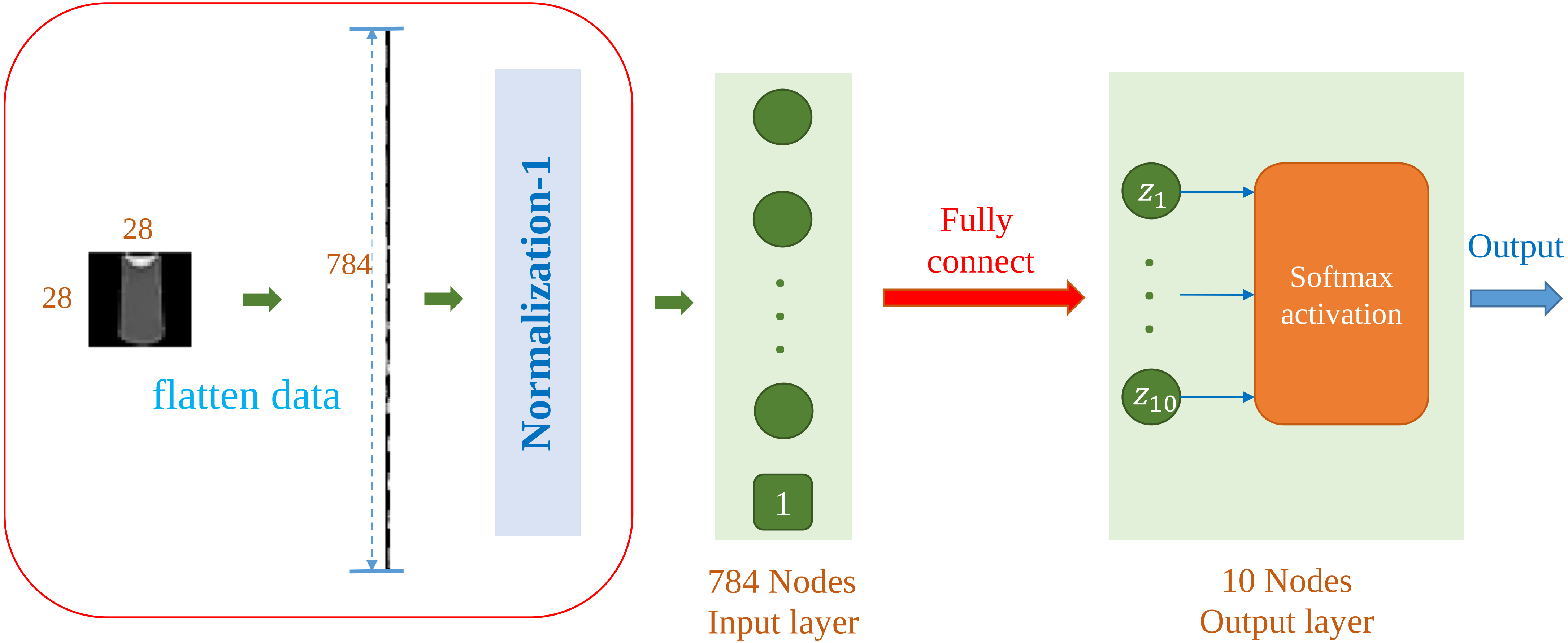
Case 3

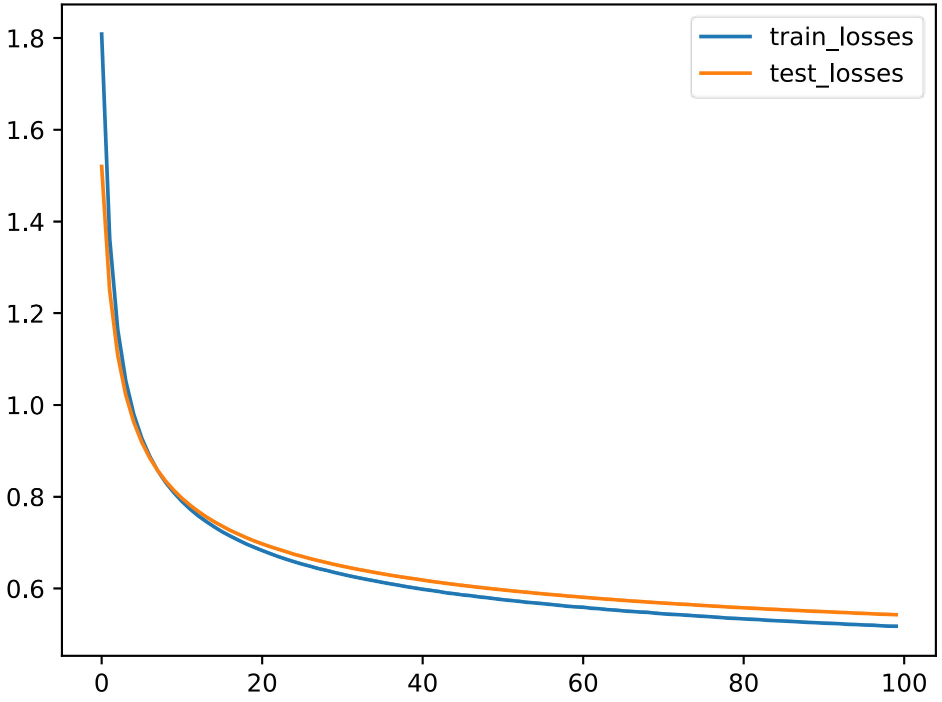
Softmax Regression + Normalization

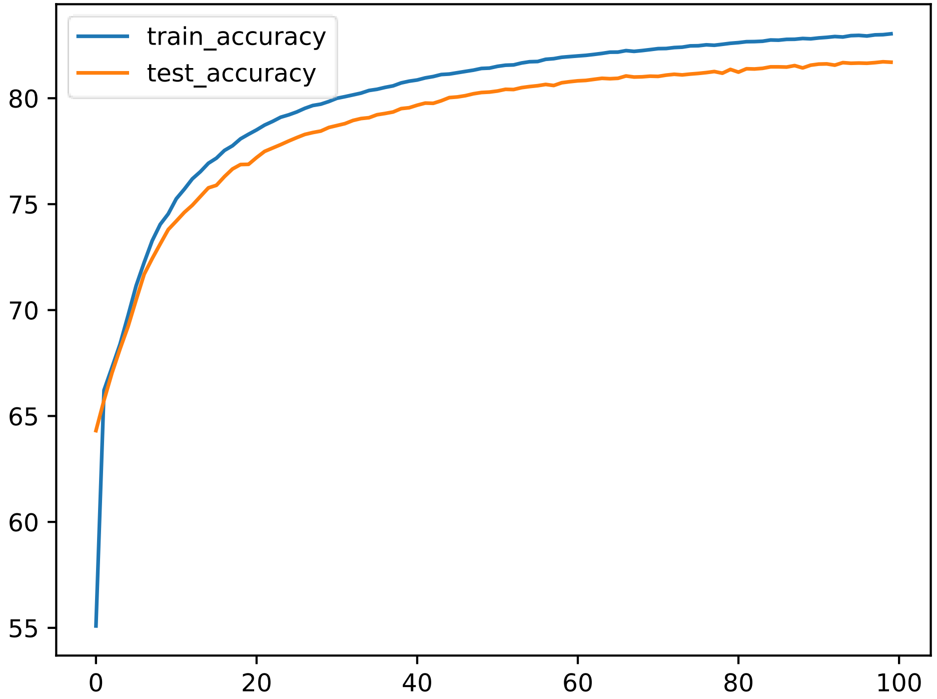
$$\text{Image} = \frac{\text{Image}}{255}$$

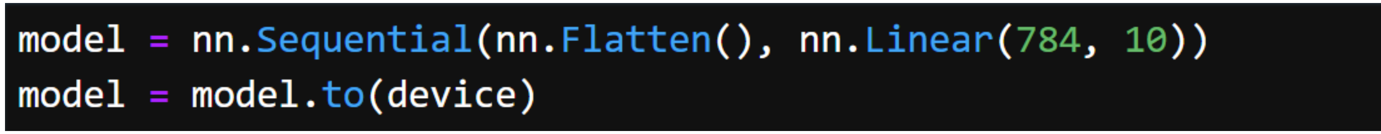


```
import torchvision.transforms as transforms

transform = transforms.Compose([transforms.ToTensor()])
trainset = torchvision.datasets.FashionMNIST(root='data',
                                             train=True,
                                             download=True,
                                             transform=transform)
```

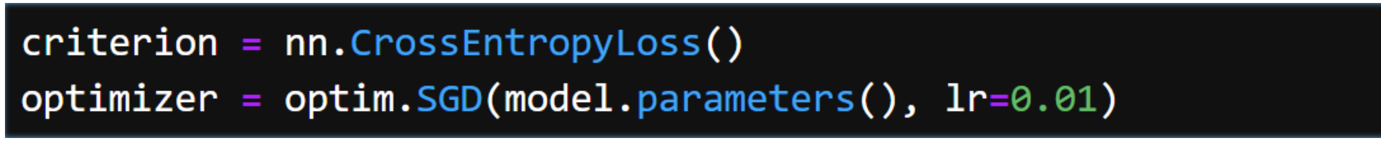




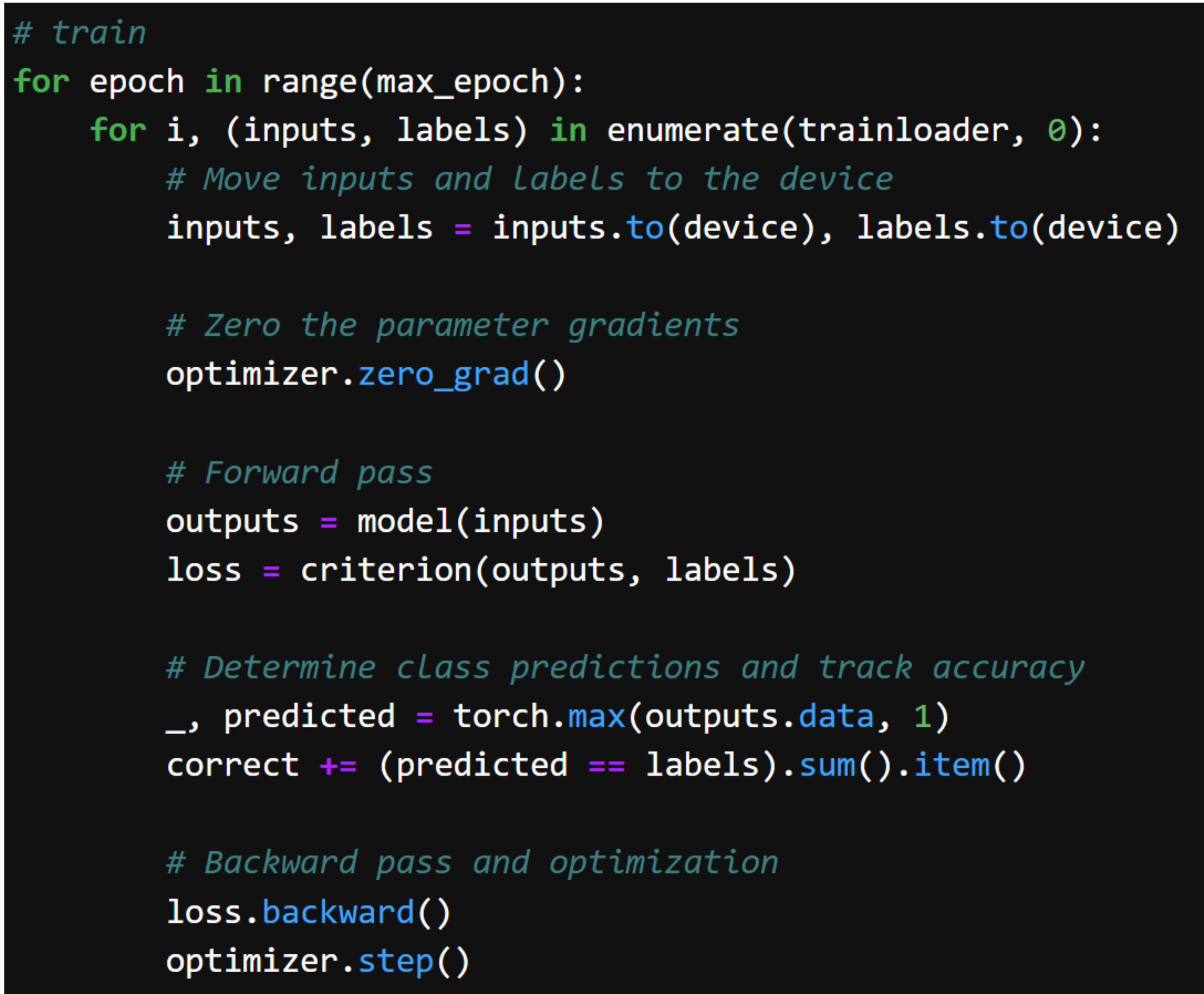




```
model = nn.Sequential(nn.Flatten(), nn.Linear(784, 10))
model = model.to(device)
```



```
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)
```

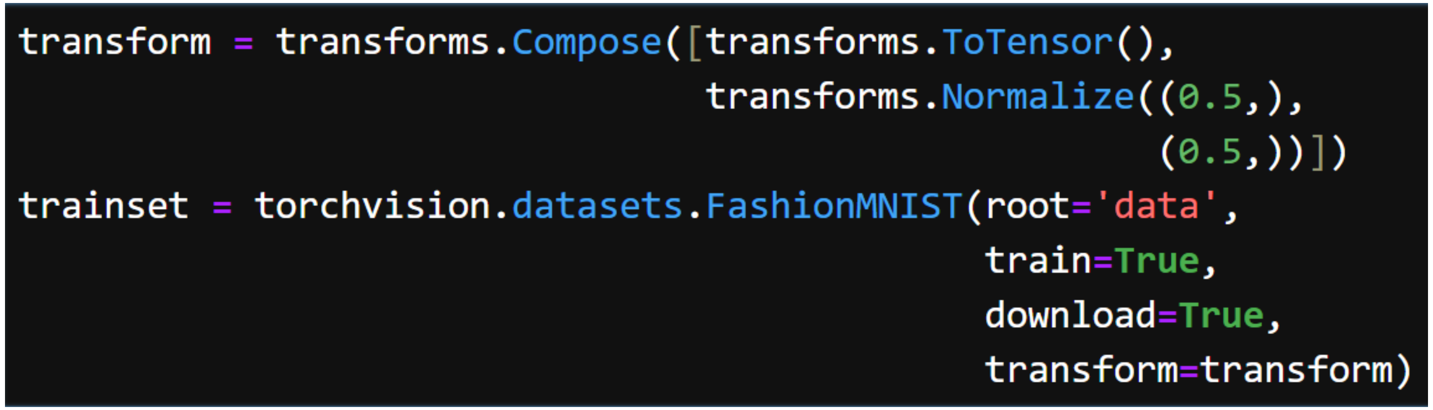


```
# train
for epoch in range(max_epoch):
    for i, (inputs, labels) in enumerate(trainloader, 0):
        # Move inputs and labels to the device
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Determine class predictions and track accuracy
        _, predicted = torch.max(outputs.data, 1)
        correct += (predicted == labels).sum().item()

        # Backward pass and optimization
        loss.backward()
        optimizer.step()
```

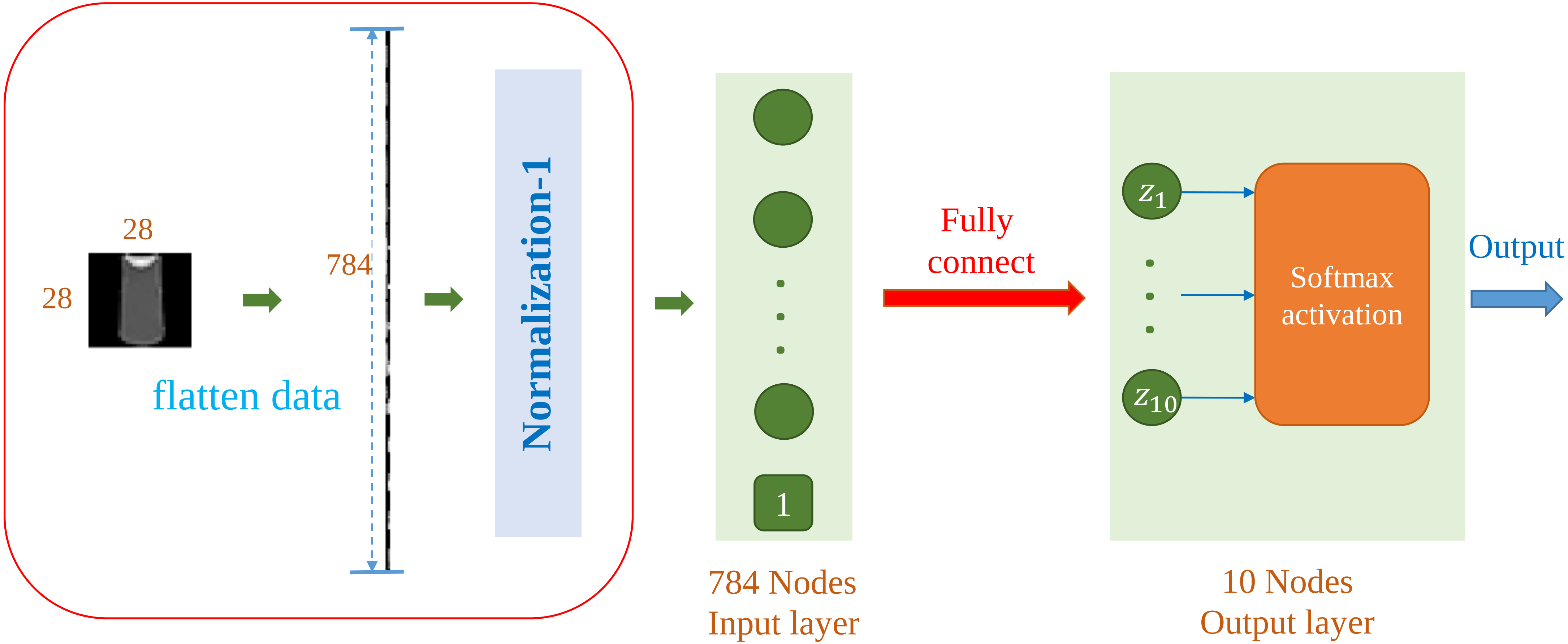
Softmax Regression + Normalization

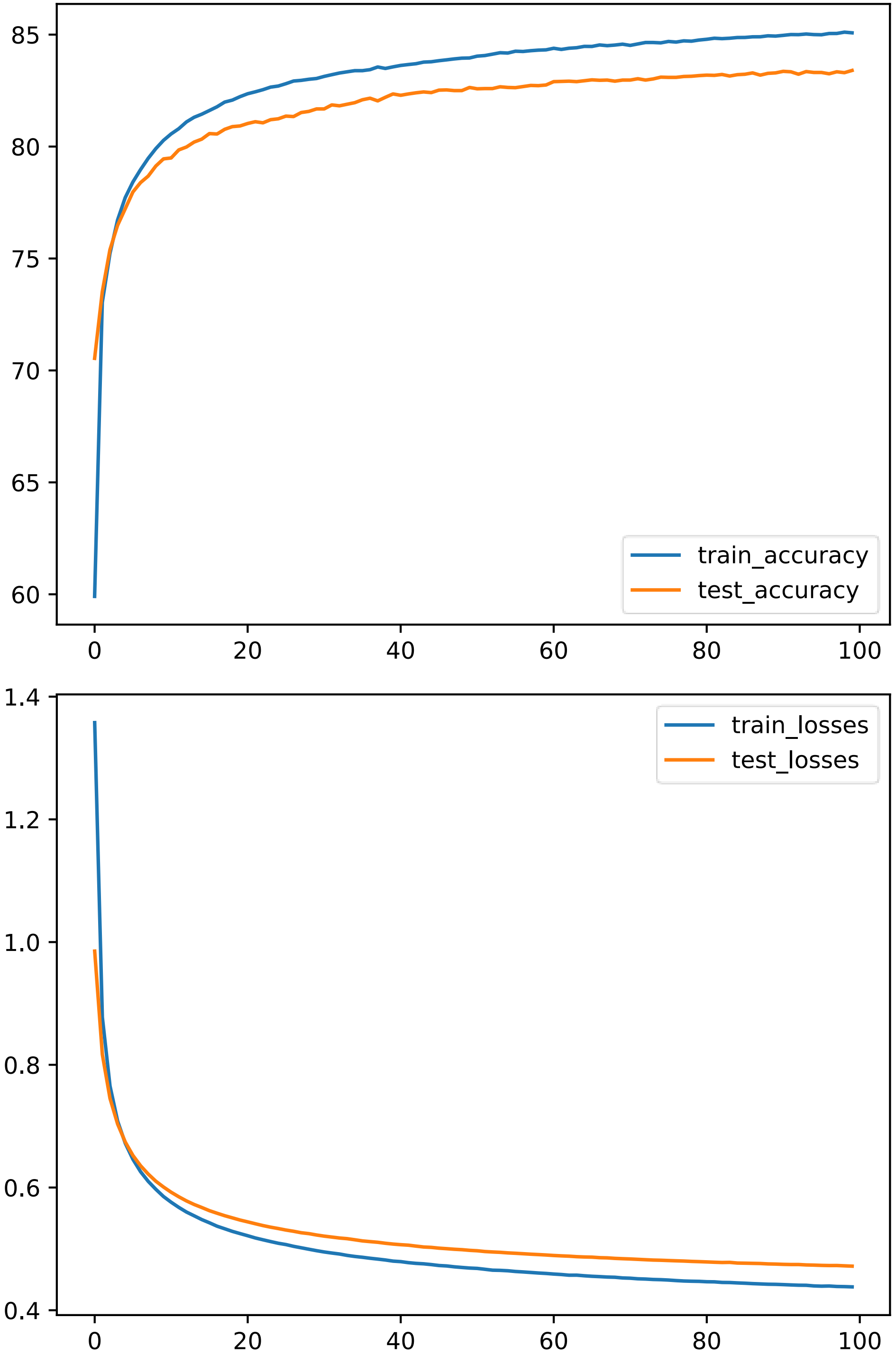
Case 4

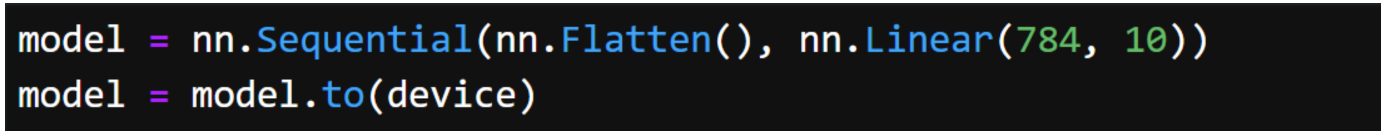
$$\text{Image} = \frac{\text{Image}}{127.5} - 1$$



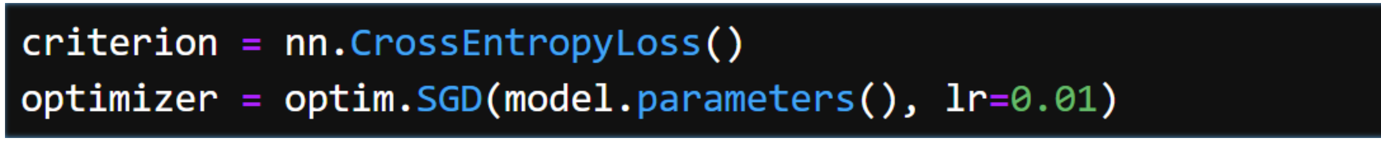
```
transform = transforms.Compose([transforms.ToTensor(),
                                transforms.Normalize((0.5,),
                                                     (0.5,))])
trainset = torchvision.datasets.FashionMNIST(root='data',
                                             train=True,
                                             download=True,
                                             transform=transform)
```



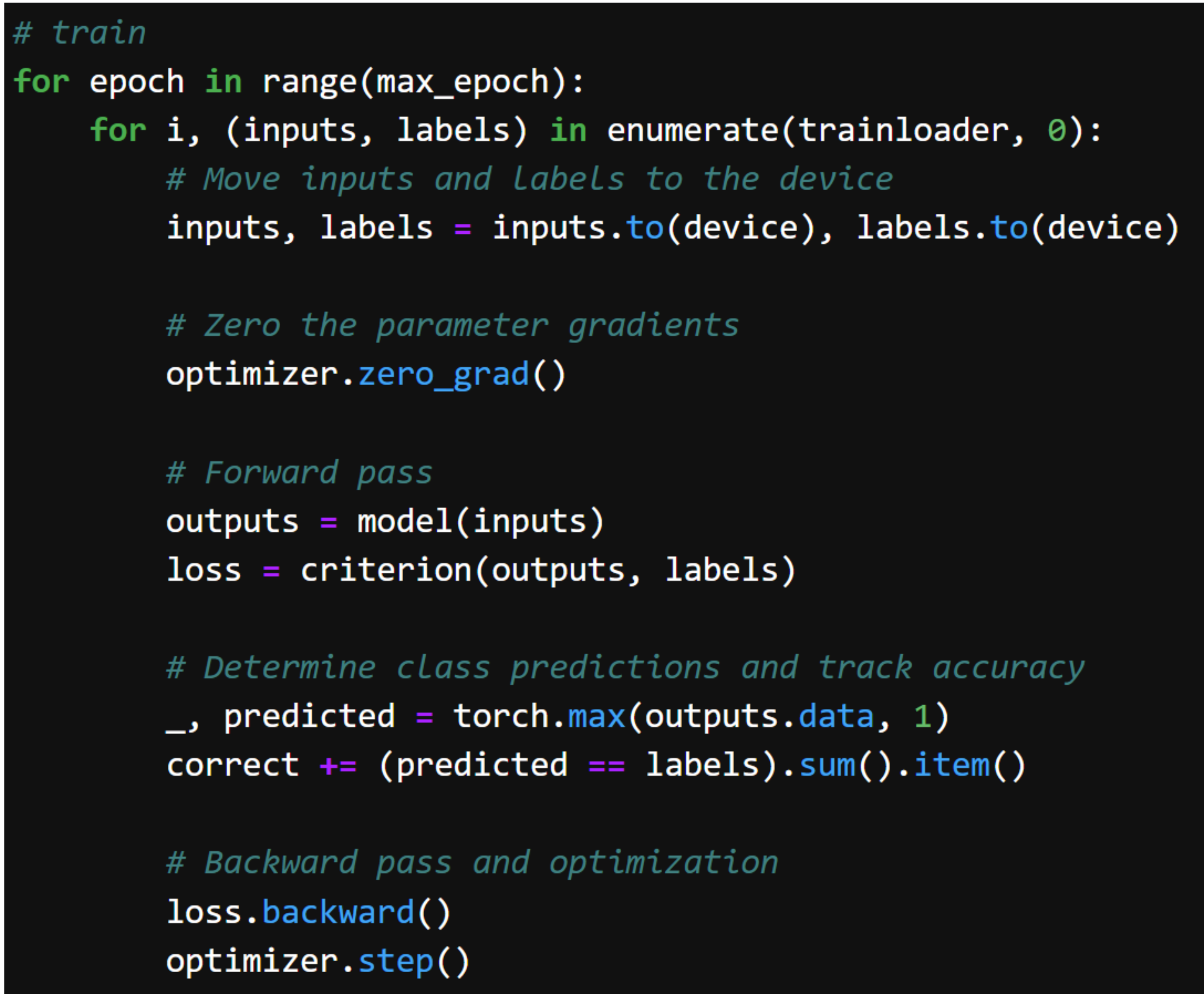




```
model = nn.Sequential(nn.Flatten(), nn.Linear(784, 10))
model = model.to(device)
```



```
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)
```

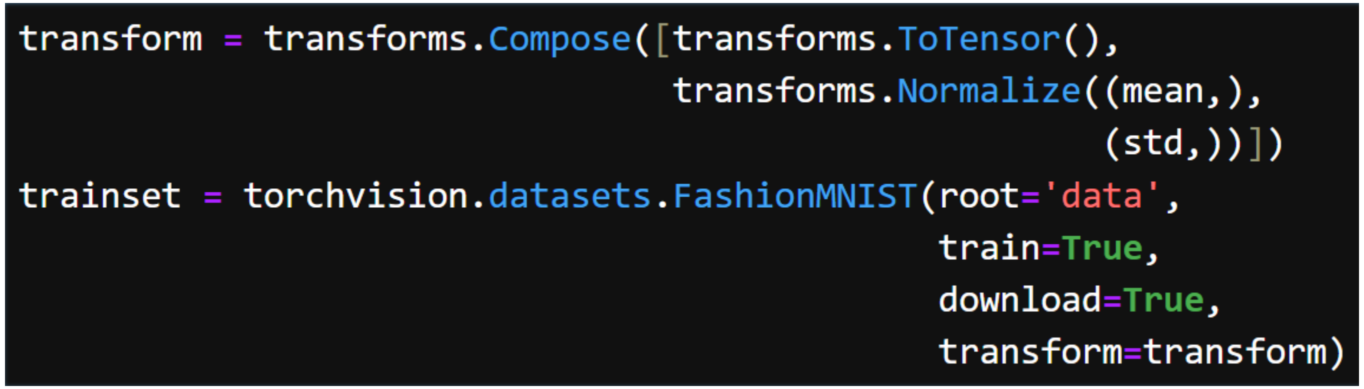


```
# train
for epoch in range(max_epoch):
    for i, (inputs, labels) in enumerate(trainloader, 0):
        # Move inputs and labels to the device
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Determine class predictions and track accuracy
        _, predicted = torch.max(outputs.data, 1)
        correct += (predicted == labels).sum().item()

        # Backward pass and optimization
        loss.backward()
        optimizer.step()
```

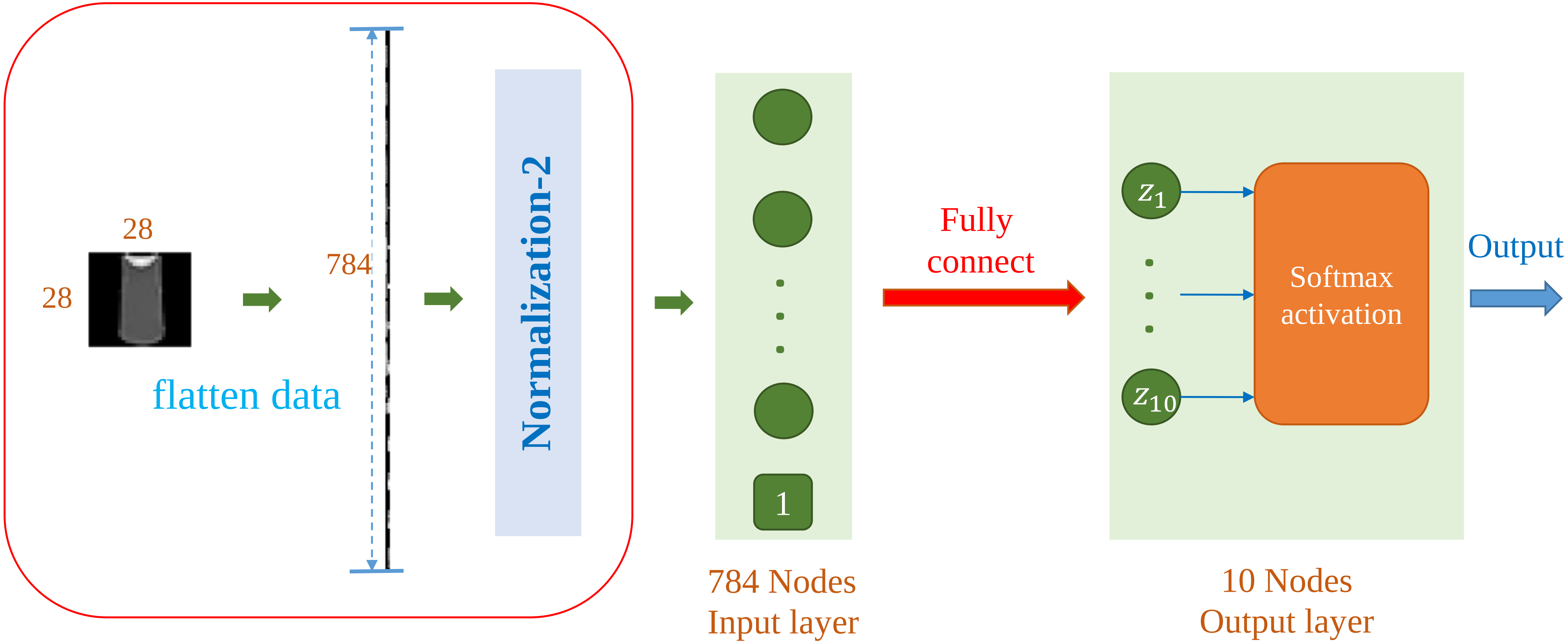
Case 5

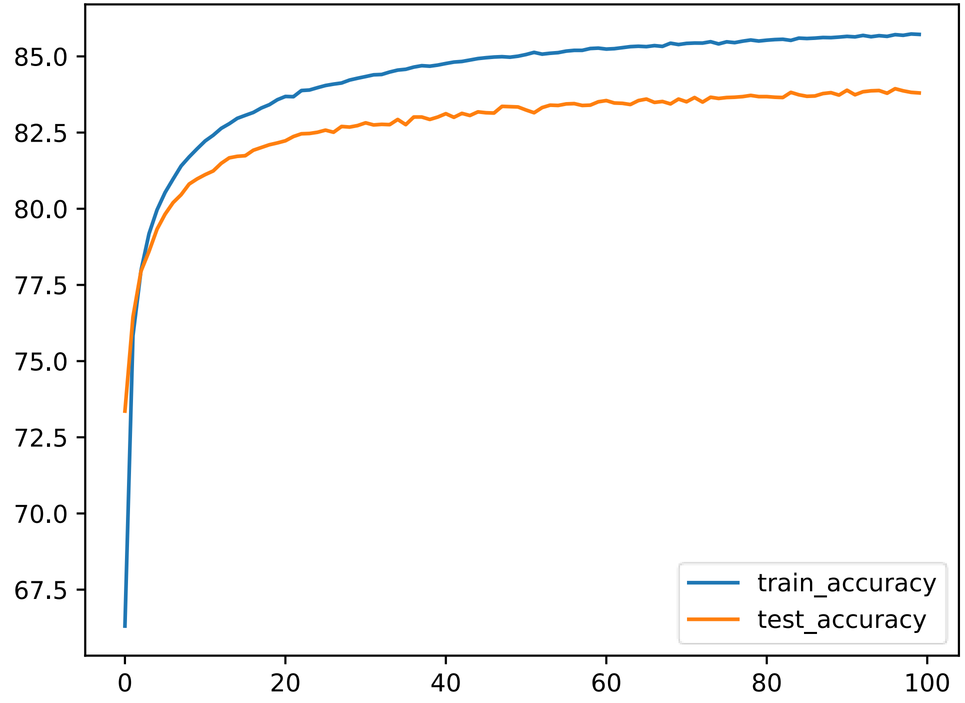
Softmax Regression + Normalization

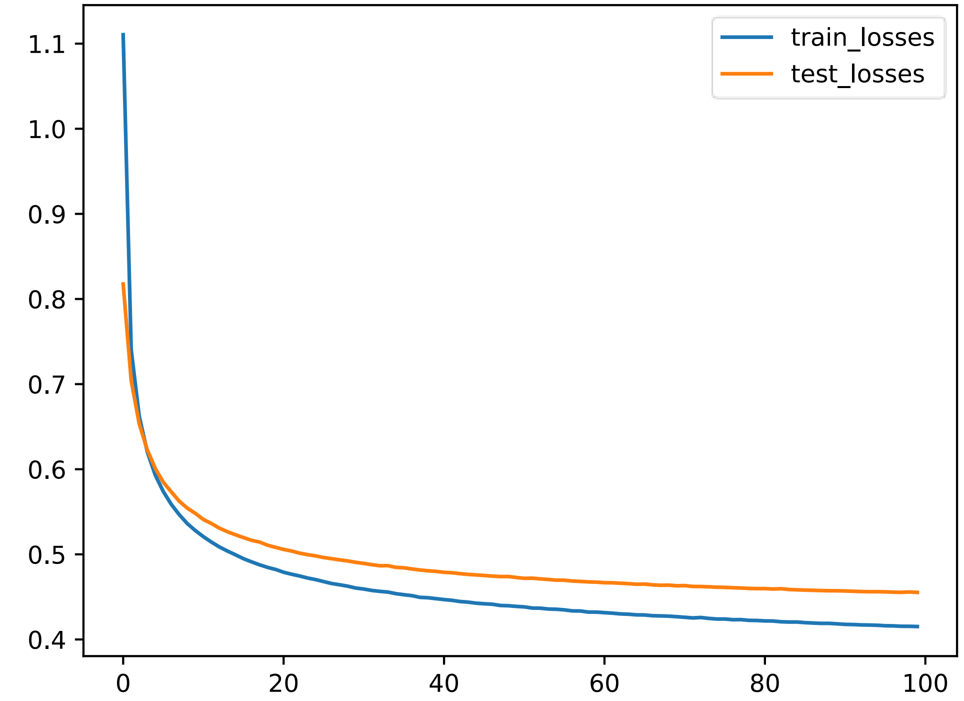
$$\text{Image} = \frac{\text{Image} - \mu}{\sigma}$$

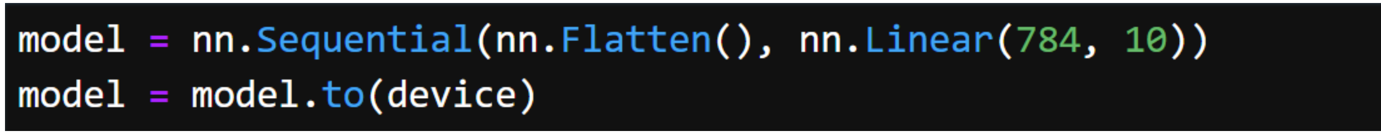


```
transform = transforms.Compose([transforms.ToTensor(),
                                transforms.Normalize((mean,),
                                                     (std,))])
trainset = torchvision.datasets.FashionMNIST(root='data',
                                             train=True,
                                             download=True,
                                             transform=transform)
```

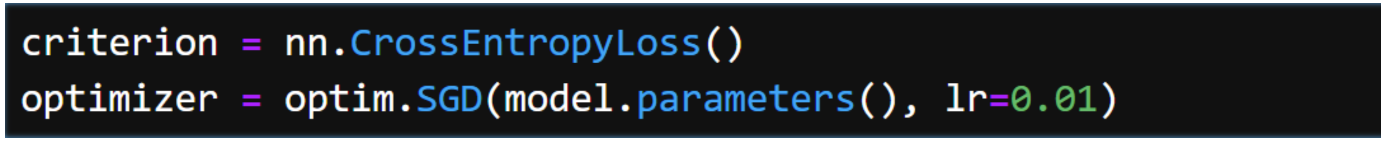




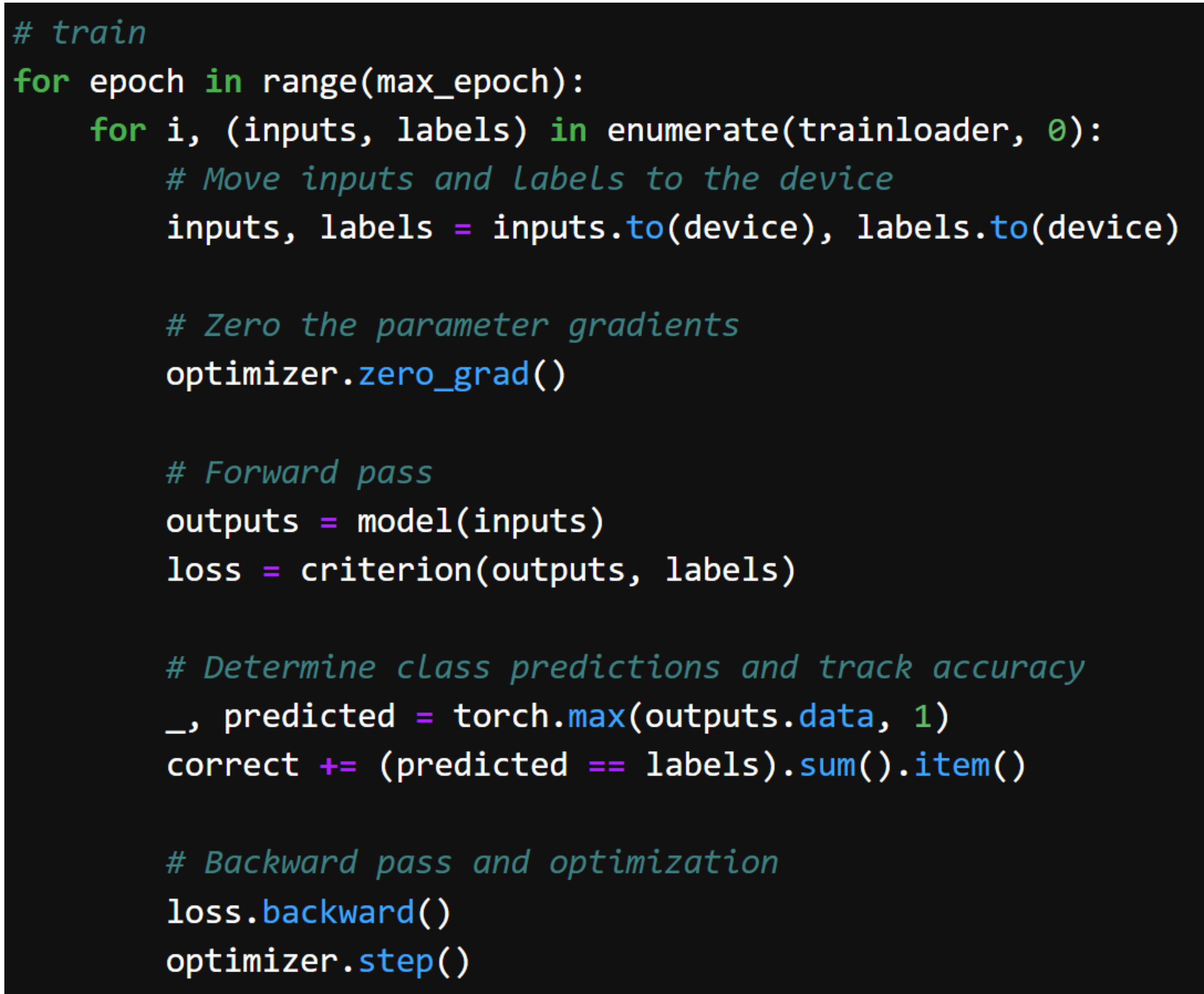




```
model = nn.Sequential(nn.Flatten(), nn.Linear(784, 10))
model = model.to(device)
```



```
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)
```



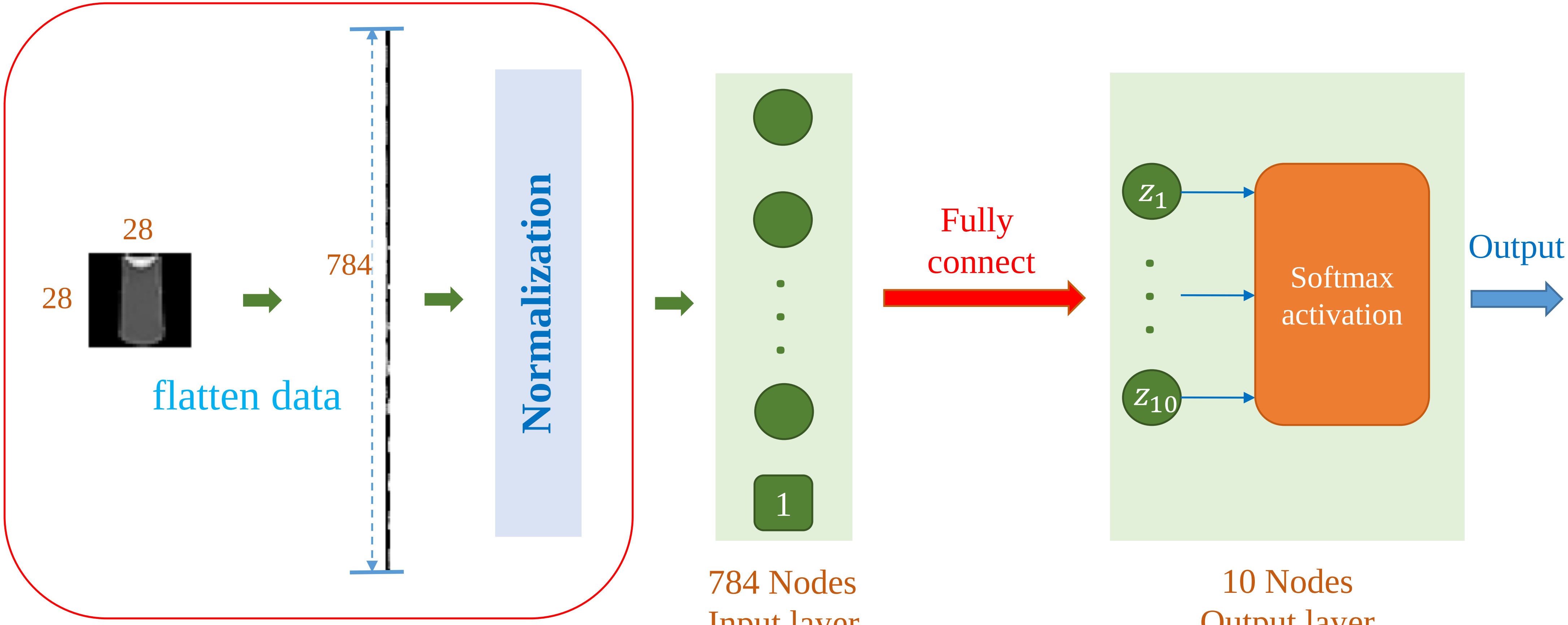
```
# train
for epoch in range(max_epoch):
    for i, (inputs, labels) in enumerate(trainloader, 0):
        # Move inputs and labels to the device
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Determine class predictions and track accuracy
        _, predicted = torch.max(outputs.data, 1)
        correct += (predicted == labels).sum().item()

        # Backward pass and optimization
        loss.backward()
        optimizer.step()
```

Outline

- Image Data Loading Using Numpy&PyTorch
- Softmax+Normalization for Fashion-MNIST
- MLP and Examples
- Step-by-Step Implementation
- Training Strategy (optional)

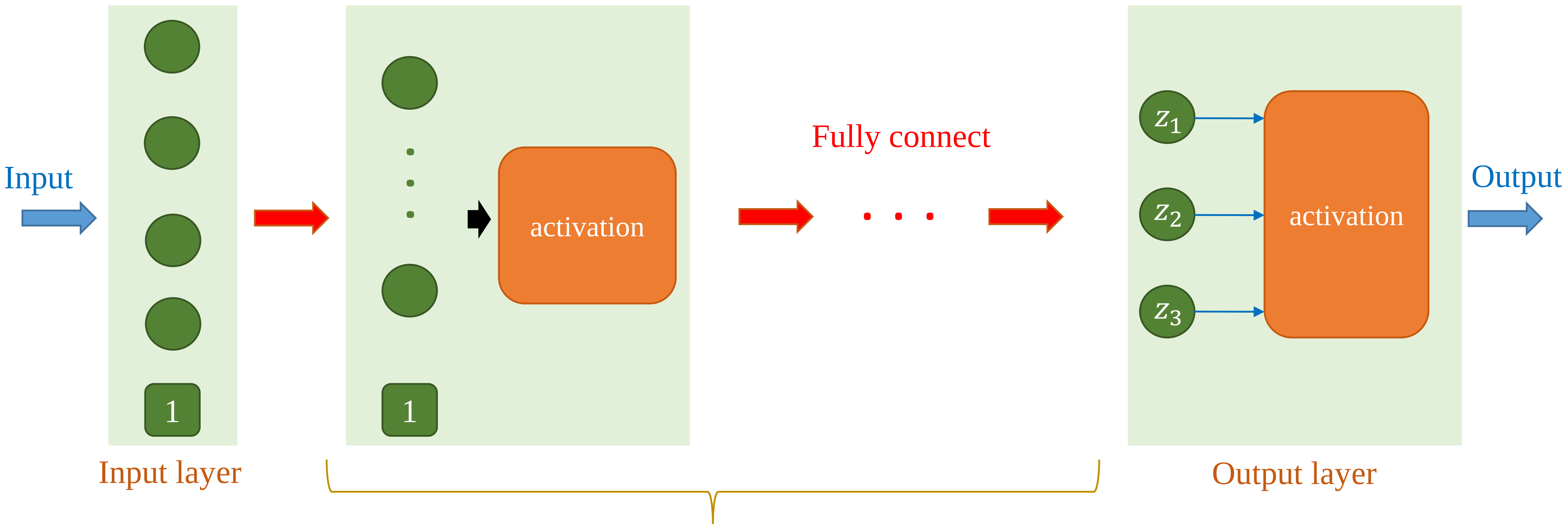
MLP - Motivation

- ❖ John Von Neumann's quote “with four parameters I can fit an elephant, with five I can make him wiggle his trunk”
- ❖ More parameters → better capacity (~stronger model)



Multi-layer Perceptron

- An idea: More parameters → better capacity (~stronger model)
  - Adding more layers



called Hidden Layers

#hidden layers is arbitrary
#nodes in a hidden layer is arbitrary

Multi-layer Perceptron

❖ ReLU function

$$\text{ReLU}(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases}$$

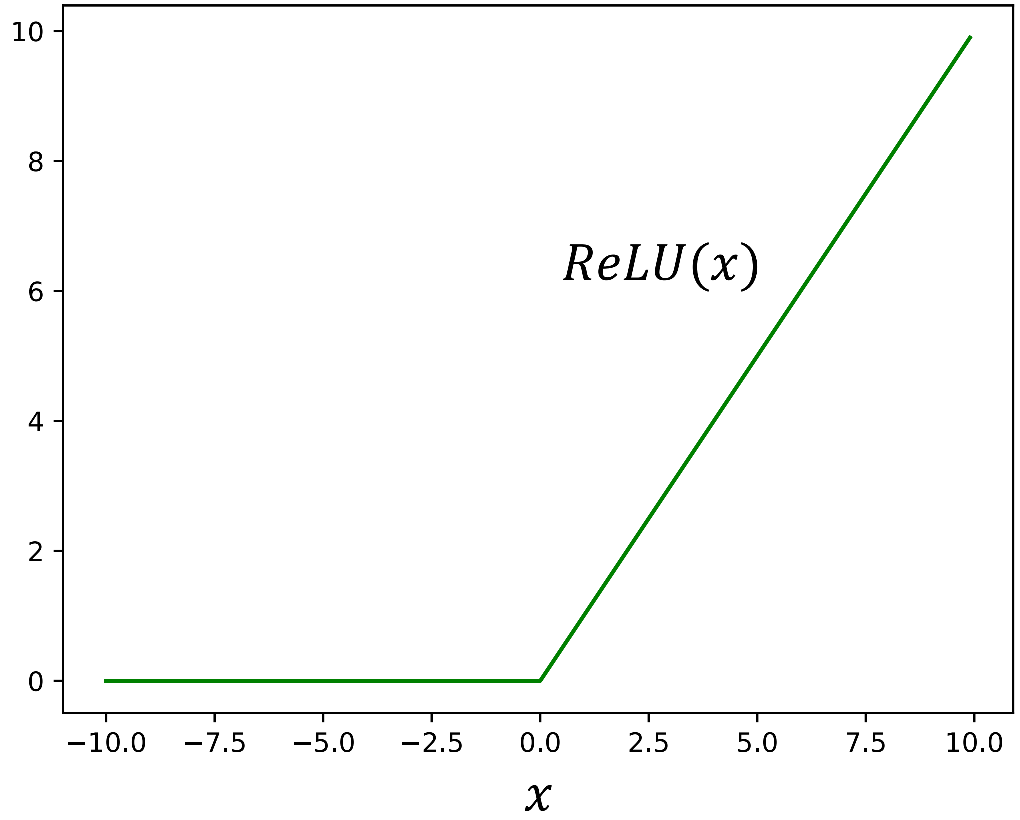
data =

1	5	-4	3	-2

data_a = ReLU(data)

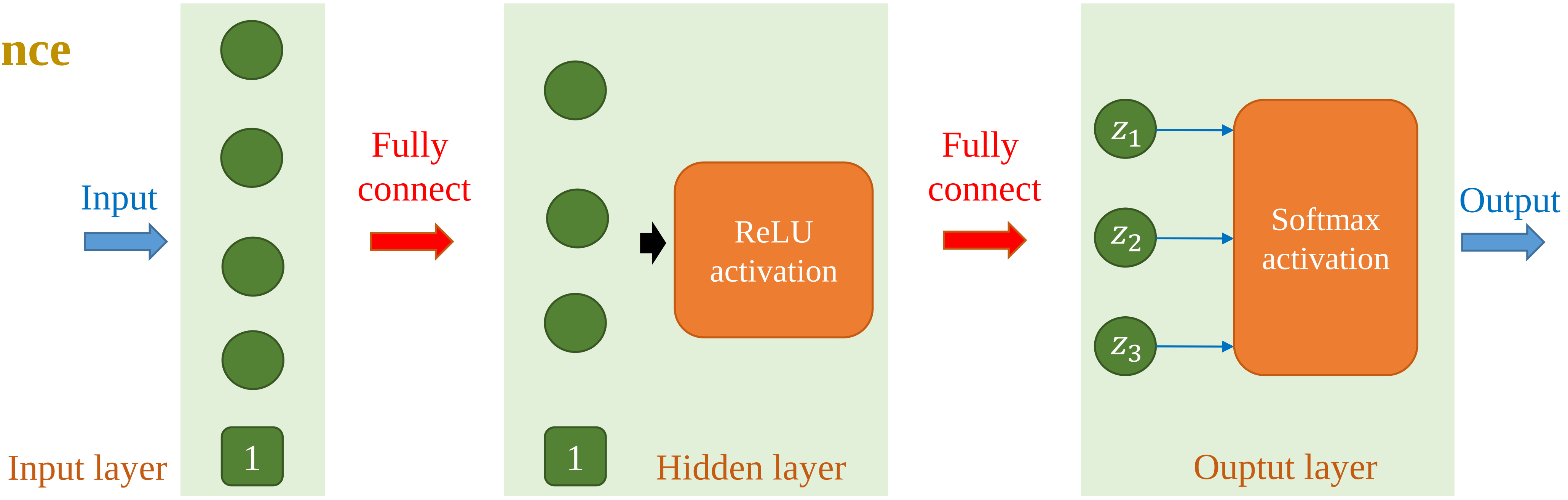
data_a =

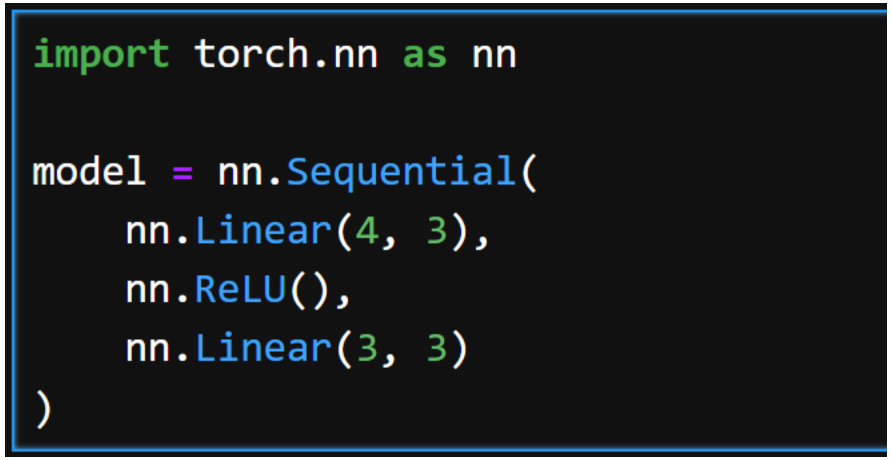
1	5	0	3	0



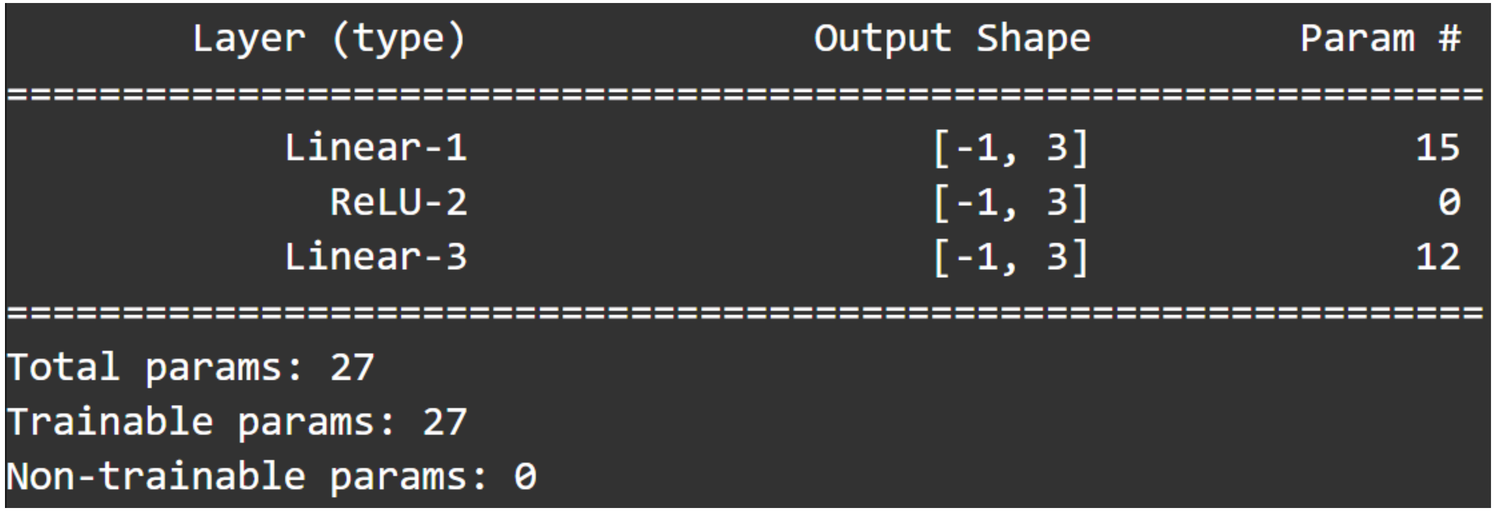
Multi-layer Perceptron

An instance



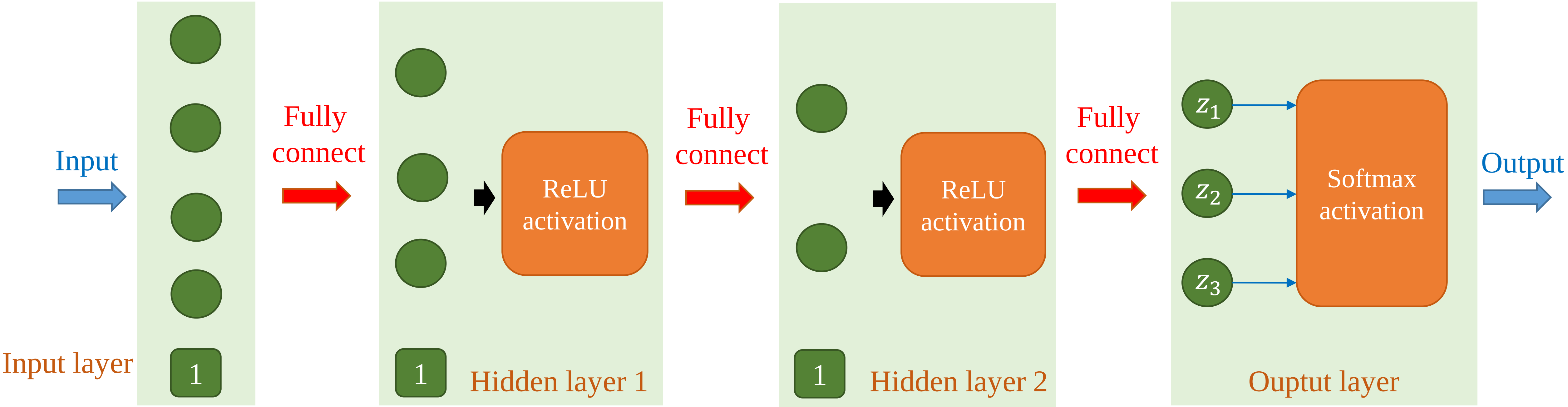


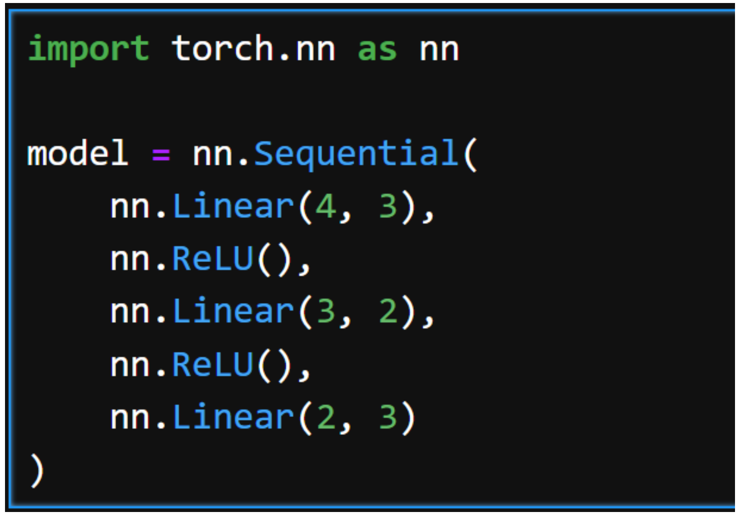
```
import torch.nn as nn

model = nn.Sequential(
    nn.Linear(4, 3),
    nn.ReLU(),
    nn.Linear(3, 3)
)
```



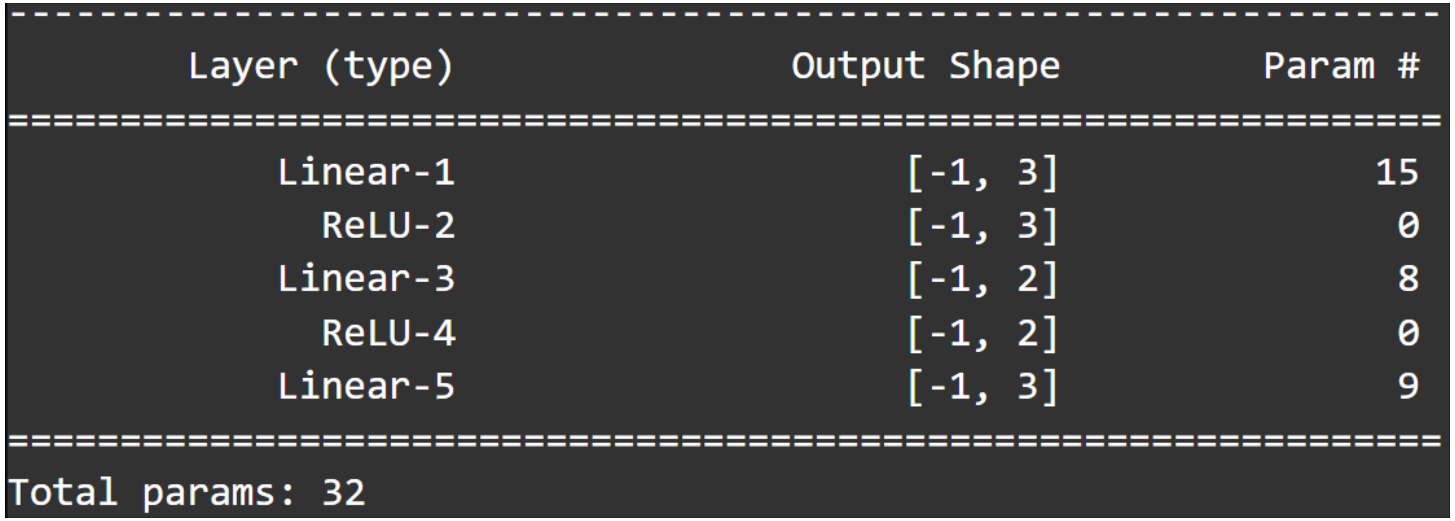
```
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                    [-1, 3]              15
              ReLU-2                    [-1, 3]               0
            Linear-3                    [-1, 3]              12
================================================================
Total params: 27
Trainable params: 27
Non-trainable params: 0
```

Multi-layer Perceptron





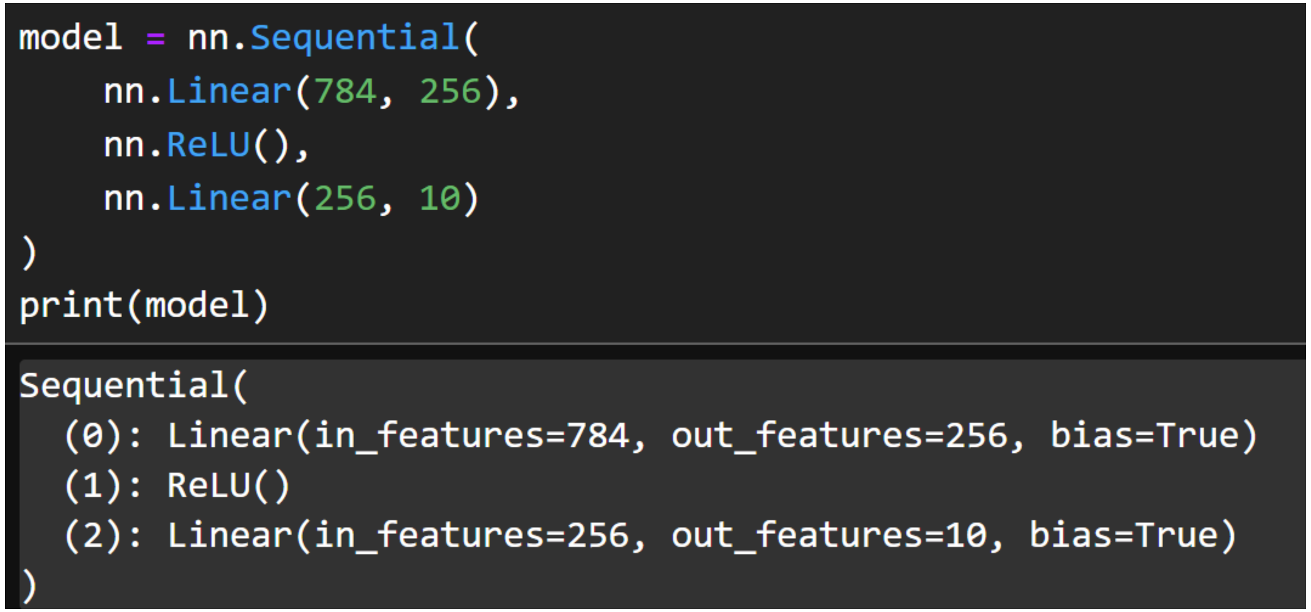
```
import torch.nn as nn

model = nn.Sequential(
    nn.Linear(4, 3),
    nn.ReLU(),
    nn.Linear(3, 2),
    nn.ReLU(),
    nn.Linear(2, 3)
)
```



```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                    [-1, 3]              15
              ReLU-2                    [-1, 3]               0
            Linear-3                    [-1, 2]               8
              ReLU-4                    [-1, 2]               0
            Linear-5                    [-1, 3]               9
================================================================
Total params: 32
```

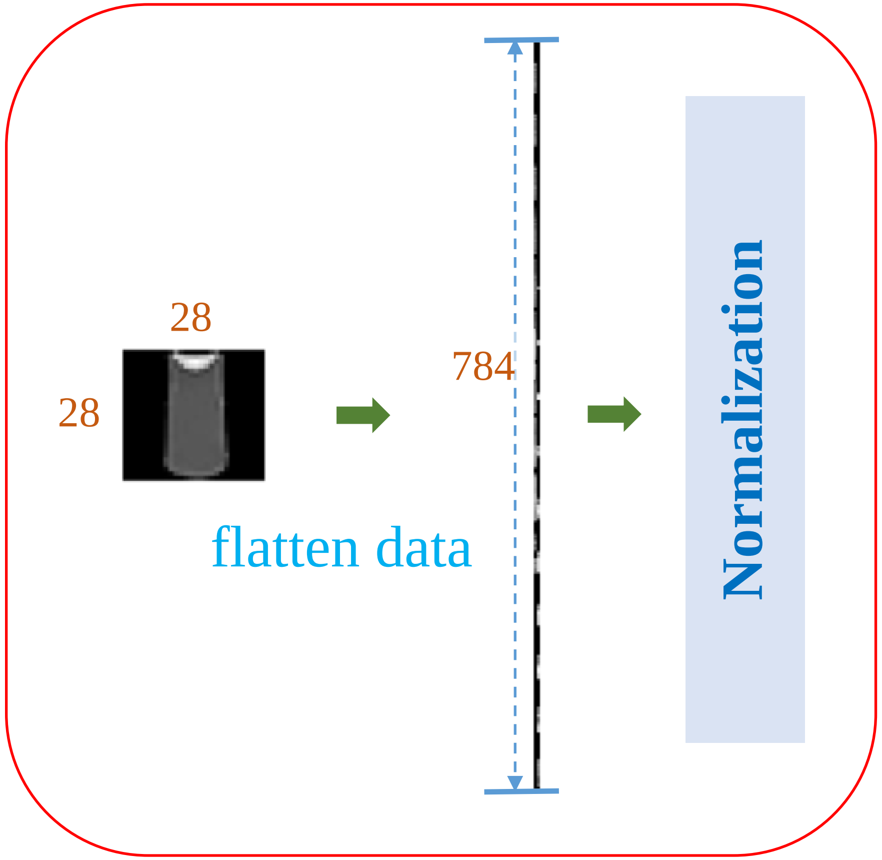
Back to Fashion-MNIST

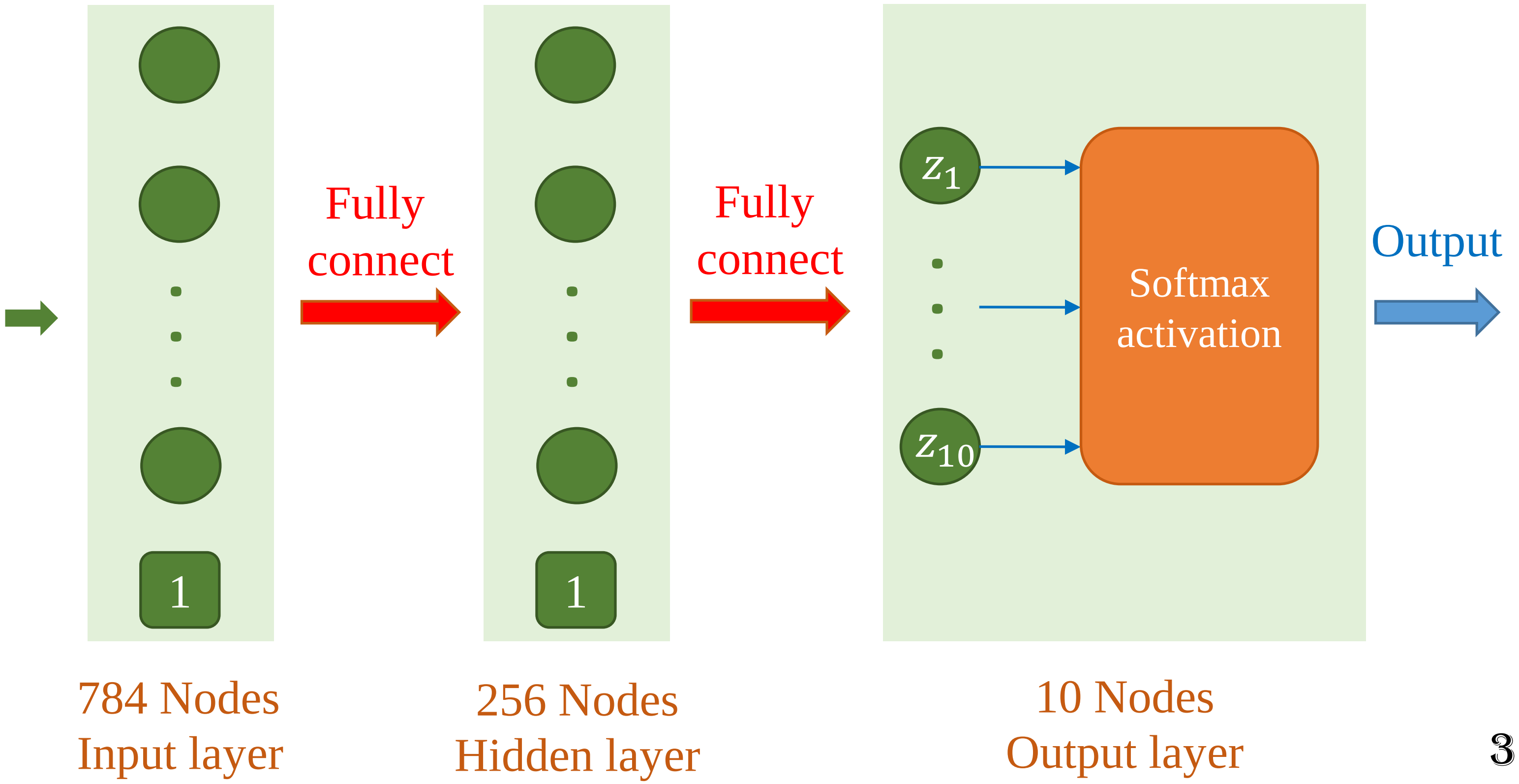
$$\text{Image} = \frac{\text{Image}}{255.0}$$



```
model = nn.Sequential(
    nn.Linear(784, 256),
    nn.ReLU(),
    nn.Linear(256, 10)
)
print(model)
```

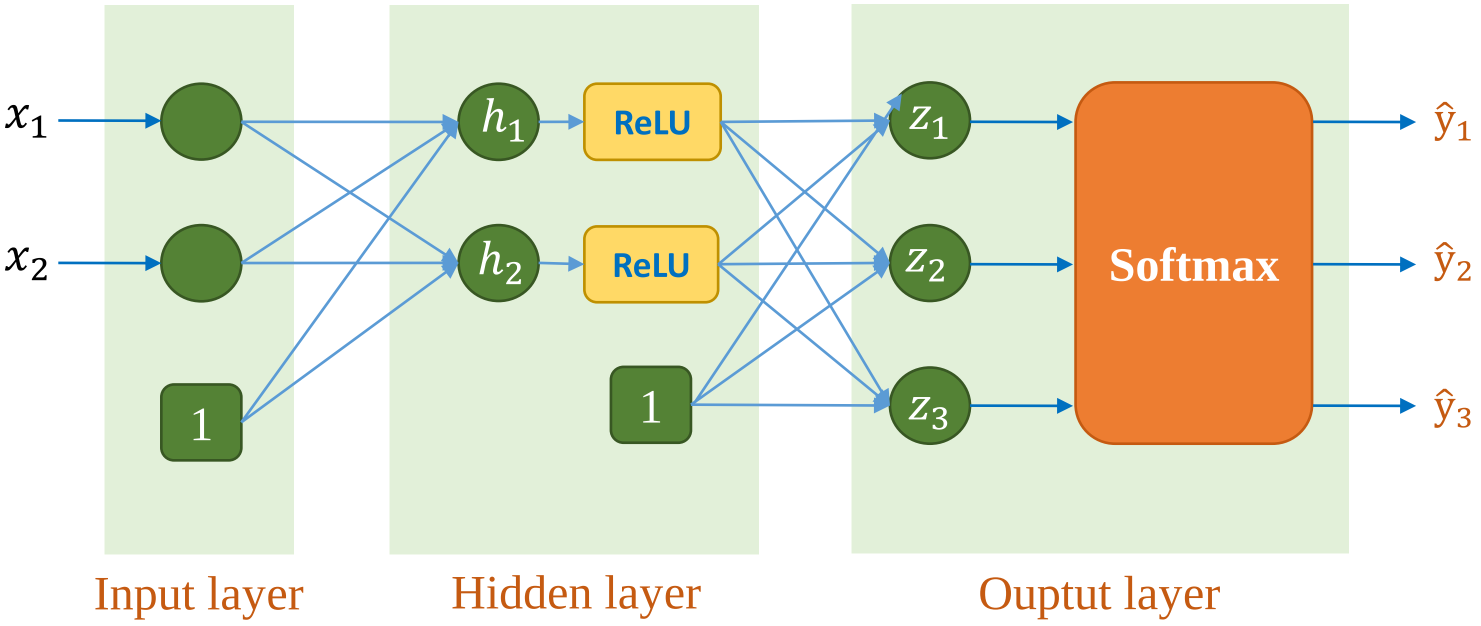
```
Sequential(
  (0): Linear(in_features=784, out_features=256, bias=True)
  (1): ReLU()
  (2): Linear(in_features=256, out_features=10, bias=True)
)
```





MLP Example

Feature		Label
Petal_Length	Petal_Width	Label
1.5	0.2	0
1.4	0.2	0
1.6	0.2	0
4.7	1.6	1
3.3	1.1	1
4.6	1.3	1
5.6	2.2	2
5.1	1.5	2
5.6	1.4	2



$$\boldsymbol{x} = \begin{bmatrix} \boldsymbol{x}^{(1)} \\ \boldsymbol{x}^{(2)} \\ \boldsymbol{x}^{(3)} \end{bmatrix} = \begin{bmatrix} 1.5 & 0.2 \\ 4.7 & 1.6 \\ 5.6 & 2.2 \end{bmatrix}$$

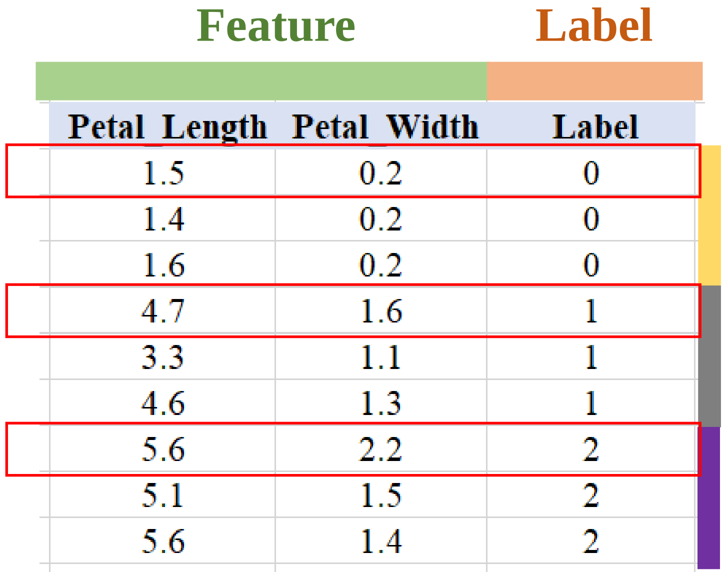
$$\boldsymbol{y} = \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix}$$

$$\boldsymbol{W}_h = [\boldsymbol{W}_{\boldsymbol{h}1} \quad \boldsymbol{W}_{h2}] = \begin{bmatrix} 0.0 & 0.0 \\ 0.86 & -1.04 \\ 0.41 & -0.65 \end{bmatrix}$$

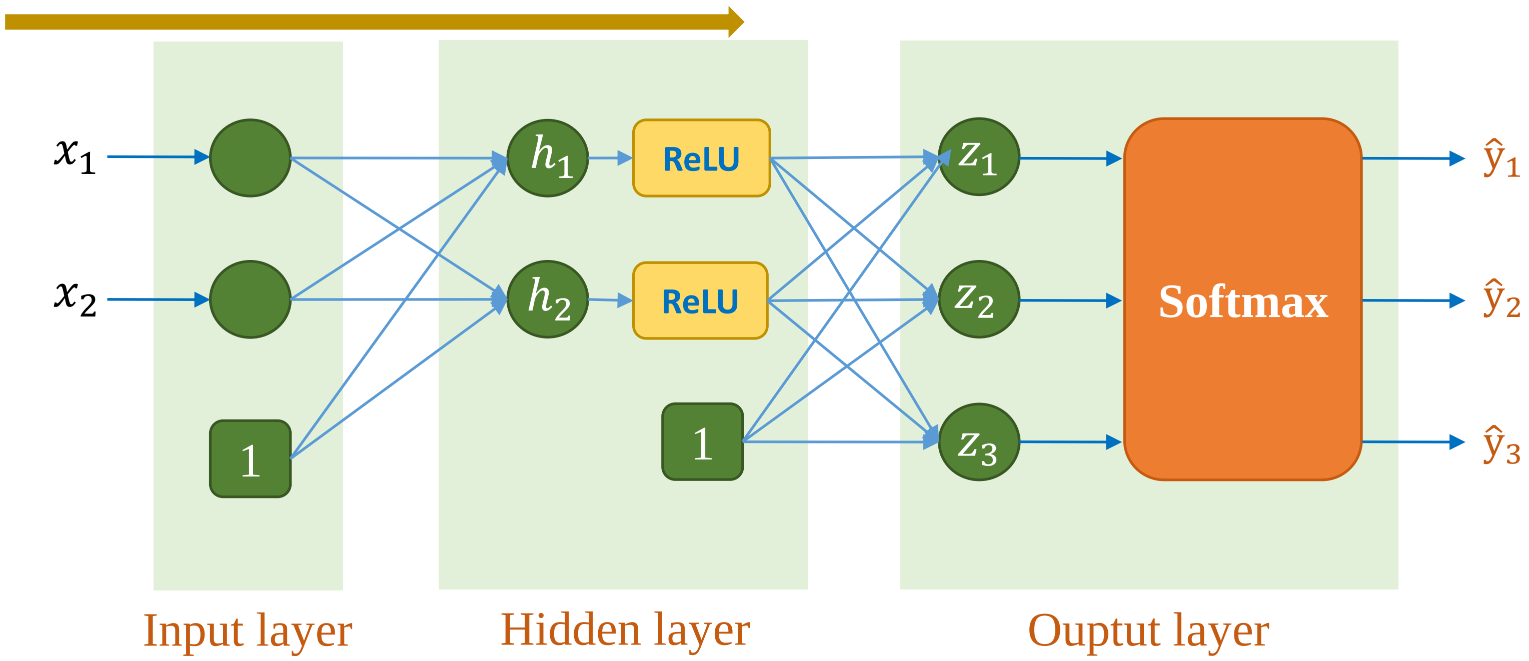
$$\boldsymbol{W}_z = [\boldsymbol{W}_{z1} \quad \boldsymbol{W}_{z2} \quad \boldsymbol{W}_{z3}] = \begin{bmatrix} 0.0 & 0.0 & 0.0 \\ 0.32 & 0.25 & 0.14 \\ -0.47 & -1.06 & 0.063 \end{bmatrix}$$

$$\boldsymbol{h} = \boldsymbol{x}\boldsymbol{W}_h = \begin{bmatrix} 1 & 1.5 & 0.2 \\ 1 & 4.7 & 1.6 \\ 1 & 5.6 & 2.2 \end{bmatrix} \begin{bmatrix} 0.0 & 0.0 \\ 0.86 & -1.04 \\ 0.41 & -0.65 \end{bmatrix} = \begin{bmatrix} 1.373 & -1.696 \\ 4.708 & -5.951 \\ 5.731 & -7.281 \end{bmatrix}$$

$$\text{ReLU}(\boldsymbol{h}) = \begin{bmatrix} 1.373 & 0 \\ 4.708 & 0 \\ 5.731 & 0 \end{bmatrix}$$



Feature		Label
Petal_Length	Petal_Width	Label
1.5	0.2	0
1.4	0.2	0
1.6	0.2	0
4.7	1.6	1
3.3	1.1	1
4.6	1.3	1
5.6	2.2	2
5.1	1.5	2
5.6	1.4	2



$$\boldsymbol{x} = \begin{bmatrix} \boldsymbol{x}^{(1)} \\ \boldsymbol{x}^{(2)} \\ \boldsymbol{x}^{(3)} \end{bmatrix} = \begin{bmatrix} 1 & 1.5 & 0.2 \\ 1 & 4.7 & 1.6 \\ 1 & 5.6 & 2.2 \end{bmatrix} \quad \boldsymbol{y} = \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix}$$

$$\boldsymbol{W}_h = [\boldsymbol{W}_{h1} \quad \boldsymbol{W}_{h2}] = \begin{bmatrix} 0.0 & 0.0 \\ 0.86 & -1.04 \\ 0.41 & -0.65 \end{bmatrix}$$

$$\boldsymbol{W}_z = [\boldsymbol{W}_{z1} \quad \boldsymbol{W}_{z2} \quad \boldsymbol{W}_{z3}] = \begin{bmatrix} 0.0 & 0.0 & 0.0 \\ 0.32 & 0.25 & 0.14 \\ -0.47 & -1.06 & 0.063 \end{bmatrix}$$

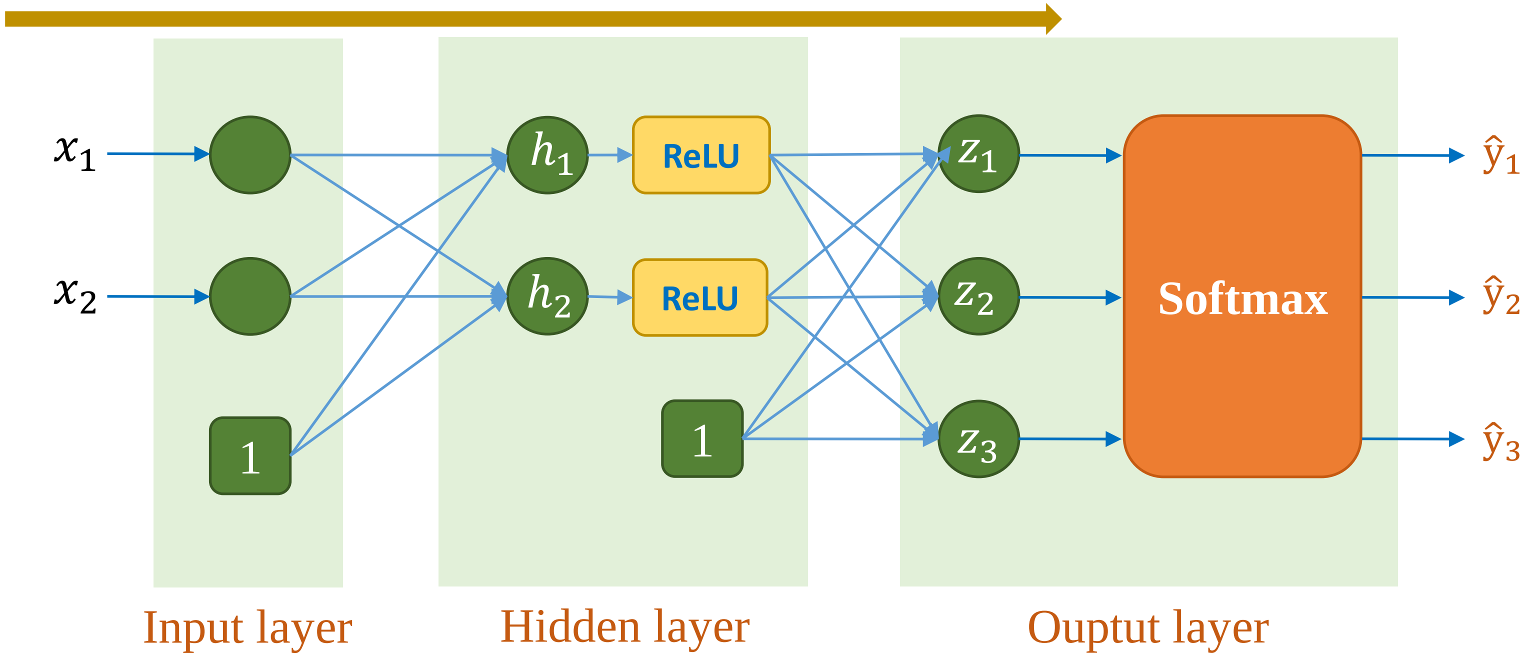
$$\mathrm{ReLU}(\boldsymbol{h}) = \begin{bmatrix} 1.373 & 0 \\ 4.708 & 0 \\ 5.731 & 0 \end{bmatrix}$$

$$[\mathbf{1} \quad \mathrm{ReLU}(\boldsymbol{h})] = \begin{bmatrix} 1 & 1.373 & 0 \\ 1 & 4.708 & 0 \\ 1 & 5.731 & 0 \end{bmatrix}$$

$$\boldsymbol{z} = [\mathbf{1} \quad \mathrm{ReLU}(\boldsymbol{h})]\boldsymbol{W}_z = \begin{bmatrix} 1 & 1.373 & 0 \\ 1 & 4.708 & 0 \\ 1 & 5.731 & 0 \end{bmatrix} \begin{bmatrix} 0.0 & 0.0 & 0.0 \\ 0.32 & 0.25 & 0.14 \\ -0.47 & -1.06 & 0.063 \end{bmatrix}$$

$$= \begin{bmatrix} 0.439 & 0.356 & 0.195 \\ 1.507 & 1.220 & 0.670 \\ 1.835 & 1.485 & 0.816 \end{bmatrix}$$

Feature		Label
Petal_Length	Petal_Width	Label
1.5	0.2	0
1.4	0.2	0
1.6	0.2	0
4.7	1.6	1
3.3	1.1	1
4.6	1.3	1
5.6	2.2	2
5.1	1.5	2
5.6	1.4	2



$$\boldsymbol{x} = \begin{bmatrix} \boldsymbol{x}^{(1)} \\ \boldsymbol{x}^{(2)} \\ \boldsymbol{x}^{(3)} \end{bmatrix} = \begin{bmatrix} 1 & 1.5 & 0.2 \\ 1 & 4.7 & 1.6 \\ 1 & 5.6 & 2.2 \end{bmatrix} \quad \boldsymbol{y} = \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix}$$

$$\boldsymbol{W}_h = [\boldsymbol{W}_{h1} \quad \boldsymbol{W}_{h2}] = \begin{bmatrix} 0.0 & 0.0 \\ 0.86 & -1.04 \\ 0.41 & -0.65 \end{bmatrix}$$

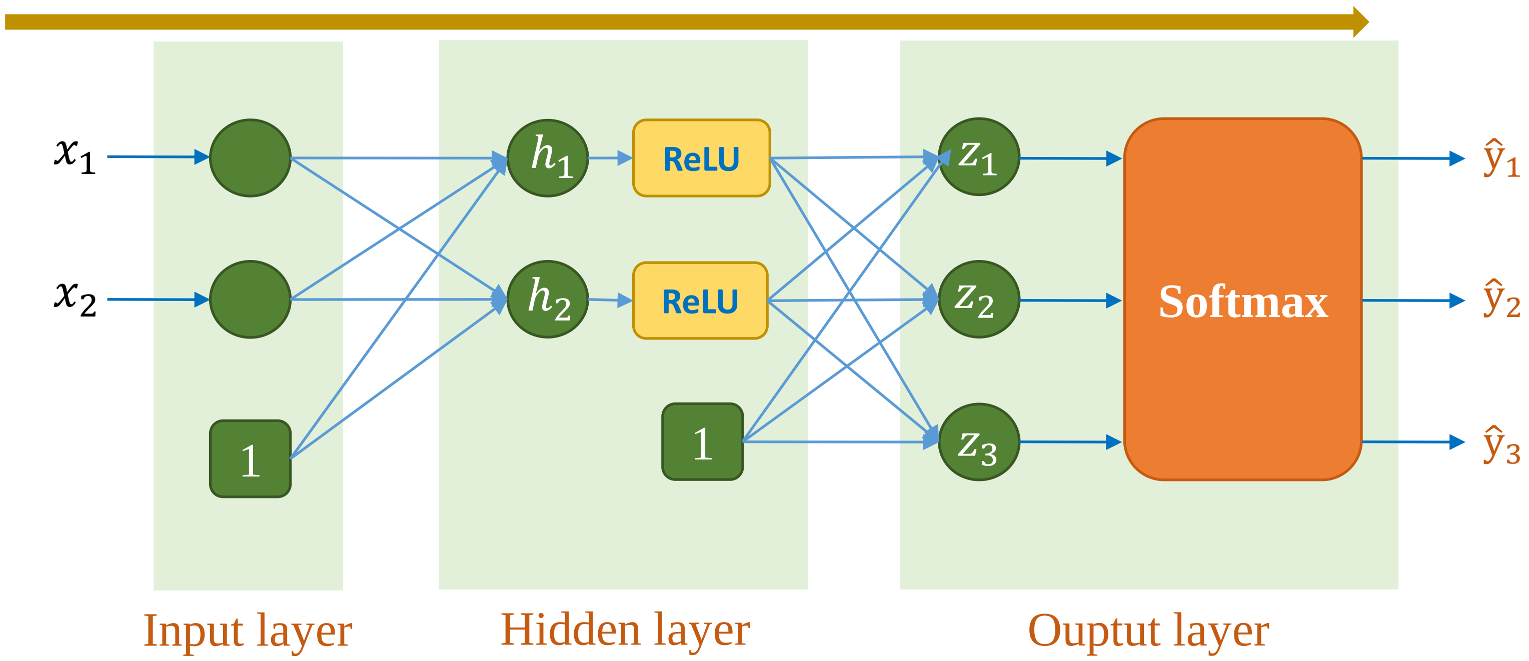
$$\boldsymbol{W}_z = [\boldsymbol{W}_{z1} \quad \boldsymbol{W}_{z2} \quad \boldsymbol{W}_{z3}] = \begin{bmatrix} 0.0 & 0.0 & 0.0 \\ 0.32 & 0.25 & 0.14 \\ -0.47 & -1.06 & 0.063 \end{bmatrix}$$

$$\boldsymbol{z} = \begin{bmatrix} 0.439 & 0.356 & 0.195 \\ 1.507 & 1.220 & 0.670 \\ 1.835 & 1.485 & 0.816 \end{bmatrix}$$

$$\hat{\boldsymbol{y}} = \text{softmax}(\boldsymbol{z}) = \begin{bmatrix} \hat{\boldsymbol{y}}^{(1)} \\ \hat{\boldsymbol{y}}^{(2)} \\ \hat{\boldsymbol{y}}^{(3)} \end{bmatrix} = \begin{bmatrix} 0.369 & 0.340 & 0.289 \\ 0.458 & 0.343 & 0.198 \\ 0.484 & 0.341 & 0.174 \end{bmatrix}$$

$$\text{loss} = 1.269$$

Feature		Label
Petal_Length	**Petal_Width**	**Label**
1.5	0.2	0
1.4	0.2	0
1.6	0.2	0
4.7	1.6	1
3.3	1.1	1
4.6	1.3	1
5.6	2.2	2
5.1	1.5	2
5.6	1.4	2

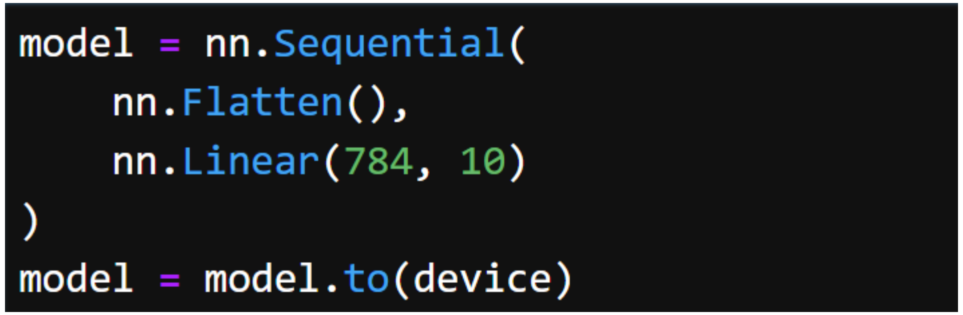


$$\boldsymbol{x} = \begin{bmatrix} \boldsymbol{x}^{(1)} \\ \boldsymbol{x}^{(2)} \\ \boldsymbol{x}^{(3)} \end{bmatrix} = \begin{bmatrix} 1 & 1.5 & 0.2 \\ 1 & 4.7 & 1.6 \\ 1 & 5.6 & 2.2 \end{bmatrix} \quad \boldsymbol{y} = \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix}$$

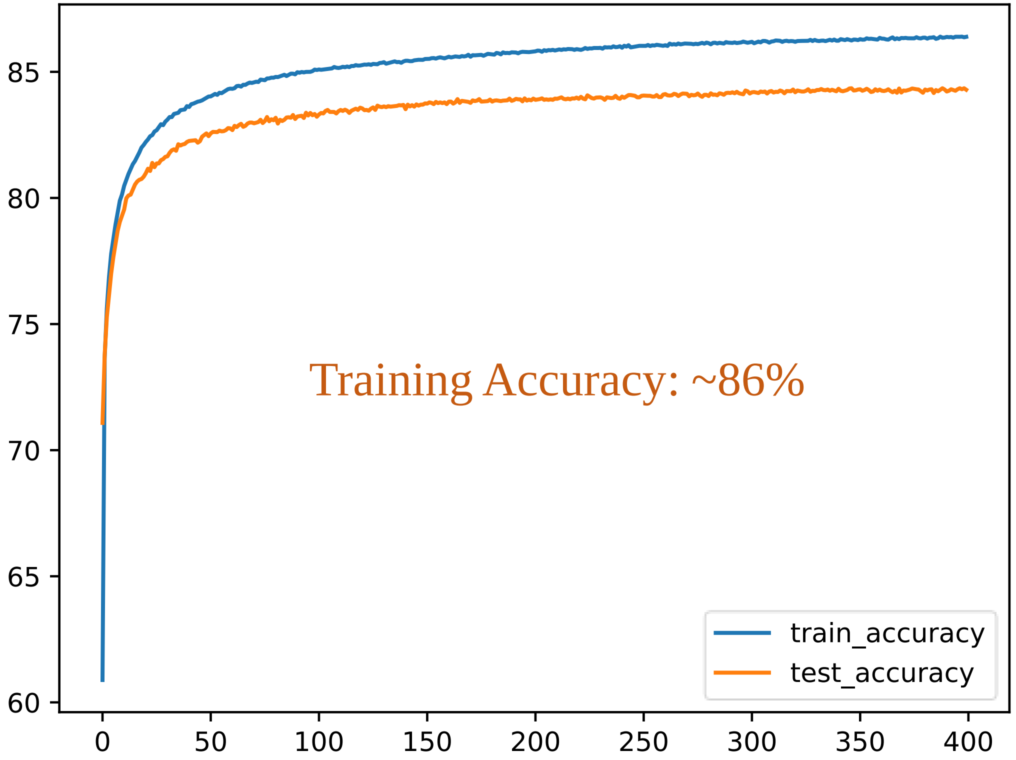
$$\boldsymbol{W}_h = [\boldsymbol{W}_{h1} \quad \boldsymbol{W}_{h2}] = \begin{bmatrix} 0.0 & 0.0 \\ 0.86 & -1.04 \\ 0.41 & -0.65 \end{bmatrix}$$

$$\boldsymbol{W}_z = [\boldsymbol{W}_{z1} \quad \boldsymbol{W}_{z2} \quad \boldsymbol{W}_{z3}] = \begin{bmatrix} 0.0 & 0.0 & 0.0 \\ 0.32 & 0.25 & 0.14 \\ -0.47 & -1.06 & 0.063 \end{bmatrix}$$

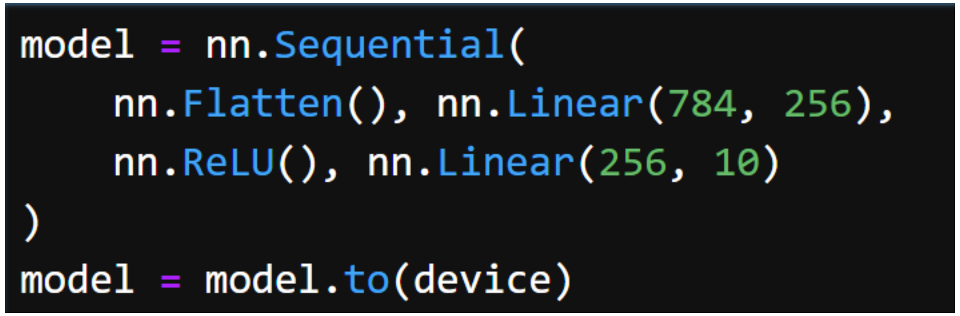
Softmax and MLP



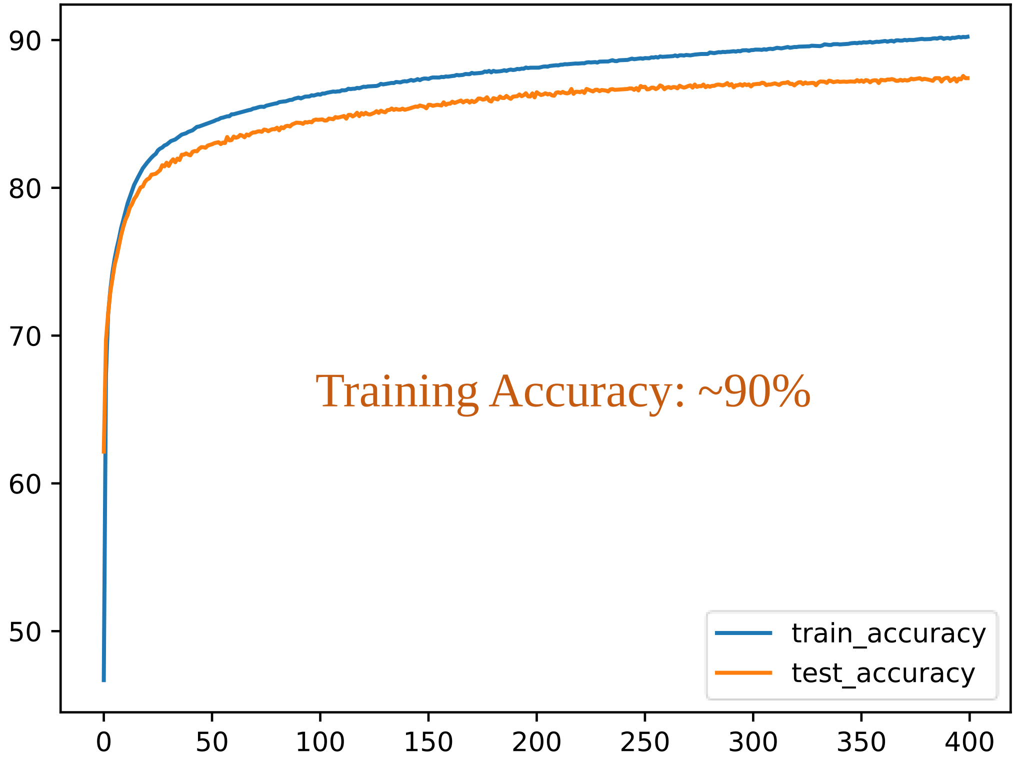
```python
model = nn.Sequential(
    nn.Flatten(),
    nn.Linear(784, 10)
)
model = model.to(device)
```



Training Accuracy: ~86%



```python
model = nn.Sequential(
    nn.Flatten(), nn.Linear(784, 256),
    nn.ReLU(), nn.Linear(256, 10)
)
model = model.to(device)
```



Training Accuracy: ~90%

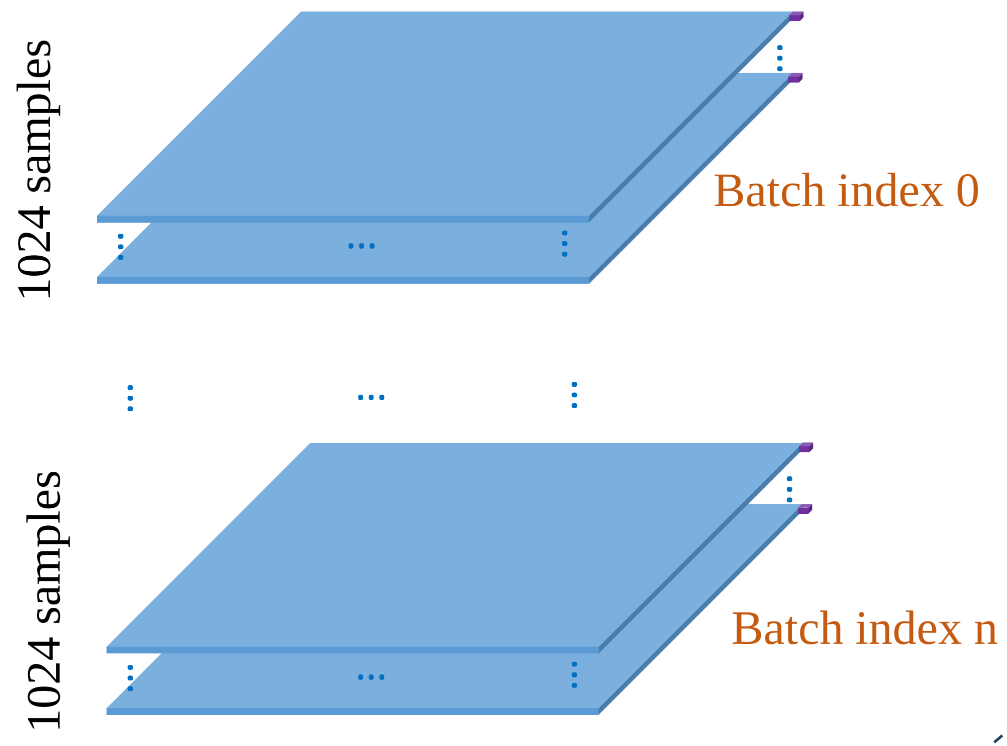
Outline

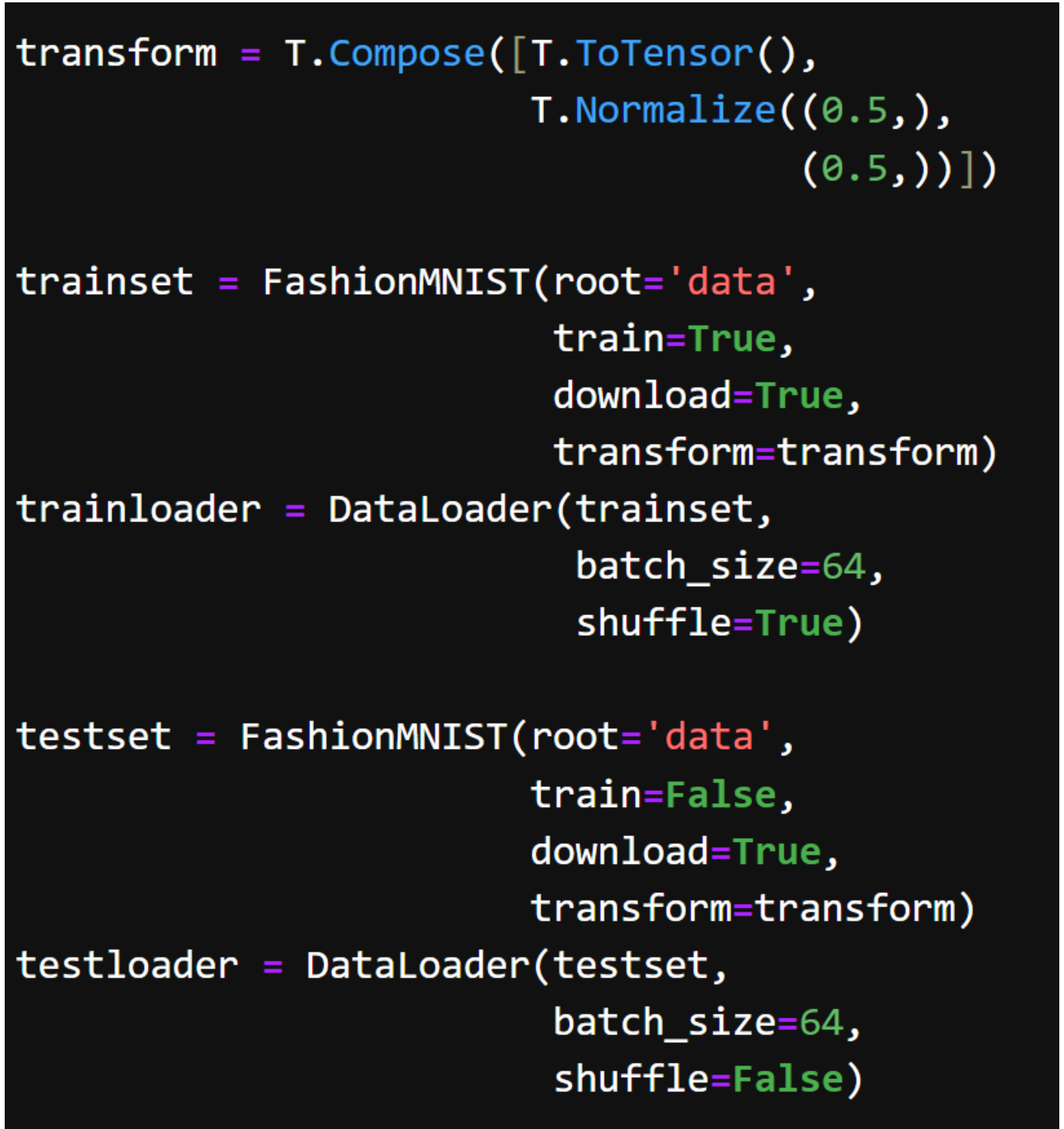
- Image Data Loading Using Numpy&PyTorch
- Softmax+Normalization for Fashion-MNIST
- MLP and Examples
- Step-by-Step Implementation
- Training Strategy (optional)

Step-by-Step Implementation

❖ 1. Data Preparation

Each sample is a tuple (image tensor, label)

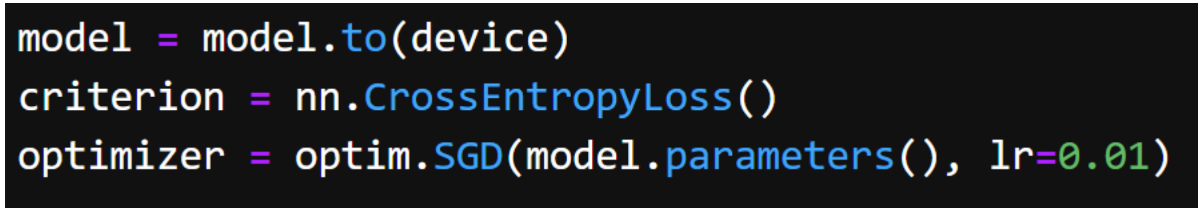




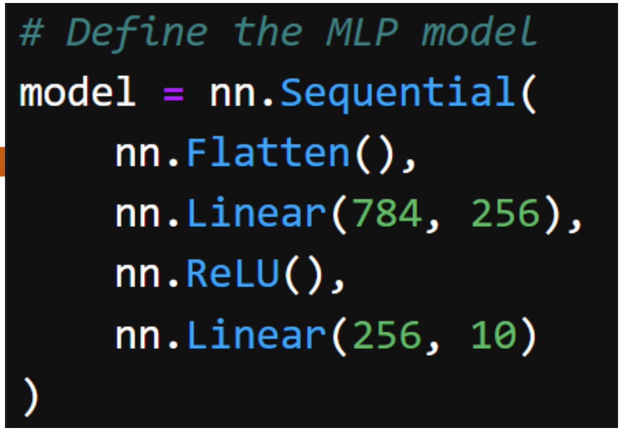
```
transform = T.Compose([T.ToTensor(),
                       T.Normalize((0.5,),
                                   (0.5,))])

trainset = FashionMNIST(root='data',
                        train=True,
                        download=True,
                        transform=transform)
trainloader = DataLoader(trainset,
                         batch_size=64,
                         shuffle=True)

testset = FashionMNIST(root='data',
                       train=False,
                       download=True,
                       transform=transform)
testloader = DataLoader(testset,
                        batch_size=64,
                        shuffle=False)
```

Step-by-Step Implementation

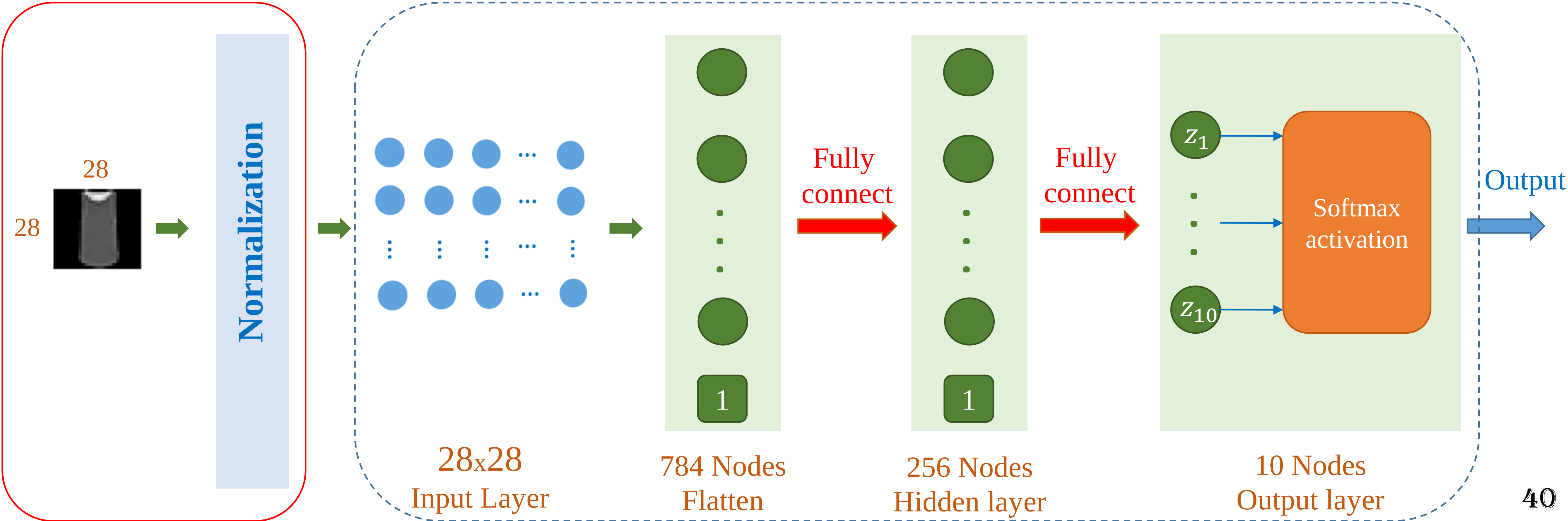
❖ 2. Model, loss and optimizer



```
model = model.to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)
```

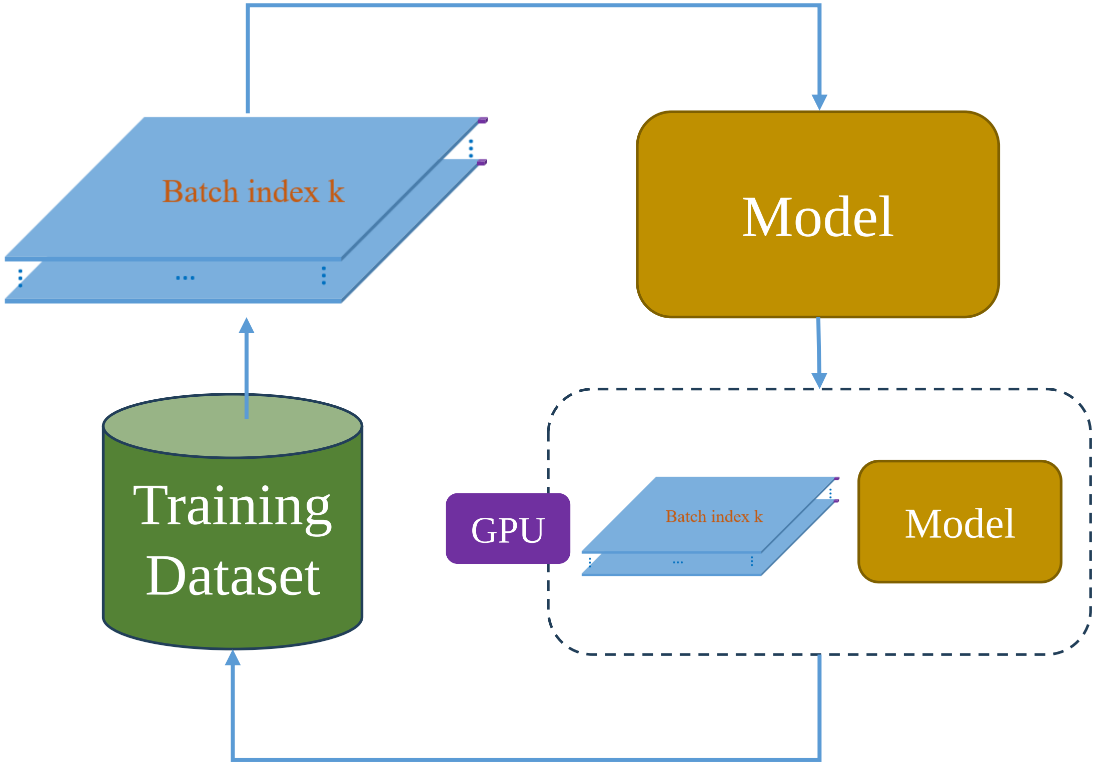


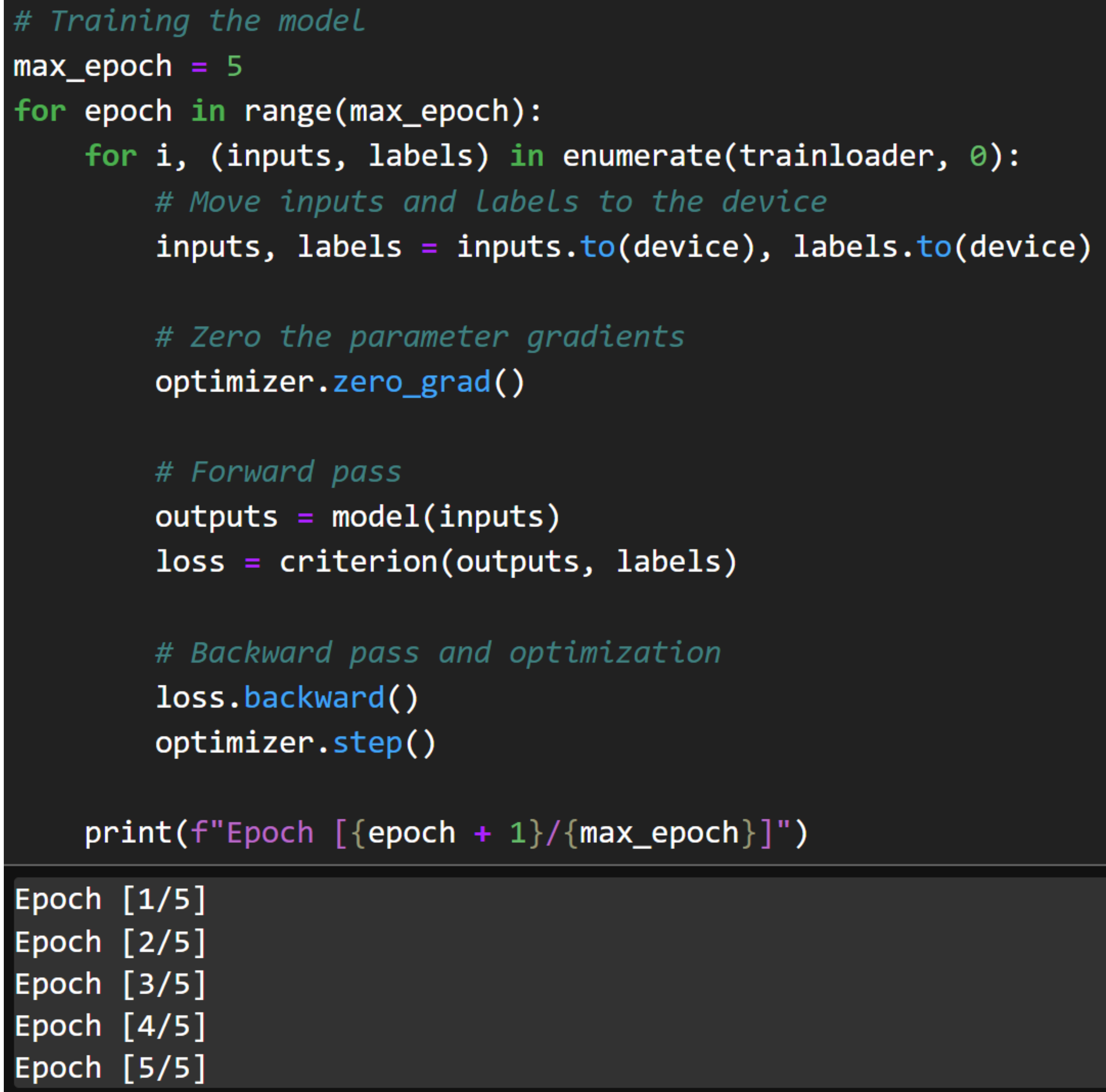
```
# Define the MLP model
model = nn.Sequential(
    nn.Flatten(),
    nn.Linear(784, 256),
    nn.ReLU(),
    nn.Linear(256, 10)
)
```



Step-by-Step Implementation

❖ 3. Training



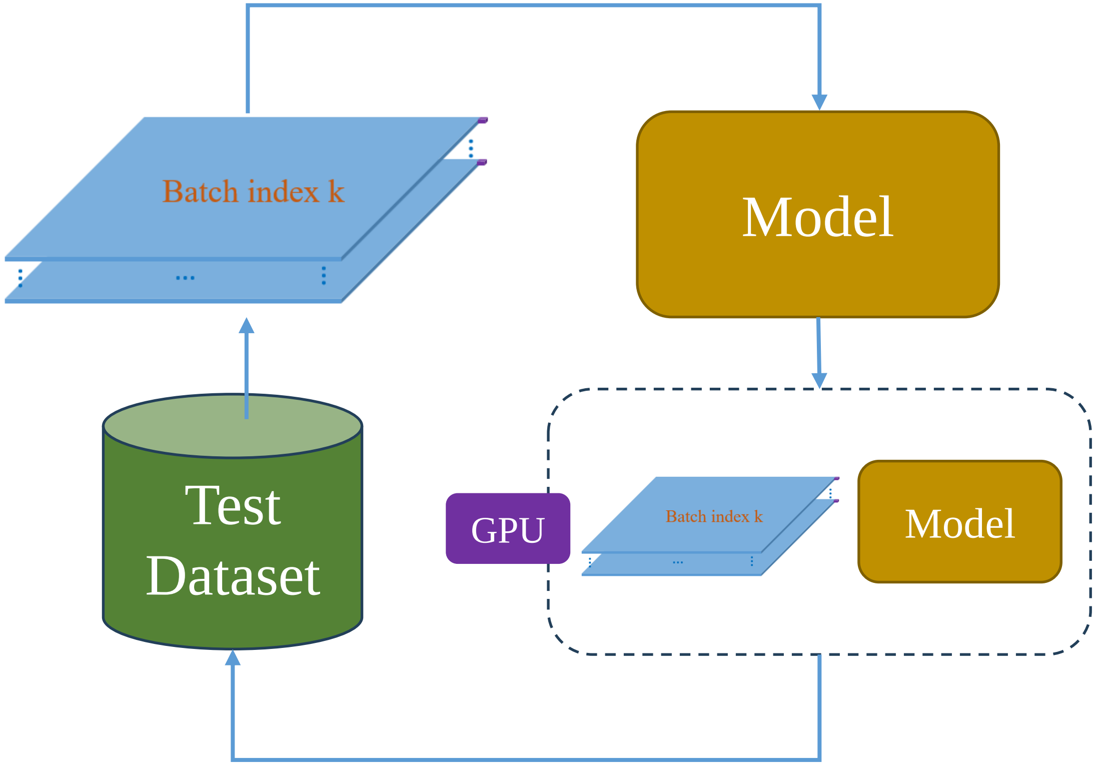


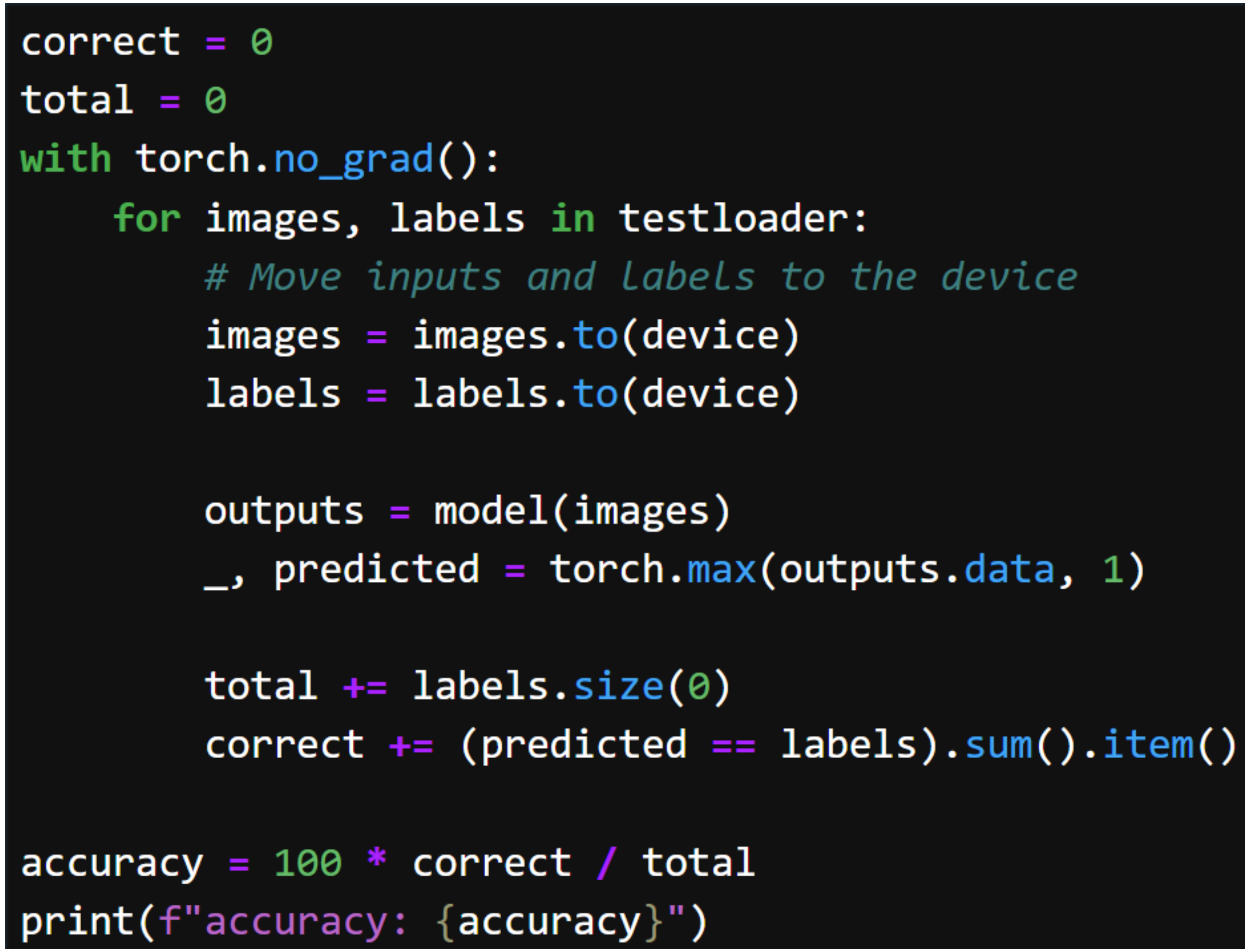
```
# Training the model
max_epoch = 5
for epoch in range(max_epoch):
    for i, (inputs, labels) in enumerate(trainloader, 0):
        # Move inputs and labels to the device
        inputs, labels = inputs.to(device), labels.to(device)

        # Zero the parameter gradients
        optimizer.zero_grad()

        # Forward pass
        outputs = model(inputs)
        loss = criterion(outputs, labels)

        # Backward pass and optimization
        loss.backward()
        optimizer.step()

    print(f"Epoch [{epoch + 1}/{max_epoch}]")
```

```
Epoch [1/5]
Epoch [2/5]
Epoch [3/5]
Epoch [4/5]
Epoch [5/5]
```

Step-by-Step Implementation

❖ 4. Inference

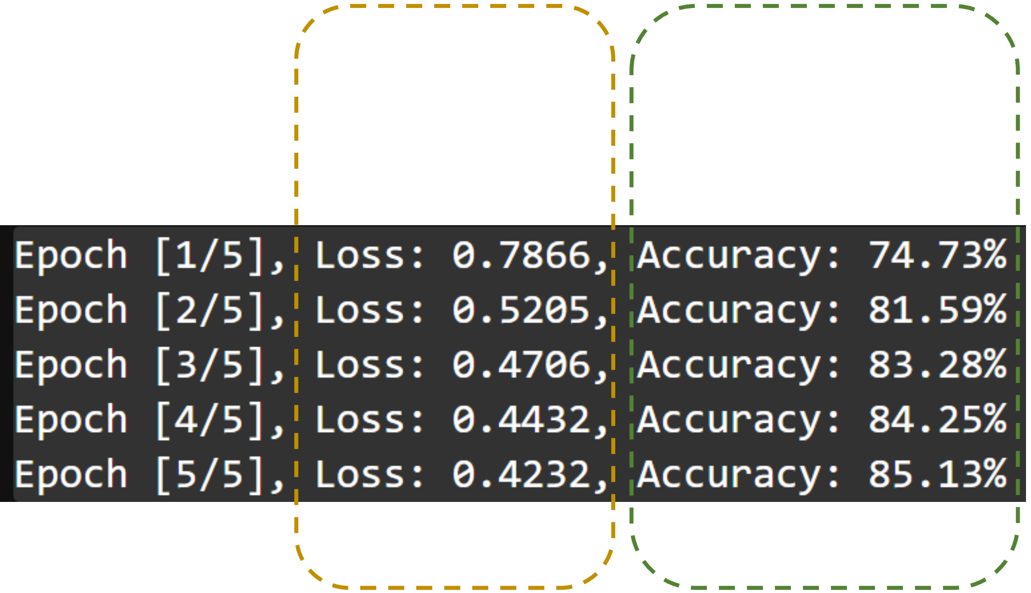




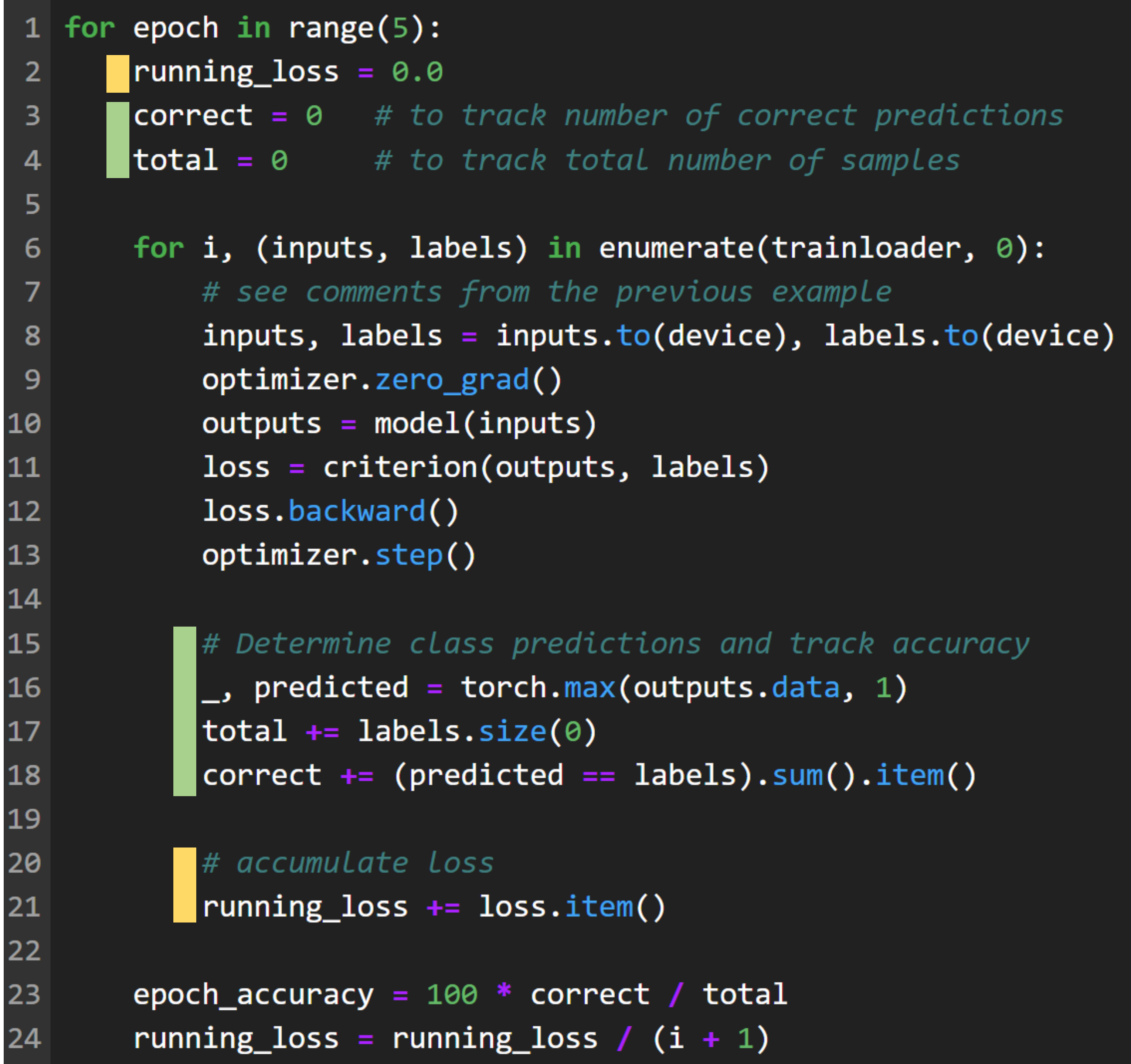
```
correct = 0
total = 0
with torch.no_grad():
    for images, labels in testloader:
        # Move inputs and labels to the device
        images = images.to(device)
        labels = labels.to(device)

        outputs = model(images)
        _, predicted = torch.max(outputs.data, 1)

        total += labels.size(0)
        correct += (predicted == labels).sum().item()

accuracy = 100 * correct / total
print(f"accuracy: {accuracy}")
```

Step-by-Step Implementation

❖ Addition 1: Compute Training Loss and Accuracy



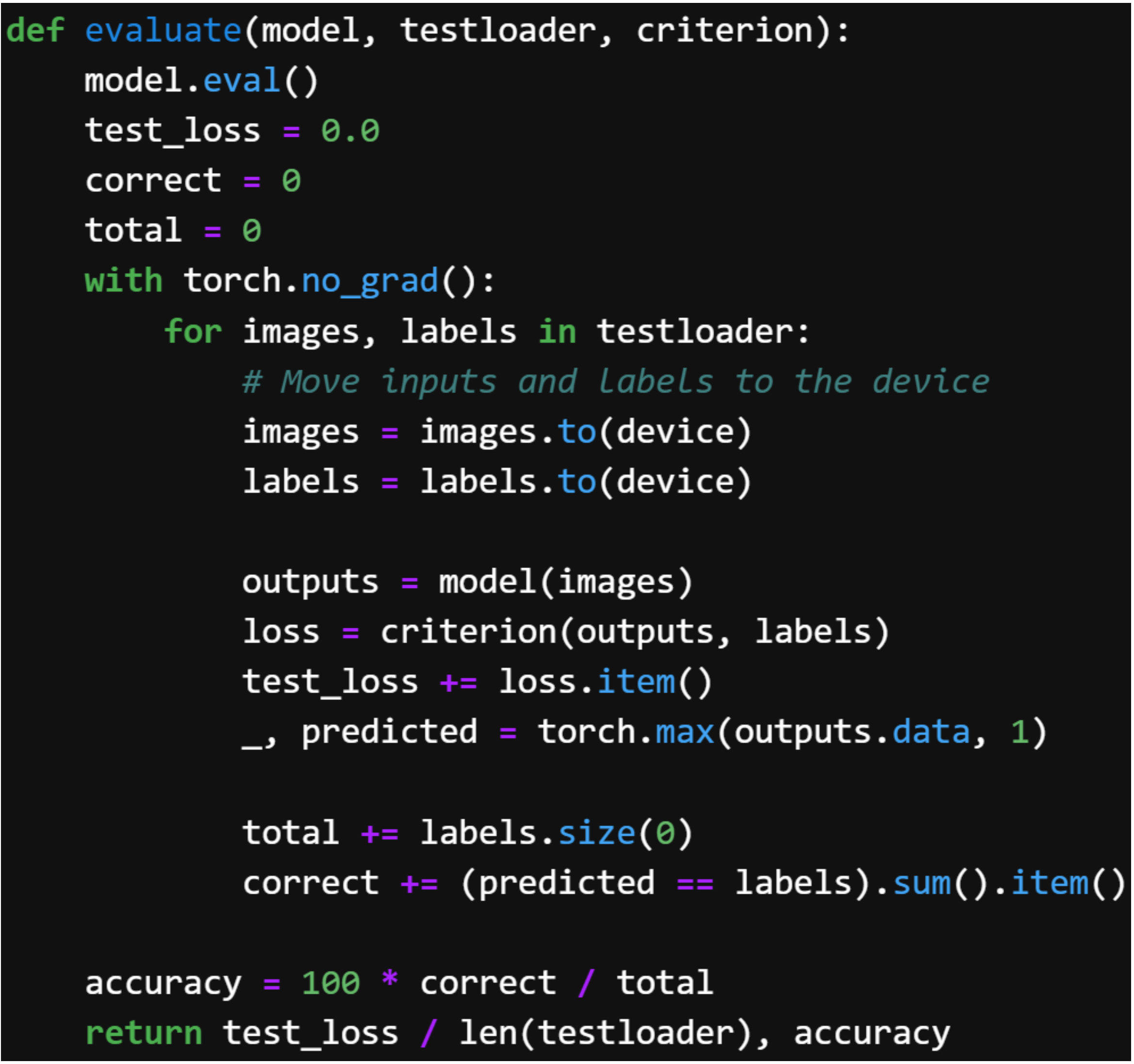
```
Epoch [1/5], Loss: 0.7866, Accuracy: 74.73%
Epoch [2/5], Loss: 0.5205, Accuracy: 81.59%
Epoch [3/5], Loss: 0.4706, Accuracy: 83.28%
Epoch [4/5], Loss: 0.4432, Accuracy: 84.25%
Epoch [5/5], Loss: 0.4232, Accuracy: 85.13%
```



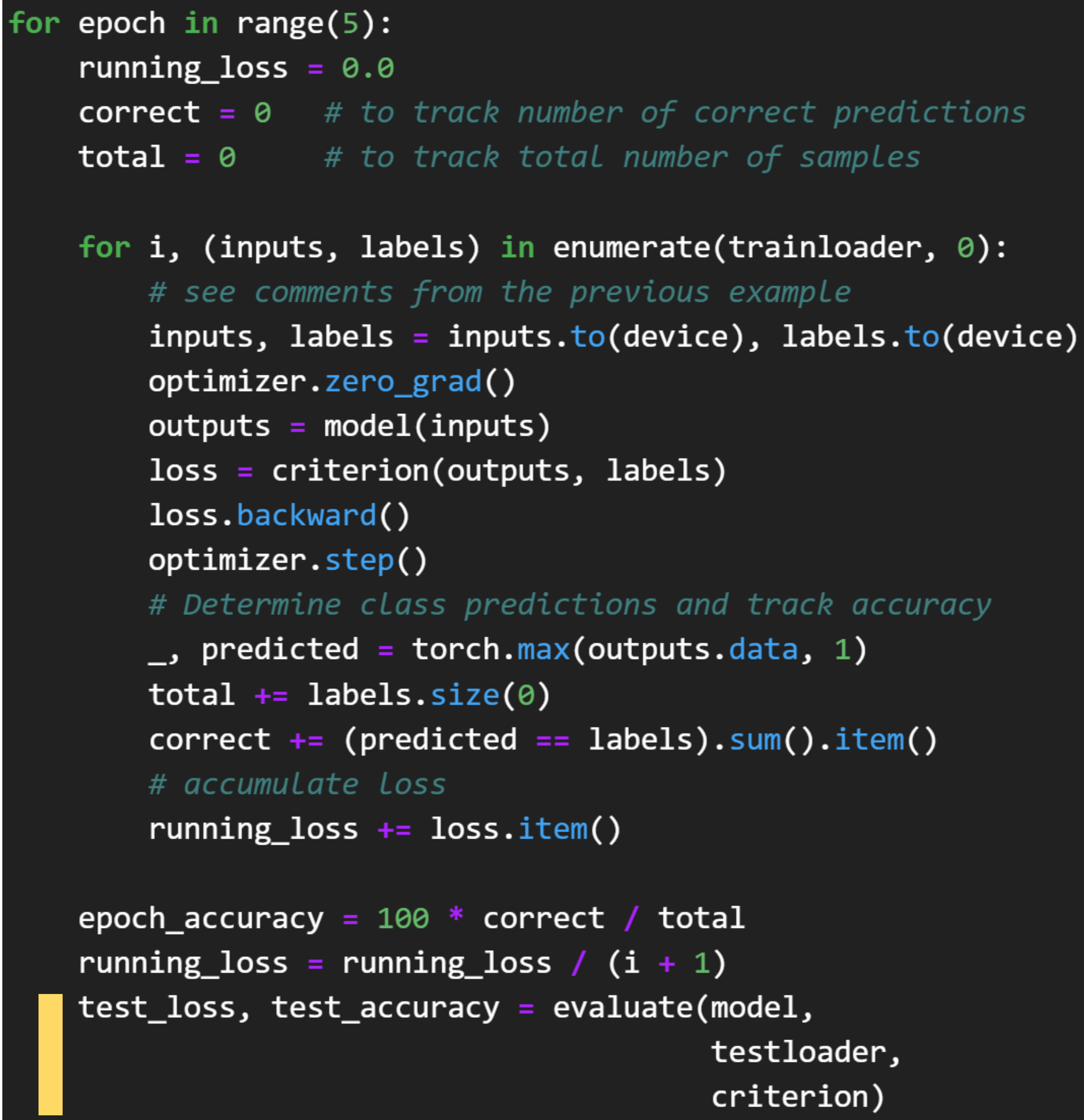
```python
for epoch in range(5):
  running_loss = 0.0
  correct = 0   # to track number of correct predictions
  total = 0     # to track total number of samples

  for i, (inputs, labels) in enumerate(trainloader, 0):
    # see comments from the previous example
    inputs, labels = inputs.to(device), labels.to(device)
    optimizer.zero_grad()
    outputs = model(inputs)
    loss = criterion(outputs, labels)
    loss.backward()
    optimizer.step()

    # Determine class predictions and track accuracy
    _, predicted = torch.max(outputs.data, 1)
    total += labels.size(0)
    correct += (predicted == labels).sum().item()

    # accumulate loss
    running_loss += loss.item()

  epoch_accuracy = 100 * correct / total
  running_loss = running_loss / (i + 1)
```

Step-by-Step Implementation

❖ Addition 2: Compute Test Loss and Accuracy



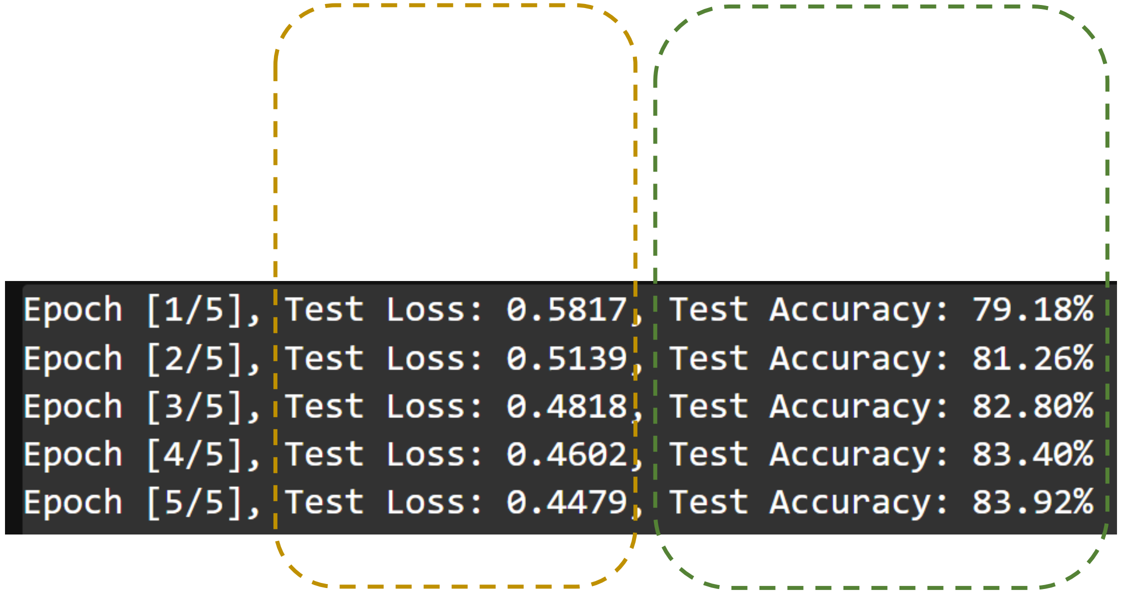
```
def evaluate(model, testloader, criterion):
    model.eval()
    test_loss = 0.0
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in testloader:
            # Move inputs and labels to the device
            images = images.to(device)
            labels = labels.to(device)

            outputs = model(images)
            loss = criterion(outputs, labels)
            test_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)

            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    accuracy = 100 * correct / total
    return test_loss / len(testloader), accuracy
```



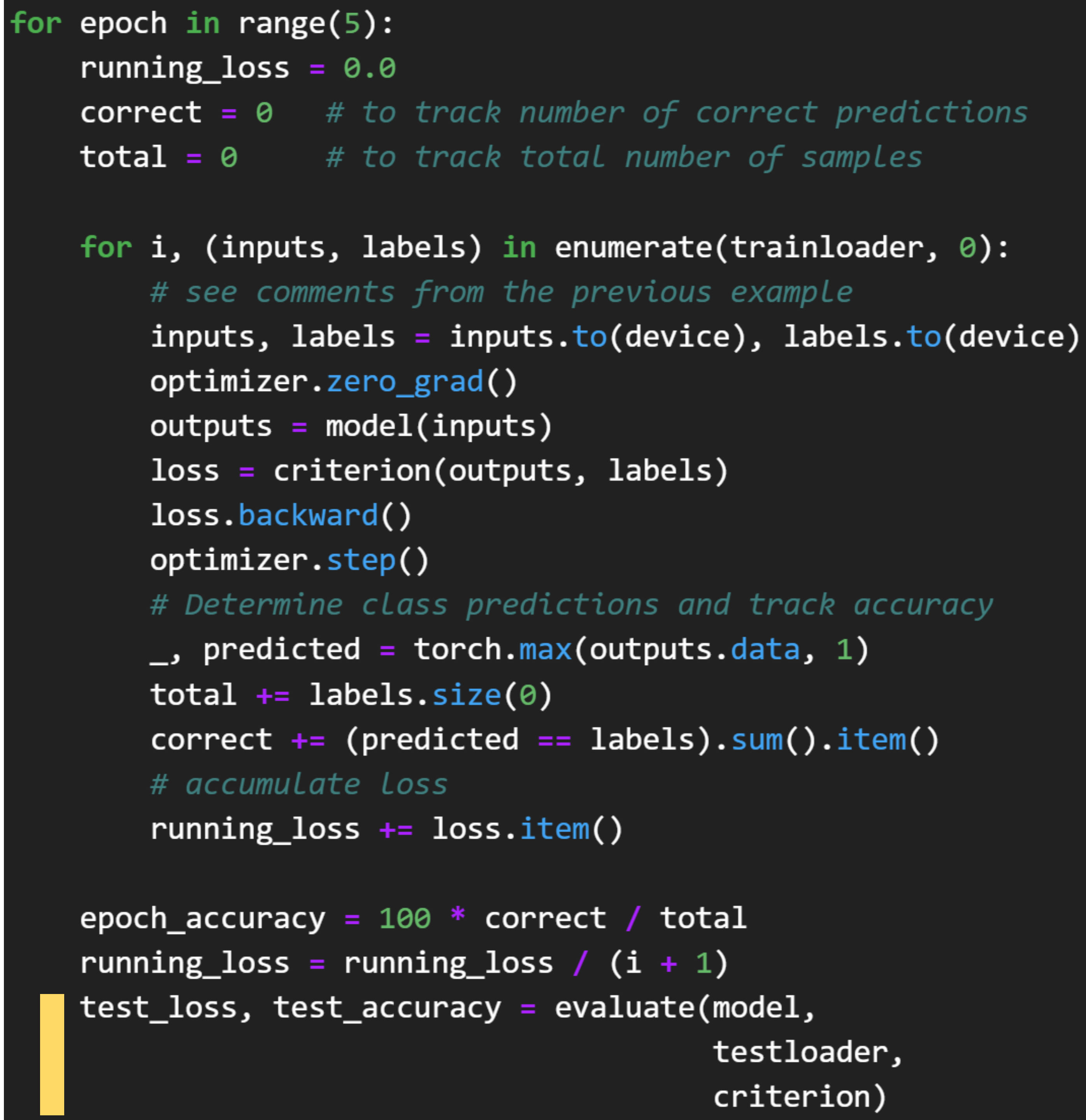
```
for epoch in range(5):
    running_loss = 0.0
    correct = 0    # to track number of correct predictions
    total = 0      # to track total number of samples

    for i, (inputs, labels) in enumerate(trainloader, 0):
        # see comments from the previous example
        inputs, labels = inputs.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        # Determine class predictions and track accuracy
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
        # accumulate loss
        running_loss += loss.item()

    epoch_accuracy = 100 * correct / total
    running_loss = running_loss / (i + 1)
    test_loss, test_accuracy = evaluate(model,
                                        testloader,
                                        criterion)
```

Step-by-Step Implementation

❖ Addition 2: Compute Test Loss and Accuracy



```
Epoch [1/5], Test Loss: 0.5817, Test Accuracy: 79.18%
Epoch [2/5], Test Loss: 0.5139, Test Accuracy: 81.26%
Epoch [3/5], Test Loss: 0.4818, Test Accuracy: 82.80%
Epoch [4/5], Test Loss: 0.4602, Test Accuracy: 83.40%
Epoch [5/5], Test Loss: 0.4479, Test Accuracy: 83.92%
```

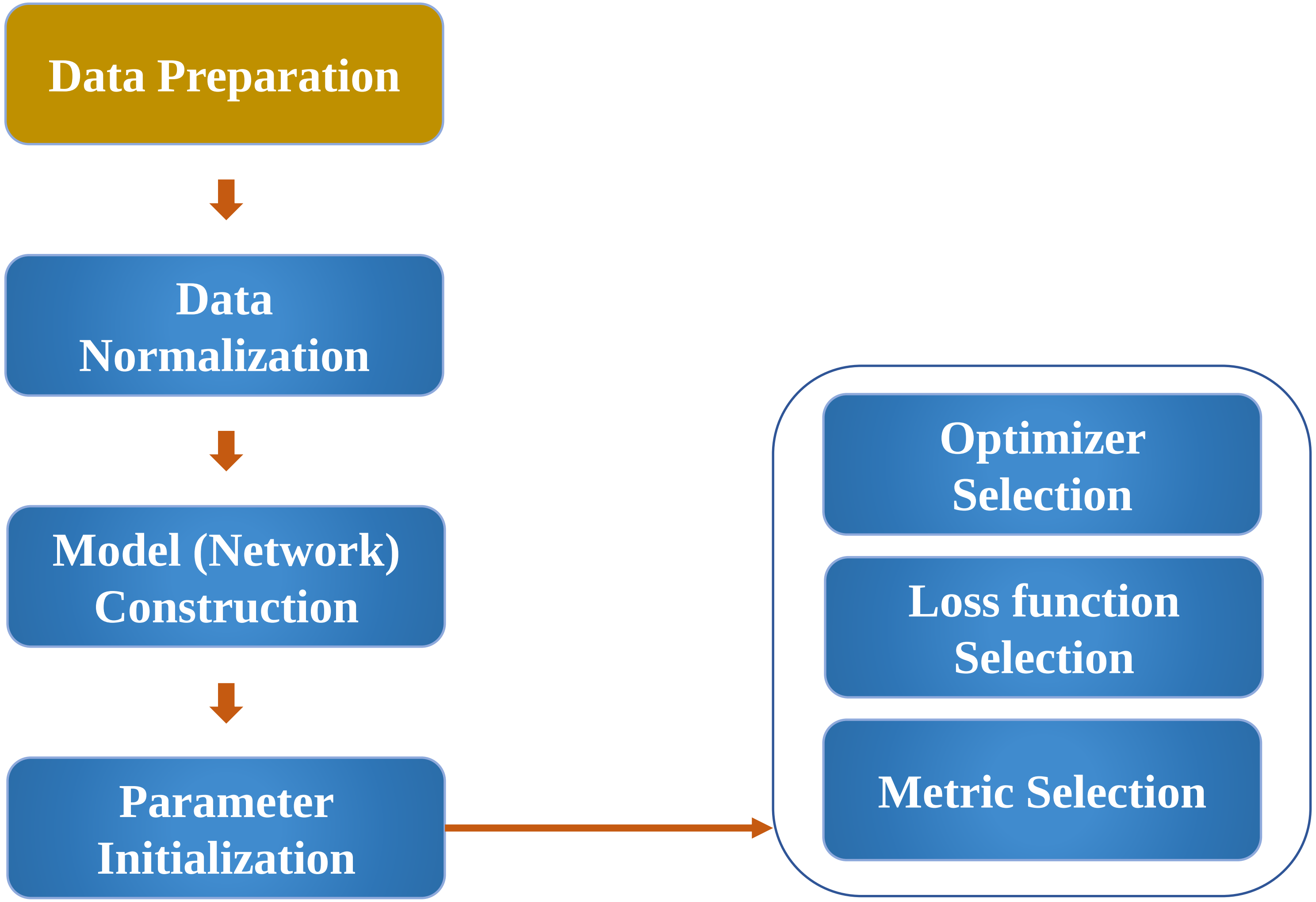


```
for epoch in range(5):
    running_loss = 0.0
    correct = 0   # to track number of correct predictions
    total = 0     # to track total number of samples

    for i, (inputs, labels) in enumerate(trainloader, 0):
        # see comments from the previous example
        inputs, labels = inputs.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        # Determine class predictions and track accuracy
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
        # accumulate loss
        running_loss += loss.item()

    epoch_accuracy = 100 * correct / total
    running_loss = running_loss / (i + 1)
    test_loss, test_accuracy = evaluate(model,
                                        testloader,
                                        criterion)
```

Outline

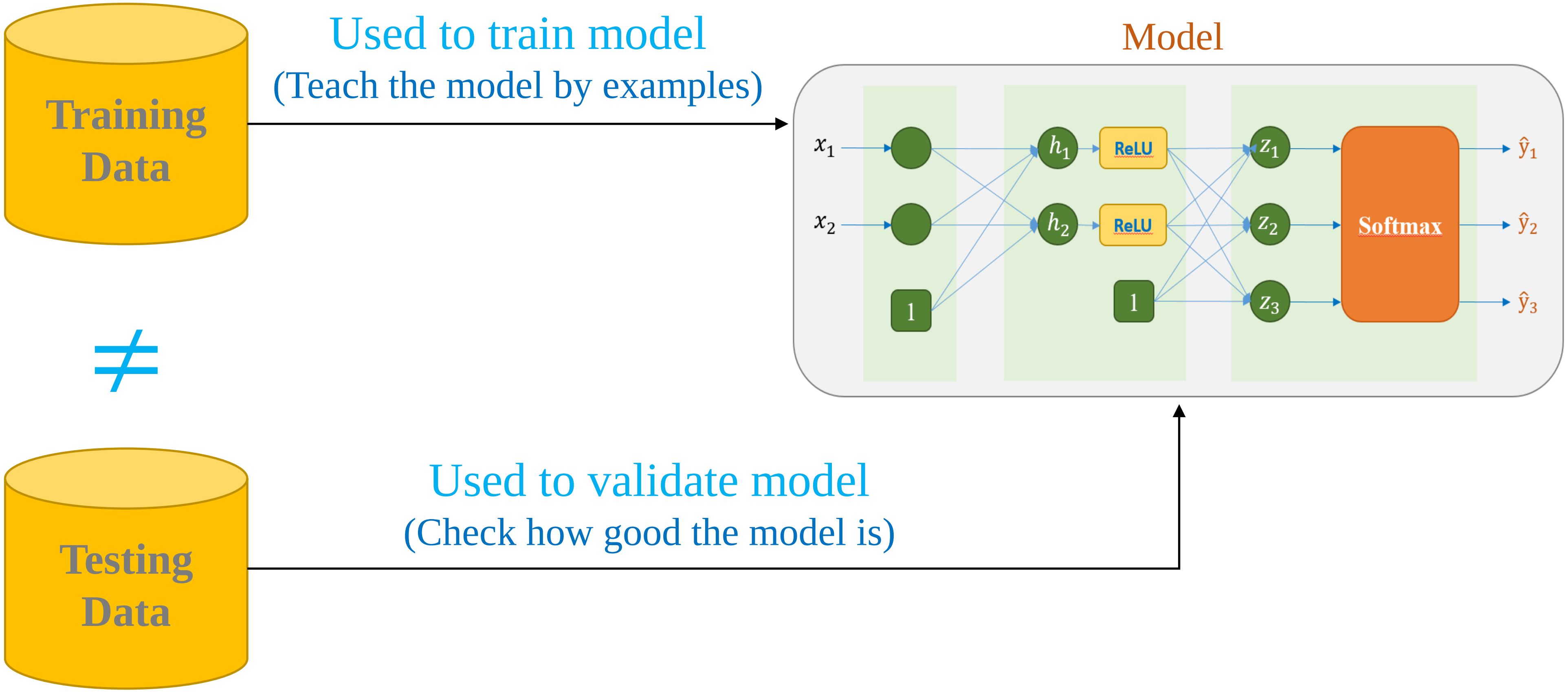
- ➢ Image Data Loading Using Numpy&PyTorch
- ➢ Softmax+Normalization for Fashion-MNIST
- ➢ MLP and Examples
- ➢ Step-by-Step Implementation
- ➢ Training Strategy (optional)

To-do List for Training



To-do List for Training

Data Preparation



Training Data

Used to train model

(Teach the model by examples)

Model

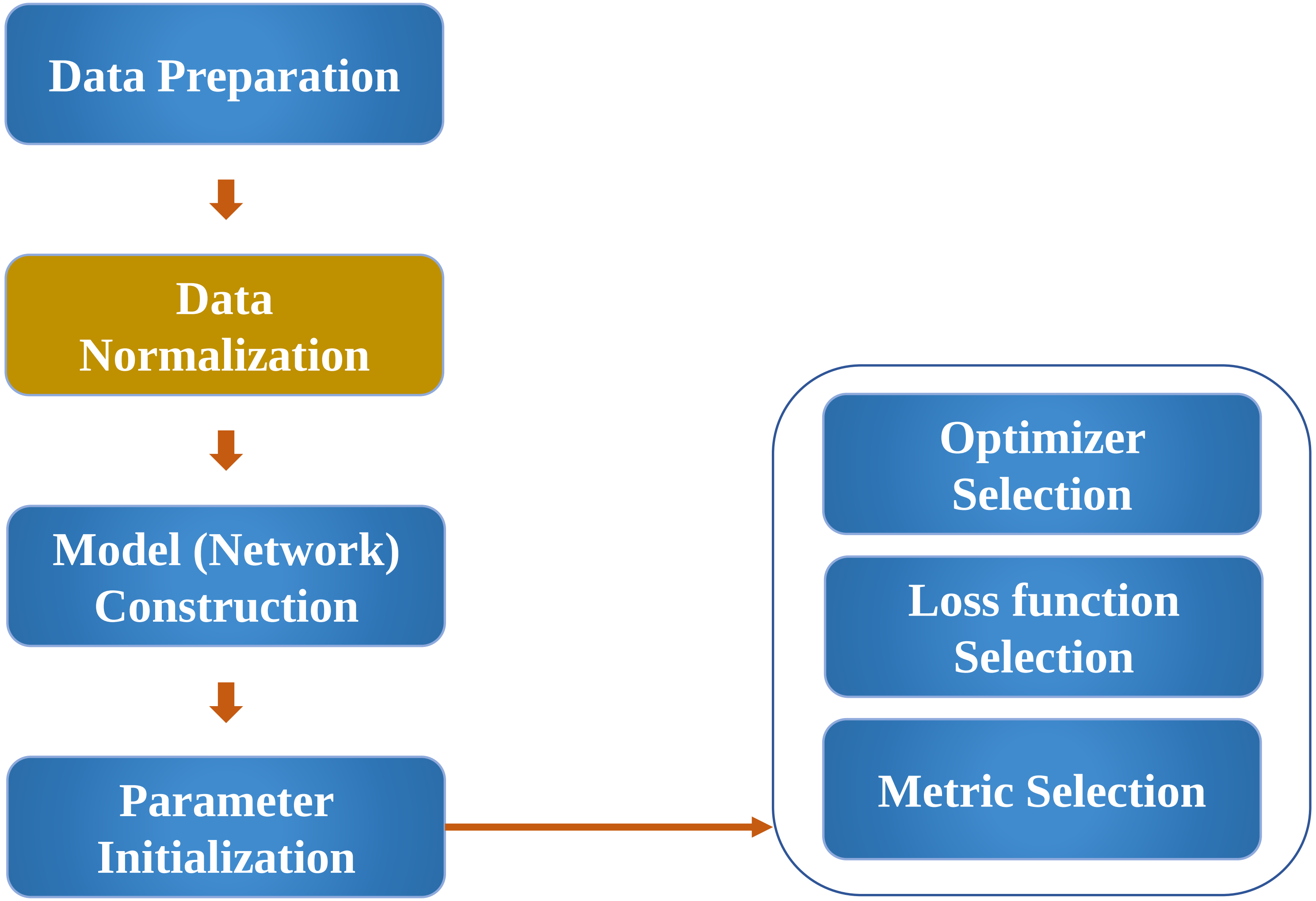
≠

Testing Data

Used to validate model

(Check how good the model is)

To-do List for Training



Data Preparation

Data Normalization

Model (Network) Construction

Parameter Initialization

Optimizer Selection

Loss function Selection

Metric Selection

To-do List for Training

Data Normalization

Convert to the range [0,1]

$$\text{Image} = \frac{\text{Image}}{255}$$

Convert to the range [-1,1]

$$\text{Image} = \frac{\text{Image}}{127.5} - 1$$

Z-score normalization

$$\text{Image} = \frac{\text{Image} - \mu}{\sigma}$$

μ is the mean of
the image (or training data)

σ is thestandard deviation
of the image (or training data)

Implmentation

In Theory

$$X \in [0, 255]$$

Convert to the range [0,1]

$$\text{Image} = \frac{\text{Image}}{255}$$

Convert to the range [-1,1]

$$\text{Image} = \frac{\text{Image}}{127.5} - 1$$

Z-score normalization

$$\text{Image} = \frac{\text{Image} - \mu}{\sigma}$$

In Pytorch

$$X \in [0, 1]$$

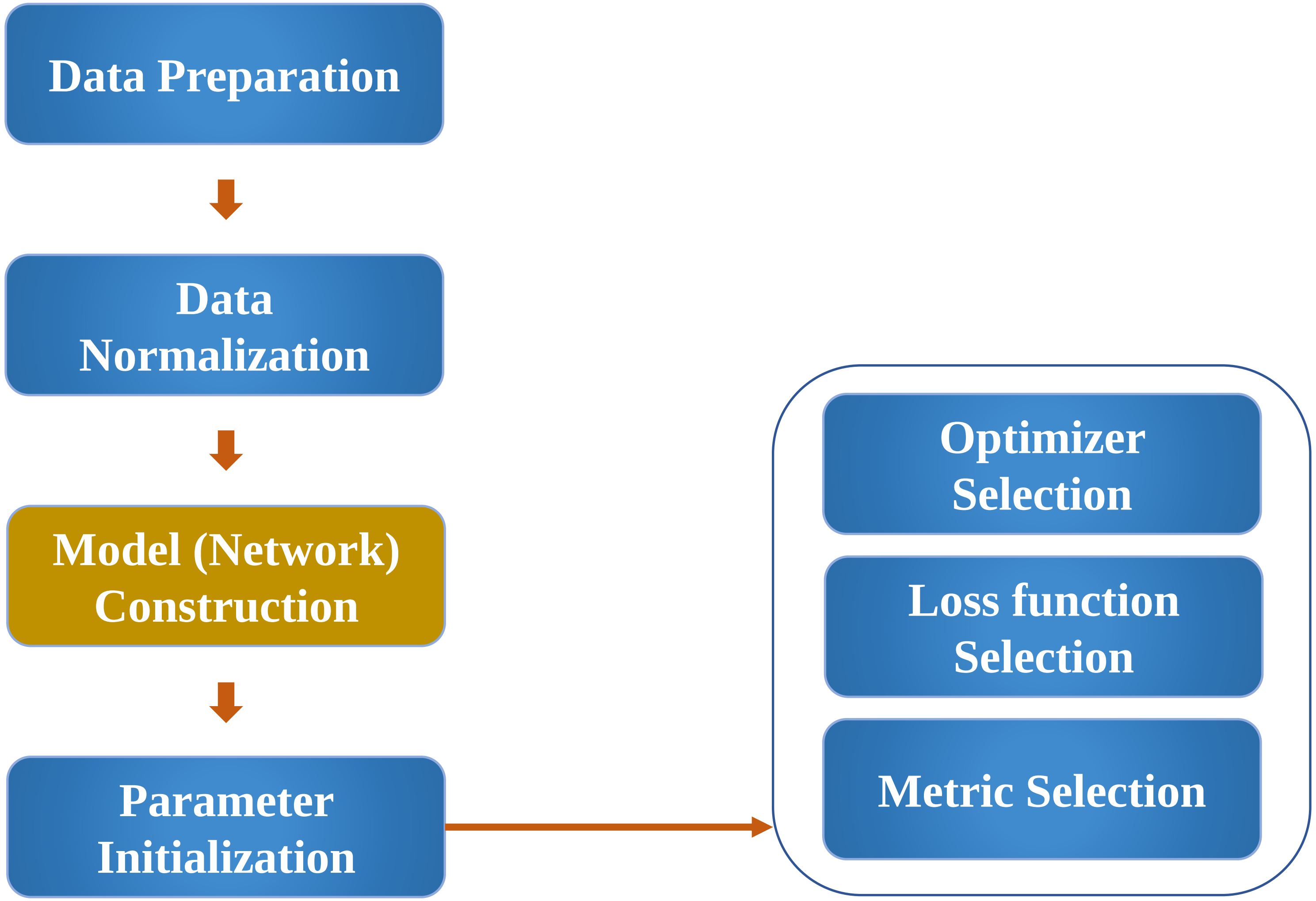
Normalize(*mean*, std)

$$\text{Image} = \frac{\text{Image} - mean}{\text{std}}$$

[0,1]	mean = 0 ; std = 1
[-1,1]	mean = 0.5; std = 0.5

Compute mean and std
from data

To-do List for Training



Data Preparation

Data Normalization

Model (Network) Construction

Parameter Initialization

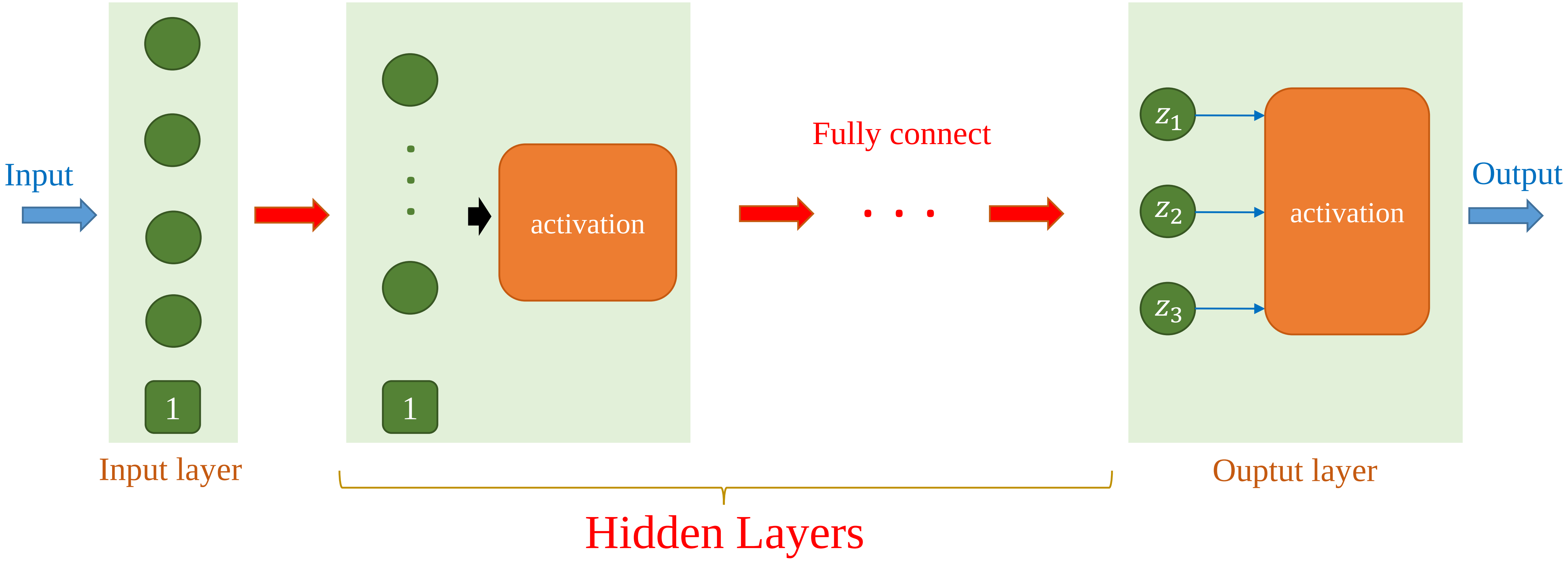
Optimizer Selection

Loss function Selection

Metric Selection

To-do List for Training

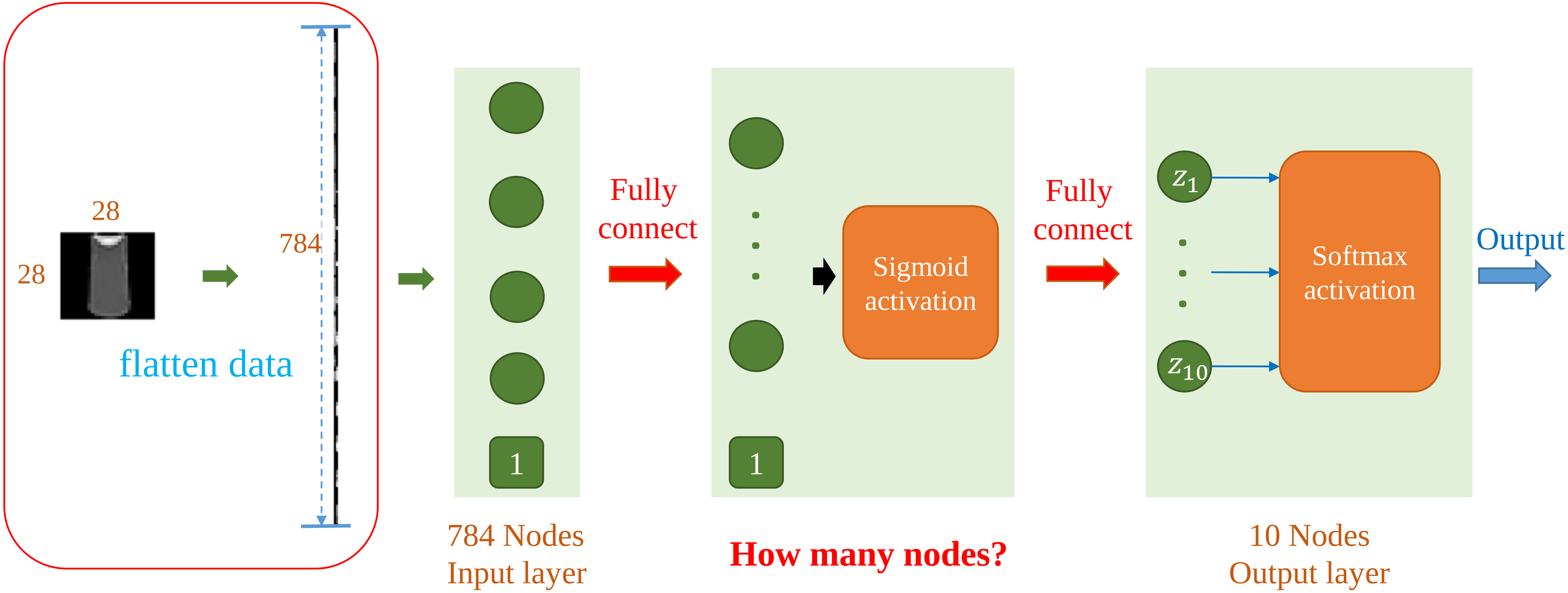
Model (Network) Construction



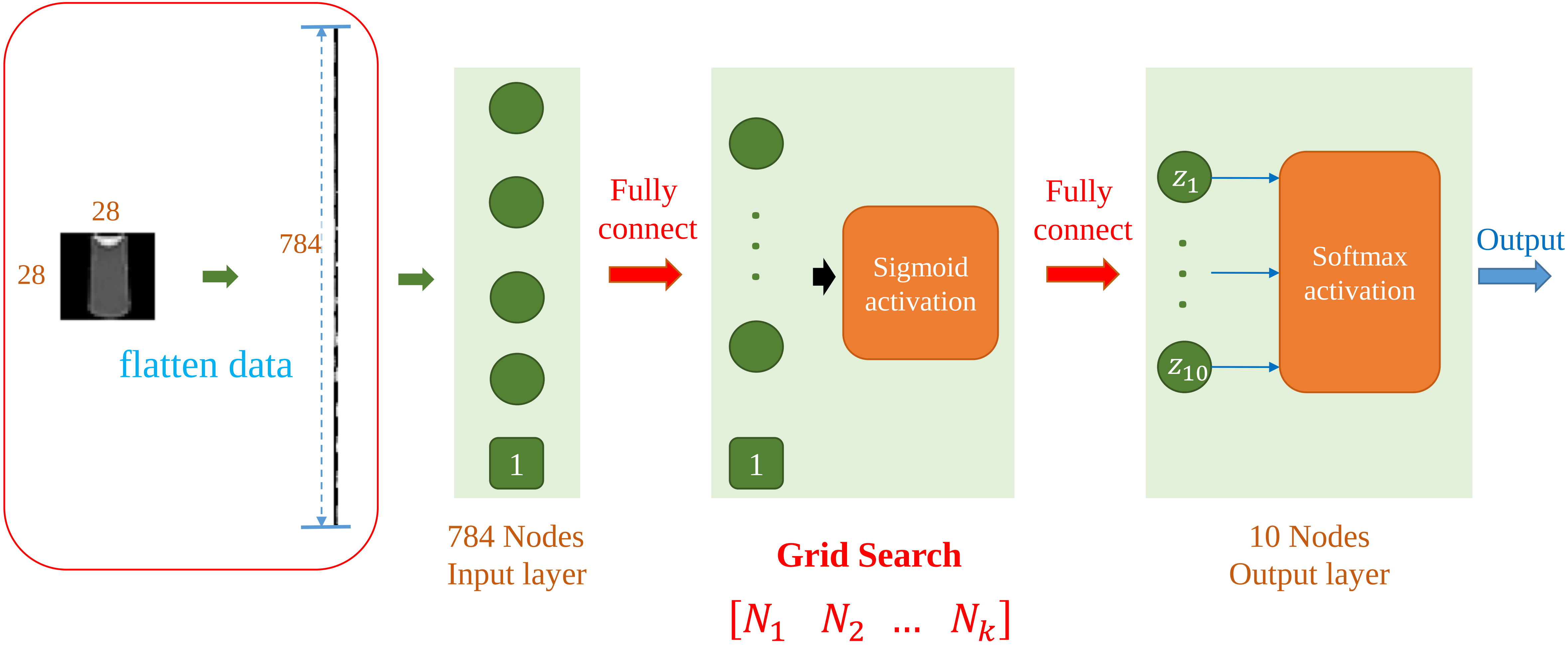
How many hidden layers?
How many nodes in a hidden layer?

Which activation function?
Which network components?

How many nodes?



How many nodes?



Grid Search

$$[N_1 \quad N_2 \quad \dots \quad N_k]$$

Image Classification

Cifar-10 dataset

Color images

Resolution=32x32

Training set: 50000 samples

Testing set: 10000 samples