NaiveBayes - Classificacao

June 14, 2020

1 Naïve Bayes - Classificação

Como alternativa ao modelo NB foram criados modelos utilizando o algoritmo Random Forest

1.0.1 Descrição do dataset

```
In [ ]: # Sex: male or female;
        # Age: Age of the patient;
        # Current Smoker: whether or not the patient is a current smoker;
        # Cigs Per Day: the number of cigarettes that the person smoked on average in one day;
        # BP Meds: whether or not the patient was on blood pressure medication;
        # Prevalent Stroke: whether or not the patient had previously had a stroke;
        # Prevalent Hyp: whether or not the patient was hypertensive;
        # Diabetes: whether or not the patient had diabetes;
        # Tot Chol: total cholesterol level;
        # Sys BP: systolic blood pressure;
        # Dia BP: diastolic blood pressure;
        # BMI: Body Mass Index;
        # Heart Rate: heart rate;
        # Glucose: glucose level;
        # 10 year risk of coronary heart disease CHD (binary: 1, means Yes, 0 means No).
```

1.0.2 Objetivo

Criar um modelo de classificação para prever a presença de doença coronariana

```
In [1]: # Carregando os módulos
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
```

```
In [2]: # Carregando o dataset
        dados = pd.read_csv('framingham.csv')
        dados.head()
```

Out[2]:

	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose	TenYearCHD
0	1	39	4.0	0	0.0	0.0	0	0	0	195.0	106.0	70.0	26.97	80.0	77.0	0
1	0	46	2.0	0	0.0	0.0	0	0	0	250.0	121.0	81.0	28.73	95.0	76.0	0
2	1	48	1.0	1	20.0	0.0	0	0	0	245.0	127.5	80.0	25.34	75.0	70.0	0
3	0	61	3.0	1	30.0	0.0	0	1	0	225.0	150.0	95.0	28.58	65.0	103.0	1
4	0	46	3.0	1	23.0	0.0	0	0	0	285.0	130.0	84.0	23.10	85.0	85.0	0

In [3]:
```
# Verificando o número de observações e variáveis
dados.shape
```

Out[3]:
```
(4238, 16)
```

1.0.3 Pré-processamento

In [4]:
```
# Verificando a presença de dados missing
dados.isnull().sum()
```

Out[4]:
```
male                0
age                 0
education         105
currentSmoker       0
cigsPerDay         29
BPMeds             53
prevalentStroke     0
prevalentHyp        0
diabetes            0
totChol            50
sysBP               0
diaBP               0
BMI                19
heartRate           1
glucose           388
TenYearCHD          0
dtype: int64
```

```
In [5]: # Eliminando os dados missing
        dados.dropna(inplace=True)

In [6]: # Verificando a distribuição das classes (valores absolutos)
        dados['TenYearCHD'].value_counts()

Out[6]: 0    3099
        1     557
        Name: TenYearCHD, dtype: int64

In [7]: # Verificando a distribuição das classes (percentuais)
        dados['TenYearCHD'].value_counts(normalize=True)

Out[7]: 0    0.847648
        1    0.152352
        Name: TenYearCHD, dtype: float64

In [8]: # Criando o conjunto de dados preditores
        dados_var = dados.iloc[:,0:15]
        dados_var.head()
```

Out[8]:

	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	\
0	1	39	4.0	0	0.0	0.0	0	
1	0	46	2.0	0	0.0	0.0	0	
2	1	48	1.0	1	20.0	0.0	0	
3	0	61	3.0	1	30.0	0.0	0	
4	0	46	3.0	1	23.0	0.0	0	

	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose
0	0	0	195.0	106.0	70.0	26.97	80.0	77.0
1	0	0	250.0	121.0	81.0	28.73	95.0	76.0
2	0	0	245.0	127.5	80.0	25.34	75.0	70.0
3	1	0	225.0	150.0	95.0	28.58	65.0	103.0
4	0	0	285.0	130.0	84.0	23.10	85.0	85.0

```
In [9]: # Criando o conjunto de dados de saída (alvo)
        dados_alvo = dados.iloc[:,15]
        dados_alvo.head()

Out[9]: 0    0
        1    0
        2    0
        3    1
        4    0
        Name: TenYearCHD, dtype: int64
```

1.0.4 Criando os conjuntos de treinamento e teste

```
In [10]: from sklearn.model_selection import train_test_split
         treino1, teste1, treino1_classes, teste1_classes = train_test_split(dados_var,
```

```
                                                                dados_alvo,
                                                                stratify = dados_alvo,
                                                                test_size=0.3, random_st
```

```
In [11]: # Verificando os tamanhos dos conjuntos de treino e teste
         print(treino1.shape)
         print(teste1.shape)
```

```
(2559, 15)
(1097, 15)
```

```
In [12]: # Verificando o distribuição das classes para treino e teste
         print(treino1_classes.value_counts(normalize=True))
         print(teste1_classes.value_counts(normalize=True))
```

```
0    0.847597
1    0.152403
Name: TenYearCHD, dtype: float64
0    0.847767
1    0.152233
Name: TenYearCHD, dtype: float64
```

1.0.5 Criando o modelo de classificação - Naive Bayes Gaussiano

```
In [13]: from sklearn.naive_bayes import GaussianNB
         gnb = GaussianNB()
         gnb.fit(treino1, treino1_classes)
```

```
Out[13]: GaussianNB(priors=None, var_smoothing=1e-09)
```

```
In [14]: # Executando as previsões para o conjunto de treino
         previsoes_treino1 = gnb.predict(treino1)
         previsoes_treino1_probs = gnb.predict_proba(treino1)[:, 1]
```

```
In [15]: # Carregando o pacote para avaliação do AUC e curva ROC
         from sklearn.metrics import roc_auc_score, roc_curve
         print(roc_auc_score(treino1_classes, previsoes_treino1_probs))
```

```
0.726639358797035
```

```
In [16]: from sklearn import metrics
         metrics.accuracy_score(treino1_classes, previsoes_treino1)*100
```

```
Out[16]: 82.45408362641658
```

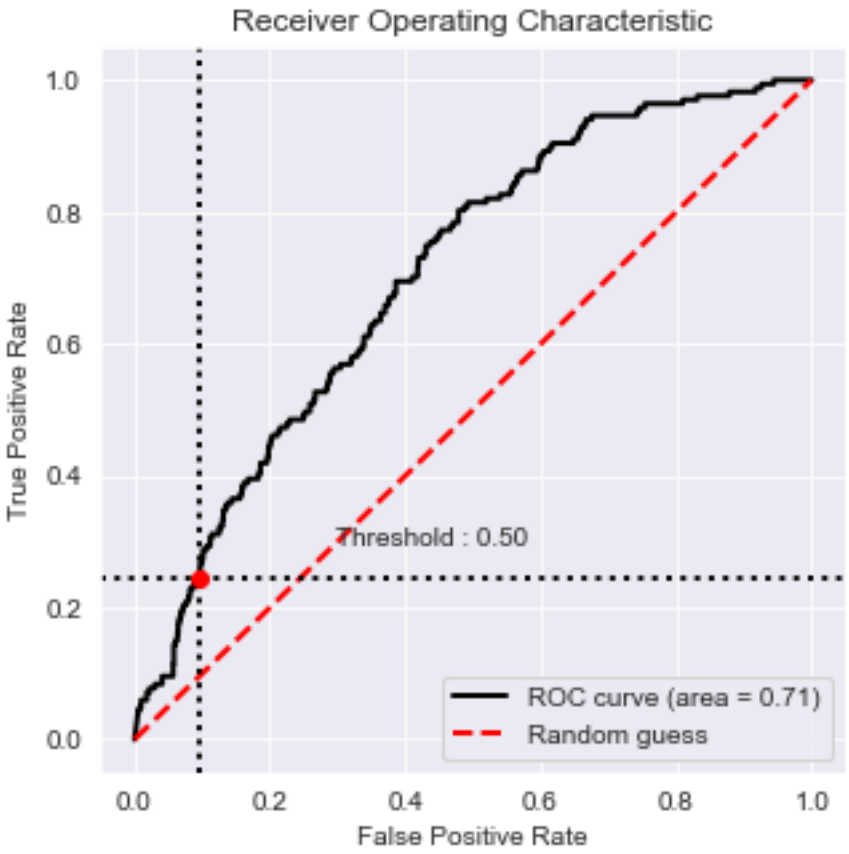
```
In [17]: # Previsões para o conjunto de teste
         previsoes_teste1 = gnb.predict(teste1)
         previsoes_teste1_probs = gnb.predict_proba(teste1)[:, 1]
```

```
In [18]: # Análise da ROC_AUC e Acurácia
         print('ROC_AUC: ', roc_auc_score(teste1_classes, previsoes_teste1_probs))
         print('Acurácia: ', metrics.accuracy_score(teste1_classes, previsoes_teste1)*100)

ROC_AUC:  0.70574013263795
Acurácia:  80.67456700091158
```

```
In [19]: # Carregando os pacotes para avaliação da matriz de confusão
         from sklearn.metrics import confusion_matrix
         confusion_matrix(previsoes_teste1, teste1_classes)

Out[19]: array([[844, 126],
                [ 86,  41]], dtype=int64)
```

```
In [20]: # Precisão, Recall e F1-Score
         from sklearn.metrics import classification_report
         nome_classes=dados_alvo.unique()
         print(classification_report(teste1_classes, previsoes_teste1, labels=nome_classes))

              precision    recall  f1-score   support

           0       0.87      0.91      0.89       930
           1       0.32      0.25      0.28       167

    accuracy                           0.81      1097
   macro avg       0.60      0.58      0.58      1097
weighted avg       0.79      0.81      0.80      1097
```

```
In [22]: # Visualizando a curva ROC (Receiver Operating Characteristic)
         %matplotlib inline
         from plot_metric.functions import BinaryClassification
         bc = BinaryClassification(teste1_classes, previsoes_teste1_probs, labels=[0,1])
         plt.figure(figsize=(5,5))
         bc.plot_roc_curve()
         plt.show()
```



1.0.6 Alterando as amostras da classe menor (Up-sample)

```
In [23]: # Separando os dados por tamanho da classe
         dados_maior = dados[dados['TenYearCHD']==0]
         dados_menor = dados[dados['TenYearCHD']==1]

In [24]: # Criando amostras (randômicas) baseadas na classe de menor tamanho
         from sklearn.utils import resample
         dados_menor_up = resample(dados_menor,
                                   replace=True,
                                   n_samples=2500,
                                   random_state=123)

In [25]: # Combinando (concatenando) as classes de maior tamanho com os novos dados gerados
         dados_up = pd.concat([dados_maior, dados_menor_up])

In [26]: # Verificando a distribuição das classes
         dados_up['TenYearCHD'].value_counts()

Out[26]: 0    3099
         1    2500
         Name: TenYearCHD, dtype: int64
```

Criando um novo modelo - versão 2

```
In [28]: dados_up_var = dados_up.iloc[:,0:15]
         dados_up_alvo = dados_up.iloc[:,15]

         treino2, teste2, treino2_classes, teste2_classes = train_test_split(dados_up_var,
                                                                             dados_up_alvo,
                                                                             stratify = dados_up_alvo
                                                                             test_size=0.3, random_st

         gnb2 = GaussianNB()
         gnb2.fit(treino2, treino2_classes)

         previsoes_teste2 = gnb2.predict(teste2)
         previsoes_teste2_probs = gnb2.predict_proba(teste2)[:, 1]

         confusion_matrix(previsoes_teste2, teste2_classes)

Out[28]: array([[807, 509],
                [123, 241]], dtype=int64)

In [29]: nome_classes=dados_up_alvo.unique()
         print(classification_report(teste2_classes, previsoes_teste2, labels=nome_classes))

              precision    recall  f1-score   support

           0       0.61      0.87      0.72       930
           1       0.66      0.32      0.43       750

    accuracy                           0.62      1680
   macro avg       0.64      0.59      0.58      1680
weighted avg       0.64      0.62      0.59      1680
```

1.0.7 Alterando as amostras da classe maior (Down-sample)

```
In [30]: # Separando os dados por tamanho da classe
         dados_maior = dados[dados['TenYearCHD']==0]
         dados_menor = dados[dados['TenYearCHD']==1]

In [31]: # Removendo amostras (randômicas) baseadas na classe de maior tamanho
         dados_maior_down = resample(dados_maior,
                                     replace=False,
                                     n_samples=600,
                                     random_state=123)

In [32]: # Combinando (concatenando) as classes de menor tamanho com os novos dados
         dados_down = pd.concat([dados_maior_down, dados_menor])
```

```
In [33]: # Verificando a distribuição das classes
         dados_down['TenYearCHD'].value_counts()
```

```
Out[33]: 0    600
         1    557
         Name: TenYearCHD, dtype: int64
```

Criando um novo modelo - versão 3

```
In [34]: dados_down_var = dados_down.iloc[:,0:15]
         dados_down_alvo = dados_down.iloc[:,15]

         treino3, teste3, treino3_classes, teste3_classes = train_test_split(dados_down_var,
                                                                             dados_down_alvo,
                                                                             stratify = dados_down_al
                                                                             test_size=0.3, random_st

         gnb3 = GaussianNB()
         gnb3.fit(treino3, treino3_classes)

         previsoes_teste3 = gnb3.predict(teste3)
         previsoes_teste3_probs = gnb3.predict_proba(teste3)[:, 1]

         confusion_matrix(previsoes_teste3, teste3_classes)
```

```
Out[34]: array([[163, 120],
                [ 17,  48]], dtype=int64)
```

```
In [35]: nome_classes=dados_down_alvo.unique()
         print(classification_report(teste3_classes, previsoes_teste3, labels=nome_classes))
```

```
              precision    recall  f1-score   support

           0       0.58      0.91      0.70       180
           1       0.74      0.29      0.41       168

    accuracy                           0.61       348
   macro avg       0.66      0.60      0.56       348
weighted avg       0.65      0.61      0.56       348
```

1.0.8 Tentativas de melhoria de performance

```
In [36]: # Extração de características - determinando as variáveis mais relevantes
         from sklearn.ensemble import ExtraTreesClassifier
         modelo = ExtraTreesClassifier(n_estimators = 1000, random_state = 123)
         modelo.fit(treino2, treino2_classes) # Usando os conjuntos do melhor modelo
         print(modelo.feature_importances_)
         print(treino2.columns)
```

```
[0.02904125 0.14719731 0.05768606 0.0207785  0.05244249 0.00765531
 0.00347366 0.04951615 0.01169151 0.10305908 0.11566396 0.10401255
 0.10135516 0.09613196 0.10029504]
Index(['male', 'age', 'education', 'currentSmoker', 'cigsPerDay', 'BPMeds',
       'prevalentStroke', 'prevalentHyp', 'diabetes', 'totChol', 'sysBP',
       'diaBP', 'BMI', 'heartRate', 'glucose'],
      dtype='object')
```

```
In [37]: # Eliminando as variáveis menos relevantes
         treino4 = treino2.drop(columns=['male', 'education', 'currentSmoker', 'cigsPerDay',
                                         'BPMeds', 'prevalentStroke', 'prevalentHyp', 'diabetes
```

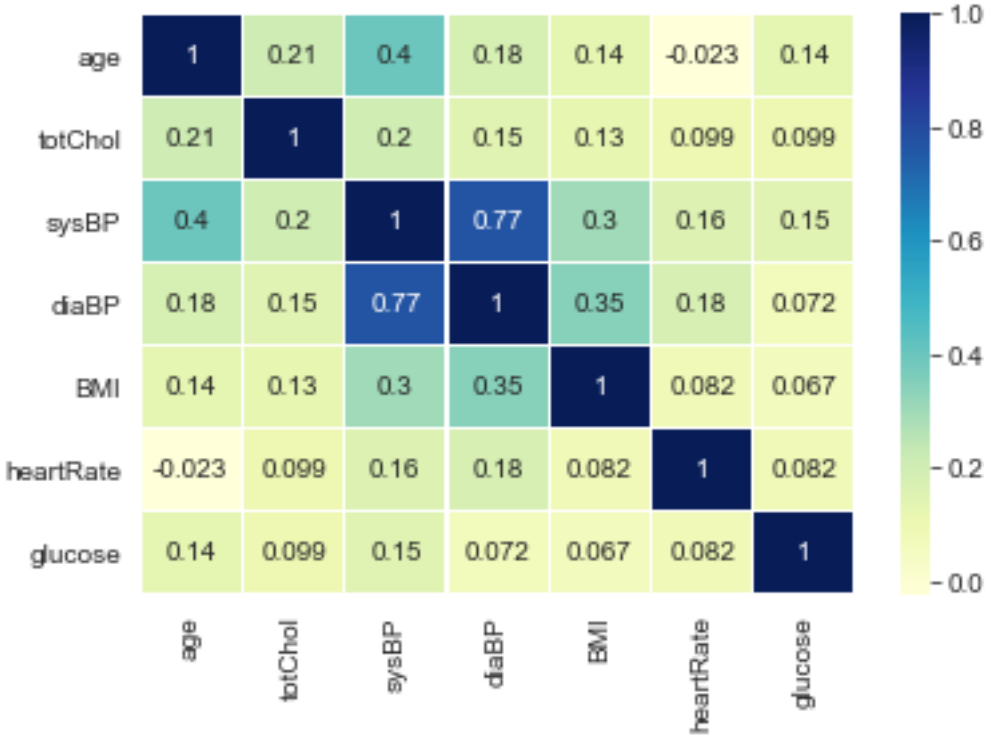
```
In [38]: treino4.head()
```

Out[38]:

	age	totChol	sysBP	diaBP	BMI	heartRate	glucose
520	59	271.0	117.5	65.0	19.77	70.0	89.0
919	42	194.0	111.0	67.5	21.34	73.0	47.0
3225	50	236.0	152.0	92.0	24.47	120.0	67.0
3731	60	220.0	167.5	110.0	30.41	90.0	84.0
4119	51	195.0	122.0	72.0	21.51	82.0	64.0

```
In [39]: # Avaliando as correlações
         sns.heatmap(treino4.corr(), cmap ="YlGnBu", linewidths = 0.1, annot=True)
```

```
Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x13575cc7b8>
```



```
In [40]: # Eliminando variáveis fortemente correlacionadas
         treino4 = treino4.drop(columns=['diaBP'])

In [41]: treino4.describe()
```

Out[41]:

	age	totChol	sysBP	BMI	heartRate	glucose
count	3919.000000	3919.000000	3919.000000	3919.000000	3919.000000	3919.000000
mean	51.165093	239.284767	135.879561	26.041000	75.966318	84.333248
std	8.740461	45.777103	24.384109	4.273407	12.206195	31.970151
min	32.000000	113.000000	83.500000	15.540000	44.000000	40.000000
25%	44.000000	208.000000	119.000000	23.140000	67.000000	72.000000
50%	51.000000	237.000000	131.500000	25.650000	75.000000	78.000000
75%	59.000000	266.000000	148.000000	28.420000	83.000000	87.500000
max	69.000000	600.000000	295.000000	51.280000	143.000000	394.000000

Criando um novo modelo - versão 4

```
In [42]: treino4_classes = treino2_classes
         teste4_classes = teste2_classes
         gnb4 = GaussianNB()
         gnb4.fit(treino4, treino4_classes)
```

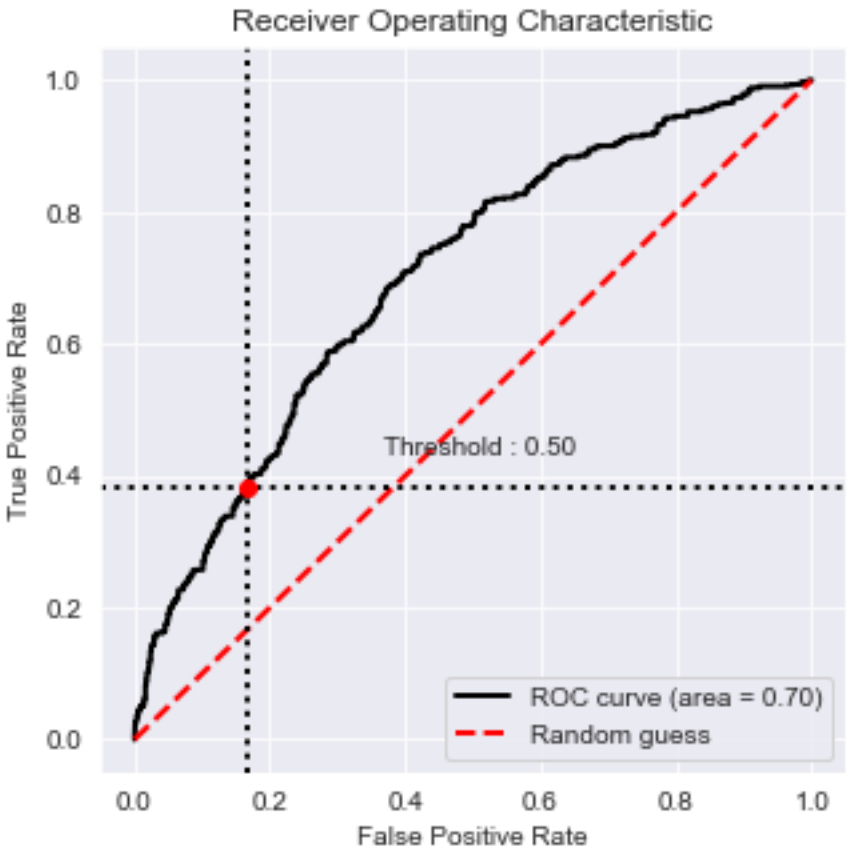
Out[42]: GaussianNB(priors=None, var_smoothing=1e-09)

```
In [43]: # Eliminando as variáveis menos relevantes do conjunto de teste
         teste4 = teste2.drop(columns=['male', 'education', 'currentSmoker', 'cigsPerDay',
                                       'BPMeds', 'prevalentStroke', 'prevalentHyp', 'diabetes
                                    'diaBP'])

In [44]: teste4.head()
```

Out[44]:

	age	totChol	sysBP	BMI	heartRate	glucose
771	63	210.0	148.0	24.01	76.0	88.0
928	58	243.0	106.0	23.72	60.0	80.0
2665	58	175.0	83.5	29.66	95.0	115.0
3254	51	342.0	110.0	28.86	72.0	87.0
3121	38	267.0	179.5	20.44	76.0	67.0

```
In [45]: # Executando as previsões
         previsoes_teste4 = gnb4.predict(teste4)
         previsoes_teste4_probs = gnb4.predict_proba(teste4)[:, 1]

In [46]: print('ROC_AUC: ',roc_auc_score(teste4_classes, previsoes_teste4_probs))
         print('Acurácia: ', metrics.accuracy_score(teste4_classes, previsoes_teste4)*100)

ROC_AUC:  0.7014831541218638
Acurácia:  63.27380952380952


In [ ]: # Matriz de confusão
        confusion_matrix(previsoes_teste4, teste4_classes)

In [47]: # Avaliação do modelo
         print(classification_report(teste4_classes, previsoes_teste4, labels=nome_classes))

              precision    recall  f1-score   support

           0       0.63      0.83      0.72       930
           1       0.65      0.38      0.48       750

    accuracy                           0.63      1680
   macro avg       0.64      0.61      0.60      1680
weighted avg       0.64      0.63      0.61      1680


In [48]: # Curva ROC
         from plot_metric.functions import BinaryClassification
         bc = BinaryClassification(teste4_classes, previsoes_teste4_probs, labels=[0,1])
         plt.figure(figsize=(5,5))
         bc.plot_roc_curve()
         plt.show()
```



1.0.9 Usando o algoritmo Random Forest - v1

```
In [49]: # Carregando o pacote do classificador Random Forest
         from sklearn.ensemble import RandomForestClassifier

         # Criando o modelo Random Forest
         rf = RandomForestClassifier(n_estimators=100,
                                     random_state=123,
                                     max_features = 'sqrt',
                                     n_jobs=-1, verbose = 1)

         # Treinando o modelo
         rf.fit(treino1, treino1_classes)

         # Executando as previsões (probabilidade)
         teste_probs_rf = rf.predict_proba(teste1)[:, 1]
         previsoes_teste_rf = rf.predict(teste1)

         # Matriz de confusão
         confusion_matrix(previsoes_teste_rf, teste1_classes)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:    0.2s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.0s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    0.0s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.0s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    0.0s finished
```

```
Out[49]: array([[916, 153],
                [ 14,  14]], dtype=int64)
```

```
In [50]: # Precisão, Recall e F1-Score
         print(classification_report(teste1_classes, previsoes_teste_rf, labels=nome_classes))
```

```
              precision    recall  f1-score   support

           0       0.86      0.98      0.92       930
           1       0.50      0.08      0.14       167

    accuracy                           0.85      1097
   macro avg       0.68      0.53      0.53      1097
weighted avg       0.80      0.85      0.80      1097
```

1.0.10 Usando o algoritmo Random Forest - v2

```
In [51]: # Carregando o pacote do classificador Random Forest
         from sklearn.ensemble import RandomForestClassifier

         # Criando o modelo Random Forest
         rf = RandomForestClassifier(n_estimators=100,
                                     random_state=123,
                                     max_features = 'sqrt',
                                     n_jobs=-1, verbose = 1)

         # Treinando o modelo
         rf.fit(treino2, treino2_classes)

         # Executando as previsões
         teste_probs_rf = rf.predict_proba(teste2)[:, 1]
         previsoes_teste_rf = rf.predict(teste2)

         # Matriz de confusão
         confusion_matrix(previsoes_teste_rf, teste2_classes)
```

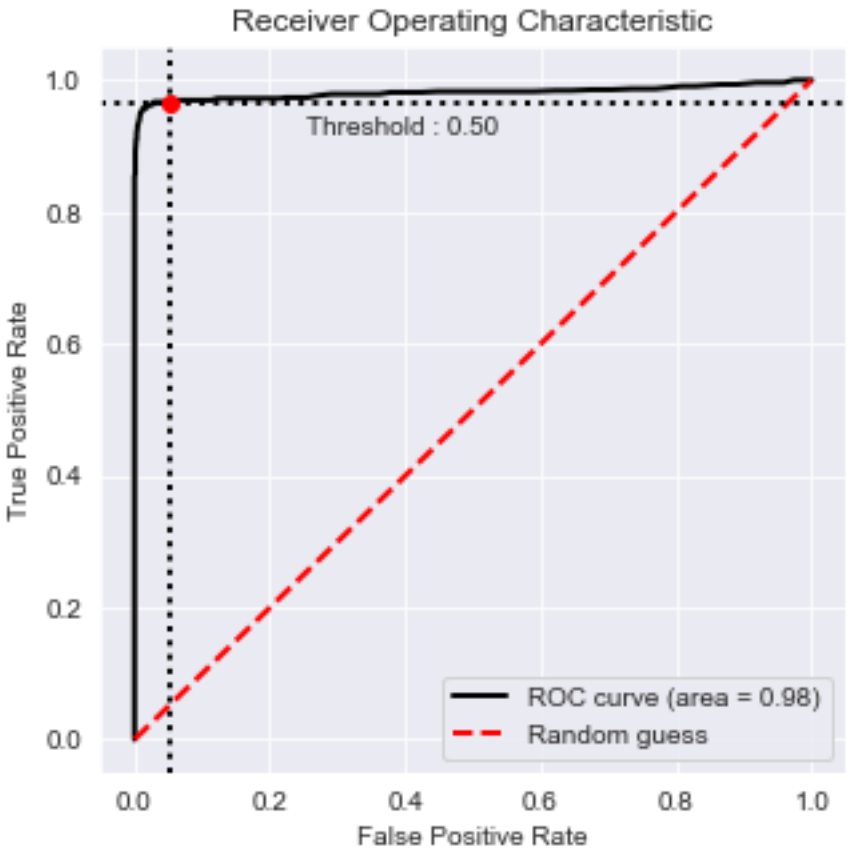
```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:    0.0s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:    0.1s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.0s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    0.0s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.0s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    0.0s finished
```

```
Out[51]: array([[885,  25],
                [ 45, 725]], dtype=int64)
```

```
In [52]: # Precisão, Recall e F1-Score
         print(classification_report(teste2_classes, previsoes_teste_rf, labels=nome_classes))
```

```
              precision    recall  f1-score   support

           0       0.97      0.95      0.96       930
           1       0.94      0.97      0.95       750

    accuracy                           0.96      1680
   macro avg       0.96      0.96      0.96      1680
weighted avg       0.96      0.96      0.96      1680
```

```
In [53]: # Curva ROC
         from plot_metric.functions import BinaryClassification
         bc = BinaryClassification(teste2_classes, teste_probs_rf, labels=[0,1])
         plt.figure(figsize=(5,5))
         bc.plot_roc_curve()
         plt.show()
```


Receiver Operating Characteristic
Threshold : 0.50
True Positive Rate
False Positive Rate
ROC curve (area = 0.98)
Random guess
0.0
0.2
0.4
0.6
0.8
1.0

In [ ]: