Atividade 1 - Pré-processamento (Transformação dos dados) - base de dados Hotel Reservations Kaggle

Análise Descritiva

1. **Visualização de Dados**
   - Apresentar um mapa de calor (heatmap) entre todas as variáveis numéricas.
2. **Transformação de Dados**
   - Efetuar as devidas transformações nos atributos categóricos.
3. **Normalização de Dados**
   - Normalizar por Z-Score (Standard Scaler).

Análise Agrupada

4. **Group-by**
   - Utilizando Group-by, responder as seguintes perguntas:
     A. Apresentar os valores mínimo, máximo e média do preço das diárias (`avg_price_per_room`) agrupados por tipo de quarto (`room_type_reserved`).
     B. Apresentar o valor médio de adultos e crianças hospedados em 2017 e 2018.

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

# We want our plots to appear in the notebook
%matplotlib inline

from sklearn.preprocessing  import LabelEncoder

## Models
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier

from sklearn.feature_selection import SelectKBest, mutual_info_classif, f
from sklearn.feature_selection import RFE, SequentialFeatureSelector as S
from feature_engine.selection import DropCorrelatedFeatures
from sklearn.pipeline import Pipeline
## Model evaluators
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
from sklearn.metrics import confusion_matrix, classification_report
```

```
from sklearn.metrics import precision_score, accuracy_score, recall_score
```

In [ ]:
```
df = pd.read_csv('Hotel Reservations.csv')
df.head(5)
```

Out[ ]:

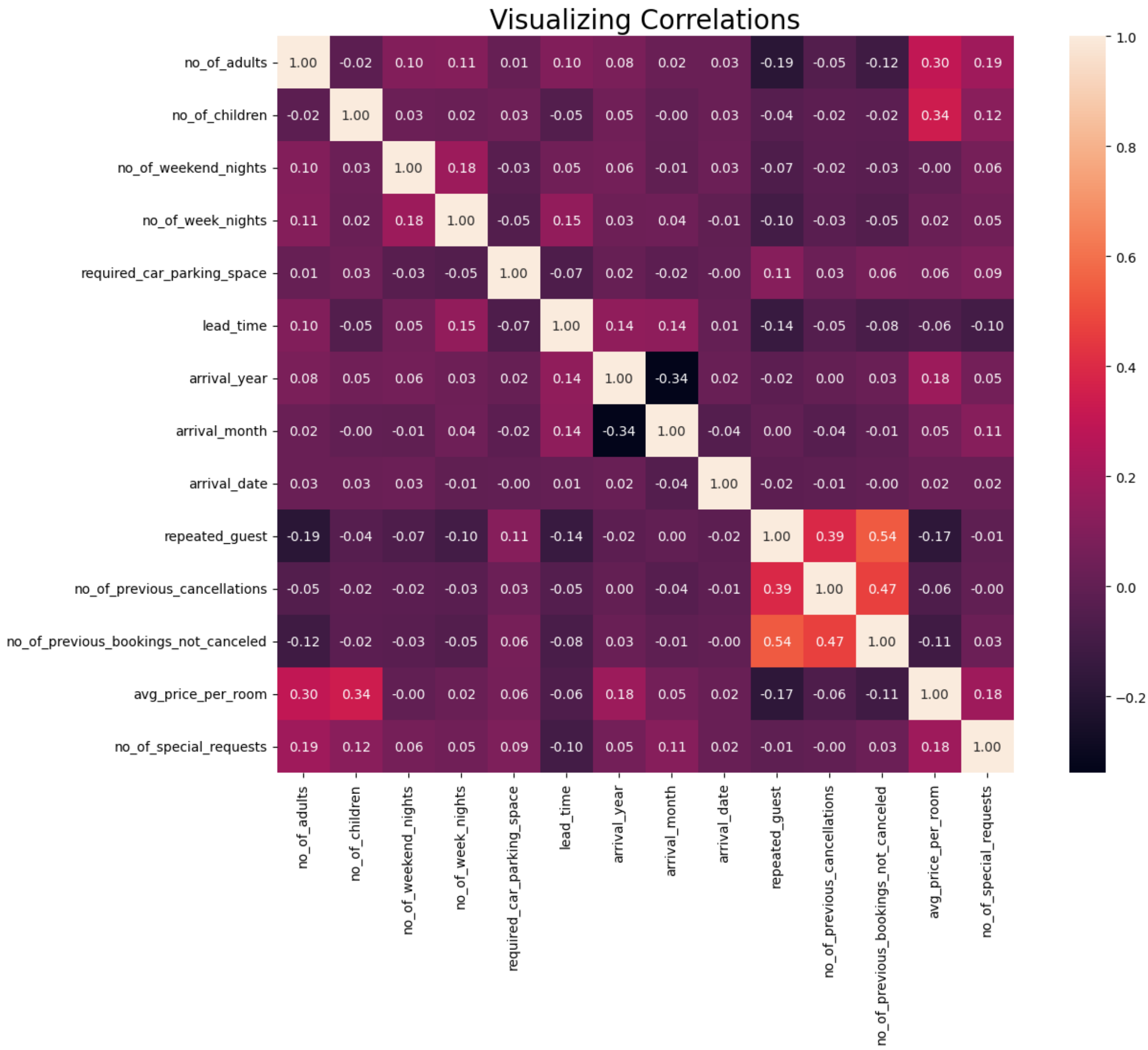
	Booking_ID	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_night
0	INN00001	2	0	1	
1	INN00002	2	0	2	
2	INN00003	1	0	2	
3	INN00004	2	0	0	
4	INN00005	2	0	1	

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36275 entries, 0 to 36274
Data columns (total 19 columns):
 #   Column                                Non-Null Count  Dtype  
---  ------                                --------------  -----  
 0   Booking_ID                            36275 non-null  object 
 1   no_of_adults                          36275 non-null  int64  
 2   no_of_children                        36275 non-null  int64  
 3   no_of_weekend_nights                  36275 non-null  int64  
 4   no_of_week_nights                     36275 non-null  int64  
 5   type_of_meal_plan                     36275 non-null  object 
 6   required_car_parking_space            36275 non-null  int64  
 7   room_type_reserved                    36275 non-null  object 
 8   lead_time                             36275 non-null  int64  
 9   arrival_year                          36275 non-null  int64  
 10  arrival_month                         36275 non-null  int64  
 11  arrival_date                          36275 non-null  int64  
 12  market_segment_type                   36275 non-null  object 
 13  repeated_guest                        36275 non-null  int64  
 14  no_of_previous_cancellations          36275 non-null  int64  
 15  no_of_previous_bookings_not_canceled  36275 non-null  int64  
 16  avg_price_per_room                    36275 non-null  float64
 17  no_of_special_requests                36275 non-null  int64  
 18  booking_status                        36275 non-null  object 
dtypes: float64(1), int64(13), object(5)
memory usage: 5.3+ MB
```

1. Apresentar um mapa de calor (heatmap) entre todas as variáveis numéricas

In [ ]:
```
plt.figure(figsize=(15, 10))
sns.heatmap(df.select_dtypes(include=['int64', 'float64']).corr(), square
plt.title("Visualizing Correlations", size = 20)
plt.show()
```



4.A Apresentar os valores mínimo, máximo e média do preço das diárias `avg_price_per_room` agrupados por tipo de quarto `room_type_reserved`.

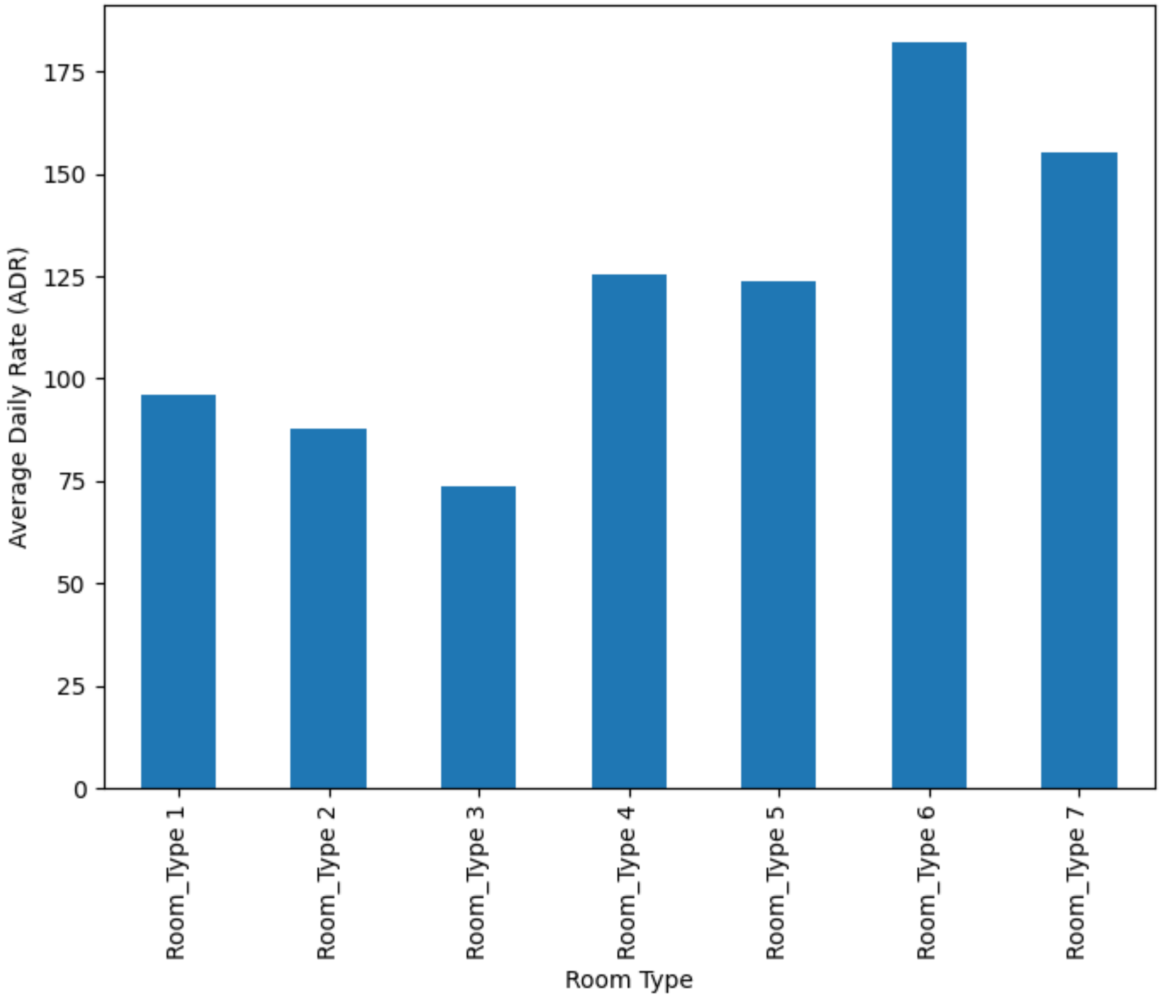
In [ ]:
```
# Calculate the minimum, maximum, and average price of the daily rates gr
grouped_data = df.groupby('room_type_reserved')['avg_price_per_room'].agg

# Rename columns for clarity
grouped_data.columns = ['Room Type', 'Minimum Price', 'Maximum Price', 'A

grouped_data
```

Out[ ]:

	Room Type	Minimum Price	Maximum Price	Average Price
0	Room_Type 1	0.0	540.00	95.918532
1	Room_Type 2	0.0	284.10	87.848555
2	Room_Type 3	0.0	130.00	73.678571
3	Room_Type 4	0.0	375.50	125.287317
4	Room_Type 5	0.0	250.00	123.733623
5	Room_Type 6	0.0	349.63	182.212836
6	Room_Type 7	0.0	306.00	155.198291

In [ ]:

```
room_type_prices = df.groupby('room_type_reserved')['avg_price_per_room']

room_type_prices.plot(kind='bar', figsize=(8, 6),)
plt.xlabel('Room Type')
plt.ylabel('Average Daily Rate (ADR)')
plt.show()
```



4.2 Apresentar os valor médio de adultos e crianças hospedados em 2017 e 2018.

In [ ]:

```
# Agrupar por 'arrival_year' e calcular a média de 'no_of_adults' e 'no_o
```

```python
grouped_data = df.groupby('arrival_year')[['no_of_adults', 'no_of_childre

# Renomear colunas para clareza
grouped_data.columns = ['Ano de Chegada', 'Média de Adultos', 'Média de C

grouped_data
```

Out[ ]:

	Ano de Chegada	Média de Adultos	Média de Crianças
0	2017	1.759902	0.065705
1	2018	1.863580	0.113941

2. Efetuar as devidas transformações nos atributos categóricos

In [ ]:
```python
df.dtypes
```

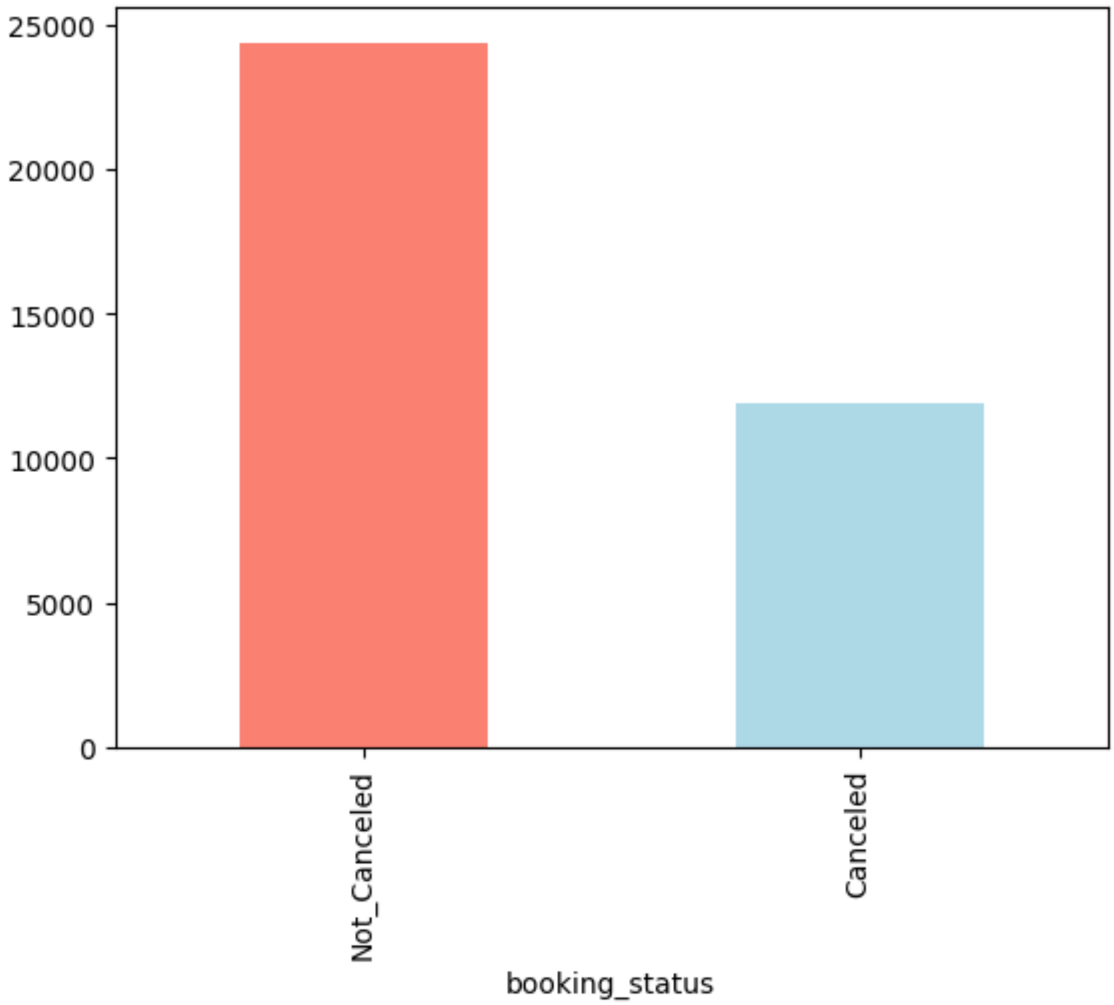
Out[ ]:
```
Booking_ID                               object
no_of_adults                              int64
no_of_children                            int64
no_of_weekend_nights                      int64
no_of_week_nights                         int64
type_of_meal_plan                        object
required_car_parking_space                int64
room_type_reserved                       object
lead_time                                 int64
arrival_year                              int64
arrival_month                             int64
arrival_date                              int64
market_segment_type                      object
repeated_guest                            int64
no_of_previous_cancellations              int64
no_of_previous_bookings_not_canceled      int64
avg_price_per_room                      float64
no_of_special_requests                    int64
booking_status                           object
dtype: object
```

pré-processamento

In [ ]:
```python
df = df.drop('Booking_ID', axis =1)
df = df.drop('arrival_year', axis = 1)
```

Vou dropar o Booking ID e o ano da reserva para evitar overfitting, já que o ID poderia acabar indicando uma relação entre as reservas e o ano é uma feature que não vai se repetir nos anos seguintes, não sendo útil para a identificação de cancelamentos futuros

In [ ]:
```python
# Target variable
df.booking_status.value_counts().plot(kind="bar", color=["salmon", "light
```



In [ ]:
```
# Import label encoder
from sklearn import preprocessing

# label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

# Encode labels in column 'species'.
df['booking_status']= label_encoder.fit_transform(df['booking_status'])

df['booking_status'].unique()
```

Out[ ]:
```
array([1, 0])
```

In [ ]:
```
# Make a copy of the original DataFrame to perform edits on
#df_tmp = df.copy()
```

In [ ]:
```
#names of columns
columns = list(df.columns)
columns
```

Out[ ]:
```
['no_of_adults',
 'no_of_children',
 'no_of_weekend_nights',
 'no_of_week_nights',
 'type_of_meal_plan',
 'required_car_parking_space',
 'room_type_reserved',
 'lead_time',
 'arrival_month',
 'arrival_date',
 'market_segment_type',
 'repeated_guest',
 'no_of_previous_cancellations',
 'no_of_previous_bookings_not_canceled',
 'avg_price_per_room',
 'no_of_special_requests',
 'booking_status']
```

In [ ]:
```
# Check for missing values
#df_tmp.isna().sum()
```

Analisar as variáveis to encode

In [ ]:
```
categorical_columns = df.select_dtypes(include=['object']).columns
```

In [ ]:
```
for categorical_feature in categorical_columns:
  print(f'{categorical_feature}: {df[categorical_feature].unique()}')
```

```
type_of_meal_plan: ['Meal Plan 1' 'Not Selected' 'Meal Plan 2' 'Meal Plan
3']
room_type_reserved: ['Room_Type 1' 'Room_Type 4' 'Room_Type 2' 'Room_Type
6' 'Room_Type 5'
 'Room_Type 7' 'Room_Type 3']
market_segment_type: ['Offline' 'Online' 'Corporate' 'Aviation' 'Complemen
tary']
```

In [ ]:
```
columns_to_encode = [ 'market_segment_type', 'type_of_meal_plan', 'room_t
encoder = LabelEncoder()
for column in columns_to_encode:
    df[column] = encoder.fit_transform(df[column])

# Applying one-hot encoding
#df = pd.get_dummies(df, columns=['type_of_meal_plan', 'room_type_reserve
```

In [ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 36275 entries, 0 to 36274
Data columns (total 17 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   no_of_adults                          36275 non-null  int64
 1   no_of_children                        36275 non-null  int64
 2   no_of_weekend_nights                  36275 non-null  int64
 3   no_of_week_nights                     36275 non-null  int64
 4   type_of_meal_plan                     36275 non-null  int64
 5   required_car_parking_space            36275 non-null  int64
 6   room_type_reserved                    36275 non-null  int64
 7   lead_time                             36275 non-null  int64
 8   arrival_month                         36275 non-null  int64
 9   arrival_date                          36275 non-null  int64
 10  market_segment_type                   36275 non-null  int64
 11  repeated_guest                        36275 non-null  int64
 12  no_of_previous_cancellations          36275 non-null  int64
 13  no_of_previous_bookings_not_canceled  36275 non-null  int64
 14  avg_price_per_room                    36275 non-null  float64
 15  no_of_special_requests                36275 non-null  int64
 16  booking_status                        36275 non-null  int64
dtypes: float64(1), int64(16)
memory usage: 4.7 MB
```

In [ ]:
```
df.head(10)
```

Out[ ]:

	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_nights	type_of_m
0	2	0	1	2	
1	2	0	2	3	
2	1	0	2	1	
3	2	0	0	2	
4	2	0	1	1	
5	2	0	0	2	
6	2	0	1	3	
7	2	0	1	3	
8	3	0	0	4	
9	2	0	0	5	

Rescaling the data

In [ ]:
```
from sklearn.preprocessing import StandardScaler

scaler_cols=['no_of_adults',
 'no_of_children',
 'no_of_weekend_nights',
 'no_of_week_nights',
 'required_car_parking_space',
 'lead_time',
 'arrival_month',
```

```
 'arrival_date',
 'repeated_guest',
 'no_of_previous_cancellations',
 'no_of_previous_bookings_not_canceled',
 'avg_price_per_room',
 'no_of_special_requests']
scaler = StandardScaler()
ajuste = scaler.fit(df[scaler_cols])
df[scaler_cols] = ajuste.transform(df[scaler_cols])
```

In [ ]:
```
df.head()
```

Out[ ]:

	no_of_adults	no_of_children	no_of_weekend_nights	no_of_week_nights	type_of_m
0	0.298893	-0.26147	0.217401	-0.144803	
1	0.298893	-0.26147	1.365993	0.563972	
2	-1.628975	-0.26147	1.365993	-0.853578	
3	0.298893	-0.26147	-0.931190	-0.144803	
4	0.298893	-0.26147	0.217401	-0.853578	

In [ ]:
```
#plt.figure(figsize=(20, 20))
#sns.heatmap(df.select_dtypes(include=['int64', 'float64']).corr(), squar
#plt.title("Visualizing Correlations", size = 20)
#plt.show()
```

Optional

In [ ]:
```
# Everything except target variable
X = df.drop("booking_status", axis=1)

# Target variable
y = df['booking_status']
```

train and test split

In [ ]:
```
# Random seed for reproducibility
np.random.seed(55)

# Split into train & test set
X_train, X_test, y_train, y_test = train_test_split(X, # independent vari
                                                    y, # dependent variab
                                                    test_size = 0.2) # pe
```

Model choices

We'll be using the following and comparing their results.

1. Decision Tree - DecisionTreeClassifier()
2. K-Nearest Neighbors - KNeighboursClassifier()
3. RandomForest - RandomForestClassifier()

In [ ]:
```
models = {
    "Decision Tree": DecisionTreeClassifier(),
    "KNN": KNeighborsClassifier(),
    "Random Forest": RandomForestClassifier()
}
```

In [ ]:
```
from sklearn.metrics import accuracy_score, recall_score, precision_score

def fit_and_evaluate(models, X_train, X_test, y_train, y_test):
    """
    Fits and evaluates given machine learning models.
    models: a dict of different Scikit-Learn machine learning models
    X_train: training data
    X_test: testing data
    y_train: target training data
    y_test: target test data
    """
    np.random.seed(42)  # Random seed for reproducible results
    model_metrics = {}  # Dictionary to keep all model metrics

    # Loop through models
    for name, model in models.items():
        model.fit(X_train, y_train) # Fit the model to the data
        y_pred = model.predict(X_test)  # Predictions
        # Calculate metrics
        accuracy = accuracy_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred)

        # Store metrics in the dictionary
        model_metrics[name] = {
            "Accuracy": accuracy,
            "Recall": recall,
            "Precision": precision,
            "F1 Score": f1
        }

    return model_metrics
```

Model comparison

In [ ]:
```
# Call the function
model_metrics = fit_and_evaluate(models=models,
                                 X_train=X_train,
                                 X_test=X_test,
                                 y_train=y_train,
```

```
                                  y_test=y_test)

# Convert model_metrics to DataFrame for better visualization
model_metrics_df = pd.DataFrame(model_metrics).T
# Display the DataFrame
print(model_metrics_df)
```

```
               Accuracy    Recall  Precision  F1 Score
Decision Tree  0.867815  0.890960   0.914609  0.902630
KNN            0.854859  0.902385   0.888319  0.895297
Random Forest  0.905720  0.943275   0.921480  0.932250
```

feature selection

In [ ]:
```
# Definindo os classificadores
classifiers = {
    "Decision Tree": DecisionTreeClassifier(),
    "KNN": KNeighborsClassifier(),
    "Random Forest": RandomForestClassifier()
}

# Técnicas de seleção de características
feature_selection_techniques = {
    "Mutual Information": SelectKBest(mutual_info_classif, k=9),
    "ANOVA": SelectKBest(f_classif, k=9),
    "Drop Correlated": DropCorrelatedFeatures(threshold=0.8, method='pear
    # Add SmartCorrelatedGroups após
}

## Configuração do pipeline de avaliação
def evaluate_pipeline(X_train, X_test, y_train, y_test, classifier, selec
    pipeline = Pipeline([
        ('selector', selector),
        ('classifier', classifier)
    ])

    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)

    return {
        "Accuracy": accuracy_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred, average='binary'),
        "Precision": precision_score(y_test, y_pred, average='binary'),
        "F1 Score": f1_score(y_test, y_pred, average='binary')
    }
```

In [ ]:
```
results = {}

for clf_name, clf in classifiers.items():
    for fs_name, fs in feature_selection_techniques.items():
        key = f"{clf_name} + {fs_name}"
        results[key] = evaluate_pipeline(X_train, X_test, y_train, y_test

# Convertendo resultados em DataFrame para visualização
results_df = pd.DataFrame(results).T
print(results_df)
```

```
                                   Accuracy    Recall  Precision  F1 Scor
e
Decision Tree + Mutual Information  0.863818  0.887753   0.911880  0.89965
5
Decision Tree + ANOVA               0.853480  0.880136   0.904242  0.89202
6
Decision Tree + Drop Correlated     0.870986  0.893766   0.916547  0.90501
3
KNN + Mutual Information            0.862991  0.905191   0.896565  0.90085
8
KNN + ANOVA                         0.856099  0.908398   0.885329  0.89671
5
KNN + Drop Correlated               0.854859  0.902385   0.888319  0.89529
7
Random Forest + Mutual Information  0.889318  0.922229   0.917265  0.91974
0
Random Forest + ANOVA               0.885596  0.924434   0.910563  0.91744
6
Random Forest + Drop Correlated     0.905720  0.942874   0.921811  0.93222
4
```

Optional2 only for studies purpose

Hyperparameter tuning and cross-validation Next steps to be taken:

1. Tune model hyperparameters
2. Perform cross-validation
3. Plot ROC curves
4. Make a confusion matrix
5. Get precision, recall and F1-score metrics
6. Find the most important model features

1. Tune model hyperparameters

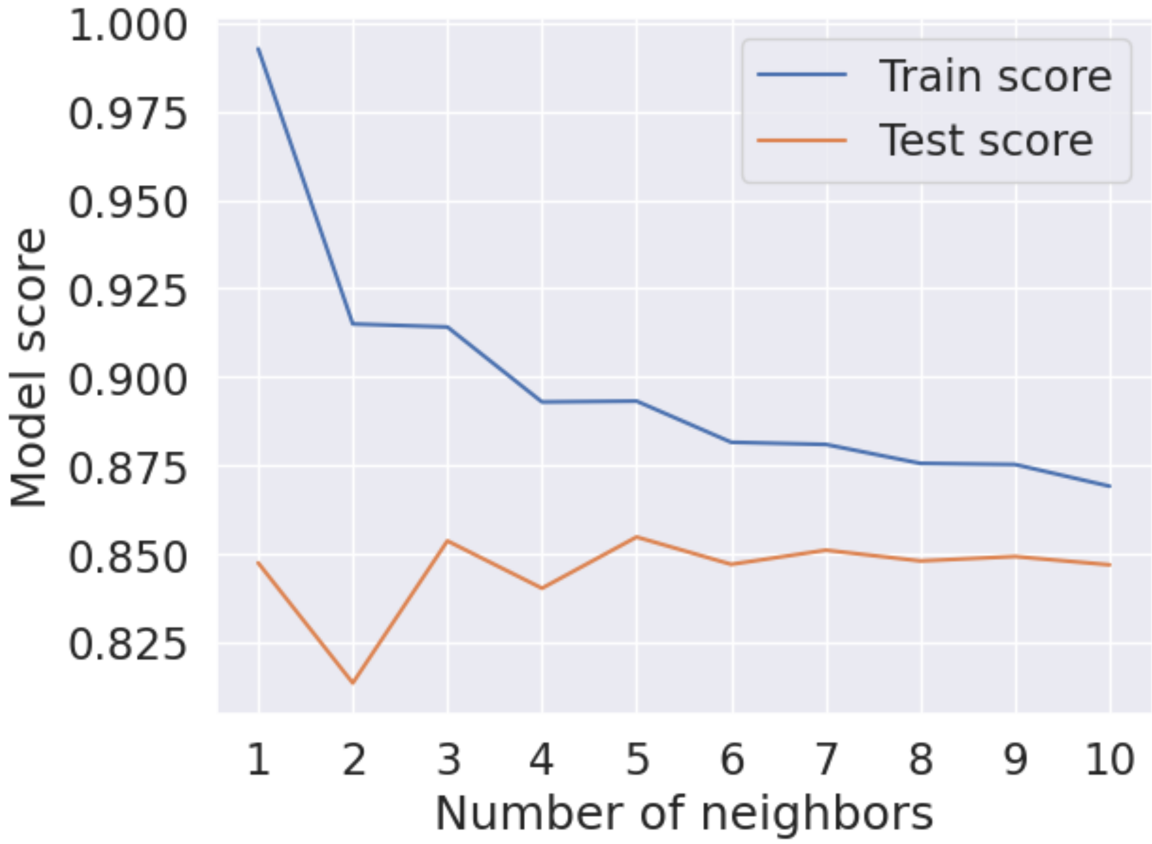
Tune by hand

In [ ]:
```
train_scores = []

test_scores = []

# Create a list of different values for n_neighbors
neighbors = range(1, 11) # 1 to 10

# Setup algorithm
knn = KNeighborsClassifier()

# Loop through different neighbors values
for i in neighbors:
    knn.set_params(n_neighbors = i) # set neighbors value

    # Fit the algorithm
    knn.fit(X_train, y_train)

    # Update the training scores
    train_scores.append(knn.score(X_train, y_train))
```

```
    # Update the test scores
    test_scores.append(knn.score(X_test, y_test))
```

In [ ]:
```
#visualizing the scores
plt.plot(neighbors, train_scores, label="Train score")
plt.plot(neighbors, test_scores, label="Test score")
plt.xticks(np.arange(1, 11, 1))
plt.xlabel("Number of neighbors")
plt.ylabel("Model score")
plt.legend()

print(f"Maximum KNN score on the test data: {max(test_scores)*100:.2f}%")
```

```
Maximum KNN score on the test data: 85.49%
```



- Tuning models with with RandomizedSearchCV

In [ ]:
```
# Different LogisticRegression hyperparameters
#log_reg_grid = {"C": np.logspace(-4, 4, 20),
#                 "solver": ["liblinear"]}

rf_grid = {
    'n_estimators': np.arange(10, 100, 3),  # Number of trees in the fore
    'max_depth': [None] + list(np.arange(5, 30)),  # Maximum number of le
    'min_samples_split': np.arange(2, 20),  # Minimum number of samples r
    'min_samples_leaf': np.arange(1, 20),  # Minimum number of samples re
    'max_features': [ 'sqrt', 'log2'],  # Number of features to consider
    'bootstrap': [True, False]  # Method of selecting samples for trainin
}
```

Now we tune RandomForestClassifier using RandomizedSearchCV

In [ ]:
```
# Setup random seed
np.random.seed(90)

# Setup random hyperparameter search for RandomForestClassifier
rs_rf = RandomizedSearchCV(RandomForestClassifier(),
                           param_distributions=rf_grid,
                           cv=5,
                           n_iter=20,
                           verbose=True)

# Fit random hyperparameter search model
rs_rf.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

Out[ ]:
```
▸ RandomizedSearchCV i ?
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier ?
```

In [ ]:
```
# Find the best parameters
rs_rf.best_params_
```

Out[ ]:
```
{'n_estimators': 79,
 'min_samples_split': 2,
 'min_samples_leaf': 1,
 'max_features': 'log2',
 'max_depth': 24,
 'bootstrap': False}
```

In [ ]:
```
# Evaluate the randomized search random forest model acc
rs_rf.score(X_test, y_test)
```

Out[ ]:
```
0.9046175051688491
```

- Tuning a model with GridSearchCV

- Evaluating a classification model

We want:

1. ROC curve and AUC score - plot_roc_curve()
2. Confusion matrix - confusion_matrix()
3. Classification report - classification_report()
4. Precision - precision_score()
5. Recall - recall_score()
6. F1-score - f1_score()

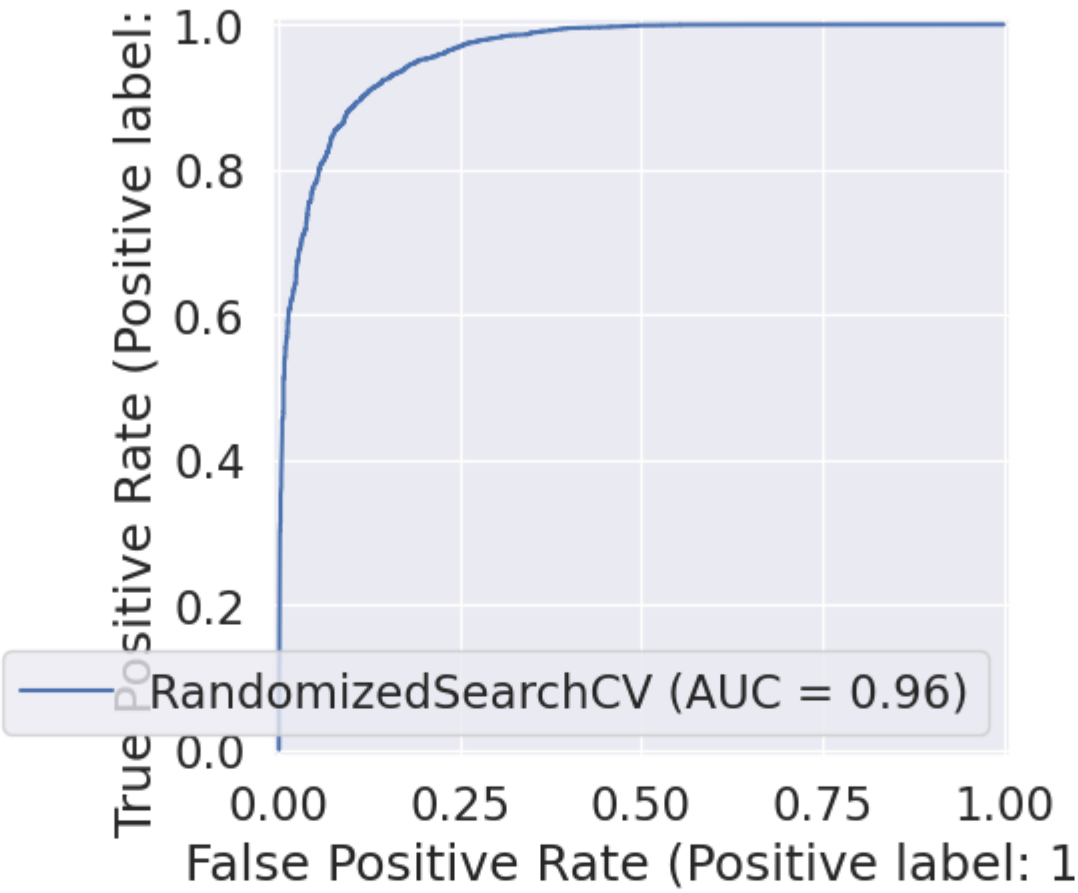
In [ ]:
```
# Make preidctions on test data
y_preds = rs_rf.predict(X_test)
```

In [ ]:
```
y_preds
```

Out[ ]: array([1, 1, 0, ..., 1, 1, 1])

In [ ]:
```
# Import ROC curve function from metrics module
from sklearn.metrics import RocCurveDisplay

# Plot ROC curve and calculate AUC metric
RocCurveDisplay.from_estimator(rs_rf, X_test, y_test)
```

Out[ ]: <sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7f28bcb04b50>



In [ ]:
```
from sklearn.metrics import roc_auc_score

roc_auc_score(y_test, y_preds)
```

Out[ ]: 0.8816313365131445

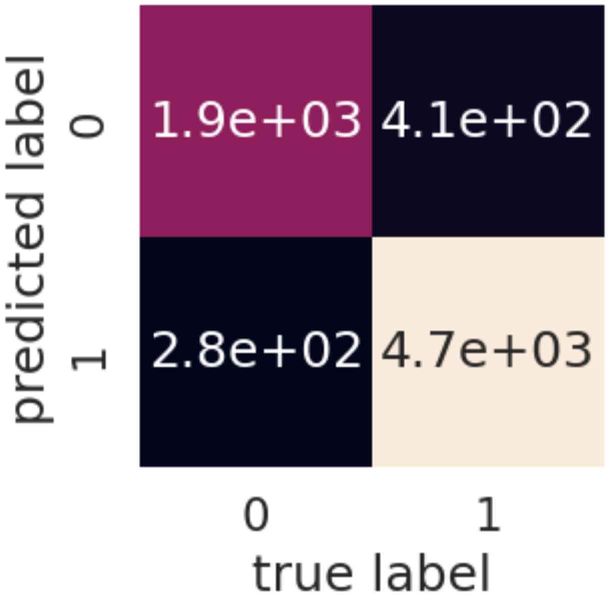
- confusion matrix

In [ ]:
```
# Display confusion matrix
print(confusion_matrix(y_test, y_preds))
```

```
[[1859  407]
 [ 285 4704]]
```

In [ ]:
```
# Import Seaborn
import seaborn as sns
sns.set(font_scale=1.5) # Increase font size

def plot_conf_mat(y_test, y_preds):
    """
    Plots a confusion matrix using Seaborn's heatmap().
```

```
    """
    fig, ax = plt.subplots(figsize=(3, 3))
    ax = sns.heatmap(confusion_matrix(y_test, y_preds),
                     annot=True, # Annotate the boxes
                     cbar=False)
    plt.xlabel("true label")
    plt.ylabel("predicted label")

plot_conf_mat(y_test, y_preds)
```



In [ ]:
```
# Show classification report
print(classification_report(y_test, y_preds))
```

```
              precision    recall  f1-score   support

           0       0.87      0.82      0.84      2266
           1       0.92      0.94      0.93      4989

    accuracy                           0.90      7255
   macro avg       0.89      0.88      0.89      7255
weighted avg       0.90      0.90      0.90      7255
```

In [ ]:
```
# Check best hyperparameters
rs_rf.best_params_
```

Out[ ]:
```
{'n_estimators': 79,
 'min_samples_split': 2,
 'min_samples_leaf': 1,
 'max_features': 'log2',
 'max_depth': 24,
 'bootstrap': False}
```

In [ ]: