In [1]:	<pre># import the Libraries  import numpy as np  # used for multidimensional array import pandas as pd  # used for import the dataset import seaborn as sns import matplotlib.pyplot as plt  # used for plotting the Graph  %matplotlib inline</pre>
In [48]:	
In [49]:	<pre>from sklearn.cluster import KMeans from sklearn.decomposition import PCA from sklearn.metrics.pairwise import cosine_similarity</pre>
In [50]: In [51]:	<pre># Import the dataset dataset= pd.read_csv('diabetes.csv')</pre>
Out[51]:	Pregnancies int64 Glucose int64 BloodPressure int64 SkinThickness int64 Insulin int64 BMI float64 DiabetesPedigreeFunction float64 Age int64
In [52]: Out[52]:	<pre>dataset.keys()  Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',</pre>
In [53]:	'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'], dtype='object')
<pre>In [54]: Out[54]:</pre>	dataset.head()
	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
In [55]: In [56]: In [57]:	#Replacing zero values with NaN dataset[["Glucose", "BloodPressure", "SkinThickness", "Insulin", "BMI"]] = dataset[["Glucose", "BloodPressure", "SkinThickness", "Insulin", "BMI"]].replace
Out[57]:	dataset.isnull().sum()
In [58]:	DiabetesPedigreeFunction 0 Age 0 Outcome 0 dtype: int64
In [59]:	<pre>dataset["SkinThickness"].fillna(dataset["SkinThickness"].mean(), inplace = True) dataset["Insulin"].fillna(dataset["Insulin"].mean(), inplace = True) dataset["BMI"].fillna(dataset["BMI"].mean(), inplace = True)  # Feature scaling using MinMaxScaler from sklearn.preprocessing import MinMaxScaler</pre>
	<pre>sc = MinMaxScaler(feature_range = (0, 1)) dataset_scaled = sc.fit_transform(dataset)  dataset1 = pd.DataFrame(dataset_scaled) dataset1</pre>
Out[60]:	0         1         2         3         4         5         6         7         8           0         0.352941         0.670968         0.489796         0.304348         0.170130         0.314928         0.234415         0.483333         1.0           1         0.058824         0.264516         0.428571         0.239130         0.170130         0.171779         0.116567         0.166667         0.0           2         0.470588         0.896774         0.408163         0.240798         0.170130         0.104294         0.253629         0.183333         1.0           3         0.058824         0.290323         0.428571         0.173913         0.096154         0.202454         0.038002         0.000000         0.0
	4         0.000000         0.600000         0.163265         0.304348         0.185096         0.509202         0.943638         0.200000         1.0                     763         0.588235         0.367742         0.530612         0.445652         0.199519         0.300613         0.039710         0.700000         0.0           764         0.117647         0.503226         0.469388         0.217391         0.170130         0.380368         0.111870         0.100000         0.0           765         0.294118         0.496774         0.489796         0.173913         0.117788         0.163599         0.071307         0.150000         0.0
In [61]:	766 0.058824 0.529032 0.367347 0.240798 0.170130 0.243354 0.115713 0.433333 1.0  767 0.058824 0.316129 0.469388 0.260870 0.170130 0.249489 0.101196 0.033333 0.0  768 rows × 9 columns
	# Heatmap sns.heatmap(dataset1.corr(), annot = True) plt.show()  0 - 1 0.13 0.21 0.0830.0560.022-0.034 0.54 0.22  - 0.13 1 0.22 0.19 0.42 0.23 0.14 0.27 0.49  - 0.8
	N - 0.21 0.22 1 0.19 0.073 0.28-0.00280.32 0.17  M -0.083 0.19 0.19 1 0.16 0.54 0.1 0.13 0.22 -0.66
In [62]:	#corr matrix shows the dataset columns that have the highest correlation to outcome = 8 #1 (Glucose), 5 (Insulin), 7 (Age)
In [63]:	<pre># Selecting Teatures = [Glucose, Insulin, BMT] X = dataset1.iloc[:, [1, 5, 7]].values Y = dataset1.iloc[:, 8].values  # Splitting X and Y from sklearn.model_selection import train_test_split</pre>
In [65]:	<pre>X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.20, random_state = 42, stratify = dataset1[8] )</pre>
In [66]:	<pre>X_train shape: (614, 3) X_test shape: (154, 3) Y_train shape: (614,) Y_test shape: (154,)</pre> <pre>import sklearn</pre>
Out[66]: In [67]:	
In [88]: In [89]:	#modelling k means cluster
In [90]:	<pre>cost=[] for i in range(1,n_clusters):     kmean= KMeans(i)     kmean.fit(X)     cost.append(kmean.inertia_)</pre>
Out[90]:	<pre>plt.plot(cost, 'bx-') [<matplotlib.lines.line2d 0x7ff253b76d90="" at="">]  70 - 60 -</matplotlib.lines.line2d></pre>
	50 - 40 - 30 - 20 - 10 -
In [91]:	0 5 10 15 20 25
<pre>In [92]: Out[92]:</pre>	clusters-pd.concat([dataset, pd.Datarrame({ Cluster : labels})], axis=1) clusters.head()
	0 140.0 72.0 00.00000 100.040220 00.0
	1       1       85.0       66.0       29.00000       155.548223       26.6       0.351       31       0       2         2       8       183.0       64.0       29.15342       155.548223       23.3       0.672       32       1       0         3       1       89.0       66.0       23.00000       94.000000       28.1       0.167       21       0       2         4       0       137.0       40.0       35.00000       168.000000       43.1       2.288       33       1       0
In [93]:	2 8 183.0 64.0 29.15342 155.548223 23.3 0.672 32 1 0 3 1 89.0 66.0 23.00000 94.000000 28.1 0.167 21 0 2 4 0 137.0 40.0 35.00000 168.000000 43.1 2.288 33 1 0  #Interpretation of Clusters for c in clusters:     grid= sns.FacetGrid(clusters, col='cluster')     grid.map(plt.hist, c)  cluster = 0 cluster = 1 cluster = 2
In [93]:	2 8 183.0 64.0 29.15342 155.548223 23.3 0.672 32 1 0 3 1 89.0 66.0 23.00000 94.000000 28.1 0.167 21 0 2 4 0 137.0 40.0 35.00000 168.000000 43.1 2.288 33 1 0  #Interpretation of Clusters for c in clusters:     grid= sns.FacetGrid(clusters, col='cluster')     grid.map(plt.hist, c)  cluster = 0 cluster = 1 cluster = 2
In [93]:	2 8 183.0 64.0 29.15342 155.548223 23.3 0.672 32 1 0 3 1 89.0 66.0 23.00000 94.000000 28.1 0.167 21 0 2 4 0 137.0 40.0 35.00000 168.000000 43.1 2.288 33 1 0  #Interpretation of Clusters for c in clusters:     grid= sns.FacetGrid(clusters, col='cluster')     grid.map(plt.hist, c)  cluster = 0 cluster = 1 cluster = 2  150 125 100 75 100 100 100 100 100 100 100 100 100 10
In [93]:	2 8 183.0 64.0 29.15342 155.548223 23.3 0.672 32 1 0 3 1 89.0 66.0 23.00000 94.000000 28.1 0.167 21 0 2 4 0 137.0 40.0 35.00000 168.000000 43.1 2.288 33 1 0  #Interpretation of Clusters for c in clusters:     grid= sns.PacetGrid(clusters, col='cluster')     grid.map(plt.hist, c)  cluster = 0 cluster = 1 cluster = 2  150 150 150 150 150 150 150 150 150 15
In [93]:	2 8 183.0 64.0 29.15342 155.548223 23.3 0.672 32 1 0 3 1 89.0 65.0 23.0000 94.000000 28.1 0.167 21 0 2 4 0 137.0 40.0 35.00000 168.000000 43.1 2.288 33 1 0  ##Interpretation of Clusters for c in clusteres:     grid-map(plt-hist, c)  cluster = 0 cluster - 1 cluster - 2  150 15 25 25 25 25 25 25 25 25 25 25 25 25 25
In [93]:	2
In [93]:	2 8 163.0 E40 25.644 25.5442 23.3 2.0 2 1 0  3 1 880 250 260 250 250 260 25.000 24.1 2.10 2  4 0 1870 4 10 250 250 250 148.0000 24.1 2.78 25 25 1 0  **Electrorecetation of Clusterer grids size. Feacheristic (statistics). colici statistics and the color of the color
In [93]:	8
In [93]:	2 8 9810 640 92°5817 18564879 783 2.877 37 10 0  3 1 920 610 220000 320000 320000 611 2.000 79 0 0  4 0 1370 40 80.0000 1850000 611 2.000 81 1 0  20 20 20 20 20 20 20 20 20 20 20 20 20 2
In [93]:	### 15   Sec.   25/100   1/2
In [93]:	2 6 790 C4C 201842 SACAMAN CALLED TO THE CAL
In [93]:	8 1930 66 25 2024 Modern 201 201 201 201 201 201 201 201 201 201
In [93]:	2
In [93]:	2
In [93]:	1
In [93]:	1
In [93]:	1
	# 1
In [68]:	Second
In [68]:	Second   S
In [68]: Out[68]: In [81]:	Column   C
In [68]: Out[69]:	The content of the
In [68]: Out[68]: In [81]: In [82]:	
In [68]: Out[68]: In [81]: In [82]: Out[82]:	1
In [68]: Out[68]: In [81]: In [82]: In [84]:	1
In [68]: Out [68]: In [81]: In [82]: In [84]:	March   Marc
In [68]: Out [68]: In [81]: In [82]: In [84]:	Martin   M
In [68]: Out [68]: In [81]: In [82]: In [84]:	No.   10   10   10   10   10   10   10   1