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
```

```
    Requirement already satisfied: torchinfo in /usr/local/lib/python3.10/dist-packages (1.8.0)
```

```
%%bash

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

```
    --2023-10-18 21:50:43--  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... 304 Not Modified
    File 'mnist-classify.pth' not modified on server. Omitting download.
```

```
# 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")
```

```
wandb: Currently logged in as: wellzhang1217 (7150). Use `wandb login --relogin` to force
Tracking run with wandb version 0.15.12
Run data is saved locally in /content/wandb/run-20231018_214449-fhpmgdn8
Syncing run dashing-thunder-3 to Weights & Biases (docs)
View project at https://wandb.ai/7150/hw3.1-ConvNets
View run at https://wandb.ai/7150/hw3.1-ConvNets/runs/fhpmgdn8
Display W&B run
```

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!
```

```
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/container.py:217: UserWarning: Implicit dimension choice for log_softmax has been
      input = module(input)
    ==========================================================================================
    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

```
# add an extra layer
def modified_simple_fc_net1():
    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(288,100), # extra layer added
        nn.ReLU(),
        nn.Linear(100,64),
        nn.ReLU(),
        nn.Linear(64,10),
        nn.LogSoftmax())
    return model


# increase the number of hidden neurons
def modified_simple_fc_net2():
    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*7,512),
        nn.ReLU(),
        nn.Linear(512,64),
        nn.ReLU(),
        nn.Linear(64,10),
        nn.LogSoftmax())
    return model


modified_fc_net1 = modified_simple_fc_net1()
modified_fc_net2 = modified_simple_fc_net2()


view_network_parameters(modified_fc_net1)
view_network_parameters(modified_fc_net2)
```

```
    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: 28800 elements
    9.bias: 100 elements
    11.weight: 6400 elements
    11.bias: 64 elements
    13.weight: 640 elements
    13.bias: 10 elements

    Total Trainable Parameters: 30002350!
    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: 802816 elements
7.bias: 512 elements
9.weight: 32768 elements
9.bias: 64 elements
11.weight: 640 elements
11.bias: 10 elements

Total Trainable Parameters: 30351274!
```

Please type your answer here ...

Adding more layers will always increase the total number of parameters since each layer has its own weights and biases. The additional layer in modified_fc_net_ introduced more parameters. The number of hidden neurons in layers does affect total number of 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),
        nn.ReLU(),
        nn.MaxPool2d(2,2),
        # TO-DO: Add layers below
        nn.Conv2d(8, 16, kernel_size=3, padding=1),
        nn.ReLU(),
        nn.MaxPool2d(2, 2),
        nn.Conv2d(16, 32, kernel_size=3, padding=1),
        nn.ReLU(),
        # TO-DO, what will your shape be after you flatten? Fill it in place of None
        nn.Flatten(),
        nn.Linear(32 * 7 * 7, 288),
        nn.ReLU(),
        nn.Linear(288, 64),
        # Do not change the code below
        nn.ReLU(),
        nn.Linear(64,10),
        nn.LogSoftmax(dim=1))
    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: 451584 elements
9.bias: 288 elements
11.weight: 18432 elements
11.bias: 64 elements
13.weight: 640 elements
13.bias: 10 elements

Total Trainable Parameters: 476906!
```

```
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, 288]                  451,872
├─ReLU: 1-11                             [1, 288]                  --
├─Linear: 1-12                           [1, 64]                   18,496
├─ReLU: 1-13                             [1, 64]                   --
├─Linear: 1-14                           [1, 10]                   650
├─LogSoftmax: 1-15                       [1, 10]                   --
==========================================================================================
Total params: 476,906
Trainable params: 476,906
Non-trainable params: 0
Total mult-adds (M): 0.99
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.09
Params size (MB): 1.91
Estimated Total Size (MB): 2.00
==========================================================================================
```

```
def simple_conv_net_no_maxpool():
    model = nn.Sequential(
        nn.Conv2d(1, 8, kernel_size=3, padding=1, stride=2),  # Stride of 2 to halve dimensions: 28x28 -> 14x14
        nn.ReLU(),

        nn.Conv2d(8, 16, kernel_size=3, padding=1, stride=2),  # Stride of 2 to halve dimensions: 14x14 -> 7x7
        nn.ReLU(),

        nn.Conv2d(16, 32, kernel_size=3, padding=1),  # No stride here, to keep 7x7 dimensions
        nn.ReLU(),

        nn.Flatten(),
        nn.Linear(32 * 7 * 7, 288),
        nn.ReLU(),

        nn.Linear(288, 64),
        nn.ReLU(),

        nn.Linear(64,10),
        nn.LogSoftmax(dim=1))
    return model


conv_net_no_maxpool = simple_conv_net_no_maxpool()


view_network_parameters(conv_net_no_maxpool)
```

```
    Model Summary

    0.weight: 72 elements
    0.bias: 8 elements
    2.weight: 1152 elements
    2.bias: 16 elements
    4.weight: 4608 elements
    4.bias: 32 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: 476906!
```

```
view_network_shapes(conv_net_no_maxpool, 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, 288]                  451,872
    ├─ReLU: 1-11                             [1, 288]                  --
    ├─Linear: 1-12                           [1, 64]                   18,496
    ├─ReLU: 1-13                             [1, 64]                   --
    ├─Linear: 1-14                           [1, 10]                   650
    ├─LogSoftmax: 1-15                       [1, 10]                   --
    ==========================================================================================
```

```
Total params: 476,906
Trainable params: 476,906
Non-trainable params: 0
Total mult-adds (M): 0.99
==========================================================================================
Input size (MB): 0.00
Forward/backward pass size (MB): 0.09
Params size (MB): 1.91
Estimated Total Size (MB): 2.00
==========================================================================================
```

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

Please type your answer here ...

Why log softmax: Traditional softmax computationally unstable. As the numbers are too big the exponents will probably blow up (computer cannot handle such big numbers) giving Nan as output. Also, dividing large numbers from , can be numerically unstable. The use of log probabilities means representing probabilities on a logarithmic scale, instead of the standard unit interval. Since the probabilities of independent events multiply, and logarithms convert multiplication to addition, log probabilities of independent events add. Log probabilities are thus practical for computations. (Reference: https://medium.com/@AbhiramiVS/softmax-vs-logsoftmax-eb94254445a2)

Softmax Function:Softmax function is used to convert a vector of real numbers into a probability distribution. For each element in the input vector, the softmax function computes the exponential of that element divided by the sum of the exponentials of all the elements in the vector. The resulting output is a probability distribution over n classes, and the sum of the output values will be 1.

ReLU?: I don't think ReLU is recommended since it doesn't generate a probability distribution. As it also allows unbounded positive values, making it less suitable for producing a final classification score. If we are able to set some threshold for classification tasks, ReLU might also work. But the interpretability might be an issue.

Exercise 3.1.3: What is the ratio of number of parameters of Conv-net to number of parameters of FC-Net
$\frac{p_{conv-net}}{p_{fc-net}}$ = 0.159
Do you see the difference ?!

```
476906 / 29985482
```

```
0.015904563415055327
```

The ratio shows the number of parameters used by a conv model to achieve a same model structure is inly about 1 percent of the number of parameters used by a fc-net.

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=[512, 256])
view_network_parameters(fc_net_custom2)

fc_net_custom3 = build_custom_fc_net(inp_dim=(1,28,28), out_dim=10, hidden_fc_dim=[256])
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: 401408 elements
    linear_1.bias: 512 elements
    linear_2.weight: 131072 elements
    linear_2.bias: 256 elements
    linear_3.weight: 2560 elements
    linear_3.bias: 10 elements

    Total Trainable Parameters: 535818!
    Model Summary

    linear_1.weight: 200704 elements
    linear_1.bias: 256 elements
    linear_2.weight: 2560 elements
    linear_2.bias: 10 elements

    Total Trainable Parameters: 203530!
```

Let's train the models to see their performace

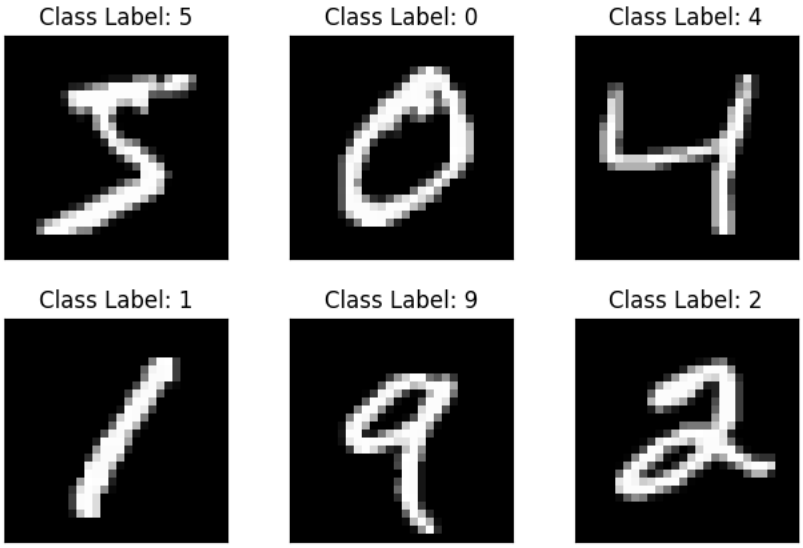
```
# downloading mnist into folder
data_dir = 'data' # make sure that this folder is created in your working dir
# transform the PIL images to tensor using torchvision.transform.toTensor method
train_data = torchvision.datasets.MNIST(data_dir, train=True, download=True, transform=torchvision.transforms.Compose([torchvision.transforms.T
test_data  = torchvision.datasets.MNIST(data_dir, train=False, download=True, transform=torchvision.transforms.Compose([torchvision.transforms.
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)
```

```
    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):
    '''
    TO-DO: please add code below to add xavier uniform initialization and remove the 'pass'
    '''
    if isinstance(m, nn.Linear) or isinstance(m, nn.Conv2d):
        torch.nn.init.xavier_uniform_(m.weight)
        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: cuda
```

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 0.433    val loss 0.116
Epoch 2/30 : train loss 0.105    val loss 0.062
Epoch 3/30 : train loss 0.070    val loss 0.050
Epoch 4/30 : train loss 0.054    val loss 0.042
Epoch 5/30 : train loss 0.043    val loss 0.042
Epoch 6/30 : train loss 0.034    val loss 0.047
Epoch 7/30 : train loss 0.029    val loss 0.028
Epoch 8/30 : train loss 0.025    val loss 0.029
Epoch 9/30 : train loss 0.020    val loss 0.036
Epoch 10/30 : train loss 0.018   val loss 0.034
Epoch 11/30 : train loss 0.018   val loss 0.027
Epoch 12/30 : train loss 0.013   val loss 0.033
Epoch 13/30 : train loss 0.012   val loss 0.038
Epoch 14/30 : train loss 0.011   val loss 0.028
Epoch 15/30 : train loss 0.008   val loss 0.039
Epoch 16/30 : train loss 0.010   val loss 0.035
Epoch 17/30 : train loss 0.007   val loss 0.028
Epoch 18/30 : train loss 0.009   val loss 0.032
Epoch 19/30 : train loss 0.007   val loss 0.030
Epoch 20/30 : train loss 0.007   val loss 0.028
Epoch 21/30 : train loss 0.004   val loss 0.031
Epoch 22/30 : train loss 0.005   val loss 0.029
Epoch 23/30 : train loss 0.005   val loss 0.039
Epoch 24/30 : train loss 0.006   val loss 0.036
Epoch 25/30 : train loss 0.003   val loss 0.035
Epoch 26/30 : train loss 0.007   val loss 0.029
Epoch 27/30 : train loss 0.007   val loss 0.030
Epoch 28/30 : train loss 0.007   val loss 0.028
Epoch 29/30 : train loss 0.003   val loss 0.032
Epoch 30/30 : train loss 0.005   val loss 0.032
Conv Net training done in 216.709 seconds!
```

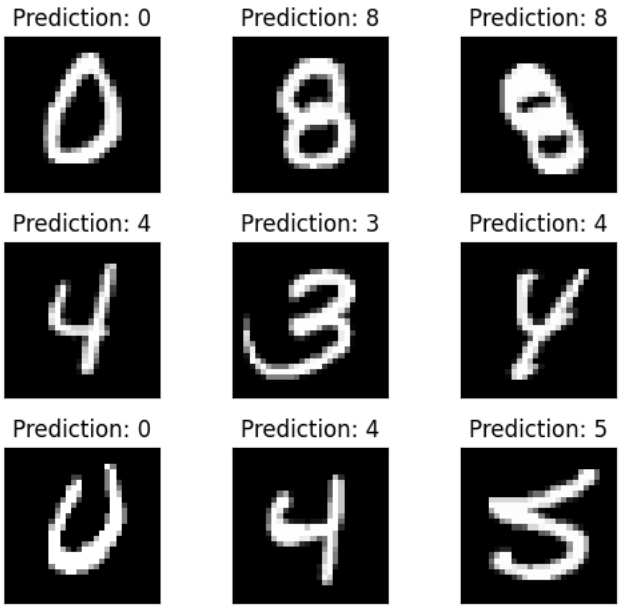
Visualizing Training Progress of Conv Net (Also check out your wandb.ai homepage)

```
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([])
```



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 = {'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,
```

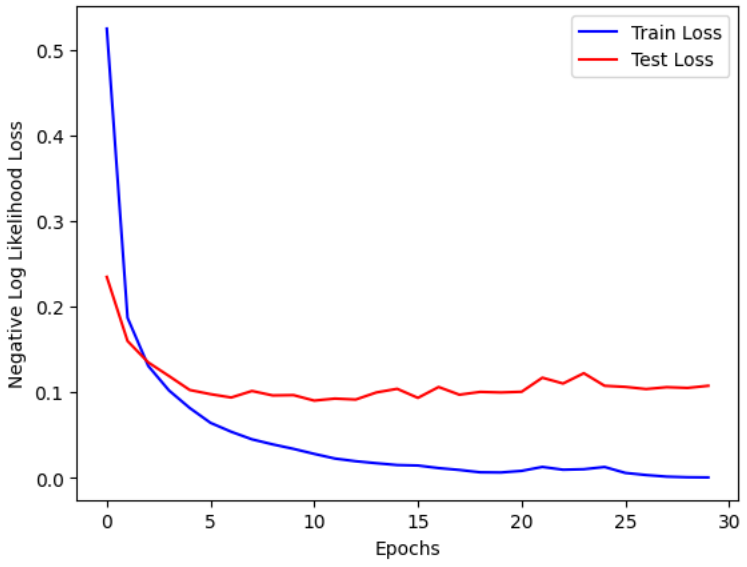
```
        test_loader=test_loader,
        device=device,
        loss_fn=loss_fn,
        input_dim=(-1,1,28,28))
    # Print Losses
    print(f'Epoch {epoch+1}/{num_epochs} : train loss {train_loss:.3f} \t val loss {val_loss:.3f}')
    history_fc['train_loss'].append(train_loss)
    history_fc['val_loss'].append(val_loss)


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

```
FC Net training started
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/container.py:217: UserWarning: Implicit dimension choice for log_softmax has been
  input = module(input)
Epoch 1/30 : train loss 0.524    val loss 0.234
Epoch 2/30 : train loss 0.187    val loss 0.160
Epoch 3/30 : train loss 0.130    val loss 0.135
Epoch 4/30 : train loss 0.102    val loss 0.119
Epoch 5/30 : train loss 0.081    val loss 0.102
Epoch 6/30 : train loss 0.064    val loss 0.098
Epoch 7/30 : train loss 0.054    val loss 0.094
Epoch 8/30 : train loss 0.045    val loss 0.101
Epoch 9/30 : train loss 0.039    val loss 0.096
Epoch 10/30 : train loss 0.034   val loss 0.096
Epoch 11/30 : train loss 0.028   val loss 0.090
Epoch 12/30 : train loss 0.022   val loss 0.092
Epoch 13/30 : train loss 0.019   val loss 0.091
Epoch 14/30 : train loss 0.017   val loss 0.100
Epoch 15/30 : train loss 0.015   val loss 0.104
Epoch 16/30 : train loss 0.014   val loss 0.093
Epoch 17/30 : train loss 0.011   val loss 0.106
Epoch 18/30 : train loss 0.009   val loss 0.097
Epoch 19/30 : train loss 0.006   val loss 0.100
Epoch 20/30 : train loss 0.006   val loss 0.100
Epoch 21/30 : train loss 0.008   val loss 0.100
Epoch 22/30 : train loss 0.013   val loss 0.117
Epoch 23/30 : train loss 0.009   val loss 0.110
Epoch 24/30 : train loss 0.010   val loss 0.122
Epoch 25/30 : train loss 0.013   val loss 0.107
Epoch 26/30 : train loss 0.006   val loss 0.106
Epoch 27/30 : train loss 0.003   val loss 0.104
Epoch 28/30 : train loss 0.001   val loss 0.106
Epoch 29/30 : train loss 0.001   val loss 0.105
Epoch 30/30 : train loss 0.000   val loss 0.107
FC Net training done in 211.915 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['train_loss'], color='blue')
plt.plot(history_fc['val_loss'], color='red')
plt.legend(['Train Loss', 'Test Loss'], loc='upper right')
plt.xlabel('Epochs')
plt.ylabel('Negative Log Likelihood Loss')
```

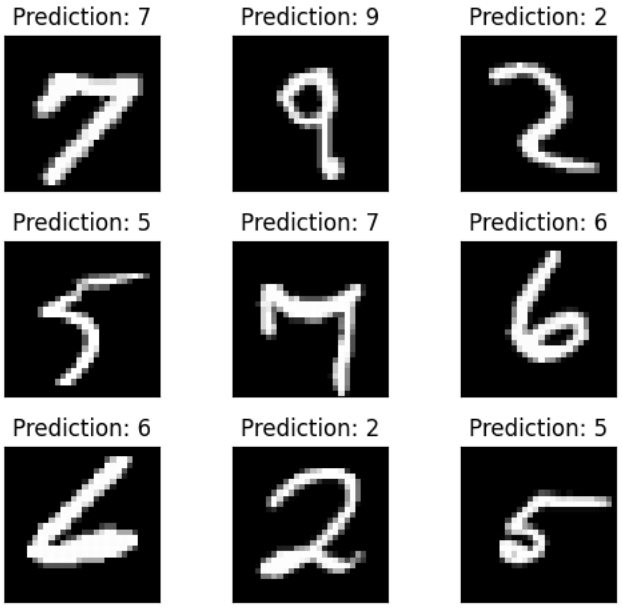
```
Text(0, 0.5, 'Negative Log Likelihood Loss')
```



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([])
```

```
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/container.py:217: UserWarning: Implicit dimension choice for log_softmax has been
  input = module(input)
```



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?

Conv net took about 217 seconds to finsih training, while it only took 212 seconds to train the fully connected network. Both models took similar times. I think this could be caused by the fact that training time is influenced by a couple of factors and not only dependent on the parameter size. Other hyperparameters such as learning rate and hardware capability could be major factors that influence training time. In this case, we happen to set them the same for both models.

```
#Please type your answer here ...
```

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.

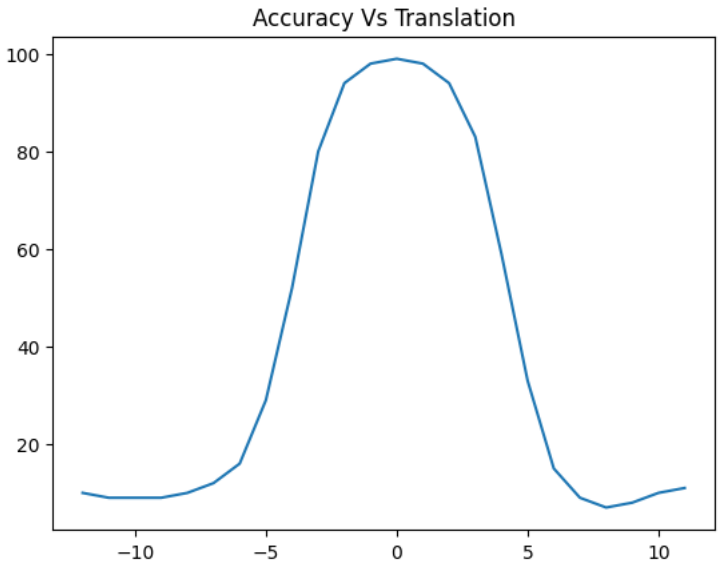
Exercise 3.1.8: In practice, however, we might not see perfect invariance under translation. What aspect of our network leads to imperfect invariance?

This is due to the sliding window operation of the convolution which processes local patches of the input image using the same kernel. Therefore, if a pattern is moved to another location in the image, the same kernel might not produce an activation for the pattern in its new position.

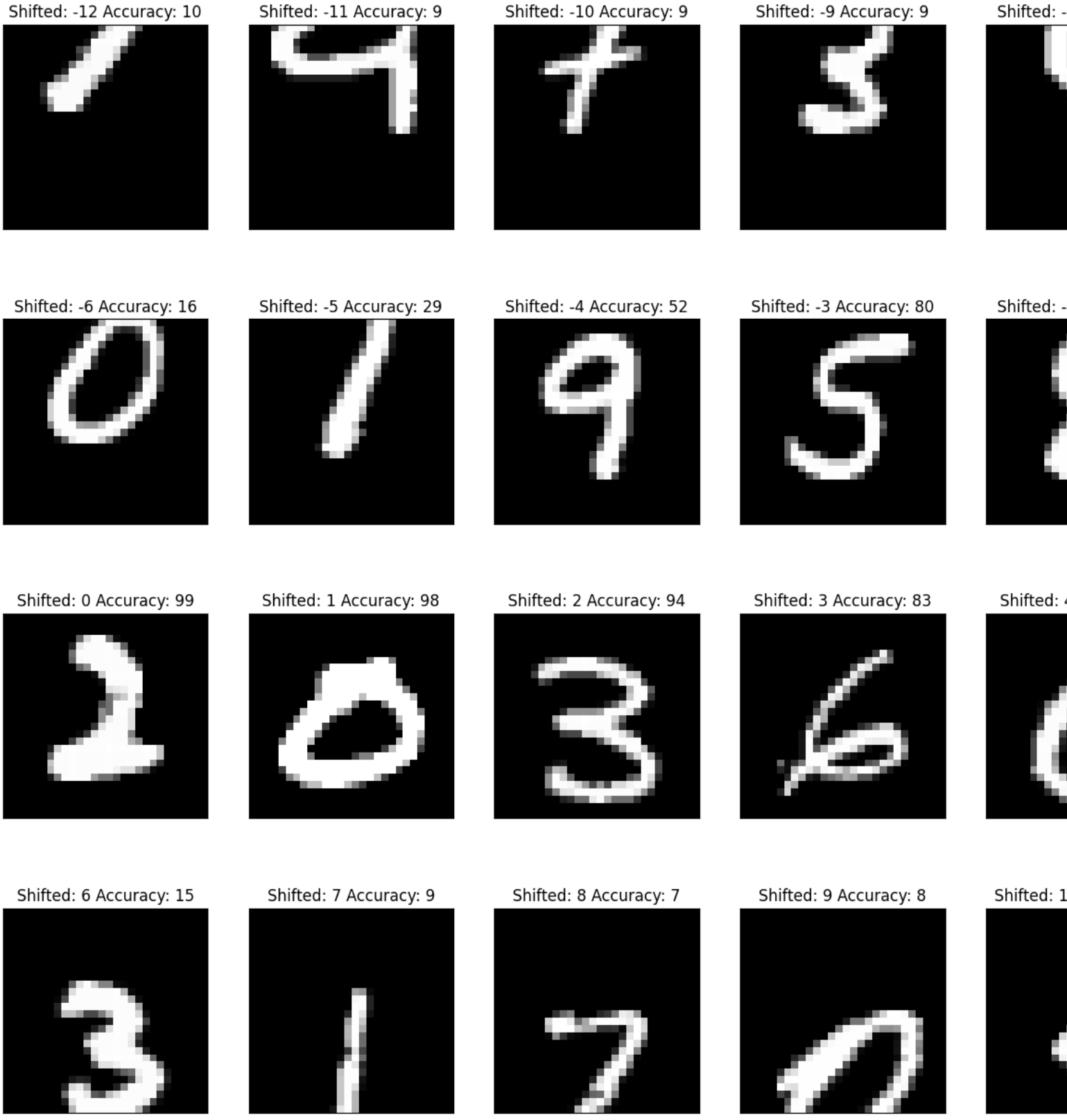
We will next measure the sensitivity of the convolutional network to translation in practice, and we will compare it to the fully-connected version.

```
## 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

The fc net's rate of accuracy degradation with translation is not the same as the Conv-Net. As we can see from the two graphies below, the accuracy for this model is highest when there's no translation, indicating that the model performs best when the test images are not shifted. The model lost the ability to track particular patterns of each number once shifting happens. Likewise, FC net follow similar trend, while it has relatively higher accuracy ar aounrd -10 mark. It does not have a smooth decline in accuracy with translation. There are noticeable dips in its accuracy.

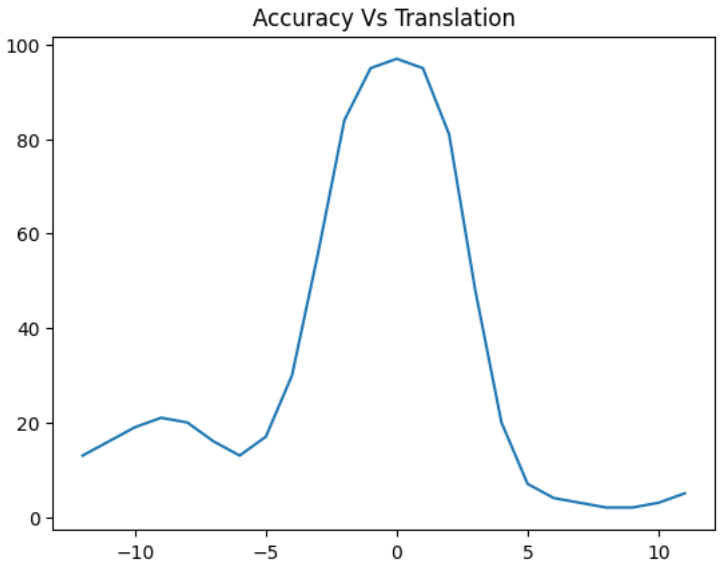
I think one possible reason causing such erratic behavior of a fc net after translation is that its inability to handle and process local spatial patterns, while conv net can. Fully connected layers treat each pixel of the image independently. Thus, even minor translations can lead to a significant drop in accuracy since the spatial relationships between pixels, crucial for recognition, get disrupted. It's also why we have a smoother line for conv net, as they can better process local pattern infomation.

```
# To-DO Write your code below
fc_accuracies,fc_shifted = shiftVsAccuracy(
        model=fc_net,
        test_loader=test_loader,
        device=device,
        shifts=12,
        loss_fn=loss_fn,
        input_dim=(-1,1,28,28))
```

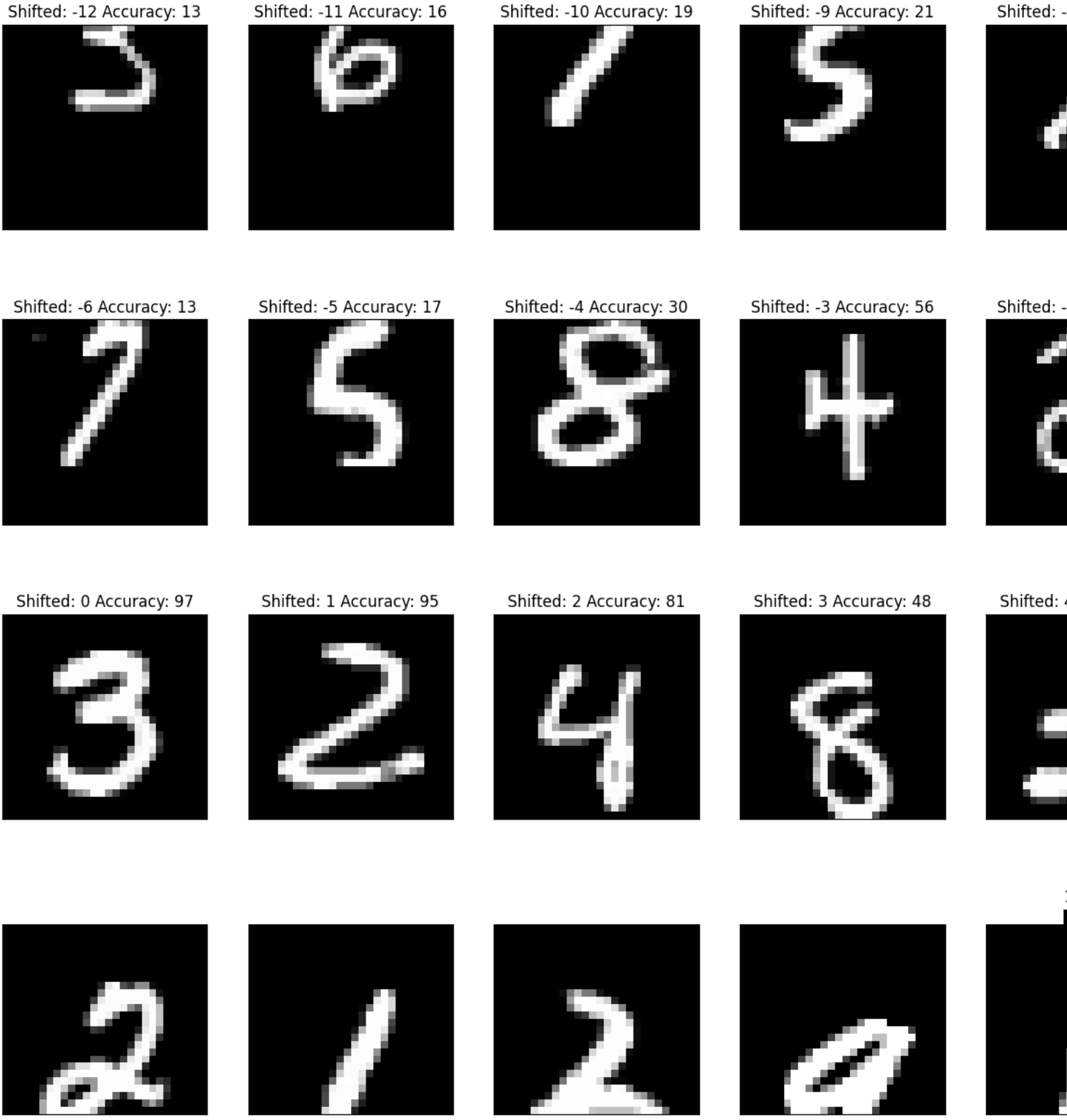
```
/usr/local/lib/python3.10/dist-packages/torch/nn/modules/container.py:217: UserWarning: Implicit dimension choice for log_softmax has beer
  input = module(input)
```

```
shifts = np.arange(-12,12)
plt.plot(shifts,fc_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(fc_shifted[plt_num], cmap='gray',interpolation='none')
    plt.title(f"Shifted: {i} Accuracy: {fc_accuracies[plt_num]}")
    plt.xticks([])
    plt.yticks([])
    plt_num+=1
```


Shifted: -12 Accuracy: 13
Shifted: -11 Accuracy: 16
Shifted: -10 Accuracy: 19
Shifted: -9 Accuracy: 21
Shifted: -6 Accuracy: 13
Shifted: -5 Accuracy: 17
Shifted: -4 Accuracy: 30
Shifted: -3 Accuracy: 56
Shifted: 0 Accuracy: 97
Shifted: 1 Accuracy: 95
Shifted: 2 Accuracy: 81
Shifted: 3 Accuracy: 48

This can be run [run on Google Colab using this link]

STABLE DIFFUSION ASSIGNMENT

Preliminary

In this homework assignment, you will delve deep into Stable Diffusion Models based on the DDPMs paper. The homework is fragmented into three main parts: Forward Diffusion, the Unet Architecture of Noise Predictor Model with training and the Sampling part of Stable Diffusion Models. By completing this assignment, you will gain a comprehensive understanding of the mathematics underlying stable diffusion and practical skills to implement and work with these models.

Setup and Data Preparation

Execute the provided cell to import essential libraries, ensure result reproducibility, set device configurations, download the MNIST dataset, and initialize DataLoaders for training, validation, and testing.

Note: Run the cell as is; no modifications are necessary.

```
###########################################################################
#                                TO DO                                    #
#               Execute the block to load & Split the Dataset             #
###########################################################################

import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F


# Ensure reproducibility
torch.manual_seed(0)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

# Check if CUDA is available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Download and Load the MNIST dataset
transform = transforms.ToTensor()
full_trainset = torchvision.datasets.MNIST(root='./data', train=True, download=True, transform=transform)

# Splitting the trainset into training and validation datasets
train_size = int(0.8 * len(full_trainset))  # 80% for training
val_size = len(full_trainset) - train_size  # remaining 20% for validation
train_dataset, val_dataset = torch.utils.data.random_split(full_trainset, [train_size, val_size])

trainloader = torch.utils.data.DataLoader(train_dataset, batch_size=32, shuffle=True)
valloader = torch.utils.data.DataLoader(val_dataset, batch_size=32, shuffle=False)

testset = torchvision.datasets.MNIST(root='./data', train=False, download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=32, shuffle=False)
```

```
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, 89190703.40it/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, 57112538.34it/s]Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw

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, 27982906.52it/s]
Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw

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, 7100457.98it/s]
```

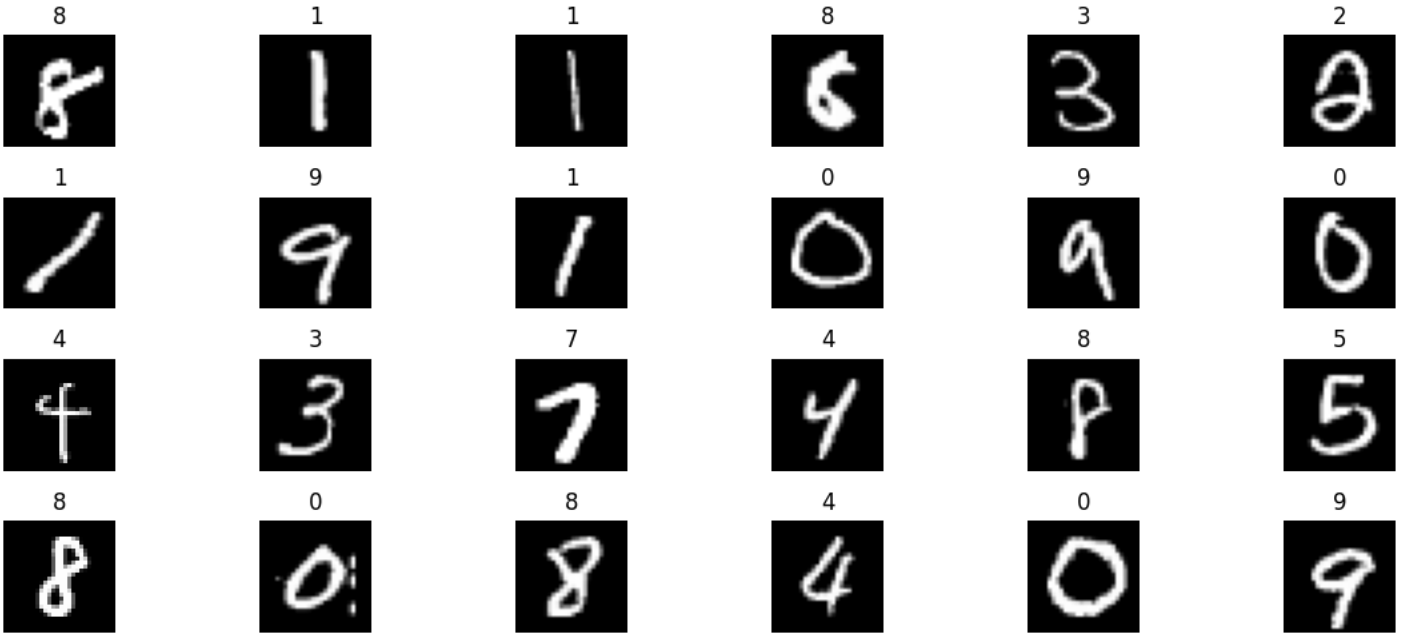
```
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
```

Image Display Function

Below is a utility function, `display_images`, used for visualizing dataset and monitoring diffusion process for slight intuitive way of choosing parameter purposes and display results post training in this assignment.

Note: Run the cell to view the images from the dataset.

```
#########################################################################
#                               TO DO                                   #
#               Execute the block to display images of MNIST            #
#########################################################################

import matplotlib.pyplot as plt

def display_images(images, n, images_per_row=5, labels = None):
    """
    Display n images in rows where each row contains a specified number of images.

    Parameters:
    - images: List/Tensor of images to display.
    - n: Number of images to display.
    - images_per_row: Number of images per row.
    """
    # Define the number of rows based on n and images_per_row
    num_rows = (n + images_per_row - 1) // images_per_row  # Rounding up
    plt.figure(figsize=(2*images_per_row, 1.25 * num_rows))
    for i in range(n):
        plt.subplot(num_rows, images_per_row, i+1)
        plt.imshow(images[i].cpu().squeeze().numpy(), cmap='gray')
        if labels is not None:
          plt.title(labels[i])
        plt.axis('off')
    plt.tight_layout()
    plt.show()


for batch in trainloader:
  # In a batch from many batches in trainloader, get the the first one and work with that
  batch_size = len(batch[0])
  display_images(images= batch[0],n = batch_size, images_per_row=8, labels = batch[1].tolist())
  break
```



EXERCISE 1: FORWARD DIFFUSION

Noise Diffusion

The following block `Noise Diffusion` is to give you a high level intuition of what forward diffusion process is and how we achieve results without any dependency on prior results. There is a detailed derivation on how we landed on the formula mentioned in the paper and below, if you're interested in the math, we recommend reading Denoising Diffusion Probabilistic Models for clear understanding of ***Forward Diffusion Process*** and mathematical details involved in it!

Noise Diffusion

The idea behind adding noise to an image is rooted in a simple linear interpolation between the original image and a noise term. Let's use the concept of a blending or mixing factor (which we'll refer to as α)

1. Linear Interpolation:

Given two values, A and B, the linear interpolation between them based on a blending factor α (where $0 \leq \alpha \leq 1$) is given by:

$$\text{Result} = \alpha A + (1 - \alpha)B$$

If $\alpha = 1$, the Result is entirely A. If $\alpha = 0$, the Result is entirely B. For values in between, you get a mixture.

2. Applying to Images and Noise:

In our context:

- A is the original image.
- B is the noise (often drawn from a standard normal distribution, but could be any other distribution or type of noise).

So, for each pixel (p) in our image, and at a given timestep (t):

$$\text{noisy\_image}_p(t) = \alpha(t) \times \text{original\_image}_p + (1 - \alpha(t)) \times \text{noise}_p$$

Where:

- $\alpha(t)$ is the blending factor at timestep t
- original_image_p is the intensity of pixel p in the original image.
- noise_p is the noise value for pixel p, typically drawn from a normal distribution.

3. Time-Dependent α:

For the Time-Dependent Alpha Noise Diffusion method, our α isn't a constant; it changes over time. That's where our linear scheduler or any other scheduler comes in: to provide a sequence of values over timesteps.

Now, considering cumulative products: The reason for introducing the cumulative product of αs was to have an accumulating influence of noise over time. With each timestep, we multiply the original image with the cumulative product of α values up to that timestep, making the original image's influence reduce multiplicatively. The noise's influence, conversely, grows because it's based on $1-$ the cumulative product of the αs.

That's why the formula becomes:

$$\text{noisy\_image}_t = \text{original\_image} \times \prod_{i=1}^{t} \alpha_i + \text{noise} \times (1 - \prod_{i=1}^{t} \alpha_i)$$

In essence, this formula is just a dynamic way to blend an original image and noise, with the blending ratios changing (and typically becoming more skewed toward noise) over time.

4. Linear Scheduling of Noise Blending:

One of the core components of this noise diffusion assignment is how the blending of noise into the original image is scheduled. To accomplish this, we utilize a linear scheduler that determines the progression of the β (noise level parameter) over a series of timesteps.

Imagine you wish to transition β from a `start_beta` of 0.1 to an `end_beta` of 0.2 over 11 timesteps. The goal is for the rate of noise blending into the image to increase progressively. In this case, the sequence of β values would look like this: [0.1, 0.11, 0.12,..., 0.2].

This sequence, `self.betas`, is precisely what the `linear_scheduler` generates.

```
self.betas = self.linear_scheduler().to(self.device)
```

In essence, the `linear_scheduler` method calculates the sequence of β values for the diffusion process, ensuring that the noise blending into the image increases linearly over the given timesteps.

Terminologies:

1. β: Represents the noise level parameter, defined between the start and end beta values.
2. α: Represents the blending factor, calculated as $(1 - \beta)$.
3. Cumulative Product of α: Understand its significance in dynamically blending the original image and noise over timesteps, without any dependency on prior timesteps.

NoiseDiffuser Class

TO DO

Implement `NoiseDiffuser` Class, ***Follow Instructions in the code cell***

```
import torch

class NoiseDiffuser:
  def __init__(self, start_beta, end_beta, total_steps, device='cpu'):

    # assert start_beta < end_beta < 1.0.      <--- COMMENTED OUT BECAUSE OF EXPLORATION FOR HIGHER START AND LOWER END

    self.device = device
    self.start_beta = start_beta
    self.end_beta = end_beta
    self.total_steps = total_steps
    ##########################################################################
    #                                TO DO                                   #
    #                  Compute the following variables needed                #
    #                      for Forward Diffusion Process                     #
    #                  schedule betas,  compute alphas & cumulative          #
    #                               product of alphas                        #
    ##########################################################################
    # raise NotImplementedError
    self.betas = self.linear_scheduler().to(self.device)
    self.alphas = 1.0 - self.betas
    self.alpha_bar = torch.cumprod(self.alphas, dim=0).to(self.device) # return a tensor


  def linear_scheduler(self):
    """Returns a linear schedule from start to end over the specified total number of steps."""
    ##########################################################################
    #                                TO DO                                   #
    #                  Return a linear schedule of `betas`                   #
    #                    from `start_beta` to `end_beta`                     #
    #                         hint: torch.linspace()                         #
    ##########################################################################
    # raise NotImplementedError
    return torch.linspace(self.start_beta, self.end_beta, self.total_steps)


  def noise_diffusion(self, image, t):
    """
    Diffuse noise into an image based on timestep t using the pre-computed cumulative product of alphas.
    """
    ##########################################################################
    #                                TO DO                                   #
    #                 Process the given `image` for timesteps `t`            #
    #                Return processed image & necessary variables            #
    ##########################################################################
    image = image.to(self.device)

    # raise NotImplementedError
    # the image is four dimensional and alpha-bar is one dimensional
    noise = torch.randn_like(image).to(self.device)
    # fetching the specific alpha_bars values for each image in the batch based on its specified timestep.
    alpha_bars = self.alpha_bar[t]
    # [:, None, None, None] reshapes the tensor to [batch_size, 1, 1, 1]
    noisy_image = alpha_bars[:, None, None, None] * image + noise * (1 - alpha_bars[:, None, None, None])

    return noisy_image, noise  # <--- might be better to specify returning true noises for later use
```

Testing NoiseDiffuser Class (SANITY CHECK)

```
# SANITY CHECK
in_channels_arg = 1
out_channels_arg = 1
batch_size = 32
height = 28
width = 28
total_timesteps = 50
start_beta, end_beta = 0.001, 0.2


# Check if CUDA is available
```

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Sanity check
x = torch.randn((batch_size, in_channels_arg, height, width)).to(device)
diffuser = NoiseDiffuser(start_beta, end_beta, total_timesteps, device)



timesteps_to_display = torch.randint(0, total_timesteps, (batch_size,), device=device).long().tolist()
y, _ = diffuser.noise_diffusion(x, timesteps_to_display)

assert len(x.shape) == len(y.shape)
assert y.shape == x.shape

print("Sanity Check for shape mismatches")
print("Shape of the input : ", x.shape)
print("Shape of the output : ", y.shape)
```

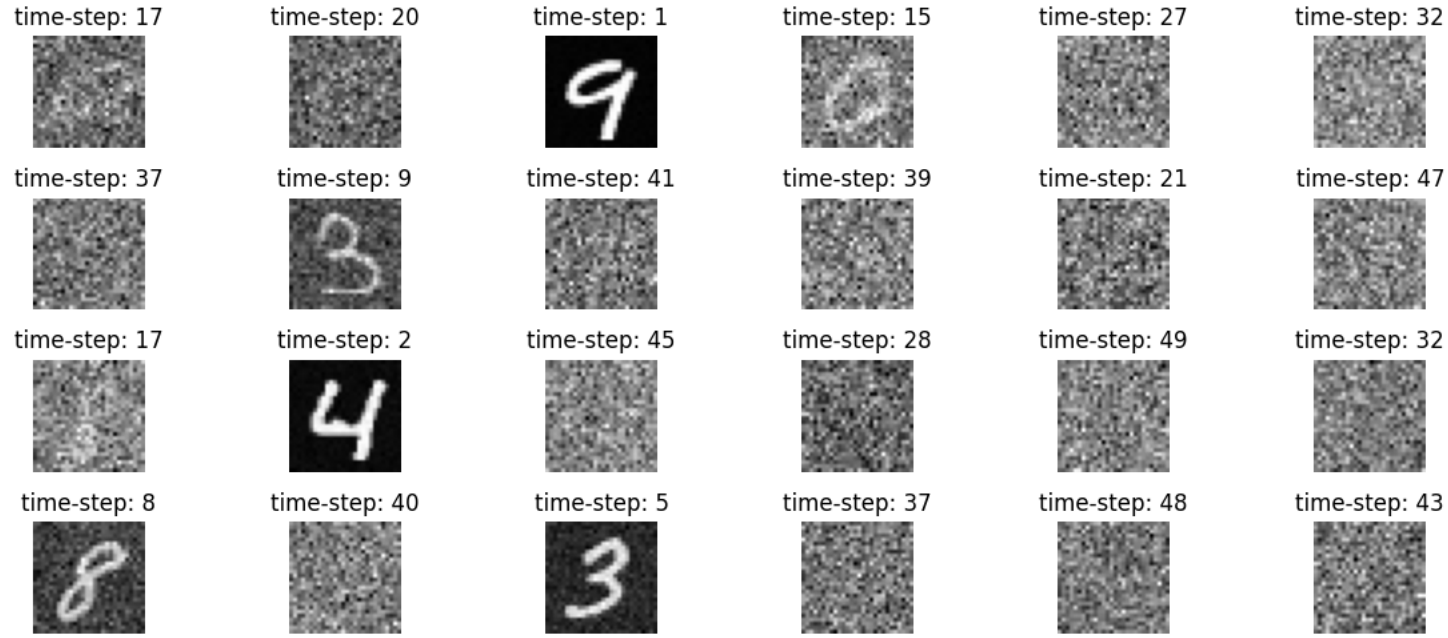
```
Sanity Check for shape mismatches
Shape of the input :  torch.Size([32, 1, 28, 28])
Shape of the output :  torch.Size([32, 1, 28, 28])
```

Demonstrating Examples

Note: Observe the visual effect of noise diffusion for different images at random timesteps. How does the noise appear?

```
#############################################################################
#                                TO DO                                      #
#       Initialize some start_beta, end_beta & total_timesteps              #
#                         and execute the block                             #
#############################################################################
# raise NotImplementedError

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
total_timesteps = 50
start_beta, end_beta = 0.001, 0.2
diffuser = NoiseDiffuser(start_beta, end_beta, total_timesteps, device)

for batch in trainloader:
    minibatch = batch[0]
    batch_size = len(minibatch)
    timesteps_to_display = torch.randint(0, total_timesteps, (batch_size,), device=device).long().tolist()
    noisy_images,_ = diffuser.noise_diffusion(minibatch, timesteps_to_display)
    display_images(images=noisy_images, n=batch_size, images_per_row=8, labels=list(map(lambda x: "time-step: " + str(x), timesteps_to_display)))
    break
```

```
cuda
```



HyperParameters

Smartly setting the start and end values of beta can control the noise diffusion's character.

- **Lower Start and Higher End**: Starting with a lower beta and ending with a higher one means that original image's contribution remains dominant in the beginning and slowly diminishes. This can be useful when the goal is to have a gradual transition from clear image to noisier version.
- **Higher Start and Lower End**: The opposite approach, starting with a Higher beta and ending with a lower one, can be useful when goal is to introduce noise more aggressively initially and taper off towards the end.
- **THINK WHAT WOULD WE NEED** `Higher Start and Lower End` or `Lower Start and Higher End`

The precise values can be fine-tuned based on specific requirements, visual assessments (like in the cell below) or even metrics.

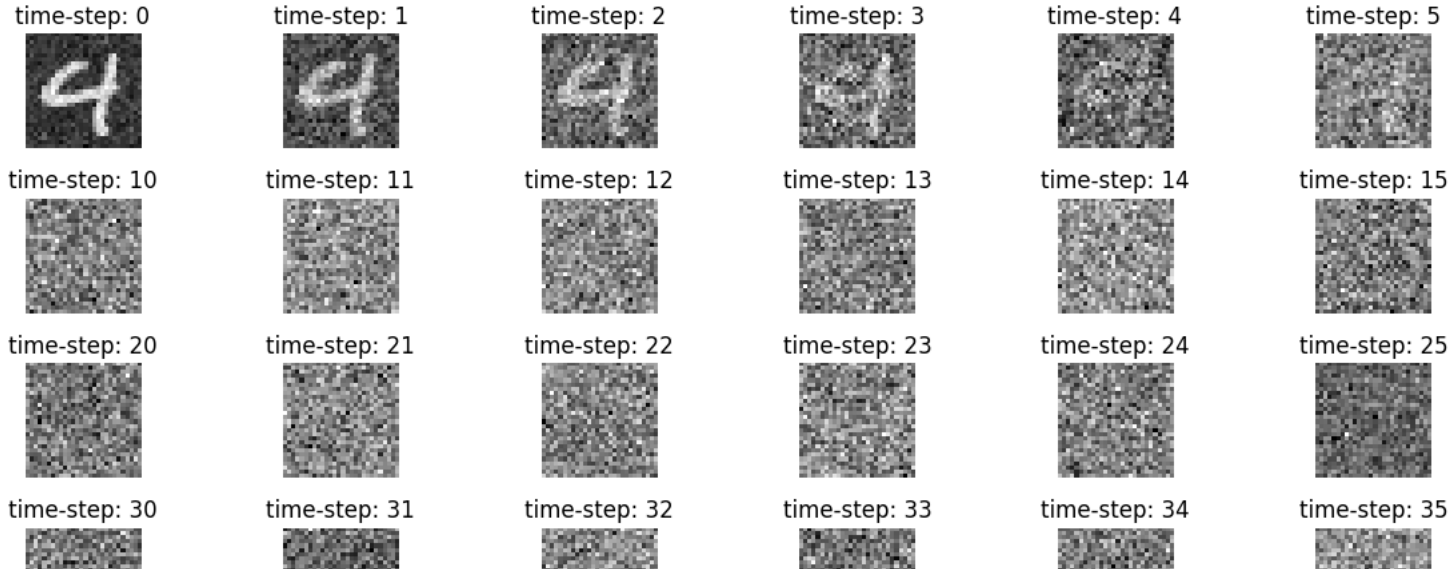
Exploration with Varied beta Values and Timesteps:

- In the below cell, you are encouraged to tweak values of `start_beta` and `end_beta` and even modify `total_timesteps` to observe the effect over a longer/shorter period

Note: Pay close attention to how the noise diffusion evolves over time. Can you see a clear transition from the start to the end timestep? How do different images react to the same noise diffusion process?

```
#############################################################################
#                               TO DO                                       #
#       Initialize some start_beta, end_beta & total_timesteps              #
#         play around and see the effect of noise introduced                #
#         and think what parameters would you use for training              #
#############################################################################
# raise NotImplementedError

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
total_timesteps = 100
start_beta, end_beta = 0.1, 0.6
minibatch_size = 1
diffuser = NoiseDiffuser(start_beta, end_beta, total_timesteps, device)

# PLay around in this cell with different value of alpha (start and end) and different number of time steps to initially guess and decide on ho
for batch in trainloader:
    repetitions = torch.tensor([total_timesteps]).repeat(minibatch_size)
    minibatch = batch[0][:minibatch_size,:,:].repeat_interleave(repetitions, dim=0)
    batch_size = len(minibatch)
    timesteps_to_display = torch.linspace(0, total_timesteps-1, total_timesteps, dtype=int).tolist() * minibatch_size
    noisy_images,_ = diffuser.noise_diffusion(minibatch, timesteps_to_display)
    display_images(images=noisy_images, n=batch_size, images_per_row=10, labels=list(map(lambda x: "time-step: " + str(x), timesteps_to_display
    break
```

```
cuda
```



EXERCISE 2: REVERSE DIFFUSION

Model Architecture

Implementing Skip Connections in U-Net Architecture

While the architecture of the U-Net is provided to you, a critical component—skip connections—needs to be integrated by you. The original paper, "U-Net: Convolutional Networks for Biomedical Image Segmentation" showcases the importance of these skip connections, as they allow the network to utilize features from earlier layers, making the segmentation more precise.

Placeholder for Skip Connections:

In the given architecture, you will find lines like the one below, which are the components of upsampling process in the U-Net:

```
y2 = self.afterup2(torch.cat([y2, torch.zeros_like(y2)], axis = 1))
```

Here, `torch.zeros_like(y2)` acts as a placeholder, indicating where the skip connection should be added. Your task is to replace this placeholder with the appropriate feature map from an earlier corresponding layer in the network.

Important Points to Keep in Mind:

- The U-Net architecture has multiple layers, so you'll need to repeat this process for each layer where skip connections are required.
- The provided helper function, `self.xLikeY(source, target)`, will be crucial in ensuring the feature maps you concatenate have matching dimensions.
- While the focus of this assignment is on crucial idea of stable diffusion, the U-Net architecture is provided to you but it is importatnt you implement skip connections, as understanding their role and significance in the U-Net architecture will be beneficial.
- ***Note: Feel free to modify architecture, parameters including number & types of layers used, kernel Sizes, padding, etc, you won't be judged on the architecture you use if you have the desired results post training.***

UNet Class

TO DO

Fill in `UNet` Class, ***Follow Instructions above***

```
class UNet(nn.Module):

    def __init__(self, in_channels, out_channels):
      """
      in_channels: input channels of the incoming image
      out_channels: output channels of the incoming image
      """
      super(UNet, self).__init__()

      #----------------------- Encoder -----------------------#
```

```
  ##############################################################################
  #        Initial Convolutions (Using doubleConvolution() function)          #
  #           Building Down Sampling Layers (Using Down() function)           #
  ##############################################################################
  self.ini = self.doubleConvolution(inC = in_channels, oC = 16)
  self.down1 = self.Down(inputC = 16, outputC = 32)
  self.down2 = self.Down(inputC = 32, outputC = 64)

  #------------------------ Decoder ------------------------#
  ##############################################################################
  #                         For each Upsampling block                          #
  #         Building Time Embeddings (Using timeEmbeddings() function)        #
  #       Building Up Sampling Layer (Using ConvTranspose2d() function)        #
  #       followed by Convolution (Using doubleConvolution() function)        #
  ##############################################################################

  self.time_emb2 = self.timeEmbeddings(1, 64)
  self.up2 = nn.ConvTranspose2d(in_channels=64, out_channels=32, kernel_size=3, stride=2)
  self.afterup2 = self.doubleConvolution(inC = 64 , oC = 32)

  self.time_emb1 = self.timeEmbeddings(1, 32)
  self.up1 = nn.ConvTranspose2d(in_channels=32, out_channels=16, kernel_size=3, stride=2)
  self.afterup1 = self.doubleConvolution(inC = 32 , oC = 16, kS1=5, kS2=4)

  #------------------------ OUTPUT ------------------------#
  ##############################################################################
  #            Constructing final Output Layer (Use Conv2d() function)         #
  ##############################################################################
  self.out = nn.Conv2d(in_channels=16, out_channels=out_channels, kernel_size=1, stride=1, padding=0)

def forward(self, x, t=None):
  assert t is not None

  #------------------------ Encoder ------------------------#
  ##############################################################################
  #                            Processing Inputs by                            #
  #                       performing Initial Convolutions                      #
  #                        followed by Down Sampling Layers                    #
  ##############################################################################
  x1 = self.ini(x)                  # Initial Double Convolution
  x2 = self.down1(x1)               # Downsampling followed by Double Convolution
  x3 = self.down2(x2)               # Downsampling followed by Double Convolution

  #------------------------ Decoder ------------------------#
  ##############################################################################
  #            For each Upsampling block, we add time Embeddings to            #
  #                   Feature Maps, process this by                            #
  #            Up Sampling followed by concatenation & Convolution             #
  ##############################################################################
  t2 = self.time_emb2(t)[:,:, None, None]
  y2 = self.up2(x3 + t2)                                                  # Upsampling
  # print("Shape of y2:", y2.shape)
  # print("Shape of reshaped x2:", self.xLikeY(y2, x2).shape)
  y2 = self.afterup2(torch.cat([y2, self.xLikeY(y2, x2)], axis = 1))                      # Crop corresponding Downsampled Feature Map, Do

  t1 = self.time_emb1(t)[:,:, None, None]
  y1 = self.up1(y2 + t1)
  # print("Shape of y1:", y1.shape)
  # print("Shape of reshaped x1:", self.xLikeY(y1, x1).shape)                                                                  # Upsampl
  y1 = self.afterup1(torch.cat([y1, self.xLikeY(y1, x1)], axis = 1))                      # Crop corresponding Downsampled Feature Map, Do

  #------------------------ OUTPUT ------------------------#
  ##############################################################################
  #                          Processing final Output                           #
  ##############################################################################
  outY = self.out(y1)               # Output Layer (ks-1, st-1, pa-0)

  return outY



#------------------------------------------------------------------------------------------------------ Helper Functions Within Model Class

def timeEmbeddings(self, inC, oSize):
  """
  inC: Input Size, (for example 1 for timestep)
  oSize: Output Size, (Number of channels you would like to match while upsampling)
  """
  return nn.Sequential(nn.Linear(inC, oSize),
                       nn.ReLU(),
                       nn.Linear(oSize, oSize))

def doubleConvolution(self, inC, oC, kS1=3, kS2=3, sT=1, pA=1):
```

```
    """
    Building Double Convolution as in original paper of Unet
    inC : inputChannels
    oC : outputChannels
    kS1 : Kernel_size of first convolution
    kS2 : Kernel_size of second convolution
    sT: stride
    pA: padding
    """
    return nn.Sequential(
          nn.Conv2d(in_channels= inC, out_channels=oC, kernel_size=kS1, stride=sT, padding=pA),
          nn.ReLU(inplace=True),
          nn.Conv2d(in_channels = oC,out_channels=oC, kernel_size=kS2, stride=sT, padding=pA),
          nn.ReLU(inplace=True),
    )


  def Down(self, inputC, outputC, dsKernelSize = None):
    """
    Building Down Sampling Part of the Unet Architecture (Using MaxPool) followed by double convolution
    inputC : inputChannels
    outputC : outputChannels
    """

    return nn.Sequential(
        nn.MaxPool2d(2),
        self.doubleConvolution(inC = inputC, oC = outputC)
    )


  def xLikeY(self, source, target):
    """
    Helper function to resize the downsampled x's to concatenate with upsampled y's as in Unet Paper
    source: tensor whose shape will be considered ---------UPSAMPLED TENSOR (y)
    target: tensor whose shape will be modified to align with target ---------DOWNSAMPLED TENSOR (x)
    """
    # x1 = source
    # x2 = target
    # diffY = x2.size()[2] - x1.size()[2]
    # diffX = x2.size()[3] - x1.size()[3]
    # x1 = F.pad(x1, [diffX // 2, diffX - diffX // 2, diffY // 2, diffY - diffY // 2])
    # return x1

    upsample = source
    downsample = target
    diffY = upsample.size()[2] - downsample.size()[2]
    diffX = upsample.size()[3] - downsample.size()[3]
    downsample = F.pad(downsample, [diffX // 2, diffX - diffX // 2, diffY // 2, diffY - diffY // 2])
    return downsample
```

Testing UNet Class (SANITY CHECK)

```
# SANITY CHECK FOR UnetBottleNeck (Single Channeled B/W Images)
in_channels_arg = 1
out_channels_arg = 1
batch_size = 32
height = 28
width = 28
total_timesteps = 50

# Check if CUDA is available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Positional Encoding Object
timesteps_to_display = torch.randint(0, total_timesteps, (batch_size,), device=device).long().tolist()

# Sanity check
x = torch.randn((batch_size, in_channels_arg, height, width)).to(device)
model = UNet(in_channels=in_channels_arg, out_channels=out_channels_arg)
model = model.to(device)

y = model.forward(x = x, t = torch.tensor(timesteps_to_display).to(torch.float32).cuda().view(-1,1))
assert len(x.shape) == len(y.shape)
assert y.shape == (batch_size, out_channels_arg, height, width)

print("Sanity Check for Single Channel B/W Images")
print("Shape of the input : ", x.shape)
```

```
print("Shape of the output : ", y.shape)
```

```
Input dtype in model: torch.float32
Sanity Check for Single Channel B/W Images
Shape of the input :  torch.Size([32, 1, 28, 28])
Shape of the output :  torch.Size([32, 1, 28, 28])
```

```
# SANITY CHECK FOR UnetBottleNeck (Colored Images)
in_channels_arg = 3
out_channels_arg = 1
batch_size = 32
height = 28
width = 28

# Check if CUDA is available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Positional Encoding Object
timesteps_to_display = torch.randint(0, total_timesteps, (batch_size,), device=device).long().tolist()

# Sanity check
x = torch.randn((batch_size, in_channels_arg, height, width)).to(device)
model = UNet(in_channels=in_channels_arg, out_channels=out_channels_arg)
model = model.to(device)

y = model.forward(x=x, t = torch.tensor(timesteps_to_display).to(torch.float32).cuda().view(-1,1))
assert len(x.shape) == len(y.shape)
assert y.shape == (batch_size, out_channels_arg, height, width)

print("Sanity Check for Multi-channel or colored Images")
print("Shape of the input : ", x.shape)
print("Shape of the output : ", y.shape)
```

```
Input dtype in model: torch.float32
Sanity Check for Multi-channel or colored Images
Shape of the input :  torch.Size([32, 3, 28, 28])
Shape of the output :  torch.Size([32, 1, 28, 28])
```

```
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)

num_params = count_parameters(model)
print(f"The model has {num_params:,} trainable parameters.")
```

```
The model has 145,233 trainable parameters.
```

Train the Model

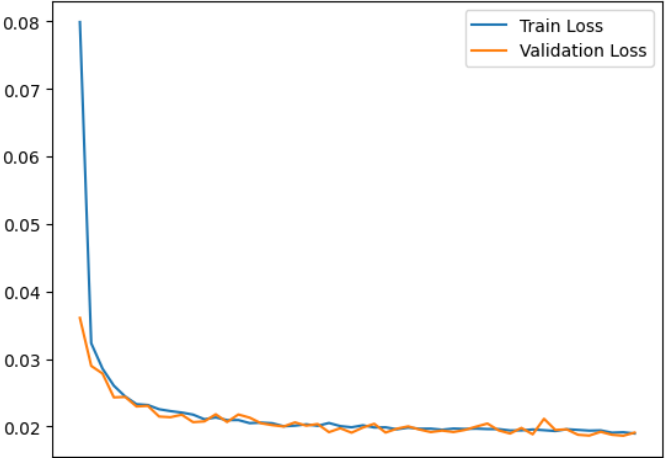
In the following block, the train function is defined. You have to calculate the noisy data, feed forward through the model and pass the predicted noise and true noise to the criterion to calculate the loss.

```
from tqdm import tqdm

def train(model, train_loader, val_loader, optimizer, criterion, device, num_epochs, diffuser, totalTrainingTimesteps):
    """
    model: Object of Unet Model to train
    train_loader: Training batches of the total data
    val_loader: Validation batches of the total data
    optimizer: The backpropagation technique
    criterion: Loas Function
    device: CPU or GPU
    num_epochs: total number of training loops
    diffuser: NoiseDiffusion class object to perform Forward diffusion
    totalTrainingTimesteps: Total number of forward diffusion timesteps the model is to be trained on
    """

    train_losses = []
    val_losses = []

    for epoch in range(num_epochs):
        model.train()
        total_train_loss = 0

        # Wrapping your loader with tqdm to display progress bar
        train_progress_bar = tqdm(enumerate(train_loader), total=len(train_loader), desc=f"Epoch {epoch+1}/{num_epochs} [Train]", leave=False)
```

```
    for batch_idx, (data, _) in train_progress_bar:
        data = data.to(device)
        optimizer.zero_grad()

        # Use a random time step for training
        batch_size = len(data)
        timesteps = torch.randint(0, totalTrainingTimesteps, (batch_size,), device=device).long().tolist()
        # timesteps = torch.randint(0, totalTrainingTimesteps, (batch_size,), device=device).long()
        # timesteps = timesteps.view(-1, 1)  # This reshapes it to [batch_size, 1]
        # print("Shape of Timesteps", timesteps.shape)


        ##############################################################################
        #                                TO DO                                       #
        #                    Calculate Noisy data, True noise                        #
        #                and Predicted Noise, & then feed it to criterion            #
        ##############################################################################
        # raise NotImplementedError
        # print("Data dtype:", data.dtype)
        # print("Timesteps dtype:", timesteps.dtype)
        # timesteps = torch.Tensor(timesteps).to(torch.float32)
        # timesteps = timesteps.view(-1, 1)
        noisy_data, true_noise = diffuser.noise_diffusion(data, timesteps)
        predicted_noise = model(noisy_data, t = torch.Tensor(timesteps).to(device).to(torch.float32).view(-1, 1))


        loss = criterion(predicted_noise, true_noise)
        loss.backward()
        optimizer.step()
        total_train_loss += loss.item()
        train_progress_bar.set_postfix({'Train Loss': f'{loss.item():.4f}'})

    avg_train_loss = total_train_loss / len(train_loader)
    train_losses.append(avg_train_loss)

    # Validation
    model.eval()
    total_val_loss = 0

    # Wrapping your validation loader with tqdm to display progress bar
    val_progress_bar = tqdm(enumerate(val_loader), total=len(val_loader), desc=f"Epoch {epoch+1}/{num_epochs} [Val]", leave=False)
    with torch.no_grad():
        for batch_idx, (data, _) in val_progress_bar:
            data = data.to(device)

            # For simplicity, we can use the same random timestep for validation
            batch_size = len(data)
            timesteps = torch.randint(0, totalTrainingTimesteps, (batch_size,), device=device).long().tolist()
            # timesteps = torch.randint(0, totalTrainingTimesteps, (batch_size,), device=device).long()
            # timesteps = timesteps.view(-1, 1)  # This reshapes it to [batch_size, 1]
            # print("Shape of Timesteps", timesteps.shape)

            ##############################################################################
            #                                TO DO                                       #
            #                    Calculate Noisy data, True noise                        #
            #                and Predicted Noise, & then feed it to criterion            #
            ##############################################################################
            # raise NotImplementedError
            # print("Data dtype:", data.dtype)
            # print("Timesteps dtype:", timesteps.dtype)
            # timesteps = torch.Tensor(timesteps).to(torch.float32)
            # timesteps = timesteps.view(-1, 1)
            noisy_data, true_noise = diffuser.noise_diffusion(data, timesteps)
            predicted_noise = model(noisy_data, t = torch.Tensor(timesteps).to(device).to(torch.float32).view(-1, 1))

            loss = criterion(predicted_noise, true_noise)
            total_val_loss += loss.item()
            val_progress_bar.set_postfix({'Val Loss': f'{loss.item():.4f}'})

    avg_val_loss = total_val_loss / len(val_loader)
    val_losses.append(avg_val_loss)

    print(f'Epoch {epoch+1}/{num_epochs}, Train Loss: {avg_train_loss:.4f}, Validation Loss: {avg_val_loss:.4f}')

return train_losses, val_losses
```

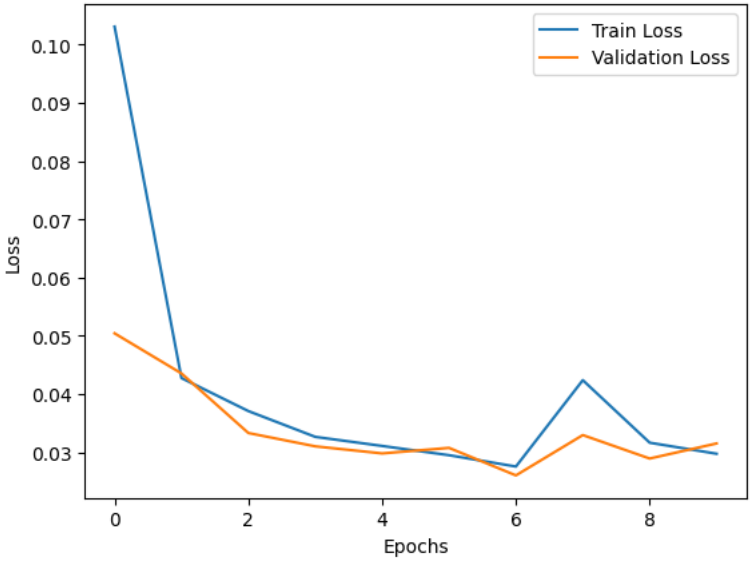
▾ In the following code block, initialize the necessary variables and then Execute to train, save model and plot the loss

Just to give you an idea of how loss curve would look like approximately (not necssarily same for everybody), x-axis represents epochs and y-axis represents loss.




```
#############################################################################
#                                TO DO                                      #
#                      Initialize the Constants below                       #
#############################################################################
"""
- `total_time_steps`: Total time steps of forward diffusion
- `start_beta`: Initial point of Noise Level Parameter
- `end_beta`: End point of Noise Level Parameter
- `inputChannels`: 1 for Grayscale Images (Since we're Using MNIST)
- `outputChannels`: How many channels of predicted noise are aiming for? THINK!
- `num_epochs`: How many epochs are you training for? (*We'd love to see best results in minimum epcohs of training*)
"""
# raise NotImplementedError
total_timesteps = 100
startBeta, endBeta = 0.001, 0.3
inputChannels, outputChannels = 1, 1
num_epochs = 10

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

#############################################################################
#                                TO DO                                      #
#                           Initialize the Model                            #
#                         Initialize the Optimizer                          #
#                       Initialize the Loss Function                        #
#                        Initialize the NoiseDiffuser                       #
#############################################################################
# raise NotImplementedError
stableDiffusionModel = UNet(inputChannels, outputChannels).to(device)
optimizer = torch.optim.Adam(stableDiffusionModel.parameters(), lr=0.001)
criterion = torch.nn.MSELoss()
diffuser = NoiseDiffuser(startBeta, endBeta, total_timesteps, device)

#############################################################################
#                                TO DO                                      #
#                 Execute this Block, Train & Save the Model                #
#                            And Plot the Progress                          #
#############################################################################
stableDiffusionModel = stableDiffusionModel.to(device)
train_losses, val_losses = train(model= stableDiffusionModel,
                                 train_loader= trainloader,
                                 val_loader= valloader,
                                 optimizer= optimizer,
                                 criterion= criterion,
                                 device= device,
                                 num_epochs= num_epochs,
                                 diffuser= diffuser,
                                 totalTrainingTimesteps=total_timesteps)

# Save the model
torch.save(stableDiffusionModel.state_dict(), 'HW3SDModel.pth')

#Plot the losses
import matplotlib.pyplot as plt
plt.plot(train_losses, label='Train Loss')
plt.plot(val_losses, label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
Epoch 1/10, Train Loss: 0.1031, Validation Loss: 0.0504
Epoch 2/10, Train Loss: 0.0427, Validation Loss: 0.0435
Epoch 3/10, Train Loss: 0.0371, Validation Loss: 0.0333
Epoch 4/10, Train Loss: 0.0326, Validation Loss: 0.0310
Epoch 5/10, Train Loss: 0.0311, Validation Loss: 0.0298
Epoch 6/10, Train Loss: 0.0295, Validation Loss: 0.0307
Epoch 7/10, Train Loss: 0.0275, Validation Loss: 0.0260
Epoch 8/10, Train Loss: 0.0424, Validation Loss: 0.0329
Epoch 9/10, Train Loss: 0.0316, Validation Loss: 0.0289
Epoch 10/10, Train Loss: 0.0297, Validation Loss: 0.0315
```



EXERCISE 3 : SAMLING GENERATION

Sampling formula

The Stable Diffusion Model sampling code involves generating images from a trained model by iteratively denoising an initial random noise tensor. This process is executed in the reverse manner as compared to the diffusion process, where the noise is incrementally added. The iteration happens for a defined number of timesteps. The goal is to move from a purely noisy state to a clear, denoised state that represents a valid sample from the data distribution learned by the model. Refer to the DDPMs Paper for detailed documentation. The formula for sampling part is as follows:

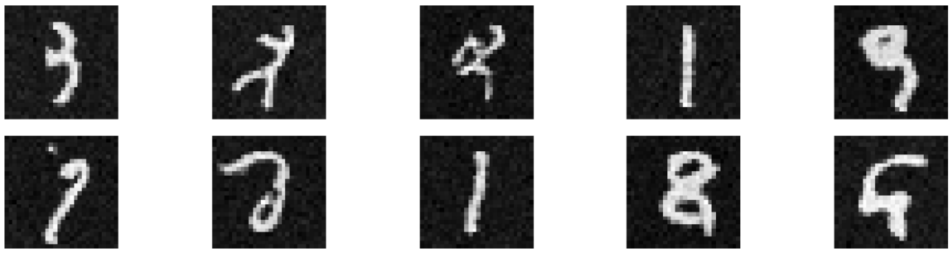
$$X_{t-1} = \frac{1}{\sqrt{\alpha}} * \left(X_t - \frac{1-\alpha}{\sqrt{(1-\bar{\alpha})}} * \epsilon_t \right) + \sqrt{\beta} * z$$

The z term ensures that the denoising process doesn't just converge to a single deterministic point, but instead produces a variety of samples from the model's learned distribution.

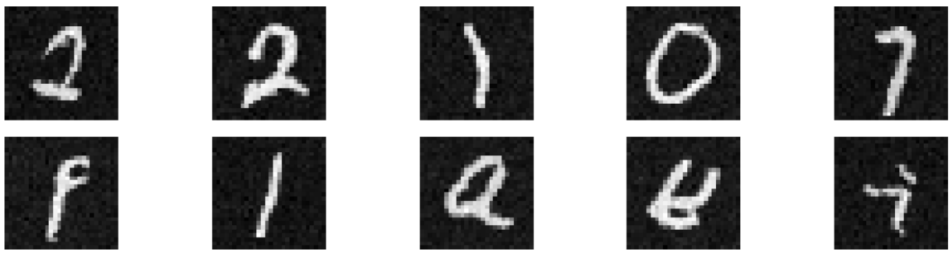
Sample Images

Some sample outputs for random seeds as specified in the code cell of sampling generation and mentioned in the image below are as follows:

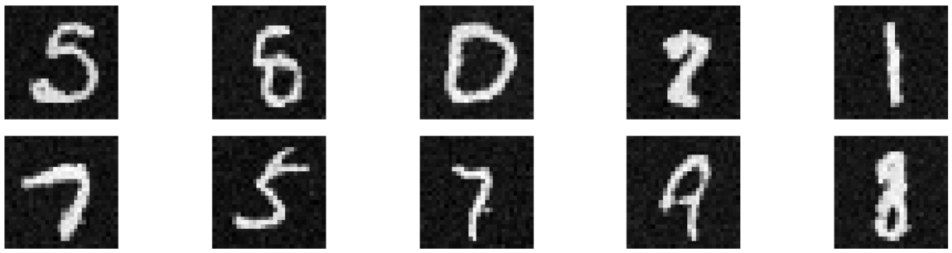
The Outputs for Random Seed {96}



The Outputs for Random Seed {786}



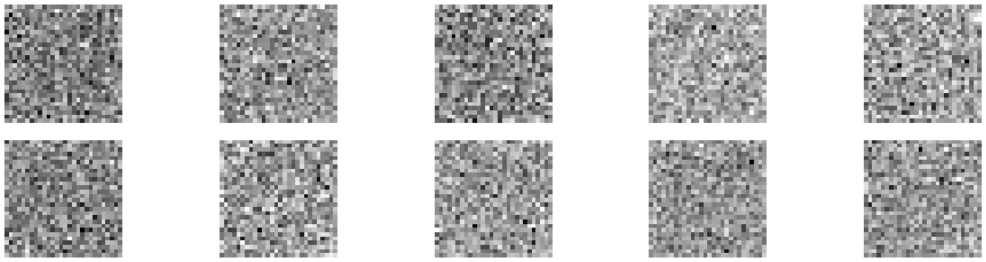
The Outputs for Random Seed {7150}



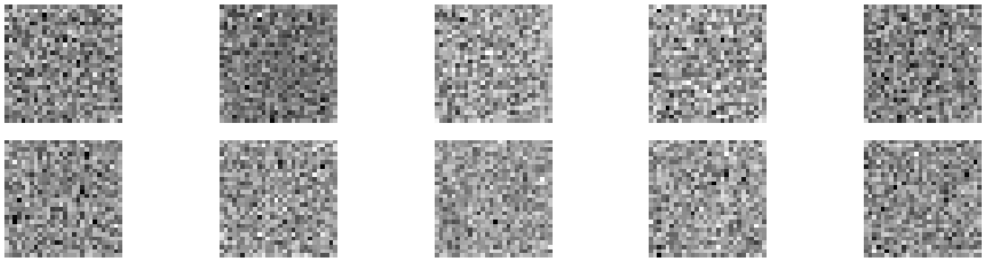
```
def generate_samples(x_t, model, num_samples, total_timesteps, diffuser, device):
    """
    Generate samples using the trained DDPM model.

    Parameters:
    - model: Trained UNetBottleneck model.
    - num_samples: Number of samples to generate.
    - total_timesteps: Total timesteps for the noise process.
    - diffuser: Instance of NoiseDiffuser.
    - device: Computing device (e.g., "cuda" or "cpu").

    Returns:
    - generated_samples: A tensor containing the generated samples.
    """



    # Varibales required by Sampling Formula
    # one_by_sqrt_alpha = 1 / torch.sqrt(diffuser.alphas)
    # beta_by_sqrt_one_minus_alpha_cumprod = diffuser.betas / torch.sqrt(1 - diffuser.alpha_bar)
    one_by_sqrt_alpha = 1 / torch.sqrt(diffuser.alphas)
    beta_by_sqrt_one_minus_alpha_cumprod = diffuser.betas / torch.sqrt(1 - diffuser.alpha_bar)

    ###############################################################################
    #                                  TO DO                                      #
    #                Implement the Sampling Algorithm, start with                 #
    #                   pure noise, using the trained model                       #
    #                 perform denoising to generate MNIST Images                  #
    ###############################################################################
    # Iterate in reverse order to "denoise" the samples
    for timestep in range(total_timesteps-1, -1, -1):
        z = torch.randn_like(x_t)
        epsilon_t = model(x_t, torch.Tensor([timestep]).to(device).to(torch.float32).view(-1, 1))
        x_t_minus_1 = one_by_sqrt_alpha[timestep] * (x_t - (1 - diffuser.alphas[timestep]) / torch.sqrt(1 - diffuser.alpha_bar[timestep]) * eps
        x_t = x_t_minus_1

    return x_t.detach()


###############################################################################
#                                  TO DO                                      #
#                Post Implementation of Sampling Algorithm,                   #
#                       Execute the following lines by                        #
#           using the same constants (timesteps and beta values)              #
#                         as you used while training,                         #
#                initializing instance of NoiseDiffuser Object                #
#                     and Loading the pretrained model                        #
```

```
#########################################################################
# Create instance of NoiseDiffuser
diffuser = NoiseDiffuser(start_beta=startBeta, end_beta=endBeta, total_steps=total_timesteps, device= device)
# Using the function:
model_path = 'HW3SDModel.pth'
model = UNet(in_channels=inputChannels, out_channels=outputChannels).to(device)
model.load_state_dict(torch.load(model_path))
model.eval()



SEED = [ 96, 786, 7150]  # You can set any integer value for the seed

for S in SEED:
  print("The Outputs for Random Seed {%d}"%S)
  # Set seed for both CPU and CUDA devices
  torch.manual_seed(S)
  if torch.cuda.is_available():
      torch.cuda.manual_seed(S)
      torch.cuda.manual_seed_all(S)
      torch.backends.cudnn.deterministic = True
      torch.backends.cudnn.benchmark = False

  num_samples_to_generate = 10
  # Initialize with random noise
  xt = torch.randn((num_samples_to_generate, 1, 28, 28), device=device)


  samples = generate_samples(xt, model, num_samples_to_generate, total_timesteps, diffuser, device)

  # Display the generated samples
  display_images(samples, num_samples_to_generate, images_per_row=5)
  print("end")
```

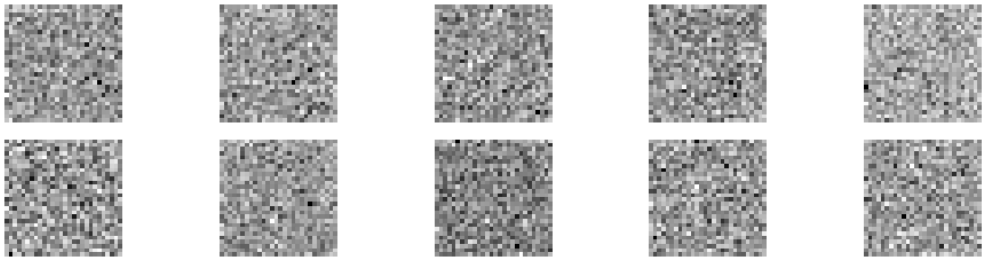
```
The Outputs for Random Seed {96}
```



```
end
The Outputs for Random Seed {786}
```



```
end
The Outputs for Random Seed {7150}
```



```
end
```

This can be run [run on Google Colab using this link]

```
!pip install git+https://github.com/davidbau/baukit
```

```
Collecting git+https://github.com/davidbau/baukit
  Cloning https://github.com/davidbau/baukit to /tmp/pip-req-build-pqx8wck0
  Running command git clone --filter=blob:none --quiet https://github.com/davidbau/baukit /tmp/pip-req-build-pqx8wck0
  Resolved https://github.com/davidbau/baukit to commit 5e23007c02fd58f063200c5dc9033e90f092630d
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Installing backend dependencies ... done
  Preparing metadata (pyproject.toml) ... done
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from baukit==0.0.1) (1.23.5)
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (from baukit==0.0.1) (2.1.0+cu118)
Requirement already satisfied: torchvision in /usr/local/lib/python3.10/dist-packages (from baukit==0.0.1) (0.16.0+cu118)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch->baukit==0.0.1) (3.12.4)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-packages (from torch->baukit==0.0.1) (4.5.0)
Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch->baukit==0.0.1) (1.12)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch->baukit==0.0.1) (3.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from torch->baukit==0.0.1) (3.1.2)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from torch->baukit==0.0.1) (2023.6.0)
Requirement already satisfied: triton==2.1.0 in /usr/local/lib/python3.10/dist-packages (from torch->baukit==0.0.1) (2.1.0)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from torchvision->baukit==0.0.1) (2.31.0)
Requirement already satisfied: pillow!=8.3.*,>=5.3.0 in /usr/local/lib/python3.10/dist-packages (from torchvision->baukit==0.0.1) (9.4.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch->baukit==0.0.1) (2.1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->torchvision->baukit==0.
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->torchvision->baukit==0.0.1) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->torchvision->baukit==0.0.1) (
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->torchvision->baukit==0.0.1) (
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/dist-packages (from sympy->torch->baukit==0.0.1) (1.3.0)
Building wheels for collected packages: baukit
  Building wheel for baukit (pyproject.toml) ... done
  Created wheel for baukit: filename=baukit-0.0.1-py3-none-any.whl size=59669 sha256=ade007b2e9f75a6b0887dda988fe04383fcc910ba944116a6eb96
  Stored in directory: /tmp/pip-ephem-wheel-cache-3p865lsl/wheels/e2/7a/dc/eb53bf0e7f86297d7d9759d9eba117036e850e1bfc3bda0176
Successfully built baukit
Installing collected packages: baukit
Successfully installed baukit-0.0.1
```

```
import torch, os, PIL.Image, numpy
from torchvision.models import alexnet, resnet18, resnet101, resnet152, efficientnet_b1
from torchvision.transforms import Compose, ToTensor, Normalize, Resize, CenterCrop
from torchvision.datasets.utils import download_and_extract_archive
from baukit import ImageFolderSet, show, renormalize, set_requires_grad, Trace, pbar
from torchvision.datasets.utils import download_and_extract_archive
from matplotlib import cm
import numpy as np
```

```
%%bash

wget -N https://cs7150.baulab.info/2022-Fall/data/dog-and-cat-example.jpg
wget -N https://cs7150.baulab.info/2022-Fall/data/hungry-cat.jpg
```

```
--2023-10-19 23:05:22--  https://cs7150.baulab.info/2022-Fall/data/dog-and-cat-example.jpg
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: 144079 (141K) [image/jpeg]
Saving to: ‘dog-and-cat-example.jpg’

     0K .......... .......... .......... .......... .......... 35%  243K 0s
    50K .......... .......... .......... .......... .......... 71%  483K 0s
   100K .......... .......... .......... ..........           100% 35.2M=0.3s

2023-10-19 23:05:23 (453 KB/s) - ‘dog-and-cat-example.jpg’ saved [144079/144079]

--2023-10-19 23:05:23--  https://cs7150.baulab.info/2022-Fall/data/hungry-cat.jpg
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: 22651 (22K) [image/jpeg]
Saving to: ‘hungry-cat.jpg’

     0K .......... .......... ..                              100%  217K=0.1s

2023-10-19 23:05:24 (217 KB/s) - ‘hungry-cat.jpg’ saved [22651/22651]
```

Visualizing the behavior of a convolutional network

Here we briefly overview some of the major categories of methods for visualizing the behavior of a convolutional network classifier: occlusion, gradients, class activation maps (CAM), and dissection.

Let's define some utility functions for manipulating images. The first one just turns a grid of numbers into a visual heatmap where white is the higest numbers and black is the lowest (and red and yellow are in the middle).

Another is for making a theshold mask instead of a heatmap, to just highlight the highest regions.

And then another one creates an overlay between two images.

With these in hand, we can create some salience map visualizations.

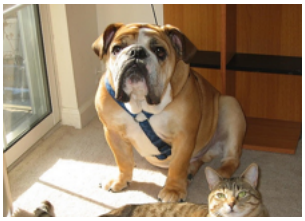
```
def rgb_heatmap(data, size=None, colormap='hot', amax=None, amin=None, mode='bicubic', symmetric=False):
    size = spec_size(size)
    mapping = getattr(cm, colormap)
    scaled = torch.nn.functional.interpolate(data[None, None], size=size, mode=mode)[0,0]
    if amax is None: amax = data.max()
    if amin is None: amin = data.min()
    if symmetric:
        amax = max(amax, -amin)
        amin = min(amin, -amax)
    normed = (scaled - amin) / (amax - amin + 1e-10)
    return PIL.Image.fromarray((255 * mapping(normed)).astype('uint8'))

def rgb_threshold(data, size=None, mode='bicubic', p=0.2):
    size = spec_size(size)
    scaled = torch.nn.functional.interpolate(data[None, None], size=size, mode=mode)[0,0]
    ordered = scaled.view(-1).sort()[0]
    threshold = ordered[int(len(ordered) * (1-p))]
    result = numpy.tile((scaled > threshold)[:,:,None], (1, 1, 3))
    return PIL.Image.fromarray((255 * result).astype('uint8'))

def overlay(im1, im2, alpha=0.5):
    import numpy
    return PIL.Image.fromarray((
        numpy.array(im1)[...,:3] * alpha +
        numpy.array(im2)[...,:3] * (1 - alpha)).astype('uint8'))

def overlay_threshold(im1, im2, alpha=0.5):
    import numpy
    return PIL.Image.fromarray((
        numpy.array(im1)[...,:3] * (1 - numpy.array(im2)[...,:3]/255) * alpha +
        numpy.array(im2)[...,:3] * (numpy.array(im1)[...,:3]/255)).astype('uint8'))

def spec_size(size):
    if isinstance(size, int): dims = (size, size)
    if isinstance(size, torch.Tensor): size = size.shape[:2]
    if isinstance(size, PIL.Image.Image): size = (size.size[1], size.size[0])
    if size is None: size = (224, 224)
    return size

def resize_and_crop(im, d):
    if im.size[0] >= im.size[1]:
        im = im.resize((int(im.size[0]/im.size[1]*d), d))
        return im.crop(((im.size[0] - d) // 2, 0, (im.size[0] + d) // 2, d))
    else:
        im = im.resize((d, int(im.size[1]/im.size[9]*d)))
        return im.crop((0, (im.size[1] - d) // 2, d, (im.size[1] + d) // 2))
```

Loading a pretrained classifier and an example image

Here is an example image, and an example network.

We will look at a resnet18. You could do any network, e.g. try a resnet152...

```
im = resize_and_crop(PIL.Image.open('dog-and-cat-example.jpg'), 224)
show(im)
data = renormalize.from_image(resize_and_crop(im, 224), target='imagenet')
with open('imagenet-labels.txt') as r:
    labels = [line.split(',')[1].strip() for line in r.readlines()]
net = resnet18(pretrained=True)
net.eval()
set_requires_grad(False, net)
```



Visualization using occlusion

First, let's try a method suggested by Zeiler 2014. Slide a window across the image and test each version.

https://arxiv.org/pdf/1311.2901.pdf

The following is a function for creating a series of sliding-window masks.

```
def sliding_window(dims=None, window=1, stride=1, hole=True):
    dims = spec_size(dims)
    assert(len(dims) == 2)
    for y in range(0, dims[0], stride):
        for x in range(0, dims[1], stride):
            mask = torch.zeros(*dims)
            mask[y:y+window, x:x+window] = 1
            if hole:
                mask = 1 - mask
            yield mask
```

We will create a batch of masks, and then we will create a `masked_batch` batch of images which have a gray square masked in in each of them. We will create some 196 versions of this masked image.

Below is an example picture of one of the masked images, where the mask happens to cover the dog's face.

```
masks = torch.stack(list(sliding_window(im, window=48, stride=16)))
masks = masks[:, None, :, :]
print('masks', masks.shape)

masked_batch = data * masks
print('masked_batch', masked_batch.shape)

show(renormalize.as_image(masked_batch[19]))
```

```
masks torch.Size([196, 1, 224, 224])
masked_batch torch.Size([196, 3, 224, 224])
```

Now let's run the network to get its predictions.

But also we will run the network on each of the masked images.

Notice that this image is guessed as both a dog ('boxer') and cat ('tiger cat').

```
base_preds = net(data[None])
masked_preds = net(masked_batch)
[(labels[i], i.item()) for i in base_preds.topk(dim=1, k=5, sorted=True)[1][0]]
```

```
[('boxer', 242),
 ('bull mastiff', 243),
 ('tiger cat', 282),
 ('American Staffordshire terrier', 180),
 ('French bulldog', 245)]
```

Exercise 3.3.1: What are the predictions of the network for the masked image shown above? Print them out like we did above. What do you think happened here? Give your thoughts

```
predictions_19th_mask = masked_preds[19]
top5_preds_19th_mask = [(labels[i], i.item()) for i in predictions_19th_mask.topk(k=5, sorted=True)[1]]
print(top5_preds_19th_mask)

# The original top prediction 'boxer' is now not in the top 5 and the prediction for a general dog category has also decreased,
# while there's more prediction on a cat. I think the region we covered hides the features that coould allow the model to know it's actually a
# As the particular patterns for a dog disappear, the model becomes more confident on its prediction of a cat.
```

```
[('tiger cat', 282), ('tabby', 281), ('Egyptian cat', 285), ('bull mastiff', 243), ('American Staffordshire terrier', 180)]
```

Exercise 3.3.2: For each of the masked image, we have predictions.

- Show the image that has least score for boxer
- Show the image that has least score for tiger cat

```
boxer_index = labels.index('boxer')
tiger_cat_index = labels.index('tiger cat')

boxer_least_score_index = masked_preds[:, boxer_index].argmin().item()
tiger_cat_least_score_index = masked_preds[:, tiger_cat_index].argmin().item()

show(renormalize.as_image(masked_batch[boxer_least_score_index]))
show(renormalize.as_image(masked_batch[tiger_cat_least_score_index]))
```

Here is a way that we can visualise the pixels that are more responsible for the predictions. It's something similar you did above in Exercise 3.3.2

```
for c in ['boxer', 'tiger cat']:
    heatmap = (base_preds[:,labels.index(c)]-masked_preds[:,labels.index(c)]).view(14,14)
    show(show.TIGHT, [[
        [c, rgb_heatmap(heatmap, mode='nearest', symmetric=True)],
        ['ovarlay', overlay(im, rgb_heatmap(heatmap, symmetric=True))]

    ]])
```

boxer ovarlay

Visualization using smoothgrad

Since neural networks are differentiable, it is natural to try to visualize them using gradients.

One simple method is smoothgrad (Smilkov 2017), which examines gradients of perturbed inputs.

https://arxiv.org/pdf/1706.03825.pdf

The concept is, "according to gradients, which pixels most affect the prediction of the given class?"

Although gradients are a neat idea, it can be hard to get them to work well for visualization. See Adebayo 2018

https://arxiv.org/pdf/1810.03292.pdf

Exercise 3.3.3: In this exercise, we will see the gradient wrt to the image. Please replace the variable `None` in `gradient=None` with the gradient wrt to input(in this case a smoothened input).

```
for label in ['boxer', 'tiger cat']:
    total = 0
    # SmoothGrad perturbs the image multiple times (with small noise) and computes gradients for each perturbed version.
    for i in range(20):
        prober = data + torch.randn(data.shape) * 0.2
        prober.requires_grad = True
        loss = torch.nn.functional.cross_entropy(
            net(prober[None]),
            torch.tensor([labels.index(label)]))
        loss.backward()


        gradient = prober.grad # TO-DO (Replace None with the gradient wrt to the perturbed input)

        # pixels with larger values in total grad have stronger influence on the model's prediction
        total += gradient**2
        prober.grad = None

    show(show.TIGHT, [[
        [label,
         renormalize.as_image(data, source='imagenet')],
        ['total grad**2',
         renormalize.as_image((total / total.max() * 5).clamp(0, 1), source='pt')],
        ['overlay',
         overlay(renormalize.as_image(data, source='imagenet'),
                 renormalize.as_image((total / total.max() * 5).clamp(0, 1), source='pt'))]
    ]])
```

Single neuron dissection

In this code, we ask "What does a single kind of neuron detect", e.g., the neurons of the 100th convolutional filter of the layer4.0.conv1 layer of resnet18.

To see that, we use dissection to visualize the neurons (Bau 2017).

https://arxiv.org/pdf/1704.05796.pdf

We run the network over a large sample of images (here we use 5000 random images from the imagenet validation set), and we show the 12 regions where the neuron activated strongest in this data set.

Can you see a pattern for neuron 100? What about for neuron 200 or neuron 50?

Some neurons activate on more than one concept. Some neurons are more understandable than others.

Below, we begin by loading the data set.

```
if not os.path.isdir('imagenet_val_5k'):
    download_and_extract_archive('https://cs7150.baulab.info/2022-Fall/data/imagenet_val_5k.zip',
                                 'imagenet_val_5k')
ds = ImageFolderSet('imagenet_val_5k', shuffle=True, transform=Compose([
    Resize(256),
    CenterCrop(224),
    ToTensor(),
    renormalize.NORMALIZER['imagenet']
]))
```

```
Downloading https://cs7150.baulab.info/2022-Fall/data/imagenet_val_5k.zip to imagenet_val_5k/imagenet_val_5k.zip
100%|██████████| 50757954/50757954 [00:02<00:00, 24062997.41it/s]
Extracting imagenet_val_5k/imagenet_val_5k.zip to imagenet_val_5k
```

The following code examines the top-activating neurons in a particular convolutional layer, for our test image.

Which is the first neuron that activates for the cat but not the dog?

Let's dissect the first filter output of the layer4.1.conv1 and see what's happening

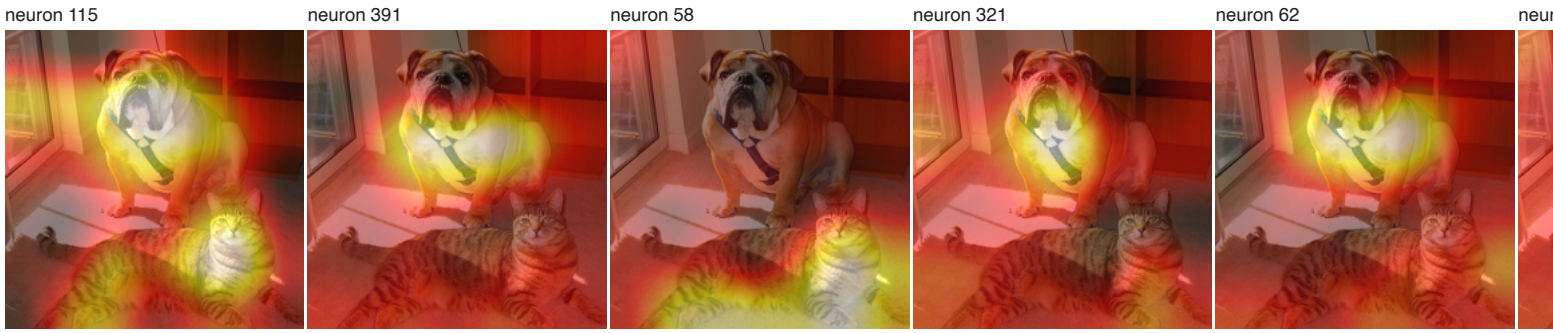
```
layer = 'layer4.1.conv1'
unit_num = 0
with Trace(net, layer) as tr:
    preds = net(data[None])
show(show.WRAP, [[f'neuron {unit_num}',
        overlay(im, rgb_heatmap(tr.output[0, unit_num]))]
    ])
```

neuron 0

Exercise 3.3: The above representation is for filter 0. Now visualise the top 12 filters that activate the most.
[Hint: To do this, we recommend using max values of each filter and show the top 12 filters]

```
def get_top_filters_activation(net, data, layer, top_k=12):
    with Trace(net, layer) as tr:
        preds = net(data[None])

    # Get the maximum activation for each filter
    max_activations = tr.output[0].max(dim=-1).values.max(dim=-1).values
    # Get the indices of target filters
    top_filters_indices = max_activations.argsort(descending=True)[:top_k]

    return top_filters_indices

# Get the top 12 filters that activate the most
```

```
top_12_filters = get_top_filters_activation(net, data, layer, top_k=12)

visualizations = []
for unit_num in top_12_filters:
    with Trace(net, layer) as tr:
        preds = net(data[None])
    visualizations.append([f'neuron {unit_num}', overlay(im, rgb_heatmap(tr.output[0, unit_num]))])

# show the outputs of single neurons
show(show.WRAP, visualizations)
```



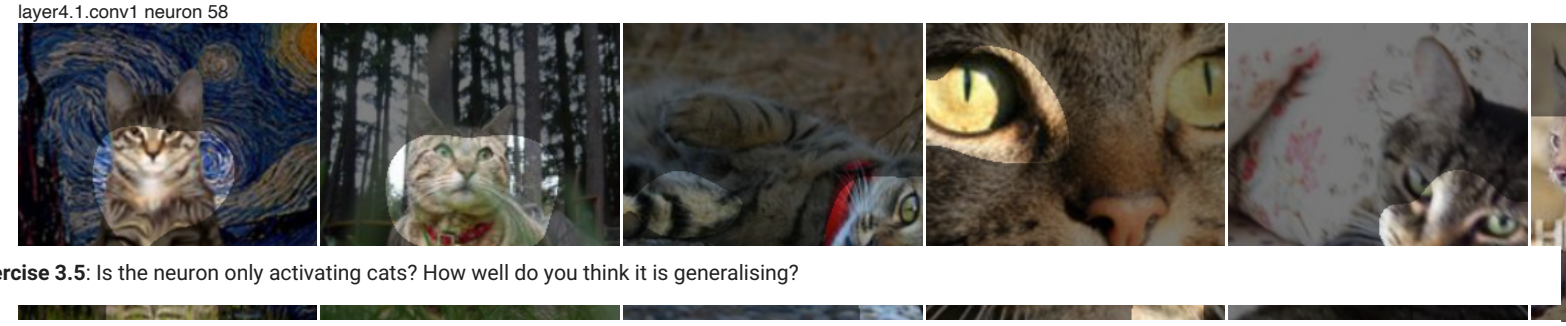
Exercise 3.4: Which of the top filters is activating the cat more?

Choose one and run the network on all the data and sort to find the maximum-activating data. Let's see how the neuron you found to be top activating generalizes. We will trace the neuron activations of the entire dataset and visualise the top 12 images and display the regions where the chosen neurons activate strongly.

Here we select neuron number 0 in layer4.1.conv1 to show how you can do it. Replace it with the number you found.

```
def dissect_unit(ds, i, net, layer, unit):
    data = ds[i][0]
    with Trace(net, layer) as tr:
        net(data[None])
    mask = rgb_threshold(tr.output[0, unit], size=data.shape[-2:])
    img = renormalize.as_image(data, source=ds)
    return overlay_threshold(img, mask)

neuron = 58
scores = []
for imagenum, [d,] in enumerate(pbar(ds)):
    with Trace(net, layer) as tr:
        _ = net(d[None])
    score = tr.output[0, neuron].view(-1).max()
    scores.append((score, imagenum))
scores.sort(reverse=True)

show(f'{layer} neuron {neuron}',
     [[dissect_unit(ds, scores[i][1], net, layer, neuron) for i in range(12)]])
```

layer4.1.conv1 neuron 58



Exercise 3.5: Is the neuron only activating cats? How well do you think it is generalising?

No, as the output from the previous question shows, the neuron also activates other items such as kids' arms, fox and vehicles. It does generalize a bit but I don't think it generalize well. It can do a pretty good job at identifying some patterns related to cats such as cat-like face (fox) and other animals' tails looking simialr to cats'. Looks like it has its own specilization. As we can also see, 6 out of 12 pictures above are strongly cat-related and 8 out of them can be said to be genrally cat-related.

Visualization using grad-cam

Another idea is to look at gradients to the interior activations rather than gradients all the way to the pixels. CAM (Zhou 2015) and Grad-CAM (Selvaraju 2016) do that.

https://arxiv.org/pdf/1512.04150.pdf https://arxiv.org/pdf/1610.02391.pdf

Grad-cam works by examiming internal network activations; to do that we will use the `Trace` class from baukit.

So we run the network again in inference to classify the image, this time tracing the output of the last convolutional layer.

```
with Trace(net, 'layer4') as tr:
    preds = net(data[None])
print('The output of layer4 is a set of neuron activations of shape', tr.output.shape)
```

```
The output of layer4 is a set of neuron activations of shape torch.Size([1, 512, 7, 7])
```

How can we make sense of these 512-dimenaional vectors? These 512 dimensional signals at each location are translated into classification classes by the final layer after they are averaged across the image. Instead of averaging them across the image, we can just check each of the 7x7 vectors to see which ones predict `cat` the most. Or we can do the same thing for `dog` (`boxer`).

The first step is to get the neuron weights for the cat and the dog neuron.

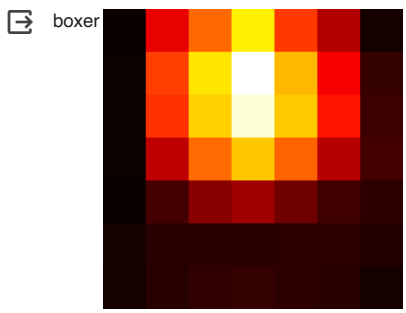
```
boxer_weights = net.fc.weight[labels.index('boxer')]
```

Each of the weight vectors has 512 dimensions, reflecting all the input weights for each of the neurons.

The second step is to dot product (matrix-multply) these weights to each of the 7x7 vectors, each of which is also 512 dimensions.

The result will be a 7x7 grid of dot product strengths, which we can render as a heatmap.

```
boxer_heatmap = torch.einsum('bcyx, c -> yx', tr.output, boxer_weights)

show(show.TIGHT,
     [
       ['boxer',
        rgb_heatmap(boxer_heatmap, mode='nearest')]])
```



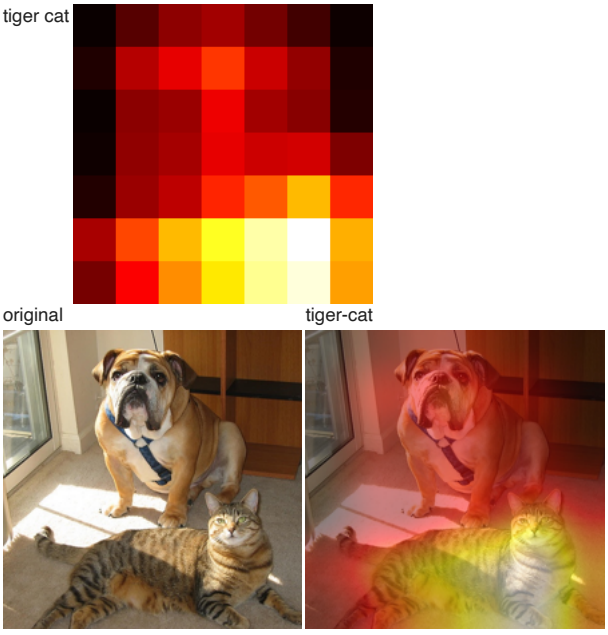
In the following code we smooth the heatmaps and overlay them on top of the original image.

```
show(show.TIGHT,
    [['original', im],
     ['boxer', overlay(im, rgb_heatmap(boxer_heatmap, im))]
    ]]
```

)

Exercise 3.6: Repeat the grad-cam to visualise the tiger-cat class

```
tigercat_index = labels.index('tiger cat')
tigercat_weights = net.fc.weight[tigercat_index]

tigercat_heatmap = torch.einsum('bcyx, c -> yx', tr.output, tigercat_weights)

# Displaying the heatmap directly
show(show.TIGHT, [['tiger cat', rgb_heatmap(tigercat_heatmap, mode='nearest')]])

# Overlaying the heatmap on the original image
show(show.TIGHT,
        [[['original', im],
         ['tiger-cat', overlay(im, rgb_heatmap(tigercat_heatmap, im))]
         ]]
        )
```

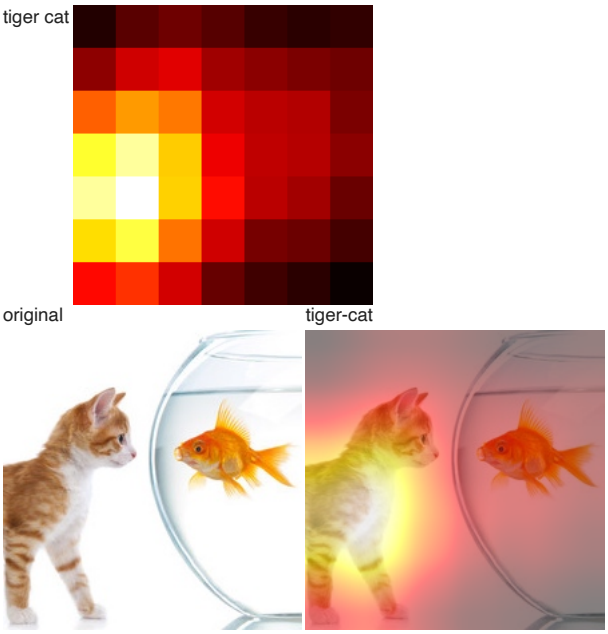


Exercise 3.6: Now consider the image hungry-cat.jpg

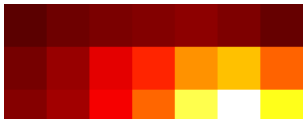
Load the image `hungry-cat.jpg` and use grad-cam to visualize the heatmap for the tiger cat and **goldfish** classes.

```
# Type your solution here

im = resize_and_crop(PIL.Image.open('hungry-cat.jpg'), 224)
show(im)

data = renormalize.from_image(resize_and_crop(im, 224), target='imagenet')

with Trace(net, 'layer4') as tr:
    preds = net(data[None])
```

```
tigercat_index = labels.index('tiger cat')
tigercat_weights = net.fc.weight[tigercat_index]

tigercat_heatmap = torch.einsum('bcyx, c -> yx', tr.output, tigercat_weights)

# Displaying the heatmap directly
show(show.TIGHT, [['tiger cat', rgb_heatmap(tigercat_heatmap, mode='nearest')]])

# Overlaying the heatmap on the original image
show(show.TIGHT,
        [[['original', im],
         ['tiger-cat', overlay(im, rgb_heatmap(tigercat_heatmap, im))]
         ]]
        )
```




```
goldfish_index = labels.index('goldfish')
goldfish_weights = net.fc.weight[goldfish_index]

goldfish_heatmap = torch.einsum('bcyx, c -> yx', tr.output, goldfish_weights)

# Displaying the heatmap directly
show(show.TIGHT, [['goldfish', rgb_heatmap(goldfish_heatmap, mode='nearest')]])

# Overlaying the heatmap on the original image
show(show.TIGHT,
        [[['original', im],
         ['goldfish', overlay(im, rgb_heatmap(goldfish_heatmap, im))]
         ]]
        )
```

goldfish 

Start coding or generate with AI.

original goldfish