CSCI 31022 - Assignment 1

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Load dataset in csv format

```
import pandas as pd

url = "https://archive.ics.uci.edu/ml/machine-learning-
databases/wine/wine.data"

column_names = [
"Class", "Alcohol", "Malic_acid", "Ash", "Alcalinity_of_ash", "Magnesium",
"Total_phenols", "Flavanoids", "Nonflavanoid_phenols", "Proanthocyanins",
"Color_intensity", "Hue", "OD280_OD315", "Proline"
]

df = pd.read_csv(url,header=None,names=column_names)
df.head(10)
```

```
   Class  Alcohol  Malic_acid   Ash  Alcalinity_of_ash  Magnesium  \
0      1    14.23        1.71  2.43               15.6        127
1      1    13.20        1.78  2.14               11.2        100
2      1    13.16        2.36  2.67               18.6        101
3      1    14.37        1.95  2.50               16.8        113
4      1    13.24        2.59  2.87               21.0        118
5      1    14.20        1.76  2.45               15.2        112
6      1    14.39        1.87  2.45               14.6         96
7      1    14.06        2.15  2.61               17.6        121
8      1    14.83        1.64  2.17               14.0         97
9      1    13.86        1.35  2.27               16.0         98

   Total_phenols  Flavanoids  Nonflavanoid_phenols  Proanthocyanins  \
0           2.80        3.06                  0.28             2.29
1           2.65        2.76                  0.26             1.28
2           2.80        3.24                  0.30             2.81
3           3.85        3.49                  0.24             2.18
4           2.80        2.69                  0.39             1.82
5           3.27        3.39                  0.34             1.97
6           2.50        2.52                  0.30             1.98
7           2.60        2.51                  0.31             1.25
8           2.80        2.98                  0.29             1.98
9           2.98        3.15                  0.22             1.85

   Color_intensity   Hue  OD280_OD315  Proline
0             5.64  1.04         3.92     1065
```

```
1              4.38  1.05          3.40     1050
2              5.68  1.03          3.17     1185
3              7.80  0.86          3.45     1480
4              4.32  1.04          2.93      735
5              6.75  1.05          2.85     1450
6              5.25  1.02          3.58     1290
7              5.05  1.06          3.58     1295
8              5.20  1.08          2.85     1045
9              7.22  1.01          3.55     1045
```

Data exploration

```
df.info() #basic infomation of dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Class                 178 non-null    int64
 1   Alcohol               178 non-null    float64
 2   Malic_acid            178 non-null    float64
 3   Ash                   178 non-null    float64
 4   Alcalinity_of_ash     178 non-null    float64
 5   Magnesium             178 non-null    int64
 6   Total_phenols         178 non-null    float64
 7   Flavanoids            178 non-null    float64
 8   Nonflavanoid_phenols  178 non-null    float64
 9   Proanthocyanins       178 non-null    float64
 10  Color_intensity       178 non-null    float64
 11  Hue                   178 non-null    float64
 12  OD280_OD315           178 non-null    float64
 13  Proline               178 non-null    int64
dtypes: float64(11), int64(3)
memory usage: 19.6 KB
```

```
df['Class'].value_counts() #figure out each class sum
```

```
Class
2    71
1    59
3    48
Name: count, dtype: int64
```

```
df.isnull().sum() #check null values sum of each column
```

```
Class                   0
Alcohol                 0
Malic_acid              0
Ash                     0
Alcalinity_of_ash       0
Magnesium               0
```

```
Total_phenols           0
Flavanoids              0
Nonflavanoid_phenols    0
Proanthocyanins         0
Color_intensity         0
Hue                     0
OD280_OD315             0
Proline                 0
dtype: int64
```

This shows no null values in each column

Data preprocessing

```
#removing outliers using zcore method
from scipy import stats
def remove_outliers_function(data,threshold=3):
    z_scores=data.apply(stats.zscore)
    return data[(z_scores<threshold).all(axis=1)]

df=remove_outliers_function(df)
df
```

```
     Class  Alcohol  Malic_acid   Ash  Alcalinity_of_ash  Magnesium  \
0        1    14.23        1.71  2.43               15.6        127   
1        1    13.20        1.78  2.14               11.2        100   
2        1    13.16        2.36  2.67               18.6        101   
3        1    14.37        1.95  2.50               16.8        113   
4        1    13.24        2.59  2.87               21.0        118   
..     ...      ...         ...   ...                ...        ...   
173      3    13.71        5.65  2.45               20.5         95   
174      3    13.40        3.91  2.48               23.0        102   
175      3    13.27        4.28  2.26               20.0        120   
176      3    13.17        2.59  2.37               20.0        120   
177      3    14.13        4.10  2.74               24.5         96   

     Total_phenols  Flavanoids  Nonflavanoid_phenols  Proanthocyanins  \
0             2.80        3.06                  0.28             2.29   
1             2.65        2.76                  0.26             1.28   
2             2.80        3.24                  0.30             2.81   
3             3.85        3.49                  0.24             2.18   
4             2.80        2.69                  0.39             1.82   
..             ...         ...                   ...              ...   
173           1.68        0.61                  0.52             1.06   
174           1.80        0.75                  0.43             1.41   
175           1.59        0.69                  0.43             1.35   
176           1.65        0.68                  0.53             1.46   
177           2.05        0.76                  0.56             1.35   

     Color_intensity   Hue  OD280_OD315  Proline  
0               5.64  1.04         3.92     1065  
```

```
1               4.38  1.05         3.40     1050
2               5.68  1.03         3.17     1185
3               7.80  0.86         3.45     1480
4               4.32  1.04         2.93      735
..               ...   ...          ...      ...
173             7.70  0.64         1.74      740
174             7.30  0.70         1.56      750
175            10.20  0.59         1.56      835
176             9.30  0.60         1.62      840
177             9.20  0.61         1.60      560

[169 rows x 14 columns]
```

```
#checking for highly correlated features to diamentional reduction
df_corr = df.corr()
df_corr
```

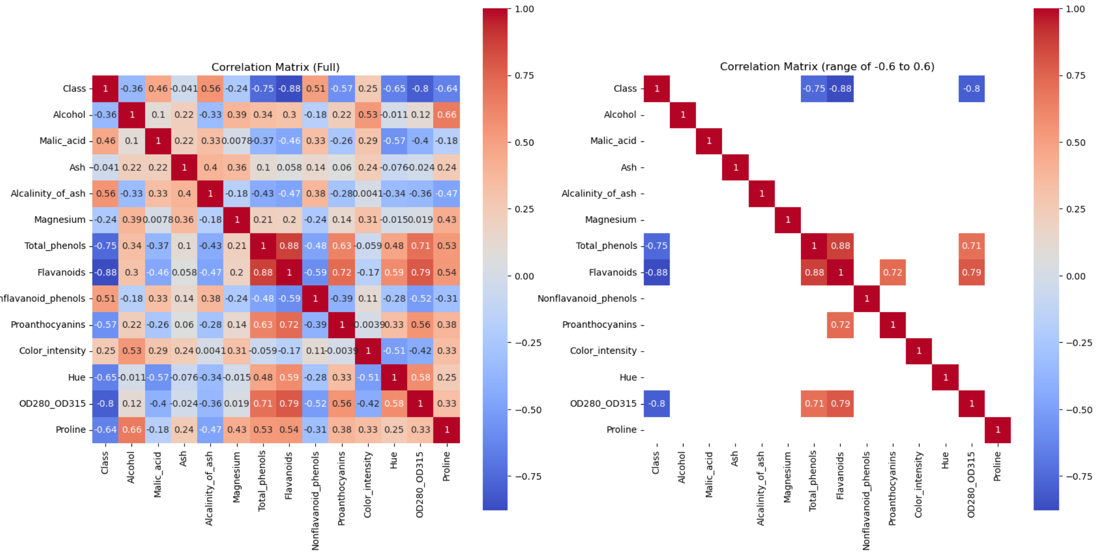
```
                         Class   Alcohol  Malic_acid       Ash  \
Class                 1.000000 -0.357820    0.463305 -0.041075
Alcohol              -0.357820  1.000000    0.100100  0.217710
Malic_acid            0.463305  0.100100    1.000000  0.220442
Ash                  -0.041075  0.217710    0.220442  1.000000
Alcalinity_of_ash     0.558514 -0.333081    0.334173  0.397545
Magnesium            -0.237854  0.386905    0.007750  0.358603
Total_phenols        -0.749746  0.337356   -0.368951  0.104570
Flavanoids           -0.879415  0.304664   -0.457109  0.058304
Nonflavanoid_phenols  0.506426 -0.178321    0.328408  0.136174
Proanthocyanins      -0.571198  0.222456   -0.256059  0.059571
Color_intensity       0.253562  0.534614    0.294579  0.242198
Hue                  -0.647688 -0.010839   -0.568548 -0.076281
OD280_OD315          -0.800414  0.116049   -0.396191 -0.024420
Proline              -0.643492  0.658710   -0.178897  0.244731

                      Alcalinity_of_ash  Magnesium  Total_phenols  Flavanoids
\
Class                          0.558514  -0.237854      -0.749746   -0.879415
Alcohol                       -0.333081   0.386905       0.337356    0.304664
Malic_acid                     0.334173   0.007750      -0.368951   -0.457109
Ash                            0.397545   0.358603       0.104570    0.058304
Alcalinity_of_ash              1.000000  -0.181780      -0.432285   -0.469168
Magnesium                     -0.181780   1.000000       0.213542    0.196746
Total_phenols                 -0.432285   0.213542       1.000000    0.875180
Flavanoids                    -0.469168   0.196746       0.875180    1.000000
Nonflavanoid_phenols           0.376861  -0.240273      -0.480293   -0.586702
Proanthocyanins               -0.282713   0.136689       0.629686    0.721467
Color_intensity                0.004077   0.311764      -0.058654   -0.168892
Hue                           -0.336307  -0.014679       0.475219    0.593101
OD280_OD315                   -0.355129   0.018876       0.705484    0.789215
Proline                       -0.471656   0.429594       0.527742    0.536099
```

```
                      Nonflavanoid_phenols  Proanthocyanins  Color_intensity  \
Class                             0.506426        -0.571198         0.253562
Alcohol                          -0.178321         0.222456         0.534614
Malic_acid                        0.328408        -0.256059         0.294579
Ash                               0.136174         0.059571         0.242198
Alcalinity_of_ash                 0.376861        -0.282713         0.004077
Magnesium                        -0.240273         0.136689         0.311764
Total_phenols                    -0.480293         0.629686        -0.058654
Flavanoids                       -0.586702         0.721467        -0.168892
Nonflavanoid_phenols              1.000000        -0.389416         0.108066
Proanthocyanins                  -0.389416         1.000000        -0.003852
Color_intensity                   0.108066        -0.003852         1.000000
Hue                              -0.283704         0.334152        -0.509474
OD280_OD315                      -0.517395         0.559015        -0.424619
Proline                          -0.313536         0.383929         0.334667

                           Hue  OD280_OD315   Proline
Class                -0.647688    -0.800414 -0.643492
Alcohol              -0.010839     0.116049  0.658710
Malic_acid           -0.568548    -0.396191 -0.178897
Ash                  -0.076281    -0.024420  0.244731
Alcalinity_of_ash    -0.336307    -0.355129 -0.471656
Magnesium            -0.014679     0.018876  0.429594
Total_phenols         0.475219     0.705484  0.527742
Flavanoids            0.593101     0.789215  0.536099
Nonflavanoid_phenols -0.283704    -0.517395 -0.313536
Proanthocyanins       0.334152     0.559015  0.383929
Color_intensity      -0.509474    -0.424619  0.334667
Hue                   1.000000     0.582499  0.252771
OD280_OD315           0.582499     1.000000  0.331440
Proline               0.252771     0.331440  1.000000
```

```
# show the correlation matrix and the correlation matrix with the range of -
0.6 to 0.6

import matplotlib.pyplot as plt
import seaborn as sns

correlation_matrix=df_corr[(df_corr>0.7)|(df_corr<-0.7)]

fig,axes=plt.subplots(nrows=1,ncols=2,figsize=(20,10))
axes=axes.flatten()

sns.heatmap(df_corr,annot=True,cmap='coolwarm',square=True,ax=axes[0])
axes[0].set_title('Correlation Matrix (Full)')

sns.heatmap(correlation_matrix,annot=True,cmap='coolwarm',square=True,ax=axes
```

```
[1])
axes[1].set_title('Correlation Matrix (range of -0.6 to 0.6)')
```

```
Text(0.5, 1.0, 'Correlation Matrix (range of -0.6 to 0.6)')
```



According to above correlation matrix,there are two highly correlated features.
1."Total_phenols" and "Flavanoids" - 0.87 2."Flavanoids" and "OD280_OD315" - 0.79

Therefore,We can drop "Total_phenols" and "OD280_OD315" features from the dataset.

```
# Drop highly correlated features
df_reduced=df.drop(['Total_phenols','OD280_OD315'],axis=1)
df_reduced
```

```
     Class  Alcohol  Malic_acid   Ash  Alcalinity_of_ash  Magnesium  \
0        1    14.23        1.71  2.43               15.6        127
1        1    13.20        1.78  2.14               11.2        100
2        1    13.16        2.36  2.67               18.6        101
3        1    14.37        1.95  2.50               16.8        113
4        1    13.24        2.59  2.87               21.0        118
..     ...      ...         ...   ...                ...        ...
173      3    13.71        5.65  2.45               20.5         95
174      3    13.40        3.91  2.48               23.0        102
175      3    13.27        4.28  2.26               20.0        120
176      3    13.17        2.59  2.37               20.0        120
177      3    14.13        4.10  2.74               24.5         96

     Flavanoids  Nonflavanoid_phenols  Proanthocyanins  Color_intensity   Hue
\
0          3.06                  0.28             2.29             5.64  1.04
1          2.76                  0.26             1.28             4.38  1.05
2          3.24                  0.30             2.81             5.68  1.03
3          3.49                  0.24             2.18             7.80  0.86
4          2.69                  0.39             1.82             4.32  1.04
```

```
..          ...                     ...               ...              ...   ...
173        0.61                    0.52              1.06             7.70  0.64
174        0.75                    0.43              1.41             7.30  0.70
175        0.69                    0.43              1.35            10.20  0.59
176        0.68                    0.53              1.46             9.30  0.60
177        0.76                    0.56              1.35             9.20  0.61

     Proline
0       1065
1       1050
2       1185
3       1480
4        735
..       ...
173      740
174      750
175      835
176      840
177      560

[169 rows x 12 columns]
```

Data preparation

separate feature variables and target variables

```
#feature variable set
x = df_reduced.drop("Class",axis=1)
x
```

```
     Alcohol  Malic_acid   Ash  Alcalinity_of_ash  Magnesium  Flavanoids  \
0      14.23        1.71  2.43               15.6        127        3.06
1      13.20        1.78  2.14               11.2        100        2.76
2      13.16        2.36  2.67               18.6        101        3.24
3      14.37        1.95  2.50               16.8        113        3.49
4      13.24        2.59  2.87               21.0        118        2.69
..       ...         ...   ...                ...        ...         ...
173    13.71        5.65  2.45               20.5         95        0.61
174    13.40        3.91  2.48               23.0        102        0.75
175    13.27        4.28  2.26               20.0        120        0.69
176    13.17        2.59  2.37               20.0        120        0.68
177    14.13        4.10  2.74               24.5         96        0.76

     Nonflavanoid_phenols  Proanthocyanins  Color_intensity   Hue  Proline
0                    0.28             2.29             5.64  1.04     1065
1                    0.26             1.28             4.38  1.05     1050
2                    0.30             2.81             5.68  1.03     1185
3                    0.24             2.18             7.80  0.86     1480
4                    0.39             1.82             4.32  1.04      735
..                    ...              ...              ...   ...      ...
```

```
173                    0.52             1.06             7.70  0.64       740
174                    0.43             1.41             7.30  0.70       750
175                    0.43             1.35            10.20  0.59       835
176                    0.53             1.46             9.30  0.60       840
177                    0.56             1.35             9.20  0.61       560

[169 rows x 11 columns]
```

```
#target variable
y = df_reduced["Class"]
y
```

```
0      1
1      1
2      1
3      1
4      1
      ..
173    3
174    3
175    3
176    3
177    3
Name: Class, Length: 169, dtype: int64
```

```
#feature scaling
from sklearn.discriminant_analysis import StandardScaler
scaler=StandardScaler()
x = scaler.fit_transform(x)
```

```
#splitting dataset into train and test data
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size =
0.2,random_state=42)
```

```
x_train.shape,y_train.shape
```

```
((135, 11), (135,))
```

```
x_test.shape,y_test.shape
```

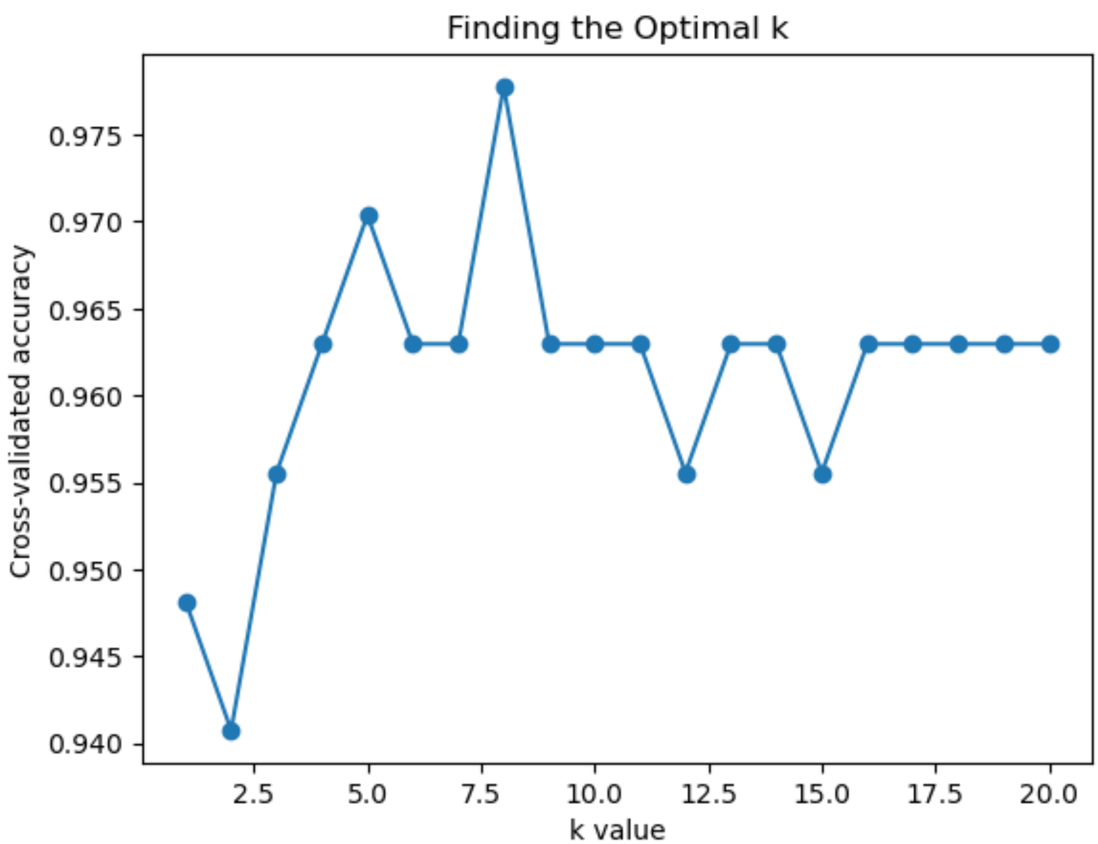
```
((34, 11), (34,))
```

figure out best k value

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
import numpy as np

# Range of k values to test
k_values = range(1, 21)
cv_scores = []
```

```python
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    # Perform 5-fold cross-validation and get the mean score for this k
    scores = cross_val_score(knn, x_train, y_train, cv=5, scoring='accuracy')
    cv_scores.append(scores.mean())

# Find the k value with the highest accuracy
optimal_k = k_values[np.argmax(cv_scores)]
print("The optimal k value is:", optimal_k)

#Plot the results
import matplotlib.pyplot as plt
plt.plot(k_values, cv_scores, marker='o')
plt.xlabel('k value')
plt.ylabel('Cross-validated accuracy')
plt.title('Finding the Optimal k')
plt.show()
```

```
The optimal k value is: 8
```




```python
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier(n_neighbors=optimal_k)
model.fit(x_train,y_train)
```

```
KNeighborsClassifier(n_neighbors=8)
```

```
pred = model.predict(x_test)
pred
```

```
array([3, 1, 2, 1, 3, 3, 3, 1, 2, 2, 1, 3, 3, 1, 2, 2, 1, 2, 1, 2, 1, 1,
       1, 1, 1, 1, 2, 2, 2, 1, 1, 1, 3, 2])
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test,pred)
cm
```

```
array([[15,  0,  0],
       [ 1, 11,  0],
       [ 0,  0,  7]])
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           1       0.94      1.00      0.97        15
           2       1.00      0.92      0.96        12
           3       1.00      1.00      1.00         7

    accuracy                           0.97        34
   macro avg       0.98      0.97      0.97        34
weighted avg       0.97      0.97      0.97        34
```

```
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test,pred)
accuracy #accuracy = 97.1%
```

```
0.9705882352941176
```

Conclusion:

This project effectively presents how the K-Nearest Neighbors algorithm can be applied in a classification problem regarding the origin of wine samples based on their chemical properties. After preprocessing the data (including handling outliers and standardization), KNN was applied, and cross-validation was used to determine the optimal k value. The model was accurate, giving the accuracy of about 97.1% when optimal k value is 8. That's rather good and showed that KNN should work for this task. Optimizing k, the model balanced bias and variance, hence avoiding underfitting and overfitting.