Final Project Submission

Please fill out:

- Student name: Margaret Mitey
- Student pace: Full time
- Scheduled project review date/time: 9/7/2023
- Instructor name: Veronica Isiaho
- Blog post URL:https://github.com/Chemami12/Phase2Project/blob/main/student.ipynb

BUSINESS UNDERSTANDING

INTRODUCTION

The real estate market is a critical driver of economic growth in many countries globally. It is a dynamic and ever-changing industry where key stakeholders (buyers and sellers) have to make accurate prediction of home prices in order to make informed decisions through use of reliable and comprehensive data.

Real estate is dramatically affected by its location and factors such as employment rates, economy, crime rates, transport facilities and land rates.

The King County House Sale dataset is a valuable source of information for analysing house sales in the Northwestern County. The dataset has several variables that can act as key indicators in price of houses in this area such as Zip code, number of bedrooms, number of bath rooms, square feet, numeric grade and the year the house was built. The dataset will be used for analysis and modelling to better understand the factor that affects house pricing.

BUSINESS PROBLEM A real estate agency that helps homeowners buy and/ or sell homes is looking into how certain features could affect the pricing of houses in King County and by what amount so as to make appropriate recommendations/ predictions to their clients.

SPECIFIC OBJECTIVES For the real estate agency to make the appropriate recommendations. The following objectives need to be answered:

1. Determine key factors that impact housing prices in King County.
2. How number of bedrooms, bathrooms, grade, square footage, year built and the zipcode of the house correlate with its sale price.
3. Predict house sale price given certain house specification.

DATA UNDERSTANDING The project will use the King County House Sales dataset

In [ ]:

```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns

import statsmodels.api as sm
import numpy as np
import scipy.stats as stats
```

In [ ]:

```
data= pd.read_csv("data\kc_house_data.csv")
data
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_baser
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	4
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	9
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	NO	NONE	...	8 Good	1530	
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	NO	NONE	...	8 Good	2310	
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	NO	NONE	...	7 Average	1020	
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	NaN	NONE	...	8 Good	1600	
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	NO	NONE	...	7 Average	1020	

21597 rows × 21 columns

In [ ]:

```
data.columns
```

Out[ ]:

```
Index(['id', 'date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
       'sqft_lot', 'floors', 'waterfront', 'view', 'condition', 'grade',
       'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode',
       'lat', 'long', 'sqft_living15', 'sqft_lot15'],
      dtype='object')
```

In [ ]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21597 non-null  int64  
 1   date           21597 non-null  object 
 2   price          21597 non-null  float64
 3   bedrooms       21597 non-null  int64  
 4   bathrooms      21597 non-null  float64
 5   sqft_living    21597 non-null  int64  
 6   sqft_lot       21597 non-null  int64  
 7   floors         21597 non-null  float64
 8   waterfront     19221 non-null  object 
 9   view           21534 non-null  object 
 10  condition      21597 non-null  object 
 11  grade          21597 non-null  object 
 12  sqft_above     21597 non-null  int64  
 13  sqft_basement  21597 non-null  object 
 14  yr_built       21597 non-null  int64  
 15  yr_renovated   17755 non-null  float64
 16  zipcode        21597 non-null  int64  
 17  lat            21597 non-null  float64
 18  long           21597 non-null  float64
 19  sqft_living15  21597 non-null  int64  
 20  sqft_lot15     21597 non-null  int64  
dtypes: float64(6), int64(9), object(6)
memory usage: 3.5+ MB
```

DATA PREPARATION This is to select the data that will be used, make necessary convertions from categorical to numerical and perform data cleaning

In [ ]:

```
# Display the first few rows of the dataset
pd.DataFrame(data.head())
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	NONE	...	7 Average	1180	0.0
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	NO	NONE	...	7 Average	2170	400.0
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	NO	NONE	...	6 Low Average	770	0.0
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	NO	NONE	...	7 Average	1050	910.0
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	NO	NONE	...	8 Good	1680	0.0

5 rows × 21 columns

In [ ]:

```
# Chec for the data type of each column in the dataframe
data.dtypes
```

Out[ ]:

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

In [ ]:

```
# Check for miising values
data.isnull().sum()
```

Out[ ]:

```
id                  0
date                0
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
view               63
condition           0
grade               0
sqft_above          0
sqft_basement       0
yr_built            0
yr_renovated     3842
zipcode             0
lat                 0
long                0
sqft_living15       0
sqft_lot15          0
dtype: int64
```

In [ ]:

```
# Drop columns with missing values
print(data.dropna(axis=1, inplace=True))
```

```
None
```

In [ ]:

```
# Check for duplicates in the row
print(data.duplicated().sum())
```

```
0
```

In [ ]:

```
data.head()
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	sqft_above	sqft_basement	yr_built	zi
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	Average	7 Average	1180	0.0	1955	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	Average	7 Average	2170	400.0	1951	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	Average	6 Low Average	770	0.0	1933	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	Very Good	7 Average	1050	910.0	1965	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	Average	8 Good	1680	0.0	1987	

In [ ]:

```
# Splitting the grade cell into numerical and descpriptive
# Define a function to extract the numeric grade from the grade column
def extract_numeric_grade(s):
    numeric_str = ''
    for char in s:
        if char.isdigit():
            numeric_str += char
    return int(numeric_str)

# Define a function to extract the grade description from the grade column
def extract_grade_desc(s):
    grade_desc = ''
    for char in s:
        if not char.isdigit() and char != ' ':
            grade_desc += char
    return grade_desc.strip()

# Extract the numeric grade and grade description using the custom functions
data['numeric_grade'] = data['grade'].apply(lambda x: extract_numeric_grade(x))
data['grade_desc'] = data['grade'].apply(lambda x: extract_grade_desc(x))

data.head()
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade	sqft_above	sqft_basement	yr_built	zi
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	Average	7 Average	1180	0.0	1955	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	Average	7 Average	2170	400.0	1951	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	Average	6 Low Average	770	0.0	1933	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	Very Good	7 Average	1050	910.0	1965	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	Average	8 Good	1680	0.0	1987	

In [ ]:

```
# Dropping id, date, condition and grade
data.drop(columns=['condition', 'grade', 'id', 'date'], inplace=True)

data.head()
```

Out[ ]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	sqft_basement	yr_built	zipcode	lat	long	sqft_living15	sqft_
0	221900.0	3	1.00	1180	5650	1.0	1180	0.0	1955	98178	47.5112	-122.257	1340	
1	538000.0	3	2.25	2570	7242	2.0	2170	400.0	1951	98125	47.7210	-122.319	1690	
2	180000.0	2	1.00	770	10000	1.0	770	0.0	1933	98028	47.7379	-122.233	2720	
3	604000.0	4	3.00	1960	5000	1.0	1050	910.0	1965	98136	47.5208	-122.393	1360	
4	510000.0	3	2.00	1680	8080	1.0	1680	0.0	1987	98074	47.6168	-122.045	1800	

In [ ]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21597 entries, 0 to 21596
Data columns (total 16 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   sqft_above     21597 non-null  int64  
 7   sqft_basement  21597 non-null  object 
 8   yr_built       21597 non-null  int64  
 9   zipcode        21597 non-null  int64  
 10  lat            21597 non-null  float64
 11  long           21597 non-null  float64
 12  sqft_living15  21597 non-null  int64  
 13  sqft_lot15     21597 non-null  int64  
 14  numeric_grade  21597 non-null  int64  
 15  grade_desc     21597 non-null  object 
dtypes: float64(5), int64(9), object(2)
memory usage: 2.6+ MB
```

In [ ]:

```
# Creating correlation of the columns
data.corr()
```

Out[ ]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	yr_built	zipcode	lat	long	sqft_livin
price	1.000000	0.308787	0.525906	0.701917	0.089876	0.256804	0.605368	0.053953	-0.053402	0.306692	0.022036	0.585
bedrooms	0.308787	1.000000	0.514508	0.578212	0.032471	0.177944	0.479386	0.155670	-0.154092	-0.009951	0.132054	0.393
bathrooms	0.525906	0.514508	1.000000	0.755758	0.088373	0.502582	0.686668	0.507173	-0.204786	0.024280	0.224903	0.569
sqft_living	0.701917	0.578212	0.755758	1.000000	0.173453	0.353953	0.876448	0.318152	-0.199802	0.052155	0.241214	0.756
sqft_lot	0.089876	0.032471	0.088373	0.173453	1.000000	-0.004814	0.184139	0.052946	-0.129586	-0.085514	0.230227	0.144
floors	0.256804	0.177944	0.502582	0.353953	-0.004814	1.000000	0.523989	0.489193	-0.059541	0.049239	0.125943	0.280
sqft_above	0.605368	0.479386	0.686668	0.876448	0.184139	0.523989	1.000000	0.424037	-0.261570	-0.001199	0.344842	0.731
yr_built	0.053953	0.155670	0.507173	0.318152	0.052946	0.489193	0.424037	1.000000	-0.347210	-0.148370	0.409993	0.326
zipcode	-0.053402	-0.154092	-0.204786	-0.199802	-0.129586	-0.059541	-0.261570	-0.347210	1.000000	0.266742	-0.564259	-0.279
lat	0.306692	-0.009951	0.024280	0.052155	-0.085514	0.049239	-0.001199	-0.148370	0.266742	1.000000	-0.135371	0.048
long	0.022036	0.132054	0.224903	0.241214	0.230227	0.125943	0.344842	0.409993	-0.564259	-0.135371	1.000000	0.335
sqft_living15	0.585241	0.393406	0.569884	0.756402	0.144763	0.280102	0.731767	0.326377	-0.279299	0.048679	0.335626	1.000
sqft_lot15	0.082845	0.030690	0.088303	0.184342	0.718204	-0.010722	0.195077	0.070777	-0.147294	-0.086139	0.255586	0.183
numeric_grade	0.667951	0.356563	0.665838	0.762779	0.114731	0.458794	0.756073	0.447865	-0.185771	0.113575	0.200341	0.713

In [ ]:

```
# Correlation of columns with price
pd.DataFrame(data.corr()['price']).sort_values(by='price',ascending=False)
```

Out[ ]:

	price
price	1.000000
sqft_living	0.701917
numeric_grade	0.667951
sqft_above	0.605368
sqft_living15	0.585241
bathrooms	0.525906
bedrooms	0.308787
lat	0.306692

floors	0.256804
sqft_lot	0.089876
sqft_lot15	0.082845
yr_built	0.053953
long	0.022036
zipcode	-0.053402

In [ ]:

```
# Selecting relevant columns to use
relevant_columns=['price', 'sqft_living','numeric_grade','bathrooms', 'bedrooms', 'yr_built', 'zipcode']
data=data[relevant_columns]
data
```

Out[ ]:

	price	sqft_living	numeric_grade	bathrooms	bedrooms	yr_built	zipcode
0	221900.0	1180	7	1.00	3	1955	98178
1	538000.0	2570	7	2.25	3	1951	98125
2	180000.0	770	6	1.00	2	1933	98028
3	604000.0	1960	7	3.00	4	1965	98136
4	510000.0	1680	8	2.00	3	1987	98074
...	...	...	...	...	...	...	...
21592	360000.0	1530	8	2.50	3	2009	98103
21593	400000.0	2310	8	2.50	4	2014	98146
21594	402101.0	1020	7	0.75	2	2009	98144
21595	400000.0	1600	8	2.50	3	2004	98027
21596	325000.0	1020	7	0.75	2	2008	98144

21597 rows × 7 columns

In [ ]:

```
# Statistical Description
data.describe()
```

Out[ ]:

	price	sqft_living	numeric_grade	bathrooms	bedrooms	yr_built	zipcode
count	2.159700e+04	21597.000000	21597.000000	21597.000000	21597.000000	21597.000000	21597.000000
mean	5.402966e+05	2080.321850	7.657915	2.115826	3.373200	1970.999676	98077.951845
std	3.673681e+05	918.106125	1.173200	0.768984	0.926299	29.375234	53.513072
min	7.800000e+04	370.000000	3.000000	0.500000	1.000000	1900.000000	98001.000000
25%	3.220000e+05	1430.000000	7.000000	1.750000	3.000000	1951.000000	98033.000000
50%	4.500000e+05	1910.000000	7.000000	2.250000	3.000000	1975.000000	98065.000000
75%	6.450000e+05	2550.000000	8.000000	2.500000	4.000000	1997.000000	98118.000000
max	7.700000e+06	13540.000000	13.000000	8.000000	33.000000	2015.000000	98199.000000

In [ ]:

```
# Remove outliers
#function to remove outliers
def remove_outliers(data, cols):
    for col in cols:
        z = np.abs(stats.zscore(data[col]))
        threshold = 3
        data = data[z < threshold]
    return data
cols_to_remove_outliers = ['sqft_living','bathrooms','bedrooms','numeric_grade','price', 'zipcode']
data = remove_outliers(data , cols_to_remove_outliers)
data
```

Out[ ]:

	price	sqft_living	numeric_grade	bathrooms	bedrooms	yr_built	zipcode
0	221900.0	1180	7	1.00	3	1955	98178
1	538000.0	2570	7	2.25	3	1951	98125
2	180000.0	770	6	1.00	2	1933	98028
3	604000.0	1960	7	3.00	4	1965	98136
4	510000.0	1680	8	2.00	3	1987	98074
...	...	...	...	...	...	...	...
21592	360000.0	1530	8	2.50	3	2009	98103
21593	400000.0	2310	8	2.50	4	2014	98146
21594	402101.0	1020	7	0.75	2	2009	98144
21595	400000.0	1600	8	2.50	3	2004	98027
21596	325000.0	1020	7	0.75	2	2008	98144

20497 rows × 7 columns

In [ ]:

```
data.describe()
```

Out[ ]:

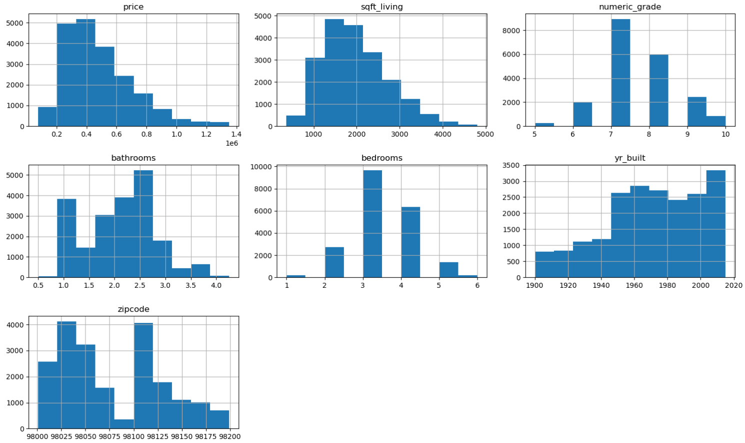
	price	sqft_living	numeric_grade	bathrooms	bedrooms	yr_built	zipcode
count	2.049700e+04	20497.000000	20497.000000	20497.000000	20497.000000	20497.000000	20497.000000
mean	4.855605e+05	1971.886325	7.532371	2.046934	3.322047	1970.575401	98078.831488
std	2.250129e+05	752.789256	1.003282	0.690846	0.855173	29.262158	53.492476
min	7.800000e+04	370.000000	5.000000	0.500000	1.000000	1900.000000	98001.000000
25%	3.150000e+05	1400.000000	7.000000	1.500000	3.000000	1951.000000	98033.000000
50%	4.399500e+05	1860.000000	7.000000	2.000000	3.000000	1974.000000	98070.000000
75%	6.075000e+05	2440.000000	8.000000	2.500000	4.000000	1996.000000	98118.000000
max	1.350000e+06	4800.000000	10.000000	4.250000	6.000000	2015.000000	98199.000000

From the data description we can see that:

1. The average price of houses in King County is $4,855,605 and the most expensive is$13,500,000.
2. The average size of houses is 1971 square feet and the biggest size is 4800 square feet.
3. The average number of bedrooms is 3 and the most number of bedrooms is 6.
4. The average number of bathrooms is 2 and the most number of bathrooms in a house is 4.

In [ ]:

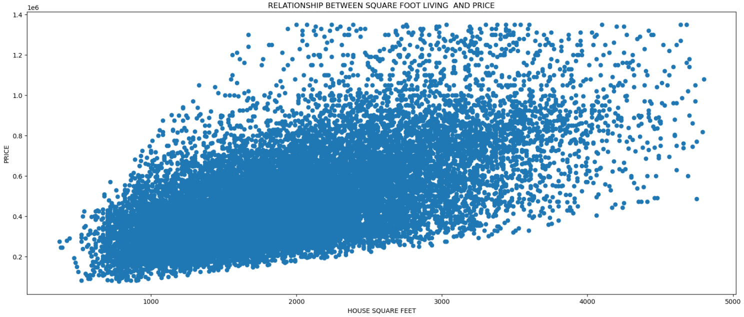
```
#Visualization of the relevant columns
data.hist(figsize=(15, 9))
plt.tight_layout()
plt.show()
```



The graphs above give visual description of the statistical analysis.

In [ ]:

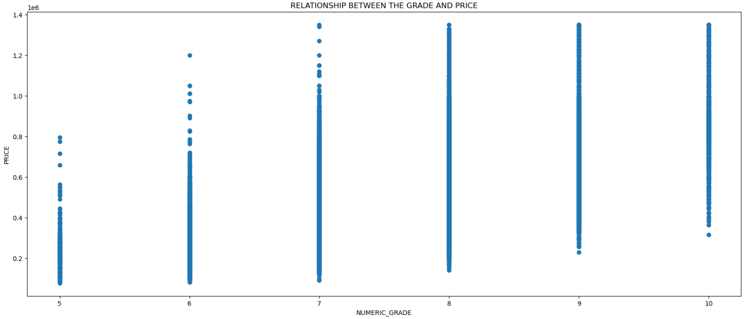
```
fig,ax=plt.subplots(figsize=(20,8))
ax.scatter(data['sqft_living'], data['price'])
ax.set_xlabel('HOUSE SQUARE FEET')
ax.set_ylabel('PRICE')
ax.set_title('RELATIONSHIP BETWEEN SQUARE FOOT LIVING  AND PRICE');
```



There is a positive linear relationship between price and house square feet

In [ ]:

```
fig,ax=plt.subplots(figsize=(20,8))
ax.scatter(data['numeric_grade'], data['price'])
ax.set_xlabel('NUMERIC_GRADE')
ax.set_ylabel('PRICE')
ax.set_title('RELATIONSHIP BETWEEN THE GRADE AND PRICE');
```

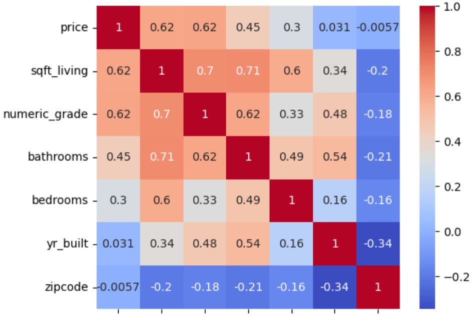


In [ ]:

```
# Checking for Multicollinearity
sns.heatmap(data.corr(), annot=True, cmap='coolwarm', square=True)
```

Out[ ]:

```
<AxesSubplot:>
```



price	1	0.62	0.62	0.45	0.3	0.031	-0.0057
sqft_living	0.62	1	0.7	0.71	0.6	0.34	-0.2
numeric_grade	0.62	0.7	1	0.62	0.33	0.48	-0.18
bathrooms	0.45	0.71	0.62	1	0.49	0.54	-0.21
bedrooms	0.3	0.6	0.33	0.49	1	0.16	-0.16
yr_built	0.031	0.34	0.48	0.54	0.16	1	-0.34
zipcode	-0.0057	-0.2	-0.18	-0.21	-0.16	-0.34	1

MODELING

In [ ]:

```python
# Modeling with one predictor to be the baseline model
x = data["sqft_living"]
y = data["price"]

x = sm.add_constant(x)

model = sm.OLS(y, sm.add_constant(x))
result = model.fit(method='pinv')
results=model.fit
result.summary()
```

Out[ ]:

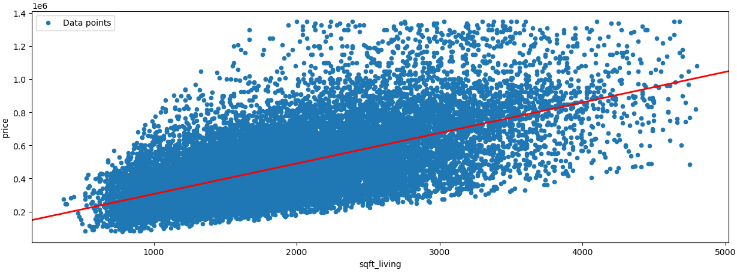
```
                    OLS Regression Results
      Dep. Variable:            price          R-squared:        0.383
             Model:              OLS      Adj. R-squared:        0.382
            Method:    Least Squares         F-statistic:    1.270e+04
              Date: Sun, 09 Jul 2023  Prob (F-statistic):         0.00
              Time:         20:00:42      Log-Likelihood:  -2.7675e+05
  No. Observations:            20497                 AIC:    5.535e+05
      Df Residuals:            20495                 BIC:    5.535e+05
          Df Model:                1
   Covariance Type:        nonrobust

                  coef   std err        t  P>|t|    [0.025    0.975]
       const  1.21e+05  3462.996   34.950  0.000  1.14e+05  1.28e+05
 sqft_living  184.8631     1.641  112.674  0.000   181.647   188.079

       Omnibus:  2335.936    Durbin-Watson:     1.968
 Prob(Omnibus):     0.000  Jarque-Bera (JB):  3666.741
          Skew:     0.823          Prob(JB):      0.00
      Kurtosis:     4.258          Cond. No.  5.92e+03



Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.92e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Interpretation of the model

1. The model is statistically significant overall, with an F-statistic p-value well below 0.05
2. The model explains about 38% of the variance in price
3. The model coefficients (const and sqft_living) are both statistically significant, with t-statistic p-values of 0.000 which is well below 0.05
4. for 0 sqft_living, the estimated price is estimated to be $121000.
5. For 1 unit increase in sqft_living, there is an associated increase in price of about $184

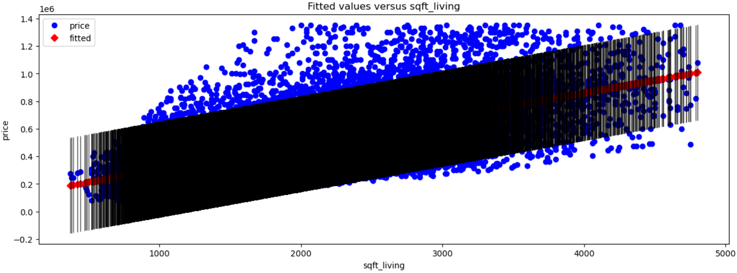
In [ ]:

```python
fig, ax = plt.subplots(figsize=(15,5))
data.plot(x="sqft_living", y="price", kind="scatter", label="Data points", ax=ax)
sm.graphics.abline_plot(model_results=model.fit(), ax=ax, color="red", linewidth=2,)
ax.legend()
plt.show()
```



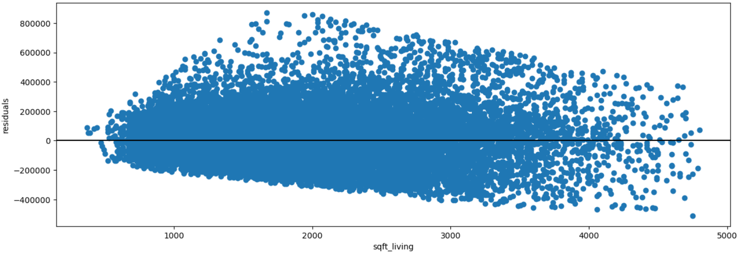
In [ ]:

```
import statsmodels.api as sm

x = data["sqft_living"]
y = data["price"]

x = sm.add_constant(x)

model = sm.OLS(y, sm.add_constant(x))
result = model.fit(method='pinv')
results=model.fit
result.summary()
fig, ax = plt.subplots(figsize=(15,5))
sm.graphics.plot_fit(result, "sqft_living", ax=ax)
plt.show()
```



In [ ]:

```
fig, ax = plt.subplots(figsize=(15,5))

ax.scatter(data["sqft_living"], result.resid)
ax.axhline(y=0, color="black")

ax.set_xlabel("sqft_living")
ax.set_ylabel("residuals");
```



The residuals exhibit homoscedasticity, indicating that the distribution of the residuals doesn't vary much based on the size of the house in square feet.

Adding more independent variables

In [ ]:

```
x = data[["sqft_living", "numeric_grade", "bathrooms", "bedrooms", "yr_built", "zipcode"]]
y = data["price"]

x = sm.add_constant(x)

model = sm.OLS(y,x)

result = model.fit(method='pinv')

result.summary()
```

Out[ ]:

```
                      OLS Regression Results
   Dep. Variable:            price        R-squared:         0.560
           Model:              OLS    Adj. R-squared:         0.560
          Method:    Least Squares         F-statistic:        4344.
            Date: Sun, 09 Jul 2023  Prob (F-statistic):        0.00
            Time:         20:00:48     Log-Likelihood:  -2.7328e+05
No. Observations:            20497                 AIC:   5.466e+05
    Df Residuals:            20490                 BIC:   5.466e+05
        Df Model:                6
 Covariance Type:        nonrobust

                      coef    std err        t   P>|t|     [0.025      0.975]
        const  -1.126e+07   2.08e+06   -5.403   0.000  -1.53e+07   -7.18e+06
  sqft_living    103.3683      2.529   40.873   0.000     98.411     108.325
numeric_grade   1.144e+05   1589.759   71.987   0.000   1.11e+05    1.18e+05
    bathrooms   4.573e+04   2455.366   18.626   0.000   4.09e+04    5.05e+04
     bedrooms  -2.058e+04   1571.866  -13.092   0.000  -2.37e+04   -1.75e+04
     yr_built  -2926.3181     46.603  -62.792   0.000  -3017.664   -2834.972
      zipcode    167.4499     20.957    7.990   0.000    126.373     208.526

      Omnibus:  2084.988     Durbin-Watson:     1.958
Prob(Omnibus):     0.000  Jarque-Bera (JB):  4050.409
         Skew:     0.674          Prob(JB):      0.00
     Kurtosis:     4.710          Cond. No.  1.96e+08
```

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.96e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

Interpretation of model with 6 predictors

1. The model explains a 56% of the variance in price which shows an increase compared to the first model which had a variance of 38% with only one predictor (sqft_living).
2. The model is statistically significant overally, with an F-statistic p-value below 0.05.
3. The model coefficients (const, sqft_living, numeric_grade, bathrooms, bedrooms, yr_built and zipcode) are all statistically significant, with t-statistic p-values of 0.000 which is below 0.05
4. For each increase of 1 sqft in sqft_living, there is an increase in price of about $103
5. For each increase in numeric grade, there is an increase in price of about $114400
6. For each increase of 1 bathroom, we see an associated increase in price of about $45730
7. For each increase of 1 bedroom , we see an associated decrease in price of about $20580
8. For a change in location zipcode, there is an increase in price by $167

RECOMMENDATIONS

1. The real estate agency should advice their clients that the pricing of houses increases with each sqft increase of the house and they

should showcase this.

2. Houses with higher numerical grade fall in high price category. Home owners should be advised to improve the grade of their houses so at to increase their value.
3. There are certain zipcodes that are more expensive than others as the price of houses increases by $167. The real estate agency should highlight this areas to home buyers and sellers.
4. Buyers who are looking for high-end properties may not necessarily prioritize the number of bedrooms. Therefore, sellers should be aware that adding additional bedrooms may not necessarily increase the value of the property as houses with more bedrooms have low prices.

CONCLUSION

This project is aimed to develop a model to predict housing prices in King County based on various features such as square footage, number of bedrooms and bathrooms, grading and zipcode.

Firstly, exploratory data analysis (EDA) was performed and found that the price of houses was positively correlated with the square footage. The location of the house also had a significant impact on the price.

Secondly, multiple linear regression models was used to predict the price of the house. The model included square footage, grade, bedrooms, bathrooms and zipcode as the predictors performed reasonably well, explaining about 56% of the variance in price.

Based on the results, we can conclude that square footage, the numeric grade and zipcode of the house are significant predictors of housing prices in King County.

A multiple linear regression was suitable for this project as it evaluated the dependent variable and several independent variables so as to access their strength of association.

Next Step

In this project, we were only looking at the coefficients in order to give our recommendations. Further research and indepth analysis can be done to improve the accuracy of the models and to gain a better understanding of the factors that influence housing prices in King County.