Real Estate House Predictions - Seattle, WA

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Clean data and interpret initial insights

We read our data into a dataframe

First, we will clean our data, that is, we will add missing data, make floats into integers, etc...

Then we'll look at which variables in our dataframe have the most correlation.

Next, we will visualize the data with the highest correlation and build a prediction model.

With this in place, we will further adjust our model to make better predictions.

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
```

```python
# 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

```python
# Delete columns not needed

df.drop(["id", "lat", "long", "sqft_basement"], axis=1, inplace=True)
```

```python
# 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)
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above
21587	507250.0	3	2.50	2270	5536	2.0	NaN	0.0	3	8	2270
21588	429000.0	3	2.00	1490	1126	3.0	0.0	0.0	3	8	1490
21589	610685.0	4	2.50	2520	6023	2.0	0.0	NaN	3	9	2520
21590	1010000.0	4	3.50	3510	7200	2.0	0.0	0.0	3	9	2600
21591	475000.0	3	2.50	1310	1294	2.0	0.0	0.0	3	8	1180
21592	360000.0	3	2.50	1530	1131	3.0	0.0	0.0	3	8	1530
21593	400000.0	4	2.50	2310	5813	2.0	0.0	0.0	3	8	2310
21594	402101.0	2	0.75	1020	1350	2.0	0.0	0.0	3	7	1020
21595	400000.0	3	2.50	1600	2388	2.0	NaN	0.0	3	8	1600
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  
---  ------         --------------  -----  
 0   price          21597 non-null  float64
 1   bedrooms       21597 non-null  int64  
 2   bathrooms      21597 non-null  float64
 3   sqft_living    21597 non-null  int64  
 4   sqft_lot       21597 non-null  int64  
 5   floors         21597 non-null  float64
 6   waterfront     19221 non-null  float64
 7   view           21534 non-null  float64
 8   condition      21597 non-null  int64  
 9   grade          21597 non-null  int64  
 10  sqft_above     21597 non-null  int64  
 11  yr_built       21597 non-null  int64  
 12  yr_renovated   17755 non-null  float64
 13  zipcode        21597 non-null  int64  
 14  sqft_living15  21597 non-null  int64  
 15  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
```

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

False

```python
# View data description and see if there are any outliers

df.describe()
```

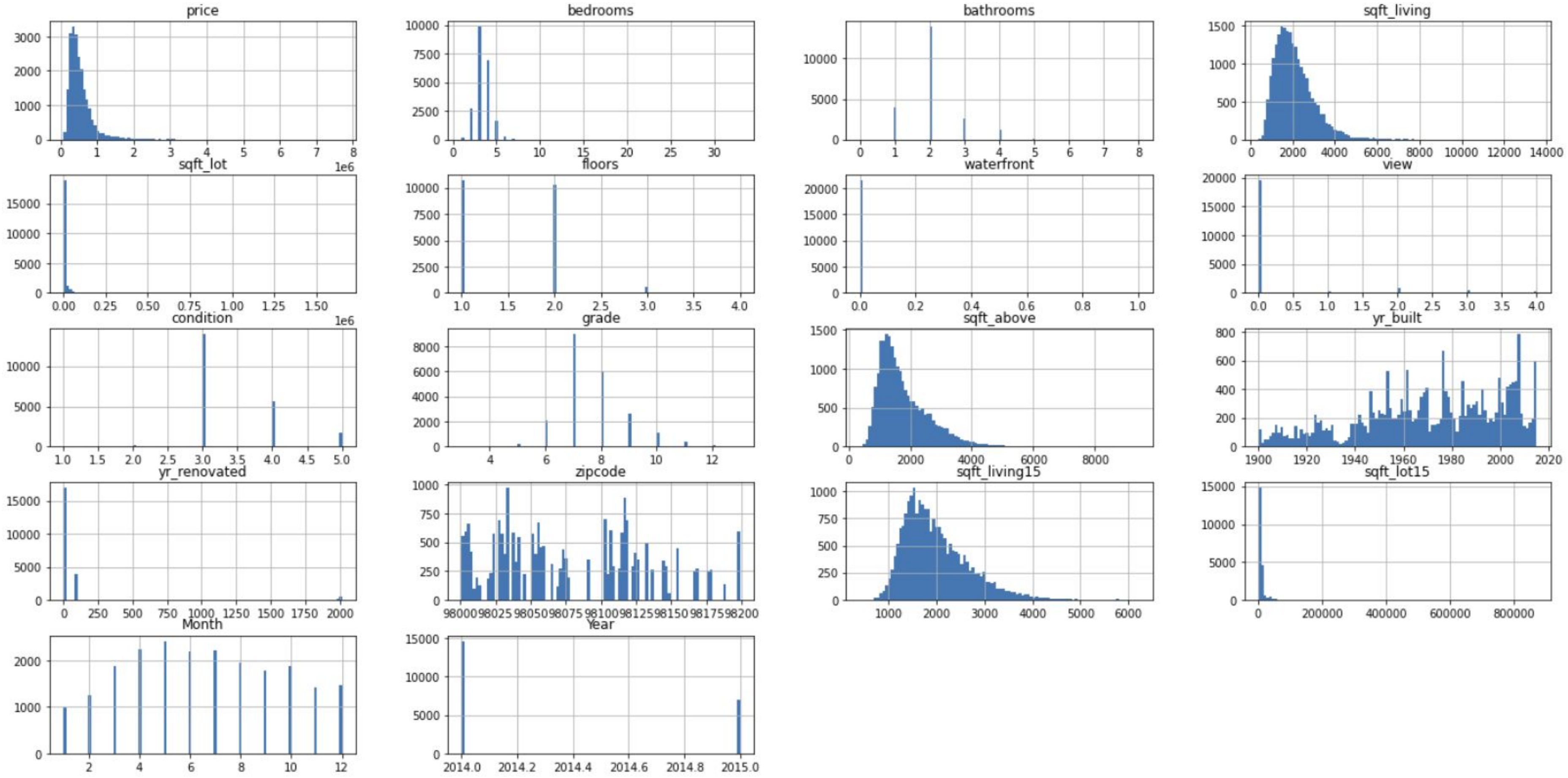
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
count	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	19221.000000	21534.000000
mean	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	0.007596	0.233863
std	3.673681e+05	0.926299	0.768984	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
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	1.000000	4.000000

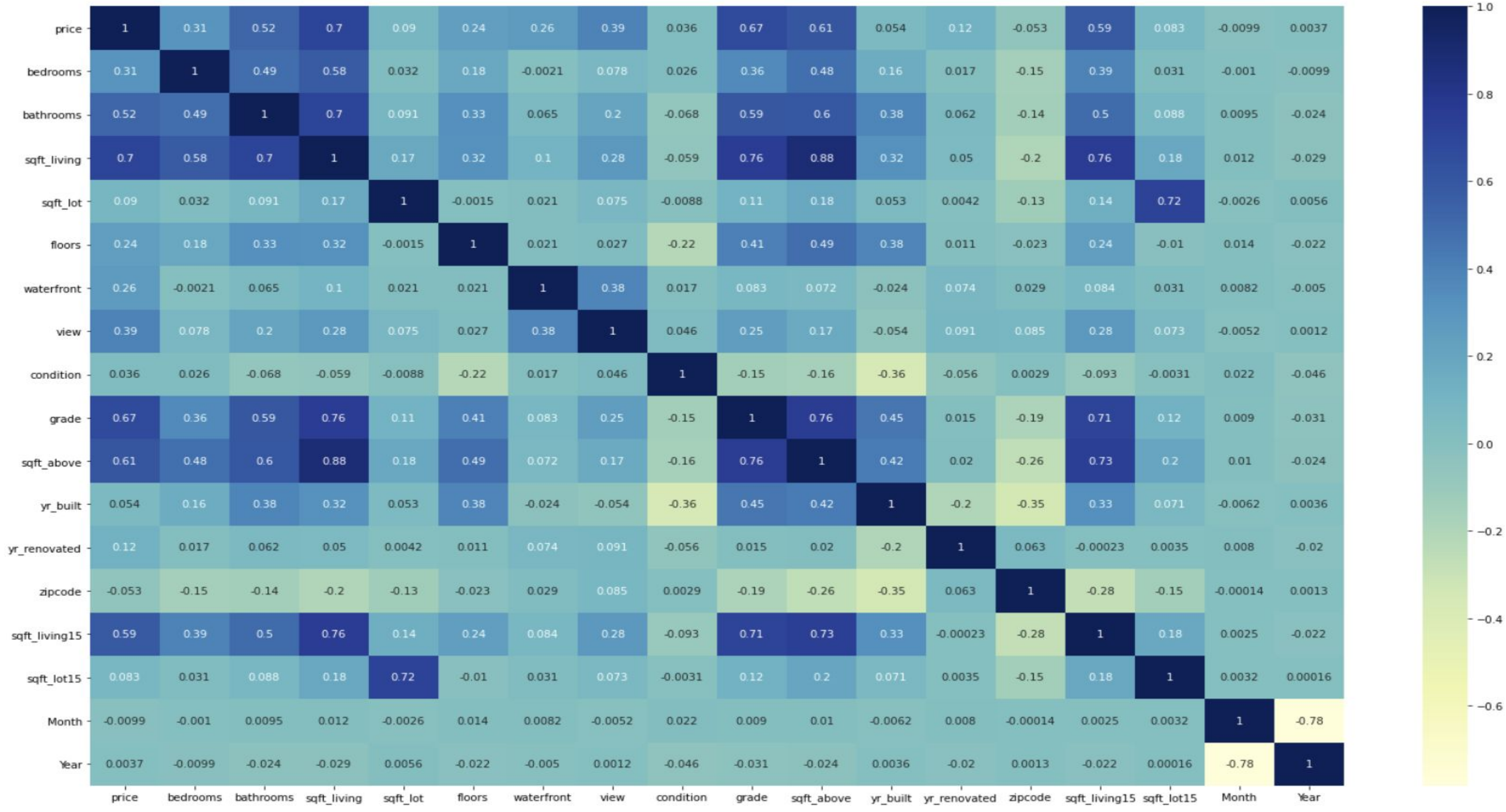
```python
# Replace the missing data, with the mean value

df['waterfront'].fillna((df['waterfront'].mean()), inplace=True)
df['yr_renovated'].fillna((df['yr_renovated'].mean()), inplace=True)
df['view'].fillna((df['view'].mean()), inplace=True)
df.dropna(inplace=True)
df.head()
```

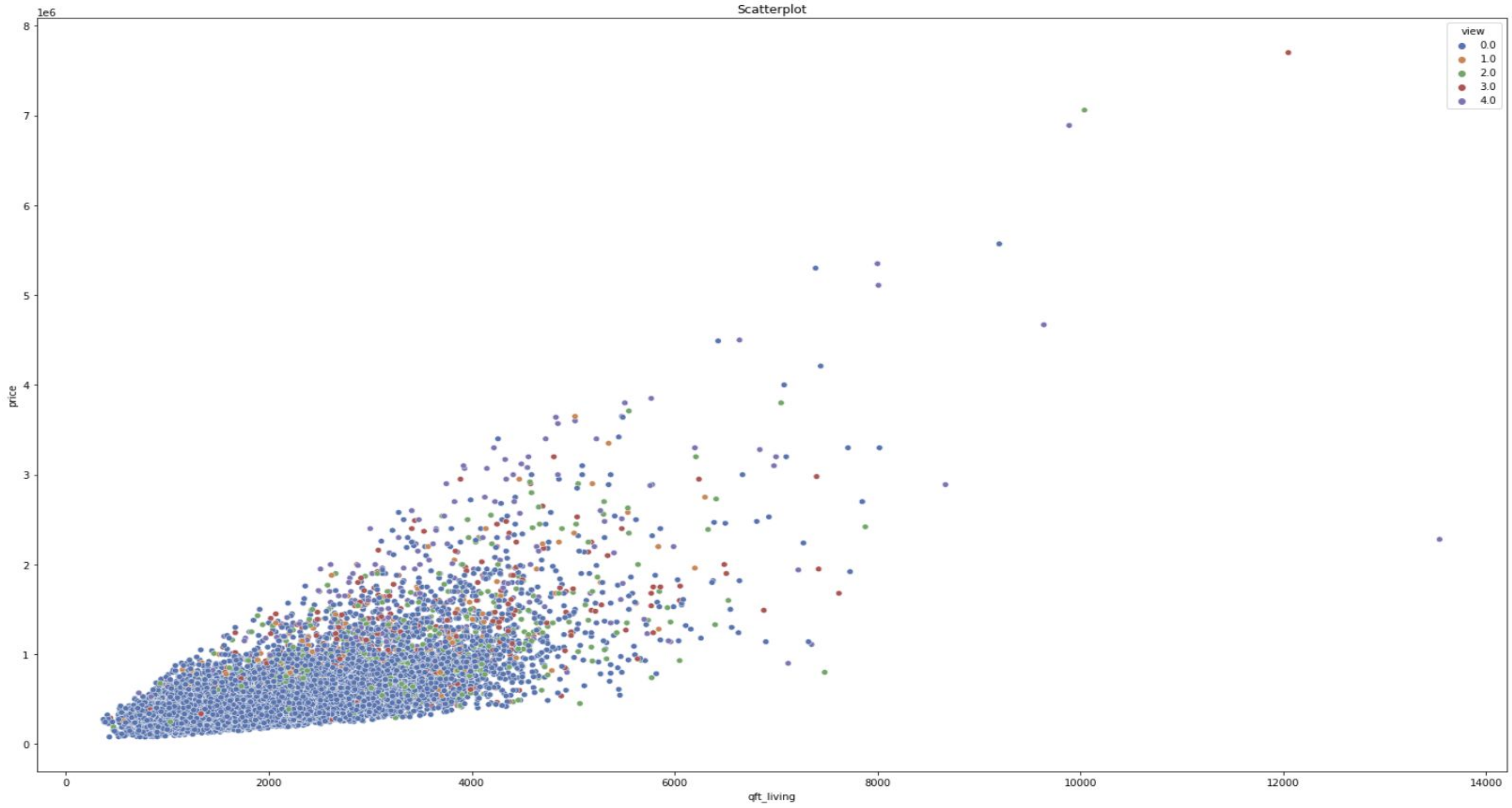
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	sqft_above	yr_built
0	221900.0	3	1.00	1180	5650	1.0	0.007596	0.0	3	7	1180	1955
1	538000.0	3	2.25	2570	7242	2.0	0.000000	0.0	3	7	2170	1951
2	180000.0	2	1.00	770	10000	1.0	0.000000	0.0	3	6	770	1933
3	604000.0	4	3.00	1960	5000	1.0	0.000000	0.0	5	7	1050	1965
4	510000.0	3	2.00	1680	8080	1.0	0.000000	0.0	3	8	1680	1987

```python
# Convert values to integer with float

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'])
df['view'] = np.round(df['view'])
df.head(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
1	538000.0	3	2.0	2570	7242	2.0	0.0	0.0	3	7	2170	1951
2	180000.0	2	1.0	770	10000	1.0	0.0	0.0	3	6	770	1933


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
1e6
1e6


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 0.31 1 0.49 0.58 0.032 0.18 -0.0021 0.078 0.026 0.36 0.48 0.16 0.017 -0.15 0.39 0.031 -0.001 -0.0099
bathrooms 0.52 0.49 1 0.7 0.091 0.33 0.065 0.2 -0.068 0.59 0.6 0.38 0.062 -0.14 0.5 0.088 0.0095 -0.024
sqft_living 0.7 0.58 0.7 1 0.17 0.32 0.1 0.28 -0.059 0.76 0.88 0.32 0.05 -0.2 0.76 0.18 0.012 -0.029
sqft_lot 0.09 0.032 0.091 0.17 1 -0.0015 0.021 0.075 -0.0088 0.11 0.18 0.053 0.0042 -0.13 0.14 0.72 -0.0026 0.0056
floors 0.24 0.18 0.33 0.32 -0.0015 1 0.021 0.027 -0.22 0.41 0.49 0.38 0.011 -0.023 0.24 -0.01 0.014 -0.022
waterfront 0.26 -0.0021 0.065 0.1 0.021 0.021 1 0.38 0.017 0.083 0.072 -0.024 0.074 0.029 0.084 0.031 0.0082 -0.005
view 0.39 0.078 0.2 0.28 0.075 0.027 0.38 1 0.046 0.25 0.17 -0.054 0.091 0.085 0.28 0.073 -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 0.36 0.59 0.76 0.11 0.41 0.083 0.25 -0.15 1 0.76 0.45 0.015 -0.19 0.71 0.12 0.009 -0.031
sqft_above 0.61 0.48 0.6 0.88 0.18 0.49 0.072 0.17 -0.16 0.76 1 0.42 0.02 -0.26 0.73 0.2 0.01 -0.024
yr_built 0.054 0.16 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 0.071 -0.0062 0.0036
yr_renovated 0.12 0.017 0.062 0.05 0.0042 0.011 0.074 0.091 -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 0.085 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 0.24 0.084 0.28 -0.093 0.71 0.73 0.33 -0.00023 -0.28 1 0.18 0.0025 -0.022
sqft_lot15 0.083 0.031 0.088 0.18 0.72 -0.01 0.031 0.073 -0.0031 0.12 0.2 0.071 0.0035 -0.15 0.18 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
1.0 0.8 0.6 0.4 0.2 0.0 −0.2 −0.4 −0.6


Scatterplot
1e6
price
qft_living
view
0.0
1.0
2.0
3.0
4.0
0
1
2
3
4
5
6
7
8
0
2000
4000
6000
8000
10000
12000
14000

price ~ sqft_living

OLS Regression Results

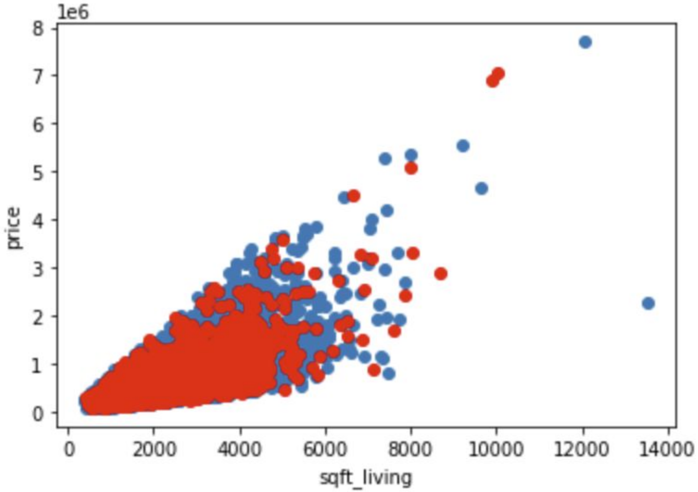
Dep. Variable:	price	**R-squared:**	0.493
Model:	OLS	**Adj. R-squared:**	0.493
Method:	Least Squares	**F-statistic:**	2.097e+04
Date:	Sun, 06 Jun 2021	**Prob (F-statistic):**	0.00
Time:	13:52:08	**Log-Likelihood:**	-3.0006e+05
No. Observations:	21597	**AIC:**	6.001e+05
Df Residuals:	21595	**BIC:**	6.001e+05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

Omnibus:	14801.942	**Durbin-Watson:**	1.982
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	542662.604
Skew:	2.820	**Prob(JB):**	0.00
Kurtosis:	26.901	**Cond. No.**	5.63e+03

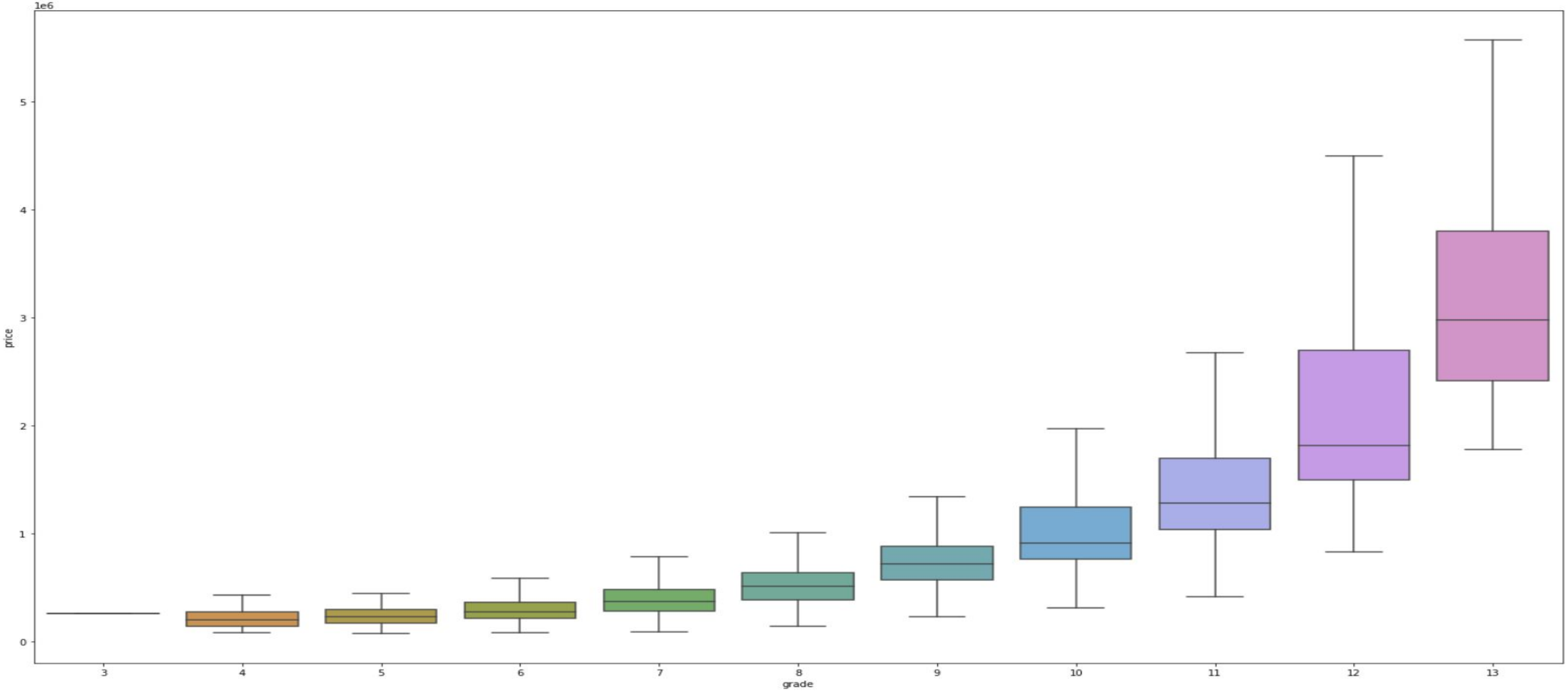
```
# We split our data into training and test data

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

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

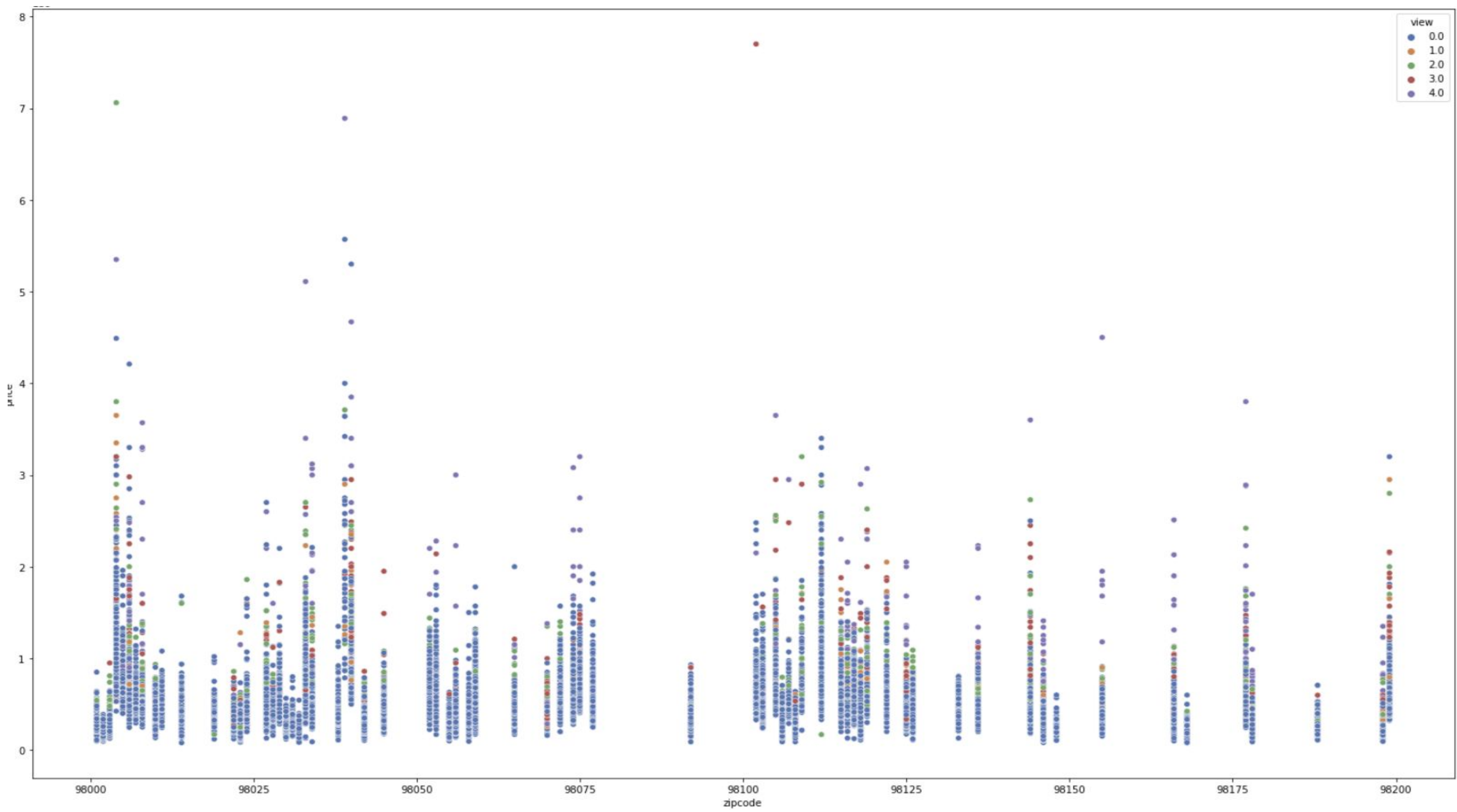
```
# How good is my prediction

plt.scatter(X_train, y_train)
plt.scatter(X_test, y_test, color="red")
plt.xlabel("sqft_living" )
plt.ylabel("price")
plt.show()
```



```python
# 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'>




view
0.0
1.0
2.0
3.0
4.0
price
zipcode
0
1
2
3
4
5
6
7
8
98000
98025
98050
98075
98100
98125
98150
98175
98200

What can we crystallize from our data.

Our null hypothesis, is not rejected.

However, we also see that our regression, with only one variable = Sqft_living, predicts very poorly.

On our heatmap, we see that the zipcode has a negative correlation, so we have it visualized again separately.

We recognize that our Zipcode is very meaningful, since we can see also over views and grade, how good the quality of life is and whether there were already many prospective customers, which is later elemantar for us, whether we invest in a house or not.

Let's separate the zipcode and include it to see if our prediction improves.

```
df = pd.get_dummies(df, columns=["zipcode"])
df.head()
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	...	zipcode_98146
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
2	180000.0	2	1.0	770	10000	1.0	0.0	0.0	3	6	...	0
3	604000.0	4	3.0	1960	5000	1.0	0.0	0.0	5	7	...	0
4	510000.0	3	2.0	1680	8080	1.0	0.0	0.0	3	8	...	0

Linear Regression & Train Test Split

Linear regression is a statistical model that studies a linear relationship between two or more variables. One of them is the dependent variable (also called explained) that we want to predict or classify. We also have at least one independent variable (also called explanatory).

Now we want to prepare the data for regression and then analyze it. First we want to split it into test and training data. For this we use the train_test_split() function of sklearn.model_selection, which returns a 4-tuple of arrays.

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

```python
model = LinearRegression()
model.fit(X_train, y_train)
#print("Intercept: " +str(model.intercept_))
#print("Coef: " +str(model.coef_))

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

```
R2_Score: 0.7674287742096019
```

```python
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
```

```
df.head(4)
```

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	...	zipcode_98146
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
2	180000.0	2	1.0	770	10000	1.0	0.0	0.0	3	6	...	0
3	604000.0	4	3.0	1960	5000	1.0	0.0	0.0	5	7	...	0

4 rows × 87 columns

```
y_test_pred = model.predict(X_test)
y_test_pred[0]
```

```
117539.74891492724
```

The difference amounts to 104360.00€

Polynomial Features

We can start improving our model by using polynomial expansions. The PolynomialFeatures class of sklearn generates a new matrix with polynomial combinations of our features.

The more variables we use in X, the higher our power(degrees of freedom).

The squared error for the test data is smaller when using polynomial expansions, which means our model gets better.

```python
from sklearn.preprocessing import PolynomialFeatures

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
```

```python
y_test_pred = model.predict(X_test_transformed)
y_test_pred[0]
```

```
212651.70591182058
```

The difference amounts to 9248.00€

```python
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold

scores = cross_val_score(LinearRegression(),X_train_transformed,y_train, cv = KFold(n_splits = 10))

print(scores)
```

```
[0.84564575 0.87702371 0.83930252 0.86351837 0.8606053  0.85888818
 0.84544622 0.87732796 0.86209637 0.80141217]
```

Summary

For our investors, Linear Regression, in this case is not accurate enough and very costly, because we can only improve it to the certain degree and we have to invest a lot of time to create the basic model.

In our particular case, a DecisionTreeRegressor would generate a significant added value.

```python
from sklearn.tree import DecisionTreeRegressor

model = DecisionTreeRegressor()
model.fit(X_train, y_train)
pred = model.predict(X_test)
score = model.score(X_train,y_train)



print(score)
```

```
0.9994304017663665
```

Thank you for your attention and have a nice day