House price prediction - Linear regression model with sklearn in Python

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Description:

This project aims to predict housing prices based on square footage using linear regression. The dataset consists of housing data with features such as square meters and corresponding prices. The goal is to build a regression model that can accurately predict housing prices based on square footage.

Objectives:

1. Build a univariable linear regression model using square footage as the independent variable and housing price as the dependent variable.
2. Train the model using the housing dataset that includes features such as square meters and corresponding prices.
3. Evaluate the accuracy and performance of the linear regression model using metrics such as the coefficient of determination (R2) and mean squared error (MSE).

Question

What is the coefficient of determination (R2) of our linear regression model that uses square footage as a feature to predict house prices?

Import libraries

In [73]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
from scipy import stats
from sklearn.linear_model import LinearRegression
```

Load dataset

'price' and 'sqft_living' were select as depending and independing columns. After 'sqft_living' were transformed to square meters.

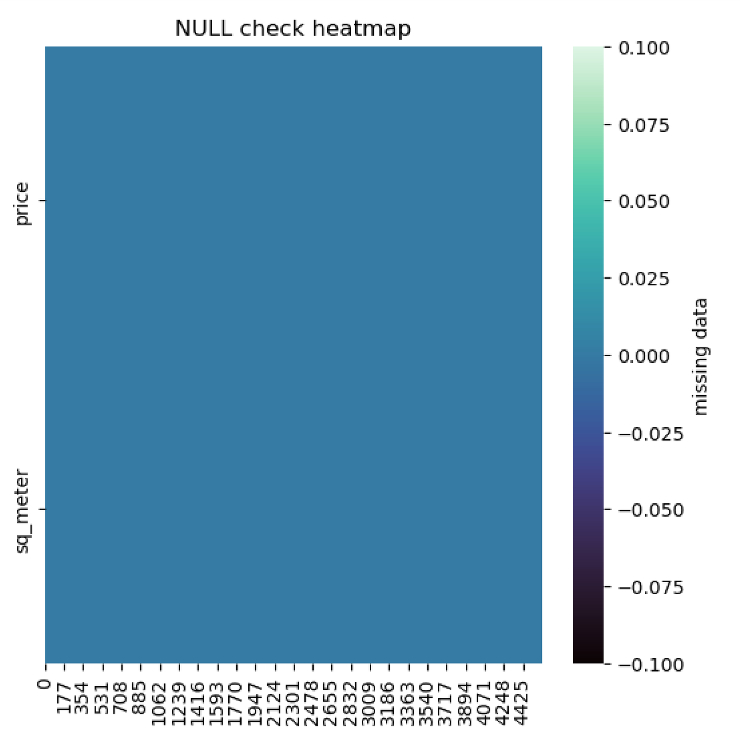
In [74]:
```
df = pd.read_csv('house_data.csv', usecols=['price', 'sqft_living'])
#Convert square foots to square meters
df['sq_meter'] = df['sqft_living']/10.764
#Reduce decimals
df['price'] = df['price'].round(2)
df['sq_meter'] = df['sq_meter'].round(2)
df = df.drop(columns='sqft_living') #drop column
df.head()
```

Out[74]:

	price	sq_meter
0	313000.0	124.49
1	2384000.0	339.09
2	342000.0	179.30
3	420000.0	185.80
4	550000.0	180.23

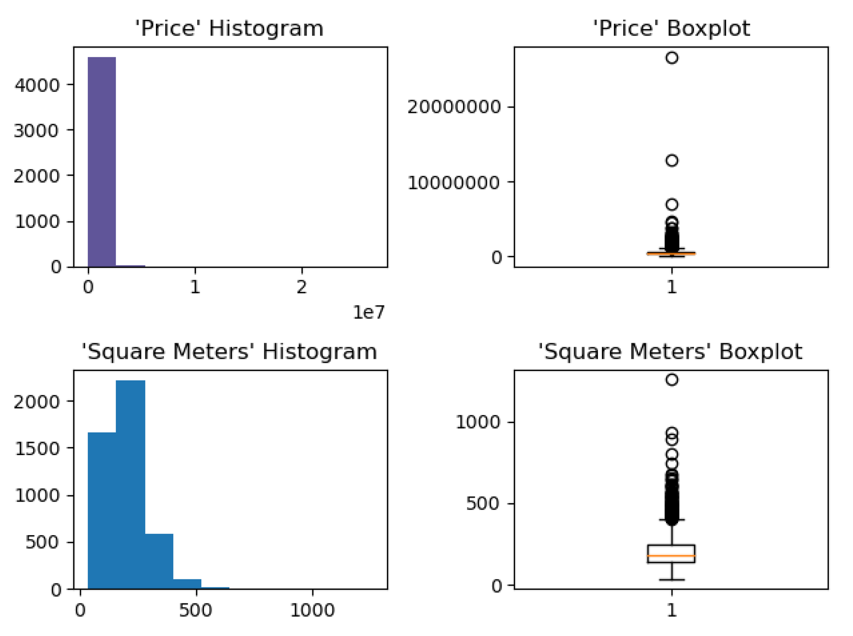
Creation of heatmap to check null values

In [75]:
```
#Create heatmap with Seaborn to view nulls.
plt.figure(figsize=(6,6))
sns.heatmap(df.isna().transpose(), cmap = "mako", cbar_kws = {"label":"missing data"})
plt.title('NULL check heatmap')
plt.show()
```



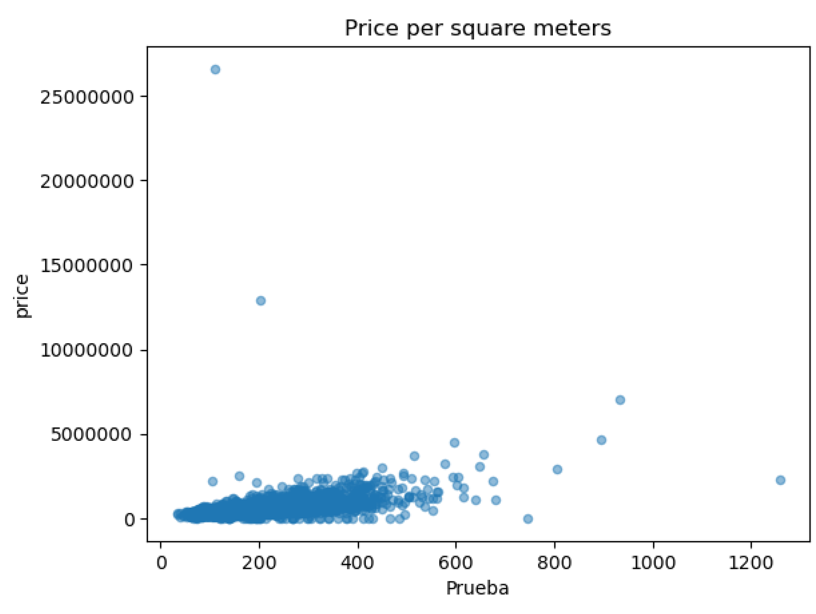
Histograms and Boxplot were created to check data distribution. After this were founds outliers.

In [76]:
```
fig, axs = plt.subplots(2, 2)

axs[0, 0].hist(df['price'], color='#1C0D6E', alpha=0.7)
axs[0, 0].set_title("'Price' Histogram")

axs[0, 1].boxplot(df['price'])
axs[0, 1].set_title("'Price' Boxplot")
axs[0, 1].ticklabel_format(style='plain', axis='y')

axs[1, 0].hist(df['sq_meter'])
axs[1, 0].set_title("'Square Meters' Histogram")

axs[1, 1].boxplot(df['sq_meter'])
axs[1, 1].set_title("'Square Meters' Boxplot")

fig.tight_layout()
plt.show()
```



When plotting a scatter chart, are identifieds some outliers.

In [77]:
```
df.plot(x='sq_meter', y='price', kind='scatter', alpha=0.5)
plt.title('Price per square meters')
plt.xlabel('Prueba')
plt.ticklabel_format(style='plain', axis='y')
plt.show()
```



It is decided to drop ouliers as possible, calculating interquartile range and fence values

$$\text{IQR} = Q3 - Q1$$
$$\text{Lower Fence} = Q1 - 1.5 \times \text{IQR}$$
$$\text{Upper Fence} = Q3 + 1.5 \times \text{IQR}$$

Because the Lower Fence for price was a negative value, it is decide to change it to 0

In [78]:
```
#Delete 'Price' outliers
q25, q75 = np.percentile(df['price'], [25, 75])
iqr_price = stats.iqr(df['price'])
print('IQR:', iqr_price)
inf_price = q25 - (1.5*iqr_price)
up_price = q75 + (1.5*iqr_price)
print(f'Lower Fence: {inf_price}, Upper Fence: {up_price}')
df = df[(df['price'] > 0)
        & (df['price'] < up_price)]
```

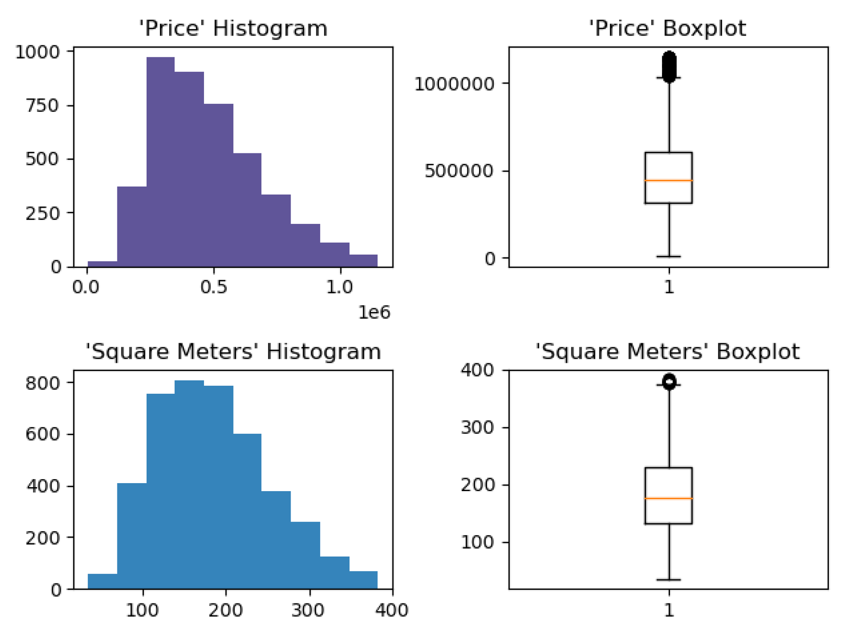
```
IQR: 332087.5
Lower Fence: -175256.25, Upper Fence: 1153093.75
```

In [79]:
```
#Delete 'sq_meter' outliers
q25, q75 = np.percentile(df['sq_meter'], [25, 75])
iqr_meter = stats.iqr(df['sq_meter'])
print('IQR:', iqr_meter)
inf_meter = q25 - (1.5*iqr_meter)
up_meter = q75 + (1.5*iqr_meter)
print(f'Lower Fence: {inf_meter}, Upper Fence: {up_meter}')
df = df[(df['sq_meter'] > inf_meter)
        & (df['sq_meter'] < up_meter)]
```

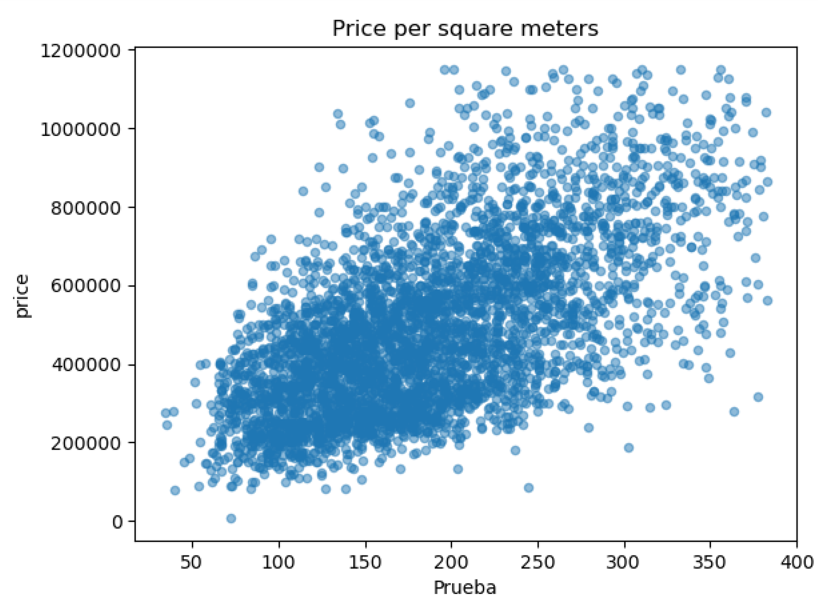
```
IQR: 100.33000000000001
Lower Fence: -17.645000000000001, Upper Fence: 383.675
```

Checked the distribution again and a better normalization was found.

In [80]:
```
fig, axs = plt.subplots(2, 2)

axs[0, 0].hist(df['price'], color = '#1C0D6E', alpha=0.7)
axs[0, 0].set_title("'Price' Histogram")
axs[0, 1].ticklabel_format(style='plain', axis='y')
axs[0, 1].boxplot(df['price'])
axs[0, 1].set_title("'Price' Boxplot")

axs[1, 0].hist(df['sq_meter'], alpha=0.9)
axs[1, 0].set_title("'Square Meters' Histogram")
axs[1, 1].boxplot(df['sq_meter'])
axs[1, 1].set_title("'Square Meters' Boxplot")

fig.tight_layout()
plt.show()
```



In [81]:
```
df.plot(x='sq_meter', y='price', kind='scatter', alpha=0.5)
plt.title('Price per square meters')
plt.xlabel('Prueba')
plt.ticklabel_format(style='plain', axis='y')
plt.show()
```



Model training

The 70% of dataset was asiggned to training and 30% to test.

In [82]:
```
training = df.sample(frac=0.7, random_state=25)
test = df.drop(training.index)

print(f'Number of training dataset: {training.shape[0]}')
print(f'Number of training dataset: {test.shape[0]}')
```

```
Number of training dataset: 2965
Number of training dataset: 1271
```

Save datasets

In [83]:
```
training.to_csv('training.csv', index=False)
test.to_csv('test.csv', index=False)
```

In [89]:
```
def train_model():
    try:
        x_train = np.array(training['sq_meter']).reshape(-1, 1)
        y_train = np.array(training['price']).reshape(-1, 1)
        reg = LinearRegression()
        reg.fit(x_train, y_train)
        print('The model was trained succesfully')
    except Exception as e:
        msg = 'An error was ocurred: '
        raise ValueError(msg) from e

train_model()
```

```
The model was trained succesfully
```

Testing de trained model with the 'test' dataframe

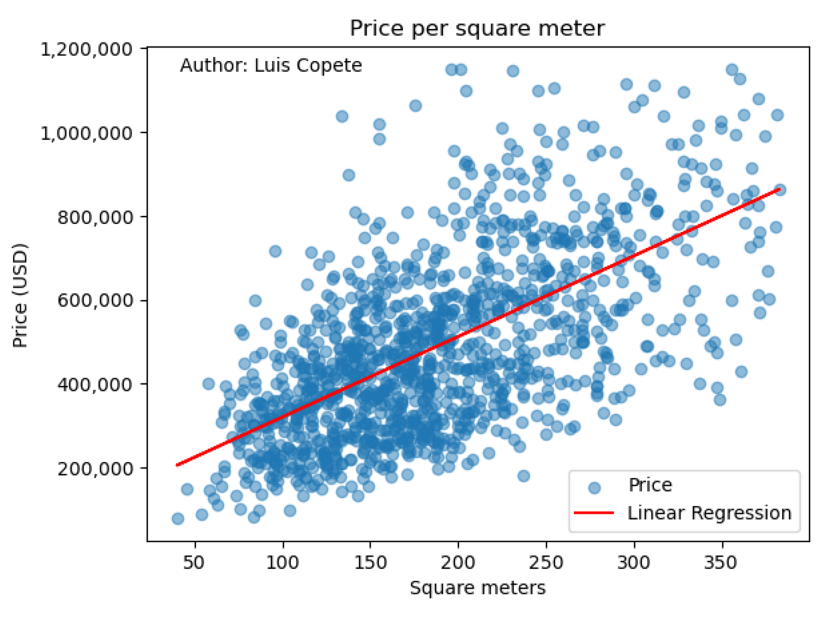
In [70]:
```
test['price_predicted'] = reg.predict(np.array(test['sq_meter']).reshape(-1,1))

test.head()
```

Out[70]:

	price	sq_meter	price_predicted
0	313000.0	124.49	367703.473600
7	482000.0	251.77	611705.664447
12	588500.0	216.46	544014.610403
13	365000.0	101.26	323170.389899
17	367500.0	288.93	682943.261964

Graphing the linear regression rect

In [71]:
```
fig, ax = plt.subplots()


ax.scatter(test['sq_meter'], test['price'], alpha=0.5, label='Price')
ax.plot(test['sq_meter'], test['price_predicted'], color='red', label='Linear Regression')

ax.yaxis.set_major_formatter(ticker.FuncFormatter(lambda x, _: '{:,.0f}'.format(x)))

plt.title('Price per square meter')
plt.xlabel('Square meters')
plt.ylabel('Price (USD)')


plt.legend()
plt.text(0.05, 0.95, 'Author: Luis Copete', transform=ax.transAxes, fontsize=10)


plt.show()
```



R2 Score

It used the r2_score module to evaluate the r2 coefficient.

In [72]:
```
from sklearn.metrics import r2_score

# Assuming y_val is original data and f_val is predicted value
y_val = test['price']
f_val = test['price_predicted']

r2 = r2_score(y_val, f_val)
print('The R2 Score for the model is: {:.2f}'.format(r2))

if r2 < 0.3:
    print("The model has a poor fit and cannot explain the variability of the data well.")
elif r2 < 0.5:
    print("The model has a moderate fit and can partially explain the variability of the data.")
elif r2 < 0.7:
    print("The model has a reasonable fit and can explain a good portion of the data variability.")
elif r2 < 0.9:
    print("The model has a good fit and can explain most of the data variability.")
else:
    print("The model has an excellent fit and can explain almost all of the data variability.")
```

```
The R2 Score for the model is: 0.38
The model has a moderate fit and can partially explain the variability of the data.
```