MODELO 1 - Avaliação do Modelo de Classificação.

Introdução.

Este Notebook é destina a avaliação do modelo de regressão logística e separação dos dados no arquivo voice_fix.csv

Resumo da análise anterior com a base tratada em python das propriedades acústicas.

In [1]:
```
%matplotlib inline
```

In [2]:
```
# Importa as bibliotecas
import pandas
import matplotlib.pyplot as plt
import numpy
#from pandas.tools.plotting import scatter_matrix
from  pandas.plotting  import scatter_matrix
import seaborn as sb
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.preprocessing import Normalizer
#Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score , roc_curve, auc ,accuracy_score,recall_score, preci
sion_score
import statsmodels.api as sm
from sklearn.metrics import confusion_matrix
```

In [3]:
```
url = "C:\\Users\\jorge\\Desktop\\TCC\\tcc_to_git\\tcc\\baseDados\\voice_fix.csv"
colunas = ["meanfreq","sd","median","Q25","Q75","IQR","skew","kurt","sp.ent","sfm","mode","cen
troid","meanfun","minfun","maxfun","meandom","mindom","maxdom","dfrange","modindx","label"]
dataset = pandas.read_csv(url, names=colunas , sep = ",")
```

In [4]:
```
dataset[["meanfreq","sd","median"]].head(2)
```

Out[4]:

	meanfreq	sd	median
0	0.172557	0.064241	0.176893
1	0.172557	0.067310	0.176893

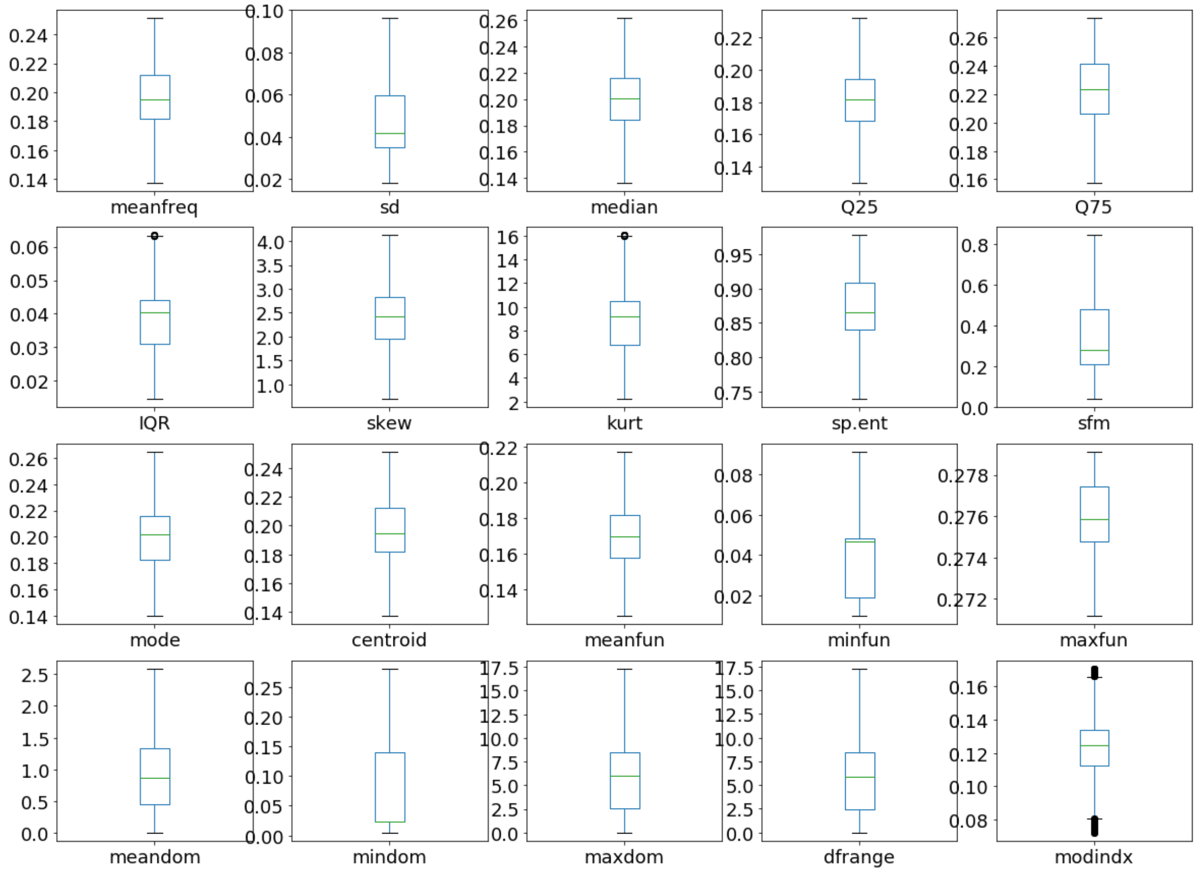
1) Refazendo boxplot.

O BOXPLOT representa os dados através de um retângulo construído com os quartis e fornece informação sobre valores extremos.

In [5]:
```
## Separação dos dados pela classe label, vozes de homens e mulheres.
dfHomens = dataset[dataset["label"] == "male"]
dfMulheres = dataset[dataset["label"] == "female"]
```

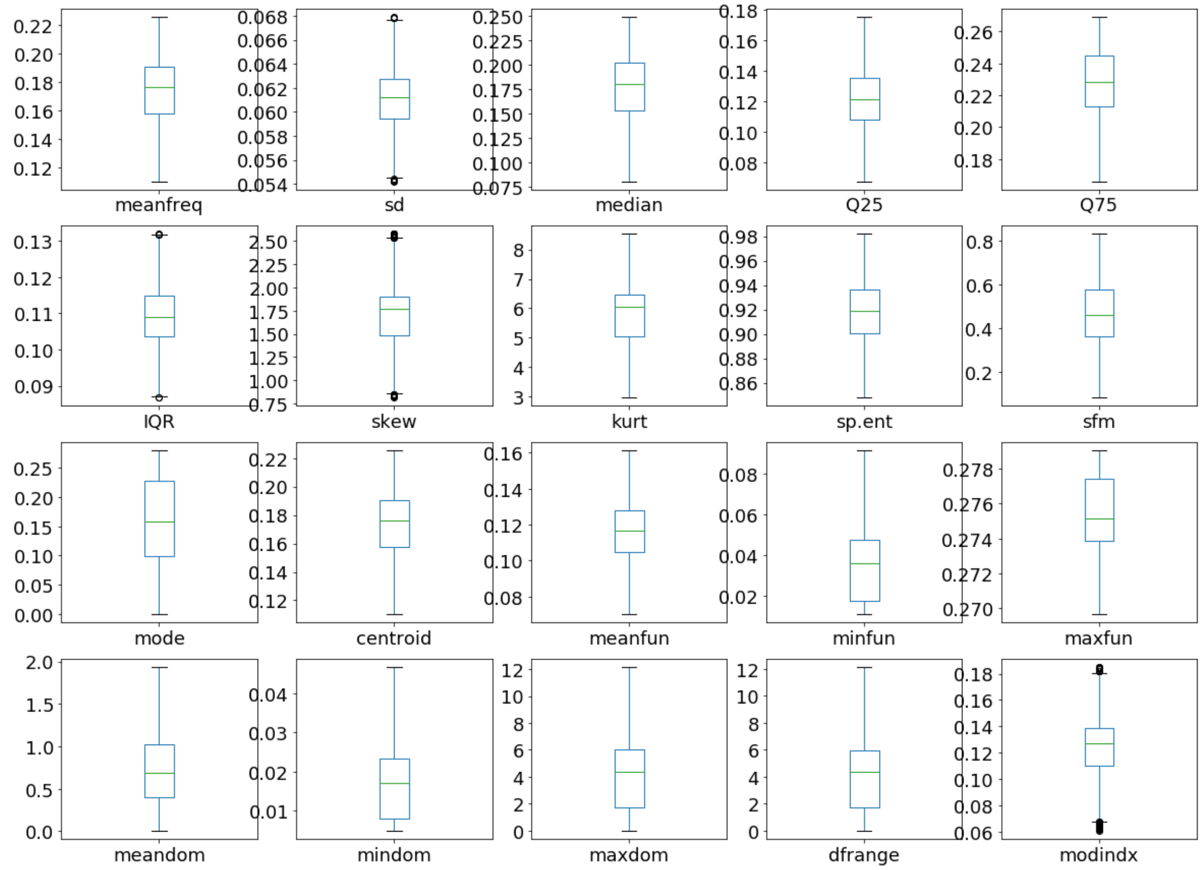
Dataframe da classe femele

In [6]:
```
plt.rcParams['figure.figsize'] = (20,15)
dfMulheres[colunas[0:20]].plot(kind='box', subplots=True, layout=(4,5), sharex=False, sharey=False,fontsize=18)
plt.show()
```



Dataframe da classe male

In [7]:
```
plt.rcParams['figure.figsize'] = (20,15)
dfHomens[colunas[0:20]].plot(kind='box', subplots=True, layout=(4,5), sharex=False, sharey=False,fontsize=18)
plt.show()
```



Fim do resumo análise.

In [8]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import Normalizer
#Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score , roc_curve, auc
```

In [9]:
```
url = ".\\baseDados\\voice_fix.csv"
colunas = ["meanfreq","sd","median","Q25","Q75","IQR","skew","kurt","sp.ent","sfm","mode","centroid","meanfun","minfun","maxfun","meandom","mindom","maxdom","dfrange","modindx","label"]
dataset = pandas.read_csv(url, names=colunas , sep = ",")
```

Procedimentos de avaliação de modelo

Train/Test Split K-Fold Cross Validation

2) Preparando a base para usar no modelo de regressão logística.

In [10]:
```
print(dataset.head(2).transpose())
```

```
                   0           1
meanfreq    0.172557    0.172557
sd         0.0642413     0.06731
median      0.176893    0.176893
Q25         0.121089    0.121089
Q75         0.227842    0.227842
IQR         0.109055    0.109055
skew         1.90605     1.90605
kurt         6.45022     6.45022
sp.ent      0.893369    0.892193
sfm         0.491918    0.513724
mode               0           0
centroid    0.172557    0.172557
meanfun    0.0842791    0.107937
minfun     0.0157017   0.0158259
maxfun      0.275862    0.273863
meandom    0.0078125  0.00901442
mindom     0.0078125   0.0078125
maxdom     0.0078125   0.0546875
dfrange            0    0.046875
modindx     0.132999    0.124688
label           male        male
```

3) Atribuindo para female=1 (Mulheres), male=0 (Homens) e adicionando a coluna gênero para representar a classe como dummy.

In [11]:
```
df_pre = dataset

df_pre['genero'] = df_pre['label'].replace({'female': 1, 'male': 0})
dataset = df_pre
```

In [12]:
```
print(df_pre.head(2).transpose())



#dataset = df_pre
```

```
                   0           1
meanfreq    0.172557    0.172557
sd         0.0642413     0.06731
median      0.176893    0.176893
Q25         0.121089    0.121089
Q75         0.227842    0.227842
IQR         0.109055    0.109055
skew         1.90605     1.90605
kurt         6.45022     6.45022
sp.ent      0.893369    0.892193
sfm         0.491918    0.513724
mode               0           0
centroid    0.172557    0.172557
meanfun    0.0842791    0.107937
minfun     0.0157017   0.0158259
maxfun      0.275862    0.273863
meandom    0.0078125  0.00901442
mindom     0.0078125   0.0078125
maxdom     0.0078125   0.0546875
dfrange            0    0.046875
modindx     0.132999    0.124688
label           male        male
genero             0           0
```

In [13]:
```python
#df =dataset.rename(columns={'label': 'genero'})
print(df_pre.tail(2).transpose())
```

```
                3166       3167
meanfreq    0.143659   0.165509
sd         0.0906283  0.0928835
median      0.184976   0.183044
Q25         0.181927   0.181927
Q75         0.219943   0.250827
IQR        0.0412693  0.0412693
skew         1.59106    1.70503
kurt          5.3883    5.76912
sp.ent      0.950436   0.938829
sfm          0.67547   0.601529
mode        0.212202   0.201041
centroid    0.143659   0.165509
meanfun     0.172375   0.185607
minfun     0.0344828  0.0622568
maxfun      0.274763   0.271186
meandom      0.79136   0.227022
mindom     0.0078125  0.0078125
maxdom       3.59375   0.554688
dfrange      3.58594   0.546875
modindx     0.133931   0.133931
label         female     female
genero             1          1
```

4) Dataset: Train/Test Split para os modelos.

Esse método divide o conjunto de dados em duas partes: um conjunto de treinamento e um conjunto de testes. O conjunto de treinamento é usado para treinar o modelo. Também podemos medir a precisão do modelo no conjunto de treinamento.

Logistic Regression coefficients na formula: y= 1 *b0* + *b1*X1 + b2*X2*+ *b3*Xn

5) Criando explicitamente y-intercept: b0.

In [14]:
```python
df_pre['int']=1
print(df_pre.head().transpose())
```

```
                   0          1           2          3          4
meanfreq    0.172557   0.172557    0.172557   0.151228    0.13512
sd         0.0642413    0.06731   0.0635487  0.0612157  0.0627691
median      0.176893   0.176893    0.176893   0.158011   0.124656
Q25         0.121089   0.121089    0.121089  0.0965817  0.0787202
Q75         0.227842   0.227842    0.227842   0.207955   0.206045
IQR         0.109055   0.109055    0.123207   0.111374   0.127325
skew         1.90605    1.90605     1.90605    1.23283    1.10117
kurt         6.45022    6.45022     6.45022     4.1773    4.33371
sp.ent      0.893369   0.892193    0.918553   0.963322   0.971955
sfm         0.491918   0.513724    0.478905   0.727232   0.783568
mode               0          0           0  0.0838782   0.104261
centroid    0.172557   0.172557    0.172557   0.151228    0.13512
meanfun    0.0842791   0.107937   0.0987063  0.0889648   0.106398
minfun     0.0157017  0.0158259   0.0156556  0.0177976  0.0169312
maxfun      0.275862   0.273863    0.271186   0.273863   0.275166
meandom    0.0078125 0.00901442  0.00799006   0.201497   0.712812
mindom     0.0078125  0.0078125   0.0078125  0.0078125  0.0078125
maxdom     0.0078125  0.0546875    0.015625     0.5625    5.48438
dfrange            0   0.046875   0.0078125   0.554688    5.47656
modindx     0.132999   0.124688    0.124688   0.130223   0.124688
label           male       male        male       male       male
genero             0          0           0          0          0
int                1          1           1          1          1
```

In [15]:
```python
## Separação dos dados pela classe label, vozes de homens e mulheres.
df_male = df_pre[df_pre["label"] == "male"]
df_female = df_pre[df_pre["label"] == "female"]
```

In [16]:
```
print(df_male.head().transpose())
```

```
                  0           1           2          3          4
meanfreq   0.172557    0.172557    0.172557   0.151228    0.13512
sd        0.0642413     0.06731   0.0635487  0.0612157  0.0627691
median     0.176893    0.176893    0.176893   0.158011   0.124656
Q25        0.121089    0.121089    0.121089  0.0965817  0.0787202
Q75        0.227842    0.227842    0.227842   0.207955   0.206045
IQR        0.109055    0.109055    0.123207   0.111374   0.127325
skew        1.90605     1.90605     1.90605    1.23283    1.10117
kurt        6.45022     6.45022     6.45022     4.1773    4.33371
sp.ent     0.893369    0.892193    0.918553   0.963322   0.971955
sfm        0.491918    0.513724    0.478905   0.727232   0.783568
mode              0           0           0  0.0838782   0.104261
centroid   0.172557    0.172557    0.172557   0.151228    0.13512
meanfun   0.0842791    0.107937   0.0987063  0.0889648   0.106398
minfun    0.0157017   0.0158259   0.0156556  0.0177976  0.0169312
maxfun     0.275862    0.273863    0.271186   0.273863   0.275166
meandom   0.0078125  0.00901442  0.00799006   0.201497   0.712812
mindom    0.0078125   0.0078125   0.0078125  0.0078125  0.0078125
maxdom    0.0078125   0.0546875    0.015625     0.5625    5.48438
dfrange           0    0.046875   0.0078125   0.554688    5.47656
modindx    0.132999    0.124688    0.124688   0.130223   0.124688
label          male        male        male       male       male
genero            0           0           0          0          0
int               1           1           1          1          1
```

In [17]:
```
print(df_female.head().transpose())
```

```
               1584       1585       1586       1587       1588
meanfreq   0.158108   0.182855   0.199807    0.19528   0.208504
sd        0.0827816  0.0677889  0.0619738  0.0720869  0.0575502
median     0.191191   0.200639   0.211358   0.204656   0.220229
Q25        0.181927   0.175489   0.184422   0.180611   0.190343
Q75        0.224552   0.226068   0.235687   0.255954   0.249759
IQR       0.0412693  0.0505788  0.0512645  0.0403311  0.0594155
skew        2.80134    3.00189    2.54384    2.39233    1.70779
kurt        9.34563    9.34563     14.922    10.0615    5.67091
sp.ent     0.952161   0.910458   0.904432   0.907115   0.879674
sfm        0.679223   0.506099   0.425289   0.524209   0.343548
mode       0.201834   0.201834   0.201834   0.193435   0.201834
centroid   0.158108   0.182855   0.199807    0.19528   0.208504
meanfun    0.185042    0.15959   0.156465   0.182629   0.162043
minfun    0.0230216  0.0187135  0.0161943  0.0249221  0.0168067
maxfun     0.275862   0.275927   0.275927   0.275862   0.275927
meandom    0.272964    0.25897   0.250446   0.269531   0.260789
mindom     0.046875  0.0546875  0.0546875  0.0546875  0.0546875
maxdom     0.742188   0.804688   0.898438   0.703125     0.8125
dfrange    0.695312       0.75    0.84375   0.648438   0.757812
modindx    0.133931   0.129735   0.133931   0.133931   0.129735
label        female     female     female     female     female
genero            1          1          1          1          1
int               1          1          1          1          1
```

Separando X e Y para dataframe_female

In [18]:
```
X_entrada_female = df_female.drop(columns=['label','genero'])
Y_entrada_female = df_female['genero']
```

In [19]:
```
print(X_entrada_female.head().transpose())

feature_cols=X_entrada_female.columns
feature_cols
```

```
               1584      1585       1586       1587      1588
meanfreq  0.158108  0.182855   0.199807   0.195280  0.208504
sd        0.082782  0.067789   0.061974   0.072087  0.057550
median    0.191191  0.200639   0.211358   0.204656  0.220229
Q25       0.181927  0.175489   0.184422   0.180611  0.190343
Q75       0.224552  0.226068   0.235687   0.255954  0.249759
IQR       0.041269  0.050579   0.051265   0.040331  0.059416
skew      2.801344  3.001890   2.543841   2.392326  1.707786
kurt      9.345630  9.345630  14.921964  10.061489  5.670912
sp.ent    0.952161  0.910458   0.904432   0.907115  0.879674
sfm       0.679223  0.506099   0.425289   0.524209  0.343548
mode      0.201834  0.201834   0.201834   0.193435  0.201834
centroid  0.158108  0.182855   0.199807   0.195280  0.208504
meanfun   0.185042  0.159590   0.156465   0.182629  0.162043
minfun    0.023022  0.018713   0.016194   0.024922  0.016807
maxfun    0.275862  0.275927   0.275927   0.275862  0.275927
meandom   0.272964  0.258970   0.250446   0.269531  0.260789
mindom    0.046875  0.054688   0.054688   0.054688  0.054688
maxdom    0.742188  0.804688   0.898438   0.703125  0.812500
dfrange   0.695312  0.750000   0.843750   0.648438  0.757812
modindx   0.133931  0.129735   0.133931   0.133931  0.129735
int       1.000000  1.000000   1.000000   1.000000  1.000000
```

Out[19]:
```
Index(['meanfreq', 'sd', 'median', 'Q25', 'Q75', 'IQR', 'skew', 'kurt',
       'sp.ent', 'sfm', 'mode', 'centroid', 'meanfun', 'minfun', 'maxfun',
       'meandom', 'mindom', 'maxdom', 'dfrange', 'modindx', 'int'],
      dtype='object')
```

In [20]:
```
print(Y_entrada_female.head())
```

```
1584    1
1585    1
1586    1
1587    1
1588    1
Name: genero, dtype: int64
```

Separando X e Y para dataframe_male

In [21]:
```
X_entrada_male = df_male.drop(columns=['label','genero'])
Y_entrada_male = df_male['genero']
```

In [22]:
```
print(X_entrada_male.head().transpose())
```

```
                 0         1         2         3         4
meanfreq  0.172557  0.172557  0.172557  0.151228  0.135120
sd        0.064241  0.067310  0.063549  0.061216  0.062769
median    0.176893  0.176893  0.176893  0.158011  0.124656
Q25       0.121089  0.121089  0.121089  0.096582  0.078720
Q75       0.227842  0.227842  0.227842  0.207955  0.206045
IQR       0.109055  0.109055  0.123207  0.111374  0.127325
skew      1.906048  1.906048  1.906048  1.232831  1.101174
kurt      6.450221  6.450221  6.450221  4.177296  4.333713
sp.ent    0.893369  0.892193  0.918553  0.963322  0.971955
sfm       0.491918  0.513724  0.478905  0.727232  0.783568
mode      0.000000  0.000000  0.000000  0.083878  0.104261
centroid  0.172557  0.172557  0.172557  0.151228  0.135120
meanfun   0.084279  0.107937  0.098706  0.088965  0.106398
minfun    0.015702  0.015826  0.015656  0.017798  0.016931
maxfun    0.275862  0.273863  0.271186  0.273863  0.275166
meandom   0.007812  0.009014  0.007990  0.201497  0.712812
mindom    0.007812  0.007812  0.007812  0.007812  0.007812
maxdom    0.007812  0.054688  0.015625  0.562500  5.484375
dfrange   0.000000  0.046875  0.007812  0.554688  5.476562
modindx   0.132999  0.124688  0.124688  0.130223  0.124688
int       1.000000  1.000000  1.000000  1.000000  1.000000
```

In [23]:
```
print(Y_entrada_male.head())
```

```
0    0
1    0
2    0
3    0
4    0
Name: genero, dtype: int64
```

6) Divisão balanceada de 30% teste e 70% para o treino.

Feito a divisão randômica de 30 test e 70 treino no dataframe_female

In [24]:
```
X_trainF,X_testF,y_trainF,y_testF = train_test_split(X_entrada_female,Y_entrada_female,test_si
ze=0.30,random_state=0)
```

Feito a divisão randômica de 30 test e 70 treino no dataframe_male

In [25]:
```
X_trainM, X_testM, y_trainM ,y_testM = train_test_split(X_entrada_male,Y_entrada_male,test_siz
e=0.30,random_state=0)
```

Concatenando os datraframes Após ad divisão dos dados de treino e test male e frame

In [26]:
```
X_train_frames = [X_trainF, X_trainM]
```

In [27]:
```
X_test_frames = [X_testF,X_testM]
```

In [28]:
```
y_test_frames = [y_testF, y_testM]
```

In [29]:
```
y_train_frames = [ y_trainF,  y_trainM]
```

Convertendo os datraframes após a divisão dos dados de: treino e test, male e frame

In [30]:
```
X_train = pandas.concat(X_train_frames)
```

In [31]:
```
X_test = pandas.concat(X_test_frames)
```

In [32]:
```
y_train = pandas.concat(y_train_frames)
```

In [33]:
```
y_test = pandas.concat(y_test_frames )
```

Mostratandos as dimensões dos dados

In [34]:
```
X_train.shape,X_test.shape , y_train.shape, y_test.shape


dictabela = {}
dictabela['Registros para treino'] = X_train.shape[0]
dictabela['Registros para teste'] = X_test.shape[0]
```

In [35]:
```
dftreinoteste = pandas.DataFrame.from_dict(dictabela, orient="index").reset_index()
```

In [36]:
```
dftreinoteste =dftreinoteste.rename(columns={'index': 'divisão dos dados'})
dftreinoteste =dftreinoteste.rename(columns={0: 'total'})
dftreinoteste
```

Out[36]:

	divisão dos dados	total
0	Registros para treino	2216
1	Registros para teste	952

In [37]:
```
y_train
```

Out[37]:
```
2858    1
2040    1
2394    1
3133    1
3005    1
       ..
763     0
835     0
1216    0
559     0
684     0
Name: genero, Length: 2216, dtype: int64
```

Total de voz por classe, masculinas e femininas na base de treino

In [38]:
```
dfContador =pandas.DataFrame(list(y_train), columns = ['genero'])
contagem = dfContador.groupby('genero').size()
print(contagem)
```

```
genero
0    1108
1    1108
dtype: int64
```

Total de voz por classe, masculinas e femininas na base de teste

In [39]:
```
dfContador =pandas.DataFrame(list(y_test), columns = ['genero'])
contagem = dfContador.groupby('genero').size()
print(contagem)
```

```
genero
0    476
1    476
dtype: int64
```

7) Normalização dos dados por questão de escala.

In [40]:
```
# Instantiate
norm = Normalizer()

# Fit
norm.fit(X_train)

# Transform both training and testing sets
X_train_norm = norm.transform(X_train)
X_test_norm = norm.transform(X_test)
```

In [41]:
```
X_train_norm.shape , X_test_norm.shape
```

Out[41]:
```
((2216, 21), (952, 21))
```

In [42]:
```
print(X_train_norm)
```

```
[[0.01070896 0.0013571  0.01063611 ... 0.4404305  0.00528321 0.04733426]
 [0.01080389 0.002876   0.01080535 ... 0.38455026 0.00730888 0.05951927]
 [0.01542367 0.00236176 0.01535375 ... 0.423673   0.00793265 0.07318508]
 ...
 [0.01959029 0.00592508 0.02281332 ... 0.490609   0.00824204 0.09827536]
 [0.01287192 0.00626938 0.011102   ... 0.49688596 0.01353424 0.10176224]
 [0.02327679 0.00906603 0.02096434 ... 0.10766927 0.02109371 0.15207357]]
```

8) Salvando os dados de treino e teste em um dicionário serializado.

In [43]:
```
dic_base_treino_test = {}
```

In [44]:
```
dic_base_treino_test['y_train'] = y_train
```

In [45]:
```
dic_base_treino_test['y_test'] = y_test
```

In [46]:
```
dic_base_treino_test['X_train_norm'] = X_train_norm
```

In [47]:
```
dic_base_treino_test['X_test_norm'] = X_test_norm
dic_base_treino_test['feature_cols'] =  feature_cols
```

Salvando os dados para avaliação dos modelos

```
In [48]: try:
             import cPickle as pickle
         except ModuleNotFoundError:
             import pickle
```

```
In [49]: output = ".\\baseDados\\voice_treino_test.pk"
         with open(output, 'wb') as pickle_file:
             pickle.dump(dic_base_treino_test, pickle_file)
```

9) Carregando os dados para avaliação do modelo

```
In [50]: try:
             import cPickle as pickle
         except ModuleNotFoundError:
             import pickle
```

```
In [51]: dic_base_treino_file = pickle.load(open( output, "rb" ))
```

```
In [52]: #print(dic_base_treino_file)
```

```
In [53]: y_train = dic_base_treino_file['y_train']
```

```
In [54]:  y_test = dic_base_treino_file['y_test']
```

```
In [55]:  X_train = dic_base_treino_file['X_train_norm']
```

```
In [56]: X_test = dic_base_treino_file['X_test_norm']
```

```
In [57]: dfContador =pandas.DataFrame(list(y_train), columns = ['genero'])
         contagem = dfContador.groupby('genero').size()
         print(contagem)
```

```
genero
0    1108
1    1108
dtype: int64
```

```
In [58]: dfContador =pandas.DataFrame(list(y_test), columns = ['genero'])
         contagem = dfContador.groupby('genero').size()
         print(contagem)
```

```
genero
0    476
1    476
dtype: int64
```

10) Declarando o modelo.

```
In [59]: #logistic Regression
         classifier = LogisticRegression(C=1, multi_class='ovr', penalty='l2', solver='liblinear')
```

11) Treinamento e teste do modelo.

In [60]:
```
classifier.fit(X_train,y_train)
```

Out[60]:
```
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='ovr', n_jobs=None, penalty='l2',
                   random_state=None, solver='liblinear', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [61]:
```
y_pred=classifier.predict(X_test)
```

---

12) Modelo de avaliação de métricas.

16) Classificação

Matriz de confusão.

Uma matriz de confusão pode ser definida livremente como uma tabela que descreve o desempenho de um modelo de classificação em um conjunto de dados de teste para os quais os valores verdadeiros são conhecidos.

In [62]:
```
cm=confusion_matrix(y_test,y_pred)
```

In [63]:
```
confusion_matrix_lda = pandas.DataFrame(cm, index = ['Negativos','Positivos'], columns = ['Previsão dos negativos','Previsão dos positivos'] )
confusion_matrix_lda['Total'] = 1
confusion_matrix_lda['Total'][0] = cm[0][0] + cm[0][1]
confusion_matrix_lda['Total'][1] = cm[1][0] + cm[1][1]
```

In [64]:
```
confusion_matrix_lda
```

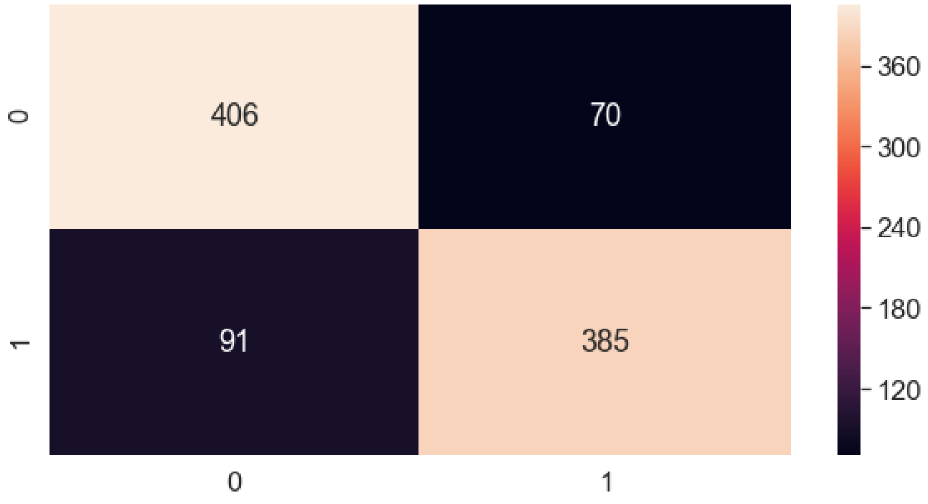
Out[64]:

	Previsão dos negativos	Previsão dos positivos	Total
Negativos	406	70	476
Positivos	91	385	476

In [65]:
```
print(confusion_matrix_lda)
```

```
           Previsão dos negativos  Previsão dos positivos  Total
Negativos                     406                      70    476
Positivos                      91                     385    476
```

In [66]:
```
#Plot the confusion matrix
plt.rcParams['figure.figsize'] = (10,5)
sb.set(font_scale=1.5)
sb.heatmap(cm, annot=True, fmt='g')
plt.show()
```



True Positives:TP

Este valor indica a quantidade de registros que foram classificados como positivos corretamente.

In [67]:
```
TP = confusion_matrix_lda['Previsão dos positivos'][1]
dfTP = pandas.DataFrame(TP, index = ['Positivos verdadeiros'], columns = ['Quantidade acertos'
] )
```

In [68]:
```
dfTP
```

Out[68]:

	Quantidade acertos
Positivos verdadeiros	385

In [69]:
```
print(dfTP)
```

```
                       Quantidade acertos
Positivos verdadeiros                 385
```

True Negatives:TN

Este valor indica a quantidade de registros que foram classificados como negativos de maneira correta.

In [70]:
```
TN = confusion_matrix_lda['Previsão dos negativos'][0]
dfTN = pandas.DataFrame(TN, index = ['Verdadeiro Negativo'], columns = ['Quantidade acertos']
)
```

In [71]:
```
dfTN
```

Out[71]:

	Quantidade acertos
Verdadeiro Negativo	406

In [72]:
```
print(dfTN)
```

```
                    Quantidade acertos
Verdadeiro Negativo                406
```

Falso Positivos - False Positives:FP

Este valor indica a quantidade de registros que foram classificados como comentários positivos de maneira incorreta.

In [73]:
```
FP = confusion_matrix_lda['Previsão dos positivos'][0]
dfFP = pandas.DataFrame(FP, index = ['Falso Positivo'], columns = ['Quantidade acertos'] )
```

In [74]:
```
dfFP
```

Out[74]:

	Quantidade acertos
Falso Positivo	70

In [75]:
```
print(dfFP)
```

```
               Quantidade acertos
Falso Positivo                 70
```

False Negatives:FN

Este valor indica a quantidade de registros que foram classificados como comentários negativos de maneira incorreta.

In [76]:
```
FN = confusion_matrix_lda['Previsão dos negativos'][1]
dfFN = pandas.DataFrame(FN, index = ['Negativos Falsos'], columns = ['Quantidade acertos'] )
```

In [77]:
```
dfFN
```

Out[77]:

	Quantidade acertos
Negativos Falsos	91

In [78]:
```
print(dfFN)
```

```
                 Quantidade acertos
Negativos Falsos                 91
```

Especificidade (Specificity)

Especificidade é a proporção de previsões negativas corretas para o total não de previsões negativas. Isso determina o grau de especificidade do classificador na previsão de instâncias positivas.

Specificity = (Numero de previsões negativas correta) / (Total do Numero Negativas prevista)

TN = / TN + FP

In [79]:
```
Specificity = TN / float(TN + FP)
dfSpecificity = pandas.DataFrame(Specificity, index = ['Specificity'], columns = ['resultado']
)
```

In [80]:
```
dfSpecificity
```
Out[80]:

	resultado
Specificity	0.852941

In [81]:
```
print(dfSpecificity)
```
```
             resultado
Specificity   0.852941
```

Precisão Geral (Accuracy)

A precisão da classificação é a proporção de previsões corretas para o total não de previsões.

Accuracy = (numero de predições corretas / numero de predições)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

In [82]:
```
#trés maneiras de fazer o caluclo
print((TP + TN) / float(TP + TN + FP + FN))
print(accuracy_score(y_test, y_pred))
print("Accuracy ", classifier.score(X_test, y_test)*100)
Accuracy= classifier.score(X_test, y_test)
```
```
0.8308823529411765
0.8308823529411765
Accuracy  83.08823529411765
```

In [83]:
```
dfAccuracy = pandas.DataFrame(Accuracy, index = ['Accuracy'], columns = ['resultado'] )
dfAccuracy
```
Out[83]:

	resultado
Accuracy	0.830882

In [84]:
```
print(dfAccuracy)
```
```
          resultado
Accuracy   0.830882
```

Sensibilidade ou recordação Recall

Sensibilidade ou recordação é a razão de previsões positivas corretas para o total não de previsões positivas, ou, mais simplesmente, quão sensível o classificador é para detectar instâncias positivas. Isso também é chamado de True Positive Rate

Recall = (Numero de positivas previstas corretamente) /(total de Predições positivas)

$$Recall = \frac{TP}{TP + FN}$$

In [85]:
```
print(TP / float(TP + FN))
print(recall_score(y_test, y_pred))
Recall= recall_score(y_test, y_pred)
```
```
0.8088235294117647
0.8088235294117647
```

```
In [86]: dfRecall = pandas.DataFrame(Recall, index = ['Sensibilidade-Recall'], columns = ['resultado']
)
dfRecall
```

Out[86]:

	resultado
Sensibilidade-Recall	0.808824

```
In [87]: print(dfRecall)
```

```
                      resultado
Sensibilidade-Recall   0.808824
```

Taxa positiva falsa (False Positive Rate)

A *false positive rate*, é a proporção de previsões negativas que foram determinadas como positivas para o número total de previsões negativas ou quando o valor real é negativo, com que frequência a previsão é incorreta.

FalsePositveRate = Números de falsos positivos / Total de predições negativas

$$FalsePositveRate = \frac{FP}{TN + FP}$$

```
In [88]: print(FP / float(TN + FP))
FalsePositveRate = FP / float(TN + FP)
```

```
0.14705882352941177
```

```
In [89]: dfFalsePositveRate = pandas.DataFrame(FalsePositveRate, index = ['Taxa de Falso Positvo'], col
umns = ['resultado'] )
dfFalsePositveRate
```

Out[89]:

	resultado
Taxa de Falso Positvo	0.147059

```
In [90]: print(dfFalsePositveRate)
```

```
                       resultado
Taxa de Falso Positvo   0.147059
```

Precisão (Precision)

A precisão é a proporção de previsões corretas para o total de não previsões preditas corretas. Isso mede a precisão do classificador ao prever instâncias positivas.

Precision = Número de positivas verdadeiras / Numero total de predicados positivos

$$Precision = \frac{TP}{TP + FP}$$

```
In [91]: print(TP / float(TP + FP))
print(precision_score(y_test, y_pred))
Precision = precision_score(y_test, y_pred)
```

```
0.8461538461538461
0.8461538461538461
```

In [92]:
```
dfPrecision = pandas.DataFrame(Precision, index = ['Precisão'], columns = ['resultado'] )
dfPrecision
```

Out[92]:

	resultado
Precisão	0.846154

In [93]:
```
print(dfPrecision)
```

```
          resultado
Precisão   0.846154
```

F1 Score

O F1 Score é uma média harmônica entre precisão (que, apesar de ter o mesmo nome, não é a mesma citada acima) e recall. Veja abaixo as definições destes dois termos.

Ela é muito boa quando você possui um dataset com classes desproporcionais, e o seu modelo não emite probabilidades. Em geral, quanto maior o F1 score, melhor.

$$F1Score = \frac{2 \times Precisão \times Recall}{Precisão + Recall}$$

In [94]:
```
F1Score = 2 * Precision *  Recall /  float(Precision + Recall)
```

In [95]:
```
print(F1Score)
```

```
0.8270676691729324
```

In [96]:
```
dfF1Score = pandas.DataFrame(F1Score, index = ['F1 Score'], columns = ['resultado'] )
dfF1Score
```

Out[96]:

	resultado
F1 Score	0.827068

In [97]:
```
print(dfF1Score)
```

```
          resultado
F1 Score   0.827068
```

13) Curva ROC

Uma curva ROC é uma forma comumente usada para visualizar o desempenho de um classificador binário, significando um classificador com duas classes de saída possíveis. A curva plota a Taxa Positiva Real (Recall) contra a Taxa Falsa Positiva (também interpretada como Especificidade 1).

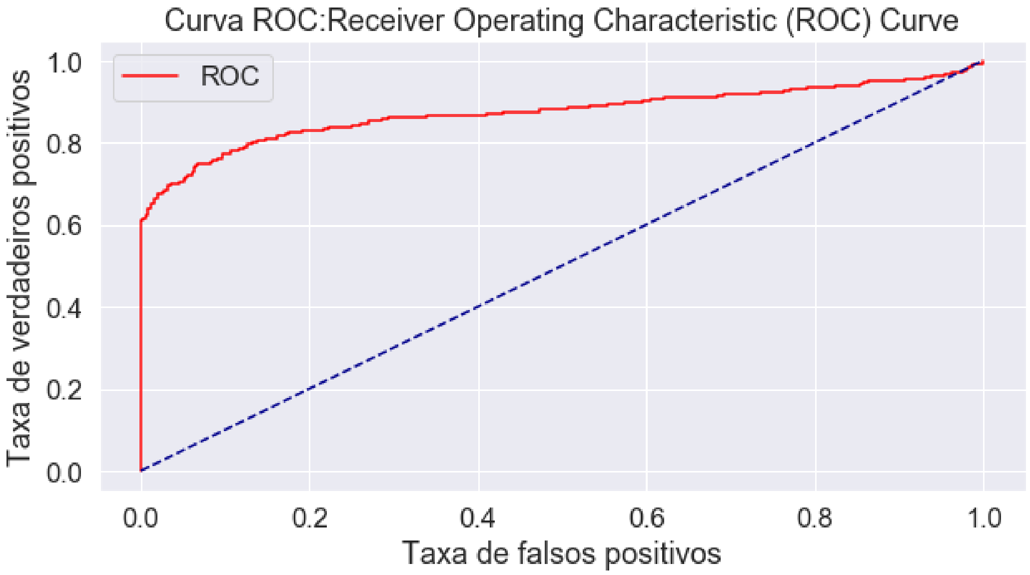
In [98]:
```
def plot_roc_curve(fpr, tpr):
    plt.plot(fpr, tpr, color='red', label='ROC')
    plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--')
    plt.xlabel('Taxa de falsos positivos')
    plt.ylabel('Taxa de verdadeiros positivos')
    plt.title('Curva ROC:Receiver Operating Characteristic (ROC) Curve')
    plt.legend()
    plt.show()
```

Calcula a propabildade de previsão.

In [99]:
```
y_pred_prob = classifier.predict_proba(X_test)[:, 1]
```

In [100]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)
```

In [101]:
```
plot_roc_curve(fpr, tpr)
```



AUC (área sob a curva) da Curva ROC

AUC ou Area Under the Curve é a porcentagem do gráfico do ROC que está abaixo da curva. AUC é útil como um único número de resumo do desempenho do classificador.

In [102]:
```
print(roc_auc_score(y_test, y_pred_prob))
Auc=roc_auc_score(y_test, y_pred_prob)
```

```
0.873181625591413
```

In [103]:
```
dfAuc = pandas.DataFrame(Auc, index = ['AUC'], columns = ['resultado'] )
dfAuc
```

Out[103]:

	resultado
AUC	0.873182

In [104]:
```
print(dfAuc)
```

```
     resultado
AUC   0.873182
```

Salva dados para usar no gráfico consolidado.

In [105]:
```
dic_logist={}
```

In [106]:
```
dic_logist['Accuracy']=Accuracy
dic_logist['Auc']=Auc
dic_logist['Recall']=Recall
dic_logist['Specificity']=Specificity
dic_logist['Precision']=Precision
dic_logist['F1Score']=F1Score
dic_logist['y_pred_prob']=y_pred_prob
dic_logist['y_test']=y_test
```

In [107]:
```
dic_logist
```

```
Out[107]: {'Accuracy': 0.8308823529411765,
           'Auc': 0.87318162559141 3,
           'Recall': 0.8088235294117647,
           'Specificity': 0.8529411764705882,
           'Precision': 0.8461538461538461,
           'F1Score': 0.8270676691729324,
           'y_pred_prob': array([0.52438612, 0.5837505 , 0.62765444, 0.57759981, 0.73036964,
                  0.6840516 , 0.61742168, 0.34323323, 0.2921634 , 0.31829328,
                  0.7619323 , 0.70412845, 0.59035486, 0.70196921, 0.68376061,
                  0.64113761, 0.48194272, 0.40465338, 0.51370326, 0.34403588,
                  0.69360089, 0.7712258 , 0.63985824, 0.6458357 , 0.39876009,
                  0.76462389, 0.59424769, 0.66190435, 0.65796666, 0.76572534,
                  0.64918765, 0.64320386, 0.47349258, 0.57051776, 0.60495435,
                  0.6613162 , 0.54919796, 0.51786193, 0.67136436, 0.53443832,
                  0.64283689, 0.41294953, 0.5903379 , 0.58460994, 0.30468684,
                  0.74566322, 0.04631068, 0.80040733, 0.78947826, 0.73623727,
                  0.59746726, 0.53664   , 0.63442447, 0.63484208, 0.75954399,
                  0.66050616, 0.48023172, 0.76896377, 0.6099209 , 0.49942254,
                  0.13776477, 0.71831004, 0.30089486, 0.37497357, 0.62148495,
                  0.42256365, 0.3616791 , 0.77240596, 0.61331559, 0.63132555,
                  0.71971194, 0.79950452, 0.60738975, 0.55831485, 0.61744568,
                  0.14868378, 0.79558948, 0.79770876, 0.56464433, 0.67488201,
                  0.68910211, 0.80550455, 0.54067244, 0.75850101, 0.55764726,
                  0.37953444, 0.6665314 , 0.63946078, 0.65191029, 0.65327736,
                  0.04909289, 0.64487437, 0.77958842, 0.67571659, 0.60745865,
                  0.28310076, 0.52516048, 0.59097269, 0.62964417, 0.63031111,
                  0.56205759, 0.71323688, 0.45490114, 0.58299907, 0.61072247,
                  0.74323506, 0.62149232, 0.45319077, 0.57444392, 0.46519681,
                  0.5682447 , 0.79679329, 0.55771264, 0.6647096 , 0.66597315,
                  0.66431603, 0.53361794, 0.71713404, 0.79815228, 0.47113728,
                  0.55410399, 0.64343592, 0.72995856, 0.36391484, 0.65948896,
                  0.77328705, 0.64579771, 0.68759587, 0.636955  , 0.76478303,
                  0.53303474, 0.75345811, 0.71681845, 0.65009036, 0.64616549,
                  0.64025803, 0.58162578, 0.78176177, 0.64499201, 0.50910917,
                  0.6265509 , 0.8261161 , 0.62826468, 0.65871558, 0.68779525,
                  0.66097952, 0.80818718, 0.61893089, 0.67891585, 0.63364776,
                  0.69329191, 0.63824496, 0.56571854, 0.63682338, 0.48827571,
                  0.33413114, 0.69238181, 0.66550859, 0.37648768, 0.66619211,
                  0.62459716, 0.26019962, 0.39796368, 0.57447788, 0.68507793,
                  0.62710176, 0.74261126, 0.61849782, 0.65283019, 0.64058678,
                  0.64447987, 0.0301876 , 0.43957631, 0.78762915, 0.57310725,
                  0.565904  , 0.7058829 , 0.57485916, 0.79434797, 0.54115938,
                  0.64956364, 0.64249135, 0.80005474, 0.60225009, 0.56350967,
                  0.66224377, 0.72358829, 0.52658988, 0.44332718, 0.66273671,
                  0.59756293, 0.67141824, 0.66997197, 0.55576597, 0.55993304,
                  0.64670187, 0.64351896, 0.63610967, 0.52084232, 0.65327203,
                  0.75440326, 0.66954943, 0.65683356, 0.80425079, 0.70715439,
                  0.22486075, 0.78355774, 0.81883876, 0.35040709, 0.65076929,
                  0.61056119, 0.23689412, 0.63244367, 0.64455426, 0.38970688,
                  0.56153877, 0.76900686, 0.78785464, 0.6755661 , 0.69099818,
                  0.5984447 , 0.6965107 , 0.72881905, 0.61031341, 0.56285385,
                  0.60739423, 0.52919484, 0.77136102, 0.80936659, 0.43724629,
                  0.84122144, 0.49334038, 0.55149601, 0.4539413 , 0.81725988,
                  0.72492491, 0.58394514, 0.68999199, 0.70167207, 0.63774118,
                  0.6789809 , 0.62588914, 0.45955091, 0.3813503 , 0.53438989,
                  0.68012814, 0.65760189, 0.81076871, 0.36869391, 0.48916542,
                  0.11642266, 0.71733645, 0.68339487, 0.38028974, 0.68933568,
                  0.80276011, 0.73768543, 0.78573478, 0.51535057, 0.69350212,
                  0.67612324, 0.73296099, 0.07569966, 0.68981415, 0.35074173,
                  0.79451835, 0.49315556, 0.65788141, 0.77823481, 0.36359575,
                  0.69240648, 0.77385905, 0.70210746, 0.79709028, 0.48203283,
                  0.14622325, 0.68640168, 0.77209623, 0.37717566, 0.39461706,
                  0.575057  , 0.58299738, 0.51296055, 0.8367531 , 0.55874783,
                  0.51294128, 0.57861308, 0.7179382 , 0.70383507, 0.65866823,
                  0.70861316, 0.84162458, 0.81548837, 0.70098391, 0.66254905,
                  0.73297666, 0.19647022, 0.64950192, 0.66138021, 0.61728294,
                  0.80677803, 0.76015717, 0.62673676, 0.65968726, 0.70090742,
                  0.51273719, 0.75192158, 0.65867733, 0.65067535, 0.71676053,
                  0.8098738 , 0.62146417, 0.60105627, 0.72715474, 0.60164015,
                  0.72212928, 0.14595401, 0.60436526, 0.74249421, 0.8019226 ,
                  0.30646876, 0.63721116, 0.29209936, 0.65818393, 0.60642699,
                  0.72206956, 0.67409612, 0.0438893 , 0.5357952 , 0.60488859,
                  0.68092925, 0.69975148, 0.61213483, 0.66014508, 0.39044702,
```

```
0.12592302, 0.64432617, 0.57320536, 0.50569431, 0.59984795,
0.65604177, 0.65973835, 0.47146276, 0.58415906, 0.69398376,
0.63484832, 0.59066001, 0.41696142, 0.75987422, 0.54203638,
0.55867003, 0.45901053, 0.4635972 , 0.19277516, 0.61974159,
0.20545083, 0.67485458, 0.64073174, 0.74875551, 0.65004705,
0.81398273, 0.76579426, 0.60094665, 0.64869274, 0.74842517,
0.69173086, 0.76465069, 0.7989992 , 0.65746846, 0.55980105,
0.59112891, 0.64757172, 0.61697875, 0.68520362, 0.79321626,
0.38937144, 0.62560235, 0.64636732, 0.63231145, 0.65869637,
0.23698506, 0.44316942, 0.619453  , 0.5790502 , 0.64380308,
0.69995201, 0.74609093, 0.79519101, 0.5668682 , 0.59795437,
0.55367232, 0.68507261, 0.71781427, 0.58035294, 0.40472502,
0.64344015, 0.72168692, 0.73065651, 0.44560371, 0.62899971,
0.38345547, 0.70334626, 0.65933031, 0.3963347 , 0.6402172 ,
0.2083143 , 0.84798985, 0.60474703, 0.55209265, 0.61565933,
0.5046731 , 0.21275525, 0.49428042, 0.59804753, 0.80465751,
0.67607268, 0.48696536, 0.82302927, 0.79649568, 0.70732535,
0.80187652, 0.80873962, 0.60152879, 0.70023027, 0.34053058,
0.84690496, 0.6978758 , 0.56051121, 0.63671088, 0.63315242,
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2477    1
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2840    1
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842     0
1199    0
790     0
247     0
Name: genero, Length: 952, dtype: int64}
```

In [108]:
```python
import pickle
```

In [109]:
```python
filename = '.\\baseDados\\regressaologitica.jss'
outfile = open(filename,'wb')
pickle.dump(dic_logist,outfile)
outfile.close()
```

In [110]:
```
infile = open(filename,'rb')
test_dict = pickle.load(infile)
infile.close()
```

In [111]:
```
#print(test_dict)
```

In [112]:
```
print(type(test_dict))
```

```
<class 'dict'>
```

Fim de avaliação individual do modelo regressão logística