CED18I042 - ASBD EndSem - Breast Cancer Wisconsin (Diagnostic) Data Set

May 1, 2022

Question: For the Given dataset, apply apt data pre-processing techniques to clean the data for further processing. Exploit the concepts discussed in Descriptive Statistics that relate to the data set to gain key insights from the data. Adopt a through exploratory data analytics approach, relating the various concepts and plots discussed in the course / tested in the lab assignments to gain key insights from the given data set. On the Pre-processing and EDA front adopt an exhaustive approach relating the maximum no of techniques / features under each set. Over the cleaned data set, apply the following algorithms.

Algorithm 1: DIC

Algorithm 2: K-NN Classification or Regression

Algorithm 3: k-means Clustering

Dataset Name: (1) Breast Cancer Wisconsin Data Dataset Link: https://www.kaggle.com/uciml/breast-cancer-wisconsin-data

General Instruction: You shall apply necessary pre-processing techniques like discretization, binning etc to make the dataset suitable for applying FIM algorithm. You may also make any valid assumptions required for the entire exercise and state them explicitly in your documents submitted. Submit a complete report describing the techniques employed, code snippets and corresponding output as done for your lab submissions or share the corresponding notebook link with all data present in the file do mention the dataset name in your answer script. : Based on the type of the assigned dataset, you shall either consider the entire set of features (or) subset of features to generate frequent patterns and apply predictive analytics.

1 Exploratory Data Analysis

The features:

a) radius (mean of distances from center to points on the perimeter)

b) texture (standard deviation of gray-scale values)

c) perimeter

d) area

e) smoothness (local variation in radius lengths)

f) compactness (perimeter^2 / area - 1.0)

g) concavity (severity of concave portions of the contour)

h) concave points (number of concave portions of the contour)

i) symmetry

j) fractal dimension ("coastline approximation" - 1)

Outcome:

Diagnosis: Malignant or Benign

[59]:
```python
# importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.offline as py
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.express as px
from sklearn.preprocessing import StandardScaler

import warnings
warnings.filterwarnings('ignore')

plt.style.use('fivethirtyeight')
%matplotlib inline
```

[60]:
```python
# read the dataset
df=pd.read_csv('data.csv')
df.head()
```

[60]:
```
         id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0    842302         M        17.99         10.38          122.80     1001.0
1    842517         M        20.57         17.77          132.90     1326.0
2  84300903         M        19.69         21.25          130.00     1203.0
3  84348301         M        11.42         20.38           77.58      386.1
4  84358402         M        20.29         14.34          135.10     1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0          0.11840           0.27760          0.3001              0.14710
1          0.08474           0.07864          0.0869              0.07017
2          0.10960           0.15990          0.1974              0.12790
3          0.14250           0.28390          0.2414              0.10520
4          0.10030           0.13280          0.1980              0.10430

   …  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0  …          17.33           184.60      2019.0            0.1622
1  …          23.41           158.80      1956.0            0.1238
```

```
2  …          25.53           152.50      1709.0            0.1444
3  …          26.50            98.87       567.7            0.2098
4  …          16.67           152.20      1575.0            0.1374

   compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0             0.6656           0.7119                0.2654          0.4601
1             0.1866           0.2416                0.1860          0.2750
2             0.4245           0.4504                0.2430          0.3613
3             0.8663           0.6869                0.2575          0.6638
4             0.2050           0.4000                0.1625          0.2364

   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
2                  0.08758          NaN
3                  0.17300          NaN
4                  0.07678          NaN

[5 rows x 33 columns]
```

[61]:
```
df.shape
```

[61]:
```
(569, 33)
```

The dataset has 569 rows and 33 columns.

[62]:
```
#information about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       569 non-null    int64
 1   diagnosis                569 non-null    object
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
```

```
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
 32  Unnamed: 32              0 non-null      float64
dtypes: float64(31), int64(1), object(1)
memory usage: 146.8+ KB
```

We see that most of the data is of float type, and that there are 32 values that are unlabeled.

[63]:
```python
#description about the dataset
df.describe()
```

[63]:
```
                 id  radius_mean  texture_mean  perimeter_mean    area_mean  \
count  5.690000e+02   569.000000    569.000000      569.000000   569.000000
mean   3.037183e+07    14.127292     19.289649       91.969033   654.889104
std    1.250206e+08     3.524049      4.301036       24.298981   351.914129
min    8.670000e+03     6.981000      9.710000       43.790000   143.500000
25%    8.692180e+05    11.700000     16.170000       75.170000   420.300000
50%    9.060240e+05    13.370000     18.840000       86.240000   551.100000
75%    8.813129e+06    15.780000     21.800000      104.100000   782.700000
max    9.113205e+08    28.110000     39.280000      188.500000  2501.000000

       smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
count       569.000000        569.000000      569.000000           569.000000
mean          0.096360          0.104341        0.088799             0.048919
std           0.014064          0.052813        0.079720             0.038803
min           0.052630          0.019380        0.000000             0.000000
25%           0.086370          0.064920        0.029560             0.020310
50%           0.095870          0.092630        0.061540             0.033500
75%           0.105300          0.130400        0.130700             0.074000
max           0.163400          0.345400        0.426800             0.201200

       symmetry_mean  …  texture_worst  perimeter_worst   area_worst  \
```

```
count      569.000000  …     569.000000     569.000000   569.000000
mean         0.181162  …      25.677223     107.261213   880.583128
std          0.027414  …       6.146258      33.602542   569.356993
min          0.106000  …      12.020000      50.410000   185.200000
25%          0.161900  …      21.080000      84.110000   515.300000
50%          0.179200  …      25.410000      97.660000   686.500000
75%          0.195700  …      29.720000     125.400000  1084.000000
max          0.304000  …      49.540000     251.200000  4254.000000

       smoothness_worst  compactness_worst  concavity_worst  \
count        569.000000         569.000000       569.000000
mean           0.132369           0.254265         0.272188
std            0.022832           0.157336         0.208624
min            0.071170           0.027290         0.000000
25%            0.116600           0.147200         0.114500
50%            0.131300           0.211900         0.226700
75%            0.146000           0.339100         0.382900
max            0.222600           1.058000         1.252000

       concave points_worst  symmetry_worst  fractal_dimension_worst  \
count            569.000000      569.000000               569.000000
mean               0.114606        0.290076                 0.083946
std                0.065732        0.061867                 0.018061
min                0.000000        0.156500                 0.055040
25%                0.064930        0.250400                 0.071460
50%                0.099930        0.282200                 0.080040
75%                0.161400        0.317900                 0.092080
max                0.291000        0.663800                 0.207500

       Unnamed: 32
count          0.0
mean           NaN
std            NaN
min            NaN
25%            NaN
50%            NaN
75%            NaN
max            NaN

[8 rows x 32 columns]
```

Dropping the columns without proper labels:

[64]:
```python
# dropping unncessary columns
df.drop("Unnamed: 32",axis=1,inplace=True)
```

Checking for null values:

[65]:
```
#checking missing values
df.isnull().sum()
```

[65]:
```
id                         0
diagnosis                  0
radius_mean                0
texture_mean               0
perimeter_mean             0
area_mean                  0
smoothness_mean            0
compactness_mean           0
concavity_mean             0
concave points_mean        0
symmetry_mean              0
fractal_dimension_mean     0
radius_se                  0
texture_se                 0
perimeter_se               0
area_se                    0
smoothness_se              0
compactness_se             0
concavity_se               0
concave points_se          0
symmetry_se                0
fractal_dimension_se       0
radius_worst               0
texture_worst              0
perimeter_worst            0
area_worst                 0
smoothness_worst           0
compactness_worst          0
concavity_worst            0
concave points_worst       0
symmetry_worst             0
fractal_dimension_worst    0
dtype: int64
```

Comparing the number of patients with and without cancer. (M: Malignant, B: Benign)

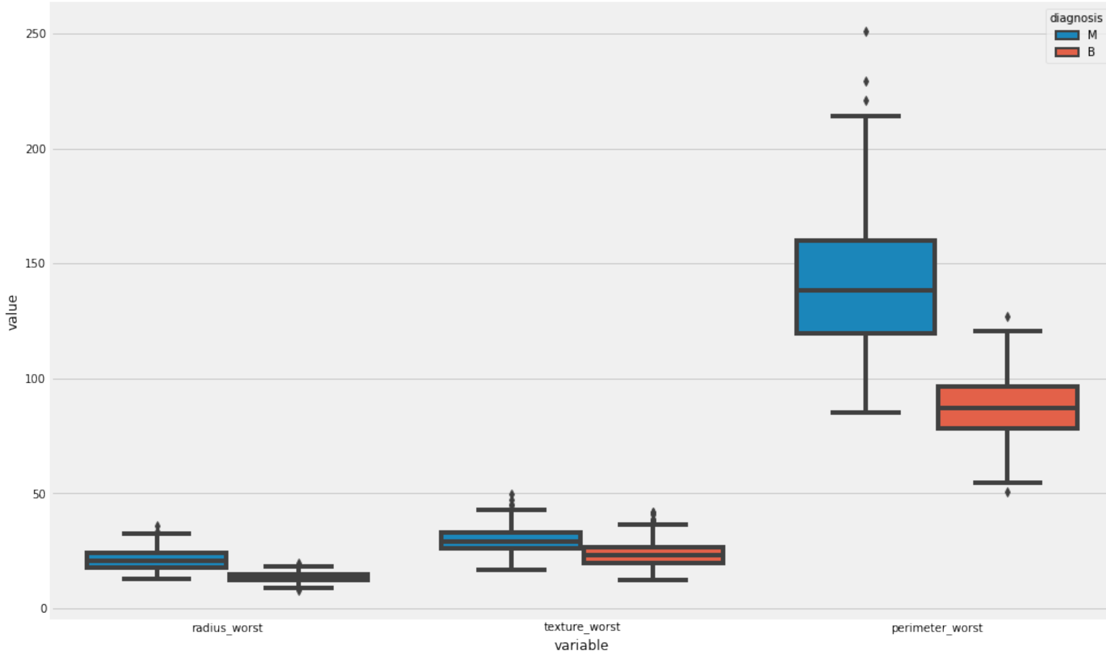
[66]:
```
fig= px.histogram(df, x='diagnosis',color='diagnosis', barmode='group')
fig.show()
```

Plotting the histogram of all the features:

[67]:
```
df.hist(figsize = (30,30), color = 'green')
plt.show()
```

Comparing selected features using boxplots:

[68]:
```
melted_data = pd.melt(df,id_vars = "diagnosis",value_vars = ['radius_worst', 'texture_worst', 'perimeter_worst'])
plt.figure(figsize = (15,10))
sns.boxplot(x = "variable", y = "value", hue="diagnosis",data= melted_data)
plt.show()
```



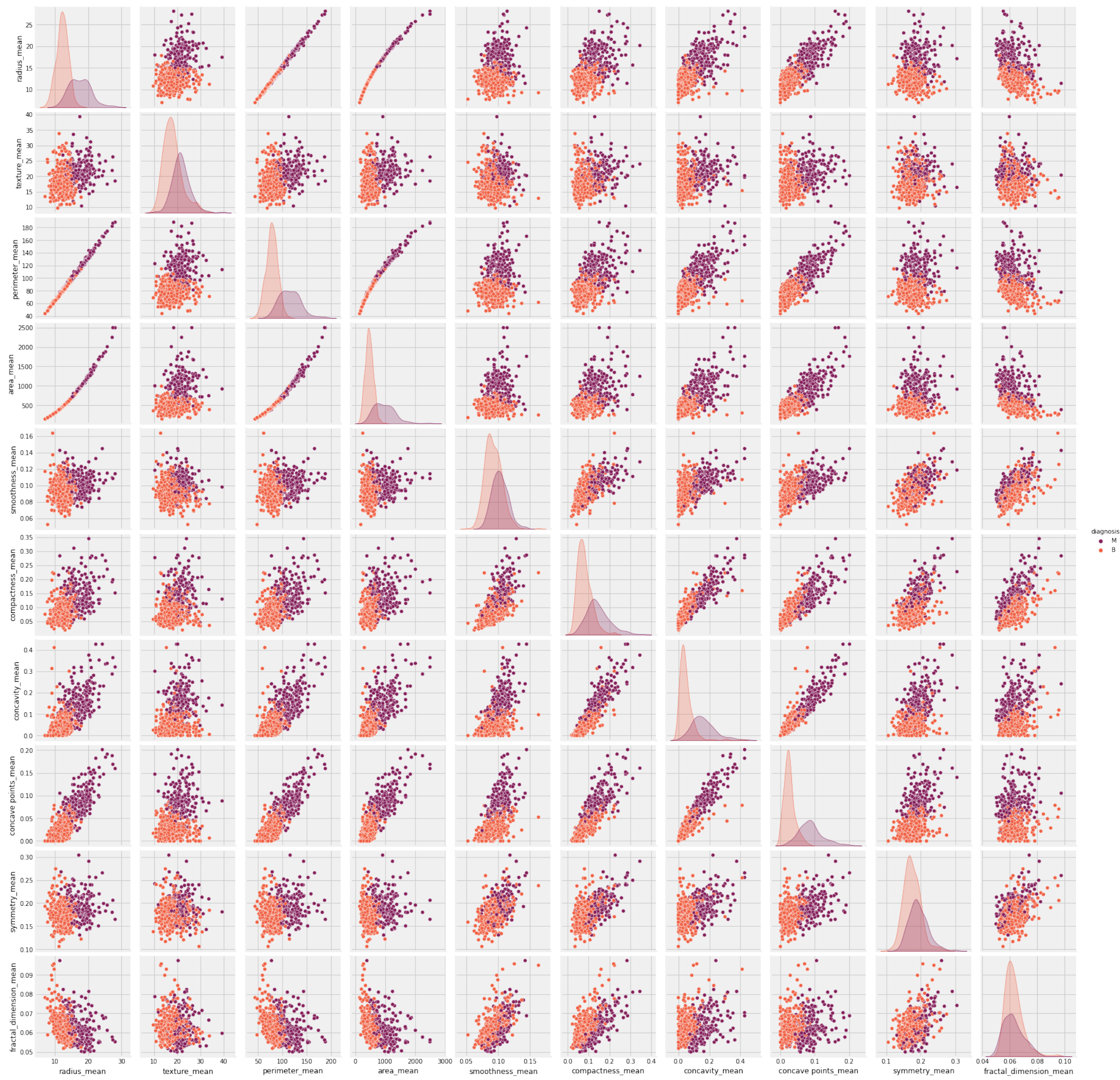
[69]:
```
df.columns
```

[69]:
```
Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean',
       'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
       'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se',
       'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se',
       'fractal_dimension_se', 'radius_worst', 'texture_worst',
       'perimeter_worst', 'area_worst', 'smoothness_worst',
       'compactness_worst', 'concavity_worst', 'concave points_worst',
       'symmetry_worst', 'fractal_dimension_worst'],
      dtype='object')
```

Generating pairplots with selected features, to view correlation:

[70]:
```
columns = ['diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean',␣
↪'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean']

sns.pairplot(data=df[columns], hue="diagnosis", palette='rocket')
```

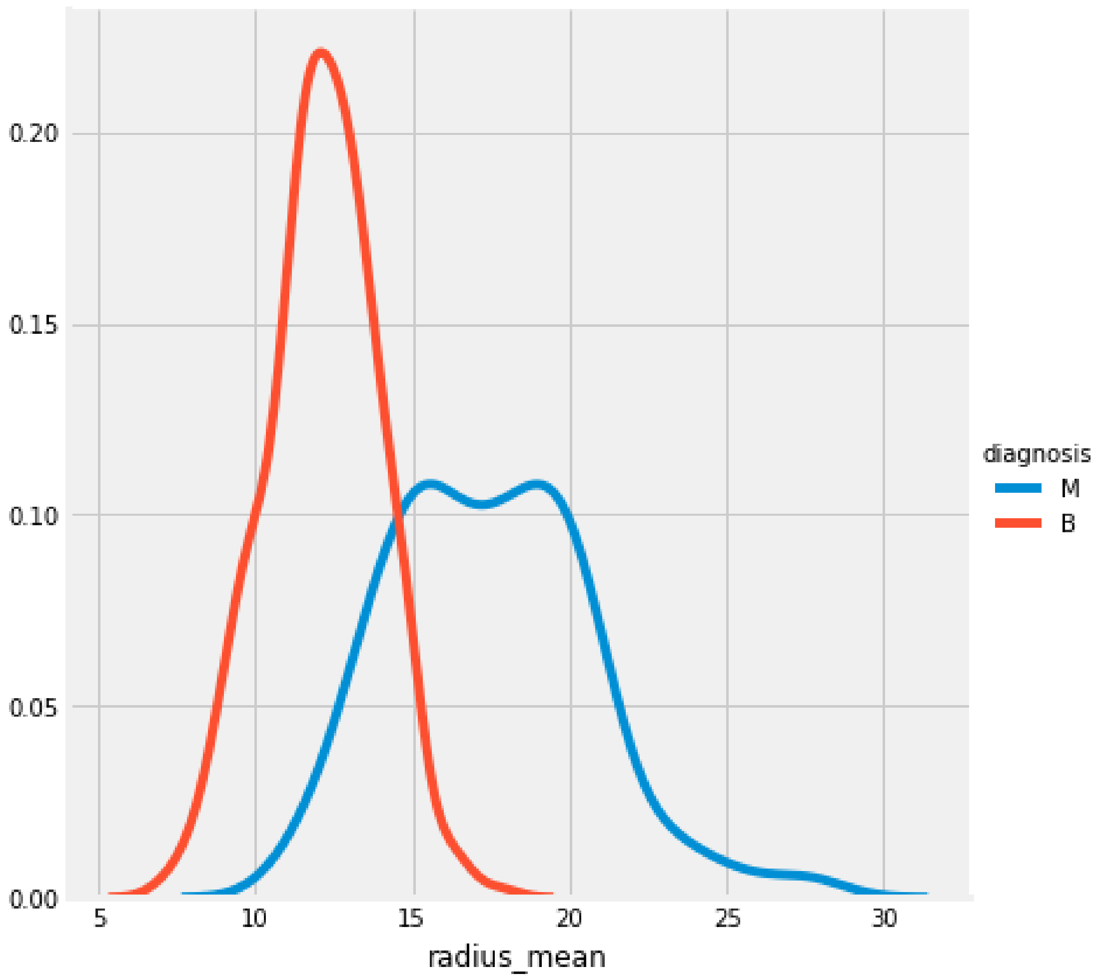
[70]:
```
<seaborn.axisgrid.PairGrid at 0x21f58189e80>
```



We see that perimeter_mean and area_mean are positively correlated.

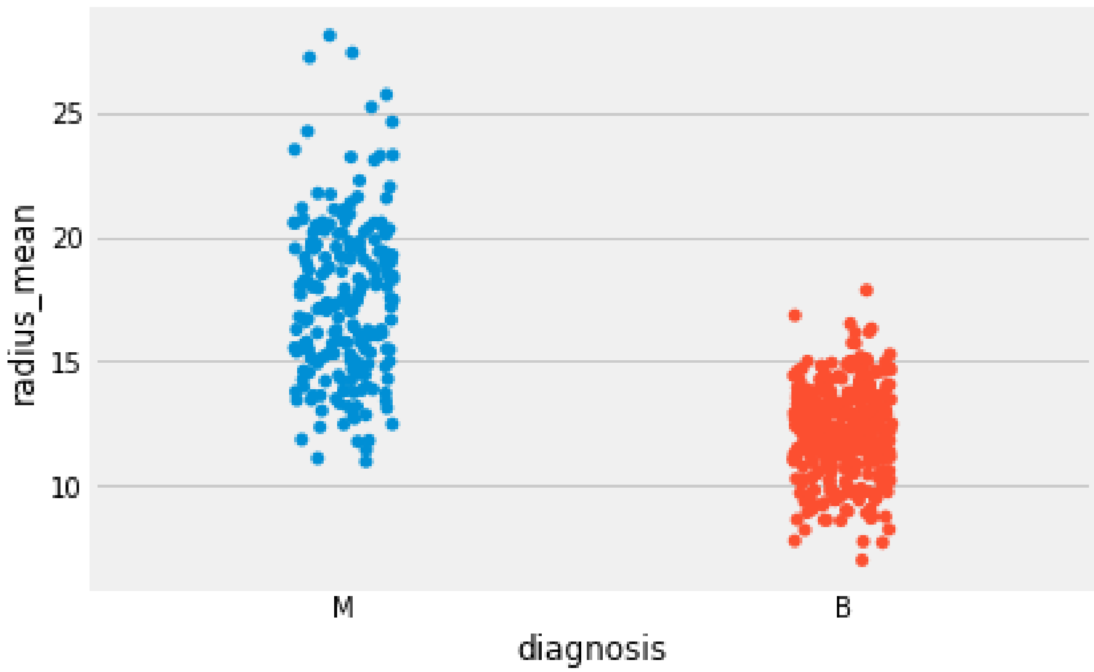
Plotting the distribution density:

[71]:
```
# Distribution density plot KDE (kernel density estimate)
sns.FacetGrid(df, hue="diagnosis", height=6).map(sns.kdeplot, "radius_mean").
 ↪add_legend()
plt.show()
```



Plotting the distribution of the mean radius

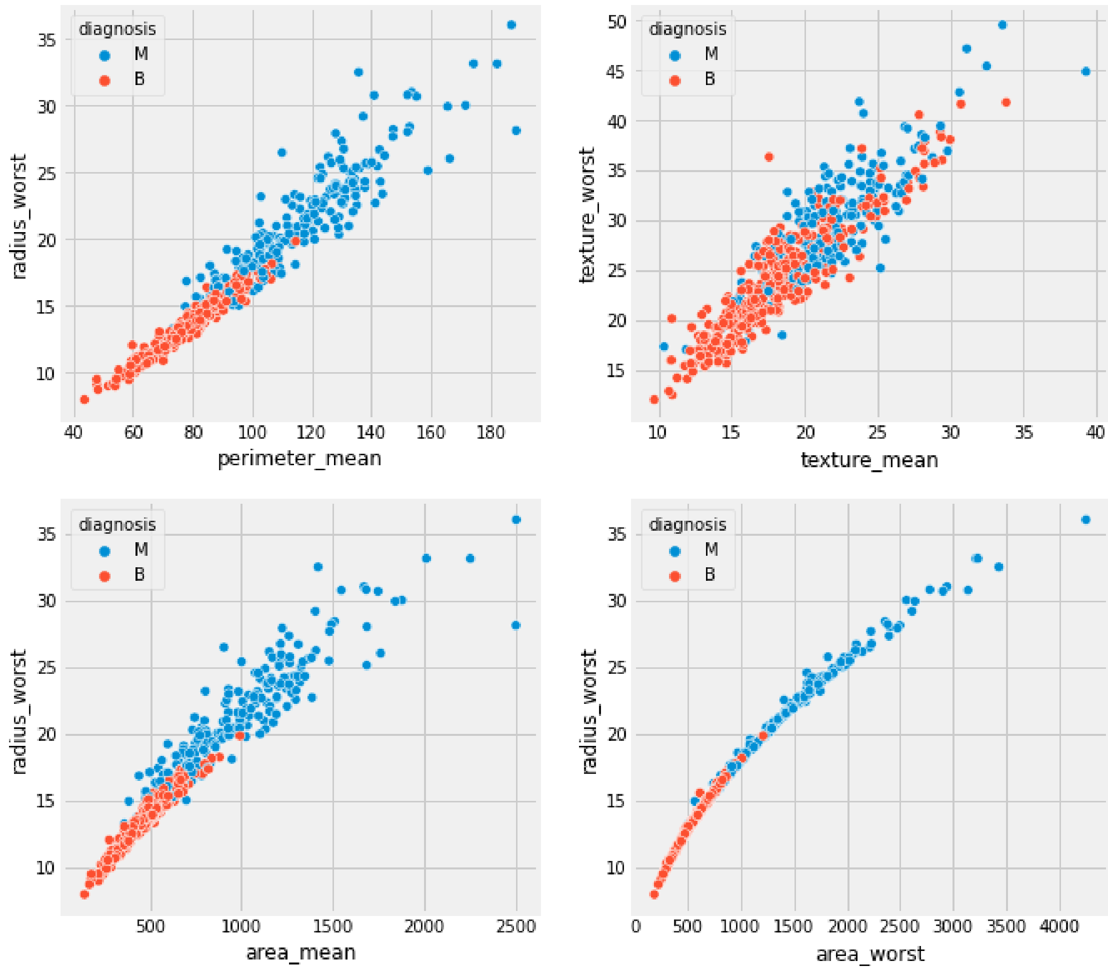
[72]:
```
# Plotting the distribution of the mean radius
sns.stripplot(x="diagnosis", y="radius_mean", data=df, jitter=True,␣
 ↪edgecolor="gray")
plt.show()
```



[73]:
```
fig = px.pie(df, values='radius_mean', names='diagnosis', title='Relation')
fig.show()
```

1.1 Positive Correlation

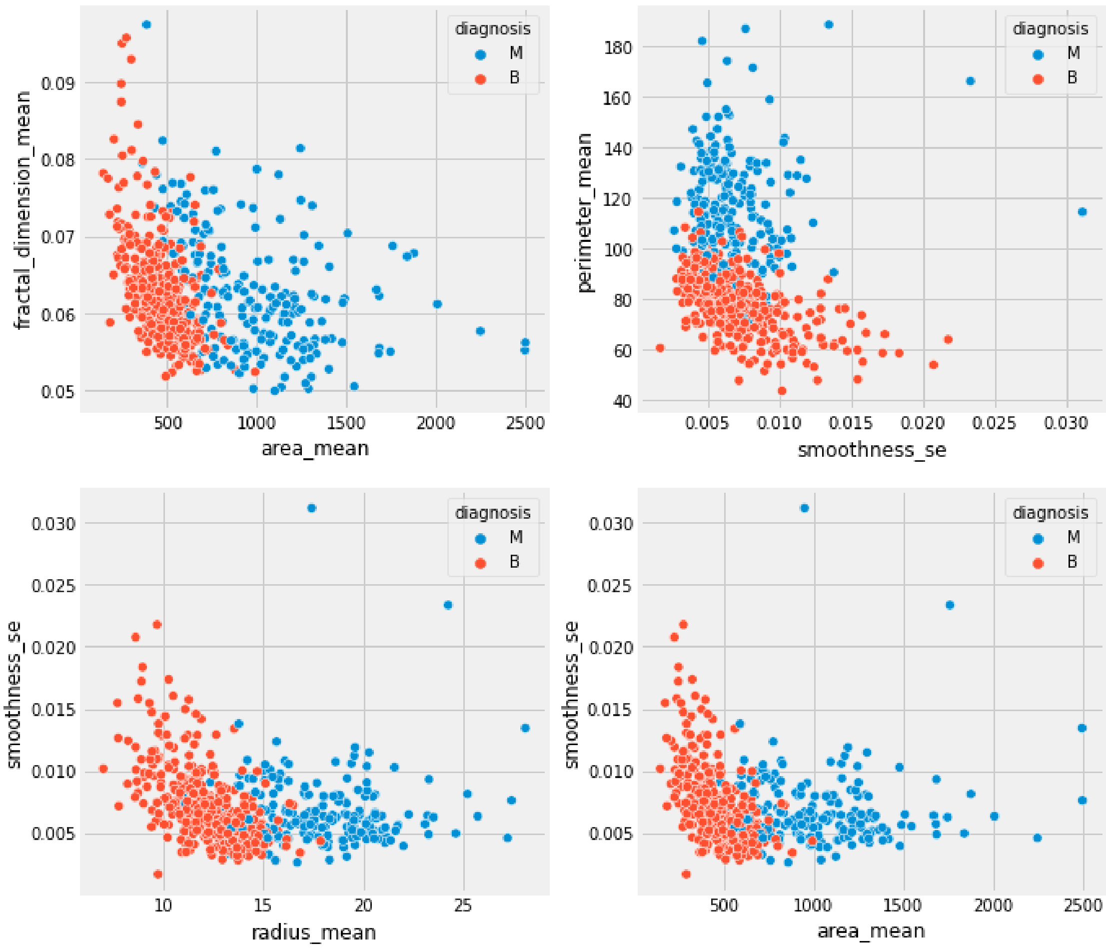
[74]:
```
#postive correlation
fig,ax=plt.subplots(2,2,figsize=(10,10))
sns.
↪scatterplot(x='perimeter_mean',y='radius_worst',data=df,hue='diagnosis',ax=ax[0][0])
sns.
↪scatterplot(x='area_mean',y='radius_worst',data=df,hue='diagnosis',ax=ax[1][0])
sns.
↪scatterplot(x='texture_mean',y='texture_worst',data=df,hue='diagnosis',ax=ax[0][1])
sns.
↪scatterplot(x='area_worst',y='radius_worst',data=df,hue='diagnosis',ax=ax[1][1])
plt.show()
```



1.2 Negative Correlation

[75]:
```
#negative correlation
fig,ax=plt.subplots(2,2,figsize=(10,10))
sns.
↪scatterplot(x='area_mean',y='fractal_dimension_mean',data=df,hue='diagnosis',ax=ax[0][0])
sns.
↪scatterplot(x='radius_mean',y='smoothness_se',data=df,hue='diagnosis',ax=ax[1][0])
sns.
↪scatterplot(x='smoothness_se',y='perimeter_mean',data=df,hue='diagnosis',ax=ax[0][1])
sns.
↪scatterplot(x='area_mean',y='smoothness_se',data=df,hue='diagnosis',ax=ax[1][1])
```

[75]: <AxesSubplot:xlabel='area_mean', ylabel='smoothness_se'>



1.3 Scatter Plot

[76]:
```
fig = px.
 ↪scatter(df,x='radius_mean',y='perimeter_mean',color='diagnosis',size_max=50)
fig.show()
```

[77]:
```
fig2=px.scatter(df,x='texture_worst',y=␣
 ↪'symmetry_worst',color='diagnosis',size_max=50)
fig2.show()
```

1.4 Distribution plot

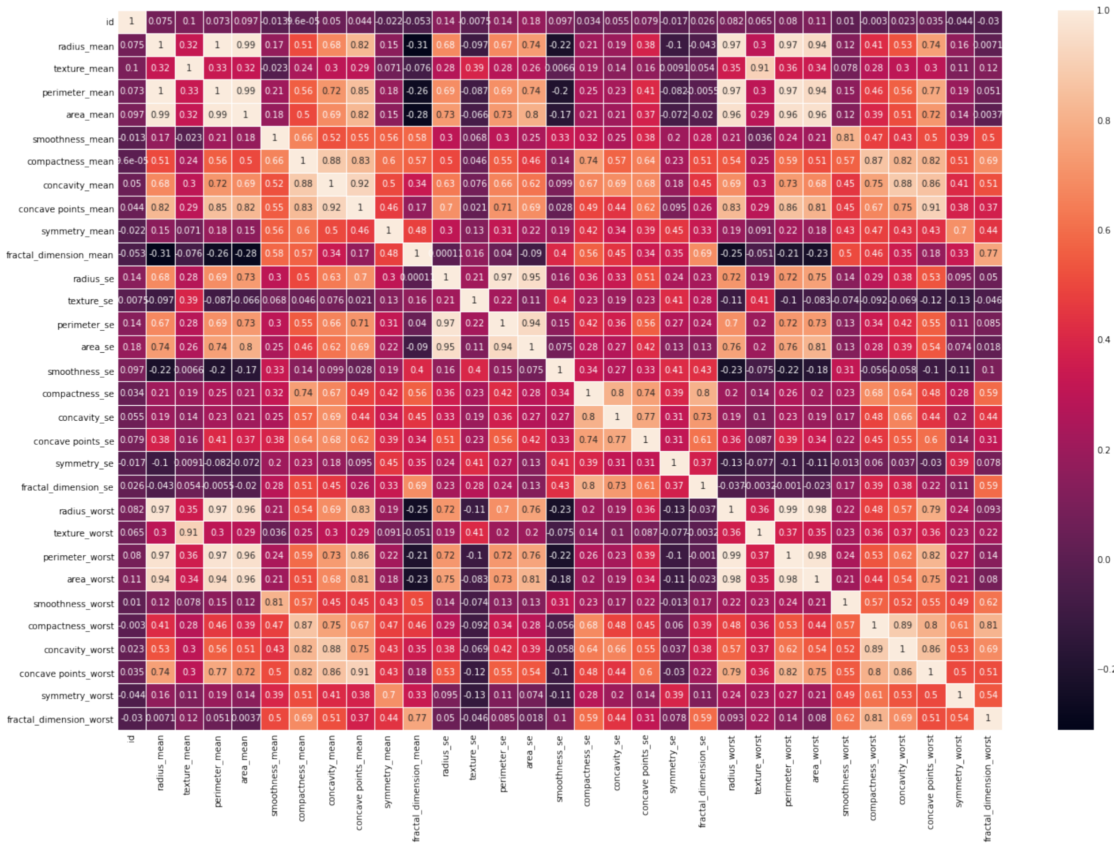
[78]:
```
import plotly.figure_factory as ff


hist_data = [df['radius_mean']]
group_labels = ['distplot'] # name of the dataset
```

```
fig = ff.create_distplot(hist_data, group_labels)
fig.show()
```

1.5 Correlation Matrix

[79]:
```
fig, ax = plt.subplots(figsize=(20,15))
sns.heatmap(df.corr(),ax=ax,annot=True,linewidth=.5)
```

[79]: <AxesSubplot:>



2 Data Preprocessing for FIM

[ ]:
```
To give the data as an input for dynamic itemset mining, we need to convert it␣
↪to either 1s and 0s or boolean values. Hence we need to encode the data.
```

[80]:
```
df
```

[80]:
```
             id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0        842302         M        17.99         10.38          122.80     1001.0
```

```
1     842517        M        20.57        17.77          132.90     1326.0
2   84300903        M        19.69        21.25          130.00     1203.0
3   84348301        M        11.42        20.38           77.58      386.1
4   84358402        M        20.29        14.34          135.10     1297.0
..       …      …         …           …            …          …
564   926424        M        21.56        22.39          142.00     1479.0
565   926682        M        20.13        28.25          131.20     1261.0
566   926954        M        16.60        28.08          108.30      858.1
567   927241        M        20.60        29.33          140.10     1265.0
568    92751        B         7.76        24.54           47.92      181.0

     smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0            0.11840           0.27760         0.30010              0.14710
1            0.08474           0.07864         0.08690              0.07017
2            0.10960           0.15990         0.19740              0.12790
3            0.14250           0.28390         0.24140              0.10520
4            0.10030           0.13280         0.19800              0.10430
..               …                 …               …                 …
564          0.11100           0.11590         0.24390              0.13890
565          0.09780           0.10340         0.14400              0.09791
566          0.08455           0.10230         0.09251              0.05302
567          0.11780           0.27700         0.35140              0.15200
568          0.05263           0.04362         0.00000              0.00000

     …  radius_worst  texture_worst  perimeter_worst  area_worst  \
0    …        25.380          17.33           184.60      2019.0
1    …        24.990          23.41           158.80      1956.0
2    …        23.570          25.53           152.50      1709.0
3    …        14.910          26.50            98.87       567.7
4    …        22.540          16.67           152.20      1575.0
..   …            …              …                …          …
564  …        25.450          26.40           166.10      2027.0
565  …        23.690          38.25           155.00      1731.0
566  …        18.980          34.12           126.70      1124.0
567  …        25.740          39.42           184.60      1821.0
568  …         9.456          30.37            59.16       268.6

     smoothness_worst  compactness_worst  concavity_worst  \
0             0.16220            0.66560           0.7119
1             0.12380            0.18660           0.2416
2             0.14440            0.42450           0.4504
3             0.20980            0.86630           0.6869
4             0.13740            0.20500           0.4000
..                …                  …               …
564           0.14100            0.21130           0.4107
565           0.11660            0.19220           0.3215
566           0.11390            0.30940           0.3403
```

```
567         0.16500          0.86810         0.9387
568         0.08996          0.06444         0.0000

     concave points_worst  symmetry_worst  fractal_dimension_worst
0                  0.2654          0.4601                  0.11890
1                  0.1860          0.2750                  0.08902
2                  0.2430          0.3613                  0.08758
3                  0.2575          0.6638                  0.17300
4                  0.1625          0.2364                  0.07678
..                    …               …                        …
564                0.2216          0.2060                  0.07115
565                0.1628          0.2572                  0.06637
566                0.1418          0.2218                  0.07820
567                0.2650          0.4087                  0.12400
568                0.0000          0.2871                  0.07039

[569 rows x 32 columns]
```

2.1 Data Encoding

[ ]:
```
The data frame is encoded to 1s and 0s:
```

[81]:
```python
from mlxtend.preprocessing import TransactionEncoder

import pandas as pd
te = TransactionEncoder()
te_ary = te.fit(df).transform(df)
te_ary = te_ary.astype("int")
df1 = pd.DataFrame(te_ary, columns=te.columns_)
df1
```

[81]:
```
        _  a  c  d  e  f  g  h  i  …  o  p  r  s  t  u  v  w  x  y
0    0  0  0  0  1  0  0  0  0  1  …  0  0  0  0  0  0  0  0  0  0
1    0  0  1  0  1  0  0  1  0  1  …  1  0  0  1  0  0  0  0  0  0
2    0  1  1  0  1  1  0  0  0  1  …  0  0  1  1  0  1  0  0  0  0
3    0  1  1  0  0  1  0  0  0  0  …  0  0  1  0  1  1  0  0  1  0
4    0  1  1  0  0  1  0  0  0  1  …  0  1  1  0  1  0  0  0  0  0
..  .. .. .. .. .. .. .. .. .. ..  …  .. .. .. .. .. .. .. .. .. ..
564  0  0  0  0  0  0  0  0  0  0  …  0  0  0  0  0  0  0  0  0  0
565  0  0  0  0  0  0  0  0  0  0  …  0  0  0  0  0  0  0  0  0  0
566  0  0  0  0  0  0  0  0  0  0  …  0  0  0  0  0  0  0  0  0  0
567  0  0  0  0  0  0  0  0  0  0  …  0  0  0  0  0  0  0  0  0  0
568  0  0  0  0  0  0  0  0  0  0  …  0  0  0  0  0  0  0  0  0  0

[569 rows x 23 columns]
```

[ ]:
```
Testing frequent itemset mining with the apriori algorithm.
```

[82]:
```python
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules

freq_itemsets = apriori(df1, min_support = 0.04, use_colnames = True)
freq_itemsets
```

[82]:

	support	itemsets
0	0.052724	(_)
1	0.040422	(a)
2	0.049209	(e)
3	0.047452	(s)
4	0.045694	(t)
5	0.049209	(_, e)
6	0.045694	(s, _)
7	0.045694	(_, t)
8	0.042179	(s, e)
9	0.042179	(e, t)
10	0.040422	(s, t)
11	0.042179	(s, _, e)
12	0.042179	(_, e, t)
13	0.040422	(s, _, t)

3 Dynamic Itemset Counting

[ ]:
```
Implement dynamic itemset counting:
```

[ ]:
```
As the dataset has a large number of features, DIC is implemented on a subset␣
↪of the dataframe:
```

[83]:
```python
df2 = df1.iloc[0:6,]
#taking first seven columns to apply dic algorithm
```

[84]:
```python
database = df2.to_numpy()
unique_itemset =[{1},{2},{3},{4},{5},{6},{7}]
min_supp = 1
M = 2
size = len(database)
```

[85]:
```python
import numpy as np
import itertools
import copy

def get_subset(S,n):
    a = itertools.combinations(S,n)
    results = []
    for i in a:
        results.append(set(i))
```

```
    return(results)

def get_superset(S,unique_itemset):
    #print(S)
    result = []
    a = set()
    for i in unique_itemset:
        if i.intersection(S)==set():
            a = i.union(S)
            result.append(a)
            a = set()

    return(result)
```

[86]:
```
def check_subset(Set,frequent_set):
    subset = get_subset(Set,len(Set)-1)
    flag = 1
    temp = []

    for i in frequent_set:
        temp.append(i[0])

    frequent_set = temp
    for i in subset:
        if i not in frequent_set:
            flag=0
            break

    if flag:
        return(True)
    else:
        return(False)

def get_itemset(T):
    result = set()
    for i in range(len(T)):
        if T[i]!=0:
            result.add(i+1)

    return(result)
```

[87]:
```
DC = []
DS = []
SC = []
SS = []

for i in unique_itemset:
```

```
    DC.append([i,0,0])

print("Initial DC:",DC,"\n")

counter = 0
T = []
while len(DC)!=0 or len(DS)!=0:

    for i in range(counter,counter+M):
        index = i%size
        T = get_itemset(database[index])
        print("Transaction :",T)

        for item in DC:
            item[2]+=1
            if item[0].issubset(T):
                item[1]+=1
        for item in DS:
            item[2]+=1
            if item[0].issubset(T):
                item[1]+=1

    for item in copy.copy(DC):
        if(item[1]>=min_supp):
            DS.append(item)
            DC.remove(item)

    for item in copy.copy(DS):
        if(item[2]==size):
            SS.append(item)
            DS.remove(item)
    for item in copy.copy(DC):
        if(item[2]==size):
            SC.append(item)
            DC.remove(item)

    frequent_set = copy.copy(DS)
    frequent_set.extend(SS)
    for item in frequent_set:
        S = get_superset(item[0],unique_itemset)
        for i in S:
            if (check_subset(i,frequent_set)):
                flag=1
                for x in DC:
                    if x[0]==i:
                        flag=0
                for x in DS:
```

```python
                    if x[0]==i:
                        flag=0
                for x in SC:
                    if x[0]==i:
                        flag=0
                for x in SS:
                    if x[0]==i:
                        flag=0
                if flag:
                    DC.append([i,0,0])

    counter+=M
    print("DS: ",DS)
    print("DC: ",DC)
    print("SS: ",SS)
    print("SC: ",SC,"\n")
```

```
Initial DC: [[{1}, 0, 0], [{2}, 0, 0], [{3}, 0, 0], [{4}, 0, 0], [{5}, 0, 0],
[{6}, 0, 0], [{7}, 0, 0]]

Transaction : {10, 5}
Transaction : {3, 5, 8, 10, 13, 14, 17}
DS:  [[{3}, 1, 2], [{5}, 2, 2]]
DC:  [[{1}, 0, 2], [{2}, 0, 2], [{4}, 0, 2], [{6}, 0, 2], [{7}, 0, 2], [{3, 5},
0, 0]]
SS:  []
SC:  []

Transaction : {2, 3, 5, 6, 10, 12, 13, 16, 17, 19}
Transaction : {2, 3, 6, 12, 13, 16, 18, 19, 22}
DS:  [[{3}, 3, 4], [{5}, 3, 4], [{2}, 2, 4], [{6}, 2, 4], [{3, 5}, 1, 2]]
DC:  [[{1}, 0, 4], [{4}, 0, 4], [{7}, 0, 4], [{2, 3}, 0, 0], [{3, 6}, 0, 0],
[{2, 5}, 0, 0], [{5, 6}, 0, 0], [{2, 6}, 0, 0]]
SS:  []
SC:  []

Transaction : {2, 3, 6, 10, 12, 13, 15, 16, 18}
Transaction : {2, 3, 6, 12, 13, 16}
DS:  [[{3, 5}, 1, 4], [{2, 3}, 2, 2], [{3, 6}, 2, 2], [{2, 6}, 2, 2]]
DC:  [[{2, 5}, 0, 2], [{5, 6}, 0, 2], [{2, 3, 6}, 0, 0]]
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6]]
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]

Transaction : {10, 5}
Transaction : {3, 5, 8, 10, 13, 14, 17}
DS:  [[{2, 3}, 2, 4], [{3, 6}, 2, 4], [{2, 6}, 2, 4]]
DC:  [[{2, 5}, 0, 4], [{5, 6}, 0, 4], [{2, 3, 6}, 0, 2]]
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6], [{3, 5}, 2, 6]]
```

```
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]

Transaction : {2, 3, 5, 6, 10, 12, 13, 16, 17, 19}
Transaction : {2, 3, 6, 12, 13, 16, 18, 19, 22}
DS:  [[{2, 3, 6}, 2, 4]]
DC:  [[{2, 3, 5}, 0, 0], [{3, 5, 6}, 0, 0], [{2, 5, 6}, 0, 0]]
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6], [{3, 5}, 2, 6], [{2,
3}, 4, 6], [{3, 6}, 4, 6], [{2, 6}, 4, 6], [{2, 5}, 1, 6], [{5, 6}, 1, 6]]
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]

Transaction : {2, 3, 6, 10, 12, 13, 15, 16, 18}
Transaction : {2, 3, 6, 12, 13, 16}
DS:  []
DC:  [[{2, 3, 5}, 0, 2], [{3, 5, 6}, 0, 2], [{2, 5, 6}, 0, 2]]
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6], [{3, 5}, 2, 6], [{2,
3}, 4, 6], [{3, 6}, 4, 6], [{2, 6}, 4, 6], [{2, 5}, 1, 6], [{5, 6}, 1, 6], [{2,
3, 6}, 4, 6]]
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]

Transaction : {10, 5}
Transaction : {3, 5, 8, 10, 13, 14, 17}
DS:  []
DC:  [[{2, 3, 5}, 0, 4], [{3, 5, 6}, 0, 4], [{2, 5, 6}, 0, 4]]
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6], [{3, 5}, 2, 6], [{2,
3}, 4, 6], [{3, 6}, 4, 6], [{2, 6}, 4, 6], [{2, 5}, 1, 6], [{5, 6}, 1, 6], [{2,
3, 6}, 4, 6]]
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]

Transaction : {2, 3, 5, 6, 10, 12, 13, 16, 17, 19}
Transaction : {2, 3, 6, 12, 13, 16, 18, 19, 22}
DS:  []
DC:  [[{2, 3, 5, 6}, 0, 0]]
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6], [{3, 5}, 2, 6], [{2,
3}, 4, 6], [{3, 6}, 4, 6], [{2, 6}, 4, 6], [{2, 5}, 1, 6], [{5, 6}, 1, 6], [{2,
3, 6}, 4, 6], [{2, 3, 5}, 1, 6], [{3, 5, 6}, 1, 6], [{2, 5, 6}, 1, 6]]
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]

Transaction : {2, 3, 6, 10, 12, 13, 15, 16, 18}
Transaction : {2, 3, 6, 12, 13, 16}
DS:  []
DC:  [[{2, 3, 5, 6}, 0, 2]]
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6], [{3, 5}, 2, 6], [{2,
3}, 4, 6], [{3, 6}, 4, 6], [{2, 6}, 4, 6], [{2, 5}, 1, 6], [{5, 6}, 1, 6], [{2,
3, 6}, 4, 6], [{2, 3, 5}, 1, 6], [{3, 5, 6}, 1, 6], [{2, 5, 6}, 1, 6]]
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]

Transaction : {10, 5}
Transaction : {3, 5, 8, 10, 13, 14, 17}
```

```
DS:  []
DC:  [[{2, 3, 5, 6}, 0, 4]]
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6], [{3, 5}, 2, 6], [{2,
3}, 4, 6], [{3, 6}, 4, 6], [{2, 6}, 4, 6], [{2, 5}, 1, 6], [{5, 6}, 1, 6], [{2,
3, 6}, 4, 6], [{2, 3, 5}, 1, 6], [{3, 5, 6}, 1, 6], [{2, 5, 6}, 1, 6]]
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]

Transaction : {2, 3, 5, 6, 10, 12, 13, 16, 17, 19}
Transaction : {2, 3, 6, 12, 13, 16, 18, 19, 22}
DS:  []
DC:  []
SS:  [[{3}, 5, 6], [{5}, 3, 6], [{2}, 4, 6], [{6}, 4, 6], [{3, 5}, 2, 6], [{2,
3}, 4, 6], [{3, 6}, 4, 6], [{2, 6}, 4, 6], [{2, 5}, 1, 6], [{5, 6}, 1, 6], [{2,
3, 6}, 4, 6], [{2, 3, 5}, 1, 6], [{3, 5, 6}, 1, 6], [{2, 5, 6}, 1, 6], [{2, 3,
5, 6}, 1, 6]]
SC:  [[{1}, 0, 6], [{4}, 0, 6], [{7}, 0, 6]]
```

4 Data Preprocessing for Classification and Clustering

For classification we need to split the data into test and train parts.

[88]:
```
X=df.iloc[:,2:].values
y=df.iloc[:,1].values
```

[89]:
```
from sklearn.preprocessing import LabelEncoder,StandardScaler
labelencode = LabelEncoder()
y=labelencode.fit_transform(y)
```

[90]:
```
#train test split
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
 ↪3,random_state=123)
```

[91]:
```
#applying standard scaler
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)
```

5 k-NN Classification

[92]:
```
X_train
```

[92]:
```
array([[-0.75450089,  1.01659115, -0.73128733, …, -0.27255521,
        -1.22412178,  0.24637476],
       [-0.10731754, -1.37755096, -0.16735748, …, -0.87152919,
        -0.08199343, -0.89975242],
```

```
[ 0.8720484 ,  0.59885153,  0.81306413, …,  1.31190285,
  0.54930958, -0.44082843],
…,
[-0.59986416,  0.74483581, -0.55511131, …, -0.0754895 ,
 -1.09721863,  0.61126664],
[ 1.80273241,  0.53372009,  1.73767584, …,  0.97127625,
 -0.4257564 , -0.93464483],
[-0.6886371 , -1.05863146, -0.6567353 , …, -0.13148291,
 -0.43378824,  0.92470699]])
```

[93]:
```
X_test
```

[93]:
```
array([[-0.82895561, -1.03841826, -0.86206574, …, -1.51467576,
        -0.09484438, -0.53072076],
       [-1.26079299, -0.8385321 , -1.2735596 , …, -0.97153965,
        -0.05307879, -0.08303331],
       [ 0.97227591, -0.01877424,  0.95883624, …,  1.24191108,
         0.08667531, -0.26518355],
       …,
       [ 1.41041331,  1.2142314 ,  1.50860537, …,  2.1035875 ,
         2.88497009,  1.22099683],
       [ 1.72827769,  0.03063582,  1.73767584, …,  1.60586827,
         0.25373769, -0.142173  ],
       [-0.9148649 ,  0.43714588, -0.84040817, …,  0.4408942 ,
         0.1445046 ,  0.76325564]])
```

[94]:
```
y_train
```

[94]:
```
array([0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1,
       1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1,
       1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0,
       0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1,
       0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0,
       1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0,
       1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1,
       1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0,
       1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
       1, 0])
```

[95]:
```
y_test
```

[95]:
```
array([0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1,
       0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0,
       1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0,
       1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1])
```

[96]:
```
from sklearn.neighbors import KNeighborsClassifier
```

[97]:
```
#k = 7
knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(X_train, y_train)
```

[97]:
```
KNeighborsClassifier(n_neighbors=7)
```

[98]:
```
print(knn.score(X_test, y_test))
```

```
0.9766081871345029
```

[100]:
```
print("Number of mislabeled points out of a total %d points : %d" % (X_test.
 ↪shape[0], (y_test != predictions).sum()))
```

```
Number of mislabeled points out of a total 171 points : 4
```

[101]:
```
knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(X_train, y_train)
print(knn.score(X_test, y_test))
```

```
0.9766081871345029
```

A high score of 97% was produced when number of neighbours = 7

6 k-Means Clustering

[102]:
```
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=2, random_state=0)

kmeans.fit(X)
```

[102]:
```
KMeans(n_clusters=2, random_state=0)
```

[103]:
```
kmeans.cluster_centers_
```

[103]:
```
array([[1.25562991e+01, 1.85703653e+01, 8.11234703e+01, 4.96061872e+02,
          9.48844977e-02, 9.10998174e-02, 6.24377642e-02, 3.34325434e-02,
          1.78057991e-01, 6.34540183e-02, 3.04190868e-01, 1.21515320e+00,
          2.15288059e+00, 2.37852922e+01, 7.17326256e-03, 2.34746895e-02,
          2.87455128e-02, 1.06363242e-02, 2.06135799e-02, 3.74750297e-03,
          1.40439018e+01, 2.47095434e+01, 9.19375114e+01, 6.19647945e+02,
          1.29959110e-01, 2.23311758e-01, 2.19214947e-01, 9.13298425e-02,
          2.83553653e-01, 8.32819406e-02],
         [1.93799237e+01, 2.16945802e+01, 1.28231298e+02, 1.18592977e+03,
          1.01294580e-01, 1.48612977e-01, 1.76939466e-01, 1.00698779e-01,
          1.91539695e-01, 6.06029008e-02, 7.42803817e-01, 1.22253817e+00,
          5.25058015e+00, 9.56781679e+01, 6.59868702e-03, 3.21766947e-02,
          4.24197710e-02, 1.56739847e-02, 2.03039695e-02, 3.95338931e-03,
          2.37094656e+01, 2.89126718e+01, 1.58496183e+02, 1.75302290e+03,
          1.40424733e-01, 3.57757710e-01, 4.49306107e-01, 1.92431069e-01,
          3.11881679e-01, 8.61654962e-02]])
```

[104]:
```python
labels = kmeans.labels_

# check how many of the samples were correctly labeled
correct_labels = sum(y == labels)

print("Result: %d out of %d samples were correctly labeled." % (correct_labels,␣
 ↪y.size))
```

```
Result: 486 out of 569 samples were correctly labeled.
```

[105]:
```python
print('Accuracy score: {0:0.2f}'. format(correct_labels/float(y.size)))
```

```
Accuracy score: 0.85
```

A high accuracy of 85% was obtained when number of clusters = 2