Trabalho Final da disciplina de Machine Learning: Classificadores e Validação de Modelos

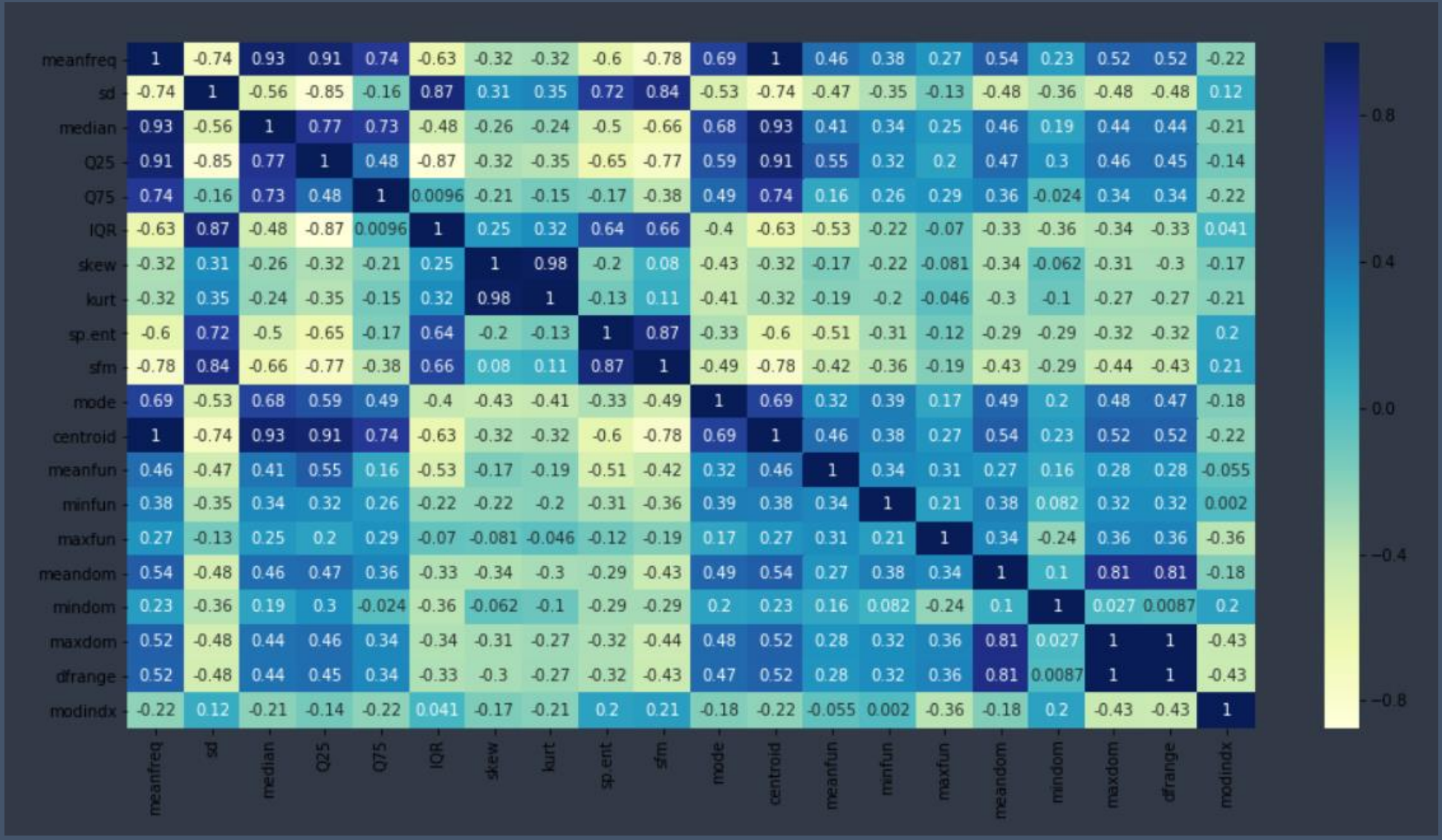
Grupo: Harlan e Emmanuel

Dataset Utilizado

- **Voice Gender:** https://www.kaggle.com/primaryobjects/voicegender

- O dataset possui a classificação de vozes de homens e mulheres baseada nas propriedades acústicas da fala humana. São 3168 pontos de dados pré-processados com a análise da frequência no intervalo de 0hz-280hz (intervalo da voz humana).

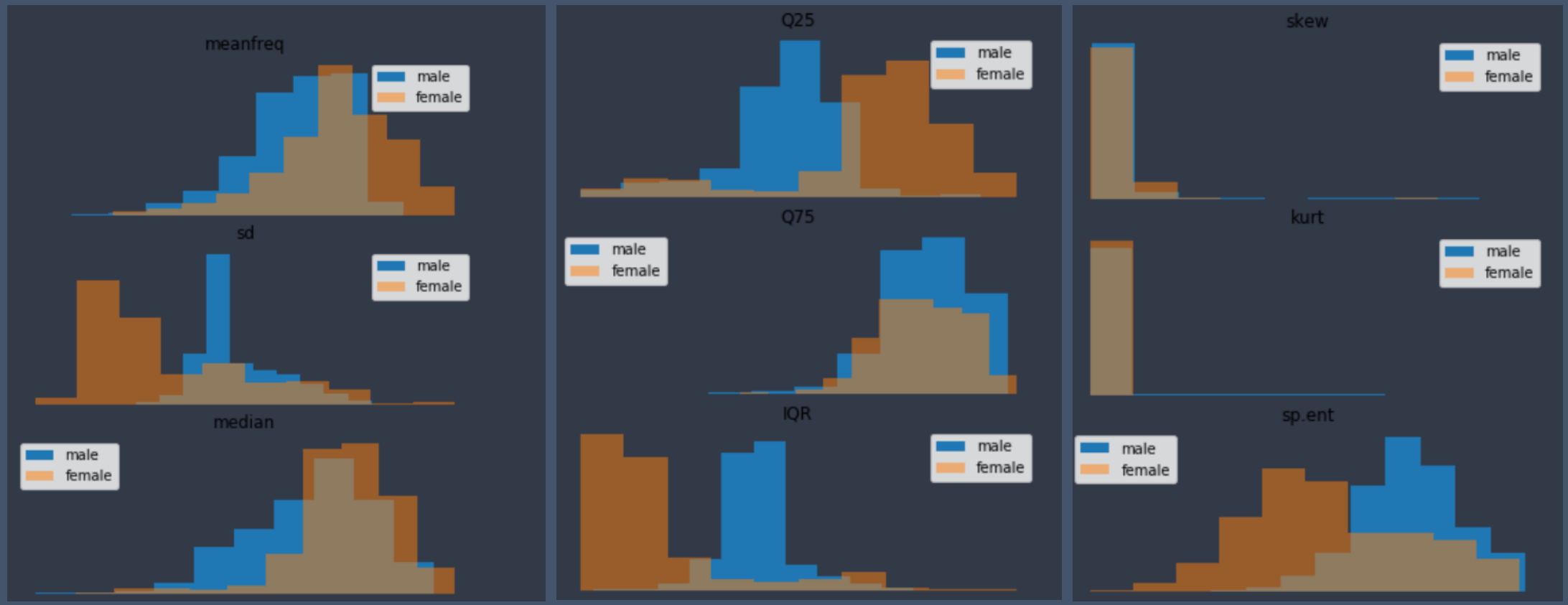
Correlação entre Variáveis



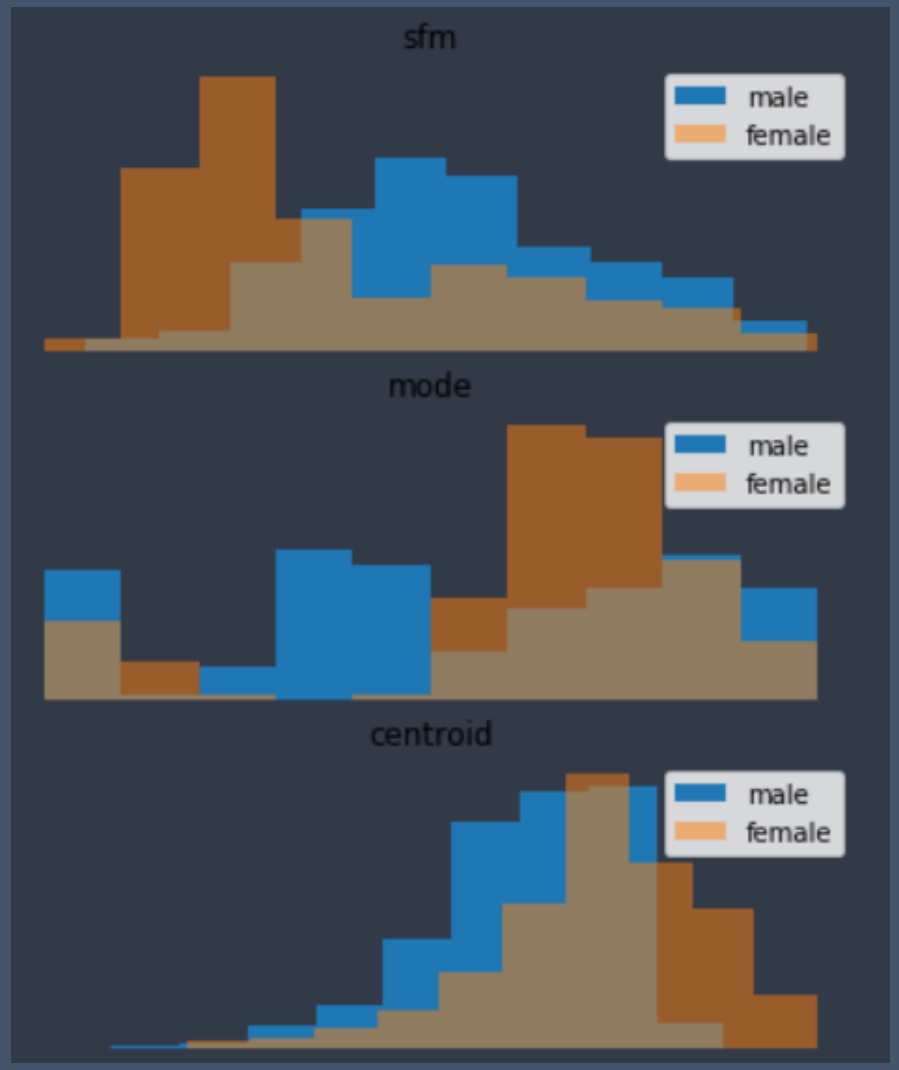
A alta correlação entre variáveis desperta a intuição de que a quantidade de variáveis é desnecessária

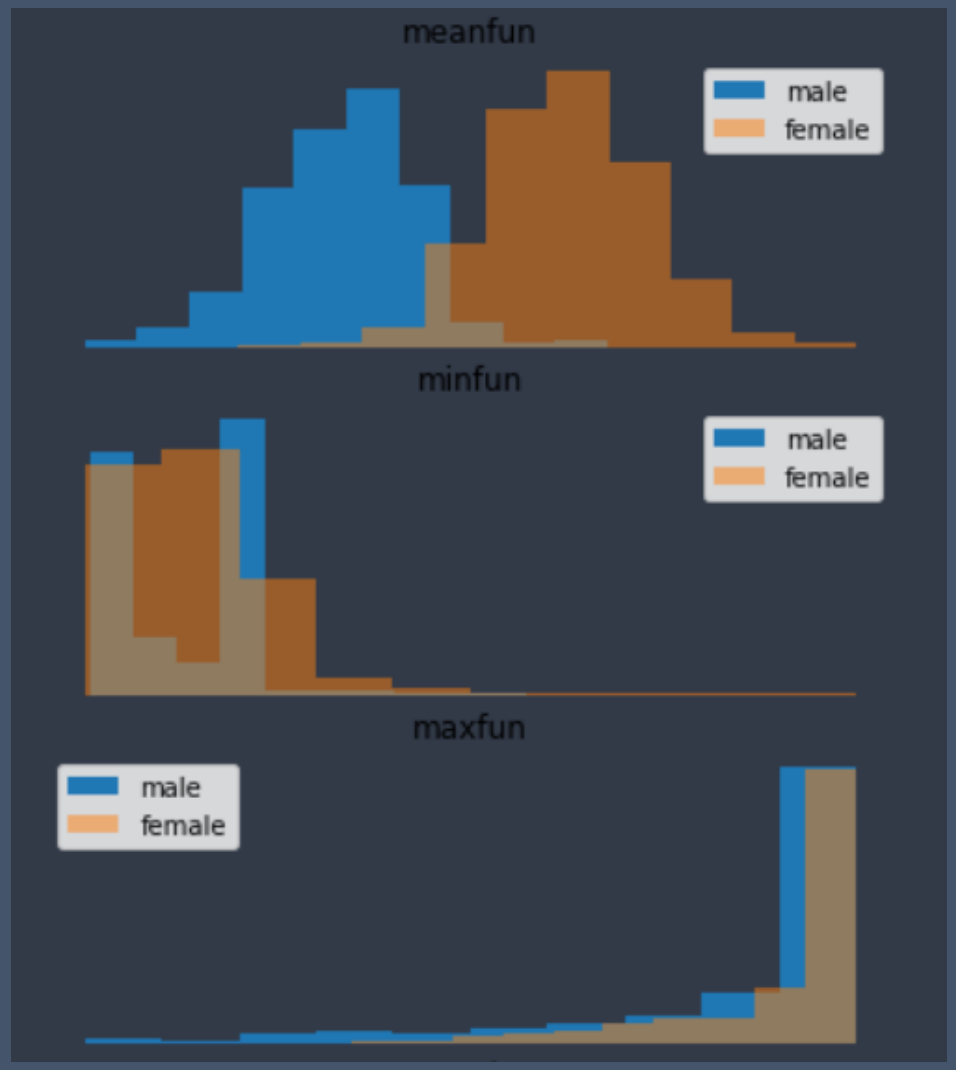
- Corr(meanfreq x median) = 0.93 (medidas de centro)
- Corr(sd x IQR) = 0.87 (medidas de variação)
- Corr(maxdom x dfrange) = 1 (maximum of dominant frequency e range of dominant frequency)
- Corr(meanfreq x centroid) = 1

Distribuição das 20 Variáveis por Label

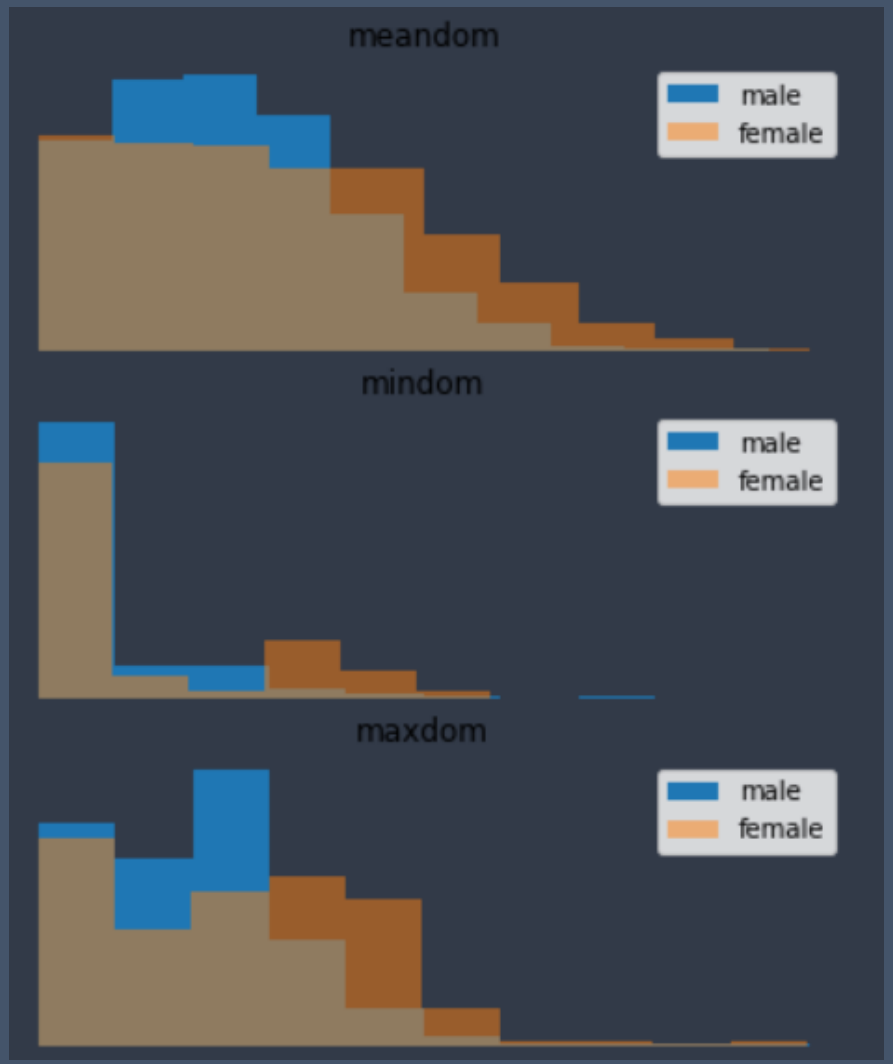


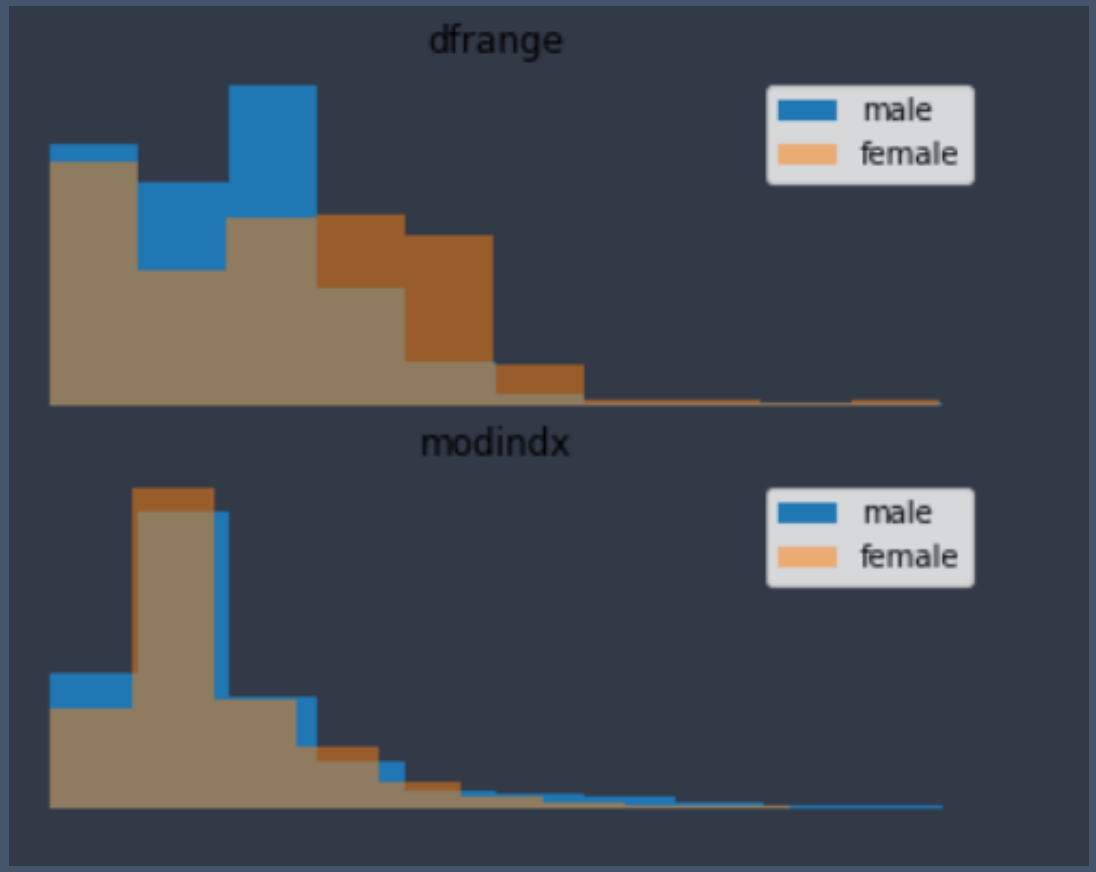
Distribuição das 20 Variáveis por Label





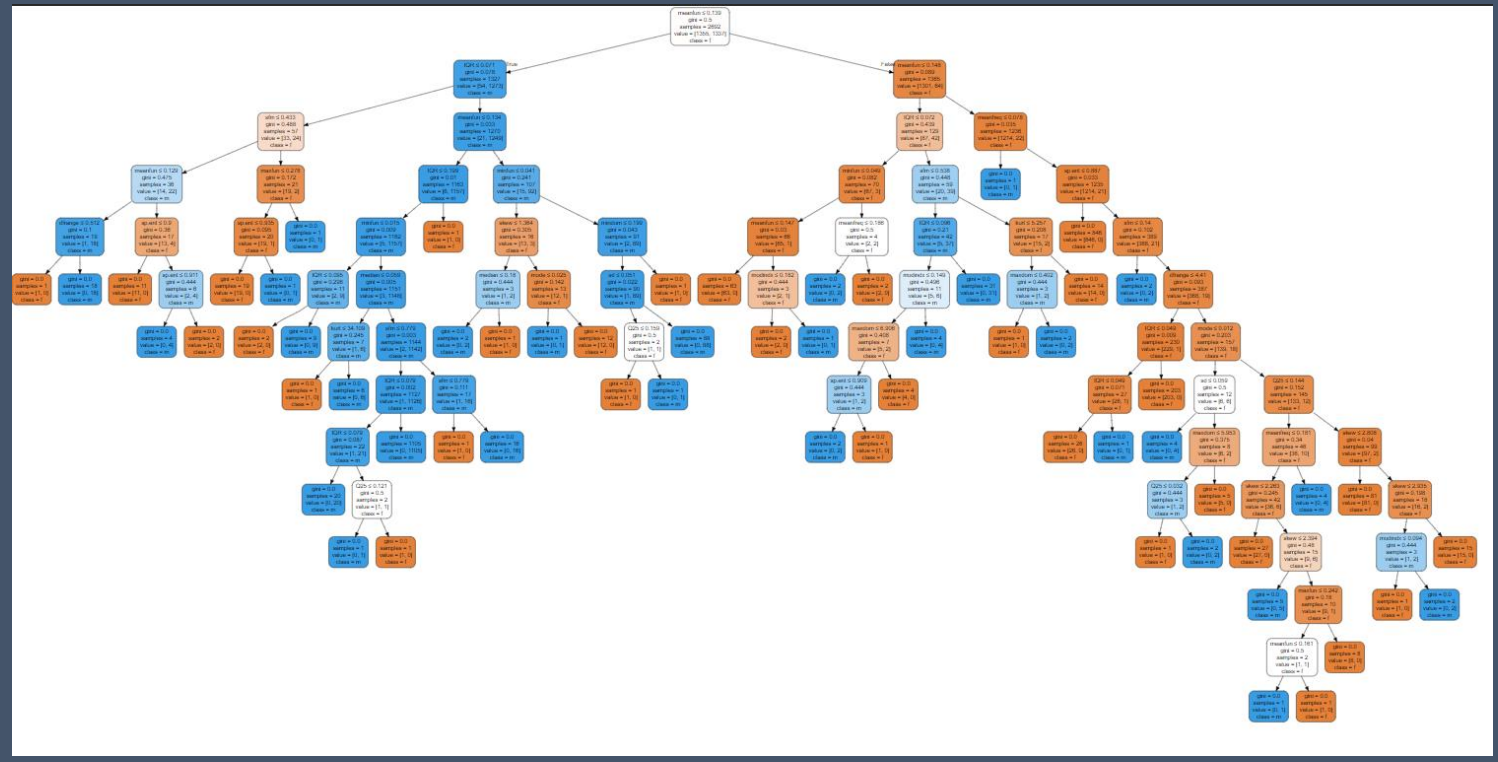
Distribuição das 20 Variáveis por Label





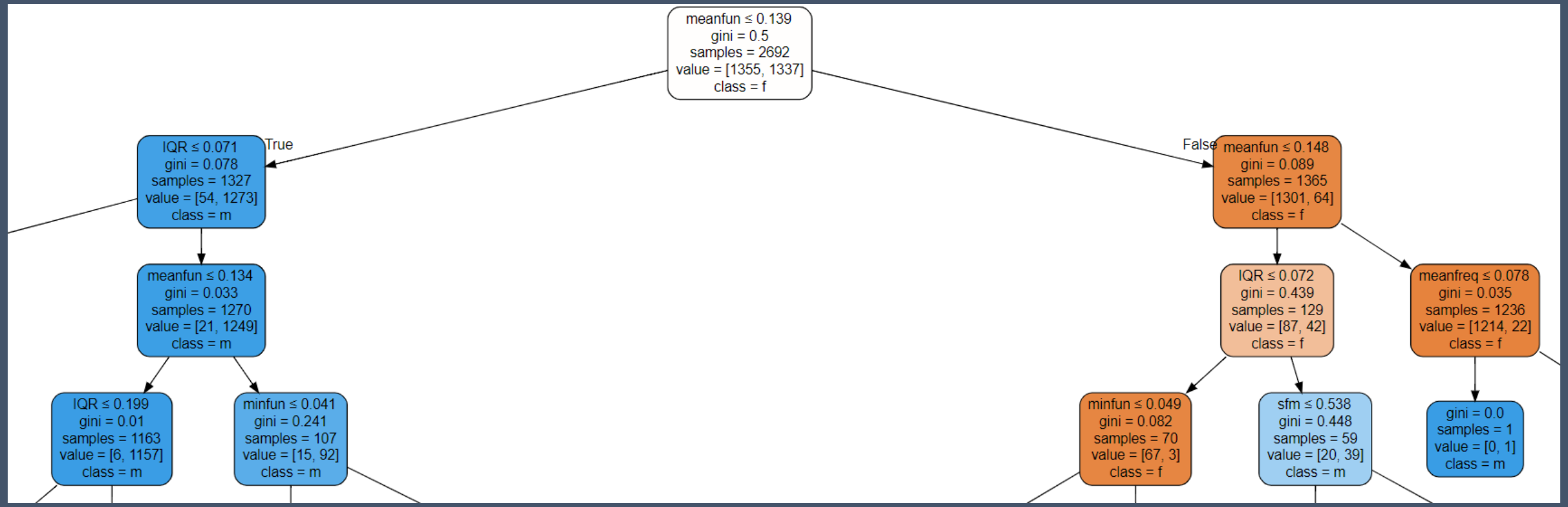
Como uma árvore de decisão dividiria o dataset?

Árvore Livre



Como uma árvore de decisão dividiria o dataset?

Árvore Livre



Como uma árvore de decisão dividiria o dataset?

Árvore Livre

In [37]:
```
pred = tree_free.predict(x_test)
```

In [38]:
```
print(confusion_matrix(y_test, pred))
```

```
[[221   8]
 [ 10 237]]
```

In [39]:
```
print(accuracy_score(y_test, pred))
```

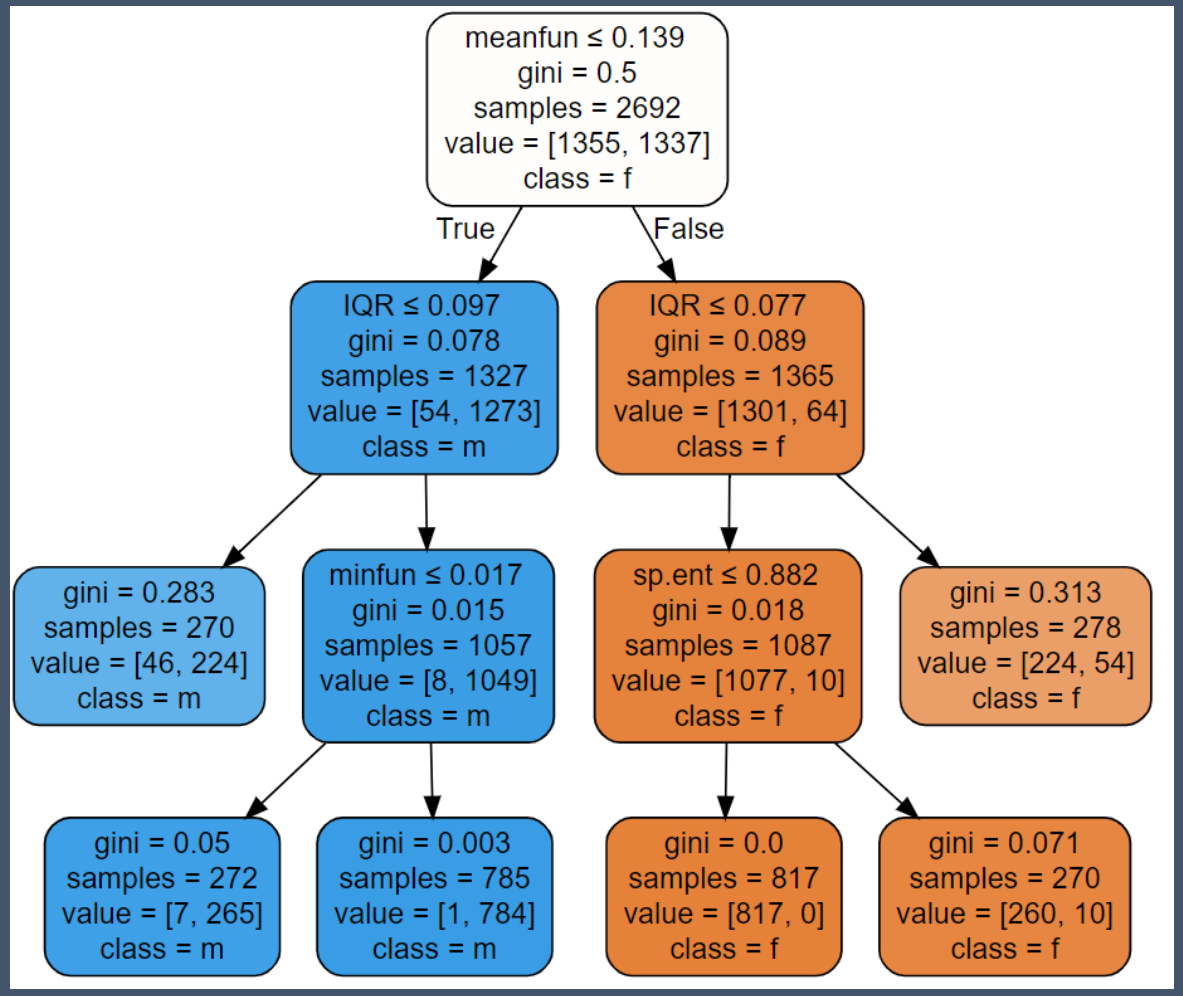
```
0.9621848739495799
```

In [40]:
```
print(classification_report(y_test, pred))
```

```
              precision    recall  f1-score   support

           0       0.96      0.97      0.96       229
           1       0.97      0.96      0.96       247

   micro avg       0.96      0.96      0.96       476
   macro avg       0.96      0.96      0.96       476
weighted avg       0.96      0.96      0.96       476
```

Como uma árvore de decisão dividiria o dataset?

Árvore Parametrizada (max_depth=3, min_samples_leaf=0.1)



Como uma árvore de decisão dividiria o dataset?

Árvore Parametrizada (max_depth=3, min_samples_leaf=0.1)

In [44]:
```
pred = tree_limited.predict(x_test)
```

In [45]:
```
print(confusion_matrix(y_test, pred))
```

```
[[218  11]
 [ 18 229]]
```

In [46]:
```
print(accuracy_score(y_test, pred))
```

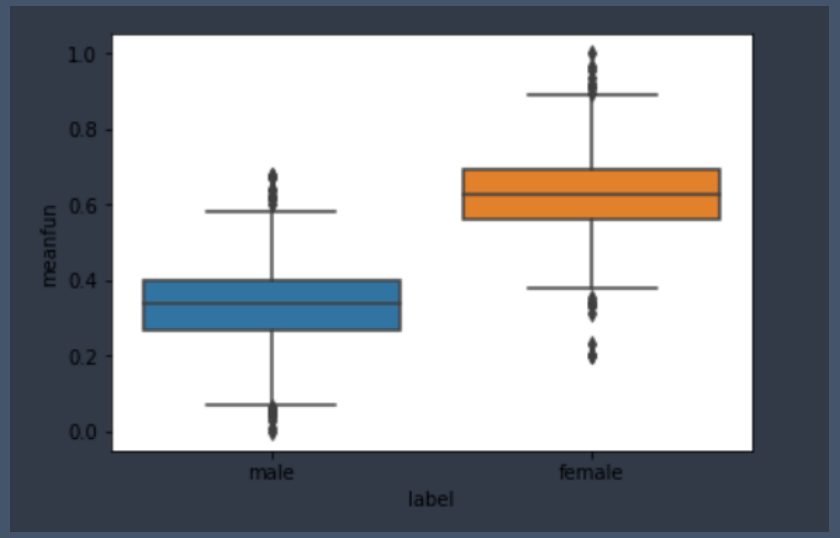
```
0.9390756302521008
```

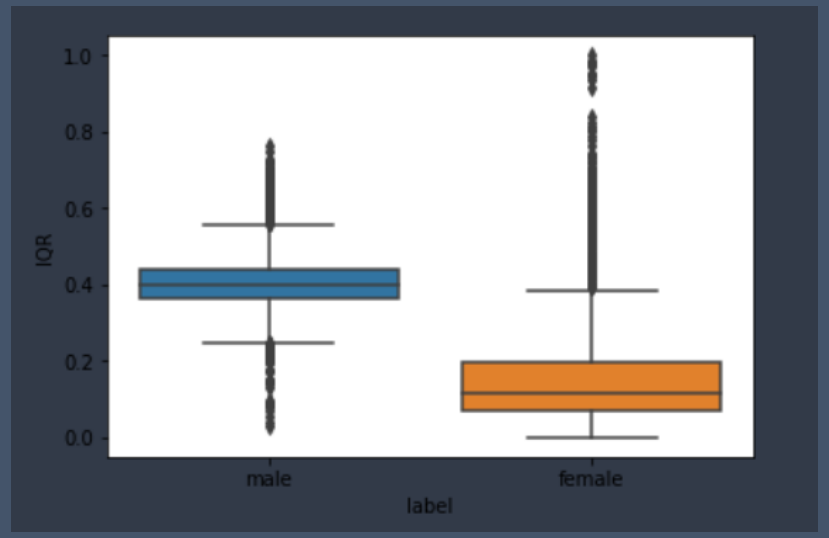
In [47]:
```
print(classification_report(y_test, pred))
```

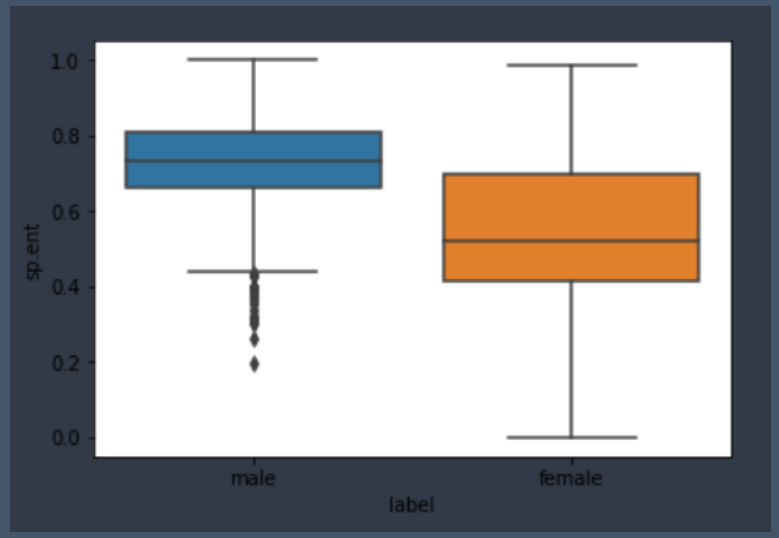
```
              precision    recall  f1-score   support

           0       0.92      0.95      0.94       229
           1       0.95      0.93      0.94       247

   micro avg       0.94      0.94      0.94       476
   macro avg       0.94      0.94      0.94       476
weighted avg       0.94      0.94      0.94       476
```

Como uma árvore de decisão dividiria o dataset?

Uso das variáveis “meanfun”, “IQR” e “sp.ent”

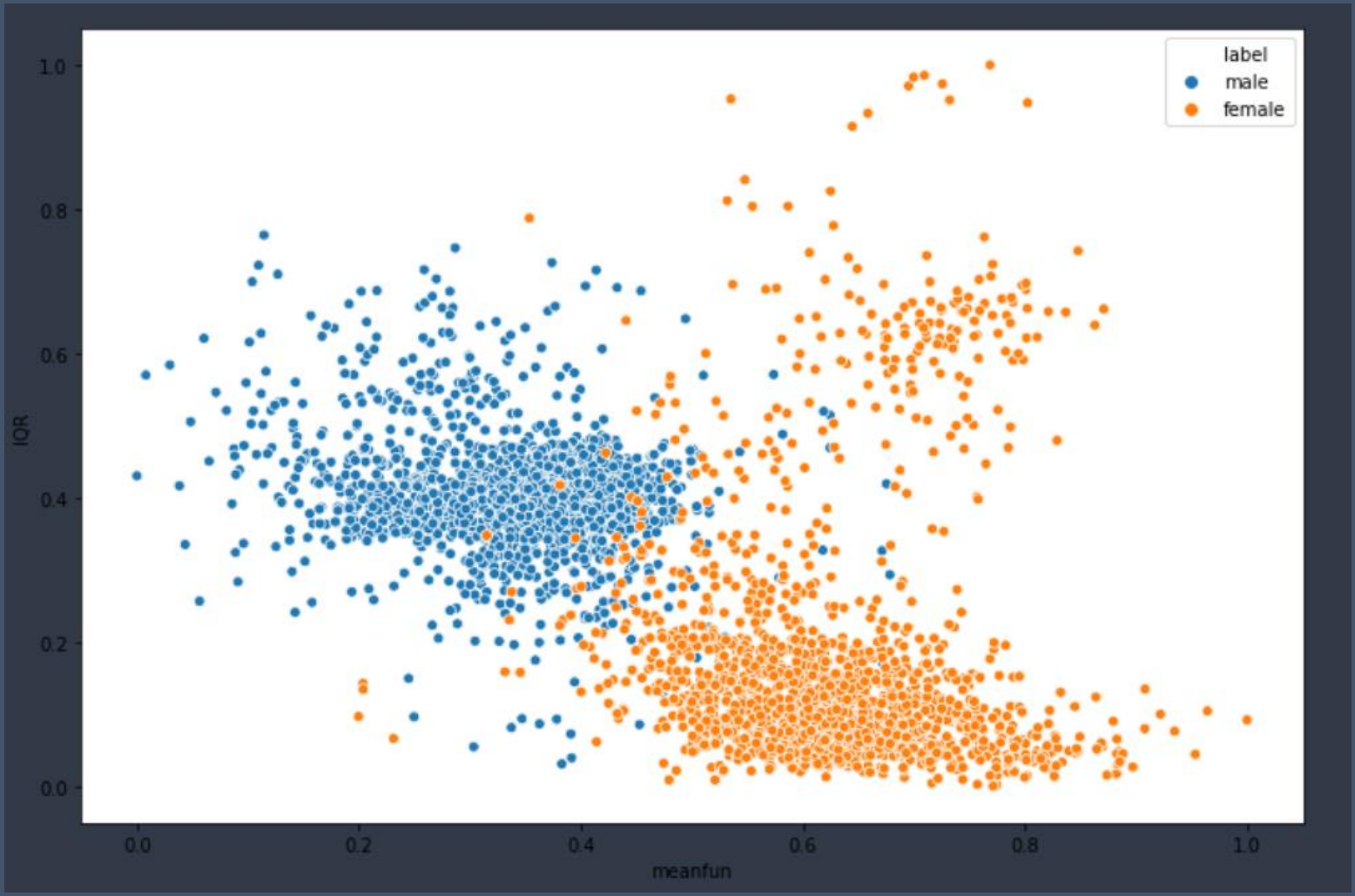






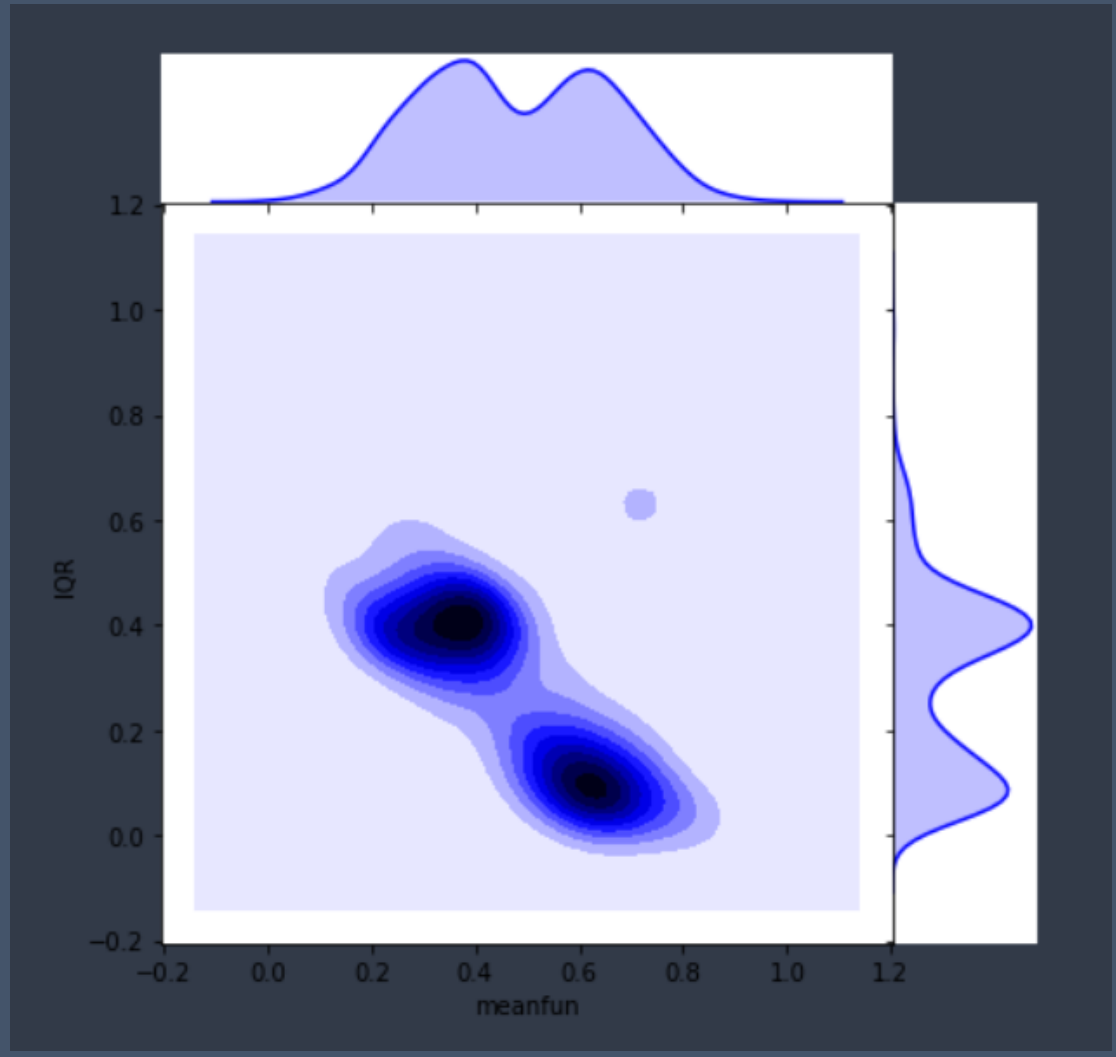
Como uma árvore de decisão dividiria o dataset?

“meanfun” x “IQR”



Como uma árvore de decisão dividiria o dataset?

"meanfun" x "IQR"

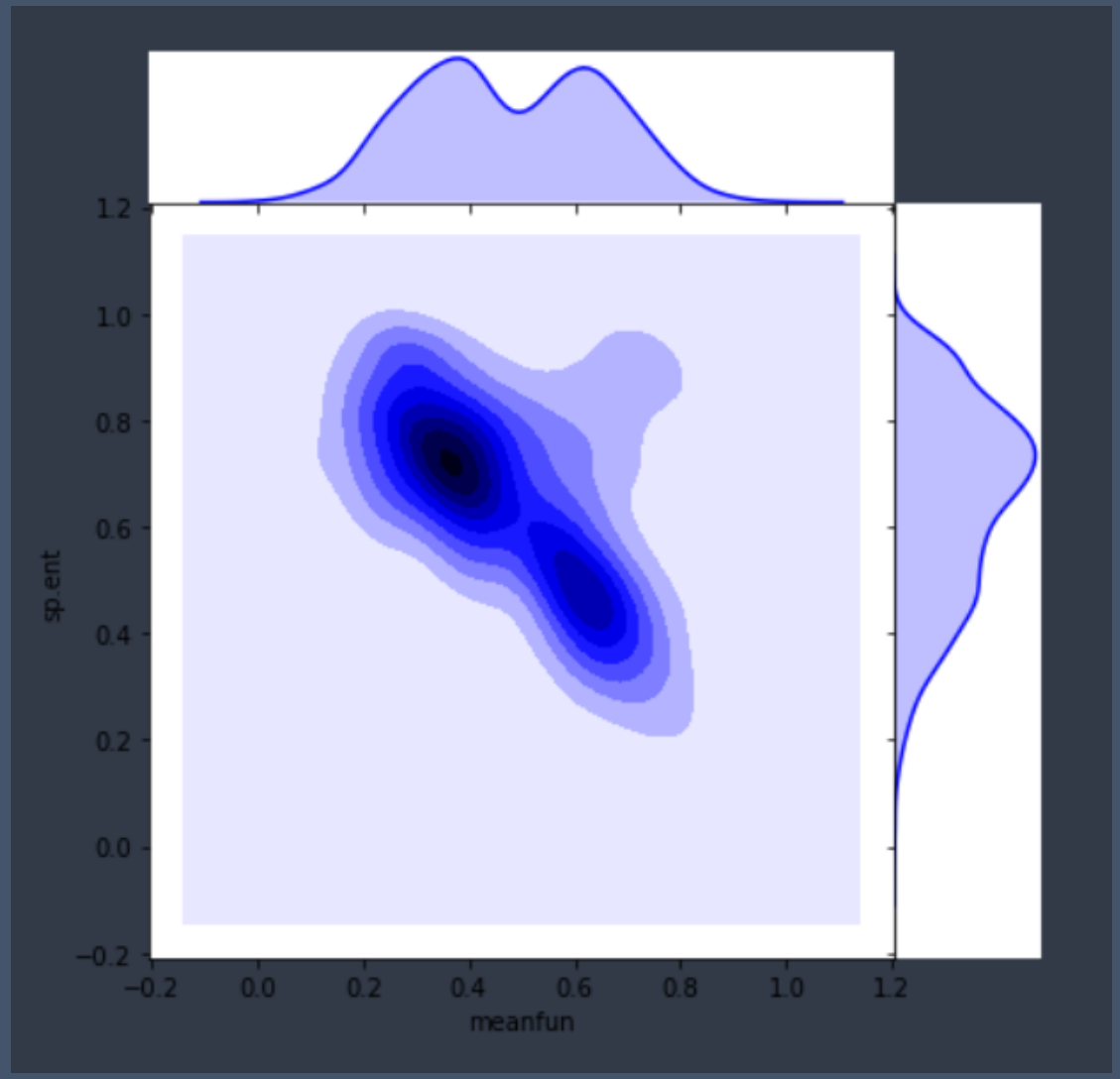


Como uma árvore de decisão dividiria o dataset?

"meanfun" x "sp.ent"

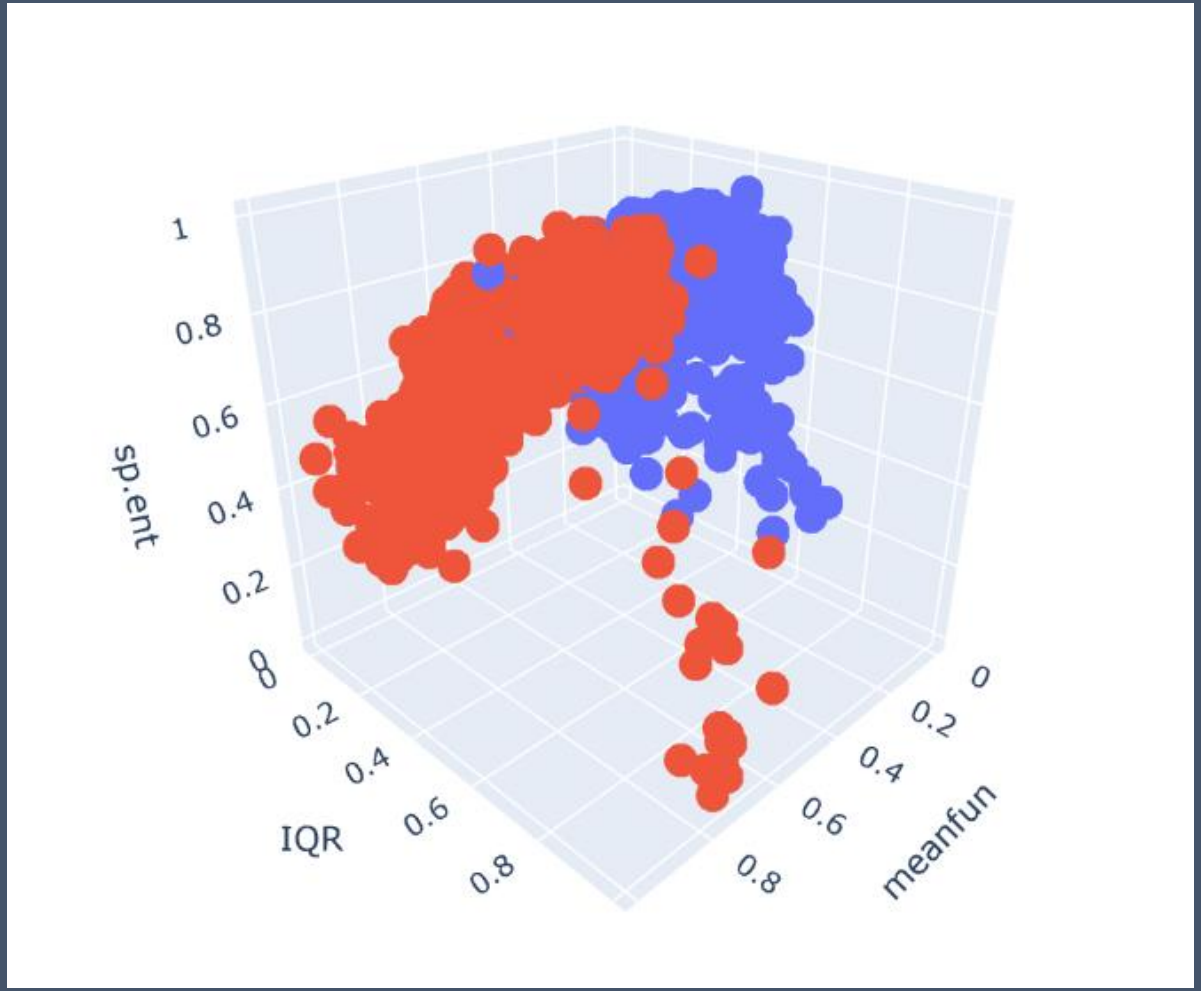
Como uma árvore de decisão dividiria o dataset?

“meanfun” x “sp.ent”



Como uma árvore de decisão dividiria o dataset?

“meanfun” x “IQR” x “sp.ent”

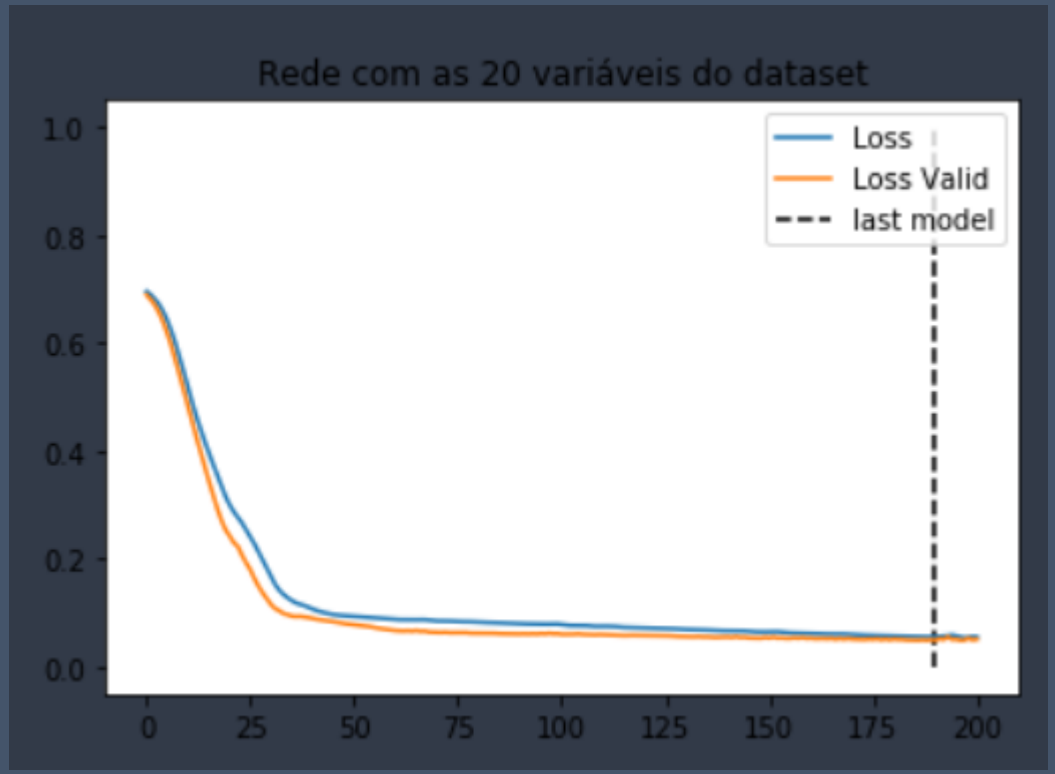


Rede Neural com as 20 Variáveis

Treino 70%
Validação 15%
Teste 15%

Early Stopping com tolerância de 10 épocas sem redução no loss da validação

```
Model(
  (conv1): Linear(in_features=20, out_features=32, bias=True)
  (conv2): Linear(in_features=32, out_features=32, bias=True)
  (conv3): Linear(in_features=32, out_features=1, bias=True)
  (relu): ReLU()
  (sigmoid): Sigmoid()
)
```



Rede Neural com as 20 Variáveis

In [65]:
```
print('TN-FP\nFN-TP')
confusion_matrix(y_test, pred.round().detach().numpy())
```

```
TN-FP
FN-TP


array([[222,   7],
       [  4, 243]], dtype=int64)
```

In [66]:
```
accuracy_score(y_test, pred.round().detach().numpy())
```

```
0.976890756302521
```

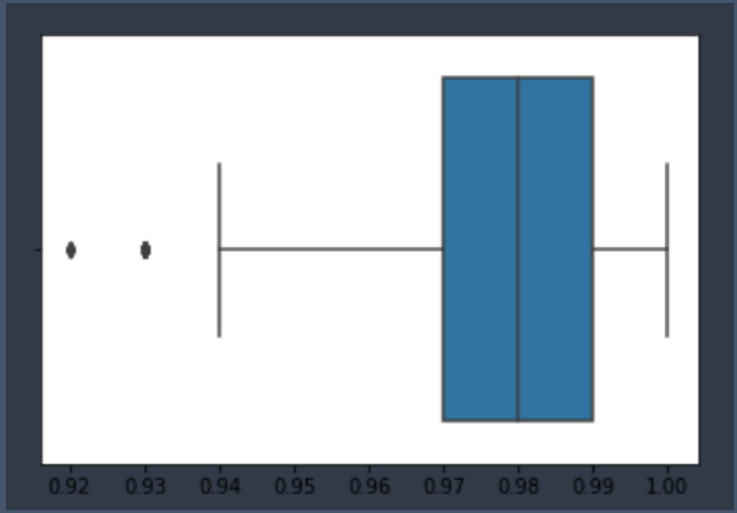
In [67]:
```
print(classification_report(y_test, pred.round().detach().numpy(),
                            target_names= ['female', 'male']))
```

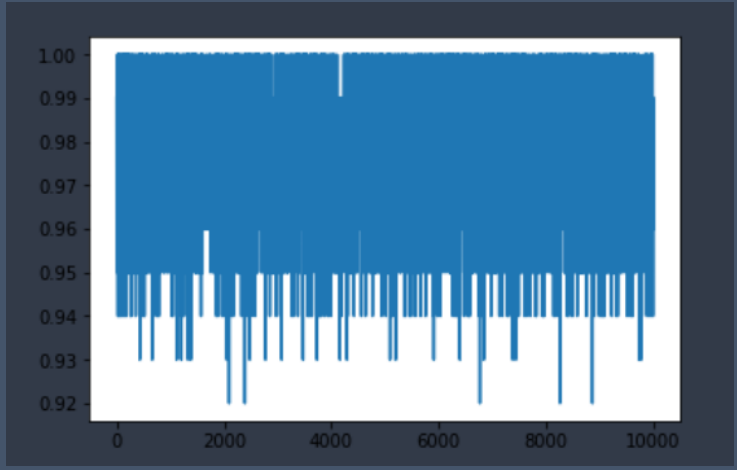
```
              precision    recall  f1-score   support

      female       0.98      0.97      0.98       229
        male       0.97      0.98      0.98       247

   micro avg       0.98      0.98      0.98       476
   macro avg       0.98      0.98      0.98       476
weighted avg       0.98      0.98      0.98       476
```

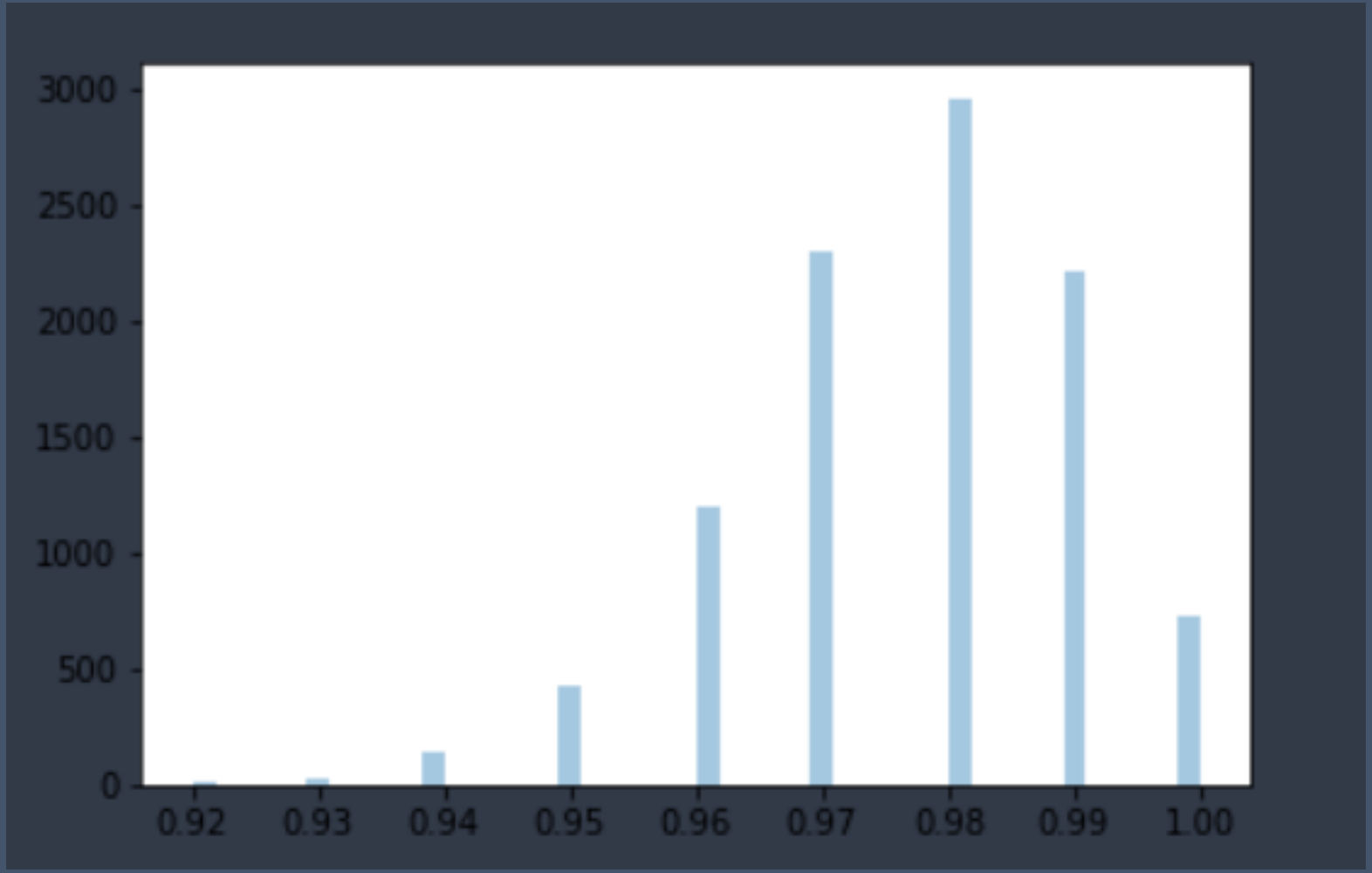
Rede Neural com as 20 Variáveis

8.356362852025466e+104 amostras diferentes de 100 elementos em 476

result_list = resultado_amostra(data, model, tam_amostra=100, quantidade_amostras=10000)





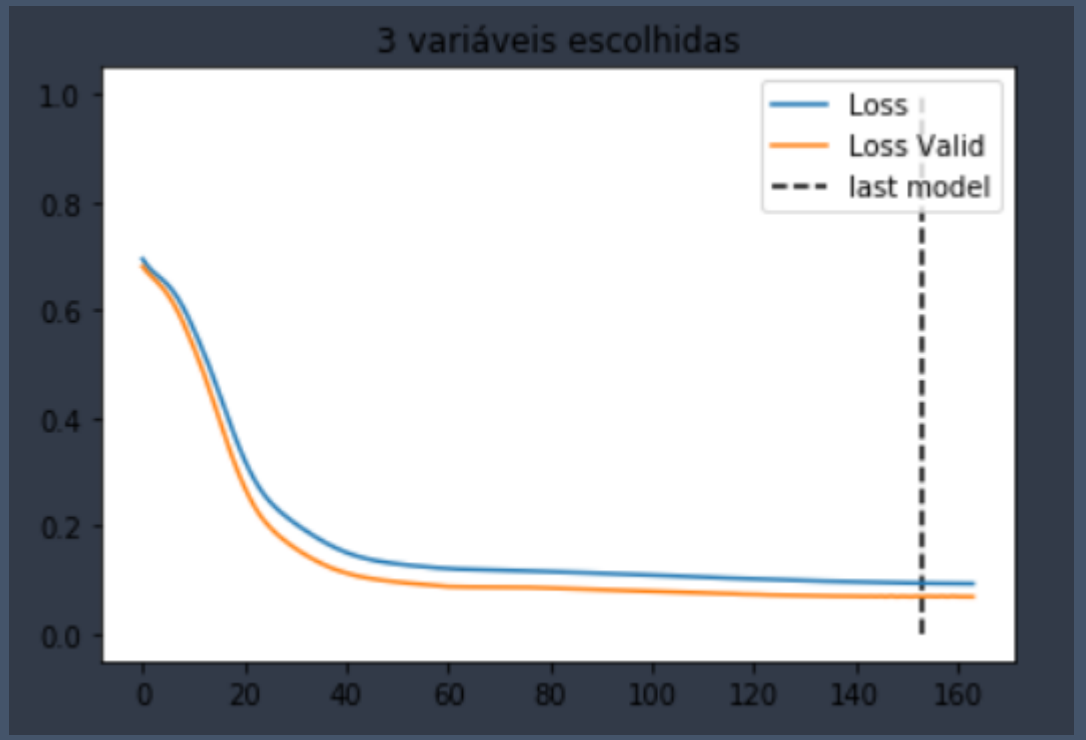


Rede Neural com as 3 Variáveis Escolhidas ('meanfun', 'IQR', 'sp.ent')

Treino 70%
Validação 15%
Teste 15%

Early Stopping com tolerância de 10 épocas sem redução no loss da validação

```
Model(
  (conv1): Linear(in_features=3, out_features=32,
bias=True)
  (conv2): Linear(in_features=32, out_features=32,
bias=True)
  (conv3): Linear(in_features=32, out_features=1,
bias=True)
  (relu): ReLU()
  (sigmoid): Sigmoid()
)
```



Rede Neural com as 3 Variáveis Escolhidas ('meanfun', 'IQR', 'sp.ent')

In [92]:
```
print('TN-FP\nFN-TP')
confusion_matrix(y_test, pred.round().detach().numpy())
```

```
TN-FP
FN-TP


array([[224,   5],
       [  4, 243]], dtype=int64)
```

In [93]:
```
accuracy_score(y_test, pred.round().detach().numpy())
```

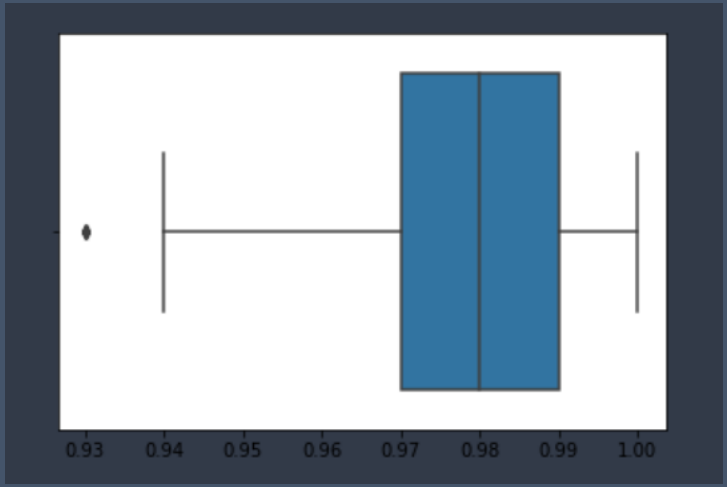
```
0.9810924369747899
```

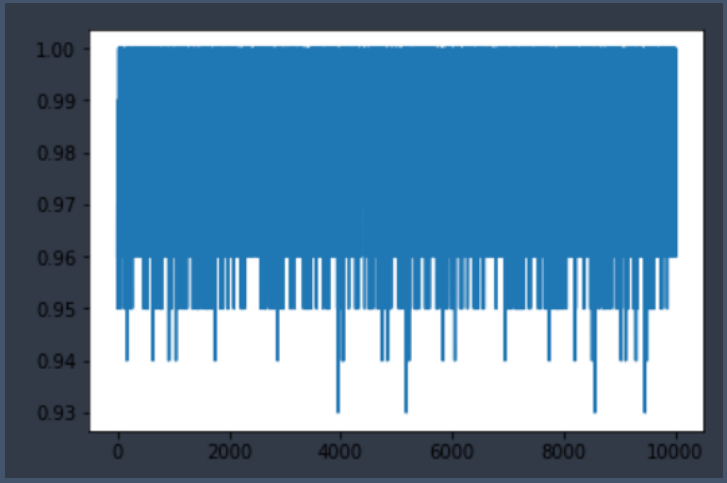
In [94]:
```
print(classification_report(y_test, pred.round().detach().numpy(),
                            target_names= ['female', 'male']))
```

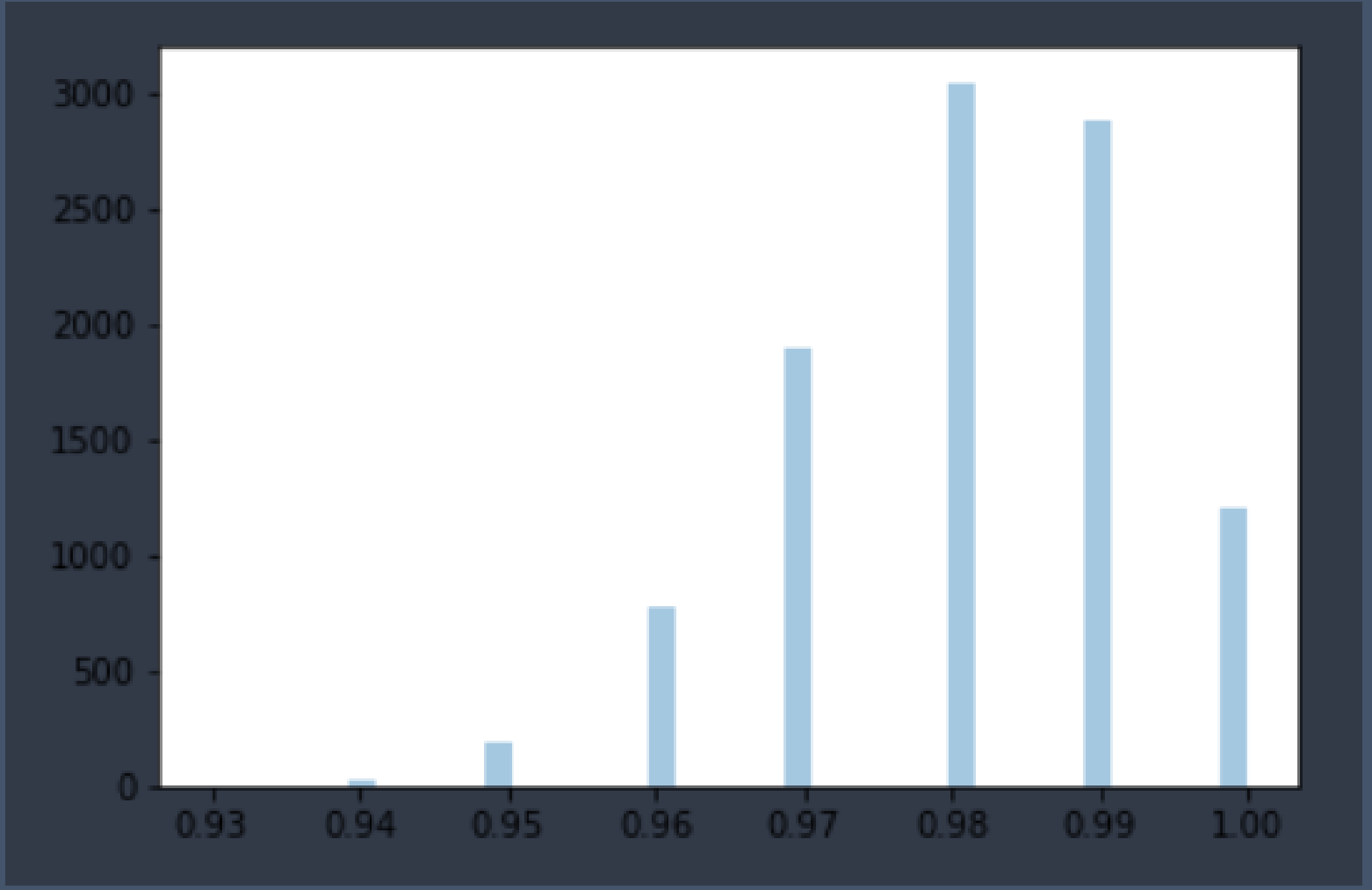
```
              precision    recall  f1-score   support

      female       0.98      0.98      0.98       229
        male       0.98      0.98      0.98       247

   micro avg       0.98      0.98      0.98       476
   macro avg       0.98      0.98      0.98       476
weighted avg       0.98      0.98      0.98       476
```

Rede Neural com as 3 Variáveis Escolhidas ('meanfun', 'IQR', 'sp.ent')

result_list = resultado_amostra(data, model, tam_amostra=100, quantidade_amostras=10000)







Rede Neural com 3 Principal Components (PCA)

In [103]:
```
pca = PCA(n_components=3)
components = pca.fit_transform(df.iloc[:,:-1])
```

In [104]:
```
pca.explained_variance_ratio_
```

```
array([0.50779229, 0.12190298, 0.08656245])
```

In [105]:
```
len(pca.explained_variance_ratio_)
```

```
3
```

In [106]:
```
np.cumsum(pca.explained_variance_ratio_)[-1]
```

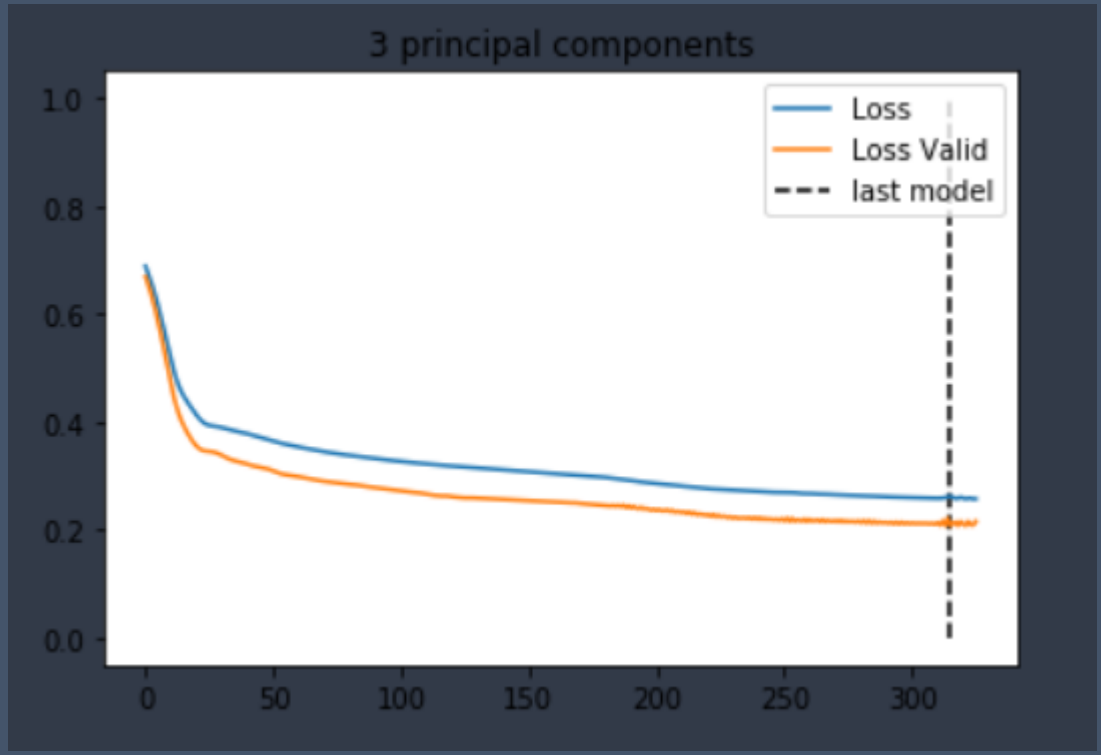
```
0.7162577187262075
```

Rede Neural com 3 Principal Components (PCA)

Treino 70%
Validação 15%
Teste 15%

Early Stopping com tolerância de 10 épocas sem redução no loss da validação

Model(
  (conv1): Linear(in_features=3, out_features=32, bias=True)
  (conv2): Linear(in_features=32, out_features=32, bias=True)
  (conv3): Linear(in_features=32, out_features=1, bias=True)
  (relu): ReLU()
  (sigmoid): Sigmoid()
)



Rede Neural com 3 Principal Components (PCA)

In [135]:
```
print('TN-FP\nFN-TP')
confusion_matrix(y_test, pred.round().detach().numpy())
```

```
TN-FP
FN-TP


array([[190,  39],
       [ 18, 229]], dtype=int64)
```

In [136]:
```
accuracy_score(y_test, pred.round().detach().numpy())
```

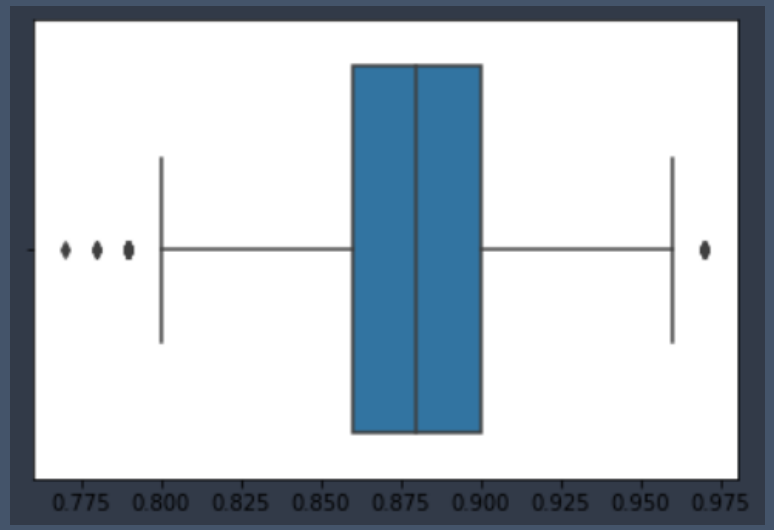
```
0.8802521008403361
```

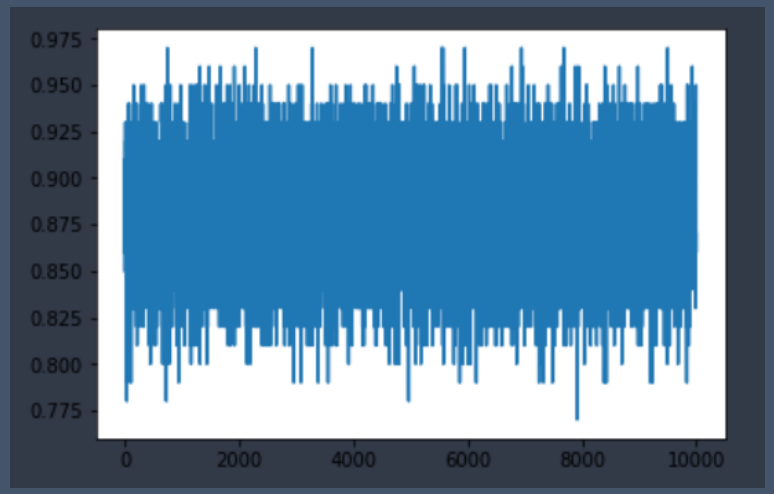
In [137]:
```
print(classification_report(y_test, pred.round().detach().numpy(),
                            target_names= ['female', 'male']))
```

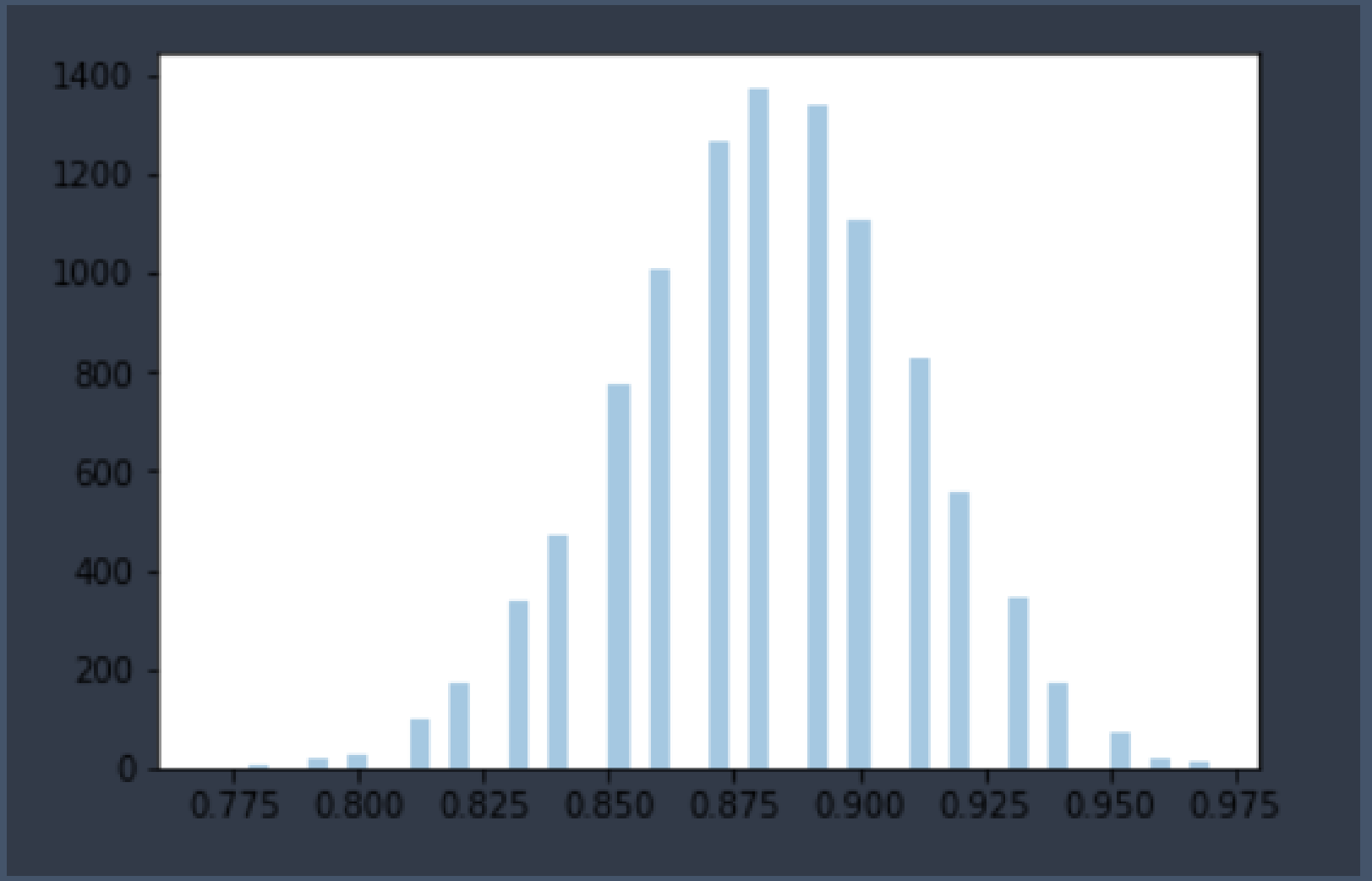
```
              precision    recall  f1-score   support

      female       0.91      0.83      0.87       229
        male       0.85      0.93      0.89       247

   micro avg       0.88      0.88      0.88       476
   macro avg       0.88      0.88      0.88       476
weighted avg       0.88      0.88      0.88       476
```

Rede Neural com 3 Principal Components (PCA)

result_list = resultado_amostra(data, model, tam_amostra=100, quantidade_amostras=10000)







Usando uma Quantidade de Componentes que Explique 95% da variação do Dataset

In [147]:
```
pca = PCA(n_components=.95)
components = pca.fit_transform(df.iloc[:,:-1])
```

In [148]:
```
pca.explained_variance_ratio_
```

```
array([0.50779229, 0.12190298, 0.08656245, 0.06103532, 0.05349789,
       0.03874441, 0.03069906, 0.0255996 , 0.02317785, 0.01706343])
```

In [149]:
```
len(pca.explained_variance_ratio_)
```

```
10
```

In [150]:
```
np.cumsum(pca.explained_variance_ratio_)[-1]
```

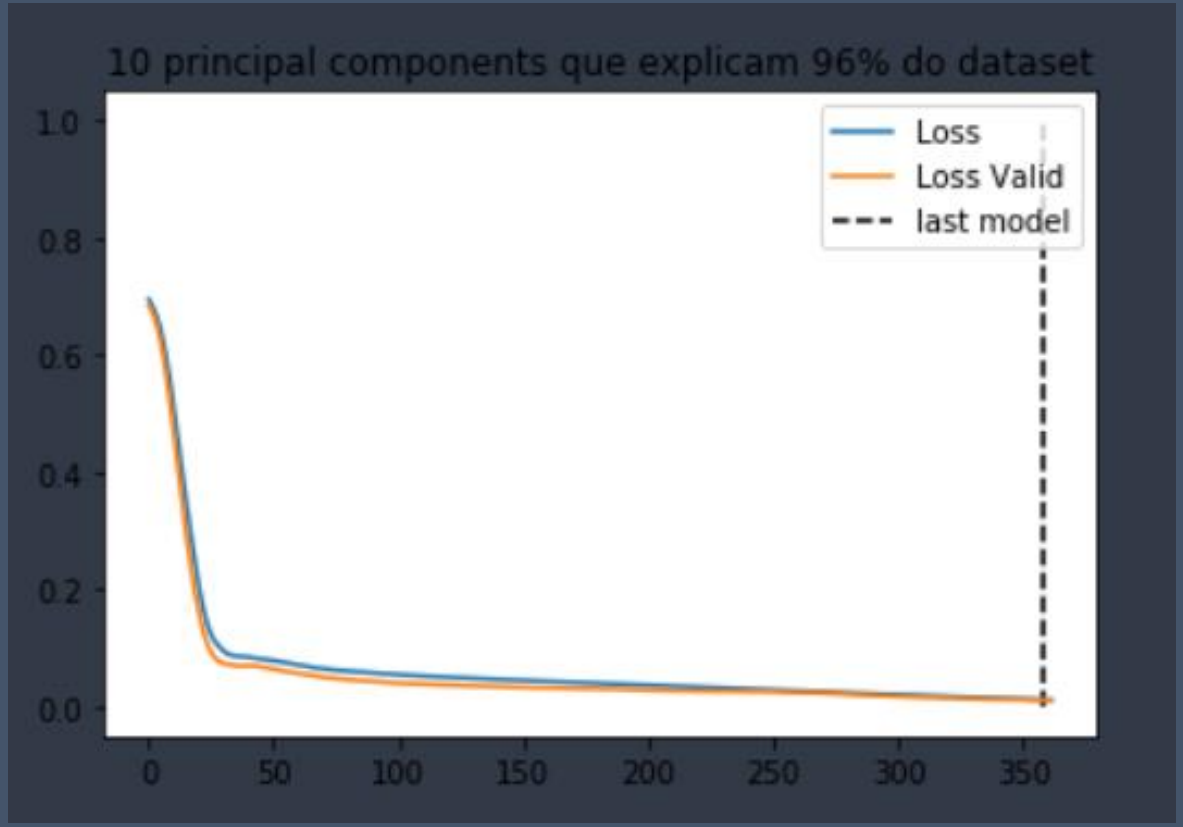
```
0.9660752899550968
```

Usando uma Quantidade de Componentes que Explique 95% da variação do Dataset

Treino 70%
Validação 15%
Teste 15%

Early Stopping com tolerância de 10 épocas sem redução no loss da validação

```
Model(
  (conv1): Linear(in_features=10, out_features=32, bias=True)
  (conv2): Linear(in_features=32, out_features=32, bias=True)
  (conv3): Linear(in_features=32, out_features=1, bias=True)
  (relu): ReLU()
  (sigmoid): Sigmoid()
)
```



Usando uma Quantidade de Componentes que Explique 95% da variação do Dataset

In [177]:
```
print('TN-FP\nFN-TP')
confusion_matrix(y_test, pred.round().detach().numpy())
```

```
TN-FP
FN-TP


array([[225,   4],
       [  7, 240]], dtype=int64)
```

In [178]:
```
accuracy_score(y_test, pred.round().detach().numpy())
```

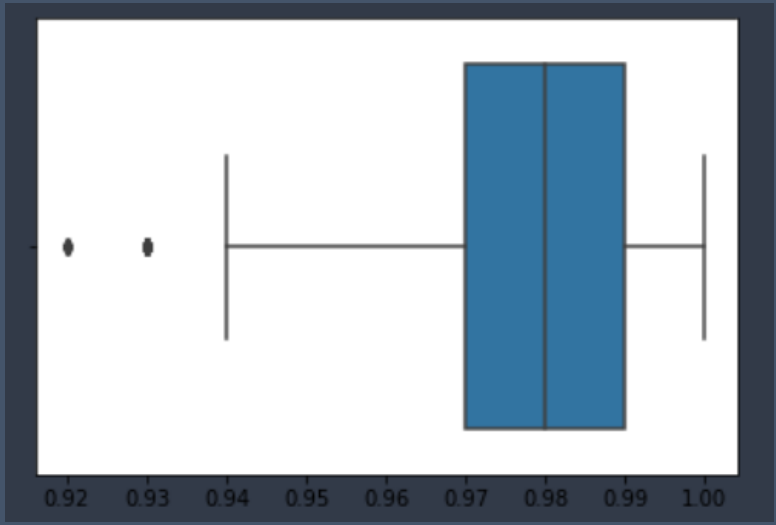
```
0.976890756302521
```

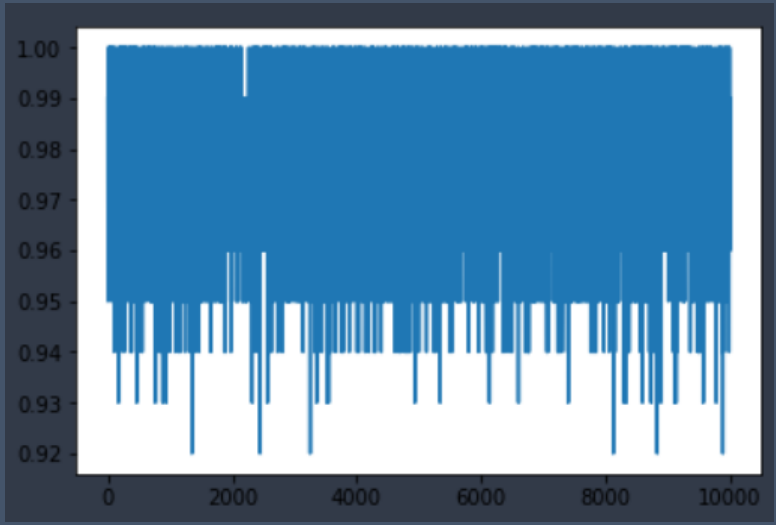
In [179]:
```
print(classification_report(y_test, pred.round().detach().numpy(),
                            target_names= ['female', 'male']))
```

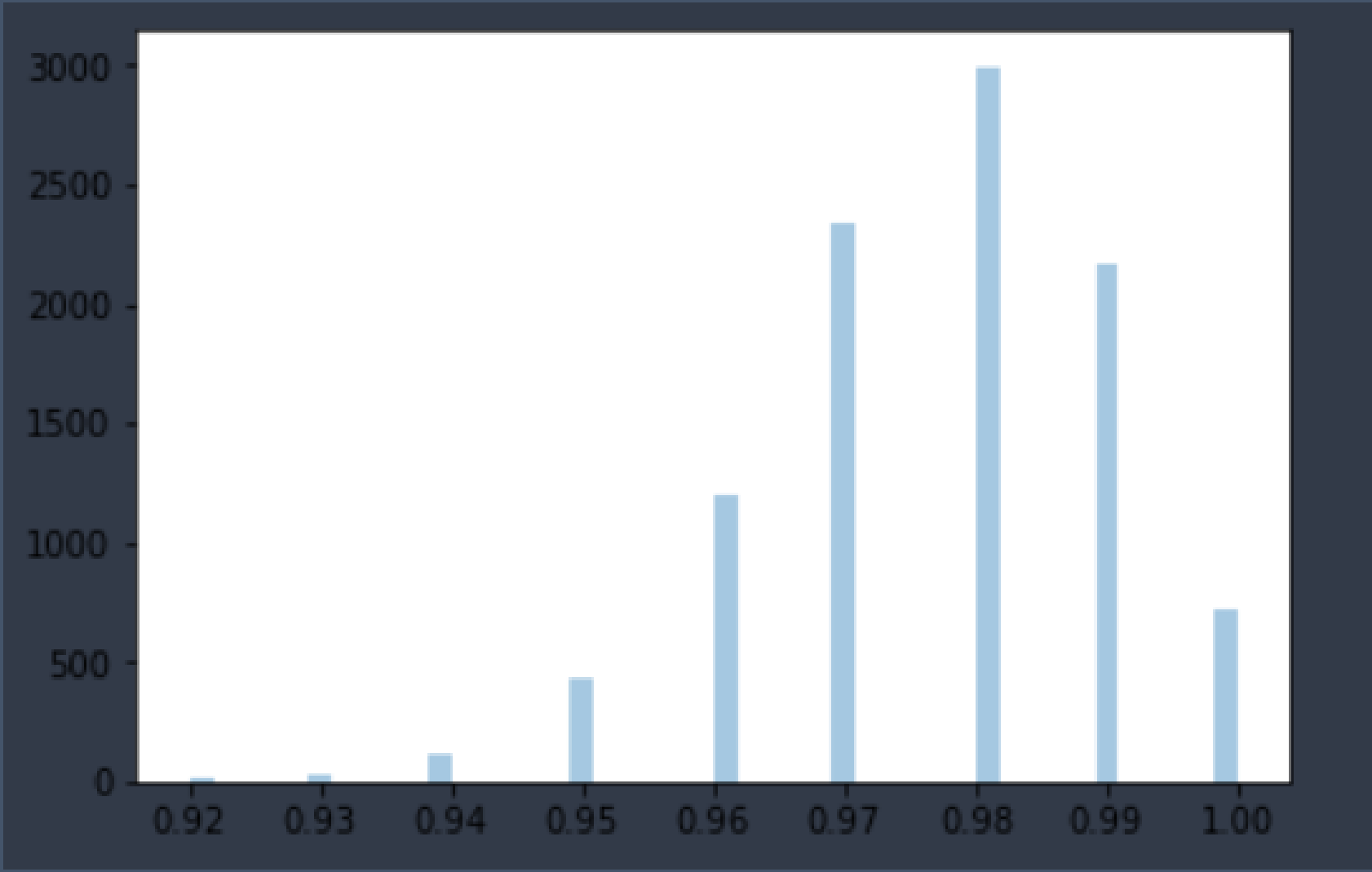
```
              precision    recall  f1-score   support

      female       0.97      0.98      0.98       229
        male       0.98      0.97      0.98       247

   micro avg       0.98      0.98      0.98       476
   macro avg       0.98      0.98      0.98       476
weighted avg       0.98      0.98      0.98       476
```

Usando uma Quantidade de Componentes que Explique 95% da variação do Dataset

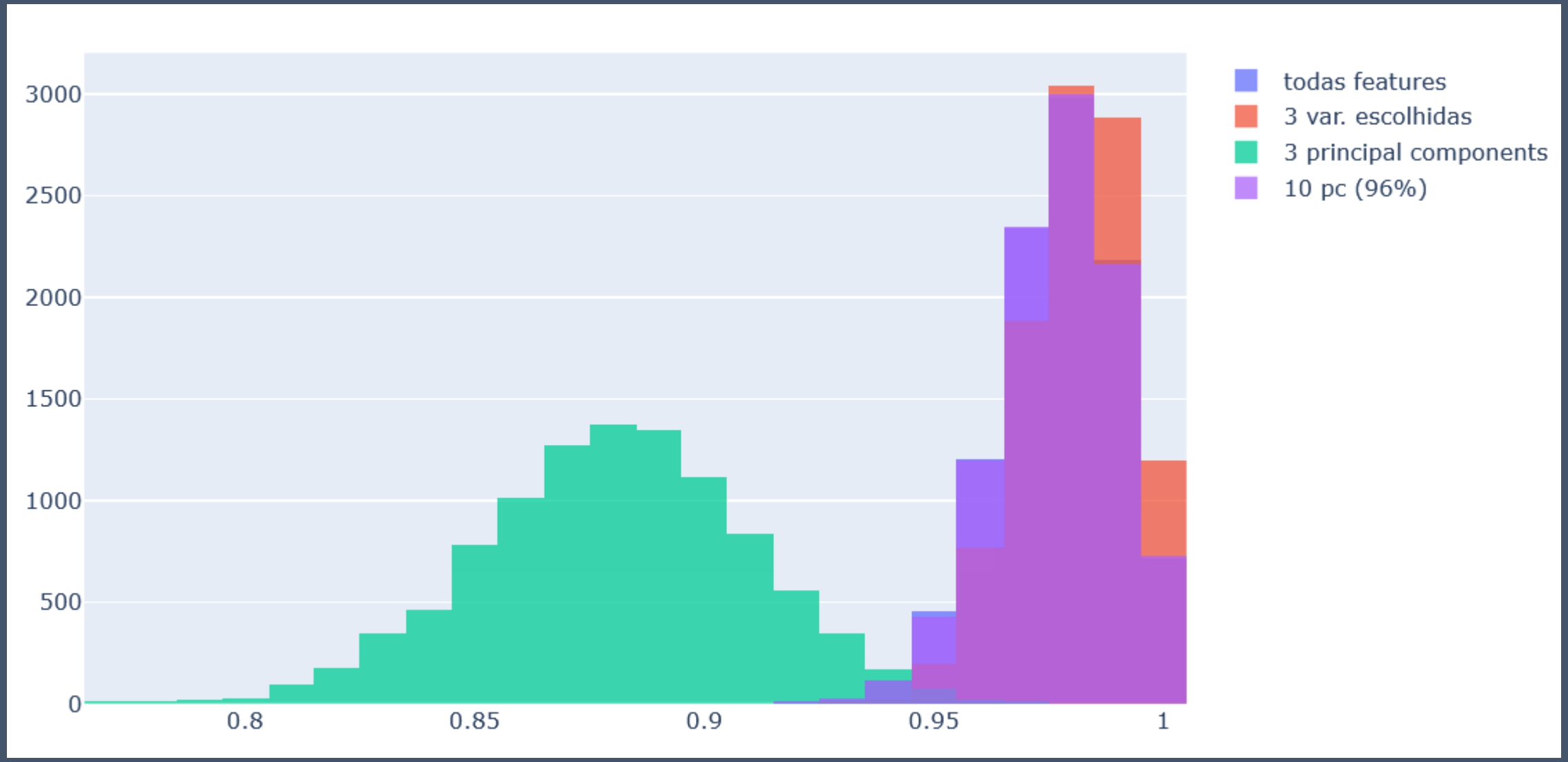
result_list = resultado_amostra(data, model, tam_amostra=100, quantidade_amostras=10000)



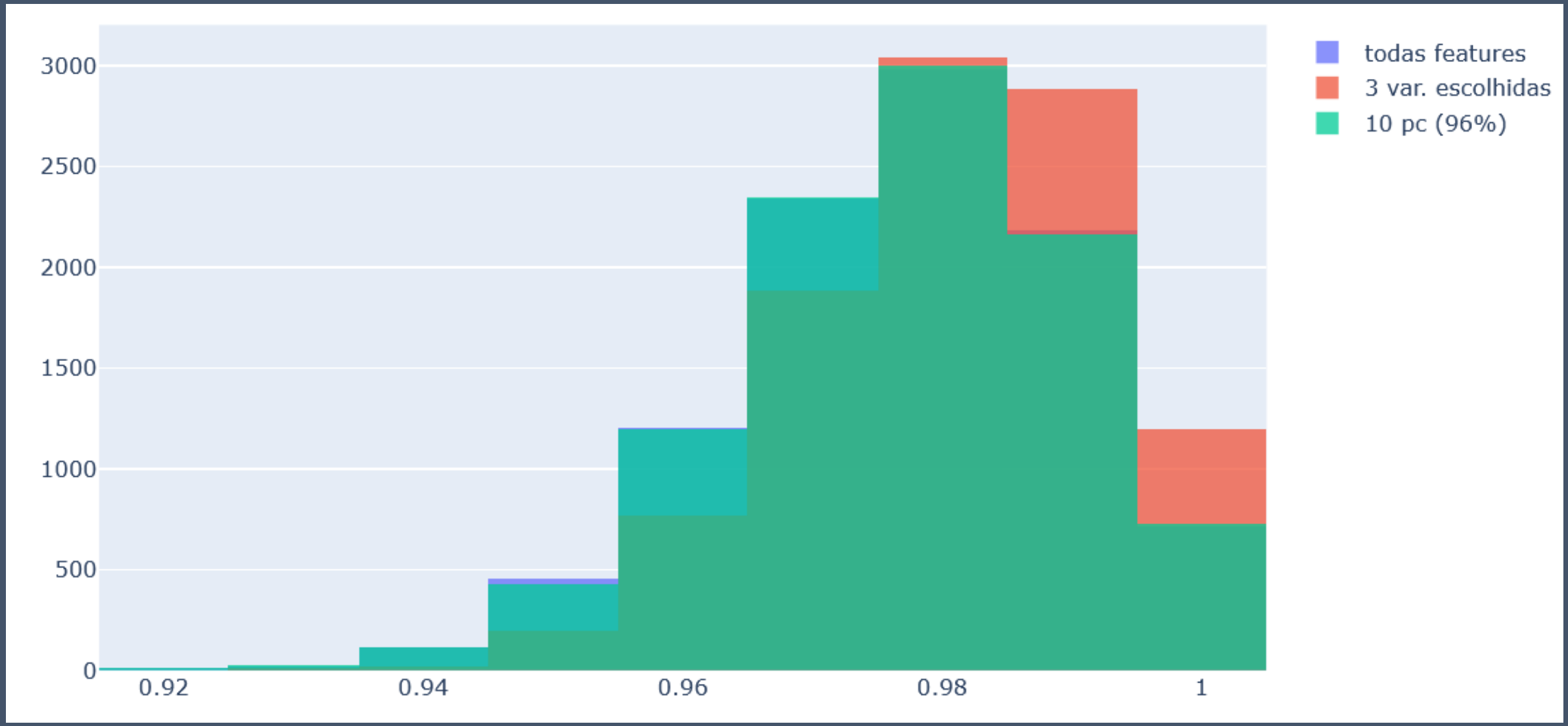




Comparando os Modelos



Comparando os Modelos



Fim