Phase 2 Group Project: Success in Seattle

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github link: https://github.com/theobigdog/DS_083021_Phase2_Project (https://github.com/theobigdog/DS_083021_Phase2_Project)

Overview and Business Understanding

Our stakeholder is a real-estate company with a new sub-division, "Seattle's Best Realty", who is looking to expand its market to King County (the greater Seattle area), starting in 2016. They need a reliable prediction metric for house prices and would like to know which features of houses are most important. Our task is to provide them with a linear regression model that will infer features that are most important in determining housing prices in this area. Given our inferences, the object is to allow for future research to predict housing prices in this market, allowing for the most competitive pricing and profit.

Data Understanding

Import necessary modules for analysis.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statsmodels
from statsmodels.formula.api import ols
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
import statsmodels.api as sm
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error
import warnings
from matplotlib.lines import Line2D
warnings.filterwarnings('ignore')
```

Import dataset

In [2]:
```
df = pd.read_csv('../data/kc_house_data.csv')
```

Let's look at some properties of the dataset

In [3]:
```
df.describe()
```

Out[3]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	sqft_above	yr_built	y
count	2.159700e+04	2.159700e+04	21597.000000	21597.000000	21597.000000	2.159700e+04	21597.000000	21597.000000	21597.000000	1
mean	4.580474e+09	5.402966e+05	3.373200	2.115826	2080.321850	1.509941e+04	1.494096	1788.596842	1970.999676	
std	2.876736e+09	3.673681e+05	0.926299	0.768984	918.106125	4.141264e+04	0.539683	827.759761	29.375234	
min	1.000102e+06	7.800000e+04	1.000000	0.500000	370.000000	5.200000e+02	1.000000	370.000000	1900.000000	
25%	2.123049e+09	3.220000e+05	3.000000	1.750000	1430.000000	5.040000e+03	1.000000	1190.000000	1951.000000	
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	1560.000000	1975.000000	
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068500e+04	2.000000	2210.000000	1997.000000	
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	9410.000000	2015.000000	

In [4]:
```
df.columns
```

Out[4]:
```
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 [5]:
```
df.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

It appears that `waterfront` , `view` and `yr_renovated` columns have some missing values. Let's resolve those issues.

In [6]:
```
df['waterfront'].value_counts()
```

Out[6]:
```
NO     19075
YES      146
Name: waterfront, dtype: int64
```

Less than 1% of listed homes have a waterfront access, so these seem like infrequent enough cases that we will fill missing values with "NO".

In [7]:
```
df['waterfront'].fillna("NO",inplace=True)
```

In [8]:
```
df['view'].value_counts()
```

Out[8]:
```
NONE         19422
AVERAGE        957
GOOD           508
FAIR           330
EXCELLENT      317
Name: view, dtype: int64
```

More than 90% of listed homes have no view, so we will use the mode to fill the missing values.

In [9]:
```
df['view'].fillna("NONE",inplace=True)
```

In [10]:
```
df['yr_renovated'].value_counts()
```

Out[10]:
```
0.0       17011
2014.0       73
2003.0       31
2013.0       31
2007.0       30
          ...
1946.0        1
1959.0        1
1971.0        1
1951.0        1
1954.0        1
Name: yr_renovated, Length: 70, dtype: int64
```

Very few homes from this list have been renovated. The 0 values may have never been renovated, but we can't know that for sure. Since there are so many 0s and also many missing entries, we decided that the column itself should be dropped.

In [11]:
```
df.drop('yr_renovated', axis=1,inplace=True)
```

Finally, let's look at the `date` column with type `object` .

In [12]:
```
df['date'].value_counts()
```

Out[12]:
```
6/23/2014    142
6/25/2014    131
6/26/2014    131
7/8/2014     127
4/27/2015    126
            ...
1/10/2015      1
1/17/2015      1
5/15/2015      1
8/30/2014      1
2/15/2015      1
Name: date, Length: 372, dtype: int64
```

`date` column includes the date each house was sold. Since this data won't be available in actual test sets since those houses don't have a sale date yet, we decided that the column itself should be dropped as it will be useless in predicting sale prices of houses that aren't sold yet.

In [13]:
```
df.drop('date', axis=1,inplace=True)
```

Upon investigation, it was observed that there is only one house that has a `grade of 3 Poor` . So, when samples will be split into training and test sets, one gets it, the other does not. This results is mismatched columns/rows at the end of the process, so we decided to drop that observation.

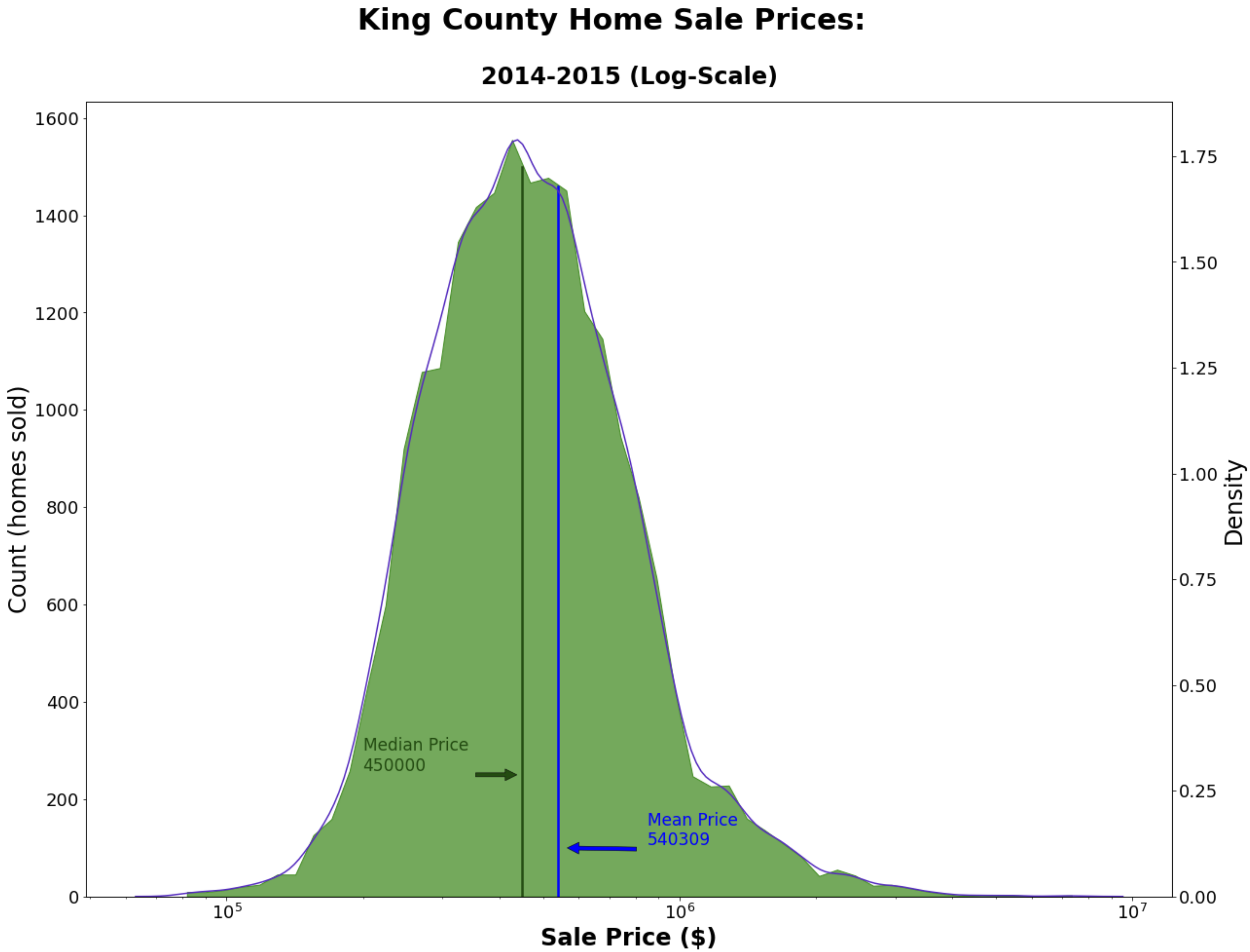
In [14]:
```
df['grade'].value_counts()
```

Out[14]:
```
7 Average        8974
8 Good           6065
9 Better         2615
6 Low Average    2038
10 Very Good     1134
11 Excellent      399
5 Fair            242
12 Luxury          89
4 Low              27
13 Mansion         13
3 Poor              1
Name: grade, dtype: int64
```

In [15]:
```
df = df[df['grade'] != "3 Poor"]
```

Now that we've trimmed and cleaned the data, let's make a population density plot to see how the target variable distribution looks.

In [16]:
```
x=df['price']
x_mean = np.mean(x)
x_median = np.median(x)
fig, ax = plt.subplots(figsize=(20,15))
fig.suptitle('King County Home Sale Prices:', fontsize=30, fontweight='bold',y=0.97)
sns.histplot(x, ax=ax, bins=50, color="#458D25", log_scale=True, element='poly')
plt.plot([x_mean,x_mean],[0,1460], color="blue",linewidth=2.5)
ax.annotate(('Mean Price\n' + str(int(x_mean))), xy=(x_mean,100), xytext=(850000,105), \
            arrowprops=dict(facecolor='blue', shrink=0.1, linewidth=0.5), fontsize=17,color="blue")
plt.plot([x_median,x_median],[0,1500], color="#244C12",linewidth=2.5)
ax.annotate(('Median Price\n' + str(int(x_median))), xy=(x_median,250), xytext=(200000,258), \
            arrowprops=dict(facecolor='#244C12', shrink=0.1, linewidth=0.5), fontsize=17,color="#244C12")
plt.xlabel('Sale Price ($)', fontsize=24, fontweight='bold')
plt.xticks(fontsize=18)
plt.ylabel('Count (homes sold)', fontsize=24,x=.95)
plt.yticks(fontsize=18)
ax2 = ax.twinx()
sns.kdeplot(x, ax=ax2, color="#552cbf", log_scale=True)
plt.title('2014-2015 (Log-Scale)', fontsize=24, fontweight='bold',y=1.015)
plt.yticks(fontsize=18)
plt.ylabel('Density', fontsize=24,x=1.1);
# plt.savefig('../Images/Home_Sales_Density.png', dpi=600);
```



Train/Test Split

It is time to split the data into training and test sets. This way, we can train our model using the training set and use the test set to see how successful our model is.

In [17]:
```
y = df['price']
X = df.drop('price',axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=69) # nice :)
```

Feature Engineering

`sqft_basement` column is also of type `object`. Let's convert that to a number type as well.

In [18]:
```
X_train['sqft_basement'].value_counts()
```

Out[18]:
```
0.0       9634
?          354
700.0      166
600.0      164
500.0      152
          ...
283.0        1
2150.0       1
1525.0       1
2080.0       1
875.0        1
Name: sqft_basement, Length: 280, dtype: int64
```

There are many 0 values, which likely means no basement. We'll assume that the `?` values have no basements as well, so we'll fill them with the mode, 0.

In [19]:
```
X_train['sqft_basement'].replace('?','0.0',inplace=True)
X_train['sqft_basement'] = pd.to_numeric(X_train['sqft_basement'], errors = 'coerce')
```

Outlier Elimination

We should get rid of outliers as they are not a part of the general trend of our dataset.

In [20]:
```
train = pd.concat([X_train, y_train], axis=1)
```

In [21]:
```
features = ['bedrooms','bathrooms','sqft_living','sqft_lot','floors','sqft_above','sqft_basement','yr_built','sc
'sqft_lot15']
for i in features:
    train = train[(np.abs(stats.zscore(train[i])) < 3)]
y_train = train['price']
X_train = train.drop('price',axis=1)
```

Outlier elimination gets rid of all mansions in the train set, so we decided to get rid of mansions in the test set as we won't be able to provide predictions for those houses if they are none in our training set.

In [22]:
```
temp_test = pd.concat([X_test, y_test], axis=1)
temp_test = temp_test[temp_test['grade'] != "13 Mansion"]
y_test = temp_test['price']
X_test = temp_test.drop('price',axis=1)
```

Feature Scaling

Feature scaling allows us to bring all continous features to the same scale, which will help with comparing the effects of each feature on the model.

In [23]:
```
features_to_scale=['sqft_living','sqft_lot','sqft_above','sqft_basement','sqft_living15','yr_built','zipcode','l
'sqft_lot15']
features_not_to_scale = ['id', 'bedrooms', 'bathrooms','floors', 'waterfront', 'view', 'condition', 'grade']
scale = X_train[features_to_scale]
no_scale = X_train[features_not_to_scale]
```

In [24]:
```
scalar = StandardScaler()
X_train_scaled = scalar.fit_transform(scale)
scaled_X_train = pd.DataFrame(data=X_train_scaled, columns=scale.columns, index=scale.index)
```

In [25]:
```
X_train = pd.concat([scaled_X_train, no_scale],axis=1)
```

Encoding Categorical Variables

Waterfront

In [26]:
```
X_train['waterfront'].value_counts()
```

Out[26]:
```
NO     14936
YES       74
Name: waterfront, dtype: int64
```

`waterfront` is a categorical variable with two categories. Therefore, we will use the `OrdinalEncoder` to encode it.

In [27]:
```
waterfront_train = X_train[['waterfront']]
encoder_waterfront = OrdinalEncoder()
encoder_waterfront.fit(waterfront_train)
encoder_waterfront.categories_[0]
waterfront_encoded_train = encoder_waterfront.transform(waterfront_train)
waterfront_encoded_train = waterfront_encoded_train.flatten()
X_train['waterfront'] = waterfront_encoded_train
```

View

In [28]:
```
X_train['view'].value_counts()
```

Out[28]:
```
NONE         13769
AVERAGE        596
GOOD           273
FAIR           207
EXCELLENT      165
Name: view, dtype: int64
```

`view` is a categorical variable with multiple categories. Therefore, we will use the `OneHotEncoder` to encode it.

In [29]:
```
view_train = X_train[['view']]
ohe = OneHotEncoder(categories="auto", sparse=False, handle_unknown="ignore")
ohe.fit(view_train)
view_encoded_train = ohe.transform(view_train)
view_encoded_train = pd.DataFrame(view_encoded_train, columns=ohe.categories_[0], index=X_train.index)
X_train.drop("view", axis=1, inplace=True)
X_train = pd.concat([X_train, view_encoded_train],axis=1)
```

Condition

In [30]:
```
X_train['condition'].value_counts()
```

Out[30]:
```
Average      9668
Good         3994
Very Good    1208
Fair          118
Poor           22
Name: condition, dtype: int64
```

`condition` is also a categorical variable with multiple categories. Therefore, we will use the `OneHotEncoder` to encode it.

In [31]:
```
condition_train = X_train[['condition']]
ohe.fit(condition_train)
condition_encoded_train = ohe.transform(condition_train)
condition_encoded_train = pd.DataFrame(condition_encoded_train, columns=ohe.categories_[0],index=X_train.index)
X_train.drop('condition', axis=1, inplace=True)
X_train = pd.concat([X_train, condition_encoded_train], axis=1)
```

Grade

In [32]:
```
X_train['grade'].value_counts()
```

Out[32]:
```
7 Average        6517
8 Good           4332
9 Better         1754
6 Low Average    1491
10 Very Good      632
5 Fair            177
11 Excellent       85
4 Low              17
12 Luxury           5
Name: grade, dtype: int64
```

`grade` is also a categorical variable with multiple categories. Therefore, we will use the `OneHotEncoder` to encode it.

In [33]:
```
grade_train = X_train[['grade']]
ohe.fit(grade_train)
grade_encoded_train = ohe.transform(grade_train)
grade_encoded_train = pd.DataFrame(grade_encoded_train, columns=ohe.categories_[0], index=X_train.index)
X_train.drop("grade", axis=1, inplace=True)
X_train = pd.concat([X_train, grade_encoded_train], axis=1)
```

Finally, now that we encoded all categorical columns, let's rename those columns for better readability.

In [34]:
```
column_names = {
    "AVERAGE" : "View_Avg",
    "EXCELLENT" : "View_Exc",
    "FAIR" : "View_Fair",
    "GOOD" : "View_Good",
    "NONE" : "View_NONE",
    "Average" : "Cond_Avg",
    "Fair" : "Cond_Fair",
    "Good" : "Cond_Good",
    "Poor" : "Cond_Poor",
    "Very Good" : "Cond_VGood",
    "10 Very Good" :  "Grade_VGood",
    "11 Excellent" :  "Grade_Exc",
    "12 Luxury" : "Grade_Lux",
    "4 Low" : "Grade_Low",
    "5 Fair" : "Grade_Fair",
    "6 Low Average" : "Grade_LAvg",
    "7 Average" : "Grade_Avg",
    "8 Good" : "Grade_Good",
    "9 Better" : "Grade_Better",
}
```

In [35]:
```
X_train.rename(column_names, axis=1,inplace=True)
```

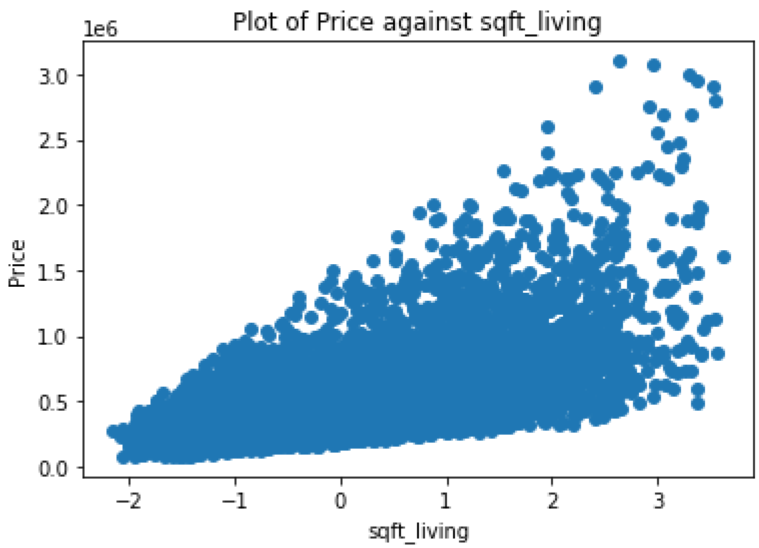
Assumptions of Linear Regression

In order to run linear regression, there are some conditions we need to check for.

1. Linear Relationship

There should be a linear relationship between independent and dependent variables. This can be checked by using scatterplots and looking at correlations.

In [36]:
```
for x in X_train.columns:
    plt.scatter(X_train[x], y_train)
    plt.title(f'Plot of Price against {x}')
    plt.xlabel(x)
    plt.ylabel('Price')
    plt.show()
```



It appears that `sqft_living` , `sqft_above` , `sqft_living15` and `bathrooms` columns have a somewhat linear relationship with `price` .

Next, let's check correlations of independent (predictor) variables with the dependent (target) variable from highest to lowest:

In [37]:
```
temp = pd.concat([X_train, y_train], axis=1)
temp.corr().abs()['price'].sort_values(ascending=False)
```

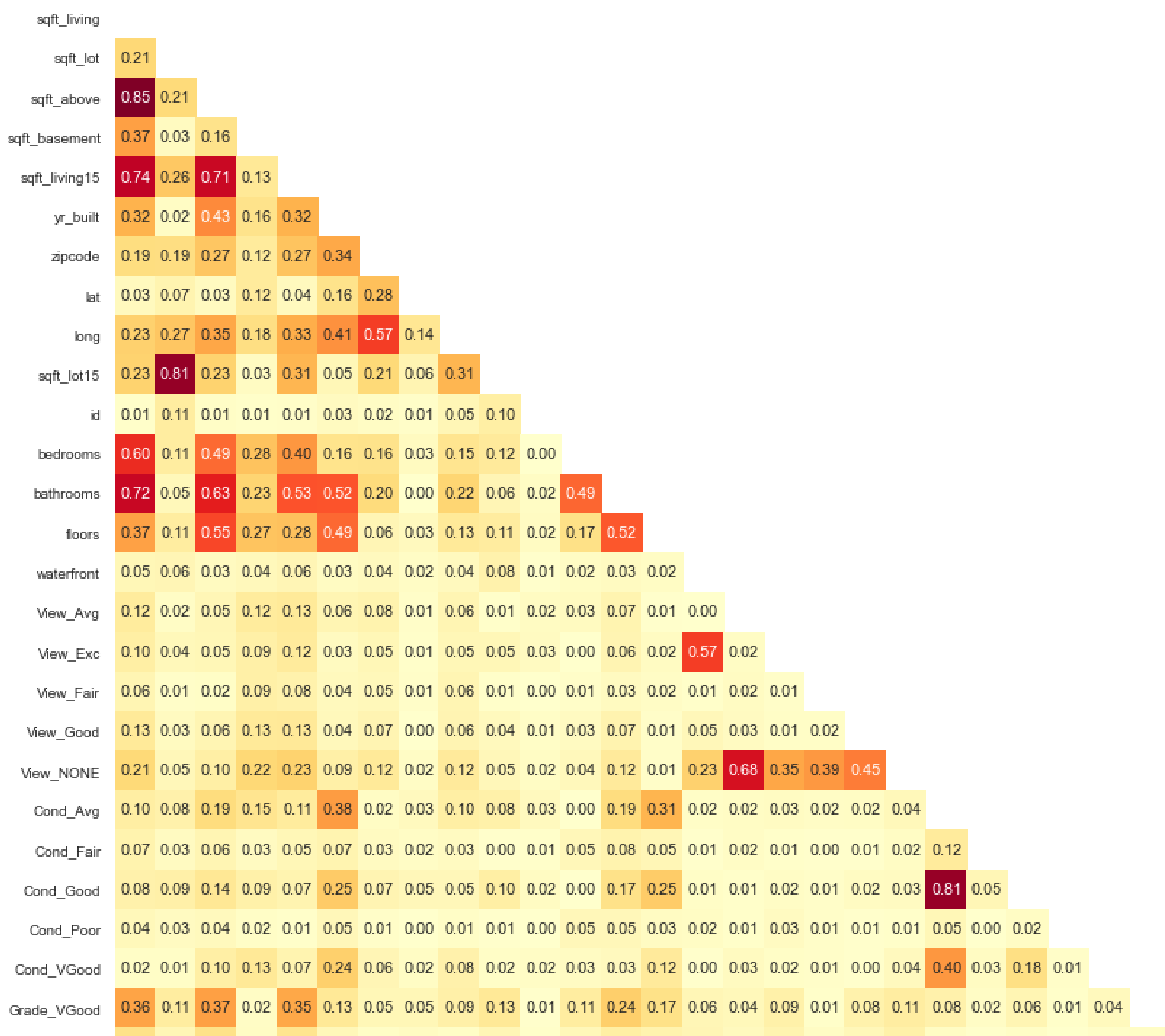
Out[37]:
```
price            1.000000
sqft_living      0.619902
sqft_living15    0.544502
sqft_above       0.514286
bathrooms        0.437250
lat              0.375590
Grade_VGood      0.365916
Grade_Better     0.340201
View_NONE        0.336194
Grade_Avg        0.317161
bedrooms         0.279526
floors           0.268613
sqft_basement    0.255543
View_Exc         0.247405
Grade_LAvg       0.242305
Grade_Exc        0.222430
waterfront       0.197582
View_Good        0.188595
View_Avg         0.156325
Grade_Lux        0.102109
Grade_Fair       0.099903
View_Fair        0.094856
Grade_Good       0.089122
sqft_lot15       0.086348
sqft_lot         0.083438
Cond_VGood       0.069397
Cond_Fair        0.060494
Grade_Low        0.037220
Cond_Poor        0.024515
Cond_Good        0.017844
id               0.011816
long             0.010514
Cond_Avg         0.009843
zipcode          0.005208
yr_built         0.001023
Name: price, dtype: float64
```

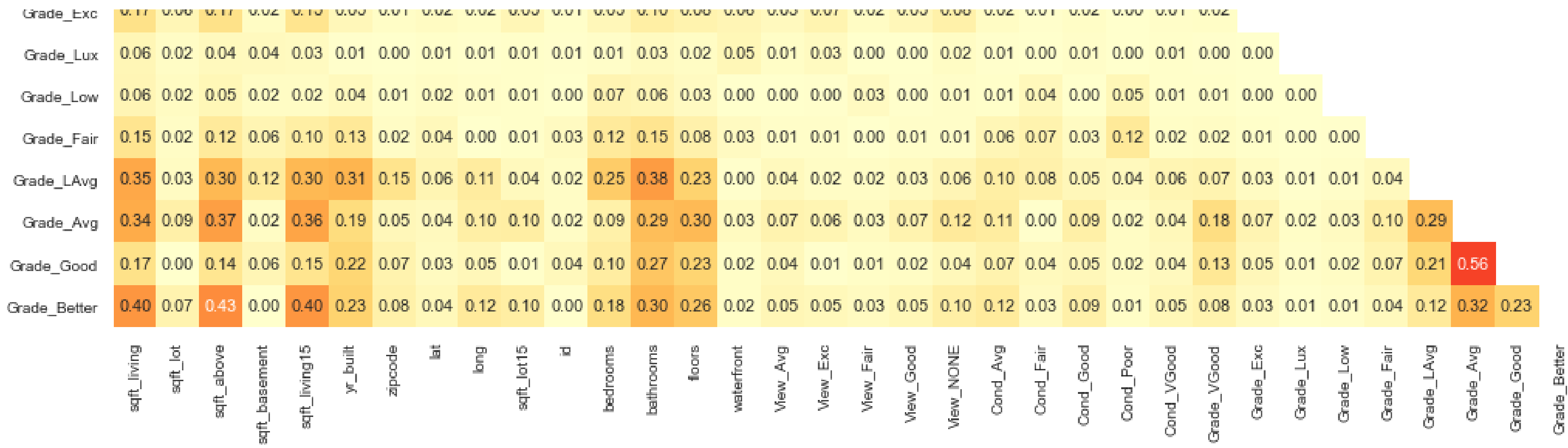
The table above agrees with the linearity observations from the scatterplot. The highest four correlations are `sqft_living` , `sqft_above` , `bathrooms` and `sqft_living15` .

2. Low Multicollinearity

In linear regression models, independent (predictor) variables shouldn't be highly correlated with each other . This can be checked by looking at the correlations. Let's do that by generating a heatmap to view these correlations visually.

In [38]:
```
plt.figure(figsize=(17,17))
sns.set(font_scale=0.9)
mask = np.triu(np.ones_like(X_train.corr(), dtype=bool))
with sns.axes_style("white"):
    sns.heatmap(X_train.corr().abs(), annot=True, fmt='.2f', cmap="YlOrRd",mask=mask, cbar=False)
sns.set(font_scale=1)
# plt.savefig('../Images/Full_Correlation_Heatmap.png', dpi=600);
```





Correlations higher than 0.7 are considered to be highly correlated, so let's look at which predictor features are highly correlated with each other.

In [39]:
```
corr_mtx = abs(X_train.corr())
filtered_corr_mtx = corr_mtx.stack().drop_duplicates()
filtered_corr_mtx[(filtered_corr_mtx.values>=0.7) & (filtered_corr_mtx.values<1)]
```

Out[39]:
```
sqft_living  sqft_above       0.852181
             sqft_living15    0.737596
             bathrooms        0.715424
sqft_lot     sqft_lot15       0.814697
sqft_above   sqft_living15    0.711584
Cond_Avg     Cond_Good        0.810044
dtype: float64
```

Now, let's apply feature engineering and categorical transformations to test set as well.

In [40]:
```
X_test['sqft_basement'].replace('?','0.0',inplace=True)
X_test['sqft_basement'] = pd.to_numeric(X_test['sqft_basement'], errors = 'coerce')

# Feature Scaling
features_to_scale=['sqft_living','sqft_lot','sqft_above','sqft_basement','sqft_living15','yr_built','zipcode','l
'sqft_lot15']
features_not_to_scale = ['id', 'bedrooms', 'bathrooms','floors', 'waterfront', 'view', 'condition', 'grade']
scale = X_test[features_to_scale]
no_scale = X_test[features_not_to_scale]
X_test_scaled = scalar.transform(scale)
scaled_X_test = pd.DataFrame(data=X_test_scaled, columns=scale.columns, index=scale.index)
X_test = pd.concat([scaled_X_test, no_scale],axis=1)

# Encode waterfront
waterfront_test = X_test[['waterfront']]
encoder_waterfront.fit(waterfront_test)
waterfront_encoded_test = encoder_waterfront.transform(waterfront_test)
waterfront_encoded_test = waterfront_encoded_test.flatten()
X_test['waterfront'] = waterfront_encoded_test

# Encode view
view_test = X_test[['view']]
ohe.fit(view_test)
view_encoded_test = ohe.transform(view_test)
view_encoded_test = pd.DataFrame(view_encoded_test, columns=ohe.categories_[0], index=X_test.index)
X_test.drop("view", axis=1, inplace=True)
X_test = pd.concat([X_test, view_encoded_test],axis=1)

# Encode condition
condition_test = X_test[['condition']]
ohe.fit(condition_test)
condition_encoded_test = ohe.transform(condition_test)
condition_encoded_test = pd.DataFrame(condition_encoded_test, columns=ohe.categories_[0],index=X_test.index)
X_test.drop('condition', axis=1, inplace=True)
X_test = pd.concat([X_test, condition_encoded_test], axis=1)

# Encode grade
grade_test = X_test[['grade']]
ohe.fit(grade_test)
grade_encoded_test = ohe.transform(grade_test)
grade_encoded_test = pd.DataFrame(grade_encoded_test, columns=ohe.categories_[0], index=X_test.index)
X_test.drop("grade", axis=1, inplace=True)
```

```
X_test = pd.concat([X_test, grade_encoded_test], axis=1)

# Rename columns
X_test.rename(column_names, axis=1,inplace=True)
```

Modeling

Let's start by modeling using all the features. This won't be the final model, however this model will be useful in analyzing the importance of each independent variable and help decide which ones to include in the final model.

In [41]:
```
predictors = sm.add_constant(X_train)
modelall = sm.OLS(y_train,predictors).fit()
modelall.summary()
```

Out[41]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.691
Model:	OLS	**Adj. R-squared:**	0.690
Method:	Least Squares	**F-statistic:**	1079.
Date:	Fri, 08 Oct 2021	**Prob (F-statistic):**	0.00
Time:	12:52:37	**Log-Likelihood:**	-2.0052e+05
No. Observations:	15010	**AIC:**	4.011e+05
Df Residuals:	14978	**BIC:**	4.014e+05
Df Model:	31		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.785e+05	9927.081	48.204	0.000	4.59e+05	4.98e+05
sqft_living	6.399e+04	1.28e+04	4.984	0.000	3.88e+04	8.92e+04
sqft_lot	4674.1692	2181.495	2.143	0.032	398.172	8950.166
sqft_above	1.279e+04	1.2e+04	1.062	0.288	-1.08e+04	3.64e+04
sqft_basement	8378.0372	6688.754	1.253	0.210	-4732.740	2.15e+04
sqft_living15	2.698e+04	2124.076	12.700	0.000	2.28e+04	3.11e+04
yr_built	-6.868e+04	1889.884	-36.343	0.000	-7.24e+04	-6.5e+04
zipcode	-2.138e+04	1637.353	-13.058	0.000	-2.46e+04	-1.82e+04
lat	8.065e+04	1366.562	59.020	0.000	7.8e+04	8.33e+04
long	-1.307e+04	1715.455	-7.620	0.000	-1.64e+04	-9709.147
sqft_lot15	-2.005e+04	2242.850	-8.940	0.000	-2.44e+04	-1.57e+04
id	-1.733e-06	4.4e-07	-3.941	0.000	-2.6e-06	-8.71e-07
bedrooms	-1.518e+04	1942.529	-7.813	0.000	-1.9e+04	-1.14e+04

bathrooms	3.228e+04	3151.458	10.242	0.000	2.61e+04	3.85e+04
floors	3.199e+04	3461.068	9.244	0.000	2.52e+04	3.88e+04
waterfront	3.419e+05	2.19e+04	15.621	0.000	2.99e+05	3.85e+05
View_Avg	5.103e+04	6596.174	7.736	0.000	3.81e+04	6.4e+04
View_Exc	2.428e+05	1.25e+04	19.464	0.000	2.18e+05	2.67e+05
View_Fair	7.286e+04	9589.367	7.598	0.000	5.41e+04	9.17e+04
View_Good	1.406e+05	8568.246	16.414	0.000	1.24e+05	1.57e+05
View_NONE	-2.876e+04	4640.055	-6.198	0.000	-3.79e+04	-1.97e+04
Cond_Avg	9.232e+04	6857.133	13.463	0.000	7.89e+04	1.06e+05
Cond_Fair	7.61e+04	1.32e+04	5.778	0.000	5.03e+04	1.02e+05
Cond_Good	1.188e+05	6926.622	17.149	0.000	1.05e+05	1.32e+05
Cond_Poor	3.894e+04	2.75e+04	1.417	0.157	-1.49e+04	9.28e+04
Cond_VGood	1.524e+05	7633.558	19.963	0.000	1.37e+05	1.67e+05
Grade_VGood	1.61e+05	1.05e+04	15.260	0.000	1.4e+05	1.82e+05
Grade_Exc	3.902e+05	1.76e+04	22.195	0.000	3.56e+05	4.25e+05
Grade_Lux	9.397e+05	6.21e+04	15.135	0.000	8.18e+05	1.06e+06
Grade_Low	-2.697e+05	3.46e+04	-7.791	0.000	-3.38e+05	-2.02e+05
Grade_Fair	-2.645e+05	1.39e+04	-19.051	0.000	-2.92e+05	-2.37e+05
Grade_LAvg	-2.3e+05	9753.580	-23.584	0.000	-2.49e+05	-2.11e+05
Grade_Avg	-1.761e+05	8911.127	-19.763	0.000	-1.94e+05	-1.59e+05
Grade_Good	-1.023e+05	8848.606	-11.566	0.000	-1.2e+05	-8.5e+04
Grade_Better	3.025e+04	9320.437	3.245	0.001	1.2e+04	4.85e+04

Omnibus:	6753.858	**Durbin-Watson:**	2.026
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	80212.409
Skew:	1.846	**Prob(JB):**	0.00
Kurtosis:	13.706	**Cond. No.**	1.18e+16

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.18e+16. This might indicate that there are
strong multicollinearity or other numerical problems.

The magnitude of each coefficient above determines how strongly each independent variable influences the target variable `price`. However, this is not the only criteria to select independent variables. The magnitude of correlation between independent and dependent variables and magnitude of intercorrelation between independent variables is also important. Looking at this model output, the correlation list and the multicollinearity list generated in the `Assumptions of Linear Regression` section, the team decided to use `sqft_living`, `lat`, `Grade_Better`, `Grade_VGood` and `View_NONE` in the final model. `sqft_above`, `sqft_living15` and `bathrooms` were not selected as they were high correlated with the `sqft_living` column.

Before we start modeling, let's revert feature scaling so that we can generate interpretable coefficients.

In [42]:
```
features_to_unscale=['sqft_living','sqft_lot','sqft_above','sqft_basement','sqft_living15','yr_built','zipcode',
'sqft_lot15']
features_not_to_unscale = ['id', 'bedrooms', 'bathrooms','floors', 'waterfront', 'View_Avg', 'View_Exc', 'View_F
'View_Good', 'View_NONE', 'Cond_Avg', 'Cond_Fair', 'Cond_Good', 'Cond_Poor', 'Cond_VGood', 'Grade_VGood', 'Grade
'Grade_Lux', 'Grade_Low', 'Grade_Fair', 'Grade_LAvg','Grade_Avg', 'Grade_Good', 'Grade_Better']
unscale = X_train[features_to_unscale]
no_unscale = X_train[features_not_to_unscale]
X_train_unscaled = scalar.inverse_transform(unscale)
unscaled_X_train = pd.DataFrame(data=X_train_unscaled, columns=unscale.columns, index=unscale.index)
X_train = pd.concat([unscaled_X_train, no_unscale],axis=1)

features_to_unscale=['sqft_living','sqft_lot','sqft_above','sqft_basement','sqft_living15','yr_built','zipcode',
'sqft_lot15']
features_not_to_unscale = ['id', 'bedrooms', 'bathrooms','floors', 'waterfront', 'View_Avg', 'View_Exc', 'View_F
'View_Good', 'View_NONE', 'Cond_Avg', 'Cond_Fair', 'Cond_Good', 'Cond_Poor', 'Cond_VGood', 'Grade_VGood', 'Grade
'Grade_Lux', 'Grade_Low', 'Grade_Fair', 'Grade_LAvg','Grade_Avg', 'Grade_Good', 'Grade_Better']
unscale = X_test[features_to_unscale]
no_unscale = X_test[features_not_to_unscale]
X_test_unscaled = scalar.inverse_transform(unscale)
unscaled_X_test = pd.DataFrame(data=X_test_unscaled, columns=unscale.columns, index=unscale.index)
X_test = pd.concat([unscaled_X_test, no_unscale],axis=1)
```

We can also and get rid of the columns that we won't be using.

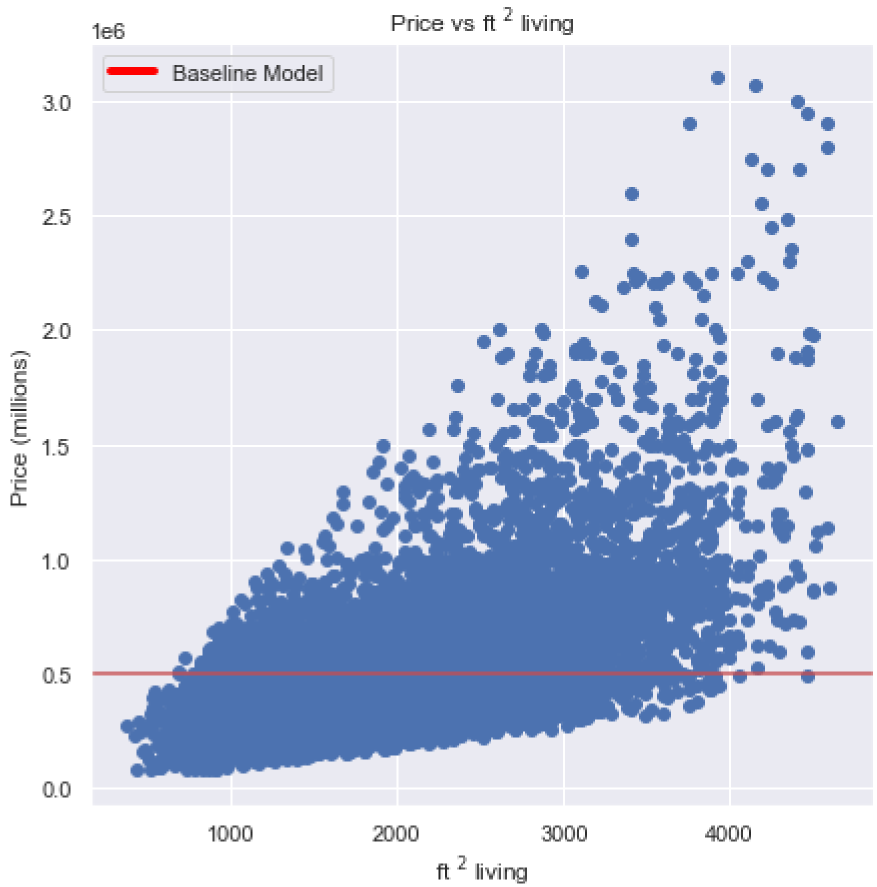
In [43]:
```
X_train = X_train[['sqft_living','lat','Grade_Better','Grade_VGood','View_NONE']]
X_test = X_test[['sqft_living','lat','Grade_Better','Grade_VGood','View_NONE']]
```

Baseline Model

Our baseline model, which is the simplest model that can be generated, is to predict that each house has the price of the average house price in the training set. Let's calculate this prediction and see what it looks like on a plot.

In [44]:
```
baseline_prediction = np.mean(y_train)
fig, ax = plt.subplots(figsize=(7,7))
ax.scatter(X_train['sqft_living'],y_train)
plt.axhline(y=baseline_prediction, color='r', linestyle='-');
ax.set_xlabel('ft $^2$ living')
ax.set_ylabel('Price (millions)')

cmap = plt.cm.coolwarm
custom_lines = [Line2D([0], [0], color='red', lw=4)]
ax.legend(custom_lines, ['Baseline Model']);
ax.set_title('Price vs ft $^2$ living');
```



Let's now run the model.

In [45]:
```
predictors = np.full(len(y_train), np.mean(y_train))
model1 = sm.OLS(y_train,predictors).fit()
model1.summary()
```

Out[45]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	nan
Date:	Fri, 08 Oct 2021	**Prob (F-statistic):**	nan
Time:	12:52:38	**Log-Likelihood:**	-2.0933e+05
No. Observations:	15010	**AIC:**	4.187e+05
Df Residuals:	15009	**BIC:**	4.187e+05
Df Model:	0		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
x1	1.0000	0.004	222.956	0.000	0.991	1.009

Omnibus:	7638.266	**Durbin-Watson:**	2.011
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	70072.566
Skew:	2.267	**Prob(JB):**	0.00
Kurtosis:	12.565	**Cond. No.**	1.00

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

R^2 value is 0, which means that 0% of the variations in dependent variable (`price`) are explained by the model. This isn't surprising as this is a baseline model.

Let's now calculate the mean-squared error of the training and test set for this baseline model.

In [46]:
```
train_mse_baseline = mean_squared_error(y_train, np.full(len(y_train), np.mean(y_train)))
test_mse_baseline = mean_squared_error(y_test, np.full(len(y_test), np.mean(y_train)))

print('Baseline Train Mean Squared Error:', train_mse_baseline)
print('Baseline Test Mean Squared Error:', test_mse_baseline)
```

```
Baseline Train Mean Squared Error: 76016598023.66982
Baseline Test Mean Squared Error: 122454117916.87492
```

Linear Regression Model #1

For the first linear regression model, the team decided to use `sqft_living` as the only independent variable since `sqft_living` has the highest correlation with the target variable, `price` .

In [47]:
```
predictors = sm.add_constant(X_train['sqft_living'])
model1 = sm.OLS(y_train,predictors).fit()
model1.summary()
```

Out[47]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.384
Model:	OLS	**Adj. R-squared:**	0.384
Method:	Least Squares	**F-statistic:**	9367.
Date:	Fri, 08 Oct 2021	**Prob (F-statistic):**	0.00
Time:	12:52:38	**Log-Likelihood:**	-2.0569e+05
No. Observations:	15010	**AIC:**	4.114e+05
Df Residuals:	15008	**BIC:**	4.114e+05
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.951e+04	4995.430	9.912	0.000	3.97e+04	5.93e+04
sqft_living	230.5006	2.382	96.782	0.000	225.832	235.169

Omnibus:	6580.613	**Durbin-Watson:**	2.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	58868.945
Skew:	1.882	**Prob(JB):**	0.00
Kurtosis:	11.942	**Cond. No.**	5.93e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.93e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

R^2 value is 0.384, which means that 38.4% of the variations in dependent variable (`price`) are explained by the independent variable (`sqft_living`). This is a substantial improvement compared to the baseline model.

The `statsmodel` method above is useful as it provides a nice table to analyze the regression. However, it doesn't allow the extraction of variables, so we will use `sklearn` to extract the intercept and coefficient.

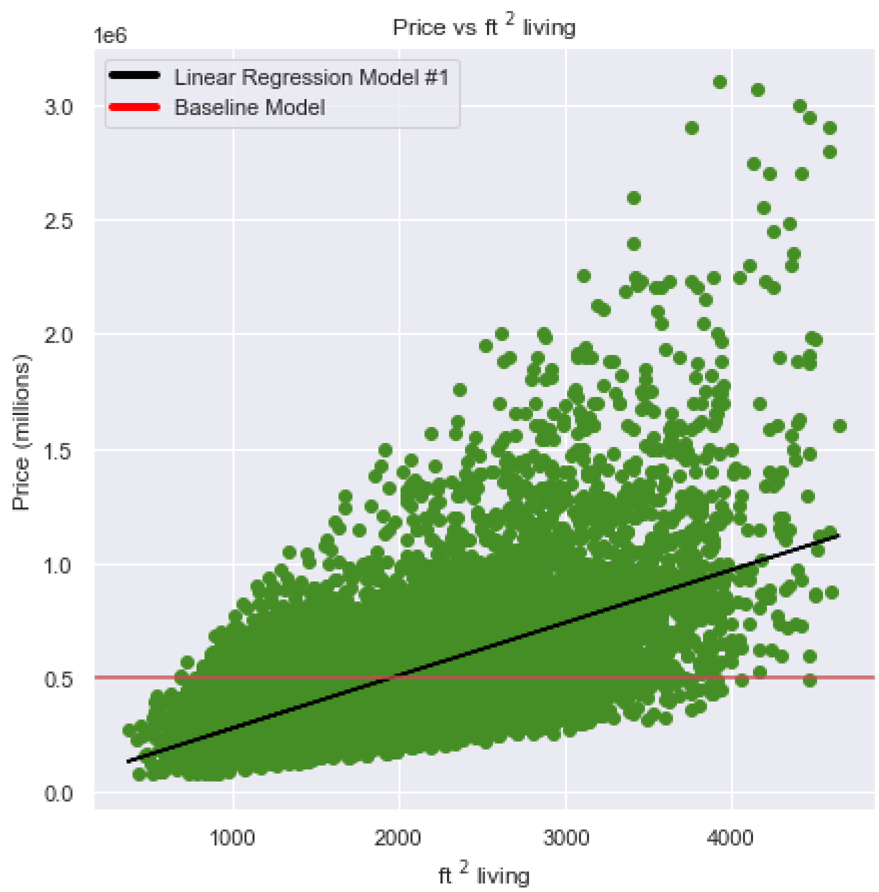
In [48]:
```
linreg_modelone = LinearRegression()
linreg_modelone.fit(X_train[['sqft_living']], y_train)
coef_m1 = linreg_modelone.coef_
intercept_m1 = linreg_modelone.intercept_
```

Now that we have the coefficients and intercept, we can look at a plot which compares the baseline model to this model.

In [49]:
```
fig, ax = plt.subplots(figsize=(7,7))
ax.scatter(X_train[['sqft_living']], y_train, color='#458D25')
ax.plot(X_train[['sqft_living']], intercept_m1 + coef_m1 * X_train[['sqft_living']], color='black')
plt.axhline(y=baseline_prediction,color='r', linestyle='-');
ax.set_xlabel('ft $^2$ living')
ax.set_ylabel('Price (millions)');

cmap = plt.cm.coolwarm
from matplotlib.lines import Line2D
custom_lines = [Line2D([0], [0], color='black', lw=4),
                Line2D([0], [0], color='red', lw=4)]

ax.legend(custom_lines, ['Linear Regression Model #1', 'Baseline Model']);
ax.set_title('Price vs ft $^2$ living');
```



Let's now calculate the mean-squared error of the training and test set for this model.

In [50]:
```
y_hat_train_modelone = linreg_modelone.predict(X_train[['sqft_living']])
y_hat_test_modelone = linreg_modelone.predict(X_test[['sqft_living']])

train_mse_modelone = mean_squared_error(y_train, y_hat_train_modelone)
test_mse_modelone = mean_squared_error(y_test, y_hat_test_modelone)

print('Linear Regression Model 1 Train Mean Squared Error:', train_mse_modelone)
print('Linear Regression Model 1 Test Mean Squared Error:', test_mse_modelone)
```

```
Linear Regression Model 1 Train Mean Squared Error: 46805012314.251434
Linear Regression Model 1 Test Mean Squared Error: 64896178765.668
```

Finally, let's compare the mean squared errors between this model and the baseline model.

In [51]:
```
train_mse_modelone < train_mse_baseline
```

Out[51]:
```
True
```

In [52]:
```
test_mse_modelone < test_mse_baseline
```

Out[52]:
```
True
```

It appears that the mean squared error of the training and test set is less in this model, which means this model is better than the baseline model.

Final Linear Regression Model

In this final linear regression model, the team decided to use `sqft_living` , `lat` , `Grade_Better` , `Grade_VGood` and `View_NONE` as independent variable for reasons explained earlier.

In [53]:
```
predictors = sm.add_constant(X_train)
finalmodel = sm.OLS(y_train,predictors).fit()
finalmodel.summary()
```

Out[53]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.586
Model:	OLS	**Adj. R-squared:**	0.586
Method:	Least Squares	**F-statistic:**	4249.
Date:	Fri, 08 Oct 2021	**Prob (F-statistic):**	0.00
Time:	12:52:38	**Log-Likelihood:**	-2.0271e+05
No. Observations:	15010	**AIC:**	4.054e+05
Df Residuals:	15004	**BIC:**	4.055e+05
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-3.185e+07	4.97e+05	-64.066	0.000	-3.28e+07	-3.09e+07
sqft_living	165.5888	2.385	69.439	0.000	160.915	170.263
lat	6.768e+05	1.04e+04	64.764	0.000	6.56e+05	6.97e+05
Grade_Better	1.207e+05	5098.229	23.669	0.000	1.11e+05	1.31e+05
Grade_VGood	2.437e+05	8014.289	30.412	0.000	2.28e+05	2.59e+05
View_NONE	-2.059e+05	5379.200	-38.280	0.000	-2.16e+05	-1.95e+05

Omnibus:	8275.683	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	136407.068
Skew:	2.293	**Prob(JB):**	0.00
Kurtosis:	17.038	**Cond. No.**	7.20e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 7.2e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

R^2 value is 0.586, which means that 58.6% of the variations in dependent variable (`price`) are explained by the independent variables. This is a substantial improvement compared to the first linear regression model.

The `statsmodel` method above is useful as it provides a nice table to analyze the regression. However, it doesn't allow the extraction of variables, so we will use `sklearn` to extract the intercept and coefficient.

In [54]:
```
linreg_finalmodel = LinearRegression()
linreg_finalmodel.fit(X_train, y_train)
coef_m1 = linreg_finalmodel.coef_
intercept_m1 = linreg_finalmodel.intercept_
```

Let's now calculate the mean-squared error of the training and test set for this final linear regression model.

In [55]:
```
y_hat_train_finalmodel = linreg_finalmodel.predict(X_train)
y_hat_test_finalmodel = linreg_finalmodel.predict(X_test)

train_mse_finalmodel = mean_squared_error(y_train, y_hat_train_finalmodel)
test_mse_finalmodel = mean_squared_error(y_test, y_hat_test_finalmodel)

print('Linear Regression Model 1 Train Mean Squared Error:', train_mse_finalmodel)
print('Linear Regression Model 1 Test Mean Squared Error:', test_mse_finalmodel)
```

```
Linear Regression Model 1 Train Mean Squared Error: 31464378752.586876
Linear Regression Model 1 Test Mean Squared Error: 50948452216.11465
```

Finally, let's compare the mean squared errors between this model and the baseline model.

In [56]:
```
train_mse_finalmodel < train_mse_modelone
```

Out[56]:
```
True
```

In [57]:
```
test_mse_finalmodel < test_mse_modelone
```

Out[57]:
```
True
```

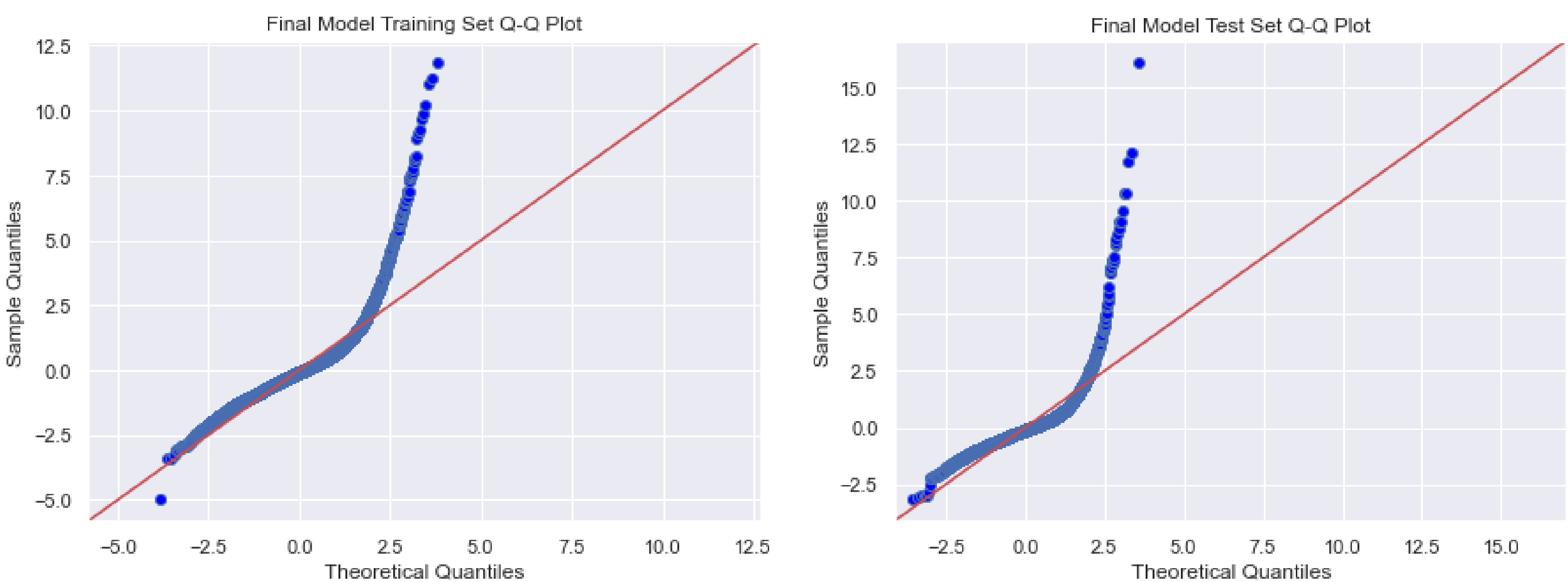
It appears that the mean squared error of the training and test set is less in this final model compared to the first model, which means this final model is better than the first model.

Assumptions of Linear Regression - Continued

Now that we have created the final model, let's check for the remaining assumptions of linear regression.

3. Normal Distribution of Errors

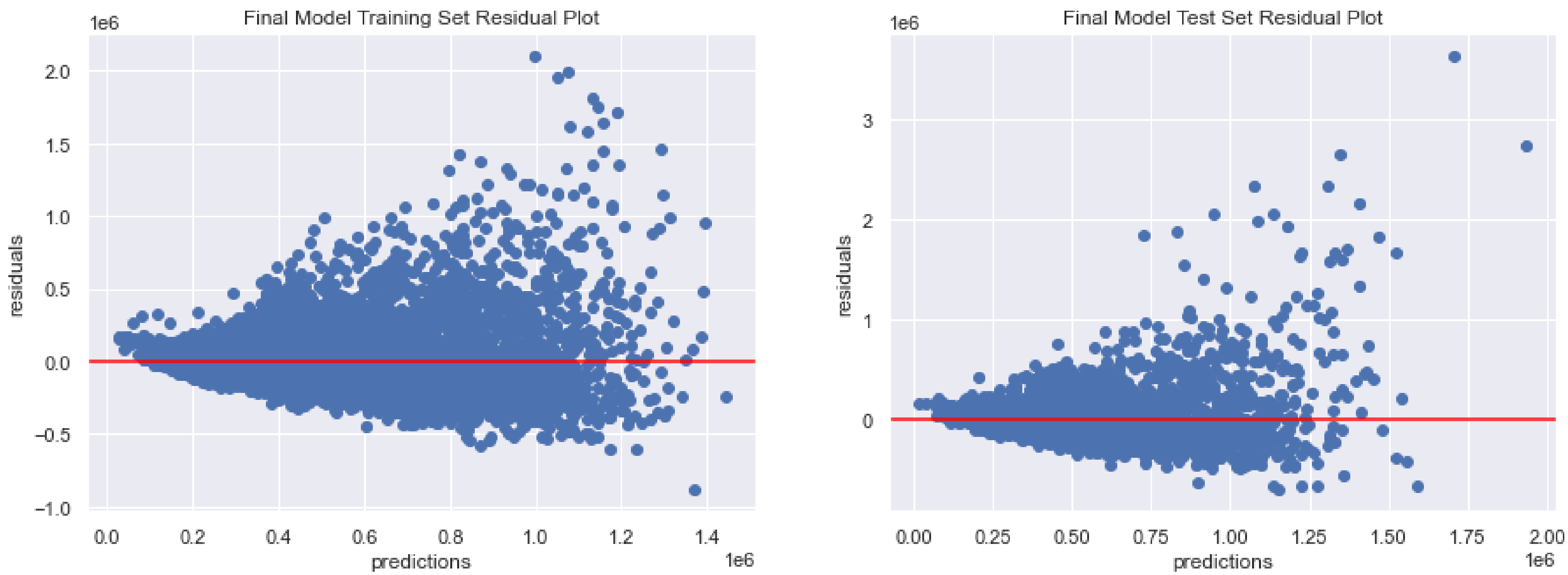
In [58]:
```
# Calculate residuals
final_train_resid = y_train - y_hat_train_finalmodel
final_test_resid = y_test - y_hat_test_finalmodel
## Generate qq-plot
fig, (ax1,ax2) = plt.subplots(nrows=1, ncols=2, figsize=(15,5))
ax1.set_title('Final Model Training Set Q-Q Plot')
ax2.set_title('Final Model Test Set Q-Q Plot')
sm.graphics.qqplot(final_train_resid, dist=stats.norm, line='45', fit=True, ax = ax1);
sm.graphics.qqplot(final_test_resid, dist=stats.norm, line='45', fit=True,  ax = ax2);
```



It appears that the for the training and test residuals (errors) do not follow a normal distribution.

4. Homoscedasticity of Errors

In [59]:
```
# for our full model
fig, (ax1,ax2) = plt.subplots(nrows=1, ncols=2, figsize=(15,5))
ax1.scatter(y_hat_train_finalmodel, final_train_resid)
ax2.scatter(y_hat_test_finalmodel, final_test_resid,)
ax1.axhline(y=0, color = 'red', label = '0')
ax2.axhline(y=0, color = 'red', label = '0')
ax1.set_xlabel('predictions')
ax1.set_ylabel('residuals')
ax2.set_xlabel('predictions')
ax2.set_ylabel('residuals');
ax1.set_title('Final Model Training Set Residual Plot')
ax2.set_title('Final Model Test Set Residual Plot');
```



It appears that the for the training and test residuals (errors) are not homoscedastic.

Evaluation

Each model that we built have built on top of each other and improved. The final model is significantly better than the baseline model as shown earlier. The model doesn't comply with some of the linear regression assumptions such as normal distribution of errors and homoscedasticity. All the features included in our final model were statistically significant in estimating the target variable for both the training and test data, so we are confident that our results would generalize beyond the data given. With this model, we are confident that the stakeholder will have general idea of how the features that are most correlated with the price influence the price of a given house in King County, Seattle.

Conclusions

We have created multiple inferential models, compared them against each other and identified the best one. However, this work can be improved. By spending more time on feature engineering, new features can be generated by combining existing features and explore their relationship with housing price for superior models.

We recommend that the stakeholder should also consider utilizing a predictive model as well. The models we have created are inferential models, meaning that a subset of features are considered and the goal is to understand how the outcome changes with these features. The priority is the interpretability of the model, not its overall accuracy. Predictive models utilize more features and therefore more complex and their goal is increase the accuracy of predictions.

We also recommend the stakeholder to gather more housing data for King County, Seattle. More data allows models to predict better and therefore, improve their performance.