Harsh Seksaria

2048011

2 - MDS

Machine Learning Lab 11

`Clustering Method`

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CHRIST (Deemed to be University)

In [1]:

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

In [2]:

```
fl = pd.read_csv('../diabetes.csv')
fl.head()
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Pre-processing

Null Values

In [3]:
```
fl.isnull().sum()
```

Out[3]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

There are no null values in the dataset.

Duplicate Values

In [4]:
```
fl.duplicated().any()
```

Out[4]:
```
False
```

There are no duplicate values in the dataset.

Exploratory Data Analysis

Dataset Shape

In [5]:
```
fl.shape
```

Out[5]:
```
(768, 9)
```

There are 768 rows and 9 columns out of which 8 are the features and 1 is the target variable.

Dataset Info

In [6]:
```
fl.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

Dataset description

In [7]:
```
fl.describe()
```

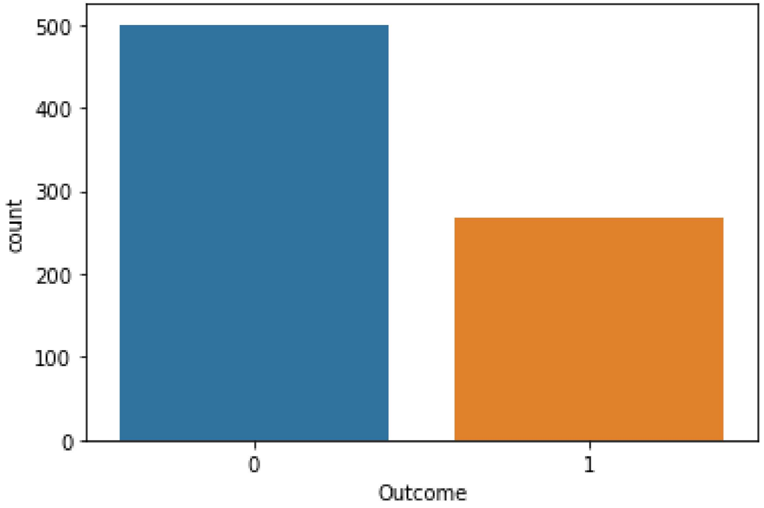
Out[7]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

Outcome Distribution

In [8]:
```
sns.countplot(x="Outcome", data=fl)
fl.Outcome.value_counts()
```

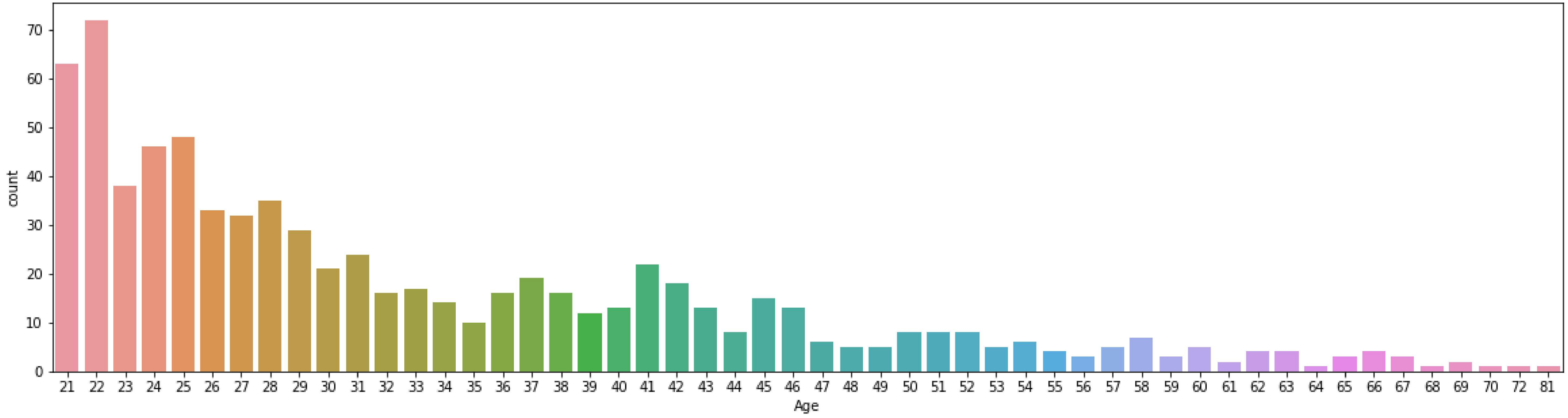
Out[8]:
```
0    500
1    268
Name: Outcome, dtype: int64
```



Age Distribution

In [9]:
```
plt.figure(figsize=(20,5))
sns.countplot(x="Age", data=fl)
```

Out[9]: <AxesSubplot:xlabel='Age', ylabel='count'>



K-Means Clustering

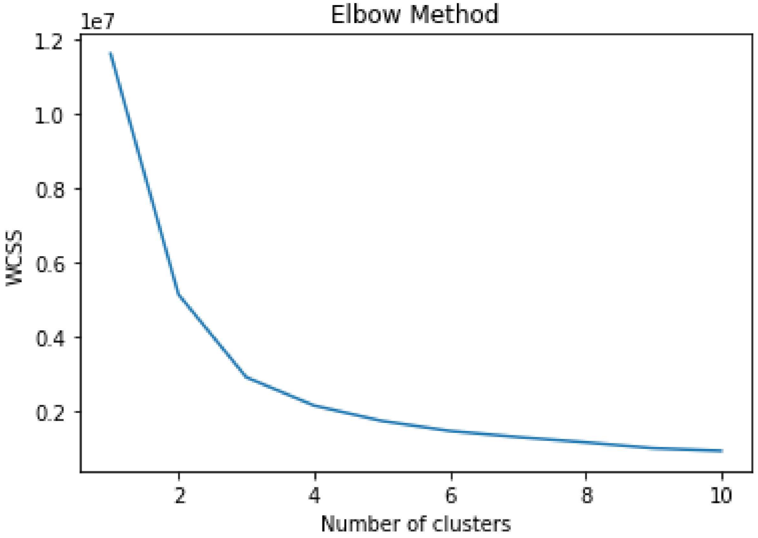
In [10]:
```
x = fl.drop(['Outcome'], axis=1)
y = fl.Outcome
```

Choosing the optimal number of clusters

Elbow method

In [11]:
```
from sklearn.cluster import KMeans
wcss = []
for n in range(1,11):
    kmeans = KMeans(n_clusters=n, random_state=11)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

plt.plot(range(1,11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



From the graph, we can take the clusters as 3 since the curve is not steep after that.

In [12]:
```
#KMeans with 3 clusters
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=3, init='k-means++', max_iter=100, n_init=8, random_state=11)
pred = kmeans.fit_predict(x)
```

In [13]:
```
frame = pd.DataFrame(x)
frame['Cluster']=pred
frame['Cluster'].value_counts()
```

Out[13]:
```
1    495
0    235
2     38
Name: Cluster, dtype: int64
```

plt.figure(figsize=(12,8)) plt.scatter(x[pred==0,0], x[pred==0,1], s=100, c='blue', label='Cluster 1') plt.scatter(x[pred==1,0], x[pred==1,1], s=100, c='red', label='Cluster 2') plt.scatter(x[pred==2,0], x[pred==2,1], s=100, c='green', label='Cluster 3')

plt.scatter(kmeans.cluster*centers*[:,0], kmeans.cluster*centers*[:,1], s=300, c='black', label='Centroids') plt.title('Clusters') plt.legend()

Evaluation of K-Means

In [14]:
```
kmeans.inertia_
```

Out[14]:
```
2913322.5800817804
```

The lesser value is better. Since value here is quite high, we can say that the model is not good fit.

K-Modes Clustering

In [29]:
```
pip install KModes
```

```
Requirement already satisfied: KModes in d:\anaconda3\lib\site-packages (0.11.0)
Requirement already satisfied: numpy>=1.10.4 in d:\anaconda3\lib\site-packages (from KModes) (1.19.2)
Requirement already satisfied: scikit-learn>=0.22.0 in d:\anaconda3\lib\site-packages (from KModes) (0.23.2)
Requirement already satisfied: scipy>=0.13.3 in d:\anaconda3\lib\site-packages (from KModes) (1.5.2)
Requirement already satisfied: joblib>=0.11 in d:\anaconda3\lib\site-packages (from KModes) (0.17.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in d:\anaconda3\lib\site-packages (from scikit-learn>=0.22.0->KModes) (2.1.0)
Note: you may need to restart the kernel to use updated packages.
```

In [30]:
```
x2 = fl.loc[:, ['BloodPressure', 'Insulin']].values
```

Choosing the optimal number of clusters

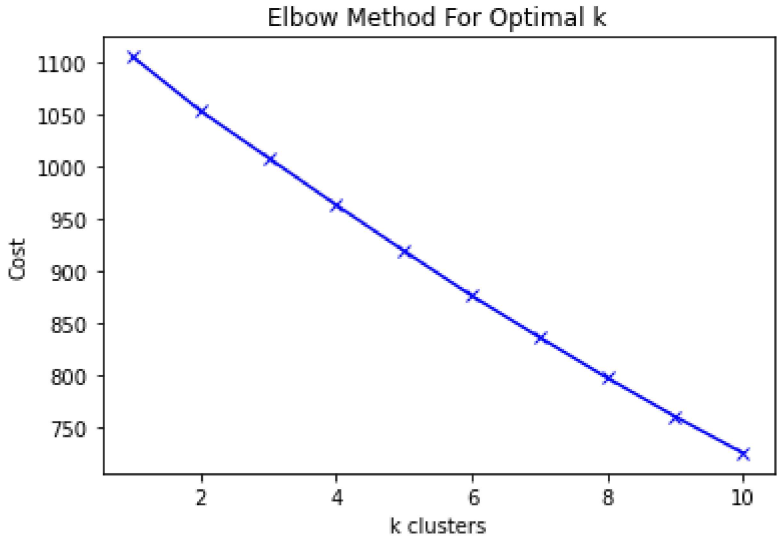
In [36]:
```
from kmodes.kmodes import KModes

cost = []
K = range(1,11)
for n in list(K):
    kmode = KModes(n_clusters=n, init = "Cao", n_init = 1, verbose=1)
    kmode.fit_predict(x2)
    cost.append(kmode.cost_)

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

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 1105.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
```

```
Run 1, iteration: 1/100, moves: 0, cost: 1053.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 1008.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 963.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 919.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 876.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 836.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 797.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 760.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 725.0
```



In [37]:
```
kmodes = KModes(n_clusters=4, init = "Cao", n_init = 1, verbose=1)
y_modes = kmodes.fit_predict(x)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 32, cost: 5110.0
Run 1, iteration: 2/100, moves: 0, cost: 5110.0
```

In [40]:
```
frame = pd.DataFrame(x)
frame['cluster'] = y_modes
frame['cluster'].value_counts()
```

Out[40]:
```
0    438
1    150
2     99
3     81
Name: cluster, dtype: int64
```

The above output indicates that 438 values belong to the cluster 0, 150 to cluster 1, and so on.