This can be run run on Google Colab using this link

MNIST Classifiers (Convolutional Neural Networks and Fully Connected Networks)

Optional: Installing Wandb to see cool analysis of you code. You can go through the documentation here. We will do it for this assignment to get a taste of the GPU and CPU utilizations. If this is creating problems to your code, please comment out all the wandb lines from the notebook

```
# Uncomment the below line to install wandb (optinal)
!pip install wandb
# Uncomment the below line to install torchinfo (https://github.com/TylerYep/torchinfo) [Mandatory]
!pip install torchinfo
```

```
Collecting wandb
  Downloading wandb-0.15.12-py3-none-any.whl (2.1 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.1/2.1 MB 8.5 MB/s eta 0:00:00
Requirement already satisfied: Click!=8.0.0,>=7.1 in /usr/local/lib/python3.10/dist-packages (from wandb) (8.1.7)
Collecting GitPython!=3.1.29,>=1.0.0 (from wandb)
  Downloading GitPython-3.1.40-py3-none-any.whl (190 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 190.6/190.6 kB 13.6 MB/s eta 0:00:00
Requirement already satisfied: requests<3,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from wandb) (2.31.0)
Requirement already satisfied: psutil>=5.0.0 in /usr/local/lib/python3.10/dist-packages (from wandb) (5.9.5)
Collecting sentry-sdk>=1.0.0 (from wandb)
  Downloading sentry_sdk-1.32.0-py2.py3-none-any.whl (240 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 241.0/241.0 kB 16.6 MB/s eta 0:00:00
Collecting docker-pycreds>=0.4.0 (from wandb)
  Downloading docker_pycreds-0.4.0-py2.py3-none-any.whl (9.0 kB)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages (from wandb) (6.0.1)
Collecting pathtools (from wandb)
  Downloading pathtools-0.1.2.tar.gz (11 kB)
  Preparing metadata (setup.py) ... done
Collecting setproctitle (from wandb)
  Downloading setproctitle-1.3.3-cp310-cp310-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_17_x86_64.manylinux2014_x86_
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from wandb) (67.7.2)
Requirement already satisfied: appdirs>=1.4.3 in /usr/local/lib/python3.10/dist-packages (from wandb) (1.4.4)
Requirement already satisfied: protobuf!=4.21.0,<5,>=3.19.0 in /usr/local/lib/python3.10/dist-packages (from wandb) (3.20.3)
Requirement already satisfied: six>=1.4.0 in /usr/local/lib/python3.10/dist-packages (from docker-pycreds>=0.4.0->wandb) (1.
Collecting gitdb<5,>=4.0.1 (from GitPython!=3.1.29,>=1.0.0->wandb)
  Downloading gitdb-4.0.10-py3-none-any.whl (62 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 62.7/62.7 kB 7.7 MB/s eta 0:00:00
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.0.0-
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.0.0->wandb) (3.4
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.0.0->wandb
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.0.0->wandb
Collecting smmap<6,>=3.0.1 (from gitdb<5,>=4.0.1->GitPython!=3.1.29,>=1.0.0->wandb)
  Downloading smmap-5.0.1-py3-none-any.whl (24 kB)
Building wheels for collected packages: pathtools
  Building wheel for pathtools (setup.py) ... done
  Created wheel for pathtools: filename=pathtools-0.1.2-py3-none-any.whl size=8791 sha256=cc53e2907dac1e484cc69bf85483b832e8
  Stored in directory: /root/.cache/pip/wheels/e7/f3/22/152153d6eb222ee7a56ff8617d80ee5207207a8c00a7aab794
Successfully built pathtools
Installing collected packages: pathtools, smmap, setproctitle, sentry-sdk, docker-pycreds, gitdb, GitPython, wandb
Successfully installed GitPython-3.1.40 docker-pycreds-0.4.0 gitdb-4.0.10 pathtools-0.1.2 sentry-sdk-1.32.0 setproctitle-1.3
Collecting torchinfo
  Downloading torchinfo-1.8.0-py3-none-any.whl (23 kB)
Installing collected packages: torchinfo
Successfully installed torchinfo-1.8.0
```

```
%%bash

wget -N https://cs7150.baulab.info/2022-Fall/data/mnist-classify.pth
```

```
--2023-10-20 02:38:42--  https://cs7150.baulab.info/2022-Fall/data/mnist-classify.pth
Resolving cs7150.baulab.info (cs7150.baulab.info)... 35.232.255.106
Connecting to cs7150.baulab.info (cs7150.baulab.info)|35.232.255.106|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 1078198 (1.0M)
Saving to: 'mnist-classify.pth'

     0K .......... .......... .......... .......... ..........  4%  586K 2s
    50K .......... .......... .......... .......... ..........  9% 1.26M 1s
   100K .......... .......... .......... .......... .......... 14% 4.33M 1s
   150K .......... .......... .......... .......... .......... 18% 1.68M 1s
   200K .......... .......... .......... .......... .......... 23% 21.7M 1s
   250K .......... .......... .......... .......... .......... 28% 12.8M 0s
   300K .......... .......... .......... .......... .......... 33% 9.73M 0s
   350K .......... .......... .......... .......... .......... 37% 1.73M 0s
```

```
  400K .......... .......... .......... .......... .......... 42% 10.6M 0s
  450K .......... .......... .......... .......... .......... 47%  258M 0s
  500K .......... .......... .......... .......... .......... 52%  298M 0s
  550K .......... .......... .......... .......... .......... 56% 20.1M 0s
  600K .......... .......... .......... .......... .......... 61% 23.7M 0s
  650K .......... .......... .......... .......... .......... 66% 21.5M 0s
  700K .......... .......... .......... .......... .......... 71% 1.69M 0s
  750K .......... .......... .......... .......... .......... 75%  136M 0s
  800K .......... .......... .......... .......... .......... 80% 21.7M 0s
  850K .......... .......... .......... .......... .......... 85%  227M 0s
  900K .......... .......... .......... .......... .......... 90% 39.5M 0s
  950K .......... .......... .......... .......... .......... 94%  234M 0s
 1000K .......... .......... .......... .......... .......... 99%  216M 0s
 1050K ..                                                     100% 5.45T=0.2s

2023-10-20 02:38:43 (4.13 MB/s) - ‘mnist-classify.pth’ saved [1078198/1078198]
```

```
# Importing libraries
import matplotlib.pyplot as plt

import torch
import torchvision
from torchvision import transforms
from torch.utils.data import DataLoader,random_split,Subset
from torch import nn
import torch.nn.functional as F
import torch.optim as optim
from torchinfo import summary
import numpy as np
import datetime

from typing import List
from collections import OrderedDict
import math
```

```
# Create an account at https://wandb.ai/site and paste the api key here (optional)
#import wandb
#wandb.init(project="hw3.1-ConvNets")
```

Some helper functions to view network parameters

```
def view_network_parameters(model):
    # Visualise the number of parameters
    tensor_list = list(model.state_dict().items())
    total_parameters = 0
    print('Model Summary\n')
    for layer_tensor_name, tensor in tensor_list:
        total_parameters += int(torch.numel(tensor))
        print('{}: {} elements'.format(layer_tensor_name, torch.numel(tensor)))
    print(f'\nTotal Trainable Parameters: {total_parameters}!')
```

```
def view_network_shapes(model, input_shape):
    print(summary(conv_net, input_size=input_shape))
```

Fully Connected Network for Image Classification

Let's build a simple fully connected network!

```
def simple_fc_net():
    model = nn.Sequential(
        nn.Flatten(),
        nn.Linear(1*28*28,8*28*28),
        nn.ReLU(),
        nn.Linear(8*28*28,16*14*14),
        nn.ReLU(),
        nn.Linear(16*14*14,32*7*7),
        nn.ReLU(),
        nn.Linear(32*7*7,288),
        nn.ReLU(),
        nn.Linear(288,64),
        nn.ReLU(),
```

```
        nn.Linear(64,10),
        nn.LogSoftmax())
    return model
```

```
fc_net = simple_fc_net()
```

```
view_network_parameters(fc_net)
```

```
Model Summary

1.weight: 4917248 elements
1.bias: 6272 elements
3.weight: 19668992 elements
3.bias: 3136 elements
5.weight: 4917248 elements
5.bias: 1568 elements
7.weight: 451584 elements
7.bias: 288 elements
9.weight: 18432 elements
9.bias: 64 elements
11.weight: 640 elements
11.bias: 10 elements

Total Trainable Parameters: 29985482!
```

```
from torchinfo import summary
summary(fc_net, input_size=(1, 1, 28,28))
```

```
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/module.py:1518: UserWarning: Implicit dimension choice for log_soft
  return self._call_impl(*args, **kwargs)
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Sequential                               [1, 10]                   --
├─Flatten: 1-1                           [1, 784]                  --
├─Linear: 1-2                            [1, 6272]                 4,923,520
├─ReLU: 1-3                              [1, 6272]                 --
├─Linear: 1-4                            [1, 3136]                 19,672,128
├─ReLU: 1-5                              [1, 3136]                 --
├─Linear: 1-6                            [1, 1568]                 4,918,816
├─ReLU: 1-7                              [1, 1568]                 --
├─Linear: 1-8                            [1, 288]                  451,872
├─ReLU: 1-9                              [1, 288]                  --
├─Linear: 1-10                           [1, 64]                   18,496
├─ReLU: 1-11                             [1, 64]                   --
├─Linear: 1-12                           [1, 10]                   650
├─LogSoftmax: 1-13                       [1, 10]                   --
==========================================================================================
Total params: 29,985,482
Trainable params: 29,985,482
Non-trainable params: 0
Total mult-adds (M): 29.99
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.09
Params size (MB): 119.94
Estimated Total Size (MB): 120.04
==========================================================================================
```

Exercise: Now try to add different layers and see how the network parameters vary. Does adding layers reduce the parameters? Does the number of hidden neurons in the layers affect the total trainable parameters?

Add a few sentences on your observations while using various architectures

```
# Adding linear layers in between the network

def simple_fc_net_2():
    model = nn.Sequential(
        nn.Flatten(),
        nn.Linear(1*28*28,8*28*28),
        nn.ReLU(),
        nn.Linear(8*28*28,16*14*14),
        nn.ReLU(),
        nn.Linear(16*14*14,32*7*7),
        nn.ReLU(),
        nn.Linear(32*7*7,64*3*3),
        nn.ReLU(),
```

```
        nn.Linear(64*3*3,288), # added linear layer
        nn.ReLU(),
        nn.Linear(288,64),
        nn.ReLU(),
        nn.Linear(64,32), ## added linear layer
        nn.ReLU(),
        nn.Linear(32,16), ## added linear layer
        nn.ReLU(),
        nn.Linear(16,10), ## added linear layer
        nn.LogSoftmax())
    return model

fc_net_2 = simple_fc_net_2()
view_network_parameters(fc_net)
summary(fc_net_2, input_size=(1, 1, 28,28))
```

```
Model Summary

1.weight: 4917248 elements
1.bias: 6272 elements
3.weight: 19668992 elements
3.bias: 3136 elements
5.weight: 4917248 elements
5.bias: 1568 elements
7.weight: 451584 elements
7.bias: 288 elements
9.weight: 18432 elements
9.bias: 64 elements
11.weight: 640 elements
11.bias: 10 elements

Total Trainable Parameters: 29985482!
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Sequential                               [1, 10]                   --
├─Flatten: 1-1                           [1, 784]                  --
├─Linear: 1-2                            [1, 6272]                 4,923,520
├─ReLU: 1-3                              [1, 6272]                 --
├─Linear: 1-4                            [1, 3136]                 19,672,128
├─ReLU: 1-5                              [1, 3136]                 --
├─Linear: 1-6                            [1, 1568]                 4,918,816
├─ReLU: 1-7                              [1, 1568]                 --
├─Linear: 1-8                            [1, 576]                  903,744
├─ReLU: 1-9                              [1, 576]                  --
├─Linear: 1-10                           [1, 288]                  166,176
├─ReLU: 1-11                             [1, 288]                  --
├─Linear: 1-12                           [1, 64]                   18,496
├─ReLU: 1-13                             [1, 64]                   --
├─Linear: 1-14                           [1, 32]                   2,080
├─ReLU: 1-15                             [1, 32]                   --
├─Linear: 1-16                           [1, 16]                   528
├─ReLU: 1-17                             [1, 16]                   --
├─Linear: 1-18                           [1, 10]                   170
├─LogSoftmax: 1-19                       [1, 10]                   --
==========================================================================================
Total params: 30,605,658
Trainable params: 30,605,658
Non-trainable params: 0
Total mult-adds (M): 30.61
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.10
Params size (MB): 122.42
Estimated Total Size (MB): 122.52
==========================================================================================
```

ANSWER

Adding additional layers increased the total parameters of the model!

The number of hidden neurons determines the size of the weight matrix and bias vector in each layer. More neurons mean more weights and biases, increasing the total trainable parameters.

Convolutional Neural Network for Image Classification

Let's build a simple CNN to classify our images. **Exercise 3.1.1:** In the function below please add the conv/Relu/Maxpool layers to match the shape of FC-Net. Suppose at the some layer the FC-Net has `28*28*16` dimension, we want your conv_net to have `16 X 28 X 28` shape at the same numbered layer.

Extra-credit: Try not to use MaxPool2d !

```
def simple_conv_net():
    model = nn.Sequential(
        nn.Conv2d(1 ,8 ,kernel_size=3 ,padding=1), #[28x28x8]
        nn.ReLU(),
        nn.MaxPool2d(2,2),
        # TO-DO: Add layers below
        nn.Conv2d(8, 16 ,kernel_size=3 ,padding=1), # [14x14x16]
        nn.ReLU(),
        nn.MaxPool2d(2,2),
        nn.Conv2d(16, 32 ,kernel_size=3 ,padding=1), # [7x7x32]
        nn.ReLU(),
        # TO-DO, what will your shape be after you flatten? Fill it in place of None
        nn.Flatten(),
        nn.Linear(1568,64),
        # Do not change the code below
        nn.ReLU(),
        nn.Linear(64,10),
        nn.LogSoftmax())
    return model
```

```
conv_net = simple_conv_net()
```

```
view_network_parameters(conv_net)
```

```
Model Summary

0.weight: 72 elements
0.bias: 8 elements
3.weight: 1152 elements
3.bias: 16 elements
6.weight: 4608 elements
6.bias: 32 elements
9.weight: 100352 elements
9.bias: 64 elements
11.weight: 640 elements
11.bias: 10 elements

Total Trainable Parameters: 106954!
```

```
view_network_shapes(conv_net, input_shape=(1,1,28,28))
```

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Sequential                               [1, 10]                   --
├─Conv2d: 1-1                            [1, 8, 28, 28]            80
├─ReLU: 1-2                              [1, 8, 28, 28]            --
├─MaxPool2d: 1-3                         [1, 8, 14, 14]            --
├─Conv2d: 1-4                            [1, 16, 14, 14]           1,168
├─ReLU: 1-5                              [1, 16, 14, 14]           --
├─MaxPool2d: 1-6                         [1, 16, 7, 7]             --
├─Conv2d: 1-7                            [1, 32, 7, 7]             4,640
├─ReLU: 1-8                              [1, 32, 7, 7]             --
├─Flatten: 1-9                           [1, 1568]                 --
├─Linear: 1-10                           [1, 64]                   100,416
├─ReLU: 1-11                             [1, 64]                   --
├─Linear: 1-12                           [1, 10]                   650
├─LogSoftmax: 1-13                       [1, 10]                   --
==========================================================================================
Total params: 106,954
Trainable params: 106,954
Non-trainable params: 0
Total mult-adds (M): 0.62
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.09
Params size (MB): 0.43
Estimated Total Size (MB): 0.52
==========================================================================================
```

```
## Extra Credit! (Without using Maxpool)
def simple_conv_net_without_maxpool():
  model = nn.Sequential(
            nn.Conv2d(1, 8,kernel_size=3,padding=1),
            nn.ReLU()
```

```
              nn.ReLU(),
              nn.Conv2d(8, 16, kernel_size=6, padding=2, stride=2),
              nn.ReLU(),
              #nn.MaxPool2d(kernel_size=2),
              nn.Conv2d(16, 32, kernel_size=2, padding=0, stride=2),
              nn.ReLU(),
              # TO-DO, what will your shape be after you flatten? Fill it in place of None
              nn.Flatten(),
              nn.Linear(1568,64),
              # Do not change the code below
              nn.ReLU(),
              nn.Linear(64,10),
              nn.LogSoftmax())
  return model

conv_net_without_maxpool = simple_conv_net_without_maxpool()
view_network_parameters(conv_net_without_maxpool)
view_network_shapes(conv_net_without_maxpool, input_shape=(1,1,28,28))
```

```
Model Summary

0.weight: 72 elements
0.bias: 8 elements
2.weight: 4608 elements
2.bias: 16 elements
4.weight: 2048 elements
4.bias: 32 elements
7.weight: 100352 elements
7.bias: 64 elements
9.weight: 640 elements
9.bias: 10 elements

Total Trainable Parameters: 107850!
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Sequential                               [1, 10]                   --
├─Conv2d: 1-1                            [1, 8, 28, 28]            80
├─ReLU: 1-2                              [1, 8, 28, 28]            --
├─MaxPool2d: 1-3                         [1, 8, 14, 14]            --
├─Conv2d: 1-4                            [1, 16, 14, 14]           1,168
├─ReLU: 1-5                              [1, 16, 14, 14]           --
├─MaxPool2d: 1-6                         [1, 16, 7, 7]             --
├─Conv2d: 1-7                            [1, 32, 7, 7]             4,640
├─ReLU: 1-8                              [1, 32, 7, 7]             --
├─Flatten: 1-9                           [1, 1568]                 --
├─Linear: 1-10                           [1, 64]                   100,416
├─ReLU: 1-11                             [1, 64]                   --
├─Linear: 1-12                           [1, 10]                   650
├─LogSoftmax: 1-13                       [1, 10]                   --
==========================================================================================
Total params: 106,954
Trainable params: 106,954
Non-trainable params: 0
Total mult-adds (M): 0.62
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.09
Params size (MB): 0.43
Estimated Total Size (MB): 0.52
==========================================================================================
```

Exercise 3.1.2: Why is the final layer a log softmax? What is a softmax function? Can we use ReLU instead of softmax? If yes, what would you do different? If not, tell us why. If you think there is a different answer, feel free to use this space to chart it down

1. **Why is the final layer a log softmax?**
   - The log softmax function provides the logarithm of the outputs from the softmax function. In classification tasks, especially when combined with the Negative Log Likelihood (NLL) loss, using log softmax can be computationally more stable and efficient.
2. **What is a softmax function?**
   - The softmax function is used in the output layer of a neural network for multi-class classification. It transforms the raw output scores (logits) into a probability distribution over the classes, where each value is in the range [0, 1], and the sum of all values is 1.
3. **Can we use ReLU instead of softmax?**
   - No, ReLU is not suitable for the output layer of a multi-class classification task. While ReLU activates and allows positive values to pass through and suppresses negative values, it doesn't provide a probability distribution over classes, which is essential for

classification tasks.

If yes, what would you do different? If not, tell us why.

- As mentioned, ReLU doesn't provide a probability distribution. Using it as the output for a classification task wouldn't allow for meaningful interpretation of the results. Softmax ensures that the output values are probabilities that sum up to 1, which aligns with the requirements of a classification task.

In summary, while ReLU is great for hidden layers to introduce non-linearity and handle the vanishing gradient problem, softmax is more appropriate for the output layer in multi-class classification tasks as it provides a meaningful probability distribution over classes.

Exercise 3.1.3: What is the ratio of number of parameters of Conv-net to number of parameters of FC-Net

$\frac{p_{conv-net}}{p_{fc-net}}$ = 106,954/29,985,482 = 0.3569%

Do you see the difference ?!

Answer

In a fully connected (FC) network, each node in the hidden layer connects to every other node. On the other hand, in a convolutional network (Conv-net), there's not a full interconnection between nodes of consecutive layers. This leads to Conv-nets generally having fewer trainable parameters than FC-nets

Exercise 3.1.4: Now try to add different layers and see how the network parameters vary. Does adding layers reduce the parameters? Does the number of hidden neurons in the layers affect the total trainable parameters? Use the `build_custom_fc_net` function given below. You do not have to understand the working of it.

Add a few sentences on your observations while using various architectures

```
def build_custom_fc_net(inp_dim: int, out_dim: int, hidden_fc_dim: List[int]):
    '''
    Inputs :

    inp_dim: Shape of the input dimensions (in MNIST case 28*28)
    out_dim: Desired classification classes (in MNIST case 10)
    hidden_fc_dim: List of the intermediate dimension shapes (list of integers). Try different values and see the shapes'

    Return: nn.Sequential (final custom model)
    '''
    assert type(hidden_fc_dim) == list, "Please define hidden_fc_dim as list of integers"
    layers = []
    layers.append((f'flatten', nn.Flatten()))
    # If no hidden layer is required
    if len(hidden_fc_dim) == 0:
        layers.append((f'linear',nn.Linear(math.prod(inp_dim),out_dim)))
        layers.append((f'activation',nn.LogSoftmax()))
    else:
        # Loop over hidden dimensions and add layers
        for idx, dim in enumerate(hidden_fc_dim):
            if idx == 0:
                layers.append((f'linear_{idx+1}',nn.Linear(math.prod(inp_dim),dim)))
                layers.append((f'activation_{idx+1}',nn.ReLU()))
            else:
                layers.append((f'linear_{idx+1}',nn.Linear(hidden_fc_dim[idx-1],dim)))
                layers.append((f'activation_{idx+1}',nn.ReLU()))
        layers.append((f'linear_{idx+2}',nn.Linear(dim,out_dim)))
        layers.append((f'activation_{idx+2}',nn.LogSoftmax()))

    model =  nn.Sequential(OrderedDict(layers))
    return model

# TO-DO build different networks (atleast 3) and see the parameters
#(You don't have to understand the function above. It is a generic way to build a FC-Net)


fc_net_custom1 = build_custom_fc_net(inp_dim=(1,28,28), out_dim=10, hidden_fc_dim=[128,64,32])
view_network_parameters(fc_net_custom1)

fc_net_custom2 = build_custom_fc_net(inp_dim=(1,28,28), out_dim=10, hidden_fc_dim=[256,64,32])
view_network_parameters(fc_net_custom2)

fc_net_custom3 = build_custom_fc_net(inp_dim=(1,28,28), out_dim=10, hidden_fc_dim=[512,64,32])
view_network_parameters(fc_net_custom3)
```

```
Model Summary

linear_1.weight: 100352 elements
linear_1.bias: 128 elements
linear_2.weight: 8192 elements
linear_2.bias: 64 elements
linear_3.weight: 2048 elements
linear_3.bias: 32 elements
linear_4.weight: 320 elements
linear_4.bias: 10 elements

Total Trainable Parameters: 111146!
Model Summary

linear_1.weight: 200704 elements
linear_1.bias: 256 elements
linear_2.weight: 16384 elements
linear_2.bias: 64 elements
linear_3.weight: 2048 elements
linear_3.bias: 32 elements
linear_4.weight: 320 elements
linear_4.bias: 10 elements

Total Trainable Parameters: 219818!
Model Summary

linear_1.weight: 401408 elements
linear_1.bias: 512 elements
linear_2.weight: 32768 elements
linear_2.bias: 64 elements
linear_3.weight: 2048 elements
linear_3.bias: 32 elements
linear_4.weight: 320 elements
linear_4.bias: 10 elements

Total Trainable Parameters: 437162!
```

Answer

1. The addition of layers increases the number of parameters not decreases.
2. Yes, the number of hidden neurons in the layers directly affects the total trainable parameters. As we can see from the provided summaries:

When hidden_fc_dim_1 is [128,64,32], the total parameters are 111,146.

When hidden_fc_dim_2 is [256,64,32], the total parameters are 219,818.

When hidden_fc_dim_3 is [512,64,32], the total parameters are 437,162.

Let's train the models to see their performace

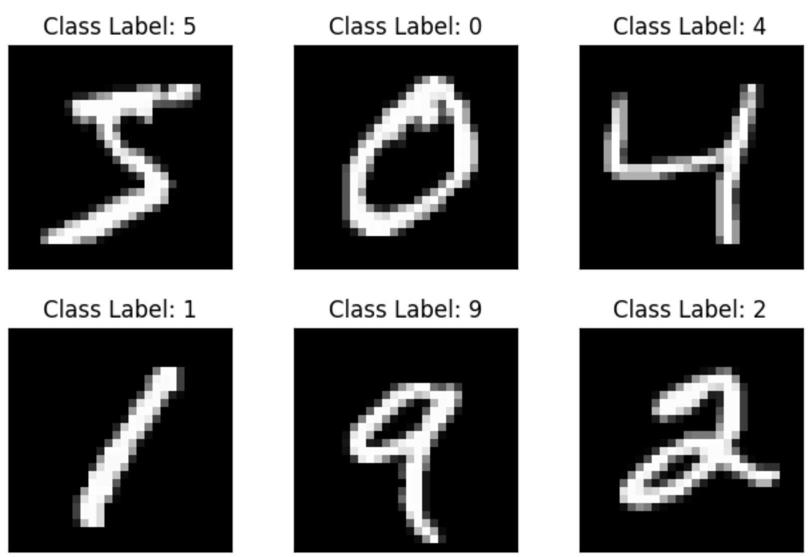
```
# downloading mnist into folder
data_dir = 'data' # make sure that this folder is created in your working dir
# transform the PIL images to tensor using torchvision.transform.toTensor method
train_data = torchvision.datasets.MNIST(data_dir, train=True, download=True, transform=torchvision.transforms.Compose([torchvisio
test_data  = torchvision.datasets.MNIST(data_dir, train=False, download=True, transform=torchvision.transforms.Compose([torchvisi
print(f'Datatype of the dataset object: {type(train_data)}')
# check the length of dataset
n_train_samples = len(train_data)
print(f'Number of samples in training data: {len(train_data)}')
print(f'Number of samples in test data: {len(test_data)}')
# Check the format of dataset
#print(f'Foramt of the dataset: \n {train_data}')

val_split = .2
batch_size=256

train_data_, val_data = random_split(train_data, [int(n_train_samples*(1-val_split)), int(n_train_samples*val_split)])

train_loader = torch.utils.data.DataLoader(train_data_, batch_size=batch_size,shuffle=True)
val_loader = torch.utils.data.DataLoader(val_data, batch_size=batch_size,shuffle=True)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size,shuffle=True)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to data/MNIST/raw/train-images-idx3-ubyte.gz
100%|██████████| 9912422/9912422 [00:00<00:00, 95315599.27it/s]
```

```
Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to data/MNIST/raw/train-labels-idx1-ubyte.gz
100%|██████████| 28881/28881 [00:00<00:00, 31124278.99it/s]Extracting data/MNIST/raw/train-labels-idx1-ubyte.gz to data/MNIS

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to data/MNIST/raw/t10k-images-idx3-ubyte.gz
100%|██████████| 1648877/1648877 [00:00<00:00, 26252344.55it/s]Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/M

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to data/MNIST/raw/t10k-labels-idx1-ubyte.gz
100%|██████████| 4542/4542 [00:00<00:00, 15526103.32it/s]
Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw

Datatype of the dataset object: <class 'torchvision.datasets.mnist.MNIST'>
Number of samples in training data: 60000
Number of samples in test data: 10000
```

Displaying the loaded dataset

```
import matplotlib.pyplot as plt

fig = plt.figure()
for i in range(6):
  plt.subplot(2, 3, i+1)
  plt.tight_layout()
  plt.imshow(train_data[i][0][0], cmap='gray', interpolation='none')
  plt.title("Class Label: {}".format(train_data[i][1]))
  plt.xticks([])
  plt.yticks([])
```



Function to train the model

```
def train_model(model, train_loader, device, loss_fn, optimizer, input_dim=(-1,1,28,28)):
    model.train()
    # Initiate a loss monitor
    train_loss = []
    # Iterate the dataloader (we do not need the label values, this is unsupervised learning and not supervised classification)
    for images, labels in train_loader: # the variable `labels` will be used for customised training
        # reshape input
        images = torch.reshape(images,input_dim)
        images = images.to(device)
        labels = labels.to(device)
        # predict the class
        predicted = model(images)
        loss = loss_fn(predicted, labels)
        # Backward pass (back propagation)
```

```
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        #wandb.log({"Training Loss": loss})
        #wandb.watch(model)
        train_loss.append(loss.detach().cpu().numpy())
    return np.mean(train_loss)
```

Function to test the model

```
# Testing Function
def test_model(model, test_loader, device, loss_fn, input_dim=(-1,1,28,28)):
    # Set evaluation mode for encoder and decoder
    model.eval()
    with torch.no_grad(): # No need to track the gradients
        # Define the lists to store the outputs for each batch
        predicted = []
        actual = []
        for images, labels in test_loader:
            # reshape input
            images = torch.reshape(images,input_dim)
            images = images.to(device)
            labels = labels.to(device)
            ## predict the label
            pred = model(images)
            # Append the network output and the original image to the lists
            predicted.append(pred.cpu())
            actual.append(labels.cpu())
        # Create a single tensor with all the values in the lists
        predicted = torch.cat(predicted)
        actual = torch.cat(actual)
        # Evaluate global loss
        val_loss = loss_fn(predicted, actual)
    return val_loss.data
```

Before we start training let's delete the huge FC-Net we built and build a reasonable FC-Net (You learnt why such larger networks are not reasonable in the previous notebook)

```
del fc_net, fc_net_custom1, fc_net_custom2, fc_net_custom3
torch.cuda.empty_cache()
# Building a reasonable fully connected network
fc_net = build_custom_fc_net(inp_dim=(1,28,28), out_dim=10, hidden_fc_dim=[128,64,32])
```

Exercise 3.1.5: Code the `weight_init_xavier` function by referring to https://pytorch.org/docs/stable/nn.init.html. Replace the weight initializations to your own function.

```
### Set the random seed for reproducible results
torch.manual_seed(0)
# Choosing a device based on the env and torch setup
device = torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu")
print(f'Selected device: {device}')

def weight_init_zero(m):
    if isinstance(m, nn.Linear) or isinstance(m, nn.Conv2d):
        torch.nn.init.constant_(m.weight, 0.0)
        m.bias.data.fill_(0.01)

def weight_init_xavier(m):
  if isinstance(m, nn.Linear) or isinstance(m, nn.Conv2d):
    torch.nn.init.xavier_uniform_(m.weight)
    if m.bias is not None:
      m.bias.data.fill_(0.01)


fc_net.to(device)
conv_net.to(device)

# Apply the weight initialization
fc_net.apply(weight_init_zero)
conv_net.apply(weight_init_zero)
```

```
# Apply the xavier weight initialization
#TO-DO: Add your function here
fc_net.apply(weight_init_xavier)
conv_net.apply(weight_init_xavier)


# Take the parameters for optimiser
params_to_optimize_fc = [
    {'params': fc_net.parameters()}
]

params_to_optimize_conv = [
    {'params': conv_net.parameters()}
]
### Define the loss function
loss_fn = torch.nn.NLLLoss()
### Define an optimizer (both for the encoder and the decoder!)
lr= 0.001

optim_fc = torch.optim.Adam(params_to_optimize_fc, lr=lr, weight_decay=1e-05)
optim_conv = torch.optim.Adam(params_to_optimize_conv, lr=lr, weight_decay=1e-05)
num_epochs = 30
'''
wandb.config = {
  "learning_rate": lr,
  "epochs": num_epochs,
  "batch_size": batch_size
}
'''
```

```
Selected device: cpu
'\nwandb.config = {\n  "learning_rate": lr,\n  "epochs": num_epochs,\n  "batch_size": batch_size\n}\n'
```

Training the Convolutional Neural Networks

```
print('Conv Net training started')
history_conv = {'train_loss':[],'val_loss':[]}
start_time = datetime.datetime.now()

for epoch in range(num_epochs):
    ### Training

    train_loss = train_model(
        model=conv_net,
        train_loader=train_loader,
        device=device,
        loss_fn=loss_fn,
        optimizer=optim_conv,
        input_dim=(-1,1,28,28))
    ### Validation  (use the testing function)
    val_loss = test_model(
        model=conv_net,
        test_loader=test_loader,
        device=device,
        loss_fn=loss_fn,
        input_dim=(-1,1,28,28))
    # Print Losses
    print(f'Epoch {epoch+1}/{num_epochs} : train loss {train_loss:.3f} \t val loss {val_loss:.3f}')
    history_conv['train_loss'].append(train_loss)
    history_conv['val_loss'].append(val_loss)


print(f'Conv Net training done in {(datetime.datetime.now()-start_time).total_seconds():.3f} seconds!')
```

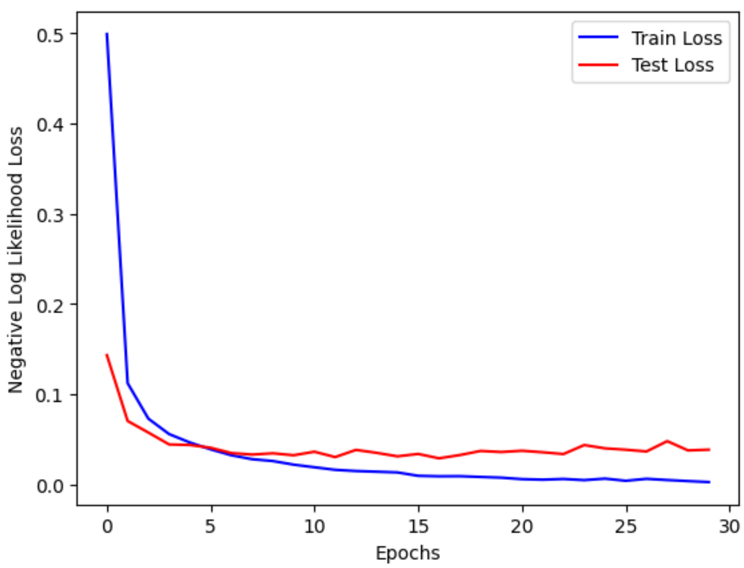
```
Conv Net training started
Epoch 1/30 : train loss 0.499    val loss 0.143
Epoch 2/30 : train loss 0.112    val loss 0.070
Epoch 3/30 : train loss 0.073    val loss 0.057
Epoch 4/30 : train loss 0.056    val loss 0.044
Epoch 5/30 : train loss 0.046    val loss 0.044
Epoch 6/30 : train loss 0.039    val loss 0.041
Epoch 7/30 : train loss 0.032    val loss 0.035
Epoch 8/30 : train loss 0.028    val loss 0.033
Epoch 9/30 : train loss 0.026    val loss 0.035
```

```
Epoch 10/30 : train loss 0.022   val loss 0.032
Epoch 11/30 : train loss 0.019   val loss 0.036
Epoch 12/30 : train loss 0.016   val loss 0.030
Epoch 13/30 : train loss 0.015   val loss 0.038
Epoch 14/30 : train loss 0.014   val loss 0.035
Epoch 15/30 : train loss 0.013   val loss 0.031
Epoch 16/30 : train loss 0.010   val loss 0.034
Epoch 17/30 : train loss 0.009   val loss 0.029
Epoch 18/30 : train loss 0.009   val loss 0.033
Epoch 19/30 : train loss 0.008   val loss 0.037
Epoch 20/30 : train loss 0.008   val loss 0.036
Epoch 21/30 : train loss 0.006   val loss 0.037
Epoch 22/30 : train loss 0.005   val loss 0.036
Epoch 23/30 : train loss 0.006   val loss 0.034
Epoch 24/30 : train loss 0.005   val loss 0.044
Epoch 25/30 : train loss 0.006   val loss 0.040
Epoch 26/30 : train loss 0.004   val loss 0.039
Epoch 27/30 : train loss 0.006   val loss 0.037
Epoch 28/30 : train loss 0.005   val loss 0.048
Epoch 29/30 : train loss 0.004   val loss 0.038
Epoch 30/30 : train loss 0.003   val loss 0.039
Conv Net training done in 671.753 seconds!
```

Visualizing Training Progress of Conv Net (Also check out your wandb.ai homepage)

```
fig = plt.figure()
plt.plot(history_conv['train_loss'], color='blue')
plt.plot(history_conv['val_loss'], color='red')
plt.legend(['Train Loss', 'Test Loss'], loc='upper right')
plt.xlabel('Epochs')
plt.ylabel('Negative Log Likelihood Loss')
```

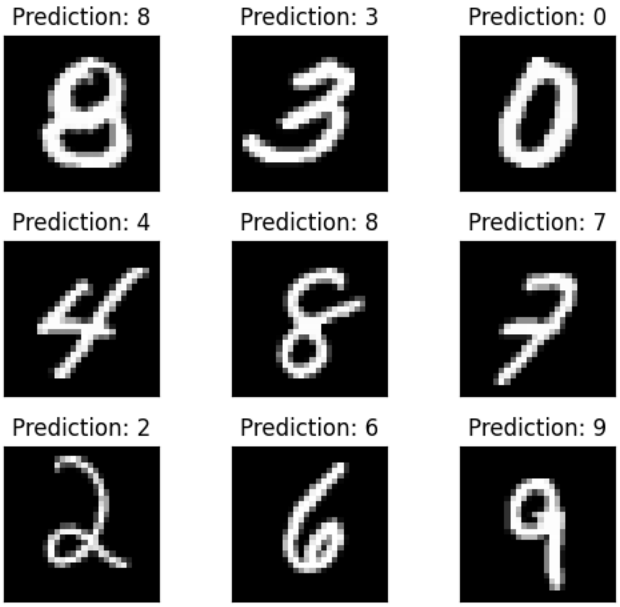
```
Text(0, 0.5, 'Negative Log Likelihood Loss')
```



Visualizing Predictions of Conv Net

```
examples = enumerate(test_loader)
batch_idx, (example_data, example_targets) = next(examples)
with torch.no_grad():
    example_data = example_data.to(device)
    output = conv_net(example_data)
example_data = example_data.cpu().detach().numpy()
fig = plt.figure(figsize=(5,5))
for i in range(9):
    plt.subplot(3,3,i+1)
    plt.tight_layout()
    plt.imshow(example_data[i][0], cmap='gray',interpolation='none')
    plt.title("Prediction: {}".format(
    output.data.max(1, keepdim=True)[1][i].item()))
    plt.xticks([])
    plt.yticks([])
```

```
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/module.py:1518: UserWarning: Implicit dimension choice for log_softm
  return self._call_impl(*args, **kwargs)
```



Training the Fully-Connected Neural Networks

Exercise 3.1.6: Train the fully connected neural network and analyse it

```
#TO-DO:Train the fc_net here
print('FC Net training started')


history_fc_net = {'train_loss':[],'val_loss':[]}
start_time = datetime.datetime.now()

for epoch in range(num_epochs):
    ### Training

    train_loss = train_model(
        model=fc_net,
        train_loader=train_loader,
        device=device,
        loss_fn=loss_fn,
        optimizer=optim_fc,
        input_dim=(-1,1,28,28))
    ### Validation  (use the testing function)
    val_loss = test_model(
        model=fc_net,
        test_loader=test_loader,
        device=device,
        loss_fn=loss_fn,
        input_dim=(-1,1,28,28))
    # Print Losses
    print(f'Epoch {epoch+1}/{num_epochs} : train loss {train_loss:.3f} \t val loss {val_loss:.3f}')
    history_fc_net['train_loss'].append(train_loss)
    history_fc_net['val_loss'].append(val_loss)


print(f'Conv Net training done in {(datetime.datetime.now()-start_time).total_seconds():.3f} seconds!')
```

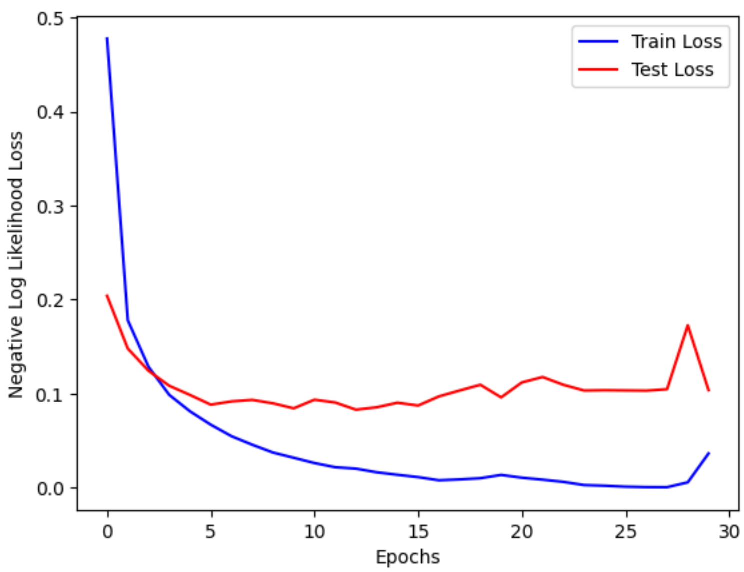
```
FC Net training started
Epoch 1/30 : train loss 0.478    val loss 0.204
Epoch 2/30 : train loss 0.178    val loss 0.148
Epoch 3/30 : train loss 0.129    val loss 0.124
Epoch 4/30 : train loss 0.099    val loss 0.108
Epoch 5/30 : train loss 0.081    val loss 0.099
Epoch 6/30 : train loss 0.067    val loss 0.088
Epoch 7/30 : train loss 0.055    val loss 0.092
Epoch 8/30 : train loss 0.046    val loss 0.093
```

```
Epoch 9/30 : train loss 0.037    val loss 0.090
Epoch 10/30 : train loss 0.032   val loss 0.084
Epoch 11/30 : train loss 0.026   val loss 0.094
Epoch 12/30 : train loss 0.022   val loss 0.091
Epoch 13/30 : train loss 0.020   val loss 0.083
Epoch 14/30 : train loss 0.016   val loss 0.085
Epoch 15/30 : train loss 0.014   val loss 0.090
Epoch 16/30 : train loss 0.011   val loss 0.087
Epoch 17/30 : train loss 0.008   val loss 0.097
Epoch 18/30 : train loss 0.009   val loss 0.103
Epoch 19/30 : train loss 0.010   val loss 0.109
Epoch 20/30 : train loss 0.014   val loss 0.096
Epoch 21/30 : train loss 0.011   val loss 0.112
Epoch 22/30 : train loss 0.008   val loss 0.118
Epoch 23/30 : train loss 0.006   val loss 0.109
Epoch 24/30 : train loss 0.003   val loss 0.103
Epoch 25/30 : train loss 0.002   val loss 0.104
Epoch 26/30 : train loss 0.001   val loss 0.103
Epoch 27/30 : train loss 0.001   val loss 0.103
Epoch 28/30 : train loss 0.000   val loss 0.105
Epoch 29/30 : train loss 0.006   val loss 0.173
Epoch 30/30 : train loss 0.036   val loss 0.104
Conv Net training done in 259.131 seconds!
```

Visualizing Training Progress of FC Net (Check out your wandb.ai project webpage)

```
# TODO - Visualize the training progress of fc_net

fig = plt.figure()
plt.plot(history_fc_net['train_loss'], color='blue')
plt.plot(history_fc_net['val_loss'], color='red')
plt.legend(['Train Loss', 'Test Loss'], loc='upper right')
plt.xlabel('Epochs')
plt.ylabel('Negative Log Likelihood Loss')
```

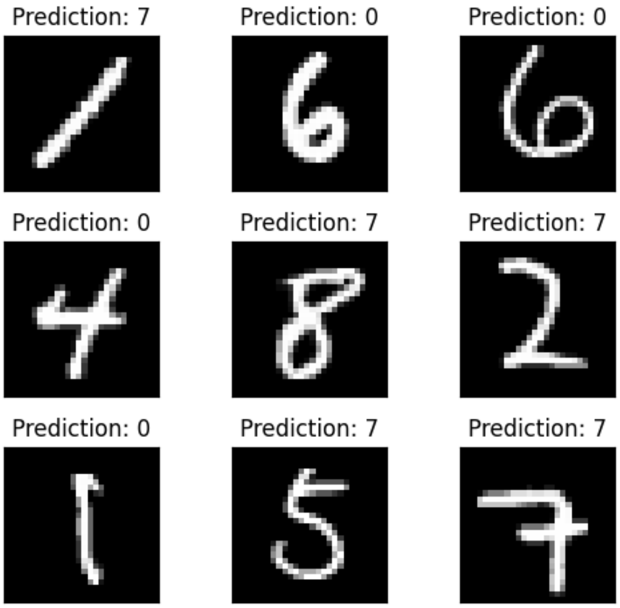
```
Text(0, 0.5, 'Negative Log Likelihood Loss')
```



Visualizing Predictions of FC Net

```
# TODO - Visualise the predictions of fc_net
examples = enumerate(test_loader)
batch_idx, (example_data, example_targets) = next(examples)
with torch.no_grad():
    example_data = example_data.to(device)
    output = fc_net(example_data)
example_data = example_data.cpu().detach().numpy()
fig = plt.figure(figsize=(5,5))
for i in range(9):
    plt.subplot(3,3,i+1)
    plt.tight_layout()
    plt.imshow(example_data[i][0], cmap='gray',interpolation='none')
```

```
    plt.title("Prediction: {}".format(
    output.data.max(1, keepdim=True)[1][i].item()))
    plt.xticks([])
    plt.yticks([])
```



Exercise 3.1.7: What are the training times for each of the model? Did both the models take similar times? If yes, why? Shouldn't CNN train faster given it's number of weights to train?

Training Time for CNN: 671.753

Training Time for FC Net: 259.131

The FC Net trained faster than the CNN. While CNNs typically have fewer weights than FC Nets, training time isn't just about weight count. Factors like the complexity of convolutions, network depth, and memory access patterns can make CNNs take longer to train. In this case, the convolutional operations in the CNN likely added to its training time compared to the FC Net.

Let's see how the models perform under translation

In principle, one of the advantages of convolutions is that they are equivariant under translation which means that a function composed out of convolutions should invariant under translation.

Exercise 3.1.8: In practice, however, we might not see perfect invariance under translation. What aspect of our network leads to imperfect invariance?

ANSWER:

Fully convolutional neural networks ensure translation invariance in image classification, thanks to the innate translation equivariance of their convolutional layers: a movement in the input mirrors similarly in the output feature map.

However, a common trait in many convolutional models is the integration of fully-connected layers, primarily for classification tasks. These layers neglect spatial relationships, disrupting the translation equivariance. Thus, a relocated input might produce different network outcomes, despite the content being the same.

For instance, consider a number "2" that's shifted downward. In an exclusively convolutional setup, the number would still be recognizable. But with the introduction of fully-connected layers, the network might mistakenly classify the shifted "2" as a "6" due to the visual overlap caused by the movement.

We will next measure the sensitivity of the convolutional network to translation in practice, and we will compare it to the fully-connected version.

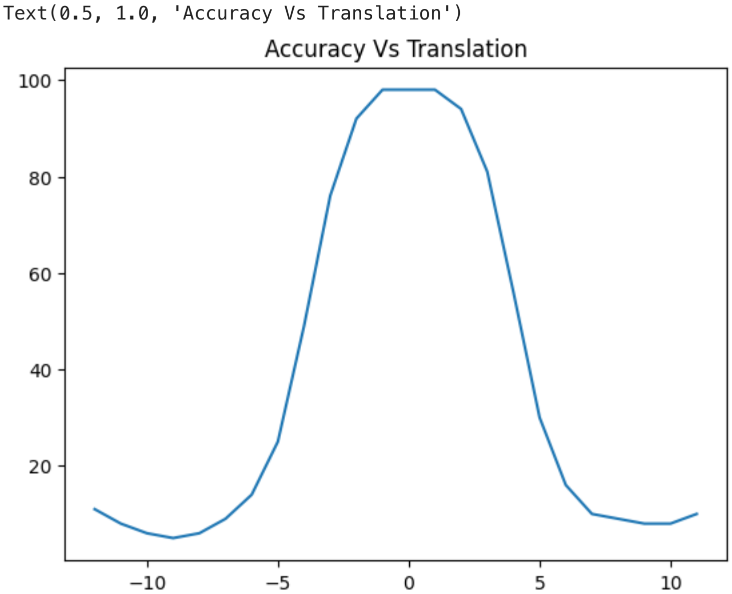
```
## function to check accuracies for unit translation
def shiftVsAccuracy(model, test_loader, device, loss_fn, shifts = 12, input_dim=(-1,1,28,28)):
```

```
    # Set evaluation mode for encoder and decoder
    accuracies = []
    shifted = []
    for i in range(-shifts,shifts):
        model.eval()
        correct = 0
        total = 0
        with torch.no_grad(): # No need to track the gradients
            # Define the lists to store the outputs for each batch
            predicted = []
            actual = []
            for images, labels in test_loader:
                # reshape input
                images = torch.roll(images,shifts=i, dims=2)
                if i == 0:
                    pass
                elif i > 0:
                    images[:,:,:i,:] = 0
                else:
                    images[:,:,i:,:] = 0
                images = torch.reshape(images,input_dim)
                images = images.to(device)
                labels = labels.to(device)
                ## predict the label
                pred = model(images)
                # Append the network output and the original image to the lists
                _ , pred = torch.max(pred.data, 1)
                total += labels.size(0)
                correct += (pred == labels).sum().item()
                predicted.append(pred.cpu())
                actual.append(labels.cpu())
            shifted.append(images[0][0].cpu())
            acc = 100 * correct // total
            accuracies.append(acc)
    return accuracies,shifted
```

```
accuracies,shifted = shiftVsAccuracy(
        model=conv_net,
        test_loader=test_loader,
        device=device,
        shifts=12,
        loss_fn=loss_fn,
        input_dim=(-1,1,28,28))
```

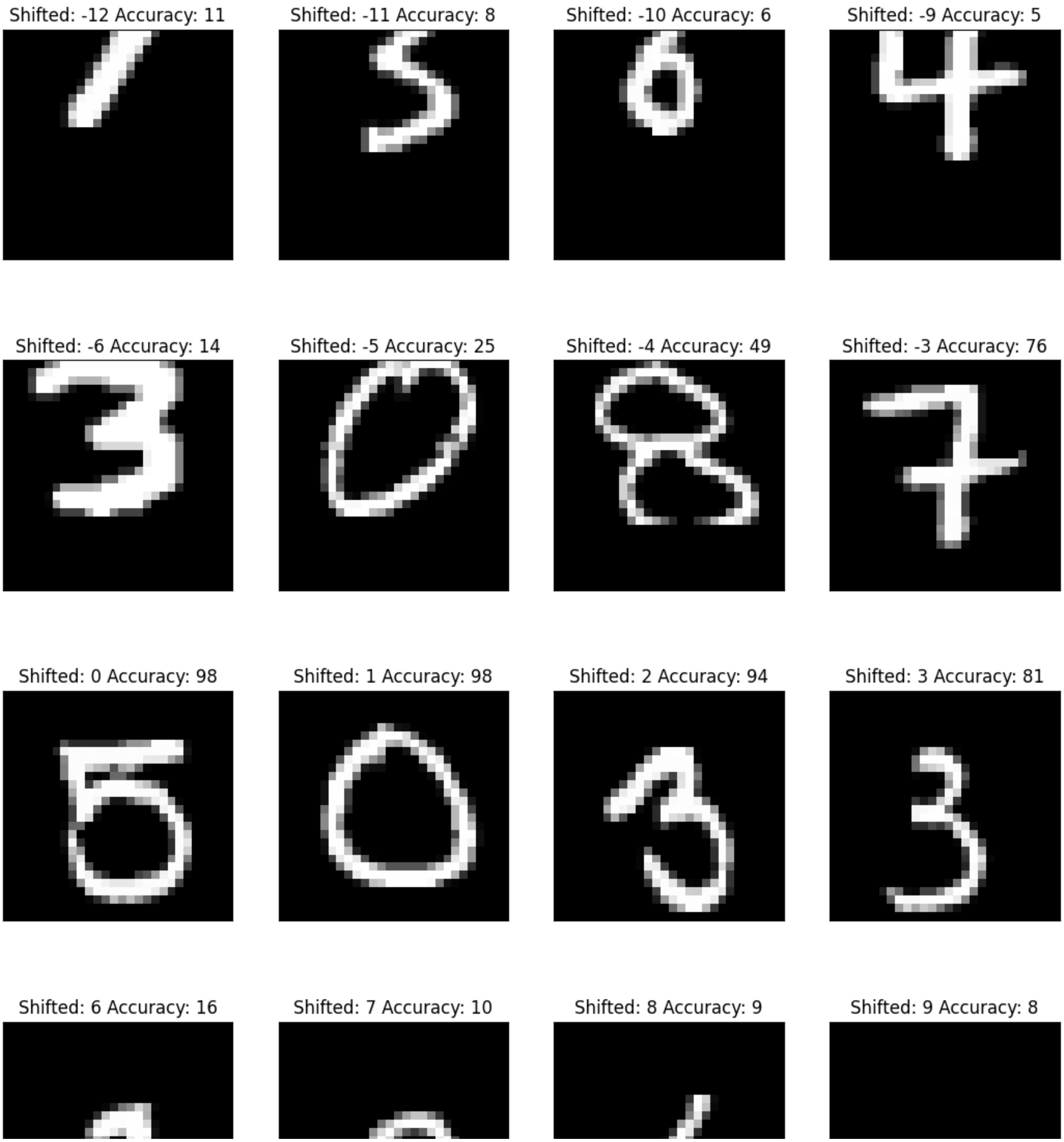
```
shifts = np.arange(-12,12)
plt.plot(shifts,accuracies)
plt.title('Accuracy Vs Translation')
```

```
Text(0.5, 1.0, 'Accuracy Vs Translation')
```




```
fig = plt.figure(figsize=(20,20))
plt_num = 0
```

```
for i in range(-12,12):
    plt.subplot(5,6,plt_num+1)
    plt.imshow(shifted[plt_num], cmap='gray',interpolation='none')
    plt.title(f"Shifted: {i} Accuracy: {accuracies[plt_num]}")
    plt.xticks([])
    plt.yticks([])
    plt_num+=1
```



Exercise 3.1.8: Do the same for FC-Net and plot the accuracies. Is the rate of accuracy degradation same as Conv-Net? Can you justify why this happened?

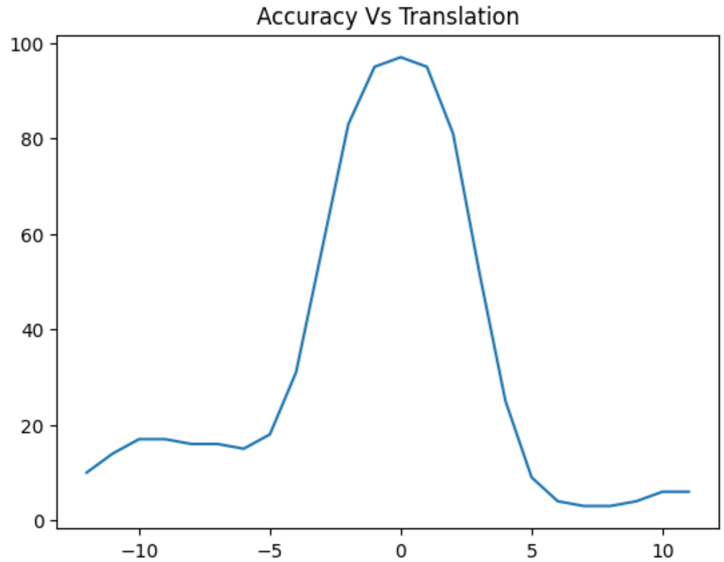
Clue: You might want to look at the way convolution layers process information

```
accuracies_fc,shifted_fc = shiftVsAccuracy(
        model=fc_net,
        test_loader=test_loader,
        device=device,
        shifts=12,
```

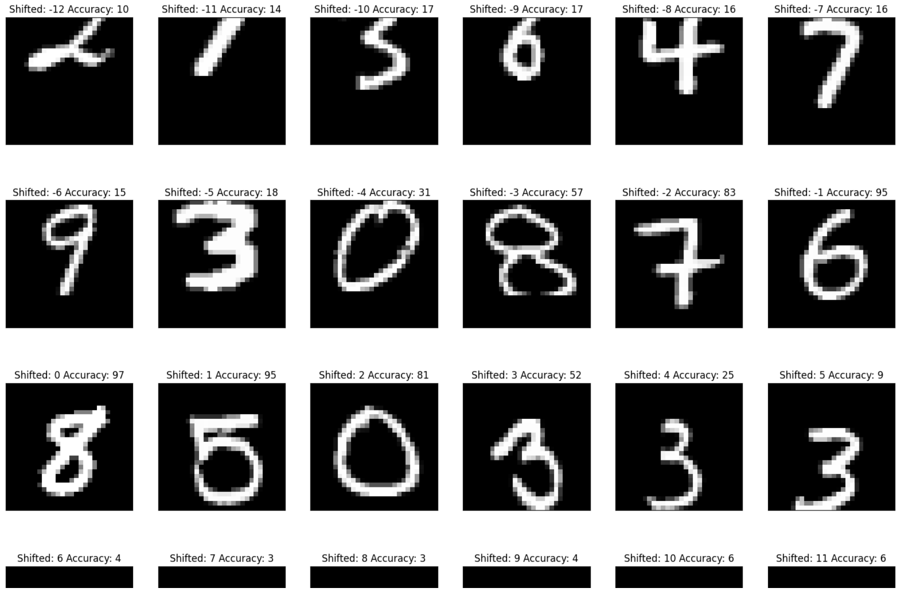
```
        loss_fn=loss_fn,
        input_dim=(-1,1,28,28))
```

```
shifts = np.arange(-12,12)
plt.plot(shifts,accuracies_fc)
plt.title('Accuracy Vs Translation')
```

```
Text(0.5, 1.0, 'Accuracy Vs Translation')
```




```
fig = plt.figure(figsize=(20,20))
plt_num = 0
for i in range(-12,12):
    plt.subplot(5,6,plt_num+1)
    plt.imshow(shifted_fc[plt_num], cmap='gray',interpolation='none')
    plt.title(f"Shifted: {i} Accuracy: {accuracies_fc[plt_num]}")
    plt.xticks([])
    plt.yticks([])
    plt_num+=1
```



ANSWER:

When assessing the accuracy of FC-Net and Conv-Net, the FC-Net shows promising results after just 30 iterations. However, over time, its performance might decrease more rapidly than the Conv-Net's. The key lies in their designs. Conv-Nets, with their unique architecture, focus on specific parts of images, allowing them to identify patterns no matter where they are located. This gives them an edge in handling varied image inputs. Conversely, FC-Nets evaluate images as a whole, making them more sensitive to minor changes like slight shifts, which could lead to a more notable drop in accuracy.