Clustering different types of wine using K-Means

Import libraries

In [1]:

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

from sklearn import metrics
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans
```

Reading the data

In [2]:

```
df = pd.read_csv("wine.csv")
print(df.shape)
df
```

```
(178, 14)
```

Out[2]:

	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Pher
0	14.23	1.71	2.43	15.6	127	2.80	3.06	(
1	13.20	1.78	2.14	11.2	100	2.65	2.76	(
2	13.16	2.36	2.67	18.6	101	2.80	3.24	(
3	14.37	1.95	2.50	16.8	113	3.85	3.49	(
4	13.24	2.59	2.87	21.0	118	2.80	2.69	(
...	...	...	...	...	...	...	...	
173	13.71	5.65	2.45	20.5	95	1.68	0.61	(
174	13.40	3.91	2.48	23.0	102	1.80	0.75	(
175	13.27	4.28	2.26	20.0	120	1.59	0.69	(
176	13.17	2.59	2.37	20.0	120	1.65	0.68	(
177	14.13	4.10	2.74	24.5	96	2.05	0.76	(

178 rows × 14 columns

Statistical Data analysis

In [3]:
```
df.describe()
```

Out[3]:

	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonfla
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	
mean	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2.029270	
std	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0.998859	
min	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0.340000	
25%	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1.205000	
50%	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2.135000	
75%	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2.875000	
max	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5.080000	

One Hot Encoding

In [4]:
```
dummies = pd.get_dummies(df['Customer_Segment'])
df = pd.concat([df, dummies], axis=1)
df.drop('Customer_Segment', axis=1, inplace=True)
df
```

Out[4]:

	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Phen
0	14.23	1.71	2.43	15.6	127	2.80	3.06	(
1	13.20	1.78	2.14	11.2	100	2.65	2.76	(
2	13.16	2.36	2.67	18.6	101	2.80	3.24	(
3	14.37	1.95	2.50	16.8	113	3.85	3.49	(
4	13.24	2.59	2.87	21.0	118	2.80	2.69	(
...	...	...	...	...	...	...	...	
173	13.71	5.65	2.45	20.5	95	1.68	0.61	(
174	13.40	3.91	2.48	23.0	102	1.80	0.75	(
175	13.27	4.28	2.26	20.0	120	1.59	0.69	(
176	13.17	2.59	2.37	20.0	120	1.65	0.68	(
177	14.13	4.10	2.74	24.5	96	2.05	0.76	(

178 rows × 16 columns

Scaling data to a similar range

In [5]:
```
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(df)
scaled_data
```

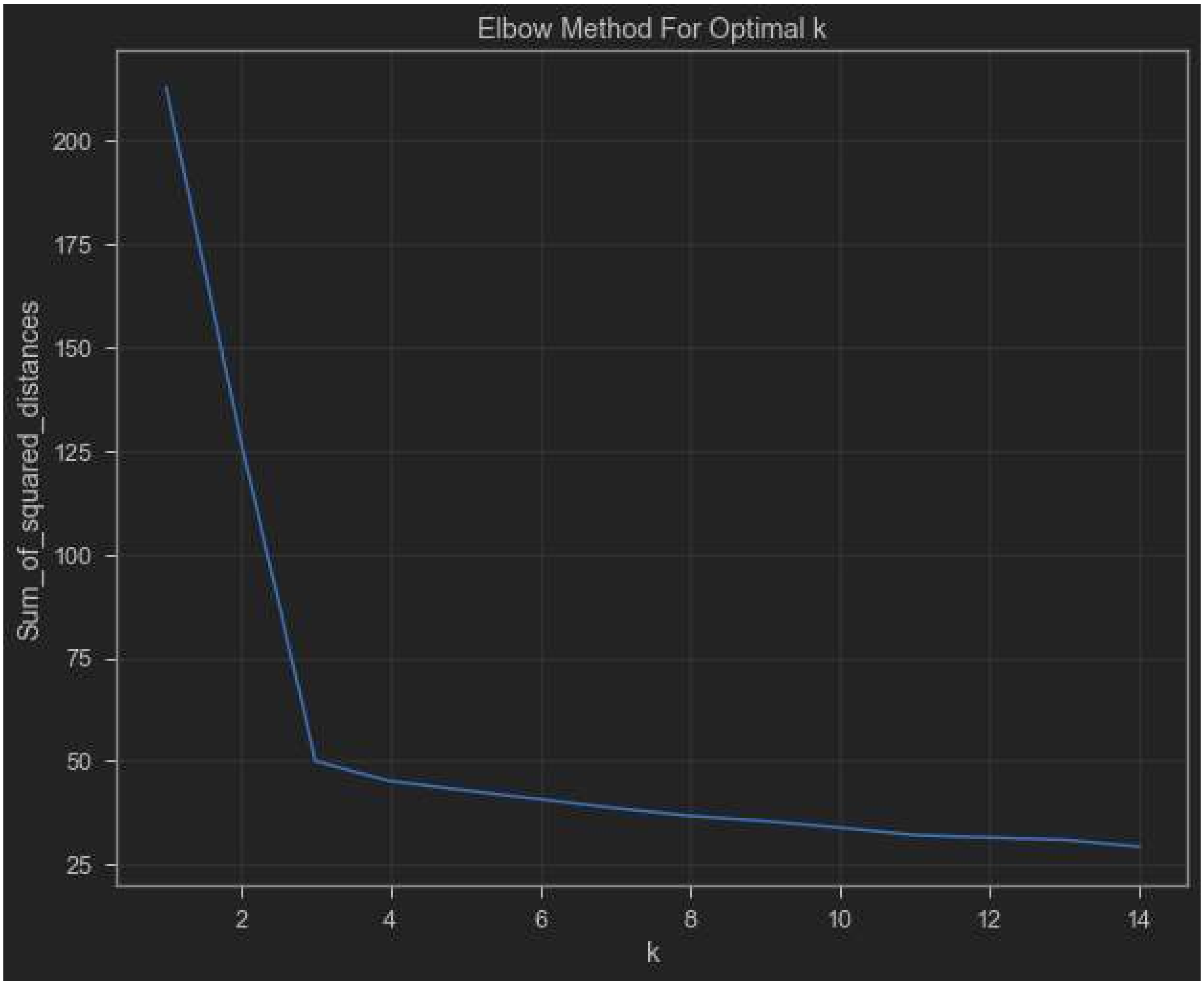
Out[5]:
```
array([[0.84210526, 0.1916996 , 0.57219251, ..., 1.        , 0.        ,
        0.        ],
       [0.57105263, 0.2055336 , 0.4171123 , ..., 1.        , 0.        ,
        0.        ],
       [0.56052632, 0.3201581 , 0.70053476, ..., 1.        , 0.        ,
        0.        ],
       ...,
       [0.58947368, 0.69960474, 0.48128342, ..., 0.        , 0.        ,
        1.        ],
       [0.56315789, 0.36561265, 0.54010695, ..., 0.        , 0.        ,
        1.        ],
       [0.81578947, 0.66403162, 0.73796791, ..., 0.        , 0.        ,
        1.        ]])
```

Using K-Means along with Elbow method using Sum of Squared Distances

In [6]:
```
Sum_of_squared_distances = []
K = range(1,15)
for k in K:
    km = KMeans(n_clusters=k)
    km = km.fit(scaled_data)
    Sum_of_squared_distances.append(km.inertia_)
```

Plotting elbow curve

In [7]:
```
plt.figure(figsize=(10, 8))
plt.plot(K, Sum_of_squared_distances, 'bx-')
plt.xlabel('k')
plt.ylabel('Sum_of_squared_distances')
plt.title('Elbow Method For Optimal k')
plt.show()
```



Optimal Value of k = 3