ELE 489: Fundamentals of Machine Learning
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Link to the github repository: https://github.com/ilgazoguz/ELE489HW1

1. After importing the proper modules, the data file itself "wine.data" is read and its columns are named appropriately with the wine.names file provided.

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn as sklearn
import numpy as np
import math as math
from collections import Counter
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

Python

Imports

```
df = pd.read_csv("wine.data", header=None)
```

Python

Reads the wine.data file and creates a Pandas DataFrame without column headers since there is none in the file.

```
column_names =["Class Labels","Alcohol","Malic acid","Ash","Alcalinity of ash","Magnesium","Total phenols","Flavanoids","Nonflavanoid phenols","Proanthocyanins",
df.columns = column_names
df
```

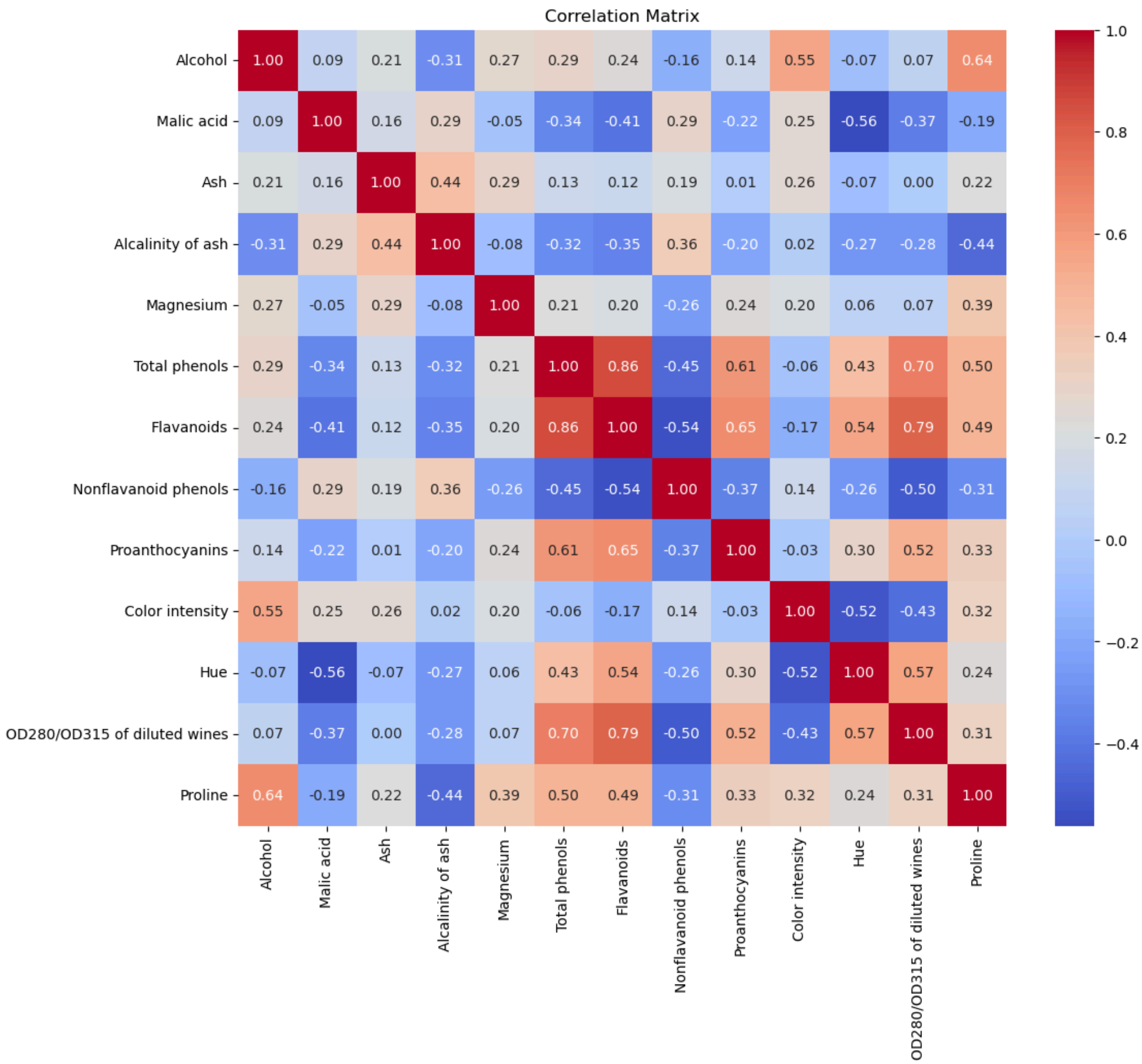
Python

	Class Labels	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	Proanthocyanins	Color intensity	Hue	OD280/OD315 of diluted wines	Proline
0	1	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	5.64	1.04	3.92	1065
1	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38	1.05	3.40	1050
2	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.68	1.03	3.17	1185
3	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.80	0.86	3.45	1480
4	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.32	1.04	2.93	735
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
173	3	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	1.06	7.70	0.64	1.74	740
174	3	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	1.41	7.30	0.70	1.56	750
175	3	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	1.35	10.20	0.59	1.56	835
176	3	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	1.46	9.30	0.60	1.62	840
177	3	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	1.35	9.20	0.61	1.60	560

178 rows × 14 columns

To see how correlated the features are to potentially eliminate them, a correlation matrix is plotted:

```python
corr_matrix = df.drop(columns=["Class Labels"]).corr()
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm")
plt.title("Correlation Matrix")
plt.show()
```
✓ 0.3s Python



I ultimately decided not to eliminate any features since there's few highly correlated features and given the number of features in the first place, it was not very necessary.

2. The next few steps are focused around pre-processing and are pretty self-explanatory in Jupyter notebook:

```python
df.isnull().sum()
dfm = df.dropna()
```
✓ 0.0s

First step of preprocessing. Checks missing values and removes the rows with missing values, if there is any. There is none in wine.data file provided.

```python
x = dfm.iloc[:, 1:].values
y = dfm.iloc[:, 0].values
```
✓ 0.0s

Splits feature columns (x) and the class column (y).

```python
standard_scaler = StandardScaler()
x = standard_scaler.fit_transform(x)
```
✓ 0.0s

As a normalization method, standard scaler is used.

```python
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, shuffle=True, random_state=3)
```
✓ 0.0s

Shuffles and then splits the data into training (80%) and testing (20%) sets.

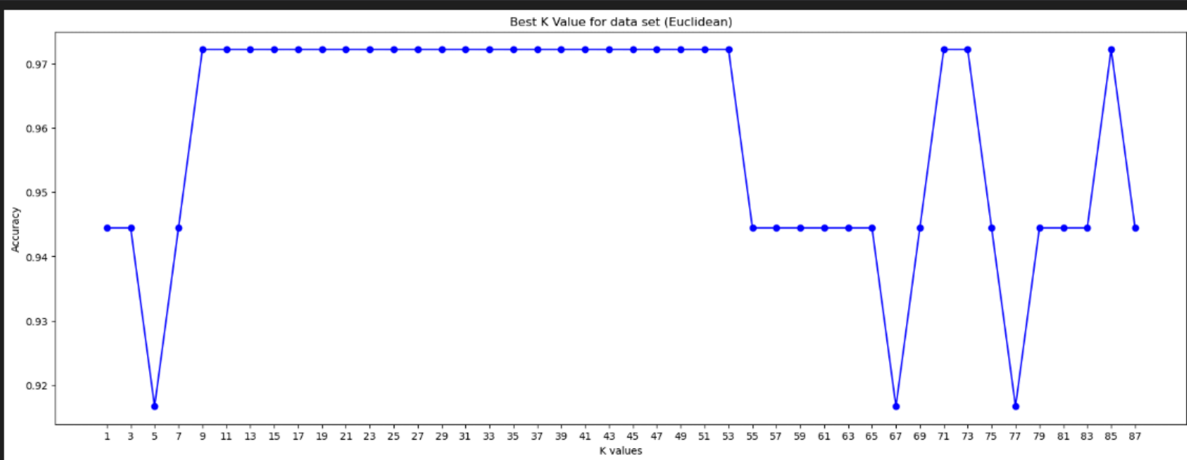
3. k-NN Implementation:

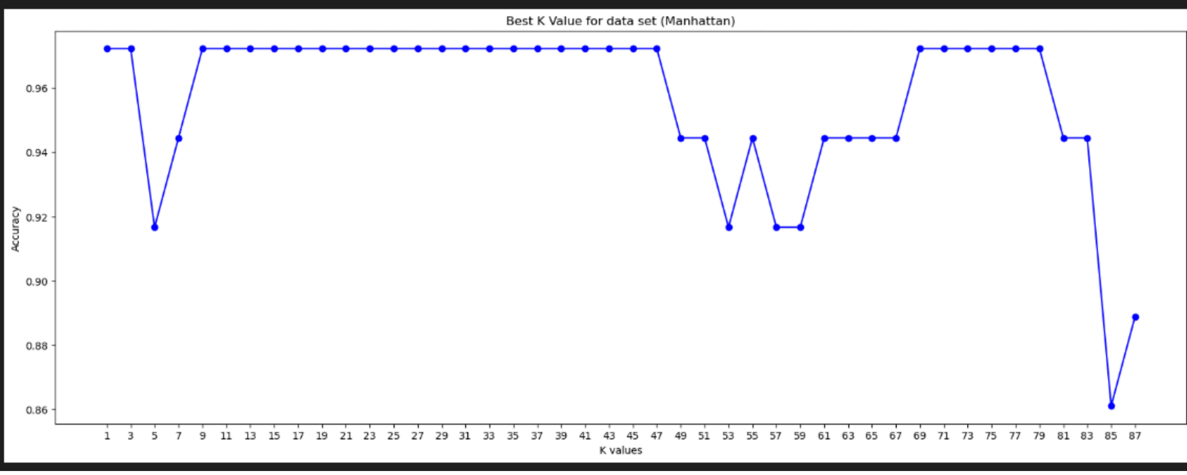
```python
def kNN(x_test,x_train,y_train,distance_metric,k):
    result = [0]*len(x_test)
    if distance_metric == "Euclidean":
        for i2 in range(len(x_test)):
            sum = [0]*len(x_train)
            distance = [0]*len(x_train)
            for i1 in range(len(x_train)):
                for j in range(len(x_train.T)):
                    sum[i1] = sum[i1] + (x_train[i1,j] - x_test[i2,j])**2
                distance[i1] = math.sqrt(sum[i1])
            minclasses = []
            for w in range(k):
                min = np.argmin(distance)
                minclasses.append(y_train[min])
                distance[min] = np.inf
            count = Counter(minclasses)
            minclass = count.most_common(1)[0][0]
            result[i2] = minclass
    elif distance_metric == "Manhattan":
        for i2 in range(len(x_test)):
            sum = [0]*len(x_train)
            distance = [0]*len(x_train)
            for i1 in range(len(x_train)):
                for j in range(len(x_train.T)):
                    sum[i1] = sum[i1] + abs(x_train[i1,j] - x_test[i2,j])
                distance[i1] = sum[i1]
                minclasses = []
            for w in range(k):
                min = np.argmin(distance)
                minclasses.append(y_train[min])
                distance[min] = np.inf
            count = Counter(minclasses)
            minclass = count.most_common(1)[0][0]
            result[i2] = minclass
    else:
        raise Exception("Choose a proper distance metric! Type Euclidean or Manhattan in quotation marks as your 4th variable of kNN function.")
    return result
```
✓ 0.0s Python

To find the best k value, accuracy vs k-value graphs are plotted for both Euclidean and Manhattan metrics. Graphs are best viewed in Jupyter for higher resolution. k is chosen as 11.

```python
knn_values_ep = []
knn_accuracies_ep = []

for i_ep in range(1, 88, 2):
    predictions_ep = kNN(x_test,x_train,y_train,"Euclidean",i_ep)
    accuracy_ep = accuracy_score(predictions_ep,y_test)
    knn_values_ep.append(i_ep)
    knn_accuracies_ep.append(accuracy_ep)

plt.figure(figsize=(20, 7))
plt.plot(knn_values_ep, knn_accuracies_ep, marker='o', linestyle='-', color='b')
plt.xlabel("K values")
plt.ylabel("Accuracy")
plt.title("Best K Value for data set (Euclidean)")
plt.xticks(knn_values_ep)
plt.show()

knn_values_mp = []
knn_accuracies_mp = []

for i_mp in range(1, 88, 2):
    predictions_mp = kNN(x_test,x_train,y_train,"Manhattan",i_mp)
    accuracy_mp = accuracy_score(predictions_mp,y_test)
    knn_values_mp.append(i_mp)
    knn_accuracies_mp.append(accuracy_mp)

plt.figure(figsize=(20, 7))
plt.plot(knn_values_mp, knn_accuracies_mp, marker='o', linestyle='-', color='b')
plt.xlabel("K values")
plt.ylabel("Accuracy")
plt.title("Best K Value for data set (Manhattan)")
plt.xticks(knn_values_mp)
plt.show()
```

✓ 3.5s Python





Finally, the confusion matrix and classification reports for both Euclidean and Manhattan metrics are as shown below.

```
predictions_e = kNN(x_test,x_train,y_train,"Euclidean",11)
print("          Euclidean Results\n\n    Accuracy: ",accuracy_score(predictions_e,y_test))
print("\n    Classification report:\n\n",classification_report(predictions_e,y_test))
print("\n    Confusion matrix:\n",confusion_matrix(predictions_e,y_test))
```

✓ 0.0s

```
          Euclidean Results

    Accuracy:  0.9722222222222222

    Classification report:

               precision    recall  f1-score   support

           1       1.00      1.00      1.00        15
           2       0.93      1.00      0.96        13
           3       1.00      0.88      0.93         8

    accuracy                           0.97        36
   macro avg       0.98      0.96      0.97        36
weighted avg       0.97      0.97      0.97        36


    Confusion matrix:
 [[15  0  0]
 [ 0 13  0]
 [ 0  1  7]]
```

Clasification report and confusion matrix for Euclidean distance metric.

```
predictions_m = kNN(x_test,x_train,y_train,"Manhattan",11)
print("          Manhattan Results\n\n    Accuracy: ",accuracy_score(predictions_m,y_test))
print("\n    Classification Report:\n\n",classification_report(predictions_m,y_test))
print("\n    Confusion Matrix:\n",confusion_matrix(predictions_m,y_test))
```

✓ 0.0s

```
          Manhattan Results

    Accuracy:  0.9722222222222222

    Classification Report:

               precision    recall  f1-score   support

           1       1.00      1.00      1.00        15
           2       0.93      1.00      0.96        13
           3       1.00      0.88      0.93         8

    accuracy                           0.97        36
   macro avg       0.98      0.96      0.97        36
weighted avg       0.97      0.97      0.97        36


    Confusion Matrix:
 [[15  0  0]
 [ 0 13  0]
 [ 0  1  7]]
```

Clasification report and confusion matrix for Manhattan distance metric.

Again, it is better to view analysis.ipynb in the github repository to view plots in higher resolution and view the code with explanations in more detail. (https://github.com/ilgazoguz/ELE489HW1)