Hotel_Booking_A2

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1 Trabalho de Machine Learning

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[1]:
```
import numpy             as np
import pandas            as pd
import seaborn           as sns
import matplotlib.pyplot as plt

from itertools                 import product

from sklearn.metrics           import *
from sklearn.base              import clone
from sklearn.tree              import plot_tree
from sklearn.tree              import export_text
from sklearn.model_selection   import cross_val_score
from sklearn.model_selection   import train_test_split
from sklearn.linear_model      import LogisticRegression
from sklearn.exceptions        import ConvergenceWarning
from sklearn.tree              import DecisionTreeClassifier
from sklearn.ensemble          import RandomForestClassifier
from sklearn.ensemble          import GradientBoostingClassifier

from warnings import simplefilter
simplefilter('ignore', category = ConvergenceWarning)
```

Nessa segunda parte irei comparar a eficiência de quatro modelos de classificação quando testados sobre o dataset escolhido. São eles: - Regresão Logística - Decision Tree - Random Forest - Gradient Boosting

Para tanto, declarei uma função que testa alguns valores de parâmetros e retorna o modelo que performa com os parâmetros testados. Essa performance é calculada por meio do cross-validation com 5 grupos. Assim, para cada um dos modelos acima, foram propostos um conjunto de parâmetros e os mesmos foram avaliados com o cross-validation, retornando o modelo dado com os melhores parâmetros segundo a validação.

Além dessa função, também declarei duas funções para avaliar os resultados, uma retornando a matriz de confusão, bem como algumas outras métricas, e outra que plota a curva ROC para o modelo.

1.1 Leitura e Processamento dos dados

[2]:
```
df = pd.read_csv('dados_limpos.csv')
variables = df.columns.to_list()
variables.remove('reservation_status')
variables.remove('reservation_status_date')

df1 = df[variables]
df = df1
```

[3]:
```
categorical_variables = ['hotel', 'meal', 'market_segment',␣
↪'distribution_channel',
                         'reserved_room_type', 'assigned_room_type',␣
↪'deposit_type',
                         'customer_type']

for variable in categorical_variables:
    cat_list = 'var' + '_' + variable
    cat_list = pd.get_dummies(df[variable], prefix = variable)
    df1 = df.join(cat_list)
    df = df1

data_vars = df.columns.values.tolist()
manter = [i for i in data_vars if i not in categorical_variables]
df1 = df[manter]
df = df1
del df1
del manter
```

[4]:
```
X = df.loc[:, df.columns != 'is_canceled']
y = df.loc[:, df.columns == 'is_canceled']
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size = 0.3,
                                                    random_state = 0)

y_train = y_train.values.ravel()
y_test = y_test.values.ravel()
```

[5]:
```
def metrics1(classificador, X_test, y_test, name = ''):
    y_pred = classificador.predict(X_test)
    print(classification_report(y_test, y_pred))
    cf_matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(cf_matrix / np.sum(cf_matrix), annot = True,
                fmt = '.2%', cmap = 'Blues')

    plt.savefig(f'confusion_matrix_{name.replace(" ", "_")}.png')
    plt.show()
```

```python
def metrics2(X_test, y_test, classificador, nome_classificador):
    roc_auc = roc_auc_score(y_test, classificador.predict(X_test))
    fpr, tpr, _ = roc_curve(y_test, classificador.predict_proba(X_test)[:, 1])

    plt.figure()
    plt.plot(fpr, tpr, label = nome_classificador + ' (AUC = %0.2f)' % roc_auc)
    plt.plot([0, 1], [0, 1], '--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.0])
    plt.xlabel('Razão de falso positivo')
    plt.ylabel('Razão de verdadeiro positivo')
    plt.title('ROC Curve')
    plt.legend(loc = 'lower right')
    plt.show()

    return fpr, tpr, roc_auc

def find_parameters(model, model_name, X_train, y_train, X_test, y_test,␣
 ↪params):
    max_score = 0
    for param in product(*params):
        if model_name == 'Regressão Logística':
            model.C = param[0]
        elif model_name == 'Decision Tree':
            model.max_depth = param[0]
            model.min_samples_split = param[1]
        elif model_name == 'Random Forest':
            model.n_estimators = param[0]
            model.max_depth = param[1]
            model.min_samples_split = param[2]
        else:
            # gradient boosting
            model.n_estimators = param[0]
            model.max_depth = param[1]
            model.learning_rate = param[2]

        scores_i = cross_val_score(model, X_train, y_train, cv = 5)
        if np.mean(scores_i) > max_score:
            optimal_model = clone(model)
            max_score = np.mean(scores_i)

    return optimal_model
```

1.2 Regressão Logística

[6]:
```
%%time
C = [0.001, 0.01, 0.1, 1, 10, 100, 1000]
logreg = LogisticRegression(random_state = 0)
logreg = find_parameters(logreg, 'Regressão Logística', X_train, y_train,␣
↪X_test, y_test, [C])
```

```
CPU times: user 2min 20s, sys: 53.1 s, total: 3min 14s
Wall time: 56.7 s
```

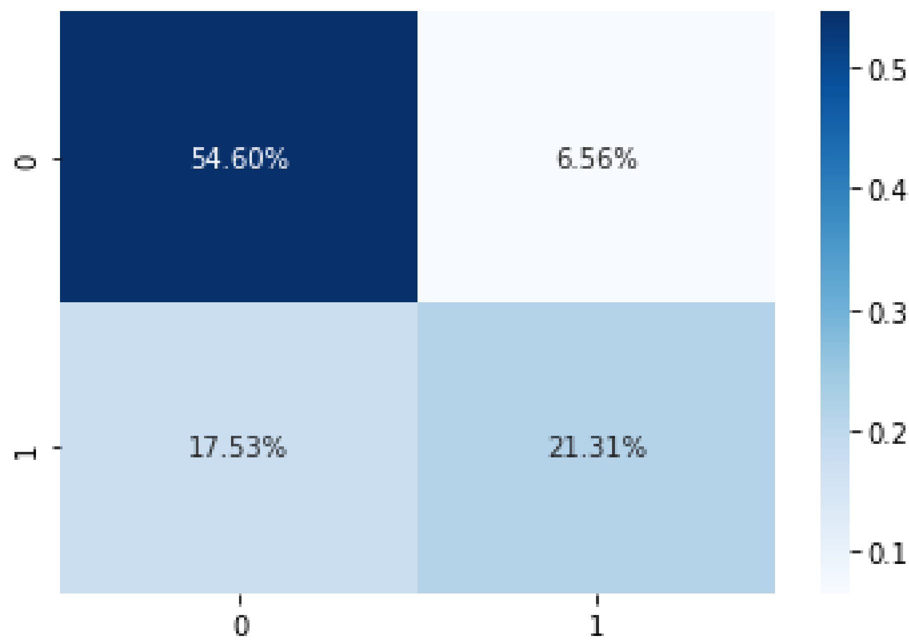
[7]:
```
%%time
logreg.fit(X_train, y_train)
```

```
CPU times: user 4.58 s, sys: 1.79 s, total: 6.36 s
Wall time: 1.68 s
```

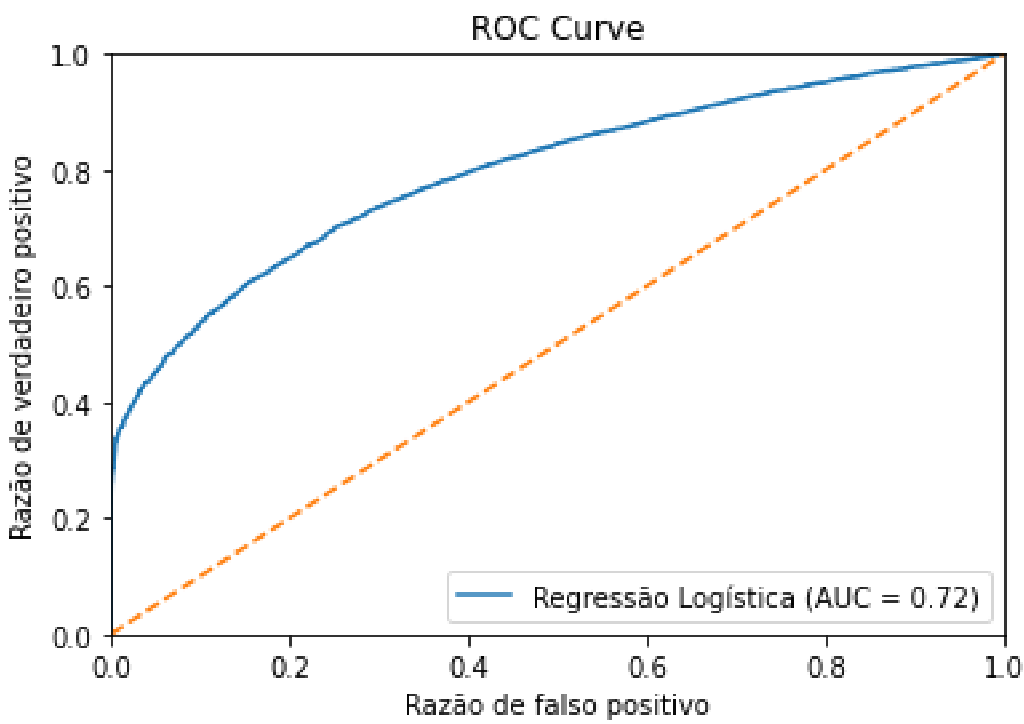
[7]:
```
LogisticRegression(C=0.1, random_state=0)
```

[8]:
```
metrics1(logreg, X_test, y_test, 'Logistic Regression')
```

```
              precision    recall  f1-score   support

           0       0.76      0.89      0.82     18471
           1       0.76      0.55      0.64     11729

    accuracy                           0.76     30200
   macro avg       0.76      0.72      0.73     30200
weighted avg       0.76      0.76      0.75     30200
```



[9]:
```
logreg_fpr, logreg_tpr, logreg_roc_auc = metrics2(X_test, y_test, logreg,␣
 ↪'Regressão Logística')
```



1.3 Decision Tree

[10]:
```
%%time
max_depth = [1, 5, 10, 15, 20, 25]
min_samples_split = [50, 100, 200, 400]
dtc = DecisionTreeClassifier(random_state = 0)
dtc = find_parameters(dtc, 'Decision Tree', X_train, y_train, X_test, y_test,␣
 ↪[max_depth,                                                                   ␣

 ↪min_samples_split])
```

```
CPU times: user 46.1 s, sys: 1.33 s, total: 47.5 s
Wall time: 47.5 s
```

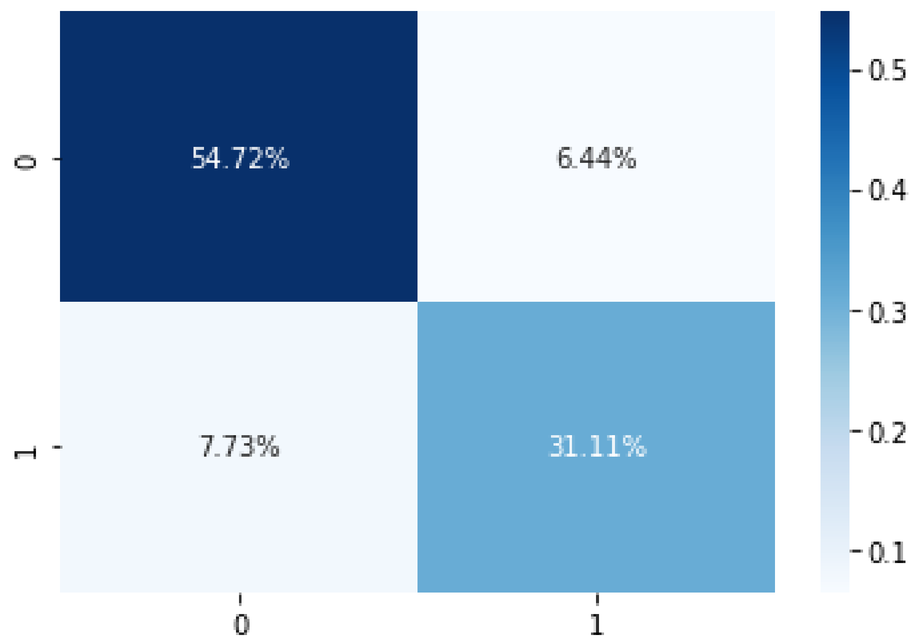
[11]:
```
%%time
dtc.fit(X_train, y_train)
```

```
CPU times: user 656 ms, sys: 9.06 ms, total: 665 ms
Wall time: 663 ms
```

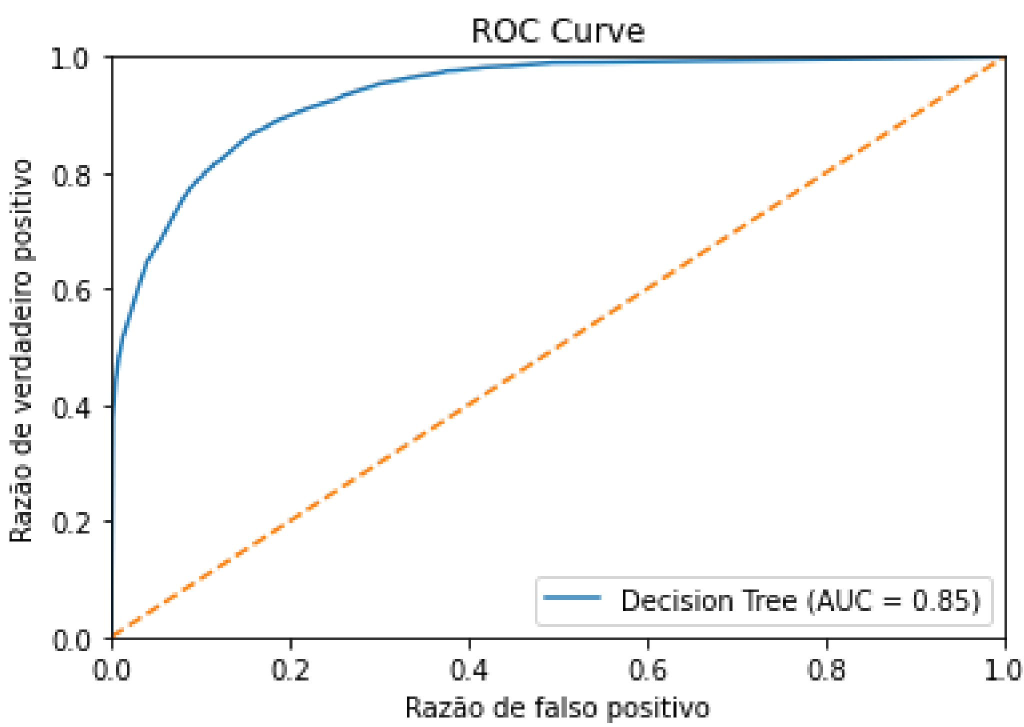
[11]: DecisionTreeClassifier(max_depth=15, min_samples_split=50, random_state=0)

[12]:
```
metrics1(dtc, X_test, y_test, 'Decision Tree')
```

```
              precision    recall  f1-score   support

           0       0.88      0.89      0.89     18471
           1       0.83      0.80      0.81     11729

    accuracy                           0.86     30200
   macro avg       0.85      0.85      0.85     30200
weighted avg       0.86      0.86      0.86     30200
```




```
[13]: dtc_fpr, dtc_tpr, dtc_roc_auc = metrics2(X_test, y_test, dtc, 'Decision Tree')
```



1.4 Random Forest

[14]:
```
%%time
estimators = [10, 50, 100]
max_depth = [1, 5, 10, 15, 20, 25]
min_samples_split = [50, 100, 200, 400]
rfc = RandomForestClassifier(random_state = 0)
rfc = find_parameters(rfc, 'Random Forest', X_train, y_train, X_test, y_test,␣
 ↪[estimators,
                                                                              ␣
 ↪max_depth,
                                                                              ␣
 ↪min_samples_split])
```

```
CPU times: user 12min 45s, sys: 1.62 s, total: 12min 47s
Wall time: 12min 47s
```

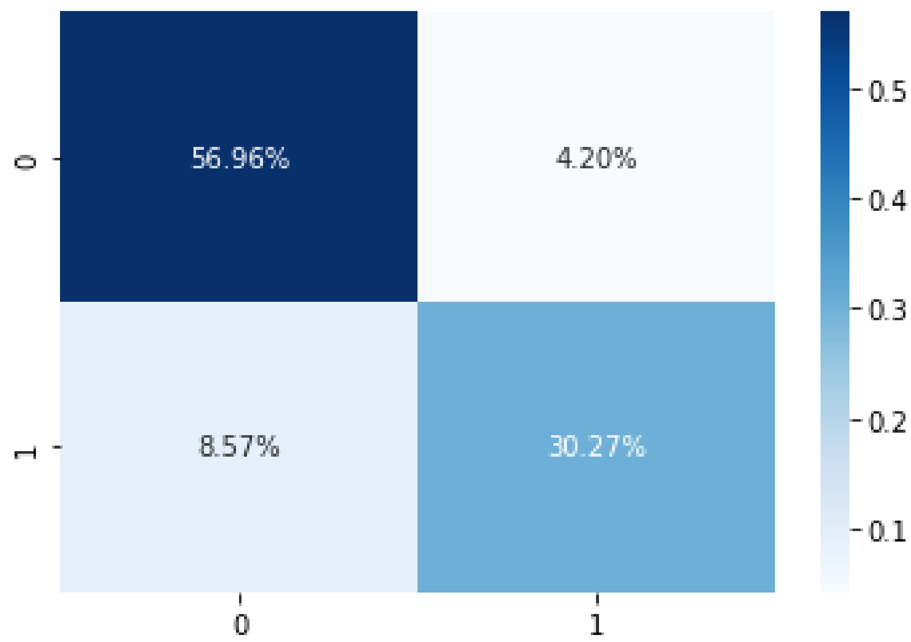
[15]:
```
%%time
rfc.fit(X_train, y_train)
```

```
CPU times: user 8.04 s, sys: 8.71 ms, total: 8.05 s
Wall time: 8.05 s
```

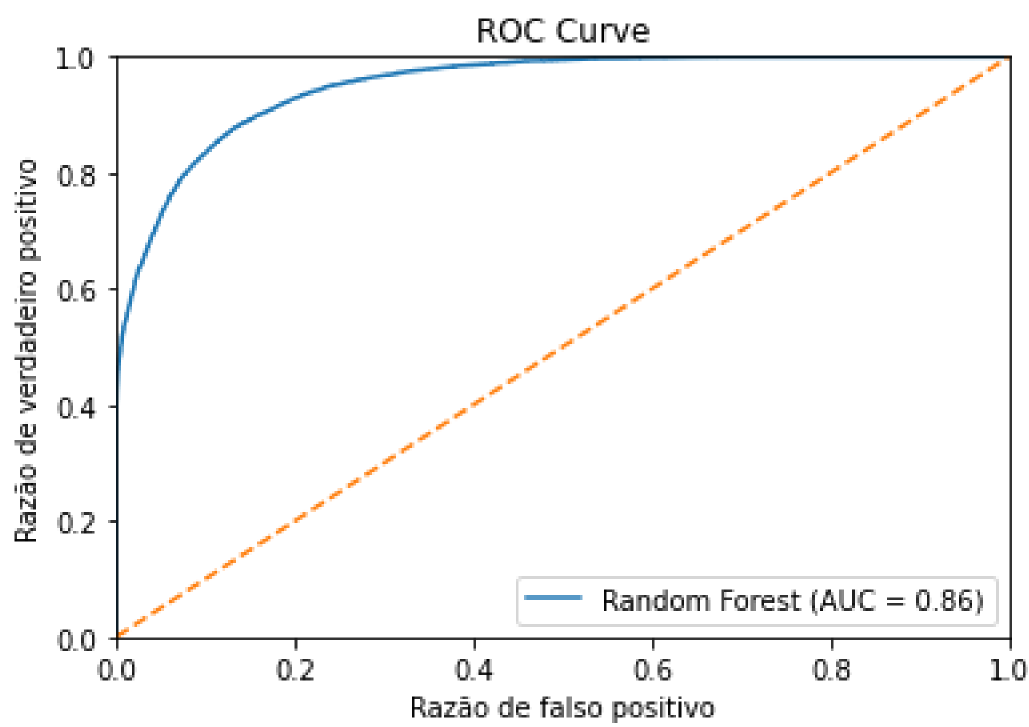
[15]:
```
RandomForestClassifier(max_depth=25, min_samples_split=50, random_state=0)
```

[16]:
```
metrics1(rfc, X_test, y_test, 'Random Forest')
```

```
              precision    recall  f1-score   support

           0       0.87      0.93      0.90     18471
           1       0.88      0.78      0.83     11729

    accuracy                           0.87     30200
   macro avg       0.87      0.86      0.86     30200
weighted avg       0.87      0.87      0.87     30200
```



[17]:
```
rfc_fpr, rfc_tpr, rfc_roc_auc = metrics2(X_test, y_test, rfc, 'Random Forest')
```



1.5 Gradient Boosting

[18]:
```
%%time
estimators = [1, 5, 10, 50]
max_depth = [1, 5, 10]
learning_rate = [0.1, 0.5, 1, 5, 10]
gbc = GradientBoostingClassifier(random_state = 0)
gbc = find_parameters(gbc, 'Gradient Boosting', X_train, y_train, X_test,␣
↪y_test, [estimators,
                                                                          ␣
↪    max_depth,
                                                                          ␣
↪    learning_rate])
```

```
CPU times: user 19min 42s, sys: 645 ms, total: 19min 43s
Wall time: 19min 43s
```

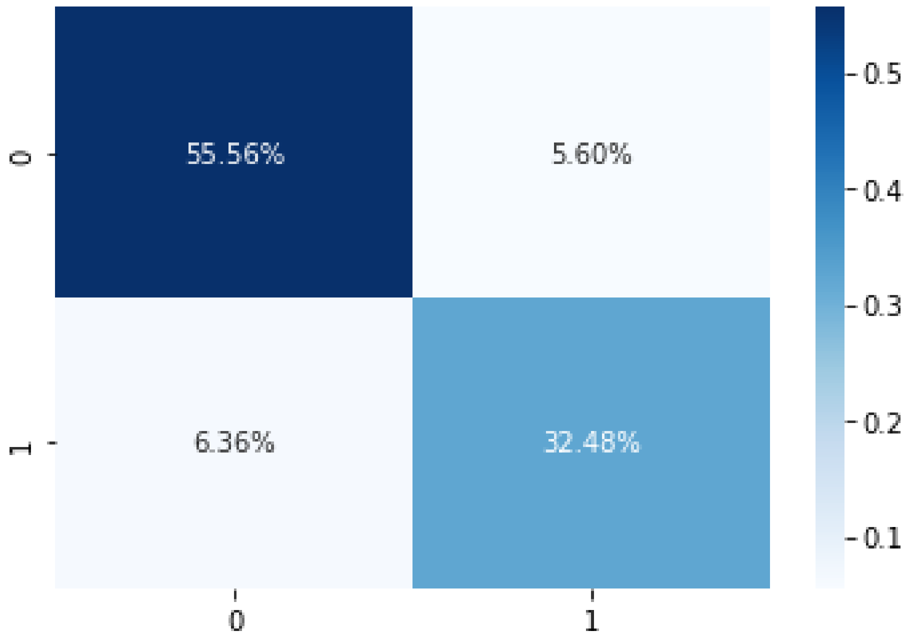
[19]:
```
%%time
gbc.fit(X_train, y_train)
```

```
CPU times: user 28.8 s, sys: 4.57 ms, total: 28.8 s
Wall time: 28.8 s
```

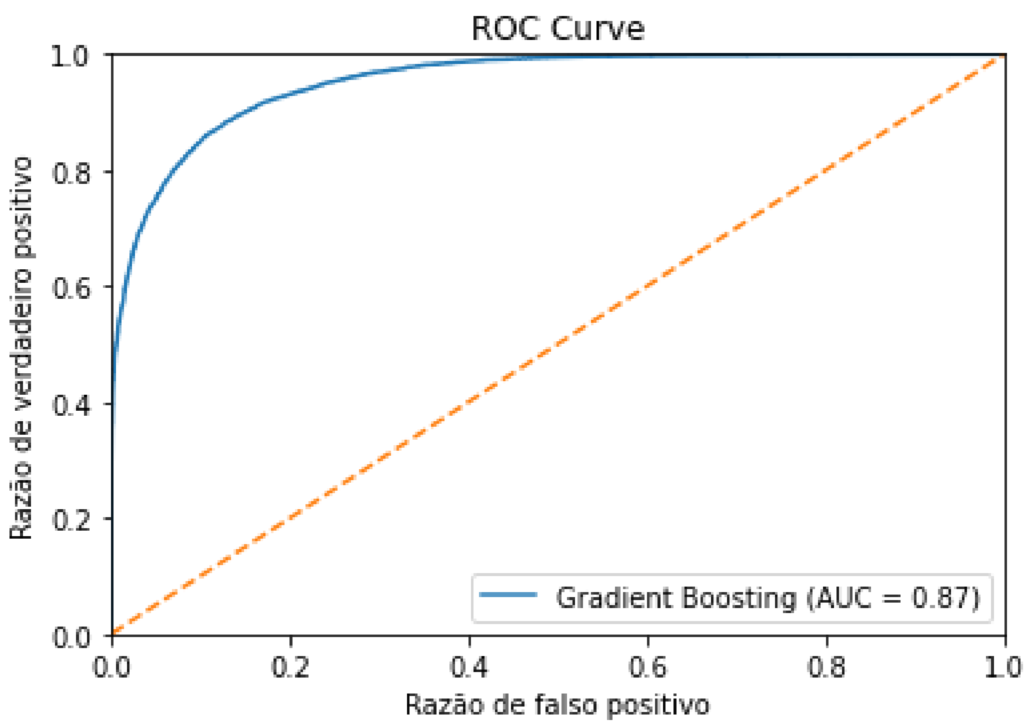
[19]:
```
GradientBoostingClassifier(learning_rate=0.5, max_depth=10, n_estimators=50,
                           random_state=0)
```

[20]:
```
metrics1(gbc, X_test, y_test, 'Gradient Boosting')
```

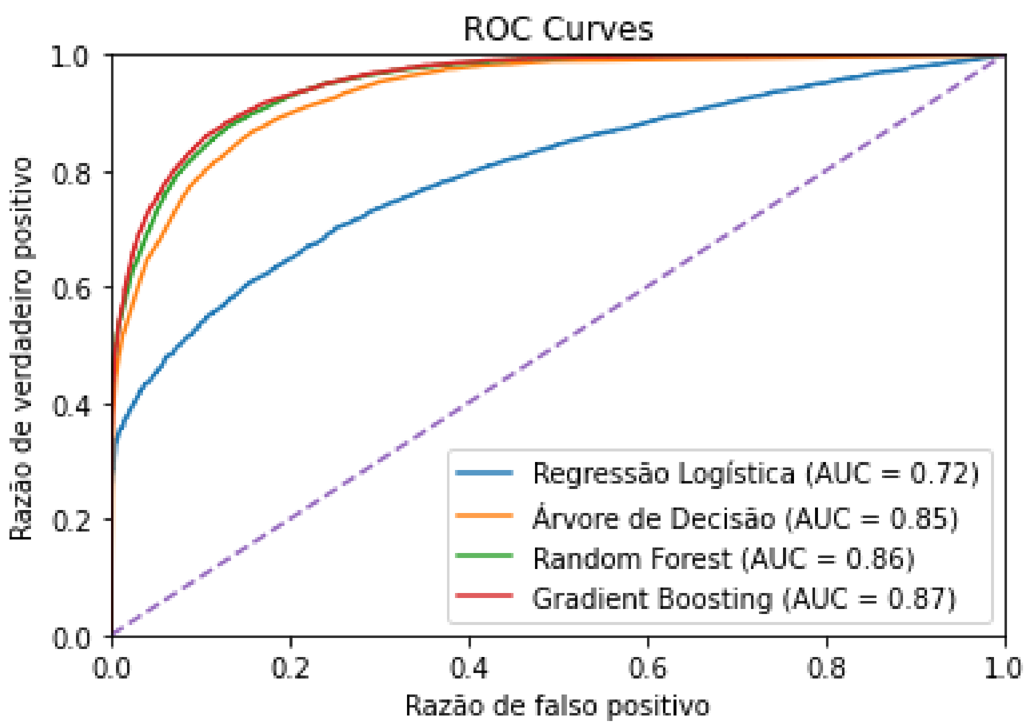
```
              precision    recall  f1-score   support

           0       0.90      0.91      0.90     18471
           1       0.85      0.84      0.84     11729

    accuracy                           0.88     30200
   macro avg       0.88      0.87      0.87     30200
weighted avg       0.88      0.88      0.88     30200
```



[21]:
```
gbc_fpr, gbc_tpr, gbc_roc_auc = metrics2(X_test, y_test, gbc, 'Gradient␣
↪Boosting')
```



[22]:
```
plt.plot(logreg_fpr, logreg_tpr, label = 'Regressão Logística (AUC = %0.2f)' %␣
 ↪logreg_roc_auc)
plt.plot(dtc_fpr, dtc_tpr, label = 'Árvore de Decisão (AUC = %0.2f)' %␣
 ↪dtc_roc_auc)
plt.plot(rfc_fpr, rfc_tpr, label = 'Random Forest (AUC = %0.2f)' % rfc_roc_auc)
plt.plot(gbc_fpr, gbc_tpr, label = 'Gradient Boosting (AUC = %0.2f)' %␣
 ↪gbc_roc_auc)
plt.plot([0, 1], [0, 1], '--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('Razão de falso positivo')
plt.ylabel('Razão de verdadeiro positivo')
plt.title('ROC Curves')
plt.legend(loc = 'lower right')
plt.savefig('ROC_curves.png')
plt.show()
```



1.6 Breve Análise das Árvores

Na primeira parte um gráfico que chamou muita atenção foi o seguinte:

Onde pudemos ver que essas duas variáveis conseguem separar bem os grupos. Assim, poderíamos dizer que "pessoas que reservam vagas de estacionamento ou fazem pedidos especiais não irão cancelar a reserva".

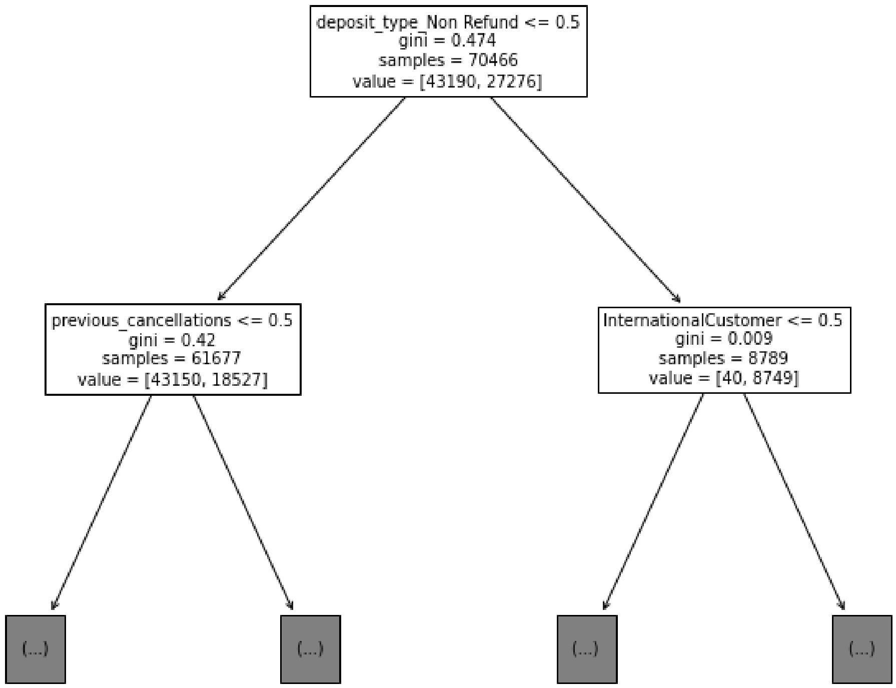
Como a ideia por trás das árvores de decisão segue uma ideia similar aos processos de decisão de nós, seres humanos, podemos ver de que modo tais decisões são realizadas pelo modelo.

1.6.1 Decision Tree

[23]:
```
print(export_text(dtc, feature_names = X.columns.to_list(), max_depth = 2))
```

```
|--- deposit_type_Non Refund <= 0.50
|   |--- previous_cancellations <= 0.50
|   |   |--- market_segment_Online TA <= 0.50
|   |   |   |--- truncated branch of depth 13
|   |   |--- market_segment_Online TA >  0.50
|   |   |   |--- truncated branch of depth 13
|   |--- previous_cancellations >  0.50
|   |   |--- previous_bookings_not_canceled <= 1.50
|   |   |   |--- truncated branch of depth 5
|   |   |--- previous_bookings_not_canceled >  1.50
|   |   |   |--- class: 0
|--- deposit_type_Non Refund >  0.50
|   |--- InternationalCustomer <= 0.50
|   |   |--- assigned_room_type_F <= 0.50
|   |   |   |--- truncated branch of depth 4
|   |   |--- assigned_room_type_F >  0.50
|   |   |   |--- class: 0
|   |--- InternationalCustomer >  0.50
|   |   |--- customer_type_Transient-Party <= 0.50
|   |   |   |--- class: 1
|   |   |--- customer_type_Transient-Party >  0.50
|   |   |   |--- class: 0
```

[24]:
```
f = plt.figure()
f.set_figwidth(12)
f.set_figheight(10)
plot_tree(dtc, feature_names = X.columns.to_list(), max_depth = 1)
plt.savefig('Decision_Tree.png')
```



1.6.2 Random Forest

[25]:
```
print(export_text(rfc.estimators_[0], feature_names = X.columns.to_list(),␣
↪max_depth = 2))
```

```
|--- total_of_special_requests <= 0.50
|   |--- assigned_room_type_A <= 0.50
|   |   |--- market_segment_Online TA <= 0.50
|   |   |   |--- truncated branch of depth 17
|   |   |--- market_segment_Online TA >  0.50
|   |   |   |--- truncated branch of depth 23
|   |--- assigned_room_type_A >  0.50
|   |   |--- deposit_type_No Deposit <= 0.50
|   |   |   |--- truncated branch of depth 7
|   |   |--- deposit_type_No Deposit >  0.50
|   |   |   |--- truncated branch of depth 23
|--- total_of_special_requests >  0.50
|   |--- arrival_date_year <= 2016.50
|   |   |--- lead_time <= 9.50
```

```
|   |   |   |--- truncated branch of depth 13
|   |   |--- lead_time >  9.50
|   |   |   |--- truncated branch of depth 23
|   |--- arrival_date_year >  2016.50
|   |   |--- agent <= 7.50
|   |   |   |--- truncated branch of depth 16
|   |   |--- agent >  7.50
|   |   |   |--- truncated branch of depth 23
```

[26]:
```
f = plt.figure()
f.set_figwidth(12)
f.set_figheight(10)
plot_tree(rfc.estimators_[0], feature_names = X.columns.to_list(), max_depth =␣
↪1)
plt.savefig('Random_Forest_Tree.png')
```