Homework 5

```
In [2]: #imports
   import numpy as np
   import pandas as pd
   import matplotlib.pyplot as plt

In [3]: wage_raw = pd.read_csv('Wage.csv')
```

1. K-Means

- 1. Instead of just having an indicator for job class we add an indicator for each of the categorical variables. The categorical variables are:
- sex
- maritl
- race
- education
- region
- jobclass
- health
- health_ins

```
In [3]: cat_var = ['sex', 'maritl', 'race', 'education', 'region', 'jobclass', 'health', 'h
wage = pd.get_dummies(wage_raw, columns=cat_var, drop_first=True)
In [102... wage
```

Out[102...

		year	age	logwage	wage	maritl_2. Married	maritl_3. Widowed	maritl_4. Divorced	maritl_5. Separated	race_2. Black
	0	2006	18	4.318063	75.043154	False	False	False	False	False
	1	2004	24	4.255273	70.476020	False	False	False	False	False
	2	2003	45	4.875061	130.982177	True	False	False	False	False
	3	2003	43	5.041393	154.685293	True	False	False	False	False
	4	2005	50	4.318063	75.043154	False	False	True	False	False
	•••						···			
2	2995	2008	44	5.041393	154.685293	True	False	False	False	False
2	2996	2007	30	4.602060	99.689464	True	False	False	False	False
2	2997	2005	27	4.193125	66.229408	True	False	False	False	True
2	2998	2005	27	4.477121	87.981033	False	False	False	False	False
2	2999	2009	55	4.505150	90.481913	False	False	False	True	False

3000 rows × 18 columns

2. Code

```
In [5]: rng = np.random.default_rng()
    train_idx = rng.binomial(1, 0.8, size = wage.shape[0]).astype(bool)
    wage_train = wage[train_idx]
    wage_test = wage[~train_idx]
```

3. We assume that everyone has completed middle school for a minimum of 9 years of schooling. If someone is a High School Grad that counts for 4 more years. If they have some college, we assume that's an associate degree. The cases where someone drops out at 1 year or 3 years average out to 2 years (most of the time). Some college should count for 2 years. College grad counts for 4 years. Advanced degrees can be masters or phds or professional degrees. Masters usually are 2 years, and Phds are usually 5-6, but often take much longer. We assume it adds a bit more years of schooling, say 4 years on average.

4. Code

```
# make education years column
education_years = 9 + wage['education_2. HS Grad'] * 4 + wage['education_3. Some Co
# make kmeans data_frame
```

```
wage_kmeans = pd.DataFrame({'jobclass': wage['jobclass_2. Information'], 'age': wag
# standardize
wage_kmeans[['age', 'education_years', 'logwage']] = (wage_kmeans[['age', 'educatio
# split
wage_kmeans_train = wage_kmeans[train_idx]
wage_kmeans_test = wage_kmeans[~train_idx]
wage_kmeans
```

Out[104...

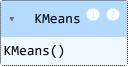
	jobclass	age	education_years	logwage
0	False	-2.115215	-1.888180	-0.954767
1	True	-1.595392	0.577880	-1.133275
2	False	0.223986	-0.038635	0.628727
3	True	0.050712	0.577880	1.101591
4	True	0.657171	-0.655150	-0.954767
•••				•••
2995	False	0.137349	-0.038635	1.101591
2996	False	-1.075570	-0.655150	-0.147391
2997	False	-1.335481	-1.888180	-1.309956
2998	False	-1.335481	-0.038635	-0.502580
2999	False	1.090356	-0.655150	-0.422897

3000 rows × 4 columns

5. Code

```
import sklearn.cluster
num_clusters = 8
kmeans_clf = sklearn.cluster.KMeans(n_clusters = num_clusters)
kmeans_clf.fit(wage_kmeans_train)
```

Out[105...



6. Predict

```
In [106...
kmeans_weights = np.zeros(num_clusters)
for i in range(num_clusters):
    kmeans_weights[i] = np.mean(wage_kmeans_train.iloc[kmeans_clf.labels_ == i]['jo
print(kmeans_weights)
```

```
[0.66666667 0.50743494 0.8 0.29299363 0.46285714 0.39732143 0.51923077 0.24096386]
```

7. Here is some code to investigate this:

As we can see, the first coordinate of each of the cluster centers (the part corresponding to the job) is exactly the fraction we calculated prior. This makes sense since each cluster center's should just be the mean of the group, otherwise the variance would increase.

8. Code

```
In [108...
kmeans_weights = kmeans_weights > 0.5
kmeans_preds_train = np.eye(num_clusters)[kmeans_clf.predict(wage_kmeans_train)] @
kmeans_err_train = np.mean(kmeans_preds_train != wage_kmeans_train['jobclass'])
print(f"The training error for the k-means classifier is {kmeans_err_train}")
```

The training error for the k-means classifier is 0.3831578947368421

9. Code

```
In [109... kmeans_preds_test = np.eye(num_clusters)[kmeans_clf.predict(wage_kmeans_test)] @ km
10. Code
```

```
In [110... kmeans_err_test = np.mean(kmeans_preds_test != wage_kmeans_test['jobclass'])
print(f"The test error for the k-means classifier is {kmeans_err_test}")
```

The test error for the k-means classifier is 0.384

2. Neural Networks

1. Code

```
In [4]: import torch
          import torch.nn as nn
          import torch.optim as optim
          import torch.functional as F
          import torch.utils.data as data
 In [9]: device = torch.accelerator.current_accelerator().type if torch.accelerator.is_avail
          print(f'Using device: {device}')
         Using device: cuda
 In [10]: class Net(nn.Module):
              def __init__(self):
                  super(Net, self).__init__()
                  self.linear_relu_logit_stack = nn.Sequential(
                      nn.Linear(3, 16),
                      nn.ReLU(),
                      nn.Linear(16, 16),
                      nn.ReLU(),
                      nn.Linear(16, 1),
                      nn.Sigmoid()
              def forward(self, x):
                  return self.linear relu logit stack(x)
         model = Net().to(device)
In [114...
          print(model)
         Net(
           (linear_relu_logit_stack): Sequential(
             (0): Linear(in_features=3, out_features=16, bias=True)
             (1): ReLU()
             (2): Linear(in_features=16, out_features=16, bias=True)
             (3): ReLU()
             (4): Linear(in_features=16, out_features=1, bias=True)
             (5): Sigmoid()
           )
         )
In [115... loss_fn = nn.BCELoss()
          optimizer = optim.Adam(model.parameters(), lr=10e-4)
In [11]: wage_nn_train = torch.tensor(wage_kmeans_train[['age', 'education_years', 'logwage'
          jobclass_nn_train = torch.tensor(wage_kmeans_train['jobclass'].values, dtype=torch.
          jobclass_nn_train = jobclass_nn_train.view(-1, 1)
          wage_nn_test = torch.tensor(wage_kmeans_test[['age', 'education_years', 'logwage']]
          jobclass_nn_test = torch.tensor(wage_kmeans_test['jobclass'].values, dtype=torch.fl
          jobclass_nn_test = jobclass_nn_test.view(-1, 1)
```

```
NameError
                                                Traceback (most recent call last)
       Cell In[11], line 1
       ----> 1 wage_nn_train = torch.tensor(wage_kmeans_train[['age', 'education_years', 'l
       ogwage']].values, dtype=torch.float32).to(device)
             2 jobclass_nn_train = torch.tensor(wage_kmeans_train['jobclass'].values, dtype
       =torch.float32).to(device)
             3 jobclass_nn_train = jobclass_nn_train.view(-1, 1)
       NameError: name 'wage kmeans train' is not defined
In [5]: def train(X,y, batch_size, model, loss_fn, optimizer):
            model.train()
            for i in np.random.permutation(range(len(X)//batch_size)):
                Xi, yi = X[i*batch_size: (i+1)*batch_size], y[i*batch_size: (i+1)*batch_siz
                Xi, yi = Xi.to(device), yi.to(device)
                # pred
                pred = model(Xi)
                loss = loss_fn(pred, yi)
                # backprop
                loss.backward()
                optimizer.step()
                optimizer.zero_grad()
                # if i % 100 == 0:
                   loss = loss.item()
                     print(f"loss: {loss:>7f} [{i:>5d}/{len(X)}]")
In [6]: def test(X, y, model, loss_fn):
            model.eval()
            size = len(X)
            test_loss, correct = 0, 0
            with torch.no_grad():
                for Xi, yi in zip(X, y):
                    Xi, yi = Xi.to(device), yi.to(device)
                    pred = model(Xi)
                    loss = loss_fn(pred, yi)
                    test_loss += loss.item()
                    correct += (pred.round() == yi).type(torch.float).item()
            test_loss /= size
            correct /= size
            print(f"Test Error: \n Accuracy: {(100*correct):>0.1f}%, Avg loss: {test_loss:>
            return correct, test_loss
In [6]: epochs = 5
        for t in range(epochs):
            print(f"Epoch {t+1}\n----")
            train(wage_nn_train, jobclass_nn_train, model, loss_fn, optimizer)
            test(wage_nn_train, jobclass_nn_train, model, loss_fn)
       Epoch 1
```

file:///C:/Users/matth/OneDrive/Documents/School/Senior Year/Winter Quarter/ECMA 31330/hw5/hw5.html

```
NameError
Cell In[6], line 4

2 for t in range(epochs):
3    print(f"Epoch {t+1}\n-----")

----> 4    train(wage_nn_train, jobclass_nn_train, model, loss_fn, optimizer)
5    test(wage_nn_train, jobclass_nn_train, model, loss_fn)

NameError: name 'train' is not defined
```

2. Code

```
In [121... model.eval()
   wage_nn_train_err = ((model(wage_nn_train) > 0.5) == jobclass_nn_train).sum().item(
   print(f"The training error for the neural network is {1 - wage_nn_train_err}")
```

The training error for the neural network is 0.3701052631578947

3. Code

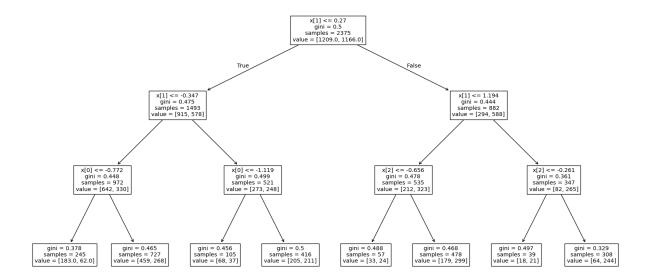
```
In [122...
model.eval()
wage_nn_test_err = ((model(wage_nn_test) > 0.5) == jobclass_nn_test).sum().item()/l
print(f"The test error for the neural network is {1 - wage_nn_test_err}")
```

3. Regression Trees

1. Code

2. Code

```
In [125... plt.figure(figsize=(20,10))
    sklearn.tree.plot_tree(dt_clf)
    plt.show()
```



3. Code

```
In [126... wage_dt_train_err = 1 - dt_clf.score(wage_dt_train, jobclass_dt_train)
print(f"The training error for the decision tree is {wage_dt_train_err}")
```

The training error for the decision tree is 0.36084210526315785

4. Code

```
In [127...
wage_dt_test_err = 1 - dt_clf.score(wage_dt_test, jobclass_dt_test)
print(f"The test error for the decision tree is {wage_dt_test_err}")
```

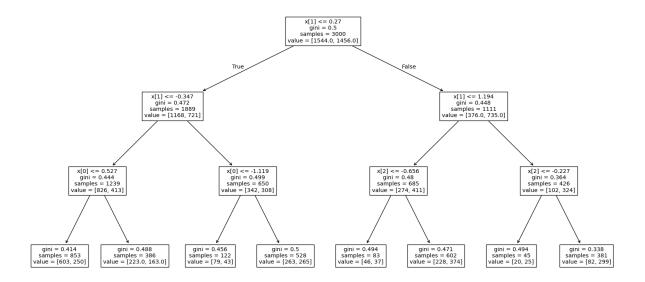
The test error for the decision tree is 0.3663999999999999

5. Code

```
In [128...
wage_dt = wage_kmeans[['age', 'education_years', 'logwage']]
jobclass_dt = wage_kmeans['jobclass']
dt_full_clf = sklearn.tree.DecisionTreeClassifier(max_depth = 3)
dt_full_clf.fit(wage_dt, jobclass_dt)
```

6. Code

```
In [129... plt.figure(figsize=(20,10))
    sklearn.tree.plot_tree(dt_full_clf)
    plt.show()
```



7. Code

```
In [130... wage_dt_full_train_err = 1 - dt_full_clf.score(wage_dt, jobclass_dt)
    print(f"The error on the training set for the decision tree is {wage_dt_full_train_
```

The error on the training set for the decision tree is 0.362

8. Code

```
In [131... wage_dt_full_test_err = 1 - dt_full_clf.score(wage_dt_test, jobclass_dt_test)
    print(f"The error on the test set for the decision tree is {wage_dt_full_test_err}'
```

The error on the test set for the decision tree is 0.3663999999999999

4. Compare All Methods

1. Code

Out[133... kmeans neural_network decision_tree decision_tree_full

train	0.383158	0.370105	0.360842	0.3620
test	0.384000	0.358400	0.366400	0.3664

- 2. All of the methods performed incredibly close to each other. They were all within 3e-2 of each other. The neural network did the best, which was expected, but all methods performed well. In theory, we should have expected the full decision tree to perform better than the standard decision tree, however, we only had 3 features, with max depth of 8, so the decision tree was quite constrained. The neural network performed the best, but not by as well as I expected. I chalk this up to there not being enough data and not using enough features.
- 3. (Optional) We are going to train a neural net with one more hidden layer and more intermediary nodes. We are also going to cross validate for the learning rate in the SGD optimizer and we are going to use the entire data set with the one-hot encoding.

```
In [ ]: wage = wage.astype('float64')
          wage_train = wage_train.astype('float64')
          wage_test = wage_test.astype('float64')
          wage
In [137...
          class Net(nn.Module):
              def __init__(self):
                  super(Net, self).__init__()
                  self.linear_relu_logit_stack = nn.Sequential(
                      nn.Linear(17, 32),
                      nn.ReLU(),
                      nn.Linear(32, 32),
                      nn.ReLU(),
                      nn.Linear(32, 32),
                      nn.ReLU(),
                      nn.Linear(32, 1),
                      nn.Sigmoid()
              def forward(self, x):
                  return self.linear_relu_logit_stack(x)
          model = Net().to(device)
          print(model)
         Net(
           (linear_relu_logit_stack): Sequential(
             (0): Linear(in_features=17, out_features=32, bias=True)
             (1): ReLU()
             (2): Linear(in_features=32, out_features=32, bias=True)
             (3): ReLU()
             (4): Linear(in_features=32, out_features=32, bias=True)
             (5): ReLU()
             (6): Linear(in_features=32, out_features=1, bias=True)
             (7): Sigmoid()
           )
         )
 In [22]: wage_nn_train = torch.tensor(wage_train.drop(columns = 'jobclass_2. Information').v
          jobclass_nn_train = torch.tensor(wage_train['jobclass_2. Information'].values, dtyp
          jobclass_nn_train = jobclass_nn_train.view(-1, 1)
```

Epoch 1 Test Error: Accuracy: 57.2%, Avg loss: 0.677338 Epoch 2 Test Error: Accuracy: 57.1%, Avg loss: 0.673603 Epoch 3 Test Error: Accuracy: 59.4%, Avg loss: 0.667718 Epoch 4 Test Error: Accuracy: 57.2%, Avg loss: 0.672373 Epoch 5 Test Error: Accuracy: 59.5%, Avg loss: 0.668015 Epoch 6 Test Error: Accuracy: 56.8%, Avg loss: 0.676829 Epoch 7 -----Test Error: Accuracy: 59.7%, Avg loss: 0.668202 Epoch 8 Test Error: Accuracy: 57.7%, Avg loss: 0.668597 Epoch 9 Test Error: Accuracy: 57.5%, Avg loss: 0.670710 Epoch 10 -----Test Error: Accuracy: 59.6%, Avg loss: 0.667262 Epoch 11 _____ Test Error: Accuracy: 57.4%, Avg loss: 0.673629

Epoch 12

Test Error: Accuracy: 59.2%, Avg loss: 0.668041 Epoch 13 -----Test Error: Accuracy: 59.7%, Avg loss: 0.671024 Epoch 14 _____ Test Error: Accuracy: 59.5%, Avg loss: 0.666076 Epoch 15 -----Test Error: Accuracy: 58.1%, Avg loss: 0.668596 Epoch 16 -----Test Error: Accuracy: 54.1%, Avg loss: 0.718041 Epoch 17 -----Test Error: Accuracy: 58.5%, Avg loss: 0.667357 Epoch 18 -----Test Error: Accuracy: 56.8%, Avg loss: 0.675292 Epoch 19 -----Test Error: Accuracy: 60.0%, Avg loss: 0.665352 Epoch 20 _____ Test Error: Accuracy: 58.4%, Avg loss: 0.670422 Epoch 21 ______ Test Error: Accuracy: 56.4%, Avg loss: 0.676622 Epoch 22 _____ Test Error: Accuracy: 60.3%, Avg loss: 0.664770 Epoch 23

```
Test Error:
    Accuracy: 59.6%, Avg loss: 0.664290

Epoch 24
------
Test Error:
    Accuracy: 59.4%, Avg loss: 0.664646

Epoch 25
-----
Test Error:
    Accuracy: 56.8%, Avg loss: 0.675412
```

```
In [153...
model.eval()
wage_nn_train_err = ((model(wage_nn_train) > 0.5) == jobclass_nn_train).sum().item(
print(f"The training error for the neural network is {1 - wage_nn_train_err}")
wage_nn_test_err = ((model(wage_nn_test) > 0.5) == jobclass_nn_test).sum().item()/l
print(f"The test error for the neural network is {1 - wage_nn_test_err}")
```

It's clear that our nn is suffering. We will drop wages because they are codependent with logwages. We also demean year and age, since only the relative age and years matter

```
In [7]:
    cat_var = ['sex', 'maritl', 'race', 'education', 'region', 'jobclass', 'health', 'h
    wage = pd.get_dummies(wage_raw, columns=cat_var, drop_first=True)
    wage = wage.astype('float64')
    wage = wage.drop(columns = 'wage')
    wage['year'] = wage['year'] - wage['year'].mean()
    wage['age'] = wage['age'] - wage['age'].mean()
    rng = np.random.default_rng()
    train_idx = rng.binomial(1, 0.8, size = wage.shape[0]).astype(bool)
    wage_train = wage[train_idx]
    wage_test = wage[~train_idx]
    wage
```

Out[7]:

•		year	age	logwage	maritl_2. Married	maritl_3. Widowed	maritl_4. Divorced	maritl_5. Separated	race_2. Black	race As
	0	0.209	-24.414667	4.318063	0.0	0.0	0.0	0.0	0.0	
	1	-1.791	-18.414667	4.255273	0.0	0.0	0.0	0.0	0.0	
	2	-2.791	2.585333	4.875061	1.0	0.0	0.0	0.0	0.0	
	3	-2.791	0.585333	5.041393	1.0	0.0	0.0	0.0	0.0	
	4	-0.791	7.585333	4.318063	0.0	0.0	1.0	0.0	0.0	
	•••							•••		
	2995	2.209	1.585333	5.041393	1.0	0.0	0.0	0.0	0.0	
	2996	1.209	-12.414667	4.602060	1.0	0.0	0.0	0.0	0.0	
	2997	-0.791	-15.414667	4.193125	1.0	0.0	0.0	0.0	1.0	
	2998	-0.791	-15.414667	4.477121	0.0	0.0	0.0	0.0	0.0	
	2999	3.209	12.585333	4.505150	0.0	0.0	0.0	1.0	0.0	

3000 rows × 17 columns

```
device = torch.accelerator.current_accelerator().type if torch.accelerator.is_avail
    print(f'Using device: {device}')
    wage_nn_train = torch.tensor(wage_train.drop(columns = 'jobclass_2. Information').v
    jobclass_nn_train = torch.tensor(wage_train['jobclass_2. Information'].values, dtyp
    jobclass_nn_train = jobclass_nn_train.view(-1, 1)
    wage_nn_test = torch.tensor(wage_test.drop(columns = 'jobclass_2. Information').val
    jobclass_nn_test = torch.tensor(wage_test['jobclass_2. Information'].values, dtype=
    jobclass_nn_test = jobclass_nn_test.view(-1, 1)
```

Using device: cuda

```
In [10]: wage_nn_train.shape
Out[10]: torch.Size([2411, 16])
In [24]: class Net(nn.Module):
```

t += 1

```
nn.ReLU(),
                     nn.Linear(16, 1),
                     nn.Sigmoid()
             def forward(self, x):
                 return self.linear_relu_logit_stack(x)
In [52]: loss_fn = nn.BCELoss()
         # epochs = 25
         batch size = 32
         model = Net(d_in = 16).to(device)
         optimizer = optim.Adam(model.parameters(), lr=10e-4)
In [53]: t = 0
         accuracy = 0
         accuracies = [0.5]
         test_accuracies = [0.5]
         while max(test_accuracies) < 0.6615384615384615:</pre>
             print(f"Epoch {t+1}\n----")
             train(wage_nn_train, jobclass_nn_train, batch_size, model, loss_fn, optimizer)
             accuracy, loss = test(wage_nn_train, jobclass_nn_train, model, loss_fn)
             test_accuracy, test_loss = test(wage_nn_test, jobclass_nn_test, model, loss_fn)
             accuracies.append(accuracy)
             test_accuracies.append(test_accuracy)
```

```
Epoch 1
-----
Test Error:
Accuracy: 54.0%, Avg loss: 0.688912
Test Error:
Accuracy: 51.5%, Avg loss: 0.692923
_____
Test Error:
Accuracy: 54.2%, Avg loss: 0.681890
Test Error:
Accuracy: 55.4%, Avg loss: 0.680201
Epoch 3
Test Error:
Accuracy: 62.3%, Avg loss: 0.655133
Test Error:
Accuracy: 60.3%, Avg loss: 0.660713
Epoch 4
-----
Test Error:
Accuracy: 63.3%, Avg loss: 0.647987
Test Error:
Accuracy: 62.4%, Avg loss: 0.647018
Epoch 5
_____
Test Error:
Accuracy: 63.9%, Avg loss: 0.641303
Test Error:
Accuracy: 63.4%, Avg loss: 0.637046
Epoch 6
Test Error:
Accuracy: 63.6%, Avg loss: 0.638212
Test Error:
Accuracy: 63.1%, Avg loss: 0.633663
Epoch 7
Test Error:
Accuracy: 64.1%, Avg loss: 0.638521
```

Accuracy: 63.4%, Avg loss: 0.638104

Test Error:

Epoch 8 -----Test Error: Accuracy: 64.0%, Avg loss: 0.634455 Test Error: Accuracy: 65.0%, Avg loss: 0.625823 _____ Test Error: Accuracy: 64.7%, Avg loss: 0.633673 Test Error: Accuracy: 63.1%, Avg loss: 0.628517 Epoch 10 Test Error: Accuracy: 64.9%, Avg loss: 0.633447 Test Error: Accuracy: 64.4%, Avg loss: 0.626766 Epoch 11 -----Test Error: Accuracy: 64.4%, Avg loss: 0.632701 Test Error: Accuracy: 64.3%, Avg loss: 0.626422 Epoch 12 _____ Test Error: Accuracy: 64.7%, Avg loss: 0.630944 Test Error: Accuracy: 64.6%, Avg loss: 0.623650 Epoch 13 Test Error: Accuracy: 64.5%, Avg loss: 0.631863 Test Error: Accuracy: 63.6%, Avg loss: 0.629885 Epoch 14

Test Error:

Accuracy: 63.4%, Avg loss: 0.638376

Test Error:

Accuracy: 62.7%, Avg loss: 0.635124

Epoch 15 Test Error: Accuracy: 64.8%, Avg loss: 0.627940 Test Error: Accuracy: 62.9%, Avg loss: 0.630257 _____ Test Error: Accuracy: 65.3%, Avg loss: 0.628684 Test Error: Accuracy: 62.9%, Avg loss: 0.631827 Epoch 17 Test Error: Accuracy: 65.6%, Avg loss: 0.624737 Test Error: Accuracy: 65.1%, Avg loss: 0.624063 Epoch 18 -----Test Error: Accuracy: 65.6%, Avg loss: 0.625201 Test Error: Accuracy: 63.2%, Avg loss: 0.627675 Epoch 19 -----Test Error: Accuracy: 65.3%, Avg loss: 0.624729 Test Error: Accuracy: 64.8%, Avg loss: 0.626835 Epoch 20 Test Error: Accuracy: 65.7%, Avg loss: 0.625187 Test Error:

Accuracy: 63.4%, Avg loss: 0.629846

Epoch 21

Test Error:

Accuracy: 66.3%, Avg loss: 0.620099

Test Error:

Accuracy: 63.4%, Avg loss: 0.627794

Epoch 22 Test Error: Accuracy: 65.8%, Avg loss: 0.619355 Test Error: Accuracy: 64.4%, Avg loss: 0.627411 _____ Test Error: Accuracy: 66.0%, Avg loss: 0.618179 Test Error: Accuracy: 62.4%, Avg loss: 0.629185 Epoch 24 Test Error: Accuracy: 66.4%, Avg loss: 0.616349 Test Error: Accuracy: 63.1%, Avg loss: 0.629715 Epoch 25 -----Test Error: Accuracy: 66.3%, Avg loss: 0.618377 Test Error: Accuracy: 64.6%, Avg loss: 0.627575 Epoch 26 _____ Test Error: Accuracy: 66.5%, Avg loss: 0.615430 Test Error: Accuracy: 63.4%, Avg loss: 0.623028 Epoch 27 Test Error: Accuracy: 65.3%, Avg loss: 0.621508 Test Error:

Accuracy: 62.9%, Avg loss: 0.631204

Epoch 28

Test Error:

Accuracy: 66.2%, Avg loss: 0.613335

Test Error:

Accuracy: 64.3%, Avg loss: 0.626733

Epoch 29 Test Error: Accuracy: 65.5%, Avg loss: 0.620411 Test Error: Accuracy: 63.8%, Avg loss: 0.632448 _____ Test Error: Accuracy: 66.7%, Avg loss: 0.613138 Test Error: Accuracy: 63.8%, Avg loss: 0.627666 Epoch 31 Test Error: Accuracy: 66.5%, Avg loss: 0.612773 Test Error: Accuracy: 61.5%, Avg loss: 0.637041 Epoch 32 · ------Test Error: Accuracy: 66.8%, Avg loss: 0.607241 Test Error: Accuracy: 62.9%, Avg loss: 0.627751 Epoch 33 -----Test Error: Accuracy: 66.7%, Avg loss: 0.606945 Test Error: Accuracy: 64.1%, Avg loss: 0.629824 Epoch 34 Test Error: Accuracy: 66.5%, Avg loss: 0.605591 Test Error: Accuracy: 65.5%, Avg loss: 0.627176

Epoch 35

Test Error:

Accuracy: 66.6%, Avg loss: 0.610121

Test Error:

Accuracy: 60.9%, Avg loss: 0.636251

Epoch 36 Test Error: Accuracy: 67.1%, Avg loss: 0.604154 Test Error: Accuracy: 61.9%, Avg loss: 0.635524 _____ Test Error: Accuracy: 67.1%, Avg loss: 0.608591 Test Error: Accuracy: 61.9%, Avg loss: 0.633077 Epoch 38 Test Error: Accuracy: 67.7%, Avg loss: 0.602258 Test Error: Accuracy: 62.6%, Avg loss: 0.626677 Epoch 39 -----Test Error: Accuracy: 66.6%, Avg loss: 0.604702 Test Error: Accuracy: 62.1%, Avg loss: 0.631172 Epoch 40 -----Test Error: Accuracy: 66.7%, Avg loss: 0.607520 Test Error: Accuracy: 61.9%, Avg loss: 0.635518 Epoch 41 Test Error: Accuracy: 66.8%, Avg loss: 0.602754 Test Error: Accuracy: 62.6%, Avg loss: 0.636054

Epoch 42

Test Error:

Accuracy: 67.4%, Avg loss: 0.601970

Test Error:

Accuracy: 62.6%, Avg loss: 0.643882

Epoch 43 Test Error: Accuracy: 67.8%, Avg loss: 0.596927 Test Error: Accuracy: 63.4%, Avg loss: 0.635919 _____ Test Error: Accuracy: 67.9%, Avg loss: 0.594442 Test Error: Accuracy: 63.6%, Avg loss: 0.632562 Epoch 45 Test Error: Accuracy: 67.7%, Avg loss: 0.595256 Test Error: Accuracy: 65.5%, Avg loss: 0.624834 Epoch 46 -----Test Error: Accuracy: 67.8%, Avg loss: 0.592588 Test Error: Accuracy: 62.9%, Avg loss: 0.630867 Epoch 47 -----Test Error: Accuracy: 67.4%, Avg loss: 0.593409 Test Error: Accuracy: 64.8%, Avg loss: 0.635298 Epoch 48 Test Error: Accuracy: 68.6%, Avg loss: 0.594090

Test Error:

Accuracy: 63.8%, Avg loss: 0.637697

Epoch 49

Test Error:

Accuracy: 68.6%, Avg loss: 0.598494

Test Error:

Accuracy: 63.6%, Avg loss: 0.634642

Epoch 50 Test Error: Accuracy: 67.5%, Avg loss: 0.592970 Test Error: Accuracy: 62.9%, Avg loss: 0.634516 _____ Test Error: Accuracy: 68.7%, Avg loss: 0.584959 Test Error: Accuracy: 64.4%, Avg loss: 0.639305 Epoch 52 Test Error: Accuracy: 67.2%, Avg loss: 0.600400 Test Error: Accuracy: 61.4%, Avg loss: 0.643227 Epoch 53 -----Test Error: Accuracy: 69.1%, Avg loss: 0.592140 Test Error: Accuracy: 62.9%, Avg loss: 0.640318 Epoch 54 -----Test Error: Accuracy: 69.2%, Avg loss: 0.583685 Test Error: Accuracy: 63.1%, Avg loss: 0.635839 Epoch 55 Test Error: Accuracy: 69.5%, Avg loss: 0.582836 Test Error: Accuracy: 61.7%, Avg loss: 0.635465

Epoch 56

Test Error:

Accuracy: 69.4%, Avg loss: 0.578892

Test Error:

Accuracy: 65.6%, Avg loss: 0.634814

Epoch 57 -----Test Error: Accuracy: 70.4%, Avg loss: 0.577554 Test Error: Accuracy: 63.2%, Avg loss: 0.644747 _____ Test Error: Accuracy: 70.6%, Avg loss: 0.575099 Test Error: Accuracy: 62.9%, Avg loss: 0.642703 Epoch 59 Test Error: Accuracy: 69.3%, Avg loss: 0.578011 Test Error: Accuracy: 62.6%, Avg loss: 0.653849 Epoch 60 -----Test Error: Accuracy: 70.1%, Avg loss: 0.571171 Test Error: Accuracy: 61.7%, Avg loss: 0.646427 Epoch 61 -----Test Error: Accuracy: 70.5%, Avg loss: 0.572552 Test Error: Accuracy: 63.9%, Avg loss: 0.652813 Epoch 62 Test Error: Accuracy: 70.5%, Avg loss: 0.565000 Test Error:

Accuracy: 63.8%, Avg loss: 0.647250

Epoch 63

Test Error:

Accuracy: 69.7%, Avg loss: 0.576659

Test Error:

Accuracy: 63.2%, Avg loss: 0.664534

Epoch 64 Test Error: Accuracy: 71.1%, Avg loss: 0.569392 Test Error: Accuracy: 64.1%, Avg loss: 0.641037 _____ Test Error: Accuracy: 70.2%, Avg loss: 0.571338 Test Error: Accuracy: 63.8%, Avg loss: 0.658674 Epoch 66 Test Error: Accuracy: 69.2%, Avg loss: 0.568884 Test Error: Accuracy: 59.7%, Avg loss: 0.667272 Epoch 67 -----Test Error: Accuracy: 71.3%, Avg loss: 0.562705 Test Error: Accuracy: 61.7%, Avg loss: 0.662775 Epoch 68 -----Test Error: Accuracy: 71.7%, Avg loss: 0.557770 Test Error: Accuracy: 64.1%, Avg loss: 0.659682 Epoch 69 Test Error: Accuracy: 71.3%, Avg loss: 0.556723 Test Error: Accuracy: 62.6%, Avg loss: 0.668302

Accuracy: 69.9%, Avg loss: 0.567010

Accuracy: 63.1%, Avg loss: 0.668768

file:///C:/Users/matth/OneDrive/Documents/School/Senior Year/Winter Quarter/ECMA 31330/hw5/hw5.html

Epoch 70

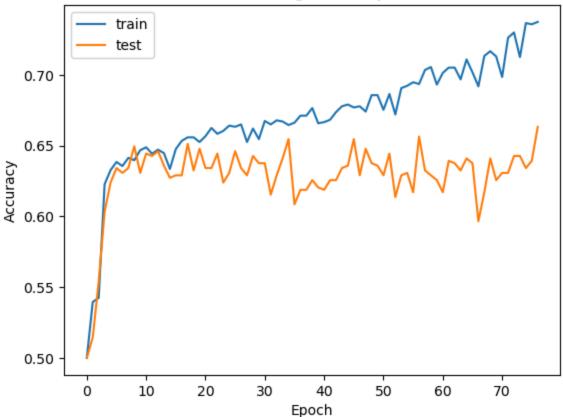
Test Error:

Test Error:

```
Epoch 71
       Test Error:
        Accuracy: 72.6%, Avg loss: 0.553586
       Test Error:
        Accuracy: 63.1%, Avg loss: 0.658022
       _____
       Test Error:
        Accuracy: 73.0%, Avg loss: 0.550672
       Test Error:
        Accuracy: 64.3%, Avg loss: 0.660483
       Epoch 73
       Test Error:
        Accuracy: 71.3%, Avg loss: 0.558513
       Test Error:
        Accuracy: 64.3%, Avg loss: 0.682630
       Epoch 74
       -----
       Test Error:
        Accuracy: 73.7%, Avg loss: 0.541067
       Test Error:
        Accuracy: 63.4%, Avg loss: 0.659616
       Epoch 75
       _____
       Test Error:
        Accuracy: 73.6%, Avg loss: 0.550955
       Test Error:
        Accuracy: 63.9%, Avg loss: 0.665608
       Epoch 76
       Test Error:
        Accuracy: 73.7%, Avg loss: 0.538043
       Test Error:
        Accuracy: 66.3%, Avg loss: 0.664403
In [54]: import os
        os.environ["KMP_DUPLICATE_LIB_OK"]="TRUE"
        plt.figure()
        plt.plot(accuracies, label = 'train')
        plt.plot(test_accuracies, label = 'test')
        plt.xlabel('Epoch')
        plt.ylabel('Accuracy')
```

```
plt.title('Training Accuracy')
plt.legend()
plt.show()
print(np.argmax(test_accuracies))
print(np.max(test_accuracies))
```

Training Accuracy



76 0.6632478632478632

```
In [60]: wage_nn_train = wage_nn_train.to(device)
    jobclass_nn_train = jobclass_nn_train.to(device)
    wage_nn_test = wage_nn_test.to(device)
    jobclass_nn_test = jobclass_nn_test.to(device)
    wage_nn_train_err = ((model(wage_nn_train.to(device)) > 0.5) == jobclass_nn_train).
    print(f"The training error for the neural network is {1 - wage_nn_train_err}")
    wage_nn_test_err = ((model(wage_nn_test) > 0.5) == jobclass_nn_test).sum().item()/l
    print(f"The test error for the neural network is {1 - wage_nn_test_err}")
```

The training error for the neural network is 0.26252587991718423 The test error for the neural network is 0.3367521367521368

This test error beats our other test error by 3%!