Softmax Classifier

Objective

- How to classify handwritten digits from the MNIST database by using Softmax classifier.

Table of Contents

In this lab, you will use a single layer Softmax to classify handwritten digits from the MNIST database.

Estimated Time Needed: **25 min**

Preparation

We'll need the following libraries

In [1]:
```
# Import the libraries we need for this lab

# Using the following line code to install the torchvision library
# !mamba install -y torchvision

!pip install torchvision==0.9.1 torch==1.8.1
import torch
import torch.nn as nn
import torchvision.transforms as transforms
import torchvision.datasets as dsets
import matplotlib.pylab as plt
import numpy as np
```

```
ERROR: Ignored the following yanked versions: 0.1.6, 0.1.7, 0.1.8, 0.1.9, 0.2.0, 0.2.1, 0.2.2, 0.2.2.post2, 0.2.2.post3
ERROR: Could not find a version that satisfies the requirement torchvision==0.9.1 (from versions: 0.21.0, 0.22.0, 0.22.1)
ERROR: No matching distribution found for torchvision==0.9.1
Defaulting to user installation because normal site-packages is not writeable
```

Use the following function to plot out the parameters of the Softmax function:

In [2]:
```
# The function to plot parameters

def PlotParameters(model):
    W = model.state_dict()['linear.weight'].data
    w_min = W.min().item()
    w_max = W.max().item()
    fig, axes = plt.subplots(2, 5)
    fig.subplots_adjust(hspace=0.01, wspace=0.1)
    for i, ax in enumerate(axes.flat):
        if i < 10:

            # Set the label for the sub-plot.
            ax.set_xlabel("class: {0}".format(i))

            # Plot the image.
            ax.imshow(W[i, :].view(28, 28), vmin=w_min, vmax=w_max, cmap='seismic')

            ax.set_xticks([])
            ax.set_yticks([])

        # Ensure the plot is shown correctly with multiple plots
        # in a single Notebook cell.
    plt.show()
```

Use the following function to visualize the data:

In [3]:
```
# Plot the data

def show_data(data_sample):
    plt.imshow(data_sample[0].numpy().reshape(28, 28), cmap='gray')
    plt.title('y = ' + str(data_sample[1]))
```

Make Some Data

Load the training dataset by setting the parameters `train` to `True` and convert it to a tensor by placing a transform object in the argument `transform`.

In [4]:
```
# Create and print the training dataset

train_dataset = dsets.MNIST(root='./data', train=True, download=True, transform=tra
print("Print the training dataset:\n ", train_dataset)
```

```
Print the training dataset:
  Dataset MNIST
    Number of datapoints: 60000
    Root location: ./data
    Split: Train
    StandardTransform
Transform: ToTensor()
```

Load the testing dataset and convert it to a tensor by placing a transform object in the argument `transform`.

In [5]:
```
# Create and print the validating dataset

validation_dataset = dsets.MNIST(root='./data', download=True, transform=transforms
print("Print the validating dataset:\n ", validation_dataset)
```

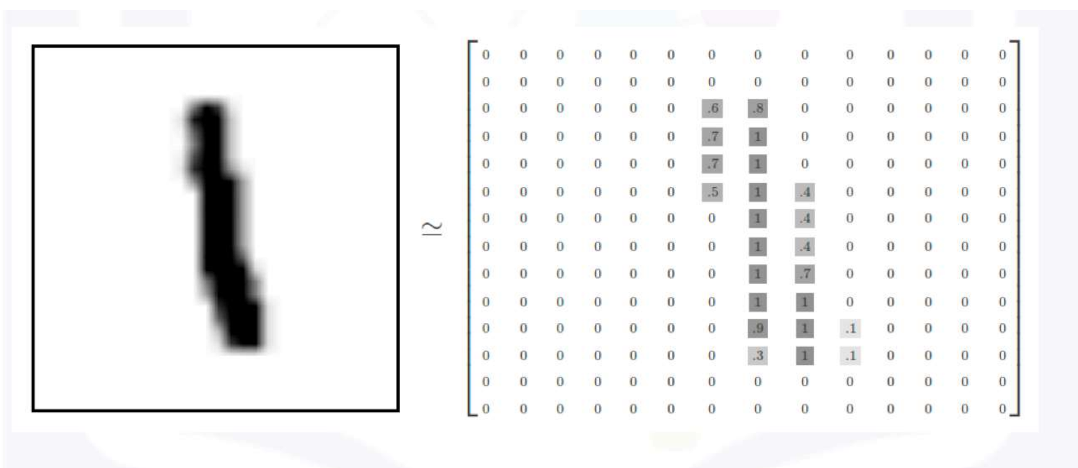
```
Print the validating dataset:
  Dataset MNIST
    Number of datapoints: 60000
    Root location: ./data
    Split: Train
    StandardTransform
Transform: ToTensor()
```

You can see that the data type is long:

In [6]:
```
# Print the type of the element

print("Type of data element: ", type(train_dataset[0][1]))
```

```
Type of data element:  <class 'int'>
```

Each element in the rectangular tensor corresponds to a number that represents a pixel intensity as demonstrated by the following image:



In this image, the values are inverted i.e back represents wight.

Print out the label of the fourth element:

In [7]:
```
# Print the label

print("The label: ", train_dataset[3][1])
```

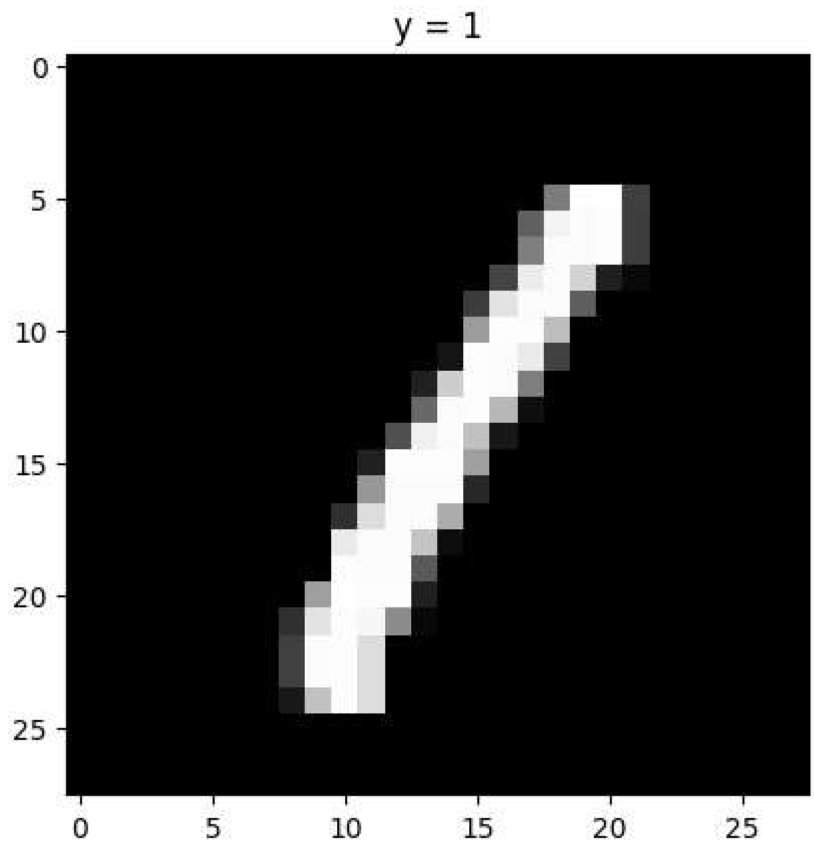
```
The label:  1
```

The result shows the number in the image is 1

Plot the fourth sample:

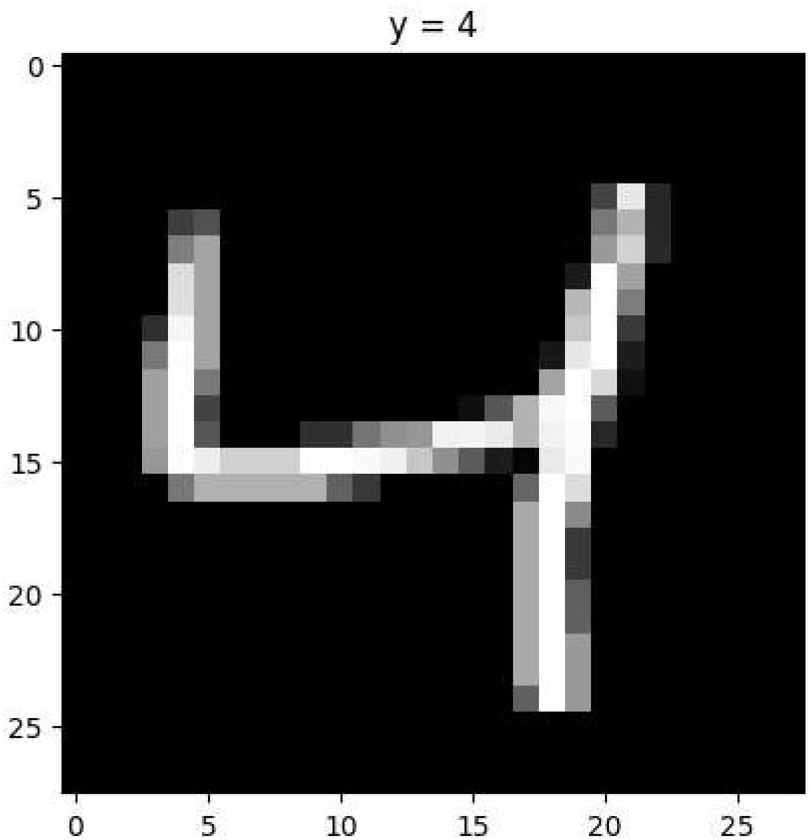
In [8]:
```
# Plot the image

print("The image: ", show_data(train_dataset[3]))
```

```
The image:  None
```



You see that it is a 1. Now, plot the third sample:

In [9]:
```
# Plot the image

show_data(train_dataset[2])
```



Build a Softmax Classifer

Build a Softmax classifier class:

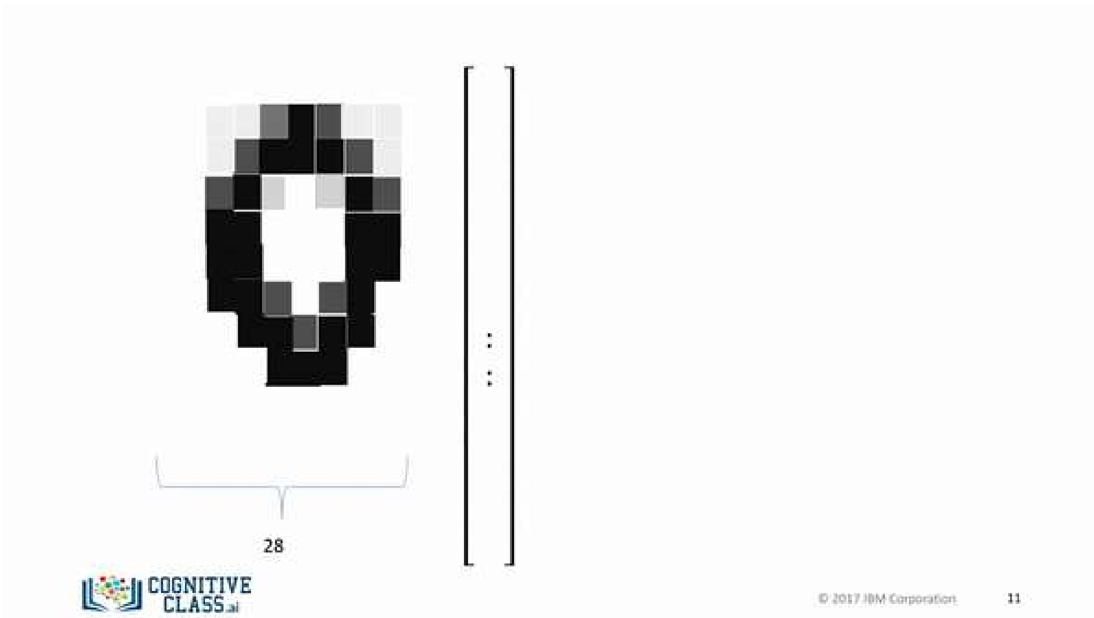
In [10]:
```
# Define softmax classifier class

class SoftMax(nn.Module):

    # Constructor
    def __init__(self, input_size, output_size):
        super(SoftMax, self).__init__()
        self.linear = nn.Linear(input_size, output_size)

    # Prediction
    def forward(self, x):
        z = self.linear(x)
        return z
```

The Softmax function requires vector inputs. Note that the vector shape is 28x28.

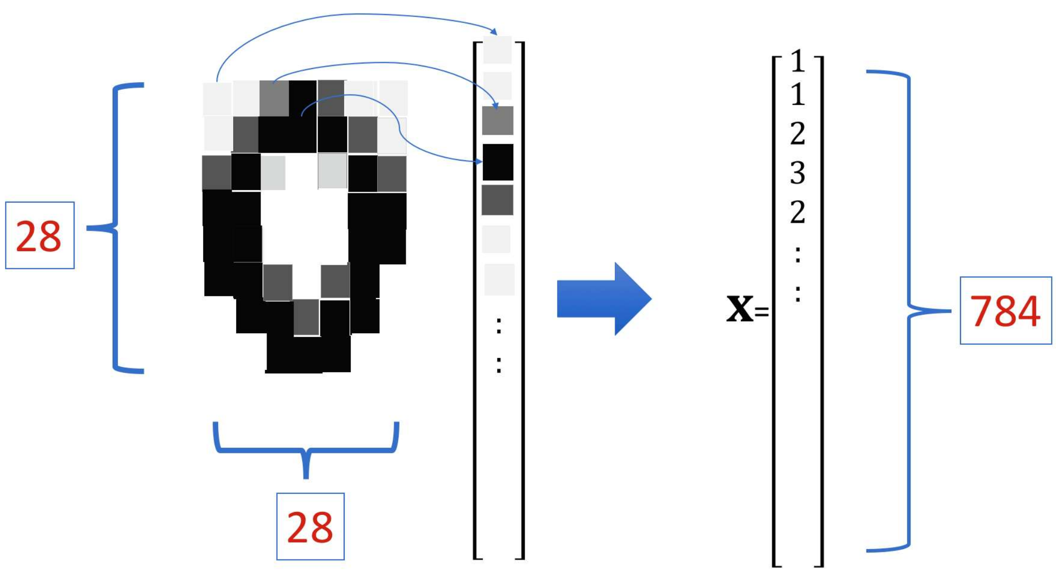
In [11]:
```
# Print the shape of train dataset

train_dataset[0][0].shape
```

Out[11]:
```
torch.Size([1, 28, 28])
```

Flatten the tensor as shown in this image:



The size of the tensor is now 784.



Set the input size and output size:

In [12]:
```
# Set input size and output size

input_dim = 28 * 28
output_dim = 10
```

Define the Softmax Classifier, Criterion Function, Optimizer, and Train the Model

In [13]:
```
# Create the model

model = SoftMax(input_dim, output_dim)
print("Print the model:\n ", model)
```

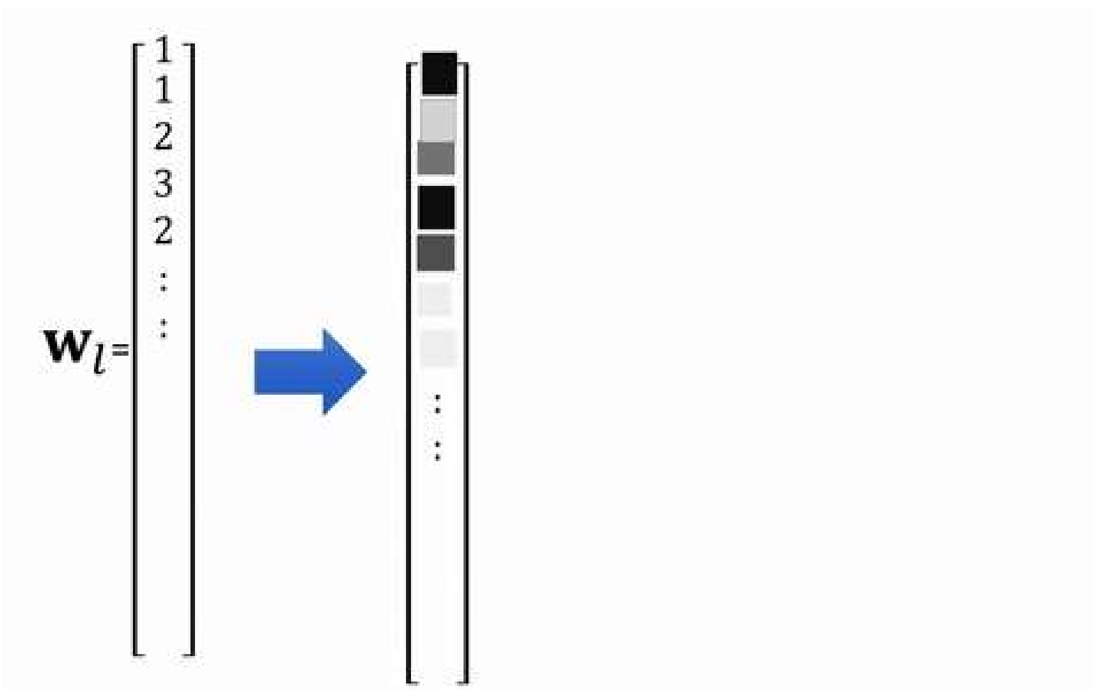
```
Print the model:
  SoftMax(
  (linear): Linear(in_features=784, out_features=10, bias=True)
)
```

View the size of the model parameters:

In [14]:
```
# Print the parameters

print('W: ',list(model.parameters())[0].size())
print('b: ',list(model.parameters())[1].size())
```

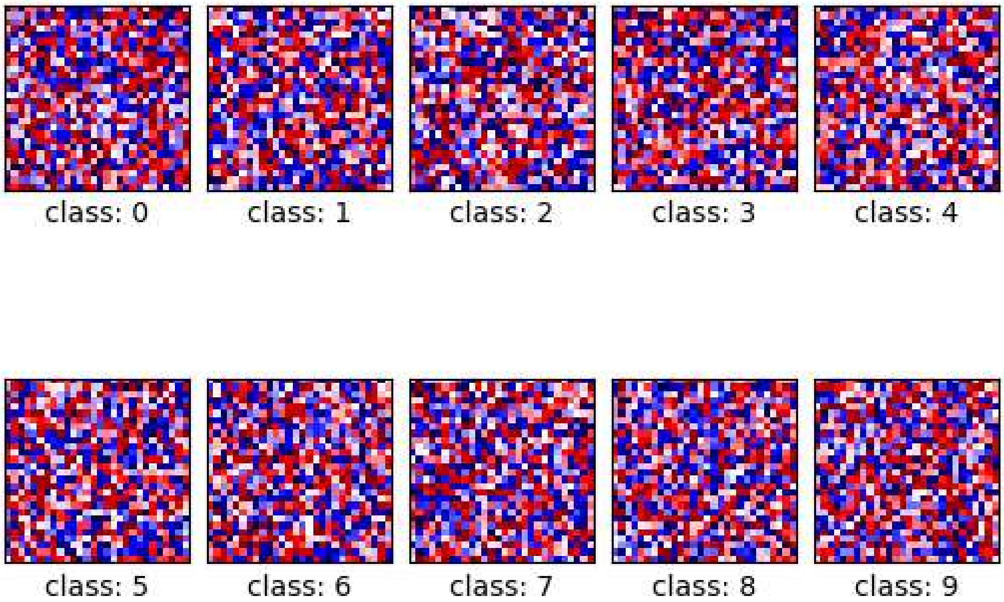
```
W:  torch.Size([10, 784])
b:  torch.Size([10])
```

You can cover the model parameters for each class to a rectangular grid:



Plot the model parameters for each class as a square image:

In [15]:
```
# Plot the model parameters for each class

PlotParameters(model)
```



Define the learning rate, optimizer, criterion, data loader:

In [16]:
```
# Define the learning rate, optimizer, criterion and data loader

learning_rate = 0.1
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
criterion = nn.CrossEntropyLoss()
train_loader = torch.utils.data.DataLoader(dataset=train_dataset, batch_size=100)
validation_loader = torch.utils.data.DataLoader(dataset=validation_dataset, batch_s
```

Train the model and determine validation accuracy **(should take a few minutes)**:

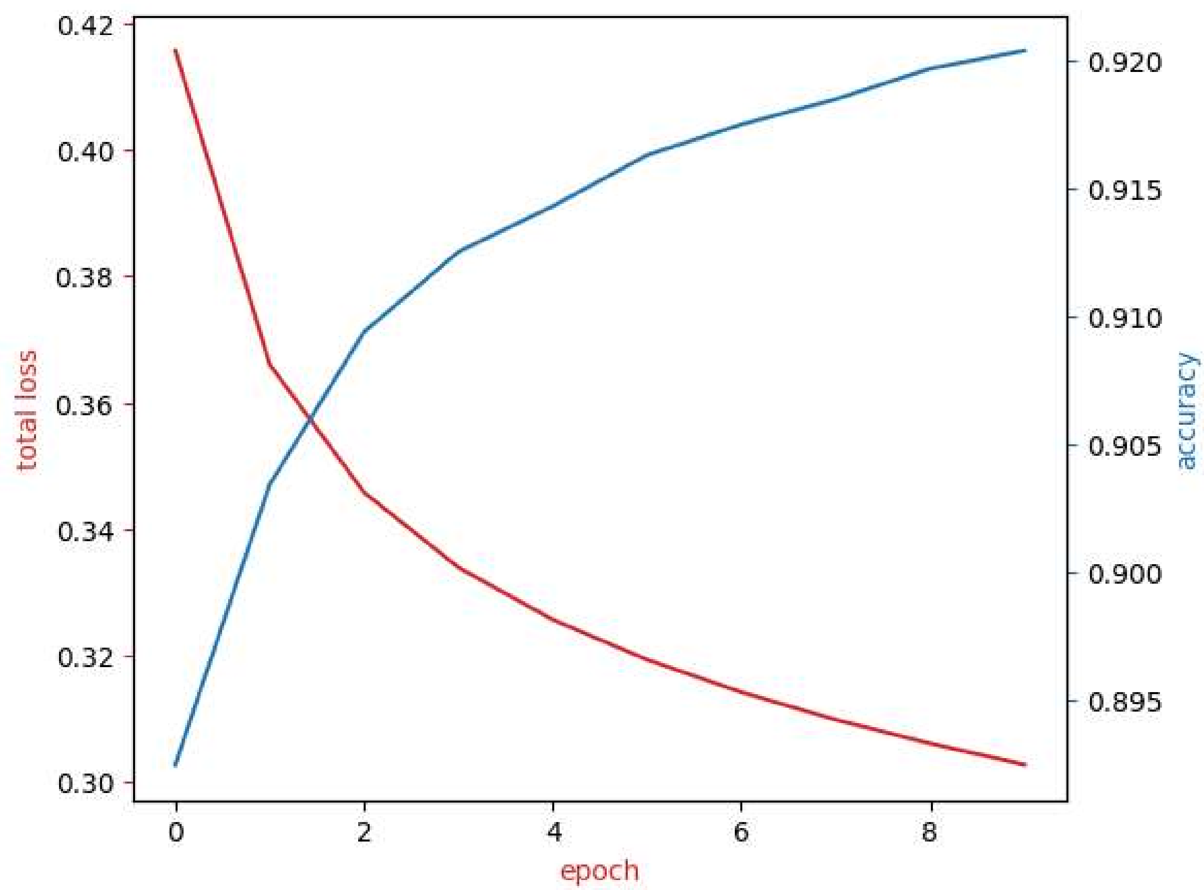
In [17]:
```
# Train the model

n_epochs = 10
loss_list = []
accuracy_list = []
N_test = len(validation_dataset)

def train_model(n_epochs):
    for epoch in range(n_epochs):
        for x, y in train_loader:
            optimizer.zero_grad()
            z = model(x.view(-1, 28 * 28))
            loss = criterion(z, y)
            loss.backward()
            optimizer.step()

        correct = 0
        # perform a prediction on the validationdata
        for x_test, y_test in validation_loader:
            z = model(x_test.view(-1, 28 * 28))
            _, yhat = torch.max(z.data, 1)
            correct += (yhat == y_test).sum().item()
        accuracy = correct / N_test
```

```
        loss_list.append(loss.data)
        accuracy_list.append(accuracy)

train_model(n_epochs)
```

Analyze Results

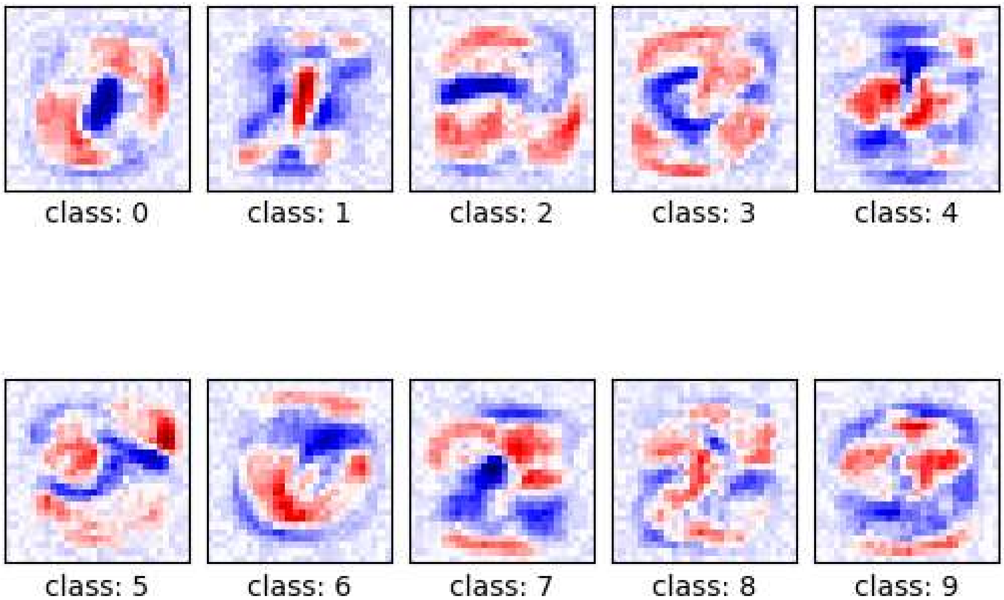
Plot the loss and accuracy on the validation data:

In [18]:
```
# Plot the loss and accuracy

fig, ax1 = plt.subplots()
color = 'tab:red'
ax1.plot(loss_list,color=color)
ax1.set_xlabel('epoch',color=color)
ax1.set_ylabel('total loss',color=color)
ax1.tick_params(axis='y', color=color)

ax2 = ax1.twinx()
color = 'tab:blue'
ax2.set_ylabel('accuracy', color=color)
ax2.plot( accuracy_list, color=color)
ax2.tick_params(axis='y', color=color)
fig.tight_layout()
```



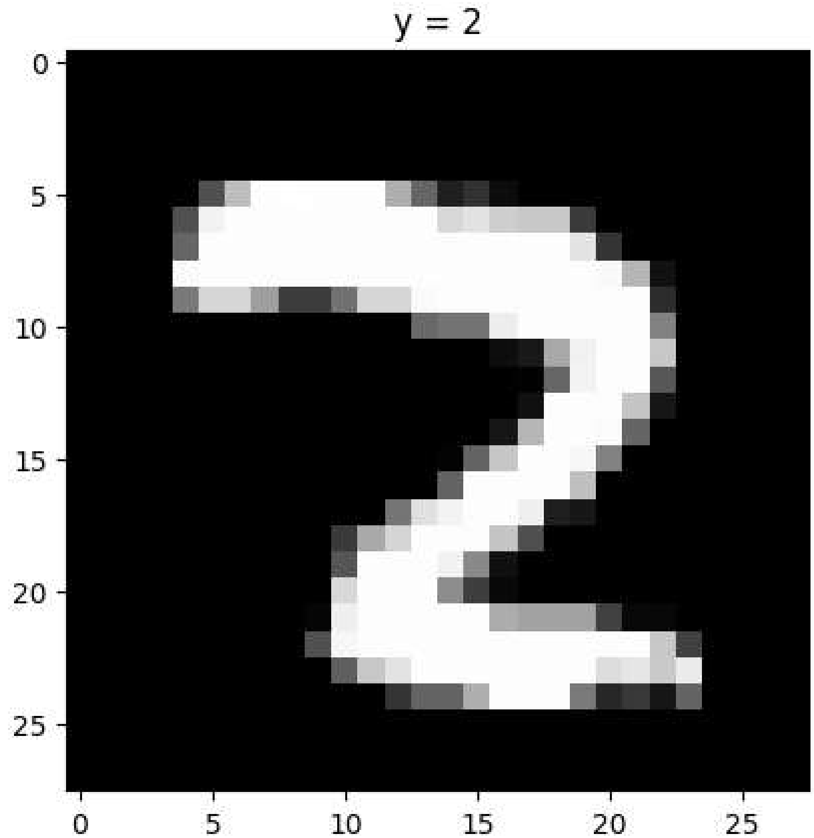
View the results of the parameters for each class after the training. You can see that they look like the corresponding numbers.

In [19]:
```
# Plot the parameters

PlotParameters(model)
```

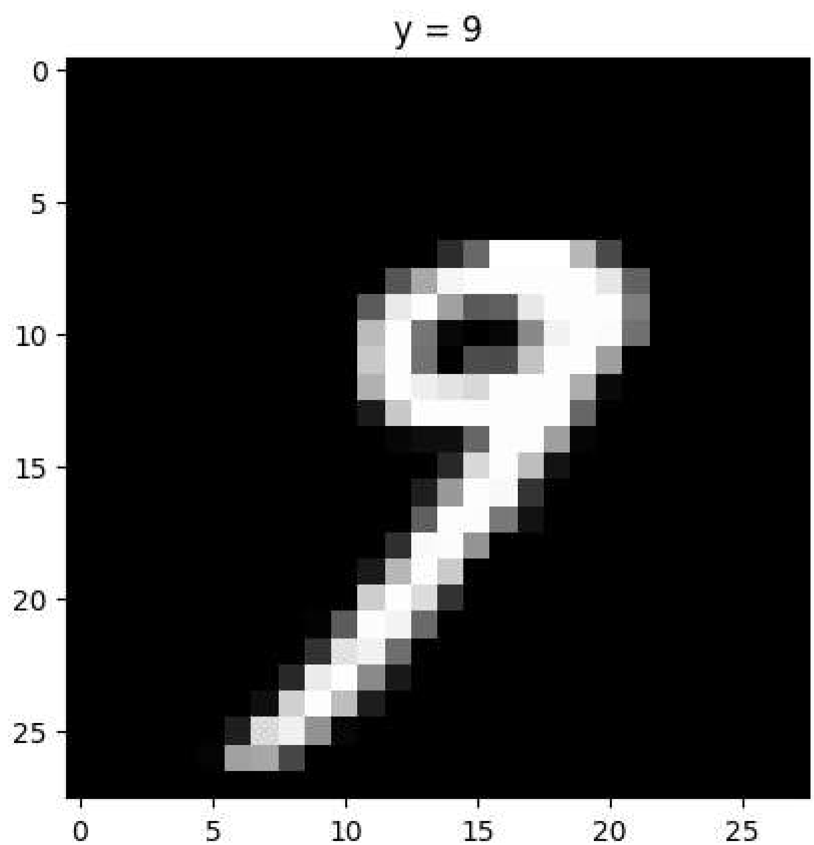


We Plot the first five misclassified samples and the probability of that class.

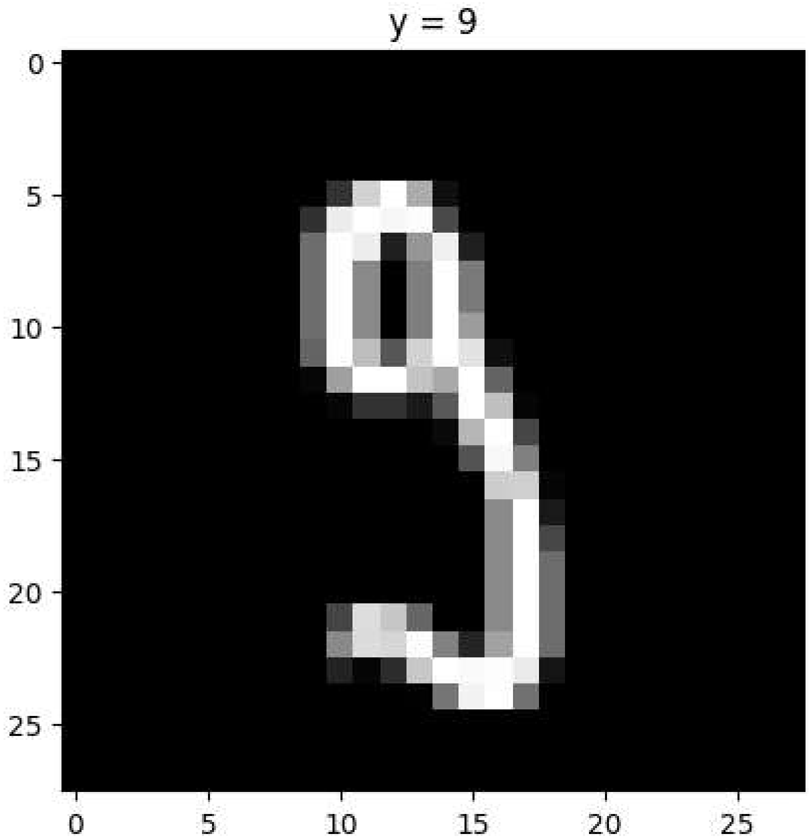
In [20]:
```
# Plot the misclassified samples
Softmax_fn=nn.Softmax(dim=-1)
count = 0
for x, y in validation_dataset:
    z = model(x.reshape(-1, 28 * 28))
    _, yhat = torch.max(z, 1)
    if yhat != y:
        show_data((x, y))
        plt.show()
        print("yhat:", yhat)
        print("probability of class ", torch.max(Softmax_fn(z)).item())
        count += 1
    if count >= 5:
        break
```



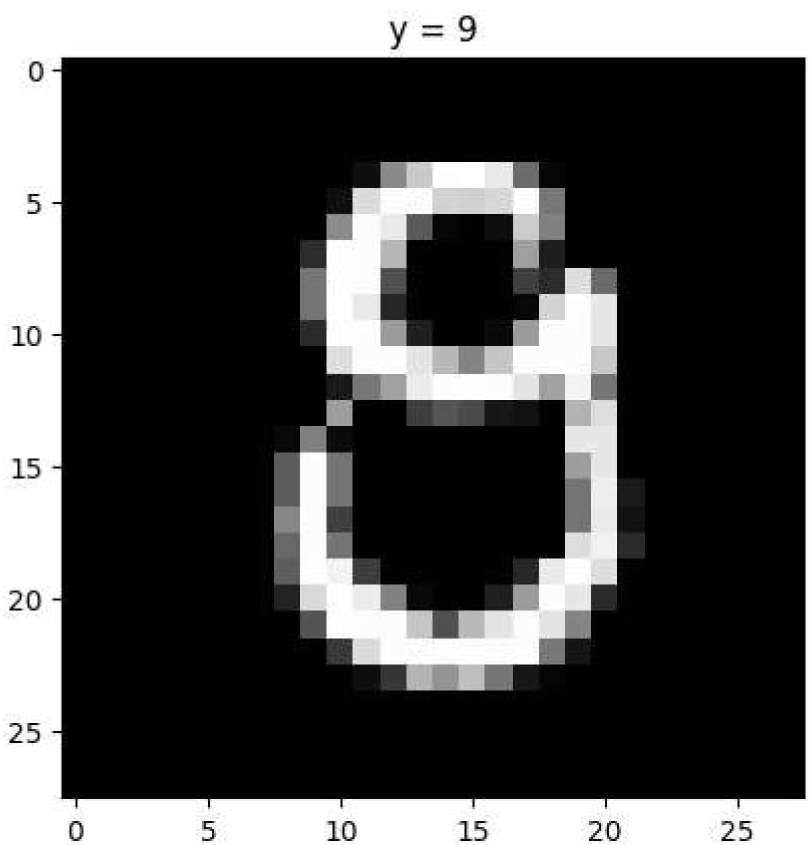

```
yhat: tensor([7])
probability of class  0.6424345374107361
```



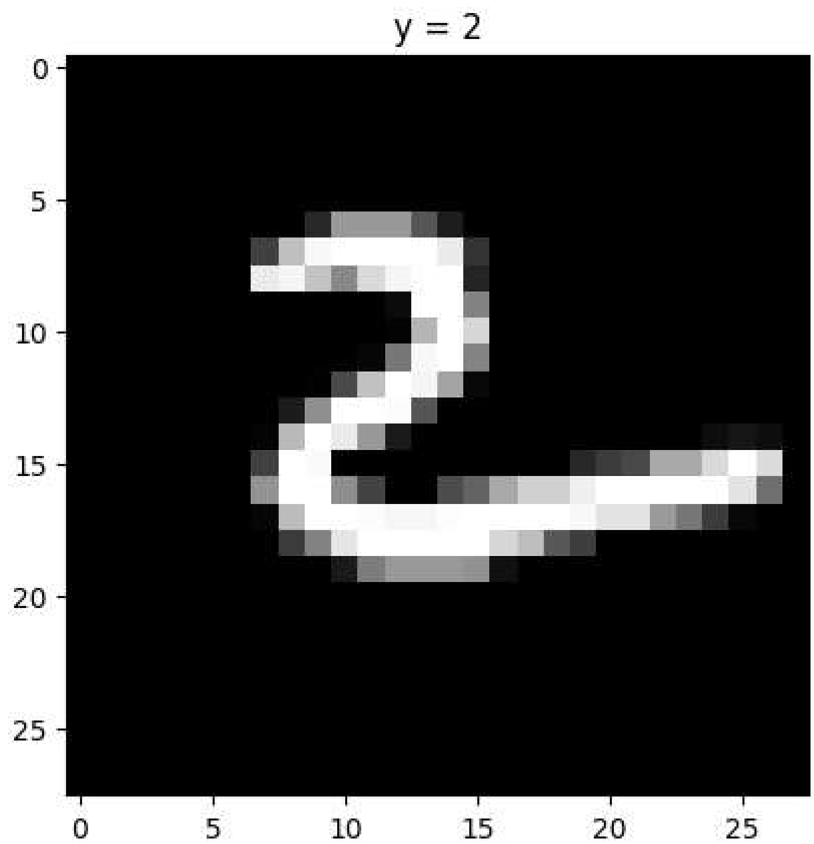

```
yhat: tensor([7])
probability of class  0.7160860300064087
```




```
yhat: tensor([5])
probability of class  0.7200515270233154
```



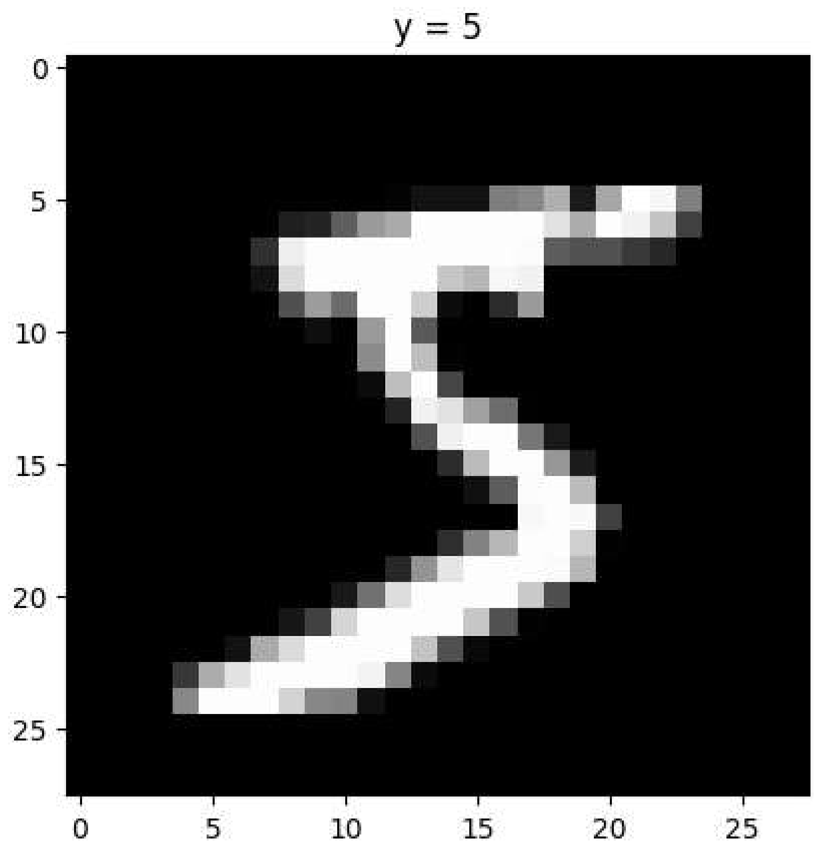

```
yhat: tensor([8])
probability of class  0.37033313512802124
```



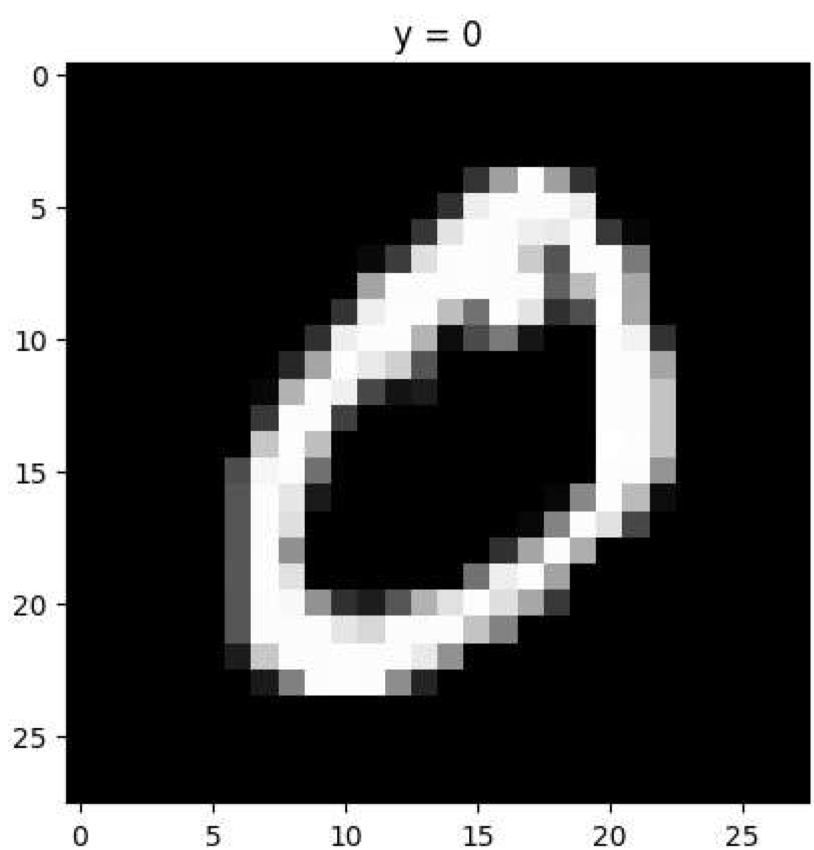

```
yhat: tensor([6])
probability of class  0.5202871561050415
```

We Plot the first five correctly classified samples and the probability of that class, we see the probability is much larger.

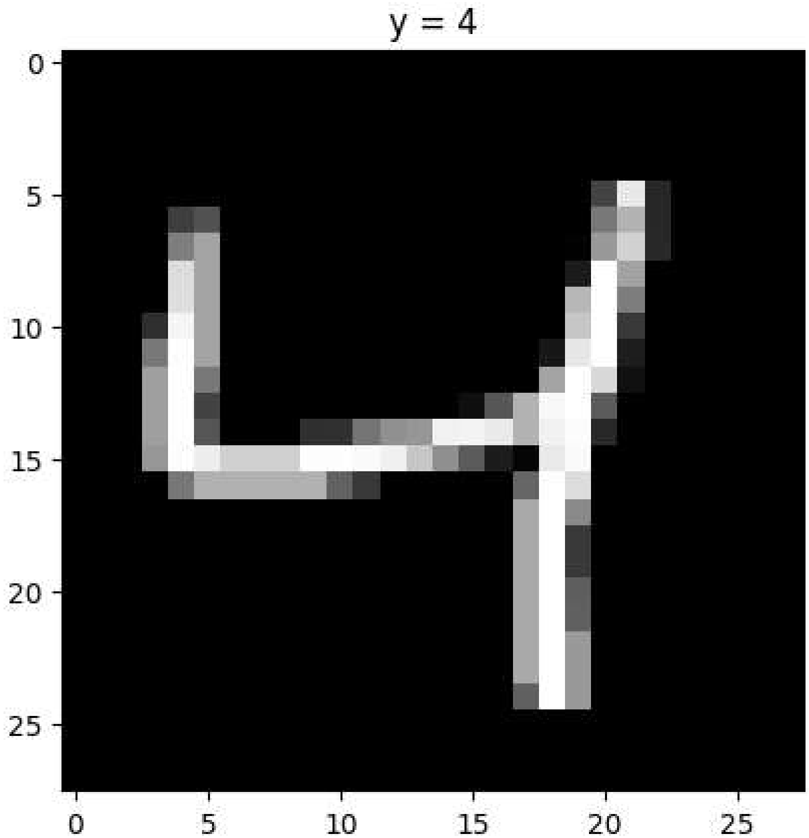
In [21]:
```python
# Plot the classified samples
Softmax_fn=nn.Softmax(dim=-1)
count = 0
for x, y in validation_dataset:
    z = model(x.reshape(-1, 28 * 28))
    _, yhat = torch.max(z, 1)
    if yhat == y:
        show_data((x, y))
        plt.show()
        print("yhat:", yhat)
        print("probability of class ", torch.max(Softmax_fn(z)).item())
        count += 1
    if count >= 5:
        break
```



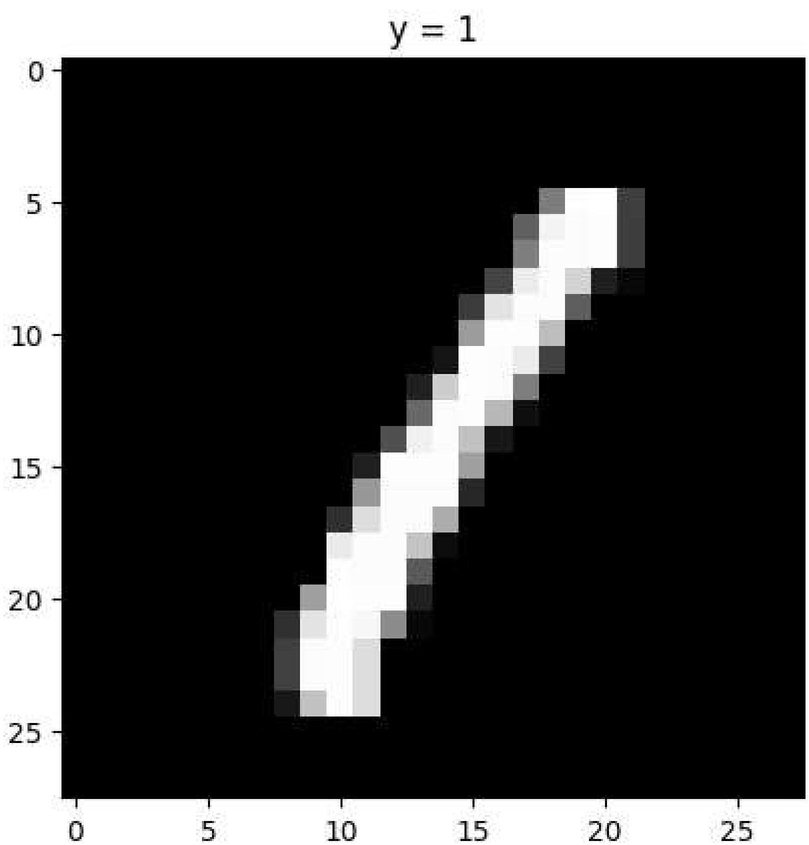

```
yhat: tensor([5])
probability of class  0.8634554743766785
```



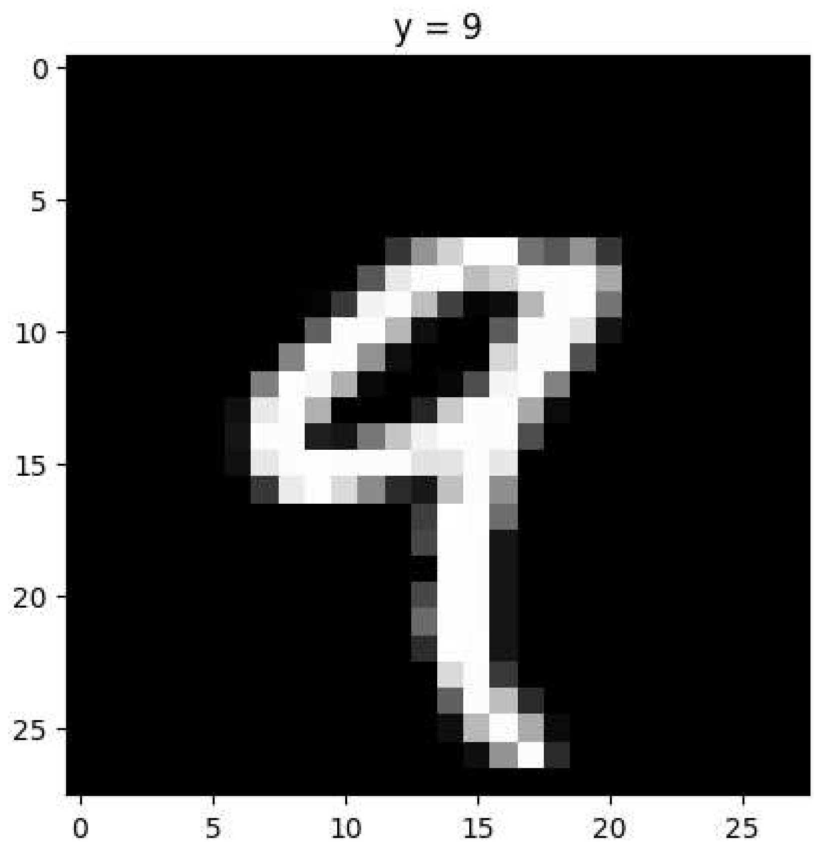

```
yhat: tensor([0])
probability of class  0.9996826648712158
```




```
yhat: tensor([4])
probability of class  0.8717507123947144
```




```
yhat: tensor([1])
probability of class  0.9656764268875122
```




```
yhat: tensor([9])
probability of class  0.9250146150588989
```