Project 2 Submission

Please fill out:

- Student name: Anni Liu
- Instructor name: Hardik Idnani

In [1]:

```
# Import libraries

import numpy as np
import pandas as pd
pd.set_option('display.max_columns', None)
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import scipy as sp
from scipy.stats import pearsonr, f_oneway
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn import metrics, linear_model
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.dummy import DummyRegressor
from sklearn.linear_model import LinearRegression
import pickle
```

In [2]:

```
# Import data

data=pd.read_csv(r'C:\Users\AnnieLiu\Desktop\King-County-House-Sales\data\kc_house_d
```

In [3]:
```
data
```

Out[3]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfron
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0
...	...	...	...	...	...	...	...	...	...
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	0.0
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	0.0
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	0.0
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	NaN
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	0.0

21597 rows × 21 columns

In [4]:
```
data.head()
```

Out[4]:

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

Data Cleaning & EDA

In [5]:
```
data.shape
```

Out[5]:
```
(21597, 21)
```

In [6]:
```
data.describe()
```

Out[6]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	flo
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500

In [7]:
```
data.describe().transpose()
```

Out[7]:

	count	mean	std	min	25%	50%	
id	21597.0	4.580474e+09	2.876736e+09	1.000102e+06	2.123049e+09	3.904930e+09	7.30
price	21597.0	5.402966e+05	3.673681e+05	7.800000e+04	3.220000e+05	4.500000e+05	6.45
bedrooms	21597.0	3.373200e+00	9.262989e-01	1.000000e+00	3.000000e+00	3.000000e+00	4.00
bathrooms	21597.0	2.115826e+00	7.689843e-01	5.000000e-01	1.750000e+00	2.250000e+00	2.50
sqft_living	21597.0	2.080322e+03	9.181061e+02	3.700000e+02	1.430000e+03	1.910000e+03	2.55
sqft_lot	21597.0	1.509941e+04	4.141264e+04	5.200000e+02	5.040000e+03	7.618000e+03	1.06
floors	21597.0	1.494096e+00	5.396828e-01	1.000000e+00	1.000000e+00	1.500000e+00	2.00
waterfront	19221.0	7.595859e-03	8.682485e-02	0.000000e+00	0.000000e+00	0.000000e+00	0.00
view	21534.0	2.338627e-01	7.656862e-01	0.000000e+00	0.000000e+00	0.000000e+00	0.00
condition	21597.0	3.409825e+00	6.505456e-01	1.000000e+00	3.000000e+00	3.000000e+00	4.00
grade	21597.0	7.657915e+00	1.173200e+00	3.000000e+00	7.000000e+00	7.000000e+00	8.00
sqft_above	21597.0	1.788597e+03	8.277598e+02	3.700000e+02	1.190000e+03	1.560000e+03	2.21
yr_built	21597.0	1.971000e+03	2.937523e+01	1.900000e+03	1.951000e+03	1.975000e+03	1.99
yr_renovated	17755.0	8.363678e+01	3.999464e+02	0.000000e+00	0.000000e+00	0.000000e+00	0.00
zipcode	21597.0	9.807795e+04	5.351307e+01	9.800100e+04	9.803300e+04	9.806500e+04	9.81
lat	21597.0	4.756009e+01	1.385518e-01	4.715590e+01	4.747110e+01	4.757180e+01	4.76
long	21597.0	-1.222140e+02	1.407235e-01	-1.225190e+02	-1.223280e+02	-1.222310e+02	-1.22
sqft_living15	21597.0	1.986620e+03	6.852305e+02	3.990000e+02	1.490000e+03	1.840000e+03	2.36
sqft_lot15	21597.0	1.275828e+04	2.727444e+04	6.510000e+02	5.100000e+03	7.620000e+03	1.00

In [8]:
```
data.sort_values("price")
```
Out[8]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfro
15279	40000362	5/6/2014	78000.0	2	1.00	780	16344	1.0	0
465	8658300340	5/23/2014	80000.0	1	0.75	430	5050	1.0	Na
16184	3028200080	3/24/2015	81000.0	2	1.00	730	9975	1.0	Na
8267	3883800011	11/5/2014	82000.0	3	1.00	860	10426	1.0	0
2139	1623049041	5/8/2014	82500.0	2	1.00	520	22334	1.0	0
...	...	...	...	...	...	...	...	...	
1446	8907500070	4/13/2015	5350000.0	5	5.00	8000	23985	2.0	0
4407	2470100110	8/4/2014	5570000.0	5	5.75	9200	35069	2.0	0
9245	9208900037	9/19/2014	6890000.0	6	7.75	9890	31374	2.0	0
3910	9808700762	6/11/2014	7060000.0	5	4.50	10040	37325	2.0	1
7245	6762700020	10/13/2014	7700000.0	6	8.00	12050	27600	2.5	0

21597 rows × 21 columns

In [9]:
```
data.sort_values("price", ascending=False).head(10)
```
Out[9]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
7245	6762700020	10/13/2014	7700000.0	6	8.00	12050	27600	2.5	0.0
3910	9808700762	6/11/2014	7060000.0	5	4.50	10040	37325	2.0	1.0
9245	9208900037	9/19/2014	6890000.0	6	7.75	9890	31374	2.0	0.0
4407	2470100110	8/4/2014	5570000.0	5	5.75	9200	35069	2.0	0.0
1446	8907500070	4/13/2015	5350000.0	5	5.00	8000	23985	2.0	0.0
1313	7558700030	4/13/2015	5300000.0	6	6.00	7390	24829	2.0	1.0
1162	1247600105	10/20/2014	5110000.0	5	5.25	8010	45517	2.0	1.0
8085	1924059029	6/17/2014	4670000.0	5	6.75	9640	13068	1.0	1.0
2624	7738500731	8/15/2014	4500000.0	5	5.50	6640	40014	2.0	1.0
8629	3835500195	6/18/2014	4490000.0	4	3.00	6430	27517	2.0	0.0

In [10]:
```python
data.sort_values("price", ascending=False).tail(10)
```

Out[10]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront
13743	1788900230	7/22/2014	86500.0	3	1.00	840	9480	1.0	0.0
10242	2422049104	9/15/2014	85000.0	2	1.00	830	9000	1.0	0.0
16700	1322049150	3/5/2015	85000.0	2	1.00	910	9753	1.0	0.0
3763	1523049188	4/30/2015	84000.0	2	1.00	700	20130	1.0	0.0
18453	7999600180	5/29/2014	83000.0	2	1.00	900	8580	1.0	0.0
2139	1623049041	5/8/2014	82500.0	2	1.00	520	22334	1.0	0.0
8267	3883800011	11/5/2014	82000.0	3	1.00	860	10426	1.0	0.0
16184	3028200080	3/24/2015	81000.0	2	1.00	730	9975	1.0	NaN
465	8658300340	5/23/2014	80000.0	1	0.75	430	5050	1.0	NaN
15279	40000362	5/6/2014	78000.0	2	1.00	780	16344	1.0	0.0

In [11]:
```python
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  float64
 9   view           21534 non-null  float64
 10  condition      21597 non-null  int64  
 11  grade          21597 non-null  int64  
 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(8), int64(11), object(2)
memory usage: 3.5+ MB
```

In [12]:
```
# check for duplicates

duplicates = data[data.duplicated()]
print(len(duplicates))
```

```
0
```

In [13]:
```
# Cheking for rows with same id

data['id'].duplicated().sum()
```

Out[13]:
```
177
```

Houses may have been sold more than one, we will keep them as unique data.

In [14]:
```
# Check for missing values
data.isnull().sum()
```

Out[14]:
```
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 [15]:
```
# Summary of data columns

data.view.describe()
```

Out[15]:
```
count    21534.000000
mean         0.233863
std          0.765686
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          4.000000
Name: view, dtype: float64
```

In [16]:
```
# Replace null values in 'view' with median
data.view = data.view.fillna(value=data.view.median())
```

In [17]:
```
data.waterfront.value_counts()
```

Out[17]:
```
0.0    19075
1.0      146
Name: waterfront, dtype: int64
```

In [18]:
```
data.waterfront.describe()
```

Out[18]:
```
count    19221.000000
mean         0.007596
std          0.086825
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
Name: waterfront, dtype: float64
```

In [19]:
```
# Replace with null (most properties were not waterfront anyways)
data.waterfront=data.waterfront.fillna(value=data.waterfront.median())
```

In [20]:
```
data.columns
```

Out[20]:
```
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 [21]:
```
data
```

Out[21]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfron
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	0.(
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.(
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.(
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.(
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.(
...	...	...	...	...	...	...	...	...	..
21592	263000018	5/21/2014	360000.0	3	2.50	1530	1131	3.0	0.(
21593	6600060120	2/23/2015	400000.0	4	2.50	2310	5813	2.0	0.(
21594	1523300141	6/23/2014	402101.0	2	0.75	1020	1350	2.0	0.(
21595	291310100	1/16/2015	400000.0	3	2.50	1600	2388	2.0	0.(
21596	1523300157	10/15/2014	325000.0	2	0.75	1020	1076	2.0	0.(

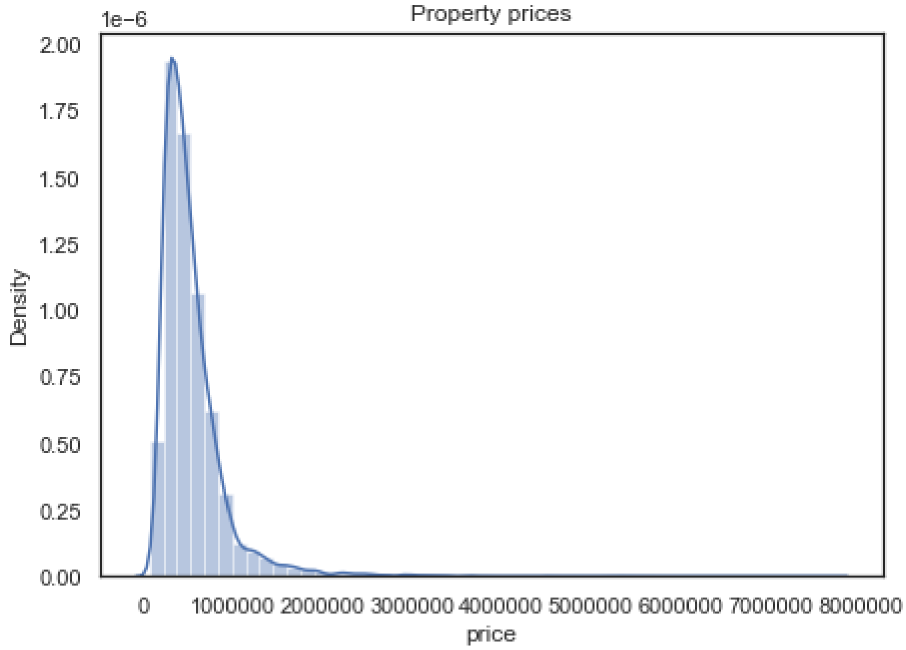
21597 rows × 21 columns

In [22]:
```
# Drop unnecessary columns
data = data.drop(['id', 'sqft_above', 'sqft_living15', 'sqft_lot15', 'zipcode'], axi
```

In [81]:
```
plt.figure(figsize= (7,5))
sns.distplot(data['price'])
plt.ticklabel_format(style='plain', axis='x')
plt.title('Property prices')
```

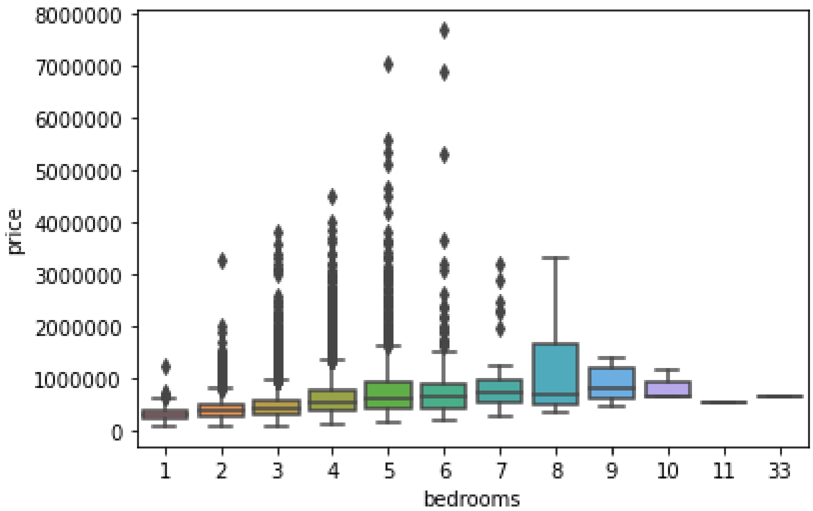
```
C:\Users\AnnieLiu\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Futur
eWarning: `distplot` is a deprecated function and will be removed in a future vers
ion. Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[81]:
```
Text(0.5, 1.0, 'Property prices')
```



Most properties sub $1mil

In [24]:
```
sns.boxplot(x='bedrooms', y='price', data=data)
plt.ticklabel_format(style='plain', axis='y')
```



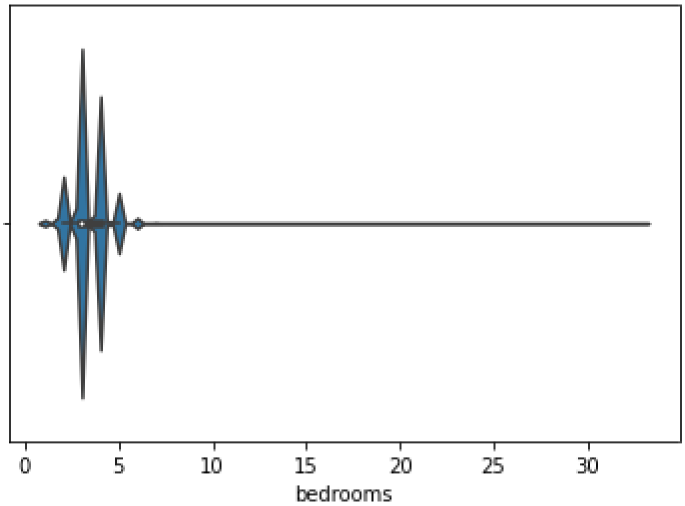
In [25]:

```python
# 33 bedrooms seems excessive, let's have a closer look

plt.figure(figsize=(6,4))
sns.violinplot(data.bedrooms)
```

```
C:\Users\AnnieLiu\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an e
xplicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[25]: `<AxesSubplot:xlabel='bedrooms'>`



In [26]:

```python
# Looks like most bedrooms are scattered between 1-6
```

In [27]:

```python
# Determine outliers

data.bedrooms.sort_values(ascending=False).head(10)
```

Out[27]:

```
15856    33
8748     11
13301    10
19239    10
15147    10
6073      9
4231      9
16830     9
8537      9
4092      9
Name: bedrooms, dtype: int64
```

In [28]:
```
data.bedrooms.sort_values(ascending=False).tail(5)
```

Out[28]:
```
12472    1
13316    1
7010     1
3578     1
14373    1
Name: bedrooms, dtype: int64
```

In [29]:

```
# Check data for larger bedrooms i.e. 33, 11 and 10 bedrooms
print(data.loc[[15856]]) # Unlikely to fit 33 bedrooms in 6000 sqft_lot
print(data.loc[[8748]]) # Unlikely to fit 11 bedroom in 4960 sqft_lot
print(data.loc[[13301]])
print(data.loc[[19239]]) #Unlikely to fit 10 bedroom in 3745 sqft_lot
print(data.loc[[15147]])
print(data.loc[[14373]])
```

```
            date     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
15856  6/25/2014  640000.0        33       1.75         1620      6000   

       floors  waterfront  view  condition  grade sqft_basement  yr_built  \
15856     1.0         0.0   0.0          5      7         580.0      1947   

       yr_renovated      lat     long  
15856           0.0  47.6878 -122.331  
           date     price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  \
8748  8/21/2014  520000.0        11        3.0         3000      4960     2.0   

      waterfront  view  condition  grade sqft_basement  yr_built  \
8748         0.0   0.0          3      7         600.0      1918   

      yr_renovated     lat     long  
8748        1999.0  47.556 -122.363  
            date      price  bedrooms  bathrooms  sqft_living  sqft_lot  \
13301  8/14/2014  1150000.0        10       5.25         4590     10920   

       floors  waterfront  view  condition  grade sqft_basement  yr_built  \
13301     1.0         0.0   2.0          3      9        2090.0      2008   

       yr_renovated      lat     long  
13301           0.0  47.5861 -122.113  
             date     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
19239  12/29/2014  660000.0        10        3.0         2920      3745   

       floors  waterfront  view  condition  grade sqft_basement  yr_built  \
19239     2.0         0.0   0.0          4      7        1060.0      1913   

       yr_renovated      lat    long  
19239           0.0  47.6635 -122.32  
             date     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
15147  10/29/2014  650000.0        10        2.0         3610     11914   

       floors  waterfront  view  condition  grade sqft_basement  yr_built  \
15147     2.0         0.0   0.0          4      7         600.0      1958   

       yr_renovated      lat     long  
15147           0.0  47.5705 -122.175  
            date     price  bedrooms  bathrooms  sqft_living  sqft_lot  \
14373  6/23/2014  335000.0         1        1.0          720      5100   

       floors  waterfront  view  condition  grade sqft_basement  yr_built  \
14373     1.0         0.0   0.0          3      6           0.0      1907   

       yr_renovated      lat    long  
14373           0.0  47.6821 -122.38  
```

In [30]:

```python
# Drop the unlikely rows from index

df = data.drop(data.index[[15856,8748,19239]])
df
```

Out[30]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
0	10/13/2014	221900.0	3	1.00	1180	5650	1.0	0.0	0.0
1	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	0.0
2	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	0.0
3	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	0.0
4	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...
21592	5/21/2014	360000.0	3	2.50	1530	1131	3.0	0.0	0.0
21593	2/23/2015	400000.0	4	2.50	2310	5813	2.0	0.0	0.0
21594	6/23/2014	402101.0	2	0.75	1020	1350	2.0	0.0	0.0
21595	1/16/2015	400000.0	3	2.50	1600	2388	2.0	0.0	0.0
21596	10/15/2014	325000.0	2	0.75	1020	1076	2.0	0.0	0.0

21594 rows × 16 columns

Does selling date/season impact price of properties?

In [31]:

```python
# Date conversion

df['date'] = pd.to_datetime(df['date'])
```

In [32]:

```python
# Date conversion to month to assess seasonsability effects

df['month_sold'] = df['date'].dt.month
```

In [33]:

```
df
```

Out[33]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0.0	0.0	3
1	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3
2	2015-02-25	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3
3	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5
4	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3
...	...	...	...	...	...	...	...	...	...	...
21592	2014-05-21	360000.0	3	2.50	1530	1131	3.0	0.0	0.0	3
21593	2015-02-23	400000.0	4	2.50	2310	5813	2.0	0.0	0.0	3
21594	2014-06-23	402101.0	2	0.75	1020	1350	2.0	0.0	0.0	3
21595	2015-01-16	400000.0	3	2.50	1600	2388	2.0	0.0	0.0	3
21596	2014-10-15	325000.0	2	0.75	1020	1076	2.0	0.0	0.0	3

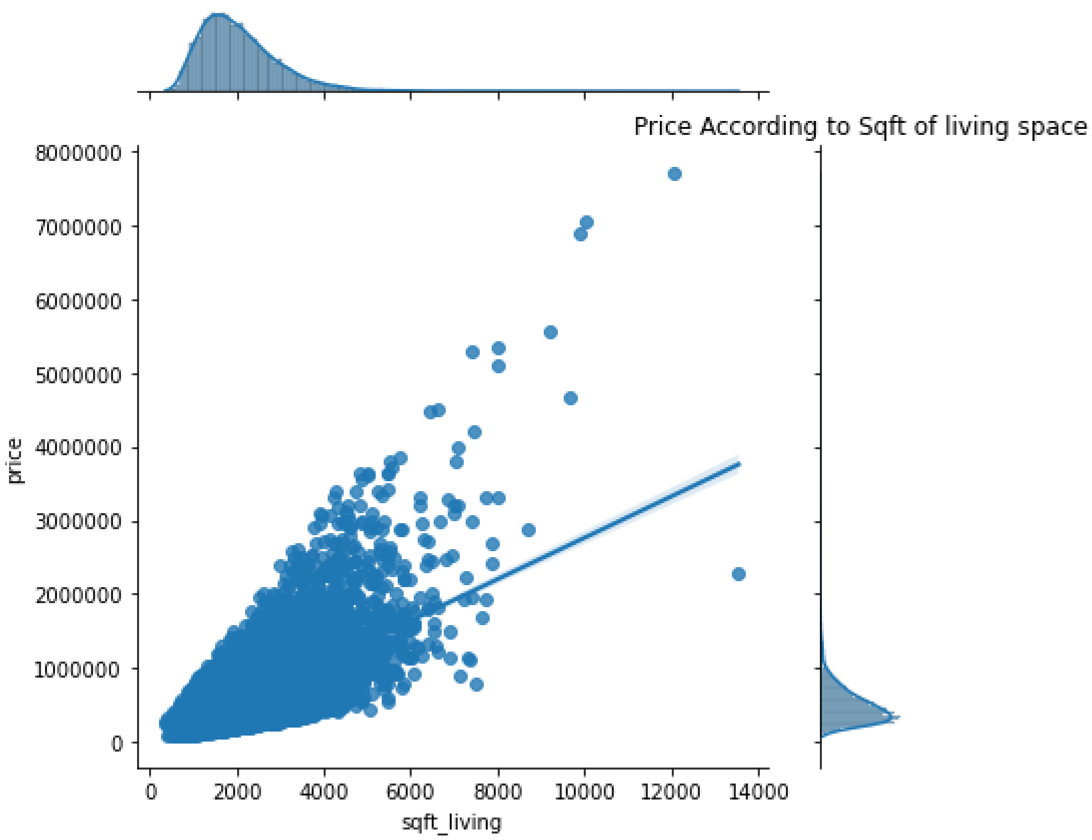
21594 rows × 17 columns

Linear regression

In [34]:

```python
# examining the relationship between sqft_living and price
sns.jointplot('sqft_living','price', data=df, kind='reg')
plt.title("Price According to Sqft of living space")
plt.tight_layout()
plt.ticklabel_format(style='plain')
```

```
C:\Users\AnnieLiu\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variables as keyword args: x, y. From version 0.12, the o
nly valid positional argument will be `data`, and passing other arguments without
an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



Sqft living and price have high positive correlation. Statistical test to confirm using Pearson's Correlation Coefficient as there are two continuous variables.

In [35]:
```
corr = pearsonr(df.sqft_living, df.price)
corr
```

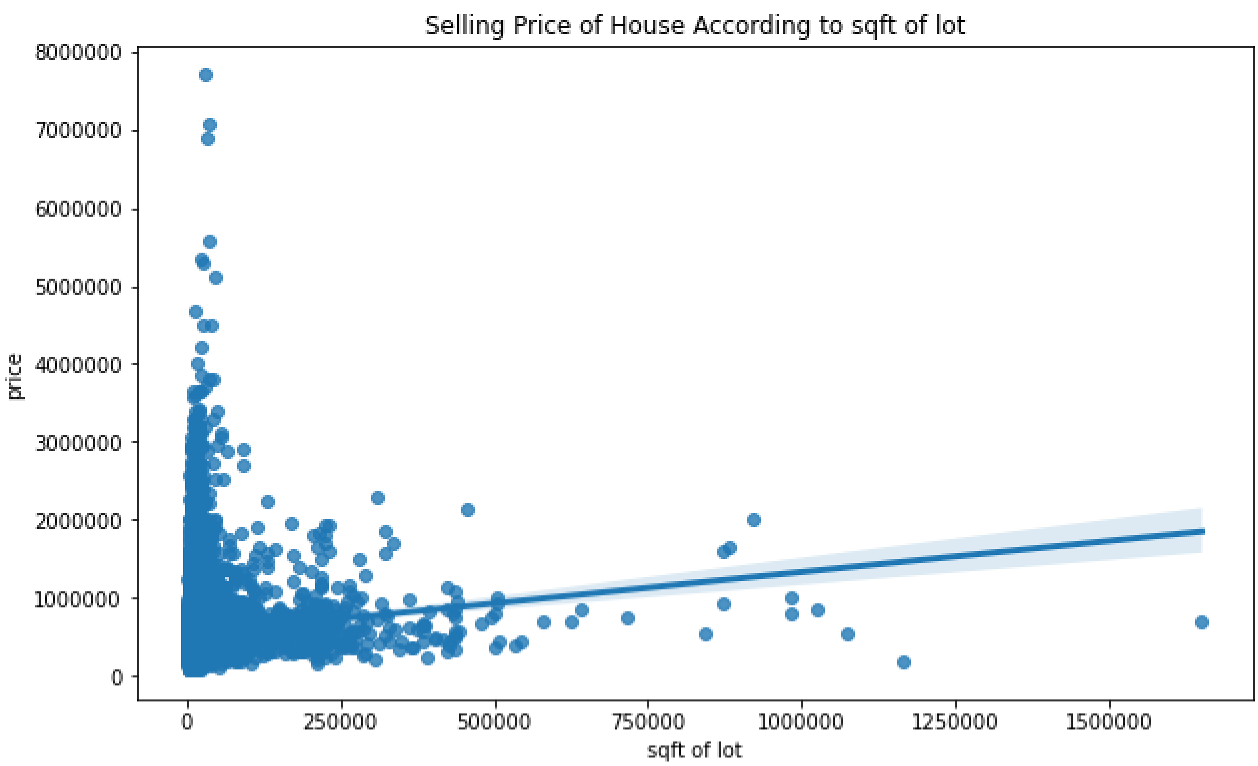
Out[35]:
```
(0.701949326358472, 0.0)
```

0.7 strong correlation - Apply feature in our model.

In [36]:
```
# Does the same for the entire property size?

fig, ax = plt.subplots(figsize=(10,6))
plt.style.use('bmh')
sns.regplot(data=df, x='sqft_lot', y='price')

ax.set_xlabel('sqft of lot', fontsize=10)
ax.set_ylabel('price', fontsize=10)
ax.set_title('Selling Price of House According to sqft of lot', fontsize=12)
ax.ticklabel_format(style='plain')
```



Larger property size does not equate to a higher price. Not much correlation between property size and sales either.

In [37]:
```
new_corr = pearsonr(df.sqft_lot, df.price)
new_corr
```

Out[37]:
```
(0.0898832559024816, 5.5626777243553564e-40)
```

Very weak, closer to no correlation at all.

Feature engineering

Generate new features that could assist with final model predictions.

Feature 1: 'Month' sold vs price relationship

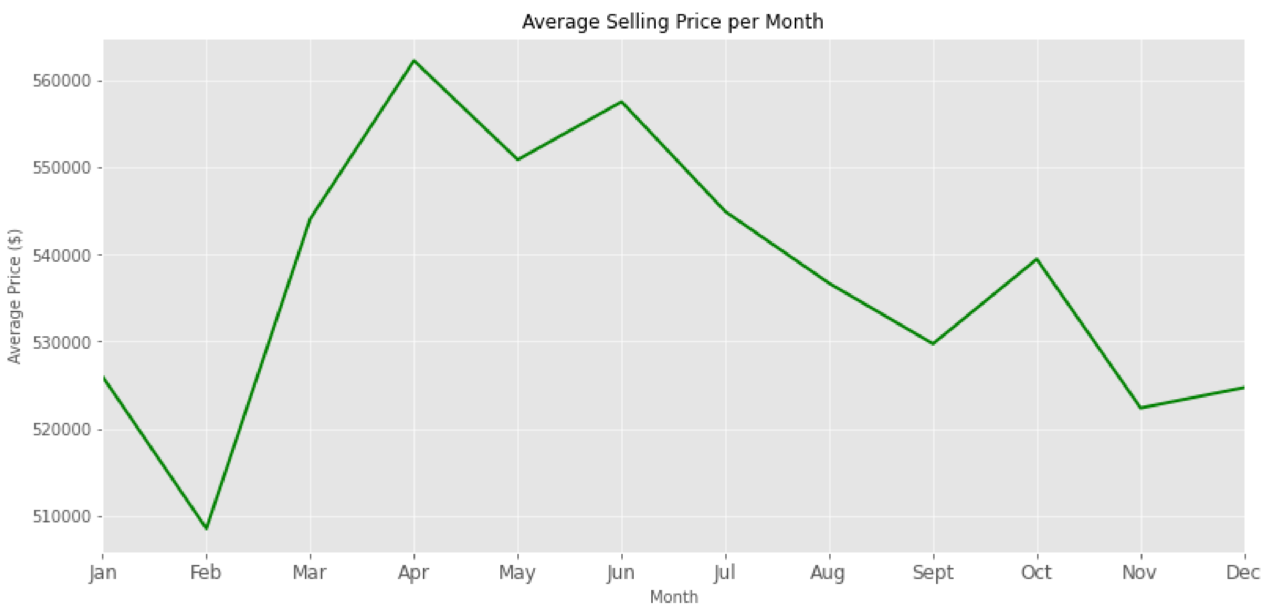
In [38]:

```
# creating a graph of average price per month to visualize if there's a trend
df.sort_values(by='month_sold', ascending=True)
months = sorted(df['month_sold'].unique())
# getting the average price for each month
avg_price = df.groupby('month_sold')['price'].mean()

# instantiating plot
plt.style.use('ggplot')
fig, ax = plt.subplots(figsize=(13,6))
ax.plot(months, avg_price, color='green')
# setting title and axis labels
ax.set_xlabel('Month', fontsize=10)
ax.set_ylabel('Average Price ($)', fontsize=10)
ax.set_title('Average Selling Price per Month', fontsize=12)
# setting month labels
ax.set_xlim(1, 12)
ax.set_xticks((1,2,3,4,5,6,7,8,9,10,11,12))
ax.set_xticklabels(['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sept',
```

Out[38]:

```
[Text(1, 0, 'Jan'),
 Text(2, 0, 'Feb'),
 Text(3, 0, 'Mar'),
 Text(4, 0, 'Apr'),
 Text(5, 0, 'May'),
 Text(6, 0, 'Jun'),
 Text(7, 0, 'Jul'),
 Text(8, 0, 'Aug'),
 Text(9, 0, 'Sept'),
 Text(10, 0, 'Oct'),
 Text(11, 0, 'Nov'),
 Text(12, 0, 'Dec')]
```



February indicates very low sales prices. Whilst May-June generate highest prices.

Hypotheses. ANOVA test - month_sold and price

We want to test how each month impacts the prices of properties sold.

Null Hypothesis: No relationship between features and target variable, price. Alternative Hypothesis: There is relationship between our features and our target variable, price. Significance level (alpha) of 0.05 to determine.

In [39]:
```
# creating a sample measurement for each month, using the month value as the first c
jan = df.loc[df['month_sold'] == 1, 'price']
feb = df.loc[df['month_sold'] == 2, 'price']
mar = df.loc[df['month_sold'] == 3, 'price']
apr = df.loc[df['month_sold'] == 4, 'price']
may = df.loc[df['month_sold'] == 5, 'price']
jun = df.loc[df['month_sold'] == 6, 'price']
jul = df.loc[df['month_sold'] == 7, 'price']
aug = df.loc[df['month_sold'] == 8, 'price']
sep = df.loc[df['month_sold'] == 9, 'price']
otb = df.loc[df['month_sold'] == 10, 'price']
nov = df.loc[df['month_sold'] == 11, 'price']
dec = df.loc[df['month_sold'] == 12, 'price']

# using scipy function f_oneway to conduct an ANOVA test for the f-statistic
sp.stats.f_oneway(jan,feb,mar,apr,may,jun,jul,aug,sep,otb,nov,dec)
```

Out[39]:
```
F_onewayResult(statistic=3.0692820292498273, pvalue=0.00039843219888828 57)
```

Output:

- f-statistic: 3.06928
- p-value: 0.00039

F-value suggests significant variance between mean price for each month is pretty high. P-value to reject null hypothesis, each month sees different selling prices for each house.

Month sold therefore impacts how much a property can sell for.

Feature 2: Age of property

Assess relationship between price and age of property.

In [40]:
```
# subtracting 'yr_built' with the current year
df['age'] = 2022 - df['yr_built']
```

In [41]:

```
df
```

Out[41]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition
0	2014-10-13	221900.0	3	1.00	1180	5650	1.0	0.0	0.0	3
1	2014-12-09	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3
2	2015-02-25	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3
3	2014-12-09	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5
4	2015-02-18	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3
...	...	...	...	...	...	...	...	...	...	...
21592	2014-05-21	360000.0	3	2.50	1530	1131	3.0	0.0	0.0	3
21593	2015-02-23	400000.0	4	2.50	2310	5813	2.0	0.0	0.0	3
21594	2014-06-23	402101.0	2	0.75	1020	1350	2.0	0.0	0.0	3
21595	2015-01-16	400000.0	3	2.50	1600	2388	2.0	0.0	0.0	3
21596	2014-10-15	325000.0	2	0.75	1020	1076	2.0	0.0	0.0	3

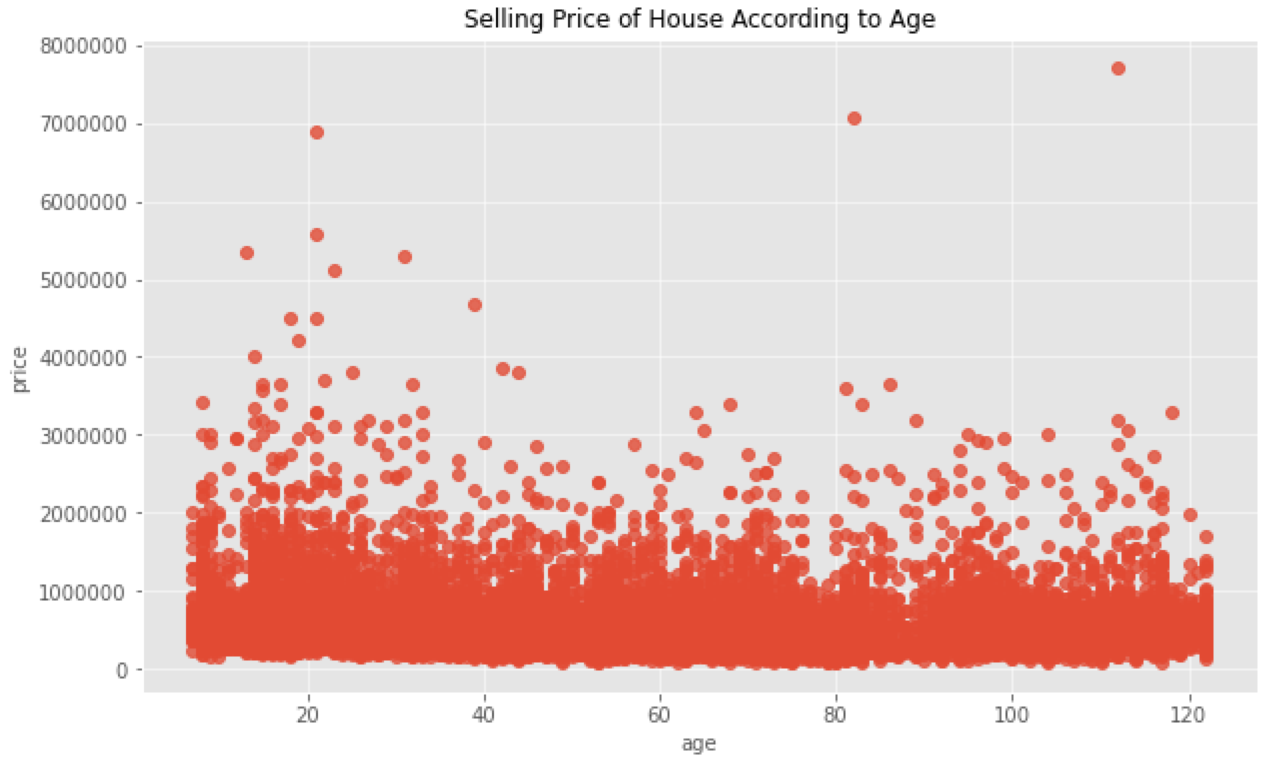
21594 rows × 18 columns

In [42]:

```
# Age of building vs price

fig, ax = plt.subplots(figsize=(10,6))
plt.style.use('bmh')
sns.regplot(data=df, x='age', y='price')

ax.set_xlabel('age', fontsize=10)
ax.set_ylabel('price', fontsize=10)
ax.set_title('Selling Price of House According to Age', fontsize=12)
ax.ticklabel_format(style='plain')
```

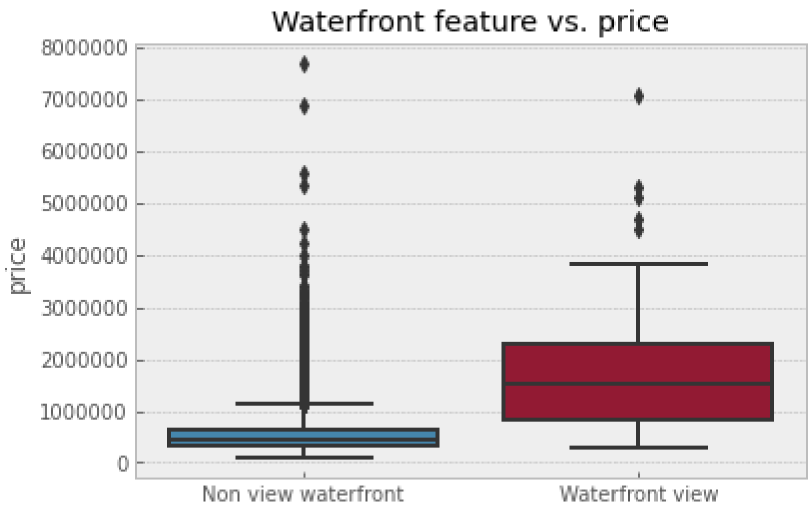


No visible relationships.

Feature 3: Waterfront

Assess relationship between price and waterfront vs non waterfront properties.

In [43]:
```python
# Plot boxplot of waterfront feature
sns.boxplot(x = df['waterfront'], y = df['price'])
plt.title("Waterfront feature vs. price")
plt.ylabel("price")
plt.ticklabel_format(style='plain', axis='y')
plt.xlabel(None)
plt.xticks(np.arange(2), ('Non view waterfront', 'Waterfront view'))
plt.show()
```



We can see the above boxplot that not having a waterfront view provides significantly lower minimum, median, Q1 and Q3 values than than having a waterfront view. However, We can see that there are still outliers in the prices for not having a waterfront view.

In [44]:
```python
waterfrontmean = df[df['waterfront'] == 1]['price'].mean()
nonwaterfrontmean = df[df['waterfront'] == 0]['price'].mean()
print(f"Mean waterfront view: {round(waterfrontmean,2)}")
print(f"Mean without waterfront view: {round(nonwaterfrontmean,2)}")
```

```
Mean waterfront view: 1717214.73
Mean without waterfront view: 532275.82
```

In [45]:
```python
len(df[df['waterfront'] == 1])/len(df)*100
```

Out[45]: 0.6761137352968417

Waterfront views homes double in price of non waterfront views. Only 0.67% of properties have waterfront views.

In [46]:
```
# Find other correlations other than correlations with price

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

Out[46]:
```
age            -0.053999
month_sold     -0.009952
long            0.022057
condition       0.036017
yr_built        0.053999
sqft_lot        0.089883
yr_renovated    0.129706
floors          0.256820
waterfront      0.264310
lat             0.306681
bedrooms        0.316790
view            0.393509
bathrooms       0.525934
grade           0.667982
sqft_living     0.701949
price           1.000000
Name: price, dtype: float64
```

Business Question Results

1. Do houses sell for more money when they have more living pace?

- Yes

2. Do houses with higher total property size sell for more?

- No

3. On average, what month generates highest prices?

- Lowest prices in February. Meanwhile, it's on average the highest prices to sell a house in April to June.

4. Do properties with waterfront views cost more than non waterfront view properties?

- Yes

Modeling with Train-test Split:

Split the housing data apart. The 'train set' will be used to fit the model to our data. The 'test set' will simulate new and unseen data, which we will disregard until the end of the analysis. Test-train split with a built-in function in sklearn

Train-test split of data:

In [47]:
```
train_set, test_set = train_test_split(df, test_size=0.2, random_state=42)
print(len(train_set), "train +", len(test_set), "test")
```

```
17275 train + 4319 test
```

Variables x_train, y_train, x_test and y_test:

In [48]:
```python
# only keeping features
X = df.drop('price', axis = 1)

# split target variable, which we're trying to predict
y = df['price']
```

In [49]:
```python
# performing the split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_sta
```

Baseline model

Find worst fit to compare real models against it later.

In [50]:
```python
# fitting the baseline model to the training set and generating a score (r-squared)
dummy = DummyRegressor()
dummy.fit(X_train, y_train)
dummy.score(X_train, y_train)

# we get an r-squared of 0, because we're predictng using NO features
# dummy models are more useful for looking at the RMSE, so let's check that out
```

Out[50]:
```
0.0
```

In [51]:
```python
# using the baseline model to predict the y_train data
y_pred = dummy.predict(X_train)
y_pred
```

Out[51]:
```
array([541332.64019759, 541332.64019759, 541332.64019759, ...,
       541332.64019759, 541332.64019759, 541332.64019759])
```

In [52]:
```python
dummy_rmse = mean_squared_error(y_train, y_pred, squared=False)
dummy_rmse
```

Out[52]:
```
370008.74126035336
```

The RSME here can be interpreted as the amount on average a data point differs from the line of best fit. This value is in units of the y variable so in our case the price of the house will differ from the predicted value on average of 370,000 dollars.

Model 1

```
Use selected features for iterations. After it's fit and predicted on, then i'll use
feature selection to specifically edit features.

Use statsmodels to assess R-Squared and feature coefficients.
Apply sklearn to fit the model to the training data. From there, we can predict on y
and generate an RMSE for how the model performs on the training data.
From there, we can do a similar transform & predict procedure on the testing data and
generate an RMSE.
With the RMSE of how the model performs on the training and testing sets, we can
determine whether the model is underfit or overfit.
```

In [53]:

```python
# generating model with statsmodels
first_model = ols(formula='price~bedrooms+bathrooms+sqft_living+floors+waterfront+vi
                data=train_set).fit()
first_model.summary()
```

Out[53]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.652
Model:	OLS	**Adj. R-squared:**	0.652
Method:	Least Squares	**F-statistic:**	3239.
Date:	Fri, 06 May 2022	**Prob (F-statistic):**	0.00
Time:	15:09:30	**Log-Likelihood:**	-2.3684e+05
No. Observations:	17275	**AIC:**	4.737e+05
Df Residuals:	17264	**BIC:**	4.738e+05
Df Model:	10		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-1.031e+06	1.99e+04	-51.761	0.000	-1.07e+06	-9.92e+05
bedrooms	-4.25e+04	2380.018	-17.857	0.000	-4.72e+04	-3.78e+04
bathrooms	5.121e+04	3864.619	13.250	0.000	4.36e+04	5.88e+04
sqft_living	167.9184	3.665	45.819	0.000	160.735	175.102
floors	2.517e+04	3843.740	6.549	0.000	1.76e+04	3.27e+04
waterfront	5.92e+05	2.23e+04	26.529	0.000	5.48e+05	6.36e+05
view	4.492e+04	2486.686	18.066	0.000	4e+04	4.98e+04
condition	1.995e+04	2781.104	7.175	0.000	1.45e+04	2.54e+04
grade	1.266e+05	2410.137	52.539	0.000	1.22e+05	1.31e+05
month_sold	-3054.5520	532.686	-5.734	0.000	-4098.671	-2010.433
age	3696.4268	74.863	49.376	0.000	3549.688	3843.165

Omnibus:	12857.379	**Durbin-Watson:**	1.992
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	849927.214
Skew:	2.988	**Prob(JB):**	0.00
Kurtosis:	36.839	**Cond. No.**	3.08e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.08e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

R-Squared .652, good indicator as close to 1.

Model into training data

With sklean, we can easily fit the model and perform the prediction on 'y' aka the price column.

In [54]:
```python
# setting 'X_train_1' to the features I want to fit in this first model
X_train_1 = X_train[['bedrooms', 'bathrooms', 'sqft_living', 'floors', 'waterfront',

# instantiate LinearRegression to use
# coefficients are learnt and stored in 'model_1'
model_1 = LinearRegression()
model_1.fit(X_train_1, y_train)
```

Out[54]: LinearRegression()

Now let's use 'X_train_1' to predict y for this training data:

In [55]:
```python
# predicting on the y (price) for train_set
y_pred = model_1.predict(X_train_1)
```

Evaluate training predictions using RMSE:

In [56]:
```python
# get the RMSE for the train set
model_1_rsme = mean_squared_error(y_train, y_pred, squared=False)
model_1_rsme
```

Out[56]: 217761.26478130033

Using the model to transform & predict on the testing set:

In [57]:
```python
# transforming and .predict on the test_set

X_test_1 = X_test[['bedrooms', 'bathrooms', 'sqft_living', 'floors', 'waterfront', '

# feeding in the training data because this is a transformation
testing_model_1 = LinearRegression().fit(X_train_1, y_train)
```

In [58]:
```python
y_pred_test = testing_model_1.predict(X_test_1)
```

In [59]:
```python
# getting R-Squared for testing_model_1
testing_model_1.score(X_test_1, y_test)
```

Out[59]: 0.6503152125150762

Slightly less than training sets (r-squared 0.652).

In [60]:
```python
# get the RMSE for the test set
testing_model_1_rmse = mean_squared_error(y_test, y_pred_test, squared=False)
testing_model_1_rmse
```

Out[60]: 212513.88350096633

Using the model to transform & predict on the testing set:

In [61]:
```
print('Training Root Mean Squared Error:' , model_1_rsme)
print('Testing Root Mean Squared Error:' , testing_model_1_rmse)
```

```
Training Root Mean Squared Error: 217761.26478130033
Testing Root Mean Squared Error: 212513.88350096633
```

When the RMSE decreases between the training and testing set, that means this model may be underfit. In this case, the RMSE did decrease from 217761 to 212513 when transformed & predicted on the test data.

Feature Selection

Considering that the baseline model produced an RMSE of 370000, the first model didnt perform that much better.

We'll use feature selection to create another iteration of the model, and try to improve the RMSE.

Check for Multicoollinearity

In [62]:
```
# creating a numerical correlation matrix
corr_matrix = X_train_1.corr().abs()
corr_matrix
```

Out[62]:

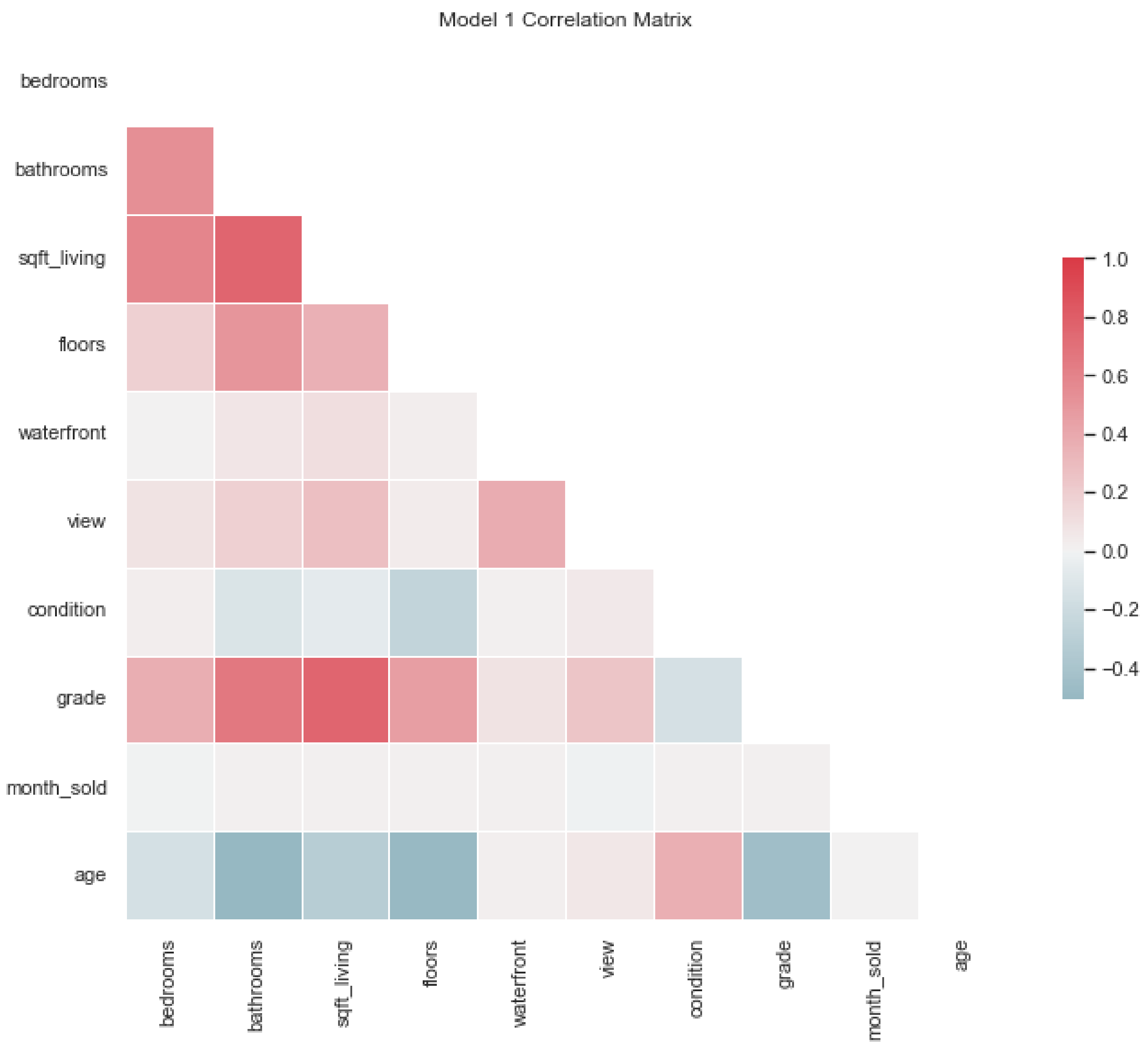
	bedrooms	bathrooms	sqft_living	floors	waterfront	view	condition	grade
bedrooms	1.000000	0.530387	0.592688	0.187754	0.004002	0.081313	0.026666	0.364918
bathrooms	0.530387	1.000000	0.756289	0.500470	0.070222	0.186128	0.120634	0.663816
sqft_living	0.592688	0.756289	1.000000	0.353782	0.106753	0.278521	0.060053	0.761849
floors	0.187754	0.500470	0.353782	1.000000	0.027203	0.031178	0.264061	0.458870
waterfront	0.004002	0.070222	0.106753	0.027203	1.000000	0.381840	0.013112	0.085311
view	0.081313	0.186128	0.278521	0.031178	0.381840	1.000000	0.048815	0.246375
condition	0.026666	0.120634	0.060053	0.264061	0.013112	0.048815	1.000000	0.148864
grade	0.364918	0.663816	0.761849	0.458870	0.085311	0.246375	0.148864	1.000000
month_sold	0.002799	0.007901	0.009773	0.016030	0.009891	0.008519	0.014675	0.009033
age	0.160535	0.505471	0.318037	0.489119	0.019676	0.057458	0.361274	0.446322

In [63]:

```python
# creating a correlation heatmap, to easily visualize high correlations and refer ba
sns.set(style="white")
# compute the correlation matrix
corr = X_train_1.corr()
# generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
# set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))
# generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)
# draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
ax.set_title('Model 1 Correlation Matrix')
```

```
C:\Users\AnnieLiu\AppData\Local\Temp/ipykernel_120912/719838915.py:6: DeprecationW
arning: `np.bool` is a deprecated alias for the builtin `bool`. To silence this wa
rning, use `bool` by itself. Doing this will not modify any behavior and is safe.
If you specifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdoc
s/release/1.20.0-notes.html#deprecations (https://numpy.org/devdocs/release/1.20.0
-notes.html#deprecations)
  mask = np.zeros_like(corr, dtype=np.bool)
```

Out[63]: Text(0.5, 1.0, 'Model 1 Correlation Matrix')



In [64]:
```python
df.corr()['grade'].sort_values()
```

Out[64]:
```
age             -0.447837
condition       -0.146853
month_sold       0.009043
yr_renovated     0.016820
waterfront       0.082814
lat              0.113624
sqft_lot         0.114715
long             0.200288
view             0.249066
bedrooms         0.367654
yr_built         0.447837
floors           0.458857
bathrooms        0.665944
price            0.667982
sqft_living      0.762869
grade            1.000000
Name: grade, dtype: float64
```

From the correlation matrix, it looks like the feature with the most correlation issues is grade. That feature has two of the highest correlation coefficients.

correlation of .76 with sqft_living correlation of .66 with bathrooms

Let's try dropping grade completely for the next model iteration and see if there's any changes.

Model 2

This model is same as first but without grade feature.

In [65]:
```
## fitting the model to the training data:
# setting 'X_train_2' to the features I want to fit in this first model
X_train_2 = X_train[['bedrooms', 'bathrooms', 'sqft_living', 'floors', 'waterfront',

# instantiate LinearRegression to use
# coefficients are learnt and stored in 'model_2'
model_2 = LinearRegression()
model_2.fit(X_train_2, y_train)

## predicting on the y (price) for train_set
y_pred = model_2.predict(X_train_2)

# get the RMSE for the train_set
model_2_rsme = mean_squared_error(y_train, y_pred, squared=False)
model_2_rsme
```

Out[65]: 234028.70822660028

In [66]:
```
## transforming and .predict on the test_set
X_test_2 = X_test[['bedrooms', 'bathrooms', 'sqft_living', 'floors', 'waterfront', '

testing_model_2 = LinearRegression().fit(X_train_2, y_train)

## predicting on the y (price) for test_set
y_pred_test = testing_model_2.predict(X_test_2)

# get the RMSE for the test_set
testing_model_2_rmse = mean_squared_error(y_test, y_pred_test, squared=False)
testing_model_2_rmse
```

Out[66]: 229364.38899539088

In [67]:
```
# comparing Model 1 and Model 2
print('Model 1 Testing RMSE:' , testing_model_1_rmse)
print('Model 2 Testing RMSE:' , testing_model_2_rmse)
```

```
Model 1 Testing RMSE: 212513.88350096633
Model 2 Testing RMSE: 229364.38899539088
```

So the RMSE got slightly higher. So we'll go back to model 1.

Model evaluation

Let's print the testing RMSE for all the models and check whether they are overfit or underfit, and determine the best model overall.

In [68]:

```
# baseline Model
print('Baseline Model RMSE:', dummy_rmse, '\n')
# training RMSEs
print('Training RMSE:')
print('Model 1:', model_1_rsme)
print('Model 2:', model_2_rsme)

# testing RMSEs
print('Testing RMSE:')
print('Model 1:', testing_model_1_rmse)
print('Model 2:', testing_model_2_rmse)

# overfit or underfit
print('Are the models overfit or underfit?')
# model 1
if model_1_rsme < testing_model_1_rmse:
    print('Model 1 is overfit')
elif model_1_rsme > testing_model_1_rmse:
    print('Model 1 is underfit')
# model 2
if model_2_rsme < testing_model_2_rmse:
    print('Model 2 is overfit')
elif model_2_rsme > testing_model_2_rmse:
    print('Model 2 is underfit')
```

```
Baseline Model RMSE: 370008.74126035336

Training RMSE:
Model 1: 217761.26478130033
Model 2: 234028.70822660028
Testing RMSE:
Model 1: 212513.88350096633
Model 2: 229364.38899539088
Are the models overfit or underfit?
Model 1 is underfit
Model 2 is underfit
```

Model 1 performed best on testing data. We will apply that on our df dataset.

Refitting final model to df dataset

In [69]:

```
features = df[['bedrooms', 'bathrooms', 'sqft_living', 'floors', 'waterfront', 'view
```

In [70]:

```
# price column of whole dataset
target = df.price
```

In [71]:

```
# instantiating final model
final_model = LinearRegression()

# fit the linear regression to the data
final_model = final_model.fit(features,target)
```

In [72]:
```
# checking final model coefficients
final_model.coef_
```

Out[72]:
```
array([-4.18464718e+04,  4.95338586e+04,  1.68514939e+02,  2.61137933e+04,
        6.11076273e+05,  4.50440847e+04,  1.87760481e+04,  1.25157552e+05,
       -2.74254404e+03,  3.67030060e+03])
```

As we can see grade and waterfront produce highest value in $.

Final model

In [73]:
```
features
```

Out[73]:

	bedrooms	bathrooms	sqft_living	floors	waterfront	view	condition	grade	month_sold	age
0	3	1.00	1180	1.0	0.0	0.0	3	7	10	67
1	3	2.25	2570	2.0	0.0	0.0	3	7	12	71
2	2	1.00	770	1.0	0.0	0.0	3	6	2	89
3	4	3.00	1960	1.0	0.0	0.0	5	7	12	57
4	3	2.00	1680	1.0	0.0	0.0	3	8	2	35
...	...	...	...	...	...	...	...	...	...	...
21592	3	2.50	1530	3.0	0.0	0.0	3	8	5	13
21593	4	2.50	2310	2.0	0.0	0.0	3	8	2	8
21594	2	0.75	1020	2.0	0.0	0.0	3	7	6	13
21595	3	2.50	1600	2.0	0.0	0.0	3	8	1	18
21596	2	0.75	1020	2.0	0.0	0.0	3	7	10	14

21594 rows × 10 columns

In [74]:
```
features.to_csv('housing_features.csv')
```

In [75]:
```
# setting the pickle file as 'model'

pickle_out = open("model.pickle","wb")
pickle.dump(final_model, pickle_out)
pickle_out.close()
```

In [76]:
```
final_model = pickle.load(open('model.pickle', 'rb'))
```

In [77]:
```
#Prediction from features

prediction = final_model.predict(features)
```

In [78]:

```
# Export predictions

prediction = pd.DataFrame(prediction, columns=['predictions'])
```

In [79]:

```
prediction.head()
```

Out[79]:

	predictions
0	280607.210322
1	612070.206758
2	230891.970563
3	464634.110380
4	444046.823607

In [80]:

```
prediction.to_csv('housing_predictions.csv')
```