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Convolutional Neral Network Simple example

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In this lab, we will use a Convolutional Neral Networks to classify horizontal an vertical Lines

Estimated Time Needed: **25 min**

Helper functions

In [37]:
```
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
import pandas as pd
```

In [38]:
```
torch.manual_seed(4)
```

Out[38]:
```
<torch._C.Generator at 0x19ef16b02b0>
```

function to plot out the parameters of the Convolutional layers

In [39]:
```
def plot_channels(W):
    #number of output channels
    n_out=W.shape[0]
    #number of input channels
    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='seismic')
        ax.set_yticklabels([])
        ax.set_xticklabels([])
        in_index=in_index+1

    plt.show()
```

`show_data` : plot out data sample

In [40]:
```
def show_data(dataset,sample):

    plt.imshow(dataset.x[sample,0,:,:].numpy(),cmap='gray')
    plt.title('y='+str(dataset.y[sample].item()))
    plt.show()
```

create some toy data

In [41]:

```
from torch.utils.data import Dataset, DataLoader
class Data(Dataset):
    def __init__(self,N_images=100,offset=0,p=0.9, train=False):
        """
        p:portability that pixel is wight
        N_images:number of images
        offset:set a random vertical and horizontal offset images by a sample should be less than 3
        """
        if train==True:
            np.random.seed(1)

        #make images multiple of 3
        N_images=2*(N_images//2)
        images=np.zeros((N_images,1,11,11))
        start1=3
        start2=1
        self.y=torch.zeros(N_images).type(torch.long)

        for n in range(N_images):
            if offset>0:

                low=int(np.random.randint(low=start1, high=start1+offset, size=1))
                high=int(np.random.randint(low=start2, high=start2+offset, size=1))
            else:
                low=4
                high=1

            if n<=N_images//2:
                self.y[n]=0
                images[n,0,high:high+9,low:low+3]= np.random.binomial(1, p, (9,3))
            elif  n>N_images//2:
                self.y[n]=1
                images[n,0,low:low+3,high:high+9] = np.random.binomial(1, p, (3,9))



        self.x=torch.from_numpy(images).type(torch.FloatTensor)
        self.len=self.x.shape[0]
        del(images)
        np.random.seed(0)
    def __getitem__(self,index):
```

```
        return self.x[index],self.y[index]
    def __len__(self):
        return self.len
```

`plot_activation` : plot out the activations of the Convolutional layers

In [42]:

```
def plot_activations(A,number_rows= 1,name=""):
    A=A[0,:,:,:].detach().numpy()
    n_activations=A.shape[0]


    print(n_activations)
    A_min=A.min().item()
    A_max=A.max().item()

    if n_activations==1:

        # Plot the image.
        plt.imshow(A[0,:], vmin=A_min, vmax=A_max, cmap='seismic')

    else:
        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()
```

Utility function for computing output of convolutions takes a tuple of (h,w) and returns a tuple of (h,w)

In [43]:

```
def conv_output_shape(h_w, kernel_size=1, stride=1, pad=0, dilation=1):
    #by Duane Nielsen
    from math import floor
    if type(kernel_size) is not tuple:
        kernel_size = (kernel_size, kernel_size)
    h = floor( ((h_w[0] + (2 * pad) - ( dilation * (kernel_size[0] - 1) ) - 1 )/ stride) + 1)
    w = floor( ((h_w[1] + (2 * pad) - ( dilation * (kernel_size[1] - 1) ) - 1 )/ stride) + 1)
    return h, w
```

Prepare Data

Load the training dataset with 10000 samples

In [44]:

```
N_images=10000
train_dataset=Data(N_images=N_images)
```

Load the testing dataset

In [45]:

```
validation_dataset=Data(N_images=1000,train=False)
validation_dataset
```

Out[45]:

```
<__main__.Data at 0x19e83e461c0>
```

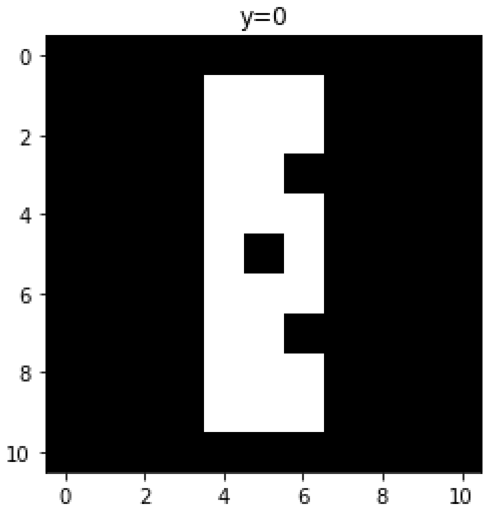
we can see the data type is long

Data Visualization

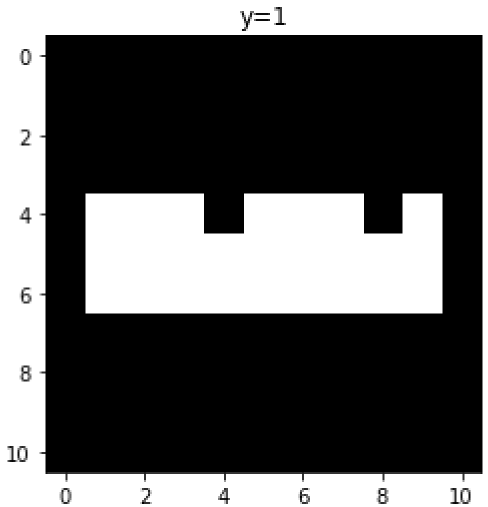
Each element in the rectangular tensor corresponds to a number representing a pixel intensity as demonstrated by the following image.

We can print out the third label

In [46]:
```
show_data(train_dataset,0)
```



In [47]:
```
show_data(train_dataset,N_images//2+2)
```



we can plot the 3rd sample

Build a Convolutional Neral Network Class

The input image is 11 x11, the following will change the size of the activations:

convolutional layer

max pooling layer

convolutional layer

max pooling layer

with the following parameters `kernel_size` , `stride` and `pad` . We use the following lines of code to change the image before we get tot he fully connected layer

In [48]:

```
out=conv_output_shape((11,11), kernel_size=2, stride=1, pad=0, dilation=1)
print(out)
out1=conv_output_shape(out, kernel_size=2, stride=1, pad=0, dilation=1)
print(out1)
out2=conv_output_shape(out1, kernel_size=2, stride=1, pad=0, dilation=1)
print(out2)

out3=conv_output_shape(out2, kernel_size=2, stride=1, pad=0, dilation=1)
print(out3)
```

```
(10, 10)
(9, 9)
(8, 8)
(7, 7)
```

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

In [49]:

```
class CNN(nn.Module):
    def __init__(self,out_1=2,out_2=1):

        super(CNN,self).__init__()
        #first Convolutional layers
        self.cnn1=nn.Conv2d(in_channels=1,out_channels=out_1,kernel_size=2,padding=0)
        self.maxpool1=nn.MaxPool2d(kernel_size=2 ,stride=1)

        #second Convolutional layers
        self.cnn2=nn.Conv2d(in_channels=out_1,out_channels=out_2,kernel_size=2,stride=1,padding=0)
        self.maxpool2=nn.MaxPool2d(kernel_size=2 ,stride=1)
        #max pooling

        #fully connected layer
        self.fc1=nn.Linear(out_2*7*7,2)

    def forward(self,x):
        #first Convolutional layers
        x=self.cnn1(x)
        #activation function
        x=torch.relu(x)
        #max pooling
        x=self.maxpool1(x)
        #first Convolutional layers
        x=self.cnn2(x)
        #activation function
        x=torch.relu(x)
        #max pooling
        x=self.maxpool2(x)
        #flatten output
        x=x.view(x.size(0),-1)
        #fully connected layer
        x=self.fc1(x)
        return x

    def activations(self,x):
        #outputs activation this is not necessary just for fun
        z1=self.cnn1(x)
        a1=torch.relu(z1)
        out=self.maxpool1(a1)
```

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

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

There are 2 output channels for the first layer, and 1 outputs channel for the second layer

In [50]:
```
model=CNN(2,1)
```

we can see the model parameters with the object

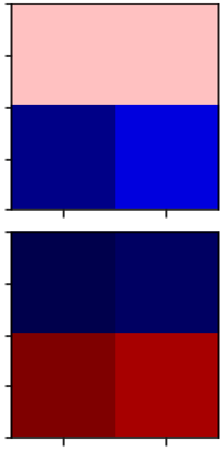
In [51]:
```
model
```

Out[51]:
```
CNN(
  (cnn1): Conv2d(1, 2, kernel_size=(2, 2), stride=(1, 1))
  (maxpool1): MaxPool2d(kernel_size=2, stride=1, padding=0, dilation=1, ceil_mode=False)
  (cnn2): Conv2d(2, 1, kernel_size=(2, 2), stride=(1, 1))
  (maxpool2): MaxPool2d(kernel_size=2, stride=1, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=49, out_features=2, bias=True)
)
```

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

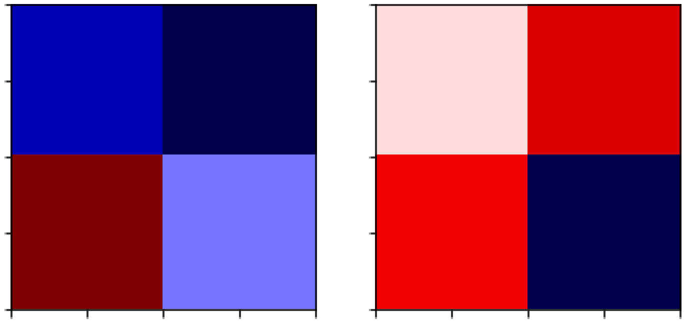
In [52]:

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



Loss function

In [53]:
```
plot_channels(model.state_dict()['cnn2.weight'])
```



Define the loss function

In [54]:
```
criterion=nn.CrossEntropyLoss()
```

optimizer class

In [55]:
```
learning_rate=0.001

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

Define the optimizer class

In [56]:
```

train_loader=torch.utils.data.DataLoader(dataset=train_dataset,batch_size=10)
validation_loader=torch.utils.data.DataLoader(dataset=validation_dataset,batch_size=20)
```

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

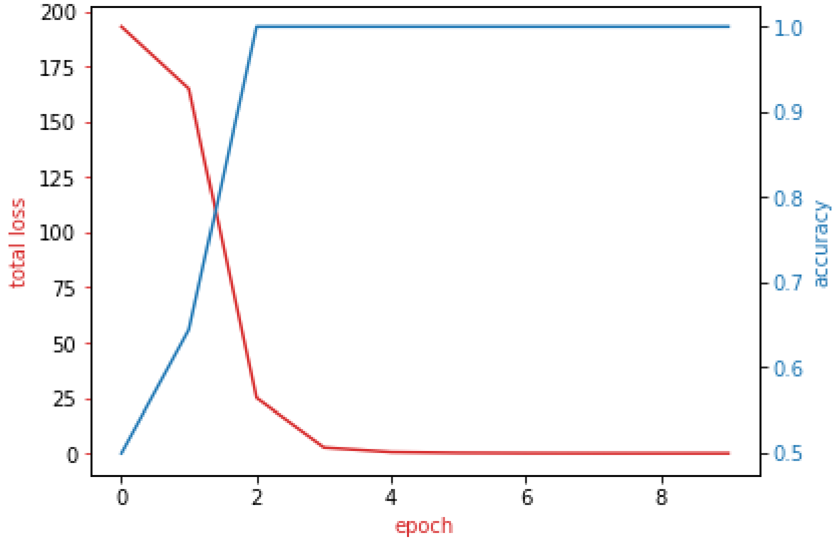
In [57]:

```
n_epochs=10
cost_list=[]
accuracy_list=[]
N_test=len(validation_dataset)
cost=0
#n_epochs
for epoch in range(n_epochs):
    cost=0
    for x, y in train_loader:


        #clear gradient
        optimizer.zero_grad()
        #make a prediction
        z=model(x)
        # calculate loss
        loss=criterion(z,y)
        # calculate gradients of parameters
        loss.backward()
        # update parameters
        optimizer.step()
        cost+=loss.item()
    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)
```

Analyse Results

Plot the loss and accuracy on the validation data:

In [58]:
```
fig, ax1 = plt.subplots()
color = 'tab:red'
ax1.plot(cost_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', labelcolor=color)
fig.tight_layout()
```

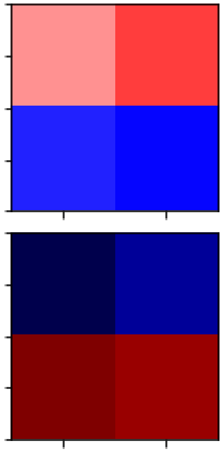


View the results of the parameters for the Convolutional layers

In [59]:
```
model.state_dict()['cnn1.weight']
```

Out[59]:
```
tensor([[[[ 0.3888,  0.5008],
          [-0.0477, -0.0855]]],


        [[[-0.4323, -0.2863],
          [ 0.9211,  0.8493]]]])
```

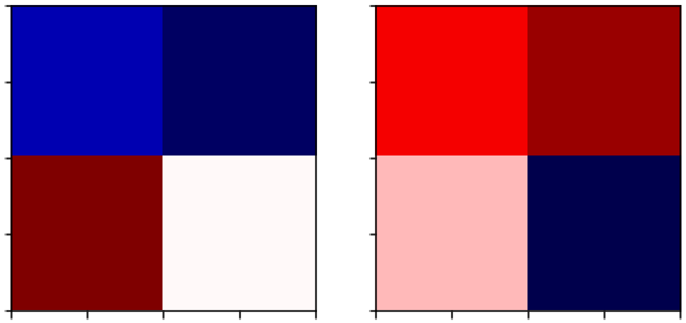
In [60]:
```
plot_channels(model.state_dict()['cnn1.weight'])
```



In [61]:
```
model.state_dict()['cnn1.weight']
```

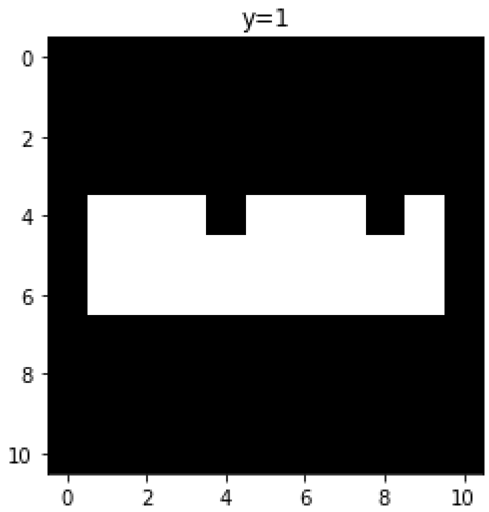
Out[61]:
```
tensor([[[[ 0.3888,  0.5008],
          [-0.0477, -0.0855]]],


        [[[-0.4323, -0.2863],
          [ 0.9211,  0.8493]]]])
```

In [62]:
```
plot_channels(model.state_dict()['cnn2.weight'])
```



Consider the following sample

In [63]:
```
show_data(train_dataset,N_images//2+2)
```



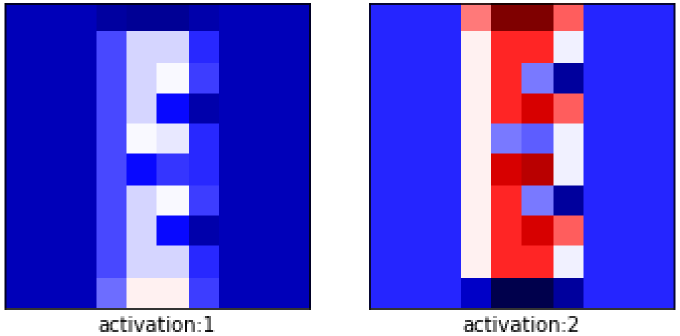
Determine the activations

In [64]:
```
out=model.activations(train_dataset[N_images//2+2][0].view(1,1,11,11))
out=model.activations(train_dataset[0][0].view(1,1,11,11))
```

Plot them out

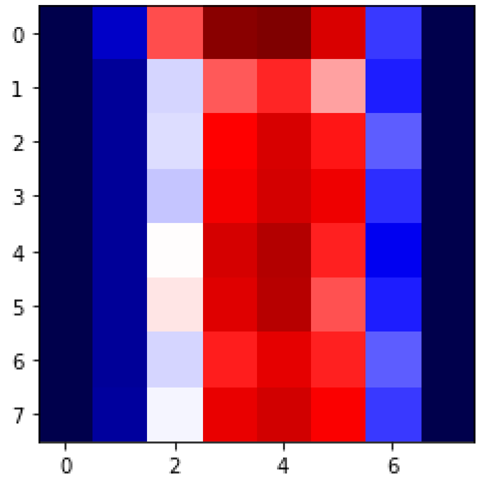
In [65]:
```
plot_activations(out[0],number_rows=1,name=" feature map")
plt.show()
```

2



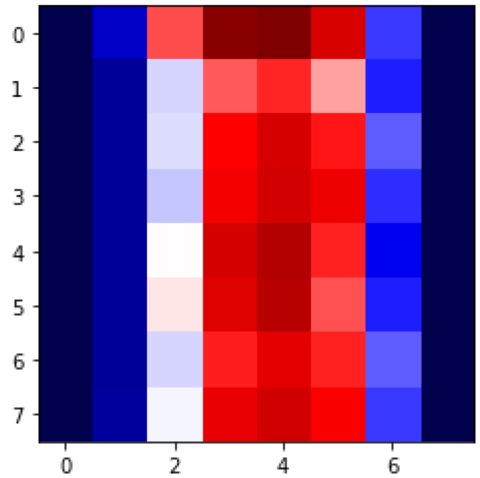
In [66]:
```
plot_activations(out[2],number_rows=1,name="2nd feature map")
plt.show()
```

1



In [67]:
```
plot_activations(out[3],number_rows=1,name="first feature map")
plt.show()
```

1



we save the output of the activation after flattening

In [68]:
```
out1=out[4][0].detach().numpy()
```

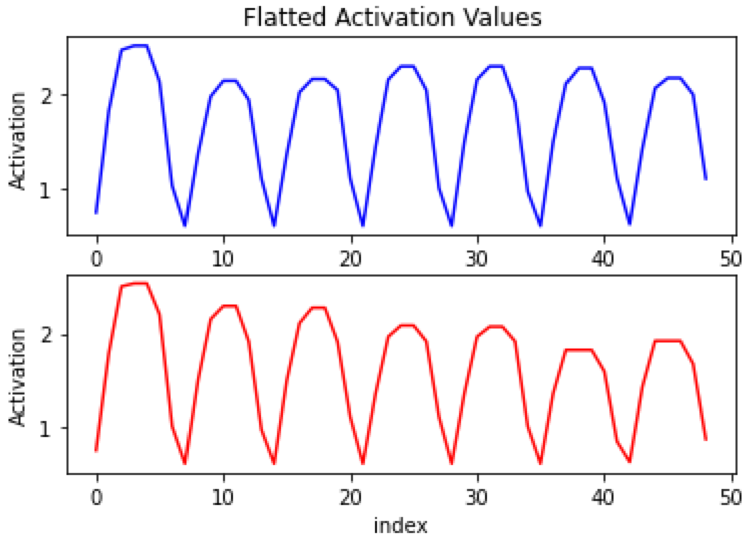
we can do the same for a sample where y=0

In [69]:
```
out0=model.activations(train_dataset[100][0].view(1,1,11,11))[4][0].detach().numpy()
out0
```

Out[69]:
```
array([0.74286526, 1.7852222 , 2.5095963 , 2.5421505 , 2.5421505 ,
       2.2080624 , 1.002023  , 0.5994579 , 1.4955455 , 2.1564963 ,
       2.297883  , 2.297883  , 1.9130136 , 0.9667071 , 0.5994579 ,
       1.4955455 , 2.1124327 , 2.2790995 , 2.2790995 , 1.9122137 ,
       1.1047952 , 0.5994579 , 1.3521382 , 1.9661635 , 2.0876038 ,
       2.0876038 , 1.9159282 , 1.1047952 , 0.5994579 , 1.3521382 ,
       1.9661635 , 2.0746133 , 2.0746133 , 1.9159282 , 1.002023  ,
       0.5994579 , 1.3521382 , 1.8227562 , 1.8227562 , 1.8227562 ,
       1.5909783 , 0.8382979 , 0.6166176 , 1.4248358 , 1.9210907 ,
       1.9210907 , 1.9210907 , 1.6721531 , 0.8639348 ], dtype=float32)
```

In [70]:
```
plt.subplot(2, 1, 1)
plt.plot( out1, 'b')
plt.title('Flatted Activation Values  ')
plt.ylabel('Activation')
plt.xlabel('index')
plt.subplot(2, 1, 2)
plt.plot(out0, 'r')
plt.xlabel('index')
plt.ylabel('Activation')
```

Out[70]:
```
Text(0, 0.5, 'Activation')
```



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In [ ]: