```
In [73]: # Name : Yvonne Lee
         # Class: MSDS 680
         # Assignment 2 Week 2
         # Analysis:
         # I first tested the KNN model with n = 1. The accuracy score came out to be 6
         1%. I then plotted the accuracy scores and redid
         # the KNN model with n = 5. The accuracy score after that became 63% which is
          a tad better than the first model. In an effort
         # to continue to improve the model, I scaled the dataset and calculated accura
         cy scores once more to plot. I then redid the
         # KNN model again with n = 15 and that resulted in an accuracy score of 84%. T
         here was a massive improvement after scaling
         # the dataset. Each n for each step was the optimal k at the time of the mode
         L.
         # Import necessary libraries.
         import pandas as pd
         import numpy as np
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.model selection import train test split
         from sklearn.decomposition import PCA
         from sklearn.metrics import confusion_matrix
         import seaborn as sns
         import matplotlib.pyplot as plt
         %matplotlib inline
         sns.set()
```

```
In [74]: import warnings
warnings.filterwarnings("ignore")
```

```
In [75]: # Upload dataset.
    df = pd.read_csv("C:\\Users\\ylee_\\Desktop\\assign_wk2\\heart.dis
    ease.data.clean.csv")
    df.head(10)
```

Out[75]:

	age	sex	ср	trestbps	chol	cigs	years	fbs	famhist	restecg	thalach	exang	thal	num
0	63	1	1	145	233	50.0	20.0	1	1	2	150	0	6	0
1	67	1	4	160	286	40.0	40.0	0	1	2	108	1	3	2
2	67	1	4	120	229	20.0	35.0	0	1	2	129	1	7	1
3	37	1	3	130	250	0.0	0.0	0	1	0	187	0	3	0
4	41	0	2	130	204	0.0	0.0	0	1	2	172	0	3	0
5	56	1	2	120	236	20.0	20.0	0	1	0	178	0	3	0
6	62	0	4	140	268	0.0	0.0	0	1	2	160	0	3	3
7	57	0	4	120	354	0.0	0.0	0	1	0	163	1	3	0
8	63	1	4	130	254	0.0	0.0	0	0	2	147	0	7	2
9	53	1	4	140	203	20.0	25.0	1	1	2	155	1	7	1

In [76]: df.info()

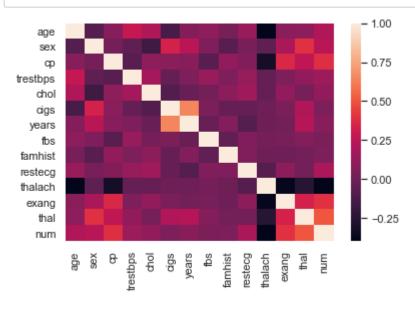
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 282 entries, 0 to 281
Data columns (total 14 columns):
            282 non-null int64
age
            282 non-null int64
sex
ср
            282 non-null int64
trestbps
            282 non-null int64
            282 non-null int64
chol
            282 non-null float64
cigs
years
            282 non-null float64
            282 non-null int64
fbs
famhist
            282 non-null int64
            282 non-null int64
restecg
            282 non-null int64
thalach
            282 non-null int64
exang
thal
            282 non-null int64
num
            282 non-null int64
dtypes: float64(2), int64(12)
memory usage: 31.0 KB
```

In [77]: df.describe()

Out[77]:

	age	sex	ср	trestbps	chol	cigs	years	
count	282.000000	282.000000	282.000000	282.000000	282.000000	282.000000	282.000000	282.
mean	54.411348	0.677305	3.163121	131.195035	247.705674	16.836011	15.347364	0.
std	9.053083	0.468338	0.955405	16.739821	46.178771	18.876755	15.276814	0.
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.000000	0.
25%	48.000000	0.000000	3.000000	120.000000	213.000000	0.000000	0.000000	0.
50%	55.000000	1.000000	3.000000	130.000000	244.000000	11.976385	15.000000	0.
75%	61.000000	1.000000	4.000000	140.000000	277.000000	30.000000	30.000000	0.
max	77.000000	1.000000	4.000000	170.000000	360.000000	75.000000	54.000000	1.

In [78]: # Checking correlation.
_ = sns.heatmap(df.corr())



```
In [79]: # Simplifying num values.
df["num"] = np.where(df["num"] >0,1,0)
```

```
In [80]: df.head(10)
```

Out[80]:

```
cp trestbps chol cigs years fbs famhist restecg thalach exang
   age
        sex
                                                                       2
0
    63
           1
                1
                        145
                              233
                                    50.0
                                                    1
                                                              1
                                                                               150
                                                                                         0
                                                                                               6
                                                                                                     0
                                            20.0
                                                                       2
1
    67
           1
                4
                        160
                              286
                                    40.0
                                            40.0
                                                    0
                                                              1
                                                                               108
                                                                                         1
                                                                                               3
                                                                                                      1
2
    67
           1
                4
                        120
                              229
                                    20.0
                                            35.0
                                                    0
                                                              1
                                                                       2
                                                                               129
                                                                                         1
                                                                                               7
                                                                                                     1
                              250
                                                              1
                                                                       0
3
    37
           1
                3
                        130
                                     0.0
                                             0.0
                                                    0
                                                                               187
                                                                                         0
                                                                                               3
                                                                                                     0
    41
                2
                        130
                              204
                                     0.0
                                             0.0
                                                              1
                                                                       2
                                                                               172
4
           0
                                                    0
                                                                                         0
                                                                                               3
                                                                                                     0
5
    56
           1
                2
                        120
                              236
                                    20.0
                                            20.0
                                                    0
                                                              1
                                                                       0
                                                                              178
                                                                                         0
                                                                                               3
                                                                                                     0
                                                              1
6
    62
           0
                4
                        140
                              268
                                     0.0
                                             0.0
                                                    0
                                                                       2
                                                                               160
                                                                                         0
                                                                                               3
                                                                                                     1
7
    57
           0
                4
                        120
                              354
                                     0.0
                                             0.0
                                                    0
                                                              1
                                                                       0
                                                                               163
                                                                                         1
                                                                                               3
                                                                                                     0
                              254
                                                              0
                                                                       2
                                                                                               7
8
    63
           1
                4
                        130
                                     0.0
                                             0.0
                                                    0
                                                                               147
                                                                                         0
                                                                                                     1
                                                                                               7
9
    53
           1
                4
                        140
                              203
                                    20.0
                                            25.0
                                                              1
                                                                       2
                                                                               155
                                                                                         1
                                                                                                     1
                                                    1
```

```
In [81]: # Splitting the dataset to build a KNN model.
    cols = df.columns
    target_col = 'num'
    feat_cols = [c for c in cols if c != target_col]
    x = df[feat_cols].values
    y = df[target_col].values
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2)
```

```
In [82]: # KNN with n = 1.
    model = KNeighborsClassifier(n_neighbors = 1, n_jobs = -1)
    model.fit(x_train, y_train)
```

```
In [83]: # Predict values.
    preds = model.predict(x_test)
    print('Actuals for test data set')
    print(y_test)
    print('Predictions for test data set')
    print(preds)
```

```
Actuals for test data set
[1 0 1 1 0 1 0 0 1 0 1 0 1 0 0 1 1 0 1 1 0 0 0 1 0 0 1 1 1 0 0 0 1 0 1 1 1 0 0 0 1 0 1 1 1 0 0 0 1 0 1 1 0 1 0 1 0 1 0 1 0 1 1 0 1 1 0 0 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1 0 1
```

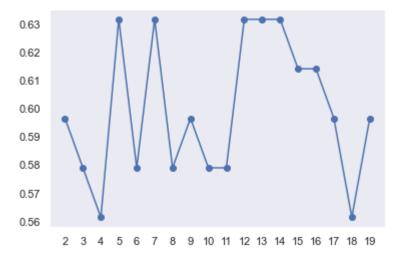
```
In [84]:
         differs = y_test - preds
         print('Differences between the two sets')
         print(differs)
         Differences between the two sets
         [0 0 0 1 0 1 0 -1 0 0 1 0 0 0 1 0
                                                         1
                                                            0
                                                              1 0 -1
          -1 0 0 0 -1 0 0 1 -1 1 1 -1 1 0 0 1
          0 1 0 -1 0 0 0
                               0 1]
In [85]: confusion_matrix(y_test, preds)
Out[85]: array([[19, 8],
               [14, 16]], dtype=int64)
In [86]:
         # We can see the summarized statistics for this model.
         from sklearn.metrics import classification_report
         print(classification_report(y_test,preds))
                      precision
                                   recall f1-score
                                                     support
                   0
                           0.58
                                     0.70
                                              0.63
                                                          27
                           0.67
                                     0.53
                                              0.59
                                                          30
                   1
                                              0.61
                                                          57
            accuracy
           macro avg
                           0.62
                                     0.62
                                              0.61
                                                          57
                                                          57
        weighted avg
                           0.62
                                     0.61
                                              0.61
In [88]:
        # Confirm the accuracy score is 61%.
         from sklearn.metrics import accuracy_score
```

print(accuracy_score(y_test,preds))

^{0.6140350877192983}

```
In [89]:
         # Getting accuracy scores to plot.
         scores = []
         print(f'Features: {feat cols} \nTarget: {target col}')
         for k in range(2, 20):
             print(f'Evaluating {k} clusters')
             model = KNeighborsClassifier(n neighbors=k, n jobs=-1)
             model.fit(x train, y train)
             scores.append(model.score(x_test, y_test))
         Features: ['age', 'sex', 'cp', 'trestbps', 'chol', 'cigs', 'years', 'fbs', 'f
         amhist', 'restecg', 'thalach', 'exang', 'thal']
         Target: num
         Evaluating 2 clusters
         Evaluating 3 clusters
         Evaluating 4 clusters
         Evaluating 5 clusters
         Evaluating 6 clusters
         Evaluating 7 clusters
         Evaluating 8 clusters
         Evaluating 9 clusters
         Evaluating 10 clusters
         Evaluating 11 clusters
         Evaluating 12 clusters
         Evaluating 13 clusters
         Evaluating 14 clusters
         Evaluating 15 clusters
         Evaluating 16 clusters
         Evaluating 17 clusters
         Evaluating 18 clusters
         Evaluating 19 clusters
In [90]:
         scores
Out[90]: [0.5964912280701754,
          0.5789473684210527,
          0.5614035087719298,
          0.631578947368421,
          0.5789473684210527,
          0.631578947368421,
          0.5789473684210527,
          0.5964912280701754,
          0.5789473684210527,
          0.5789473684210527,
          0.631578947368421,
          0.631578947368421,
          0.631578947368421,
          0.6140350877192983,
          0.6140350877192983,
          0.5964912280701754,
          0.5614035087719298,
          0.5964912280701754]
```

```
In [91]: # Plotting accuracy scores.
    plt.plot(range(2, 20), scores)
    plt.scatter(range(2, 20), scores)
    plt.grid()
    _ =plt.xticks(range(2, 20))
```



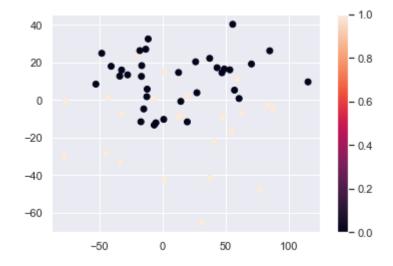
```
In [92]: # KNN
    model = KNeighborsClassifier(n_neighbors=5, n_jobs=-1)
    model.fit(x_train, y_train)

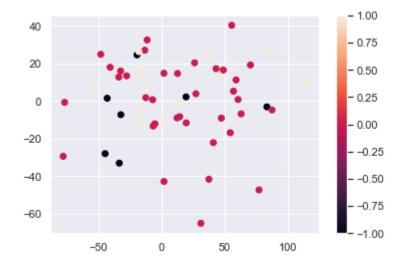
    preds = model.predict(x_test)

    print('Actuals for test data set')
    print(y_test)
    print('Predictions for test data set')
    print(preds)
```

```
In [93]: # CHecking stats and accuracy score is 63%.
differs = y_test - preds
print(f'Differences between the two sets:\n{differs}')
print(f'accuracy score: {accuracy_score(y_test,preds)}')
```

```
In [94]: confusion_matrix(y_test, preds)
Out[94]: array([[20, 7],
                  [14, 16]], dtype=int64)
In [95]: pc = PCA()
          tr_pca = pc.fit_transform(x_train)
          te_pca = pc.transform(x_test)
          _ = plt.scatter(tr_pca[:, 0], tr_pca[:, 1], c=y_train)
In [96]:
          _ = plt.colorbar()
                                                           - 1.0
            60
            40
                                                           - 0.8
            20
                                                           - 0.6
             0
                                                           - 0.4
            -20
                                                            0.2
            -40
                                                            0.0
                  -100
                          -50
                                   0
                                          50
                                                 100
In [97]:
            = plt.scatter(te_pca[:, 0], te_pca[:, 1], c=y_test)
          _ = plt.colorbar()
                                                           - 1.0
            40
                                                           - 0.8
            20
             0
                                                           - 0.6
            -20
                                                            - 0.4
            -40
                                                            - 0.2
            -60
                                                            0.0
                                        50
                                                 100
                     -50
```





In [100]: df.describe()

Out[100]:

	age	sex	ср	trestbps	chol	cigs	years	
count	282.000000	282.000000	282.000000	282.000000	282.000000	282.000000	282.000000	282.
mean	54.411348	0.677305	3.163121	131.195035	247.705674	16.836011	15.347364	0.
std	9.053083	0.468338	0.955405	16.739821	46.178771	18.876755	15.276814	0.
min	29.000000	0.000000	1.000000	94.000000	126.000000	0.000000	0.000000	0.
25%	48.000000	0.000000	3.000000	120.000000	213.000000	0.000000	0.000000	0.
50%	55.000000	1.000000	3.000000	130.000000	244.000000	11.976385	15.000000	0.
75%	61.000000	1.000000	4.000000	140.000000	277.000000	30.000000	30.000000	0.
max	77.000000	1.000000	4.000000	170.000000	360.000000	75.000000	54.000000	1.

In [101]: df.head(10)

Out[101]:

	age	sex	ср	trestbps	chol	cigs	years	fbs	famhist	restecg	thalach	exang	thal	num
0	63	1	1	145	233	50.0	20.0	1	1	2	150	0	6	0
1	67	1	4	160	286	40.0	40.0	0	1	2	108	1	3	1
2	67	1	4	120	229	20.0	35.0	0	1	2	129	1	7	1
3	37	1	3	130	250	0.0	0.0	0	1	0	187	0	3	0
4	41	0	2	130	204	0.0	0.0	0	1	2	172	0	3	0
5	56	1	2	120	236	20.0	20.0	0	1	0	178	0	3	0
6	62	0	4	140	268	0.0	0.0	0	1	2	160	0	3	1
7	57	0	4	120	354	0.0	0.0	0	1	0	163	1	3	0
8	63	1	4	130	254	0.0	0.0	0	0	2	147	0	7	1
9	53	1	4	140	203	20.0	25.0	1	1	2	155	1	7	1

In [102]: # Scaling the dataset.

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(x_train)
```

x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)

```
In [104]: new_df_tr = pd.DataFrame(x_train, columns=feat_cols)
    new_df_tr['num'] = y_train
    new_df_tr.head(10)
```

Out[104]:

	age	sex	ср	trestbps	chol	cigs	years	fbs	famhi
0	-2.726464	0.658119	-1.183867	-0.058320	-0.891198	-0.808009	-0.649990	-0.414578	-1.32056
1	-1.849944	-1.519481	-0.147408	-0.671498	-0.654050	-0.913716	-1.051226	-0.414578	0.75724
2	1.437006	-1.519481	0.889052	-1.529947	-0.481579	0.143348	2.292409	-0.414578	-1.32056
3	0.231791	0.658119	-2.220326	-0.671498	-1.128346	1.200413	1.489937	-0.414578	0.75724
4	-0.535164	0.658119	-0.147408	-0.794134	-2.076939	0.407615	1.623682	-0.414578	0.75724
5	2.203960	-1.519481	-1.183867	-0.671498	0.510132	-0.913716	-1.051226	-0.414578	0.75724
6	-0.096904	0.658119	0.889052	0.677494	-0.416902	1.200413	0.954955	-0.414578	0.75724
7	0.889181	-1.519481	0.889052	0.432222	1.049105	0.143348	0.620592	2.412091	0.75724
8	0.560486	0.658119	-1.183867	0.554858	-0.524696	0.143348	1.623682	-0.414578	0.75724
9	-0.973424	-1.519481	-1.183867	-1.162040	-1.839791	-0.913716	-1.051226	-0.414578	-1.32056

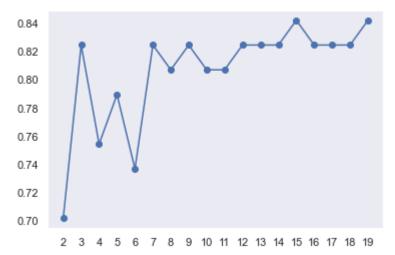
Out[105]:

	age	sex	ср	trestbps	chol	cigs	years	fbs	famhi
0	-1.192554	0.658119	0.889052	0.064316	0.035836	0.936147	0.286228	2.412091	0.75724
1	0.012661	-1.519481	-0.147408	1.781214	-0.955875	-0.913716	-1.051226	-0.414578	0.75724
2	0.889181	-1.519481	0.889052	1.781214	-1.753555	-0.913716	-1.051226	-0.414578	0.75724
3	-0.316034	0.658119	0.889052	0.554858	1.135341	-0.913716	-1.051226	-0.414578	-1.32056
4	0.012661	-1.519481	-0.147408	0.248269	1.264695	2.257477	0.954955	2.412091	-1.32056
5	0.779616	-1.519481	0.889052	0.861447	1.329371	0.143348	0.620592	-0.414578	0.75724
6	0.012661	0.658119	-1.183867	-1.407312	1.372489	0.671881	1.222446	-0.414578	-1.32056
7	-1.302119	0.658119	0.889052	0.554858	-0.416902	0.143348	0.620592	-0.414578	0.75724
8	0.560486	0.658119	-2.220326	2.394392	0.919752	-0.913716	-1.051226	-0.414578	-1.32056
9	0.560486	0.658119	-0.147408	1.168036	-0.718727	1.728945	0.954955	2.412091	-1.32056

```
In [107]: # New accuracy scores after dataset is scaled.
          scores norm = []
          print(f'Features: {feat_cols} \nTarget: {target_col}')
          for k in range(2, 20):
              print(f'Evaluating {k} clusters')
              model norm = KNeighborsClassifier(n neighbors=k, n jobs=-1)
              model_norm.fit(x_train, y_train)
              scores norm.append(model norm.score(x test, y test))
          Features: ['age', 'sex', 'cp', 'trestbps', 'chol', 'cigs', 'years', 'fbs', 'f
          amhist', 'restecg', 'thalach', 'exang', 'thal']
          Target: num
          Evaluating 2 clusters
          Evaluating 3 clusters
          Evaluating 4 clusters
          Evaluating 5 clusters
          Evaluating 6 clusters
          Evaluating 7 clusters
          Evaluating 8 clusters
          Evaluating 9 clusters
          Evaluating 10 clusters
          Evaluating 11 clusters
          Evaluating 12 clusters
          Evaluating 13 clusters
          Evaluating 14 clusters
          Evaluating 15 clusters
          Evaluating 16 clusters
          Evaluating 17 clusters
          Evaluating 18 clusters
```

Evaluating 19 clusters

```
In [108]: # New accuracy score plot.
    plt.plot(range(2, 20), scores_norm)
    plt.scatter(range(2, 20), scores_norm)
    plt.grid()
    _ =plt.xticks(range(2, 20))
```



```
In [110]: # KNN with the new n value based on the plot.
    model_norm = KNeighborsClassifier(n_neighbors=15, n_jobs=-1)
    model_norm.fit(x_train, y_train)

    preds_norm = model_norm.predict(x_test)

    print('Actuals for test data set')
    print(y_test)
    print('Predictions for test data set')
    print(preds_norm)
```

Actuals for test data set
[1 0 1 1 0 1 0 0 1 0 1 0 1 1 0 1 1 1 0 0 0 1 0 0 1 1 1 0 0 0 1 0 1 1 1 0 0 0 1 0 1 1 0 0 0 0 1 0 0 1 0 0 1 0 0 1 0 0 0 0 0 0 1 1 1 0 0 0 0 1 0 0 1 0 0 1 0 0 0 0 0 1 1 1 1 0 0 0 1 0 1 0 1 1 1 1 1 1 1 1 0 0 0]

```
In [111]: # Checking the new accuracy score.
    differs_norm = y_test - preds_norm
    print(f'Differences between the two sets:\n{differs_norm}')
    print(f'accuracy score: {accuracy_score(y_test,preds_norm)}')
```

```
In [ ]:
```