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(http://cocl.us/pytorch_link_top)

Convolutional Neural Network with Small Images

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In this lab, we will use a Convolutional Neural Network to classify handwritten digits from the MNIST database. We will reshape the images to make them faster to process

Estimated Time Needed: **25 min** 14 min to train model

Preparation

In [1]:

```
# Import the libraries we need to use in this lab

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

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
```

Define the function `plot_channels` to plot out the kernel parameters of each channel

In [2]:

```
# Define the function for plotting the channels

def plot_channels(W):
    n_out = W.shape[0]
    n_in = W.shape[1]
    w_min = W.min().item()
    w_max = W.max().item()
    fig, axes = plt.subplots(n_out, n_in)
    fig.subplots_adjust(hspace=0.1)
    out_index = 0
    in_index = 0

    #plot outputs as rows inputs as columns
    for ax in axes.flat:
        if in_index > n_in-1:
            out_index = out_index + 1
            in_index = 0
        ax.imshow(W[out_index, in_index, :, :], vmin=w_min, vmax=w_max, cmap='seism
ic')
        ax.set_yticklabels([])
        ax.set_xticklabels([])
        in_index = in_index + 1

    plt.show()
```

Define the function `plot_parameters` to plot out the kernel parameters of each channel with Multiple outputs .

In [3]:

```
# Define the function for plotting the parameters

def plot_parameters(W, number_rows=1, name="", i=0):
    W = W.data[:, i, :, :]
    n_filters = W.shape[0]
    w_min = W.min().item()
    w_max = W.max().item()
    fig, axes = plt.subplots(number_rows, n_filters // number_rows)
    fig.subplots_adjust(hspace=0.4)

    for i, ax in enumerate(axes.flat):
        if i < n_filters:
            # Set the label for the sub-plot.
            ax.set_xlabel("kernel:{0}".format(i + 1))

            # Plot the image.
            ax.imshow(W[i, :], vmin=w_min, vmax=w_max, cmap='seismic')
            ax.set_xticks([])
            ax.set_yticks([])
    plt.suptitle(name, fontsize=10)
    plt.show()
```

Define the function `plot_activation` to plot out the activations of the Convolutional layers

In [4]:

```
# Define the function for plotting the activations

def plot_activations(A, number_rows=1, name="", i=0):
    A = A[0, :, :, :].detach().numpy()
    n_activations = A.shape[0]
    A_min = A.min().item()
    A_max = A.max().item()
    fig, axes = plt.subplots(number_rows, n_activations // number_rows)
    fig.subplots_adjust(hspace = 0.4)

    for i, ax in enumerate(axes.flat):
        if i < n_activations:
            # Set the label for the sub-plot.
            ax.set_xlabel("activation:{0}".format(i + 1))

            # Plot the image.
            ax.imshow(A[i, :], vmin=A_min, vmax=A_max, cmap='seismic')
            ax.set_xticks([])
            ax.set_yticks([])
    plt.show()
```

Define the function `show_data` to plot out data samples as images.

In [5]:

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

Get the Data

we create a transform to resize the image and convert it to a tensor .

In [6]:

```
IMAGE_SIZE = 16


composed = transforms.Compose([transforms.Resize((IMAGE_SIZE, IMAGE_SIZE)), transfo
rms.ToTensor()])
```

Load the training dataset by setting the parameters `train` to `True` . We use the transform defined above.

In [7]:

```
train_dataset = dsets.MNIST(root='./data', train=True, download=True, transform=com
posed)
```

Load the testing dataset by setting the parameters train `False` .

In [8]:

```
# Make the validating

validation_dataset = dsets.MNIST(root='./data', train=False, download=True, transfo
rm=composed)
```

We can see the data type is long.

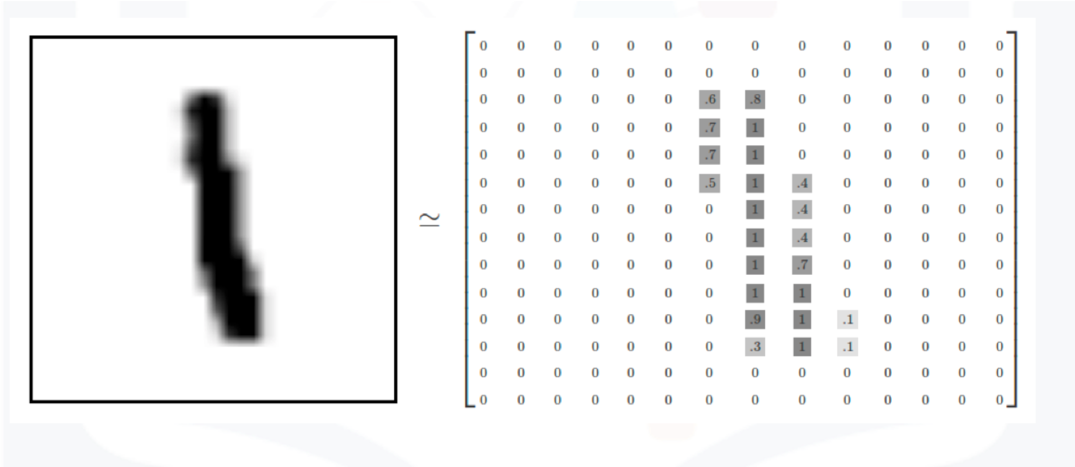
In [9]:

```
# Show the data type for each element in dataset

train_dataset[0][1].type()
```

Out[9]:

```
'torch.LongTensor'
```

Each element in the rectangular tensor corresponds to a number representing a pixel intensity as demonstrated by the following image.



Print out the fourth label

In [10]:

```
# The label for the fourth data element

train_dataset[3][1]
```

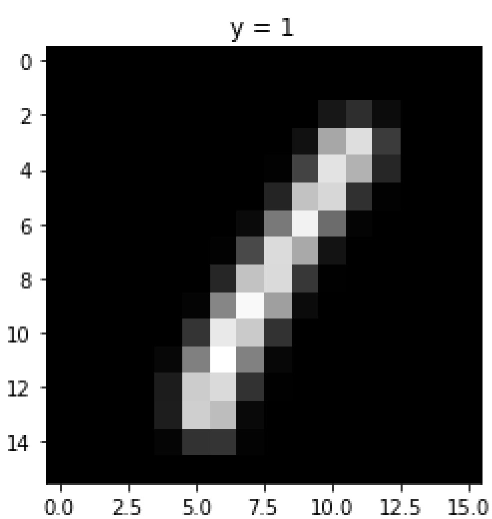
Out[10]:

```
tensor(1)
```

Plot the fourth sample

In [11]:

```
# The image for the fourth data element
show_data(train_dataset[3])
```



The fourth sample is a "1".

Build a Convolutional Neural Network Class

Build a Convolutional Network class with two Convolutional layers and one fully connected layer. Pre-determine the size of the final output matrix. The parameters in the constructor are the number of output channels for the first and second layer.

In [12]:

```
class CNN(nn.Module):

    # Contructor
    def __init__(self, out_1=16, out_2=32):
        super(CNN, self).__init__()
        self.cnn1 = nn.Conv2d(in_channels=1, out_channels=out_1, kernel_size=5, pad
ding=2)
        self.maxpool1=nn.MaxPool2d(kernel_size=2)

        self.cnn2 = nn.Conv2d(in_channels=out_1, out_channels=out_2, kernel_size=5,
stride=1, padding=2)
        self.maxpool2=nn.MaxPool2d(kernel_size=2)
        self.fc1 = nn.Linear(out_2 * 4 * 4, 10)

    # Prediction
    def forward(self, x):
        x = self.cnn1(x)
        x = torch.relu(x)
        x = self.maxpool1(x)
        x = self.cnn2(x)
        x = torch.relu(x)
        x = self.maxpool2(x)
        x = x.view(x.size(0), -1)
        x = self.fc1(x)
        return x

    # Outputs in each steps
    def activations(self, x):
        #outputs activation this is not necessary
        z1 = self.cnn1(x)
        a1 = torch.relu(z1)
        out = self.maxpool1(a1)

        z2 = self.cnn2(out)
        a2 = torch.relu(z2)
        out1 = self.maxpool2(a2)
        out = out.view(out.size(0),-1)
        return z1, a1, z2, a2, out1,out
```

Define the Convolutional Neural Network Classifier, Criterion function, Optimizer and Train the Model

There are 16 output channels for the first layer, and 32 output channels for the second layer

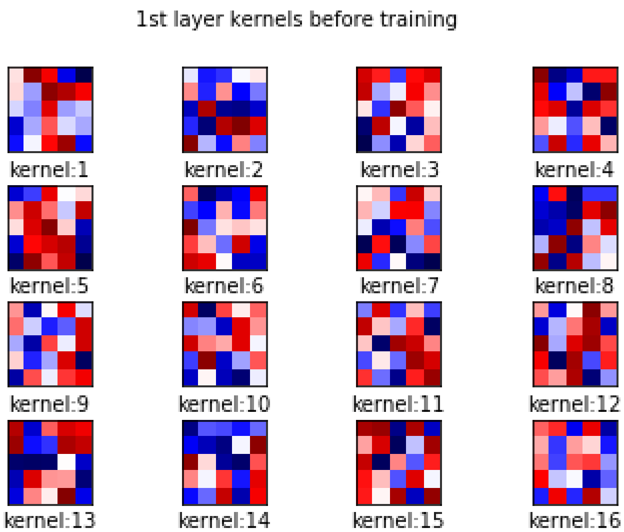
In [13]:

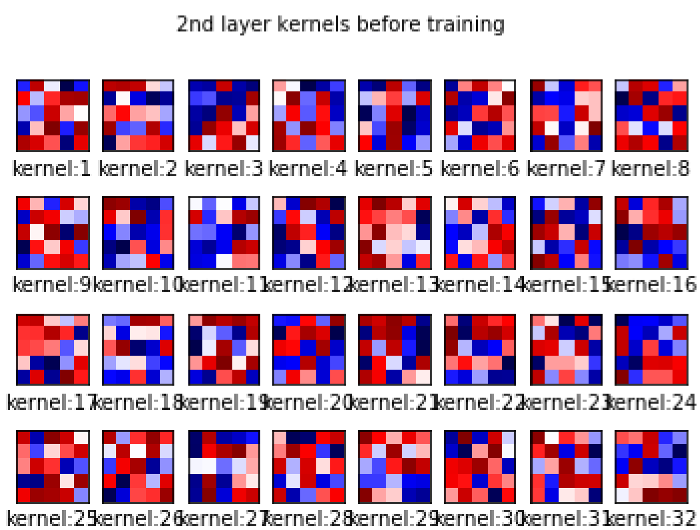
```python
# Create the model object using CNN class

model = CNN(out_1=16, out_2=32)
```

Plot the model parameters for the kernels before training the kernels. The kernels are initialized randomly.

In [14]:

```python
# Plot the parameters

plot_parameters(model.state_dict()['cnn1.weight'], number_rows=4, name="1st layer k
ernels before training ")
plot_parameters(model.state_dict()['cnn2.weight'], number_rows=4, name='2nd layer k
ernels before training' )
```





Define the loss function, the optimizer and the dataset loader

In [15]:

```
criterion = nn.CrossEntropyLoss()
learning_rate = 0.1
optimizer = torch.optim.SGD(model.parameters(), lr = learning_rate)
train_loader = torch.utils.data.DataLoader(dataset=train_dataset, batch_size=100)
validation_loader = torch.utils.data.DataLoader(dataset=validation_dataset, batch_s
ize=5000)
```

Train the model and determine validation accuracy technically test accuracy **(This may take a long time)**

In [ ]:

```
# Train the model

n_epochs=3
cost_list=[]
accuracy_list=[]
N_test=len(validation_dataset)
COST=0

def train_model(n_epochs):
    for epoch in range(n_epochs):
        COST=0
        for x, y in train_loader:
            optimizer.zero_grad()
            z = model(x)
            loss = criterion(z, y)
            loss.backward()
            optimizer.step()
            COST+=loss.data

        cost_list.append(COST)
        correct=0
        #perform a prediction on the validation  data
        for x_test, y_test in validation_loader:
            z = model(x_test)
            _, yhat = torch.max(z.data, 1)
            correct += (yhat == y_test).sum().item()
        accuracy = correct / N_test
        accuracy_list.append(accuracy)

train_model(n_epochs)
```

Analyze Results

Plot the loss and accuracy on the validation data:

In [ ]:

```
# Plot the loss and accuracy

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

ax2 = ax1.twinx()
color = 'tab:blue'
ax2.set_ylabel('accuracy', color=color)
ax2.set_xlabel('epoch', 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 the Convolutional layers

In [ ]:

```
# Plot the channels

plot_channels(model.state_dict()['cnn1.weight'])
plot_channels(model.state_dict()['cnn2.weight'])
```

Consider the following sample

In [ ]:

```
# Show the second image

show_data(train_dataset[1])
```

Determine the activations

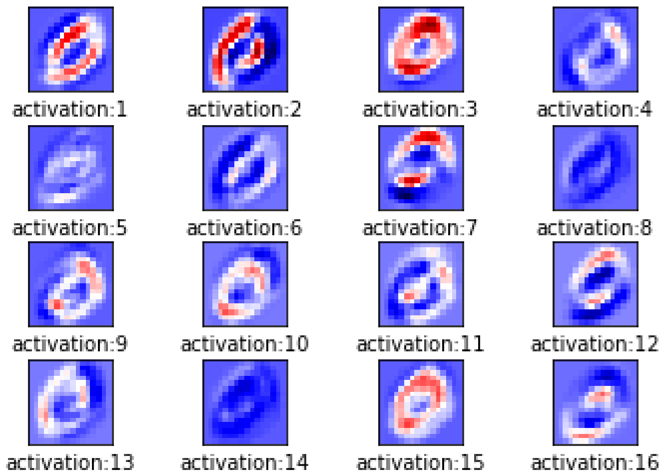
In [38]:

```
# Use the CNN activations class to see the steps

out = model.activations(train_dataset[1][0].view(1, 1, IMAGE_SIZE, IMAGE_SIZE))
```

Plot out the first set of activations

In [39]:

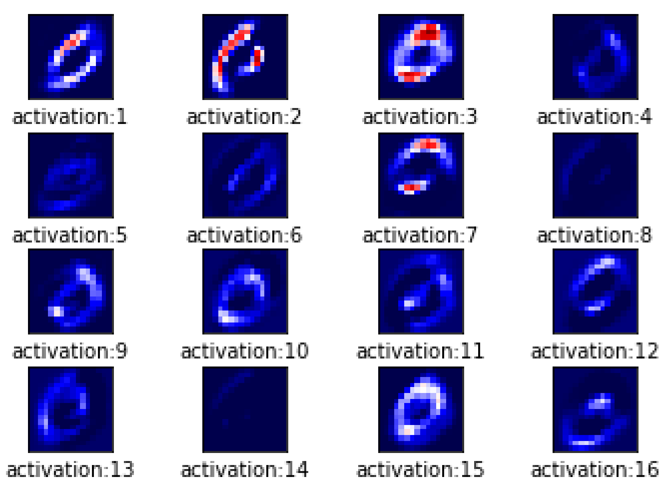
```
# Plot the outputs after the first CNN

plot_activations(out[0], number_rows=4, name="Output after the 1st CNN")
```



The image below is the result after applying the relu activation function

In [40]:

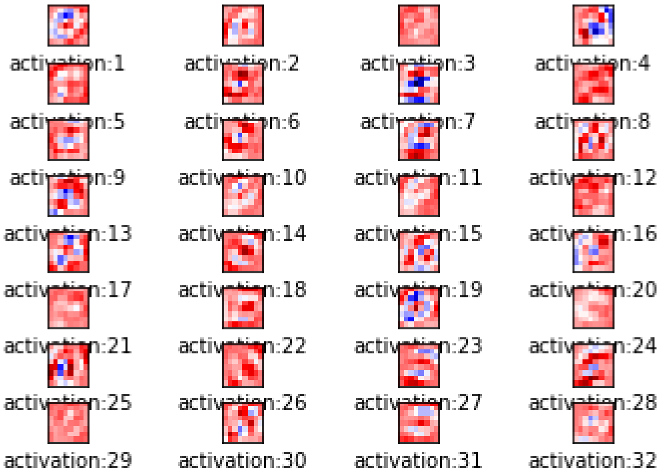
```
# Plot the outputs after the first Relu

plot_activations(out[1], number_rows=4, name="Output after the 1st Relu")
```



The image below is the result of the activation map after the second output layer.

In [41]:

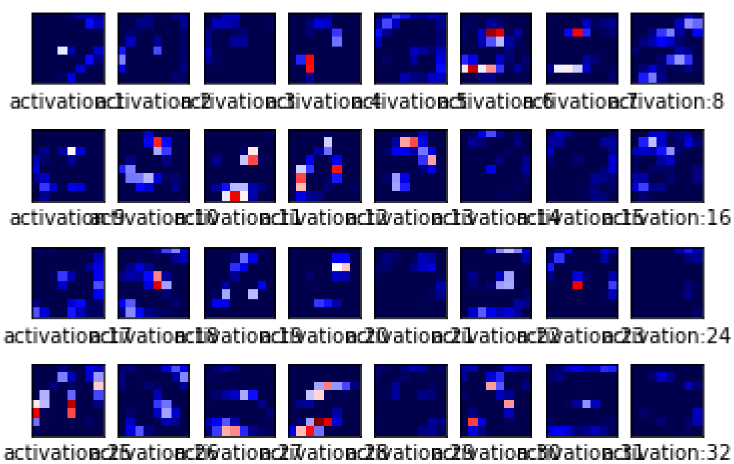
```python
# Plot the outputs after the second CNN

plot_activations(out[2], number_rows=32 // 4, name="Output after the 2nd CNN")
```



The image below is the result of the activation map after applying the second relu

In [42]:

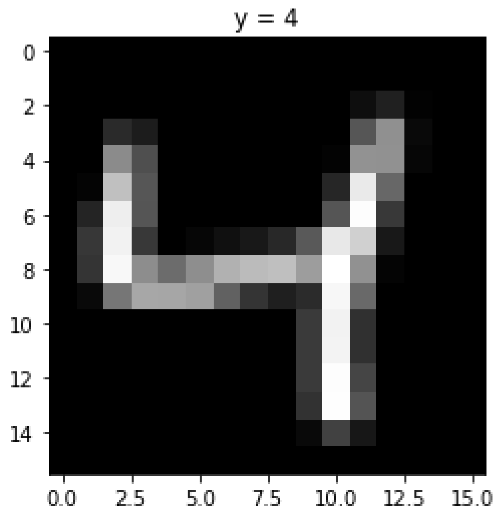
```python
# Plot the outputs after the second Relu

plot_activations(out[3], number_rows=4, name="Output after the 2nd Relu")
```



We can see the result for the third sample

In [43]:

```
# Show the third image

show_data(train_dataset[2])
```

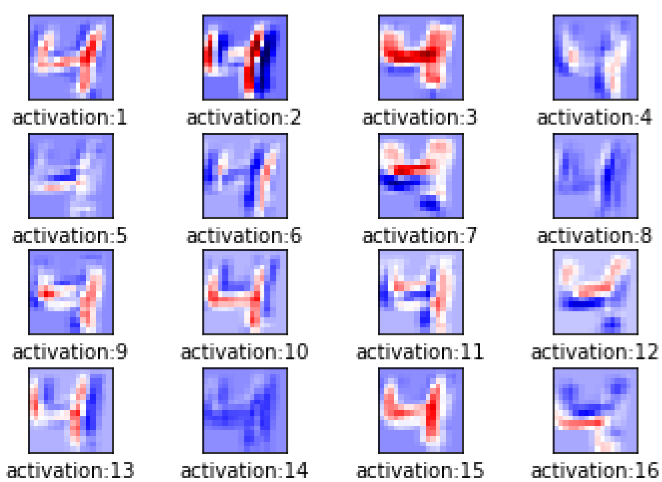


In [44]:

```
# Use the CNN activations class to see the steps

out = model.activations(train_dataset[2][0].view(1, 1, IMAGE_SIZE, IMAGE_SIZE))
```

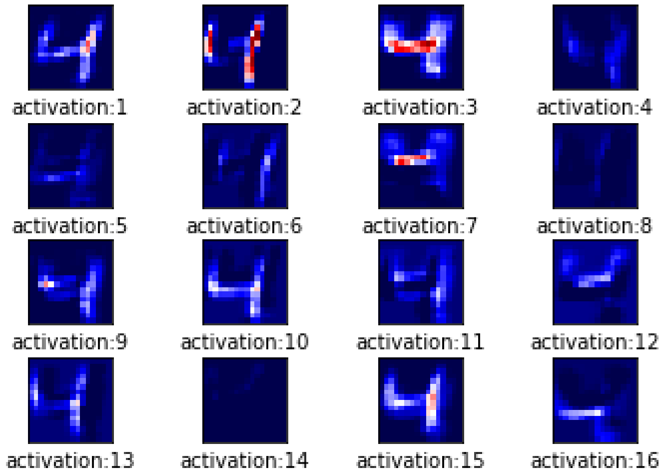
In [45]:

```
# Plot the outputs after the first CNN

plot_activations(out[0], number_rows=4, name="Output after the 1st CNN")
```



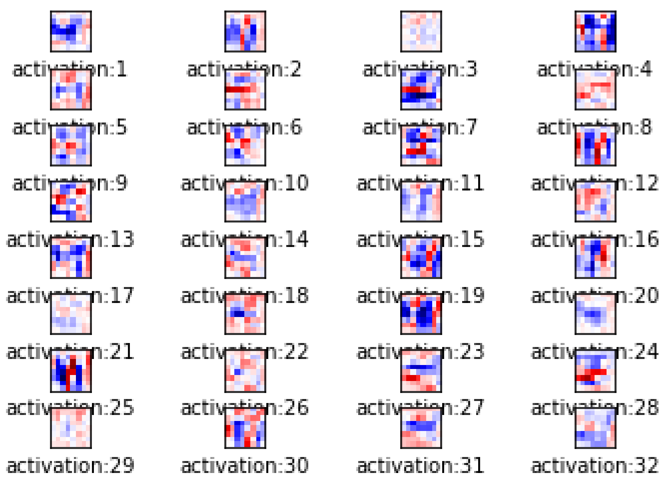
In [46]:

```python
# Plot the outputs after the first Relu

plot_activations(out[1], number_rows=4, name="Output after the 1st Relu")
```



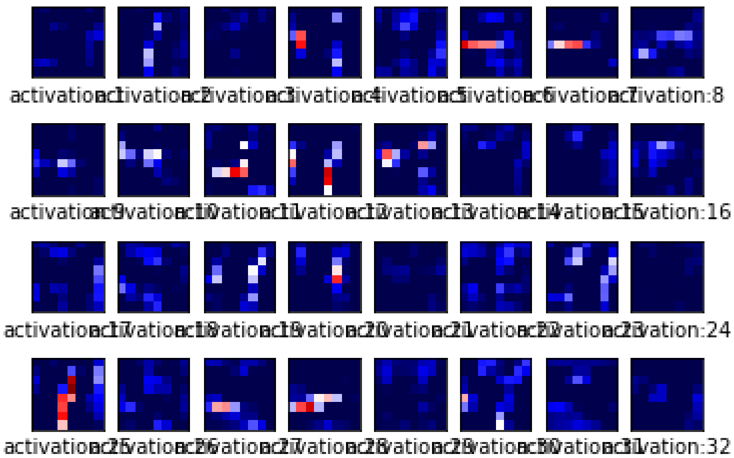
In [47]:

```python
# Plot the outputs after the second CNN

plot_activations(out[2], number_rows=32 // 4, name="Output after the 2nd CNN")
```



In [48]:

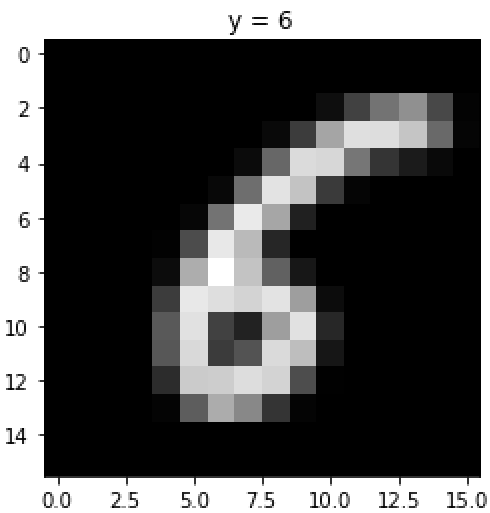
```
# Plot the outputs after the second Relu

plot_activations(out[3], number_rows=4, name="Output after the 2nd Relu")
```



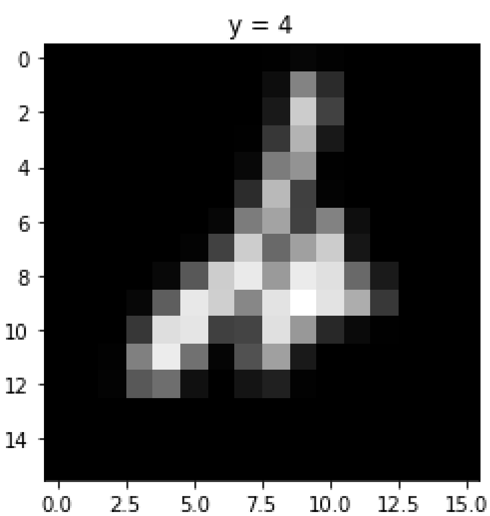
Plot the first five mis-classified samples:

In [49]:

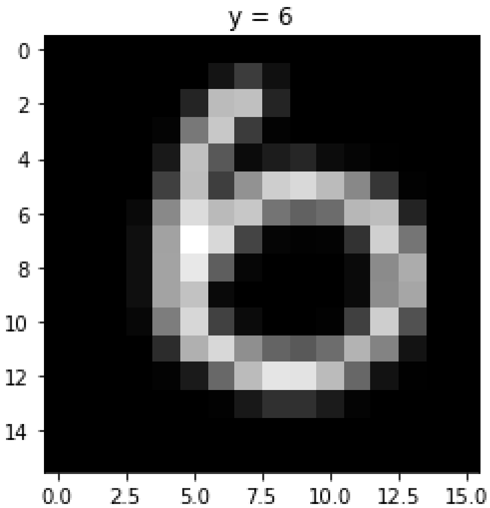
```
# Plot the mis-classified samples

count = 0
for x, y in torch.utils.data.DataLoader(dataset=validation_dataset, batch_size=1):
    z = model(x)
    _, yhat = torch.max(z, 1)
    if yhat != y:
        show_data((x, y))
        plt.show()
        print("yhat: ",yhat)
        count += 1
    if count >= 5:
        break
```



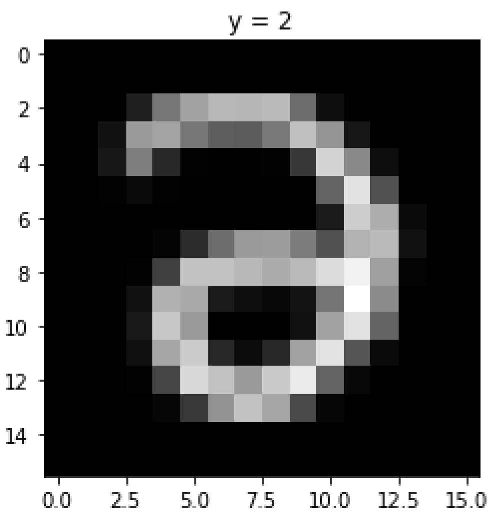
yhat: tensor([5])



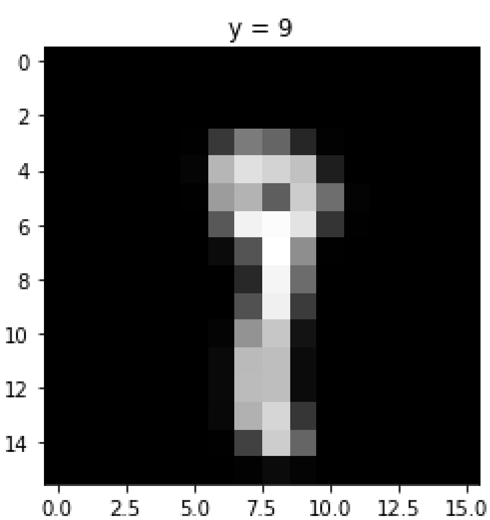
yhat: tensor([2])




```
yhat:  tensor([0])
```




```
yhat:  tensor([3])
```




```
yhat:  tensor([1])
```

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