Smarkio – Desafio Prático Ciência de Dados

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Datasets

1. Primeira aba - Análise_ML:

   a. pred_class - A classe que foi identificada pelo modelo;

   b. probabilidade - A probabilidade da classe que o modelo identificou;

   c. status - status da classificação de acordo com um especialista (approved);

   d. true_class - A classe verdadeira (se nula, assumir o pred_class);

   Obs: Se pred_class é igual a true_class, temos que o modelo acertou.

2. Segunda aba - NLP:

   a. letra - trecho de música;

   b. artista - cantora referente a letra.

Bibliotecas

In [1]:

```
import numpy as np
import pandas as pd
import pandas_profiling as pdpf
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

from sklearn.preprocessing import StandardScaler
from sklearn import model_selection
from sklearn.model_selection import (train_test_split,
StratifiedKFold)
from sklearn.linear_model import (LinearRegression,
                                  LogisticRegression,
                                  SGDClassifier,
                                  RidgeClassifier)
from sklearn.naive_bayes import (GaussianNB, MultinomialNB)
from sklearn.neighbors import (KNeighborsClassifier)
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import (RandomForestClassifier,
                              GradientBoostingClassifier,
                             BaggingClassifier,
                             ExtraTreesClassifier,
                             AdaBoostClassifier,
                             VotingClassifier)
from sklearn import impute
from sklearn.experimental import enable_iterative_imputer
from sklearn.multiclass import OneVsRestClassifier
from skmultilearn.problem_transform import (ClassifierChain,
BinaryRelevance)
from skmultilearn.adapt import MLkNN
from sklearn.neural_network import MLPClassifier

from sklearn.feature_extraction.text import (CountVectorizer,
                                             TfidfVectorizer)
from sklearn.metrics import (
    average_precision_score,
    recall_score,
    precision_score,
    balanced_accuracy_score,
```

```
    confusion_matrix,
    roc_auc_score,
    hamming_loss,
    roc_curve)

import xgboost

from yellowbrick.classifier import (ConfusionMatrix, ROCAUC)
from yellowbrick.model_selection import (LearningCurve,
ValidationCurve)

import pickle
```

Dataset "Análise_ML"

Dados

In [2]:
```
df_analise_ml = pd.read_excel('teste_smarkio_lbs.xls',
sheet_name = "Análise_ML")
```

Análise Exploratória dos Dados

In [3]:
```
# verificando os 5 primeiros
df_analise_ml.head()
```

Out[3]:

	Pred_class	probabilidade	status	True_class
0	2	0.079892	approved	0.0
1	2	0.379377	approved	74.0
2	2	0.379377	approved	74.0
3	2	0.420930	approved	74.0
4	2	0.607437	approved	NaN

In [4]:
```
# verificando o tipo dos dados
df_analise_ml.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 643 entries, 0 to 642
```

```
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Pred_class     643 non-null    int64  
 1   probabilidade  643 non-null    float64
 2   status         643 non-null    object 
 3   True_class     181 non-null    float64
dtypes: float64(2), int64(1), object(1)
```

Trocando 0 pela classe correta em 'true_class'

Conforme descrição:

- "d. true_class - A classe verdadeira (se nula, assumir o pred_class);

In [5]:
```
for i in range(len(df_analise_ml)):
    if df_analise_ml.True_class[i] == 0:
        df_analise_ml.True_class[i] =
df_analise_ml.Pred_class[i]
```

In [6]:
```
# verificando o resultado
df_analise_ml.sample(20)
```

Out[6]:

	Pred_class	probabilidade	status	True_class
527	76	1.000000	approved	NaN
39	60	0.402339	approved	3.0
23	11	0.263713	approved	79.0
28	24	0.738060	approved	NaN
178	2	0.834910	approved	NaN
24	11	1.000000	approved	NaN
97	108	1.000000	approved	NaN
251	3	0.617418	approved	40.0
486	52	0.328479	approved	NaN
139	96	0.591297	approved	NaN
372	78	0.527347	approved	NaN
608	77	0.403734	revision	NaN
286	22	0.959694	approved	NaN
544	90	0.317060	approved	NaN
585	3	0.617056	approved	74.0
257	3	0.877316	approved	NaN
454	15	0.408993	approved	70.0
370	77	1.000000	approved	NaN
494	56	0.926657	approved	NaN
260	3	0.951381	approved	NaN

Análise geral por meio do

In [7]:
```
pdpf.ProfileReport(df_analise_ml)
```

Overview

Dataset statistics

Number of variables	4
Number of observations	643
Missing cells	462
Missing cells (%)	18.0%
Duplicate rows	128
Duplicate rows (%)	19.9%
Total size in memory	20.2 KiB
Average record size in memory	32.2 B

Variable types

NUM	3
CAT	1

Warnings

Dataset has 128 (19.9%) duplicate rows	**Duplicates**
`True_class` has 462 (71.9%) missing values	**Missing**

Reproduction

Analysis started	2021-02-28 00:30:13.443873

Out[7]:

Análise da varíavel 'status'

A variável 'status', a única não numérica, apresenta apenas dois valores possíves: 'approved' e 'revision', dos quais a maior frequência é da variável 'approved' com 93.3% dos casos.

Um ponto importante da variável é que não apresenta dados ausentes.

Análise da varíavel 'True_class'

In [8]:
```
df_analise_ml.isnull().sum()
```

Out[8]:
```
Pred_class         0
probabilidade      0
status             0
True_class       462
dtype: int64
```

A variável em questão é a única com dados ausentes.

Estes dados representam uma parcela significativa no total de informações fornecidas, cerca de 71.9%.

Os valores mais comuns nesta variável são:

Valor	Contagem	Porcentagem
74	23	3.6
2	16	2.5
52	14	2.2
3	12	1.9

Relação da variável 'status' e da varíavel 'True_class'

Sabe-se que temos que tomar uma atitude em relação aos dados ausentes na variável 'True_class'.

Pode-se simplesmente excluí-los da base de dados ou completar os valores ausentes utilizando-se de um critério específico.

Antes de decidir deve-se investigar se a exclusão trará prejuízo significativo para a construção do modelo.

In [9]:
```
df_apenas_revision =
df_analise_ml[df_analise_ml['status']=='revision']
print(len(df_apenas_revision))
df_apenas_revision
```

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Out[9]:

	Pred_class	probabilidade	status	True_class
600	2	0.752448	revision	NaN
601	24	0.817525	revision	NaN

	Pred_class	probabilidade	status	True_class
602	24	0.909148	revision	NaN
603	25	0.509871	revision	NaN
604	25	0.629700	revision	NaN
605	25	0.633426	revision	NaN
606	32	0.621226	revision	NaN
607	55	0.740292	revision	NaN
608	77	0.403734	revision	NaN
609	77	0.419723	revision	NaN
610	86	0.545478	revision	NaN
611	114	0.487069	revision	NaN
612	11	0.320702	revision	NaN
613	24	0.287126	revision	NaN
614	60	0.511118	revision	NaN
615	2	0.331168	revision	NaN
616	3	0.399808	revision	NaN
617	4	0.405327	revision	NaN
618	22	0.324137	revision	NaN
619	24	0.737133	revision	NaN
620	39	0.812112	revision	NaN
621	39	0.812112	revision	NaN
622	43	0.725794	revision	NaN
623	60	0.421998	revision	NaN
624	81	0.351401	revision	NaN
625	96	0.313003	revision	NaN
626	113	0.516733	revision	NaN
627	2	0.334350	revision	NaN
628	3	0.351031	revision	NaN
629	3	0.784920	revision	NaN
630	4	0.278516	revision	NaN
631	4	0.301915	revision	NaN
632	12	0.574756	revision	NaN
633	17	0.506654	revision	NaN
634	24	0.318306	revision	NaN
635	36	0.285545	revision	NaN
636	43	0.740075	revision	NaN
637	55	0.675269	revision	NaN
638	60	0.543772	revision	NaN

	Pred_class	probabilidade	status	True_class
639	60	0.553846	revision	NaN

Quando o filtro em recision em 'status' é realizado percebe-se que todos neste estado estão com dados ausentes para a variável 'True_class', deste modo, fica inviável excluir as linhas com dados ausentes.

Mais adiante o completamento dos valores ausentes será realizado.

Desempenho do modelo comparando 'pred_class' e 'true_class'

In [10]:
```
df_des_modelo = df_analise_ml.copy().dropna()
df_des_modelo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 181 entries, 0 to 599
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Pred_class     181 non-null    int64  
 1   probabilidade  181 non-null    float64
 2   status         181 non-null    object 
 3   True_class     181 non-null    float64
dtypes: float64(2), int64(1), object(1)
memory usage: 7.1+ KB
```

In [11]:
```
y_pred = df_des_modelo.Pred_class
y_true = df_des_modelo.True_class


labels = y_true.unique()
```

Métricas

In [12]:
```
print('accuracy_score',accuracy_score(y_pred, y_true))
print('balanced_accuracy_score',balanced_accuracy_score(y_pred,
y_true))
print('hamming_loss',hamming_loss(y_pred, y_true))
print('precision_score', precision_score(y_pred, y_true,
labels=labels, average='macro'))
print('recall_score',recall_score(y_pred, y_true, labels=labels,
average='macro'))
print('f1_score',f1_score(y_pred, y_true, labels=labels,
average='macro'))
```

```
accuracy_score 0.2983425414364641
balanced_accuracy_score 0.2712572920906254
hamming_loss 0.7016574585635359
precision_score 0.3509594739667204
recall_score 0.27125729209062543
```

```
f1_score 0.27776624609957945
```

Conclusão

Ao avaliar as 6 métricas acima concluí-se que o modelo é **ruim**, visto que:

1. As métricas (`accuracy_score` , `balanced_accuracy_score` , `precision_score` , `recall_score` e `f1_score`) onde o melhor é o quanto mais próximo de 1, estão mais próximas de 0 do que de 1;

2. A métrica (`hamming_loss`) onde o melhor é o quanto mais próximo de 0, esta mais próximas de 1 do que de 0.

Criando Classificador

Trocando as variáveis 'approved' e 'revision' por números

In [13]:
```
df_analise_ml['status'] =
df_analise_ml['status'].map({'approved':1,

'revision':0})
df_analise_ml.head()
```

Out[13]:

	Pred_class	probabilidade	status	True_class
0	2	0.079892	1	2.0
1	2	0.379377	1	74.0
2	2	0.379377	1	74.0
3	2	0.420930	1	74.0
4	2	0.607437	1	NaN

Preenchendo 'NaN'

In [14]:
```
y = df_analise_ml['status']
X = df_analise_ml.drop(columns=[
    "status"])

X_train, X_test, y_train, y_test =
model_selection.train_test_split(X, y, test_size=0.3,

random_state=42)
```

In [15]:
```
imputer = impute.IterativeImputer()
imputed = imputer.fit_transform(X_train)
X_train.loc[:, :] = imputed
imputed = imputer.transform(X_test)
X_test.loc[:, :] = imputed
```

In [16]:
```
X = pd.concat([X_train,X_test])
X.isnull().sum()
```

Out[16]:
```
Pred_class       0
probabilidade    0
True_class       0
dtype: int64
```

In [17]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 643 entries, 234 to 271
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Pred_class     643 non-null    float64
 1   probabilidade  643 non-null    float64
 2   True_class     643 non-null    float64
dtypes: float64(3)
memory usage: 20.1 KB
```

In [18]:
```
X.True_class = X.True_class.astype(int)
X.Pred_class = X.Pred_class.astype(int)
X
```

Out[18]:

	Pred_class	probabilidade	True_class
234	2	0.623210	52
428	2	0.969559	52
210	60	0.580529	57
9	2	1.000000	52
518	74	0.443712	58
...	...	...	...
546	92	0.834073	4
277	17	0.964834	53
310	52	0.057740	52
137	74	1.000000	58
271	12	0.121687	52

643 rows × 3 columns

In [19]:
```
df_mod = X.join(y)
df_mod
```

Out[19]:

	Pred_class	probabilidade	True_class	status
234	2	0.623210	52	1
428	2	0.969559	52	1
210	60	0.580529	57	1
9	2	1.000000	52	1
518	74	0.443712	58	1
...	...	...	...	...
546	92	0.834073	4	1
277	17	0.964834	53	1
310	52	0.057740	52	1
137	74	1.000000	58	1
271	12	0.121687	52	1

643 rows × 4 columns

Construindo dataset para criação do modelo

In [20]:
```
df_mod['correta'] = 0
df_mod['status_correto'] = 0
```

In [21]:
```
for i in range(len(df_mod)):
    if df_mod['Pred_class'][i] == df_mod['True_class'][i]:
        df_mod['correta'][i] = 1
    else:
        df_mod['correta'][i] = 0

for i in range(len(df_mod)):
    if df_mod['status'][i] == df_mod['correta'][i]:
        df_mod['status_correto'][i] = 1
    else:
        df_mod['status_correto'][i] = 0

df_mod
```

Out[21]:

	Pred_class	probabilidade	True_class	status	correta	status_correto
234	2	0.623210	52	1	0	0
428	2	0.969559	52	1	0	0

	Pred_class	probabilidade	True_class	status	correta	status_correto
210	60	0.580529	57	1	0	0
9	2	1.000000	52	1	0	0
518	74	0.443712	58	1	0	0
...	...	...	...	...	...	...
546	92	0.834073	4	1	0	0
277	17	0.964834	53	1	0	0
310	52	0.057740	52	1	1	1
137	74	1.000000	58	1	0	0
271	12	0.121687	52	1	0	0

In [22]:
```
df_mod.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 643 entries, 234 to 271
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Pred_class      643 non-null    int64
 1   probabilidade   643 non-null    float64
 2   True_class      643 non-null    int64
 3   status          643 non-null    int64
 4   correta         643 non-null    int64
 5   status_correto  643 non-null    int64
dtypes: float64(1), int64(5)
memory usage: 55.2 KB
```

In [23]:
```
df_mod.correta.value_counts()
```

Out[23]:
```
0    586
1     57
Name: correta, dtype: int64
```

In [24]:
```
df_mod.status_correto.value_counts()
```

Out[24]:
```
0    543
1    100
Name: status_correto, dtype: int64
```

Modelo

Criação

In [25]:
```
y = df_mod['status_correto']
X = df_mod.drop(columns=["status_correto"])

X_train, X_test, y_train, y_test =
model_selection.train_test_split(X,

y,

test_size = 0.3,

stratify=y,

random_state = 123)
```

In [26]:
```
classificador = RandomForestClassifier()
classificador.fit(X_train,y_train)
```

Out[26]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto
',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

Avaliação

In [27]:
```
X_revision = X[X['status']==0]
y_revision_test = df_mod[df_mod['status']==0]['status_correto']
display(X_revision.head())
display(y_revision_test.head())
```

	Pred_class	probabilidade	True_class	status	correta
628	3	0.351031	52	0	0
617	4	0.405327	52	0	0
635	36	0.285545	54	0	0
642	96	0.340740	60	0	0
633	17	0.506654	53	0	0

```
628    1
617    1
635    1
642    1
633    1
Name: status_correto, dtype: int64
```

In [28]:
```
y_predicted = classificador.predict(X_revision)
```

In [29]:
```
print('accuracy_score',accuracy_score(y_predicted,
y_revision_test))
print('balanced_accuracy_score',balanced_accuracy_score(y_predicte
y_revision_test))
print('hamming_loss',hamming_loss(y_predicted, y_revision_test))
print('precision_score', precision_score(y_predicted,
y_revision_test, labels=labels, average='macro'))
print('recall_score',recall_score(y_predicted, y_revision_test,
labels=labels, average='macro'))
print('f1_score',f1_score(y_predicted, y_revision_test,
labels=labels, average='macro'))
```

```
accuracy_score 1.0
balanced_accuracy_score 1.0
hamming_loss 0.0
precision_score 0.0
recall_score 0.0
f1_score 0.0
```

Conclusão

Não pode-se utilizar a falsa ilusão das métricas anteriores para validar o modelo, uma vez que, utilizou-se de "vazamento de informações" para treinar o modelo, e deste modo, o modelo teve este comportamento.

Dataset "NLP"

Realizou-se duas abordagens básicas, apenas para o início do projeto:

1. Construir um preditor de classes:

   a. utilizar algoritmos de classificação supervisionados;

   b. utilizar os algoritimos no seu modo "default";

   c. comparar os modelos através de algumas métricas;

   d. escolher o melhor modelo em seu formato "default".

2. Construir um preditor multilabel:

   a. neste caso em específico temos apenas letras de músicas de artistas individuais, mas poderíamos ter músicas com a participação de mais de um artista e deste modo, deveríamos fazer a classificação multilabel;

   b. utilizar algoritmos de classificação supervisionados;

c. utilizar os algoritimos no seu modo "default";

d. comparar os modelos através de duas métricas;

e. escolher o melhor modelo em seu formato "default".

3. Escolher a melhor abordagem:

a. treinar o modelo;

b. salvar o modelo treinado;

c. realizar algumas predições.

4. OBSERVAÇÃO: vale ressaltar que este é apenas um trabalho inicial, deve-se ainda:

a. melhorar a estrutura dos dados de entrada no modelo, utilizando-se de técnicas de PNL para "faxinar" os dados;

b. fazer stacking de modelos para verificar se obtemos uma melhora significativa;

c. obter os melhores hiperparâmetros dos melhores modelos para verificar se obtemos uma melhora significativa.

Preditor de Classes

Dados

In [30]:
```
df_nlp = pd.read_excel('teste_smarkio_lbs.xls',
sheet_name="NLP")
df_nlp.sample(20)
```

Out[30]:

	letra	artista
343	Mama, I found a man Who loves me and understan...	Rihanna
124	[Verse 1:] He's always laughing And flirting w...	Beyoncé
311	I came fluttering in from Neverland No, no, n...	Rihanna
231	[P. Diddy - talking] Yeah There's three things...	Beyoncé
283	(trecho) You're my sunrise My baby brown eyes...	Rihanna
224	My body is magnified In the sun set me alight ...	Beyoncé
287	[Rick Ross] Rick Rozay Rihanna Rich forever St...	Rihanna
330	Why do you call When I'm not feelin' you (baby...	Rihanna
97	I wish I could look in your eyes And tell you ...	Beyoncé
222	Yeah, yeah and the wind is talking Yeah, yeah ...	Beyoncé
187	Boy, you'll be the death to me You're my James...	Beyoncé
142	Listen, To the song here in my heart A melody ...	Beyoncé
4	Six inch heels She walked in the club like nob...	Beyoncé
457	All along it was a fever A cold sweat hot-head...	Rihanna

	letra	artista
122	When I First met you you told me exactly how i...	Beyoncé
138	Don't you worry about a club Just come and lay...	Beyoncé
392	Red lipstick, rose petals, heart break I was h...	Rihanna
459	Oh Stupid in love Oh Stupid in love Let me te...	Rihanna
373	I'd rather be smoking weed Whenever we breathe...	Rihanna

In [31]:
```
df_nlp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 518 entries, 0 to 517
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   letra    518 non-null    object
 1   artista  518 non-null    object
dtypes: object(2)
memory usage: 8.2+ KB
```

In [32]:
```
df_nlp.artista.unique()
```

Out[32]:
```
array(['Beyoncé', 'Rihanna'], dtype=object)
```

In [33]:
```
df_nlp.artista.value_counts()
```

Out[33]:
```
Beyoncé    274
Rihanna    244
Name: artista, dtype: int64
```

In [34]:
```
df_nlp['target'] = df_nlp['artista'].map({'Rihanna' :
0,'Beyoncé' : 1})
y = df_nlp.target
df_nlp.sample(20)
```

Out[34]:

	letra	artista	target
379	Kiss it, kiss it better, baby Kiss it, kiss it...	Rihanna	0
517	[Rihanna] I remember when the world was just m...	Rihanna	0
154	I've been watching for the signs Took a trip t...	Beyoncé	1
489	Yellow diamonds in the light And we're standin...	Rihanna	0
103	Recuerde que esos muros que construí Así que s...	Beyoncé	1
485	You can say that I'm not perfect If you tell m...	Rihanna	0
50	Oh killing me softly And I'm still falling, st...	Beyoncé	1
342	[Rihanna] I came to win, to fight, to conquer,...	Rihanna	0
384	Aw, Aw, Aw, Rihanna Ey, Ey Dreamer Aw, Aw, Ey,...	Rihanna	0
270	I said yes to your number And yes to you datin...	Beyoncé	1
493	I've been ignoring this big lump in my throat ...	Rihanna	0

	letra	artista	target
88	I'm a train wreck in the morning I'm a Bitch i...	Beyoncé	1
123	Feels like I'm losing my mind Love is so hard ...	Beyoncé	1
229	[B] Yo where the brother by my side at? [M] Yo...	Beyoncé	1
312	Who am I living for? Is this my limit? Can I e...	Rihanna	0
439	[Rihanna] Na-na-na, come on Na-na-na, come on ...	Rihanna	0
387	What am I supposed to do with this heart (with...	Rihanna	0
214	I read all of the magazines While waiting arou...	Beyoncé	1
24	Oh, Beyonce, Beyonce Oh, Shakira, Shakira (Hey...	Beyoncé	1

In [35]:
```
def vetorizador_transform(X, metodo, max_features, max_df):
    vetorizar = metodo(max_features=max_features,max_df=max_df,
stop_words='english')
    X_df =
pd.DataFrame.sparse.from_spmatrix(vetorizar.fit_transform(X),

columns=vetorizar.get_feature_names())
    return X_df
```

In [36]:
```
#modelos a serem utilizados no modo default
models = [LogisticRegression,
          SGDClassifier,
          RidgeClassifier,
          KNeighborsClassifier,
          MultinomialNB,
          SVC,
          RandomForestClassifier,
          GradientBoostingClassifier,
          BaggingClassifier,
          ExtraTreesClassifier,
          AdaBoostClassifier,
          xgboost.XGBClassifier,
          MLPClassifier]

#metricas iniciais
scores = ['accuracy','precision','recall','f1']
```

In [37]:
```
colunas_scoring = ['model','AUC']

for i in range(len(scores)):

colunas_scoring.extend(['avg_'+scores[i],'std_'+scores[i]])

colunas_scoring
```

Out[37]:
```
['model',
 'AUC',
 'avg_accuracy',
 'std_accuracy',
 'avg_precision',
 'std_precision',
 'avg_recall',
 'std_recall',
 'avg_f1',
 'std_f1']
```

In [38]:
```
def best_scores(df_scoring,score):
    print("Máximo ===", score)
    best_score = df_scoring['avg_'+score].max()
    return
display(df_scoring[df_scoring['avg_'+score]==best_score])
```

In [39]:

```
def comparar_modelos(lista_modelos, X, X_train,X_test, y,
y_train, y_test, lista_scores):

    scoring = pd.DataFrame(columns=colunas_scoring)
    scoring['model'] = lista_modelos
    models_names = []
    lista_auc = []

    cont_models = 0
    for model in lista_modelos:
        models_names.append(model.__name__)
        cls = model()
        kfold = model_selection.StratifiedKFold(n_splits=5,
shuffle=True, random_state=42)

        cont_scores = 0
        for score in lista_scores:
            s = model_selection.cross_val_score(cls, X, y,
scoring=score, cv=kfold)
            scoring['avg_' + scores[cont_scores]][cont_models] =
s.mean()
            scoring['std_' + scores[cont_scores]][cont_models] =
s.std()
            cont_scores += 1

        print('====='+ model.__name__+' default'+'=====')
        cls.fit(X_train, y_train)
        y_predicted = cls.predict(X_test)
        roc_auc = roc_auc_score(y_test,y_predicted)
        lista_auc.append(roc_auc)
        print(classification_report(y_test,
                                    y_predicted,
                                    target_names=["Rihanna",
"Beyoncé"]))
        fpr, tpr, thresold = roc_curve(y_test, y_predicted)

        plt.plot(fpr, tpr, lw = 1)
        plt.plot([0,1],[0,1], '--', color=(0.6, 0.6, 0.6),
label="sorte")
        plt.xlim([-0.05,1.05])
        plt.ylim([-0.05,1.05])
```

```
        mapping = {0: "Rihanna", 1: "Beyoncé"}
        fig, ax = plt.subplots(figsize=(6, 6))
        cm_viz = ConfusionMatrix(cls, classes=["Rihanna",
"Beyoncé"], label_encoder=mapping)
        cm_viz.score(X_test, y_test)
        cm_viz.poof()

        cont_models += 1

    scoring['model'] = models_names
    scoring['AUC'] = lista_auc

    for i in range(len(scores)):
        best_scores(scoring,scores[i])

    print("====Resumo de Métricas (cross_val_score)====")
    return scoring
```

Análise de diferentes vetorizações

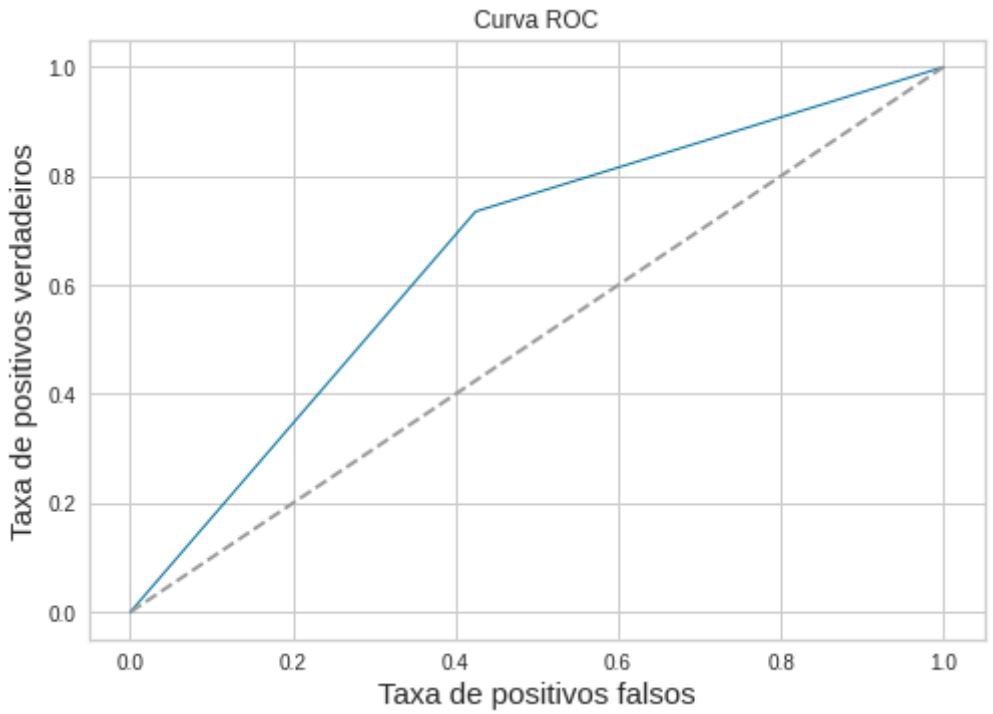
CountVectorizer

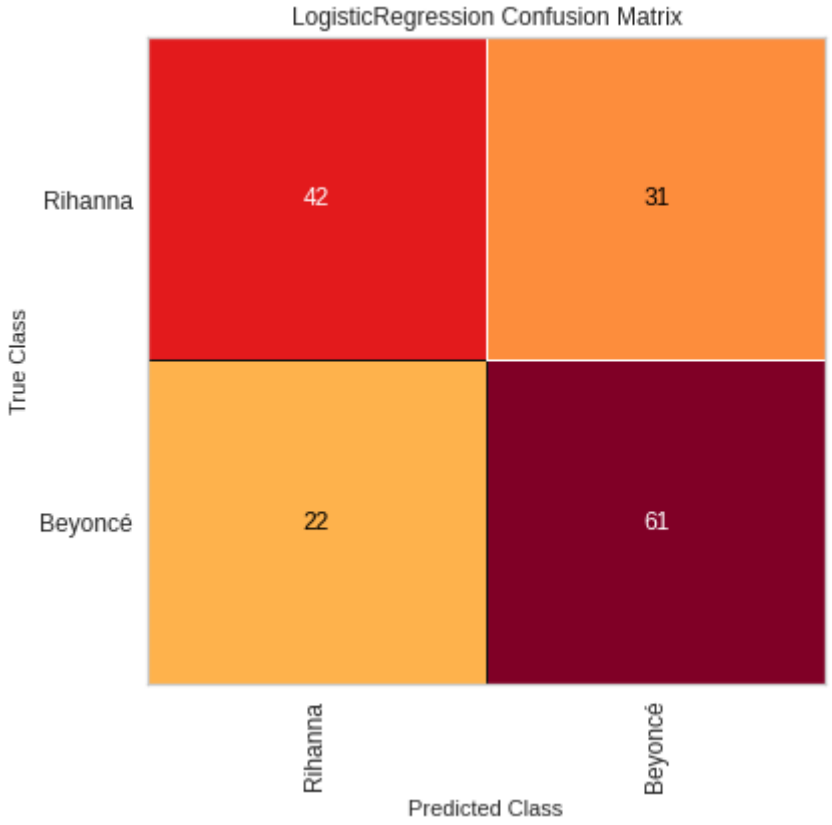
In [40]:

```
X_cvec = vetorizador_transform(df_nlp.letra,CountVectorizer,
4000, 0.85)

X_train, X_test, y_train, y_test =
model_selection.train_test_split(X_cvec,

y,

test_size = 0.3,

stratify=y,

random_state = 123)
```

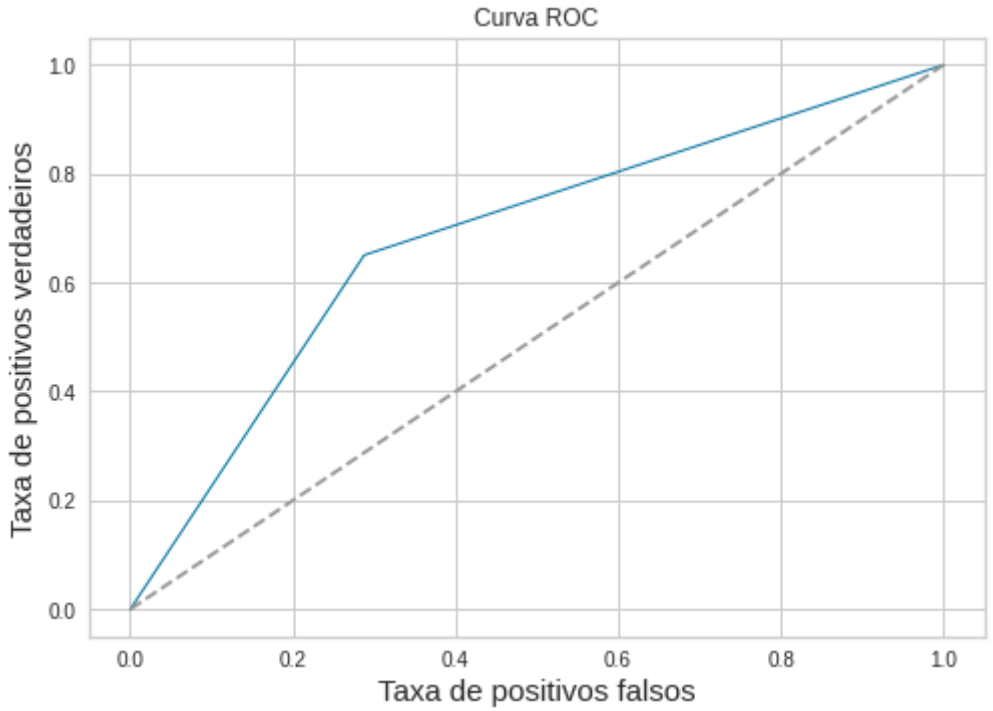
In [41]:
```
comparar_modelos(models, X_cvec, X_train,X_test, y, y_train,
y_test, scores)
```

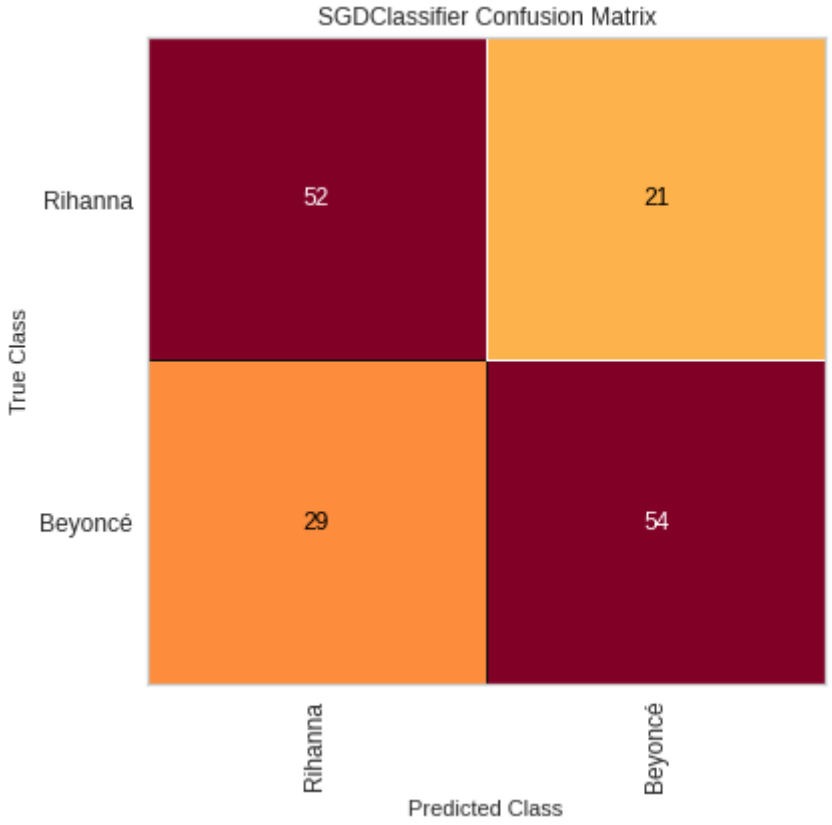
```
=====LogisticRegression default=====
              precision    recall  f1-score   support

     Rihanna       0.66      0.58      0.61        73
     Beyoncé       0.66      0.73      0.70        83

    accuracy                           0.66       156
   macro avg       0.66      0.66      0.66       156
weighted avg       0.66      0.66      0.66       156
```



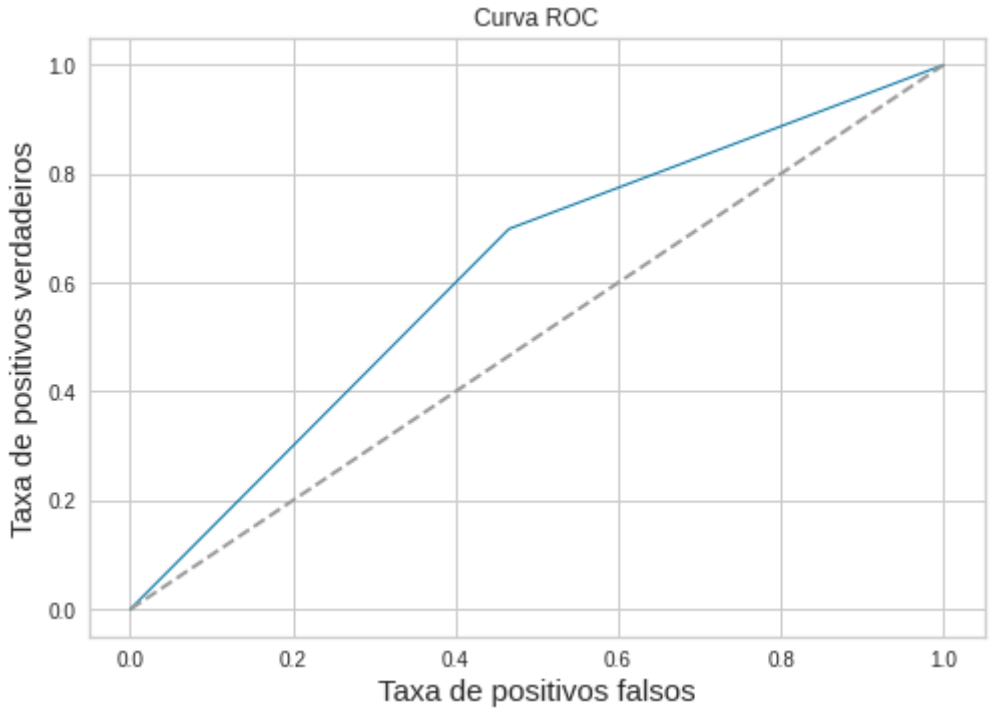


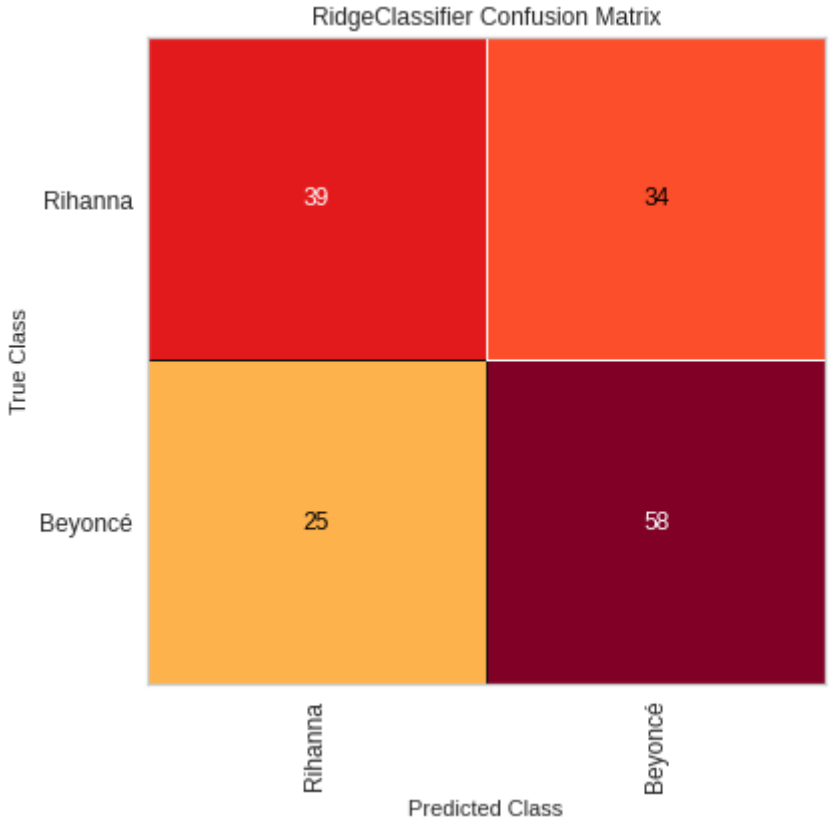

```
=====SGDClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.64      0.71      0.68        73
     Beyoncé       0.72      0.65      0.68        83

    accuracy                           0.68       156
   macro avg       0.68      0.68      0.68       156
weighted avg       0.68      0.68      0.68       156
```



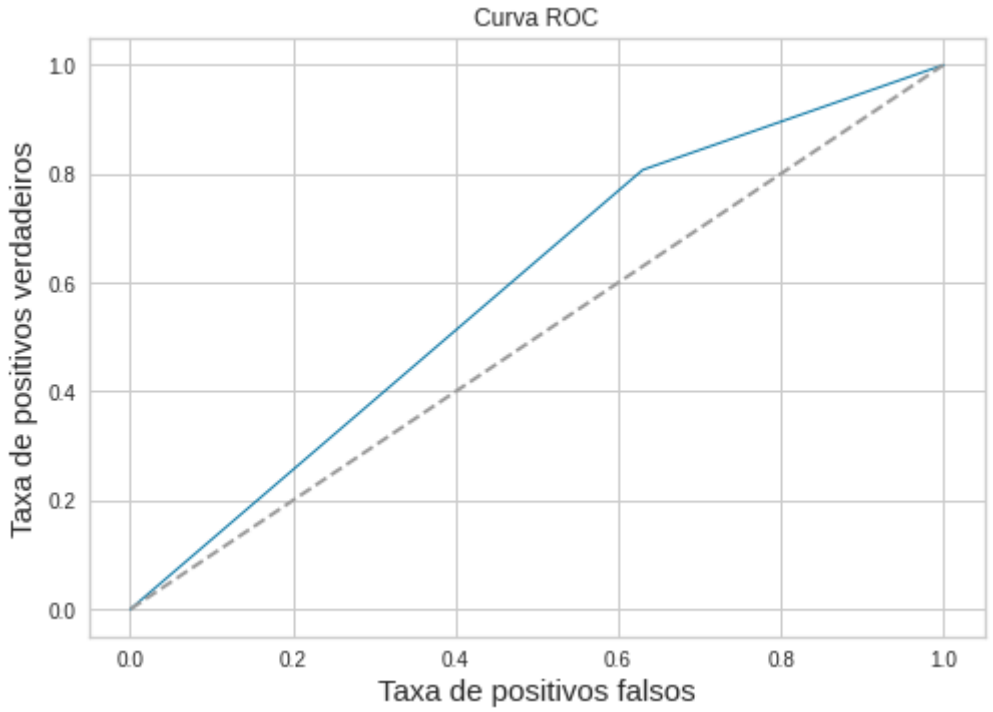


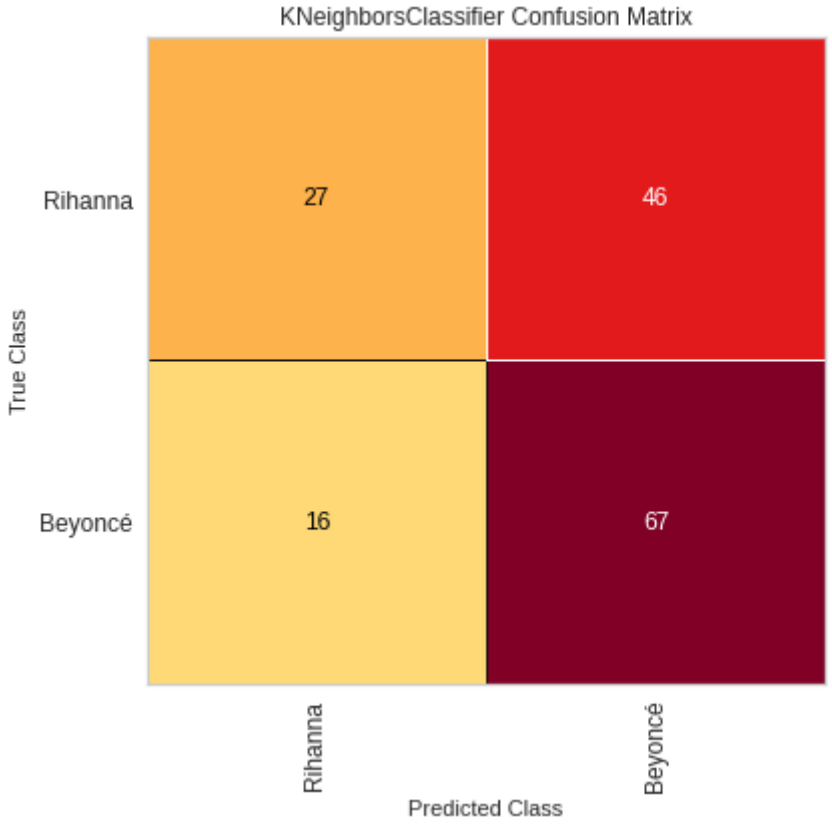

```
=====RidgeClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.61      0.53      0.57        73
     Beyoncé       0.63      0.70      0.66        83

    accuracy                           0.62       156
   macro avg       0.62      0.62      0.62       156
weighted avg       0.62      0.62      0.62       156
```



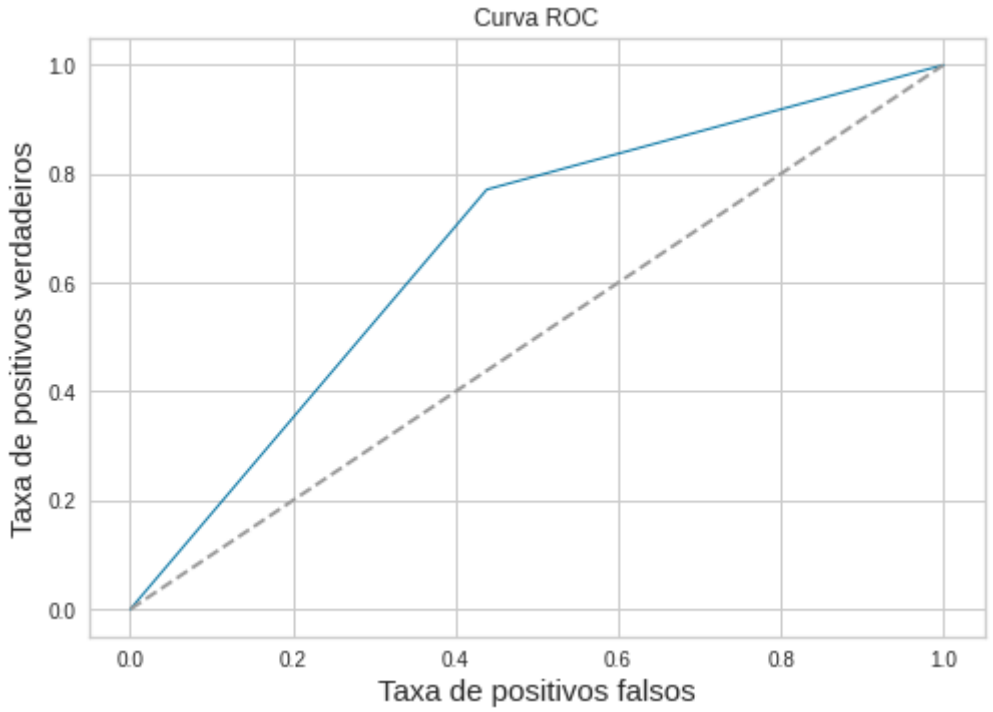


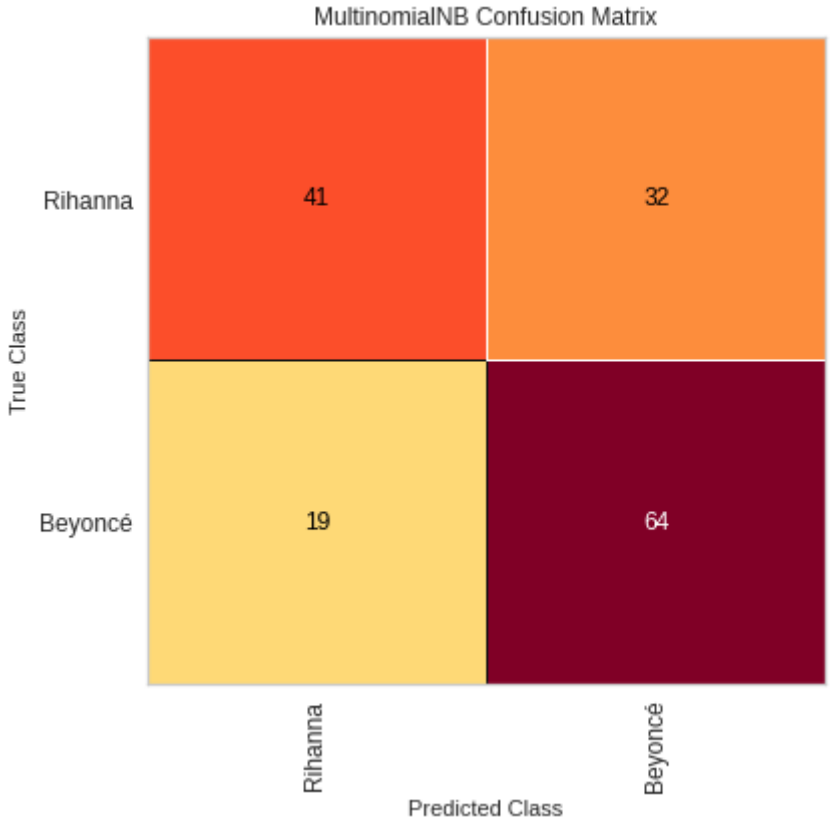

```
=====KNeighborsClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.63      0.37      0.47        73
     Beyoncé       0.59      0.81      0.68        83

    accuracy                           0.60       156
   macro avg       0.61      0.59      0.57       156
weighted avg       0.61      0.60      0.58       156
```



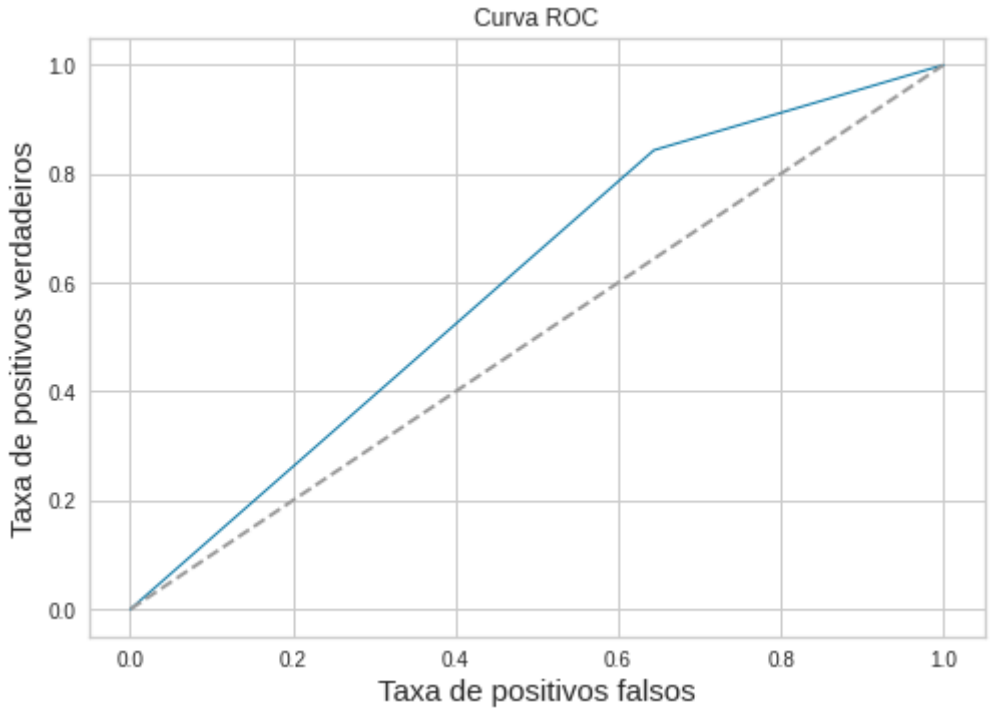


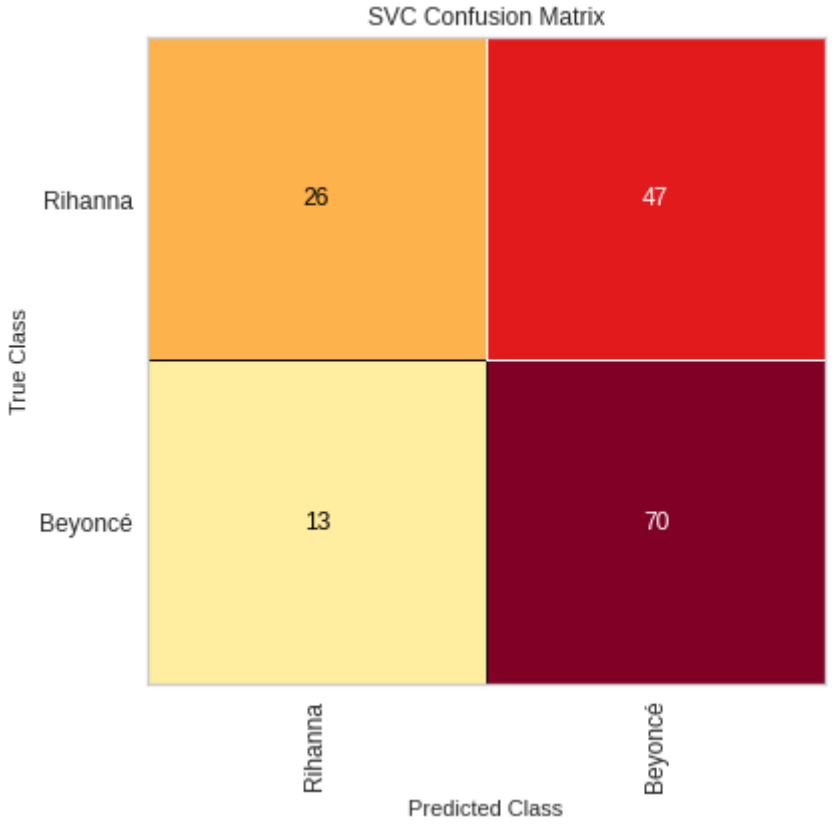

```
=====MultinomialNB default=====
              precision    recall  f1-score   support

     Rihanna       0.68      0.56      0.62        73
     Beyoncé       0.67      0.77      0.72        83

    accuracy                           0.67       156
   macro avg       0.68      0.67      0.67       156
weighted avg       0.67      0.67      0.67       156
```



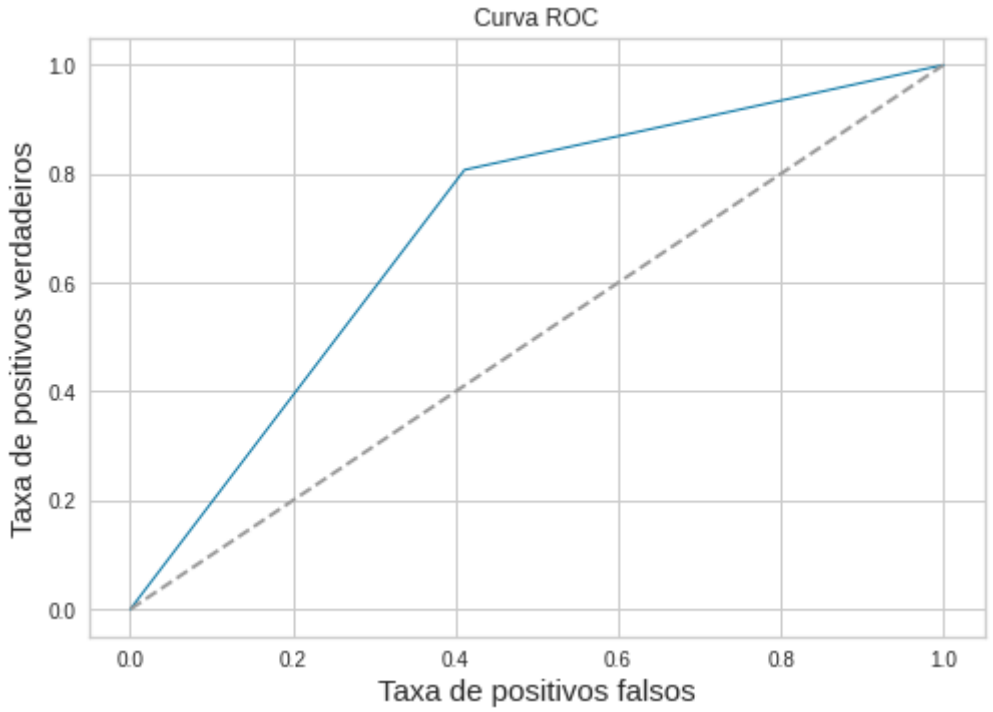


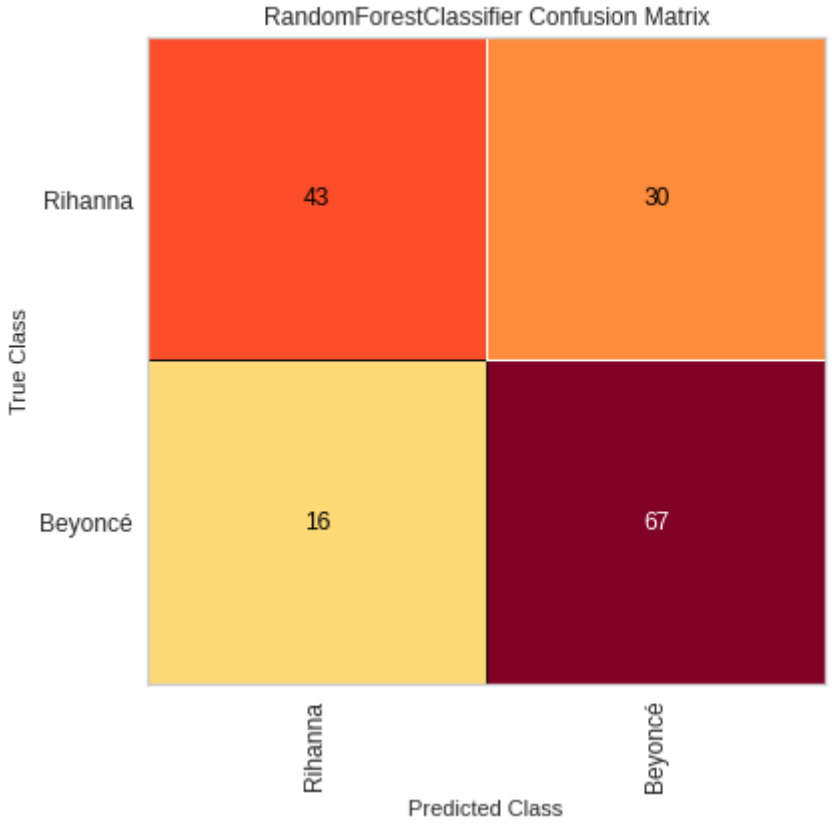

```
=====SVC default=====
              precision    recall  f1-score   support

     Rihanna       0.67      0.36      0.46        73
     Beyoncé       0.60      0.84      0.70        83

    accuracy                           0.62       156
   macro avg       0.63      0.60      0.58       156
weighted avg       0.63      0.62      0.59       156
```



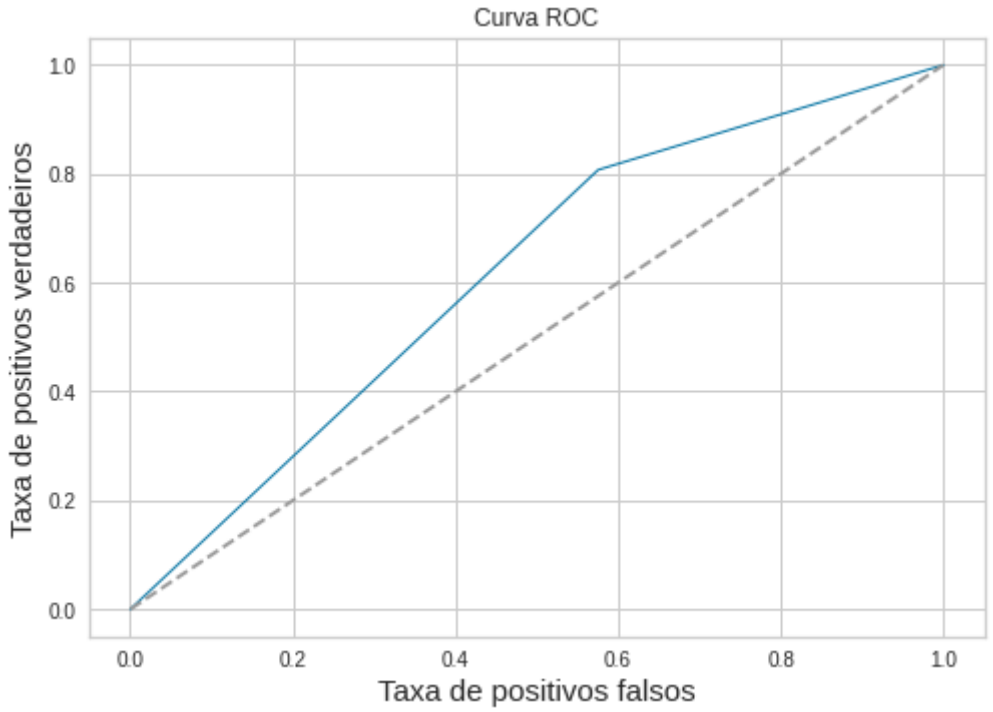


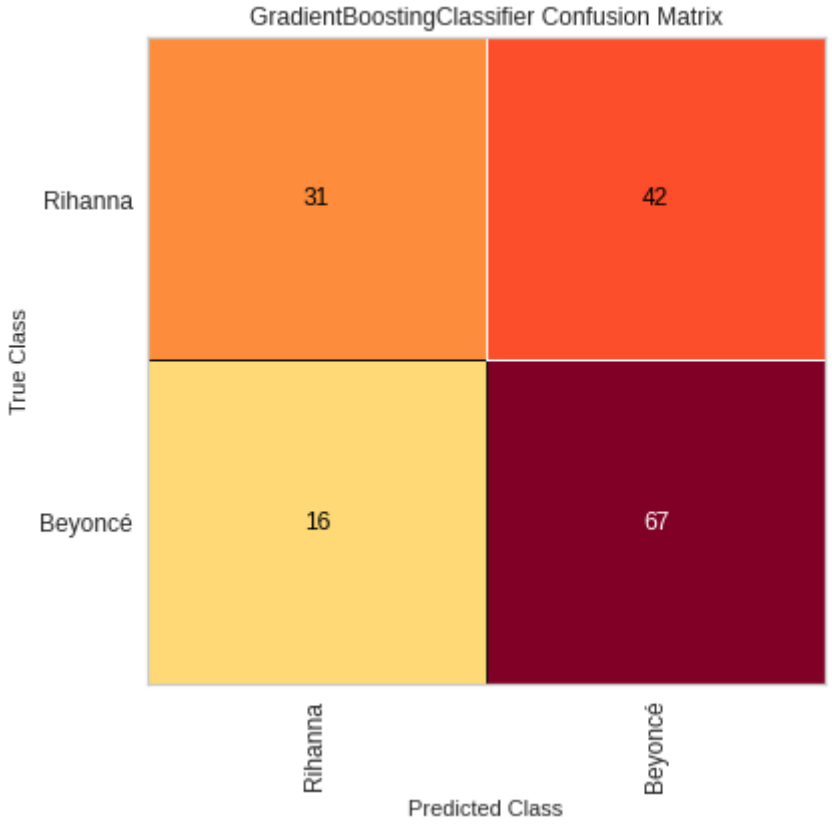

```
=====RandomForestClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.73      0.59      0.65        73
     Beyoncé       0.69      0.81      0.74        83

    accuracy                           0.71       156
   macro avg       0.71      0.70      0.70       156
weighted avg       0.71      0.71      0.70       156
```



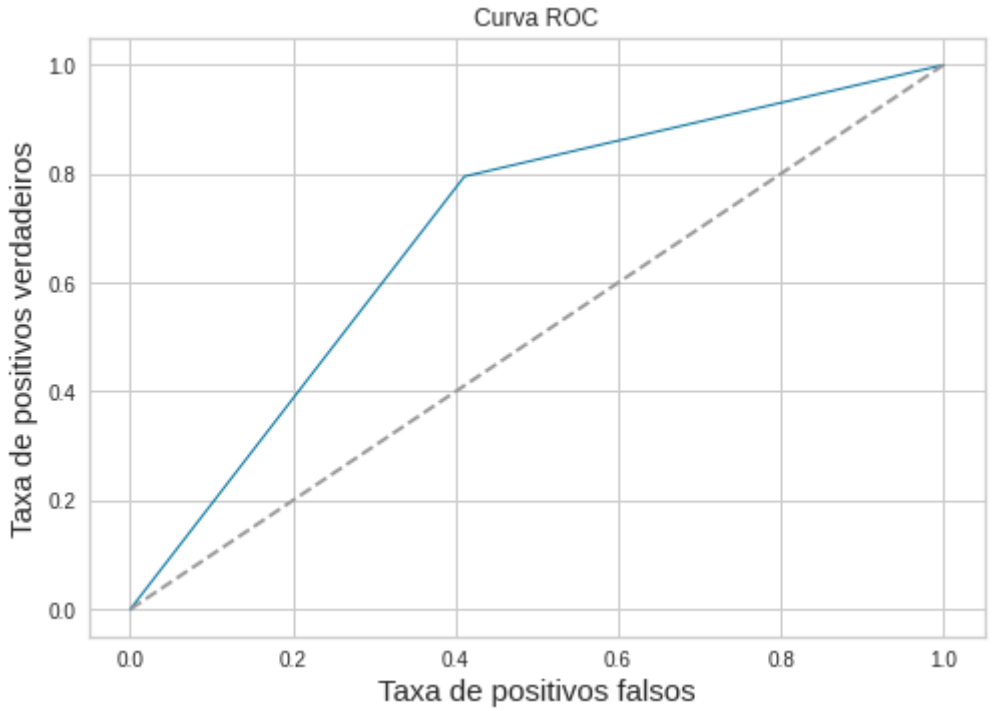


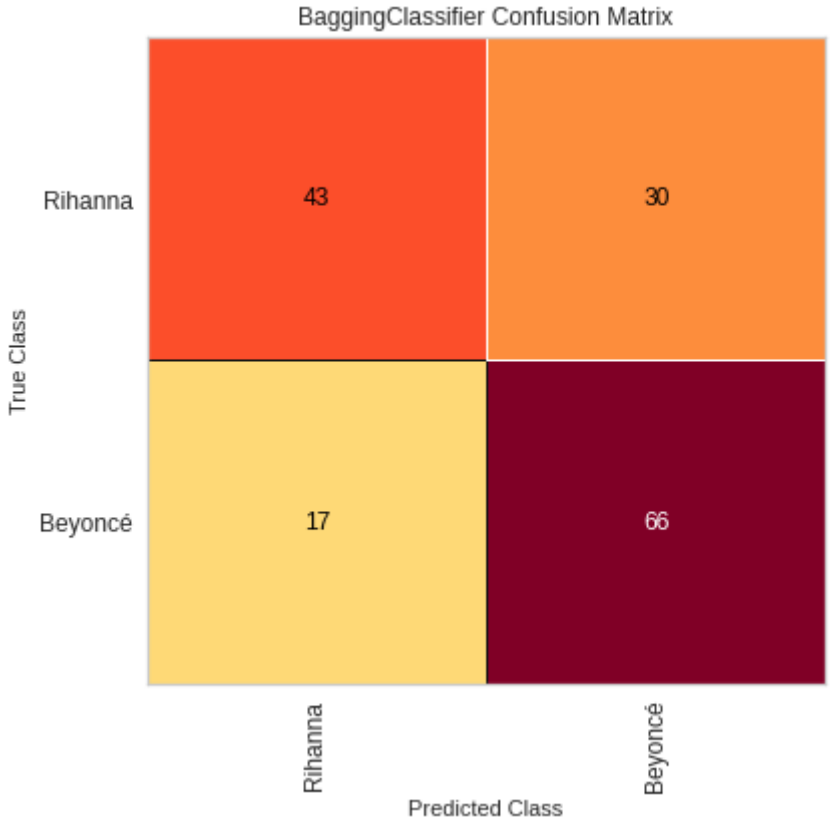

```
=====GradientBoostingClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.66      0.42      0.52        73
     Beyoncé       0.61      0.81      0.70        83

    accuracy                           0.63       156
   macro avg       0.64      0.62      0.61       156
weighted avg       0.64      0.63      0.61       156
```



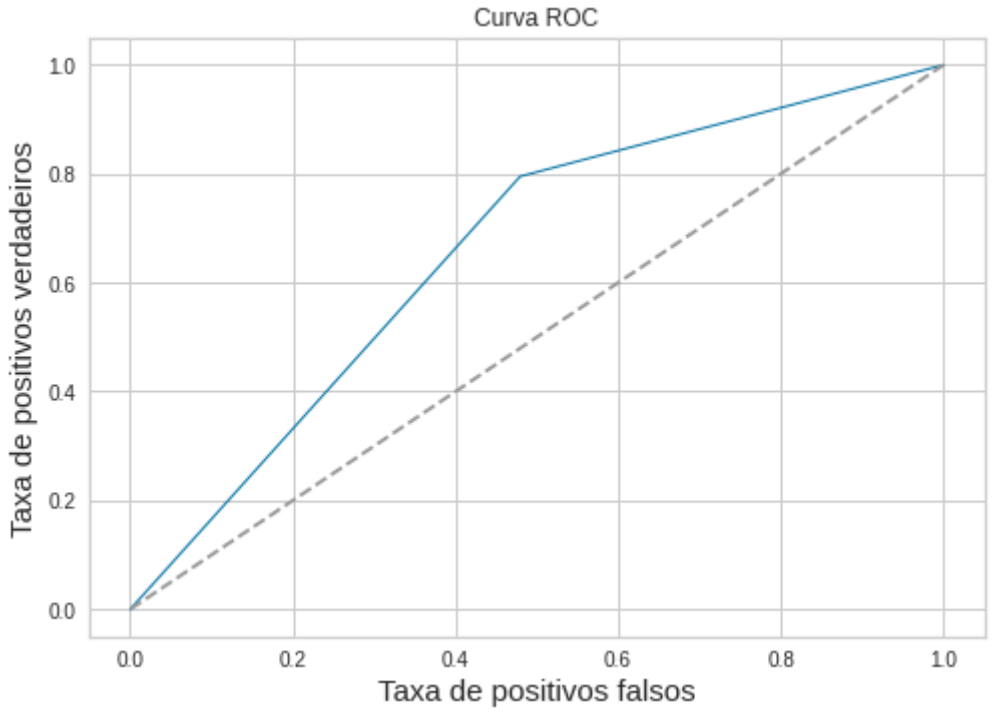


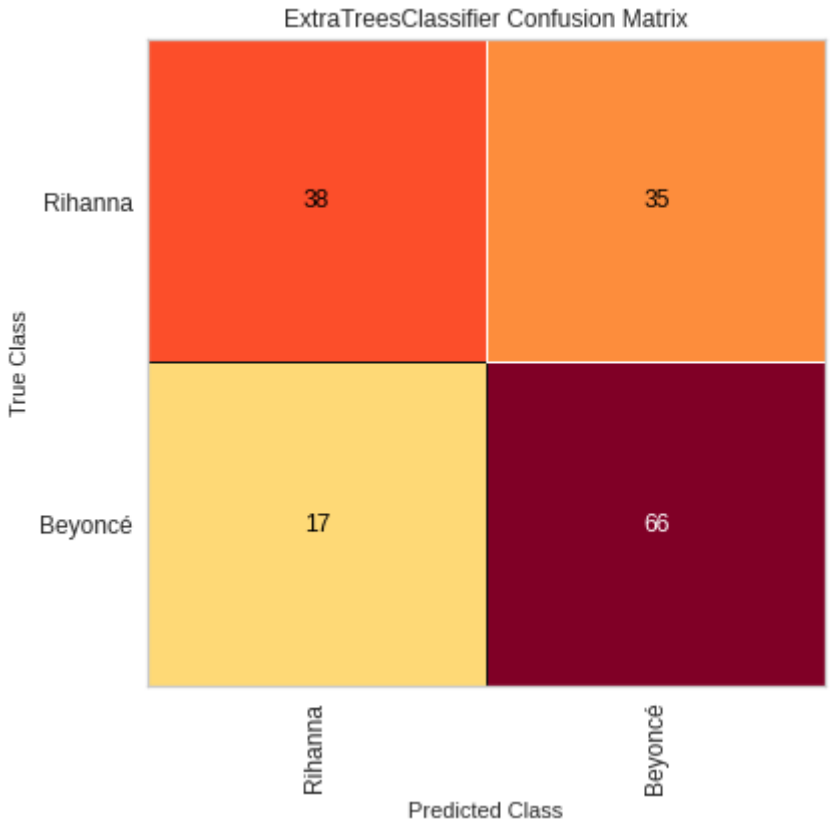

```
=====BaggingClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.72      0.59      0.65        73
     Beyoncé       0.69      0.80      0.74        83

    accuracy                           0.70       156
   macro avg       0.70      0.69      0.69       156
weighted avg       0.70      0.70      0.69       156
```



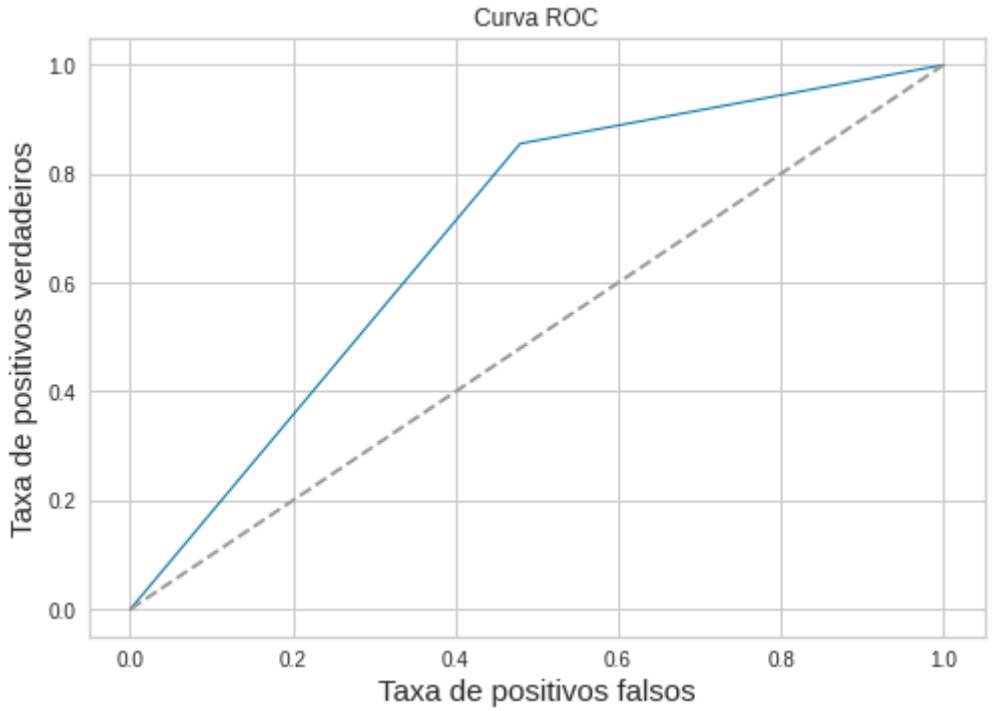


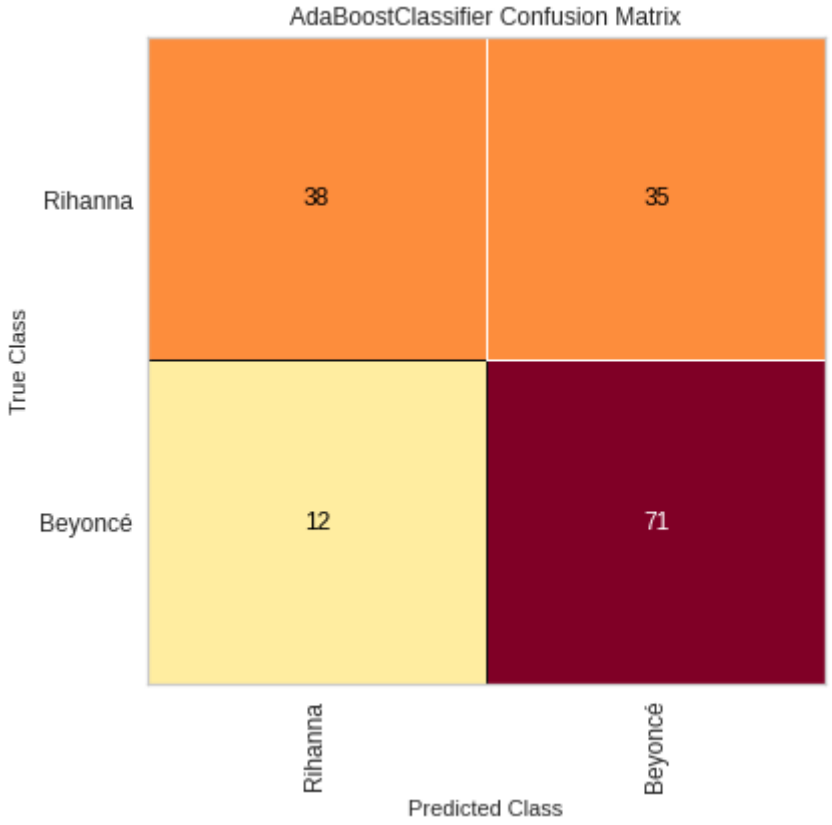

```
=====ExtraTreesClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.69      0.52      0.59        73
     Beyoncé       0.65      0.80      0.72        83

    accuracy                           0.67       156
   macro avg       0.67      0.66      0.66       156
weighted avg       0.67      0.67      0.66       156
```



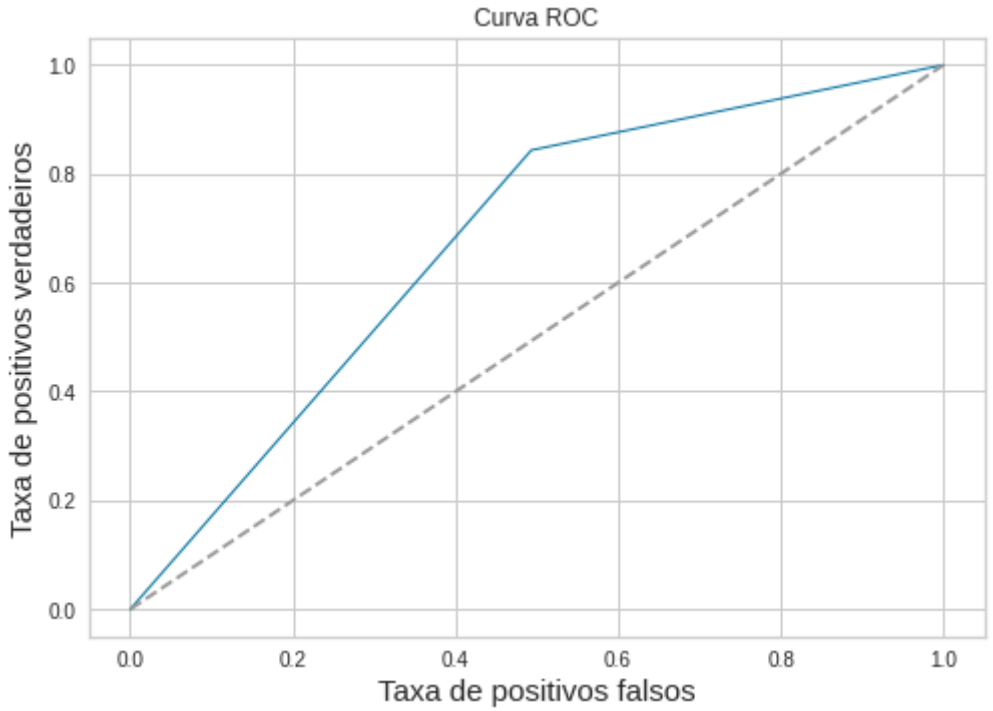


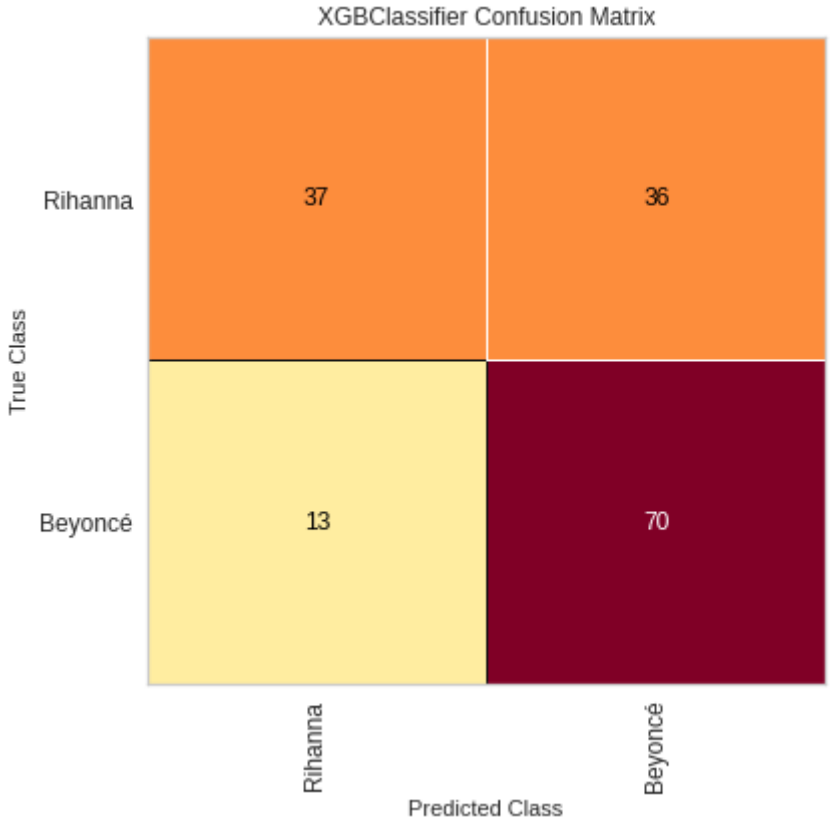

```
=====AdaBoostClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.76      0.52      0.62        73
     Beyoncé       0.67      0.86      0.75        83

    accuracy                           0.70       156
   macro avg       0.71      0.69      0.68       156
weighted avg       0.71      0.70      0.69       156
```



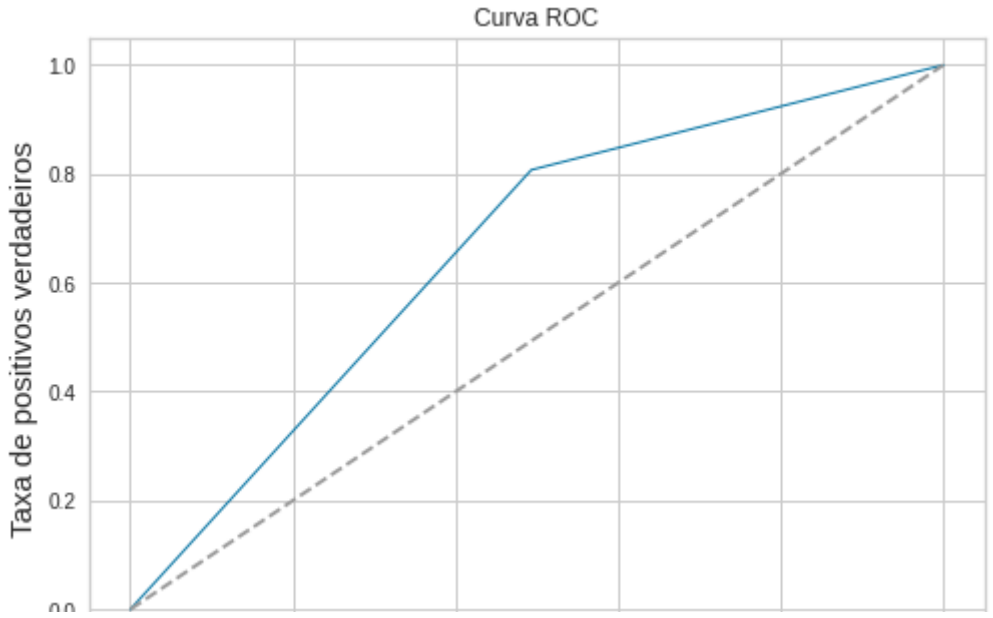



```
=====XGBClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.74      0.51      0.60        73
     Beyoncé       0.66      0.84      0.74        83

    accuracy                           0.69       156
   macro avg       0.70      0.68      0.67       156
weighted avg       0.70      0.69      0.68       156
```






```
=====MLPClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.70      0.51      0.59        73
     Beyoncé       0.65      0.81      0.72        83

    accuracy                           0.67       156
   macro avg       0.67      0.66      0.65       156
weighted avg       0.67      0.67      0.66       156
```

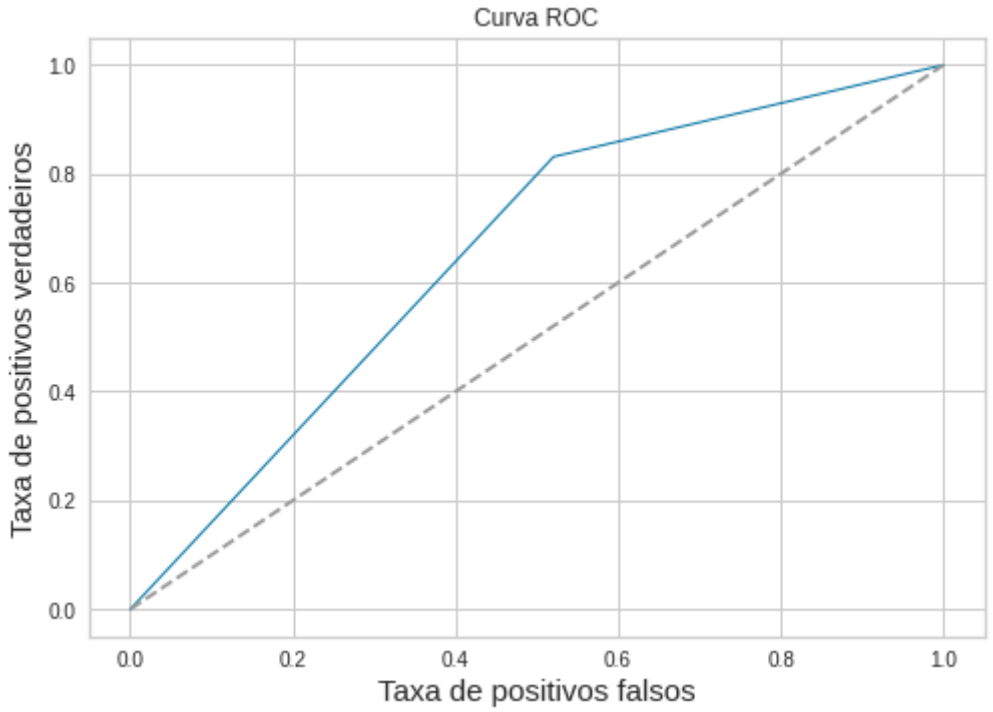


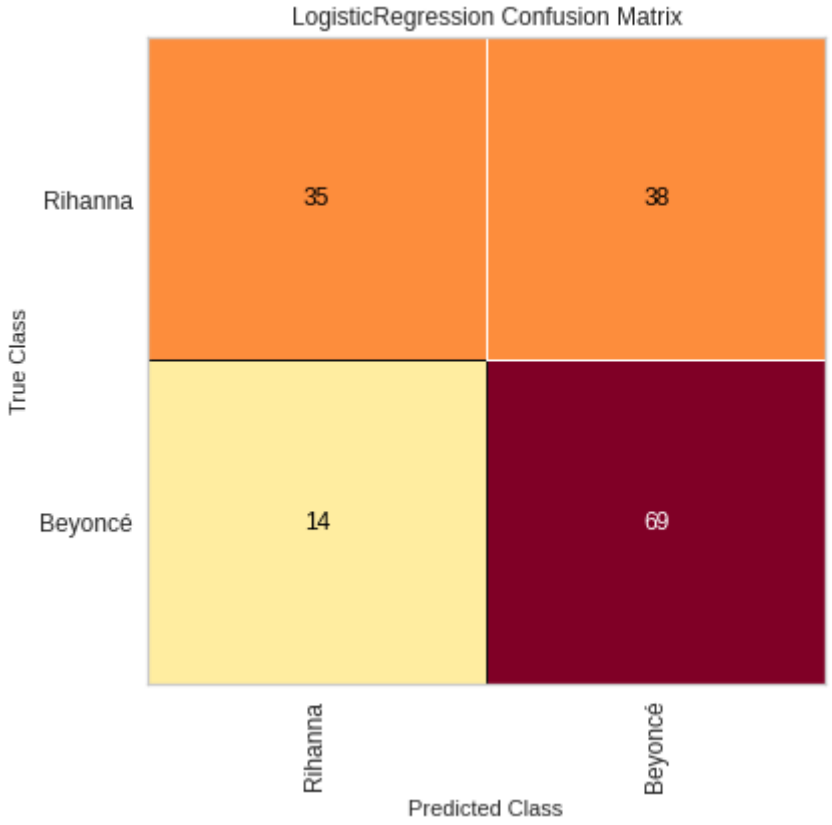
TfidfVectorizer

In [42]:
```
X_tfidfv = vetorizador_transform(df_nlp.letra,TfidfVectorizer,
4000, 0.85)

X_train, X_test, y_train, y_test =
model_selection.train_test_split(X_tfidfv,

y,

test_size = 0.3,

stratify=y,

random_state = 123)
```

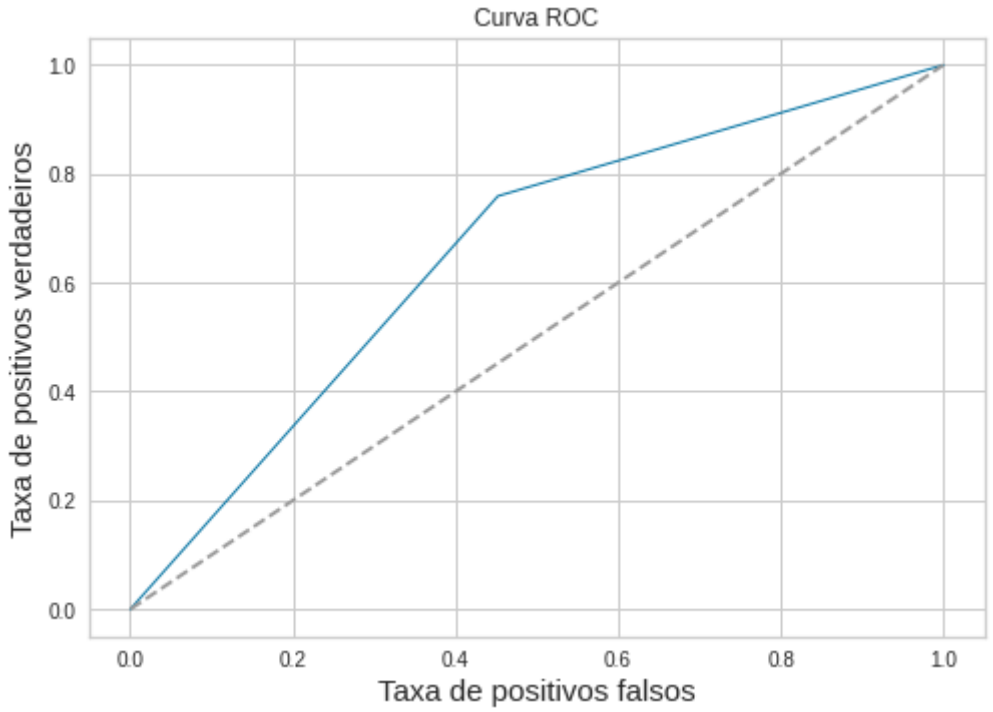
In [43]:
```
comparar_modelos(models, X_tfidfv, X_train,X_test, y, y_train,
y_test, scores)
```

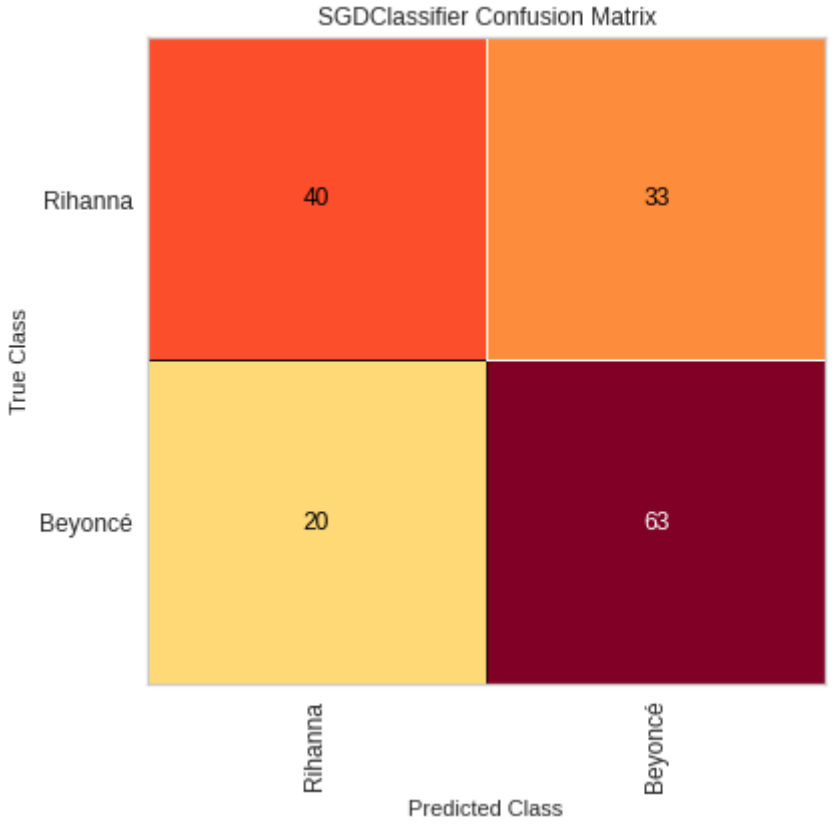
```
=====LogisticRegression default=====
              precision    recall  f1-score   support

     Rihanna       0.71      0.48      0.57        73
     Beyoncé       0.64      0.83      0.73        83

    accuracy                           0.67       156
   macro avg       0.68      0.66      0.65       156
weighted avg       0.68      0.67      0.65       156
```



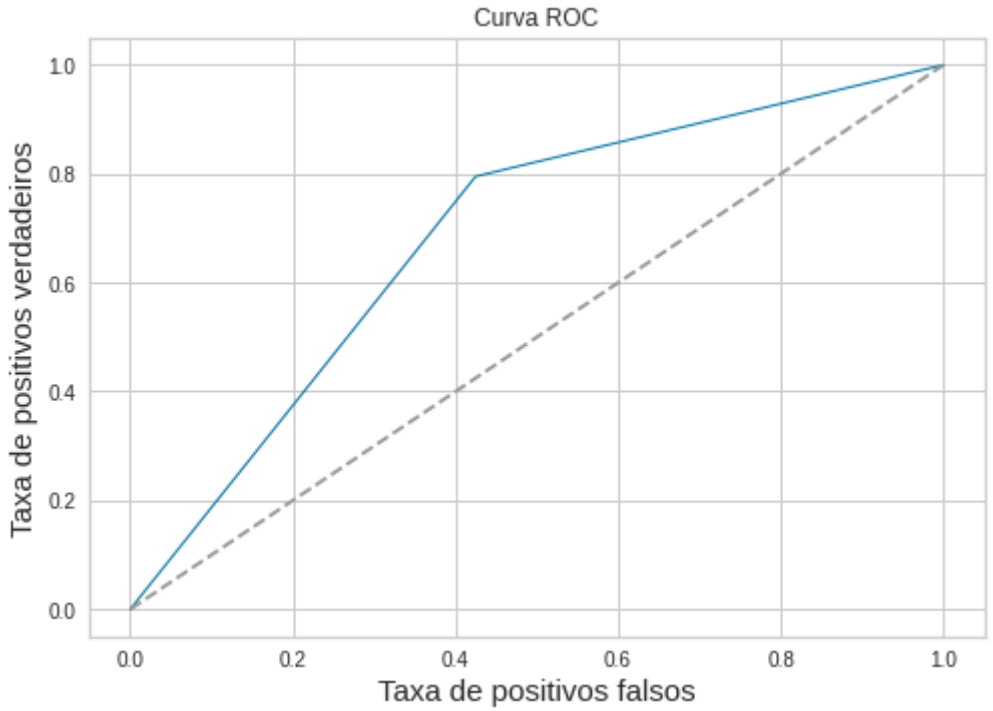


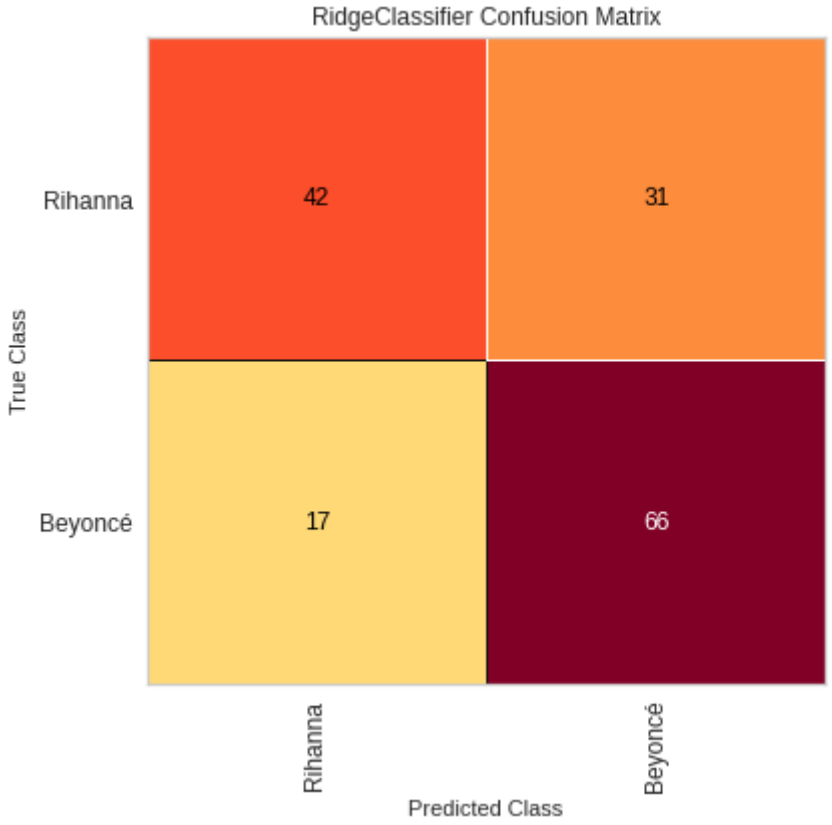

```
=====SGDClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.67      0.55      0.60        73
     Beyoncé       0.66      0.76      0.70        83

    accuracy                           0.66       156
   macro avg       0.66      0.65      0.65       156
weighted avg       0.66      0.66      0.66       156
```



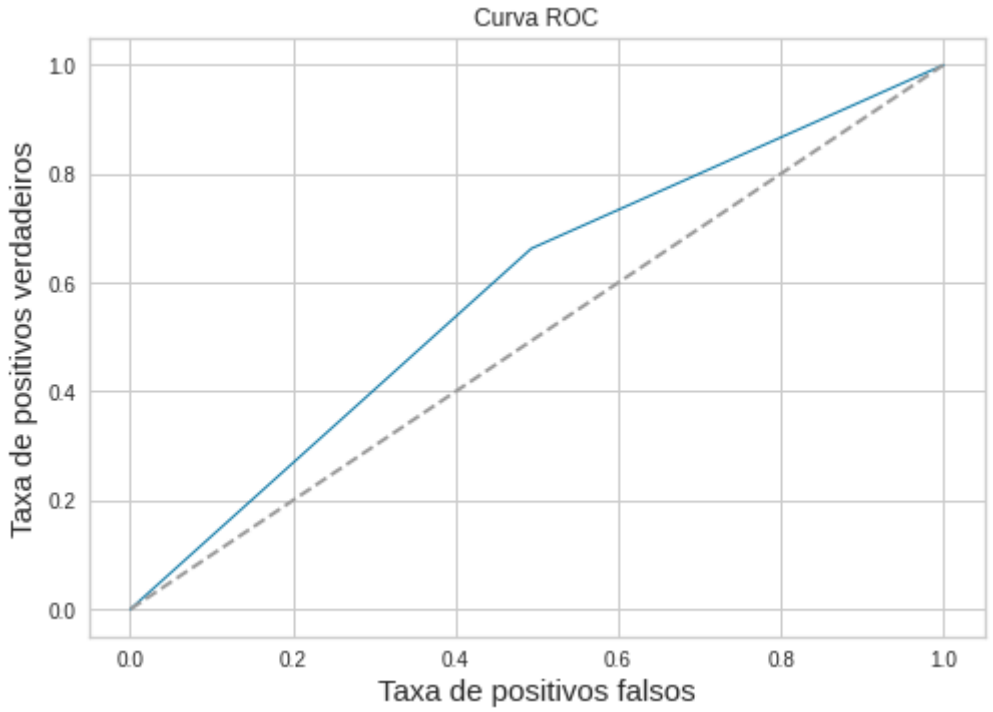


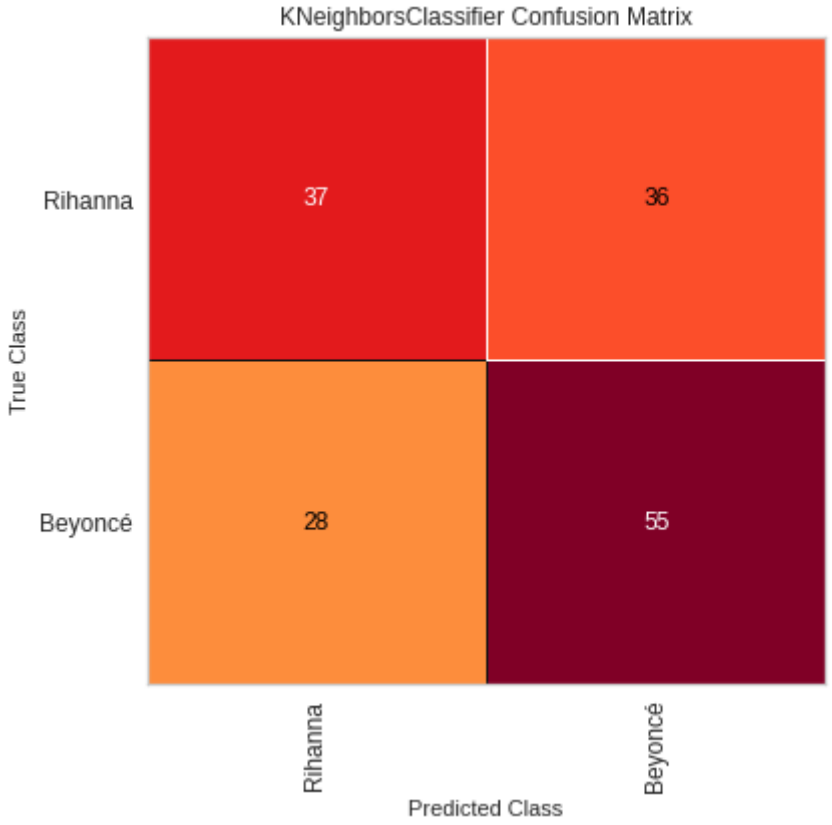

```
=====RidgeClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.71      0.58      0.64        73
     Beyoncé       0.68      0.80      0.73        83

    accuracy                           0.69       156
   macro avg       0.70      0.69      0.68       156
weighted avg       0.70      0.69      0.69       156
```



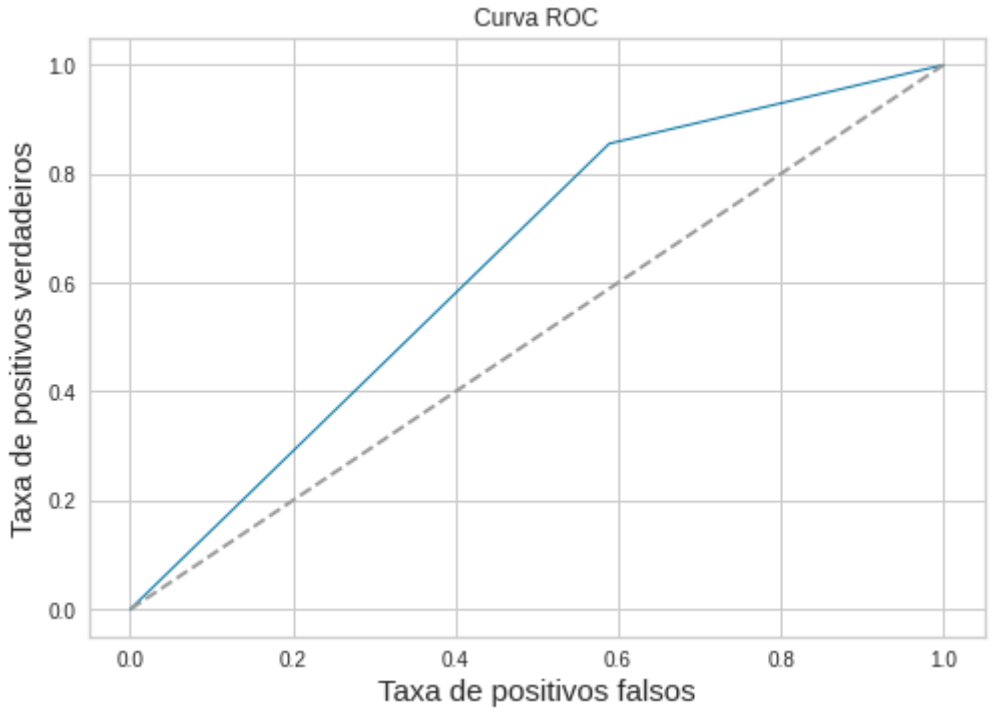


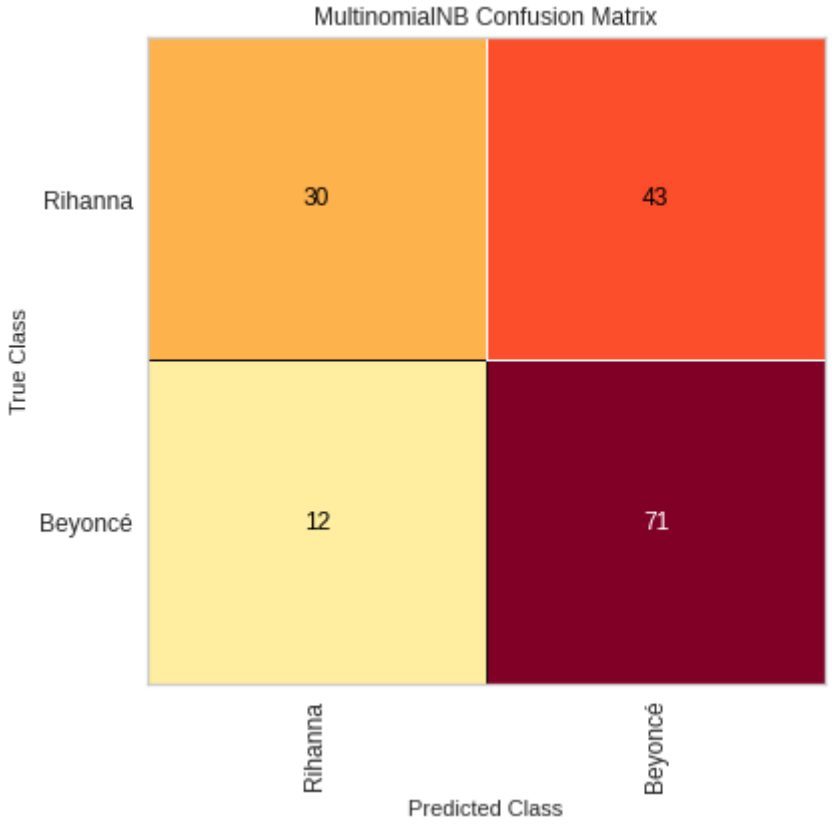

```
=====KNeighborsClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.57      0.51      0.54        73
     Beyoncé       0.60      0.66      0.63        83

    accuracy                           0.59       156
   macro avg       0.59      0.58      0.58       156
weighted avg       0.59      0.59      0.59       156
```



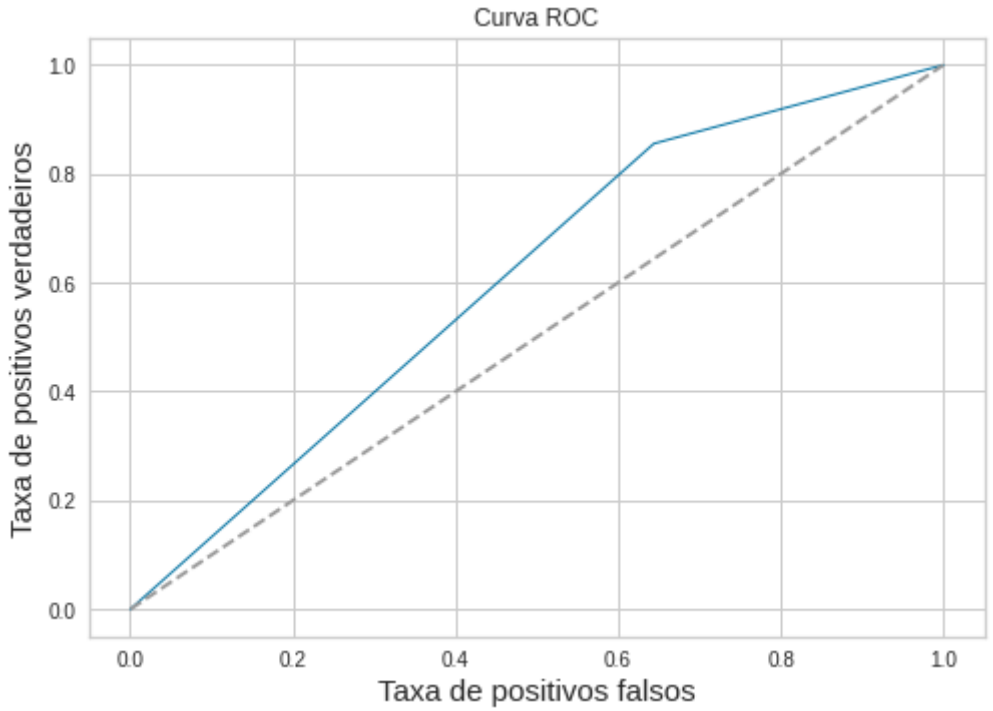


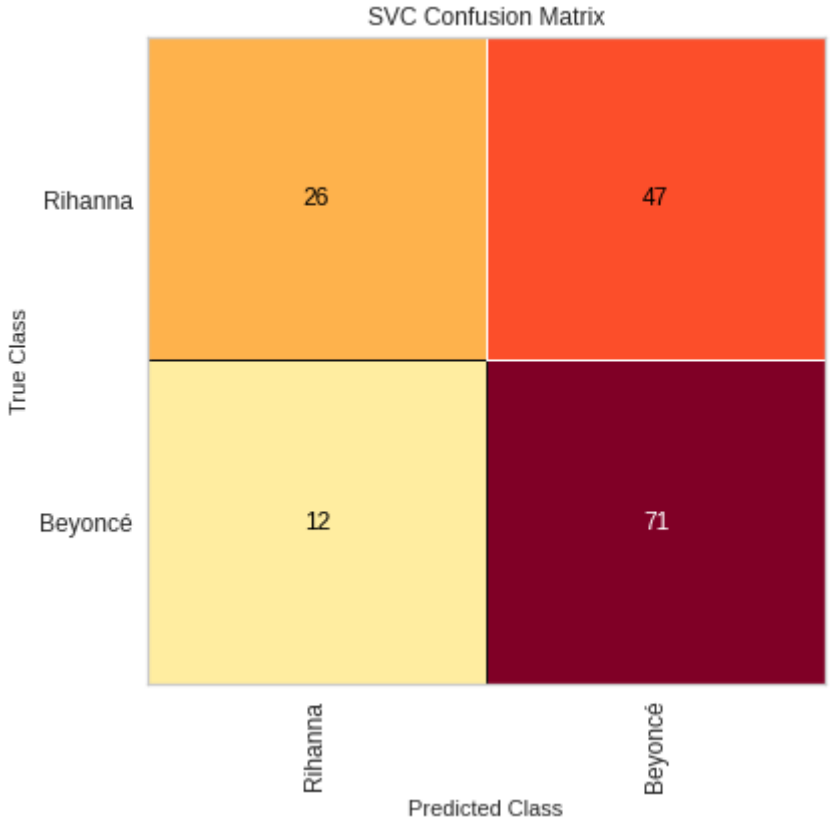

```
=====MultinomialNB default=====
              precision    recall  f1-score   support

     Rihanna       0.71      0.41      0.52        73
     Beyoncé       0.62      0.86      0.72        83

    accuracy                           0.65       156
   macro avg       0.67      0.63      0.62       156
weighted avg       0.67      0.65      0.63       156
```



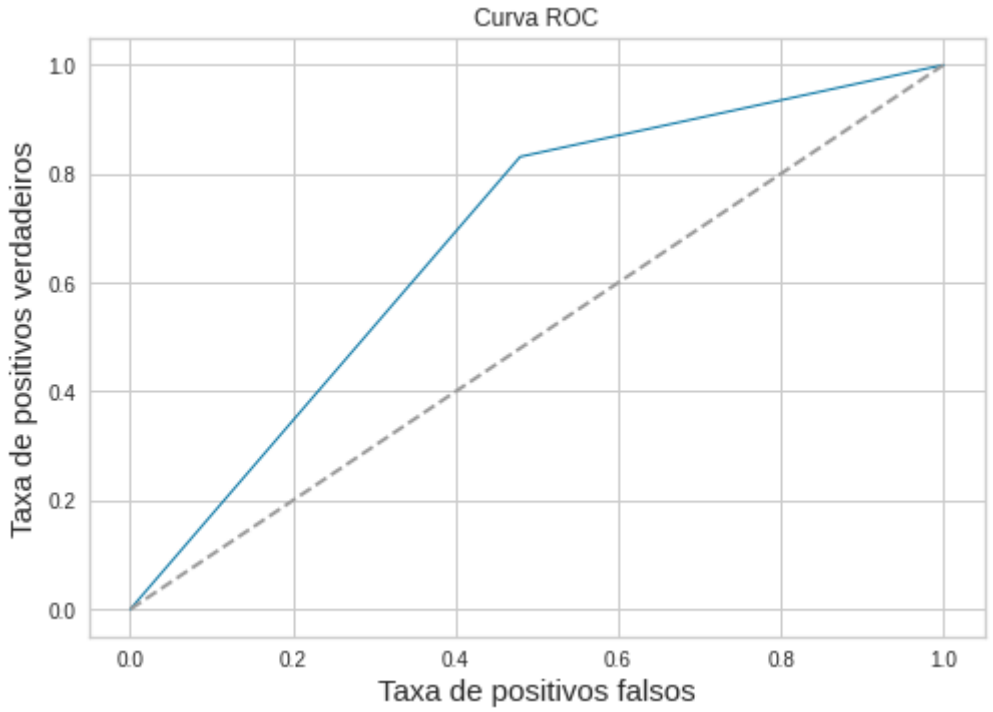


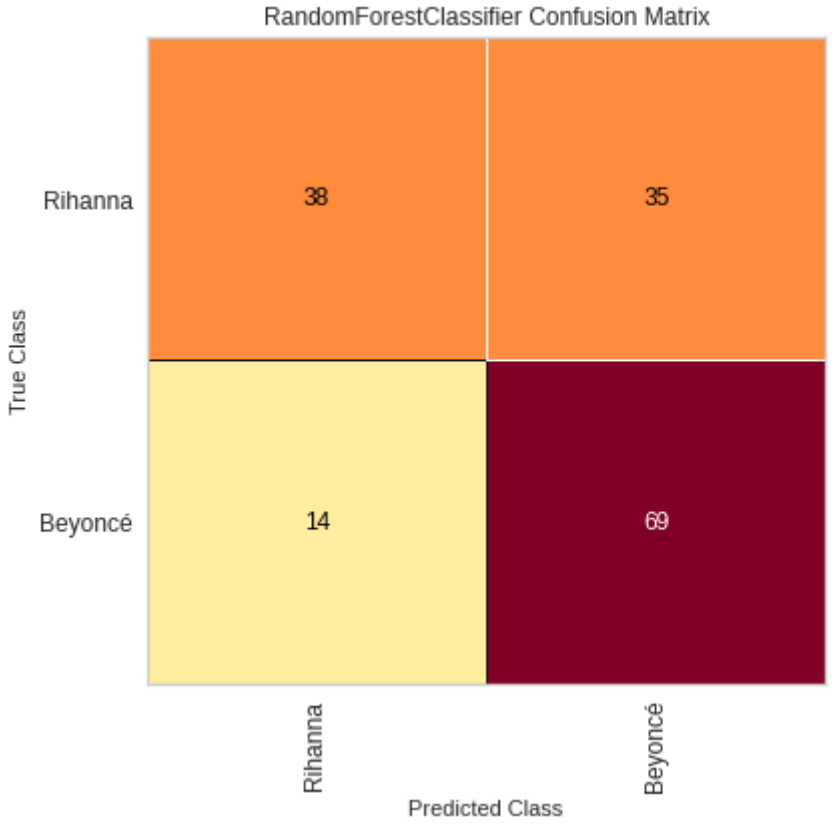

```
=====SVC default=====
              precision    recall  f1-score   support

     Rihanna       0.68      0.36      0.47        73
     Beyoncé       0.60      0.86      0.71        83

    accuracy                           0.62       156
   macro avg       0.64      0.61      0.59       156
weighted avg       0.64      0.62      0.60       156
```



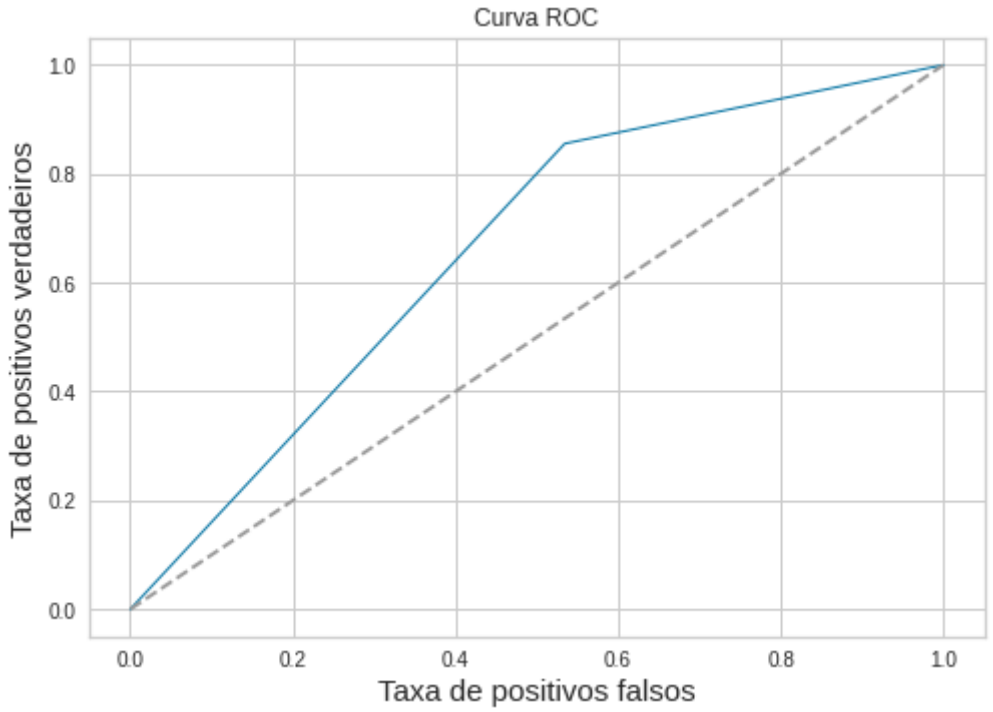


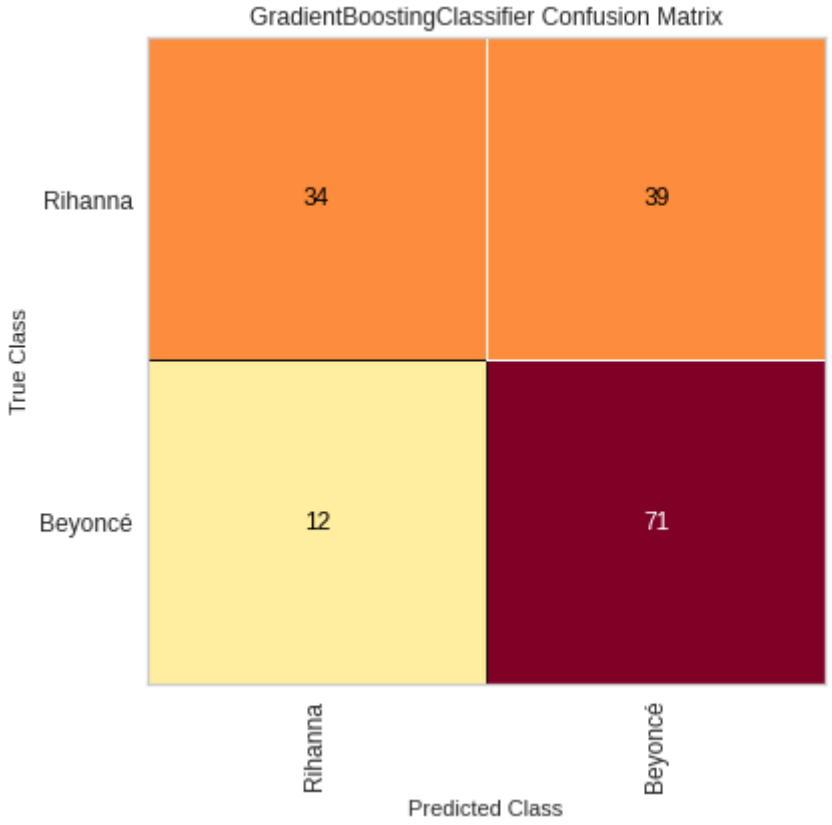

```
=====RandomForestClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.73      0.52      0.61        73
     Beyoncé       0.66      0.83      0.74        83

    accuracy                           0.69       156
   macro avg       0.70      0.68      0.67       156
weighted avg       0.69      0.69      0.68       156
```



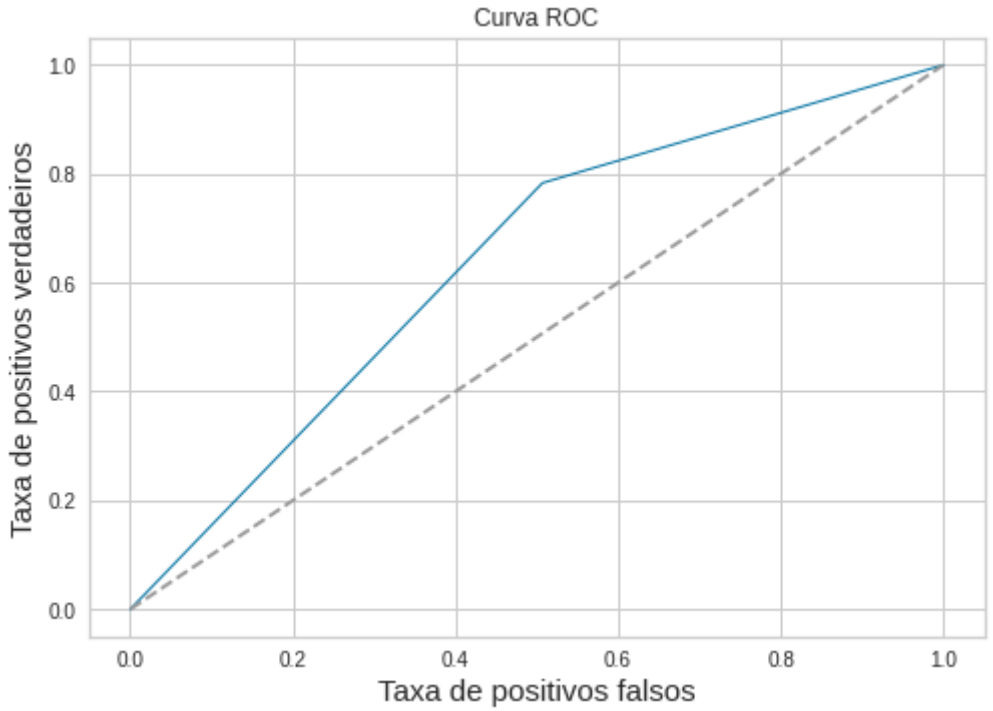


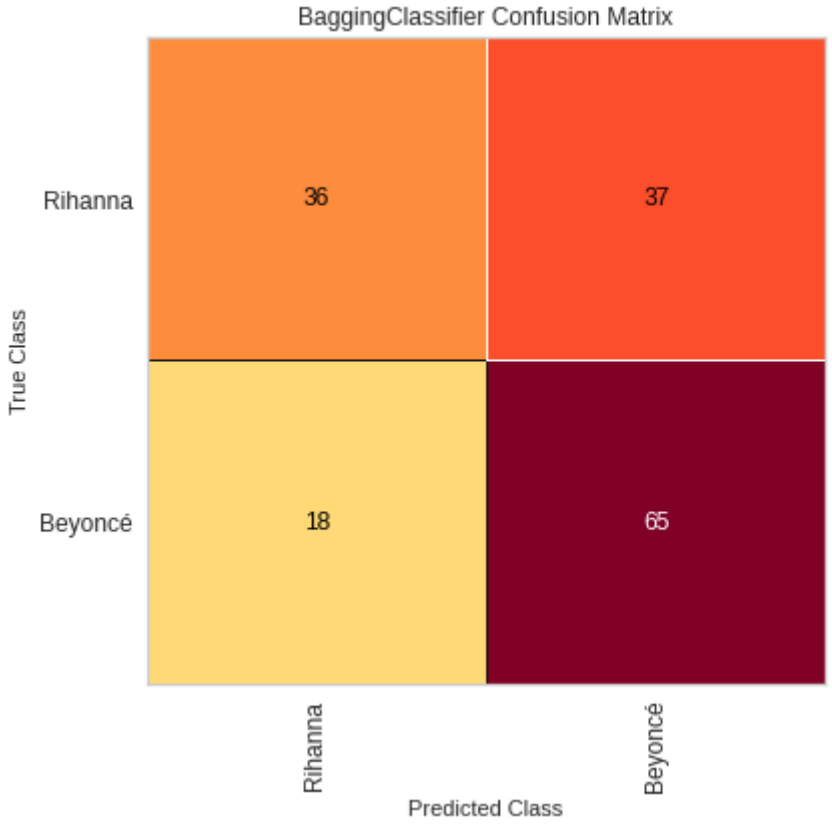

```
=====GradientBoostingClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.74      0.47      0.57        73
     Beyoncé       0.65      0.86      0.74        83

    accuracy                           0.67       156
   macro avg       0.69      0.66      0.65       156
weighted avg       0.69      0.67      0.66       156
```



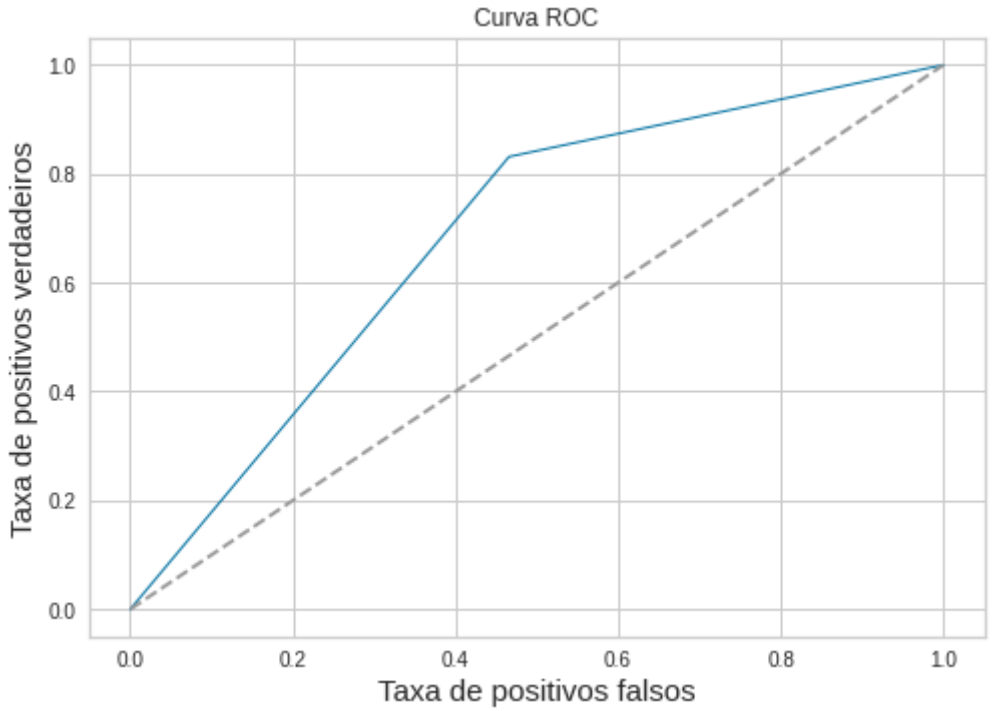


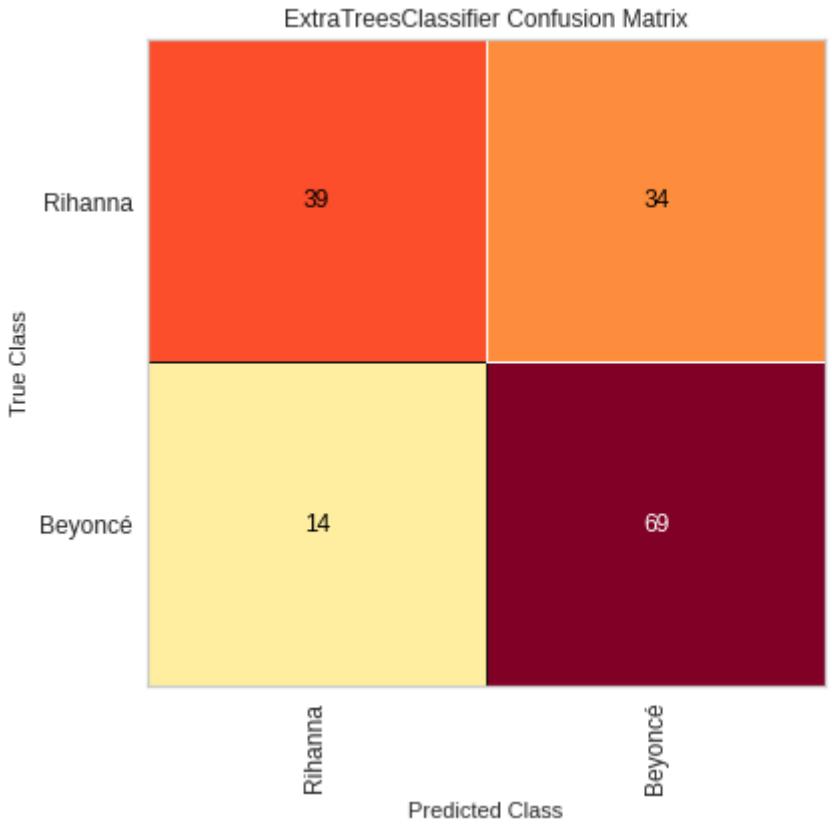

```
=====BaggingClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.67      0.49      0.57        73
     Beyoncé       0.64      0.78      0.70        83

    accuracy                           0.65       156
   macro avg       0.65      0.64      0.63       156
weighted avg       0.65      0.65      0.64       156
```



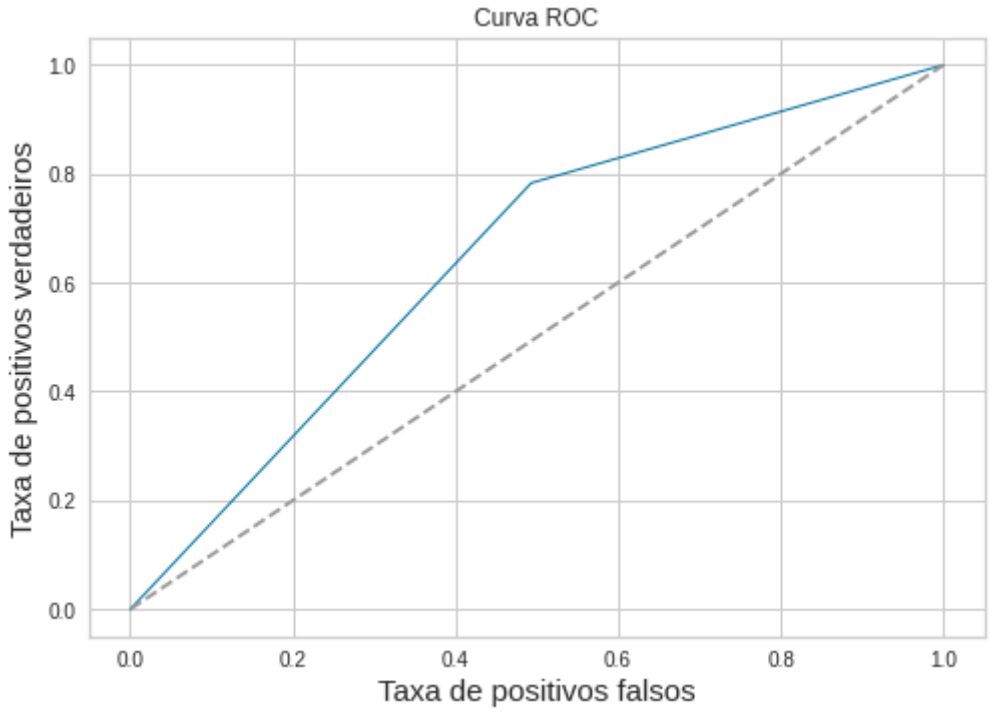


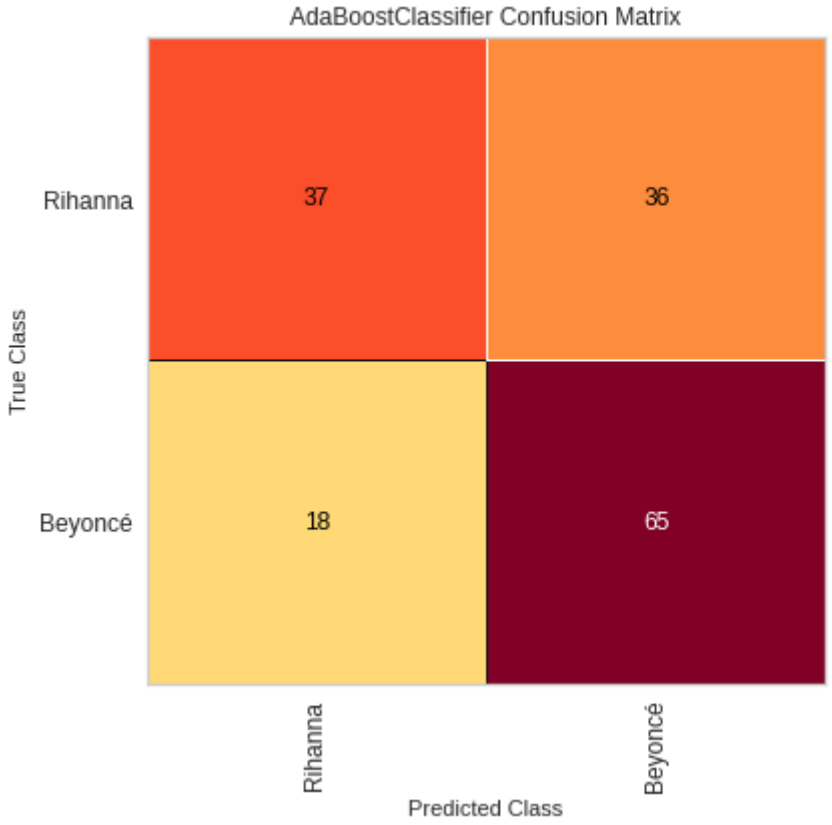

```
=====ExtraTreesClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.74      0.53      0.62        73
     Beyoncé       0.67      0.83      0.74        83

    accuracy                           0.69       156
   macro avg       0.70      0.68      0.68       156
weighted avg       0.70      0.69      0.68       156
```



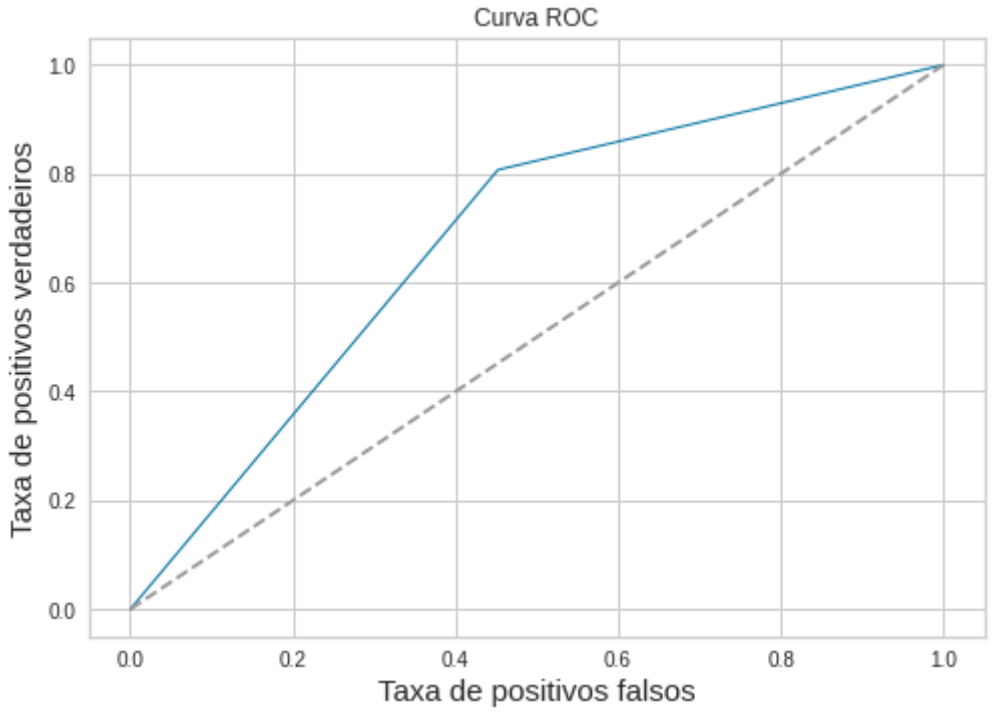


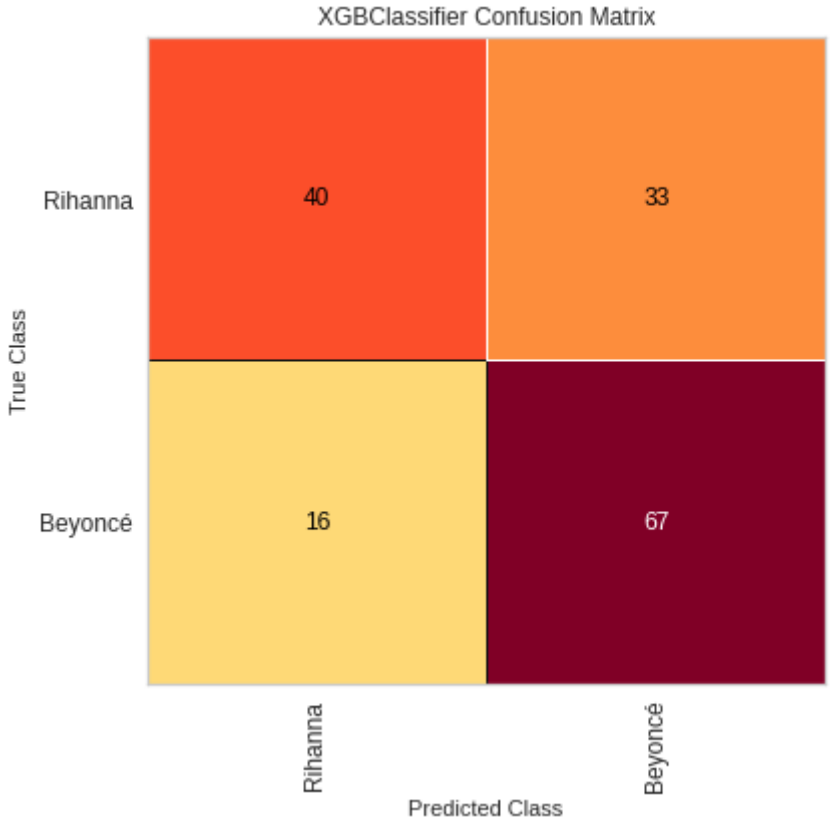

```
=====AdaBoostClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.67      0.51      0.58        73
     Beyoncé       0.64      0.78      0.71        83

    accuracy                           0.65       156
   macro avg       0.66      0.64      0.64       156
weighted avg       0.66      0.65      0.65       156
```



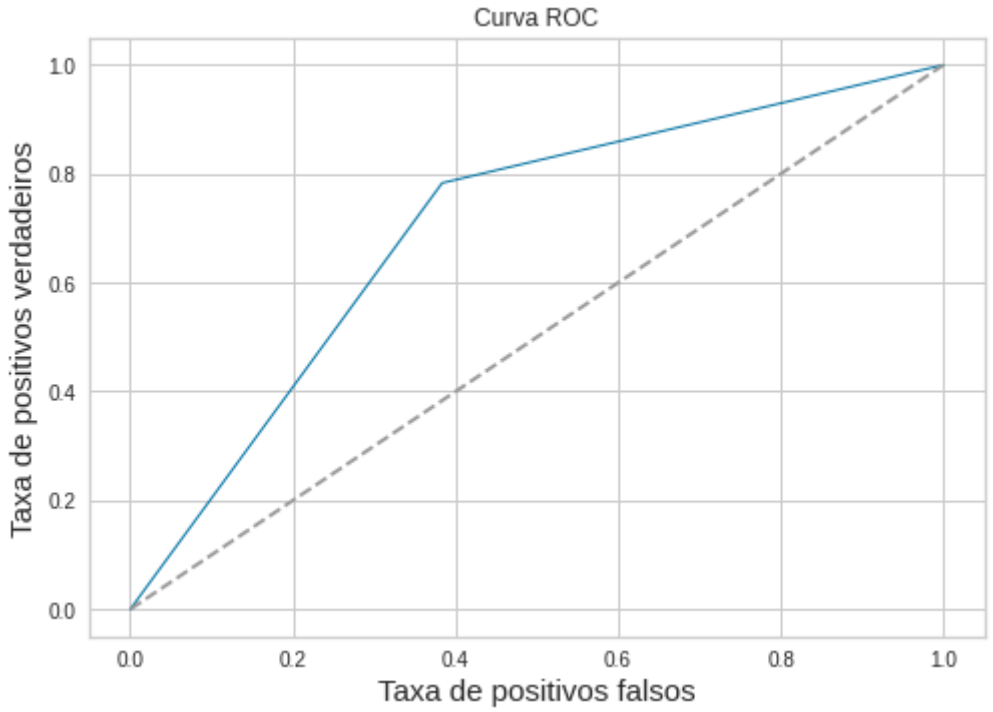


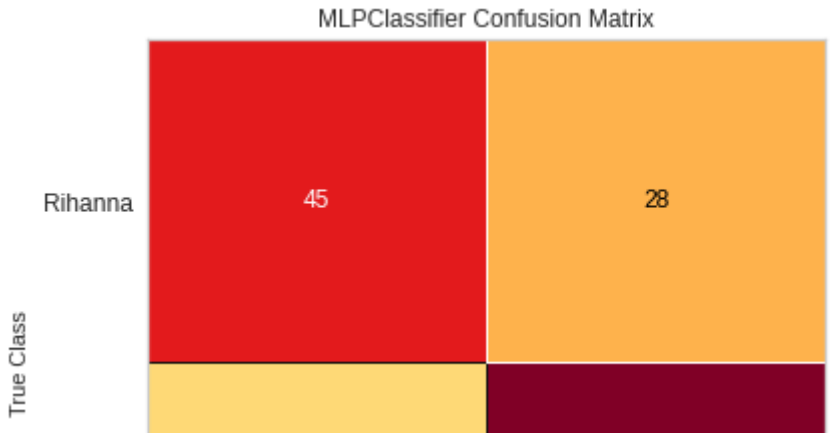

```
=====XGBClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.71      0.55      0.62        73
     Beyoncé       0.67      0.81      0.73        83

    accuracy                           0.69       156
   macro avg       0.69      0.68      0.68       156
weighted avg       0.69      0.69      0.68       156
```






```
=====MLPClassifier default=====
              precision    recall  f1-score   support

     Rihanna       0.71      0.62      0.66        73
     Beyoncé       0.70      0.78      0.74        83

    accuracy                           0.71       156
   macro avg       0.71      0.70      0.70       156
weighted avg       0.71      0.71      0.70       156
```





Preditor Multlabel

Importação dos dados

In [44]:
```
lista_de_artistas = list(df_nlp.artista.unique())
lista_de_artistas
```

Out[44]:
```
['Beyoncé', 'Rihanna']
```

In [45]:
```
def nova_coluna(lista_artistas, dataframe, nome_artista):
    for artista in lista_artistas:
        coluna = []
        for linha_artista in dataframe[nome_artista]:
            if artista in linha_artista:
                coluna.append(1)
            else:
                coluna.append(0)
        dataframe[artista] = coluna
```

In [46]:
```
nova_coluna(lista_de_artistas,df_nlp,"artista")
df_nlp.sample(20)
```

Out[46]:

	letra	artista	target	Beyoncé	Rihanna
287	[Rick Ross] Rick Rozay Rihanna Rich forever St...	Rihanna	0	0	1
54	[Intro - Jay Z] Yes! It's so crazy right now! ...	Beyoncé	1	1	0
363	[Intro] I got the hotness (hotness, hotness, h...	Rihanna	0	0	1
310	I came fluttering in from Neverland Time can n...	Rihanna	0	0	1
361	This whiskey got me feelin' pretty So pardon i...	Rihanna	0	0	1
90	Okay, ladies, now let's get in formation Okay,...	Beyoncé	1	1	0
190	Ring the alarm I been through this too long Bu...	Beyoncé	1	1	0
272	You Changed (Feat. Beyoncé, Michelle Williams)...	Beyoncé	1	1	0
107	I fought for you The hardest, it made me the s...	Beyoncé	1	1	0

	letra	artista	target	Beyoncé	Rihanna
183	Looking for a job in the city Working for the ...	Beyoncé	1	1	0
431	Yeaahh, Yeaahh, Yeaahh, Yeaahh Yeaahh, eh-eh-e...	Rihanna	0	0	1
240	That's How You Like It, huh That's How You Lik...	Beyoncé	1	1	0
447	Boy you standin real close to me Tell me now w...	Rihanna	0	0	1
3	If I ain't got nothing I got you If I ain't go...	Beyoncé	1	1	0
400	Mustard on the beat, ho! I was good on my own...	Rihanna	0	0	1
346	I think I've had enough I might get a little d...	Rihanna	0	0	1
338	Wherever you're going I wanna go Wherever you ...	Rihanna	0	0	1
343	Mama, I found a man Who loves me and understan...	Rihanna	0	0	1
432	Come here Rude boy, boy Can you get it up Come...	Rihanna	0	0	1

In [47]:
```
lista_zip_artistas = list(zip(df_nlp[lista_de_artistas[0]],
                      df_nlp[lista_de_artistas[1]]))

df_nlp["todos_artistas"] = lista_zip_artistas
df_nlp.sample(10)
```

Out[47]:

	letra	artista	target	Beyoncé	Rihanna	todos_artistas
101	Remember those walls I built Well baby they're...	Beyoncé	1	1	0	(1, 0)
496	[Rihanna] Ooh na na, what's my name Ooh na na,...	Rihanna	0	0	1	(0, 1)
78	It's over and done, But the heartache lives on...	Beyoncé	1	1	0	(1, 0)
139	Child of the wilderness Born into emptiness Le...	Beyoncé	1	1	0	(1, 0)
29	What goes around comes back around (hey) (4x) ...	Beyoncé	1	1	0	(1, 0)
2	Dum-da-de-da Do, do, do, do, do, do (Coming do...	Beyoncé	1	1	0	(1, 0)
404	You'll always be mine Sing it to the world Alw...	Rihanna	0	0	1	(0, 1)
284	I guess you know I'm bad, bad I got a problem ...	Rihanna	0	0	1	(0, 1)
128	Go shorty, it's beyonce, We gon' party like, i...	Beyoncé	1	1	0	(1, 0)
27	Oh Beyonce, Beyonce Oh Beyonce, Beyonce Mient...	Beyoncé	1	1	0	(1, 0)

In [48]:
```
X_tfidfv = vetorizador_transform(df_nlp.letra,TfidfVectorizer,
4000, 0.85)

X_train, X_test, y_train, y_test =
model_selection.train_test_split(X_tfidfv,

df_nlp.todos_artistas,

test_size = 0.3,

stratify=df_nlp.todos_artistas,

random_state = 123)

y_train_array = np.asarray(list(y_train))
y_test_array = np.asarray(list(y_test))
```

In [49]:
```
regressao_logistica = LogisticRegression(solver = 'lbfgs')
```

In [50]:
```
def comparar_multlabel(classificador, X_train,
y_train_array,X_test, y_test_array):
    if classificador == MLkNN:
        classificador = classificador()
        classificador.fit(X_train, y_train_array)
        resultado = classificador.score(X_test, y_test_array)
        previsao = classificador.predict(X_test)
        hamming_loss_cls = hamming_loss(y_test_array, previsao)
        print("Hamming Loss {0: .2f}".format(hamming_loss_cls))
        print("Resultado {0: .2f}%".format(resultado*100))
    else:
        classificador = classificador(regressao_logistica)
        classificador.fit(X_train, y_train_array)
        resultado = classificador.score(X_test, y_test_array)
        previsao = classificador.predict(X_test)
        hamming_loss_cls = hamming_loss(y_test_array, previsao)
        print("Hamming Loss {0: .2f}".format(hamming_loss_cls))
        print("Resultado {0: .2f}%".format(resultado*100))
```

In [51]:
```
lista_cls_multilabel = [OneVsRestClassifier,
                        ClassifierChain,
                        BinaryRelevance,
                       MLkNN]
```

In [52]:
```
for cls_mult in lista_cls_multilabel:
    print('===='+cls_mult.__name__+'====')
    comparar_multlabel(cls_mult, X_train, y_train_array,X_test,
y_test_array)
```

```
====OneVsRestClassifier====
Hamming Loss  0.33
Resultado  66.67%
====ClassifierChain====
Hamming Loss  0.33
Resultado  66.67%
====BinaryRelevance====
Hamming Loss  0.33
Resultado  66.67%
====MLkNN====
Hamming Loss  0.42
Resultado  57.69%
```

Escolha do modelo a ser utilizado

Treinamento do modelo

In [53]:
```
X_tfidfv = vetorizador_transform(df_nlp.letra,TfidfVectorizer,
4000, 0.85)

X_train, X_test, y_train, y_test =
model_selection.train_test_split(X_tfidfv,

y,

test_size = 0.3,

stratify=y,

random_state = 123)
```

In [54]:
```
cls = MLPClassifier()
cls.fit(X_train, y_train)
```

Out[54]:
```
MLPClassifier(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.
9,
              beta_2=0.999, early_stopping=False, epsilon=1e-08,
```

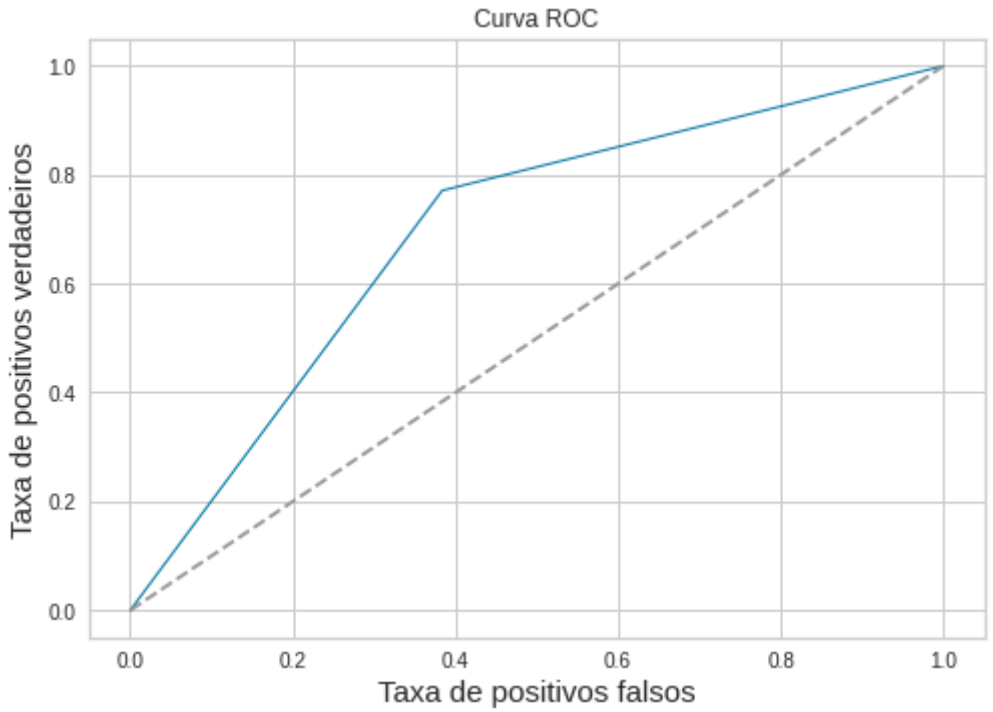
```
hidden_layer_sizes=(100,), learning_rate='constant',
learning_rate_init=0.001, max_fun=15000, max_iter=200,
momentum=0.9, n_iter_no_change=10, nesterovs_momentum=True,
power_t=0.5, random_state=None, shuffle=True, solver='adam',
tol=0.0001, validation_fraction=0.1, verbose=False,
warm_start=False)
```

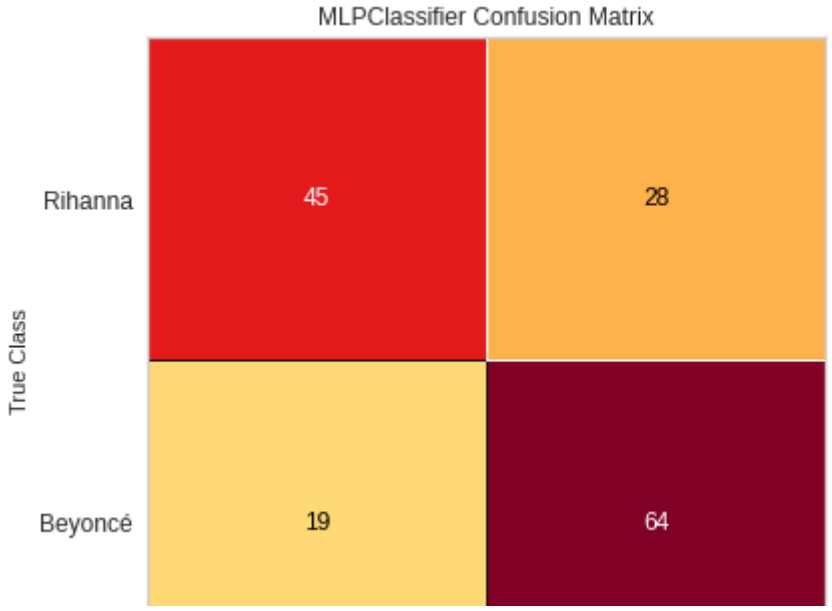
Predição e avaliação

In [55]:

```
y_predicted = cls.predict(X_test)
roc_auc = roc_auc_score(y_test,y_predicted)

print(classification_report(y_test, y_predicted, target_names=
["Rihanna", "Beyoncé"]))

fpr, tpr, thresold = roc_curve(y_test, y_predicted)
plt.plot(fpr, tpr, lw = 1)
plt.plot([0,1],[0,1], '--', color=(0.6, 0.6, 0.6),
label="sorte")
plt.xlim([-0.05,1.05])
plt.ylim([-0.05,1.05])
plt.xlabel("Taxa de positivos falsos", fontsize=15)
plt.ylabel("Taxa de positivos verdadeiros", fontsize=15)
plt.title("Curva ROC", fontsize=12)

mapping = {0: "Rihanna", 1: "Beyoncé"}
fig, ax = plt.subplots(figsize=(6, 6))
cm_viz = ConfusionMatrix(cls, classes=["Rihanna", "Beyoncé"],
label_encoder=mapping)
cm_viz.score(X_test, y_test)
cm_viz.poof()

plt.show()
```

```
              precision    recall  f1-score   support

     Rihanna       0.70      0.62      0.66        73
     Beyoncé       0.70      0.77      0.73        83

    accuracy                           0.70       156
   macro avg       0.70      0.69      0.69       156
weighted avg       0.70      0.70      0.70       156
```

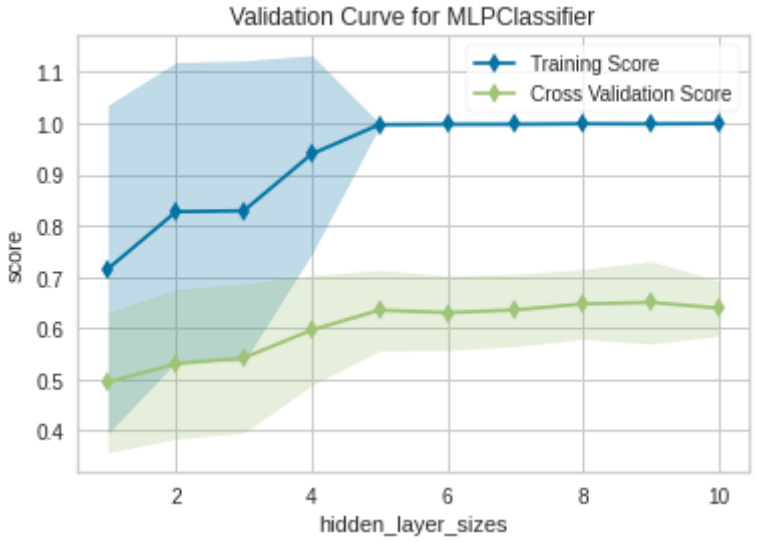




Curva de Validação

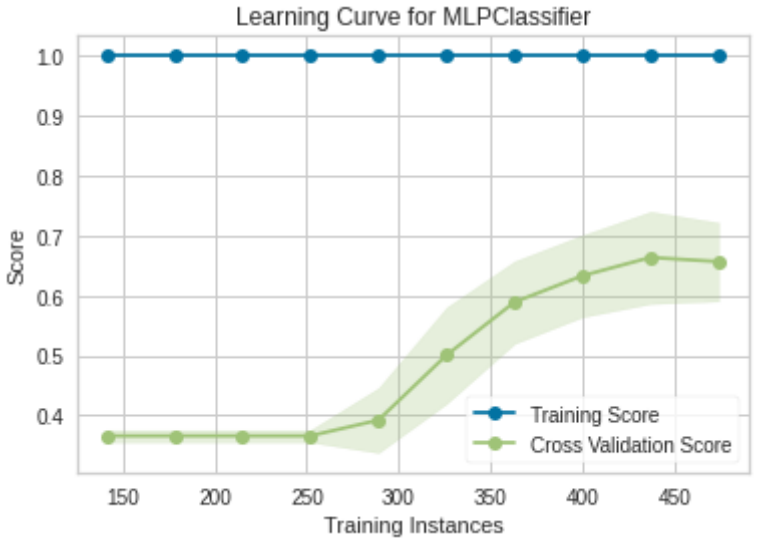
In [56]:

```
fig, ax = plt.subplots(figsize=(6, 4))
cv = StratifiedKFold(12)
hidden_layer_sizes = np.arange(1,11)
vc_viz = ValidationCurve(cls,param_name="hidden_layer_sizes",
scoring="f1_weighted",
                         param_range=hidden_layer_sizes,
cv=cv,n_jobs=-1,ax=ax)
vc_viz.fit(X_tfidfv, y)
vc_viz.poof()
plt.show()
```



Curva de Aprendizagem

In [57]:
```
fig, ax = plt.subplots(figsize=(6, 4))
cv = StratifiedKFold(12)
sizes = np.linspace(0.3, 1.0, 10)
lc_viz = LearningCurve(cls, cv=cv, train_sizes=sizes,
scoring="f1_weighted", n_jobs=-1, ax=ax)
lc_viz.fit(X_tfidfv, y)
lc_viz.poof()
plt.show()
```



Salvando modelo treinado

In [58]:
```
with open('model_nlp.pkl', 'wb') as file:
    pickle.dump(cls, file)

print("modelo salvo")
```

```
modelo salvo
```

Utilizando modelo treinado para realizar previsão

In [108…
```
# Carregar modelo
with open('model_nlp.pkl', 'rb') as f:
    model = pickle.load(f)
```

In [109…
```
df_letras_duvidodas = X_tfidfv.copy().head(20)
df_letras_duvidodas.head()
```

Out[109…

	10	11	16	20	22	2x	3rd	3x	40	45	...	yuh	yup	yé	zac	zone	zoom	zz	ça
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 4000 columns

In [110…
```
predicao = cls.predict(df_letras_duvidodas)
```

In [111…
```
df_nlp.iloc[3]
```

Out[111…
```
letra             If I ain't got nothing I got you If I ain't go...
artista                                                     Beyoncé
target                                                            1
Beyoncé                                                           1
Rihanna                                                           0
todos_artistas                                               (1, 0)
Name: 3, dtype: object
```

In [112…
```
predicao[3]
```

Out[112…
```
1
```