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(https://colab.research.google.com/github/Python-Charmer/Final-Project-Team-Python-Charmer/blob/master/Phase%203/Code/FinalProject.ipynb)

Python Final Project - Team Python Charmers

In [ ]:
```
# Loading Packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
```

In [ ]:
```
# Loading Data From Source.
def load_data():
  url = r'https://raw.githubusercontent.com/Python-Charmer/Final-Project-Team-Python-Charmer/master/Phase1/Data/BreastCancerWisconsin.csv'
  df = pd.read_csv(url)
  names = ['Scn','A2','A3','A4','A5','A6','A7', 'A8','A9','A10','Class']
  df.columns = names
  return df
```

In [ ]:
```
# Understanding Missing Values
def clean_missing(df):
  df['A7'] = df['A7'].replace('?',np.NaN)
  df['A7'] = pd.to_numeric(df['A7'])
  print("Below are how many missing values for each column\n")
  print(df.isnull().sum())
  print("\nCleaning missing values with column means\n")
  df = df.fillna(round(df.mean(skipna = True),2))
  print(df.isnull().sum())
  return df
```

In [ ]:
```
# Calculating Summary Metrics
def  sum_metrics(df):
  print("\n Below are the summary metrics of the data \n" + str(df.describe()))
  print ("\n\nThere are " + str(df.shape[0]) + " rows and " + str(df.shape[1]) + " Columns in this data frame")
  print("\nThere are " + str(len(df['Scn'].unique())) + " unique scn values in the dataset.\n")
  print("Below are the duplicate rows in the dataset.\n")
  print(str(df.loc[df.duplicated(), :]) + "\n")
```

In [ ]:
```
# Plotting graphs
def plot_graphs(df):
  print("\nBelow are the histograms of A2:A10 \n")
  df.iloc[:,1:10].hist(bins = 8, color="blue", grid="False",alpha = .5, figsize=(12,6))
  plt.tight_layout(rect=(0,0,1.2,1.2))
  plt.show()
  df['Class'].value_counts().plot.bar().set_title("Class Variable: 2 = Benign 4 = Malignant")
  df.plot.scatter(x='A3', y='A4').set_title("Scatter of A3 & A4 90% corr")
```

In [ ]:
```
# We are getting centers for K = 4 clusters
def get_mids(X):
  clss = KMeans(n_clusters = 4)
  clss.fit(X)
  cent = clss.cluster_centers_
  print("\n Below are the centers of K = 4 clusters \n")
  print(pd.DataFrame(cent ,columns  = X.columns))
```

In [ ]:
```
# We are plotting intertia plot to find optimal K
def find_optimal_K(X):
  print("\n Below is the intertia chart \n")
  inertia = []
  k = []
  for i in range(1,15):
    clss = KMeans(n_clusters = i)
    clss.fit(X)
    iner = clss.inertia_
    k.append(i)
    inertia.append(iner)
  res  = pd.concat([pd.DataFrame(k), pd.DataFrame(inertia)],axis = 1)
  res.columns = ['K','Inertia']
  ax = res.plot("K",marker='o', linestyle='dashed', title = "Optimal K = 2" )
  ax.set_xlabel("Number of Clusters")
  ax.set_ylabel("Inertia")
```

In [ ]:
```
# Plotting SD plot to understand the data variance
def sd_plot(X):
  dt = pd.DataFrame(X.std()).sort_values(by = 0, ascending = False)
  dt.reset_index()
  fig, ay = plt.subplots()
  x_val = dt.index
  y_val = dt[0].values
  ay.bar(x = x_val, height = y_val)
  ay.set_xlabel("Features")
  ay.set_ylabel("Standard Deviation")
  ay.set_title("Standard Deviation Plot")


# Plotting Box plot to understand the data variance
def var_plot(df):
  # Box plot showing variation of the columns A2:A10
  data = []
  for i in range(1, 10):
      data.append(df.iloc[:, i])

  # Multiple box plots on one Axes
  fig, ax = plt.subplots()
  plt.title("Boxplot showing Variation of Features")
  plt.xlabel("Columns A2 thru A10")
  plt.ylabel("Values")
  ax.boxplot(data, 0,showbox=True,showmeans=True)
  top = 12
  bottom = -2
  ax.set_ylim(bottom, top)
  ax.set_xticklabels(df.iloc[:,1:-1].columns, rotation=45, fontsize=8)
  plt.show()
```

In [ ]:

```
#Getting centers of optimal K  = 2
def get_centers(X):
  print("\n Below are the centers of K = 2 clusters \n \n")
  mdl = make_pipeline(StandardScaler(), KMeans(n_clusters = 2, n_init=20))
  mdl.fit(X)
  centers = pd.DataFrame(mdl.named_steps['kmeans'].cluster_centers_)
  centers.columns = X.columns
  print(centers)
```

In [ ]:

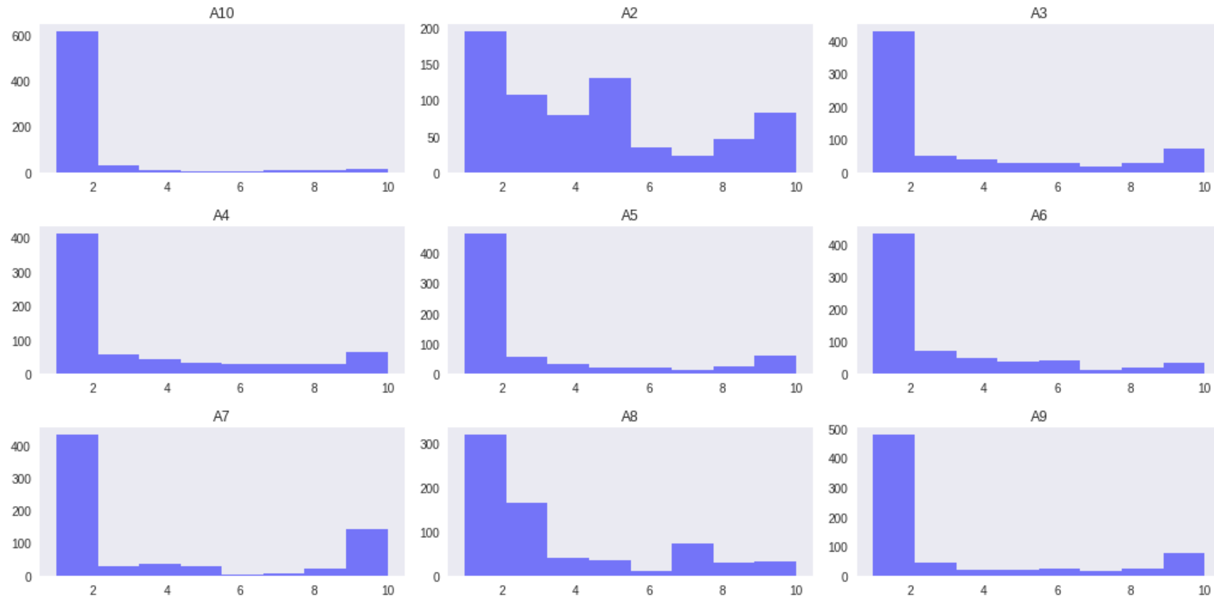
```
# Cross tabulating the cluster labels with "Class"
def lables(i,df):
  print("\nBelow are the predicted labels with k = " + str(i) + "\n")
  if i == 4:
    mdl = KMeans(n_clusters = i)
  else:
    mdl =  make_pipeline(StandardScaler(), KMeans(n_clusters = i, n_init=20))
  labels = mdl.fit_predict(df.iloc[:,1:-1])
  ctf = pd.DataFrame({'labels': labels, 'Class': df["Class"]})
  print(pd.crosstab(ctf['labels'], ctf['Class']))
```

In [11]:
```
# Main Function Phase 1
df = load_data()
df = clean_missing(df)
sum_metrics(df)
plot_graphs(df)
print("The columns that need standardization are: A7,A3,& A9 because they have the highe
st amount of variance compared to other factors.")
```

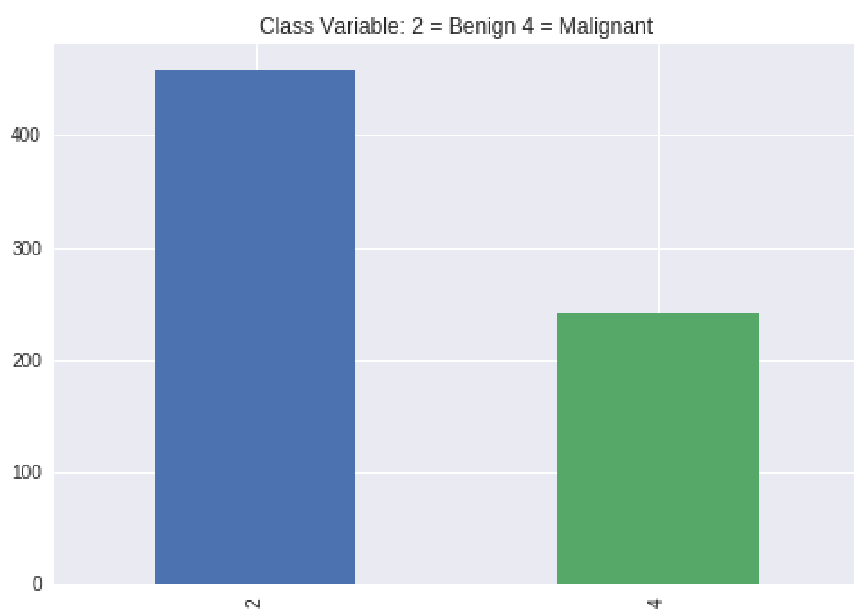
```
Below are how many missing values for each column

Scn       0
A2        0
A3        0
A4        0
A5        0
A6        0
A7       16
A8        0
A9        0
A10       0
Class     0
dtype: int64

Cleaning missing values with column means

Scn      0
A2       0
A3       0
A4       0
A5       0
A6       0
A7       0
A8       0
A9       0
A10      0
Class    0
dtype: int64

 Below are the summary metrics of the data
                Scn          A2          A3          A4          A5  \
count  6.990000e+02  699.000000  699.000000  699.000000  699.000000   
mean   1.071704e+06    4.417740    3.134478    3.207439    2.806867   
std    6.170957e+05    2.815741    3.051459    2.971913    2.855379   
min    6.163400e+04    1.000000    1.000000    1.000000    1.000000   
25%    8.706885e+05    2.000000    1.000000    1.000000    1.000000   
50%    1.171710e+06    4.000000    1.000000    1.000000    1.000000   
75%    1.238298e+06    6.000000    5.000000    5.000000    4.000000   
max    1.345435e+07   10.000000   10.000000   10.000000   10.000000   

               A6          A7          A8          A9         A10       Class  
count  699.000000  699.000000  699.000000  699.000000  699.000000  699.000000  
mean     3.216023    3.544549    3.437768    2.866953    1.589413    2.689557  
std      2.214300    3.601852    2.438364    3.053634    1.715078    0.951273  
min      1.000000    1.000000    1.000000    1.000000    1.000000    2.000000  
25%      2.000000    1.000000    2.000000    1.000000    1.000000    2.000000  
50%      2.000000    1.000000    3.000000    1.000000    1.000000    2.000000  
75%      4.000000    5.000000    5.000000    4.000000    1.000000    4.000000  
max     10.000000   10.000000   10.000000   10.000000   10.000000    4.000000  


There are 699 rows and 11 Columns in this data frame

There are 645 unique scn values in the dataset.

Below are the duplicate rows in the dataset.

         Scn  A2  A3  A4  A5  A6    A7  A8  A9  A10  Class
208  1218860   1   1   1   1   1   1.0   3   1    1      2
253  1100524   6  10  10   2   8  10.0   7   3    3      4
254  1116116   9  10  10   1  10   8.0   3   3    1      4
258  1198641   3   1   1   1   2   1.0   3   1    1      2
```

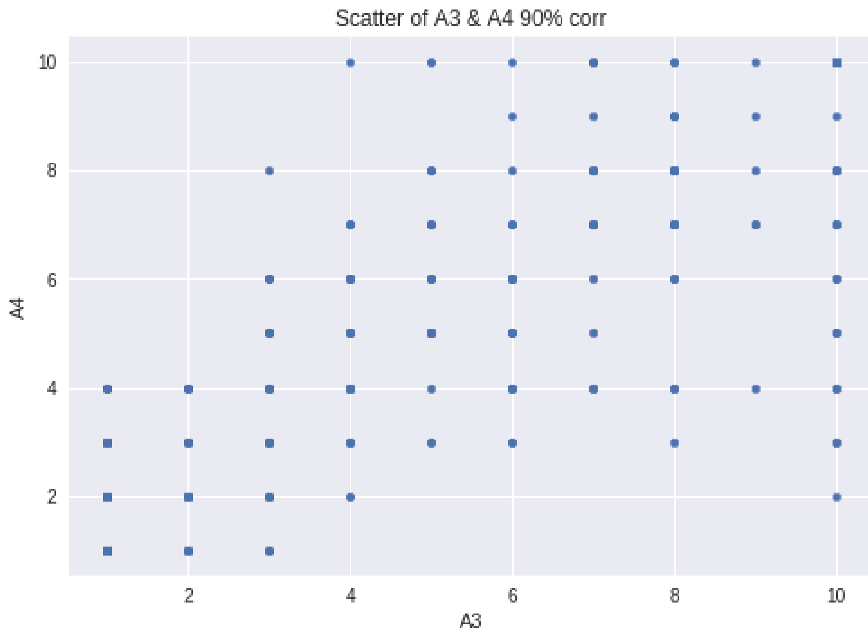
272	320675	3	3	5	2	3	10.0	7	1	1	4
338	704097	1	1	1	1	1	1.0	2	1	1	2
561	1321942	5	1	1	1	2	1.0	3	1	1	2
684	466906	1	1	1	1	2	1.0	1	1	1	2

Below are the histograms of A2:A10



The columns that need standardization are: A7,A3,& A9 because they have the highest amount of variance compared to other factors.




Scatter of A3 & A4 90% corr
10
8
6
4
2
A4
2
4
6
8
10
A3

In [12]:

```
#Main Functions Phase 2
X  = df.drop(['Scn','Class'], axis  = 1)
y = df['Class']
get_mids(X)
lables(4,df)
find_optimal_K(X)
sd_plot(X)
var_plot(df)
print('\n Based on the Box and SD plot above we can see features A7,A9 has the most vari
ations.\n')
get_centers(X)
lables(2,df)
```

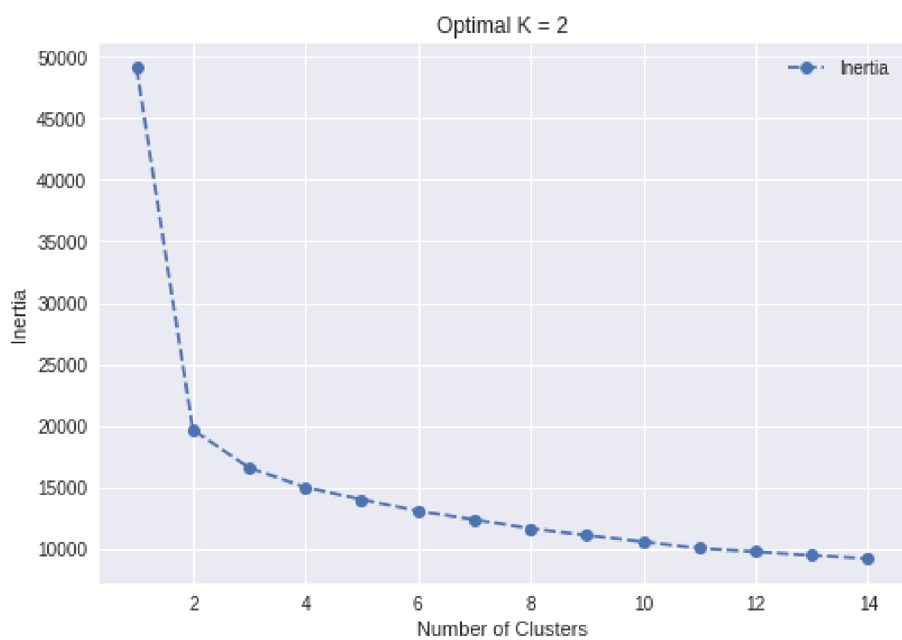
Below are the centers of K = 4 clusters

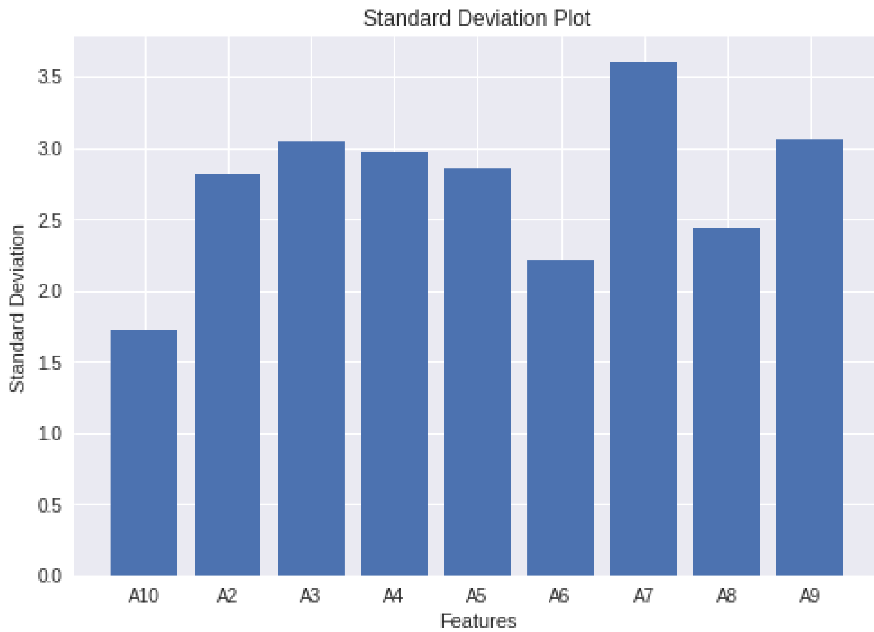
```
         A2        A3        A4        A5        A6        A7        A8  \
0  7.204082  4.846939  5.010204  4.816327  4.071429  9.158571  5.224490
1  2.984716  1.266376  1.386463  1.312227  2.054585  1.352576  2.080786
2  6.721519  8.367089  8.405063  7.810127  6.734177  9.227848  7.367089
3  7.562500  7.421875  7.062500  4.250000  5.875000  3.619063  5.562500

         A9       A10
0  3.795918  1.642857
1  1.213974  1.102620
2  7.822785  3.822785
3  7.156250  2.234375
```

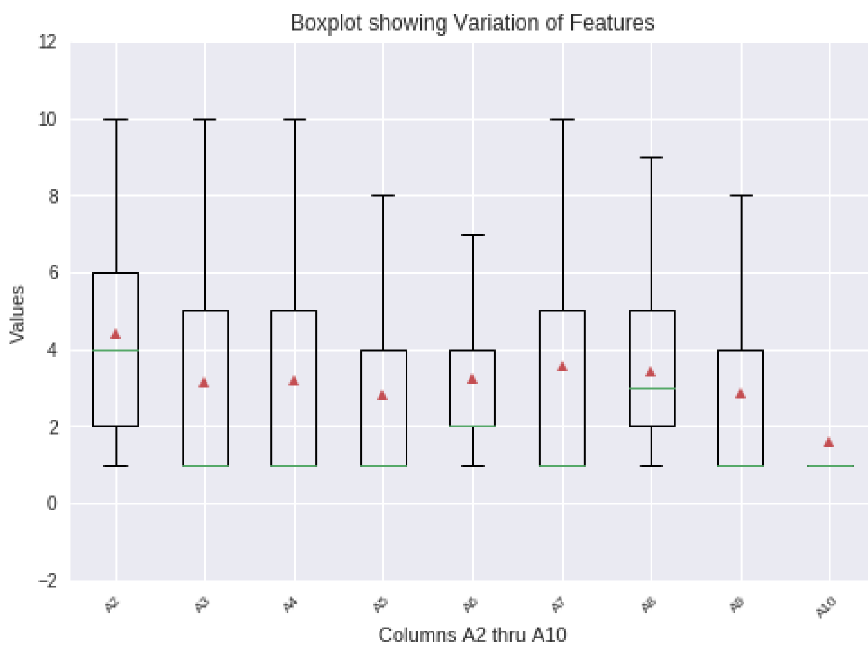
Below are the predicted labels with k = 4

```
Class     2   4
labels
0         7  64
1       444  10
2         7  87
3         0  80
```

Below is the intertia chart




Standard Deviation Plot
Standard Deviation
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
A10
A2
A3
A4
A5
A6
A7
A8
A9
Features


Boxplot showing Variation of Features
Values
12
10
8
6
4
2
0
−2
A2
A3
A4
A5
A6
A7
A8
A9
A10
Columns A2 thru A10

Based on the Box and SD plot above we can see features A7,A9 has the most variations.

Below are the centers of K = 2 clusters

	A2	A3	A4	A5	A6	A7	A8
0	-0.496223	-0.60690	-0.602092	-0.514917	-0.509713	-0.580604	-0.547702
1	0.986083	1.20602	1.196465	1.023233	1.012892	1.153765	1.088383

	A9	A10
0	-0.530778	-0.303758
1	1.054751	0.603622

Below are the predicted labels with k = 2

Class labels	2	4
0	446	19
1	12	222

In [25]:

```
#Main Phase 3
mdl =  make_pipeline(StandardScaler(), KMeans(n_clusters = 2, n_init=20, max_iter = 500
))
labels = mdl.fit_predict(X)
df['Predicted'] = labels

for x in range(df.shape[0]):
  if df.iloc[x,11] == 0:
    df.iloc[x,11] = 2
  else:
    df.iloc[x,11] = 4

print("\nBelow are the first 15 rows of the dataframe \n")
print(df.head(15))

print("\nBelow are the observtions where the predicted did not match the class \n")

print(df[df['Class'] != df['Predicted']])


def error_rate(predicted,actual):
  tab = pd.crosstab(actual,predicted)
  error2 = tab.iloc[0,1]
  total2 = tab.iloc[0,0] +  tab.iloc[1,0]

  error4  = tab.iloc[1,0]
  total4 = tab.iloc[0,1] + tab.iloc[1,1]

  B  = str(round(error2/total2,4)*100) + "%"
  M = str(round(error4/total4,4)*100) + "%"
  tot_error = str(round((error2 + error4)/(total2 + total4),4)*100) + "%"

  print("\nThe error rate for beningn cells is " + str(B) + "\n")
  print("The error rate for malignent cells is " +str(M) + "\n")
  print("The total error rate is " +str(tot_error) + "\n")

error_rate(df['Predicted'], df['Class'])
```

Below are the first 15 rows of the dataframe

	Scn	A2	A3	A4	A5	A6	A7	A8	A9	A10	Class	Predicted
0	1000025	5	1	1	1	2	1.0	3	1	1	2	2
1	1002945	5	4	4	5	7	10.0	3	2	1	2	4
2	1015425	3	1	1	1	2	2.0	3	1	1	2	2
3	1016277	6	8	8	1	3	4.0	3	7	1	2	4
4	1017023	4	1	1	3	2	1.0	3	1	1	2	2
5	1017122	8	10	10	8	7	10.0	9	7	1	4	4
6	1018099	1	1	1	1	2	10.0	3	1	1	2	2
7	1018561	2	1	2	1	2	1.0	3	1	1	2	2
8	1033078	2	1	1	1	2	1.0	1	1	5	2	2
9	1033078	4	2	1	1	2	1.0	2	1	1	2	2
10	1035283	1	1	1	1	1	1.0	3	1	1	2	2
11	1036172	2	1	1	1	2	1.0	2	1	1	2	2
12	1041801	5	3	3	3	2	3.0	4	4	1	4	2
13	1043999	1	1	1	1	2	3.0	3	1	1	2	2
14	1044572	8	7	5	10	7	9.0	5	5	4	4	4

Below are the observtions where the predicted did not match the class

	Scn	A2	A3	A4	A5	A6	A7	A8	A9	A10	Class	Predicted
1	1002945	5	4	4	5	7	10.00	3	2	1	2	4
3	1016277	6	8	8	1	3	4.00	3	7	1	2	4
12	1041801	5	3	3	3	2	3.00	4	4	1	4	2
25	1065726	5	2	3	4	2	7.00	3	6	1	4	2
40	1096800	6	6	6	9	6	3.54	7	8	1	2	4
51	1108449	5	3	3	4	2	4.00	3	4	1	4	2
57	1113038	8	2	4	1	5	1.00	5	4	4	4	2
58	1113483	5	2	3	1	6	10.00	5	1	1	4	2
59	1113906	9	5	5	2	2	2.00	5	1	1	4	2
63	1116132	6	3	4	1	5	2.00	3	9	1	4	2
101	1167439	2	3	4	4	2	5.00	2	5	1	4	2
103	1168359	8	2	3	1	6	3.00	7	1	1	4	2
146	1185609	3	4	5	2	6	8.00	4	1	1	4	2
179	1202812	5	3	3	3	6	10.00	3	1	1	4	2
196	1213375	8	4	4	5	4	7.00	7	8	2	2	4
222	1226012	4	1	1	3	1	5.00	2	1	1	4	2
247	145447	8	4	4	1	2	9.00	3	3	1	4	2
252	1017023	6	3	3	5	3	10.00	3	5	3	2	4
259	242970	5	7	7	1	5	8.00	3	4	1	2	4
273	428903	7	2	4	1	3	4.00	3	3	1	4	2
296	616240	5	3	4	3	4	5.00	4	7	1	2	4
315	704168	4	6	5	6	7	3.54	4	9	1	2	4
319	721482	4	4	4	4	6	5.00	7	3	1	2	4
326	752904	10	1	1	1	2	10.00	5	4	1	4	2
348	832226	3	4	4	10	5	1.00	3	3	1	4	2
352	846832	3	4	5	3	7	3.00	4	6	1	2	4
356	859164	5	3	3	1	3	3.00	3	3	3	4	2
434	1293439	6	9	7	5	5	8.00	4	2	1	2	4
455	1246562	10	2	2	1	2	6.00	1	1	2	4	2
489	1084139	6	3	2	1	3	4.00	4	1	1	4	2
657	1333877	5	4	5	1	8	1.00	3	6	1	2	4

The error rate for beningn cells is 2.58%

The error rate for malignent cells is 8.12%

The total error rate is 4.43%

In [ ]: