# Data Analysis with Python: House Sales in King County, USA

October 6, 2022

**Stephane DEDIEU, August 2022.** Final Assignment for "IBM Course - Data Analysis with Python", May 2nd, 2022. This project is part of IBM Data Science certificate. We reviewed it and improved it in August 2022.

Link of interest: https://www.opendoor.com/w/blog/factors-that-influence-home-value

# 1 Introduction

## 1.1 Business Case

The project consists of finding the best model for predicting home prices in a county: King County, USA in Washington state, based on a dataset of homes sold between May 2014 and May 2015, including prices and a set of factors. Based on the literature*, eight critical factors influence a home's value.

1. Neighborhood comps: Recency, Feature Similarity, Distance,
2. Location: quality of local schools, employment opportunities, proximity to shopping, entertainment, and recreational centers
3. Home size and usable space
4. Age and condition
5. Upgrades and updates
6. The local market
7. Economic indicators
8. Interest rates

The dataset available, covers most critical factors except "economic ones" 7 and 8. The local market can somewhat be deduced from an early analysis. First we analyze and visualize the data. Second we develop a model with several ML predictive methods.

*Reference: https://www.opendoor.com/w/blog/factors-that-influence-home-value

Business understanding Analytic Approach Data Requirements Data Collection Data Understanding and Preparation Modeling and Evaluation

1. Data collection from open Data base.
2. Data wrangling.
3. Exploratory data analysis.
4. Visual analytics with Folium.
5. Regression Models development and validations. Selection of best predictive model.

## 1.2 Dataset: House Sales in King County, USA

This dataset contains house sale prices for King County, which includes Seattle. It includes homes sold between May 2014 and May 2015.

[112]:
```
from IPython import display
from PIL import Image

image = Image.open('House_features_Table1.png')
#print(f"Original size : {image.size}") # 5464x3640

img_resized = image.resize((700, 600))
img_resized.save('House_features_Table1.png')
display.Image('House_features_Table1.png')
```

[112]:

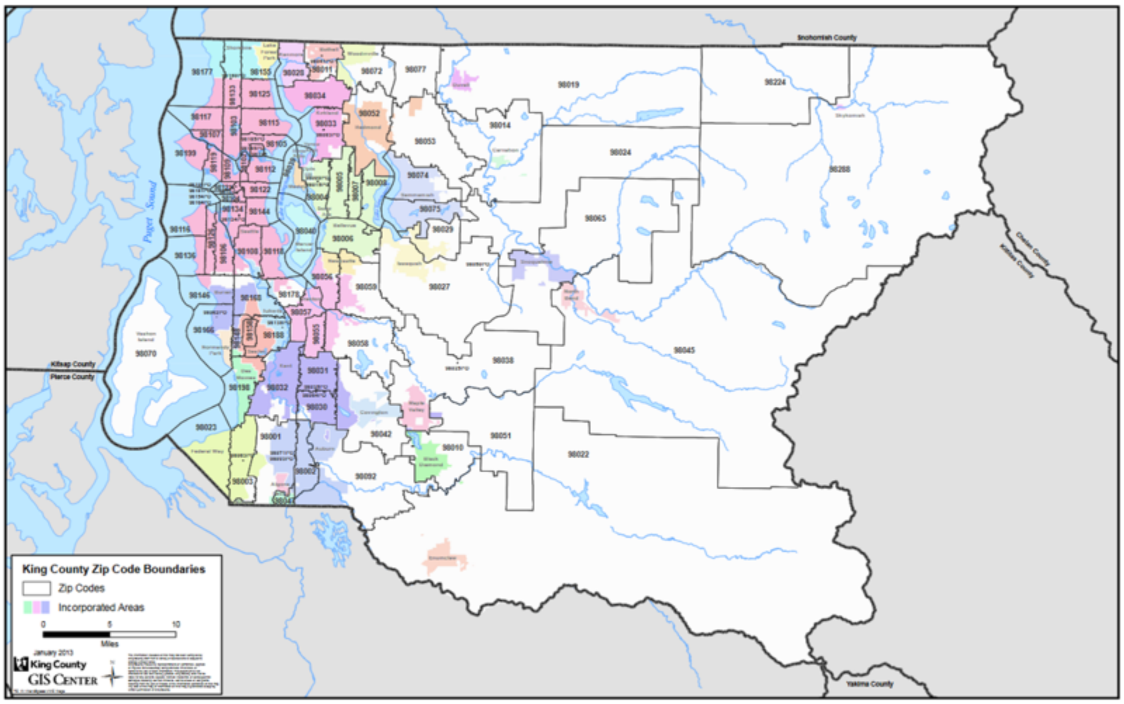
| Variable | Description |
|---|---|
| id | A notation for a house |
| date | Date house was sold |
| price | Price is prediction target |
| bedrooms | Number of bedrooms |
| bathrooms | Number of bathrooms |
| sqft_living | Square footage of the home |
| sqft_lot | Square footage of the lot |
| floors | Total floors (levels) in house |
| waterfront | House which has a view to a waterfront |
| view | Has been viewed |
| condition | How good the condition is overall |
| 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 | Built Year |
| yr_renovated | Year when house was renovated |
| zipcode | Zip code |
| lat | Latitude coordinate |
| long | Longitude coordinate |
| sqft_living15 | Living room area in 2015(implies-- some renovations) This might or might not have affected the lotsize area |
| sqft_lot15 | LotSize area in 2015(implies-- some renovations) |

### 1.3 King County, USA

[60]:
```python
image = Image.open('Zip_codes_KingCounty_64.png')
print(f"Original size : {image.size}") # 5464x3640
img_resized = image.resize((800, 500))
img_resized.save('Zip_codes_KingCounty_64.png')
display.Image('Zip_codes_KingCounty_64.png')
```

```
Original size : (800, 500)
```

[60]:




King county is made up of Seattle and its suburbs to the west and rural areas to the east, boarded by the Columbia river. The Zip code is expected to have an influence on house prices. Since latitude and longitude are part of the data, and may bring additional information about home's prices v. location, we will implement interactive maps with Folium.

### 1.4 Required libraries

[34]:
```python
from IPython.display import display, HTML
display(HTML("<style>.container { width:90% !important; }</style>"))

#-------  For centering figures
from IPython.core.display import HTML
HTML("""
<style>
.output_png {
```

```
    display: table-cell;
    text-align: center;
    vertical-align: middle;
}
</style>
""")
```

```
<IPython.core.display.HTML object>
```

[34]:
```
<IPython.core.display.HTML object>
```

[61]:
```
!pip install webdriver-manager
```

```
Requirement already satisfied: webdriver-manager in
c:\users\stefo\anaconda3\lib\site-packages (3.8.3)
Requirement already satisfied: python-dotenv in
c:\users\stefo\anaconda3\lib\site-packages (from webdriver-manager) (0.21.0)
Requirement already satisfied: requests in c:\users\stefo\anaconda3\lib\site-
packages (from webdriver-manager) (2.28.1)
Requirement already satisfied: tqdm in c:\users\stefo\anaconda3\lib\site-
packages (from webdriver-manager) (4.62.3)
Requirement already satisfied: charset-normalizer<3,>=2 in
c:\users\stefo\anaconda3\lib\site-packages (from requests->webdriver-manager)
(2.0.4)
Requirement already satisfied: certifi>=2017.4.17 in
c:\users\stefo\anaconda3\lib\site-packages (from requests->webdriver-manager)
(2022.6.15)
Requirement already satisfied: idna<4,>=2.5 in
c:\users\stefo\anaconda3\lib\site-packages (from requests->webdriver-manager)
(3.2)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
c:\users\stefo\anaconda3\lib\site-packages (from requests->webdriver-manager)
(1.26.7)
Requirement already satisfied: colorama in c:\users\stefo\anaconda3\lib\site-
packages (from tqdm->webdriver-manager) (0.4.4)
```

[62]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

import folium
from folium import plugins
from folium.plugins import HeatMap
from folium.plugins import MarkerCluster
```

[63]:
```
import seaborn as sns
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, PolynomialFeatures,␣
↪SplineTransformer
from sklearn.linear_model import LinearRegression

from sklearn.linear_model import Ridge
from sklearn.pipeline import make_pipeline
```

[64]:
```
import io
from PIL import Image
#!pip install selenium
```

[65]:
```
from selenium import webdriver
import os
import time
```

from webdriver_manager.firefox import GeckoDriverManager # Code 2 driver = webdriver.Firefox(executable_path=GeckoDriverManager().install()) # Code 3

from selenium import webdriver from webdriver_manager.firefox import GeckoDriverManager

driver = webdriver.Firefox(executable_path=GeckoDriverManager().install())

driver.get("http://www.python.org")

driver.close()

## 2 Importing Data Sets

Load the csv file:

[66]:
```
file_name='https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/
↪IBMDeveloperSkillsNetwork-DA0101EN-SkillsNetwork/labs/FinalModule_Coursera/
↪data/kc_house_data_NaN.csv'
df=pd.read_csv(file_name)
```

[67]:
```
df.head()
```

[67]:
```
   Unnamed: 0          id             date     price  bedrooms  bathrooms  \
0           0  7129300520  20141013T000000  221900.0       3.0       1.00
1           1  6414100192  20141209T000000  538000.0       3.0       2.25
2           2  5631500400  20150225T000000  180000.0       2.0       1.00
3           3  2487200875  20141209T000000  604000.0       4.0       3.00
4           4  1954400510  20150218T000000  510000.0       3.0       2.00

   sqft_living  sqft_lot  floors  waterfront  …  grade  sqft_above  \
0         1180      5650     1.0           0  …      7        1180
1         2570      7242     2.0           0  …      7        2170
2          770     10000     1.0           0  …      6         770
3         1960      5000     1.0           0  …      7        1050
4         1680      8080     1.0           0  …      8        1680

   sqft_basement  yr_built  yr_renovated  zipcode      lat     long  \
0              0      1955             0    98178  47.5112 -122.257
1            400      1951          1991    98125  47.7210 -122.319
2              0      1933             0    98028  47.7379 -122.233
3            910      1965             0    98136  47.5208 -122.393
4              0      1987             0    98074  47.6168 -122.045
```

```
   sqft_living15  sqft_lot15
0           1340        5650
1           1690        7639
2           2720        8062
3           1360        5000
4           1800        7503

[5 rows x 22 columns]
```

### 2.0.1 Data types

Display the data types of each column using the function dtypes, then take a screenshot and submit it, include your code in the image.

[68]:
```
df.dtypes
```

[68]:
```
Unnamed: 0         int64
id                 int64
date              object
price            float64
bedrooms         float64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

We use the method "describe" to obtain a statistical summary of the dataframe.

[69]:
```
df.describe()
```

[69]:
```
        Unnamed: 0            id         price      bedrooms     bathrooms  \
count  21613.00000  2.161300e+04  2.161300e+04  21600.000000  21603.000000
mean   10806.00000  4.580302e+09  5.400881e+05      3.372870      2.115736
std     6239.28002  2.876566e+09  3.671272e+05      0.926657      0.768996
min        0.00000  1.000102e+06  7.500000e+04      1.000000      0.500000
25%     5403.00000  2.123049e+09  3.219500e+05      3.000000      1.750000
50%    10806.00000  3.904930e+09  4.500000e+05      3.000000      2.250000
75%    16209.00000  7.308900e+09  6.450000e+05      4.000000      2.500000
max    21612.00000  9.900000e+09  7.700000e+06     33.000000      8.000000

        sqft_living      sqft_lot        floors    waterfront          view  \
count  21613.000000  2.161300e+04  21613.000000  21613.000000  21613.000000
mean    2079.899736  1.510697e+04      1.494309      0.007542      0.234303
std      918.440897  4.142051e+04      0.539989      0.086517      0.766318
min      290.000000  5.200000e+02      1.000000      0.000000      0.000000
25%     1427.000000  5.040000e+03      1.000000      0.000000      0.000000
50%     1910.000000  7.618000e+03      1.500000      0.000000      0.000000
75%     2550.000000  1.068800e+04      2.000000      0.000000      0.000000
max    13540.000000  1.651359e+06      3.500000      1.000000      4.000000

       …          grade    sqft_above  sqft_basement      yr_built  \
count  …   21613.000000  21613.000000   21613.000000  21613.000000
```

```
mean    ...    7.656873   1788.390691     291.509045   1971.005136
std     ...    1.175459    828.090978     442.575043     29.373411
min     ...    1.000000    290.000000       0.000000   1900.000000
25%     ...    7.000000   1190.000000       0.000000   1951.000000
50%     ...    7.000000   1560.000000       0.000000   1975.000000
75%     ...    8.000000   2210.000000     560.000000   1997.000000
max     ...   13.000000   9410.000000    4820.000000   2015.000000

       yr_renovated       zipcode           lat          long  sqft_living15  \
count  21613.000000  21613.000000  21613.000000  21613.000000   21613.000000
mean      84.402258  98077.939805     47.560053   -122.213896    1986.552492
std      401.679240     53.505026      0.138564      0.140828     685.391304
min        0.000000  98001.000000     47.155900   -122.519000     399.000000
25%        0.000000  98033.000000     47.471000   -122.328000    1490.000000
50%        0.000000  98065.000000     47.571800   -122.230000    1840.000000
75%        0.000000  98118.000000     47.678000   -122.125000    2360.000000
max     2015.000000  98199.000000     47.777600   -121.315000    6210.000000

          sqft_lot15
count   21613.000000
mean    12768.455652
std     27304.179631
min       651.000000
25%      5100.000000
50%      7620.000000
75%     10083.000000
max    871200.000000

[8 rows x 21 columns]
```

# 3 Data Wrangling

### 3.0.1 Cleaning the dataframe

Drop the columns "id" and "Unnamed: 0" from axis 1 using the method drop(), then use the method describe() to obtain a statistical summary of the data. Take a screenshot and submit it, make sure the inplace parameter is set to True

[70]:
```
df.drop(['id', 'Unnamed: 0'], axis=1, inplace=True)
df.head()
df.describe()
```

[70]:
```
              price      bedrooms     bathrooms   sqft_living      sqft_lot  \
count  2.161300e+04  21600.000000  21603.000000  21613.000000  2.161300e+04
mean   5.400881e+05      3.372870      2.115736   2079.899736  1.510697e+04
std    3.671272e+05      0.926657      0.768996    918.440897  4.142051e+04
min    7.500000e+04      1.000000      0.500000    290.000000  5.200000e+02
25%    3.219500e+05      3.000000      1.750000   1427.000000  5.040000e+03
50%    4.500000e+05      3.000000      2.250000   1910.000000  7.618000e+03
75%    6.450000e+05      4.000000      2.500000   2550.000000  1.068800e+04
max    7.700000e+06     33.000000      8.000000  13540.000000  1.651359e+06

             floors    waterfront          view     condition         grade  \
count  21613.000000  21613.000000  21613.000000  21613.000000  21613.000000
mean       1.494309      0.007542      0.234303      3.409430      7.656873
std        0.539989      0.086517      0.766318      0.650743      1.175459
min        1.000000      0.000000      0.000000      1.000000      1.000000
25%        1.000000      0.000000      0.000000      3.000000      7.000000
50%        1.500000      0.000000      0.000000      3.000000      7.000000
75%        2.000000      0.000000      0.000000      4.000000      8.000000
max        3.500000      1.000000      4.000000      5.000000     13.000000

         sqft_above  sqft_basement      yr_built  yr_renovated       zipcode  \
count  21613.000000   21613.000000  21613.000000  21613.000000  21613.000000
mean    1788.390691     291.509045   1971.005136     84.402258  98077.939805
std      828.090978     442.575043     29.373411    401.679240     53.505026
min      290.000000       0.000000   1900.000000      0.000000  98001.000000
25%     1190.000000       0.000000   1951.000000      0.000000  98033.000000
50%     1560.000000       0.000000   1975.000000      0.000000  98065.000000
75%     2210.000000     560.000000   1997.000000      0.000000  98118.000000
max     9410.000000    4820.000000   2015.000000   2015.000000  98199.000000

                lat          long  sqft_living15     sqft_lot15
count  21613.000000  21613.000000   21613.000000   21613.000000
mean      47.560053   -122.213896    1986.552492   12768.455652
std        0.138564      0.140828     685.391304   27304.179631
min       47.155900   -122.519000     399.000000     651.000000
25%       47.471000   -122.328000    1490.000000    5100.000000
50%       47.571800   -122.230000    1840.000000    7620.000000
```

```
75%       47.678000   -122.125000     2360.000000    10083.000000
max       47.777600   -121.315000     6210.000000   871200.000000
```

Based on "count", the maximum number of houses and records is 21613. If information is available for most features, there are missing values in "bedroom" and "bathrooms". Respectively, only 21600 and 21603 values. Instead of 21613. We replace missing values and replace them with the mean value in each column.

### 3.0.2 Detect and replace missing values

We can see we have missing values for the columns bedrooms and bathrooms

[71]:
```python
print("number of NaN values for the column bedrooms :", df['bedrooms'].isnull().
 ↪sum())
print("number of NaN values for the column bathrooms :", df['bathrooms'].
 ↪isnull().sum())
```

```
number of NaN values for the column bedrooms : 13
number of NaN values for the column bathrooms : 10
```

We can replace the missing values of the column 'bedrooms' with the mean of the column 'bedrooms' using the method replace(). Don't forget to set the inplace parameter to True

[72]:
```python
meanBed=df['bedrooms'].mean()
df['bedrooms'].replace(np.nan, meanBed, inplace=True)
```

We also replace the missing values of the column 'bathrooms' with the mean of the column 'bathrooms' using the method replace(). Don't forget to set the inplace parameter top True

[73]:
```python
meanBath=df['bathrooms'].mean()
df['bathrooms'].replace(np.nan, meanBath, inplace=True)
```

[74]:
```python
print("number of NaN values for the column bedrooms :", df['bedrooms'].isnull().
 ↪sum())
print("number of NaN values for the column bathrooms :", df['bathrooms'].
 ↪isnull().sum())
```

```
number of NaN values for the column bedrooms : 0
number of NaN values for the column bathrooms : 0
```

# 4 Exploratory Data Analysis (EDA)

## 4.1 Number of houses with unique floor values

[75]:
```python
dfloor=df['floors'].value_counts()
df_floors_counts = dfloor.to_frame()
df_floors_counts = df_floors_counts.reset_index()
df_floors_counts.columns = ['Number of floors', 'Counts of houses'] # change␣
 ↪column names
```

```
df_floors_counts
```

[75]:

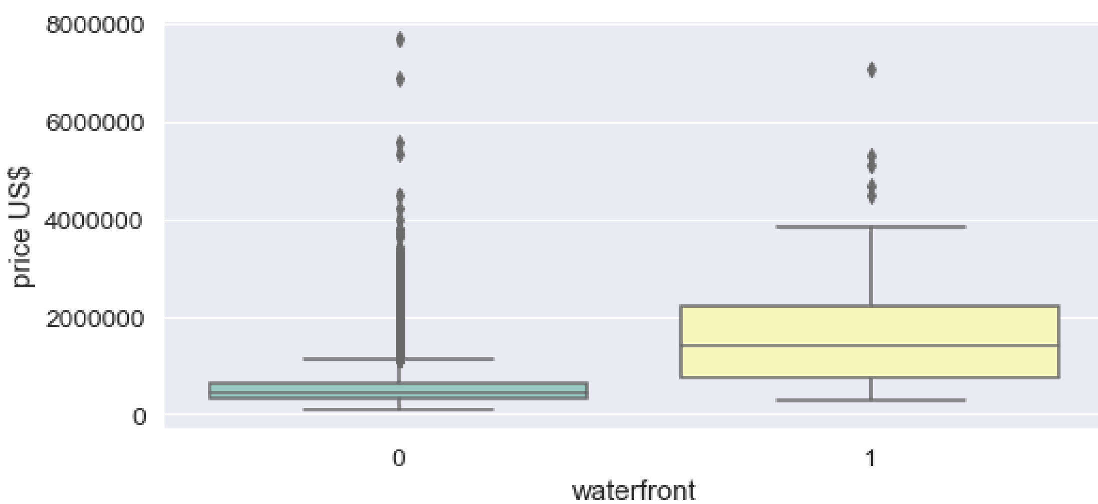
| | Number of floors | Counts of houses |
|---|---|---|
| 0 | 1.0 | 10680 |
| 1 | 2.0 | 8241 |
| 2 | 1.5 | 1910 |
| 3 | 3.0 | 613 |
| 4 | 2.5 | 161 |
| 5 | 3.5 | 8 |

### 4.2 Home price outliers

Use the function boxplot in the seaborn library to determine whether houses with a waterfront view or without a waterfront view have more price outliers.

[76]:
```
sns.set_style("ticks",{'axes.grid' : True})
sns.set(font_scale = 1.25)
plt.figure(figsize=(9,4))
plt.ticklabel_format(style='plain', axis='y')
p=sns.boxplot(x="waterfront", y="price", data=df, palette="Set3")
p.set_ylabel("price US$")
```

[76]: Text(0, 0.5, 'price US$')




[77]:
```
d_wf=df['waterfront'].value_counts()
d_wf_counts = d_wf.to_frame()
d_wf_counts = d_wf_counts.reset_index()
d_wf_counts.columns = ['Waterfront', 'Counts of houses'] # change column names
d_wf_counts
```

[77]:
```
   Waterfront  Counts of houses
0           0             21450
1           1               163
```

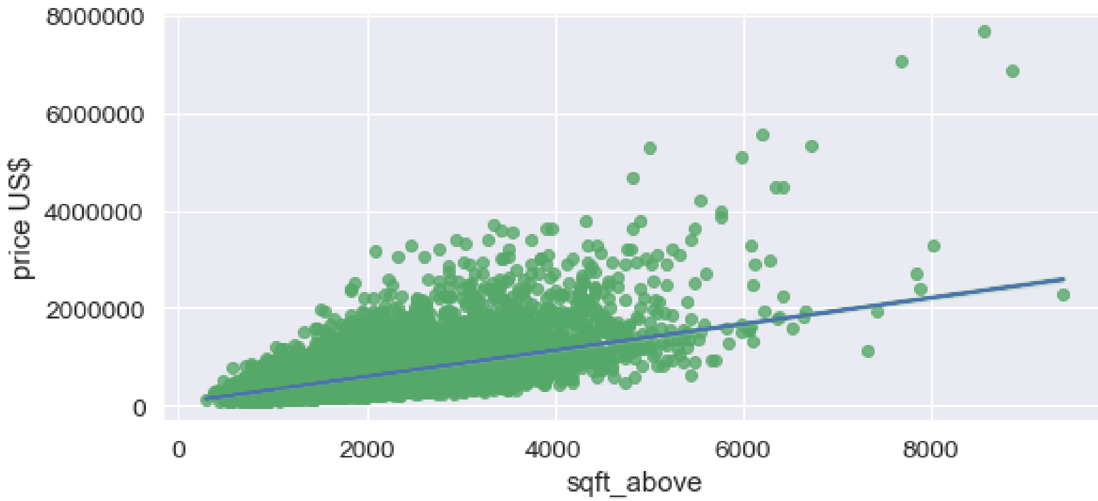
Houses without a waterfront view have more price outliers. But the number of waterfront houses is low, and this criteria may not be significant.

### 4.3 Correlation sqft_above with price.

[78]:
```
# we compute LinearRegression separately and will plot the regression line.
X=df["sqft_above"].to_numpy()
X=X.reshape(-1, 1)
Y=df["price"].to_numpy()
reg = LinearRegression().fit(X, Y)
#print(reg.coef_, reg.intercept_)
print("R\N{SUPERSCRIPT TWO}=", reg.score(X, Y))
#import matplotlib.pyplot as plt
sns.set_style("ticks",{'axes.grid' : True})
sns.set_theme(color_codes=True)
sns.set(font_scale = 1.25)
plt.figure(figsize=(9,4))
plt.ticklabel_format(style='plain', axis='y')


#p=sns.regplot(x="sqft_above", y="price", data=df, order=1, marker="+",␣
↪color="g")
p=sns.regplot(x="sqft_above", y="price", data=df, order=1, color="g")
plt.plot(X, reg.coef_*X + reg.intercept_,  color="b"    )
p.set_xlabel("sqft_above")
p.set_ylabel("price US$")
```

```
R²= 0.3667117528382794
```

[78]:
```
Text(0, 0.5, 'price US$')
```




Based on the positive slope of the linear regression line, feature 'sqft_above' is positively correlated with price. Meaning home value increases with sqft, which is pretty "intuitive", but not the single factor.

## 4.4 Price v. features. Correlation table.

We can use the Pandas method corr() to find the feature other than price that is most correlated with price.

[79]:
```
df.corr()['price'].sort_values()
```

[79]:
```
zipcode         -0.053203
long             0.021626
condition        0.036362
yr_built         0.054012
sqft_lot15       0.082447
sqft_lot         0.089661
yr_renovated     0.126434
floors           0.256794
waterfront       0.266369
lat              0.307003
bedrooms         0.308797
sqft_basement    0.323816
view             0.397293
bathrooms        0.525738
sqft_living15    0.585379
sqft_above       0.605567
grade            0.667434
sqft_living      0.702035
price            1.000000
```

```
Name: price, dtype: float64
```

Most features are positively correlated with price, including sqft_above, which confirms the previous results. Nevertheless, correlation is weak for many features: after "floors", correlation drops significantly. Particularly longitude and ZipCode don't seem to have an impact on prices, when we would expect to find inexpensive homes in rural areas.
We investigate homes prices v. location with interactive maps.

# 5 Visual analytics with Folium

[80]:
```
# Import folium MarkerCluster plugin
from folium.plugins import MarkerCluster
# Import folium MousePosition plugin
from folium.plugins import MousePosition
# Import folium DivIcon plugin
from folium.features import DivIcon
#import folium
import webbrowser
```

Interactive maps will show homes location the dataset. By clicking on markers whose colors depends on prices from yellow(low) to red (high), price and sqft will be displayed. Zoom can be used for more accurate price v. location analysis.

Most houses in the dataset are located west of King County, in a vertical corridor along the coast: Seattle and suburbs (greater Seattle area, GSA?). Therefore longitude does not have a strong impact on prices. Latitude is a more important features. Let's examine if most expensive houses and least expensive houses prices, resp. with prices above the 95% and below the 5% quantiles, defines specific areas of the GSA.

[81]:
```
price95= df['price'].quantile(0.95)
price5= df['price'].quantile(0.05)

np.floor(price5), np.floor(price95)
```

[81]:
```
(210000.0, 1156479.0)
```

## 5.1 Most expensive houses

[82]:
```
# Seattle location = [47.65, -122.0]

# top home prices  > 95%
# make a dataframe with the quantile
expensive_homes = df[(df['price'] >= price95)]
##print(expensive_homes.head())
#---
f = folium.Figure(width=1000, height=500)
#---
```

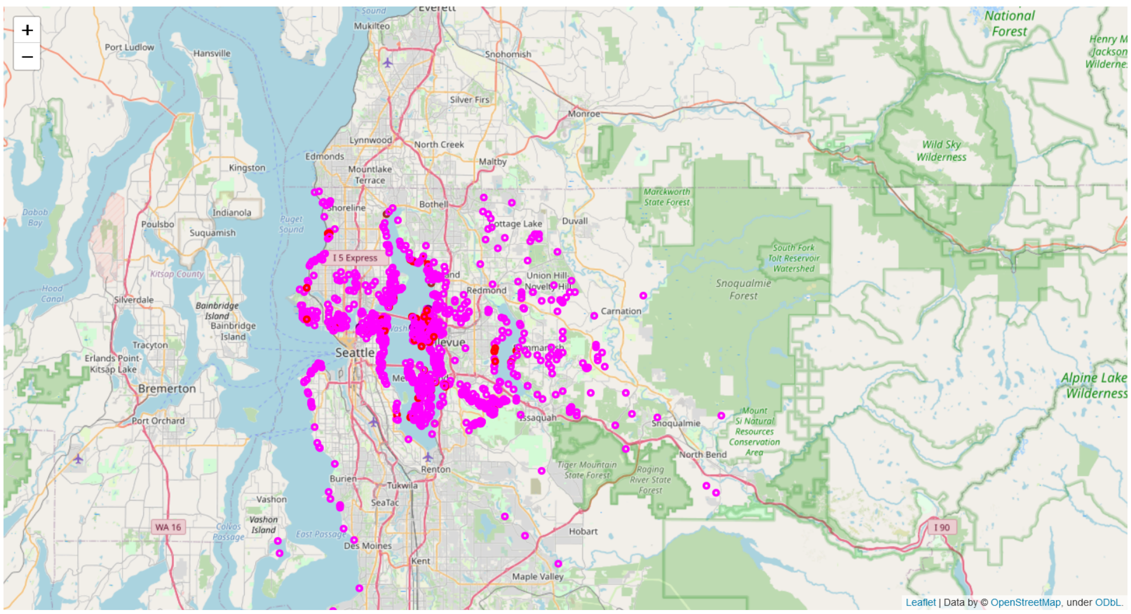
```
expensive_homes_map = folium.Map(location=[47.65, -122.0], zoom_start=10,␣
 ↪tiles='openstreetmap').add_to(f)

#-- for proper indexing...
df1 = pd.DataFrame(columns=["marker_color"])
expensive_homes = expensive_homes.join(df1, how="outer")
####print(expensive_homes.head())
#expensive_homes["marker_color"]= pd.cut(x= expensive_homes["price"], bins=4,␣
 ↪labels=['yellow', 'green', 'blue', 'red'])
expensive_homes["marker_color"]= pd.cut(x= expensive_homes["price"], bins=4,␣
 ↪labels=['magenta', 'red', 'brown','purple'])



for i in expensive_homes.index:
    lat = expensive_homes.lat[i]
    long = expensive_homes.long[i]
    price = expensive_homes.price[i]
    sqft_living = expensive_homes.sqft_living[i]
    color_mark=expensive_homes.marker_color[i]
    #marker = folium.Marker([lat, long]).add_to(expensive_homes_map)
    popup_text = "Price $: {} , Sqft: {}".format(price,sqft_living)
    popup = folium.Popup(popup_text, parse_html=True)
   # marker = folium.Marker([lat, long], radius=15, color=color_exp ,␣
 ↪popup=popup).add_to(expensive_homes_map)
    folium.CircleMarker([lat,long],  radius=3, color= color_mark, popup=popup).
 ↪add_to(expensive_homes_map)
             #       radius=15, color=expensive_homes['marker_color']).
 ↪add_to(expensive_homes_map)




#-----------------------------------------------------------------------------------
# THE FOLLOWING INSTRUCTION DISPLAYS THE INTERACTIVE MAP... that will not show␣
 ↪up when exporting the notebook to LateX !
#-----------------------------------------------------------------------------------
#expensive_homes_map
```

[83]:

```
#-----------------------------------------------------------------------------------
# THIS SET OF INSTRUCTIONS IS INTENDED TO SAVE FOLIUM MAP as an Image. For␣
 ↪LaTeX and build a nice PDF report.
# Interactivity is LOST !
#␣
 ↪---------------------------------------------------------------------------------
# save the map as html
mapFname = 'expensive_homes_map_output.html'
expensive_homes_map.save(mapFname)
```

```
mapUrl = 'file://{0}/{1}'.format(os.getcwd(), mapFname)
# download gecko driver for firefox from here - https://github.com/mozilla/
↪geckodriver/releases
# use selenium to save the html as png image
driver = webdriver.Firefox()
driver.get(mapUrl)
# wait for 5 seconds for the maps and other assets to be loaded in the browser
time.sleep(5)
driver.save_screenshot('expensive_homes_map.png')
driver.quit()
#-------------------------------------------
display.Image('expensive_homes_map.png')
```

[83]:




Location is an important feature, most expensive homes are located on a waterfront either the ocean or a lake.

## 5.2 Least expensive houses

[84]:

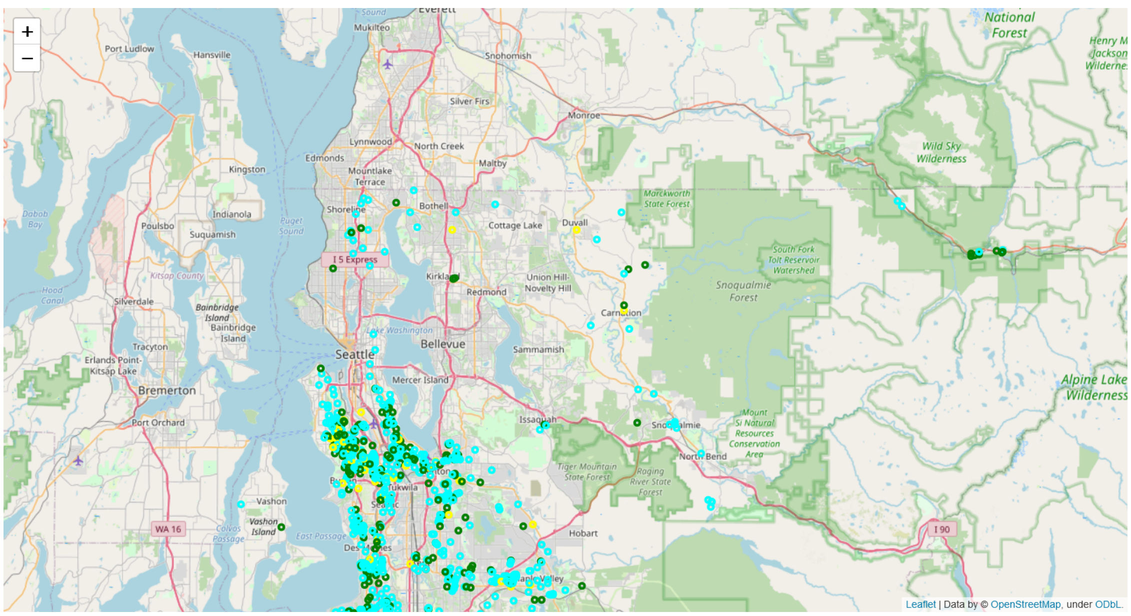
```
# lower prices < 5%
# make a dataframe with the quantile
inexpensive_homes = df[(df['price'] <= price5)]
inexpensive_homes.head()

# make a dataframe with the quantile
inexpensive_homes = df[(df['price'] <= price5)]
#inexpensive_homes.head()
```

```
f = folium.Figure(width=1000, height=500)
#---
inexpensive_homes_map = folium.Map(location=[47.65, -122.0], zoom_start=10,␣
↪tiles='openstreetmap').add_to(f)

#-- for proper indexing...
df1 = pd.DataFrame(columns=["marker_color"])
inexpensive_homes = inexpensive_homes.join(df1, how="outer")
####print(expensive_homes.head())
#inexpensive_homes["marker_color"]= pd.cut(x= inexpensive_homes["price"],␣
↪bins=4, labels=['yellow', 'green', 'blue', 'red'])
inexpensive_homes["marker_color"]= pd.cut(x= inexpensive_homes["price"],␣
↪bins=3, labels=['yellow', 'green', 'cyan'])



for i in inexpensive_homes.index:
    lat = inexpensive_homes.lat[i]
    long = inexpensive_homes.long[i]
    price = inexpensive_homes.price[i]
    sqft_living = inexpensive_homes.sqft_living[i]
    color_exp=inexpensive_homes.marker_color[i]
    #marker = folium.Marker([lat, long]).add_to(expensive_map)
    popup_text = "Price $: {} , Sqft: {}".format(price,sqft_living)
    popup = folium.Popup(popup_text, parse_html=True)
   # marker = folium.Marker([lat, long], radius=15, color=color_exp ,␣
↪popup=popup).add_to(expensive_map)
    folium.CircleMarker([lat,long],  radius=3, color= color_exp, popup=popup).
↪add_to(inexpensive_homes_map)
             #       radius=15, color=expensive['marker_color']).
↪add_to(expensive_map)

#----------------------------------------------------------------------------------------------
# THE FOLLOWING INSTRUCTION DISPLAYS THE INTERACTIVE MAP... that will not show␣
↪up when exporting the notebook to LateX !
#----------------------------------------------------------------------------------------------
#inexpensive_homes_map
```

[85]:
```
#----------------------------------------------------------------------------------------------
# THIS SET OF INSTRUCTIONS IS INTENDED TO SAVE the FOLIUM MAP as an Image. For␣
↪LaTeX and build a nice PDF report.
# Interactivity is LOST !
#␣
↪---------------------------------------------------------------------------------------------
# save the map as html
mapFname = 'inexpensive_homes_map_output.html'
```

```
inexpensive_homes_map.save(mapFname)

mapUrl = 'file://{0}/{1}'.format(os.getcwd(), mapFname)

# download gecko driver for firefox from here - https://github.com/mozilla/
↪geckodriver/releases

# use selenium to save the html as png image
driver = webdriver.Firefox()
driver.get(mapUrl)
# wait for 5 seconds for the maps and other assets to be loaded in the browser
time.sleep(5)
driver.save_screenshot('inexpensive_homes_map.png')
driver.quit()

display.Image('inexpensive_homes_map.png')
```

[85]:




Least expensive houses are located in southern suburbs close to Tacoma. There are probably other details such as: schools, .... that are not available in the dataset, that could explain the concentration south of Seattle. We will retain latitude as a feature when we develop our model. And discard longitude.

# 6 Model Development

## 6.1 Preliminary stage.

**Longitude** We look at single feature at the moment. First a feature weakly correlated with prices: longitude, We can Fit a linear regression model using the longitude feature 'long' and calculate the

R^2.

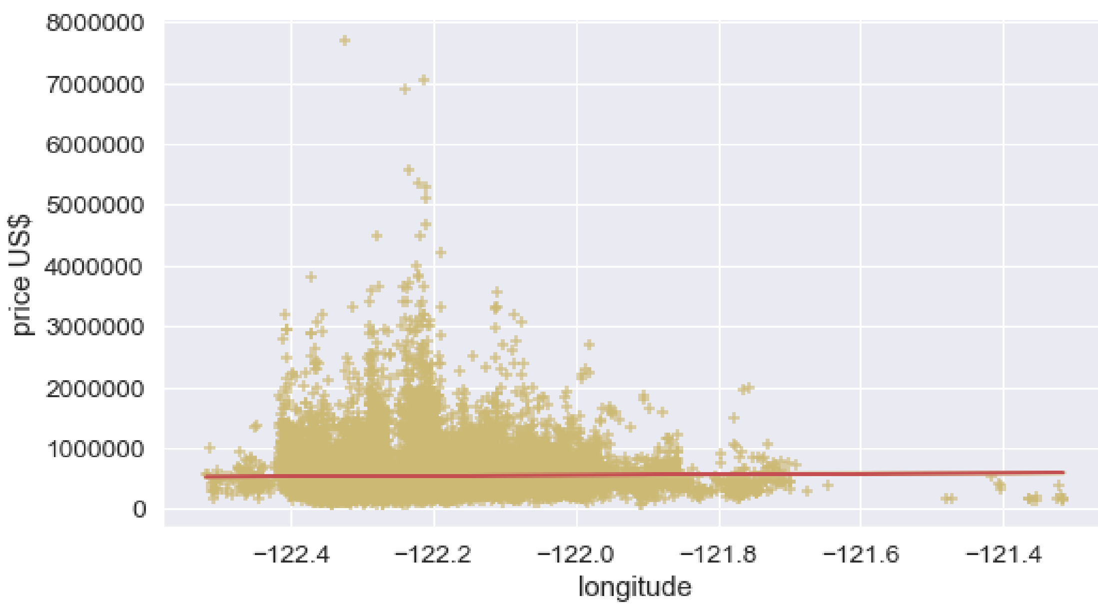
[86]:
```
X = df[['long']]
Y = df['price']
lm = LinearRegression()
lm.fit(X,Y)
y_pred= lm.predict(X)
print("R\N{SUPERSCRIPT TWO}=", lm.score(X, Y))
```

```
R²= 0.00046769430149007363
```

$R^2$ is close to 0 and confirms previous results (correlation) and observations with the interactive map. We can visualize the lack of correlation price v. longitude.

[87]:
```
#import matplotlib.pyplot as plt
sns.set_style("ticks",{'axes.grid' : True})
sns.set_theme(color_codes=True)
sns.set(font_scale = 1.25)
plt.figure(figsize=(9,5))
plt.ticklabel_format(style='plain', axis='y')

p=sns.regplot(x="long", y="price", data=df, order=1, marker="+", color="y")
plt.plot(X, y_pred,  color="r")

p.set_xlabel("longitude")
p.set_ylabel("price US$")
```

[87]:
```
Text(0, 0.5, 'price US$')
```



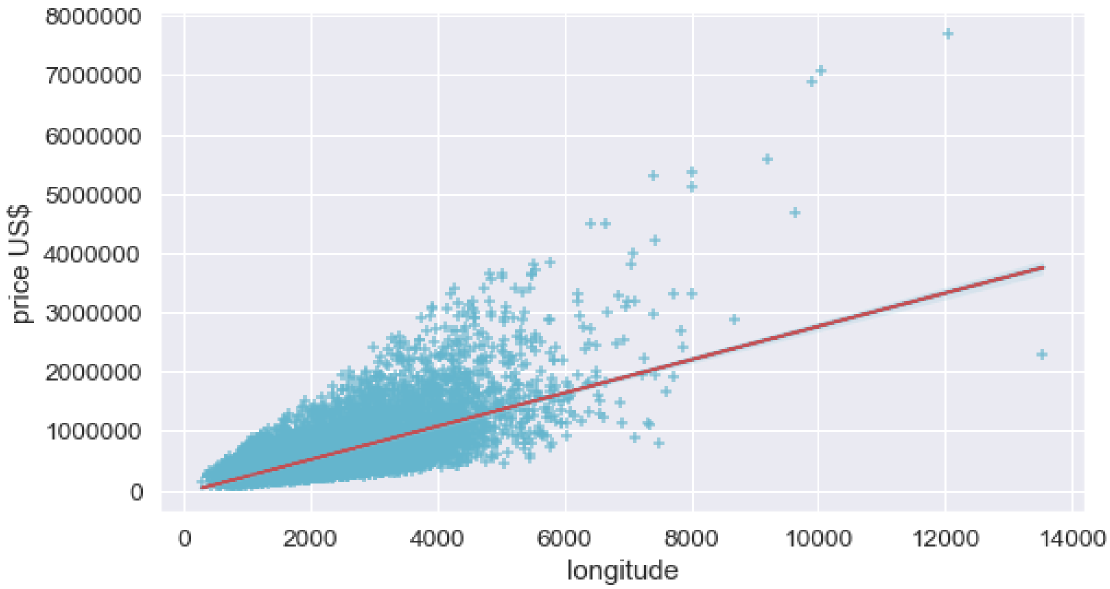
Longitude refers to various areas of the city of Seattle. But this feature is poorly correlated with house prices. A classification of houses per neighborhoods in the county, would be more useful. Although zipcode does not seem to help much, correlation is even weaker and negative. Further analysis is required in terms of houses price per neighborhood. Longitude has little effect, probably because most houses are in the Seattle area. Latitude has a stronger influence. Based on localized areas with high prices on the map, we should create a (long, lat) feature.

**Square ft living** Based on the correlation Table, price should be significantly correlated with 'sqft_living'. Fit a linear regression model to predict the 'price' using the feature 'sqft_living' then calculate the R^2.

[88]:
```
X2 = df[['sqft_living']]
#Y = df['price']
lm2 = LinearRegression()
lm2.fit(X2,Y)
y_pred= lm2.predict(X2)
print("R\N{SUPERSCRIPT TWO}=", lm2.score(X2, Y))

#import matplotlib.pyplot as plt
sns.set_style("ticks",{'axes.grid' : True})
sns.set_theme(color_codes=True)
sns.set(font_scale = 1.25)
plt.figure(figsize=(9,5))
plt.ticklabel_format(style='plain', axis='y')

p=sns.regplot(x="sqft_living", y="price", data=df, order=1, marker="+",␣
 ↪color="c")
plt.plot(X2, y_pred,  color="r")

p.set_xlabel("longitude")
p.set_ylabel("price US$")
```

```
R²= 0.4928532179037931
```

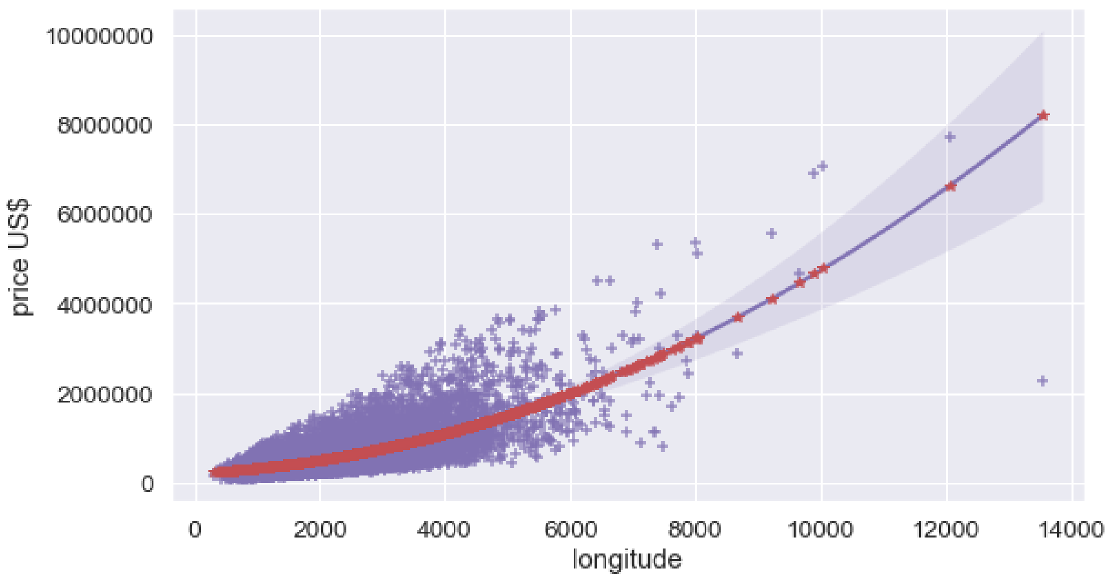
[88]:
```
Text(0, 0.5, 'price US$')
```




[89]:
```
X2 = df[['sqft_living']]
#Y = df['price']

poly = PolynomialFeatures(degree = 2)
Xpf2 = poly.fit_transform(X2)
lm2 = LinearRegression()
lm2.fit(Xpf2,Y)
y_pred= lm2.predict(Xpf2)

print("R\N{SUPERSCRIPT TWO}=", lm2.score(Xpf2, Y))
sns.set_style("ticks",{'axes.grid' : True})
sns.set_theme(color_codes=True)
sns.set(font_scale = 1.25)
plt.figure(figsize=(9,5))
plt.ticklabel_format(style='plain', axis='y')
#------------
p=sns.regplot(x="sqft_living", y="price", data=df, order=2, marker="+",␣
 ↪color="m")
plt.plot(X2, y_pred,'r*')
#------------
p.set_xlabel("longitude")
p.set_ylabel("price US$")
```

R²= 0.5327430940591443

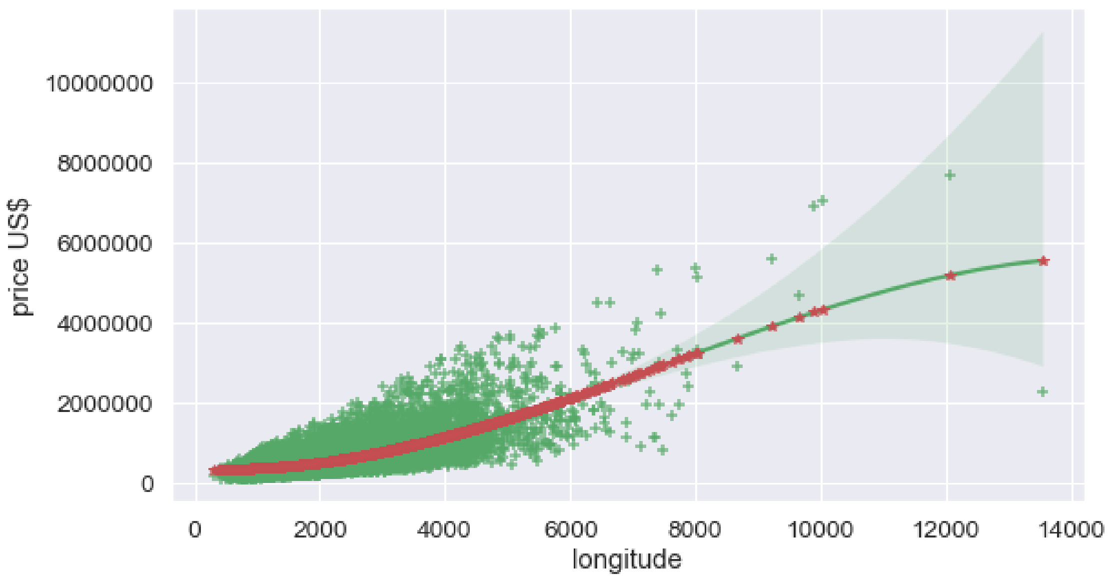
[89]: Text(0, 0.5, 'price US$')




[90]:
```
X2 = df[['sqft_living']]
#Y = df['price']

poly = PolynomialFeatures(degree = 3)
Xpf2 = poly.fit_transform(X2)
lm2 = LinearRegression()
lm2.fit(Xpf2,Y)
y_pred= lm2.predict(Xpf2)

print("R\N{SUPERSCRIPT TWO}=", lm2.score(Xpf2, Y))
sns.set_style("ticks",{'axes.grid' : True})
sns.set_theme(color_codes=True)
sns.set(font_scale = 1.25)
plt.figure(figsize=(9,5))
plt.ticklabel_format(style='plain', axis='y')
#------------
p=sns.regplot(x="sqft_living", y="price", data=df, order=3, marker="+",␣
 ↪color="g")
plt.plot(X2, y_pred,'r*')
#------------
p.set_xlabel("longitude")
p.set_ylabel("price US$")
```

```
R²= 0.5390045510503199
```

[90]:
```
Text(0, 0.5, 'price US$')
```




"sqft_living" and related surface areas features are strongly correlated with house prices. Polynomial interpolation of order 2 is a better fit on this feature. Order 3 does not improve the score. And may lead to over-fitting. —- Given the importance of "sqft_living" and other dependent "sqft" features on home price, in fitting a regression with multiple features, we expect polynomial interpolation of order 2 to be more efficient than pure linear regression.

## 6.2 Fitting linear model regression with multiple features

Fit a linear regression model to predict the 'price' using the list of features with most correlated with prices in correlation Table :

[91]:
```
features =["floors", "waterfront","lat" ,"bedrooms" ,"sqft_basement" ,"view"␣
 ↪,"bathrooms","sqft_living15","sqft_above","grade","sqft_living"]
```

### 6.2.1 Polynomial regression

Linear regression model with Polynomial interpolation We test: Order 1 (linear), 2, 3, 4 . We define PipeLines, including "features scaling", polynomial interpolation order from 1 to 4, and a Linear regression model.

[92]:
```
Input= np.empty([5]).astype(list)

for j in range(1,5) :
     Input[j]=[('scale',StandardScaler()),('polynomial',␣
 ↪PolynomialFeatures(j,include_bias=False)),('model',LinearRegression())]
```

Use the list to create a pipeline object to predict the 'price', fit the object using the features in the list features, and calculate the R^2. As we increase the order of the polynomial, computation time becomes prohibitive.

[93]:
```
X_feat = df[features]

for j in range(1,5):
    pipe_line=Pipeline(Input[j])
    #print(pipe_line)
    pipe_line.fit(X_feat,Y)
    print("Regresion Order:",j , " R\N{SUPERSCRIPT TWO}=", pipe_line.
 ↪score(X_feat,Y))
```

```
Regresion Order: 1  R²= 0.657626396659731
Regresion Order: 2  R²= 0.7513404101380663
Regresion Order: 3  R²= 0.8141672842838007
Regresion Order: 4  R²= 0.8562565267209652
```

After scaling, increasing the order of the polynomial, significantly improves the fit. This does not guarantee that the model will properly fit new data. As we see in the next section.

## 6.3 Polynomial Regression - Model Evaluation and Refinement

In this section we split the dataset in Training and Testing sets for validating the accuracy of the best model.

[94]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
```

[95]:
```
X = df[features]
Y = df['price']
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=13)
print("number of test samples:", x_test.shape[0])
print("number of training samples:",x_train.shape[0])
```

```
number of test samples: 4323
number of training samples: 17290
```

### 6.3.1 Polynomial regression order 2 and 3

[96]:
```
from sklearn import preprocessing
#transform = preprocessing.StandardScaler()
X = df[features]
Y = df['price']
#Xt = transform.fit_transform(X)
#x_train, x_test, y_train, y_test = train_test_split(Xt, Y, test_size=0.2,␣
 ↪random_state=13)


poly2 = PolynomialFeatures(degree = 2)
Xpf2 = poly2.fit_transform(X)
```

```
x_train, x_test, y_train, y_test = train_test_split(Xpf2, Y, test_size=0.2,␣
↪random_state=13)
```

[97]:
```
model = LinearRegression()
```

[98]:
```
model.fit(x_train, y_train)
expected_y  = y_test
predicted_y = model.predict(x_test)
```

[99]:
```
print(model.score(x_test,y_test))
```

```
0.7492502664714935
```

[100]:
```
poly3 = PolynomialFeatures(degree = 3)
Xpf3 = poly3.fit_transform(X)
x_train, x_test, y_train, y_test = train_test_split(Xpf3, Y, test_size=0.2,␣
↪random_state=13)
```

[101]:
```
model.fit(x_train, y_train)
expected_y  = y_test
predicted_y = model.predict(x_test)
```

[102]:
```
print(model.score(x_test,y_test))
```

```
0.655739446361362
```

order= 3: degrades the performance of the regression model. From order=4 the polynomial transform does not allow a proper fit on the test set. Which means that we over-fitted the training set.

### 6.3.2 Ridge regression order 2, 3.

Will adding regularization to higher order transform improve accuracy ?

Initial method in IBM project was a Ridge regression for improving previous results with porder=2. Create and fit a Ridge regression object using the training data, set the regularization parameter to 0.1, and calculate the R^2 using the test data. Linear least squares with l2 regularization. Minimizes the objective function: ||y - Xw||^2_2 + alpha * ||w||^2_2
This model solves a regression model where the loss function is the linear least squares function and regularization is given by the l2-norm. Also known as Ridge Regression or Tikhonov regularization. This estimator has built-in support for multi-variate regression (i.e., when y is a 2d-array of shape (n_samples, n_targets)).

[103]:
```
from sklearn.linear_model import Ridge
```

[104]:
```
X = df[features]
Y = df['price']
```

```
poly = PolynomialFeatures(degree = 2)
X = poly.fit_transform(X)

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=13)
```

[105]:
```
ridge_model = Ridge(alpha=0.25)
ridge_model.fit(x_train, y_train)
ridge_model.score(x_test, y_test)

print("R\N{SUPERSCRIPT TWO}=", ridge_model.score(x_test, y_test))
```

```
R²= 0.7340742546019136
```

Regularization does not help with order 2 polynomial interpolation and order 3 overfitting.

### 6.3.3 Spline Regression Model

Spline interpolation : This is the simple approach to model non-linear relationships. It add polynomial terms or quadratic terms (square, cubes, etc) to a regression. Spline regression. Fits a smooth curve with a series of polynomial segments. The values delimiting the spline segments are called Knots. Several parameters "n_knots", "alpha" can improve previous polynomial regression. We present the best result.

[106]:
```
X = df[features]
Y = df['price']

x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,␣
 ↪random_state=13)

model_spline = make_pipeline(SplineTransformer(n_knots=6, degree=3),␣
 ↪Ridge(alpha=1e-3))
model_spline.fit(x_train, y_train)
```

[106]:
```
Pipeline(steps=[('splinetransformer', SplineTransformer(n_knots=6)),
                ('ridge', Ridge(alpha=0.001))])
```

[107]:
```
print("R\N{SUPERSCRIPT TWO}=", model_spline.score(x_test, y_test))
```

```
R²= 0.7908562522533551
```

Spline interpolation has improved the accuracy of the model. From $R^2 = 0.75$ to $R^2 = 0.79$

# 7 CONCLUSIONS

A regression model with proper interpolation is capable of predicting the price of homes based after multiple features (11) selected among the most relevant ones in the "Price v. Features" correlation table. The feature set covers six out of eight critical factors influencing a home's value described in the introduction. We tested several methods, with polynomial interpolation having increasing order. Regression with polynomial interpolation of order 2 proved to be the best compromise. We were able to improve the model further by using a spline interpolation with order =3. Regarding the two missing critical factors: interest rates, global economic environment. Overall, the dataset includes home sold between May 2014 and May 2015, these factors did not change much during that time frame, home prices had a linear evolution until 2019. Nevertheless, home prices evolution was exponential after 2019 due to low interest rates and monetary creation. These features are not reflected in the dataset. Which would force a regular update of the model. Or an inclusion of features “Interest rates”, “Money creation”.

In general, Linear regression with polynomial interpolation or polynomial regression, is sensitive to outliers. We tried to remove some of them, without targeting a particular feature. The method did not improve accuracy, even with a spline interpolation. The “outlier method” could be refined by targeting specific features, like “waterfront” for example. This could be investigated in future development.