

cs 7180 Algorithmic and Statistical Aspects of Deep Learning
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Problem Set 1

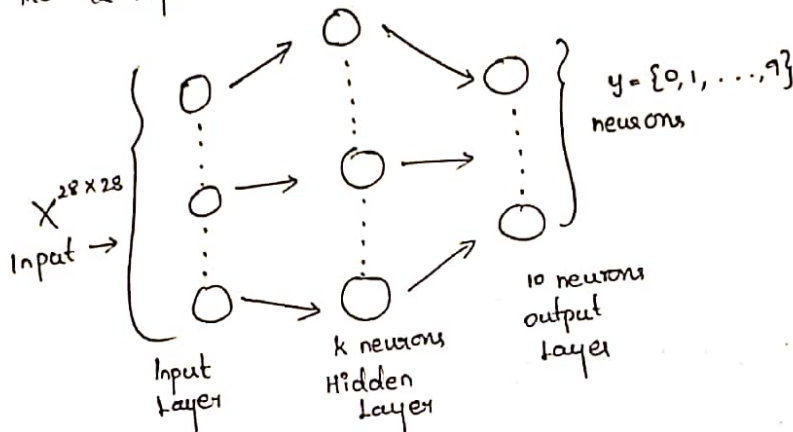
1) w_1 and w_2 denote the weight matrices of each layer.

Sample $\rightarrow x \in \mathbb{R}^{28 \times 28}$

label $\rightarrow y \in \{0, 1, 2, \dots, 9\}$

$y_{\text{pred}} = ?$

Let the 2 layer neural network architecture be like,



Equation of y_{pred} as a function of w_1 and w_2 , given input x is written as,
output from hidden layer $\Rightarrow \text{ReLU}(w_1 \cdot x)$
 $[w_{\text{input-hidden}}] \cdot \mathbb{P/P} \rightarrow$ input of output layer along with weights and activation.

$$y_{\text{pred}} = \text{ReLU}[w_2(\text{ReLU}(w_1 \cdot x + b_1)) + b_2]$$

x - input matrix of size 784×1

b_1 and b_2 are bias vector.

ReLU - activation function

w_1 - weight matrix of size $k \times 784$

w_2 - weight matrix of size $10 \times k$

$$\begin{aligned} \text{Output of hidden layer} &\Rightarrow \text{ReLU}(w_1 \cdot x) \\ &\Rightarrow \text{ReLU}([k \times 784] \cdot [784 \times 1]) \end{aligned}$$

$$x_2 = \text{ReLU}[k \times 1]$$

$$\text{hidden layer to output layer} = \text{ReLU}(w_2 \cdot x_2)$$

$$\begin{aligned} &\Rightarrow \text{ReLU}([10 \times k] \cdot [k \times 1]) \\ \text{output} &= \text{ReLU}[10 \times 1] \end{aligned}$$

1b) Given:

$(x_1, y_1), \dots, (x_m, y_m)$ where $m = 50,000$ - training data

$$x_i \in \mathbb{R}^{28 \times 28}$$

$$y_i \in \{0, 1, \dots, 9\}, i = 1 \dots m$$

Loss of predicted label compared to correct label = ?

Here, optimization of the network refers to, reducing the loss of predicted label and bringing close to correct label.

Cross-entropy is widely used loss function for optimizing classification models. So let's minimize that.

Cross-entropy equation,

$$L(w) = - \left[\sum_{i=1}^m \sum_{k=1}^{10} \mathbb{I}\{y_i = k\} \log \frac{\exp(w_k^T x_i)}{\sum_{j=1}^{10} \exp(w_j^T x_i)} \right]$$

where $\mathbb{I}\{y_i = k\}$ - indicator function

$W - w_1$ and w_2 weight matrices together

k - no. of classes.

$L(w)$ - loss

Prob 2 a)

Given:

w_1, w_2 - weight matrices of the network

ReLU activation and

Quadratic loss function is used.

Training data $= (x_1, y_1), \dots, (x_m, y_m)$

$$x_i \in \mathbb{R}^{28 \times 28 \times 3}$$

$$y_i \in \mathbb{R}$$

Training loss,

$$L(w) = \frac{\sum_{i=1}^m (y_i - y_{(i)}^{\text{pred}})^2}{m}$$

$y_{(i)}^{\text{pred}}$ can be written as $[\text{ReLU}(w_2(\text{ReLU}(w_1 \cdot x_i + b_1)) + b_2)]$

[referred from prob 1 a)]

2b) Backpropagation algorithm.

Back-propagation is the practice of fine-tuning the weights of neural net based on the error rate obtained in the previous epoch)
loss.

Neural networks uses back propagation as a learning algorithm. It is used to calculate derivatives quickly. The weights are updated backwards, from output towards input.

Proper tuning of weights results in lower error rates, making the model more reliable by generalizing it.

This algorithm looks for minimum value of the error function in the weight space using a technique called delta rule (or) gradient descent.
[Gradient descent is an iterative optimization algorithm for finding the minimum of a function (error function)]

The error function derivation for w_1 & w_2 ,

$$\frac{\partial L(w)}{\partial w_2} = \frac{\partial L(w)}{\partial y_{\text{pred}}} \cdot \frac{\partial y_{\text{pred}}}{\partial w_2}.$$

$$\frac{\partial L(w)}{\partial w_2} = \frac{\partial L(w)}{\partial o} \cdot \frac{\partial o}{\partial z} \cdot \frac{\partial z}{\partial w_2}$$

Forward Pass: \downarrow $\begin{cases} o_2 = \text{ReLU}(w_2 (\text{ReLU}(w_1 x + b_1)) + b_2) \\ o_1 = \text{ReLU}(w_1 x + b_1) \\ z = w_1 x + b_1 \end{cases} [o_1 \text{ and } o_2]$

Backward Pass: computing gradients,

$$\frac{\partial L(w)}{\partial w_2} = \frac{\partial L(w)}{\partial o} \cdot \frac{\partial o}{\partial z} \cdot \frac{\partial z}{\partial w_2}$$

$$\therefore \frac{\partial L(w)}{\partial w_2} \Rightarrow \frac{\partial L(w)}{\partial o_2} \cdot \frac{\partial o_2}{\partial w_2}$$

$$\frac{\partial L(w)}{\partial w_1} = \frac{\partial L(w)}{\partial o_2} \cdot \frac{\partial o_2}{\partial o_1} \cdot \frac{\partial o_1}{\partial z} \cdot \frac{\partial z}{\partial w_1}$$

PS1-MNIST-Handout

October 3, 2020

1 CS7180 Problem Set 1: Implement a two-layer neural network to recognize hand-written digits (40 points)

Welcome to CS7180!

Before you start, make sure to read the problem description in the handout pdf.

```
[1]: # Uncomment the below line and run to install required packages if you have not
    ↪ done so

    # !pip install torch torchvision matplotlib tqdm
```

```
[2]: # pip install torch
```

```
[17]: # Setup
import torch
import matplotlib.pyplot as plt
from torchvision import datasets, transforms
from tqdm import trange
from torch.autograd import Variable

%matplotlib inline
DEVICE = 'cuda' if torch.cuda.is_available() else 'cpu'

# Set random seed for reproducibility
seed = 1234
# cuDNN uses nondeterministic algorithms, set some options for reproducibility
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False
torch.manual_seed(seed)
```

```
[17]: <torch._C.Generator at 0x2ddc1192030>
```

1.1 Get MNIST Data

The `torchvision` package provides a wrapper to download MNIST data. The cell below downloads the training and test datasets and creates dataloaders for each.

```
[18]: # Initial transform (convert to PyTorch Tensor only)
transform = transforms.Compose([
    transforms.ToTensor(),
])

train_data = datasets.MNIST('data', train=True, download=True,
    ↪transform=transform)
test_data = datasets.MNIST('data', train=False, download=True,
    ↪transform=transform)

# Calculate training data mean and standard deviation to apply normalization to
    ↪data
# train_data.data are of type uint8 (range 0,255) so divide by 255.
# train_mean = train_data.data.double().mean() / 255.
# train_std = train_data.data.double().std() / 255.
# print(f'Train Data: Mean={train_mean}, Std={train_std}')

# Perform normalization of train and test data using calculated training mean
    ↪and standard deviation
# This will convert data to be in the range [-1, 1]
#transform = transforms.Compose([
#    transforms.ToTensor(),
#    transforms.Normalize((train_mean, ), (train_std, ))
#])
train_data.transform = transform
test_data.transform = transform

batch_size = 64
torch.manual_seed(seed)
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,
    ↪shuffle=True, num_workers=True)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size,
    ↪shuffle=False, num_workers=True)
```

1.2 Part 0: Inspect dataset (0 points)

```
[19]: test_data
```

```
[19]: Dataset MNIST
      Number of datapoints: 10000
      Root location: data
      Split: Test
      StandardTransform
      Transform: Compose(
          ToTensor()
      )
```

```
[20]: # Randomly sample 20 images of the training dataset
# To visualize the i-th sample, use the following code
# > plt.subplot(4, 5, i+1)
# > plt.imshow(images[i].squeeze(), cmap='gray', interpolation='none')
# > plt.title(f'Label: {labels[i]}', fontsize=14)
# > plt.axis('off')

images, labels = iter(train_loader).next()

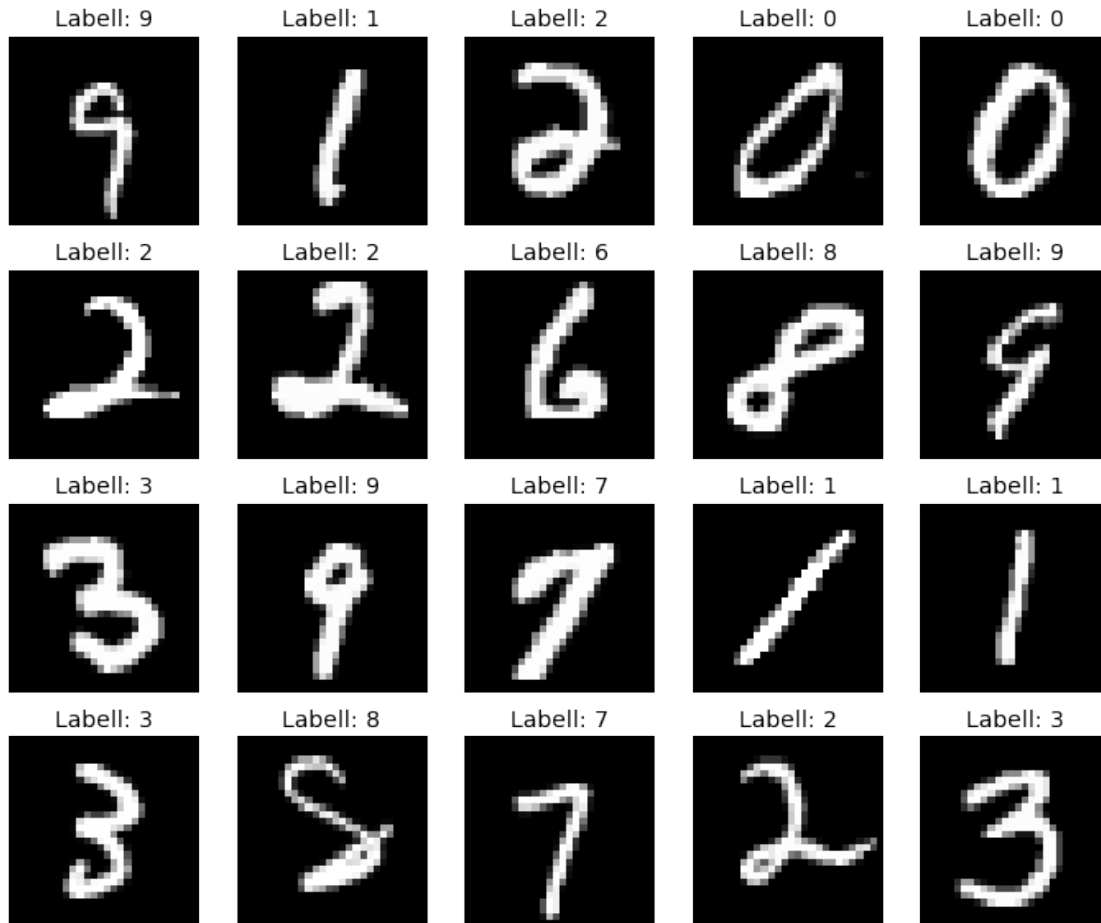
# Print information and statistics of the first batch of images
print("Images shape: ", images.shape)
print("Labels shape: ", labels.shape)
print(f'Mean={images.mean()}, Std={images.std()}')

fig = plt.figure(figsize=(12, 10))
# -----

for i in range(20):
    plt.subplot(4, 5, i+1)
    plt.imshow(images[i].squeeze(), cmap='gray', interpolation='none')
    plt.title(f'Label: {labels[i]}', fontsize=14)
    plt.axis('off')

# -----

Images shape:  torch.Size([64, 1, 28, 28])
Labels shape:  torch.Size([64])
Mean=0.12825286388397217, Std=0.3058689832687378
```

1.3 Part 1: Implement a two-layer neural network (10 points)

Write a class that constructs a two-layer neural network as specified in the handout. The class consists of two methods, an initialization that sets up the architecture of the model, and a forward pass function given an input feature.

```
[21]: input_size = 1 * 28 * 28  # input spatial dimension of images
      hidden_size = 128         # width of hidden layer
      output_size = 10         # number of output neurons

class MNISTClassifierMLP(torch.nn.Module):

    def __init__(self):

        super().__init__()
        self.flatten = torch.nn.Flatten(start_dim=1)

        # -----
```

```

        # Linear layer obtaining input to the hidden layer from the input layer
        self.fc1 = torch.nn.Linear(input_size,hidden_size)

        # Applying activation to the output of hidden layer before feeding into
        ↪ final layer
        self.act = torch.nn.ReLU()

        # Linear layer -> narrowing to 10 outputs from hidden layer
        self.fc2 = torch.nn.Linear(hidden_size,output_size)

        # Prevent overfitting
        # self.dropout = torch.nn.Dropout(0.2)
        self.log_softmax = torch.nn.LogSoftmax(dim=1)

        # -----

    def forward(self, x):
        # Input image is of shape [batch_size, 1, 28, 28]
        # Need to flatten to [batch_size, 784] before feeding to fc1
        x = self.flatten(x)

        # -----

        x = self.act(self.fc1(x))
        x = self.act(x)
        x = self.fc2(x)
        x = self.log_softmax(x)
        y_output = x

        return y_output

        # -----

model = MNISTClassifierMLP().to(DEVICE)

# sanity check
print(model)

```

```

MNISTClassifierMLP(
  (flatten): Flatten()
  (fc1): Linear(in_features=784, out_features=128, bias=True)
  (act): ReLU()
  (fc2): Linear(in_features=128, out_features=10, bias=True)
  (log_softmax): LogSoftmax()
)

```


1.4 Part 2: Implement an optimizer to train the neural net model (10 points)

Write a method called `train_one_epoch` that runs one step using the optimizer.

```
[22]: def train_one_epoch(train_loader, model, device, optimizer, log_interval,
    ↪epoch):
    model.train()
    losses = []
    counter = []

    for i, (img, label) in enumerate(train_loader):
        img, label = img.to(device), label.to(device)

#         img, label = Variable(img), Variable(label)
#         # clear the gradients of all optimized variables
        optimizer.zero_grad()
#         # forward pass: compute predicted outputs by passing inputs to the model
        output = model(img)
#         # calculate the loss
        loss = torch.nn.functional.nll_loss(output, label)
#         # backward pass: compute gradient of the loss with respect to model
    ↪parameters
        loss.backward()
#         # perform a single optimization step (parameter update)
        optimizer.step()

#         # Record training loss every log_interval and keep counter of total
    ↪training images seen
        if (i+1) % log_interval == 0:
            losses.append(loss.item())
            counter.append(
                (i * batch_size) + img.size(0) + epoch * len(train_loader.
    ↪dataset))

    return losses, counter
```

1.5 Part 3: Run the optimization procedure and test the trained model (10 points)

Write a method called `test_one_epoch` that evaluates the trained model on the test dataset. Return the average test loss and the number of samples that the model predicts correctly.

```
[23]: def test_one_epoch(test_loader, model, device):
    model.eval()
    test_loss = 0
    num_correct = 0

#     model.eval()
```

```

with torch.no_grad():
    for i, (img, label) in enumerate(test_loader):
        img, label = img.to(device), label.to(device)

#         img, label = Variable(img), Variable(label)
        output = model(img)
        pred = output.argmax(dim=1)
        test_loss += torch.nn.functional.
        ↪nll_loss(output, label, reduction='sum').item()
        num_correct += pred.eq(label.view_as(pred)).sum().item()

test_loss /= len(test_loader.dataset)
#     test_loss /= len(test_loader)
return test_loss, num_correct

```

Train the model using the cell below. Hyperparameters are given.

```

[24]: # Hyperparameters
lr = 0.01
max_epochs=10
gamma = 0.95

# Recording data
log_interval = 100

# Instantiate optimizer (model was created in previous cell)
optimizer = torch.optim.SGD(model.parameters(), lr=lr)

train_losses = []
train_counter = []
test_losses = []
test_correct = []
for epoch in trange(max_epochs, leave=True, desc='Epochs'):
    train_loss, counter = train_one_epoch(train_loader, model, DEVICE, ↪
    ↪optimizer, log_interval, epoch)
    test_loss, num_correct = test_one_epoch(test_loader, model, DEVICE)

    # Record results
    train_losses.extend(train_loss)
    train_counter.extend(counter)
    test_losses.append(test_loss)
    test_correct.append(num_correct)

print(f"Test accuracy: {test_correct[-1]/len(test_loader.dataset)}")

```

Epochs:

100%|
10/10 [01:44<00:00, 10.44s/it]

Test accuracy: 0.9305

1.6 Part 4: Ablation studies (10 points)

1. Plot the loss curve as the number of epochs increases
2. Show the predictions of the first 20 images of the test set (4 points)
3. Show the first 20 images that the model predicted incorrectly. Discuss about some of the common scenarios that the model predicted incorrectly (4 points)
4. Go back to Part 0, where we created the transform component to apply on the training and test datasets. Re-run the code after normalizing the training and test dataset to have mean zero and unit variance. Report what you find (2 points)

```
[25]: # 1. Draw training loss curve
fig = plt.figure(figsize=(12,8))
plt.plot(train_counter, train_losses, label='Train loss')
plt.plot([i * len(train_loader.dataset) for i in range(1, max_epochs + 1)],
         test_losses, label='Test loss', marker='o')
plt.xlim(left=0)
plt.ylim(bottom=0)
plt.title('Loss curve', fontsize=24)
plt.xlabel('Number of training examples seen', fontsize=16)
plt.ylabel('NLL', fontsize=16)
plt.legend(loc='upper right', fontsize=14)
```

```
[25]: <matplotlib.legend.Legend at 0x2ddc419e608>
```



```
[26]: # 2. Show the predictions of the first 20 images of the test dataset
images, labels = iter(test_loader).next()
images, labels = images.to(DEVICE), labels.to(DEVICE)

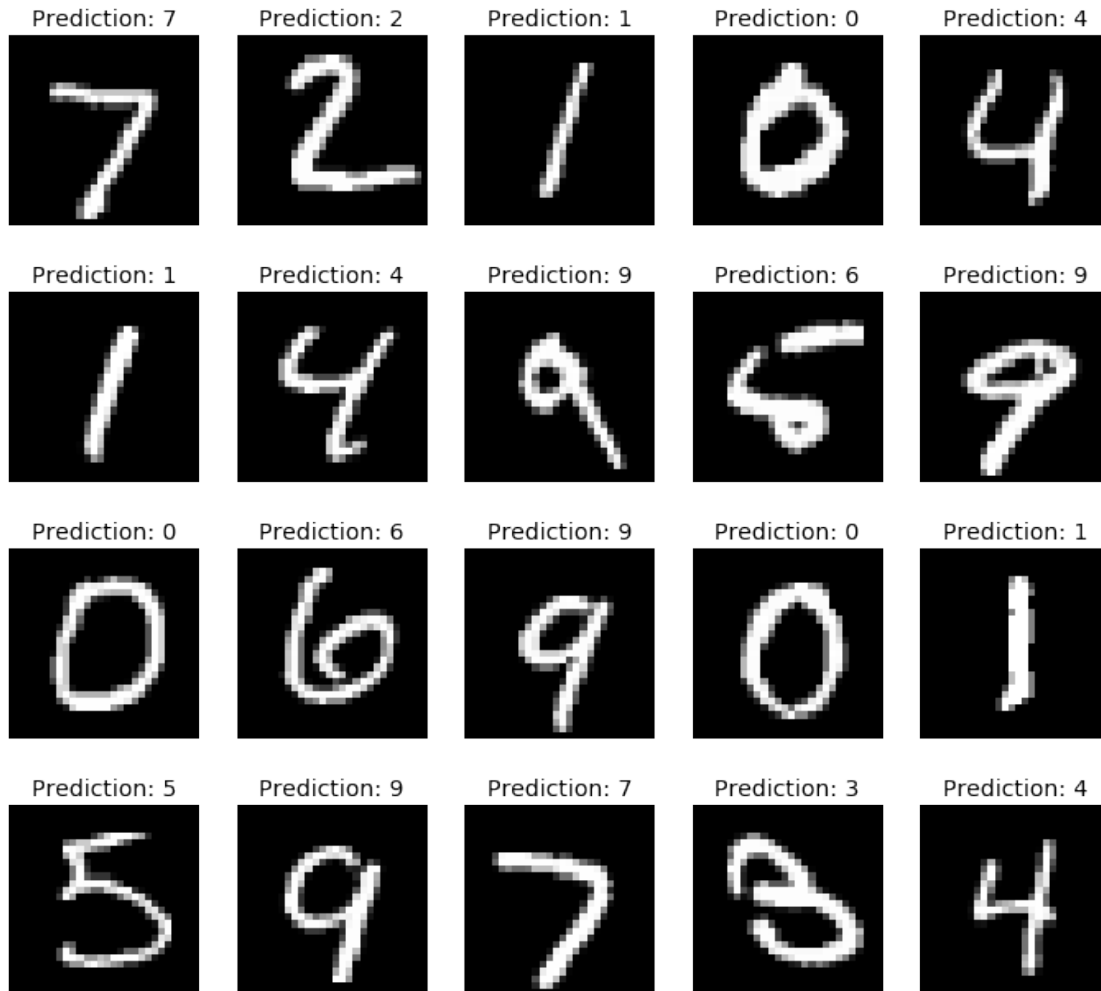
output = model(images)
pred = output.argmax(dim=1)

fig = plt.figure(figsize=(12, 11))

# -----
# Write your implementation here. Use the code provided in Part 0 to visualize
# the images.

for i in range(20):
    plt.subplot(4,5,i+1)
    plt.imshow(images[i].squeeze().cpu().numpy(), cmap='gray',
    interpolation='none')
    plt.title(f'Prediction: {pred[i]}',fontsize=14)
    plt.axis('off')

# -----
```



```
[27]: # 3. Get 20 incorrect predictions in test dataset

# Collect the images, predictions, labels for the first 20 incorrect predictions
# Initialize empty tensors and then keep appending to the tensor.
# Make sure that the first dimension of the tensors is the total number of
→incorrect
# predictions seen so far
# Ex) incorrect_imgs should be of shape i x C x H x W, where i is the total
→number of
# incorrect images so far.

incorrect_imgs = torch.Tensor().to(DEVICE)

# creating lists as we cannot append predictions and labels to tensor objects
incorrect_preds = []
incorrect_labels = []
```

```

with torch.no_grad():
    # Test set iterator
    it = iter(test_loader)
    # Loop over the test set batches until incorrect_imgs.size(0) >= 20
    while incorrect_imgs.size(0) < 20:
        images, labels = it.next()
        images, labels = images.to(DEVICE), labels.to(DEVICE)

        # -----
        # Write your implementation here.

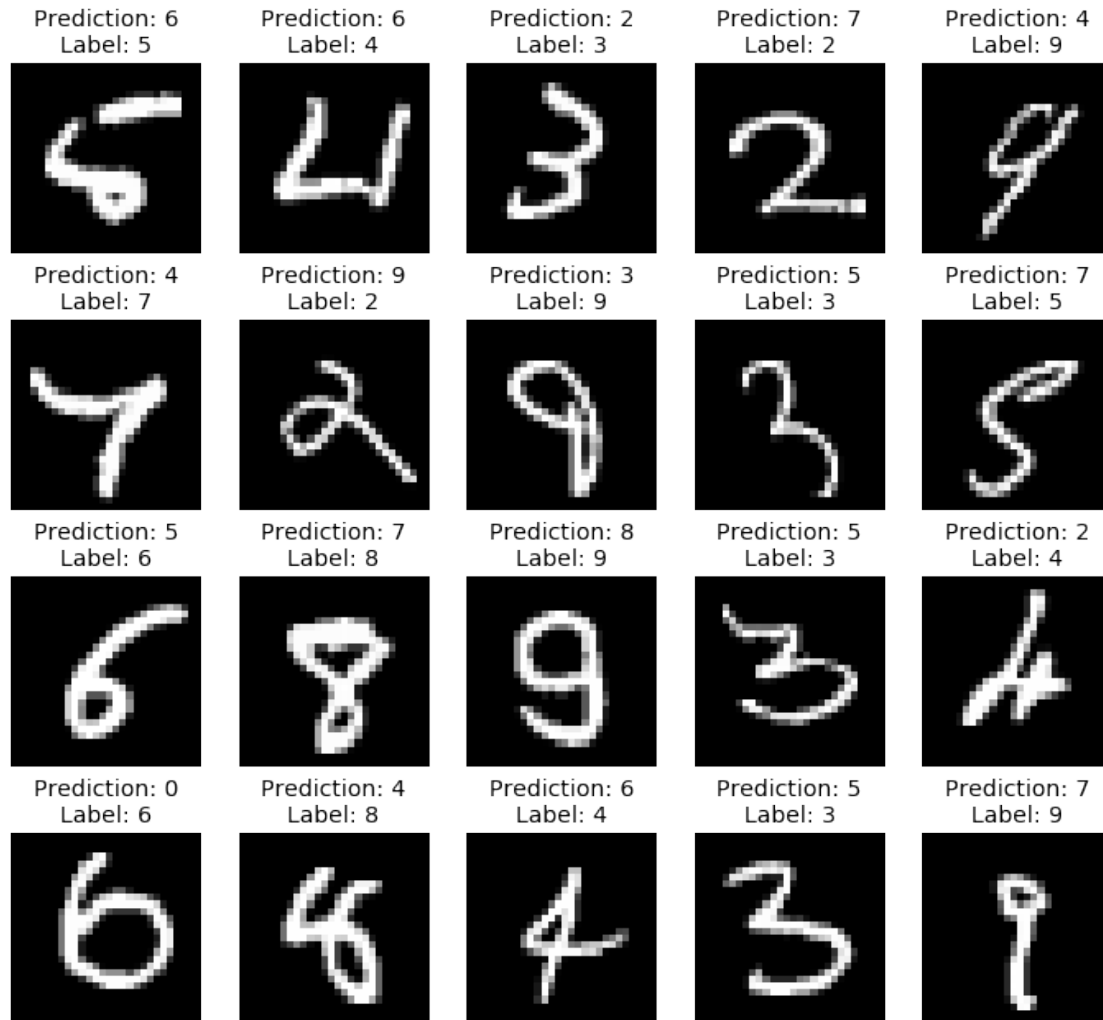
        output = model(images)
        pred = output.argmax(dim=1)

        # Compare prediction and true labels and append the incorrect_
→ predictions
        # using `torch.cat`.
        for index, i in enumerate(output):
            if pred[index] != labels[index]:
                incorrect_imgs = torch.cat([incorrect_imgs,
→ images[index]], dim=0)
                incorrect_preds.append(pred[index])
                incorrect_labels.append(labels[index])

        # -----

# Show the first 20 wrong predictions in test set
# incorrect_labels = str(incorrect_labels)
# incorrect_preds = str(incorrect_preds)
fig = plt.figure(figsize=(12, 11))
for i in range(20):
    plt.subplot(4, 5, i+1)
    plt.imshow(incorrect_imgs[i].squeeze().cpu().numpy(), cmap='gray',
→ interpolation='none')
    plt.title(f'Prediction: {incorrect_preds[i].item()}\nLabel:
→ {incorrect_labels[i].item()}', fontsize=14)
    plt.axis('off')

```



Discuss about some of the common scenarios that the model predicted incorrectly (4 points)

The numbers that are predicted incorrectly might be because of training data being too similar to each other, so when deployed on testing data gives poor accuracy.

Also, few digits are hard to recognize for human eyes.

MNSIT data is already somewhat preprocessed. So model might expect to preprocess our test images as well. (like normalizing the training and testing data in the same way). Can also follow PCA or normalizing by Z-score.

Go back to Part 0, where we created the transform component to apply on the training and test datasets. Re-run the code after normalizing the training and test dataset to have mean zero and unit variance. Report what you find (2 points)

```
[28]: # Initial transform (convert to PyTorch Tensor only)
transform = transforms.Compose([
    transforms.ToTensor(),
```



```

])

train_data = datasets.MNIST('data', train=True, download=True,
    ↳transform=transform)
test_data = datasets.MNIST('data', train=False, download=True,
    ↳transform=transform)

# Calculate training data mean and standard deviation to apply normalization to
    ↳data
# train_data.data are of type uint8 (range 0,255) so divide by 255.
train_mean = train_data.data.double().mean() / 255.
train_std = train_data.data.double().std() / 255.
print(f'Train Data: Mean={train_mean}, Std={train_std}')

# Perform normalization of train and test data using calculated training mean
    ↳and standard deviation
# This will convert data to be in the range [-1, 1]
transform = transforms.Compose([transforms.ToTensor(),transforms.
    ↳Normalize((train_mean, ), (train_std, ))])
train_data.transform = transform
test_data.transform = transform

batch_size = 64
torch.manual_seed(seed)
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size,
    ↳shuffle=True, num_workers=True)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size,
    ↳shuffle=False, num_workers=True)

```

Train Data: Mean=0.1306604762738429, Std=0.30810780717887876

```

[29]: # Hyperparameters
lr = 0.01
max_epochs=10
gamma = 0.95

# Recording data
log_interval = 100

# Instantiate optimizer (model was created in previous cell)
optimizer = torch.optim.SGD(model.parameters(), lr=lr)

train_losses = []
train_counter = []
test_losses = []
test_correct = []
for epoch in trange(max_epochs, leave=True, desc='Epochs'):

```

```

    train_loss, counter = train_one_epoch(train_loader, model, DEVICE,
    ↪optimizer, log_interval, epoch)
    test_loss, num_correct = test_one_epoch(test_loader, model, DEVICE)

    # Record results
    train_losses.extend(train_loss)
    train_counter.extend(counter)
    test_losses.append(test_loss)
    test_correct.append(num_correct)

print(f"Test accuracy: {test_correct[-1]/len(test_loader.dataset)}")

```

Epochs:

100%|

|

10/10 [02:38<00:00, 15.80s/it]

Test accuracy: 0.968

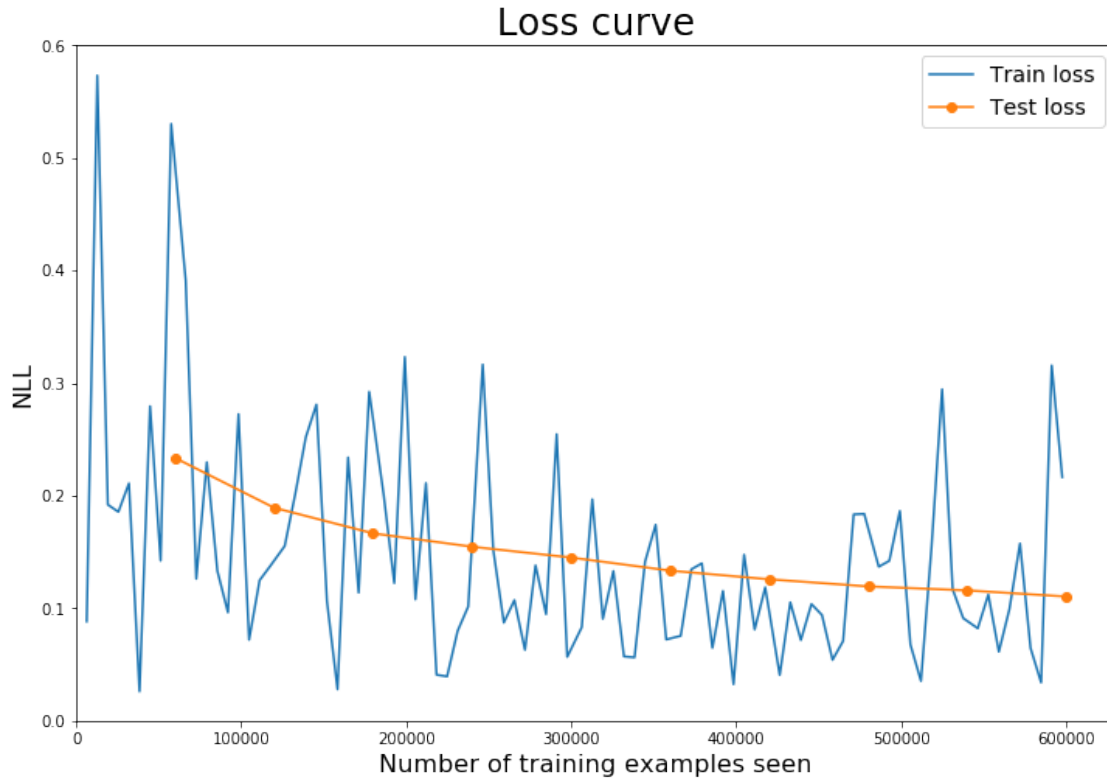
The accuracy of the model has however improved from 0.93 to 0.96.

```

[30]: # 1. Draw training loss curve
fig = plt.figure(figsize=(12,8))
plt.plot(train_counter, train_losses, label='Train loss')
plt.plot([i * len(train_loader.dataset) for i in range(1, max_epochs + 1)],
         test_losses, label='Test loss', marker='o')
plt.xlim(left=0)
plt.ylim(bottom=0)
plt.title('Loss curve', fontsize=24)
plt.xlabel('Number of training examples seen', fontsize=16)
plt.ylabel('NLL', fontsize=16)
plt.legend(loc='upper right', fontsize=14)

```

[30]: <matplotlib.legend.Legend at 0x2ddc66a0d08>



The curve depicts that the train loss is fluctuating with samples but the test loss is decreasing with increase in samples or examples. The pattern is quite similar to what we obtained before normalizing our data but the numbers and depth of curves vary slightly. Say the test loss is going below 0.2 in the above plot whereas before normalizing it was between 0.3 to 0.5

```
[31]: # 2. Show the predictions of the first 20 images of the test dataset
images, labels = iter(test_loader).next()
images, labels = images.to(DEVICE), labels.to(DEVICE)

output = model(images)
pred = output.argmax(dim=1)

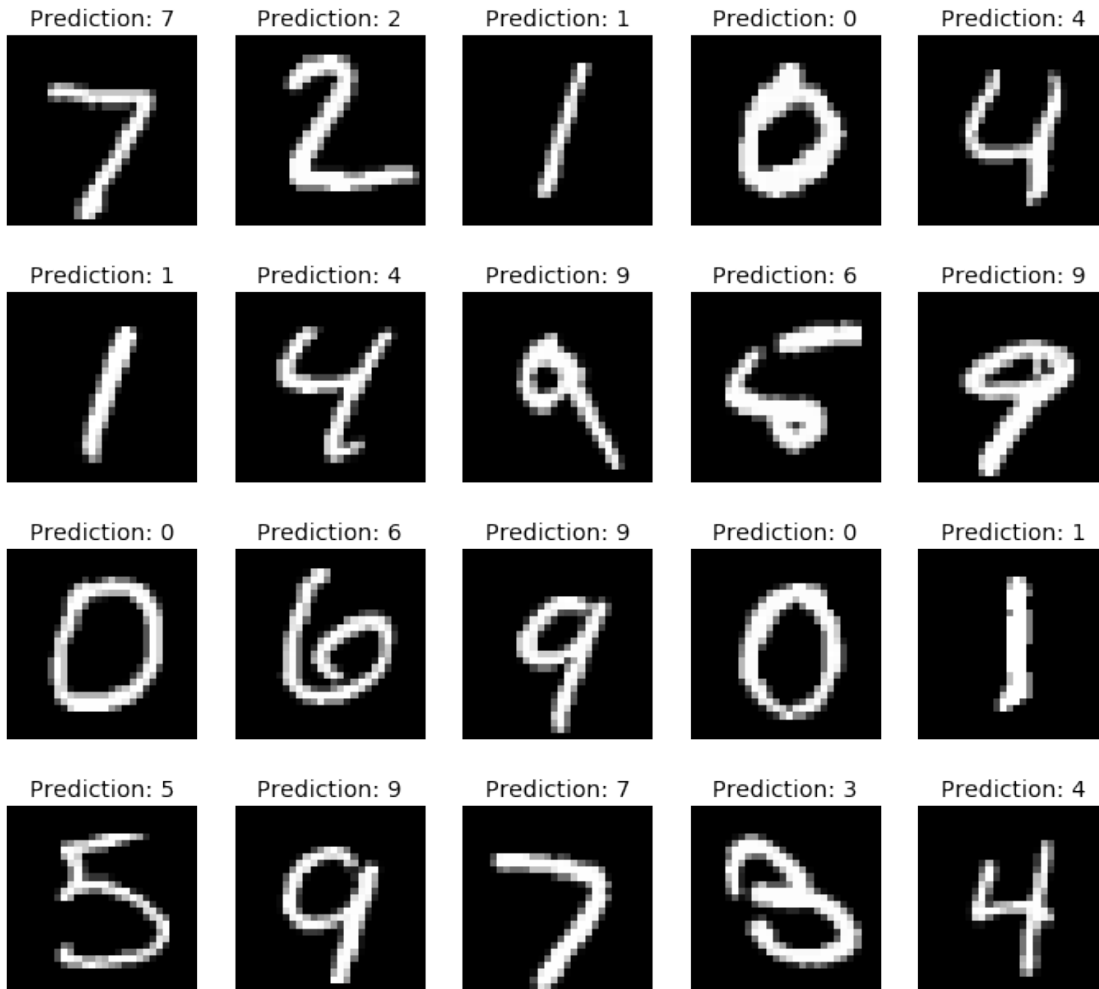
fig = plt.figure(figsize=(12, 11))

# -----
# Write your implementation here. Use the code provided in Part 0 to visualize
# the images.

for i in range(20):
    plt.subplot(4,5,i+1)
    plt.imshow(images[i].squeeze().cpu().numpy(), cmap='gray',
        interpolation='none')
```

```
plt.title(f'Prediction: {pred[i]}',fontsize=14)
plt.axis('off')
```

```
# -----
```



```
[32]: # 3. Get 20 incorrect predictions in test dataset

# Collect the images, predictions, labels for the first 20 incorrect predictions
# Initialize empty tensors and then keep appending to the tensor.
# Make sure that the first dimension of the tensors is the total number of
↳ incorrect
# predictions seen so far
# Ex) incorrect_imgs should be of shape i x C x H x W, where i is the total
↳ number of
# incorrect images so far.
incorrect_imgs = torch.Tensor().to(DEVICE)
```

```

incorrect_preds = []
incorrect_labels = []

with torch.no_grad():
    # Test set iterator
    it = iter(test_loader)
    # Loop over the test set batches until incorrect_imgs.size(0) >= 20
    while incorrect_imgs.size(0) < 20:
        images, labels = it.next()
        images, labels = images.to(DEVICE), labels.to(DEVICE)

        # -----
        # Write your implementation here.

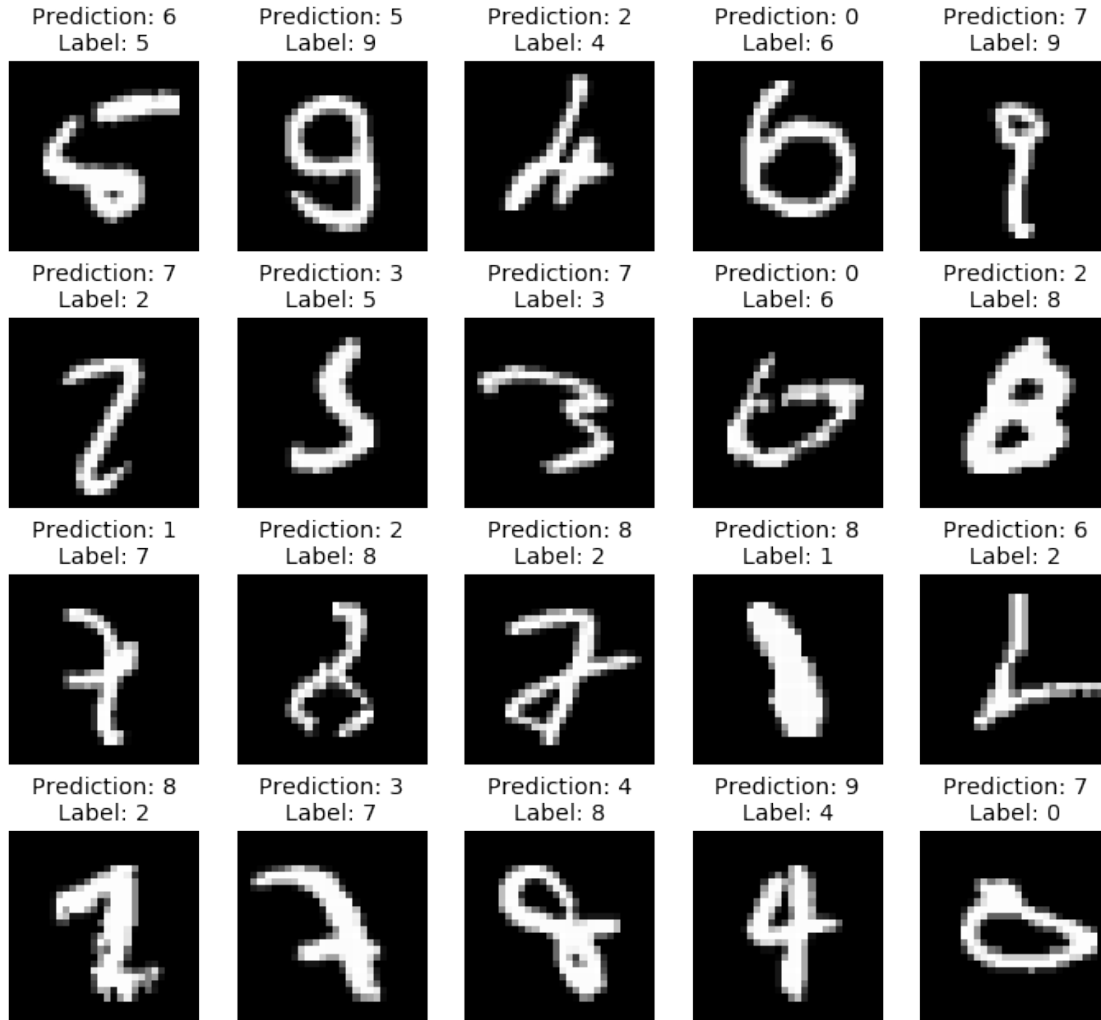
        output = model(images)
        pred = output.argmax(dim=1)

        # Compare prediction and true labels and append the incorrect
        ↪ predictions
        # using `torch.cat`.
        for index, i in enumerate(output):
            if pred[index] != labels[index]:
                incorrect_imgs = torch.cat([incorrect_imgs,
        ↪ images[index]], dim=0)
                incorrect_preds.append(pred[index])
                incorrect_labels.append(labels[index])

        # -----

# Show the first 20 wrong predictions in test set
# incorrect_labels = str(incorrect_labels)
# incorrect_preds = str(incorrect_preds)
fig = plt.figure(figsize=(12, 11))
for i in range(20):
    plt.subplot(4, 5, i+1)
    plt.imshow(incorrect_imgs[i].squeeze().cpu().numpy(), cmap='gray',
    ↪ interpolation='none')
    plt.title(f'Prediction: {incorrect_preds[i].item()}\nLabel:
    ↪ {incorrect_labels[i].item()}', fontsize=14)
    plt.axis('off')

```



In terms of Predictions, the model has improved after normalizing the data. The incorrect predictions above are genuinely hard for humans too recognize at times. *Prediction: 6, Label:2* is hard to predict and there are chances for predicting it as 4 or 6. Similarly all the above incorrect predictions are genuine and the model performance has improved considerably after data normalization.

PS1-Synthetic-Handout

October 3, 2020

1 CS7180 Problem Set 1: Implement a teacher-student network setting for Gaussian inputs (20 points)

Welcome to CS7180!

Before you start, make sure to read the problem description in the handout pdf.

Collaborators: Apoorva Durai, Manaswini, Sinjini Bose. Discussed concepts.

```
[24]: # Dependencies
import argparse
import torch
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms
import numpy as np

# hyper parameters
batch_size = 100
width = 5
d_input = 100
```

2 Part 1: Implement a two-layer neural network with ReLU activation (5 points)

```
[2]: class Net(torch.nn.Module):

    def __init__(self, d_input, width):

        super(Net, self).__init__()
        # -----
        # Write your implementation here.

        # Linear layer obtaining input to the hidden layer from the input layer
        self.fc1 = torch.nn.Linear(d_input, width)
```



```

        # Applying activation to the output of hidden layer before feeding into
        ↪ final layer
        self.act = torch.nn.ReLU()

        # Linear layer -> narrowing to 1 output from hidden layer
        self.fc2 = torch.nn.Linear(width,1)

        # -----

    def forward(self, x):

        x = x.view(-1, d_input)
        # -----
        # Write your implementation here.

        x = self.act(self.fc1(x))
        x = self.fc2(x)
        return x

        # -----

```

2.0.1 Generating the data

```

[21]: # sample size
N = 5 * width * d_input

# random data from standard normal distribution
x_train = torch.randn(N, d_input)
x_test = torch.randn(N, d_input)

# teacher network with random weights
teacher = Net(d_input, width)

# generate labels using the teacher network
y_train = torch.FloatTensor([teacher.forward(x) for x in x_train])
y_test = torch.FloatTensor([teacher.forward(x) for x in x_test])

# combine the data and labels into pytorch friendly format
train_data = torch.utils.data.TensorDataset(x_train, y_train)
test_data = torch.utils.data.TensorDataset(x_test, y_test)

# prepare data loaders
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size)

```

3 Part 2: Set up the quadratic loss function and an SGD optimizer (10 points)

```
[6]: n_epochs = 2000 # the number of epochs can be tuned for better performance

criterion = torch.nn.MSELoss()
optimizer = torch.optim.SGD(teacher.parameters(), lr=0.01)
teacher.train() # prep model for training

for epoch in range(n_epochs):
    train_loss = 0.0

    # train the model
    for idx, (data, labels) in enumerate(train_loader):
        # -----
        # Write your implementation here.

        # clear the gradients of all optimized variables
        optimizer.zero_grad()
        # forward pass: compute predicted outputs by passing inputs to the model
        output = teacher(data)
        # calculate the loss
        loss = criterion(output, labels)
        # backward pass: compute gradient of the loss with respect to model_
        ↪parameters
        loss.backward()
        # perform a single optimization step (parameter update)
        optimizer.step()
        # update running training loss
        train_loss += loss

    # -----

    # print the mean squared loss of the training dataset normalized by the_
    ↪mean square of the training dataset labels
    print('Epoch: {} \tTraining Loss: {:.6f}'.format(
        epoch+1,
        train_loss / torch.mean(torch.pow(y_train, 2))))
```

```
C:\Users\mouni\Anaconda3\lib\site-packages\torch\nn\modules\loss.py:431:
UserWarning: Using a target size (torch.Size([100])) that is different to the
input size (torch.Size([100, 1])). This will likely lead to incorrect results
due to broadcasting. Please ensure they have the same size.
    return F.mse_loss(input, target, reduction=self.reduction)
```

```
Epoch: 1          Training Loss: 21.061852
Epoch: 2          Training Loss: 19.397266
```

Epoch: 3	Training Loss: 18.120869
Epoch: 4	Training Loss: 17.117247
Epoch: 5	Training Loss: 16.312916
Epoch: 6	Training Loss: 15.657936
Epoch: 7	Training Loss: 15.116551
Epoch: 8	Training Loss: 14.664048
Epoch: 9	Training Loss: 14.281998
Epoch: 10	Training Loss: 13.956030
Epoch: 11	Training Loss: 13.675710
Epoch: 12	Training Loss: 13.432755
Epoch: 13	Training Loss: 13.220798
Epoch: 14	Training Loss: 13.034711
Epoch: 15	Training Loss: 12.870484
Epoch: 16	Training Loss: 12.724731
Epoch: 17	Training Loss: 12.594853
Epoch: 18	Training Loss: 12.478600
Epoch: 19	Training Loss: 12.374182
Epoch: 20	Training Loss: 12.280092
Epoch: 21	Training Loss: 12.194963
Epoch: 22	Training Loss: 12.117729
Epoch: 23	Training Loss: 12.047459
Epoch: 24	Training Loss: 11.983365
Epoch: 25	Training Loss: 11.924751
Epoch: 26	Training Loss: 11.871025
Epoch: 27	Training Loss: 11.821671
Epoch: 28	Training Loss: 11.776239
Epoch: 29	Training Loss: 11.734344
Epoch: 30	Training Loss: 11.695641
Epoch: 31	Training Loss: 11.659824
Epoch: 32	Training Loss: 11.626631
Epoch: 33	Training Loss: 11.595822
Epoch: 34	Training Loss: 11.567187
Epoch: 35	Training Loss: 11.540544
Epoch: 36	Training Loss: 11.515714
Epoch: 37	Training Loss: 11.492553
Epoch: 38	Training Loss: 11.470922
Epoch: 39	Training Loss: 11.450697
Epoch: 40	Training Loss: 11.431772
Epoch: 41	Training Loss: 11.414046
Epoch: 42	Training Loss: 11.397429
Epoch: 43	Training Loss: 11.381837
Epoch: 44	Training Loss: 11.367195
Epoch: 45	Training Loss: 11.353436
Epoch: 46	Training Loss: 11.340497
Epoch: 47	Training Loss: 11.328319
Epoch: 48	Training Loss: 11.316852
Epoch: 49	Training Loss: 11.306046
Epoch: 50	Training Loss: 11.295859

Epoch: 51	Training Loss: 11.286248
Epoch: 52	Training Loss: 11.277178
Epoch: 53	Training Loss: 11.268612
Epoch: 54	Training Loss: 11.260519
Epoch: 55	Training Loss: 11.252872
Epoch: 56	Training Loss: 11.245639
Epoch: 57	Training Loss: 11.238796
Epoch: 58	Training Loss: 11.232322
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Epoch: 69	Training Loss: 11.179991
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Epoch: 71	Training Loss: 11.173314
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Epoch: 1990	Training Loss: 11.108255
Epoch: 1991	Training Loss: 11.108255
Epoch: 1992	Training Loss: 11.108255
Epoch: 1993	Training Loss: 11.108254
Epoch: 1994	Training Loss: 11.108254
Epoch: 1995	Training Loss: 11.108254
Epoch: 1996	Training Loss: 11.108253
Epoch: 1997	Training Loss: 11.108254
Epoch: 1998	Training Loss: 11.108254
Epoch: 1999	Training Loss: 11.108254
Epoch: 2000	Training Loss: 11.108254

```
[ ]: # Test the performance of the trained model

teacher.eval()
test_loss = 0.0

for idx, (data, labels) in enumerate(test_loader):
    # forward pass
    output = teacher(data)
    test_loss += criterion(output, labels).item()

# print the mean squared loss of the test dataset normalized by the mean square
# of the test labels
print('Average mean squared error {:.6f}'.format(test_loss / torch.mean(torch.
    pow(y_test, 2))))
```

4 Part 3: Vary the width parameter, and plot the test error for different widths (5 points)

1. How does the test error vary as we change the width? In particular, consider varying the width of the student network from 1 to 20.
2. [Bonus] What happens if we vary the sample size?
3. [Bonus] How about adding a small amount of noise to the labels of the training dataset?

Report what you found and include the results in your submission.

```
[10]: n_epochs = 2000 # the number of epochs can be tuned for better performance
```

```
criterion = torch.nn.MSELoss()
```

```
[14]: def student_net(w):
    std_net = Net(d_input,w)
    std_net.train() # prep model for training
    optimizer = torch.optim.SGD(std_net.parameters(), lr=0.01)

    for epoch in range(n_epochs):
        train_loss = 0.0

        # train the model
        for idx, (data, labels) in enumerate(train_loader):
            # -----
            # Write your implementation here.

            # clear the gradients of all optimized variables
            optimizer.zero_grad()
            # forward pass: compute predicted outputs by passing inputs to the
            →model
            output = std_net(data)
            # calculate the loss
            loss = criterion(output,labels)
            # backward pass: compute gradient of the loss with respect to model
            →parameters
            loss.backward()
            # perform a single optimization step (parameter update)
            optimizer.step()
            # update running training loss
            train_loss += loss

            t_loss = train_loss / torch.mean(torch.pow(y_train, 2))

            # -----

        # Test the performance of the trained model
        std_net.eval()
```

```

test_loss = 0.0

for idx, (data, labels) in enumerate(test_loader):
    # forward pass
    output = std_net(data)
    test_loss += criterion(output, labels).item()

    # print the mean squared loss of the test dataset normalized by the mean
    ↪square of the test labels
    print('Average mean squared error {:.6f}'.format(test_loss / torch.
    ↪mean(torch.pow(y_test, 2))))

```

```

[17]: test_error = []
      for w in range(1,21):
          print("width:",w)
          test_error.append(student_net(w))

```

```

width: 1
Average mean squared error 10.930061
width: 2
Average mean squared error 10.916376
width: 3
Average mean squared error 10.914468
width: 4
Average mean squared error 10.910889
width: 5
Average mean squared error 10.913124
width: 6
Average mean squared error 10.910731
width: 7
Average mean squared error 10.910593
width: 8
Average mean squared error 10.910300
width: 9
Average mean squared error 10.910397
width: 10
Average mean squared error 10.910455
width: 11
Average mean squared error 10.910155
width: 12
Average mean squared error 10.910148
width: 13
Average mean squared error 10.909992
width: 14
Average mean squared error 10.909336
width: 15
Average mean squared error 10.910934

```



```
width: 16
Average mean squared error 10.909252
width: 17
Average mean squared error 10.909606
width: 18
Average mean squared error 10.909761
width: 19
Average mean squared error 10.908634
width: 20
Average mean squared error 10.908721
```

Varying Sample size

Having width as 20 and changing the Sample size

```
[18]: # sample size
N1 = 5 * 20 * d_input

# random data from standard normal distribution
x_train = torch.randn(N1, d_input)
x_test = torch.randn(N1, d_input)

# teacher network with random weights
teacher = Net(d_input, width)

# generate labels using the teacher network
y_train = torch.FloatTensor([teacher.forward(x) for x in x_train])
y_test = torch.FloatTensor([teacher.forward(x) for x in x_test])

# combine the data and labels into pytorch friendly format
train_data = torch.utils.data.TensorDataset(x_train, y_train)
test_data = torch.utils.data.TensorDataset(x_test, y_test)

# prepare data loaders
train_loader = torch.utils.data.DataLoader(train_data, batch_size=batch_size)
test_loader = torch.utils.data.DataLoader(test_data, batch_size=batch_size)
```

```
[19]: def student_net(w):
    std_net = Net(d_input, w)
    std_net.train() # prep model for training
    optimizer = torch.optim.SGD(std_net.parameters(), lr=0.01)

    for epoch in range(n_epochs):
        train_loss = 0.0

        # train the model
        for idx, (data, labels) in enumerate(train_loader):
            # -----
```

```

        # Write your implementation here.

        # clear the gradients of all optimized variables
        optimizer.zero_grad()
        # forward pass: compute predicted outputs by passing inputs to the
→model
        output = std_net(data)
        # calculate the loss
        loss = criterion(output, labels)
        # backward pass: compute gradient of the loss with respect to model
→parameters
        loss.backward()
        # perform a single optimization step (parameter update)
        optimizer.step()
        # update running training loss
        train_loss += loss

        t_loss = train_loss / torch.mean(torch.pow(y_train, 2))

        # -----

        # Test the performance of the trained model
        std_net.eval()
        test_loss = 0.0

        for idx, (data, labels) in enumerate(test_loader):
            # forward pass
            output = std_net(data)
            test_loss += criterion(output, labels).item()

            # print the mean squared loss of the test dataset normalized by the mean
→square of the test labels
            print('Average mean squared error {:.6f}'.format(test_loss / torch.
→mean(torch.pow(y_test, 2))))

```

```

[20]: test_error = []
      test_error.append(student_net(20))

```

Average mean squared error 87.164070

Varying sample size is increasing the *mean squared error*. However we can try for different vlaues of *Width* and *d_input* to experiment what actually happens for smaller to larger values of *N*(*Sample Size*)

```

[25]: # generate labels using the teacher network
      y_train = torch.FloatTensor([teacher.forward(x) for x in x_train])
      x_train = torch.randn(N, d_input)

```

```

dim1 = x_train.shape #to get the dimesion of the data
dim2 = y_train.shape

noise1 = np.random.rand(dim1)
noise2 = np.random.rand(dim2)

noisy_data_x = x_train + noise1
noisy_data_y = y_train + noise2 # to add noise the existing data

noisy_train_data = torch.utils.data.TensorDataset(noisy_data_x, noisy_data_y)

noisy_data_loader = torch.utils.data.DataLoader(noisy_train_data,
↪batch_size=batch_size)

```

```

↪-----
TypeError                                Traceback (most recent call↪
↪last)

```

```

<ipython-input-25-fa668226c435> in <module>
      6 dim1 = x_train.shape #to get the dimesion of the data
      7 dim2 = y_train.shape
----> 8 noise1 = np.random.rand(dim1)
      9 noise2 = np.random.rand(dim2)
     10

```

```

mtrand.pyx in mtrand.RandomState.rand()

```

```

mtrand.pyx in mtrand.RandomState.random_sample()

```

```

mtrand.pyx in mtrand.cont0_array()

```

```

TypeError: 'torch.Size' object cannot be interpreted as an integer

```