module4-nn-12

May 20, 2023

1 Lab Session #6.2

1.1 Computational Neurophysiology [E010620A]

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1.2 Neural-network exercise

Before executing this notebook make sure that you have a recent version of PyTorch and Torchvision installed. The packages can easily be installed within an Anaconda environment: - conda install -c pytorch pytorch torchvision

Otherwise, the packages can also be installed using pip: - pip install torch torchvision

The notebook was tested in an Anaconda environment (v4.9.2) with Python v3.7.9 and Pytorch v1.6.0.

[1]:
```
# this solves an error with plotting images when using Pytorch
import os
os.environ["KMP_DUPLICATE_LIB_OK"]="TRUE"
```

[2]:
```
# import all necessary modules
from pathlib import Path

import numpy as np
import matplotlib.pyplot as plt
import time
from collections import defaultdict

import torch
from torchvision import datasets
import torchvision.transforms as transforms

import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
```

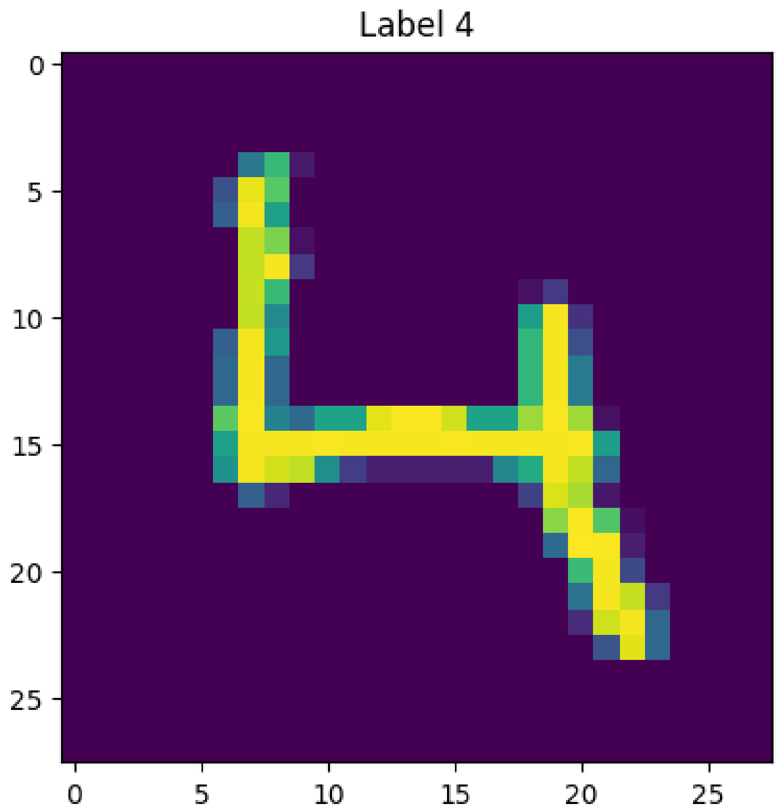
1.2.1 1. Analysis and tuning of neural-network responses

Train a CNN model to classify handwritten digits We will use the MNIST dataset to train a neural-network that can classify handwritten digits.

[21]:
```
# Download MNIST dataset
path = Path('./')
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.1307,), (0.3081,)), # normalize based on the mean␣
 ↪and std
     ])
trainset = datasets.MNIST(path, train=True, download=True,transform=transform)
train_loader = torch.utils.data.DataLoader(trainset, batch_size=16,␣
 ↪shuffle=True)

testset = datasets.MNIST(path, train=False, transform=transform)
test_loader = torch.utils.data.DataLoader(testset, batch_size=256, shuffle=True)
```

[22]:
```
# Visualize an image from the dataset
for i, data in enumerate(train_loader):
    images, labels = data
    break
print('Shape of images from one batch : ', images.shape)
print('Shape of labels from one batch : ', labels.shape)

plt.imshow(images[0, 0])
plt.title('Label {}'.format(labels[0]));
plt.show()
```

```
Shape of images from one batch :  torch.Size([16, 1, 28, 28])
Shape of labels from one batch :  torch.Size([16])
```



Define the neural network.

[48]:
```
# the CNN is defined here
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 3x3 square convolution
        # kernel
        self.conv1 = nn.Conv2d(1, 6, 3, padding=1)
        self.conv2 = nn.Conv2d(6, 16, 3, padding=1)
        self.fc1 = nn.Linear(16 * 7 * 7, 120)  # 7*7 from image dimension
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

        # Set whether to readout activation
        self.readout = False

    def forward(self, x):
        # Max pooling over a (2, 2) window
        l1 = F.max_pool2d(F.relu(self.conv1(x)), 2)
```

```
        l2 = F.max_pool2d(F.relu(self.conv2(l1)), 2)
        l2_flat = torch.flatten(l2, start_dim=1)  # flatten tensor, while␣
↪keeping batch dimension
        l3 = F.relu(self.fc1(l2_flat))
        l4 = F.relu(self.fc2(l3))
        y = self.fc3(l4)

        if self.readout:
            return {'l1': l1, 'l2': l2, 'l3': l3, 'l4': l4, 'y': y} # names of␣
↪the layers
        else:
            return y
```

Train the network on MNIST until it reaches 95% accuracy. It should take only ~500-1000 training steps.

[49]:
```
# Instantiate the network and print information
net = Net()
print(net)

# Use Adam optimizer
optimizer = optim.Adam(net.parameters(), lr=0.01)
criterion = nn.CrossEntropyLoss()

# Train for only one epoch
running_loss = 0
running_acc = 0
for i, data in enumerate(train_loader):
    image, label = data

    # in your training loop:
    optimizer.zero_grad()   # zero the gradient buffers
    output = net(image)
    loss = criterion(output, label)
    loss.backward()
    optimizer.step()    # Does the update

    # prediction
    prediction = torch.argmax(output, axis=-1)
    acc = torch.mean((label == prediction).float())

    running_loss += loss.item()
    running_acc += acc
    if i % 100 == 99:
        running_loss /= 100
        running_acc /= 100
        print('Step {}, Loss {:0.4f}, Acc {:0.3f}'.format(
```

```
            i+1, running_loss, running_acc))
        if running_acc > 0.95:
            break
        running_loss, running_acc = 0, 0
```

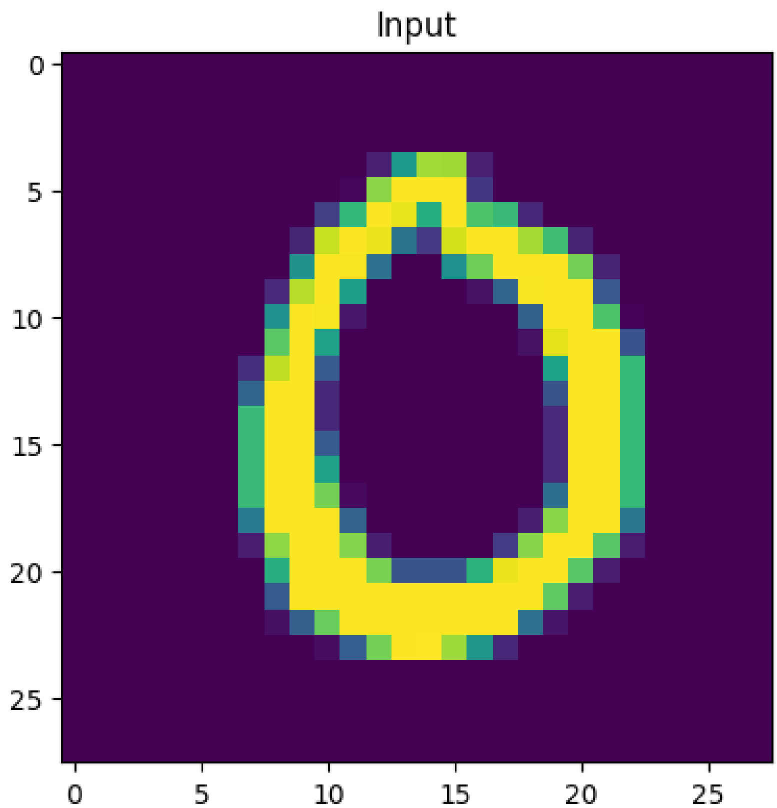
```
Net(
  (conv1): Conv2d(1, 6, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(6, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (fc1): Linear(in_features=784, out_features=120, bias=True)
  (fc2): Linear(in_features=120, out_features=84, bias=True)
  (fc3): Linear(in_features=84, out_features=10, bias=True)
)
Step 100, Loss 0.9354, Acc 0.676
Step 200, Loss 0.3131, Acc 0.909
Step 300, Loss 0.2772, Acc 0.921
Step 400, Loss 0.2572, Acc 0.928
Step 500, Loss 0.2462, Acc 0.933
Step 600, Loss 0.1989, Acc 0.941
Step 700, Loss 0.2612, Acc 0.933
Step 800, Loss 0.1684, Acc 0.952
```

Visualize the activity of each layer of the trained network to an input digit from the test dataset.

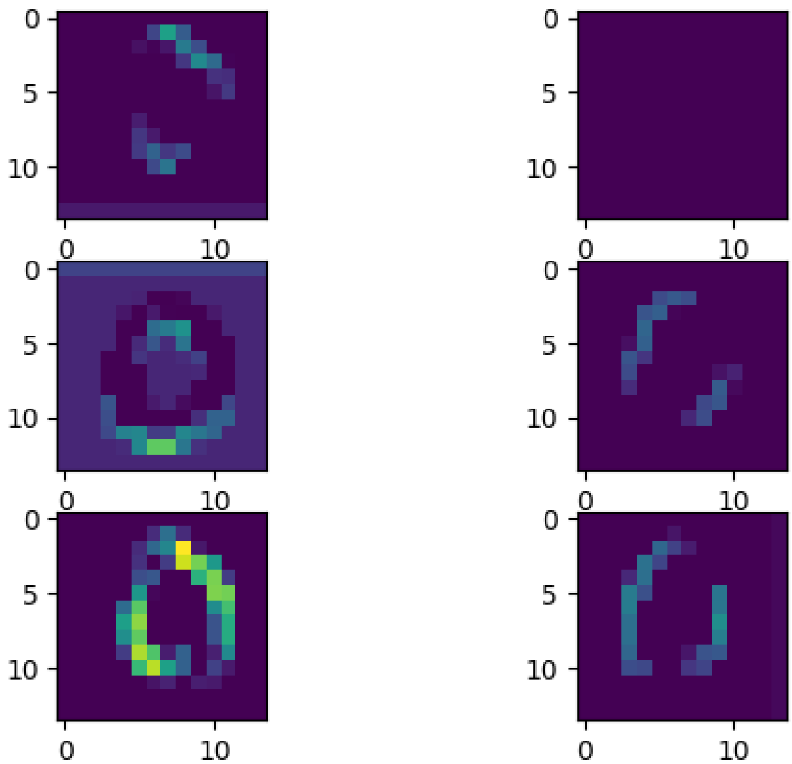
[84]:
```
for i, data in enumerate(test_loader):
    images, labels = data
    break

# Readout network activity
net.readout = True
activity = net(images)

n_images = len(labels)
# transform the input and output data to numpy variables
ind = np.argsort(labels.numpy())
images = images.detach().numpy()[ind]
labels = labels.numpy()[ind]

# extract the activity of each layer
for key, val in activity.items():
    new_val = val.detach().numpy()[ind]
    activity[key] = new_val

# pick one image
i_image = 0

plt.imshow(images[i_image, 0]) # show the input
plt.title('Input')
```

```
layers = ['l1', 'l2', 'l3', 'l4', 'y'] # the layer names
layers_titles = ['Layer 1 (6 channels)','Layer 2 (16 channels)','Layer 3 (120␣
↪Units)','Layer 4 (84 Units)','Output (10 Classes)']

for layeri, layer in enumerate(layers):
    act = activity[layer]
    act = act[i_image]
    if len(act.shape) == 3:
        n_channels = act.shape[0]
        if n_channels == 6:
            n_x, n_y = 2, 3
        elif n_channels == 16:
            n_x, n_y = 4, 4
        else:
            n_x, n_y = n_channels, 1
        vmax = np.max(act)
        fig, axs = plt.subplots(n_y, n_x)
        fig.suptitle(layers_titles[layeri])
        for i_channel in range(n_channels):
            ax = axs[np.mod(i_channel, n_y), i_channel//n_y]
            ax.imshow(act[i_channel], vmin=0, vmax=vmax)
            #ax.set_axis_off()
        #plt.tight_layout()
    elif len(act.shape) == 1:
        if act.shape[0] == 10:
            print("!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
↪!!!!!!!!!!!!!!!!!!!!!!!!1")
            print(act.shape)
        fig = plt.figure()
        plt.imshow(act[:, np.newaxis], aspect='auto')
        plt.title(layers_titles[layeri])
        #plt.axis('off')
print('Predicted label:', labels[i_image])
```

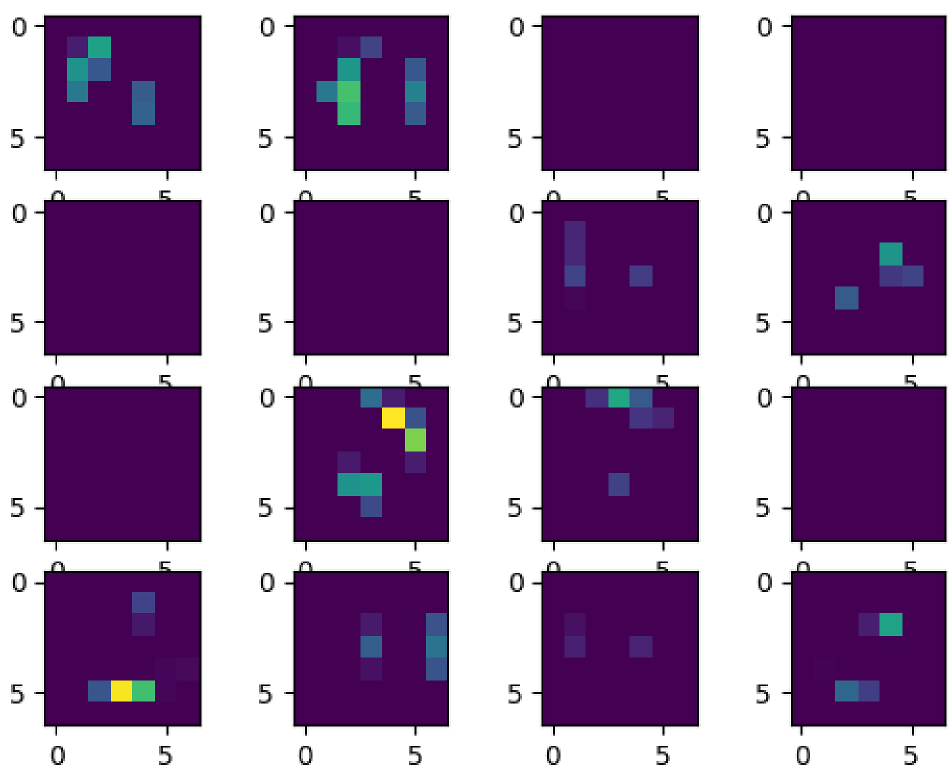
```
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
!!!!!1
(10,)
Predicted label: 0
```

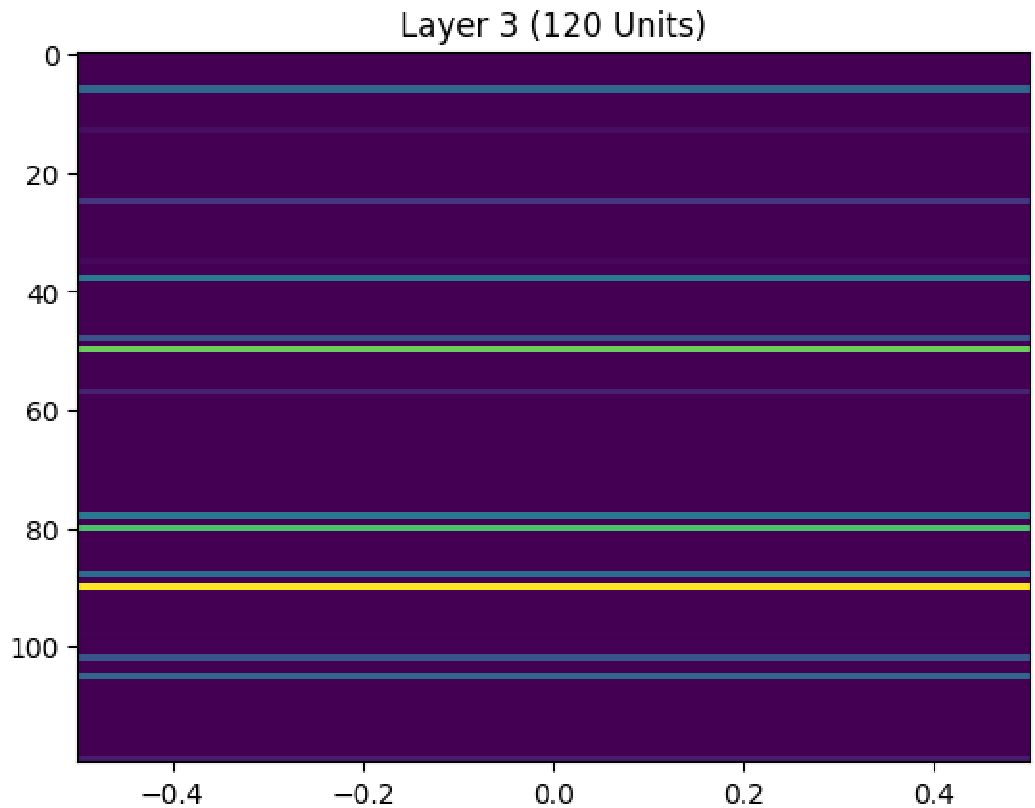

Input
0
5
10
15
20
25
0
5
10
15
20
25

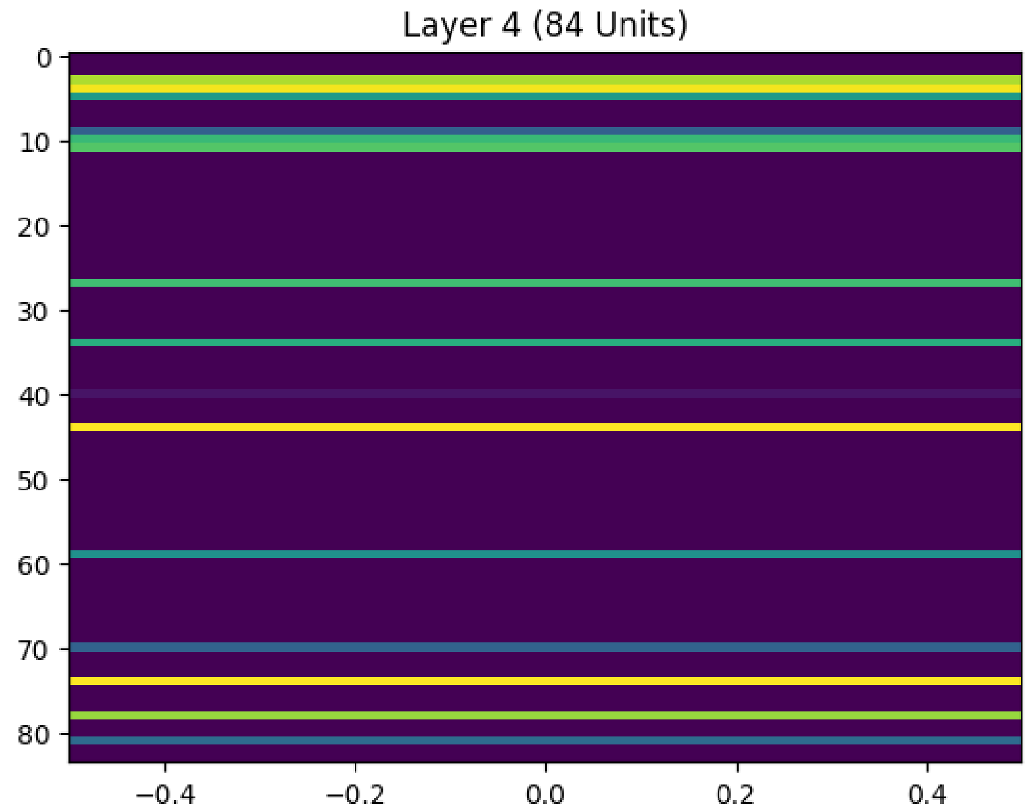
Layer 1 (6 channels)

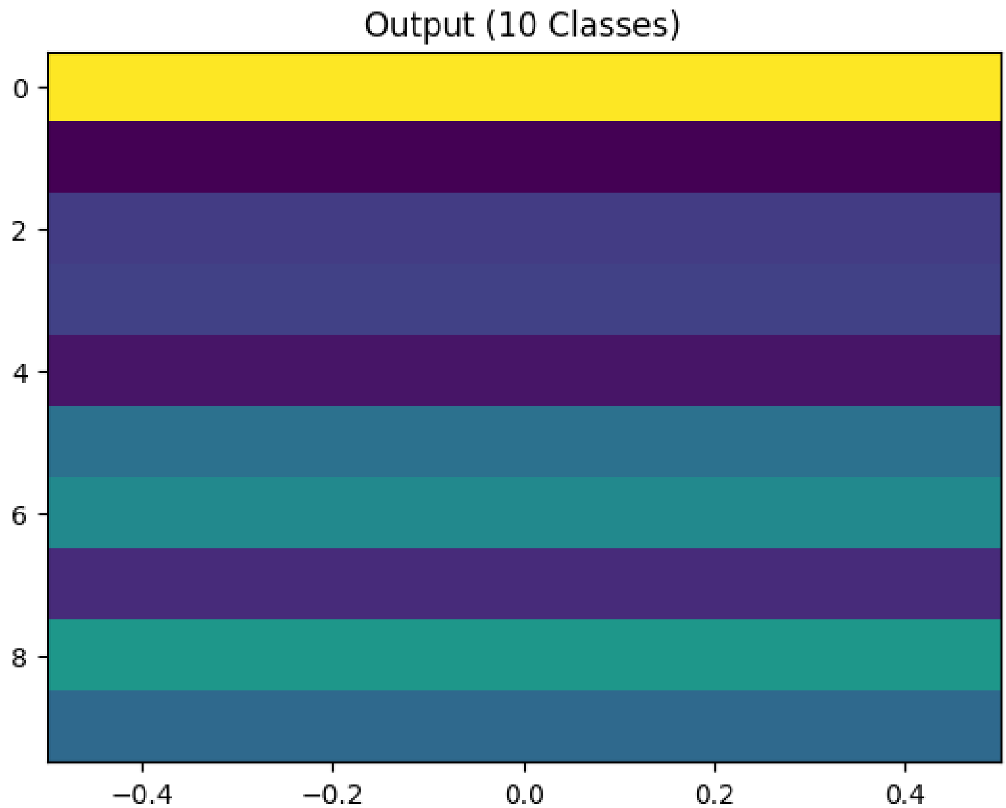


Layer 2 (16 channels)




Layer 3 (120 Units)
0
20
40
60
80
100
−0.4
−0.2
0.0
0.2
0.4


Layer 4 (84 Units)
0
10
20
30
40
50
60
70
80
−0.4
−0.2
0.0
0.2
0.4



Tuning analysis of specific neurons of the neural-network Studying tuning properties of single neurons has been one of the most important analysis techniques in neuroscience. In neuroscience, it is interesting to know how certain stimuli can activate specific neurons. A tuning can be performed to investigate what the most optimal input stimulus is to fully activate a neuron (eg. an auditory stimulus with a specific frequency pattern that activates a specific neuron in the auditory cortex, a visual stimulus with a specific pattern that activates neurons in the visual cortex, etc.). Using this knowledge, these inputs can be used as building blocks to investigate more complex stimuli by decomposing it into its building blocks.

Similar to tuning methods of biological neurons, we will choose a neuron (node) from a layer of the trained CNN and find the preferred input image that most strongly activates this specific neuron (node) using gradient-based optimization. This can give us an idea of which patterns in an image are important to activate specific neurons (nodes) and therefore to decide on which number is visualized in the image. This method is particularly useful for studying neurons with complex tuning properties in higher layers.

[104]:
```
# the gradient-based optimization function is defined here
def get_syn_image(layer,ind=[]):
    # Here syn_image is the variable to be optimized
    # Initialized randomly for search in parallel
    # the ind variable can be given to manually select the
```

```python
    # neuron index
    batch_size = 64
    image_size = [batch_size] + list(images.shape[1:])
    syn_image_init = np.random.rand(*image_size)
    syn_image = torch.tensor(syn_image_init, requires_grad=True, dtype=torch.
↪float32)

    # Use Adam optimizer
    optimizer = optim.Adam([syn_image], lr=0.01)

    running_loss = 0
    running_loss_reg = 0
    for i in range(1000):
        optimizer.zero_grad()   # zero the gradient buffers
        syn_image.data.clamp_(min=0.0, max=1.0)
        syn_image_transform = (syn_image - 0.1307) / 0.3081
        activity = net(syn_image_transform)

        # Pick a neuron, and minimize its negative activity
        neuron = activity[layer]

        # Choose a neuron that is already most activated
        if i == 0 and not ind:
            neuron_avg = np.mean(neuron.detach().numpy(), axis=0)
            ind = np.argsort(neuron_avg.flatten())[-1]
            print('Chosen unit', ind) # the selected neuron

        neuron = neuron.view(batch_size, -1)[:, ind]
        if i == 0:
            print('Layer', layer)
            neuron_init = neuron.detach().numpy()

        loss = -torch.mean(torch.square(neuron))
        loss_reg = torch.mean(torch.square(syn_image_transform)) * 100
        loss += loss_reg
        loss.backward()
        optimizer.step()

        running_loss += loss.item()
        running_loss_reg += loss_reg.item()
        if i % 100 == 99:
            running_loss /= 100
            running_loss_reg /= 100
            print('Step {}, Loss {:0.4f} Loss Regularization {:0.4f}'.format(
                i+1, running_loss, running_loss_reg))
            running_loss, running_loss_reg = 0, 0
```

```
    neuron = neuron.detach().numpy()
    syn_image = syn_image.detach().numpy()
    return syn_image, syn_image_init, neuron, ind

# run the optimization
layer = 'y' # the output layer is chosen
syn_image, syn_image_init, neuron, neuron_ind = get_syn_image(layer)
```

```
Chosen unit 3
Layer y
Step 100, Loss -839.0787 Loss Regularization 143.9943
Step 200, Loss -2907.6027 Loss Regularization 213.6456
Step 300, Loss -3357.7404 Loss Regularization 236.9315
Step 400, Loss -3529.1842 Loss Regularization 245.1437
Step 500, Loss -3605.4151 Loss Regularization 249.0957
Step 600, Loss -3642.4528 Loss Regularization 251.3316
Step 700, Loss -3665.3252 Loss Regularization 252.7163
Step 800, Loss -3683.0979 Loss Regularization 253.8221
Step 900, Loss -3695.6238 Loss Regularization 254.5184
Step 1000, Loss -3705.9981 Loss Regularization 255.0857
```

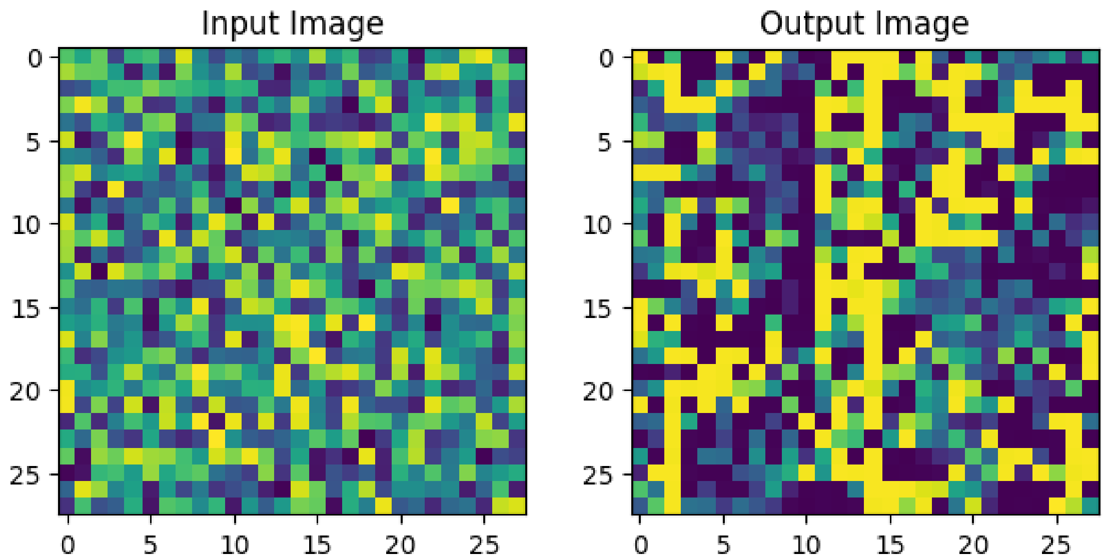
The above method takes a randomly selected input (syn_image_init) and optimizes it to maximize the activity of a specific neuron (neuron_ind) of the selected layer (layer). The result is the optimized input (syn_image) that most strongly activates the specific neuron of the selected layer. Visualize the input before and after the optimization procedure to see the effect that this procedure has on the stimulus. What can you tell about the optimized stimulus?

[105]:
```
syn_image, syn_image_init, neuron, neuron_ind = get_syn_image(layer, ind=1)
print(syn_image.shape)
```

```
Layer y
Step 100, Loss -407.4940 Loss Regularization 117.9935
Step 200, Loss -1666.9794 Loss Regularization 174.6702
Step 300, Loss -2052.6148 Loss Regularization 206.8713
Step 400, Loss -2196.5263 Loss Regularization 219.6785
Step 500, Loss -2269.6942 Loss Regularization 226.2585
Step 600, Loss -2312.0900 Loss Regularization 230.0019
Step 700, Loss -2344.9901 Loss Regularization 232.4174
Step 800, Loss -2369.0643 Loss Regularization 234.1936
Step 900, Loss -2387.9859 Loss Regularization 235.4100
Step 1000, Loss -2400.3677 Loss Regularization 236.4267
(64, 1, 28, 28)
```

[113]:
```
input_image = syn_image_init[0].squeeze() # .squeeze() gets rid of the 1 in the␣
↪shapes
output_image = syn_image[0].squeeze()

fig, axs = plt.subplots(1, 2)
```

```
fig.tight_layout()

axs[0].imshow(input_image)
axs[0].set_title('Input Image')

axs[1].imshow(output_image)
axs[1].set_title('Output Image')

plt.show()
```



Answer

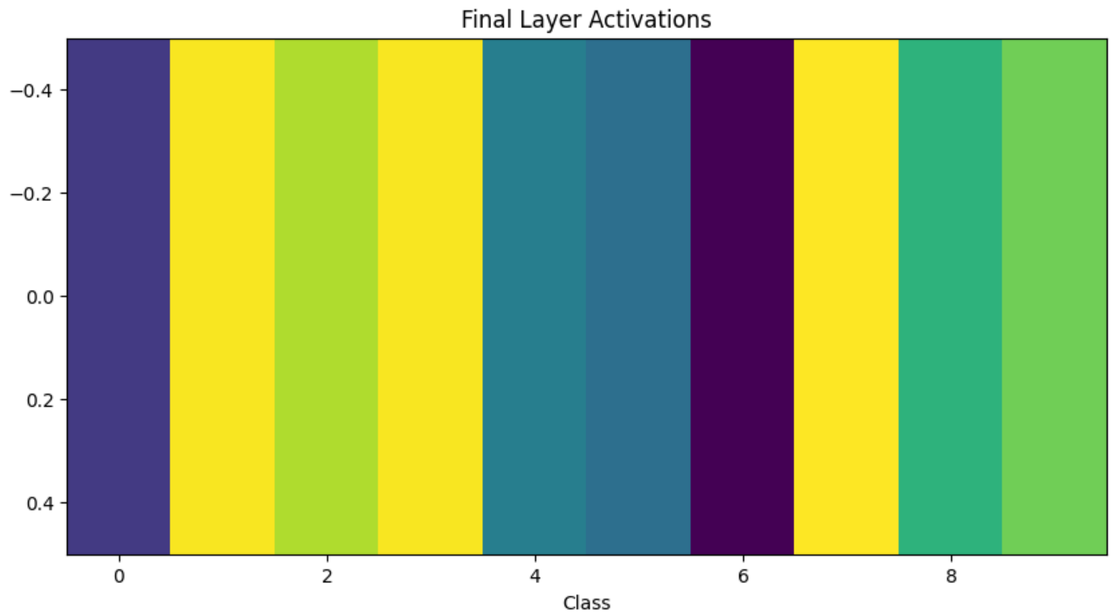
Your answer here

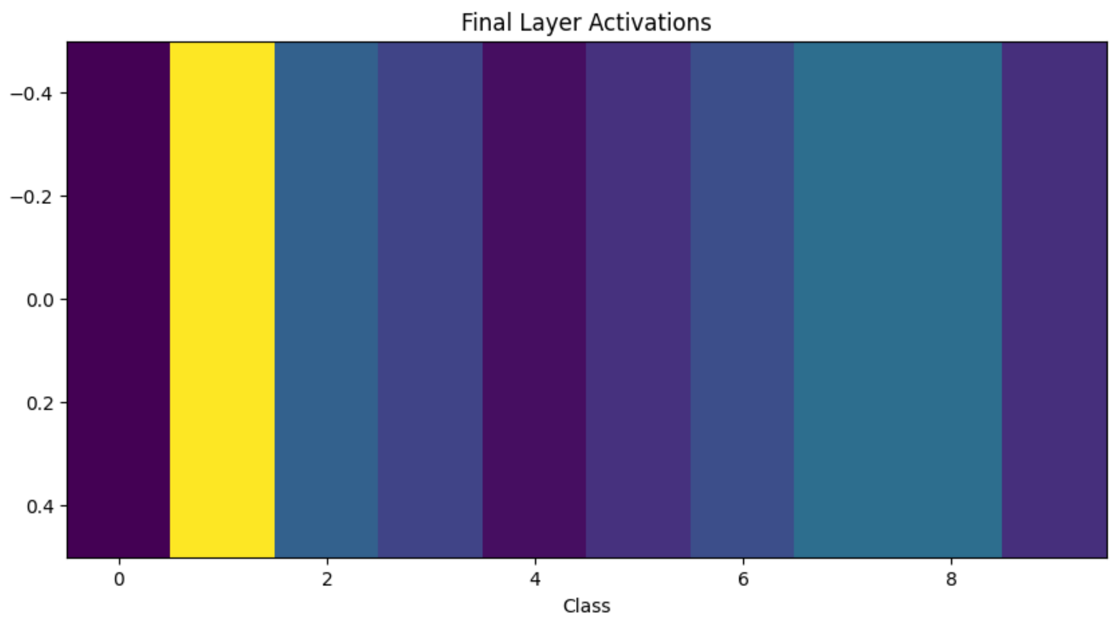
Now give the two images (before and after the optimization) as inputs to the neural-network and visualize the outputs of the selected layer to these two inputs. For this, you can use the code of the previous section ("Visualize the activity of each layer of the trained network to an input digit from the test dataset") and plot only the output of the last layer. Can you tell from the plotted outputs of the layer which neuron was optimized? Do you notice a difference in the activity of the specific neuron after driving the neural-network with the optimized input?

Make sure that the inputs to the neural-network are of float32 type and 4-dimensional (B, 1, H, W), where B is the batch size (here 1) and H, W are the height and width dimensions of the image. To facilitate a better comparison, it is better to use the same colorscale for both inputs and outputs (by setting one common vmax limit for imshow).

[114]:
```
# reshaping input images
```

```python
original_input = torch.from_numpy(syn_image_init).float() # read as tensor instead of array
original_input = F.interpolate(original_input, size=(28, 28), mode='bilinear', align_corners=False) # resize to 28x28

optimized_input = torch.from_numpy(syn_image).float()
optimized_input = F.interpolate(optimized_input, size=(28, 28), mode='bilinear', align_corners=False)

# imgs to NN:
net.readout = True  # get layer outputs
output_original = net(original_input)
output_optimized = net(optimized_input)

# last layer's output
output_original_last = output_original['y'].detach().numpy()
output_optimized_last = output_optimized['y'].detach().numpy()


# plotting input
plt.figure(figsize=(10, 5))
plt.imshow(output_original_last[0, np.newaxis], aspect='auto')
plt.xlabel('Class')
plt.title('Final Layer Activations')
plt.show()

# plotting output
plt.figure(figsize=(10, 5))
plt.imshow(output_optimized_last[0, np.newaxis], aspect='auto')
plt.xlabel('Class')
plt.title('Final Layer Activations')
plt.show()
```





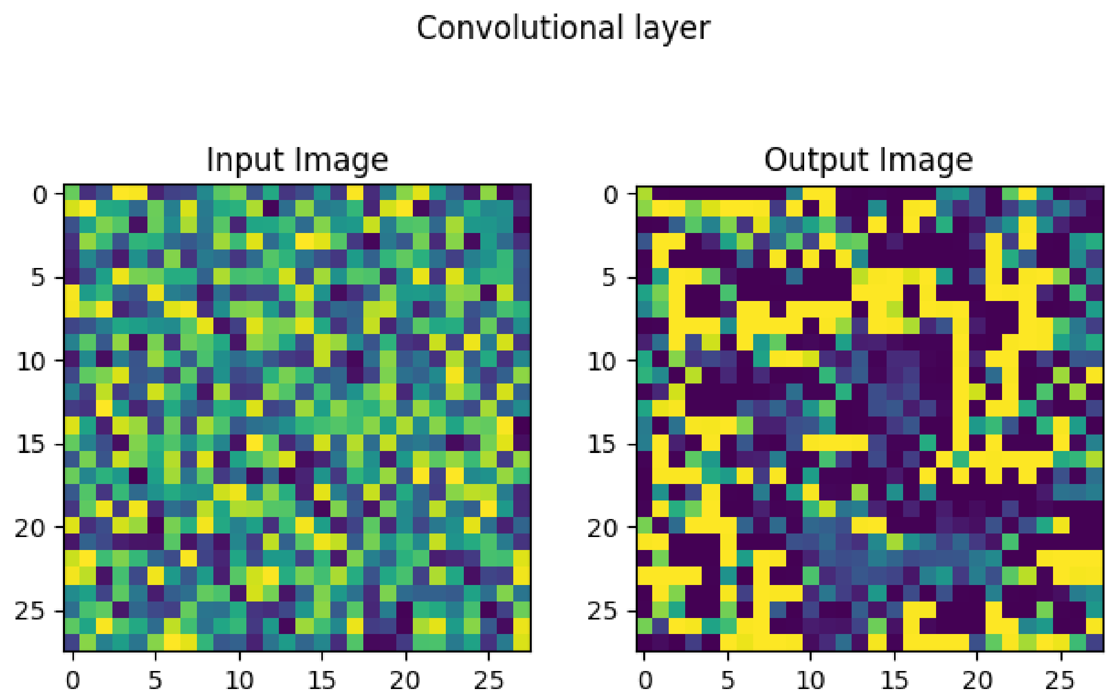
Answer

Your answer here

Perform the same tuning analysis for a neuron of a convolutional layer of the neural-network. What differences do you see in the image that the optimization method gives for a convolutional layer, when compared to the one you got for the output (dense) layer of the neural network?

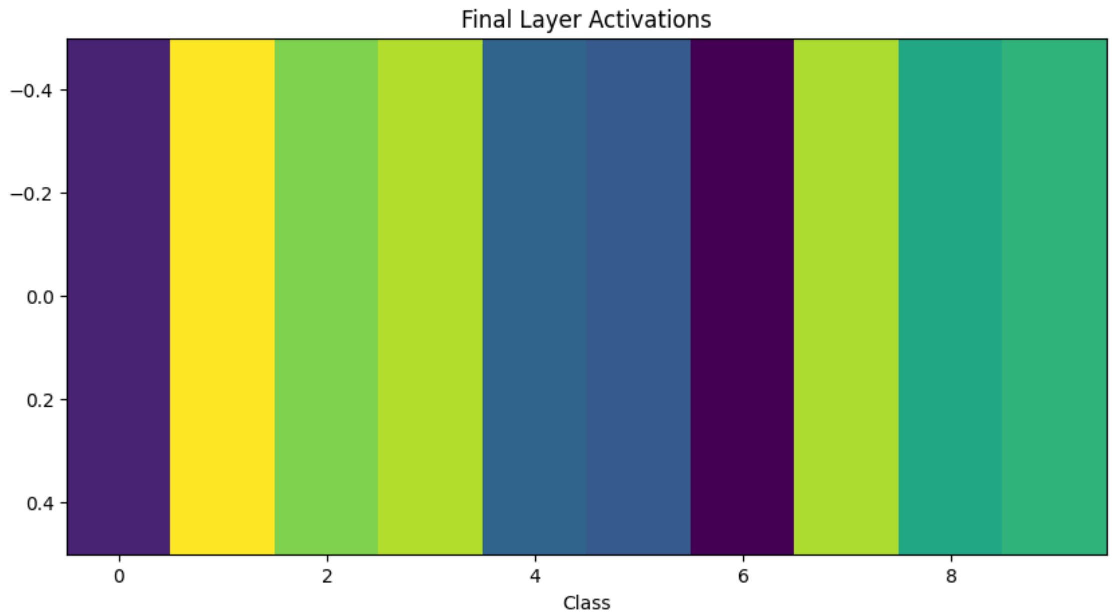
[120]:
```
layer = 'l3' # the output layer is chosen
syn_image_con, syn_image_init_con, neuron_con, neuron_ind_con =␣
 ↪get_syn_image(layer)

input_image_con = syn_image_init_con[0].squeeze() # .squeeze() gets rid of the␣
 ↪1 in the shapes
output_image_con = syn_image_con[0].squeeze()

fig, axs = plt.subplots(1, 2)
fig.tight_layout()
fig.suptitle("Convolutional layer")

axs[0].imshow(input_image_con)
axs[0].set_title('Input Image')

axs[1].imshow(output_image_con)
axs[1].set_title('Output Image')

plt.show()
```

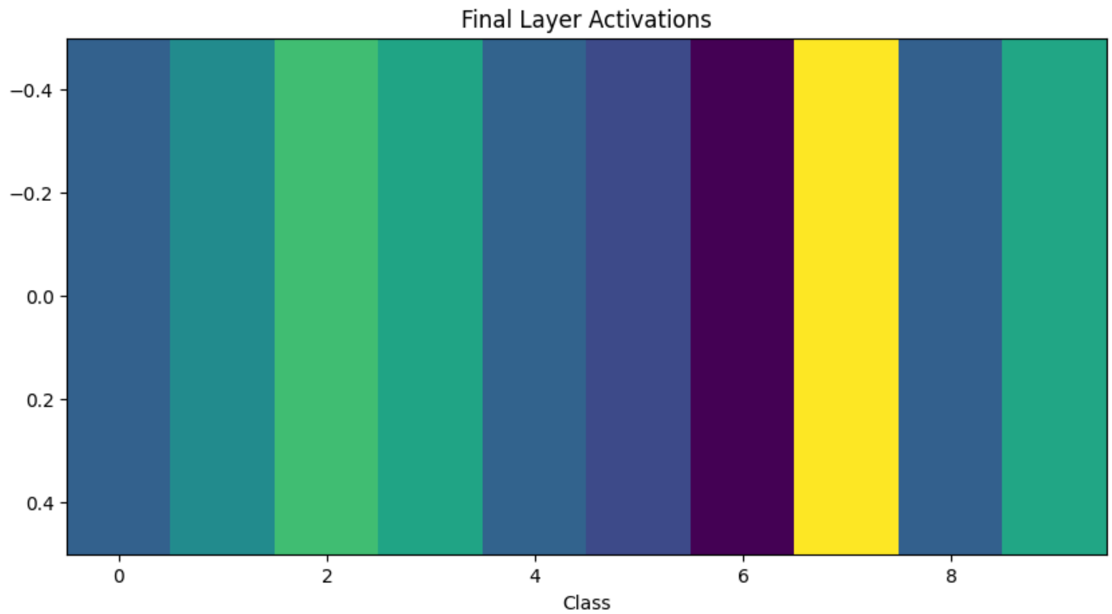
```
Chosen unit 48
Layer l3
Step 100, Loss -91.0352 Loss Regularization 105.7331
Step 200, Loss -646.7165 Loss Regularization 171.2205
Step 300, Loss -774.4980 Loss Regularization 200.5946
Step 400, Loss -807.8452 Loss Regularization 208.5060
Step 500, Loss -823.4282 Loss Regularization 211.6003
Step 600, Loss -832.2222 Loss Regularization 213.2554
Step 700, Loss -835.2106 Loss Regularization 213.9934
Step 800, Loss -837.7871 Loss Regularization 214.3758
Step 900, Loss -839.8371 Loss Regularization 214.7700
Step 1000, Loss -840.8332 Loss Regularization 215.0745
```



[121]:
```
# reshaping input images
original_input_con = torch.from_numpy(syn_image_init_con).float() # read as␣
↪tensor instead of array
original_input_con = F.interpolate(original_input_con, size=(28, 28),␣
↪mode='bilinear', align_corners=False) # resize to 28x28

output_con = torch.from_numpy(syn_image_con).float()
output_con = F.interpolate(output_con, size=(28, 28), mode='bilinear',␣
↪align_corners=False)

# imgs to NN:
net.readout = True  # get layer outputs
output_original_con = net(original_input_con)
output_optimized_con = net(output_con)

# last layer's output
output_original_con_last = output_original_con['y'].detach().numpy()
output_optimized_con_last = output_optimized_con['y'].detach().numpy()


# plotting input
plt.figure(figsize=(10, 5))
plt.imshow(output_original_con_last[0, np.newaxis], aspect='auto')
plt.xlabel('Class')
```

```
plt.title('Final Layer Activations')
plt.show()

# plotting output
plt.figure(figsize=(10, 5))
plt.imshow(output_optimized_con_last[0, np.newaxis], aspect='auto')
plt.xlabel('Class')
plt.title('Final Layer Activations')
plt.show()
```





Answer

7 IS SIMILAR TO 1

1.2.2 2. Predicting cognitive tasks with neural-networks

Training an LSTM to perform a simple memory task An input stream of numbers (from -1 to 1) is sequentially presented at fixed time intervals (e.g. every 1 ms). The task is to keep in memory the presented number when the "memorize" stimulus is given and report back the memorized value when the "report" stimulus is given. The "memorize" and "report" signals can be given at any time point inside the selected sequence length (seq_len), which corresponds to the memory duration needed to perform the task. This will demonstrate how you can implement a neural network with a temporal memory.

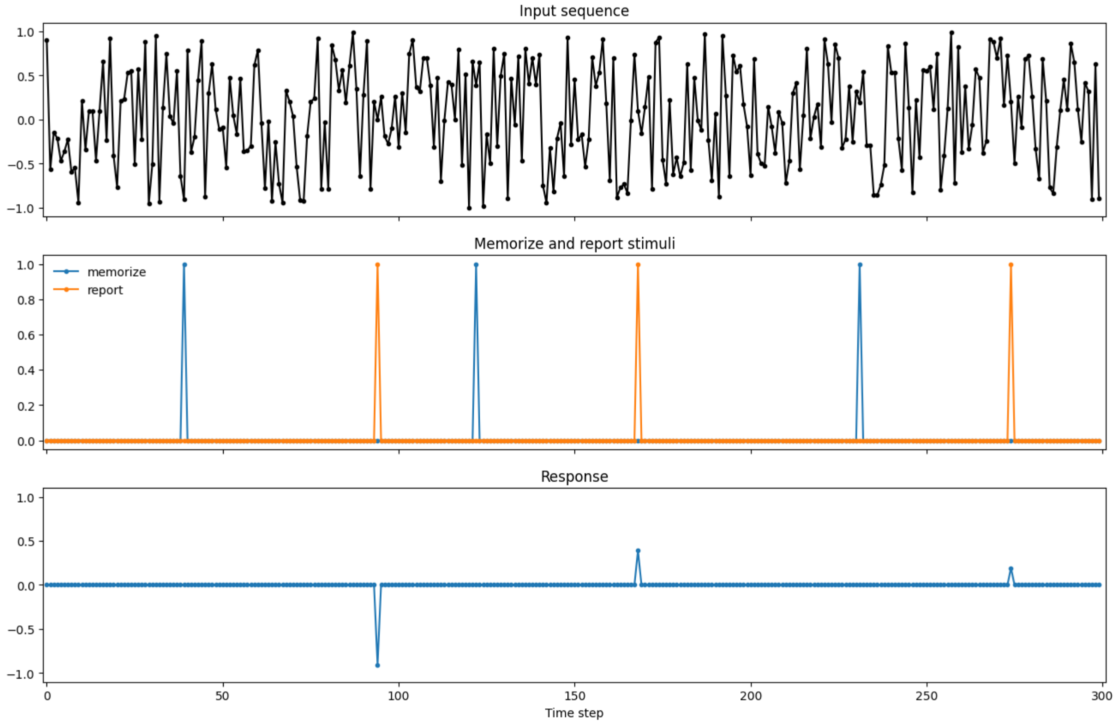
[122]:
```
# the memory task is defined here
def memory_task(seq_len, batch_size, n_repeat=1):
    """Return a batch from a simple memory task."""
    # seq_len defines the sequence length of the task and n_repeat the number␣
↪of sequences
    inputs = np.zeros((seq_len * n_repeat, batch_size, 3))
    outputs = np.zeros((seq_len * n_repeat, batch_size, 1))

    for i in range(n_repeat):
        t_start = i * seq_len
        inputs[t_start:t_start+seq_len, :, 0] = np.random.uniform(-1, 1,␣
↪size=(seq_len, batch_size))
```

```
        t_stim = np.random.randint(int(seq_len)/2, size=(batch_size,))
        t_test = np.random.randint(int(seq_len)/2, seq_len-1,␣
↪size=(batch_size,))
        inputs[t_start + t_stim, range(batch_size), 1] = 1
        inputs[t_start + t_test, range(batch_size), 2] = 1

        outputs[t_start + t_test, range(batch_size), 0] = inputs[t_start +␣
↪t_stim, range(batch_size), 0]

    return inputs, outputs

# generate the input and output datasets providing the desired parameters of␣
↪the memory task
inputs, outputs = memory_task(seq_len=100, batch_size=32, n_repeat=3)
```

Show an example case of the task for a sample trial.

[123]:
```
# pick a trial to visualize
i_trial = 0

kwargs = {'marker': 'o', 'markersize': 3}
fig, axes = plt.subplots(3, 1, sharex=True, figsize=(16,10))
ax = axes[0]
ax.plot(inputs[:, i_trial, 0], label='stimulus', color='black', **kwargs)
ax.title.set_text('Input sequence')
ax.set_ylim(-1.1,1.1);ax.set_xlim(-1,301)
ax = axes[1]
ax.plot(inputs[:, i_trial, 1], label='memorize', **kwargs)
ax.plot(inputs[:, i_trial, 2], label='report', **kwargs)
ax.title.set_text('Memorize and report stimuli')
ax.legend(frameon=False)
ax = axes[2]
ax.plot(outputs[:, i_trial, 0], label='target', **kwargs)
ax.title.set_text('Response')
ax.set_xlabel('Time step')
ax.set_ylim(-1.1,1.1)
```

[123]:
```
(-1.1, 1.1)
```



We define an one-unit LSTM network that will be trained to perform this task. A custom LSTM implementation in raw pytorch is used to provide access to the neural-network's gating variables.

[124]:
```
# the LSTM is defined here
class MyLSTM(nn.Module):
    """Manual implementation of LSTM."""

    def __init__(self, input_size, hidden_size):
        super().__init__()
        self.input_size = input_size
        self.hidden_size = hidden_size

        self.input2h = nn.Linear(input_size, 4*hidden_size)
        self.h2h = nn.Linear(hidden_size, 4*hidden_size)

        self.readout = False  # whether to readout activity

    def init_hidden(self, input):
        batch_size = input.shape[1]
        return (torch.zeros(batch_size, self.hidden_size).to(input.device),
                torch.zeros(batch_size, self.hidden_size).to(input.device))

    def recurrence(self, input, hidden):
        """Recurrence helper."""
```

```
        hx, cx = hidden
        gates = self.input2h(input) + self.h2h(hx)
        ingate, forgetgate, cellgate, outgate = gates.chunk(4, dim=1)

        ingate = torch.sigmoid(ingate)
        forgetgate = torch.sigmoid(forgetgate)
        cellgate = torch.tanh(cellgate)
        outgate = torch.sigmoid(outgate)

        cy = (forgetgate * cx) + (ingate * cellgate)
        hy = outgate * torch.tanh(cy)

        if self.readout:
            result = {
                'ingate': ingate,
                'outgate': outgate,
                'forgetgate': forgetgate,
                'input': cellgate,
                'cell': cy,
                'output': hy,
            }
            return (hy, cy), result
        else:
            return hy, cy

    def forward(self, input, hidden=None):
        if hidden is None:
            hidden = self.init_hidden(input)

        if not self.readout:
            # Regular forward
            output = []
            for i in range(input.size(0)):
                hidden = self.recurrence(input[i], hidden)
                output.append(hidden[0])

            output = torch.stack(output, dim=0)
            return output, hidden

        else:
            output = []
            result = defaultdict(list)  # dictionary with default as a list
            for i in range(input.size(0)):
                hidden, res = self.recurrence(input[i], hidden)
                output.append(hidden[0])
                for key, val in res.items():
```

```
                    result[key].append(val)

            output = torch.stack(output, dim=0)
            for key, val in result.items():
                result[key] = torch.stack(val, dim=0)

            return output, hidden, result

class Net(nn.Module):
    """Recurrent network model."""
    def __init__(self, input_size, hidden_size, output_size, **kwargs):
        super().__init__()

        # self.rnn = nn.LSTM(input_size, hidden_size, **kwargs)
        self.rnn = MyLSTM(input_size, hidden_size, **kwargs)
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        rnn_activity, _ = self.rnn(x)
        out = self.fc(rnn_activity)
        return out, rnn_activity
```

Train the network until it reaches a loss close to 0 (<1e-4). Sometimes the training takes some time to reach the desired loss, you can wait or otherwise restart the training.

[126]:
```
# Using custom LSTM, ~30% slower on CPUs compare to native LSTM
net = Net(input_size=3, hidden_size=1, output_size=1)

# Use Adam optimizer
optimizer = optim.Adam(net.parameters(), lr=0.01)
criterion = nn.MSELoss()

running_loss = 0
start_time = time.time()

print_step = 500
for i in range(20000):
    seq_len = np.random.randint(5, 20)  # Help learning and generalization
    inputs, labels = memory_task(seq_len=seq_len, batch_size=16, n_repeat=3)
    inputs = torch.from_numpy(inputs).type(torch.float)
    labels = torch.from_numpy(labels).type(torch.float)

    optimizer.zero_grad()   # zero the gradient buffers
    output, activity = net(inputs)

    loss = criterion(output, labels)
    loss.backward()
```

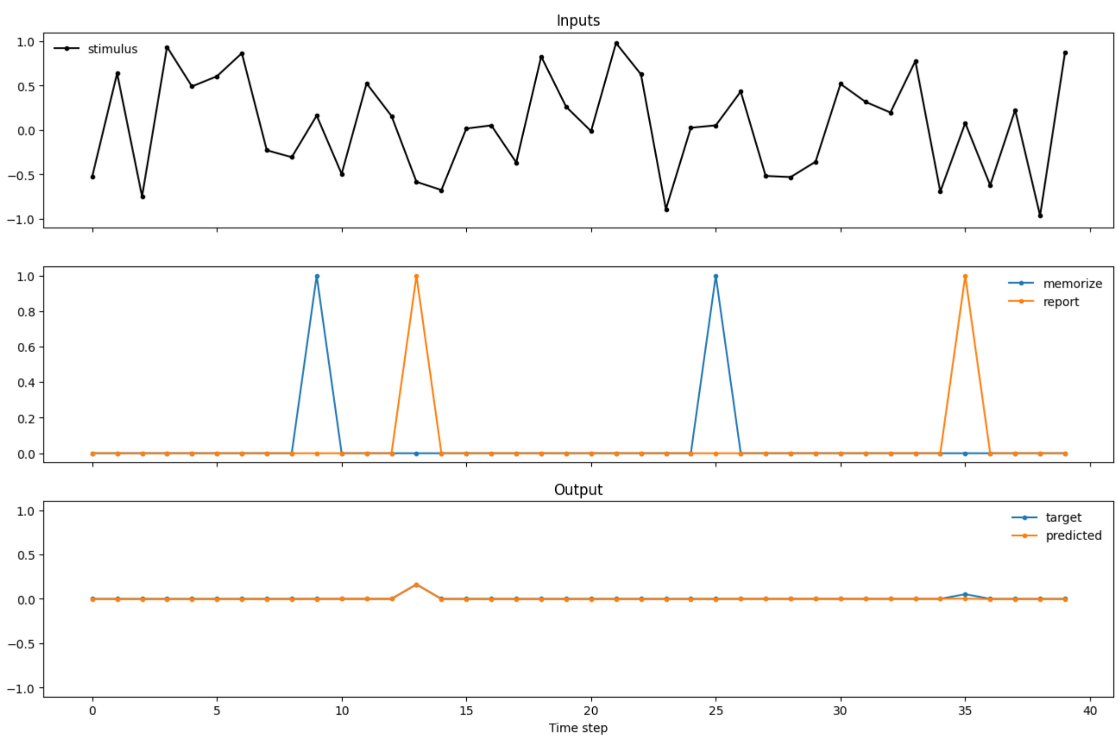
```
    optimizer.step()    # Does the update

    running_loss += loss.item()
    if i % print_step == (print_step - 1):
        running_loss /= print_step
        print('Step {}, Loss {:0.4f}'.format(i+1, running_loss))
#          print('Time per step {:0.3f}ms'.format((time.time()-start_time)/
 ↪i*1e3))
        if running_loss < 1e-4:
            break
        running_loss = 0
```

```
Step 500, Loss 0.0306
Step 1000, Loss 0.0057
Step 1500, Loss 0.0006
Step 2000, Loss 0.0003
Step 2500, Loss 0.0004
Step 3000, Loss 0.0002
Step 3500, Loss 0.0002
Step 4000, Loss 0.0002
Step 4500, Loss 0.0002
Step 5000, Loss 0.0001
Step 5500, Loss 0.0001
Step 6000, Loss 0.0002
Step 6500, Loss 0.0001
Step 7000, Loss 0.0002
Step 7500, Loss 0.0001
Step 8000, Loss 0.0001
```

Visualize the predicted performance of the trained LSTM model for a sequence length (memory duration) of 20 ms.

[127]:
```
# initialize the RNN network
rnn = net.rnn
rnn.readout = True

# generate the inputs and target outputs of the desired memory task
inputs, labels = memory_task(seq_len=20, batch_size=16, n_repeat=2)
inputs = torch.from_numpy(inputs).type(torch.float)

# simulate the predicted output of the LSTM network to the generated set of␣
 ↪inputs
with torch.no_grad():
    rnn_activity, _, result = rnn(inputs)
    output = net.fc(rnn_activity).detach()
```

[128]:
```python
# pick a trial to visualize
i_trial = 0

kwargs = {'marker': 'o', 'markersize': 3}
fig, axes = plt.subplots(3, 1, sharex=True, figsize=(16,10))
ax = axes[0]
ax.plot(inputs[:, i_trial, 0], label='stimulus', color='black', **kwargs)
ax.legend(frameon=False)
ax.title.set_text('Inputs')
ax.set_ylim(-1.1,1.1)
ax = axes[1]
ax.plot(inputs[:, i_trial, 1], label='memorize', **kwargs)
ax.plot(inputs[:, i_trial, 2], label='report', **kwargs)
ax.legend(frameon=False)
ax = axes[2]
ax.plot(labels[:, i_trial, 0], label='target', **kwargs)
ax.plot(output[:, i_trial, 0], label='predicted', **kwargs)
ax.title.set_text('Output')
ax.set_xlabel('Time step')
ax.legend(frameon=False)
ax.set_ylim(-1.1,1.1)
```

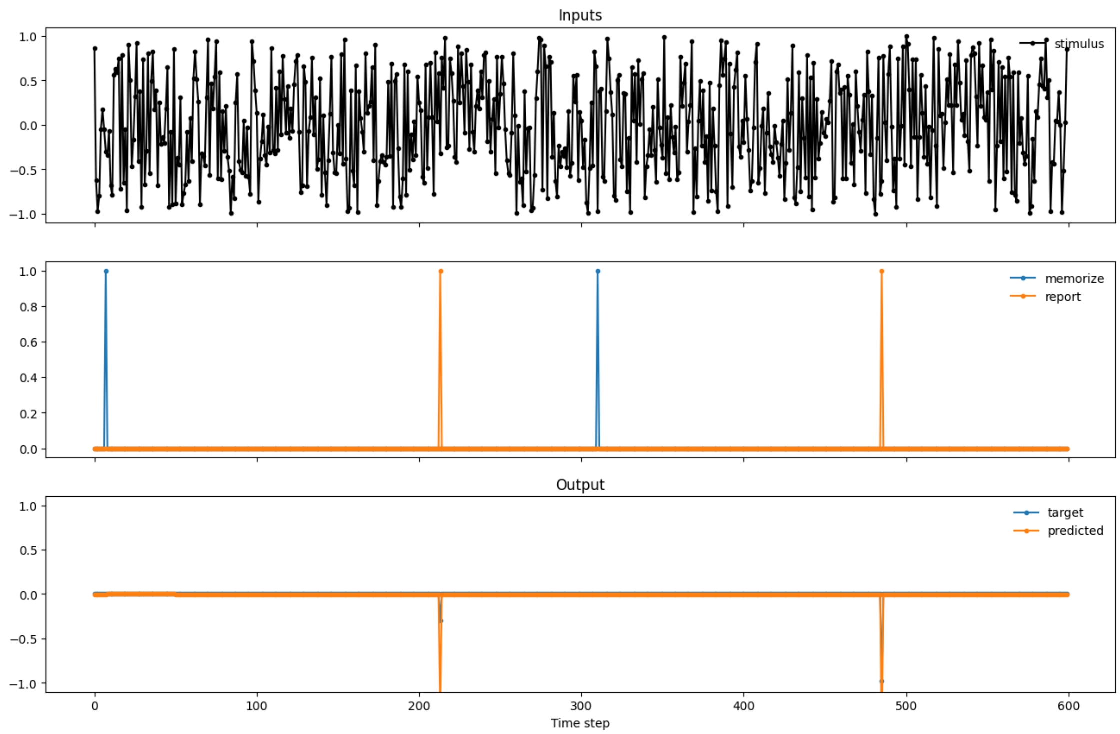


Depending on how successful the training was, you will see that the LSTM can perform the task almost perfectly for short memory durations (20 ms). The last panel of the plot (Output) shows the expected response of the memory task (target) and the one generated by the trained LSTM (predicted).

You can now use the trained LSTM to simulate the outcomes of the task for longer sequence durations. After which point approximately do you see that the network loses accuracy, failing to report the correct numbers? What would you change in the training datasets or the architecture to improve the model so that it performs better for longer memory durations in this task?

[135]:
```
# initialize the RNN network
rnn = net.rnn
rnn.readout = True

# generate the inputs and target outputs of the desired memory task
inputs, labels = memory_task(seq_len=300, batch_size=16, n_repeat=2)
inputs = torch.from_numpy(inputs).type(torch.float)

# simulate the predicted output of the LSTM network to the generated set of␣
 ↪inputs
with torch.no_grad():
    rnn_activity, _, result = rnn(inputs)
    output = net.fc(rnn_activity).detach()



# pick a trial to visualize
i_trial = 0

kwargs = {'marker': 'o', 'markersize': 3}
fig, axes = plt.subplots(3, 1, sharex=True, figsize=(16,10))
ax = axes[0]
ax.plot(inputs[:, i_trial, 0], label='stimulus', color='black', **kwargs)
ax.legend(frameon=False)
ax.title.set_text('Inputs')
ax.set_ylim(-1.1,1.1)
ax = axes[1]
ax.plot(inputs[:, i_trial, 1], label='memorize', **kwargs)
ax.plot(inputs[:, i_trial, 2], label='report', **kwargs)
ax.legend(frameon=False)
ax = axes[2]
ax.plot(labels[:, i_trial, 0], label='target', **kwargs)
ax.plot(output[:, i_trial, 0], label='predicted', **kwargs)
ax.title.set_text('Output')
ax.set_xlabel('Time step')
ax.legend(frameon=False)
ax.set_ylim(-1.1,1.1)
```

[135]: (-1.1, 1.1)



Answer

Sequence of duration 300ms

Gating in neural-networks The LSTM we used consists of three types of gating variables that control the cell state of the neural-network. When trained on this specific memory task, can you explain what the specific role of each gating variable is and how each one affects the cell state (memory) of the neural network? Visualizing the gate values of the three variables over the time course of the task (extracted from the "result" dictionary variable) can help you with that.

[19]:
```
# Your code goes here
```

Answer

Your answer here

How does gating in LSTMs compare to gating in biological neural circuits?

Answer

Your answer here