Bibliotecas

```
## Importando as Bibliotecas Necessárias ##
import warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import tree
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score, confusion_matrix, ConfusionMatrixDisplay, f1_score, cohen_kappa_score, pre
from sklearn.neural_network import MLPClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.datasets import make_classification
from sklearn import metrics
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from numpy.linalg import inv
from copy import copy
from sklearn.metrics import RocCurveDisplay

sns.set()
```

```
# Lendo a base de dados
df = pd.read_excel("m.xlsx")

xp = copy(df)

xraw = copy(xp)

xp.shape
```

```
     (25976, 25)
```

Codigo processamento

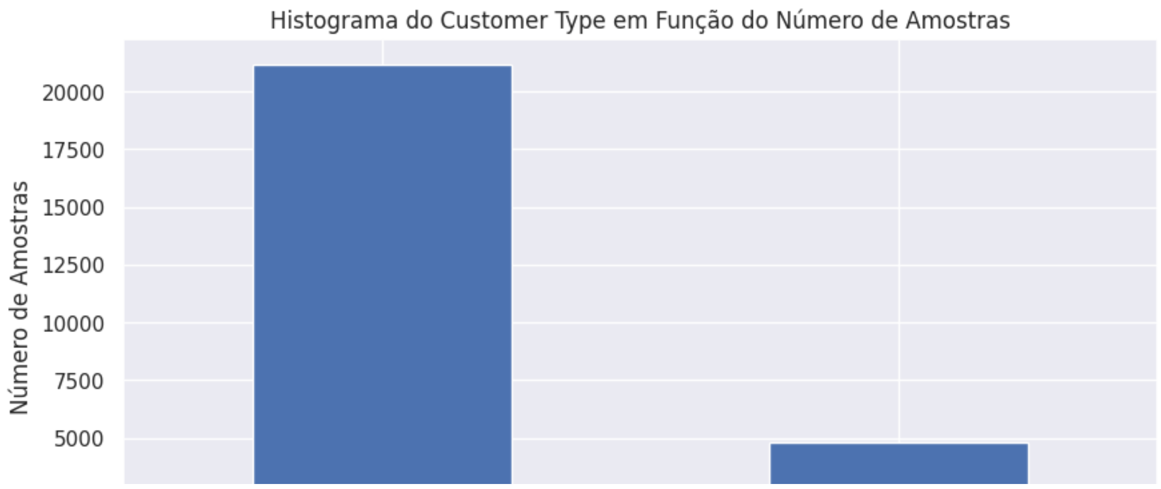
```
df = copy(xp)
df.isnull().sum()
```

```
     Column1                              0
     id                                   0
     Gender                               0
     Customer Type                        0
     Age                                  0
     Type of Travel                       0
     Class                                0
     Flight Distance                      0
     Inflight wifi service                0
     Departure/Arrival time convenient    0
     Ease of Online booking               0
     Gate location                        0
     Food and drink                       0
     Online boarding                      0
     Seat comfort                         0
     Inflight entertainment               0
     On-board service                     0
     Leg room service                     0
     Baggage handling                     0
     Checkin service                      0
     Inflight service                     0
     Cleanliness                          0
     Departure Delay in Minutes           0
     Arrival Delay in Minutes             0
     satisfaction                         0
     dtype: int64
```

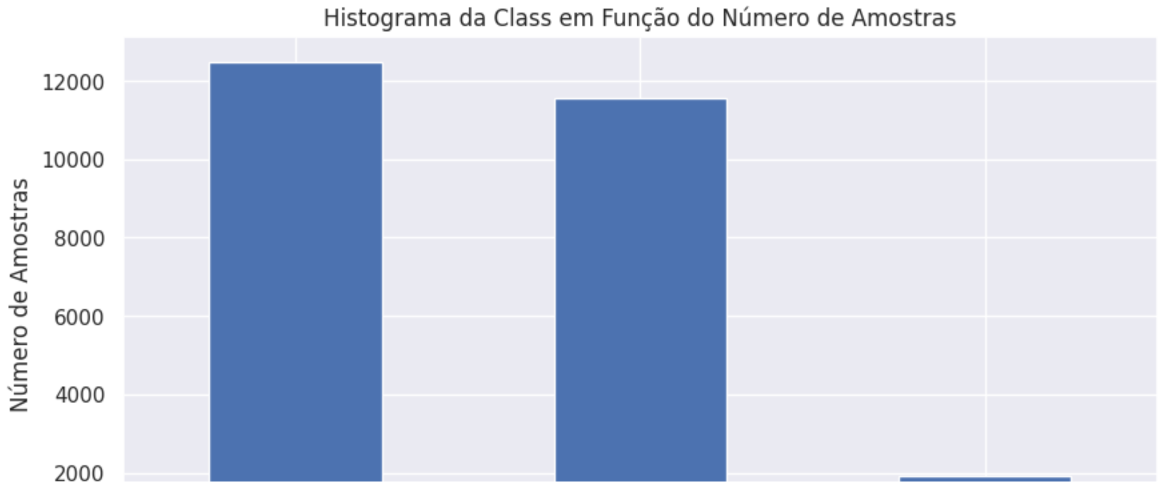
```
xp['Arrival Delay in Minutes'] = xp['Arrival Delay in Minutes'].replace(np.nan, 0)
```

```
# Contando a quantidade de dados de cada classe
df=xp
contagem_classes = df['Customer Type'].value_counts()

# Plotando o histograma das classes
plt.figure(figsize=(10, 5))
contagem_classes.plot(kind='bar')
```

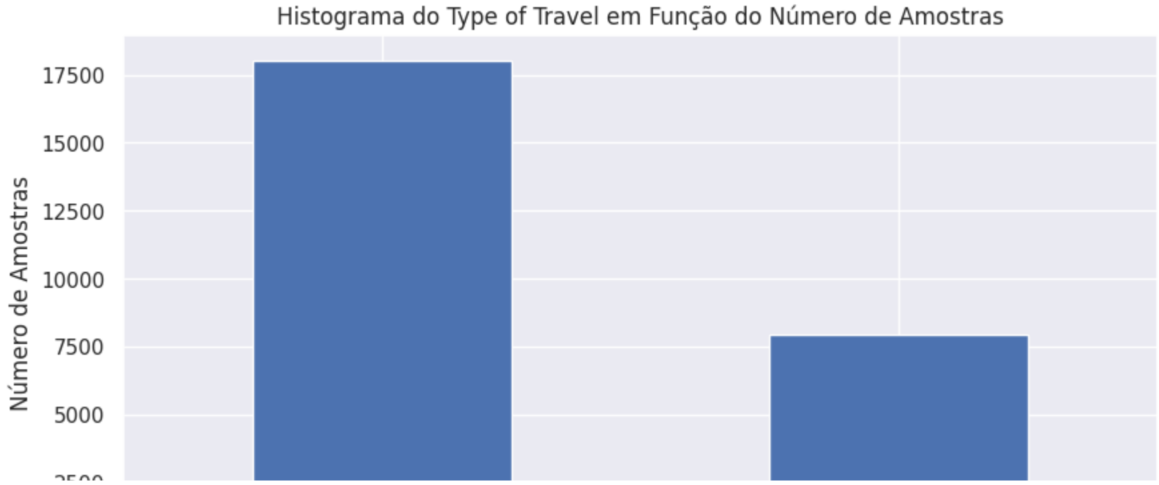
```
plt.xlabel('Customer Type')
plt.ylabel('Número de Amostras')
plt.title('Histograma do Customer Type em Função do Número de Amostras')
plt.xticks(rotation=360)
plt.show()
```



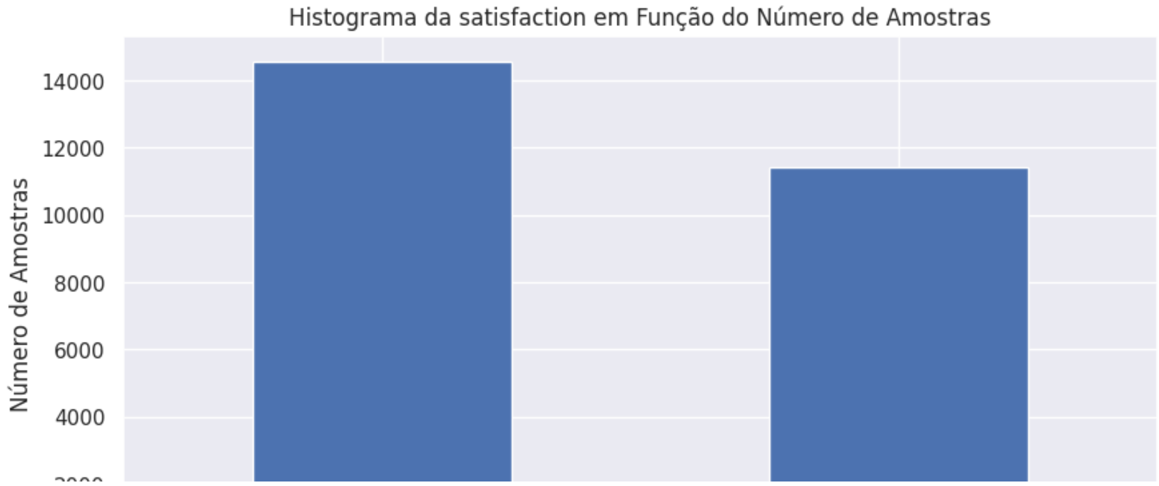
```
# Contando a quantidade de dados de cada classe
df=xp
contagem_classes = df['Class'].value_counts()

# Plotando o histograma das classes
plt.figure(figsize=(10, 5))
contagem_classes.plot(kind='bar')
plt.xlabel('Class')
plt.ylabel('Número de Amostras')
plt.title('Histograma da Class em Função do Número de Amostras')
plt.xticks(rotation=360)
plt.show()
```



```
# Contando a quantidade de dados de cada classe
df=xp
contagem_classes = df['Type of Travel'].value_counts()

# Plotando o histograma das classes
plt.figure(figsize=(10, 5))
contagem_classes.plot(kind='bar')
plt.xlabel('Type of Travel')
plt.ylabel('Número de Amostras')
plt.title('Histograma do Type of Travel em Função do Número de Amostras')
plt.xticks(rotation=360)
plt.show()
```



```
# Contando a quantidade de dados de cada classe
df=xp
contagem_classes = df['satisfaction'].value_counts()

# Plotando o histograma das classes
plt.figure(figsize=(10, 5))
contagem_classes.plot(kind='bar')
plt.xlabel('satisfaction')
plt.ylabel('Número de Amostras')
plt.title('Histograma da satisfaction em Função do Número de Amostras')
plt.xticks(rotation=360)
plt.show()
```

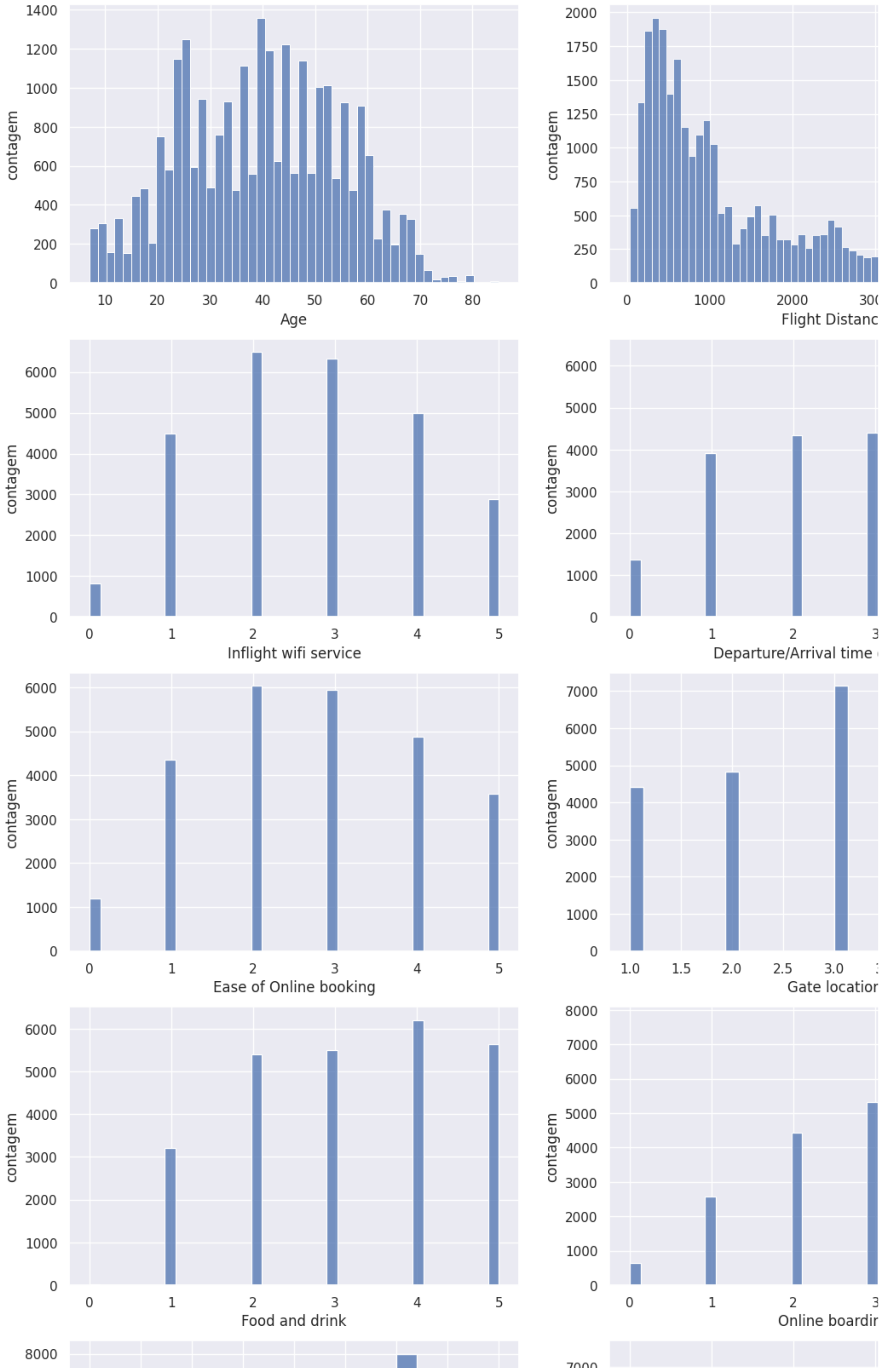


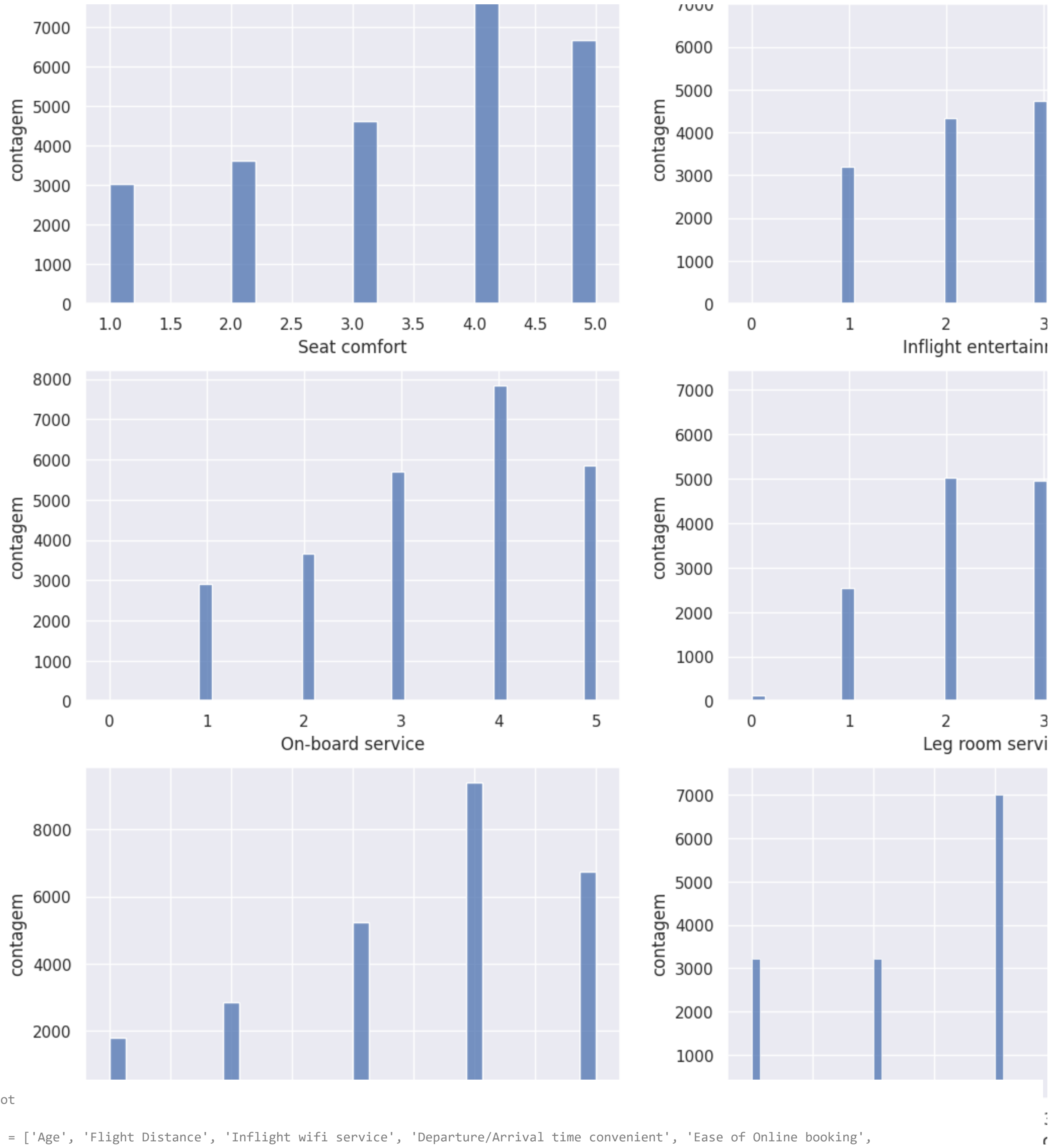
```
atributos_numericos = df.select_dtypes(include=['float64', 'int64'])

# Calcula a assimetria para cada atributo numérico
assimetria = atributos_numericos.skew()

# Exibe a assimetria de cada atributo
print(assimetria)
```

```
    Column1                              0.000000
    id                                  -0.011364
    Age                                 -0.000088
    Flight Distance                      1.102927
    Inflight wifi service                0.040792
    Departure/Arrival time convenient   -0.324685
```

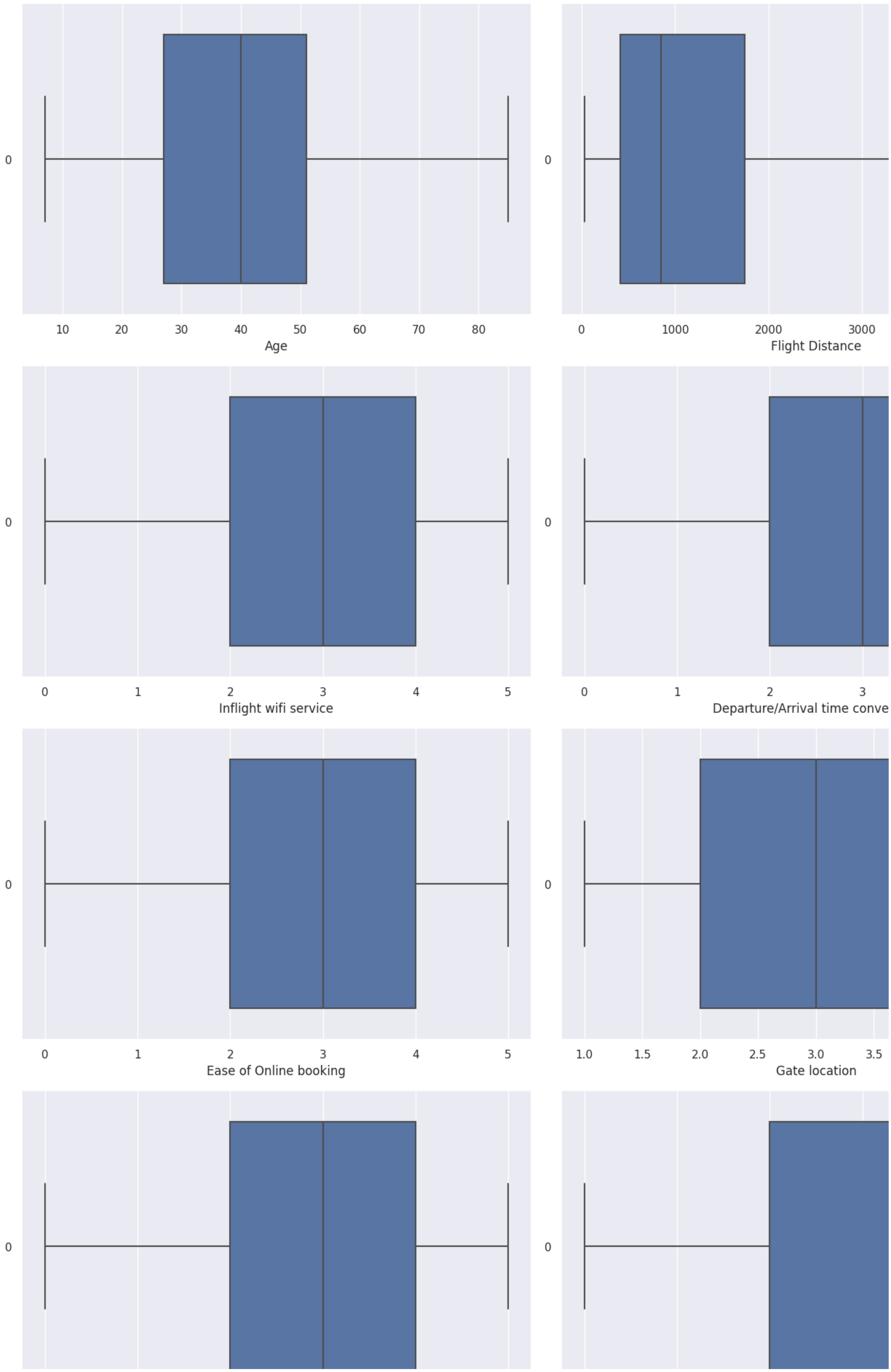
```
Ease of Online booking                -0.020655
Gate location                         -0.055798
Food and drink                        -0.170229
Online boarding                       -0.469218
Seat comfort                          -0.498047
Inflight entertainment                -0.371353
On-board service                      -0.426507
Leg room service                      -0.341210
Baggage handling                      -0.678863
Checkin service                       -0.373016
Inflight service                      -0.696803
Cleanliness                           -0.304285
Departure Delay in Minutes             7.193970
Arrival Delay in Minutes               6.994086
dtype: float64
```

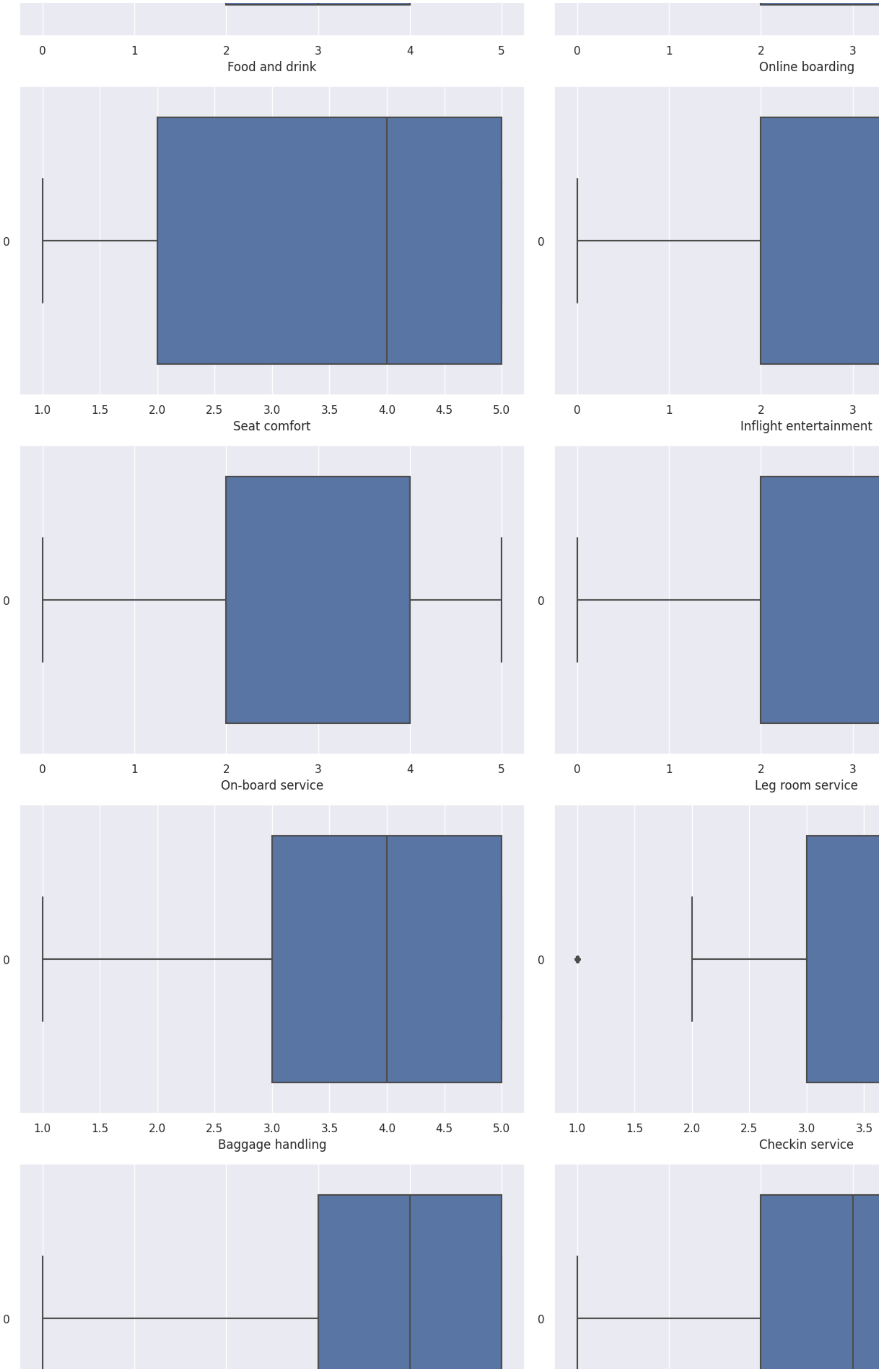
```
#aplicando histogramas para os atributos contínuos:
def multigraficos_histograma(data, nrows, ncols, nomes):
    fig, axs = plt.subplots(nrows = nrows, ncols = ncols, figsize=(15, 5*nrows))
    k = 0
    for i in range(nrows):
        for j in range(ncols):
            sns.histplot(ax = axs[i,j], data = data, x = nomes[k])
            axs[i, j].set_xlabel(nomes[k])
            axs[i, j].set_ylabel("contagem")
            k+=1
        #
    #
#

nrows = 9
ncols = 2
multigraficos_histograma(df, nrows, ncols, var_num)
```

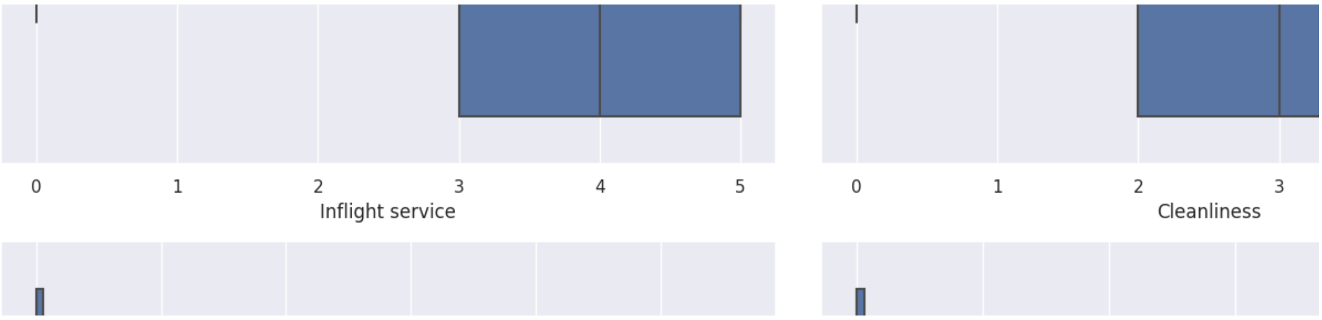

contagem
0
200
400
600
800
1000
1200
1400
10
20
30
40
50
60
70
80
Age
contagem
0
250
500
750
1000
1250
1500
1750
2000
0
1000
2000
300
Flight Distanc
contagem
0
1000
2000
3000
4000
5000
6000
0
1
2
3
4
5
Inflight wifi service
contagem
0
1000
2000
3000
4000
5000
6000
0
1
2
3
Departure/Arrival time
contagem
0
1000
2000
3000
4000
5000
6000
0
1
2
3
4
5
Ease of Online booking
contagem
0
1000
2000
3000
4000
5000
6000
7000
1.0
1.5
2.0
2.5
3.0
Gate locatior
contagem
0
1000
2000
3000
4000
5000
6000
0
1
2
3
4
5
Food and drink
contagem
0
1000
2000
3000
4000
5000
6000
7000
8000
0
1
2
3
Online boardir
8000
7000



```
# boxplot

var_num = ['Age', 'Flight Distance', 'Inflight wifi service', 'Departure/Arrival time convenient', 'Ease of Online booking',
           'Gate location', 'Food and drink', 'Online boarding', 'Seat comfort', 'Inflight entertainment', 'On-board service',
           'Leg room service', 'Baggage handling', 'Checkin service', 'Inflight service', 'Cleanliness',
           'Departure Delay in Minutes', 'Arrival Delay in Minutes']

nrows = 9
ncols = 2
fig, axs = plt.subplots(nrows=nrows, ncols=ncols, figsize=(15, 5*nrows))

for i, var in enumerate(var_num):
    row = i // ncols
    col = i % ncols
    sns.boxplot(ax=axs[row, col], data=df[var].dropna(), orient='h')
    axs[row, col].set_xlabel(var)

plt.tight_layout()
```


0
10
20
30
40
50
60
70
80
Age
0
1000
2000
3000
Flight Distance
0
1
2
3
4
5
Inflight wifi service
0
1
2
3
Departure/Arrival time conve
0
1
2
3
4
5
Ease of Online booking
1.0
1.5
2.0
2.5
3.0
3.5
Gate location


0 1 2 3 4 5
Food and drink
0 1 2 3
Online boarding
0
1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
Seat comfort
0
0 1 2 3
Inflight entertainment
0
0 1 2 3 4 5
On-board service
0
0 1 2 3
Leg room service
0
1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0
Baggage handling
0
1.0 1.5 2.0 2.5 3.0 3.5
Checkin service
0
0


0
1
2
3
4
5
Inflight service
0
1
2
3
Cleanliness

```
print("Variaveis com outliers: \n")

dsc = df[var_num].describe() #obtendo estatísticas descritivas dos atributos numericos

for name in dsc.columns:
    q1 = dsc[name]["25%"]
    q3 = dsc[name]["75%"]
    iqr = q3-q1

    min_ = q1 - 1.5*iqr
    max_ = q3 + 1.5*iqr

    out_inf = np.where(df[name] < min_)[0]
    out_sup = np.where(df[name] > max_)[0]

    if ((out_inf.shape[0] > 0) or (out_sup.shape[0] > 0)):
        print(name)
    #
#
```

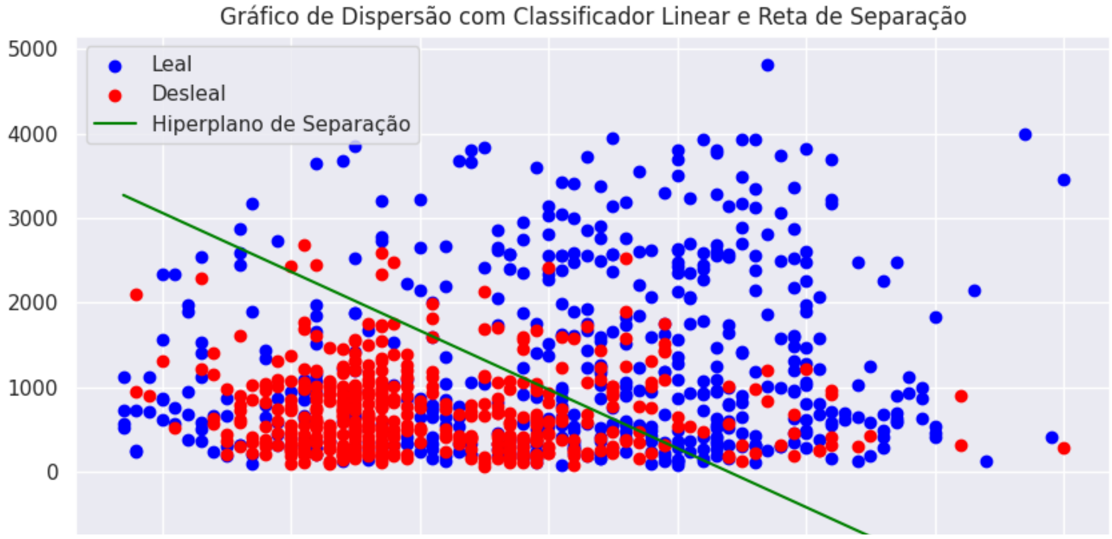
```
Variaveis com outliers:

Flight Distance
Checkin service
Departure Delay in Minutes
Arrival Delay in Minutes
```

Classificação Linear

```
df.corr(method='spearman').style.background_gradient(cmap='coolwarm')
```

	Column1	id	Age	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	S comf
Column1	1.000000	0.006889	-0.008206	-0.002322	-0.003532	-0.003789	-0.002222	-0.001078	-0.010043	0.001093	-0.004
id	0.006889	1.000000	0.014094	0.134367	-0.031660	-0.003406	0.009216	0.002237	-0.007904	0.056276	0.051
Age	-0.008206	0.014094	1.000000	0.074394	0.007254	0.029867	0.010127	0.001820	0.021836	0.206976	0.153
Flight Distance	-0.002322	0.134367	0.074394	1.000000	0.002596	-0.008876	0.057619	0.006139	0.044451	0.192243	0.138
Inflight wifi service	-0.003532	-0.031660	0.007254	0.002596	1.000000	0.343469	0.707514	0.345670	0.119902	0.435962	0.111
Departure/Arrival time convenient	-0.003789	-0.003406	0.029867	-0.008876	0.343469	1.000000	0.442511	0.463909	-0.017700	0.070337	-0.001
Ease of Online booking	-0.002222	0.009216	0.010127	0.057619	0.707514	0.442511	1.000000	0.469197	0.021621	0.369473	0.017
Gate location	-0.001078	0.002237	0.001820	0.006139	0.345670	0.463909	0.469197	1.000000	-0.010186	0.002201	-0.002
Food and drink	-0.010043	-0.007904	0.021836	0.044451	0.119902	-0.017700	0.021621	-0.010186	1.000000	0.236103	0.560
Online boarding	0.001093	0.056276	0.206976	0.192243	0.435962	0.070337	0.369473	0.002201	0.236103	1.000000	0.437
Seat comfort	-0.004468	0.051489	0.153589	0.138861	0.111958	-0.001597	0.017355	-0.002925	0.560461	0.437239	1.000
Inflight entertainment	-0.011029	-0.000835	0.073733	0.112542	0.192678	-0.025824	0.039318	-0.002203	0.613431	0.296994	0.607
On-board service	0.000951	0.054226	0.067881	0.109271	0.109330	0.061351	0.038749	-0.032194	0.050640	0.171435	0.141
Leg room service	-0.003310	0.038373	0.044322	0.119719	0.149755	-0.001714	0.103574	-0.002347	0.033438	0.132556	0.112
Baggage handling	0.001747	0.066637	-0.029406	0.069701	0.109526	0.078020	0.035720	-0.015915	0.050351	0.119922	0.108

```
df = copy(xp)
leal = df[df['Customer Type'] == 'Loyal Customer'].iloc[:500]
desleal = df[df['Customer Type'] == 'disloyal Customer'].iloc[:500]

df = pd.concat([leal, desleal])


df['Customer Type'] = df['Customer Type'].map({'Loyal Customer': 1, 'disloyal Customer': -1})

df['Age'] = (df['Age'])
df['Flight Distance'] = (df['Flight Distance'])
df['Gate location'] = (df['Gate location'])
df['Food and drink'] = (df['Food and drink'])
df['On-board service'] = (df['On-board service'])
df['Leg room service'] = (df['Leg room service'])
df['Baggage handling'] = (df['Baggage handling'])
df['Checkin service'] = (df['Checkin service'])

X = df[['Age', 'Flight Distance', 'Checkin service', 'Baggage handling', 'Leg room service', 'On-board service', 'Food and drink', 'Gate location'
y = df['Customer Type'].values

X = np.concatenate((X, np.ones((X.shape[0], 1))), axis=1)

w = np.dot(inv(np.dot(X.T, X)), np.dot(X.T, y))

w1, w2, w0 = w[0], w[1], w[8]

x_hyperplane = np.linspace(X[:, 0].min(), X[:, 0].max(), 1000)
y_hyperplane = (-w0 - w1 * x_hyperplane) / w2

plt.figure(figsize=(10, 6))
plt.scatter(X[y == 1][:, 0], X[y == 1][:, 1], label='Leal', c='blue')
plt.scatter(X[y == -1][:, 0], X[y == -1][:, 1], label='Desleal', c='red')
plt.plot(x_hyperplane, y_hyperplane, color='green', label='Hiperplano de Separação')
plt.legend()
plt.title('Gráfico de Dispersão com Classificador Linear e Reta de Separação')
plt.grid(True)
plt.show()
```



Criação dos dados iniciais

```
df = copy(xp)

leal = df[df['Customer Type'] == 'Loyal Customer'].iloc[:12000]
desleal = df[df['Customer Type'] == 'disloyal Customer'].iloc[:12000]

df = pd.concat([leal, desleal])

df['Customer Type'] = df['Customer Type'].map({'Loyal Customer': 1, 'disloyal Customer': -1})
df['Gender'] = df['Gender'].map({'Male': 1, 'Female': 0})
df['Type of Travel'] = df['Type of Travel'].map({'Business travel': 1, 'Personal Travel': 0})
df['Class'] = df['Class'].map({'Business': 1, 'Eco': -1, 'Eco Plus': 0})
df['satisfaction'] = df['satisfaction'].map({'satisfied': 1, 'neutral or dissatisfied': 0})
```

```
df['Flight Distance'] = np.log(df['Flight Distance'])
df['Arrival Delay in Minutes'] = np.log1p(df['Arrival Delay in Minutes'])
df['Age'] = np.sqrt(df['Age'])
df['Departure Delay in Minutes'] = np.log1p(df['Arrival Delay in Minutes'])

df.drop(['id'], axis = 1, inplace = True)
df.drop(['Column1'], axis = 1, inplace = True)
df.drop(['Cleanliness'], axis = 1, inplace = True)
df.drop(['Ease of Online booking'], axis = 1, inplace = True)
df.drop(['Inflight entertainment'], axis = 1, inplace = True)
df.drop(['Arrival Delay in Minutes'], axis = 1, inplace = True)

X = df.drop(['satisfaction'], axis = 1).values
y = df['satisfaction'].values
```

Classifição Naive-Bayes

```
#Frequencia:
#    Não     Sim
#0 = 2     = 811  = 813/25976  = 0.0313%
#1 = 2966  = 1522 = 4488/25976 = 0.1727%
#2 = 4923  = 1567 = 6490/25976 = 0.2498%
#3 = 4694  = 1623 = 6317/25976 = 0.2431%
#4 = 1953  = 3028 = 4981/25976 = 0.1917%
#5 = 35    = 2852 = 2887/25976 = 0.1111%
#Total = 14573/25976 = 0.561% | 11403/25976 = 0.439%
#TotalTudo = 25976

#Prob ser insatisfeito e dar 0:
#P0N = 2/14573 PN = 14573/25976 P0 = 813/25976
PN0 = (2/14573) * (0.561)/(0.0313)
PS0 = 1 - PN0
#Prob ser insatisfeito e dar 1:
#P0N = 2/14573 PN = 14573/25976 813/25976
PN1 = (2966/14573) * (0.561)/(0.1727)
PS1 = 1 - PN1
#Prob ser insatisfeito e dar 2:
#P0N = 2/14573 PN = 14573/25976 813/25976
PN2 = (4923/14573) * (0.561)/(0.2498)
PS2 = 1 - PN2
#Prob ser insatisfeito e dar 3:
#P0N = 2/14573 PN = 14573/25976 813/25976
PN3 = (4694/14573) * (0.561)/(0.2431)
PS3 = 1 - PN3
#Prob ser insatisfeito e dar 4:
#P0N = 2/14573 PN = 14573/25976 813/25976
PN4 = (1953/14573) * (0.561)/(0.1917)
PS4 = 1 - PN4
#Prob ser insatisfeito e dar 5:
#P0N = 2/14573 PN = 14573/25976 813/25976
PN5 = (35/14573) * (0.561)/(0.1111)
PS5 = 1/100 - PN5
```

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=125, stratify = y
)
```

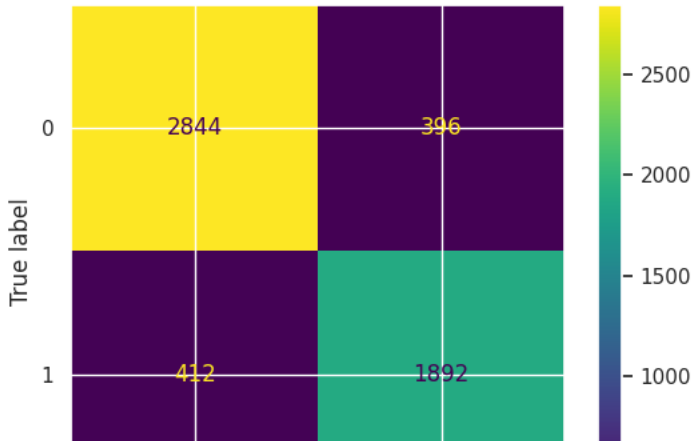
```
# Build a Gaussian Classifier
clf = GaussianNB()

# Model training
clf.fit(X_train, y_train)

# Predict Output
predicted = clf.predict([X_test[6]])

print("Actual Value:", y_test[6])
print("Predicted Value:", predicted[0])
```

```
Actual Value: 0
Predicted Value: 0
```

```
y_pred = clf.predict(X_test)
accuray = accuracy_score(y_pred, y_test)
f1 = f1_score(y_pred, y_test, average="weighted")
kappa = cohen_kappa_score(y_pred, y_test)
prec = precision_score(y_pred, y_test)
recal = recall_score(y_pred, y_test)

print("Accuracy:", accuray)
print("F1 Score:", f1)
print("Kappa:", kappa)
print("Precision:", prec)
print("Recall:", recal)
```

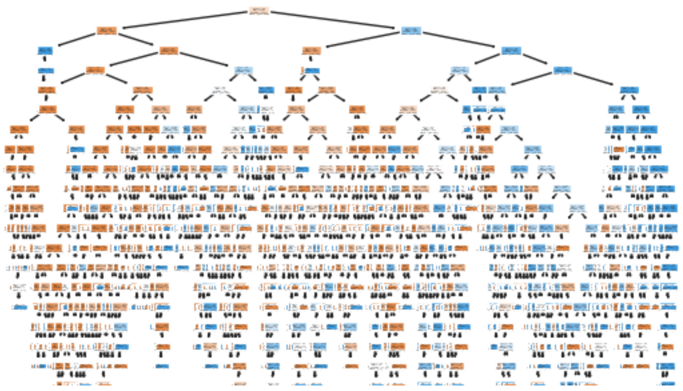
```
    Accuracy: 0.8542568542568543
    F1 Score: 0.8543312755435788
    Kappa: 0.699660152931181
    Precision: 0.8211805555555556
    Recall: 0.8269230769230769
```

```
labels = [0,1]
cm = confusion_matrix(y_test, y_pred, labels=labels)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
disp.plot();
```



Classificação Árvore de Decisão (simples)

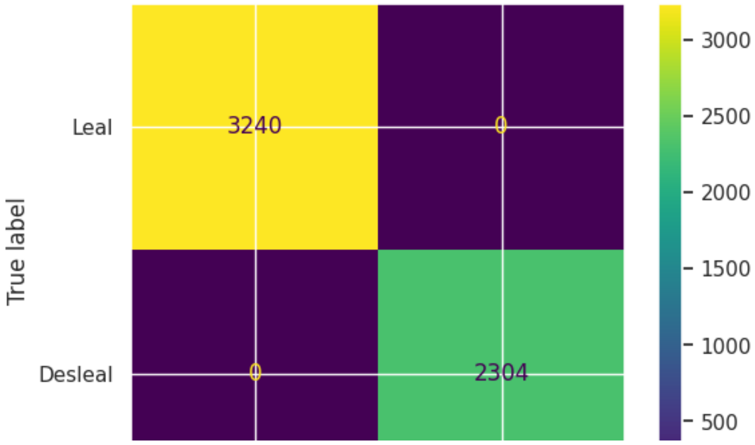
```
clf = tree.DecisionTreeClassifier()
clf = clf.fit(X, y.astype(float))
tree.plot_tree(clf,filled=True)
y_pred = clf.predict(X_test)
```



```
accuray = accuracy_score(y_pred, y_test)
f1 = f1_score(y_pred, y_test, average="weighted")
kappa = cohen_kappa_score(y_pred, y_test)
prec = precision_score(y_pred, y_test)
recal = recall_score(y_pred, y_test)

print("Accuracy:", accuray)
print("F1 Score:", f1)
print("Kappa:", kappa)
print("Precision:", prec)
print("Recall:", recal)
```

```
     Accuracy: 1.0
     F1 Score: 1.0
     Kappa: 1.0
     Precision: 1.0
     Recall: 1.0
```

```
labels = ["Leal", "Desleal"]
cm = confusion_matrix(y_test, y_pred)
labels = ["Leal", "Desleal"]
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
disp.plot();
```

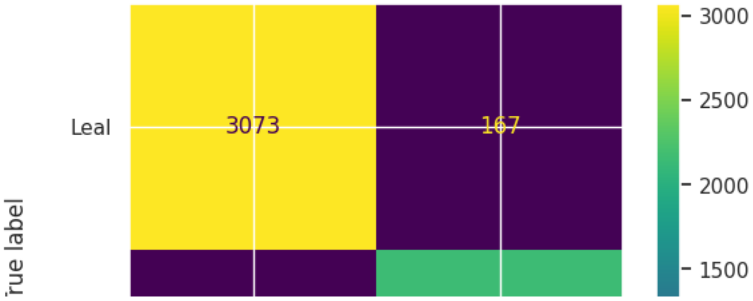


Classificação Rede Neural MLP

```
clf = MLPClassifier(random_state=1, max_iter=300).fit(X_train, y_train)
clf.predict_proba(X_test[:1])
y_pred = clf.predict(X_test)

accuray = accuracy_score(y_pred, y_test)
f1 = f1_score(y_pred, y_test, average="weighted")
kappa = cohen_kappa_score(y_pred, y_test)
prec = precision_score(y_pred, y_test)
recal = recall_score(y_pred, y_test)

print("Accuracy:", accuray)
print("F1 Score:", f1)
print("Kappa:", kappa)
print("Precision:", prec)
print("Recall:", recal)
```

```
     Accuracy: 0.9431818181818182
     F1 Score: 0.9431487042288005
     Kappa: 0.8831686792834539
     Precision: 0.9357638888888888
     Recall: 0.9281102023245803
```

```
labels = ["Leal", "Desleal"]
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
disp.plot();
```

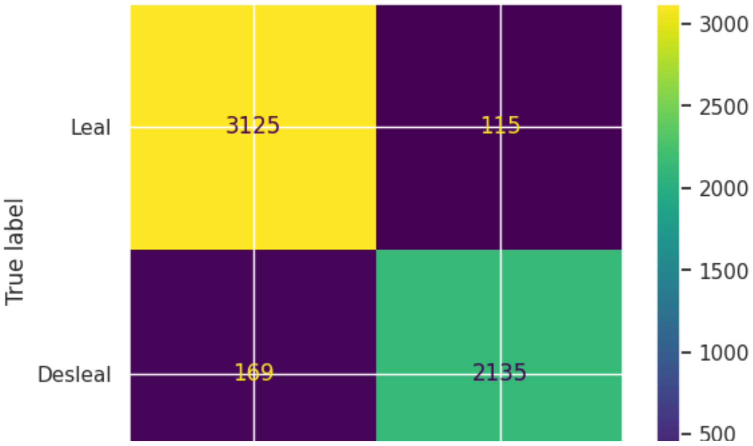


Random Florest

```
clf = RandomForestClassifier(n_estimators = 800)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)

accuracy = metrics.accuracy_score(y_test, y_pred)
f1 = f1_score(y_pred, y_test, average="weighted")
kappa = cohen_kappa_score(y_pred, y_test)
prec = precision_score(y_pred, y_test)
recal = recall_score(y_pred, y_test)

print("Accuracy:", accuray)
print("F1 Score:", f1)
print("Kappa:", kappa)
print("Precision:", prec)
print("Recall:", recal)
```

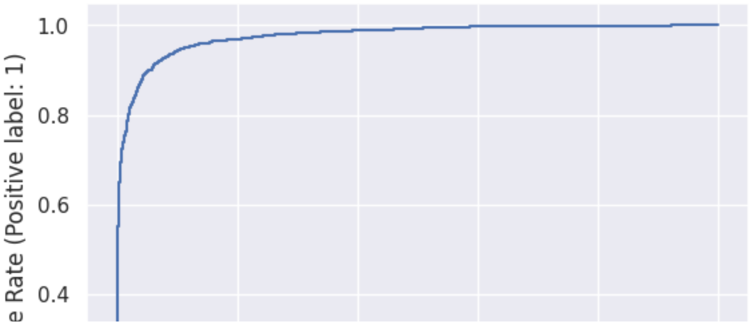
```
Accuracy: 0.9431818181818182
F1 Score: 0.9488654835402949
Kappa: 0.8941826592728082
Precision: 0.9266493055555556
Recall: 0.9488888888888889
```

```
labels = ["Leal", "Desleal"]
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
disp.plot();
```



ROC

```
clf = SVC(random_state=0).fit(X_train, y_train)
y_pred = clf.decision_function(X_test)
RocCurveDisplay.from_predictions(y_test, y_pred,name='classe')
plt.show()
```


1.0
0.8
0.6
0.4
e Rate (Positive label: 1)