Homework 1

In [ ]:

```python
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier, export_graphviz, plot_tree
from sklearn.metrics import accuracy_score, confusion_matrix, classification
from IPython.display import Image

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import pydotplus
import seaborn as sns
```

Data Preprocess

Question 1: Remove the rows with missing labels ('label') and rows with more than 7 missing features. Report the remaining number of rows. (2 mark)

In [ ]:

```python
# load data
dat = pd.read_csv('data/customer_data.csv')
dat.head()
```

Out[ ]:

	label	id	fea_1	fea_2	fea_3	fea_4	fea_5	fea_6	fea_7	fea_8	fea_9	fe
0	0.0	59004779	4.0	1277.0	1.0	113000.0	2.0	8.0	-1.0	100.0	3.0	341
1	0.0	58990862	7.0	1298.0	1.0	110000.0	2.0	11.0	-1.0	101.0	5.0	72
2	1.0	58995168	7.0	1335.5	1.0	151000.0	2.0	11.0	5.0	110.0	3.0	60
3	0.0	54987320	7.0	NaN	2.0	59000.0	2.0	11.0	5.0	108.0	4.0	450
4	0.0	59005995	6.0	1217.0	3.0	56000.0	2.0	6.0	-1.0	100.0	3.0	60

In [ ]:

```python
print('Original Rows: %s' % len(dat))

dat_remove_label = dat.dropna(subset=['label'])
print('after remove NA-label row: %s' % len(dat_remove_label))

dat_remove_7_missing = dat_remove_label.iloc[:, 2:] # drop `label` because i
dat_remove_7_missing = dat_remove_7_missing.dropna(thresh=8)
print('after drop more than 7 feature: %s' % len(dat_remove_7_missing))
```

```
Original Rows: 1124
after remove NA-label row: 1110
after drop more than 7 feature: 1095
```

Question 2: Remove features with > 50% of missing values. For other features with missing values fill them with the mean of the corresponding features. Report the removed features (if any) and standard deviation of features with missing values after filling. (2 marks)

In [ ]:
```
print('original columns: %s' % len(dat_remove_7_missing.columns))

dat_remove_50pct = dat_remove_7_missing.dropna(thresh=0.5 * len(dat_remove_7
dat_fill_mean = dat_remove_50pct.fillna(dat_remove_50pct.mean())
print('columns after remove feature has 50pct missing values: %s' % len(dat_

for feature in dat_remove_7_missing.columns:
    if feature not in dat_fill_mean.columns:
        print('removed feature --> %s' % feature)

dat_fill_mean.std()
```

```
original columns: 11
columns after remove feature has 50pct missing values: 10
removed feature --> fea_11
```

Out[ ]:
```
fea_1          1.378574
fea_2         48.151339
fea_3          0.876765
fea_4      89256.523379
fea_5          0.260353
fea_6          2.676198
fea_7          2.970648
fea_8         11.977444
fea_9          0.857937
fea_10    152455.809399
dtype: float64
```

Decision Trees

In [ ]:
```
train_feature = pd.read_csv('data/customer_data_train.csv', index_col=0)
train_label = pd.read_csv('data/customer_data_train_labels.csv', index_col=0

test_feature = pd.read_csv('data/customer_data_test.csv', index_col=0)
test_label = pd.read_csv('data/customer_data_test_labels.csv', index_col=0)

valid_feature = pd.read_csv('data/customer_data_valid.csv', index_col=0)
valid_label = pd.read_csv('data/customer_data_valid_labels.csv', index_col=0

valid_feature.head()
```

Out[ ]:

	fea_1	fea_2	fea_3	fea_4	fea_5	fea_6	fea_7	fea_8	fea_9	fea_10
1086	5.0	1304.0	3.0	140000.0	2.0	15.0	5.0	80.0	3.0	151300.0
584	7.0	1325.0	1.0	80000.0	2.0	12.0	-1.0	82.0	3.0	60026.0
475	7.0	1292.0	1.0	130000.0	2.0	11.0	5.0	108.0	3.0	60040.0
999	4.0	1224.5	3.0	59000.0	2.0	8.0	5.0	80.0	3.0	60044.0
900	5.0	1229.0	3.0	46000.0	2.0	15.0	-1.0	111.0	4.0	450071.0

In [ ]:
```
criterions = ['gini', 'entropy']
min_split = [2, 5, 10, 20]
samples_cut = [50, 100, 200, 400, 600, 704]
```

Question 3: Train Decision Tree model on train data for criterions = {'gini', 'entropy'} and report the accuracies on the validation data. Select the best criterion and report the accuracy on the test data. (1 mark)

In [ ]:
```
bestAcc = 0
bestCri = ''

for cri in criterions:

    clf = DecisionTreeClassifier(criterion=cri, random_state=34)
    clf.fit(train_feature, train_label)
    predictions = clf.predict(test_feature)
    accuracy = accuracy_score(test_label, predictions)

    if accuracy > bestAcc:
        bestAcc = accuracy
        bestCri = cri

print(f'The best criterion is {bestCri} and the accuracy is {bestAcc}')
```

```
The best criterion is entropy and the accuracy is 0.7194570135746606
```

Question 4: Use the criterion selected above to train Decision Tree model on train data for min samples split={2,5,10,20} and report the accuracies on the validation data. Select the best parameter and report the accuracy on the test data. (2 marks)

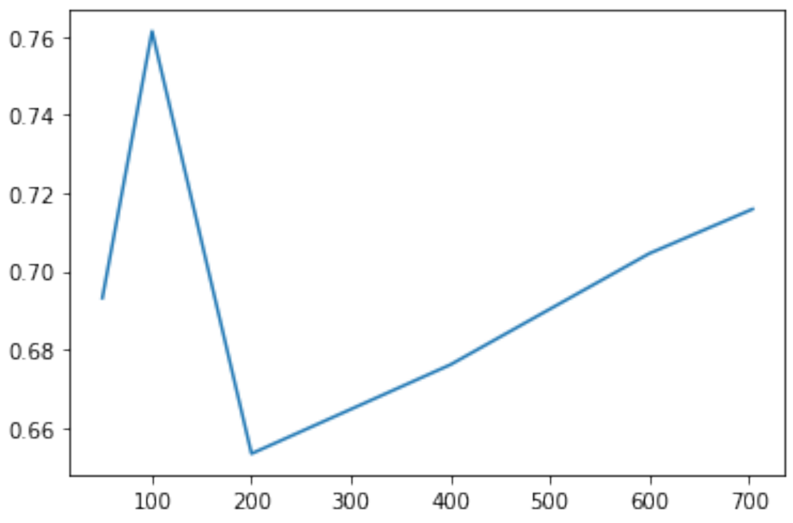
In [ ]:
```
bestAcc = 0
bestMinSplit = 0

for minsplit in min_split:

    clf = DecisionTreeClassifier(criterion='entropy', min_samples_split=mins
    clf.fit(train_feature, train_label)
    predictions = clf.predict(test_feature)
    accuracy = accuracy_score(test_label, predictions)

    if accuracy > bestAcc:
        bestAcc = accuracy
        bestMinSplit = minsplit

print(f'The best min split is {bestMinSplit} and the accuracy is {bestAcc}')
```

```
The best min split is 20 and the accuracy is 0.7330316742081447
```

Question 5: Use the parameters selected above (Q4 and Q5) to train Decision Tree model using the first 50, 100, 200, 400, 600 and 704 samples from train data. Keep the validation set unchanged during this analysis. Report and plot the accuracies on the validation data. (2 marks)

In [ ]:
```
bestAcc = 0
bestCut = 0
bestClf = 0

acc = []

for cut in samples_cut:

    clf = DecisionTreeClassifier(criterion='entropy', min_samples_split=20,
    clf.fit(train_feature[:cut], train_label[:cut])
    predictions = clf.predict(valid_feature)
    accuracy = accuracy_score(valid_label, predictions)

    acc.append(accuracy)

    if accuracy > bestAcc:
        bestAcc = accuracy
        bestCut = cut
        bestClf = clf

print(f'The best cut is {bestCut} and the accuracy is {bestAcc}')

# plt.figure(figsize=(60,30))
# plot_tree(bestClf, filled=True)

x = samples_cut
y = acc
plt.plot(x, y)
plt.show()
```

```
The best cut is 100 and the accuracy is 0.7613636363636364
```



Question 6: Use the test data to compute the confusion matrix for the predictions of your model. Report the confusion matrix. (1 mark)

In [ ]:
```
bestClf.fit(train_feature[:bestCut], train_label[:bestCut])
pred = bestClf.predict(test_feature)
real = test_label

print(confusion_matrix(real, pred))
```

```
[[149  25]
 [ 35  12]]
```

Nearest Neighbor

Normalize Data: Normalize features such that for each feature the mean is 0 and the standard deviation is 1 in the train+validation data. Use the normalizing factors calculated on train+validation data to modify the values in train, validation and test data.

In [ ]:
```
# normalize data
dataTrainVaild = pd.concat([train_feature, valid_feature])

XTrain = (train_feature - dataTrainVaild.mean() / dataTrainVaild.std())
XVaild = (valid_feature - dataTrainVaild.mean() / dataTrainVaild.std())
XTest = (test_feature - dataTrainVaild.mean() / dataTrainVaild.std())
```

Question 7: Train k-nn model on train + validation data and report accuracy on test data. Use Euclidean distance and k=3. (1 mark)

```
In [ ]: XTrainVaild = pd.concat([XTrain, XVaild])
        YTrainVaild = pd.concat([train_label, valid_label])

        k = 3
        clf = KNeighborsClassifier(k, p=2)
        clf.fit(XTrainVaild, YTrainVaild.squeeze())
        predictions = clf.predict(XTest)
        accuracy = np.sum((predictions == test_label.squeeze()) / (len(test_label.sq

        print(f'accuracy = {accuracy} for test data')
```

```
accuracy = 0.751131221719457 for test data
```

Question 8: Train the model on train data for distance metrics defined by l_1,l_{inf}, l_2. Report the accuracies on the validation data. Select the best metric and report the accuracy on the test data for the selected metric. Use k=3. (1 mark)

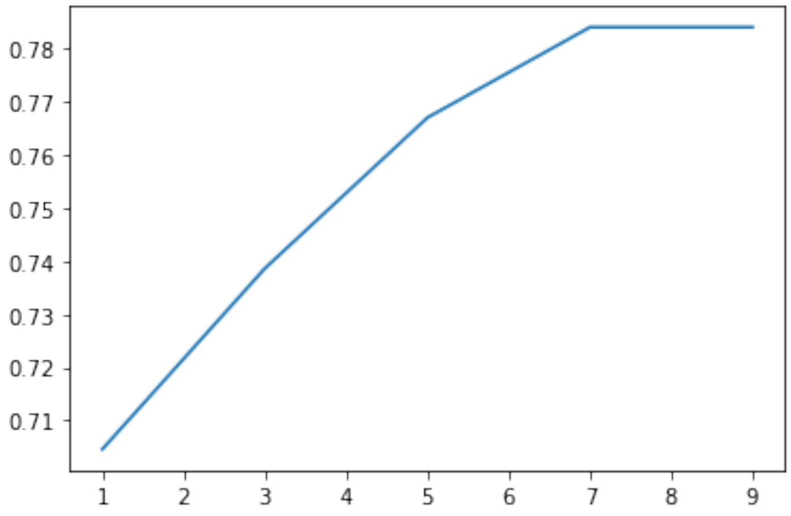
```
In [ ]: pList = [1, np.inf, 2]
        k = 3

        bestP = 0
        bestAcc = 0

        for i in pList:

            clf = KNeighborsClassifier(k, p=i)
            clf.fit(XTrain, train_label.squeeze())
            predictions = clf.predict(XVaild)
            accuracy = np.sum((predictions == valid_label.squeeze()) / (len(valid_la

            if accuracy > bestAcc:
                bestAcc = accuracy
                bestP = i

        print(f'The best accuracy is {bestAcc} when p = {bestP}')
```

```
The best accuracy is 0.7556818181818183 when p = 2
```

Question 9: Train the k-nn model on train data for k=1,3,5,7,9. Report and plot the accuracies on the validation data. Select the best 'k' value and report the accuracy on the test data for the selected 'k'. Use Chebyshev distance. (2 marks)

```
In [ ]: kList = [1, 3, 5, 7, 9]
        accList = []

        bestK = 0
        bestAcc = 0

        for k in kList:

            clf = KNeighborsClassifier(n_neighbors=k, p=np.inf)
            clf.fit(XTrain, train_label.squeeze())
            predictions = clf.predict(XVaild)
            accuracy = np.sum((predictions == valid_label.squeeze()) / (len(valid_la

            accList.append(accuracy)

            if accuracy > bestAcc:
                bestAcc = accuracy
                bestK = k

        print(f'The best accuracy is {bestAcc} when k = {bestK}')

        x = kList
        y = accList
        plt.plot(x, y)
        plt.show()
```

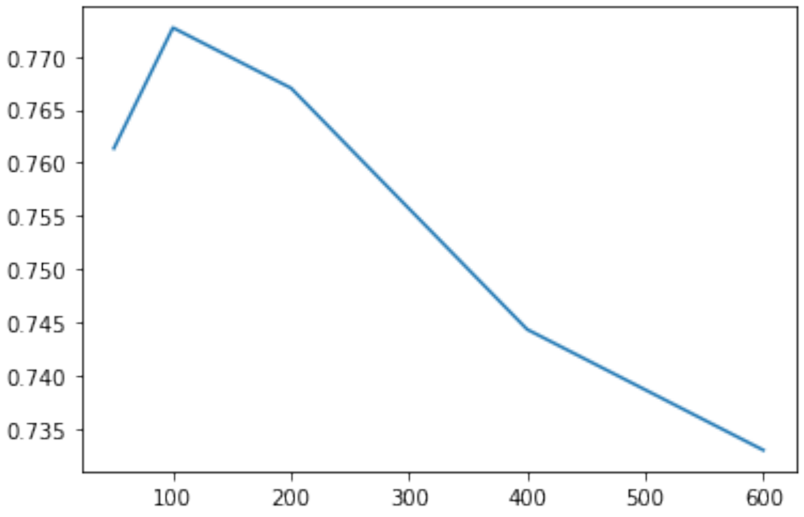
```
0.7045454545454547
0.7386363636363638
0.7670454545454547
0.7840909090909093
0.7840909090909093
The best accuracy is 0.7840909090909093 when k = 7
```



Question 10: Instead of using full train data, train the model using the first 50, 100, 200, 400, 600 and 704 data samples from train data. Keep the validation set unchanged during this analysis. Report and plot the accuracies on the validation data. Use Chebyshev distance and k=3. Note: Don’t shuffle the data and use only the ‘first n samples’, otherwise your answers may differ. (2 marks)

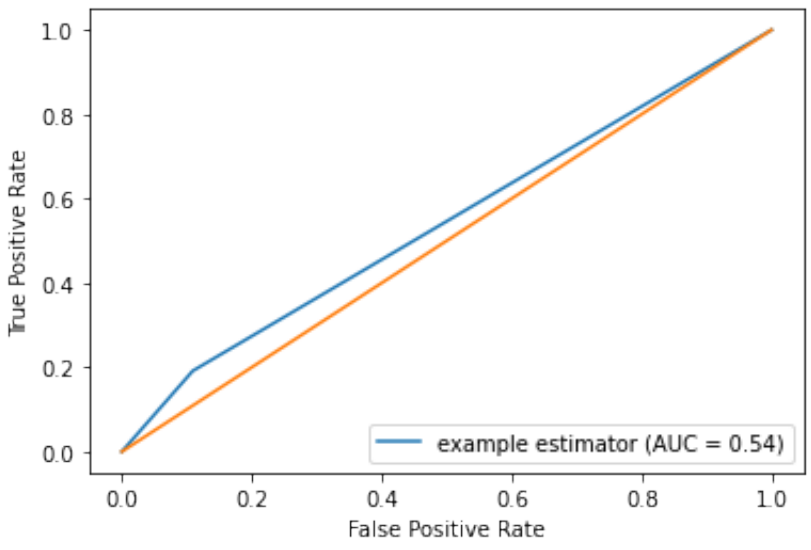
```
In [ ]: cutList = [50, 100, 200, 400, 600]
        accList = []

        bestCut = 0
        bestAcc = 0

        for cut in cutList:

            k = 3
            clf = KNeighborsClassifier(k, p=np.inf)
            clf.fit(XTrain[:cut], train_label.squeeze()[:cut])
            predictions = clf.predict(XVaild)
            accuracy = np.sum((predictions == valid_label.squeeze()) / (len(valid_la

            accList.append(accuracy)

            if accuracy > bestAcc:
                bestAcc = accuracy
                bestCut= cut

        print(f'The best accuracy is {bestAcc} when cut = {bestCut}')

        x = cutList
        y = accList
        plt.plot(x, y)
        plt.show()
```

```
The best accuracy is 0.7727272727272729 when cut = 100
```

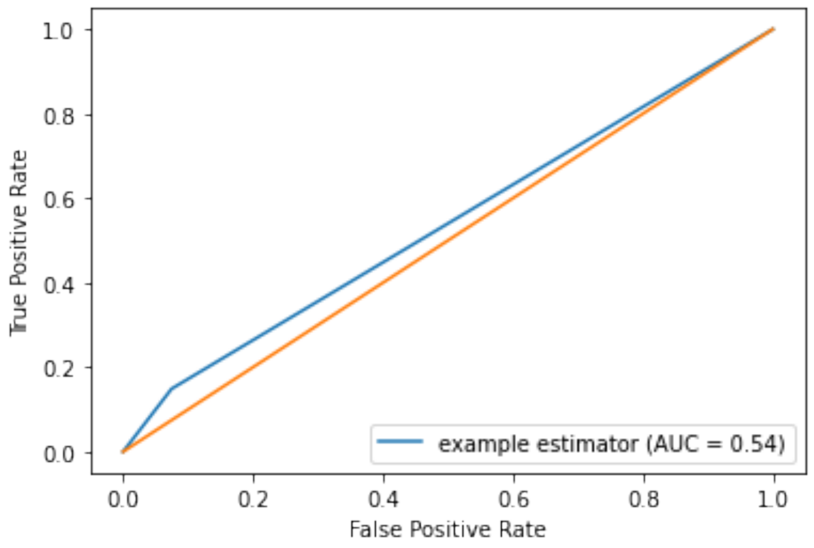


Question 11: Train a k-nn model with k=3 and k=7 with the Chebyshev distance on the train and validation data combined. Plot the ROC curve for the prediction you get on the test data for both models. Also report the accuracy, precision, recall and F-1 score. Please comment on the evaluation results and the ROC curve, which model is better?(4 points)

```
In [ ]: kList = [3, 7]
        predictionList = []

        for k in kList:

            clf = KNeighborsClassifier(n_neighbors=k, p=np.inf)
            clf.fit(XTrainVaild, YTrainVaild.squeeze())
            predictions = clf.predict(XTest)
            predictionList.append(predictions)
            accuracy = np.sum((predictions == test_label.squeeze()) / (len(test_labe
            # accuracy = clf.score(XTest, test_label)

            # plot ROC curve
            fpr, tpr, threshold = metrics.roc_curve(test_label, predictions)
            rocAuc = metrics.auc(fpr, tpr)
            xBenchmark, yBenchmark = np.linspace(0, 1, 10), np.linspace(0, 1, 10)
            display = metrics.RocCurveDisplay(fpr=fpr, tpr=tpr, roc_auc=rocAuc, esti
            display.plot()
            plt.plot(xBenchmark, yBenchmark)
            plt.show()

            # report precision, recall, F-1
            precision = metrics.precision_score(test_label, predictions)
            recall = metrics.recall_score(test_label, predictions)
            f1Score = metrics.f1_score(test_label, predictions)

            print(f'accuracy = {accuracy}, precision = {precision}, recall = {recall
```



```
accuracy = 0.7420814479638009, precision = 0.32142857142857145, recall = 0.1
9148936170212766, F-1 score = 0.24, given k = 3
```



```
accuracy = 0.7601809954751131, precision = 0.35, recall = 0.1489361702127659
5, F-1 score = 0.208955223880597, given k = 7
```

Base on the evaluations we can see that the AUC(area under curve) are almost the same. But model 2 has a higher accuracy, precision, and F-1 score. Model 2 is slightly better.