Installing scikit-learn-extra for KMedoids

```
pip install scikit-learn-extra
```

Importing Libraries

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

import matplotlib.pyplot as plt
from math import sqrt
from sklearn import preprocessing
from sklearn.metrics import silhouette_score
from sklearn_extra.cluster import KMedoids
from sklearn.cluster import KMeans
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score
```

Import CSV

```
df = pd.read_csv('stdData 1.csv')
```

```
df.head()
```

	V1	V2	V3	V4	V5	V6	V7	V8
0	1.221400	128.101200	80.035036	35.431417	180.956968	42.944951	1.320305	-0.779046
1	2.609743	85.891549	58.543681	14.454311	52.545356	33.426070	-0.786571	-1.656509
2	2.682163	99.782456	68.000884	26.339627	71.578043	37.542894	0.534953	-3.394990
3	3.196969	115.189168	65.307845	-0.539337	0.269863	20.857287	0.562433	-0.534598
4	4.790932	144.487763	80.800220	18.937774	-0.033570	31.346055	0.789162	-4.069492

Task

1) Normalize Dataset with Zero-Mean and Unit-Variance

According to this page, preprocessing.scale uses both zero-mean and unit-variance by default so I will use this package for normalization.

`sklearn.preprocessing.scale`(*X, *, axis=0, with_mean=True, with_std=True, copy=True*) [source]

Standardize a dataset along any axis.

Center to the mean and component wise scale to unit variance.

Read more in the User Guide.

Parameters:	**X : *{array-like, sparse matrix} of shape (n_samples, n_features)*** The data to center and scale. **axis : *int, default=0*** axis used to compute the means and standard deviations along. If 0, independently standardize each feature, otherwise (if 1) standardize each sample. **with_mean : *bool, default=True*** If True, center the data before scaling. **with_std : *bool, default=True*** If True, scale the data to unit variance (or equivalently, unit standard deviation). **copy : *bool, default=True*** set to False to perform inplace row normalization and avoid a copy (if the input is already a numpy array or a scipy.sparse CSC matrix and if axis is 1).
Returns:	**X_tr : *{ndarray, sparse matrix} of shape (n_samples, n_features)*** The transformed data.

```
scaled = preprocessing.scale(df)
```

Here you can see the dataset that is normalized with zero-mean and unit-variance

```
scaled
```

```
array([[-0.76945294,  0.23648162,  0.64327854, ...,  1.38966708,
         0.92904772, -0.08883983],
       [-0.3372092 , -1.05563171, -0.44776456, ...,  0.17960193,
        -1.18555885, -0.35330593],
       [-0.31466209, -0.63040605,  0.03234549, ...,  0.70294335,
         0.14081448, -0.87728171],
       ...,
       [-0.38180548, -1.05246099, -3.43710653, ..., -0.11956457,
         0.1175073 , -1.28193232],
       [ 1.91672977, -1.5847247 ,  1.89013292, ...,  0.6278864 ,
        -1.41140105, -1.87223471],
```

```
[ 0.23008769,  2.06324196, -0.18828286, ..., -0.14195884,
  1.79826771, -0.5663782 ]])
```

Euclidean Distance Metric

2 and 3) Apply K-means and K between 1-15, Report WSS

For each k value, we will initialise k-means and use the inertia to identify the sum of squared distances of samples to the nearest cluster centre. You can also see the WSS values as well.

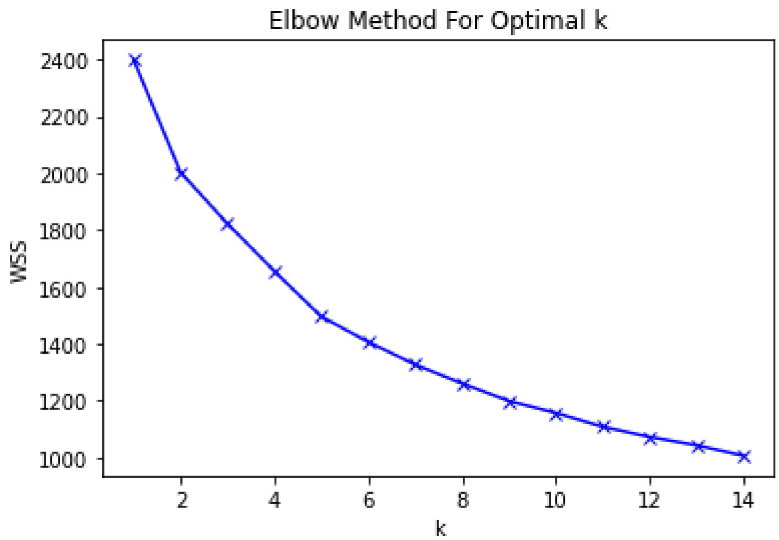
```
WSS = []

K = range(1,15)
for k in K:
    km = KMeans(n_clusters=k)
    km = km.fit(scaled)
    labels = km.labels_
    WSS.append(km.inertia_)

WSS
```

```
[2400.0,
 2003.1097725953355,
 1822.344254277449,
 1655.4244530694486,
 1496.0201710912415,
 1406.3159591205601,
 1327.0514340795207,
 1260.4276834379743,
 1198.7864889891862,
 1156.5432880065841,
 1107.8244679387974,
 1071.7598346238156,
 1042.3292645384183,
 1005.8031352316389]
```

3) Best Fitting K-Value

As you can see in the figure below, after K=5 , reduction in total distance changes more slowly and the slope of the line significantly decreased. From this figure, we can infer that going beyond this K value(5) will not contribute much to our clustering algorithm and will only make our clusters more complicated. Therefore, our optimal k-value is 5.

```
plt.plot(K, WSS, 'bx-')
plt.xlabel('k')
plt.ylabel('WSS')
plt.title('Elbow Method For Optimal k')
plt.show()
```



Cosine Similarity Metric

2 and 3) Apply K-means and K between 1-15, Report WSS

For each k value, we will initialise k-means and use the inertia to identify the sum of squared distances of samples to the nearest cluster centre. You can also see the WSS values as well.

```
WSS = []
K = range(1,15)
for k in K:
    km = KMedoids(n_clusters=k, metric="cosine")
    km = km.fit(scaled)
    WSS.append(km.inertia_)

WSS
```

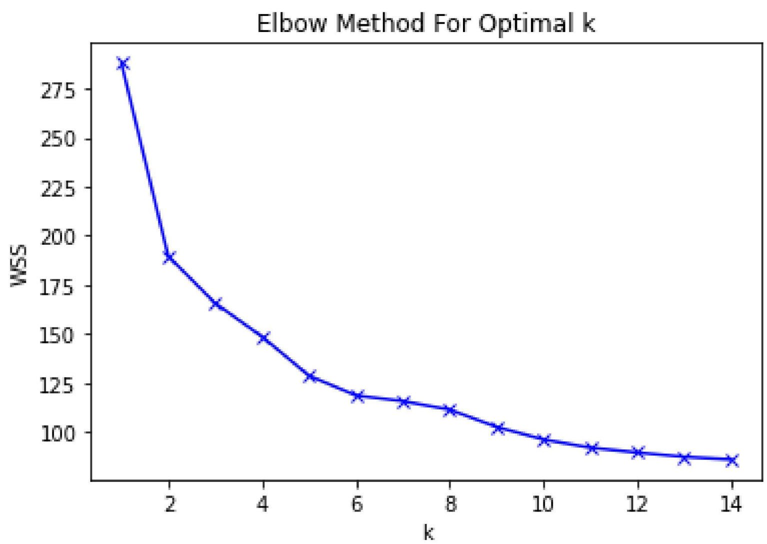
```
[288.242970310129,
 189.5839212478348,
 165.68308920594598,
 148.56757480024038,
 128.65777265237813,
 118.61246071483353,
 115.6873751909107,
 111.35304898042251,
```

```
 102.52333696062567,
 96.10463645382804,
 91.93472052318718,
 89.45889094030024,
 87.25874166929518,
 85.93042749442456]
```

3) Best Fitting K-Value

Our optimal k-value in this case is K=5 again.

```
plt.plot(K, WSS, 'bx-')
plt.xlabel('k')
plt.ylabel('WSS')
plt.title('Elbow Method For Optimal k')
plt.show()
```



5) Conclusion

In conclusion, I researched about which packages to use for normalizing with unit-variance and zero-mean. I found out that scale() does exactly that by default.

Afterwards, I used KMeans, Kmeans uses "Euclidean" metric. However sklearn's KMeans doesn't have "Cosine" Metric, therefore I had to find another package for this reason. I found out about KMedoids, which lets me use "Cosine" as a metric.

I gave the models a range between k=1 and k=15, and to see which k is better, I ran a loop and tried them all. In each increment, I got their WSS value by using interia. Thanks to WSS, I plotted a graph and used the Elbow Technique to see what k value is the optimal approximately.