LinearRegression

June 11, 2022

1 Simple Linear Regression

Our goal is create a model to predict the house pricing in King County; to do that, we'll use a dataset which contains house sale prices for King County (houses sold between May 2014 and May 2015) from: https://www.kaggle.com/datasets/harlfoxem/housesalesprediction

1.0.1 Import data set

[ ]:
```
import pandas as pd

dfHouses = pd.read_csv('../Fundamentals/data/kc_house_data.csv', sep=',')
```

1.0.2 Basic EDA and cleaning data

[ ]:
```
dfHouses.head()
```

[ ]:
```
           id             date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520  20141013T000000  221900.0         3       1.00         1180
1  6414100192  20141209T000000  538000.0         3       2.25         2570
2  5631500400  20150225T000000  180000.0         2       1.00          770
3  2487200875  20141209T000000  604000.0         4       3.00         1960
4  1954400510  20150218T000000  510000.0         3       2.00         1680

   sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement  \
0      5650     1.0           0     0  …      7      1180.0              0
1      7242     2.0           0     0  …      7      2170.0            400
2     10000     1.0           0     0  …      6       770.0              0
3      5000     1.0           0     0  …      7      1050.0            910
4      8080     1.0           0     0  …      8      1680.0              0

   yr_built  yr_renovated  zipcode      lat     long  sqft_living15  \
0      1955             0    98178  47.5112 -122.257           1340
1      1951          1991    98125  47.7210 -122.319           1690
2      1933             0    98028  47.7379 -122.233           2720
3      1965             0    98136  47.5208 -122.393           1360
```

```
4      1987             0     98074   47.6168 -122.045           1800

   sqft_lot15
0        5650
1        7639
2        8062
3        5000
4        7503

[5 rows x 21 columns]
```

[ ]:
```python
# Just use python variable replacement syntax to make the text dynamic.
from IPython.display import Markdown as md

md(f"The KC houses data set consists of {dfHouses.shape[1]} different␣
 ↪parameters for {dfHouses.shape[0]} samples.")
```

[ ]: The KC houses data set consists of 21 different parameters for 21613 samples.

Type data and memory usage

[ ]:
```python
dfHouses.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21613 non-null  int64
 1   date           21613 non-null  object
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64
 6   sqft_lot       21613 non-null  int64
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64
 9   view           21613 non-null  int64
 10  condition      21613 non-null  int64
 11  grade          21613 non-null  int64
 12  sqft_above     21611 non-null  float64
 13  sqft_basement  21613 non-null  int64
 14  yr_built       21613 non-null  int64
 15  yr_renovated   21613 non-null  int64
 16  zipcode        21613 non-null  int64
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64
```

```
 20  sqft_lot15     21613 non-null  int64
dtypes: float64(6), int64(14), object(1)
memory usage: 3.5+ MB
```

One object type and the rest of data is numerical.

Now we write down some notes about what the colums mean:

- id: self explanatory
- date: the date house was sold
- price: our target
- bedrooms: self explanatory
- bathrooms: self explanatory
- sqft_living: square footage of the home
- sqft_lot: square footage of the lot
- floors: Total levels in house
- waterfront: Does the house have waterfront?
- view: Has the house been viewed?
- condition: How good the condition is
- grade: overall grade given to the housing unit, based on King County grading system
- sqft_above: square footage of house apart from basement
- sqft_basement: square footage of the basement
- yr_built: self explanatory
- yr_renovated: self explanatory
- zipcode: self explanatory
- lat: Latitude
- long: Longitude
- sqft_living15: The square footage of interior housing living space for the nearest 15 neighbors
- sqft_lot15: The square footage of the land lots of the nearest 15 neighbors

The next step is searching for missing, NA and null values.

[ ]:
```
(dfHouses.isnull() | dfHouses.empty | dfHouses.isna()).sum()
```

[ ]:
```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       2
```

```
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

We've found missing data about sqft_above (fortunately only two NaN!). Let's see what they are and then replace them with mean.

[ ]:
```
dfHouses[dfHouses.isna().any(axis=1)]
```

[ ]:
```
            id             date     price  bedrooms  bathrooms  sqft_living  \
10  1736800520  20150403T000000  662500.0         3        2.5         3560
17  6865200140  20140529T000000  485000.0         4        1.0         1600

    sqft_lot  floors  waterfront  view  …  grade  sqft_above  sqft_basement  \
10      9796     1.0           0     0  …      8         NaN           1700
17      4300     1.5           0     0  …      7         NaN              0

    yr_built  yr_renovated  zipcode      lat     long  sqft_living15  \
10      1965             0    98007  47.6007 -122.145           2210
17      1916             0    98103  47.6648 -122.343           1610

    sqft_lot15
10        8925
17        4300

[2 rows x 21 columns]
```

[ ]:
```
dfHouses["sqft_above"] = dfHouses["sqft_above"].fillna(dfHouses["sqft_above"].
 ↪mean())
```

[ ]:
```
nr = dfHouses["sqft_above"].isna().sum()
print(f"Now we have {nr} missing values on sqft_above column!")
```

```
Now we have 0 missing values on sqft_above column!
```

Some other checks.

[ ]:
```
dfHouses.max()
```

[ ]:
```
id                    9900000190
date             20150527T000000
price                    7.7e+06
```

```
bedrooms                    33
bathrooms                    8
sqft_living              13540
sqft_lot               1651359
floors                     3.5
waterfront                   1
view                         4
condition                    5
grade                       13
sqft_above                9410
sqft_basement             4820
yr_built                  2015
yr_renovated              2015
zipcode                  98199
lat                    47.7776
long                  -121.315
sqft_living15             6210
sqft_lot15              871200
dtype: object
```

We notice that: - date has ISO 8601 format; - price has a scientific notation "7.7e+06".

It would be convenient reformat date in pandas datetime object and price in float format.

[ ]:
```
dfHouses['date'] = pd.to_datetime(dfHouses['date'],infer_datetime_format=True)
# about all numeric values (price included)
pd.options.display.float_format = '{:.2f}'.format
```

A quick check on date format...

[ ]:
```
pr = dfHouses["date"].max()
print(f"Now 20150527T000000 has become {pr}")
```

```
Now 20150527T000000 has become 2015-05-27 00:00:00
```

... and price format.

[ ]:
```
pr = dfHouses["price"].max()
print(f"Now 7.7e+06 has become {pr}")
```

```
Now 7.7e+06 has become 7700000.0
```

At this point we can elaborate some descriptions of the data.

[ ]:
```
dfHouses.sort_index(axis=1, ascending=True).describe().T
```

[ ]:

	count	mean	std	min	25% \
bathrooms	21613.00	2.11	0.77	0.00	1.75

bedrooms	21613.00	3.37	0.93	0.00	3.00
condition	21613.00	3.41	0.65	1.00	3.00
floors	21613.00	1.49	0.54	1.00	1.00
grade	21613.00	7.66	1.18	1.00	7.00
id	21613.00	4580301520.86	2876565571.31	1000102.00	2123049194.00
lat	21613.00	47.56	0.14	47.16	47.47
long	21613.00	-122.21	0.14	-122.52	-122.33
price	21613.00	540088.14	367127.20	75000.00	321950.00
sqft_above	21613.00	1788.40	828.09	290.00	1190.00
sqft_basement	21613.00	291.51	442.58	0.00	0.00
sqft_living	21613.00	2079.90	918.44	290.00	1427.00
sqft_living15	21613.00	1986.55	685.39	399.00	1490.00
sqft_lot	21613.00	15106.97	41420.51	520.00	5040.00
sqft_lot15	21613.00	12768.46	27304.18	651.00	5100.00
view	21613.00	0.23	0.77	0.00	0.00
waterfront	21613.00	0.01	0.09	0.00	0.00
yr_built	21613.00	1971.01	29.37	1900.00	1951.00
yr_renovated	21613.00	84.40	401.68	0.00	0.00
zipcode	21613.00	98077.94	53.51	98001.00	98033.00

	50%	75%	max
bathrooms	2.25	2.50	8.00
bedrooms	3.00	4.00	33.00
condition	3.00	4.00	5.00
floors	1.50	2.00	3.50
grade	7.00	8.00	13.00
id	3904930410.00	7308900445.00	9900000190.00
lat	47.57	47.68	47.78
long	-122.23	-122.12	-121.31
price	450000.00	645000.00	7700000.00
sqft_above	1560.00	2210.00	9410.00
sqft_basement	0.00	560.00	4820.00
sqft_living	1910.00	2550.00	13540.00
sqft_living15	1840.00	2360.00	6210.00
sqft_lot	7618.00	10688.00	1651359.00
sqft_lot15	7620.00	10083.00	871200.00
view	0.00	0.00	4.00
waterfront	0.00	0.00	1.00
yr_built	1975.00	1997.00	2015.00
yr_renovated	0.00	0.00	2015.00
zipcode	98065.00	98118.00	98199.00

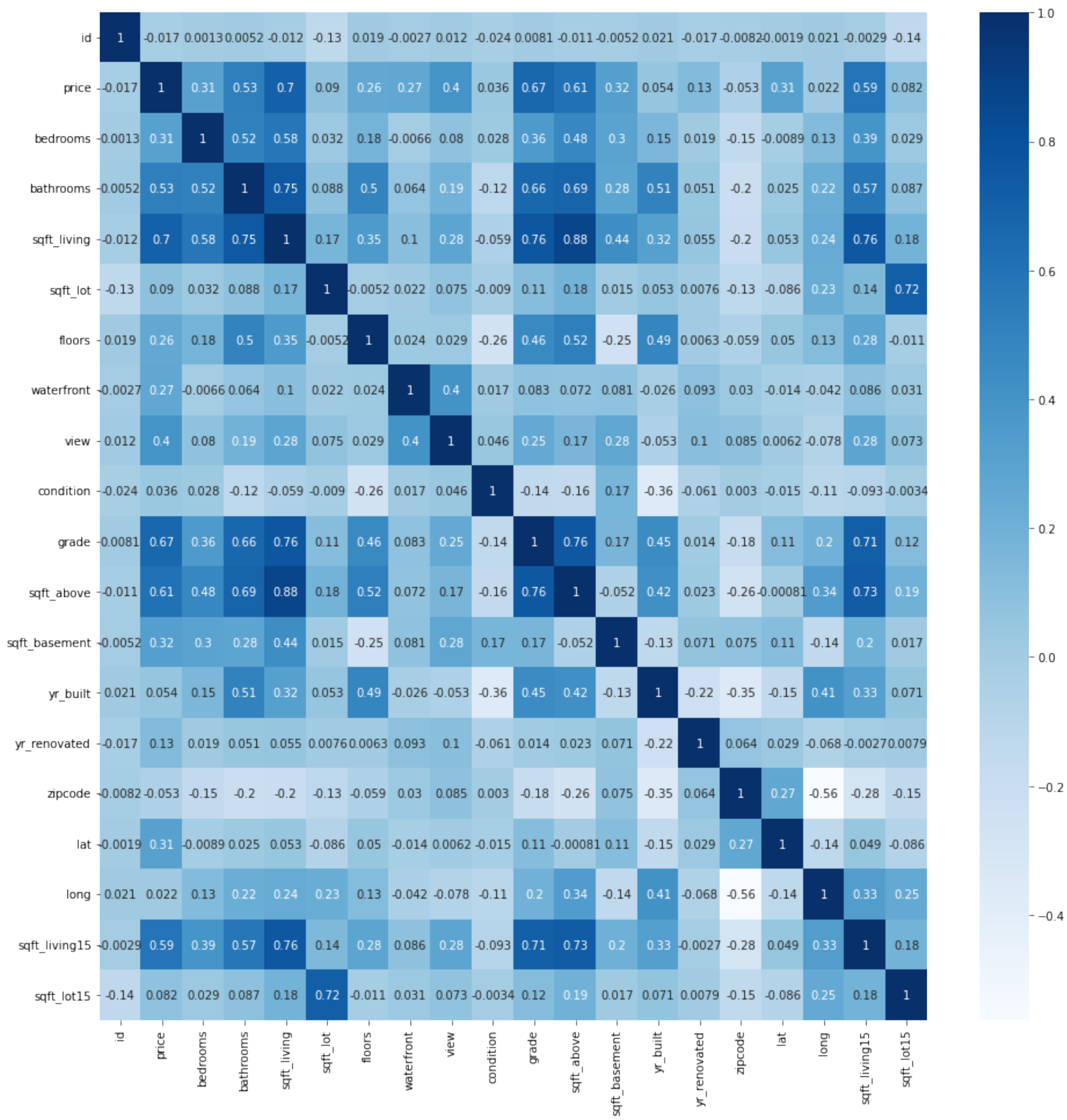
1.0.3 Checking the correlation between attributes

[ ]:
```
dfHouses["price"].describe()
```

[ ]:
```
count      21613.00
mean      540088.14
std       367127.20
min        75000.00
25%       321950.00
50%       450000.00
75%       645000.00
max      7700000.00
Name: price, dtype: float64
```

[ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

corrMatrix = dfHouses.corr(method='pearson')
plt.figure(figsize=(16, 16))
sns.heatmap(corrMatrix, cmap="Blues", annot=True)
plt.show()
```



So many numbers! But we're interested on large correlation numbers; and for "large" we mean greater than or equal to 0.75.

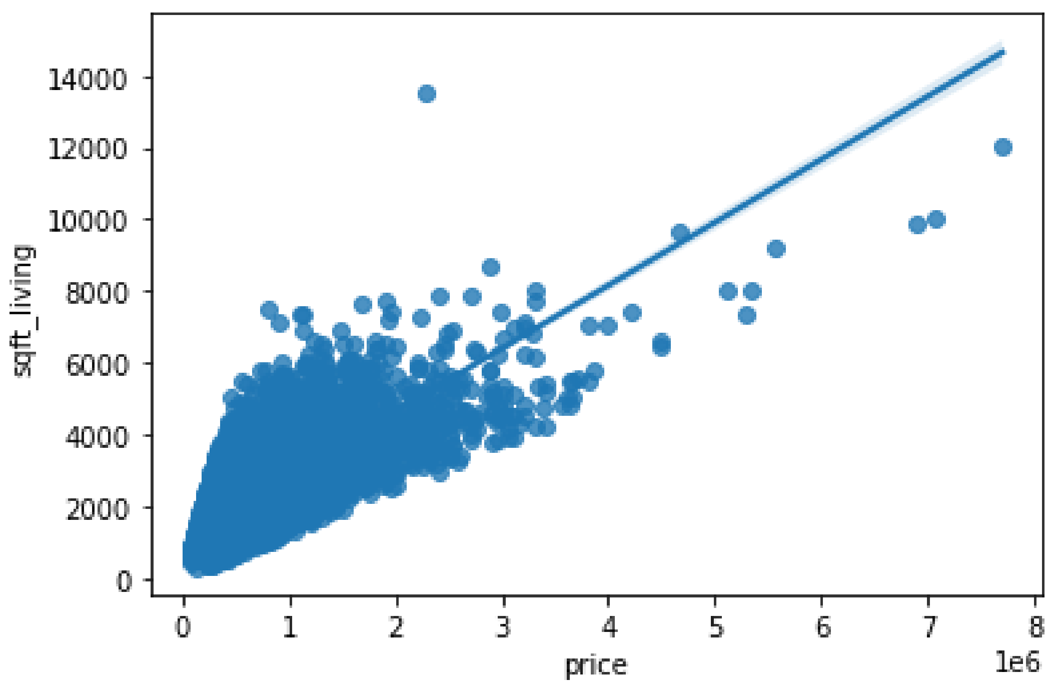
[ ]:
```
s = corrMatrix.unstack()
so = s.where((s >= 0.75) & (s < 1)).dropna().sort_values(kind="quicksort",␣
↪ascending=False)
so
```

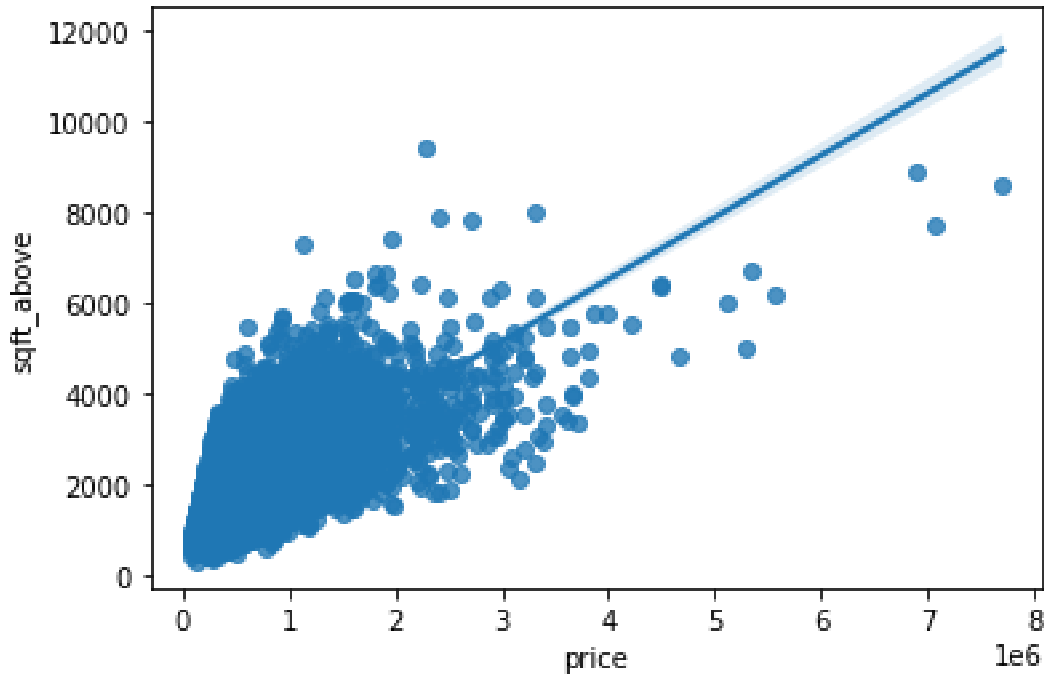
[ ]:
```
sqft_above     sqft_living     0.88
sqft_living    sqft_above      0.88
grade          sqft_living     0.76
sqft_living    grade           0.76
```

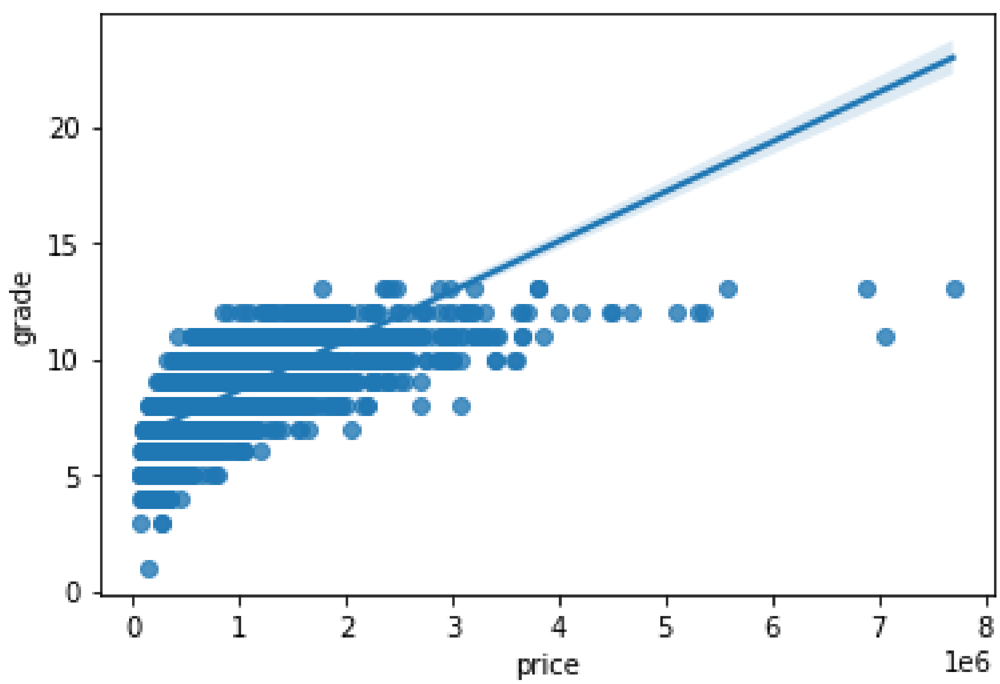
```
sqft_living15  sqft_living     0.76
sqft_living    sqft_living15   0.76
sqft_above     grade           0.76
grade          sqft_above      0.76
sqft_living    bathrooms       0.75
bathrooms      sqft_living     0.75
dtype: float64
```

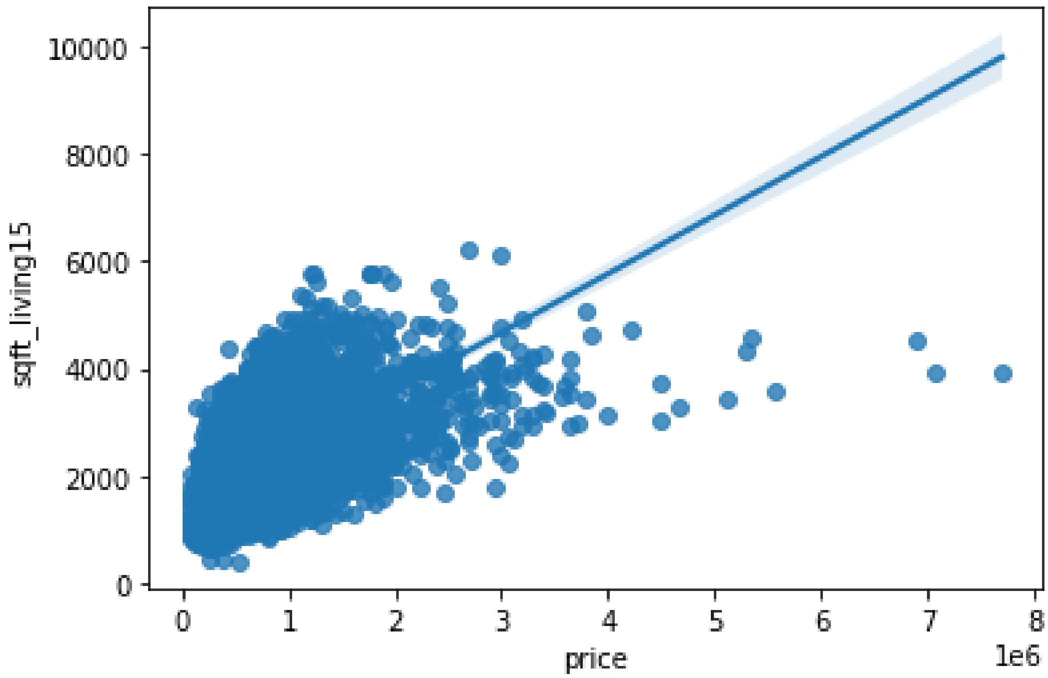
OK, but what happens between them and the price?

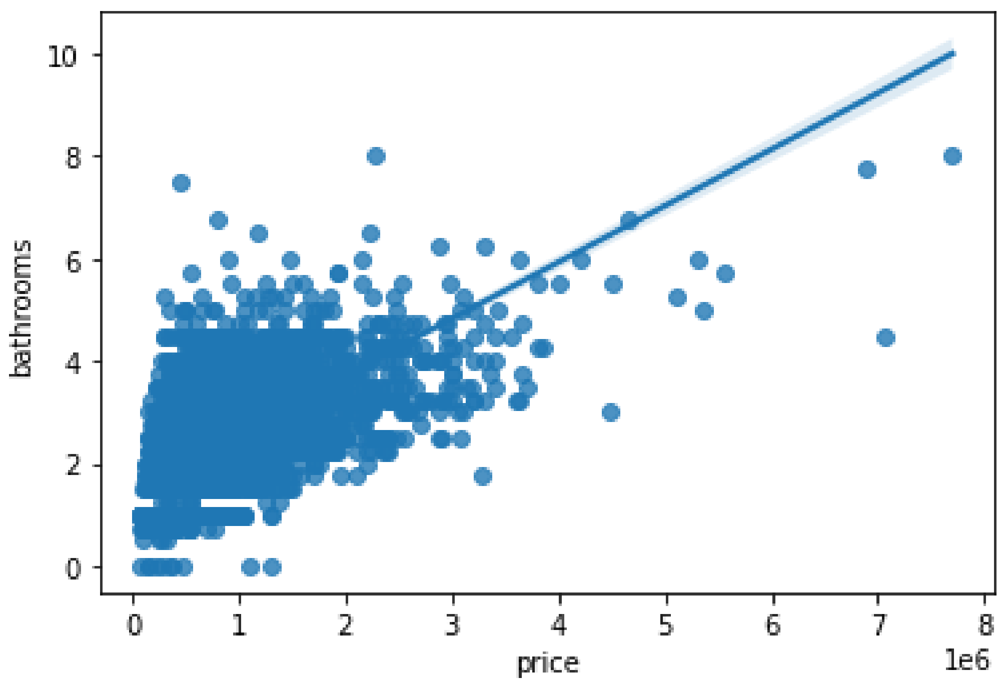
[ ]:
```
cols_names = ["sqft_living", "sqft_above", "grade", "sqft_living15",␣
↪"bathrooms"]
for name in cols_names:
    sns.regplot(x=dfHouses["price"], y=dfHouses[name])
    plt.show()
```




sqft_above
12000
10000
8000
6000
4000
2000
0
0
1
2
3
4
5
6
7
8
price
1e6


grade
20
15
10
5
0
0
1
2
3
4
5
6
7
8
price
1e6


10000
8000
6000
4000
2000
0
sqft_living15
0
1
2
3
4
5
6
7
8
price
1e6


10
8
6
4
2
0
bathrooms
0
1
2
3
4
5
6
7
8
price
1e6

1.0.4 Train and test the model

Split data in train and test parts.

[ ]:
```
dfHouses['date'] = dfHouses['date'].apply(lambda x: x.toordinal())
```

[ ]:
```
from sklearn.model_selection import train_test_split

X = dfHouses.drop('price', axis=1)
y = dfHouses['price']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

[ ]:
```
from sklearn.linear_model import LinearRegression

model = LinearRegression()

model.fit(X_train, y_train)
y_predict = model.predict(X_test)

scoreTrain = model.score(X_train, y_train)
scoreTest = model.score(X_test, y_test)

print(f"Train accuracy {round(scoreTrain * 100,0)} %")
print(f"Test accuracy {round(scoreTest* 100,0)} %")
```

```
Train accuracy 70.0 %
Test accuracy 71.0 %
```

We can improve the model performance by using the "Polynomial Features", that are a type of feature engineering where we raise existing features to an exponent in order to increases the capacity/complexity of the model. The ``degree'' of the polynnnomial is used to control the number of features added: ex. 3 --> add two new variables for each input variable (typically a small degree is used such as 2 or 3 because of greater values also increases complexity).

[ ]:
```
from sklearn.preprocessing import PolynomialFeatures

degree = 2
poly = PolynomialFeatures(degree, include_bias=False)

X_poly = poly.fit_transform(X)
y_poly = y

X_train_poly, X_test_poly, y_train_poly, y_test_poly = train_test_split(X_poly,␣
↪y_poly, random_state=12)

model_poly = LinearRegression()
```

```python
model_poly.fit(X_train_poly, y_train_poly)
y_predict_poly = model_poly.predict(X_test_poly)

score_poly_Train = model_poly.score(X_train_poly, y_train_poly)
score_poly_Test = model_poly.score(X_test_poly, y_test_poly)


print(f"Train accuracy {round(score_poly_Train * 100,0)} %")
print(f"Test accuracy {round(score_poly_Test * 100,0)} %")
```

```
Train accuracy 75.0 %
Test accuracy 77.0 %
```

[ ]:
```python
y_test_poly
```

[ ]:
```
array([ 286437.84287802,  150217.67921718,  300618.8644215 , …,
       1613285.47693206,  629127.25004601,  292144.97319891])
```

[ ]:
```python
y_test_poly[0]
```

[ ]:
```
221900.0
```

[ ]:
```python
sublesson = pd.DataFrame()
sublesson["id"] = y_test_poly.index
sublesson["price"] = y_predict_poly
sublesson
```

[ ]:
```
         id      price
0      2019  286437.84
1      3435  150217.68
2     15940  300618.86
3      9811  689280.69
4     18665  447547.50
…       …          …
5399  17756 1444787.70
5400  15053  258028.88
5401  17838 1613285.48
5402  12691  629127.25
5403   1800  292144.97

[5404 rows x 2 columns]
```