Reg. Linear - Preço de Carros

Fonte: https://www.kaggle.com/datasets/hellbuoy/car-price-prediction/data

Exercício de EDA e RL com algoritmo de ML e prática do uso de dummies.

Conteúdo:

- Processamento e tratamento dos dados iniciais.
- Visualizações e análise descritiva.
- Iniciando o modelo.
- Instanciando o modelo.
- Resultado.
- Visualização dos R² de treino e teste.

Variáveis do dataset:

Car_ID	Unique id of each observation (Interger)
Symboling	Its assigned insurance risk rating, A value of +3 indicates that the auto is risky, -3 that it is probably pretty safe.(Categorical)
carCompany	Name of car company (Categorical)
fueltype	Car fuel type i.e gas or diesel (Categorical)
aspiration	Aspiration used in a car (Categorical)
doornumber	Number of doors in a car (Categorical)
carbody	body of car (Categorical)
drivewheel	type of drive wheel (Categorical)
enginelocation	Location of car engine (Categorical)
wheelbase	Weelbase of car (Numeric)
carlength	Length of car (Numeric)
carwidth	Width of car (Numeric)
carheight	height of car (Numeric)
curbweight	The weight of a car without occupants or baggage. (Numeric)
enginetype	Type of engine. (Categorical)
cylindernumber	cylinder placed in the car (Categorical)
enginesize	Size of car (Numeric)
fuelsystem	Fuel system of car (Categorical)
boreratio	Boreratio of car (Numeric)
stroke	Stroke or volume inside the engine (Numeric)
compressionratio	compression ratio of car (Numeric)
horsepower	Horsepower (Numeric)
peakrpm	car peak rpm (Numeric)
citympg	Mileage in city (Numeric)
highwaympg	Mileage on highway (Numeric)
price(Dependent variable)	Price of car (Numeric)

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
```

Processamento e tratamento dos dados iniciais:

In [2]:
```
df=pd.read_csv('car_price.csv')
df.head()
```

Out[2]:

	car_ID	symboling	CarName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	...	enginesize	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highw
0	1	3	alfa-romero giulia	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	111	5000	21	
1	2	3	alfa-romero stelvio	gas	std	two	convertible	rwd	front	88.6	...	130	mpfi	3.47	2.68	9.0	111	5000	21	
2	3	1	alfa-romero Quadrifoglio	gas	std	two	hatchback	rwd	front	94.5	...	152	mpfi	2.68	3.47	9.0	154	5000	19	
3	4	2	audi 100 ls	gas	std	four	sedan	fwd	front	99.8	...	109	mpfi	3.19	3.40	10.0	102	5500	24	
4	5	2	audi 100ls	gas	std	four	sedan	4wd	front	99.4	...	136	mpfi	3.19	3.40	8.0	115	5500	18	

5 rows × 26 columns

In [3]:
```
df.shape
```

Out[3]:
```
(205, 26)
```

In [4]:
```
df.isna().sum()
```

Out[4]:

	0
car_ID	0
symboling	0
CarName	0
fueltype	0
aspiration	0
doornumber	0
carbody	0
drivewheel	0
enginelocation	0
wheelbase	0
carlength	0
carwidth	0
carheight	0
curbweight	0
enginetype	0
cylindernumber	0
enginesize	0
fuelsystem	0
boreratio	0
stroke	0
compressionratio	0
horsepower	0
peakrpm	0
citympg	0
highwaympg	0
price	0

dtype: int64

In [5]:
```
df.isnull().sum()
```

Out[5]:

	0
car_ID	0
symboling	0
CarName	0
fueltype	0
aspiration	0
doornumber	0
carbody	0
drivewheel	0
enginelocation	0
wheelbase	0
carlength	0
carwidth	0
carheight	0
curbweight	0
enginetype	0
cylindernumber	0
enginesize	0
fuelsystem	0
boreratio	0
stroke	0
compressionratio	0
horsepower	0
peakrpm	0
citympg	0
highwaympg	0
price	0

dtype: int64

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   car_ID            205 non-null    int64
 1   symboling         205 non-null    int64
 2   CarName           205 non-null    object
 3   fueltype          205 non-null    object
 4   aspiration        205 non-null    object
 5   doornumber        205 non-null    object
 6   carbody           205 non-null    object
 7   drivewheel        205 non-null    object
 8   enginelocation    205 non-null    object
 9   wheelbase         205 non-null    float64
 10  carlength         205 non-null    float64
 11  carwidth          205 non-null    float64
 12  carheight         205 non-null    float64
 13  curbweight        205 non-null    int64
 14  enginetype        205 non-null    object
 15  cylindernumber    205 non-null    object
 16  enginesize        205 non-null    int64
 17  fuelsystem        205 non-null    object
 18  boreratio         205 non-null    float64
 19  stroke            205 non-null    float64
 20  compressionratio  205 non-null    float64
 21  horsepower        205 non-null    int64
 22  peakrpm           205 non-null    int64
 23  citympg           205 non-null    int64
 24  highwaympg        205 non-null    int64
 25  price             205 non-null    float64
dtypes: float64(8), int64(8), object(10)
memory usage: 41.8+ KB
```

In [7]:
```
Company_name=df['CarName'].apply(lambda x : x.split(' ')[0])
df.insert(3,'CompanyName',Company_name)
```

In [8]:
```
df.drop(['CarName', 'car_ID', 'symboling'], axis=1, inplace=True, errors='ignore')
df.head()
```

Out[8]:

	CompanyName	fueltype	aspiration	doornumber	carbody	drivewheel	enginelocation	wheelbase	carlength	carwidth	...	enginesize	fuelsystem	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg
0	alfa-romero	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	...	130	mpfi	3.47	2.68	9.0	111	5000	21
1	alfa-romero	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	...	130	mpfi	3.47	2.68	9.0	111	5000	21
2	alfa-romero	gas	std	two	hatchback	rwd	front	94.5	171.2	65.5	...	152	mpfi	2.68	3.47	9.0	154	5000	19
3	audi	gas	std	four	sedan	fwd	front	99.8	176.6	66.2	...	109	mpfi	3.19	3.40	10.0	102	5500	24
4	audi	gas	std	four	sedan	4wd	front	99.4	176.6	66.4	...	136	mpfi	3.19	3.40	8.0	115	5500	18

5 rows × 24 columns

In [9]:
```
df.columns
```

Out[9]:
```
Index(['CompanyName', 'fueltype', 'aspiration', 'doornumber', 'carbody',
       'drivewheel', 'enginelocation', 'wheelbase', 'carlength', 'carwidth',
       'carheight', 'curbweight', 'enginetype', 'cylindernumber', 'enginesize',
       'fuelsystem', 'boreratio', 'stroke', 'compressionratio', 'horsepower',
       'peakrpm', 'citympg', 'highwaympg', 'price'],
      dtype='object')
```

In [10]:
```
df['carbody'].unique()
```

Out[10]:
```
array(['convertible', 'hatchback', 'sedan', 'wagon', 'hardtop'],
      dtype=object)
```

In [11]:
```
df['doornumber'].unique()
```

Out[11]:
```
array(['two', 'four'], dtype=object)
```

In [12]:
```
df['doornumber'] = df['doornumber'].replace({'four': 4, 'two': 2})
df['doornumber'].unique()
```

Out[12]:
```
array([2, 4])
```

In [13]:
```
df['fueltype'].unique()
```

Out[13]:
```
array(['gas', 'diesel'], dtype=object)
```

In [14]:
```
df['CompanyName'].unique()
```

Out[14]:
```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'maxda', 'mazda', 'buick', 'mercury',
       'mitsubishi', 'Nissan', 'nissan', 'peugeot', 'plymouth', 'porsche',
       'porcshce', 'renault', 'saab', 'subaru', 'toyota', 'toyouta',
       'vokswagen', 'volkswagen', 'vw', 'volvo'], dtype=object)
```

In [15]:
```
df['cylindernumber'].unique()
```

Out[15]:
```
array(['four', 'six', 'five', 'three', 'twelve', 'two', 'eight'],
      dtype=object)
```

In [16]:
```
df['cylindernumber'] = df['cylindernumber'].replace({'four': 4, 'six': 6,
                                                      'five': 5, 'three': 3,
                                                      'twelve': 12,'two': 2,
                                                      'eight': 8})
df['cylindernumber'].unique()
```

Out[16]:
```
array([ 4,  6,  5,  3, 12,  2,  8])
```

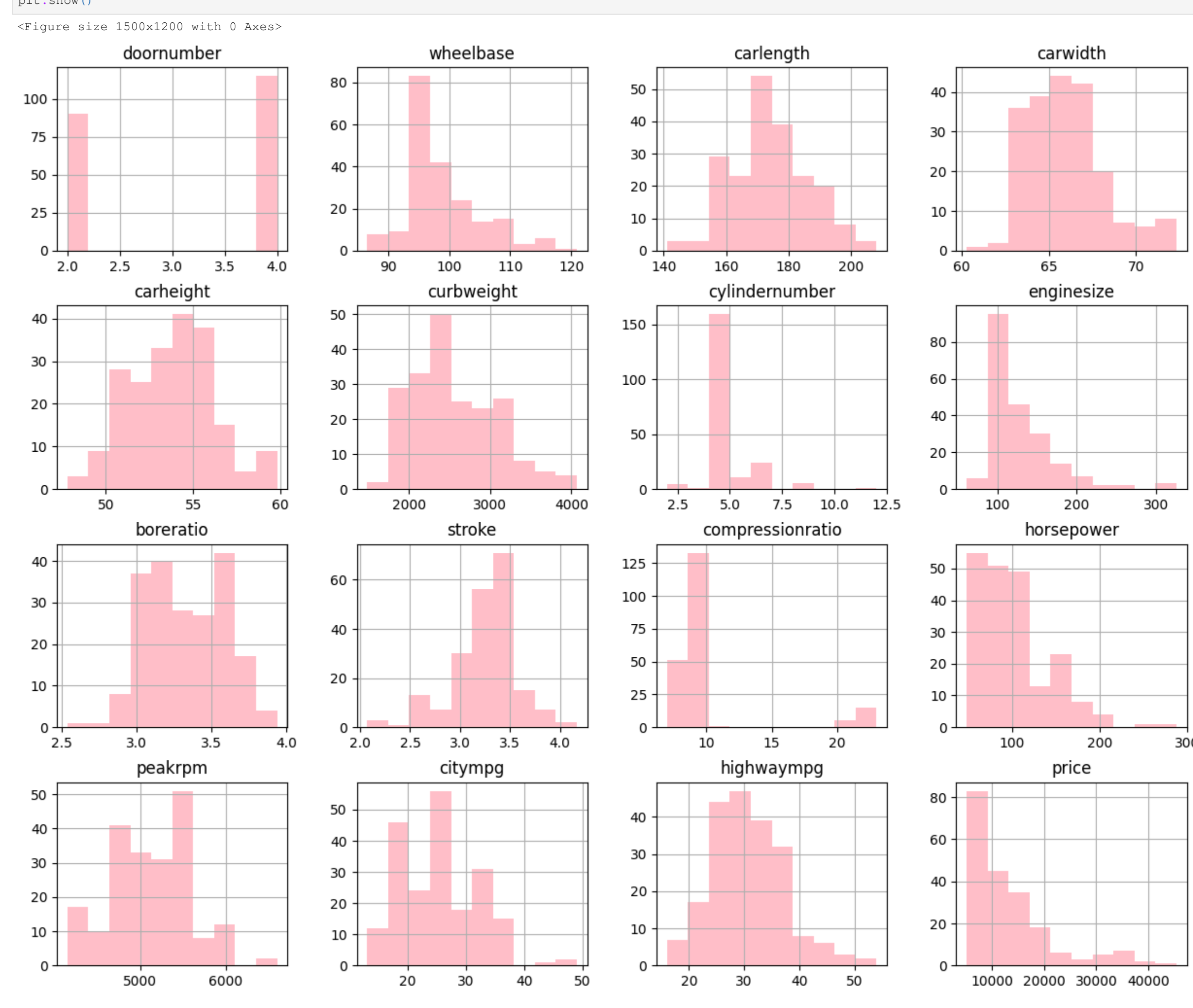
In [17]:
```
def replace_name(x,y):
    df['CompanyName'].replace(x,y,inplace=True)

replace_name('maxda','mazda')
replace_name('porcshce','porsche')
replace_name('toyouta','toyota')
replace_name('vokswagen','volkswagen')
replace_name('Nissan','nissan')
replace_name('vw','volkswagen')

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

Out[17]:
```
array(['alfa-romero', 'audi', 'bmw', 'chevrolet', 'dodge', 'honda',
       'isuzu', 'jaguar', 'mazda', 'buick', 'mercury', 'mitsubishi',
       'nissan', 'peugeot', 'plymouth', 'porsche', 'renault', 'saab',
       'subaru', 'toyota', 'volkswagen', 'volvo'], dtype=object)
```

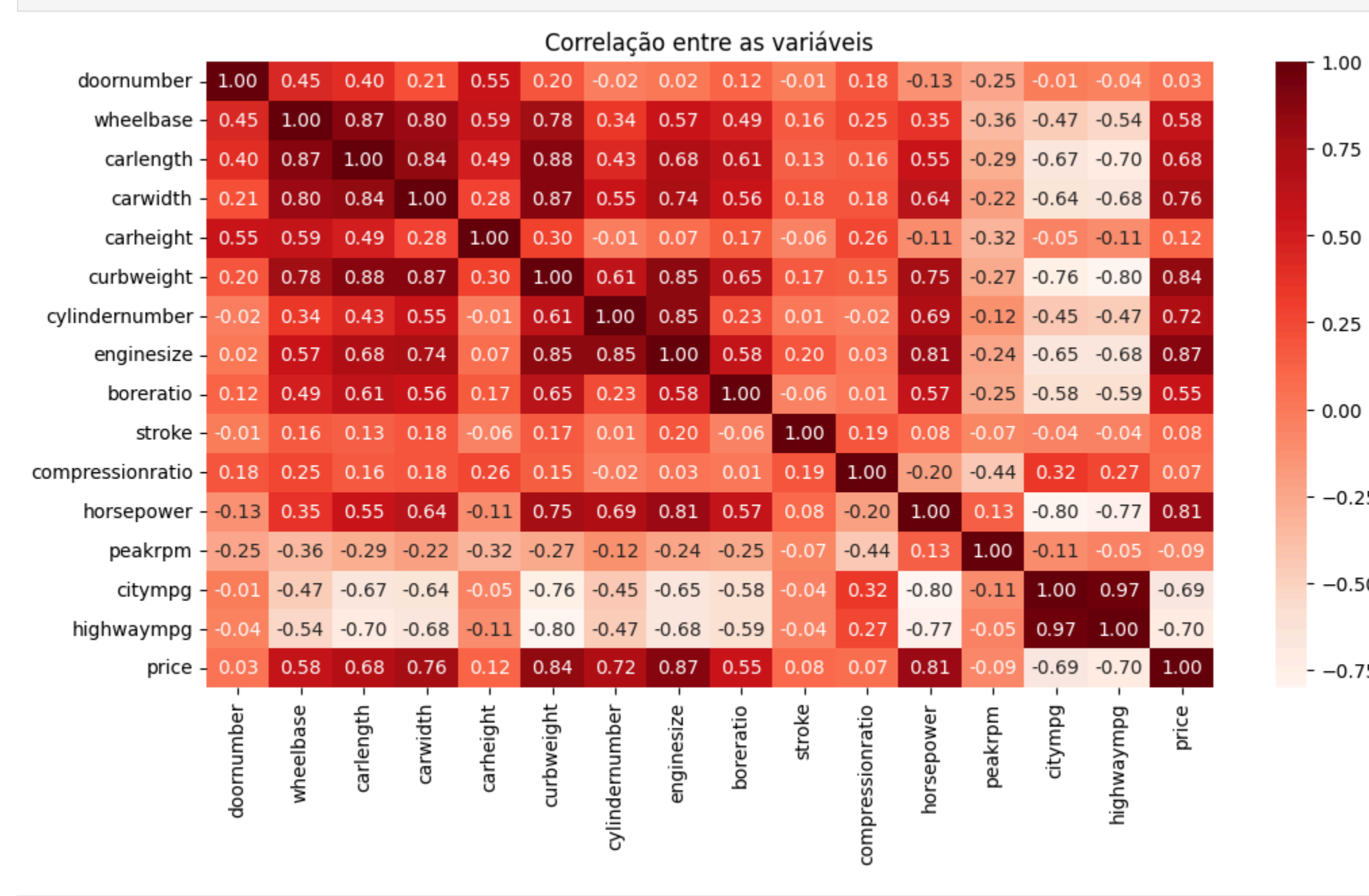
Visualizações e análise descritiva:

In [39]:
```
#visualização das variáveis numéricas por grid
plt.figure(figsize=(15,12))
df.hist(figsize=(15,12), color='pink')
plt.show()
```

```
<Figure size 1500x1200 with 0 Axes>
```



In [19]:
```
#correlação entre as variáveis
numerical_df = df.select_dtypes(include=['number'])
plt.figure(figsize=(12,6))
sns.heatmap(numerical_df.corr(), annot=True, cmap='Reds',
            fmt='.2f')
plt.title('Correlação entre as variáveis')
plt.show()
```



In [20]:
```
df.describe()
```

Out[20]:

	doornumber	wheelbase	carlength	carwidth	carheight	curbweight	cylindernumber	enginesize	boreratio	stroke	compressionratio	horsepower	peakrpm	citympg	highwaympg	price
count	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000	205.000000
mean	3.121951	98.756585	174.049268	65.907805	53.724878	2555.565854	4.380488	126.907317	3.329756	3.255415	10.142537	104.117073	5125.121951	25.219512	30.751220	13276.710571
std	0.994966	6.021776	12.337289	2.145204	2.443522	520.680204	1.080854	41.642693	0.270844	0.313597	3.972040	39.544167	476.985643	6.542142	6.886443	7988.852332
min	2.000000	86.600000	141.100000	60.300000	47.800000	1488.000000	2.000000	61.000000	2.540000	2.070000	7.000000	48.000000	4150.000000	13.000000	16.000000	5118.000000
25%	2.000000	94.500000	166.300000	64.100000	52.000000	2145.000000	4.000000	97.000000	3.150000	3.110000	8.600000	70.000000	4800.000000	19.000000	25.000000	7788.000000
50%	4.000000	97.000000	173.200000	65.500000	54.100000	2414.000000	4.000000	120.000000	3.310000	3.290000	9.000000	95.000000	5200.000000	24.000000	30.000000	10295.000000
75%	4.000000	102.400000	183.100000	66.900000	55.500000	2935.000000	4.000000	141.000000	3.580000	3.410000	9.400000	116.000000	5500.000000	30.000000	34.000000	16503.000000
max	4.000000	120.900000	208.100000	72.300000	59.800000	4066.000000	12.000000	326.000000	3.940000	4.170000	23.000000	288.000000	6600.000000	49.000000	54.000000	45400.000000

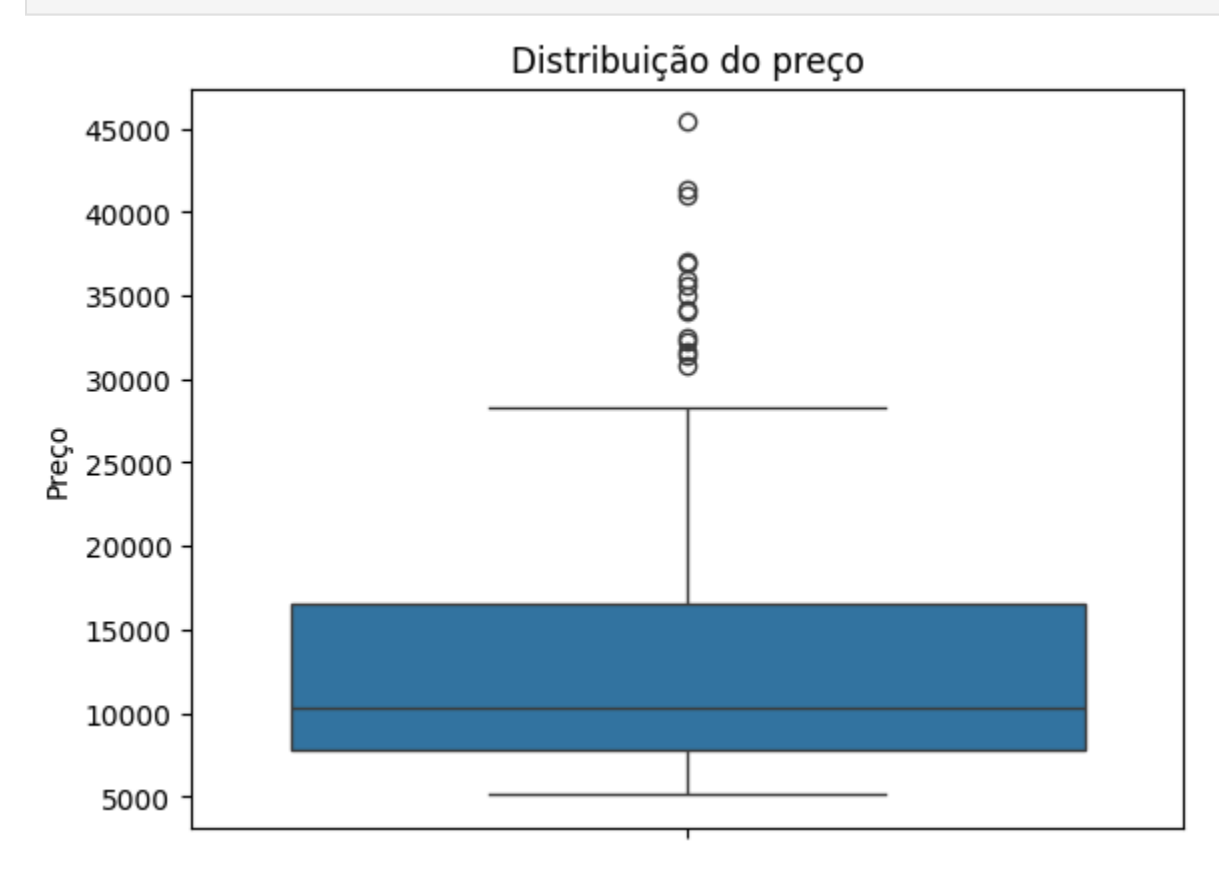
In [21]:
```
df['price'].describe()
```

Out[21]:

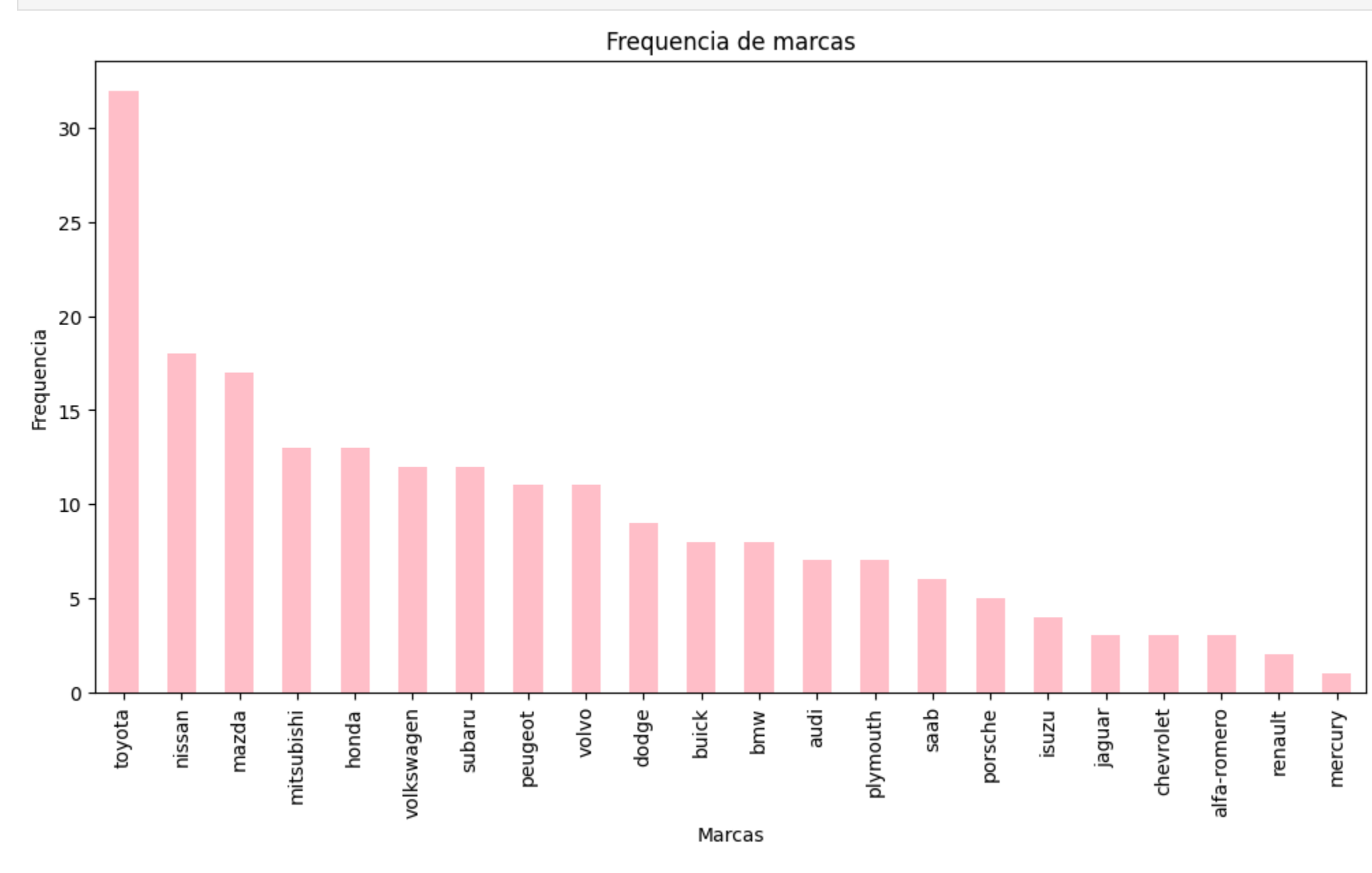
	price
count	205.000000
mean	13276.710571
std	7988.852332
min	5118.000000
25%	7788.000000
50%	10295.000000
75%	16503.000000
max	45400.000000

dtype: float64

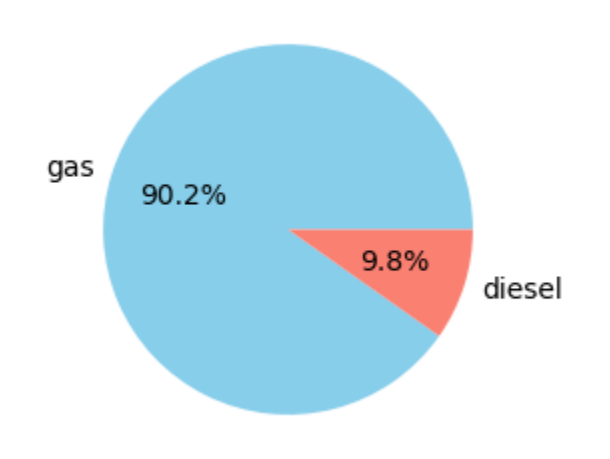
In [22]:
```
sns.boxplot(data = df, y='price')
plt.ylabel('Preço')
plt.title('Distribuição do preço')
plt.show()
```



In [23]:
```
plt.figure(figsize=(12,6))
num_comp = df['CompanyName'].value_counts().plot(kind='bar', color = 'pink',
                                                 legend=False)
plt.title('Frequencia de marcas')
plt.xlabel('Marcas')
plt.ylabel('Frequencia')
plt.show()
```



In [24]:
```
plt.figure(figsize=(5,3))
colors = ['skyblue', 'salmon']
plt.pie(df['fueltype'].value_counts(),
        labels = df['fueltype'].value_counts().index,
        colors=colors, autopct = '%1.1f%%')
plt.show()
```



Iniciando o modelo:

In [25]:
```
#utilizando dummies
train_df = pd.get_dummies(df, columns=['fueltype', 'aspiration', 'carbody',
                                       'drivewheel', 'enginelocation',
                  'enginetype', 'CompanyName', 'fuelsystem'], drop_first=True,
                          dtype='int64')
```

In [26]:
```
X= train_df.drop('price',axis=1)
y= train_df['price']
```

In [27]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42
                                                ,shuffle=True)
```

Instanciando o modelo:

In [28]:
```
model = LinearRegression()
model.fit(X_train,y_train)
```

Out[28]:
```
LinearRegression
LinearRegression()
```

Resultado:

In [41]:
```
score_test = model.score(X_train,y_train)
mae = mean_absolute_error(y_test,model.predict(X_test),multioutput='uniform_average')
mse = mean_squared_error(y_test,model.predict(X_test),multioutput='uniform_average')
rmse = np.sqrt(mse)
print(f'Teste R²: {score_test * 100:.2f}%')
print(f'MAE: {mae:.0f}')
print(f'MSE:{mse:.0f}')
print(f'RMSE:{rmse:.0f}')
```

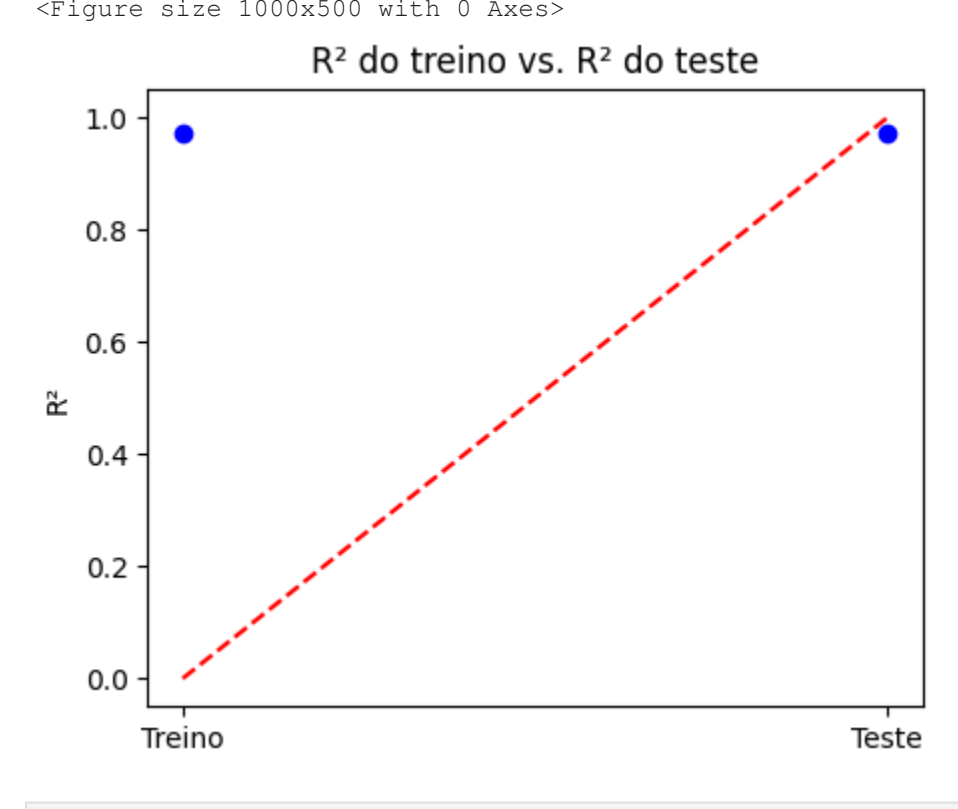
```
Teste R²: 97.26%
MAE: 1918
MSE:8206643
RMSE:2865
```

Com um R² alto de 97,26%, o modelo está bem ajustado, explicando a maior parte da variação nos dados. Os valores de erro (MAE, MSE, e RMSE) indicam o desvio médio das previsões em relação aos valores reais, mas a quantidade de erros do modelo, apesar de bons, ainda são altos.

Visualização do R²:

In [44]:
```
plt.figure(figsize=(10,5))
score_train = model.score(X_train, y_train)
r2_values = [score_train, score_test]
labels = ['Treino', 'Teste']

plt.figure(figsize=(5, 4))
plt.scatter(labels, r2_values, color='blue')
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.title('R² do treino vs. R² do teste')
plt.ylabel('R²')
plt.show()
```

```
<Figure size 1000x500 with 0 Axes>
```



In [ ]: