ClassificacaoTop200

June 26, 2022

1 Classificação Top 200

1.1 Objetivo do Notebook

Prever se uma música entrará ou não no Top 200 Global do Spotify Charts

1.2 Dados a serem utilizados

São duas as bases de dados utilizadas de forma combinada para este problema: 1. Músicas que apareceram pelo menos uma vez no Top 200 Global nos últimos anos 2. Músicas que não apareceram no Top 200 Global

1.3 Modelos Implementados

São **n** os modelos de classificação implementados

1. Regressão Logística
2. Random Forest

1.4 Aperfeiçoamentos Implementados

Foi realizada uma busca de hiperparametros para selecionar a melhor combinacao possível de parametros para cada modelo.

Além disso, foi realizada seleção de variáveis com PCA (Principal Component Analysis) e RFE (Recursive Feature Elimination). Além disso, com o resultado do REF, foram treinados modelos sem variáveis importantes sobre o artista.

1.5 Importação das bibliotecas necessárias

[ ]:
```
#Utilidades
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

#Pre-processamento
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
```

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,␣
↪accuracy_score,auc,precision_score,recall_score
from sklearn.inspection import permutation_importance
from sklearn.decomposition import PCA

#Modelos
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier

from google.colab import drive
drive.mount('/content/drive')

import random
random.seed(0)
np.random.seed(0)
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

1.6 Obtenção dos dados

[ ]:
```
path_dados_consolidados = '/content/drive/My Drive/INF1032 - Spotify/Dados/
↪Consolidados/'
dados = pd.read_csv(path_dados_consolidados+"dataset_previsao_charts.
↪csv",index_col="Unnamed: 0")
print("Quantidade de músicas: ",dados.shape[0])
print("Variáveis disponíveis:",dados.columns.values)
dados = dados.reset_index(drop=True)
print("Qtd musicas repetidas = ",dados.duplicated().sum())
dados.head()
```

```
Quantidade de músicas:  8160
Variáveis disponíveis: ['danceability' 'energy' 'key' 'loudness' 'mode'
'speechiness'
 'acousticness' 'instrumentalness' 'liveness' 'valence' 'tempo' 'type'
 'id' 'uri' 'track_href' 'analysis_url' 'duration_ms' 'time_signature'
 'nome' 'data_lancamento' 'Popularidade Musica' 'Artista' 'ano_lancamento'
 'mes_lancamento' 'dia_semana_lancamento' 'Popularidade Artista'
 'Seguidores' 'Estilos' 'Top']
Qtd musicas repetidas =  0
```

[ ]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	\
0	0.520	0.731	6	-5.338	0	0.0557	0.3420	
1	0.905	0.563	8	-6.135	1	0.1020	0.0254	
2	0.761	0.525	11	-6.900	1	0.0944	0.4400	
3	0.591	0.764	1	-5.484	1	0.0483	0.0383	
4	0.756	0.697	8	-6.377	1	0.0401	0.1820	

```
   instrumentalness  liveness  valence  …  data_lancamento  \
0          0.001010    0.3110    0.662  …       2022-03-31
1          0.000010    0.1130    0.324  …       2022-04-08
2          0.000007    0.0921    0.531  …       2020-08-06
3          0.000000    0.1030    0.478  …       2021-07-23
4          0.000000    0.3330    0.956  …       2022-04-07

  Popularidade Musica         Artista ano_lancamento mes_lancamento  \
0                 100    Harry Styles         2022.0            3.0
1                  94     Jack Harlow         2022.0            4.0
2                  90   Glass Animals         2020.0            8.0
3                  88   The Kid LAROI         2021.0            7.0
4                  85  Camila Cabello         2022.0            4.0

  dia_semana_lancamento  Popularidade Artista  Seguidores  \
0                   3.0                    94    21444145
1                   4.0                    86     2247792
2                   3.0                    80     2960684
3                   4.0                    83     3778109
4                   3.0                    83    27026106

                                          Estilos Top
0                                         ['pop']   1
1  ['deep underground hip hop', 'kentucky hip hop…   1
2        ['gauze pop', 'indietronica', 'shiver pop']   1
3                            ['australian hip hop']   1
4            ['dance pop', 'pop', 'post-teen pop']   1

[5 rows x 29 columns]
```

[ ]:
```
dados.tail()
```

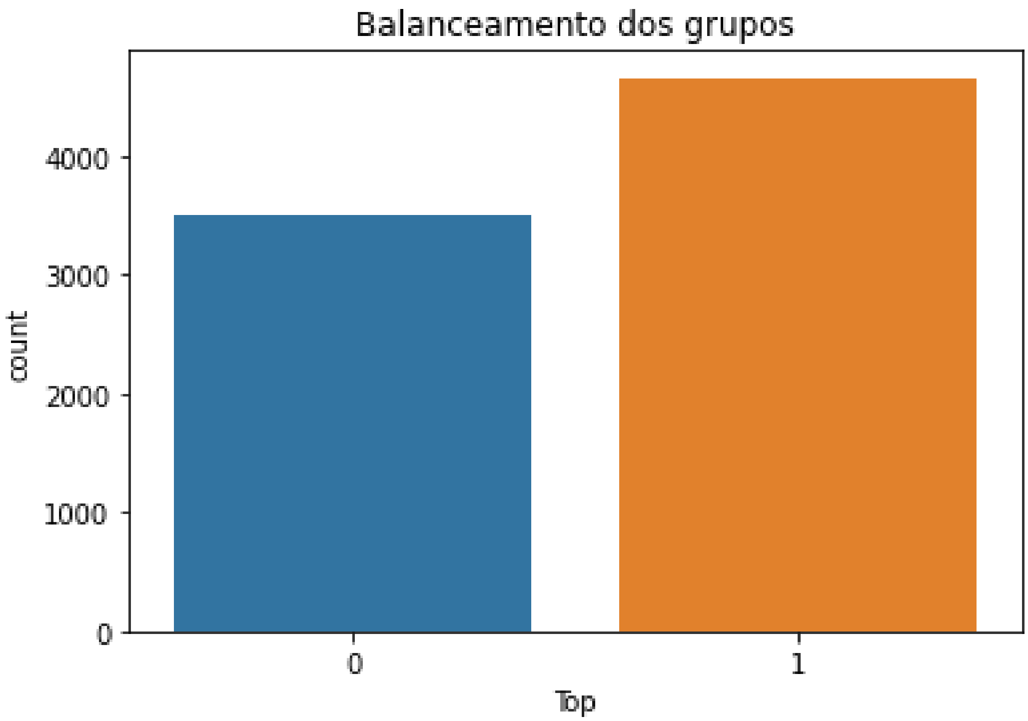
[ ]:
```
      danceability  energy  key  loudness  mode  speechiness  acousticness  \
8155         0.609   0.777    9    -7.712     1       0.0636       0.01480
8156         0.631   0.932    5    -4.142     1       0.0354       0.04360
8157         0.481   0.435    4    -8.795     1       0.0321       0.67800
8158         0.522   0.889    1    -4.137     1       0.0461       0.00328
8159         0.613   0.589    0   -10.388     1       0.0458       0.10700

      instrumentalness  liveness  valence  …  data_lancamento  \
8155          0.074600    0.1530    0.546  …       2021-10-15
8156          0.137000    0.0918    0.971  …       1981-08-24
8157          0.000000    0.0928    0.107  …       2014-01-01
8158          0.000000    0.3450    0.852  …       2006-01-29
8159          0.000036    0.1140    0.757  …       2000-01-01
```

```
      Popularidade Musica              Artista ano_lancamento mes_lancamento  \
8155                   50            Remi Wolf         2021.0           10.0
8156                    0   The Rolling Stones         1981.0            8.0
8157                   60         Taylor Swift         2014.0            1.0
8158                   60       Arctic Monkeys         2006.0            1.0
8159                   50  Yusuf / Cat Stevens         2000.0            1.0

      dia_semana_lancamento  Popularidade Artista  Seguidores  \
8155                    4.0                    65      283640
8156                    0.0                    77    11805172
8157                    2.0                    92    54364596
8158                    6.0                    82    14770606
8159                    5.0                    67     1532558

                                                Estilos Top
8155             ['indie pop', 'modern alternative pop']   0
8156        ['british invasion', 'classic rock', 'rock']   0
8157                                             ['pop']   0
8158  ['garage rock', 'permanent wave', 'rock', 'she…   0
8159  ['british folk', 'classic rock', 'folk', 'folk…   0

[5 rows x 29 columns]
```

1.7 Label do grupo para classificação

[ ]:
```
plt.figure()
plt.title("Balanceamento dos grupos")
sns.countplot(dados.Top)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



1.8 Selecionando apenas as features úteis

```
[ ]: features = ['danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',
            'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',␣
      ↪'duration_ms',
            'time_signature', 'nome', 'data_lancamento', 'Popularidade Musica',
            'Artista', 'ano_lancamento', 'mes_lancamento',␣
      ↪'dia_semana_lancamento','Popularidade Artista','Estilos','Seguidores',
            'Top']

     dados = dados[features]
     print(dados.columns.values)
```

```
['danceability' 'energy' 'key' 'loudness' 'mode' 'speechiness'
 'acousticness' 'instrumentalness' 'liveness' 'valence' 'tempo'
 'duration_ms' 'time_signature' 'nome' 'data_lancamento'
 'Popularidade Musica' 'Artista' 'ano_lancamento' 'mes_lancamento'
 'dia_semana_lancamento' 'Popularidade Artista' 'Estilos' 'Seguidores'
 'Top']
```

1.9 Analisando as variáveis

[ ]:
```
dados.isna().sum()
dados = dados.dropna()
dados.isna().sum()
```

[ ]:
```
danceability             0
energy                   0
key                      0
loudness                 0
mode                     0
speechiness              0
acousticness             0
instrumentalness         0
liveness                 0
valence                  0
tempo                    0
duration_ms              0
time_signature           0
nome                     0
data_lancamento          0
Popularidade Musica      0
Artista                  0
ano_lancamento           0
mes_lancamento           0
dia_semana_lancamento    0
Popularidade Artista     0
Estilos                  0
Seguidores               0
Top                      0
dtype: int64
```

[ ]:
```
dados.dtypes
```

[ ]:
```
danceability             float64
energy                   float64
key                        int64
loudness                 float64
mode                       int64
speechiness              float64
acousticness             float64
instrumentalness         float64
liveness                 float64
valence                  float64
tempo                    float64
duration_ms                int64
time_signature             int64
nome                      object
```

```
data_lancamento           object
Popularidade Musica        int64
Artista                   object
ano_lancamento           float64
mes_lancamento           float64
dia_semana_lancamento    float64
Popularidade Artista       int64
Estilos                   object
Seguidores                 int64
Top                        int64
dtype: object
```

1.9.1 Comentários:

Artista, Estilos, Nome da Música e Data Lançamento são objetos.

Para data usaremos a outras features que contém informação da data.

Nome da música e artista deixaremos de fora.

Precisamos analisar melhor as variáveis **key** e **mode**.

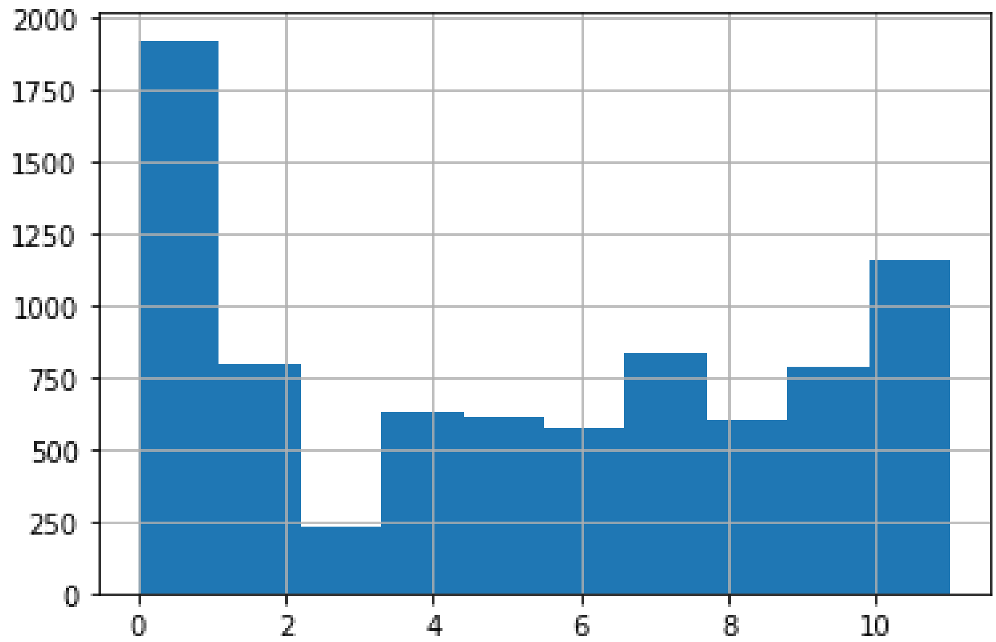
Popularidade da música será retirada.

[ ]:
```
dados = dados.drop(columns=["Artista","data_lancamento","Popularidade␣
 ↪Musica"],axis=1)
dados.columns
```

[ ]:
```
Index(['danceability', 'energy', 'key', 'loudness', 'mode', 'speechiness',
       'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
       'duration_ms', 'time_signature', 'nome', 'ano_lancamento',
       'mes_lancamento', 'dia_semana_lancamento', 'Popularidade Artista',
       'Estilos', 'Seguidores', 'Top'],
      dtype='object')
```

[ ]:
```
dados.key.hist()
```

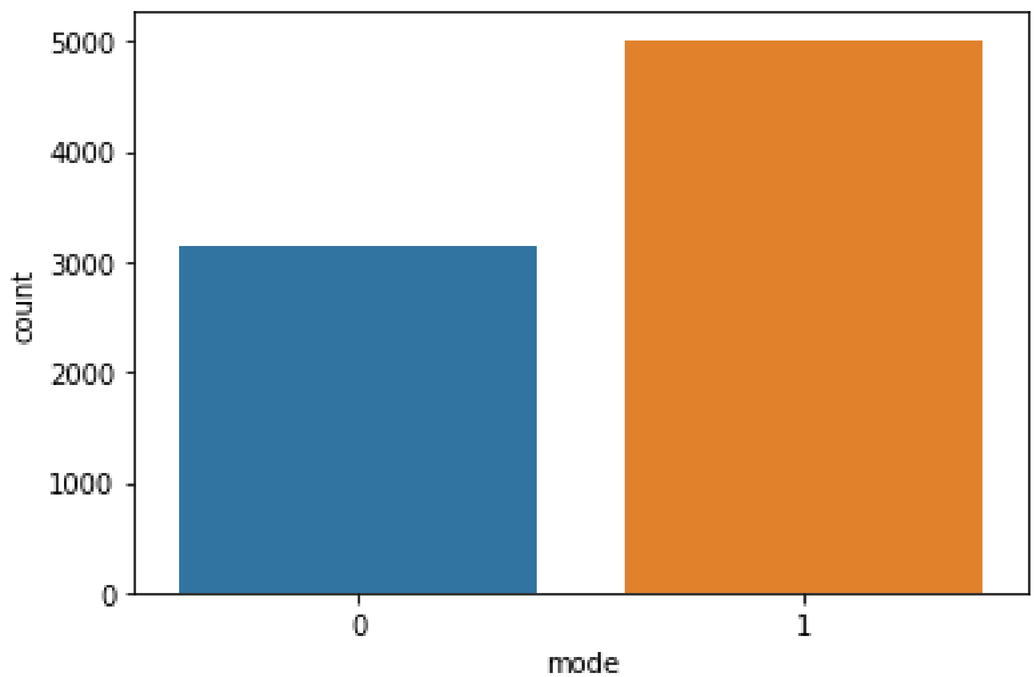
[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1874246cd0>
```




```
[ ]: sns.countplot(dados["mode"])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7f18741d2390>
```



1.9.2 Comentários:

Mode é uma variáveis binária, não precisamos fazer nada.

Key, por sua vez, é uma variável aparentemente categórica. Vamos aplicar um One Hot Encoding nela, via pd.get_dummines()

1.10 Adequação das variáveis

[ ]:
```
dummies_key = pd.get_dummies(dados.key,drop_first=True)
dummies_key.rename(columns = {1:'key1',2:'key2',
                              3:'key3',4:'key4',
                              5:'key5',6:'key6',
                              7:'key7',8:'key8',
                              9:'key9',10:'key10',
                              11:'key11',0:'key0'}, inplace = True)

dummies_key
```

[ ]:

	key1	key2	key3	key4	key5	key6	key7	key8	key9	key10	key11
0	0	0	0	0	0	1	0	0	0	0	0
1	0	0	0	0	0	0	0	1	0	0	0
2	0	0	0	0	0	0	0	0	0	0	1
3	1	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	1	0	0	0

```
…     …    …    …    …    …    …    …    …    …    …    …
8155  0    0    0    0    0    0    0    0    1    0    0
8156  0    0    0    0    1    0    0    0    0    0    0
8157  0    0    0    1    0    0    0    0    0    0    0
8158  1    0    0    0    0    0    0    0    0    0    0
8159  0    0    0    0    0    0    0    0    0    0    0

[8153 rows x 11 columns]
```

[ ]:

```python
dados = dados.drop(columns=["key"])
dados = pd.concat([dados,dummies_key],axis=1)
dados
```

[ ]:

```
      danceability  energy  loudness  mode  speechiness  acousticness  \
0            0.520   0.731    -5.338     0       0.0557       0.34200
1            0.905   0.563    -6.135     1       0.1020       0.02540
2            0.761   0.525    -6.900     1       0.0944       0.44000
3            0.591   0.764    -5.484     1       0.0483       0.03830
4            0.756   0.697    -6.377     1       0.0401       0.18200
…                …       …         …     …            …             …
8155         0.609   0.777    -7.712     1       0.0636       0.01480
8156         0.631   0.932    -4.142     1       0.0354       0.04360
8157         0.481   0.435    -8.795     1       0.0321       0.67800
8158         0.522   0.889    -4.137     1       0.0461       0.00328
8159         0.613   0.589   -10.388     1       0.0458       0.10700

      instrumentalness  liveness  valence    tempo  …  key2  key3  key4  \
0             0.001010    0.3110    0.662  173.930  …     0     0     0
1             0.000010    0.1130    0.324  106.998  …     0     0     0
2             0.000007    0.0921    0.531   80.870  …     0     0     0
3             0.000000    0.1030    0.478  169.928  …     0     0     0
4             0.000000    0.3330    0.956   94.996  …     0     0     0
…                    …         …        …        …  …     …     …     …
8155          0.074600    0.1530    0.546  164.024  …     0     0     0
8156          0.137000    0.0918    0.971  122.429  …     0     0     0
8157          0.000000    0.0928    0.107  143.950  …     0     0     1
8158          0.000000    0.3450    0.852  144.499  …     0     0     0
8159          0.000036    0.1140    0.757   82.376  …     0     0     0

      key5  key6  key7  key8  key9  key10  key11
0        0     1     0     0     0      0      0
1        0     0     0     1     0      0      0
2        0     0     0     0     0      0      1
3        0     0     0     0     0      0      0
4        0     0     0     1     0      0      0
…        …     …     …     …     …      …      …
8155     0     0     0     0     1      0      0
```

```
8156     1    0    0    0    0     0     0
8157     0    0    0    0    0     0     0
8158     0    0    0    0    0     0     0
8159     0    0    0    0    0     0     0

[8153 rows x 31 columns]
```

[ ]:
```
dummies_mes_lancamento = pd.get_dummies(dados.mes_lancamento,drop_first=True)
dummies_mes_lancamento.rename(columns = {1:'jan',2:'fev',
                              3:'mar',4:'abr',
                              5:'mai',6:'jun',
                              7:'jul',8:'ago',
                              9:'set',10:'out',
                              11:'nov',12:'dez'}, inplace = True)

dummies_mes_lancamento
```

[ ]:
```
      fev  mar  abr  mai  jun  jul  ago  set  out  nov  dez
0       0    1    0    0    0    0    0    0    0    0    0
1       0    0    1    0    0    0    0    0    0    0    0
2       0    0    0    0    0    0    1    0    0    0    0
3       0    0    0    0    0    1    0    0    0    0    0
4       0    0    1    0    0    0    0    0    0    0    0
…     …   …   …   …   …   …   …   …   …   …   …
8155    0    0    0    0    0    0    0    0    1    0    0
8156    0    0    0    0    0    0    1    0    0    0    0
8157    0    0    0    0    0    0    0    0    0    0    0
8158    0    0    0    0    0    0    0    0    0    0    0
8159    0    0    0    0    0    0    0    0    0    0    0

[8153 rows x 11 columns]
```

[ ]:
```
dados = dados.drop(columns=["mes_lancamento"])
dados = pd.concat([dados,dummies_mes_lancamento],axis=1)
dados
```

[ ]:
```
      danceability  energy  loudness  mode  speechiness  acousticness  \
0            0.520   0.731    -5.338     0       0.0557       0.34200
1            0.905   0.563    -6.135     1       0.1020       0.02540
2            0.761   0.525    -6.900     1       0.0944       0.44000
3            0.591   0.764    -5.484     1       0.0483       0.03830
4            0.756   0.697    -6.377     1       0.0401       0.18200
…              …       …        …      …          …
8155         0.609   0.777    -7.712     1       0.0636       0.01480
8156         0.631   0.932    -4.142     1       0.0354       0.04360
8157         0.481   0.435    -8.795     1       0.0321       0.67800
8158         0.522   0.889    -4.137     1       0.0461       0.00328
```

```
8159          0.613   0.589   -10.388     1       0.0458       0.10700

      instrumentalness  liveness  valence    tempo  …  mar  abr  mai  jun  \
0             0.001010    0.3110    0.662  173.930  …    1    0    0    0
1             0.000010    0.1130    0.324  106.998  …    0    1    0    0
2             0.000007    0.0921    0.531   80.870  …    0    0    0    0
3             0.000000    0.1030    0.478  169.928  …    0    0    0    0
4             0.000000    0.3330    0.956   94.996  …    0    1    0    0
…                  …         …        …        …  …  …  …  ..  …
8155          0.074600    0.1530    0.546  164.024  …    0    0    0    0
8156          0.137000    0.0918    0.971  122.429  …    0    0    0    0
8157          0.000000    0.0928    0.107  143.950  …    0    0    0    0
8158          0.000000    0.3450    0.852  144.499  …    0    0    0    0
8159          0.000036    0.1140    0.757   82.376  …    0    0    0    0

      jul  ago  set  out  nov  dez
0       0    0    0    0    0    0
1       0    0    0    0    0    0
2       0    1    0    0    0    0
3       1    0    0    0    0    0
4       0    0    0    0    0    0
…    …   …  ..   …   …   …
8155    0    0    0    1    0    0
8156    0    1    0    0    0    0
8157    0    0    0    0    0    0
8158    0    0    0    0    0    0
8159    0    0    0    0    0    0

[8153 rows x 41 columns]
```

[ ]:
```python
dummies_dia_semana = pd.get_dummies(dados.dia_semana_lancamento,drop_first=True)
dummies_dia_semana.rename(columns = {1:'ter',2:'qua',
                              3:'qui',4:'sex',
                              5:'sab',6:'dom',
                              0:'seg'}, inplace = True)

dummies_dia_semana
```

[ ]:
```
      ter  qua  qui  sex  sab  dom
0       0    0    1    0    0    0
1       0    0    0    1    0    0
2       0    0    1    0    0    0
3       0    0    0    1    0    0
4       0    0    1    0    0    0
…    …   …   …   …   …   …
8155    0    0    0    1    0    0
8156    0    0    0    0    0    0
```

```
8157    0    1    0    0    0    0
8158    0    0    0    0    0    1
8159    0    0    0    0    1    0

[8153 rows x 6 columns]
```

[ ]:
```python
dados = dados.drop(columns=["dia_semana_lancamento"])
dados = pd.concat([dados,dummies_dia_semana],axis=1)
dados
```

[ ]:
```
      danceability  energy  loudness  mode  speechiness  acousticness  \
0            0.520   0.731    -5.338     0       0.0557       0.34200
1            0.905   0.563    -6.135     1       0.1020       0.02540
2            0.761   0.525    -6.900     1       0.0944       0.44000
3            0.591   0.764    -5.484     1       0.0483       0.03830
4            0.756   0.697    -6.377     1       0.0401       0.18200
…            …      …        …      …           …            …
8155         0.609   0.777    -7.712     1       0.0636       0.01480
8156         0.631   0.932    -4.142     1       0.0354       0.04360
8157         0.481   0.435    -8.795     1       0.0321       0.67800
8158         0.522   0.889    -4.137     1       0.0461       0.00328
8159         0.613   0.589   -10.388     1       0.0458       0.10700

      instrumentalness  liveness  valence    tempo  …  set  out  nov  dez  \
0             0.001010    0.3110    0.662  173.930  …    0    0    0    0
1             0.000010    0.1130    0.324  106.998  …    0    0    0    0
2             0.000007    0.0921    0.531   80.870  …    0    0    0    0
3             0.000000    0.1030    0.478  169.928  …    0    0    0    0
4             0.000000    0.3330    0.956   94.996  …    0    0    0    0
…                  …         …        …        …  …  …  …  ..  …
8155          0.074600    0.1530    0.546  164.024  …    0    1    0    0
8156          0.137000    0.0918    0.971  122.429  …    0    0    0    0
8157          0.000000    0.0928    0.107  143.950  …    0    0    0    0
8158          0.000000    0.3450    0.852  144.499  …    0    0    0    0
8159          0.000036    0.1140    0.757   82.376  …    0    0    0    0

      ter qua  qui  sex  sab  dom
0       0   0    1    0    0    0
1       0   0    0    1    0    0
2       0   0    1    0    0    0
3       0   0    0    1    0    0
4       0   0    1    0    0    0
…    …  ..  …   …   …   …
8155    0   0    0    1    0    0
8156    0   0    0    0    0    0
8157    0   1    0    0    0    0
8158    0   0    0    0    0    1
```

```
8159    0   0    0    0    1    0

[8153 rows x 46 columns]
```

1.10.1 Variável Seguidores

[ ]:
```python
dados.Seguidores
```

[ ]:
```
0        21444145
1         2247792
2         2960684
3         3778109
4        27026106
           …
8155       283640
8156     11805172
8157     54364596
8158     14770606
8159      1532558
Name: Seguidores, Length: 8153, dtype: int64
```

[ ]:
```python
def normaliza(X):
  return (X - X.min(axis=0)) / (X.max(axis=0) - X.min(axis=0))

dados.Seguidores = normaliza(dados['Seguidores'])
dados.Seguidores
```

[ ]:
```
0       0.217540
1       0.022803
2       0.030035
3       0.038327
4       0.274166
           …
8155    0.002877
8156    0.119757
8157    0.551501
8158    0.149840
8159    0.015547
Name: Seguidores, Length: 8153, dtype: float64
```

1.10.2 Variável Estilos

[ ]:
```python
estilos = []
for estilo in dados.Estilos:
  print(estilo)
estilos
```

```
[ ]: #Por enquanto vamos ignorar estilos musicas
dados = dados.drop(columns=["Estilos"])
```

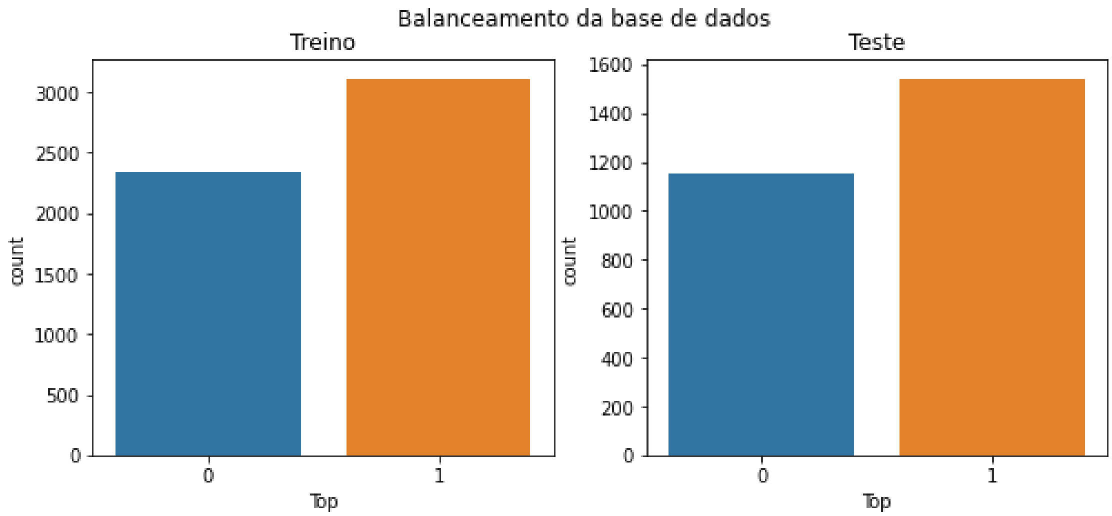
1.11 Separação teste treino

```
[ ]: y = dados.Top
X = dados.drop(columns=["Top","nome"])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
 ↪random_state=0)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(5462, 43)
(2691, 43)
(5462,)
(2691,)
```

```
[ ]: plt.figure(figsize=(10,4))
plt.suptitle("Balanceamento da base de dados")
plt.subplot(1,2,1)
plt.title("Treino")
sns.countplot(y_train)
plt.subplot(1,2,2)
plt.title("Teste")
sns.countplot(y_test)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



1.12 Implementando os modelos

1.12.1 Técnicas a serem utilizadas

Vamos implementar os modelos com *Grid Search Cross Validation* para sermos capazes de escolher a melhor combinação de hiperparametros.

[ ]:
```
#Escolhendo os hiper-parametros para busca

params_logist = {'random_state':[0],
                 'solver':['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],
                 'max_iter':[10,50,100,200]}

params_rf = {'n_estimators':[10,50,100,200],
             'criterion':['gini', 'entropy', 'log_loss'],
             'max_depth': [None,5,10,20,50],
             'bootstrap':[False,True],
             'random_state':[0],
             'max_samples':[10,20,50,100]}


rf = RandomForestClassifier()
logreg = LogisticRegression()
```

1.12.2 Treinando os modelos com busca de hiperparametros

[ ]:
```
grid_logreg = GridSearchCV(logreg,
                    param_grid=params_logist,
                    scoring='accuracy').fit(X_train, y_train)
```

```
[ ]: grid_rf = GridSearchCV(rf,
                          param_grid=params_rf,
                          scoring='accuracy').fit(X_train, y_train)
```

```
[ ]: melhor_logreg = grid_logreg.best_estimator_
     melhor_rf = grid_rf.best_estimator_

     print("Melhores modelos")
     print(melhor_logreg)
     print(melhor_rf)
```

```
Melhores modelos
LogisticRegression(max_iter=200, random_state=0, solver='newton-cg')
RandomForestClassifier(max_samples=100, n_estimators=200, random_state=0)
```

1.12.3 Previsão com os melhores modelos

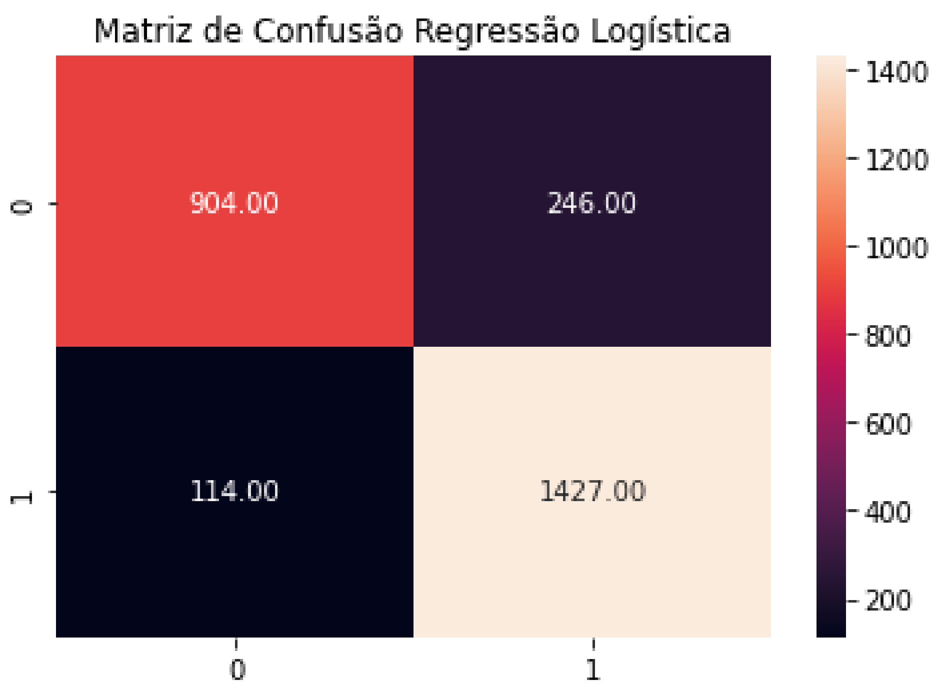
```
[ ]: prev_logreg = melhor_logreg.predict(X_test)
     prev_rf = melhor_rf.predict(X_test)

     acur_logreg = accuracy_score(y_test,prev_logreg)
     acur_rf = accuracy_score(y_test,prev_rf)

     prec_logreg = precision_score(y_test,prev_logreg)
     prec_rf = precision_score(y_test,prev_rf)

     recal_logreg = recall_score(y_test,prev_logreg)
     recal_rf = recall_score(y_test,prev_rf)

     print("Scores de previsao\n")
     print("Regressao Logistica: \nAcurácia = %.2f\nPrecisão = %.2f\nRecall = %.
      ↪2f\n"%(acur_logreg,prec_logreg,recal_logreg))
     print("Random Forest: \nAcurácia = %.2f\nPrecisão = %.2f\nRecall = %.
      ↪2f"%(acur_rf,prec_rf,recal_rf))

     resultados = pd.DataFrame(columns=["Modelo","Acuracia","Precisao","Recall"])
     resultados.loc[len(resultados.index)] = ["Logistic␣
      ↪Regression",acur_logreg,prec_logreg,recal_logreg]
     resultados.loc[len(resultados.index)] = ["Random␣
      ↪Forest",acur_rf,prec_rf,recal_rf]
     resultados.to_csv(path_dados_consolidados+"resultados_geral.csv")
```

```
Scores de previsao

Regressao Logistica:
Acurácia = 0.87
Precisão = 0.85
Recall = 0.93
```

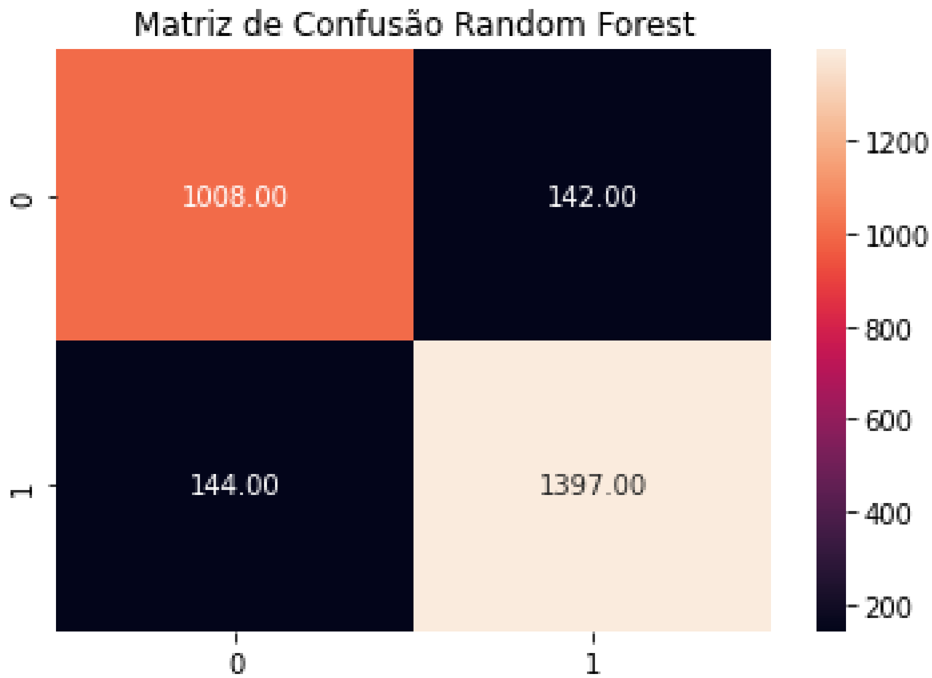
```
Random Forest:
Acurácia = 0.89
Precisão = 0.91
Recall = 0.91
```

1.12.4 Matriz de Confusão

[ ]:
```python
cm_logreg = confusion_matrix(y_test,prev_logreg)
cm_rf = confusion_matrix(y_test,prev_rf)

plt.figure()
plt.title("Matriz de Confusão Regressão Logística")
sns.heatmap(cm_logreg,annot=True,fmt=".2f")
plt.savefig(path_dados_consolidados+"matrizconfusao_logreg_geral.png")
plt.show()
```



[ ]:
```python
plt.figure()
plt.title("Matriz de Confusão Random Forest")
sns.heatmap(cm_rf,annot=True,fmt=".2f")
plt.savefig(path_dados_consolidados+"matrizconfusao_rf_geral.png")
plt.show()
```



1.13 Importância de variáveis

[ ]:
```
importancia_logreg = permutation_importance(melhor_logreg, X, y,␣
↪n_repeats=10,random_state=0)
importancia_rf = permutation_importance(melhor_rf, X, y,␣
↪n_repeats=10,random_state=0)
```

[ ]:
```
df_importancias_rf = pd.DataFrame(columns=["Variavel","Mean","Std"])
df_importancias_rf["Variavel"] = X.columns
df_importancias_rf["Mean"] = importancia_rf.importances_mean
df_importancias_rf["Std"] = importancia_rf.importances_std
df_importancias_rf = df_importancias_rf.sort_values(by="Mean",ascending=False)
df_importancias_rf.
↪to_csv(path_dados_consolidados+"importancia_varivaeis_rf_geral.csv")
df_importancias_rf
```

[ ]:

	Variavel	Mean	Std
12	ano_lancamento	1.410278e-01	0.001701
13	Popularidade Artista	3.884460e-02	0.001925
14	Seguidores	1.410524e-02	0.001303
4	speechiness	8.389550e-03	0.001127
0	danceability	7.813075e-03	0.001331
6	instrumentalness	6.709187e-03	0.000774
9	tempo	2.072857e-03	0.000582

```
2           loudness  1.741690e-03  0.001716
5       acousticness  1.324666e-03  0.000387
1             energy  1.140684e-03  0.000738
39               qui  6.868637e-04  0.000184
15              key1  5.764749e-04  0.000135
10       duration_ms  5.396786e-04  0.000754
35               nov  5.028824e-04  0.000260
8            valence  4.415553e-04  0.000541
24             key10  2.943702e-04  0.000125
23              key9  2.698393e-04  0.000238
36               dez  2.453085e-04  0.000123
26               fev  2.085122e-04  0.000135
33               set  2.085122e-04  0.000156
3               mode  1.839814e-04  0.000422
29               mai  1.717159e-04  0.000207
32               ago  1.471851e-04  0.000107
38               qua  8.585797e-05  0.000165
37               ter  3.679627e-05  0.000311
17              key3 -1.110223e-17  0.000055
27               mar -2.453085e-05  0.000163
41               sab -3.679627e-05  0.000079
11    time_signature -3.679627e-05  0.000096
22              key8 -3.679627e-05  0.000165
28               abr -4.906170e-05  0.000137
18              key4 -6.132712e-05  0.000148
20              key6 -8.585797e-05  0.000263
21              key7 -9.812339e-05  0.000180
25             key11 -1.103888e-04  0.000194
34               out -1.471851e-04  0.000244
42               dom -1.471851e-04  0.000120
19              key5 -1.594505e-04  0.000123
7           liveness -2.085122e-04  0.000623
40               sex -2.453085e-04  0.000606
30               jun -2.575739e-04  0.000116
31               jul -3.802281e-04  0.000086
16              key2 -5.887403e-04  0.000262
```

[ ]:
```
df_importancias_logreg = pd.DataFrame(columns=["Variavel","Mean","Std"])
df_importancias_logreg["Variavel"] = X.columns
df_importancias_logreg["Mean"] = importancia_logreg.importances_mean
df_importancias_logreg["Std"] = importancia_logreg.importances_std
df_importancias_logreg = df_importancias_logreg.
 ↪sort_values(by="Mean",ascending=False)
df_importancias_logreg.
 ↪to_csv(path_dados_consolidados+"importancia_varivaeis_logreg_geral.csv")
df_importancias_logreg
```

[ ]:

	Variavel	Mean	Std
13	Popularidade Artista	0.113455	0.003189
12	ano_lancamento	0.048510	0.002517
40	sex	0.018815	0.001735
0	danceability	0.016374	0.001700
39	qui	0.013750	0.001119
6	instrumentalness	0.012449	0.001843
2	loudness	0.009714	0.002087
4	speechiness	0.008058	0.001231
10	duration_ms	0.006660	0.001775
1	energy	0.004918	0.001484
38	qua	0.004195	0.000706
3	mode	0.001913	0.000633
27	mar	0.001852	0.000349
32	ago	0.001435	0.000526
42	dom	0.001325	0.000608
24	key10	0.000932	0.000415
9	tempo	0.000871	0.000800
5	acousticness	0.000810	0.000830
36	dez	0.000785	0.000479
18	key4	0.000748	0.000366
41	sab	0.000687	0.000482
31	jul	0.000662	0.000518
30	jun	0.000540	0.000446
26	fev	0.000540	0.000339
20	key6	0.000527	0.000347
22	key8	0.000478	0.000655
15	key1	0.000454	0.000679
28	abr	0.000356	0.000423
8	valence	0.000270	0.000598
29	mai	0.000221	0.000680
33	set	0.000086	0.000252
11	time_signature	-0.000012	0.000260
25	key11	-0.000025	0.000074
16	key2	-0.000049	0.000192
37	ter	-0.000049	0.000214
17	key3	-0.000074	0.000221
14	Seguidores	-0.000086	0.000291
23	key9	-0.000110	0.000086
35	nov	-0.000123	0.000165
7	liveness	-0.000123	0.000239
34	out	-0.000135	0.000476
21	key7	-0.000147	0.000074
19	key5	-0.000196	0.000264

1.14 Agora apenas com as informações técnicas de cada música, excluindo variáveis sobre o artista

[ ]:
```
#Selecionando as variaveis de entrada
dados_sem_artista = dados.drop(columns=["Seguidores","Popularidade Artista"])

y = dados_sem_artista.Top
X = dados_sem_artista.drop(columns=["Top","nome"])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33,␣
 ↪random_state=0)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(5462, 41)
(2691, 41)
(5462,)
(2691,)
```

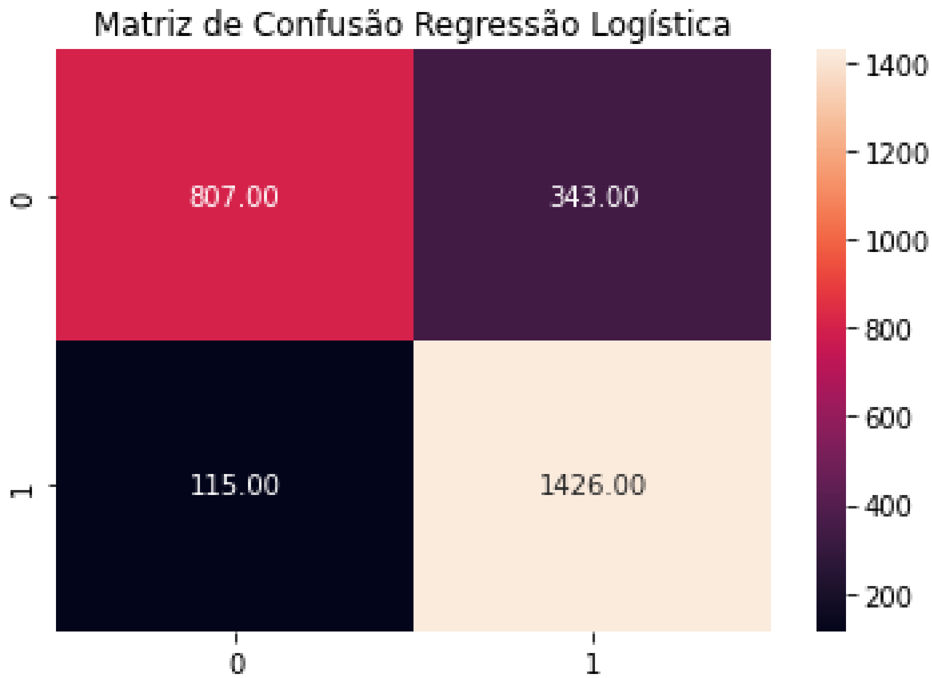
[ ]:
```
#Treinando os modelos
grid_logreg = GridSearchCV(logreg,
                    param_grid=params_logist,
                    scoring='accuracy').fit(X_train, y_train)

grid_rf = GridSearchCV(rf,
                    param_grid=params_rf,
                    scoring='accuracy').fit(X_train, y_train)
```

[ ]:
```
#Selecionando o melhor modelo do Grid Search
melhor_logreg = grid_logreg.best_estimator_
melhor_rf = grid_rf.best_estimator_

print("Melhores modelos")
print(melhor_logreg)
print(melhor_rf)

#Previsão dos modelos
prev_logreg = melhor_logreg.predict(X_test)
prev_rf = melhor_rf.predict(X_test)

acur_logreg = accuracy_score(y_test,prev_logreg)
acur_rf = accuracy_score(y_test,prev_rf)

prec_logreg = precision_score(y_test,prev_logreg)
prec_rf = precision_score(y_test,prev_rf)
```

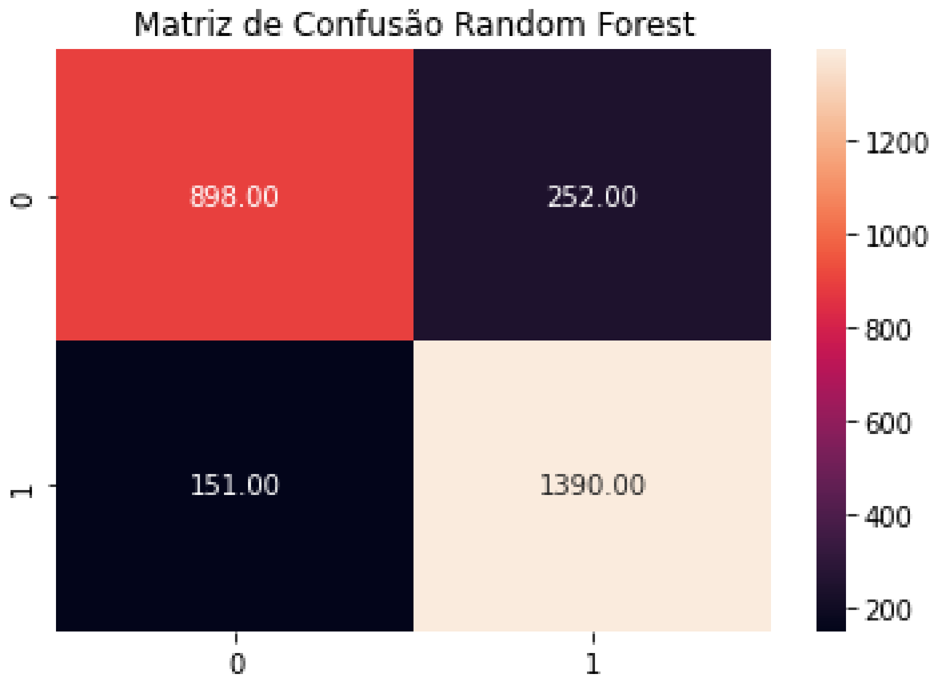
```
recal_logreg = recall_score(y_test,prev_logreg)
recal_rf = recall_score(y_test,prev_rf)

print("Scores de previsao\n")
print("Regressao Logistica: \nAcurácia = %.2f\nPrecisão = %.2f\nRecall = %.
↪2f\n"%(acur_logreg,prec_logreg,recal_logreg))
print("Random Forest: \nAcurácia = %.2f\nPrecisão = %.2f\nRecall = %.
↪2f"%(acur_rf,prec_rf,recal_rf))

resultados = pd.DataFrame(columns=["Modelo","Acuracia","Precisao","Recall"])
resultados.loc[len(resultados.index)] = ["Logistic␣
↪Regression",acur_logreg,prec_logreg,recal_logreg]
resultados.loc[len(resultados.index)] = ["Random␣
↪Forest",acur_rf,prec_rf,recal_rf]
resultados.to_csv(path_dados_consolidados+"resultados_semArtista.csv")
```

```
Melhores modelos
LogisticRegression(max_iter=200, random_state=0, solver='newton-cg')
RandomForestClassifier(criterion='entropy', max_depth=10, max_samples=100,
                       n_estimators=200, random_state=0)
Scores de previsao

Regressao Logistica:
Acurácia = 0.83
Precisão = 0.81
Recall = 0.93

Random Forest:
Acurácia = 0.85
Precisão = 0.85
Recall = 0.90
```

[ ]:
```
#Matriz de confusao
cm_logreg = confusion_matrix(y_test,prev_logreg)
cm_rf = confusion_matrix(y_test,prev_rf)

plt.figure()
plt.title("Matriz de Confusão Regressão Logística")
sns.heatmap(cm_logreg,annot=True,fmt=".2f")
plt.savefig(path_dados_consolidados+"matrizconfusao_logreg_semArtista.png")
plt.show()
```



[ ]:
```
plt.figure()
plt.title("Matriz de Confusão Random Forest")
sns.heatmap(cm_rf,annot=True,fmt=".2f")
plt.savefig(path_dados_consolidados+"matrizconfusao_rf_semArtista.png")
plt.show()
```



[ ]:
```
importancia_logreg = permutation_importance(melhor_logreg, X, y,␣
 ↪n_repeats=10,random_state=0)
importancia_rf = permutation_importance(melhor_rf, X, y,␣
 ↪n_repeats=10,random_state=0)
```

[ ]:
```
df_importancias_rf = pd.DataFrame(columns=["Variavel","Mean","Std"])
df_importancias_rf["Variavel"] = X.columns
df_importancias_rf["Mean"] = importancia_rf.importances_mean
df_importancias_rf["Std"] = importancia_rf.importances_std
df_importancias_rf = df_importancias_rf.sort_values(by="Mean",ascending=False)
df_importancias_rf.
 ↪to_csv(path_dados_consolidados+"importancia_varivaeis_rf_semArtista.csv")
df_importancias_rf
```

[ ]:

	Variavel	Mean	Std
12	ano_lancamento	2.016436e-01	0.003440
6	instrumentalness	1.090396e-02	0.001296
4	speechiness	5.237336e-03	0.001670
2	loudness	4.587268e-03	0.001262
0	danceability	3.618300e-03	0.000688
1	energy	3.225806e-03	0.001071
9	tempo	2.391758e-03	0.000883
5	acousticness	1.741690e-03	0.001001
10	duration_ms	1.692628e-03	0.000872

```
7           liveness  1.214277e-03  0.000743
37               qui  8.953759e-04  0.000311
3               mode  8.708451e-04  0.000412
8            valence  6.868637e-04  0.000596
13              key1  5.274132e-04  0.000206
34               dez  4.047590e-04  0.000096
25               mar  3.802281e-04  0.000128
20              key8  3.066356e-04  0.000148
18              key6  2.575739e-04  0.000201
17              key5  2.453085e-04  0.000134
32               out  2.330431e-04  0.000102
35               ter  2.207776e-04  0.000691
16              key4  2.085122e-04  0.000252
14              key2  1.839814e-04  0.000207
27               mai  1.717159e-04  0.000166
38               sex  1.226542e-04  0.000532
33               nov  1.103888e-04  0.000159
26               abr  9.812339e-05  0.000143
36               qua  8.585797e-05  0.000146
22             key10  7.359254e-05  0.000175
19              key7  7.359254e-05  0.000125
28               jun  6.132712e-05  0.000176
24               fev  6.132712e-05  0.000158
15              key3  4.906170e-05  0.000060
29               jul  3.679627e-05  0.000110
40               dom  2.220446e-17  0.000110
21              key9 -3.679627e-05  0.000275
39               sab -3.679627e-05  0.000220
23             key11 -6.132712e-05  0.000113
30               ago -6.132712e-05  0.000200
31               set -1.103888e-04  0.000086
11    time_signature -1.103888e-04  0.000177
```

[ ]:
```
df_importancias_logreg = pd.DataFrame(columns=["Variavel","Mean","Std"])
df_importancias_logreg["Variavel"] = X.columns
df_importancias_logreg["Mean"] = importancia_logreg.importances_mean
df_importancias_logreg["Std"] = importancia_logreg.importances_std
df_importancias_logreg = df_importancias_logreg.
 ↪sort_values(by="Mean",ascending=False)
df_importancias_logreg.
 ↪to_csv(path_dados_consolidados+"importancia_varivaeis_logreg_semArtista.csv")
df_importancias_logreg
```

[ ]:
```
             Variavel          Mean       Std
12     ano_lancamento  6.614743e-02  0.003000
2            loudness  4.411873e-02  0.002900
6    instrumentalness  3.261376e-02  0.001583
```

```
38               sex  2.818594e-02  0.001697
37               qui  2.038513e-02  0.001177
0       danceability  2.023795e-02  0.002007
1             energy  1.351650e-02  0.002070
4        speechiness  9.468907e-03  0.001881
10       duration_ms  4.758984e-03  0.001601
36               qua  4.047590e-03  0.000593
8            valence  3.949466e-03  0.000800
29               jul  3.041825e-03  0.000520
34               dez  2.146449e-03  0.000636
3               mode  2.023795e-03  0.001246
30               ago  1.741690e-03  0.000520
40               dom  1.557709e-03  0.000403
27               mai  1.226542e-03  0.000446
28               jun  1.152950e-03  0.000422
32               out  1.103888e-03  0.000611
25               mar  7.604563e-04  0.000598
39               sab  6.868637e-04  0.000472
33               nov  4.660861e-04  0.000577
20              key8  4.170244e-04  0.000422
16              key4  3.556973e-04  0.000507
24               fev  2.943702e-04  0.000443
22             key10  1.962468e-04  0.000389
19              key7  1.839814e-04  0.000473
35               ter  4.906170e-05  0.000137
21              key9  4.440892e-17  0.000465
14              key2  3.330669e-17  0.000368
7           liveness  0.000000e+00  0.000000
31               set -2.453085e-05  0.000452
18              key6 -4.906170e-05  0.000385
26               abr -7.359254e-05  0.000207
17              key5 -2.207776e-04  0.000180
13              key1 -2.698393e-04  0.000898
23             key11 -3.189010e-04  0.000316
15              key3 -3.434319e-04  0.000153
11    time_signature -3.802281e-04  0.000298
9              tempo -5.028824e-04  0.000794
5       acousticness -1.128419e-03  0.000462
```

1.15 Implementação dos modelos utilizando PCA

Vou aplicar o PCA para redução de dimensionalidade apenas nos dados que não foram separados em dummies

[ ]:
```
dados.columns
```

[ ]: Index(['danceability', 'energy', 'loudness', 'mode', 'speechiness',
       'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
       'duration_ms', 'time_signature', 'ano_lancamento',
       'Popularidade Artista', 'Seguidores', 'Top', 'key1', 'key2', 'key3',
       'key4', 'key5', 'key6', 'key7', 'key8', 'key9', 'key10', 'key11', 'fev',
       'mar', 'abr', 'mai', 'jun', 'jul', 'ago', 'set', 'out', 'nov', 'dez',
       'ter', 'qua', 'qui', 'sex', 'sab', 'dom'],
      dtype='object')

[ ]:
```
print(dados.shape)
dados_semDummies = dados[['danceability', 'energy', 'loudness', 'mode',␣
 ↪'speechiness',
       'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
       'duration_ms', 'time_signature', 'ano_lancamento',
       'Popularidade Artista', 'Seguidores', 'Top']]

dados_dummies = dados[['key1', 'key2', 'key3',
       'key4', 'key5', 'key6', 'key7', 'key8', 'key9', 'key10', 'key11', 'fev',
       'mar', 'abr', 'mai', 'jun', 'jul', 'ago', 'set', 'out', 'nov', 'dez',
       'ter', 'qua', 'qui', 'sex', 'sab', 'dom']]

dados_semDummies = dados_semDummies.reset_index(drop=True)
dados_dummies = dados_dummies.reset_index(drop=True)
print(dados_semDummies.shape)
print(dados_dummies.shape)
```

```
(8153, 44)
(8153, 16)
(8153, 28)
```

[ ]:
```
#Selecionando as variaveis de entrada
y = dados_semDummies.Top
X = dados_semDummies.drop(columns="Top")

print(X.shape)
print(y.shape)
```

```
(8153, 15)
(8153,)
```

[ ]:
```
#Aplicando PCA
pca = PCA(copy=True,n_components=5,svd_solver="full",random_state=0).fit(X)
print(pca.explained_variance_)
print(abs(pca.components_))
```

```
[4.58071822e+09 8.69686444e+02 3.13110973e+02 1.62485140e+02
 1.29785324e+01]
[[5.36612578e-07 9.84661380e-08 3.58059899e-06 1.12198577e-08
  1.55560769e-07 1.52446130e-07 1.19571596e-07 9.99089544e-08
```

```
 4.42191847e-07 1.25891355e-05 9.99999999e-01 2.40171520e-08
 4.84831210e-05 2.54948519e-06 2.79207433e-08]
[1.22379655e-04 1.33989498e-03 2.12931355e-02 4.05780948e-04
 4.26270155e-04 1.58742528e-03 6.33353317e-04 5.02737997e-05
 6.38098514e-04 9.98593041e-01 1.29646486e-05 9.54915560e-05
 3.99956212e-03 4.83428808e-02 1.18978782e-04]
[2.68418179e-03 1.88714552e-03 8.60614449e-02 1.71112302e-03
 1.19671065e-03 4.02451038e-03 3.90774466e-03 2.52192628e-04
 8.65122392e-04 4.73926692e-02 2.18783587e-05 1.88596866e-03
 4.09518101e-01 9.06944294e-01 6.58576553e-03]
[1.57483793e-03 1.33050373e-04 3.94091614e-02 3.08664923e-03
 6.74217175e-04 8.39840046e-06 1.62989654e-03 4.27541171e-04
 2.97134237e-03 1.55432673e-02 4.33761800e-05 2.58147523e-04
 9.09467654e-01 4.13576354e-01 2.07213794e-03]
[1.34257334e-02 4.43328700e-02 9.92504151e-01 5.11992712e-03
 1.05837986e-04 4.22167691e-02 2.29099960e-02 3.55419027e-03
 2.59164316e-02 1.79730448e-02 2.88260836e-07 1.83396585e-02
 7.13575887e-02 6.32914298e-02 3.88987628e-03]]
```

[ ]:
```
X_pca = pca.transform(X)
print(X_pca.shape)
```

```
(8153, 5)
```

[ ]:
```
X_pca_completo = pd.DataFrame(X_pca)
X_pca_completo = X_pca_completo.reset_index(drop=True)
# print(X_pca_completo.shape)
# print(dados_dummies.shape)
X_pca_completo = pd.concat([X_pca_completo,dados_dummies],axis=1)
# print(X_pca_completo.shape)
# print(X_pca_completo.shape)
X_pca_completo.rename(columns = {1:'pca1',2:'pca2',
                                 3:'pca3',4:'pca4',
                                 0:'pca0'}, inplace = True)
X_pca_completo
```

[ ]:
```
              pca0       pca1       pca2       pca3      pca4  key1  key2  \
0    -48770.760761 -52.745448 -22.011202   1.478583  0.945992     0     0
1    -42125.759903  14.409537 -18.003923  -1.045578  0.022111     0     0
2     22731.240458  39.974837 -14.332362  -4.084236 -0.176133     0     0
3    -74267.760601 -47.880410 -11.243355  -0.985392  0.228485     1     0
4    -10002.759785  26.128002 -16.534070  -3.480805 -0.147549     0     0
…              …          …          …          …          …     …   …
8148 -49755.760504 -41.384947   4.457710  -9.313441  1.199315     0     0
8149  -3006.758144  -0.951092   6.653398  30.507602 -5.187711     0     0
8150  34019.239917 -23.677825 -19.854779   4.940361  3.203812     0     0
8151 -74940.759555 -22.399303  -5.500526  12.615976 -2.715516     1     0
8152  34926.241439  39.094815   5.752316   8.314625  1.045459     0     0
```

```
      key3  key4  key5  ...  set  out  nov  dez  ter  qua  qui  sex  sab  dom
0        0     0     0  ...    0    0    0    0    0    0    1    0    0    0
1        0     0     0  ...    0    0    0    0    0    0    0    1    0    0
2        0     0     0  ...    0    0    0    0    0    0    1    0    0    0
3        0     0     0  ...    0    0    0    0    0    0    0    1    0    0
4        0     0     0  ...    0    0    0    0    0    0    1    0    0    0
...    ...   ...   ...  ...  ...  ...  ...  ...  ...  ...  ...  ...  ...  ...
8148     0     0     0  ...    0    1    0    0    0    0    0    1    0    0
8149     0     0     1  ...    0    0    0    0    0    0    0    0    0    0
8150     0     1     0  ...    0    0    0    0    0    1    0    0    0    0
8151     0     0     0  ...    0    0    0    0    0    0    0    0    0    1
8152     0     0     0  ...    0    0    0    0    0    0    0    0    1    0

[8153 rows x 33 columns]
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X_pca_completo, y,
 ↪test_size=0.33, random_state=0)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(5462, 33)
(2691, 33)
(5462,)
(2691,)
```

[ ]:
```
#Treinando os modelos
grid_logreg = GridSearchCV(logreg,
                    param_grid=params_logist,
                    scoring='accuracy').fit(X_train, y_train)

grid_rf = GridSearchCV(rf,
                    param_grid=params_rf,
                    scoring='accuracy').fit(X_train, y_train)
```

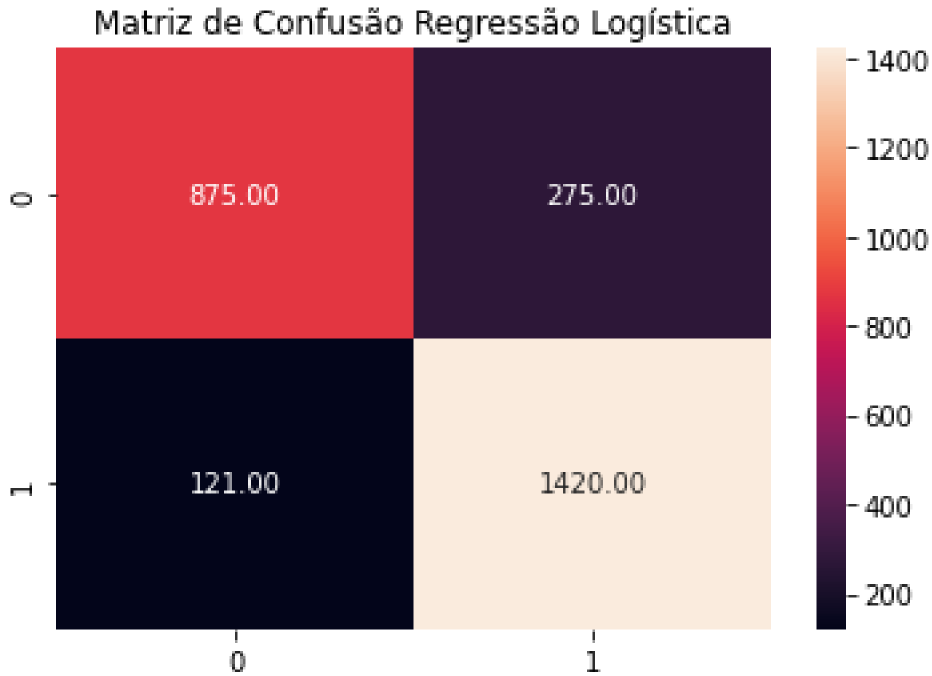
[ ]:
```
#Selecionando o melhor modelo do Grid Search
melhor_logreg = grid_logreg.best_estimator_
melhor_rf = grid_rf.best_estimator_

print("Melhores modelos")
print(melhor_logreg)
print(melhor_rf)

#Previsão dos modelos
prev_logreg = melhor_logreg.predict(X_test)
```

```
prev_rf = melhor_rf.predict(X_test)

acur_logreg = accuracy_score(y_test,prev_logreg)
acur_rf = accuracy_score(y_test,prev_rf)

prec_logreg = precision_score(y_test,prev_logreg)
prec_rf = precision_score(y_test,prev_rf)

recal_logreg = recall_score(y_test,prev_logreg)
recal_rf = recall_score(y_test,prev_rf)

print("Scores de previsao\n")
print("Regressao Logistica: \nAcurácia = %.2f\nPrecisão = %.2f\nRecall = %.
↪2f\n"%(acur_logreg,prec_logreg,recal_logreg))
print("Random Forest: \nAcurácia = %.2f\nPrecisão = %.2f\nRecall = %.
↪2f"%(acur_rf,prec_rf,recal_rf))

resultados = pd.DataFrame(columns=["Modelo","Acuracia","Precisao","Recall"])
resultados.loc[len(resultados.index)] = ["Logistic␣
↪Regression",acur_logreg,prec_logreg,recal_logreg]
resultados.loc[len(resultados.index)] = ["Random␣
↪Forest",acur_rf,prec_rf,recal_rf]
resultados.to_csv(path_dados_consolidados+"resultados_PCA.csv")
```

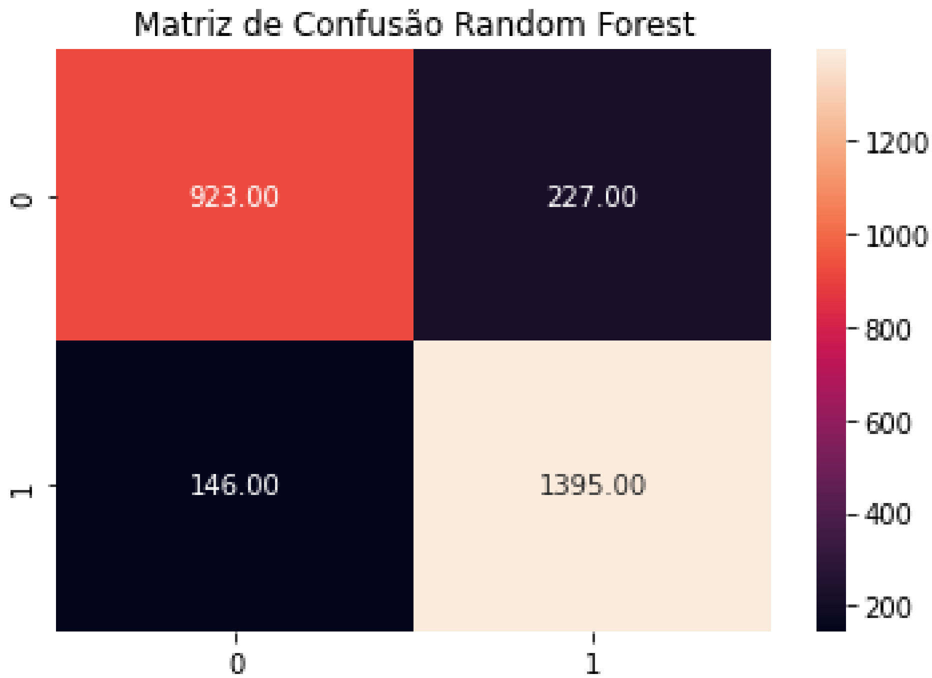
```
Melhores modelos
LogisticRegression(max_iter=200, random_state=0, solver='newton-cg')
RandomForestClassifier(criterion='entropy', max_samples=100, random_state=0)
Scores de previsao

Regressao Logistica:
Acurácia = 0.85
Precisão = 0.84
Recall = 0.92

Random Forest:
Acurácia = 0.86
Precisão = 0.86
Recall = 0.91
```

[ ]:
```
#Matriz de confusao
cm_logreg = confusion_matrix(y_test,prev_logreg)
cm_rf = confusion_matrix(y_test,prev_rf)

plt.figure()
plt.title("Matriz de Confusão Regressão Logística")
sns.heatmap(cm_logreg,annot=True,fmt=".2f")
plt.savefig(path_dados_consolidados+"matrizconfusao_logreg_PCA.png")
```

```
plt.show()
```



[ ]:
```
plt.figure()
plt.title("Matriz de Confusão Random Forest")
sns.heatmap(cm_rf,annot=True,fmt=".2f")
plt.savefig(path_dados_consolidados+"matrizconfusao_rf_PCA.png")
plt.show()
```




```
[ ]: importancia_logreg = permutation_importance(melhor_logreg, X_pca_completo, y,␣
      ↪n_repeats=10,random_state=0)
     importancia_rf = permutation_importance(melhor_rf, X_pca_completo, y,␣
      ↪n_repeats=10,random_state=0)
```

```
[ ]: df_importancias_rf = pd.DataFrame(columns=["Variavel","Mean","Std"])
     df_importancias_rf["Variavel"] = X_pca_completo.columns
     df_importancias_rf["Mean"] = importancia_rf.importances_mean
     df_importancias_rf["Std"] = importancia_rf.importances_std
     df_importancias_rf = df_importancias_rf.sort_values(by="Mean",ascending=False)
     df_importancias_rf.to_csv(path_dados_consolidados+"importancia_varivaeis_rf_PCA.
      ↪csv")
     df_importancias_rf
```

[ ]:

	Variavel	Mean	Std
2	pca2	0.225475	0.004393
3	pca3	0.048841	0.001916
0	pca0	0.014154	0.001447
4	pca4	0.006219	0.001474
30	sex	0.006047	0.001032
1	pca1	0.004281	0.000592
29	qui	0.001864	0.000481
27	ter	0.001766	0.000633
25	nov	0.001545	0.000446

```
26       dez  0.000944  0.000258
5       key1  0.000908  0.000500
19       mai  0.000834  0.000402
11      key7  0.000797  0.000385
24       out  0.000773  0.000315
14     key10  0.000699  0.000246
9       key5  0.000699  0.000296
28       qua  0.000564  0.000460
6       key2  0.000429  0.000411
17       mar  0.000405  0.000174
16       fev  0.000392  0.000262
18       abr  0.000343  0.000231
12      key8  0.000319  0.000400
20       jun  0.000196  0.000440
13      key9  0.000172  0.000227
23       set  0.000159  0.000311
15     key11  0.000123  0.000212
22       ago  0.000123  0.000315
8       key4  0.000086  0.000252
32       dom  0.000061  0.000148
10      key6  0.000061  0.000247
21       jul -0.000012  0.000222
7       key3 -0.000037  0.000135
31       sab -0.000159  0.000376
```

[ ]:
```
df_importancias_logreg = pd.DataFrame(columns=["Variavel","Mean","Std"])
df_importancias_logreg["Variavel"] = X_pca_completo.columns
df_importancias_logreg["Mean"] = importancia_logreg.importances_mean
df_importancias_logreg["Std"] = importancia_logreg.importances_std
df_importancias_logreg = df_importancias_logreg.
 ↪sort_values(by="Mean",ascending=False)
df_importancias_logreg.
 ↪to_csv(path_dados_consolidados+"importancia_varivaeis_logreg_PCA.csv")
df_importancias_logreg
```

[ ]:
```
   Variavel          Mean       Std
2      pca2  2.561388e-01  0.004176
0      pca0  2.787931e-02  0.001688
30      sex  2.775665e-02  0.002523
29      qui  1.810377e-02  0.001006
3      pca3  1.514780e-02  0.001498
4      pca4  5.801545e-03  0.001094
28      qua  3.017294e-03  0.000868
5      key1  2.514412e-03  0.000609
14    key10  2.256838e-03  0.000494
17      mar  1.852079e-03  0.000566
32      dom  1.741690e-03  0.000442
```

```
10     key6  1.692628e-03  0.000567
18      abr  1.668098e-03  0.000515
26      dez  1.594505e-03  0.000532
31      sab  1.398258e-03  0.000500
1      pca1  1.091623e-03  0.000592
16      fev  1.054826e-03  0.000631
24      out  8.831105e-04  0.000680
23      set  7.359254e-04  0.000586
21      jul  7.236600e-04  0.000741
20      jun  6.255366e-04  0.000423
22      ago  5.519441e-04  0.000473
25      nov  3.924936e-04  0.000244
6      key2  2.821047e-04  0.000334
19      mai  2.821047e-04  0.000649
7      key3  2.207776e-04  0.000180
9      key5  1.349197e-04  0.000229
13     key9  1.349197e-04  0.000102
12     key8  1.226542e-04  0.000529
27      ter  1.226542e-04  0.000343
11     key7  1.110223e-17  0.000095
8      key4 -4.170244e-04  0.000535
15    key11 -5.151478e-04  0.000577
```

1.16 Implementação dos modelos com remoção de anomalias

Vou aproveitar que implementamos um detector de anomalias para ver se a qualidade da previsão aumenta ao retirar as músicas que são, possivelmente, anômalas.

[ ]:
```
anomalias_boas = pd.
 ↪read_csv(path_dados_consolidados+"resultado_anomalias_musicas_boas.
 ↪csv",index_col="Unnamed: 0")
anomalias_ruins = pd.
 ↪read_csv(path_dados_consolidados+"resultado_anomalias_musicas_ruins.
 ↪csv",index_col="Unnamed: 0")

anomalias_boas = anomalias_boas.drop(columns=["Unnamed: 0.1"])
anomalias_ruins = anomalias_ruins.drop(columns=["Unnamed: 0.1"])
```

[ ]:
```
mask_boas = anomalias_boas["probabilidade"]>0.5
mask_ruins = anomalias_ruins["probabilidade"]>0.5

print(mask_boas.sum())
print(mask_ruins.sum())
```

```
22
20
```

[ ]:
```
anomalias_ruins = anomalias_ruins[mask_ruins]
nomes_anomalias_ruins = anomalias_ruins.nome
anomalias_ruins
```

[ ]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	\
79	0.1840	0.00275	1	-39.619	0	0.0512	0.99500	
154	0.6890	0.73500	2	-4.545	1	0.2670	0.00922	
377	0.3130	0.34500	8	-13.495	1	0.0573	0.84800	
726	0.3650	0.74100	9	-11.513	0	0.0516	0.00150	
940	0.1280	0.37400	7	-11.184	0	0.0385	0.69500	
1087	0.1660	0.94800	11	-8.503	0	0.0631	0.00374	
1113	0.7260	0.71900	6	-5.122	0	0.2340	0.13700	
1162	0.8250	0.65200	1	-3.183	0	0.0802	0.58100	
1977	0.2120	0.24500	8	-16.939	1	0.0455	0.87500	
2353	0.7950	0.37800	4	-9.979	1	0.3160	0.85900	
2406	0.7010	0.42500	7	-10.965	1	0.3750	0.32800	
2482	0.3310	0.12500	9	-22.329	0	0.0495	0.96000	
2538	0.8930	0.65100	0	-8.647	0	0.3670	0.09950	
2874	0.6410	0.32400	11	-5.851	1	0.0299	0.69800	
3157	0.5260	0.32800	1	-9.864	1	0.0461	0.69400	
3360	0.7540	0.86900	4	-3.843	1	0.3030	0.13700	
3523	0.6080	0.81200	7	-12.318	0	0.0422	0.45000	
3609	0.0692	0.04630	2	-25.350	0	0.0373	0.87000	
3707	0.8080	0.74500	10	-5.260	0	0.3420	0.14500	
3908	0.4570	0.90600	5	-2.278	0	0.3420	0.24900	

	instrumentalness	liveness	valence	…	abod	prob abod	autoencoder	\
79	0.93400	0.1140	0.1630	…	1	0.030771	1	
154	0.00072	0.3650	0.0590	…	0	0.969229	1	
377	0.00989	0.7250	0.2160	…	1	0.030771	1	
726	0.84700	0.1470	0.3090	…	1	0.030771	1	
940	0.91200	0.1430	0.0701	…	1	0.030771	1	
1087	0.01310	0.7690	0.4760	…	1	0.030771	1	
1113	0.00000	0.6600	0.8260	…	0	0.969229	1	
1162	0.00000	0.0931	0.9310	…	0	0.969230	1	
1977	0.00527	0.4060	0.1780	…	1	0.030771	1	
2353	0.00000	0.2040	0.5760	…	0	0.969229	1	
2406	0.13000	0.1000	0.5620	…	0	0.969253	1	
2482	0.69800	0.6880	0.1210	…	1	0.030771	1	
2538	0.00000	0.3710	0.6000	…	0	0.969229	1	
2874	0.00000	0.3280	0.2730	…	0	0.969229	1	
3157	0.00000	0.1120	0.1100	…	1	0.030771	1	
3360	0.00000	0.7520	0.7840	…	0	0.969229	1	
3523	0.73100	0.2600	0.8890	…	1	0.030771	1	
3609	0.30800	0.0937	0.0714	…	1	0.030771	1	
3707	0.00000	0.2920	0.8290	…	0	0.969229	1	
3908	0.00000	0.1820	0.5400	…	1	0.030771	1	

```
      prob autoencoder  lof  prob lof  if   prob if  total votos  \
79            0.999999    0  1.000000   1  0.999783            3
154           0.969113    1  0.793117   1  0.987032            3
377           1.000000    1  0.000000   1  0.989009            4
726           0.994146    1  0.000000   1  0.992308            4
940           0.998682    1  0.000000   1  0.981851            4
1087          0.990608    1  0.000000   1  0.989598            4
1113          0.999831    1  0.999088   1  0.996598            3
1162          0.998320    1  1.000000   1  0.969319            3
1977          0.996396    1  0.000000   1  0.988322            4
2353          0.980518    1  1.000000   1  0.977152            3
2406          0.987758    1  1.000000   1  0.939483            3
2482          0.999919    1  0.000000   1  0.998459            4
2538          0.992505    1  0.999291   1  0.995497            3
2874          0.998259    1  1.000000   1  0.980624            3
3157          0.999560    1  0.976788   1  0.943512            4
3360          0.994915    1  0.999986   1  0.985398            3
3523          0.997621    1  0.000000   1  0.976059            4
3609          0.998888    0  1.000000   1  0.999878            3
3707          0.993334    1  0.999037   1  0.983607            3
3908          0.991579    1  0.991357   1  0.985040            4

      probabilidade
79         0.507638
154        0.687316
377        0.504945
726        0.504306
940        0.502826
1087       0.502744
1113       0.748879
1162       0.741910
1977       0.503872
2353       0.739417
2406       0.731810
2482       0.507287
2538       0.746823
2874       0.744721
3157       0.737658
3360       0.745075
3523       0.501113
3609       0.507384
3707       0.743994
3908       0.749687

[20 rows x 29 columns]
```

[ ]:
```
anomalias_boas = anomalias_boas[mask_boas]
nomes_anomalias_boas = anomalias_boas.nome
anomalias_boas
```

[ ]:

	danceability	energy	key	loudness	mode	speechiness	acousticness	\
171	0.454	0.910	6	-7.766	1	0.0448	0.0866	
309	0.271	0.551	2	-7.480	1	0.0457	0.5820	
444	0.526	0.328	1	-9.864	1	0.0461	0.6940	
1016	0.773	0.859	11	-4.913	1	0.0747	0.0855	
1144	0.602	0.553	11	-9.336	1	0.0328	0.1080	
1160	0.920	0.654	11	-3.051	0	0.0401	0.0236	
1330	0.671	0.373	9	-18.064	1	0.0323	0.2570	
1821	0.336	0.231	1	-6.217	1	0.0497	0.9420	
1867	0.636	0.335	11	-13.327	1	0.9660	0.9930	
1952	0.647	0.814	11	-16.493	0	0.9410	0.8100	
2223	0.553	0.337	10	-10.334	1	0.0300	0.8180	
2451	0.153	0.138	6	-21.877	0	0.0503	0.8370	
2896	0.368	0.286	9	-13.031	0	0.0294	0.9130	
3193	0.413	0.130	0	-25.166	0	0.0336	0.9000	
3261	0.429	0.231	5	-20.430	1	0.4020	0.8780	
3653	0.184	0.297	2	-14.534	1	0.0359	0.4730	
3655	0.231	0.457	6	-10.773	0	0.0318	0.0126	
3774	0.396	0.373	9	-14.097	0	0.0989	0.9910	
4163	0.331	0.513	11	-15.392	0	0.6320	0.9720	
4393	0.631	0.518	0	-8.771	1	0.0303	0.2740	
4859	0.445	0.131	7	-13.778	1	0.0564	0.6630	
4980	0.476	0.161	8	-11.665	0	0.0407	0.9670	

	instrumentalness	liveness	valence	…	abod	prob abod	autoencoder	\
171	0.099600	0.1160	0.6290	…	1	0.023365	1	
309	0.000042	0.2560	0.4280	…	1	0.023365	1	
444	0.000000	0.1120	0.1100	…	1	0.023365	1	
1016	0.000180	0.9140	0.8130	…	1	0.023365	1	
1144	0.000000	0.0512	0.9710	…	1	0.023365	1	
1160	0.015800	0.0359	0.8470	…	1	0.023365	1	
1330	0.000080	0.0481	0.7320	…	1	0.023365	1	
1821	0.000000	0.1880	0.4290	…	1	0.023365	1	
1867	0.000000	0.3420	0.5610	…	1	0.023365	1	
1952	0.000000	0.4450	0.0787	…	1	0.023365	1	
2223	0.000000	0.1130	0.6620	…	1	0.023365	1	
2451	0.550000	0.2540	0.0503	…	1	0.023365	1	
2896	0.177000	0.0990	0.3120	…	1	0.023365	1	
3193	0.820000	0.1110	0.0676	…	1	0.023365	1	
3261	0.000000	0.2790	0.9140	…	1	0.023365	1	
3653	0.893000	0.5270	0.1130	…	1	0.023365	1	
3655	0.875000	0.3270	0.0588	…	1	0.023365	1	
3774	0.097800	0.5450	0.5260	…	1	0.023365	1	

4163	0.953000	0.8820	0.4200	…	1	0.023365	1
4393	0.000000	0.0880	0.2050	…	1	0.023365	1
4859	0.000002	0.1080	0.1010	…	0	0.976635	1
4980	0.038100	0.1090	0.0908	…	0	0.976635	1

	prob autoencoder	lof	prob lof	if	prob if	total votos	\
171	0.969456	1	1.000000	1	0.971554	4	
309	0.991113	0	0.909872	1	0.998930	3	
444	0.999609	1	0.999999	1	0.987996	4	
1016	0.999853	0	0.530942	1	0.999119	3	
1144	0.999978	0	1.000000	1	0.998983	3	
1160	0.987869	0	0.551385	1	0.994511	3	
1330	0.997729	0	1.000000	1	0.996387	3	
1821	0.963463	1	0.961607	1	0.961043	4	
1867	0.999998	1	0.845565	1	0.999989	4	
1952	0.999912	0	1.000000	1	0.999804	3	
2223	0.999998	0	0.931955	1	0.999439	3	
2451	1.000000	0	1.000000	1	0.999991	3	
2896	0.999983	0	0.861603	1	0.999489	3	
3193	1.000000	1	0.540486	1	0.999990	4	
3261	0.999756	1	0.516008	1	0.999006	4	
3653	1.000000	0	1.000000	1	0.999954	3	
3655	1.000000	0	1.000000	1	0.999756	3	
3774	0.987127	1	0.999319	1	0.999557	4	
4163	1.000000	1	0.570289	1	1.000000	4	
4393	0.999918	1	1.000000	0	0.230140	3	
4859	0.975297	1	0.701504	1	0.986142	3	
4980	0.919189	1	0.510191	1	0.954392	3	

	probabilidade
171	0.741094
309	0.503352
444	0.752742
1016	0.505584
1144	0.505581
1160	0.501436
1330	0.504370
1821	0.727369
1867	0.717229
1952	0.505770
2223	0.505701
2451	0.505839
2896	0.505709
3193	0.640960
3261	0.634534
3653	0.505830
3655	0.505780

```
3774       0.752342
4163       0.648413
4393       0.505821
4859       0.665736
4980       0.595943

[22 rows x 29 columns]
```

```
[ ]: #Retirando as musicas anomalas dos dados
colunas_comuns = ['danceability', 'energy', 'loudness', 'mode', 'speechiness',
       'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
       'duration_ms', 'ano_lancamento', 'Popularidade Artista',
       'Seguidores']

colunas_referencia = ["nome","duration_ms","Popularidade␣
 ↪Artista","ano_lancamento"]


anomalias_boas = anomalias_boas[colunas_referencia]
anomalias_ruins = anomalias_ruins[colunas_referencia]
dados_aux = dados[colunas_referencia]
print(anomalias_boas.shape,anomalias_ruins.shape,dados_aux.shape)

lista_indices_anomalias = []

for idx,row in anomalias_boas.iterrows():
  for idx_2,row2 in dados.iterrows():
    if row2["nome"] == row["nome"] and row2["duration_ms"] ==␣
 ↪row["duration_ms"]:
      lista_indices_anomalias.append(idx_2)

print(len(lista_indices_anomalias))

for idx,row in anomalias_ruins.iterrows():
  for idx_2,row2 in dados.iterrows():
    if row2["nome"] == row["nome"] and row2["duration_ms"] ==␣
 ↪row["duration_ms"]:
      lista_indices_anomalias.append(idx_2)

print(len(lista_indices_anomalias))
```

```
(22, 4) (20, 4) (8153, 4)
22
42
```

```
[ ]: nomes_anomalias = pd.concat([anomalias_boas.nome,anomalias_ruins.nome],axis=0)
nomes_anomalias.sort_values()
```

```
[ ]: 1330                                                    Africa
     2874                                                 Afterglow
     3261                                        Alfred - Interlude
     4393    All Too Well (10 Minute Version) (Taylor's Ver…
     1977    Amazing Grace - Live at New Temple Missionary …
     377     Amazing Grace - Live at New Temple Missionary …
     4163                                            Beautiful Trip
     1160                                               Billie Jean
     3655                                              Chromatica I
     3653                                             Chromatica II
     309          Fairytale of New York (feat. Kirsty MacColl)
     940                                                    Finale
     3908                                                   Forever
     444                                               Give Me Love
     3157                                              Give Me Love
     3707                               Godzilla (feat. Juice WRLD)
     1952                                         I Love You Dwayne
     3523                                           It Ain't No Use
     3193                                                  JACKBOYS
     2223                                          Joy To The World
     3774                   Juice WRLD Speaks From Heaven - Outro
     2538                                                  Killshot
     1144                              Little Saint Nick - 1991 Remix
     154                                             Lose Yourself
     2353                                             Love Yourself
     726                                                  Malvinas
     2482                                          Moon River - Live
     1867                                              Paul - Skit
     79      Piano Sonata No. 14 in C-Sharp Minor, Op. 27 N…
     3360                                                 Remind Me
     1162                                              Shape of You
     1113                                 Sing - Live and in Session
     1087                                                 Stargazer
     4859    State Of Grace (Acoustic Version) (Taylor's Ve…
     171                                        Sweet Child O' Mine
     1016                                                  Thriller
     3609                                 Toccata and Fugue in D minor
     2896                                              Venice Bitch
     4980                                         Yebba’s Heartbreak
     2406                                                   bad guy
     2451                                                   goodbye
     1821                                 raindrops (an angel cried)
     Name: nome, dtype: object
```

```
[ ]: dados.nome[lista_indices_anomalias].sort_values()
```

[ ]:
```
1254                                                  Africa
3789                                               Afterglow
2972                                      Alfred - Interlude
3987     All Too Well (10 Minute Version) (Taylor's Ver…
6437     Amazing Grace - Live at New Temple Missionary …
5001     Amazing Grace - Live at New Temple Missionary …
3781                                          Beautiful Trip
1106                                             Billie Jean
3340                                            Chromatica I
3338                                           Chromatica II
306          Fairytale of New York (feat. Kirsty MacColl)
5497                                                  Finale
8143                                                 Forever
437                                             Give Me Love
437                                             Give Me Love
2946                              Godzilla (feat. Juice WRLD)
1820                                        I Love You Dwayne
7813                                          It Ain't No Use
2914                                                JACKBOYS
2053                                         Joy To The World
3448                   Juice WRLD Speaks From Heaven - Outro
1788                                                Killshot
1092                             Little Saint Nick - 1991 Remix
4802                                           Lose Yourself
6773                                           Love Yourself
5307                                                Malvinas
6884                                        Moon River - Live
1739                                              Paul - Skit
4732     Piano Sonata No. 14 in C-Sharp Minor, Op. 27 N…
1064                                               Remind Me
120                                             Shape of You
5649                              Sing - Live and in Session
5625                                               Stargazer
4404     State Of Grace (Acoustic Version) (Taylor's Ve…
171                                         Sweet Child O' Mine
977                                                 Thriller
7884                             Toccata and Fugue in D minor
2669                                             Venice Bitch
4510                                        Yebba’s Heartbreak
2255                                                 bad guy
2266                                                 goodbye
1696                               raindrops (an angel cried)
Name: nome, dtype: object
```

[ ]:
```
dados_sem_anomalias = dados.drop(labels=lista_indices_anomalias,axis="index")
print(dados.shape)
print(dados_sem_anomalias.shape)
```

```
print(dados_sem_anomalias.columns)
```

```
(8153, 45)
(8112, 45)
Index(['danceability', 'energy', 'loudness', 'mode', 'speechiness',
       'acousticness', 'instrumentalness', 'liveness', 'valence', 'tempo',
       'duration_ms', 'time_signature', 'nome', 'ano_lancamento',
       'Popularidade Artista', 'Seguidores', 'Top', 'key1', 'key2', 'key3',
       'key4', 'key5', 'key6', 'key7', 'key8', 'key9', 'key10', 'key11', 'fev',
       'mar', 'abr', 'mai', 'jun', 'jul', 'ago', 'set', 'out', 'nov', 'dez',
       'ter', 'qua', 'qui', 'sex', 'sab', 'dom'],
      dtype='object')
```

[ ]:
```
#Selecionando as variaveis de entrada
y_sem_anomalias = dados_sem_anomalias.Top
X_sem_anomalias = dados_sem_anomalias.drop(columns=["Top","nome"])

print(X_sem_anomalias.shape)
print(y_sem_anomalias.shape)
```

```
(8112, 43)
(8112,)
```

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X_sem_anomalias,␣
 ↪y_sem_anomalias, test_size=0.33, random_state=0)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(5435, 43)
(2677, 43)
(5435,)
(2677,)
```

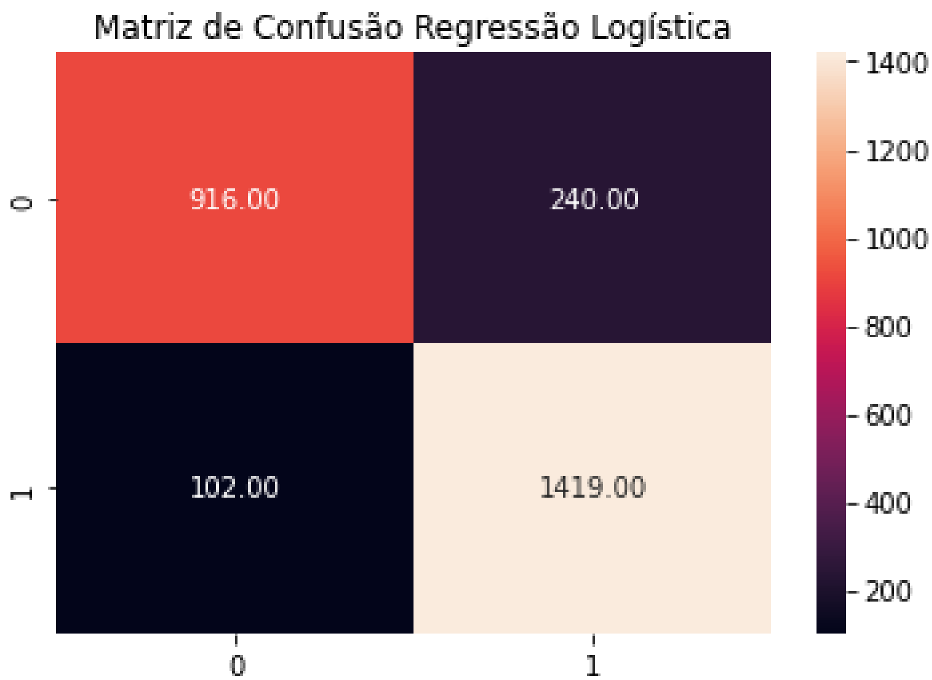
[ ]:
```
#Treinando os modelos
grid_logreg = GridSearchCV(logreg,
                    param_grid=params_logist,
                    scoring='accuracy').fit(X_train, y_train)

grid_rf = GridSearchCV(rf,
                    param_grid=params_rf,
                    scoring='accuracy').fit(X_train, y_train)
```

[ ]:
```
#Selecionando o melhor modelo do Grid Search
melhor_logreg = grid_logreg.best_estimator_
melhor_rf = grid_rf.best_estimator_
```

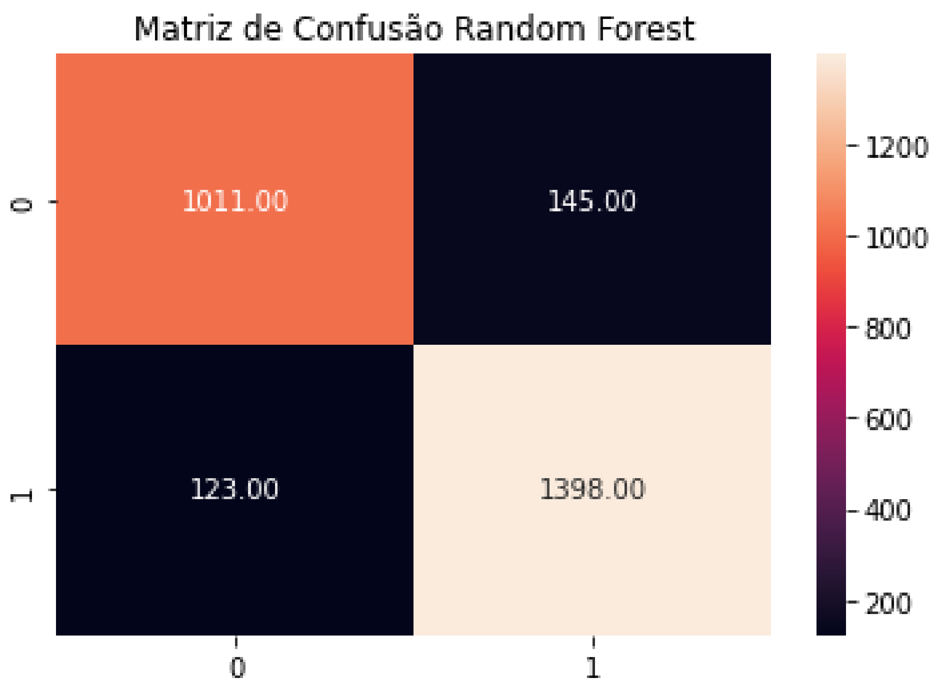
```python
print("Melhores modelos")
print(melhor_logreg)
print(melhor_rf)

# Previsão dos modelos
prev_logreg = melhor_logreg.predict(X_test)
prev_rf = melhor_rf.predict(X_test)

acur_logreg = accuracy_score(y_test,prev_logreg)
acur_rf = accuracy_score(y_test,prev_rf)

prec_logreg = precision_score(y_test,prev_logreg)
prec_rf = precision_score(y_test,prev_rf)

recal_logreg = recall_score(y_test,prev_logreg)
recal_rf = recall_score(y_test,prev_rf)

print("Scores de previsao\n")
print("Regressao Logistica: \nAcurácia = %.2f\nPrecisão = %.2f\nRecall = %.
↪2f\n"%(acur_logreg,prec_logreg,recal_logreg))
print("Random Forest: \nAcurácia = %.2f\nPrecisão = %.2f\nRecall = %.
↪2f"%(acur_rf,prec_rf,recal_rf))

resultados = pd.DataFrame(columns=["Modelo","Acuracia","Precisao","Recall"])
resultados.loc[len(resultados.index)] = ["Logistic␣
↪Regression",acur_logreg,prec_logreg,recal_logreg]
resultados.loc[len(resultados.index)] = ["Random␣
↪Forest",acur_rf,prec_rf,recal_rf]
resultados.to_csv(path_dados_consolidados+"resultados_semAnomalia.csv")
```

```
Melhores modelos
LogisticRegression(max_iter=200, random_state=0, solver='newton-cg')
RandomForestClassifier(criterion='entropy', max_samples=100, n_estimators=200,
                       random_state=0)
Scores de previsao

Regressao Logistica:
Acurácia = 0.87
Precisão = 0.86
Recall = 0.93

Random Forest:
Acurácia = 0.90
Precisão = 0.91
Recall = 0.92
```

[ ]:
```python
#Matriz de confusao
cm_logreg = confusion_matrix(y_test,prev_logreg)
cm_rf = confusion_matrix(y_test,prev_rf)

plt.figure()
plt.title("Matriz de Confusão Regressão Logística")
sns.heatmap(cm_logreg,annot=True,fmt=".2f")
plt.savefig(path_dados_consolidados+"matrizconfusao_logreg_semAnomalia.png")
plt.show()
```



[ ]:
```python
plt.figure()
plt.title("Matriz de Confusão Random Forest")
sns.heatmap(cm_rf,annot=True,fmt=".2f")
plt.savefig(path_dados_consolidados+"matrizconfusao_rf_semAnomalia.png")
plt.show()
```



[ ]:
```
importancia_logreg = permutation_importance(melhor_logreg, X_sem_anomalias,␣
 ↪y_sem_anomalias, n_repeats=10,random_state=0)
importancia_rf = permutation_importance(melhor_rf, X_sem_anomalias,␣
 ↪y_sem_anomalias, n_repeats=10,random_state=0)
```

[ ]:
```
df_importancias_rf = pd.DataFrame(columns=["Variavel","Mean","Std"])
df_importancias_rf["Variavel"] = X_sem_anomalias.columns
df_importancias_rf["Mean"] = importancia_rf.importances_mean
df_importancias_rf["Std"] = importancia_rf.importances_std
df_importancias_rf = df_importancias_rf.sort_values(by="Mean",ascending=False)
df_importancias_rf.
 ↪to_csv(path_dados_consolidados+"importancia_varivaeis_rf_semAnomalia.csv")
df_importancias_rf
```

[ ]:

	Variavel	Mean	Std
12	ano_lancamento	1.272806e-01	0.003216
13	Popularidade Artista	3.288955e-02	0.001345
14	Seguidores	1.931706e-02	0.001166
4	speechiness	1.012081e-02	0.001429
0	danceability	8.185404e-03	0.001631
6	instrumentalness	6.200690e-03	0.000977
1	energy	2.921598e-03	0.000578
2	loudness	1.577909e-03	0.000873
9	tempo	1.429980e-03	0.000689

```
5         acousticness  1.232742e-03  0.000517
10         duration_ms  1.047830e-03  0.000993
39                 qui  6.533531e-04  0.000146
40                 sex  5.177515e-04  0.000553
3                 mode  3.821499e-04  0.000309
22                key8  3.205128e-04  0.000158
37                 ter  2.958580e-04  0.000836
30                 jun  1.972387e-04  0.000242
16                key2  1.725838e-04  0.000184
23                key9  1.356016e-04  0.000102
21                key7  7.396450e-05  0.000193
26                 fev  4.930966e-05  0.000082
36                 dez  1.232742e-05  0.000116
33                 set -3.330669e-17  0.000110
35                 nov -4.440892e-17  0.000191
24               key10 -5.551115e-17  0.000240
42                 dom -1.232742e-05  0.000037
8              valence -1.232742e-05  0.000597
17                key3 -2.465483e-05  0.000107
20                key6 -3.698225e-05  0.000146
27                 mar -3.698225e-05  0.000156
18                key4 -6.163708e-05  0.000148
11      time_signature -7.396450e-05  0.000126
41                 sab -9.861933e-05  0.000092
38                 qua -9.861933e-05  0.000107
19                key5 -1.356016e-04  0.000129
7             liveness -1.479290e-04  0.000708
29                 mai -1.602564e-04  0.000191
32                 ago -1.849112e-04  0.000099
28                 abr -2.218935e-04  0.000074
25               key11 -2.342209e-04  0.000116
31                 jul -2.465483e-04  0.000078
15                key1 -2.712032e-04  0.000285
34                 out -3.944773e-04  0.000269
```

[ ]:
```
df_importancias_logreg = pd.DataFrame(columns=["Variavel","Mean","Std"])
df_importancias_logreg["Variavel"] = X_sem_anomalias.columns
df_importancias_logreg["Mean"] = importancia_logreg.importances_mean
df_importancias_logreg["Std"] = importancia_logreg.importances_std
df_importancias_logreg = df_importancias_logreg.
 ↪sort_values(by="Mean",ascending=False)
df_importancias_logreg.
 ↪to_csv(path_dados_consolidados+"importancia_varivaeis_logreg_semAnomalia.
 ↪csv")
df_importancias_logreg
```

[ ]:

	Variavel	Mean	Std
13	Popularidade Artista	0.105843	0.002784
12	ano_lancamento	0.053267	0.002644
40	sex	0.020180	0.001323
0	danceability	0.020044	0.001673
39	qui	0.015212	0.000888
6	instrumentalness	0.014756	0.001502
2	loudness	0.010207	0.002377
4	speechiness	0.009825	0.001813
10	duration_ms	0.007162	0.001328
38	qua	0.004056	0.000456
1	energy	0.002823	0.000948
5	acousticness	0.001750	0.001199
27	mar	0.001615	0.000510
15	key1	0.001541	0.000521
8	valence	0.001418	0.000732
26	fev	0.001381	0.000454
24	key10	0.001245	0.000600
42	dom	0.001233	0.000362
3	mode	0.000949	0.000465
30	jun	0.000851	0.000337
32	ago	0.000814	0.000424
9	tempo	0.000542	0.000438
35	nov	0.000468	0.000144
41	sab	0.000431	0.000541
31	jul	0.000419	0.000371
25	key11	0.000333	0.000461
36	dez	0.000296	0.000435
19	key5	0.000296	0.000184
11	time_signature	0.000284	0.000357
22	key8	0.000284	0.000420
28	abr	0.000234	0.000210
37	ter	0.000185	0.000277
14	Seguidores	0.000173	0.000428
17	key3	0.000136	0.000140
20	key6	0.000123	0.000427
7	liveness	0.000111	0.000202
18	key4	0.000099	0.000164
21	key7	-0.000160	0.000234
16	key2	-0.000173	0.000099
23	key9	-0.000222	0.000433
34	out	-0.000247	0.000520
29	mai	-0.000259	0.000550
33	set	-0.000764	0.000361