Análisis de Datos y Aprendizaje Máquina con Tensorflow 2.0: Clasificación

2019/09/30

1 Naive Bayes

Objetivo: El aprendizaje máquina se puede usar para clasificación y regresión. Se comprenderá el concepto y funcionamiento de un clasificador, así como su evaluación y como implementarlo a un dataset.

Esta técnica está basada en el teorema de Bayes. Se utiliza para clasificar vectores de características. Se asume que las características son independientes dada la clase, es por esto la palabra 'naive'. Este clasificador trabaja bien incluso si las características son dependientes, además de que no sufre de sobreajuste.

https://scikit-learn.org/stable/modules/naive_bayes.html

$$P(y \mid x_1, \dots, x_n) = \frac{P(y)P(x_1, \dots x_n \mid y)}{P(x_1, \dots, x_n)}$$

Usando la regla de al cadena

$$P(y \mid x_1, \dots, x_n) = \frac{P(y) \prod_{i=1}^{n} P(x_i \mid y)}{P(x_1, \dots, x_n)}$$

Dado que $P(x_1, \dots, x_n)$ es constante dada la entrada, se puede usar la siguiente regla de clasificación:

$$P(y \mid x_1, \dots, x_n) \propto P(y) \prod_{i=1}^{n} P(x_i \mid y)$$

$$\hat{y} = \arg\max_y P(y) \prod_{i=1}^{n} P(x_i \mid y)$$

Se encuentra la clase y con máxima probabilidad.

- Bernoulli Naive Bayes implementa la regla de decisión

$$P(x_i|y) = P(i|y)x_i + (1 - P(i|y))(1 - x_i)$$

Se asume que las características son binarias, si no es el caso el parámetro 'binarize' debe ser indicado

- Complement Naive Bayes sirve para datos no balanceados y ha mostrado superar a Multinomial Naive Bayes para clasificación de texto. Este algoritmo calcula pesos.

- Gaussian Naive Bayes implementa el algoritmo Gaussian Naive Bayes para la clasificación. Se asume que la probabilidad de las características es gaussiana:

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2})$$

Los parámetros σ_y y μ_y de los valores x están asociados con la clase y

```
In [1]: import sklearn
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt
```

1.1 Análisis exploratorio

1.1.1 Etiquetas de clase a valor numérico

- Diagnosis (M = malignant, B = benign)

```
In [2]: %matplotlib inline

        df = pd.read_csv("data-breast.csv",index_col=0)

        df.head(10)
```

```
Out[2]:          diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
        id
        842302           M        17.99         10.38          122.80     1001.0
        842517           M        20.57         17.77          132.90     1326.0
        84300903         M        19.69         21.25          130.00     1203.0
        84348301         M        11.42         20.38           77.58      386.1
        84358402         M        20.29         14.34          135.10     1297.0
        843786           M        12.45         15.70           82.57      477.1
        844359           M        18.25         19.98          119.60     1040.0
        84458202         M        13.71         20.83           90.20      577.9
        844981           M        13.00         21.82           87.50      519.8
        84501001         M        12.46         24.04           83.97      475.9

                  smoothness_mean  compactness_mean  concavity_mean  \
        id
        842302            0.11840           0.27760         0.30010
        842517            0.08474           0.07864         0.08690
        84300903          0.10960           0.15990         0.19740
        84348301          0.14250           0.28390         0.24140
        84358402          0.10030           0.13280         0.19800
        843786            0.12780           0.17000         0.15780
        844359            0.09463           0.10900         0.11270
```

```
84458202          0.11890           0.16450         0.09366
844981            0.12730           0.19320         0.18590
84501001          0.11860           0.23960         0.22730

          concave points_mean  symmetry_mean  …  texture_worst  \
id                                            …
842302                0.14710         0.2419  …          17.33
842517                0.07017         0.1812  …          23.41
84300903              0.12790         0.2069  …          25.53
84348301              0.10520         0.2597  …          26.50
84358402              0.10430         0.1809  …          16.67
843786                0.08089         0.2087  …          23.75
844359                0.07400         0.1794  …          27.66
84458202              0.05985         0.2196  …          28.14
844981                0.09353         0.2350  …          30.73
84501001              0.08543         0.2030  …          40.68

          perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
id
842302             184.60      2019.0            0.1622             0.6656
842517             158.80      1956.0            0.1238             0.1866
84300903           152.50      1709.0            0.1444             0.4245
84348301            98.87       567.7            0.2098             0.8663
84358402           152.20      1575.0            0.1374             0.2050
843786             103.40       741.6            0.1791             0.5249
844359             153.20      1606.0            0.1442             0.2576
84458202           110.60       897.0            0.1654             0.3682
844981             106.20       739.3            0.1703             0.5401
84501001            97.65       711.4            0.1853             1.0580

          concavity_worst  concave points_worst  symmetry_worst  \
id
842302             0.7119                0.2654          0.4601
842517             0.2416                0.1860          0.2750
84300903           0.4504                0.2430          0.3613
84348301           0.6869                0.2575          0.6638
84358402           0.4000                0.1625          0.2364
843786             0.5355                0.1741          0.3985
844359             0.3784                0.1932          0.3063
84458202           0.2678                0.1556          0.3196
844981             0.5390                0.2060          0.4378
84501001           1.1050                0.2210          0.4366

          fractal_dimension_worst  Unnamed: 32
id
842302                    0.11890          NaN
842517                    0.08902          NaN
84300903                  0.08758          NaN
84348301                  0.17300          NaN
```

```
84358402                0.07678         NaN
843786                  0.12440         NaN
844359                  0.08368         NaN
84458202                0.11510         NaN
844981                  0.10720         NaN
84501001                0.20750         NaN

[10 rows x 32 columns]
```

```
In [3]: df.iloc[:,1:].describe()
```

```
Out[3]:        radius_mean  texture_mean  perimeter_mean    area_mean  \
count   569.000000    569.000000      569.000000   569.000000
mean     14.127292     19.289649       91.969033   654.889104
std       3.524049      4.301036       24.298981   351.914129
min       6.981000      9.710000       43.790000   143.500000
25%      11.700000     16.170000       75.170000   420.300000
50%      13.370000     18.840000       86.240000   551.100000
75%      15.780000     21.800000      104.100000   782.700000
max      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  fractal_dimension_mean  …  texture_worst  \
count     569.000000              569.000000  …     569.000000
mean        0.181162                0.062798  …      25.677223
std         0.027414                0.007060  …       6.146258
min         0.106000                0.049960  …      12.020000
25%         0.161900                0.057700  …      21.080000
50%         0.179200                0.061540  …      25.410000
75%         0.195700                0.066120  …      29.720000
max         0.304000                0.097440  …      49.540000

       perimeter_worst   area_worst  smoothness_worst  compactness_worst  \
count       569.000000   569.000000        569.000000         569.000000
mean        107.261213   880.583128          0.132369           0.254265
std          33.602542   569.356993          0.022832           0.157336
min          50.410000   185.200000          0.071170           0.027290
25%          84.110000   515.300000          0.116600           0.147200
50%          97.660000   686.500000          0.131300           0.211900
75%         125.400000  1084.000000          0.146000           0.339100
max         251.200000  4254.000000          0.222600           1.058000
```

```
       concavity_worst  concave points_worst  symmetry_worst  \
count       569.000000            569.000000      569.000000
mean          0.272188              0.114606        0.290076
std           0.208624              0.065732        0.061867
min           0.000000              0.000000        0.156500
25%           0.114500              0.064930        0.250400
50%           0.226700              0.099930        0.282200
75%           0.382900              0.161400        0.317900
max           1.252000              0.291000        0.663800

       fractal_dimension_worst  Unnamed: 32
count               569.000000          0.0
mean                  0.083946          NaN
std                   0.018061          NaN
min                   0.055040          NaN
25%                   0.071460          NaN
50%                   0.080040          NaN
75%                   0.092080          NaN
max                   0.207500          NaN

[8 rows x 31 columns]
```

```
In [4]: df = df.replace({'B':0, 'M':1})
        df
```

```
Out[4]:           diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
        id
        842302            1        17.99         10.38          122.80     1001.0
        842517            1        20.57         17.77          132.90     1326.0
        84300903          1        19.69         21.25          130.00     1203.0
        84348301          1        11.42         20.38           77.58      386.1
        84358402          1        20.29         14.34          135.10     1297.0
        …               …          …           …             …          …
        926424            1        21.56         22.39          142.00     1479.0
        926682            1        20.13         28.25          131.20     1261.0
        926954            1        16.60         28.08          108.30      858.1
        927241            1        20.60         29.33          140.10     1265.0
        92751             0         7.76         24.54           47.92      181.0

                  smoothness_mean  compactness_mean  concavity_mean  \
        id
        842302            0.11840           0.27760         0.30010
        842517            0.08474           0.07864         0.08690
        84300903          0.10960           0.15990         0.19740
        84348301          0.14250           0.28390         0.24140
        84358402          0.10030           0.13280         0.19800
        …                     …               …              …
        926424            0.11100           0.11590         0.24390
        926682            0.09780           0.10340         0.14400
```

```
926954            0.08455           0.10230         0.09251
927241            0.11780           0.27700         0.35140
92751             0.05263           0.04362         0.00000

          concave points_mean  symmetry_mean  …  texture_worst  \
id                                            …                  
842302                0.14710         0.2419  …          17.33   
842517                0.07017         0.1812  …          23.41   
84300903              0.12790         0.2069  …          25.53   
84348301              0.10520         0.2597  …          26.50   
84358402              0.10430         0.1809  …          16.67   
…                       …            …  …     …      …           
926424                0.13890         0.1726  …          26.40   
926682                0.09791         0.1752  …          38.25   
926954                0.05302         0.1590  …          34.12   
927241                0.15200         0.2397  …          39.42   
92751                 0.00000         0.1587  …          30.37   

          perimeter_worst  area_worst  smoothness_worst  compactness_worst  \
id                                                                           
842302             184.60      2019.0           0.16220            0.66560   
842517             158.80      1956.0           0.12380            0.18660   
84300903           152.50      1709.0           0.14440            0.42450   
84348301            98.87       567.7           0.20980            0.86630   
84358402           152.20      1575.0           0.13740            0.20500   
…                   …         …               …                …            
926424             166.10      2027.0           0.14100            0.21130   
926682             155.00      1731.0           0.11660            0.19220   
926954             126.70      1124.0           0.11390            0.30940   
927241             184.60      1821.0           0.16500            0.86810   
92751               59.16       268.6           0.08996            0.06444   

          concavity_worst  concave points_worst  symmetry_worst  \
id                                                                
842302             0.7119                0.2654          0.4601   
842517             0.2416                0.1860          0.2750   
84300903           0.4504                0.2430          0.3613   
84348301           0.6869                0.2575          0.6638   
84358402           0.4000                0.1625          0.2364   
…                   …                   …             …           
926424             0.4107                0.2216          0.2060   
926682             0.3215                0.1628          0.2572   
926954             0.3403                0.1418          0.2218   
927241             0.9387                0.2650          0.4087   
92751              0.0000                0.0000          0.2871   

          fractal_dimension_worst  Unnamed: 32  
id                                              
842302                    0.11890          NaN  
```

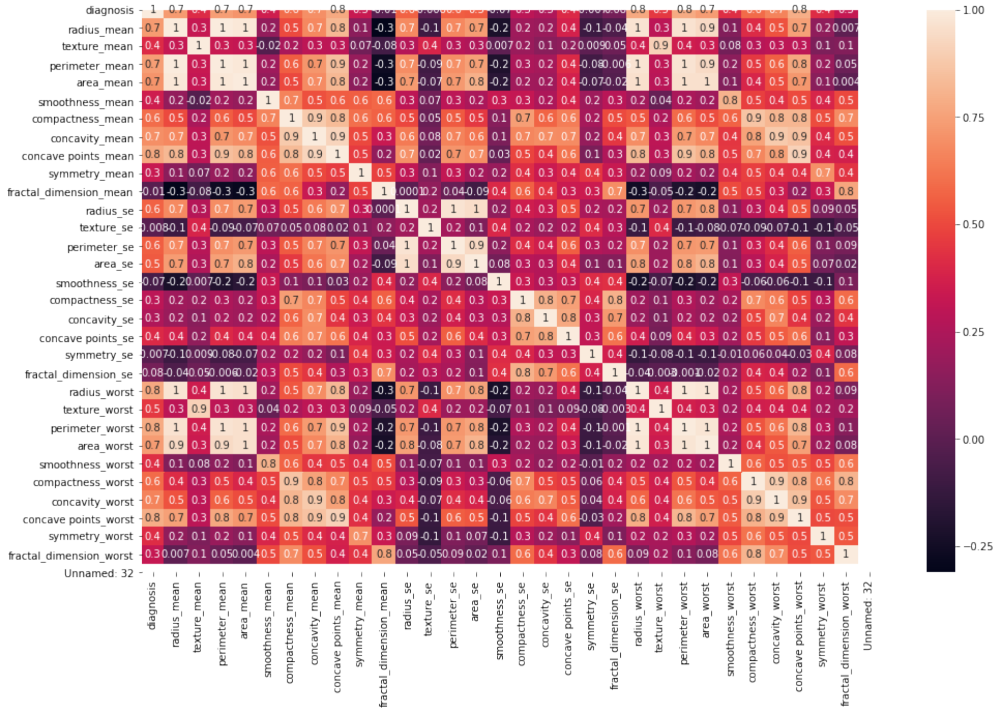
```
842517                    0.08902          NaN
84300903                  0.08758          NaN
84348301                  0.17300          NaN
84358402                  0.07678          NaN
…                           …          …
926424                    0.07115          NaN
926682                    0.06637          NaN
926954                    0.07820          NaN
927241                    0.12400          NaN
92751                     0.07039          NaN

[569 rows x 32 columns]
```

1.2 Coeficientes de correlación

- Para selección de características se puede conocer que variables estan mas relacionadas con la variable de clase con la matriz de correlación
- El resultado del método 'corr()' de pandas se puede plotear con 'heatmap'

```
In [5]: import numpy as np
        corr = df.corr()
        plt.figure(figsize=(16, 10))
        sns.heatmap(corr, annot=True, fmt='.1g')
```

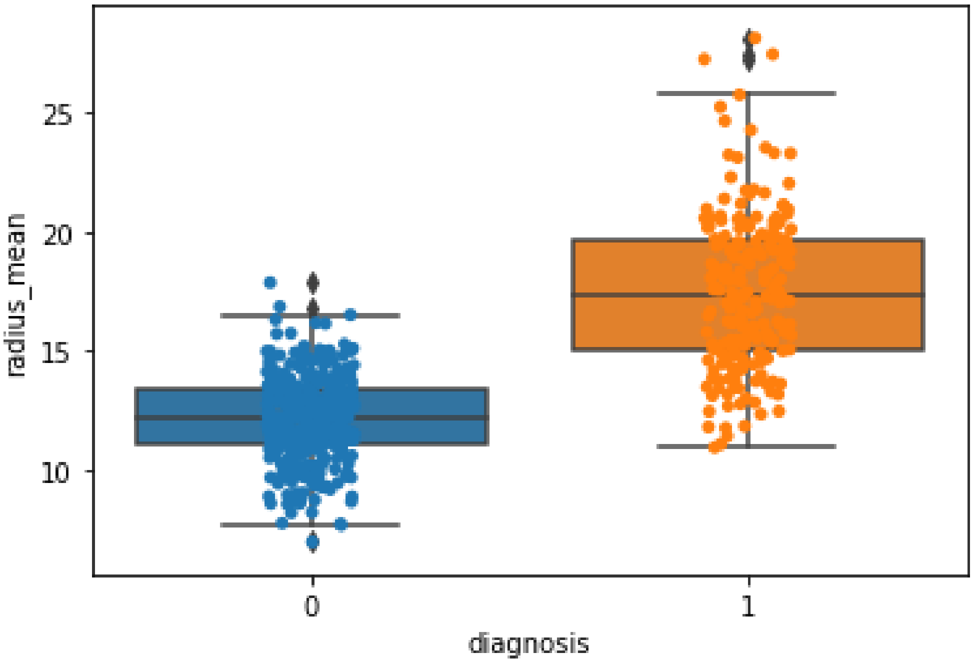
```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x7f345d871f10>
```

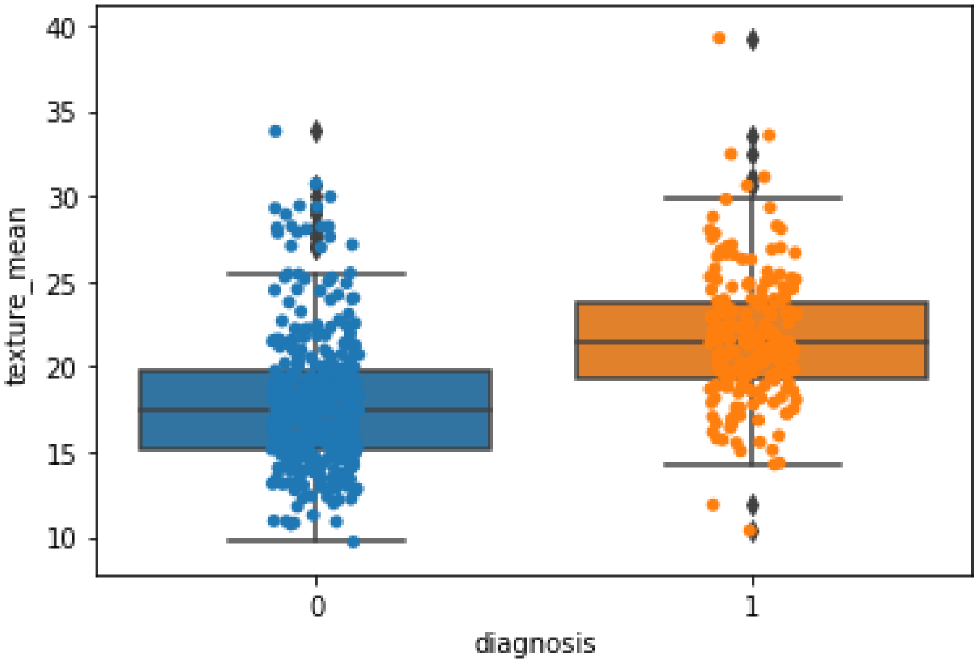


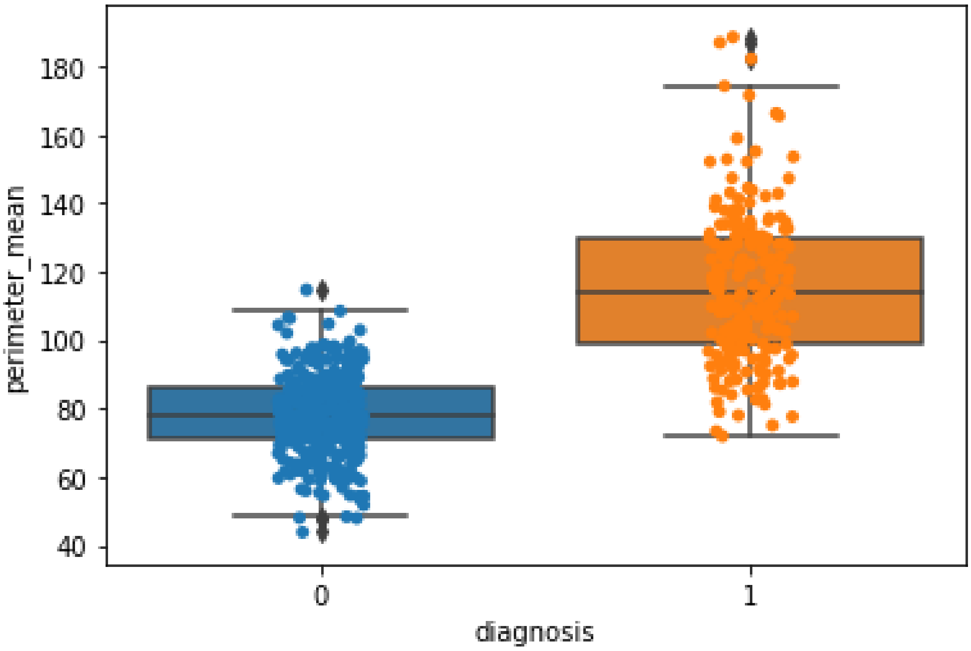
1.3 Boxplots de variables por clase

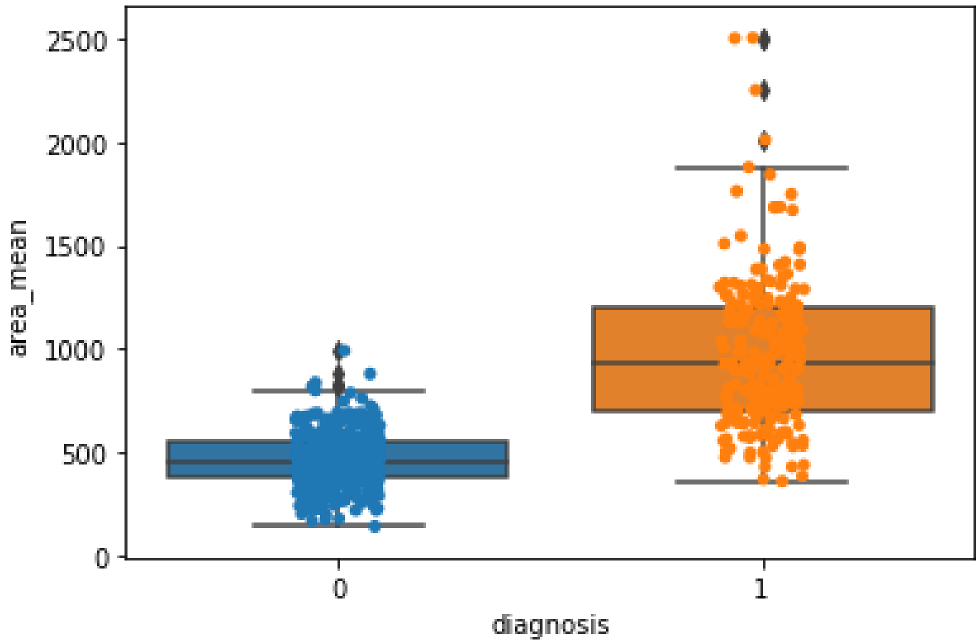
- 'sns.boxplot' recibe el nombre de la variable a plotear

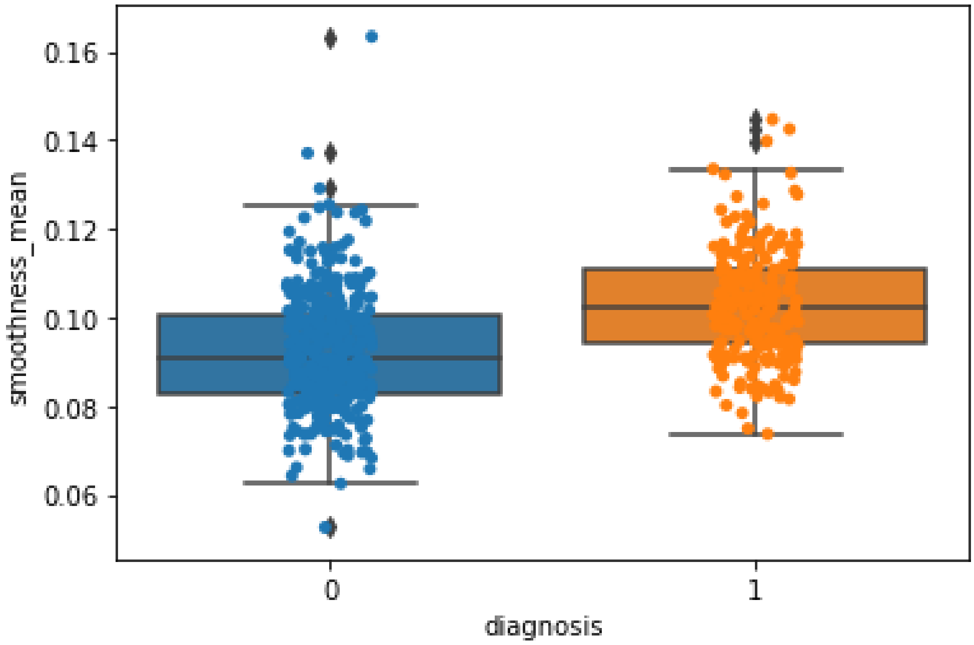
```
In [6]: import matplotlib as mpl
        mpl.rc('figure', max_open_warning = 0)
        l=list(df.columns)
        l[0:len(l)-1]
        for i in range(1,len(l)-1):
            sns.boxplot(x='diagnosis' ,y=l[i], data=df)
            sns.stripplot(x='diagnosis' ,y=l[i], data=df)
            plt.figure()
```

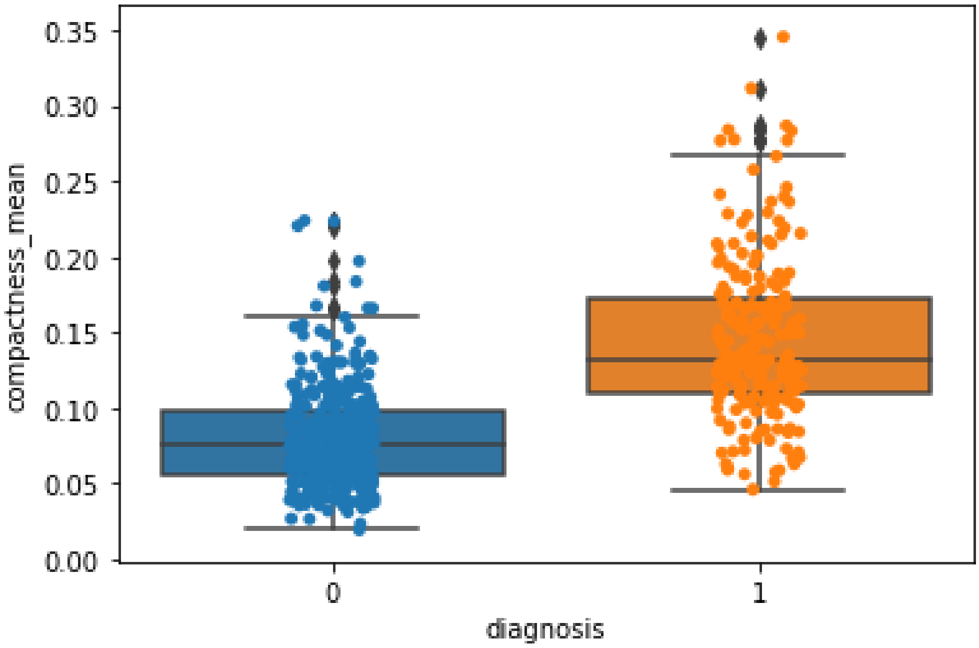


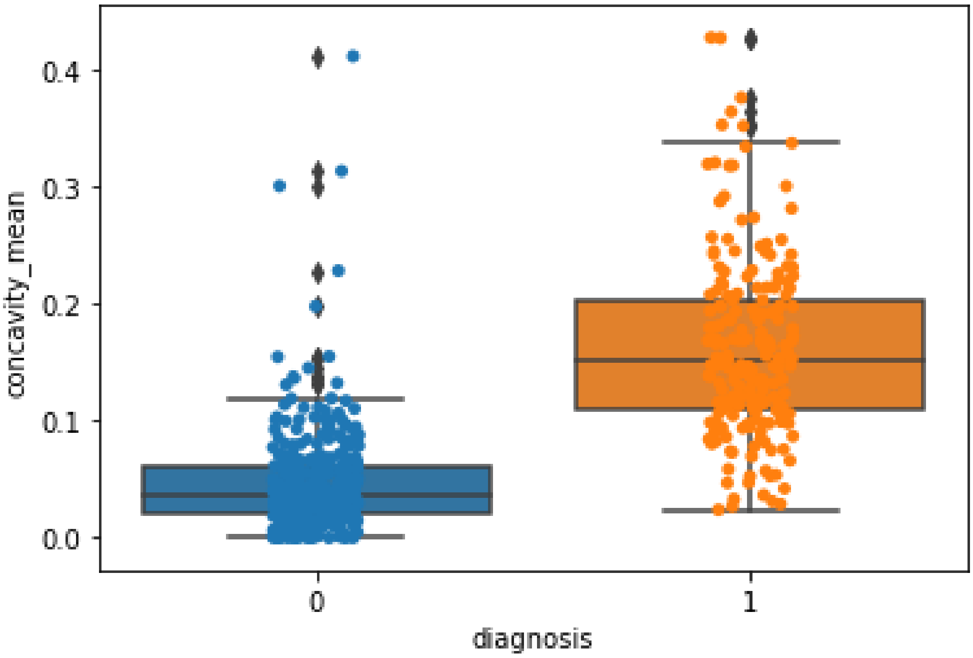

40
35
30
25
20
15
10
texture_mean
0
1
diagnosis

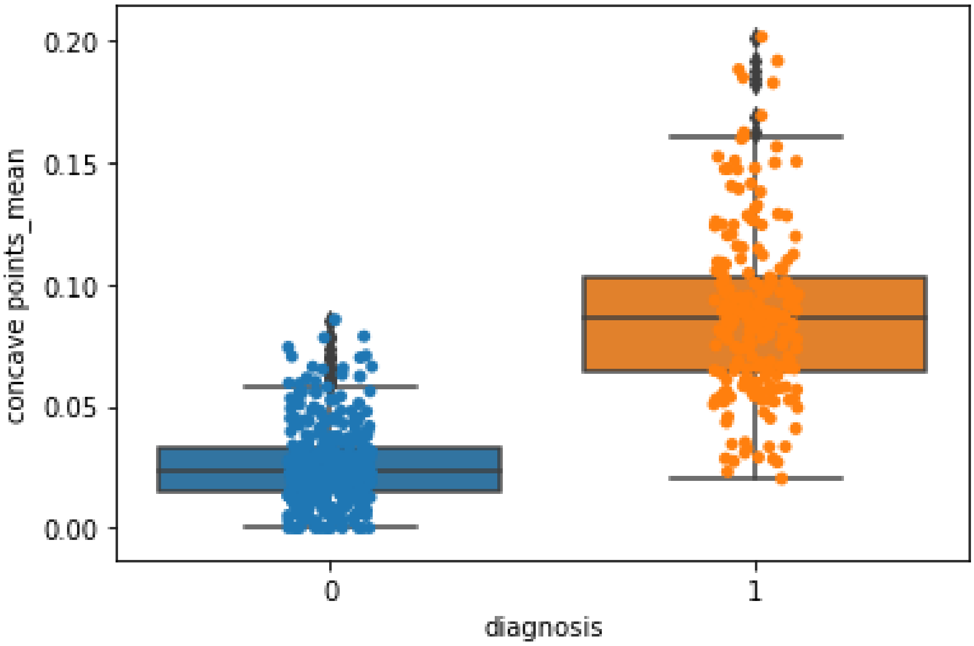

180
160
140
120
100
80
60
40
perimeter_mean
0
1
diagnosis

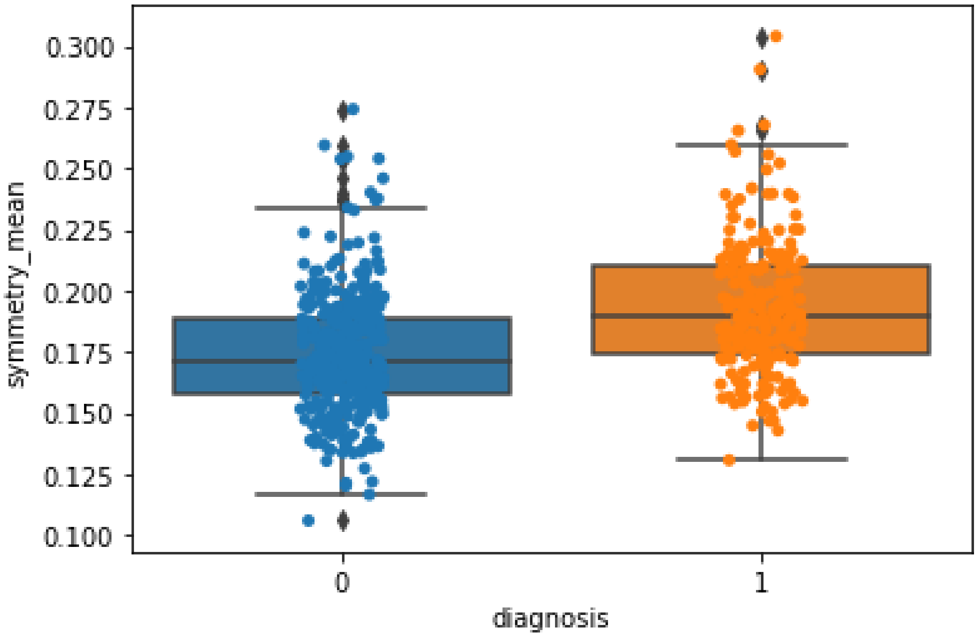

area_mean
2500
2000
1500
1000
500
0
0
1
diagnosis

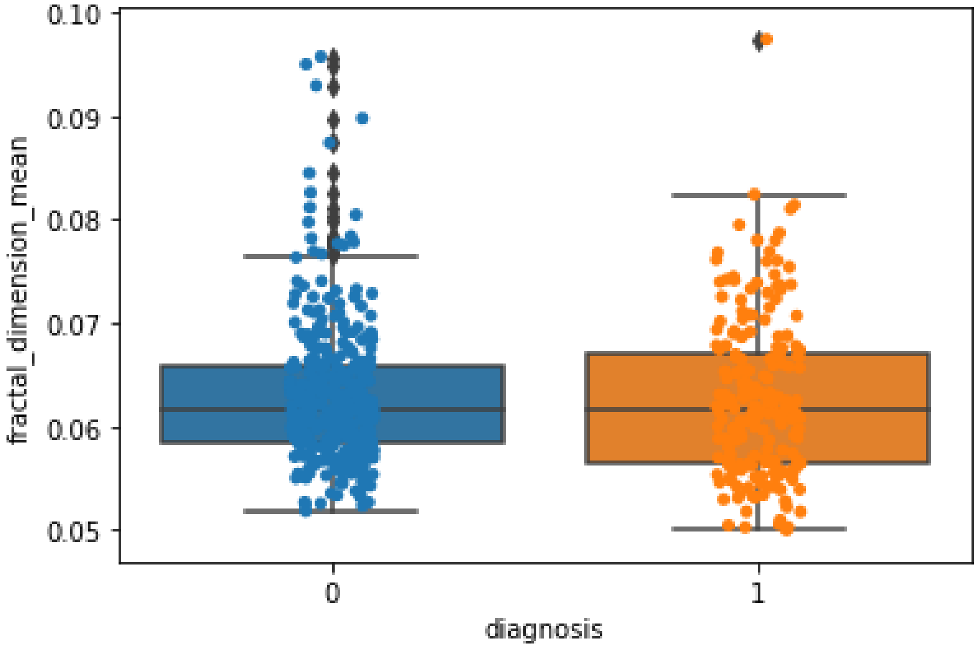

smoothness_mean
0.16
0.14
0.12
0.10
0.08
0.06
0
1
diagnosis

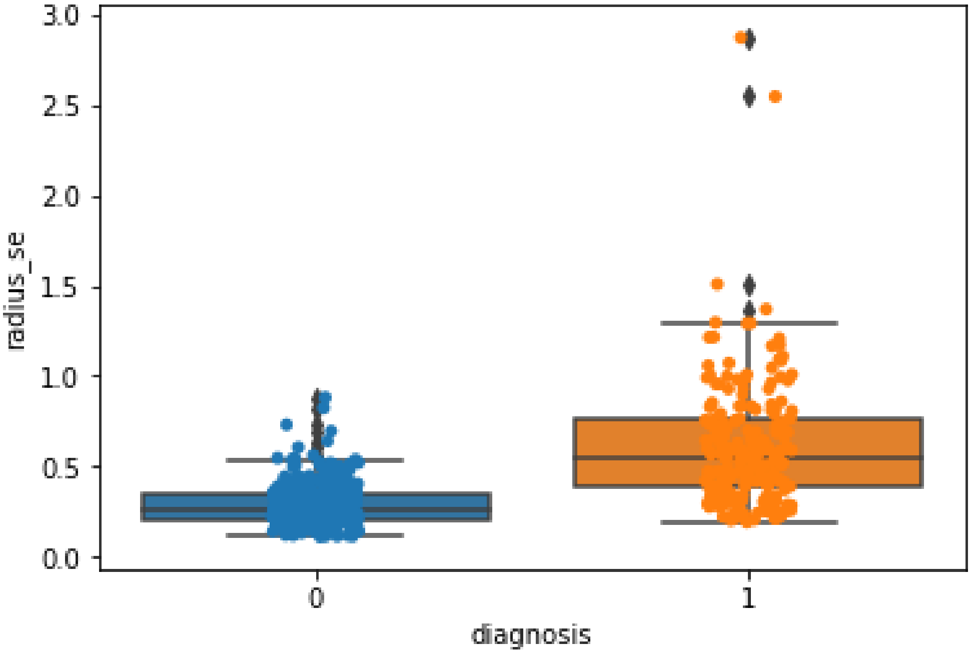

0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
compactness_mean
0
1
diagnosis

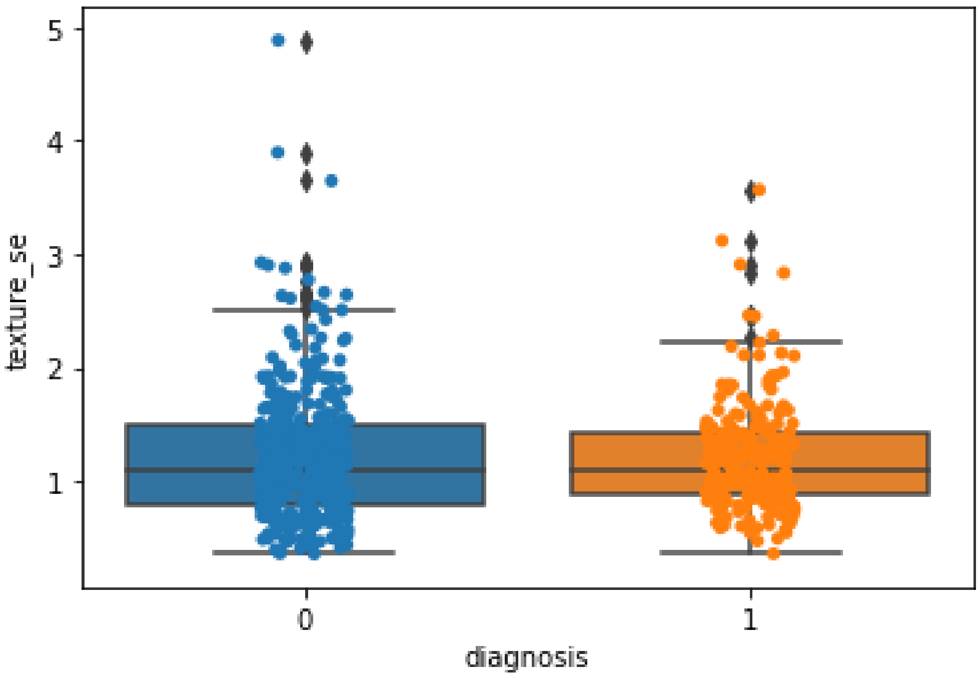

0.4
0.3
0.2
0.1
0.0
concavity_mean
0
1
diagnosis

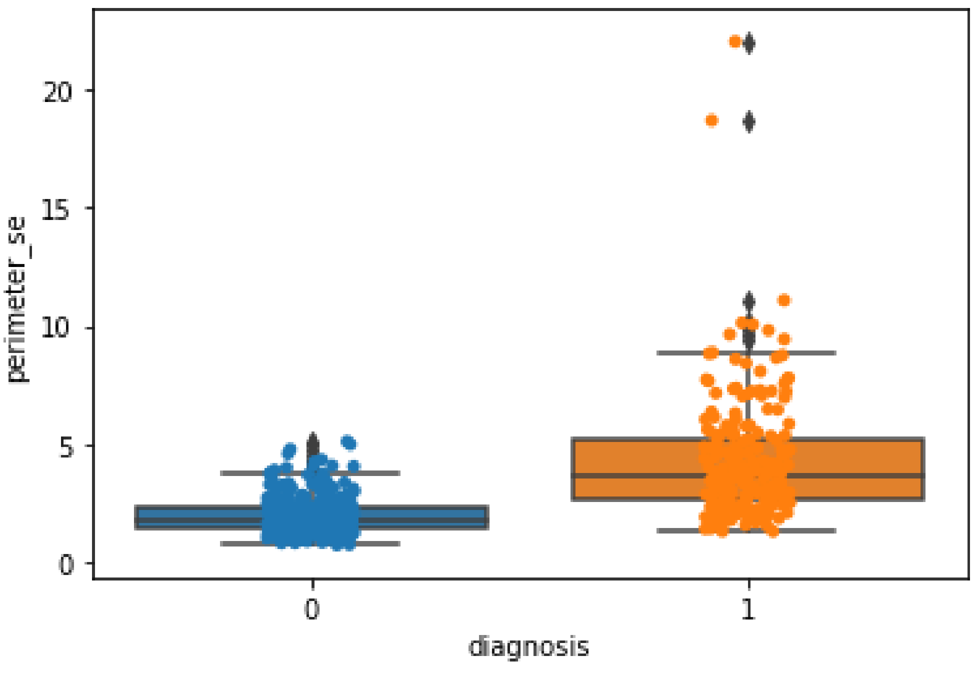

0.20
0.15
0.10
0.05
0.00
concave points_mean
0
1
diagnosis

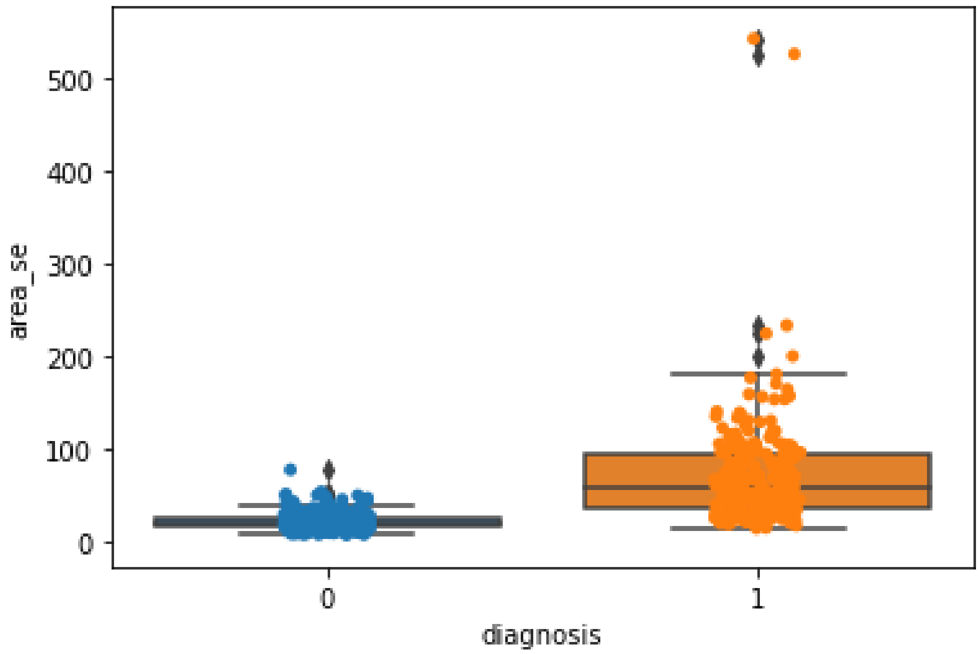

0.300
0.275
0.250
0.225
0.200
0.175
0.150
0.125
0.100
symmetry_mean
0
1
diagnosis

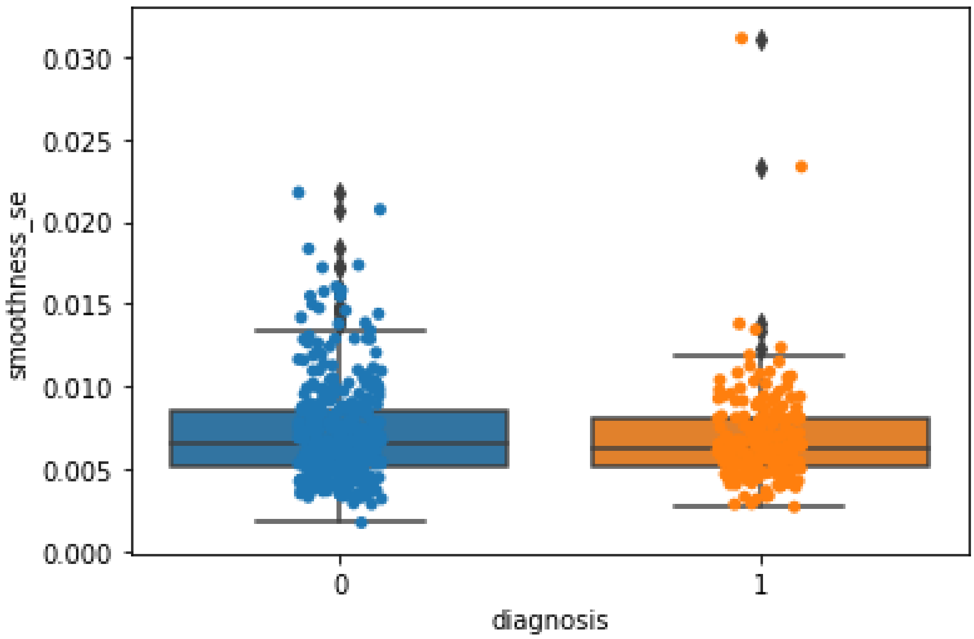

0.10
0.09
0.08
0.07
0.06
0.05
fractal_dimension_mean
0
1
diagnosis

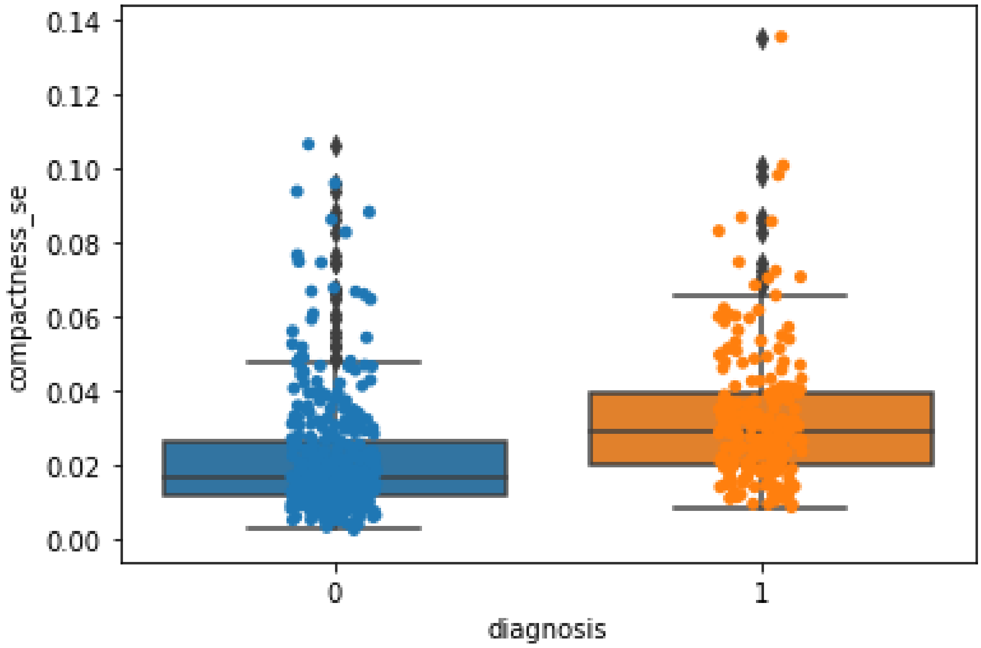

3.0
2.5
2.0
1.5
1.0
0.5
0.0
radius_se
0
1
diagnosis

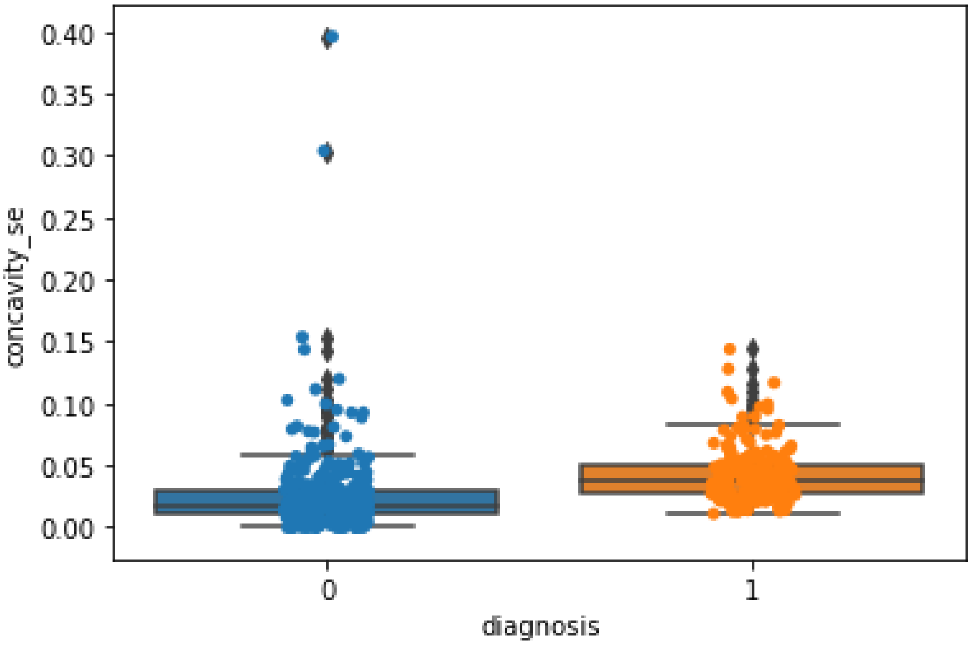

5
4
3
2
1
texture_se
0
1
diagnosis

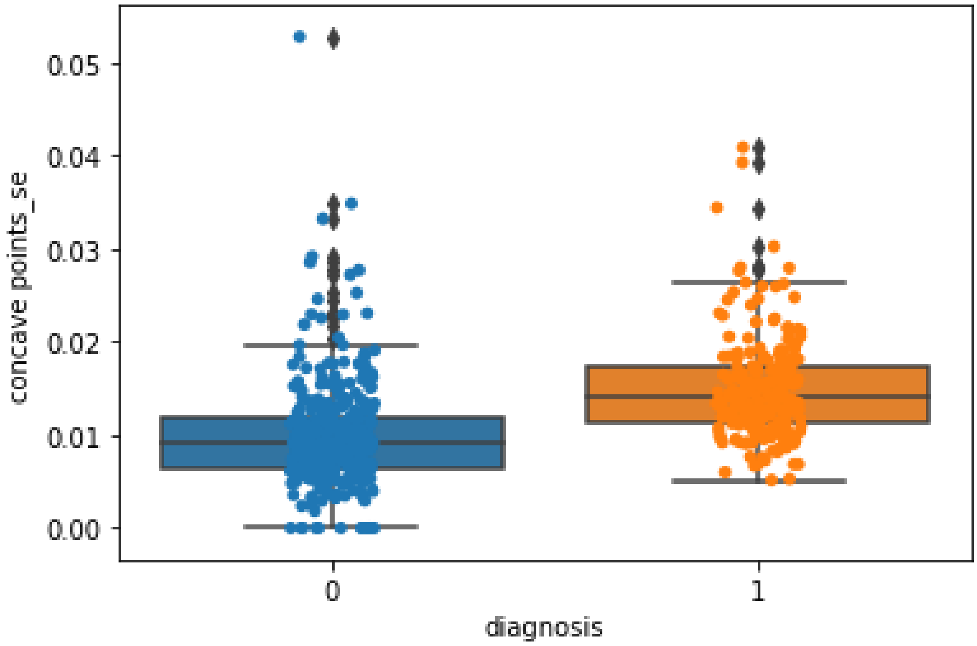

20
15
10
5
0
perimeter_se
0
1
diagnosis

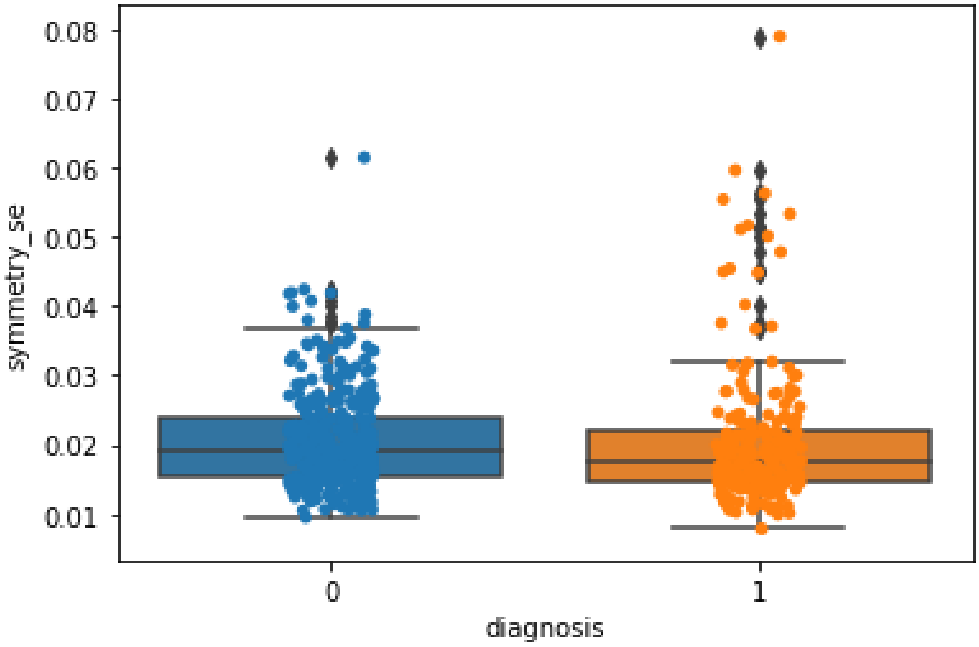

500
400
300
200
100
0
area_se
0
1
diagnosis

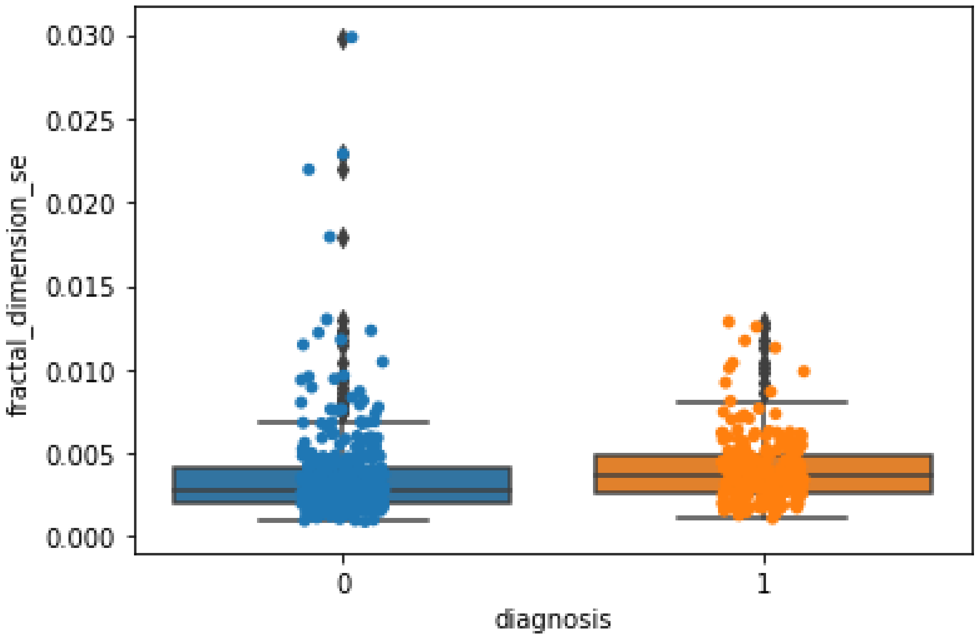

0.030
0.025
0.020
0.015
0.010
0.005
0.000
smoothness_se
0
1
diagnosis

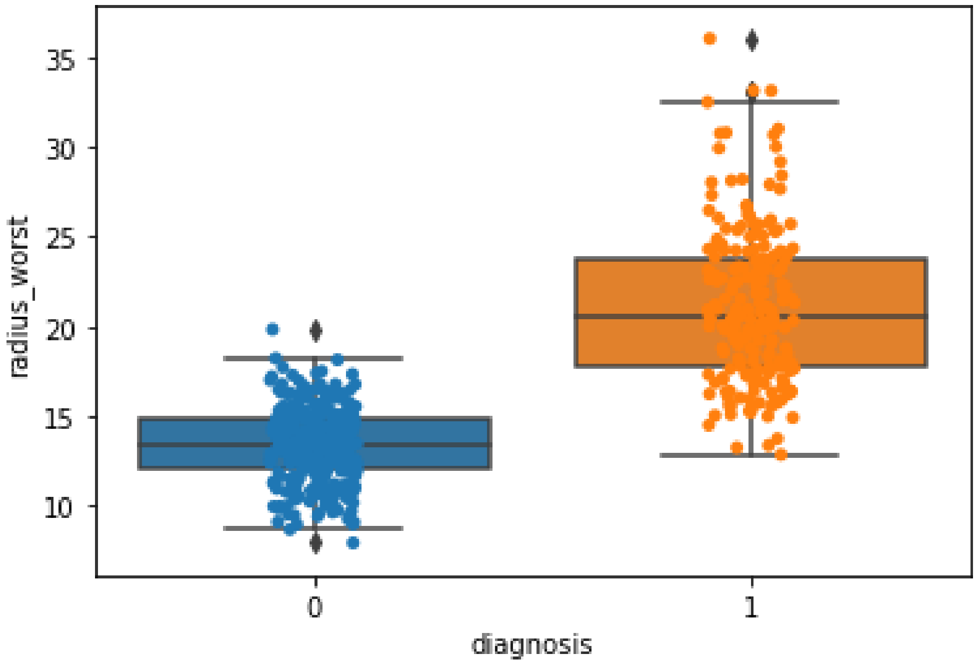

0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
compactness_se
0
1
diagnosis

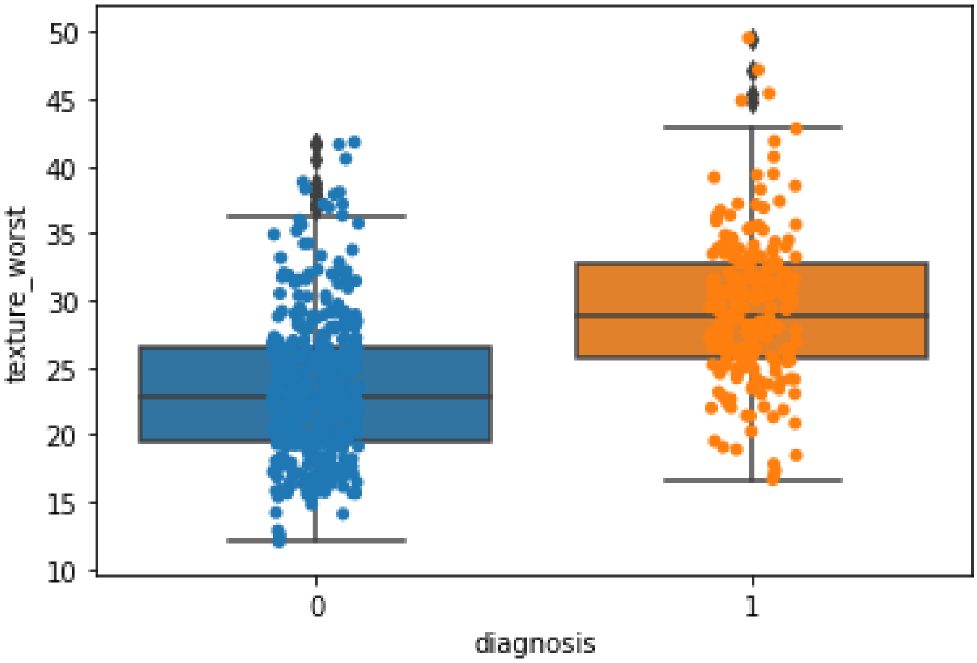

0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
concavity_se
0
1
diagnosis

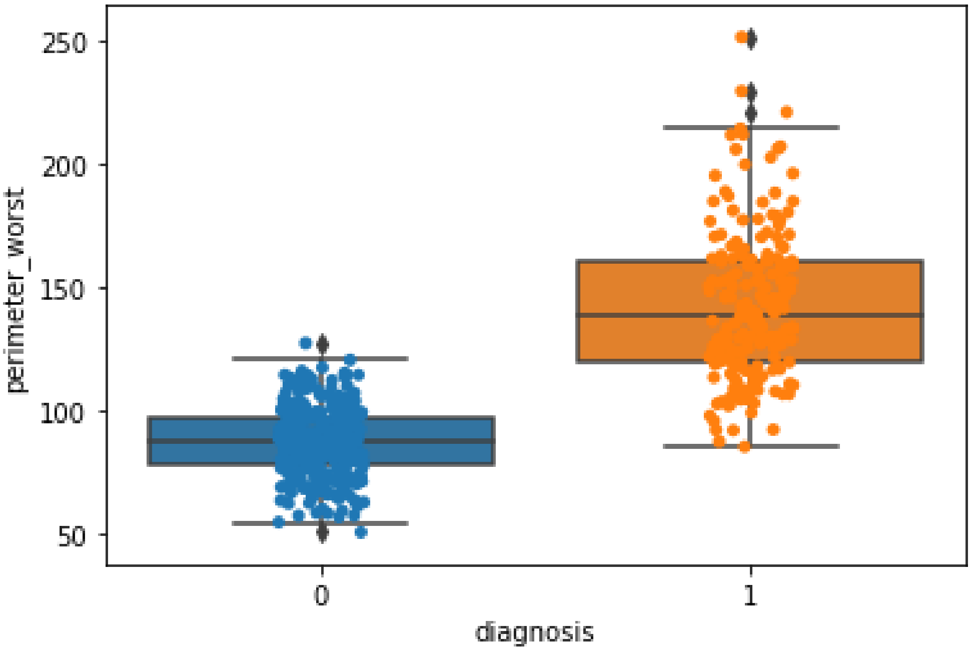

0.05
0.04
0.03
0.02
0.01
0.00
concave points_se
0
1
diagnosis

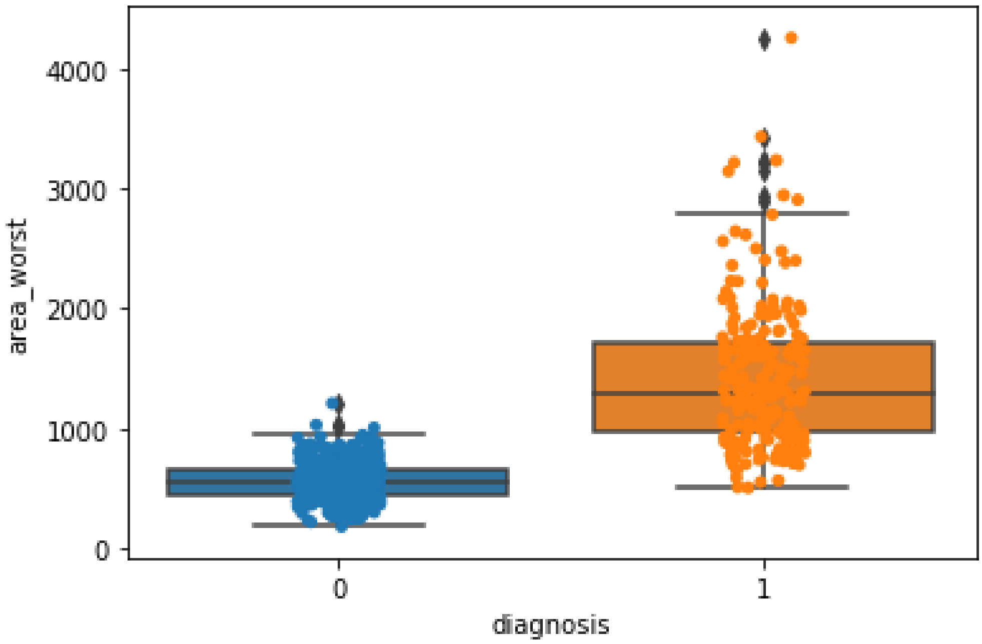

0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
symmetry_se
0
1
diagnosis

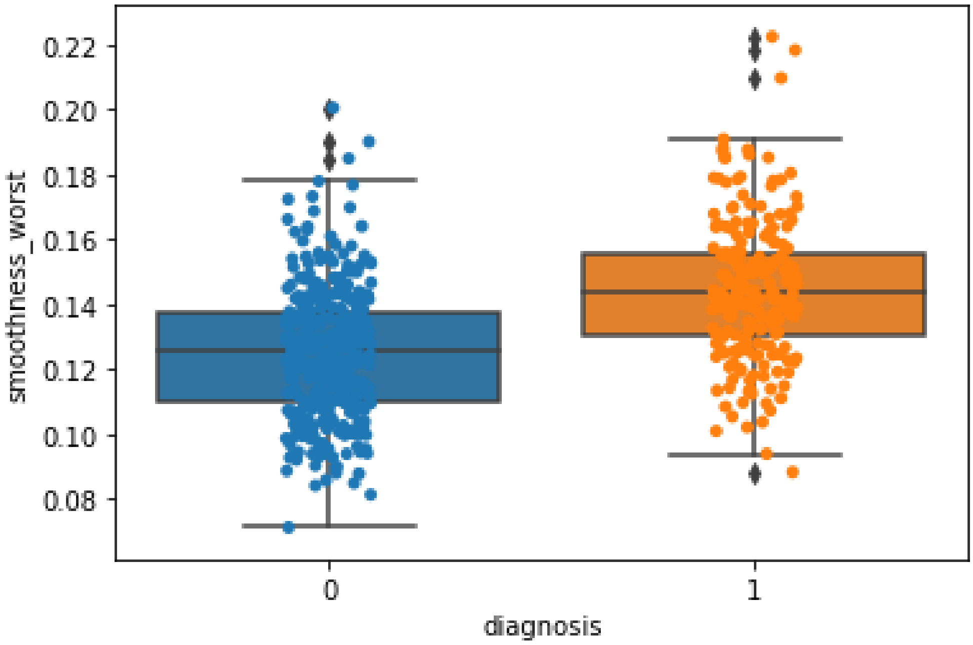

0.030
0.025
0.020
0.015
0.010
0.005
0.000
fractal_dimension_se
0
1
diagnosis

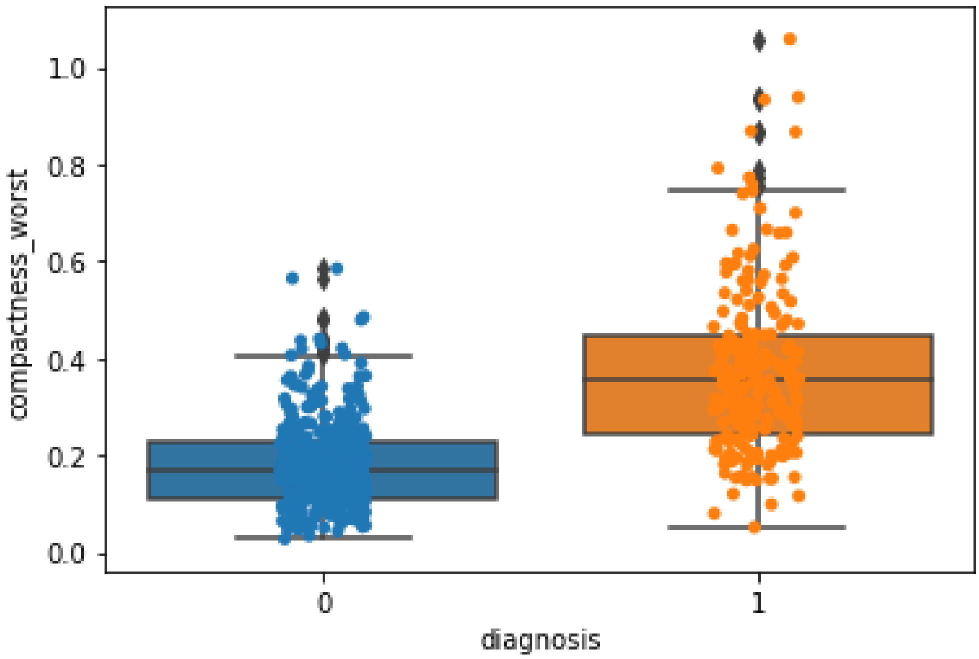

35
30
25
20
15
10
radius_worst
0
1
diagnosis

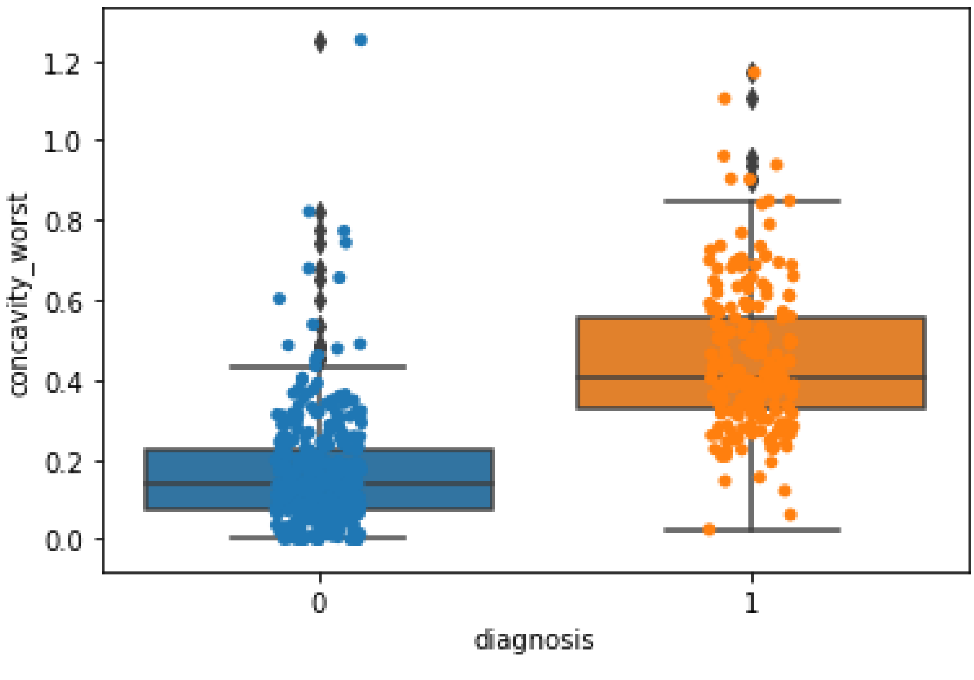

50
45
40
35
30
25
20
15
10
texture_worst
0
1
diagnosis

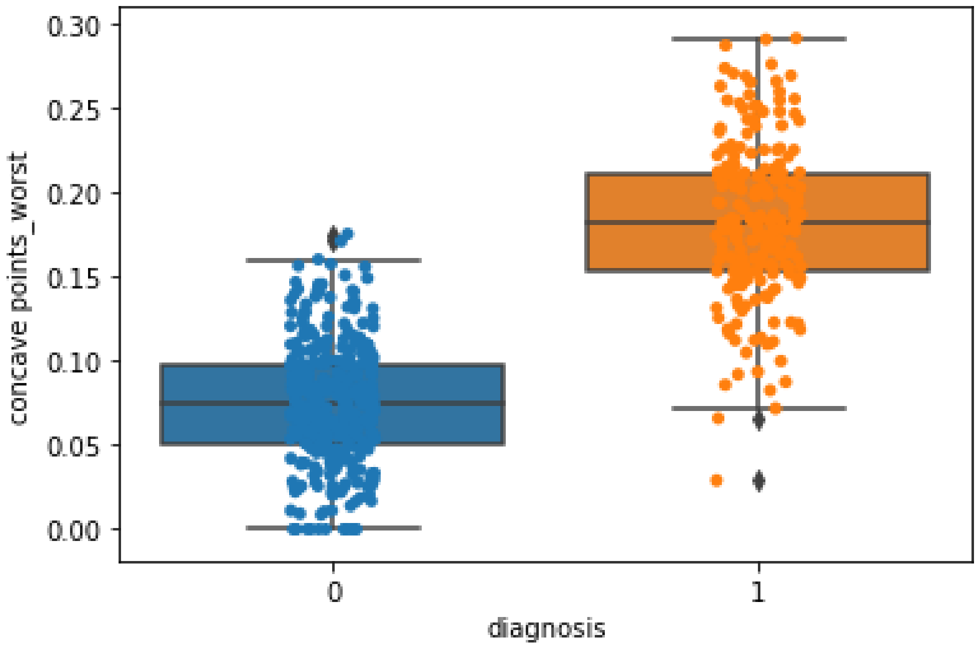

250
200
150
100
50
perimeter_worst
0
1
diagnosis


4000
3000
2000
1000
0
area_worst
0
1
diagnosis

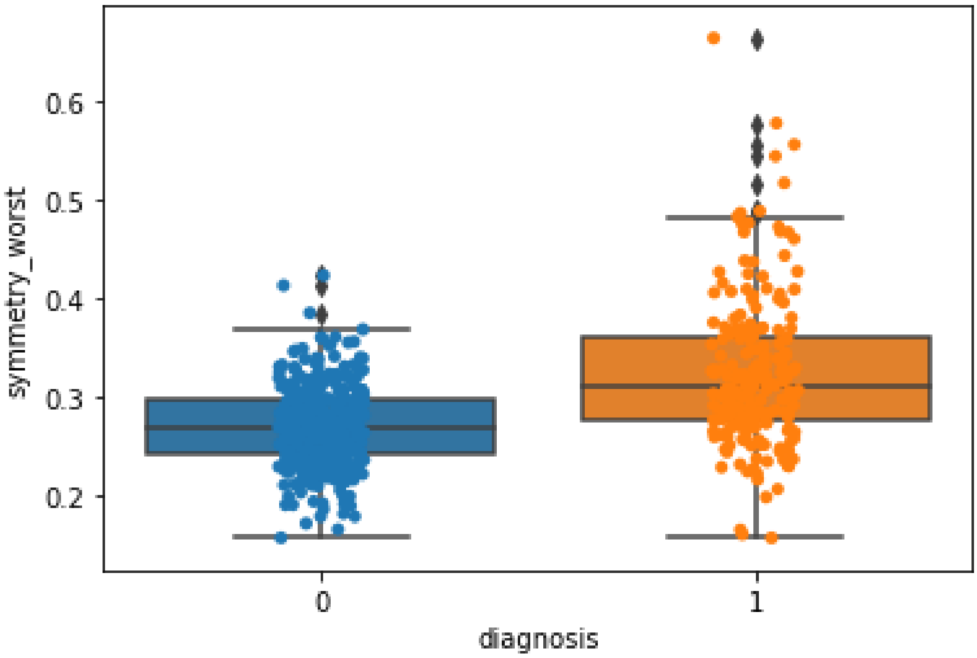

0.22
0.20
0.18
0.16
0.14
0.12
0.10
0.08
smoothness_worst
0
1
diagnosis


1.0
0.8
0.6
0.4
0.2
0.0
compactness_worst
0
1
diagnosis

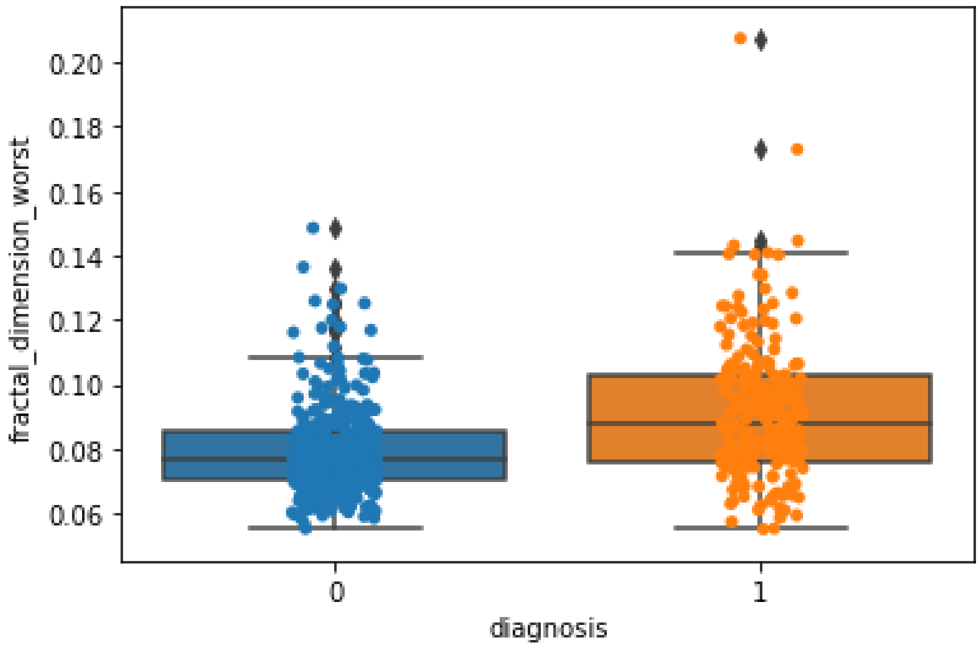

1.2
1.0
0.8
0.6
0.4
0.2
0.0
concavity_worst
0
1
diagnosis



0.30
0.25
0.20
0.15
0.10
0.05
0.00
concave points_worst
0
1
diagnosis



0.6
0.5
0.4
0.3
0.2
symmetry_worst
0
1
diagnosis

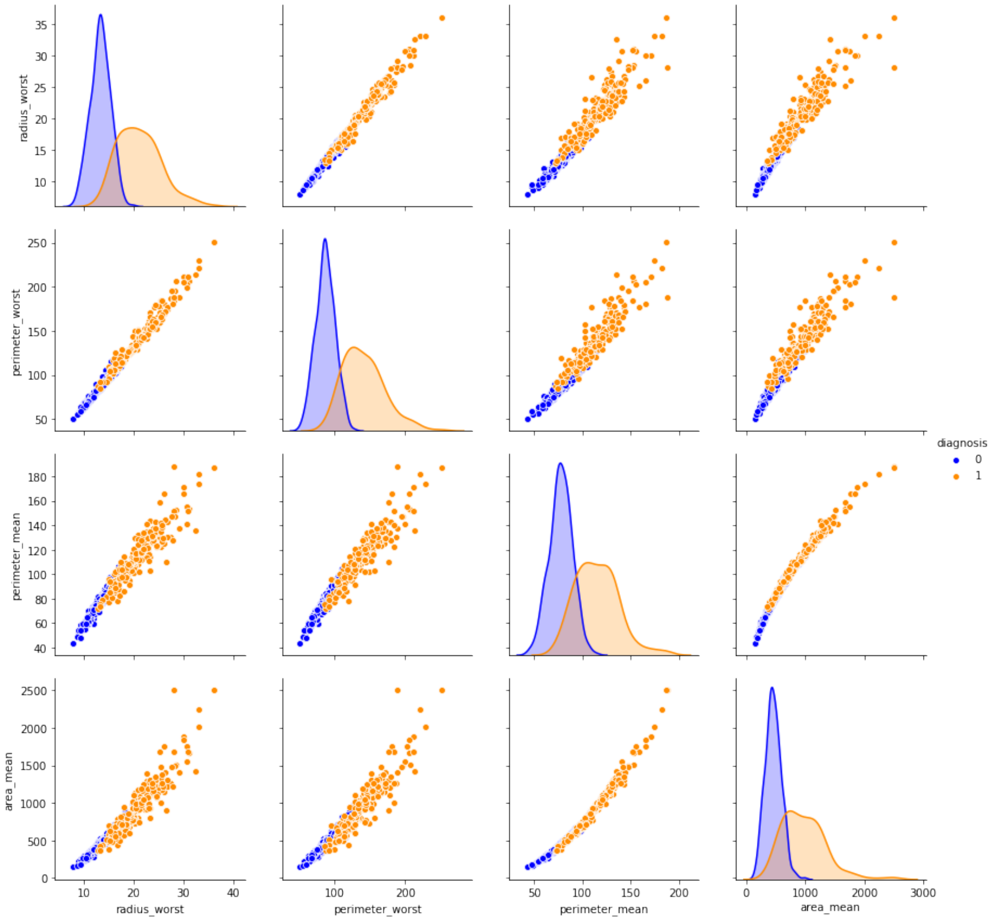


```
<Figure size 432x288 with 0 Axes>
```

1.4 Visualizar variables en plano ‘x y’

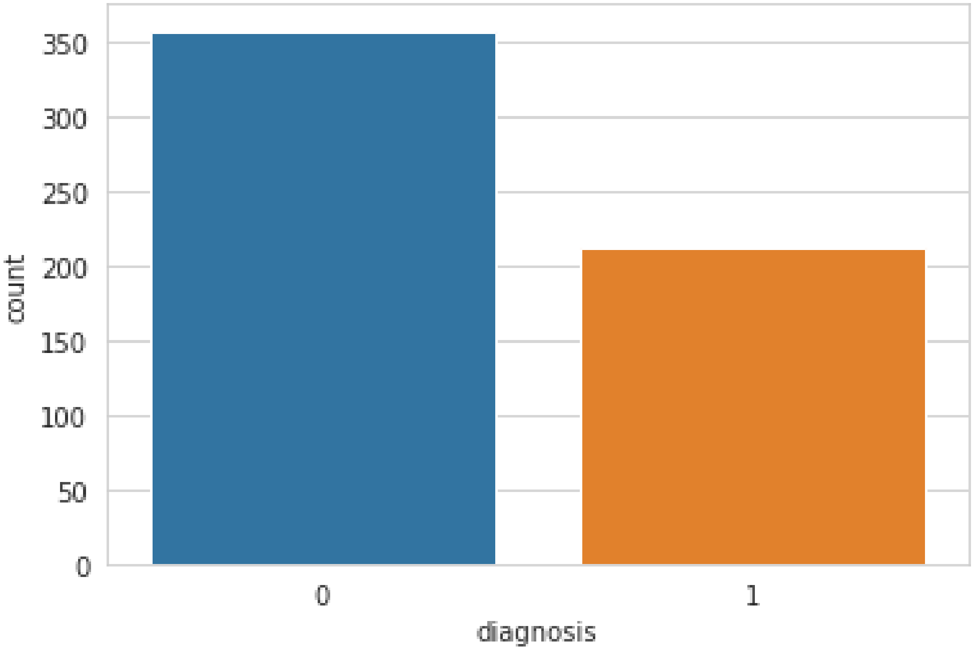
- Con ‘pairplot’ se pueden visualizar las características de una forma clara y rápida. Se recibe como argumento la lista de variables a plotear

```
In [7]: sns.pairplot(df, vars=["radius_worst", "perimeter_worst", "perimeter_mean", "area_mean"],
                     palette=sns.color_palette(['blue', 'darkorange']), hue='diagnosis', height=3
        plt.show()
```



1.5 Conteo de clases

```
In [8]: sns.set_style('whitegrid')
        sns.countplot(x='diagnosis',data=df)

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f345ab98c90>
```



1.6 Preparar datos para entrenamiento

```
In [9]: from sklearn.model_selection import train_test_split

        X = df.drop('diagnosis',axis=1)
        X = X.drop('Unnamed: 32',axis=1)
        y = df['diagnosis']
        # dividir datos
        train, test, train_labels, test_labels = train_test_split(X, y,
                                                 test_size = 0.33, random_state = 3)
```

```
In [10]: train.head()
```

```
Out[10]:           radius_mean  texture_mean  perimeter_mean  area_mean  \
         id
         917896          13.71         18.68           88.73      571.0
         8611792         19.10         26.29          129.10     1132.0
         864877          15.78         22.91          105.70      782.6
         904689          12.96         18.29           84.18      525.2
         89382602        12.76         13.37           82.29      504.1

                   smoothness_mean  compactness_mean  concavity_mean  \
         id
         917896            0.09916           0.10700         0.05385
         8611792           0.12150           0.17910         0.19370
```

```
864877            0.11550           0.17520         0.21330
904689            0.07351           0.07899         0.04057
89382602          0.08794           0.07948         0.04052

          concave points_mean  symmetry_mean  fractal_dimension_mean  …  \
id                                                                    …
917896                0.03783         0.1714                 0.06843  …
8611792               0.14690         0.1634                 0.07224  …
864877                0.09479         0.2096                 0.07331  …
904689                0.01883         0.1874                 0.05899  …
89382602              0.02548         0.1601                 0.06140  …

          radius_worst  texture_worst  perimeter_worst  area_worst  \
id
917896           15.11          25.63            99.43       701.9
8611792          20.33          32.72           141.30      1298.0
864877           20.19          30.50           130.30      1272.0
904689           14.13          24.61            96.31       621.9
89382602         14.19          16.40            92.04       618.8

          smoothness_worst  compactness_worst  concavity_worst  \
id
917896             0.14250             0.2566           0.1935
8611792            0.13920             0.2817           0.2432
864877             0.18550             0.4925           0.7356
904689             0.09329             0.2318           0.1604
89382602           0.11940             0.2208           0.1769

          concave points_worst  symmetry_worst  fractal_dimension_worst
id
917896                 0.12840       0.2849                  0.09031
8611792                0.18410       0.2311                  0.09203
864877                 0.20340       0.3274                  0.12520
904689                 0.06608       0.3207                  0.07247
89382602               0.08411       0.2564                  0.08253

[5 rows x 30 columns]
```

2 Evaluación de modelos

- Se obtienen las predicciones, informe de clasificación y matriz de confusión.
- Se crea lista para guardar evaluaciones

```
In [11]: from sklearn.metrics import confusion_matrix
         from sklearn.metrics import accuracy_score
```

```
In [12]: ev = []
```

2.1 BernoulliNB

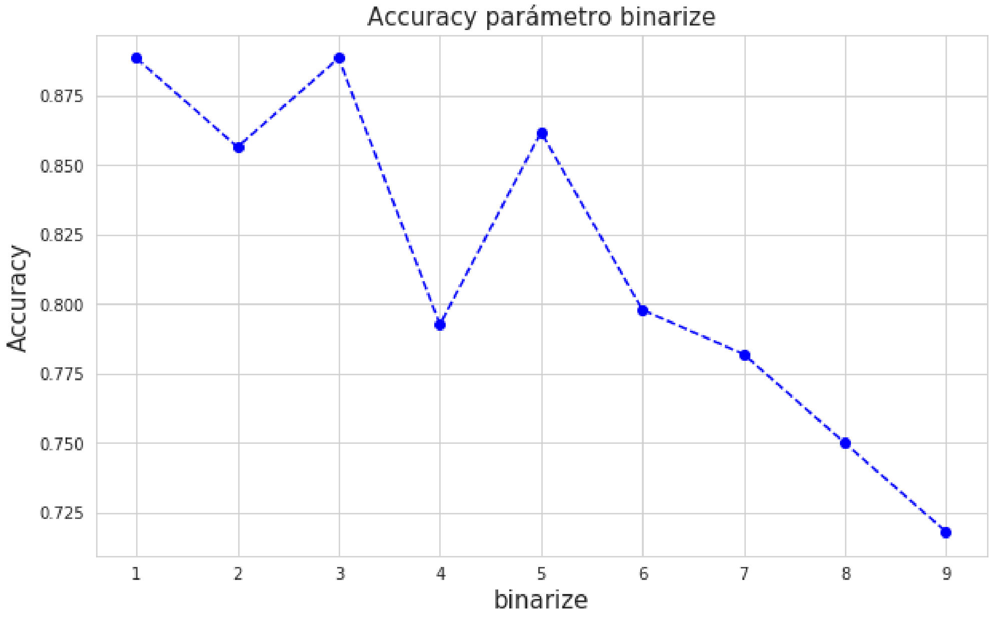
- Se ajusta el parámetro 'binarize'

```
In [13]: from sklearn.naive_bayes import BernoulliNB
```

```
In [14]: acc = []


         for b in range(1,10):

             bnb = BernoulliNB(binarize=0.1*b)
             bnb.fit(train,train_labels)
             pred = bnb.predict(test)
             acc.append(accuracy_score(test_labels, pred))
```

```
In [15]: plt.figure(figsize=(10,6))
         plt.plot(range(1,10),acc,color='blue', linestyle='--', marker='o')
         plt.title('Accuracy parámetro binarize', fontsize=15)
         plt.xlabel('binarize',fontsize=15)
         plt.ylabel('Accuracy',fontsize=15)
```

```
Out[15]: Text(0, 0.5, 'Accuracy')
```



- Con 'binarize' con valor de 0.3 se obtiene el mejor resultado

```
In [16]: bnb = BernoulliNB(binarize=0.3)
         bnb.fit(train, train_labels)
         ev.append(bnb.score(test, test_labels))
         bnb.score(test, test_labels)

Out[16]: 0.8882978723404256

In [17]: from sklearn.metrics import classification_report

In [18]: predictions = bnb.predict(test)
         print("Predicciones:\n")
         print(predictions)
         print("\nReporte de clasificación:\n")
         print(classification_report(predictions,test_labels))
```

```
Predicciones:

[0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0
 0 1 1 1 0 0 0 0 1 0 0 1 0 1 0 0 1 1 0 0 0 0 0 0 0 1 0 0 0 1 0 1 0 0 1 1 1
 0 1 0 1 1 1 1 0 1 0 0 1 0 0 0 0 1 1 1 0 0 1 0 1 0 0 0 0 0 0 0 1 1 0 0 0 0
 1 0 0 1 0 0 1 1 1 0 0 1 0 1 0 1 1 1 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 0 1 0 0
 1 0 1 1 0 0 0 1 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 1 1 0 1 0 0 0 0 1 1 0 0
 0 0 0]

Reporte de clasificación:

              precision    recall  f1-score   support

           0       0.95      0.88      0.92       129
           1       0.78      0.90      0.83        59

    accuracy                           0.89       188
   macro avg       0.86      0.89      0.88       188
weighted avg       0.90      0.89      0.89       188
```

```
In [19]: print("Confusion matrix")
         conf_mat=confusion_matrix(predictions,test_labels)
         print(conf_mat)
```

```
Confusion matrix
[[114  15]
 [  6  53]]
```

2.2 ComplementNB

```
In [20]: from sklearn.naive_bayes import ComplementNB

In [21]: cnb = ComplementNB()
         cnb.fit(train, train_labels)
         ev.append(cnb.score(test, test_labels))
         cnb.score(test, test_labels)
```

```
Out[21]: 0.898936170212766
```

```
In [22]: predictions = cnb.predict(test)
         print("Predicciones:\n")
         print(predictions)
         print("\nReporte de clasificación:\n")
         print(classification_report(predictions,test_labels))
```

```
Predicciones:

[0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 1 0 1 0 0 0 0 0 0
 0 1 1 1 0 0 1 0 0 0 0 1 0 1 0 0 1 1 0 0 1 0 0 0 0 1 0 0 0 1 0 1 1 0 0 1 1
 0 1 0 1 0 1 1 0 0 0 0 0 0 0 0 0 1 1 1 1 0 1 0 1 0 0 0 0 0 0 0 1 0 0 1 0 0
 1 0 0 1 1 0 1 1 1 0 0 1 0 0 0 1 0 0 0 0 0 1 0 0 0 0 1 0 1 0 0 1 0 0 1 0 0
 1 0 0 1 0 0 0 0 1 0 1 0 0 1 1 0 0 0 0 1 0 0 0 0 0 1 1 0 1 0 0 0 0 1 1 0 0
 1 0 0]

Reporte de clasificación:

              precision    recall  f1-score   support

           0       0.96      0.89      0.92       129
           1       0.79      0.92      0.85        59

    accuracy                           0.90       188
   macro avg       0.88      0.90      0.89       188
weighted avg       0.91      0.90      0.90       188
```

```
In [23]: print("Confusion matrix")
         conf_mat=confusion_matrix(predictions,test_labels)
         print(conf_mat)
```

```
Confusion matrix
[[115  14]
 [  5  54]]
```

2.3 GaussianNB

```
In [24]: from sklearn.naive_bayes import GaussianNB

         gnb = GaussianNB()

         gnb.fit(train, train_labels)
         ev.append(gnb.score(test, test_labels))
         gnb.score(test, test_labels)
```

```
Out[24]: 0.9574468085106383
```

```
In [25]: predictions = gnb.predict(test)
         print("Predicciones:\n")
         print(predictions)
         print("\nReporte de clasificación:\n")
         print(classification_report(predictions,test_labels))
```

```
Predicciones:

[0 0 0 0 1 0 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 0 1 0 0 0 1 1 0 1 0 0 0 0 0 0
 0 1 1 1 0 0 1 0 0 0 0 1 0 1 0 0 1 1 0 0 1 0 0 0 0 1 0 0 0 1 0 1 1 0 0 1 1
 0 1 0 1 1 1 1 0 0 0 0 1 0 0 0 0 1 1 1 0 0 1 0 1 0 0 0 0 0 0 0 1 1 0 1 0 0
 1 0 0 1 1 0 1 1 1 0 0 1 0 1 0 1 0 1 0 0 1 1 0 0 0 0 1 0 0 0 0 1 0 0 1 0 0
 1 0 0 1 0 0 0 1 1 0 1 0 0 0 1 0 0 1 0 1 0 0 0 0 0 1 1 0 1 0 0 0 0 1 1 0 0
 1 0 0]

Reporte de clasificación:

              precision    recall  f1-score   support

           0       0.97      0.96      0.97       122
           1       0.93      0.95      0.94        66

    accuracy                           0.96       188
   macro avg       0.95      0.96      0.95       188
weighted avg       0.96      0.96      0.96       188
```

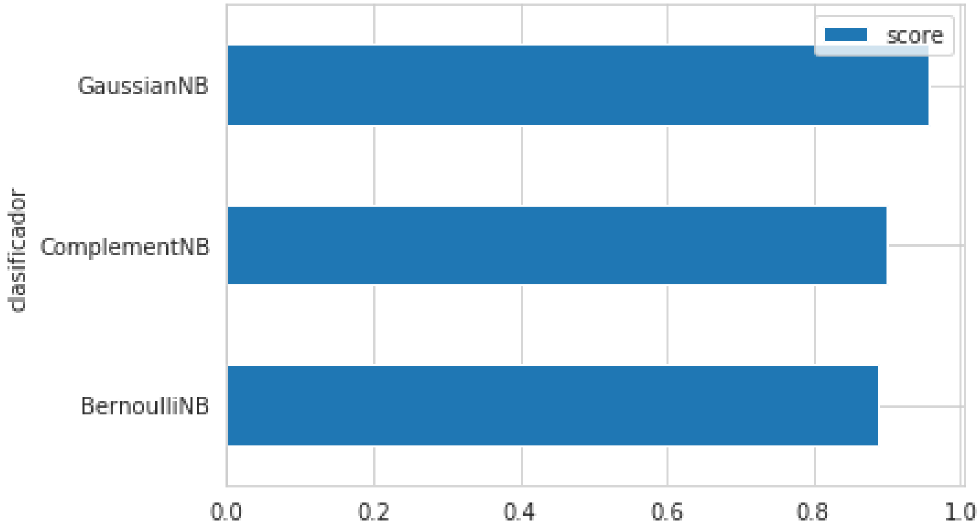
```
In [26]: print("Confusion matrix")
         conf_mat=confusion_matrix(predictions,test_labels)
         print(conf_mat)
```

```
Confusion matrix
[[117   5]
 [  3  63]]
```

```
In [27]: df = pd.DataFrame({'clasificador':['BernoulliNB','ComplementNB', 'GaussianNB'], 'score':
         df
```

```
Out[27]:    clasificador     score
         0   BernoulliNB  0.888298
         1  ComplementNB  0.898936
         2    GaussianNB  0.957447
```

```
In [28]: ax = df.plot.barh(x='clasificador', y='score')
```



- Usar el clasificador en otro dataset