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2048011

2 - MDS

Machine Learning Lab 12 & 13

Hierarchical Clustering & DBSCAN

30 April, 2021

CHRIST (Deemed to be University)

```
In [10]: 1 #Import Libraries
          2 import pandas as pd
          3 import seaborn as sns
          4 import matplotlib.pyplot as plt
```

```
In [27]: 1 #Reading dataset
          2 fl = pd.read_csv('../diabetes.csv')
          3 fl.head()
```

```
Out[27]:
```

	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

```
In [28]: 1 #Null values
          2 fl.isnull().sum()
```

```
Out[28]: Pregnancies      0
          Glucose         0
          BloodPressure    0
          SkinThickness    0
          Insulin          0
          BMI              0
          DiabetesPedigreeFunction  0
          Age             0
          Outcome         0
          dtype: int64
```

Therefore, we can say that there is no null value in the dataset.

```
In [29]: 1 #Duplicate data
          2 fl.duplicated().any()
```

```
Out[29]: False
```

So there are no duplicated values.

Exploratory Data Analysis

```
In [30]: 1 #Dataset shape
          2 print("No. of rows: ", fl.shape[0])
          3 print("No. of columns: ", fl.shape[1])
```

```
No. of rows: 768
No. of columns: 9
```

In [31]:

```
1 #Dataset info
2 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
```

In [32]:

```
1 #Dataset describe
2 fl.describe()
```

Out[32]:

	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

```
In [33]: 1 #Correlation matrix
          2 fl.corr()
```

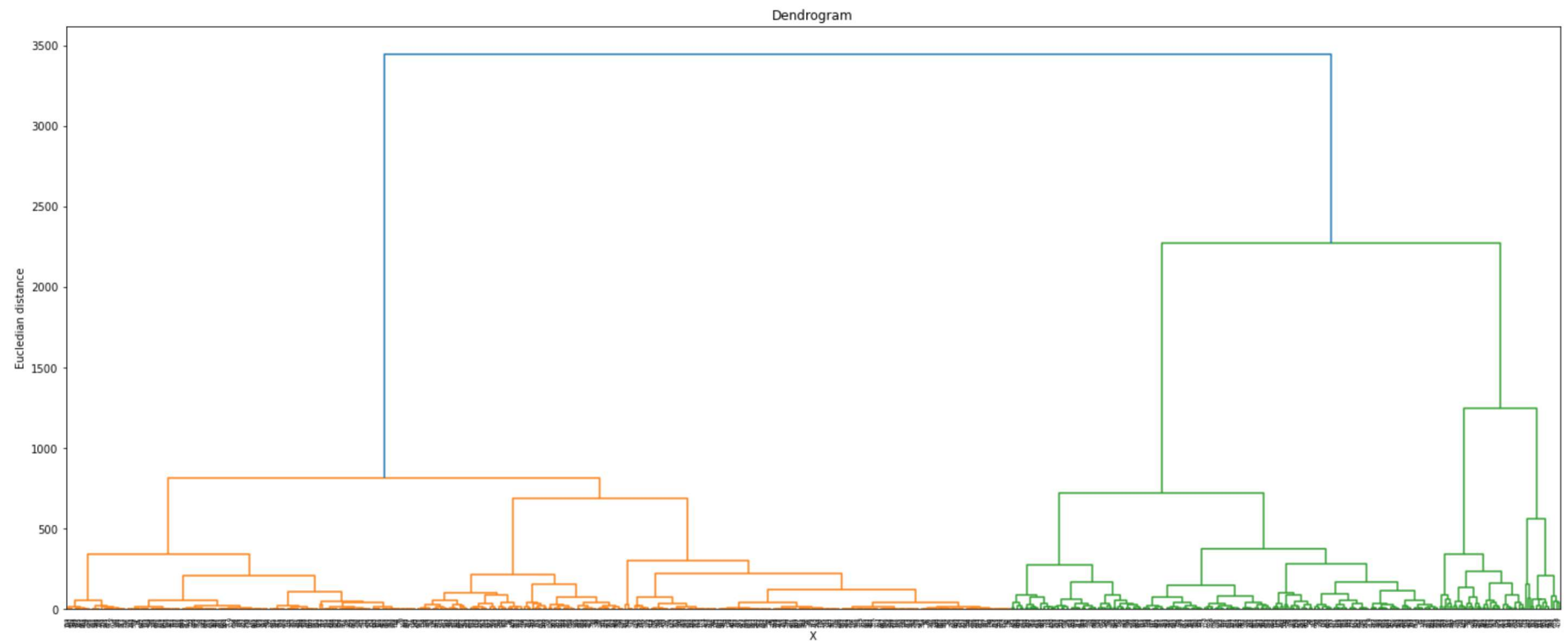
Out[33]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535	0.017683	-0.033523	0.544341	0.221898
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357	0.221071	0.137337	0.263514	0.466581
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933	0.281805	0.041265	0.239528	0.065068
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783	0.392573	0.183928	-0.113970	0.074752
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000	0.197859	0.185071	-0.042163	0.130548
BMI	0.017683	0.221071	0.281805	0.392573	0.197859	1.000000	0.140647	0.036242	0.292695
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071	0.140647	1.000000	0.033561	0.173844
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163	0.036242	0.033561	1.000000	0.238356
Outcome	0.221898	0.466581	0.065068	0.074752	0.130548	0.292695	0.173844	0.238356	1.000000

Heirarchical Clustering

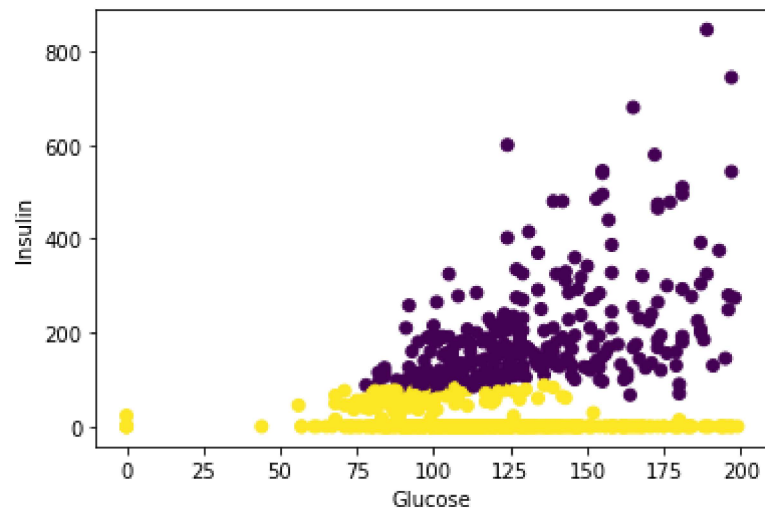
```
In [34]: 1 x = fl.loc[:,['Glucose', 'Insulin']]
```

```
In [35]: 1 # Visualising the dendrogram
2 import scipy.cluster.hierarchy as sch
3
4 fig = plt.figure(figsize=(25, 10))
5 dendrogram=sch.dendrogram(sch.linkage(x,method='ward'))
6 plt.title("Dendrogram")
7 plt.xlabel("X")
8 plt.ylabel("Eucledian distance")
9 plt.show()
```

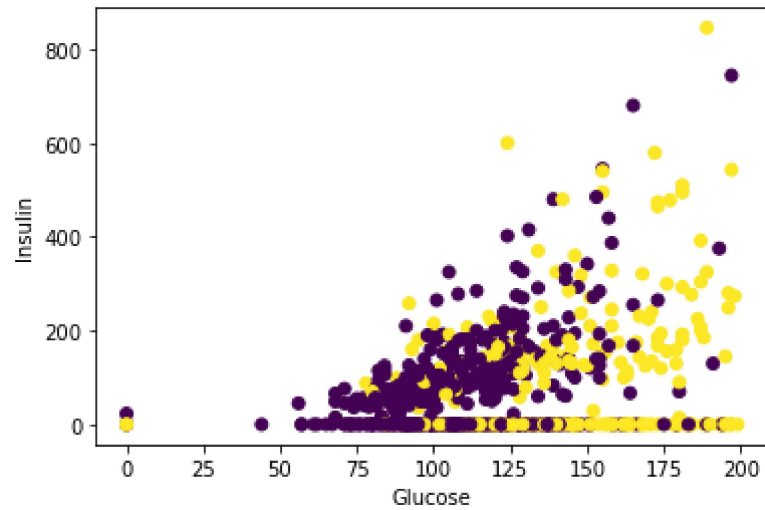


```
In [52]: 1 from sklearn.cluster import AgglomerativeClustering
2
3 hierarchical_clustering = AgglomerativeClustering(n_clusters = 2, affinity = 'euclidean', linkage = 'ward')
4 predicted_hc = hierarchical_clustering.fit_predict(x)
5 predicted_hc
6 x['Label'] = predicted_hc
```

```
In [45]: 1 plt.scatter(x['Glucose'], x['Insulin'], c = predicted_hc)
2 plt.xlabel('Glucose')
3 plt.ylabel('Insulin')
4 plt.show()
```



```
In [47]: 1 plt.scatter(f1['Glucose'], f1['Insulin'], c = f1['Outcome'])  
2 plt.xlabel('Glucose')  
3 plt.ylabel('Insulin')  
4 plt.show()
```



DBSCAN

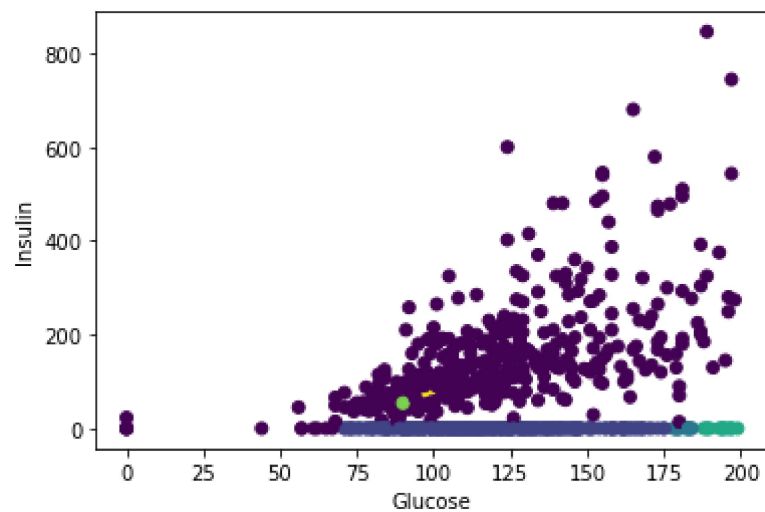
```
In [50]: 1 from sklearn.cluster import DBSCAN
          2
          3 db_clustering = DBSCAN(eps=3,min_samples=5,metric='euclidean')
          4 predicted_db = db_clustering.fit_predict(x)
          5 predicted_db
```

```
Out[50]: array([ 0,  0,  1, -1, -1,  0, -1,  0, -1,  0,  0,  0,  0, -1, -1,  0, -1,
                0, -1, -1, -1,  0,  2,  0, -1, -1,  0, -1, -1,  0,  0, -1,  3,  0,
                0, -1,  0,  0,  0, -1, -1,  0,  0, -1,  0,  1,  0,  0,  0,  0, -1,
               -1, -1, -1, -1,  0, -1, -1,  0, -1,  0,  0, -1, -1,  0,  0,  0,  0,
               -1, -1, -1, -1,  0, -1,  0, -1, -1,  0,  0,  0,  0,  0, -1,  0,  0,
               -1,  0, -1, -1,  0,  0, -1, -1,  0, -1, -1,  0, -1, -1, -1,  0,  0,
                0, -1,  0, -1,  0, -1, -1, -1, -1, -1, -1,  0, -1,  0,  0,  0,  0,
               -1, -1,  0, -1,  0,  0, -1, -1, -1, -1,  0, -1,  0, -1,  0, -1, -1,
               -1, -1,  0, -1,  0,  0, -1,  0, -1,  0, -1, -1,  0,  0, -1,  0, -1,
               -1,  2,  0, -1, -1,  3, -1,  0, -1, -1,  0,  0, -1,  0,  0,  0, -1,
                0, -1,  0, -1, -1, -1,  0, -1,  0,  0,  0, -1, -1,  0,  0,  2, -1,
               -1, -1, -1,  0, -1,  0,  0,  0, -1,  0, -1, -1, -1,  0,  0,  0, -1,
               -1,  0, -1,  0, -1,  1,  0,  0,  1, -1, -1, -1, -1, -1,  0,  0, -1,
                0,  0, -1, -1, -1,  0,  0, -1, -1,  0, -1, -1,  0, -1,  0, -1,  1,
                0,  0,  0, -1,  0, -1, -1,  1,  0, -1, -1,  0,  0,  0,  3,  0, -1,
                0,  0,  0, -1, -1, -1,  0,  0,  0,  0, -1,  0,  0,  0,  0,  0, -1,
                0, -1,  0, -1,  0, -1,  0, -1,  0, -1, -1,  0,  0, -1, -1, -1, -1,
               -1, -1, -1, -1, -1,  0, -1, -1, -1, -1,  0,  0, -1, -1,  0,  0, -1,
               -1, -1, -1, -1,  0, -1, -1, -1,  0, -1, -1,  1, -1,  2, -1,  0,  0,
               -1,  0, -1, -1,  1, -1, -1,  0,  3,  1,  0, -1, -1,  0,  0, -1,  1,
               -1, -1, -1,  0,  0, -1, -1,  0, -1, -1,  0,  0, -1, -1,  0,  0, -1,
                0,  3, -1, -1,  0,  0,  0, -1,  4,  0,  0, -1, -1, -1, -1, -1, -1,
               -1, -1,  4, -1,  0, -1, -1,  0, -1, -1, -1, -1,  0,  0, -1,  4, -1,
                0, -1, -1,  0, -1, -1,  0,  0,  2,  0,  0, -1,  0,  0, -1,  0,  0,
                2, -1,  0, -1, -1, -1, -1, -1,  0,  0,  0, -1, -1, -1, -1,  0, -1,
               -1,  0, -1, -1, -1,  0, -1, -1,  0,  0,  0,  0,  0,  0,  0,  2, -1,
               -1,  0,  0, -1, -1, -1, -1, -1,  0, -1,  0, -1,  0,  0, -1, -1,
               -1, -1,  0, -1,  0,  0, -1, -1, -1,  0, -1,  0,  0,  0,  0,  0,
               -1, -1, -1,  0, -1,  0, -1, -1,  0, -1, -1, -1,  0,  2, -1,  0,  0,
               -1,  0,  0,  0, -1, -1, -1, -1,  0, -1, -1,  0,  0, -1, -1, -1,  0,
                0, -1,  0,  0,  4, -1, -1,  0,  0, -1, -1, -1,  0,  0,  0,  0,  4,
               -1, -1,  0, -1,  0, -1,  0, -1,  0,  0, -1, -1, -1, -1, -1,  0, -1,
               -1, -1, -1, -1, -1,  2,  0, -1,  0, -1, -1, -1,  0,  0,  0,  0,
               -1, -1, -1,  0, -1, -1, -1, -1, -1,  0,  0, -1, -1, -1, -1, -1,  0,
                0,  2,  0,  0,  0,  0, -1,  0,  0,  0, -1,  0,  0, -1,  0, -1, -1,
```



```
-1, -1, -1, 0, -1, 0, 0, 0, -1, 1, 0, -1, -1, -1, -1, -1, -1,
-1, 0, -1, 0, 0, -1, 0, 0, -1, 0, 1, -1, 0, 3, 0, 0, 0,
0, 0, -1, 0, -1, 0, 0, 0, -1, -1, -1, -1, 0, 0, 0, -1, -1,
-1, -1, -1, 0, -1, -1, -1, 0, -1, -1, -1, -1, 0, -1, 0, 2, -1,
-1, 0, -1, 0, 0, -1, -1, -1, 0, -1, -1, 0, 2, 0, 0, 0, -1,
-1, 0, -1, 0, 0, -1, 0, 0, -1, -1, 0, 0, -1, -1, 0, -1, -1,
0, -1, 0, -1, 0, 0, 0, -1, 0, 0, -1, 0, -1, -1, -1, 0, -1,
0, -1, -1, 0, -1, 0, 0, -1, -1, -1, 0, 0, -1, 0, 0, 0, -1,
0, -1, -1, 0, 0, -1, -1, -1, 0, -1, -1, -1, 0, -1, -1, 0, -1,
-1, 0, 0, -1, 0, -1, 0, -1, 0, 0, 0, 2, -1, 0, 0, -1, 0,
-1, 0, 0], dtype=int64)
```

```
In [51]: 1 plt.scatter(x['Glucose'], x['Insulin'], c = predicted_db)
2 plt.xlabel('Glucose')
3 plt.ylabel('Insulin')
4 plt.show()
```



In [54]:

```
1 correct = []
2 for i in range(0,767):
3     if x['Label'][i] == f1['Outcome'][i]:
4         correct.append(1)
5     else:
6         correct.append(0)
7 correct[0:10] # -> if we find correctly 1, if not 0
8
9
10
11 print("Hierarchical Clustering Accuracy : ", (correct.count(1)/x['Label'].size)*100)
```

Hierarchical Clustering Accuracy : 40.36458333333333