CHEM277B Homework 7

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Problem 1

(A)

Read the data from the mnist.pkl file and normalize the training set data.

```
import pandas as pd
import numpy as np

training_set, validation_set = pd.read_pickle('mnist.pkl')

#examine the shape of the training set
print(len(training_set[0]))
print(len(training_set[0][0]))
print(len(validation_set[0]))

#normalized the training data and reshape to shape (ndata, nfeatures)
normalized_train_set = tuple([z / 255 for z in training_set])
normalized_train_set_x = np.array(normalized_train_set[0])
normalized_train_set_x = normalized_train_set_x.reshape(60000, 1024)
print(normalized_train_set_x.shape)

train_set_y = np.array(training_set[1])
#print(normalized_train_set_y.shape)

#normalized the test data and reshape to shape (ndata, nfeatures)
normalized_test_set = tuple([z / 255 for z in validation_set])
normalized_test_set_x = np.array(normalized_test_set[0])
normalized_test_set_x = normalized_test_set_x.reshape(10000, 1024)
print(normalized_test_set_x.shape)

test_set_y = np.array(validation_set[1])
```

```
60000
32
10000
(60000, 1024)
(10000, 1024)
```

(B), (C)

(C) Do a 3-fold validation of the data with a learning rate of 2e-3, 50 epochs, batch size 128, and plot the loss and accuracy as a function of the epoch number.

```
from torch import nn
import torch

class MLP(nn.Module):
    def __init__(self):
        super(MLP, self).__init__()
        self.layers = nn.Sequential(
            nn.Linear(1024, 3),
            nn.Sigmoid(),
            nn.Linear(3, 10),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.layers(x)


from functools import wraps
from time import time

def timing(f):
    @wraps(f)
    def wrap(*args, **kw):
        ts = time()
        result = f(*args, **kw)
        te = time()
        print('func:%r  took: %2.4f sec' % (f.__name__,  te-ts))
        return result
    return wrap


from torch.optim import SGD, Adam
import torch.nn.functional as F
import random
from tqdm import tqdm
import math
from sklearn.model_selection import train_test_split, KFold

def create_chunks(complete_list, chunk_size=None, num_chunks=None):
    '''
    Cut a list into multiple chunks, each having chunk_size (the last chunk might b
    '''
    chunks = []
    if num_chunks is None:
        num_chunks = math.ceil(len(complete_list) / chunk_size)
```

```
    elif chunk_size is None:
        chunk_size = math.ceil(len(complete_list) / num_chunks)
    for i in range(num_chunks):
        chunks.append(complete_list[i * chunk_size: (i + 1) * chunk_size])
    return chunks

class Trainer():
    def __init__(self, model, optimizer_type, learning_rate, epoch, batch_size, inp
        """ The class for training the model
        model: nn.Module
            A pytorch model
        optimizer_type: 'adam' or 'sgd'
        learning_rate: float
        epoch: int
        batch_size: int
        input_transform: func
            transforming input. Can do reshape here
        """
        self.model = model
        if optimizer_type == "sgd":
            self.optimizer = SGD(model.parameters(), learning_rate,momentum=0.9)
        elif optimizer_type == "adam":
            self.optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

        self.epoch = epoch
        self.batch_size = batch_size
        self.input_transform = input_transform
        self.learning_rate = learning_rate


    @timing
    def train(self, inputs, outputs, val_inputs, val_outputs,early_stop=False,l2=Fa
        """ train self.model with specified arguments
        inputs: np.array, The shape of input_transform(input) should be (ndata,nfea
        outputs: np.array shape (ndata,)
        val_nputs: np.array, The shape of input_transform(val_input) should be (nda
        val_outputs: np.array shape (ndata,)
        early_stop: bool
        l2: bool
        silent: bool. Controls whether or not to print the train and val error duri

        @return
        a dictionary of arrays with train and val losses and accuracies
        """
        ### convert data to tensor of correct shape and type here ###
        inputs = torch.tensor(inputs, dtype=torch.float32)
        outputs = torch.tensor(outputs, dtype=torch.long)
        val_inputs = torch.tensor(val_inputs, dtype=torch.float32)
        val_outputs = torch.tensor(val_outputs, dtype=torch.long)

        losses = []
```

```
        accuracies = []
        val_losses = []
        val_accuracies = []
        weights = self.model.state_dict()
        lowest_val_loss = np.inf

        for n_epoch in tqdm(range(self.epoch), leave=False):
            self.model.train()
            batch_indices = list(range(inputs.shape[0]))
            random.shuffle(batch_indices)
            batch_indices = create_chunks(batch_indices, chunk_size=self.batch_size
            epoch_loss = 0
            epoch_acc = 0
            for batch in batch_indices:
                batch_importance = len(batch) / len(outputs)
                batch_input = inputs[batch]
                batch_output = outputs[batch]
                ### make prediction and compute loss with loss function of your cho
                batch_predictions = self.model.forward(batch_input)
                loss_func = nn.CrossEntropyLoss()
                loss = loss_func(batch_predictions, batch_output)
                if l2:
                    ### Compute the loss with L2 regularization ###
                    self.optimizer = torch.optim.Adam(model.parameters(), lr = self
                    loss = loss_func(batch_predictions, batch_output)
                self.optimizer.zero_grad()
                loss.backward()
                self.optimizer.step()
                ### Compute epoch_loss and epoch_acc
            epoch_loss, epoch_acc = self.evaluate(inputs, outputs)
            val_loss, val_acc = self.evaluate(val_inputs, val_outputs, print_acc=Fa
            if n_epoch % 10 ==0 and not silent:
                print("Epoch %d/%d - Loss: %.3f - Acc: %.3f" % (n_epoch + 1, self.e
                print("              Val_loss: %.3f - Val_acc: %.3f" % (val_loss, v
            losses.append(epoch_loss.detach().numpy())
            accuracies.append(epoch_acc)
            val_losses.append(val_loss.detach().numpy())
            val_accuracies.append(val_acc)
            if early_stop:
                if val_loss < lowest_val_loss:
                    lowest_val_loss = val_loss
                    weights = self.model.state_dict()

        if early_stop:
            self.model.load_state_dict(weights)

        return {"losses": losses, "accuracies": accuracies, "val_losses": val_losse

    def evaluate(self, inputs, outputs, print_acc=False):
        """ evaluate model on provided input and output
```

```
        inputs: np.array, The shape of input_transform(input) should be (ndata,nfea
        outputs: np.array shape (ndata,)
        print_acc: bool

        @return
        losses: float
        acc: float
        """

        inputs = torch.tensor(inputs, dtype=torch.float32)
        outputs = torch.tensor(outputs, dtype=torch.long)

        loss_func = nn.CrossEntropyLoss()

        pred = self.model.forward(inputs)

        losses = loss_func(pred, outputs)
        #print("pred = ", pred)
        #print("truth = " ,outputs)

        sum = 0
        for i in range(len(outputs)):
          if outputs[i] == torch.argmax(pred[i]):
            sum += 1
        acc = sum / len(outputs)
        if print_acc:
            print("Accuracy: %.3f" % acc)
        return losses, acc


import matplotlib.pyplot as plt
def Kfold_validation(n, inputs, outputs):

    total_num=len(inputs)
    kf=KFold(n_splits=n,shuffle=True)



    for train_selector,test_selector in kf.split(range(total_num)):
        ### Decide training examples and testing examples for this fold ###
        train_Xs= inputs[train_selector]
        test_Xs=  inputs[test_selector]
        train_ys= outputs[train_selector]
        test_ys= outputs[test_selector]

        model = MLP()
        t = Trainer(model, optimizer_type='adam', learning_rate=2e-3, epoch=50, bat
        train_in,val_in,train_real,val_real=train_test_split(train_Xs,train_ys, tra

        dictionary = t.train(train_in, train_real, val_in, val_real,early_stop=Fals
```

```
    return dictionary
```

```
dictionary = Kfold_validation(3, normalized_train_set_x, train_set_y)
```

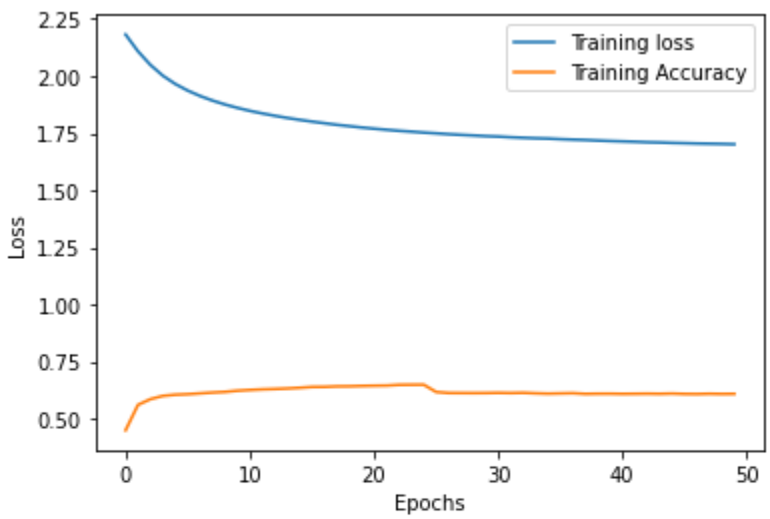
```
  0%|          | 0/50 [00:00<?, ?it/s]<ipython-input-86-5a654197e45b>:125: Us
  inputs = torch.tensor(inputs, dtype=torch.float32)
<ipython-input-86-5a654197e45b>:126: UserWarning: To copy construct from a te
  outputs = torch.tensor(outputs, dtype=torch.long)
  2%|▏         | 1/50 [00:01<00:59,  1.22s/it]Epoch 1/50 - Loss: 2.180 - Acc:
             Val_loss: 2.181 - Val_acc: 0.342
 22%|██▏       | 11/50 [00:12<00:39,  1.01s/it]Epoch 11/50 - Loss: 1.821 - Ac
             Val_loss: 1.825 - Val_acc: 0.599
 42%|████▏     | 21/50 [00:22<00:29,  1.03s/it]Epoch 21/50 - Loss: 1.741 - Ac
             Val_loss: 1.749 - Val_acc: 0.629
 62%|██████▏   | 31/50 [00:33<00:19,  1.04s/it]Epoch 31/50 - Loss: 1.706 - Ac
             Val_loss: 1.716 - Val_acc: 0.621
 82%|████████▏ | 41/50 [00:44<00:10,  1.13s/it]Epoch 41/50 - Loss: 1.689 - Ac
             Val_loss: 1.702 - Val_acc: 0.617
func:'train'  took: 54.0464 sec
  2%|▏         | 1/50 [00:01<01:04,  1.32s/it]Epoch 1/50 - Loss: 2.175 - Acc:
             Val_loss: 2.175 - Val_acc: 0.315
 22%|██▏       | 11/50 [00:11<00:39,  1.02s/it]Epoch 11/50 - Loss: 1.833 - Ac
             Val_loss: 1.837 - Val_acc: 0.539
 42%|████▏     | 21/50 [00:21<00:28,  1.00it/s]Epoch 21/50 - Loss: 1.752 - Ac
             Val_loss: 1.761 - Val_acc: 0.563
 62%|██████▏   | 31/50 [00:32<00:19,  1.00s/it]Epoch 31/50 - Loss: 1.717 - Ac
             Val_loss: 1.730 - Val_acc: 0.579
 82%|████████▏ | 41/50 [00:43<00:09,  1.04s/it]Epoch 41/50 - Loss: 1.697 - Ac
             Val_loss: 1.714 - Val_acc: 0.587
func:'train'  took: 53.5946 sec
  2%|▏         | 1/50 [00:01<00:49,  1.02s/it]Epoch 1/50 - Loss: 2.182 - Acc:
             Val_loss: 2.181 - Val_acc: 0.453
 22%|██▏       | 11/50 [00:11<00:44,  1.13s/it]Epoch 11/50 - Loss: 1.848 - Ac
             Val_loss: 1.849 - Val_acc: 0.625
 42%|████▏     | 21/50 [00:22<00:35,  1.24s/it]Epoch 21/50 - Loss: 1.770 - Ac
             Val_loss: 1.773 - Val_acc: 0.636
 62%|██████▏   | 31/50 [00:32<00:18,  1.00it/s]Epoch 31/50 - Loss: 1.735 - Ac
             Val_loss: 1.741 - Val_acc: 0.608
 82%|████████▏ | 41/50 [00:43<00:08,  1.01it/s]Epoch 41/50 - Loss: 1.714 - Ac
             Val_loss: 1.722 - Val_acc: 0.601
                                      func:'train'  took: 53.5131 se
```

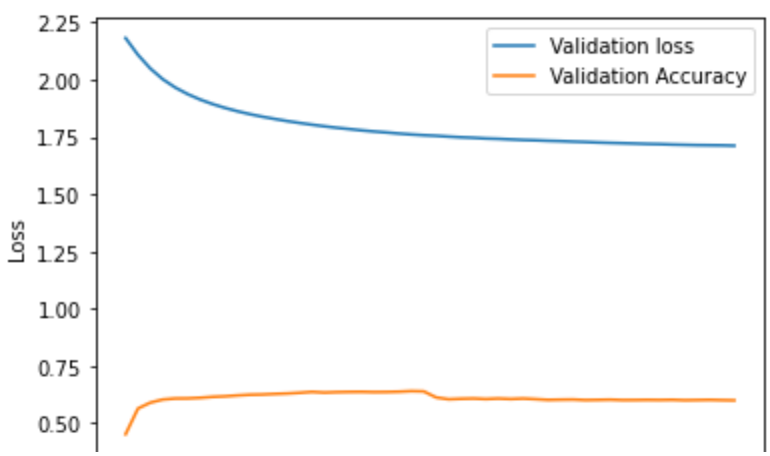
After running the model on three folds I saved the most recent data from the third fold and plot the validation accuracy and the validation loss on the chart below. It looks like the validation loss is approaching a horizontal asymptote but the accuracy seems to be increasing as the epochs progress. It does not seem like there is a trade off to consider when the number of epochs is 50 or lower, because it looks like the accuracy is still increasing, but since the validation loss is leveling out it may be unnecessary to train for more than 50 epochs. Also, this is only the third fold, so the most effective model that was generated could have not been saved. The model has some accuracy which is better than guessing, but it is still wrong in many cases.

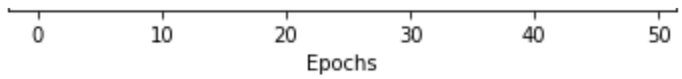
```
losses = dictionary['losses']
accuracies = dictionary['accuracies']
accuracies = np.asarray(accuracies)
losses = np.asarray(losses)
plt.figure()
plt.plot(np.arange(len(losses)),losses,label='Training loss')
plt.plot(np.arange(len(accuracies)),accuracies,label='Training Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

val_losses = dictionary['val_losses']
val_accuracies = dictionary['val_accuracies']
val_accuracies = np.asarray(val_accuracies)
val_losses = np.asarray(val_losses)
plt.figure()
plt.plot(np.arange(len(val_losses)),val_losses,label='Validation loss')
plt.plot(np.arange(len(val_accuracies)),val_accuracies,label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7fd343da5fa0>
```







(D)

Run the k-fold validation on a model that uses a hidden layer of 50 nodes.

```
class MLP_50(nn.Module):
    def __init__(self):
        super(MLP_50, self).__init__()
        self.layers = nn.Sequential(
            nn.Linear(1024, 50),
            nn.Sigmoid(),
            nn.Linear(50, 10),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.layers(x)
```

```
def Kfold_validation_2(n, inputs, outputs):

    total_num=len(inputs)
    kf=KFold(n_splits=n,shuffle=True)



    for train_selector,test_selector in kf.split(range(total_num)):
        ### Decide training examples and testing examples for this fold ###
        train_Xs= inputs[train_selector]
        test_Xs=  inputs[test_selector]
        train_ys= outputs[train_selector]
        test_ys= outputs[test_selector]

        model = MLP_50()
        t = Trainer(model, optimizer_type='adam', learning_rate=2e-3, epoch=50, bat
        train_in,val_in,train_real,val_real=train_test_split(train_Xs,train_ys, tra

        dictionary = t.train(train_in, train_real, val_in, val_real,early_stop=Fals

    return dictionary
```

```
dictionary = Kfold_validation_2(3, normalized_train_set_x, train_set_y)
```

```
  0%|          | 0/50 [00:00<?, ?it/s]<ipython-input-86-5a654197e45b>:125: Use
  inputs = torch.tensor(inputs, dtype=torch.float32)
<ipython-input-86-5a654197e45b>:126: UserWarning: To copy construct from a ten
  outputs = torch.tensor(outputs, dtype=torch.long)
```

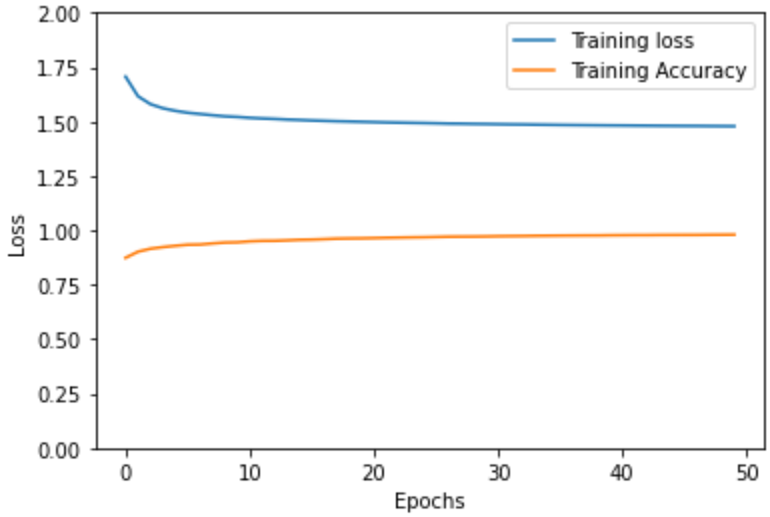
```
        outputs = torch.tensor(outputs, dtype=torch.long)
          2%|         | 1/50 [00:01<01:02,  1.27s/it]Epoch 1/50 - Loss: 1.698 - Acc:
                       Val_loss: 1.701 - Val_acc: 0.856
         22%|██       | 11/50 [00:14<00:50,  1.29s/it]Epoch 11/50 - Loss: 1.515 - Ac
                       Val_loss: 1.530 - Val_acc: 0.935
         42%|████     | 21/50 [00:28<00:37,  1.29s/it]Epoch 21/50 - Loss: 1.496 - Ac
                       Val_loss: 1.517 - Val_acc: 0.945
         62%|██████   | 31/50 [00:41<00:24,  1.28s/it]Epoch 31/50 - Loss: 1.486 - Ac
                       Val_loss: 1.513 - Val_acc: 0.949
         82%|████████ | 41/50 [00:54<00:11,  1.27s/it]Epoch 41/50 - Loss: 1.480 - Ac
                       Val_loss: 1.512 - Val_acc: 0.951
        func:'train'  took: 67.2057 sec
          2%|         | 1/50 [00:01<01:00,  1.23s/it]Epoch 1/50 - Loss: 1.708 - Acc:
                       Val_loss: 1.710 - Val_acc: 0.872
         22%|██       | 11/50 [00:14<00:48,  1.26s/it]Epoch 11/50 - Loss: 1.516 - Ac
                       Val_loss: 1.530 - Val_acc: 0.936
         42%|████     | 21/50 [00:28<00:37,  1.28s/it]Epoch 21/50 - Loss: 1.497 - Ac
                       Val_loss: 1.519 - Val_acc: 0.943
         62%|██████   | 31/50 [00:41<00:26,  1.41s/it]Epoch 31/50 - Loss: 1.487 - Ac
                       Val_loss: 1.515 - Val_acc: 0.947
         82%|████████ | 41/50 [00:55<00:13,  1.46s/it]Epoch 41/50 - Loss: 1.482 - Ac
                       Val_loss: 1.514 - Val_acc: 0.948
        func:'train'  took: 67.3112 sec
          2%|         | 1/50 [00:01<01:13,  1.51s/it]Epoch 1/50 - Loss: 1.706 - Acc:
                       Val_loss: 1.706 - Val_acc: 0.878
         22%|██       | 11/50 [00:14<00:55,  1.42s/it]Epoch 11/50 - Loss: 1.517 - Ac
                       Val_loss: 1.529 - Val_acc: 0.936
         42%|████     | 21/50 [00:28<00:39,  1.38s/it]Epoch 21/50 - Loss: 1.497 - Ac
                       Val_loss: 1.517 - Val_acc: 0.946
         62%|██████   | 31/50 [00:41<00:26,  1.40s/it]Epoch 31/50 - Loss: 1.488 - Ac
                       Val_loss: 1.512 - Val_acc: 0.950
         82%|████████ | 41/50 [00:55<00:13,  1.49s/it]Epoch 41/50 - Loss: 1.482 - Ac
                       Val_loss: 1.511 - Val_acc: 0.951
                                                             func:'train'  took: 67.9454 se
```

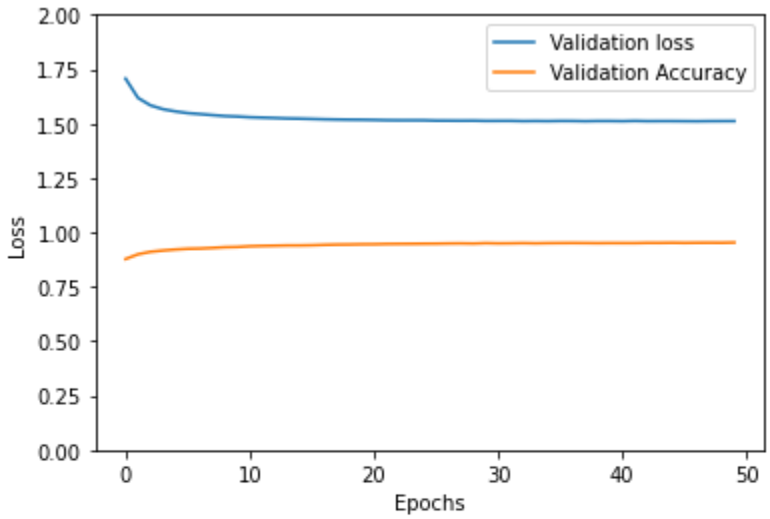
```
losses = dictionary['losses']
accuracies = dictionary['accuracies']
accuracies = np.asarray(accuracies)
losses = np.asarray(losses)
plt.figure()
plt.plot(np.arange(len(losses)),losses,label='Training loss')
plt.plot(np.arange(len(accuracies)),accuracies,label='Training Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.ylim(0, 2)
plt.legend()

val_losses = dictionary['val_losses']
val_accuracies = dictionary['val_accuracies']
val_accuracies = np.asarray(val_accuracies)
val_losses = np.asarray(val_losses)
plt.figure()
plt.plot(np.arange(len(val_losses)),val_losses,label='Validation loss')
```

```
plt.plot(np.arange(len(val_accuracies)),val_accuracies,label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylim(0, 2)
plt.ylabel('Loss')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7fd3456d5100>
```





The model which implements a hidden layer of 50 nodes turns out to predict the output with high accuracy after just one epoch of training. This one step iterates through the batches and results in a trained model which is close to perfect classification of the validation data. Here the bias-variance tradeoff is to train the model a minimum amount of times because the training occurs fast. And as we add more epochs to the validation, model seems to perform close to perfect yet will not reach 100%.

Problem 2

(A)

Use a dropout of 15% with the ANN from 1D and compare the training and test accuracy against the previous outputs.

```
class MLP_50B(nn.Module):
    def __init__(self):
        super(MLP_50B, self).__init__()
        self.layers = nn.Sequential(
            nn.Linear(1024, 50),
            nn.Dropout(0.15),
            nn.Sigmoid(),
            nn.Linear(50, 10),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.layers(x)
```

```
model = MLP_50B()
t = Trainer(model, optimizer_type='adam', learning_rate=2e-3, epoch=50, batch_size=
train_in,val_in,train_real,val_real=train_test_split(normalized_train_set_x,train_s

dictionary = t.train(train_in, train_real, val_in, val_real,early_stop=False,l2=Fal
```

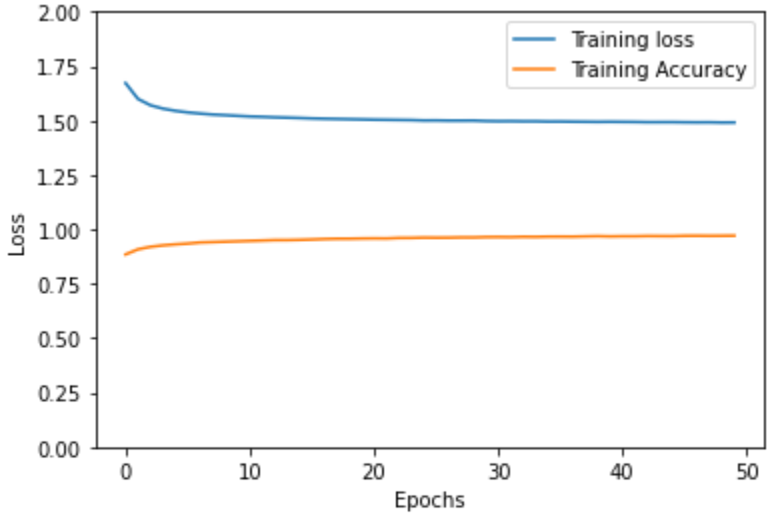
```
  0%|          | 0/50 [00:00<?, ?it/s]<ipython-input-86-5a654197e45b>:125: Us
  inputs = torch.tensor(inputs, dtype=torch.float32)
<ipython-input-86-5a654197e45b>:126: UserWarning: To copy construct from a te
  outputs = torch.tensor(outputs, dtype=torch.long)
  2%|▏         | 1/50 [00:02<01:38,  2.02s/it]Epoch 1/50 - Loss: 1.672 - Acc:
            Val_loss: 1.675 - Val_acc: 0.880
 22%|██        | 11/50 [00:23<01:23,  2.14s/it]Epoch 11/50 - Loss: 1.519 - Ac
            Val_loss: 1.533 - Val_acc: 0.932
 42%|████      | 21/50 [00:43<00:56,  1.96s/it]Epoch 21/50 - Loss: 1.504 - Ac
            Val_loss: 1.523 - Val_acc: 0.939
 62%|██████    | 31/50 [01:04<00:38,  2.02s/it]Epoch 31/50 - Loss: 1.497 - Ac
            Val_loss: 1.519 - Val_acc: 0.941
 82%|████████  | 41/50 [01:25<00:19,  2.19s/it]Epoch 41/50 - Loss: 1.494 - Ac
            Val_loss: 1.517 - Val_acc: 0.942
                                   func:'train'  took: 104.3052 s
```

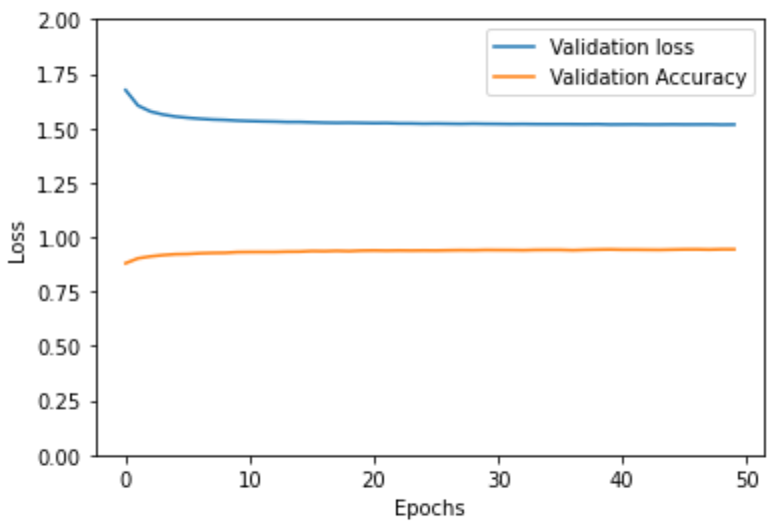
```
losses = dictionary['losses']
accuracies = dictionary['accuracies']
accuracies = np.asarray(accuracies)
losses = np.asarray(losses)
plt.figure()
plt.plot(np.arange(len(losses)),losses,label='Training loss')
plt.plot(np.arange(len(accuracies)),accuracies,label='Training Accuracy')
```

```
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.ylim(0, 2)
plt.legend()

val_losses = dictionary['val_losses']
val_accuracies = dictionary['val_accuracies']
val_accuracies = np.asarray(val_accuracies)
val_losses = np.asarray(val_losses)
plt.figure()
plt.plot(np.arange(len(val_losses)),val_losses,label='Validation loss')
plt.plot(np.arange(len(val_accuracies)),val_accuracies,label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylim(0, 2)
plt.ylabel('Loss')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7fd34542c550>
```






```
#feed forward into the model with the test data from MNIST and compare the results
output = model.forward(torch.tensor(normalized_test_set_x, dtype = torch.float32))
sum = 0
```

```
for i in range(len(output)):
  if (test_set_y[i] == torch.argmax(output[i])):
    sum += 1
print(sum/len(output))
```

```
0.9509
```

Using a dropout before the first hidden layer has not made any significant changes in the chart other than the fact that it takes longer. I trained the model over 50 epochs just using one fold. The model predicts 93-95 percent of the classifications correctly after training over one fold of the training data.

(B)

Use L2 Regularization on the ANN from 1D and compare the results.

```
model = MLP_50B()
t = Trainer(model, optimizer_type='adam', learning_rate=2e-3, epoch=50, batch_size=
train_in,val_in,train_real,val_real=train_test_split(normalized_train_set_x,train_s

dictionary = t.train(train_in, train_real, val_in, val_real,early_stop=False,l2=Tru
```

```
  0%|          | 0/50 [00:00<?, ?it/s]<ipython-input-86-5a654197e45b>:125: Use
  inputs = torch.tensor(inputs, dtype=torch.float32)
<ipython-input-86-5a654197e45b>:126: UserWarning: To copy construct from a ten
  outputs = torch.tensor(outputs, dtype=torch.long)
  2%|▏         | 1/50 [00:02<01:39,  2.03s/it]Epoch 1/50 - Loss: 1.653 - Acc:
            Val_loss: 1.654 - Val_acc: 0.874
 22%|██▏       | 11/50 [00:24<01:27,  2.24s/it]Epoch 11/50 - Loss: 1.536 - Acc
            Val_loss: 1.544 - Val_acc: 0.922
 42%|████▏     | 21/50 [00:44<00:58,  2.03s/it]Epoch 21/50 - Loss: 1.530 - Acc
            Val_loss: 1.539 - Val_acc: 0.925
 62%|██████▏   | 31/50 [01:06<00:39,  2.09s/it]Epoch 31/50 - Loss: 1.526 - Acc
            Val_loss: 1.536 - Val_acc: 0.927
 82%|████████▏ | 41/50 [01:28<00:19,  2.19s/it]Epoch 41/50 - Loss: 1.528 - Acc
            Val_loss: 1.538 - Val_acc: 0.929
                                    func:'train'  took: 107.3078 se
```

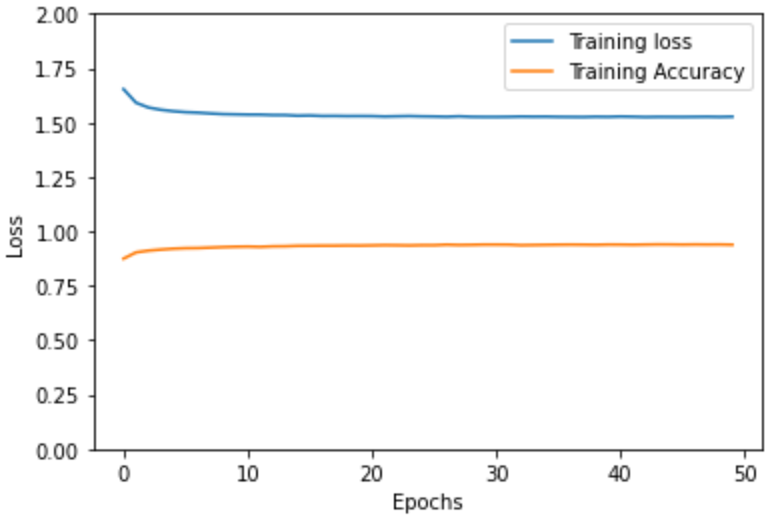
Using the L2 regularization option and dropout before the first hidden layer increases the amount of time it takes to train the model on one single training and validation fold from the original normalized data, and it performs well on the training data and validation data with very high accuracy around 93 percent.

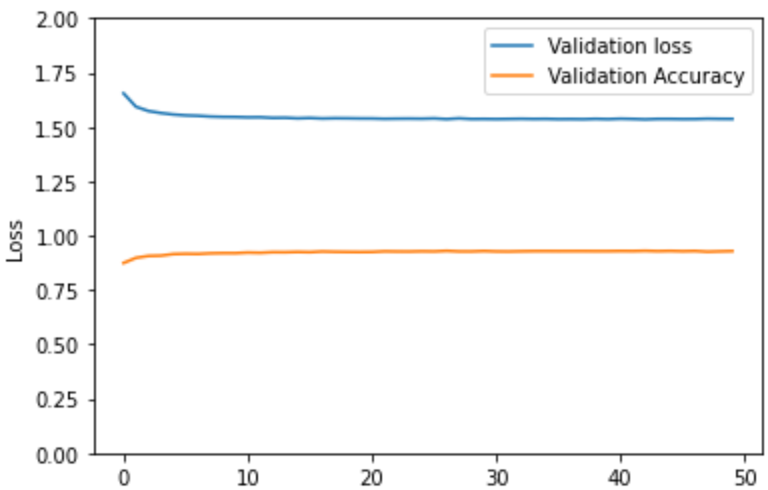
```
losses = dictionary['losses']
accuracies = dictionary['accuracies']
```

```
accuracies = dictionary['accuracies']
accuracies = np.asarray(accuracies)
losses = np.asarray(losses)
plt.figure()
plt.plot(np.arange(len(losses)),losses,label='Training loss')
plt.plot(np.arange(len(accuracies)),accuracies,label='Training Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.ylim(0, 2)
plt.legend()

val_losses = dictionary['val_losses']
val_accuracies = dictionary['val_accuracies']
val_accuracies = np.asarray(val_accuracies)
val_losses = np.asarray(val_losses)
plt.figure()
plt.plot(np.arange(len(val_losses)),val_losses,label='Validation loss')
plt.plot(np.arange(len(val_accuracies)),val_accuracies,label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylim(0, 2)
plt.ylabel('Loss')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7fd3452a9c70>
```





Epochs

```
#feed forward into the model with the test data from MNIST and compare the results
output = model.forward(torch.tensor(normalized_test_set_x, dtype = torch.float32))
sum = 0
for i in range(len(output)):
  if (test_set_y[i] == torch.argmax(output[i])):
    sum += 1
print(sum/len(output))
```

```
0.9353
```

After training the model on the normalized test data and comparing it to the true y values it shows that it has achieved around 93 percent accuracy, which is less than what the training model suggests as it performs near perfectly on the validation data during the train/test split.

(C)

Use PCA to simplify the input features.

```
from sklearn.decomposition import PCA
pca = PCA(n_components=0.99)
stacked_data = np.vstack((normalized_train_set_x, normalized_test_set_x))
train_and_test_pca = pca.fit_transform(stacked_data)
train_and_test_pca.shape
```

```
reduced_train_set = train_and_test_pca[0:60000]
reduced_test_set = train_and_test_pca[60000:70000]
print(reduced_train_set.shape)
print(reduced_test_set.shape)
```

```
(60000, 331)
(10000, 331)
```

The transformed input has only 331 features instead of 1024, which makes me assume that it would be faster to run but we would need to edit the model to accept inputs of size 331. If 99% of the variance is preserved in the transformation then the model should perform just as good, and even a little bit faster. Next we run the model with the reduced input features and compare against the previous ANN.

(D)

Using the model MLP_50C with 15 percent dropout and L2 regularization disabled I train the model on the reduced set of input features and compare the accuracy on the test data to the previous ANNs.

```
class MLP_50C(nn.Module):
    def __init__(self):
        super(MLP_50C, self).__init__()
        self.layers = nn.Sequential(
            nn.Linear(331, 50),
            nn.Dropout(0.15),
            nn.Sigmoid(),
            nn.Linear(50, 10),
            nn.Sigmoid()
        )

    def forward(self, x):
        return self.layers(x)

model = MLP_50C()
t = Trainer(model, optimizer_type='adam', learning_rate=2e-3, epoch=50, batch_size=
train_in,val_in,train_real,val_real=train_test_split(reduced_train_set,train_set_y,

dictionary = t.train(train_in, train_real, val_in, val_real,early_stop=False,l2=Fal
```

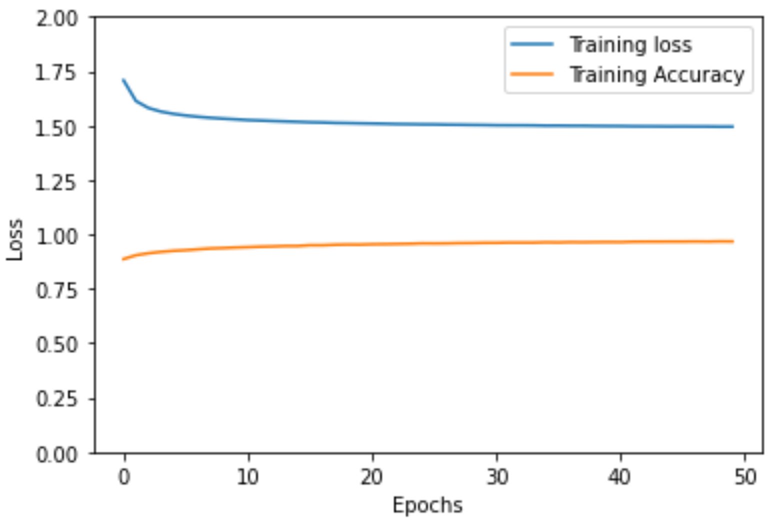
```
  0%|          | 0/50 [00:00<?, ?it/s]<ipython-input-86-5a654197e45b>:125: Use
  inputs = torch.tensor(inputs, dtype=torch.float32)
<ipython-input-86-5a654197e45b>:126: UserWarning: To copy construct from a ten
  outputs = torch.tensor(outputs, dtype=torch.long)
  2%|▏         | 1/50 [00:01<01:14,  1.52s/it]Epoch 1/50 - Loss: 1.708 - Acc:
         Val_loss: 1.710 - Val_acc: 0.882
 22%|██▏       | 11/50 [00:17<01:01,  1.57s/it]Epoch 11/50 - Loss: 1.525 - Acc
         Val_loss: 1.538 - Val_acc: 0.927
 42%|████▏     | 21/50 [00:32<00:42,  1.46s/it]Epoch 21/50 - Loss: 1.509 - Acc
         Val_loss: 1.528 - Val_acc: 0.933
 62%|██████▏   | 31/50 [00:48<00:32,  1.69s/it]Epoch 31/50 - Loss: 1.501 - Acc
         Val_loss: 1.524 - Val_acc: 0.938
 82%|████████▏ | 41/50 [01:03<00:14,  1.56s/it]Epoch 41/50 - Loss: 1.498 - Acc
         Val_loss: 1.523 - Val_acc: 0.937
                                func:'train'  took: 77.8303 sec
```

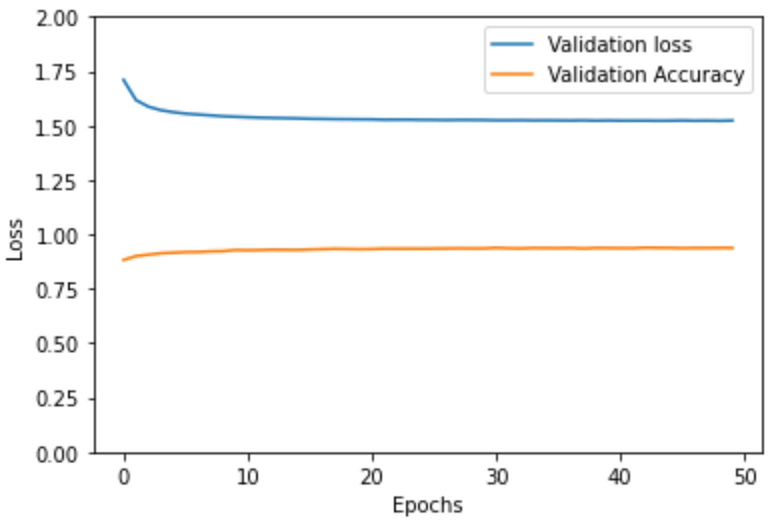
```
losses = dictionary['losses']
accuracies = dictionary['accuracies']
accuracies = np.asarray(accuracies)
losses = np.asarray(losses)
plt.figure()
plt.plot(np.arange(len(losses)),losses,label='Training loss')
plt.plot(np.arange(len(accuracies)),accuracies,label='Training Accuracy')
plt.xlabel('Epochs')
```

```
plt.ylabel('Loss')
plt.ylim(0, 2)
plt.legend()

val_losses = dictionary['val_losses']
val_accuracies = dictionary['val_accuracies']
val_accuracies = np.asarray(val_accuracies)
val_losses = np.asarray(val_losses)
plt.figure()
plt.plot(np.arange(len(val_losses)),val_losses,label='Validation loss')
plt.plot(np.arange(len(val_accuracies)),val_accuracies,label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylim(0, 2)
plt.ylabel('Loss')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7fd345202b80>
```






```
#feed forward into the model with the test data from MNIST and compare the results
output = model.forward(torch.tensor(reduced_test_set, dtype = torch.float32))
sum = 0
for i in range(len(output)):
```

```
    if (test_set_y[i] == torch.argmax(output[i])):
      sum += 1
print(sum/len(output))
```

```
0.9433
```

After running the training function with the new model it seems that the accuracy has not improved on the validation set. The training may be slightly slower judging by the curve of Validation Loss in the above charts. When I use the model to predict based on the given test data I get around 94% which is just as good as the previous ANN architecture. Using PCA in this case likely reduces the amount of memory needed but has not really improved in accuracy over the model with 1024 inputs.