

```

import numpy as np
import pandas as pd
from collections import Counter
import matplotlib.pyplot as plt
plt.style.use('seaborn')
import seaborn as sns

#listings_csv descrito e fazendo uma amostragem.

listings_file = 'F:\FIAPdes4\dados\listings.csv'

```

```

# Colunas que teoricamente vamos utilizar
columns = ['price',
           'summary',
           'neighbourhood_group_cleansed',
           'property_type',
           'room_type',
           'price',
           'number_of_reviews',
           'instant_bookable',
           'review_scores_rating',
           'beds',
           'bedrooms',
           'bathrooms',
           'accommodates',
           'amenities',
           'cancellation_policy',
           'reviews_per_month',
           'latitude',
           'longitude',
           'cleaning_fee',
           'security_deposit',
           'minimum_nights',
           'host_listings_count']

```

```
df = pd.read_csv(listings_file, usecols=columns)
```

```
df.head()
```

	summary
host_listings_count \	
0	Pls note that special rates apply for Carnival...
2.0	
1	Our apartment is a little gem, everyone loves ...
3.0	
2	This nice and clean 1 bedroom apartment is loc...
1.0	
3	This cosy apartment is just a few steps away ...
1.0	
4	Our newly renovated studio is located in the b...

1.0

	neighbourhood_group_cleansed	latitude	longitude	property_type	\
0	NaN	-22.96592	-43.17896	Condominium	
1	NaN	-22.97712	-43.19045	Apartment	
2	NaN	-22.98302	-43.21427	Apartment	
3	NaN	-22.98816	-43.19359	Apartment	
4	NaN	-22.98127	-43.19046	Loft	

	room_type	accommodates	bathrooms	bedrooms	...	\
0	Entire home/apt	5	1.0	2.0	...	
1	Entire home/apt	2	1.0	1.0	...	
2	Entire home/apt	3	1.0	1.0	...	
3	Entire home/apt	3	1.5	1.0	...	
4	Entire home/apt	2	1.0	1.0	...	

	amenities	price	\
0	{TV,"Cable TV",Internet,Wifi,"Air conditioning...	\$332.00	
1	{TV,"Cable TV",Internet,Wifi,"Air conditioning...	\$160.00	
2	{TV,"Cable TV",Internet,Wifi,"Air conditioning...	\$273.00	
3	{TV,"Cable TV",Internet,Wifi,"Air conditioning...	\$378.00	
4	{TV,"Cable TV",Wifi,"Air conditioning",Kitchen...	\$130.00	

	security_deposit	cleaning_fee	minimum_nights	number_of_reviews	\
0	\$0.00	\$378.00	4	243	
1	\$1,000.00	\$250.00	7	235	
2	\$0.00	\$84.00	2	271	
3	\$1,050.00	\$172.00	2	169	
4	\$400.00	\$140.00	3	316	

	review_scores_rating	instant_bookable	cancellation_policy	\
0	93.0	t	strict_14_with_grace_period	
1	94.0	f	strict_14_with_grace_period	
2	96.0	t	strict_14_with_grace_period	
3	94.0	f	strict_14_with_grace_period	
4	98.0	f	strict_14_with_grace_period	

	reviews_per_month
0	2.13
1	2.04
2	2.38
3	2.28
4	2.84

[5 rows x 21 columns]

*#todos os campos que são nulos no dataset*

df.isna().sum()

*#estatísticas básicas do dataset airbnb*

df.describe()

*#tipos de colunas*

df.info()

	host_listings_count	neighbourhood_group_cleansed	latitude
\count	33695.000000	0.0	33715.000000
mean	7.347559	NaN	-22.965208
std	32.194777	NaN	0.035244
min	0.000000	NaN	-23.073400
25%	1.000000	NaN	-22.984710
50%	1.000000	NaN	-22.970850
75%	3.000000	NaN	-22.946725
max	1259.000000	NaN	-22.750380

	longitude	accommodates	bathrooms	bedrooms
beds \count	33715.000000	33715.000000	33661.000000	33673.000000
33667.000000				
mean	-43.254228	4.199941	1.694765	1.646126
2.574242				
std	0.097488	2.625252	1.508228	1.075649
2.121490				
min	-43.737090	1.000000	0.000000	0.000000
0.000000				
25%	-43.323360	2.000000	1.000000	1.000000
1.000000				
50%	-43.200220	4.000000	1.000000	1.000000
2.000000				
75%	-43.187085	6.000000	2.000000	2.000000
3.000000				
max	-43.104060	160.000000	200.000000	20.000000
69.000000				

minimum\_nights   number\_of\_reviews   review\_scores\_rating \

count	33715.000000	33715.000000	18293.000000
mean	4.789826	9.374344	94.777565
std	22.640328	24.815311	9.141386
min	1.000000	0.000000	20.000000
25%	1.000000	0.000000	93.000000
50%	2.000000	1.000000	98.000000
75%	4.000000	6.000000	100.000000
max	1123.000000	372.000000	100.000000

	reviews_per_month
count	19149.000000
mean	0.707232
std	0.927453
min	0.010000
25%	0.110000
50%	0.340000
75%	0.980000
max	10.080000

```
# Nos campos numéricos, substituir os valores nulos por 0
df.review_scores_rating.fillna(0, inplace=True)
```

```
# remover o $
df.price = df.price.str.replace('$', '').str.replace(',', ' ',
').astype(float)
```

```
# Remover registros que estão com valores nulos em bathrooms, bedrooms
e beds
df.dropna(subset=['bathrooms', 'bedrooms', 'beds'], inplace=True)
```

```
C:\Users\edu\AppData\Local\Temp\ipykernel_88584\677663314.py:5:
FutureWarning: The default value of regex will change from True to
False in a future version. In addition, single character regular
expressions will *not* be treated as literal strings when regex=True.
df.price = df.price.str.replace('$', '').str.replace(',', ' ',
').astype(float)
```

```
#nesse, vimos que a maioria do campo property_value é apartamento,
quase 80% do total:
tipo_ac_df = df.property_type.value_counts(normalize = True)
```

```
print(tipo_ac_df)
```

Apartment	0.764499
House	0.103854
Condominium	0.055022
Serviced apartment	0.021455
Loft	0.018450
Guest suite	0.006011
Bed and breakfast	0.004166
Guesthouse	0.003988

Villa	0.003273
Hostel	0.003035
Other	0.002797
Hotel	0.002678
Townhouse	0.001904
Aparthotel	0.001756
Cottage	0.000952
Chalet	0.000922
Earth house	0.000863
Boutique hotel	0.000863
Tiny house	0.000803
Boat	0.000684
Bungalow	0.000298
Cabin	0.000298
Nature lodge	0.000298
Casa particular (Cuba)	0.000298
Island	0.000149
Treehouse	0.000119
Hut	0.000089
Castle	0.000089
Farm stay	0.000060
Camper/RV	0.000060
Houseboat	0.000060
Dorm	0.000060
Tent	0.000030
Yurt	0.000030
Campsite	0.000030
Barn	0.000030
Igloo	0.000030

Name: property\_type, dtype: float64

*#retirando os campos que não serão utilizados*

```
data = df[['price',
           'room_type',
           'review_scores_rating',
           'beds',
           'bedrooms',
           'bathrooms',
           'accommodates'
          ]]
```

*# get\_dummies function para transformar os valores em colunas, e os valores das colunas em 1 ou 0*

```
room_type = pd.get_dummies(data.room_type).astype(int)
```

*# alterar a coluna original para transformar em colunas*

```
data = data.drop(['room_type'], axis = 1)
data = pd.concat((data, room_type), axis = 1)
```

```
data.head()
```

	price	review_scores_rating	beds	bedrooms	bathrooms
accommodates \					
0	332.0	93.0	2.0	2.0	1.0
5					
1	160.0	94.0	2.0	1.0	1.0
2					
2	273.0	96.0	2.0	1.0	1.0
3					
3	378.0	94.0	2.0	1.0	1.5
3					
4	130.0	98.0	1.0	1.0	1.0
2					

	Entire home/apt	Hotel room	Private room	Shared room
0	1	0	0	0
1	1	0	0	0
2	1	0	0	0
3	1	0	0	0
4	1	0	0	0

```
#https://www.sharpsightlabs.com/blog/scikit-train\_test\_split/
# import train_test_split , para separar os dados de treino e teste.
from sklearn.model_selection import train_test_split
# import metrics
from sklearn.metrics import mean_squared_error, r2_score
```

```
# create target and features. No treino, colocamos todas as colunas,
# menos o preço, pois vamos verificar a importância a partir do preço.
# Essa coluna é a característica.
```

```
a = data.drop(['price'], axis = 1)
```

```
#No teste, utilizaremos o preço, que é o que temos que descobrir, ou
# seja, a variação desse campo em relação aos demais. Esse é o alvo
```

```
b = data.price
```

```
#A tabela (dataframe) é a melhor forma de utilizarmos x e y, pois
# nesse caso, as duas tem que ter a mesma quantidade de linhas.
```

```
# Separar os dados de treino e teste. O tamanho é de 20% dos dados.
# Random_state é o modo em que ele ordena para fazer os testes.
```

```
X_train, X_test, y_train, y_test = train_test_split(a, b,
# test_size=0.2, random_state=2)
```

```
# Normalizar as características ( a )
```

```
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.dummy import DummyRegressor
```

```
#criamos um objeto dummy regressor, para fazer regressão.
```

```
dummy_regressor = DummyRegressor()
```

```
dummy_regressor.fit(X_train, y_train)
```

```
#criamos um objeto do sklearn, um standardscaler
```

```

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

#Preços preditos pelo dummyRegressor, que é a média de preços
encontrada.
dummy_regressor.predict(X_test)

array([654.43107424, 654.43107424, 654.43107424, ..., 654.43107424,
       654.43107424, 654.43107424])

#Linear Regression
from sklearn import linear_model
from sklearn import metrics

# linear regression testing
reg = linear_model.LinearRegression()
reg.fit(X_train, y_train)
linear = metrics.r2_score(y_test, reg.predict(X_test))

y_test_pred = reg.predict(X_test)
y_train_pred = reg.predict(X_train)

print (f"Linear Regression: {round(linear, 5)}")

Linear Regression: 0.14433

# Modelo ridge
ridge = linear_model.Ridge()
ridge.fit(X_train, y_train)
ridge_result = metrics.r2_score(y_test, ridge.predict(X_test))

y_test_pred = ridge.predict(X_test)
y_train_pred = ridge.predict(X_train)

print (f"Linear Ridge: {round(ridge_result, 5)}")

Linear Ridge: 0.14436

#mostrar os valores dos dados autais e os dados que serão usados para
treino.
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
fig.suptitle('Valores Previstos x Atual', fontsize=14, y=1)
plt.subplots_adjust(top=0.93, wspace=0)

ax1.scatter(y_test, y_test_pred, s=2, alpha=0.7)
ax1.plot(list(range(2,8)), list(range(2,8)), color='black',
linestyle='--')
ax1.set_title('Dados teste')

```

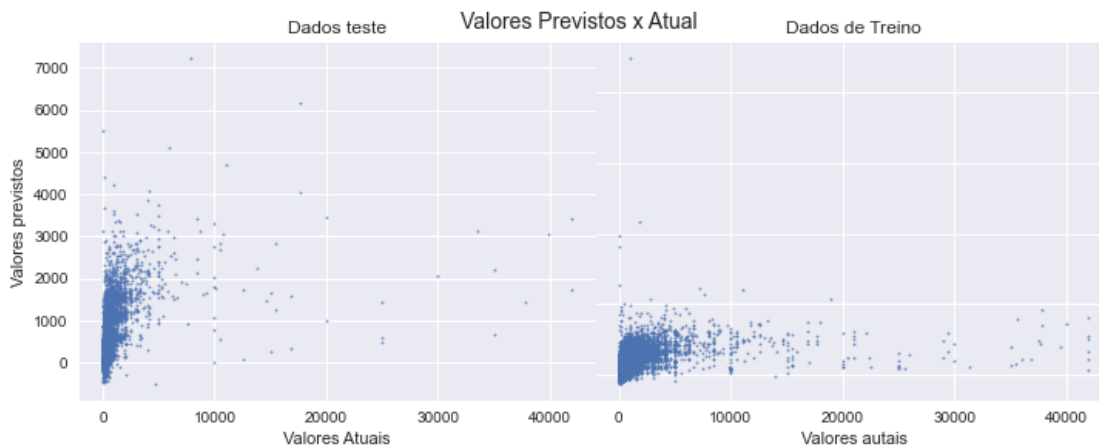
```

ax1.set_xlabel('Valores Atuais')
ax1.set_ylabel('Valores previstos')

ax2.scatter(y_train, y_train_pred, s=2, alpha=0.7)
ax2.plot(list(range(2,8)), list(range(2,8)), color='black',
linestyle='--')
ax2.set_title('Dados de Treino')
ax2.set_xlabel('Valores atuais')
ax2.set_ylabel('')
ax2.set_yticklabels(labels='')

plt.show()

```



[https://github.com/carlosfab/sigmoidal\\_ai/blob/master/XGBoost%20-%20aprenda%20este%20algoritmo%20de%20Machine%20Learning%20em%20Python.ipynb](https://github.com/carlosfab/sigmoidal_ai/blob/master/XGBoost%20-%20aprenda%20este%20algoritmo%20de%20Machine%20Learning%20em%20Python.ipynb)

```

import xgboost as xgb
# cria o modelo de predição do xgb regressor
modelo = xgb.XGBRegressor()

```

<https://www.projectpro.io/recipes/find-optimal-parameters-using-gridsearchcv-for-regression>

<https://www.kaggle.com/code/stuarthallows/using-xgboost-with-scikit-learn>

```

from sklearn.model_selection import GridSearchCV

```

*# criar grid de parâmetros, para aprender e selecionar o melhor parâmetro*

```

param_grid = {'n_estimators': [100, 150, 200, 300], #modelos ou funções que vamos passar

```

```

               'learning_rate': [0.01, 0.05, 0.1], #taxa de aprendizado

```

```

               'max_depth': [4,6,8,10],
               'colsample_bytree': [0.6, 0.7, 1],
               'gamma': [0.0, 0.1, 0.2]}

```



```
# instantiate the tuned random forest
modelo_grid = GridSearchCV(modelo, param_grid, cv=2, n_jobs=-1)
#njobs=-1 quer dizer que pode utilizar toda a cpu. cv é o número de
divisões que ele faz para a validação cruzada.
```

```
# treinar o grid do modelo
modelo_grid.fit(X_train, y_train)
```

```
# Imprimir os melhores estimos
print(modelo_grid.best_estimator_)
# Imprimir os melhores parâmetros
print(modelo_grid.best_params_)
# Imprimir os melhores scores
print(modelo_grid.best_score_)
```

```
XGBRegressor(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.6, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None,
              feature_types=None,
              gamma=0.0, gpu_id=None, grow_policy=None,
              importance_type=None,
              interaction_constraints=None, learning_rate=0.01,
              max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=4, max_leaves=None,
              min_child_weight=None, missing=nan,
              monotone_constraints=None,
              n_estimators=300, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
{'colsample_bytree': 0.6, 'gamma': 0.0, 'learning_rate': 0.01,
 'max_depth': 4, 'n_estimators': 300}
0.22502950590493975
```

```
# Iniciar o xgboost com os parâmetros obtidos na célula anterior
modelo = xgb.XGBRegressor(colsample_bytree=0.6, gamma=0.0,
                           learning_rate=0.01,
                           max_depth=4, n_estimators=300,
                           random_state=4)
```

```
# Treinar o modelo
modelo.fit(X_train, y_train)
```

```
# Predizer os valores usando o predict
y_pred_train = modelo.predict(X_train)
y_pred_test = modelo.predict(X_test)
```

```
# Erro médio absoluto do modelo
```

```
RMSE = np.sqrt(mean_squared_error(y_test, y_pred_test))
```

```
print(f"RMSE: {round(RMSE, 5)}")
```

```
RMSE: 1159.54724
```

```
print(X_train.size)
```

```
print(X_test.size)
```

```
print(y_train.size)
```

```
print(y_test.size)
```

```
241956
```

```
60489
```

```
26884
```

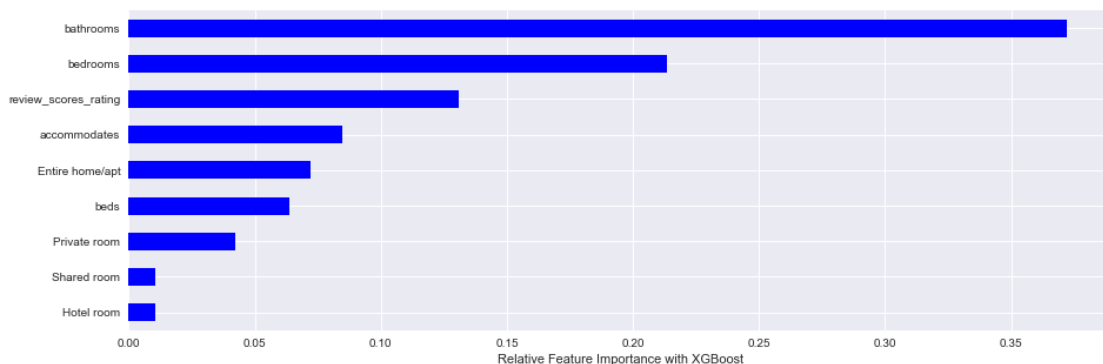
```
6721
```

```
# características mais importantes nos dados, de acordo com o preço
```

```
features_importance = pd.Series(modelo.feature_importances_,  
index=a.columns)
```

```
features_importance.nlargest(15).sort_values().plot(kind='barh',  
color='blue', figsize=(15,5))
```

```
plt.xlabel('Relative Feature Importance with XGBoost');
```



```
#retirando o valor de 200 banheiros, que podem estar errados.
```

```
df2 = df[data.bathrooms != 200]
```

```
#Analisando os fatores mais importantes, conforme gráfico anterior, o  
número de banheiros:
```

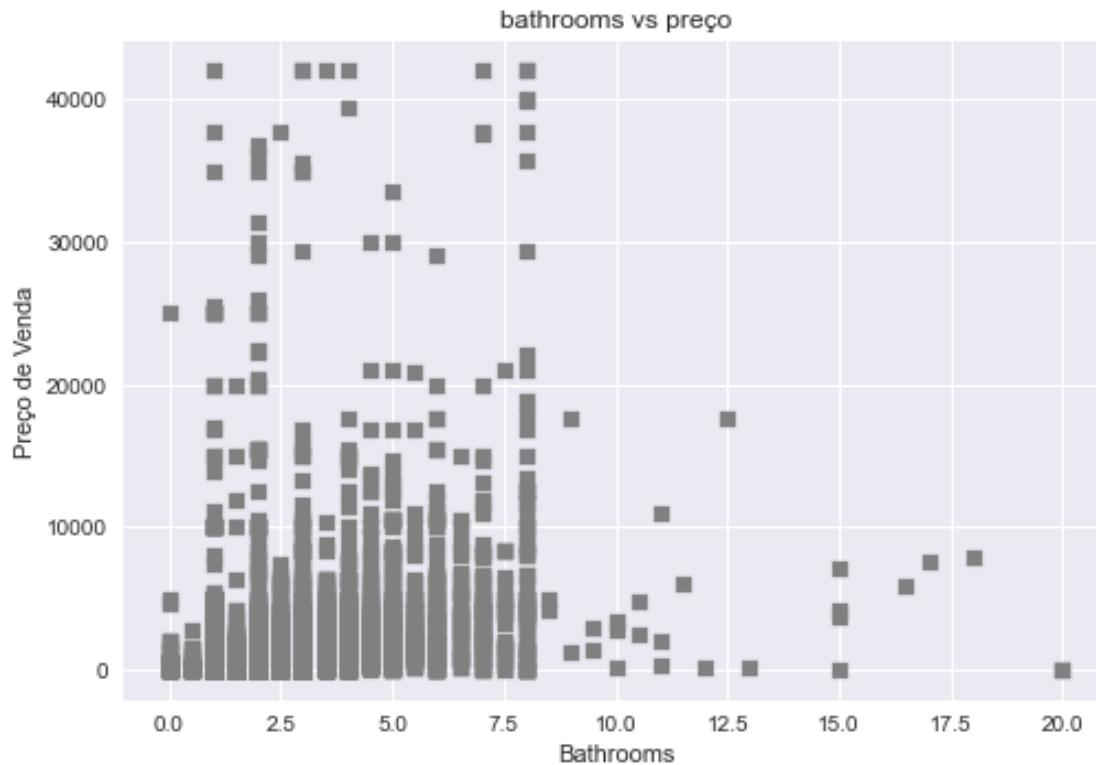
```
plt.scatter(df2.bathrooms, df2.price, c = "gray", marker = "s")
```

```
plt.title("bathrooms vs preço")
```

```
plt.xlabel("Bathrooms")
```

```
plt.ylabel("Preço de Venda")
```

```
plt.show()
```



*#Analisando os fatores mais importantes, conforme gráfico anterior, o número de quartos:*

```
plt.scatter(df2.bedrooms, df2.price, c = "gray", marker = "s")  
plt.title("bedrooms vs preço")  
plt.xlabel("bedrooms")  
plt.ylabel("Preço de Venda")  
plt.show()
```

