

Set environment and libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model selection import train_test_split
from scipy import stats
import statsmodels.api as sms
import statsmodels.formula.api as smf
from IPython.display import Image
import seaborn as sns
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
%matplotlib inline
```

Read data in dataframe df = pd.read_csv("King_County_House_prices_dataset.csv") df.head()

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	 grade
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	0.0	 7
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	 7
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	0.0	 6
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	 7
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	 8

5 rows × 21 columns

2/18/2015

```
# Delete columns not needed
df.drop(["id", "lat", "long", "sqft basement"], axis=1, inplace=True)
# Convent date in readable format
df["date"] = pd.to datetime(df["date"])
df["Month"] = df["date"].apply(lambda date: date.month)
df["Year"] = df["date"].apply(lambda date: date.year)
df.drop("date", axis=1, inplace =True)
df.tail(10)
                            bathrooms sqft_living
                                                   sqft_lot floors waterfront view condition grade sqft_above
                 bedrooms
                         3
                                                                               0.0
                                                                                                  8
21587
        507250.0
                                  2.50
                                             2270
                                                      5536
                                                              2.0
                                                                         NaN
                                                                                           3
                                                                                                           2270
21588
        429000.0
                         3
                                  2.00
                                             1490
                                                      1126
                                                              3.0
                                                                          0.0
                                                                               0.0
                                                                                           3
                                                                                                  8
                                                                                                           1490
                                                                                           3
                                                                                                  9
21589
        610685.0
                         4
                                  2.50
                                             2520
                                                      6023
                                                              2.0
                                                                          0.0
                                                                              NaN
                                                                                                           2520
21590
       1010000.0
                         4
                                  3.50
                                             3510
                                                      7200
                                                              2.0
                                                                          0.0
                                                                               0.0
                                                                                           3
                                                                                                  9
                                                                                                          2600
                         3
                                                              2.0
                                                                          0.0
                                                                               0.0
                                                                                           3
                                                                                                  8
21591
        475000.0
                                  2.50
                                             1310
                                                      1294
                                                                                                           1180
                         3
                                                              3.0
                                                                               0.0
                                                                                           3
                                                                                                  8
21592
        360000.0
                                  2.50
                                             1530
                                                      1131
                                                                          0.0
                                                                                                           1530
21593
        400000.0
                         4
                                  2.50
                                             2310
                                                      5813
                                                              2.0
                                                                          0.0
                                                                               0.0
                                                                                           3
                                                                                                  8
                                                                                                           2310
        402101.0
                         2
                                  0.75
                                                              2.0
                                                                               0.0
                                                                                           3
                                                                                                  7
                                                                                                           1020
21594
                                             1020
                                                      1350
                                                                          0.0
                         3
                                                                                           3
                                                                                                  8
21595
       400000.0
                                  2.50
                                             1600
                                                      2388
                                                              2.0
                                                                               0.0
                                                                                                           1600
                                                                         NaN
21596
        325000.0
                         2
                                  0.75
                                             1020
                                                      1076
                                                              2.0
                                                                          0.0
                                                                               0.0
                                                                                           3
                                                                                                  7
                                                                                                           1020
```

```
# Show size of the dataset
df.shape
(21597, 18)
# Show overview of the data set
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 18 columns):
    Column
                   Non-Null Count Dtype
    price
                   21597 non-null float64
     bedrooms
                   21597 non-null int64
    bathrooms
                   21597 non-null float64
    sqft_living
                   21597 non-null int64
     sqft_lot
                   21597 non-null int64
    floors
                   21597 non-null float64
                   19221 non-null float64
    waterfront
    view
                   21534 non-null float64
     condition
                   21597 non-null int64
                   21597 non-null int64
    grade
                   21597 non-null int64
    sqft_above
    yr_built
                   21597 non-null int64
 12 yr renovated
                   17755 non-null float64
 13 zipcode
                   21597 non-null int64
    sqft_living15
                   21597 non-null int64
    sqft_lot15
                   21597 non-null int64
 16
    Month
                   21597 non-null int64
 17 Year
                   21597 non-null int64
dtypes: float64(6), int64(12)
memory usage: 3.0 MB
```

Check if zeros are contained df.isnull().values.any()

7.700000e+06

False

View data description and see if there are any outliers

33.000000

df.describe()													
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view					
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	19221.000000	21534.000000					
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	0.007596	0.233863					
std	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	0.086825	0.765686					
min	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	0.000000	0.000000					
25%	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	0.000000	0.000000					
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	0.000000	0.000000					
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	0.000000	0.000000					

8.000000 13540.000000 1.651359e+06

3.500000

1.000000

4.000000

```
# Replace the missing data, with the mean value
df['waterfront'].fillna((df['waterfront'].mean()), inplace=True)
df['vr renovated'].fillna((df['vr renovated'].mean()). inplace=True)
```

2.25

1.00

3.00

2.00

3

2

4

3

538000.0

180000.0

604000.0

510000.0

df df	['view'].		If['view'].				, inplace-	iiue
		bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	viev
0	221900.0	3	1.00	1180	5650	1.0	0.007596	0.0

<pre>df.dropna(inplace=True) df.head()</pre>										
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view		
0	221900.0	3	1.00	1180	5650	1.0	0.007596	0.0		

2570

770

1960

1680

7242

10000

5000

8080

2.0

1.0

1.0

1.0

0.000000

0.000000

0.000000

0.000000

0.0

0.0

0.0

0.0

condition grade sqft_above yr_built

1180

2170

770

1050

1680

1955

1951

1933

1965

1987

7

7

6

7

8

3

3

3

5

3

```
df['waterfront'] = np.round(df['waterfront'])
df['bathrooms'] = np.round(df['bathrooms'])
df['yr_renovated'] = np.round(df['yr_renovated'])
df['floors'] = np.round(df['floors'])
```

Convert values to integer with float

```
df['view'] = np.round(df['view'])
df hoad(2)
```

3

538000.0

180000.0

2.0

1.0

a i	. nead (3)											
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	yr_built
0	221900.0	3	1.0	1180	5650	1.0	0.0	0.0	3	7	1180	1955

7242

10000

2570

770

2.0

1.0

0.0

0.0

0.0

0.0

2170

770

3

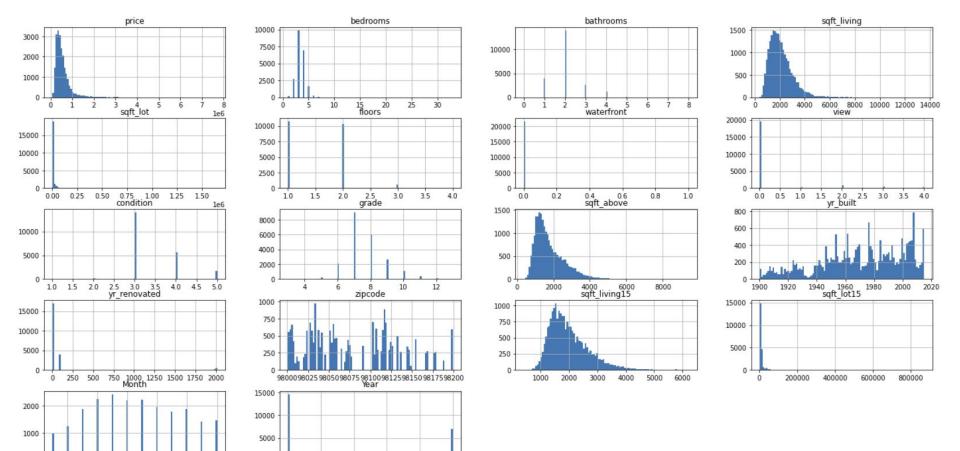
3

7

6

1951

1933



2014.0 2014.2 2014.4 2014.6 2014.8 2015.0

price -	1	0.31	0.52	0.7	0.09	0.24	0.26	0.39	0.036	0.67	0.61	0.054	0.12	-0.053	0.59	0.083	-0.0099	0.0037
bedrooms -		1	0.49	0.58	0.032		-0.0021		0.026	0.36	0.48		0.017	-0.15	0.39	0.031	-0.001	-0.0099
bathrooms -	0.52	0.49	1	0.7			0.065		-0.068	0.59	0.6	0.38	0.062	-0.14	0.5		0.0095	-0.024
sqft_living -	0.7	0.58	0.7	1				0.28	-0.059	0.76	0.88		0.05	-0.2	0.76		0.012	-0.029
sqft_lot -		0.032		0.17	1	-0.0015	0.021		-0.0088			0.053	0.0042	-0.13		0.72	-0.0026	0.0056
floors -					-0.0015	1	0.021	0.027	-0.22	0.41	0.49	0.38	0.011	-0.023		-0.01	0.014	-0.022
waterfront -		-0.0021	0.065		0.021	0.021	1	0.38	0.017			-0.024		0.029		0.031	0.0082	-0.005
view -	0.39	0.078				0.027	0.38	1	0.046			-0.054					-0.0052	0.0012
condition -	0.036	0.026	-0.068	-0.059	-0.0088	-0.22	0.017	0.046	1	-0.15	-0.16	-0.36	-0.056	0.0029	-0.093	-0.0031	0.022	-0.046
grade -	0.67		0.59	0.76			0.083		-0.15		0.76	0.45	0.015	-0.19	0.71		0.009	-0.031
sqft_above -	0.61	0.48	0.6	0.88		0.49	0.072		-0.16	0.76	1	0.42	0.02	-0.26	0.73		0.01	-0.024
yr_built -	0.054		0.38	0.32	0.053	0.38	-0.024	-0.054	-0.36	0.45	0.42	1	-0.2	-0.35	0.33		-0.0062	0.0036
yr_renovated -		0.017	0.062	0.05	0.0042	0.011			-0.056	0.015	0.02	-0.2	1	0.063	-0.00023	0.0035	0.008	-0.02
zipcode -	-0.053	-0.15	-0.14	-0.2	-0.13	-0.023	0.029		0.0029	-0.19	-0.26	-0.35	0.063	1	-0.28	-0.15	-0.00014	0.0013
sqft_living15 -	0.59	0.39	0.5	0.76	0.14				-0.093	0.71	0.73		-0.00023	-0.28	1	0.18	0.0025	-0.022
sqft_lot15 -		0.031		0.18	0.72	-0.01	0.031		-0.0031				0.0035	-0.15		1	0.0032	0.00016
Month -	-0.0099	-0.001	0.0095	0.012	-0.0026	0.014	0.0082	-0.0052	0.022	0.009	0.01	-0.0062	0.008	-0.00014	0.0025	0.0032	1	-0.78
Year -	0.0037	-0.0099	-0.024	-0.029	0.0056	-0.022	-0.005	0.0012	-0.046	-0.031	-0.024	0.0036	-0.02	0.0013	-0.022	0.00016	-0.78	1
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	yr_built	yr_renovated	zipcode	sqft_living15	sqft_lot15	Month	Year

- 0.8

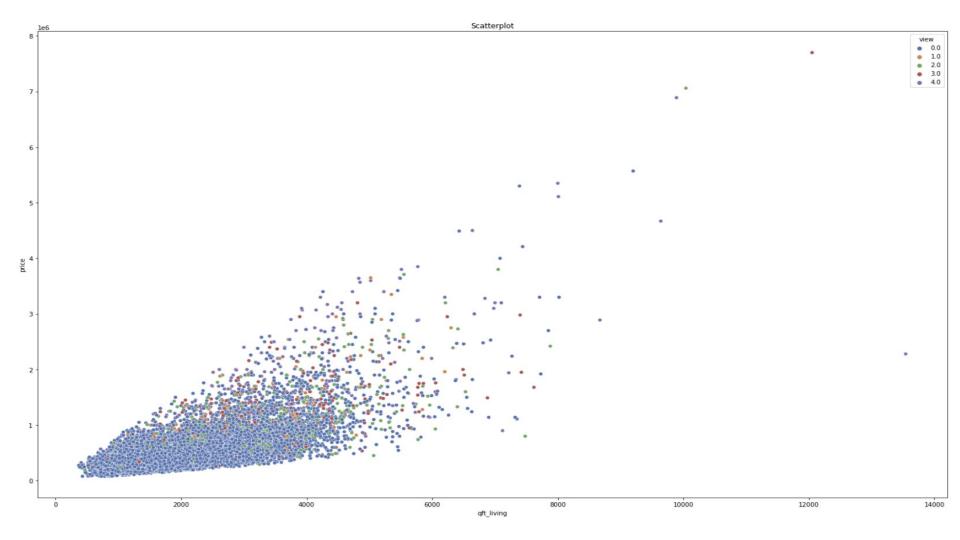
- 0.6

- 0.2

- 0.0

- -0.2

- -0.4



price ~ sqft_living

OLS Regression Results

Dep. Variable:	price	R-squared:	0.493
Model:	OLS	Adj. R-squared:	0.493
Method:	Least Squares	F-statistic:	2.097e+04
Date:	Sun, 06 Jun 2021	Prob (F-statistic):	0.00
Time:	13:52:08	Log-Likelihood:	-3.0006e+05
No. Observations:	21597	AIC:	6.001e+05
Df Residuals:	21595	BIC:	6.001e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]	
Intercept	-4.399e+04	4410.023	-9.975	0.000	-5.26e+04	-3.53e+04	
sqft_living	280.8630	1.939	144.819	0.000	277.062	284.664	
Omni	hue. 149010	142 D ur	hin Wates	· .	1002		

1.502	Dui biii-watsoii.	14601.942	Ollillibus.
542662.604	Jarque-Bera (JB):	0.000	Prob(Omnibus):
0.00	Prob(JB):	2.820	Skew:
5.63e+03	Cond. No.	26.901	Kurtosis:

```
# We split our data into training and test data
```

```
X = df[['sqft_living']].values
y = df['price'].values
```

How good is my prediction

2000

4000

6000

sqft_living

8000

10000

12000

14000

plt.scatter(X_train, y_train)

plt.scatter(X_test, y_test, color="red")

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42, test_size=0.25)

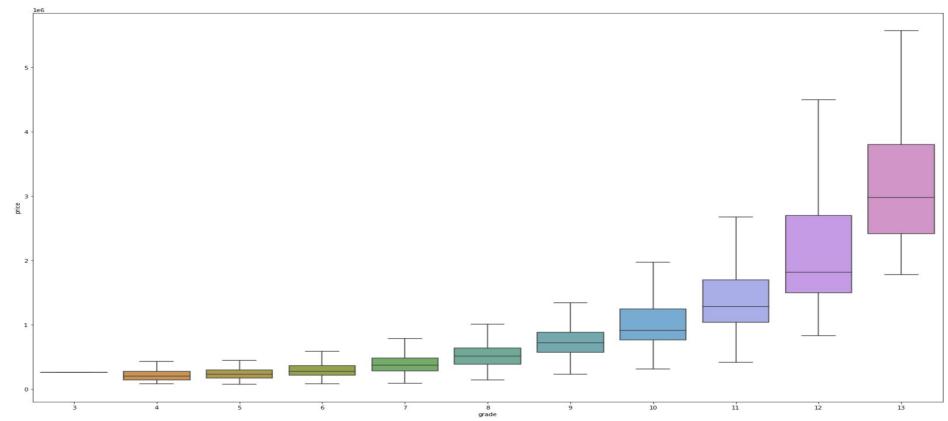
```
plt.xlabel("sqft_living")
plt.ylabel("price")
plt.show()

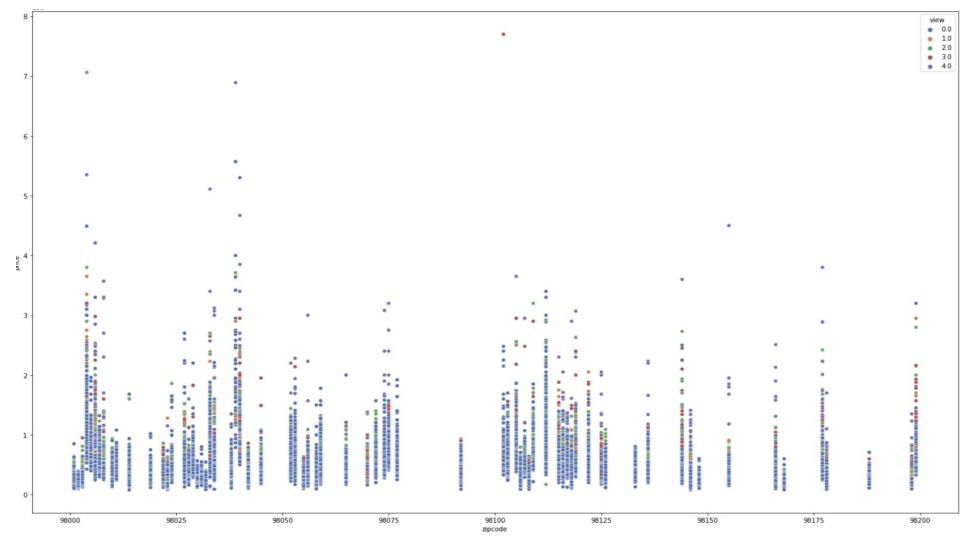
8
1e6
5
94
3
2
```

The second strongest correlation between independent and target varibale plots

```
fig, ax = plt.subplots(figsize=(25,15))
sns.boxplot(x='grade',y='price',data=df,showfliers=False, ax=ax)
```

<AxesSubplot:xlabel='grade', ylabel='price'>





df = df.he		t_dummies((df, column	rs=["zipcoo	de"])						
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	 zipcode_98146

2

4

3

1.0

3.0

2.0

770

1960

1680

180000.0

604000.0

510000.0

0 221900.0	3	1.0	1180	5650	1.0	0.0	0.0	3	7	0
1 538000.0	3	2.0	2570	7242	2.0	0.0	0.0	3	7	0

10000

5000

8080

1.0

1.0

1.0

0.0

0.0

0.0

0.0

0.0

0.0

3

5

3

6

8

7 ...

```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42, test_size=0.25)
model = LinearRegression()
```

```
#print("Intercept: " +str(model.intercept_))
#print("Coef: " +str(model.coef_))

print("R2_Score: " + str(model.score(X_test, y_test)))
```

```
R2_Score: 0.7674287742096019
```

```
from sklearn.metrics import mean_squared_error
import math
```

```
print("MSE: " + str(mean_squared_error(y_test, y_test_pred)))
print("RMSE: " + str(math.sqrt(mean_squared_error(y_test, y_test_pred))))
```

MSE: 31908704848.957275 RMSE: 178630.07823140334

model.fit(X train, y train)

df.head(4)

221900.0

y_test_pred[0]

117539.74891492724

•	538000.0	3	2.0	
2	180000.0	2	1.0	
3	604000.0	4	3.0	

price bedrooms

```
770
1960
```

1180

2570

1.0

1.0

bathrooms sqft_living sqft_lot floors waterfront view condition grade ... zipcode_98146

0.0

0.0

3

3

5

7 ...

7 ...

6

0

0

4 rows x 87 columns

5650

7242

10000

5000

y_test_pred = model.predict(X_test)

The difference amounts to 104360.00€

```
pf = PolynomialFeatures()
pf.fit(X_train)
X_train_transformed = pf.transform(X_train)
X test transformed = pf.transform(X test)
model = model.fit(X_train_transformed, y_train)
print(model.score(X test transformed, y test))
0.8616663800874034
y_test_pred = model.predict(X_test_transformed)
y test pred[0]
212651,70591182058
```

from sklearn.preprocessing import PolynomialFeatures

The difference amounts to 9248.00€