King County Millenial homeowner program

Buying a property in King County recommendations for Millennials

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Overview

King County in Washington State is growing in population made up of Millenials and Generation Z who either grew up or migrated to the area and found life in the region. We, the Data Analysts at the Greek Honey Real Estate are working on building a model that predicts house prices in King County with the goal to help folks from the demographic to find their dream house that fits their lifestyle and their budget!

Business Problem

Housing market in King County region, especially in the major cities such as Seattle, are becoming more and more financially inaccessible for many demographics. The demographic of interest for our real-estate is millenials who are building their career, family and trying to break into the housing market to have a stable housing for themselves. With our house price predicition model, we will help them to find the market value of their ideal house that are in proximity to city centers.

Data Understanding

1. King County Housing data (kc_house_data.csv (https://github.com/hanis-z/Phase-2-project/blob/main/data/kc_house_data.csv))

Source: This data was provided to us by Flatiron School. This data file is available in the project repo in the folder "data".

Contents: This [file (data/column_names.md)](data/column_names.md) which provides information regarding the column names and descriptions for King County data set in the years of 2014-2015.

2. Incorporated & Unincorporated cities in King county

Source: We downloaded this data from [King County GIS website (https://gis-kingcounty.opendata.arcgis.com/datasets/kingcounty::cities-and-unincorporated-king-county-city-kc-area/explore?location=47.430582%2C-121.809200%2C10.02)](https://gis-kingcounty.opendata.arcgis.com/datasets/kingcounty::cities-and-unincorporated-king-county-city-kc-area/explore?location=47.430582%2C-121.809200%2C10.02). The data is also easily accessible in our project repo in the folder "data".

Contents: This dateset provided us with city boundaries of cities in King County in a shapefile along with `CITYNAME` .

3. Neighborhood Map of Seattle

Source: We attained this data from [Seattle city GIS website (https://data-seattlecitygis.opendata.arcgis.com/datasets/neighborhood-map-atlas-districts/explore?location=47.628714%2C-122.338313%2C11.43%5D)](https://data-seattlecitygis.opendata.arcgis.com/datasets/neighborhood-map-atlas-districts/explore?location=47.628714%2C-122.338313%2C11.43%5D). This data is also easily accessible in our project repo in the folder "data".

Contents: This dataset provided us with neighborhood boundaries of neighborhoods in Seattle city along with neighborhood (`L_HOOD`).

Importing python libraries required for the analysis.

Note: To ensure that all packages are loaded successfully, please ensure that you have set up the right python environment using the [YML file (geo_env.yml)](geo_env.yml) provided in this project repository.

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OrdinalEncoder, OneHotEncoder, PolynomialFeatures
from sklearn.compose import ColumnTransformer
from sklearn.dummy import DummyRegressor

from statsmodels.formula.api import ols
from patsy import dmatrices
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
```

Define Helper Functions for Data Exploration and Cleaning

In [2]:
```
def dataframe_info(df):
    '''
    Takes Pandas dataframe (df). Prints number of rows, number of columns, and three sample rows.
    Returns list of numerical columns and list of non-numerical columns.
    '''
    numeric_cols = df.select_dtypes(include=np.number).columns.tolist()
    object_cols  = df.select_dtypes(exclude=np.number).columns.tolist()

    nrows, ncol = df.shape
    nmid = nrows // 2

    print(f"Dimensions: {nrows} rows and {ncol} columns")
    print(f"Numeric columns: {len(numeric_cols)}")
    print(f"Object columns: {len(object_cols)}")

    display(df.iloc[[0,nmid,nrows-1]]) # show three rows: first, mid, and last

    return numeric_cols, object_cols
```

In [3]:
```python
def cleaned_column_names(column_list):
    '''
    Takes list of column names (e.g. from df.columns).
    Returns list of cleaned column names that can be assigned to DataFrame.
    Usage: df.columns = cleaned_column_names(df.columns)
    '''
    return [name.strip().lower().replace(' ','').replace('-', '_') for name in column_list]
```

Data Exploration & Preparation for Linear Regression Modelling

Load King County Housing data

In [4]:
```python
housing_df = pd.read_csv('data/housing_gdf_complete.csv')
housing_df.columns = cleaned_column_names(housing_df.columns)
```

In [5]:
```python
num, obj = dataframe_info(housing_df)
```

```
Dimensions: 21596 rows and 28 columns
Numeric columns: 17
Object columns: 11
```

	unnamed:0	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	...	lat	long
0	0	8856004730	9/17/2014	199950.0	2	2.75	1590	20917	1.5	NO	...	47.2786	-122.250
10798	10798	7237500590	11/17/2014	1320000.0	4	5.25	6110	10369	2.0	NO	...	47.5285	-122.135
21595	21595	9808100150	4/2/2015	3350000.0	5	3.75	5350	15360	1.0	NO	...	47.6480	-122.218

3 rows × 28 columns

In [6]:
```python
print("List of numeric columns: ", num)
print("List of object columns: ", obj)
```

```
List of numeric columns:  ['unnamed:0', 'id', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floo
rs', 'sqft_above', 'yr_built', 'yr_renovated', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15', 'dist_se
attle']
List of object columns:  ['date', 'waterfront', 'view', 'condition', 'grade', 'sqft_basement', 'coord', 'geometr
y', 'city', 'neighborhood', 'in_seattle']
```

The original distance estimates from geopandas is in meters.

To make it more relevant, let's convert the distances to miles.

In [7]:
```python
# convert dist_seattle from meters to miles
housing_df['dist_seattle'] = housing_df['dist_seattle'] / 1609.34
```

Data Cleaning

Basement

Creating a feature if the house has a basement or not.

In [8]:
```python
# sqft_basement should equal difference between sqft_living and sqft_above
sqft_basement_computed = housing_df['sqft_living'] - housing_df['sqft_above']

housing_df['has_basement'] = (sqft_basement_computed > 0).astype(int)
```

Year renovated

Creating a feature of houses that have been renovated in the past 5 years.

In [9]:
```
housing_df['sold_dt'] = pd.to_datetime(housing_df['date']) #made a new column with date by using the pd.to_dateti
housing_df['sold_year'] = pd.DatetimeIndex(housing_df['sold_dt']).year #made a new column year sold
housing_df['sold_month'] = pd.DatetimeIndex(housing_df['sold_dt']).month #made a new column month sold
```

In [10]:
```
housing_df['yr_renovated_missing'] = (housing_df['yr_renovated'].isna()).astype(int) #saving nulls for accessibil
housing_df['yr_renovated'].fillna(0, inplace=True) # Rewriting dataframe filling null values with zeros

housing_df['renovated'] = ((housing_df['sold_year'] - housing_df['yr_renovated']) <= 5).astype(int)
#houses renovated within the past 5 years
```

Age of the house

Creating a feature of the age in years of the houses.

In [11]:
```
housing_df['house_age'] = housing_df['sold_year'] - housing_df['yr_built'] #year sold minus year built gets the a
housing_df['house_age'].describe()
```

Out[11]:
```
count    21596.000000
mean        43.323810
std         29.377864
min         -1.000000
25%         18.000000
50%         40.000000
75%         63.000000
max        115.000000
Name: house_age, dtype: float64
```

View

Cleaning up missing values in the view column before using it as a feature.

In [12]:
```
housing_df['view_missing'] = (housing_df['view'].isna()).astype(int) #saving nulls for accessibility
housing_df['view'].fillna('NONE', inplace=True) #Rewriting dataframe filling null values with NONE
```

Waterfront

Cleaning up missing values in the waterfront column before using it as a feature.

In [13]:
```
housing_df['waterfront_missing'] = (housing_df['waterfront'].isna()).astype(int)#saving nulls for accessibility
housing_df['waterfront'].fillna('NO', inplace=True) #Rewriting dataframe filling null values with NO
```

Duplicate records (house resold)

Creating a feature of individual houses that were sold more than once (stated as a boolean value).

In [14]:
```
print(f"Number of rows:\t\t{len(housing_df['id'])}") #Total number of houses sold on id including repeats
print(f"Number unique:\t\t{len(housing_df['id'].unique())}") #First time houses being sold in this data set
print(f"Number duplicates:\t{sum(housing_df['id'].duplicated() == True)}") #houses being resold
```

```
Number of rows:         21596
Number unique:          21419
Number duplicates:      177
```

In [15]:

```
#sorting df by their dates so that resold rows come later in the dataframe
housing_df = housing_df.sort_values(by=['sold_year', 'sold_month'])

#creates a boolean column for duplicated id of houses, then changes to int [0, 1]
housing_df['resold'] = housing_df.id.duplicated().astype(int)
```

Fill NaNs in neighborhood column

Replace NaNs with 'NA' string, to create category where Seattle neighborhood is "not applicable"

In [16]:

```
housing_df['neighborhood'] = housing_df['neighborhood'].fillna('NA')
```

Ratio between bedrooms and bathrooms

Creating a feature of the ratio between bedrooms and bathrooms.

In [17]:

```
housing_df['br_bth'] = housing_df.bedrooms / housing_df.bathrooms
```

Category `in_seattle`

Creating a feature of the with 1 correlating to yes and 0 as no if they are in the city of Seattle or not.

In [18]:

```
housing_df['in_seattle'] = housing_df['in_seattle'].astype(int)
```

Verify that columns are not collinear

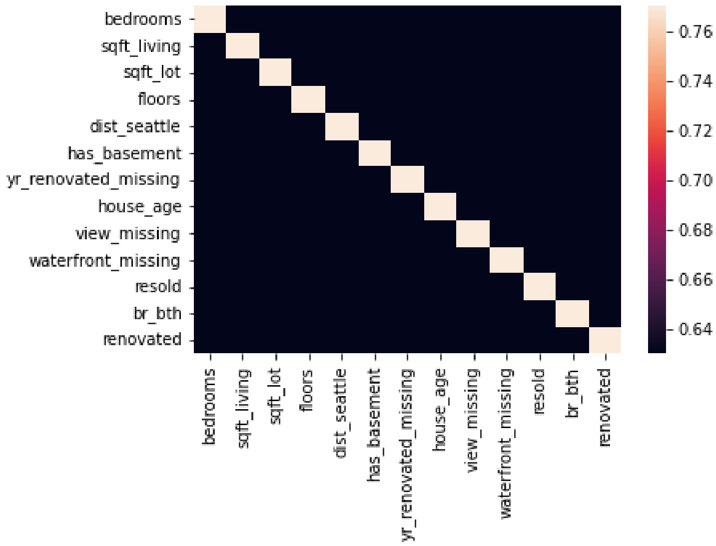
Manually remove collinear numeric columns

As we tested collinearity of individual features with other features, we manually edited columns in `relevant_num_cols` to eliminate columns correlated > 0.7 with other columns

In [19]:

```
relevant_num_cols = [
    'bedrooms',
    'sqft_living',
    'sqft_lot',
    'floors',
    'dist_seattle',
    'has_basement',
    'yr_renovated_missing',
    'house_age',
    'view_missing',
    'waterfront_missing',
    'resold',
    'br_bth',
    'renovated'
] #list of relevant numerical columns
```

In [20]:
```
sns.heatmap(housing_df[relevant_num_cols].corr().abs(), vmin=.7, vmax=0.7);
#checking for multicollinearity between features using .7 as the cut off value
```



Remove collinear categorical columns

Collinearity of categorical columns will need to be verified using VIF after running statsmodels. Here, we are creating a list of categorical columns that we want to keep for our model. As we find that the columns were collinear (using VIF), we removed the column from this list.

In [21]:
```
relevant_cat_col =  [
    'waterfront',
    'zipcode',
    'view',
    'condition',
    'grade',
    'city',
    'neighborhood'
  ]
```

Train test split

We will log transform our target feature (house price) to reduce the skew in distribution of price as well as reduce residuals in our model.

In [22]:
```
y = np.log(housing_df['price'])
X = housing_df[relevant_num_cols+relevant_cat_col]
```

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42) #train test split
```

One Hot Encoder

In [24]:

```
# Version of One Hot Encoder in learn-env doesn't allow setting drop flag and handle_unknown flag simultaneously
# Be sure to choose columns to drop manually to avoid perfect collinearity
encoder = OneHotEncoder(handle_unknown='ignore',
                        categories='auto')

# Create ColumnTransformer to transform all relevant_cat_col columns with OHE encoder
ct = ColumnTransformer(transformers=[ ('ohe', encoder, relevant_cat_col) ],
                       remainder='passthrough')

# Now that we have ct, fit it to the X_train, and apply that transformation to both X_train and X_test
ct.fit(X_train)
X_train_enc = ct.transform(X_train)
X_test_enc = ct.transform(X_test)
```

In [25]:

```
# Put encoder output back into DataFrame for X_train and X_test
X_train = pd.DataFrame(X_train_enc.todense(), columns= ct.get_feature_names(), index=X_train.index)
X_test = pd.DataFrame(X_test_enc.todense(), columns= ct.get_feature_names(), index=X_test.index)
```

Column names in output of OHE ColumnTransformer are unwieldy.

I'm creating a dict mapping changes from automated naming convention to something more readable.

In [26]:

```
replace_dict = {
    'ohe__': '',
    'x0': 'waterfront',
    'x1': 'zip',
    'x2': 'view',
    'x3': 'condition',
    'x4': 'grade',
    'x5': 'city',
    'x6': 'neighborhood'
}
```

In [27]:

```
# Use cleaned_column_names to remove spaces
X_train.columns = cleaned_column_names(X_train.columns)

for key, value in replace_dict.items():
    X_train.columns = [ x.replace(key, value) for x in list(X_train.columns) ]
```

In [28]:

```
# Use cleaned_column_names to remove spaces
X_test.columns = cleaned_column_names(X_test.columns)

for key, value in replace_dict.items():
    X_test.columns = [ x.replace(key, value) for x in list(X_test.columns) ]
```

We will use the function below to group together One Hot Encoded columns into the same feature category.

In [29]:

```
#Separate gruop OHE columns by features

def ohe_list(string_id, col_list):
    """
    This function takes the string, search the string (that specifies feature) in the col names,
    and group the columns together in a list
    """
    ohe_list_group = [x for x in col_list if string_id in x]
    return ohe_list_group
```

In [30]:

```
#Get ohe columns for zipcode & drop the first one
ohe_zip_cols = ohe_list('zip',X_train.columns)
ohe_zip_cols = ohe_zip_cols[1:]

#Get ohe columns for grade & drop grade 7
ohe_grade_cols = ohe_list('grade',X_train.columns)
ohe_grade_cols.remove('grade_7average')

#Get ohe columns for neighborhoods & drop na
ohe_neigh_cols = ohe_list('neighborhood',X_train.columns)
ohe_neigh_cols.remove('neighborhood_na')

#get ohe columns for view & drop none
ohe_view_cols = ohe_list('view', X_train.columns)
ohe_view_cols.remove('view_none')
```

Get model metrics and validation using sklearn LinearRegression

Create functions to assist with evaluation of model assumptions and model fitting

In [31]:

```
def build_model(X_train, X_test, y_train, y_test):

    """
    Build a regression model

    """

    lr = LinearRegression()
    lr.fit(X_train,y_train)
    R2_train = lr.score(X_train,y_train)
    R2_test = lr.score(X_test,y_test)


    yhat_train = lr.predict(X_train)
    train_rmse = mean_squared_error(np.exp(y_train), np.exp(yhat_train), squared = False)

    yhat_test = lr.predict(X_test)
    test_rmse = mean_squared_error(np.exp(y_test), np.exp(yhat_test), squared = False)

    residuals_train = y_train - yhat_train
    residuals_test = y_test - yhat_test


    print(f'Train R2: {lr.score(X_train,y_train)}')
    print(f'Test R2: {lr.score(X_test,y_test)}')
    print(f'Train RMSE: {train_rmse}')
    print(f'Test RMSE: {test_rmse}')

    return yhat_train, residuals_train, yhat_test, residuals_test
```

Below are functions that will plot the residuals between our dataset and predicted values, to test for the Linear Regressions assumptions

In [32]:
```python
def plot_qq_norm(yhat_train, resids_train, yhat_test, resids_test):

    fig, ax= plt.subplots(2,1)
    sm.qqplot(resids_train, line = 'r',ax=ax[0]);
    sns.histplot(resids_train, stat='density', label='residuals',ax=ax[1])
    plt.show()
    return

def plot_skedacity (yhat_train, resids_train, yhat_test, resids_test):
    plt.scatter(yhat_train, resids_train)

    plt.axhline(y=0, color = 'red', label = '0')
    plt.xlabel('predictions')
    plt.ylabel('residuals')
    plt.show();
    return
```

Assess fit of DummyRegressor model

We ran an initial model fit using DummyRegressor, to get an estimated RMSE for a model that uses nothing other than the mean as a predictor.

In [33]:
```python
dr = DummyRegressor()

dummy_model = dr.fit(X_train, y_train)
R2_dummy_train =dr.score(X_train,y_train)
R2_dummy_test = dr.score(X_test,y_test)


dr_yhat_train = dr.predict(X_train)
dr_train_rmse = mean_squared_error(np.exp(y_train), np.exp(dr_yhat_train), squared = False)

dr_yhat_test = dr.predict(X_test)
dr_test_rmse = mean_squared_error(np.exp(y_test), np.exp(dr_yhat_test), squared = False)

dr_residuals_train = y_train - dr_yhat_train
dr_residuals_test = y_test - dr_yhat_test


print(f'Train R2: {R2_dummy_train}')
print(f'Test R2: {R2_dummy_test}')
print(f'Train RMSE: {dr_train_rmse}')
print(f'Test RMSE: {dr_test_rmse}')
```

```
Train R2: 0.0
Test R2: -0.0009711682946567102
Train RMSE: 373215.90277156036
Test RMSE: 377524.87079765
```

Begin by assessing baseline model predicting price with key descriptors

Advertisements for houses *always* include `sqft_living` , `bedrooms` , `sqft_lot` , `floors` and `has_basement`

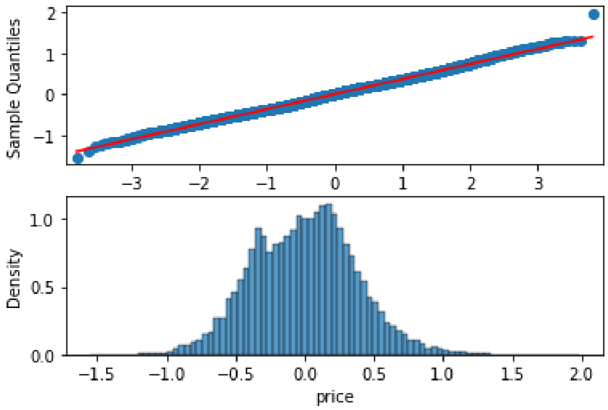
We've removed `bathrooms` because it is highly collinear with `sqft_living` .

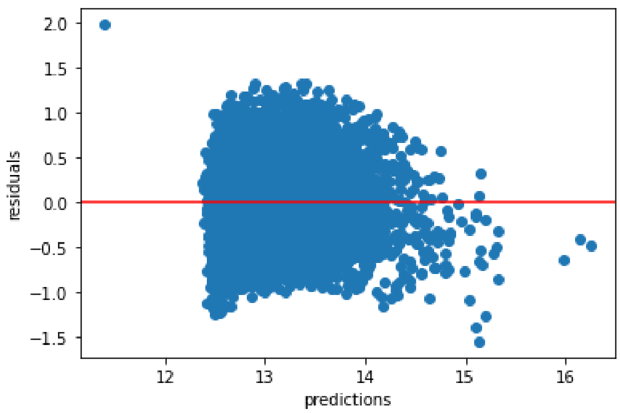
In [35]:
```python
simple_model_cols = ['sqft_living', 'bedrooms','sqft_lot','floors','has_basement']

Xsimple_train = X_train[simple_model_cols]
Xsimple_test = X_test[simple_model_cols]

simple_yhat_train, simple_residuals_train, simple_yhat_test, simple_residuals_test = build_model(Xsimple_train, X
# Used the function build_model() on model_base_cols
# saved variables for accessability
```

```
Train R2: 0.5115611935831419
Test R2: 0.488911639859115
Train RMSE: 260078.65200150886
Test RMSE: 606752.1036079298
```

It seems that our first simple model did better in terms of R2 our dummy model but our RMSE for our test dataset is worst off. Let's see if our first simple model haven't violated the assumptions of Linear Regression.

In [36]:
```python
plot_qq_norm(simple_yhat_train, simple_residuals_train, simple_yhat_test, simple_residuals_test)
plot_skedacity(simple_yhat_train, simple_residuals_train, simple_yhat_test, simple_residuals_test)
```





We haven't violated our Linear Regression model assumptions. Yay!

Model 1 : Attempt to improve model predictions by including features that describe house condition

Key features that describe house condition include `house_age` , whether it was recently `renovated` , and overall building `grade` of the house. Description of grade categories is provided at the [King County Assessor (https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r)](https://info.kingcounty.gov/assessor/esales/Glossary.aspx?type=r).

We removed `condition` categories because they did not correlate with house `price` (when coded as an ordinal variable.)

We'll call this Model 1

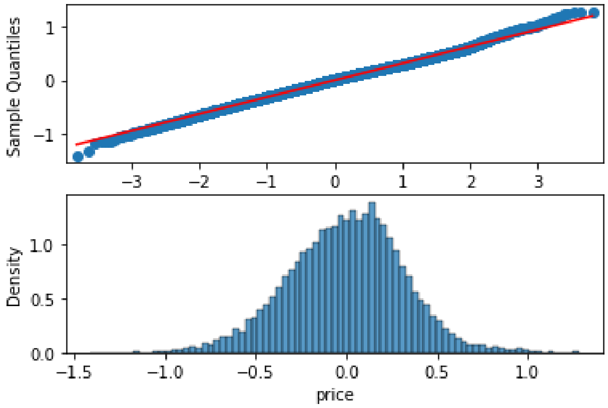
In [38]:
```python
# drop 'grade_7average' from OHE grade cols
model_1_cols = simple_model_cols + \
    ['renovated', 'house_age'] + ohe_grade_cols

X1_train = X_train[model_1_cols]
X1_test = X_test[model_1_cols]

m1_yhat_train,m1_residuals_train, m1_yhat_test, m1_residuals_test = build_model(X1_train, X1_test, y_train, y_tes
```

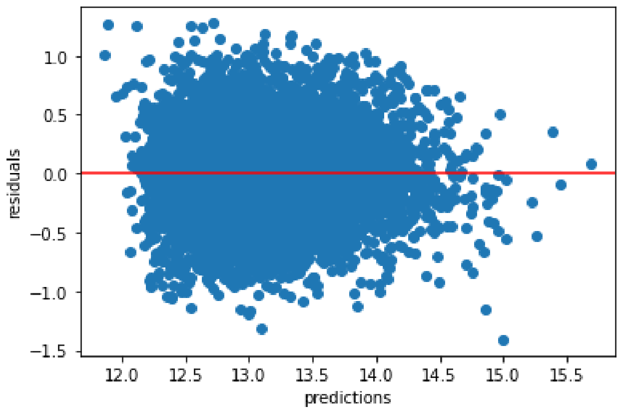
```
Train R2: 0.6415772007933189
Test R2: 0.630846255390473
Train RMSE: 213537.07281110913
Test RMSE: 258567.10304245935
```

Our R2 and RMSE is improving and already better than our dummy model. Yay! Let's check for our assumptions again.

In [39]:

```
plot_qq_norm(m1_yhat_train,m1_residuals_train, m1_yhat_test,m1_residuals_test)
plot_skedacity(m1_yhat_train,m1_residuals_train, m1_yhat_test,m1_residuals_test)
```





Model 2: Attempt to further improve model predictions with premium location features

Key features in this category describe whether the house is on `waterfront` property, and whether the house has a scenic `view` of landmarks in the area.

We'll call this Model 2.

In [40]:

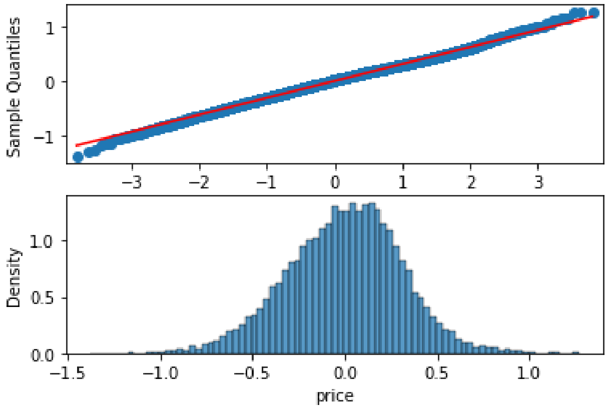
```
model_2_cols = model_1_cols + \
    ['waterfront_yes'] + ohe_view_cols

X2_train = X_train[model_2_cols]
X2_test = X_test[model_2_cols]

m2_yhat_train,m2_residuals_train, m2_yhat_test, m2_residuals_test = build_model(X2_train, X2_test, y_train, y_tes
```

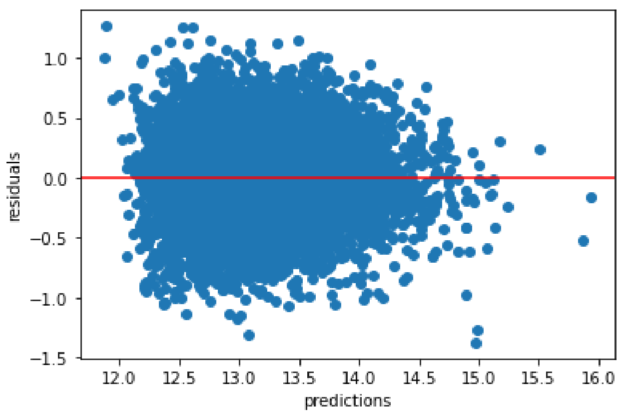
```
Train R2: 0.6528675826515022
Test R2: 0.6424297359772333
Train RMSE: 203962.52131985629
Test RMSE: 250554.67584106108
```

Check for assumptions.

In [41]:

```
plot_qq_norm(m2_yhat_train,m2_residuals_train, m2_yhat_test,m2_residuals_test)
plot_skedacity(m2_yhat_train,m2_residuals_train, m2_yhat_test,m2_residuals_test)
```





Model 3: Improve predictions by capturing neighborhoods or distance relative to center of Seattle

Key features include `dist_seattle` , which is the number of miles away from the geographic centroid of Seattle city limits, and the `neighborhood` if the house is located within Seattle.

In [42]:

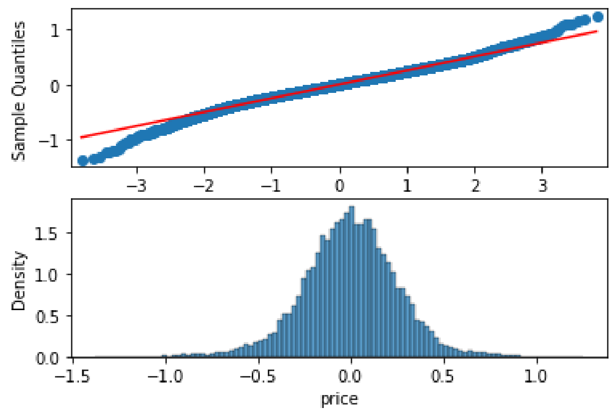
```python
model_3_cols = model_2_cols + \
    ['dist_seattle'] + ohe_neigh_cols

X3_train = X_train[model_3_cols]
X3_test = X_test[model_3_cols]

m3_yhat_train,m3_residuals_train, m3_yhat_test, m3_residuals_test= build_model(X3_train, X3_test, y_train, y_test
```

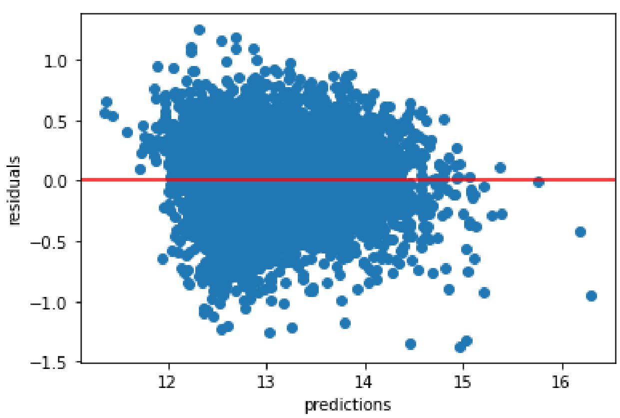
```
Train R2: 0.766748661389074
Test R2: 0.7562951260928505
Train RMSE: 183213.33485501073
Test RMSE: 298454.0958228795
```

The additional featuresin our model have improved our model so much compared to the dummy, simple and 2 models after.

In [43]:

```python
plot_qq_norm(m3_yhat_train,m3_residuals_train, m3_yhat_test,m3_residuals_test)
plot_skedacity(m3_yhat_train,m3_residuals_train, m3_yhat_test,m3_residuals_test)
```





And we're still great on assumptions!

Model 4: Attempt to improve model predictions with information about the `zipcode` of the house

The `zipcode` of each house is used as a set of categorical predictors.

In [44]:
```
model_4_cols = model_3_cols + ohe_zip_cols

X4_train = X_train[model_4_cols]
X4_test = X_test[model_4_cols]

m4_yhat_train,m4_residuals_train, m4_yhat_test, m4_residuals_test = build_model(X4_train, X4_test, y_train, y_tes
# Used the function build_model() on model_4_cols
# saved variables for accessability
```

```
Train R2: 0.876641953026694
Test R2: 0.8747088117471509
Train RMSE: 157683.73132459912
Test RMSE: 220798.88026453074
```

Get human readable coefficients using statsmodels ols model summary

Many of the inferential statistics about the models are easier to access from a standard OLS regression table. We produced ols model summaries (using `statsmodels.formula.api.ols`) and assessed multicollinearity of features in the model (using `statsmodels.stats.outliers_influence.variance_inflation_factor` , aka VIF)

We ran these models predicting the untransformed target variable `price` , so that coefficients would be interpretable in $ values.

Create functions to run model summary and check VIF.

In [45]:
```
def build_ols_model(cols_list,training_df):

    """
    This function takes in columns list from which to build formula from and the training dataframe to build mode
    The function then returns the model summary of an ordinary linear regression model and the formula used.
    """

    model_formula = 'price ~ ' + ' + '.join(cols_list)
    print(model_formula)

    model = ols(model_formula, train_df).fit()
    model_summary = model.summary()
    return model_summary, model_formula
```

In [46]:
```
# Code borrowed from lecture slides and put into function
def make_vif(formula, df):

    y, X = dmatrices(formula, data=df, return_type='dataframe')

    # make empty VIF dataframe
    vif = pd.DataFrame()
    vif["feature"] = X.columns

    # calculate VIF for each feature
    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]

    return vif
```

Concatenate X_train and y_train back together into a DataFrame to make working with ols easier.

In [47]:
```
y_train = np.exp(y_train)
```

In [48]:
```
train_df = pd.concat([X_train,y_train], axis=1)
```

Baseline model: Check coefficients and multicollinearity of simple model

Simple model includes `sqft_living` and `bedrooms` features

In [49]:
```python
simple_mod_summary, simple_mod_formula = build_ols_model(simple_model_cols,train_df)
simple_mod_summary
```

```
price ~ sqft_living + bedrooms + sqft_lot + floors + has_basement
```

Out[49]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.511
Model:	OLS	**Adj. R-squared:**	0.511
Method:	Least Squares	**F-statistic:**	3025.
Date:	Fri, 01 Apr 2022	**Prob (F-statistic):**	0.00
Time:	14:47:48	**Log-Likelihood:**	-2.0068e+05
No. Observations:	14469	**AIC:**	4.014e+05
Df Residuals:	14463	**BIC:**	4.014e+05
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.968e+04	9566.982	6.239	0.000	4.09e+04	7.84e+04
sqft_living	308.3734	3.147	97.977	0.000	302.204	314.543
bedrooms	-5.753e+04	2792.892	-20.597	0.000	-6.3e+04	-5.21e+04
sqft_lot	-0.2711	0.051	-5.293	0.000	-0.371	-0.171
floors	1.614e+04	4504.657	3.582	0.000	7306.608	2.5e+04
has_basement	3.759e+04	4789.778	7.849	0.000	2.82e+04	4.7e+04

Omnibus:	9585.139	**Durbin-Watson:**	1.999
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	312457.419
Skew:	2.713	**Prob(JB):**	0.00
Kurtosis:	25.109	**Cond. No.**	2.16e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.16e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

In [50]:
```python
display(make_vif(simple_mod_formula, train_df))
```

	feature	VIF
0	Intercept	20.291716
1	sqft_living	1.847287
2	bedrooms	1.507749
3	sqft_lot	1.053890
4	floors	1.319007
5	has_basement	1.212025

Model 1: Check coefficients and multicollinearity of model adding house condition features

Adds `renovated` , `house_age` , and building `grade` features

In [51]:
```python
model_1_summary, model_1_formula = build_ols_model(model_1_cols,train_df)
model_1_summary
```

```
price ~ sqft_living + bedrooms + sqft_lot + floors + has_basement + renovated + house_age + grade_10verygood + g
rade_11excellent + grade_12luxury + grade_13mansion + grade_3poor + grade_4low + grade_5fair + grade_6lowaverage
+ grade_8good + grade_9better
```

Out[51]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.639
Model:	OLS	**Adj. R-squared:**	0.639
Method:	Least Squares	**F-statistic:**	1505.
Date:	Fri, 01 Apr 2022	**Prob (F-statistic):**	0.00
Time:	14:47:52	**Log-Likelihood:**	-1.9849e+05
No. Observations:	14469	**AIC:**	3.970e+05
Df Residuals:	14451	**BIC:**	3.971e+05
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-5.548e+04	1.07e+04	-5.184	0.000	-7.65e+04	-3.45e+04
sqft_living	168.7119	3.907	43.187	0.000	161.055	176.369
bedrooms	-2.689e+04	2492.657	-10.786	0.000	-3.18e+04	-2.2e+04
sqft_lot	-0.1971	0.044	-4.471	0.000	-0.284	-0.111
floors	5.498e+04	4290.870	12.813	0.000	4.66e+04	6.34e+04
has_basement	4.666e+04	4246.458	10.988	0.000	3.83e+04	5.5e+04
renovated	3.859e+04	2.08e+04	1.859	0.063	-2103.649	7.93e+04
house_age	3412.5698	76.633	44.532	0.000	3262.360	3562.780
grade_10verygood	4.435e+05	1.07e+04	41.604	0.000	4.23e+05	4.64e+05
grade_11excellent	7.212e+05	1.68e+04	42.947	0.000	6.88e+05	7.54e+05
grade_12luxury	1.222e+06	3.07e+04	39.764	0.000	1.16e+06	1.28e+06
grade_13mansion	2.203e+06	9.18e+04	23.999	0.000	2.02e+06	2.38e+06
grade_3poor	-1.2e+05	2.2e+05	-0.546	0.585	-5.51e+05	3.11e+05
grade_4low	-1.244e+05	4.94e+04	-2.517	0.012	-2.21e+05	-2.75e+04
grade_5fair	-1.297e+05	1.83e+04	-7.097	0.000	-1.66e+05	-9.39e+04
grade_6lowaverage	-8.741e+04	6989.184	-12.506	0.000	-1.01e+05	-7.37e+04
grade_8good	9.891e+04	5017.086	19.715	0.000	8.91e+04	1.09e+05
grade_9better	2.482e+05	7496.449	33.108	0.000	2.34e+05	2.63e+05

Omnibus:	10047.686	**Durbin-Watson:**	2.007
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	496009.579
Skew:	2.767	**Prob(JB):**	0.00
Kurtosis:	31.144	**Cond. No.**	5.44e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.44e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [52]:
```
display(make_vif(model_1_formula, train_df))
```

	feature	VIF
0	Intercept	34.342912
1	sqft_living	3.849686
2	bedrooms	1.624676
3	sqft_lot	1.056685
4	floors	1.618957
5	has_basement	1.288711
6	renovated	1.010497
7	house_age	1.531593
8	grade_10verygood	1.744503
9	grade_11excellent	1.548827
10	grade_12luxury	1.227109
11	grade_13mansion	1.047677
12	grade_3poor	1.000881
13	grade_4low	1.010961
14	grade_5fair	1.054875
15	grade_6lowaverage	1.264832
16	grade_8good	1.532754
17	grade_9better	1.807774

Model 2: Check coefficients and multicollinearity of model adding premium location features

Adds `waterfront` and scenic `view` features

In [53]:
```
model_2_summary, model_2_formula = build_ols_model(model_2_cols,train_df)
model_2_summary
```

```
price ~ sqft_living + bedrooms + sqft_lot + floors + has_basement + renovated + house_age + grade_10verygood + g
rade_11excellent + grade_12luxury + grade_13mansion + grade_3poor + grade_4low + grade_5fair + grade_6lowaverage
+ grade_8good + grade_9better + waterfront_yes + view_average + view_excellent + view_fair + view_good + view_mi
ssing
```

Out[53]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.676
Model:	OLS	**Adj. R-squared:**	0.675
Method:	Least Squares	**F-statistic:**	1308.
Date:	Fri, 01 Apr 2022	**Prob (F-statistic):**	0.00
Time:	14:47:55	**Log-Likelihood:**	-1.9771e+05
No. Observations:	14469	**AIC:**	3.955e+05
Df Residuals:	14445	**BIC:**	3.957e+05
Df Model:	23		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-3.593e+04	1.02e+04	-3.533	0.000	-5.59e+04	-1.6e+04
sqft_living	151.8692	3.736	40.652	0.000	144.547	159.192
bedrooms	-1.862e+04	2373.665	-7.846	0.000	-2.33e+04	-1.4e+04
sqft_lot	-0.2134	0.042	-5.091	0.000	-0.296	-0.131
floors	5.264e+04	4069.892	12.935	0.000	4.47e+04	6.06e+04
has_basement	3.667e+04	4059.754	9.034	0.000	2.87e+04	4.46e+04
renovated	4.229e+04	1.97e+04	2.148	0.032	3698.595	8.09e+04
house_age	3083.9138	73.528	41.942	0.000	2939.790	3228.038
grade_10verygood	4.202e+05	1.02e+04	41.387	0.000	4e+05	4.4e+05
grade_11excellent	6.852e+05	1.6e+04	42.878	0.000	6.54e+05	7.17e+05
grade_12luxury	1.175e+06	2.92e+04	40.186	0.000	1.12e+06	1.23e+06
grade_13mansion	2.196e+06	8.72e+04	25.178	0.000	2.02e+06	2.37e+06
grade_3poor	-1.053e+05	2.08e+05	-0.505	0.613	-5.14e+05	3.03e+05
grade_4low	-1.26e+05	4.69e+04	-2.690	0.007	-2.18e+05	-3.42e+04
grade_5fair	-1.399e+05	1.73e+04	-8.072	0.000	-1.74e+05	-1.06e+05
grade_6lowaverage	-8.838e+04	6626.625	-13.338	0.000	-1.01e+05	-7.54e+04
grade_8good	9.359e+04	4773.742	19.606	0.000	8.42e+04	1.03e+05
grade_9better	2.389e+05	7141.866	33.457	0.000	2.25e+05	2.53e+05
waterfront_yes	6.064e+05	2.55e+04	23.818	0.000	5.57e+05	6.56e+05
view_average	5.206e+04	8543.891	6.093	0.000	3.53e+04	6.88e+04
view_excellent	2.383e+05	1.74e+04	13.724	0.000	2.04e+05	2.72e+05
view_fair	1.248e+05	1.44e+04	8.677	0.000	9.66e+04	1.53e+05
view_good	1.109e+05	1.16e+04	9.597	0.000	8.83e+04	1.34e+05
view_missing	3.841e+04	3.11e+04	1.234	0.217	-2.26e+04	9.94e+04

Omnibus:	8388.329	**Durbin-Watson:**	2.014
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	313968.099
Skew:	2.178	**Prob(JB):**	0.00
Kurtosis:	25.401	**Cond. No.**	5.44e+06

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

[2] The condition number is large, 5.44e+06. This might indicate that there are strong multicollinearity or other numerical problems.

In [54]:
```
display(make_vif(model_2_formula, train_df))
```

	feature	VIF
0	Intercept	34.502619
1	sqft_living	3.917287
2	bedrooms	1.639238
3	sqft_lot	1.063208
4	floors	1.620585
5	has_basement	1.310577
6	renovated	1.010975
7	house_age	1.568852
8	grade_10verygood	1.760301
9	grade_11excellent	1.560675
10	grade_12luxury	1.236351
11	grade_13mansion	1.052049
12	grade_3poor	1.000887
13	grade_4low	1.011161
14	grade_5fair	1.055377
15	grade_6lowaverage	1.265103
16	grade_8good	1.544005
17	grade_9better	1.825651
18	waterfront_yes	1.396248
19	view_average	1.057393
20	view_excellent	1.438421
21	view_fair	1.023687
22	view_good	1.066790
23	view_missing	1.002660

Model 3: Check coefficients and multicollinearity of model adding neighborhood and distance from Seattle features

Adds `dist_seattle` and `neighborhood` category features

In [55]:
```
model_3_summary, model_3_formula = build_ols_model(model_3_cols, train_df)
model_3_summary
```

```
price ~ sqft_living + bedrooms + sqft_lot + floors + has_basement + renovated + house_age + grade_10verygood + g
rade_11excellent + grade_12luxury + grade_13mansion + grade_3poor + grade_4low + grade_5fair + grade_6lowaverage
+ grade_8good + grade_9better + waterfront_yes + view_average + view_excellent + view_fair + view_good + view_mi
ssing + dist_seattle + neighborhood_ballard + neighborhood_beaconhill + neighborhood_capitolhill + neighborhood_
cascade + neighborhood_centralarea + neighborhood_delridge + neighborhood_downtown + neighborhood_greaterduwamis
h + neighborhood_interbay + neighborhood_lakecity + neighborhood_magnolia + neighborhood_northcentral + neighbor
hood_northeast + neighborhood_northgate + neighborhood_northwest + neighborhood_queenanne + neighborhood_rainier
valley + neighborhood_sewardpark + neighborhood_universitydistrict + neighborhood_westseattle
```

Out[55]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.749
Model:	OLS	**Adj. R-squared:**	0.748
Method:	Least Squares	**F-statistic:**	976.3
Date:	Fri, 01 Apr 2022	**Prob (F-statistic):**	0.00
Time:	14:47:58	**Log-Likelihood:**	-1.9587e+05
No. Observations:	14469	**AIC:**	3.918e+05
Df Residuals:	14424	**BIC:**	3.922e+05
Df Model:	44		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3.144e+05	1.09e+04	28.934	0.000	2.93e+05	3.36e+05
sqft_living	188.0333	3.394	55.407	0.000	181.381	194.685
bedrooms	-1.311e+04	2110.344	-6.214	0.000	-1.72e+04	-8976.331
sqft_lot	0.2815	0.038	7.413	0.000	0.207	0.356
floors	-2.413e+04	4081.816	-5.911	0.000	-3.21e+04	-1.61e+04
has_basement	-3.8e+04	3879.763	-9.794	0.000	-4.56e+04	-3.04e+04
renovated	5.521e+04	1.74e+04	3.176	0.001	2.11e+04	8.93e+04
house_age	660.2538	78.500	8.411	0.000	506.383	814.125
grade_10verygood	3.088e+05	9128.040	33.825	0.000	2.91e+05	3.27e+05
grade_11excellent	5.308e+05	1.43e+04	37.101	0.000	5.03e+05	5.59e+05
grade_12luxury	9.707e+05	2.6e+04	37.377	0.000	9.2e+05	1.02e+06
grade_13mansion	1.905e+06	7.71e+04	24.714	0.000	1.75e+06	2.06e+06
grade_3poor	3.255e+05	1.84e+05	1.772	0.076	-3.46e+04	6.86e+05
grade_4low	-8776.2096	4.14e+04	-0.212	0.832	-8.99e+04	7.23e+04
grade_5fair	-4.255e+04	1.54e+04	-2.767	0.006	-7.27e+04	-1.24e+04
grade_6lowaverage	-3.671e+04	5973.345	-6.146	0.000	-4.84e+04	-2.5e+04
grade_8good	5.683e+04	4253.011	13.363	0.000	4.85e+04	6.52e+04
grade_9better	1.591e+05	6434.307	24.721	0.000	1.46e+05	1.72e+05
waterfront_yes	6.341e+05	2.25e+04	28.217	0.000	5.9e+05	6.78e+05
view_average	5.933e+04	7564.910	7.842	0.000	4.45e+04	7.42e+04
view_excellent	2.505e+05	1.53e+04	16.321	0.000	2.2e+05	2.81e+05
view_fair	1.092e+05	1.28e+04	8.557	0.000	8.42e+04	1.34e+05
view_good	1.213e+05	1.02e+04	11.854	0.000	1.01e+05	1.41e+05
view_missing	5.593e+04	2.74e+04	2.038	0.042	2145.181	1.1e+05
dist_seattle	-1.533e+04	329.996	-46.456	0.000	-1.6e+04	-1.47e+04
neighborhood_ballard	4.473e+04	1.08e+04	4.124	0.000	2.35e+04	6.6e+04
neighborhood_beaconhill	-1.311e+05	1.41e+04	-9.298	0.000	-1.59e+05	-1.03e+05
neighborhood_capitolhill	2.313e+05	1.48e+04	15.580	0.000	2.02e+05	2.6e+05
neighborhood_cascade	8.929e+04	3.52e+04	2.535	0.011	2.03e+04	1.58e+05

neighborhood_centralarea	4.084e+04	1.15e+04	3.566	0.000	1.84e+04	6.33e+04
neighborhood_delridge	-1.163e+05	1.08e+04	-10.760	0.000	-1.38e+05	-9.51e+04
neighborhood_downtown	-4.15e+04	1.84e+05	-0.226	0.821	-4.01e+05	3.18e+05
neighborhood_greaterduwamish	-1.813e+05	3.5e+04	-5.182	0.000	-2.5e+05	-1.13e+05
neighborhood_interbay	3345.9111	9.19e+04	0.036	0.971	-1.77e+05	1.84e+05
neighborhood_lakecity	-3.793e+04	1.28e+04	-2.970	0.003	-6.3e+04	-1.29e+04
neighborhood_magnolia	5.544e+04	1.4e+04	3.961	0.000	2.8e+04	8.29e+04
neighborhood_northcentral	8.56e+04	1.09e+04	7.882	0.000	6.43e+04	1.07e+05
neighborhood_northeast	1.109e+05	1.04e+04	10.675	0.000	9.06e+04	1.31e+05
neighborhood_northgate	-4.31e+04	1.16e+04	-3.706	0.000	-6.59e+04	-2.03e+04
neighborhood_northwest	-1.615e+04	1.01e+04	-1.592	0.111	-3.6e+04	3730.652
neighborhood_queenanne	1.559e+05	1.42e+04	11.008	0.000	1.28e+05	1.84e+05
neighborhood_rainiervalley	-9.275e+04	1.03e+04	-8.965	0.000	-1.13e+05	-7.25e+04
neighborhood_sewardpark	-1.886e+04	2.13e+04	-0.884	0.377	-6.07e+04	2.29e+04
neighborhood_universitydistrict	4.68e+04	3.87e+04	1.210	0.226	-2.9e+04	1.23e+05
neighborhood_westseattle	-3.208e+04	8825.591	-3.634	0.000	-4.94e+04	-1.48e+04

Omnibus:	9635.713	**Durbin-Watson:**	2.019
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	576862.142
Skew:	2.528	**Prob(JB):**	0.00
Kurtosis:	33.517	**Cond. No.**	5.44e+06

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.44e+06. This might indicate that there are
strong multicollinearity or other numerical problems.

In [56]:
```
display(make_vif(model_3_formula, train_df) )
```

	feature	VIF
0	Intercept	50.756521
1	sqft_living	4.164756
2	bedrooms	1.669364
3	sqft_lot	1.123854
4	floors	2.100168
5	has_basement	1.542109
6	renovated	1.015546
7	house_age	2.303891
8	grade_10verygood	1.833618
9	grade_11excellent	1.611808
10	grade_12luxury	1.256946
11	grade_13mansion	1.059229
12	grade_3poor	1.002495
13	grade_4low	1.015335
14	grade_5fair	1.070521
15	grade_6lowaverage	1.324396
16	grade_8good	1.578938
17	grade_9better	1.909146
18	waterfront_yes	1.401569
19	view_average	1.068007
20	view_excellent	1.448341
21	view_fair	1.039114
22	view_good	1.076967
23	view_missing	1.003426
24	dist_seattle	2.292722
25	neighborhood_ballard	1.220484
26	neighborhood_beaconhill	1.084679
27	neighborhood_capitolhill	1.170740
28	neighborhood_cascade	1.029972
29	neighborhood_centralarea	1.249537
30	neighborhood_delridge	1.152918
31	neighborhood_downtown	1.002015
32	neighborhood_greaterduwamish	1.016425
33	neighborhood_interbay	1.004128
34	neighborhood_lakecity	1.063706
35	neighborhood_magnolia	1.120151
36	neighborhood_northcentral	1.280330
37	neighborhood_northeast	1.193618
38	neighborhood_northgate	1.118840
39	neighborhood_northwest	1.151835
40	neighborhood_queenanne	1.193254
41	neighborhood_rainiervalley	1.143616
42	neighborhood_sewardpark	1.035516
43	neighborhood_universitydistrict	1.021185
44	neighborhood_westseattle	1.282164

Model 4: Check coefficients and multicollinearity of model adding King County zipcodes features

Adds `zipcodes` category features

In [57]:

```
model_4_summary, model_4_formula = build_ols_model(model_4_cols, train_df)
model_4_summary
```

```
price ~ sqft_living + bedrooms + sqft_lot + floors + has_basement + renovated + house_age + grade_10verygood + g
rade_11excellent + grade_12luxury + grade_13mansion + grade_3poor + grade_4low + grade_5fair + grade_6lowaverage
+ grade_8good + grade_9better + waterfront_yes + view_average + view_excellent + view_fair + view_good + view_mi
ssing + dist_seattle + neighborhood_ballard + neighborhood_beaconhill + neighborhood_capitolhill + neighborhood_
cascade + neighborhood_centralarea + neighborhood_delridge + neighborhood_downtown + neighborhood_greaterduwamis
h + neighborhood_interbay + neighborhood_lakecity + neighborhood_magnolia + neighborhood_northcentral + neighbor
hood_northeast + neighborhood_northgate + neighborhood_northwest + neighborhood_queenanne + neighborhood_rainier
valley + neighborhood_sewardpark + neighborhood_universitydistrict + neighborhood_westseattle + zip_98002 + zip_
98003 + zip_98004 + zip_98005 + zip_98006 + zip_98007 + zip_98008 + zip_98010 + zip_98011 + zip_98014 + zip_9801
9 + zip_98022 + zip_98023 + zip_98024 + zip_98027 + zip_98028 + zip_98029 + zip_98030 + zip_98031 + zip_98032 +
zip_98033 + zip_98034 + zip_98038 + zip_98039 + zip_98040 + zip_98042 + zip_98045 + zip_98052 + zip_98053 + zip_
98055 + zip_98056 + zip_98058 + zip_98059 + zip_98065 + zip_98070 + zip_98072 + zip_98074 + zip_98075 + zip_9807
7 + zip_98092 + zip_98102 + zip_98103 + zip_98105 + zip_98106 + zip_98107 + zip_98108 + zip_98109 + zip_98112 +
zip_98115 + zip_98116 + zip_98117 + zip_98118 + zip_98119 + zip_98122 + zip_98125 + zip_98126 + zip_98133 + zip_
98136 + zip_98144 + zip_98146 + zip_98148 + zip_98155 + zip_98166 + zip_98168 + zip_98177 + zip_98178 + zip_9818
8 + zip_98198 + zip_98199
```

Out[57]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.836
Model:	OLS	**Adj. R-squared:**	0.834
Method:	Least Squares	**F-statistic:**	646.1
Date:	Fri, 01 Apr 2022	**Prob (F-statistic):**	0.00
Time:	14:48:01	**Log-Likelihood:**	-1.9279e+05
No. Observations:	14469	**AIC:**	3.858e+05
Df Residuals:	14355	**BIC:**	3.867e+05
Df Model:	113		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.687e+05	2.42e+04	6.974	0.000	1.21e+05	2.16e+05
sqft_living	170.6962	2.805	60.844	0.000	165.197	176.195
bedrooms	-8643.9812	1727.211	-5.005	0.000	-1.2e+04	-5258.424
sqft_lot	0.2176	0.032	6.806	0.000	0.155	0.280
floors	-1.748e+04	3381.881	-5.167	0.000	-2.41e+04	-1.08e+04
has_basement	-3.239e+04	3202.024	-10.115	0.000	-3.87e+04	-2.61e+04
renovated	6.535e+04	1.41e+04	4.628	0.000	3.77e+04	9.3e+04
house_age	396.9622	65.511	6.059	0.000	268.552	525.372
grade_10verygood	2.335e+05	7676.219	30.419	0.000	2.18e+05	2.49e+05
grade_11excellent	4.171e+05	1.18e+04	35.238	0.000	3.94e+05	4.4e+05
grade_12luxury	8.012e+05	2.14e+04	37.474	0.000	7.59e+05	8.43e+05
grade_13mansion	1.768e+06	6.29e+04	28.125	0.000	1.65e+06	1.89e+06
grade_3poor	1.754e+05	1.49e+05	1.175	0.240	-1.17e+05	4.68e+05
grade_4low	2.255e+04	3.37e+04	0.670	0.503	-4.34e+04	8.85e+04
grade_5fair	-1.287e+04	1.26e+04	-1.021	0.307	-3.76e+04	1.18e+04
grade_6lowaverage	-1.077e+04	4943.918	-2.178	0.029	-2.05e+04	-1077.946
grade_8good	2.888e+04	3551.225	8.131	0.000	2.19e+04	3.58e+04
grade_9better	1.059e+05	5382.121	19.678	0.000	9.54e+04	1.16e+05
waterfront_yes	6.457e+05	1.85e+04	34.824	0.000	6.09e+05	6.82e+05
view_average	7.06e+04	6232.878	11.327	0.000	5.84e+04	8.28e+04
view_excellent	2.882e+05	1.26e+04	22.872	0.000	2.64e+05	3.13e+05
view_fair	7.56e+04	1.04e+04	7.241	0.000	5.51e+04	9.61e+04
view_good	1.466e+05	8417.558	17.416	0.000	1.3e+05	1.63e+05

view_missing	5.843e+04	2.23e+04	2.622	0.009	1.47e+04	1.02e+05
dist_seattle	-8709.7813	953.394	-9.136	0.000	-1.06e+04	-6841.007
neighborhood_ballard	6.63e+04	2.01e+04	3.297	0.001	2.69e+04	1.06e+05
neighborhood_beaconhill	-5.006e+04	2.77e+04	-1.807	0.071	-1.04e+05	4240.306
neighborhood_capitolhill	8052.6629	3.64e+04	0.221	0.825	-6.33e+04	7.94e+04
neighborhood_cascade	-1.408e+04	5.12e+04	-0.275	0.783	-1.14e+05	8.63e+04
neighborhood_centralarea	-2.304e+04	3.03e+04	-0.760	0.447	-8.24e+04	3.64e+04
neighborhood_delridge	1.767e+04	2.43e+04	0.729	0.466	-2.99e+04	6.52e+04
neighborhood_downtown	-8.672e+04	1.52e+05	-0.570	0.569	-3.85e+05	2.12e+05
neighborhood_greaterduwamish	-8.479e+04	4.12e+04	-2.056	0.040	-1.66e+05	-3972.534
neighborhood_interbay	4.13e+04	1.9e+05	0.217	0.828	-3.31e+05	4.14e+05
neighborhood_lakecity	3.387e+04	2.36e+04	1.437	0.151	-1.23e+04	8.01e+04
neighborhood_magnolia	1.196e+05	1.75e+05	0.683	0.495	-2.24e+05	4.63e+05
neighborhood_northcentral	1.201e+05	1.81e+04	6.634	0.000	8.46e+04	1.56e+05
neighborhood_northeast	1.303e+05	2.13e+04	6.119	0.000	8.86e+04	1.72e+05
neighborhood_northgate	1.391e+04	1.62e+04	0.860	0.390	-1.78e+04	4.56e+04
neighborhood_northwest	2.289e+04	1.46e+04	1.566	0.117	-5761.085	5.15e+04
neighborhood_queenanne	1.58e+05	9.2e+04	1.718	0.086	-2.22e+04	3.38e+05
neighborhood_rainiervalley	2.54e+04	2.29e+04	1.109	0.267	-1.95e+04	7.03e+04
neighborhood_sewardpark	1.397e+05	2.99e+04	4.677	0.000	8.12e+04	1.98e+05
neighborhood_universitydistrict	-3.42e+04	3.88e+04	-0.881	0.379	-1.1e+05	4.19e+04
neighborhood_westseattle	6.137e+04	2.17e+04	2.823	0.005	1.88e+04	1.04e+05
zip_98002	2.18e+04	1.61e+04	1.353	0.176	-9789.242	5.34e+04
zip_98003	-1.329e+04	1.47e+04	-0.904	0.366	-4.21e+04	1.55e+04
zip_98004	6.334e+05	2e+04	31.648	0.000	5.94e+05	6.73e+05
zip_98005	2.102e+05	2.09e+04	10.045	0.000	1.69e+05	2.51e+05
zip_98006	1.718e+05	1.68e+04	10.250	0.000	1.39e+05	2.05e+05
zip_98007	1.53e+05	2.17e+04	7.066	0.000	1.11e+05	1.95e+05
zip_98008	1.819e+05	1.81e+04	10.027	0.000	1.46e+05	2.18e+05
zip_98010	9.599e+04	2.19e+04	4.374	0.000	5.3e+04	1.39e+05
zip_98011	5.833e+04	1.88e+04	3.108	0.002	2.15e+04	9.51e+04
zip_98014	1.131e+05	1.91e+04	5.912	0.000	7.56e+04	1.51e+05
zip_98019	8.508e+04	1.68e+04	5.062	0.000	5.21e+04	1.18e+05
zip_98022	1.016e+05	1.88e+04	5.396	0.000	6.47e+04	1.38e+05
zip_98023	-2.24e+04	1.29e+04	-1.742	0.081	-4.76e+04	2797.852
zip_98024	1.596e+05	2.17e+04	7.362	0.000	1.17e+05	2.02e+05
zip_98027	1.229e+05	1.45e+04	8.492	0.000	9.46e+04	1.51e+05
zip_98028	3.101e+04	1.8e+04	1.724	0.085	-4245.644	6.63e+04
zip_98029	1.838e+05	1.5e+04	12.227	0.000	1.54e+05	2.13e+05
zip_98030	-1.711e+04	1.5e+04	-1.144	0.253	-4.64e+04	1.22e+04
zip_98031	-2.136e+04	1.53e+04	-1.399	0.162	-5.13e+04	8570.878
zip_98032	-4.551e+04	2e+04	-2.276	0.023	-8.47e+04	-6317.630
zip_98033	2.521e+05	1.79e+04	14.099	0.000	2.17e+05	2.87e+05
zip_98034	1.053e+05	1.69e+04	6.244	0.000	7.22e+04	1.38e+05
zip_98038	4.745e+04	1.24e+04	3.817	0.000	2.31e+04	7.18e+04
zip_98039	1.203e+06	3.2e+04	37.598	0.000	1.14e+06	1.27e+06
zip_98040	4.079e+05	2e+04	20.415	0.000	3.69e+05	4.47e+05
zip_98042	6342.1540	1.27e+04	0.499	0.618	-1.86e+04	3.13e+04

zip_98045	1.523e+05	1.73e+04	8.793	0.000	1.18e+05	1.86e+05
zip_98052	1.636e+05	1.54e+04	10.599	0.000	1.33e+05	1.94e+05
zip_98053	1.607e+05	1.45e+04	11.115	0.000	1.32e+05	1.89e+05
zip_98055	-2.609e+04	1.67e+04	-1.562	0.118	-5.88e+04	6654.083
zip_98056	9858.9585	1.68e+04	0.586	0.558	-2.31e+04	4.28e+04
zip_98058	-1.894e+04	1.44e+04	-1.319	0.187	-4.71e+04	9201.971
zip_98059	2.063e+04	1.52e+04	1.360	0.174	-9092.329	5.03e+04
zip_98065	1.119e+05	1.46e+04	7.663	0.000	8.32e+04	1.4e+05
zip_98070	-4.475e+04	2.1e+04	-2.134	0.033	-8.58e+04	-3642.807
zip_98072	1.032e+05	1.65e+04	6.239	0.000	7.08e+04	1.36e+05
zip_98074	1.091e+05	1.49e+04	7.342	0.000	8e+04	1.38e+05
zip_98075	1.293e+05	1.51e+04	8.554	0.000	9.96e+04	1.59e+05
zip_98077	7.396e+04	1.71e+04	4.328	0.000	4.05e+04	1.07e+05
zip_98092	-1.12e+04	1.37e+04	-0.817	0.414	-3.81e+04	1.57e+04
zip_98102	2.79e+05	4.57e+04	6.103	0.000	1.89e+05	3.69e+05
zip_98103	1.062e+05	2.34e+04	4.534	0.000	6.03e+04	1.52e+05
zip_98105	2.288e+05	2.83e+04	8.098	0.000	1.73e+05	2.84e+05
zip_98106	-2.981e+04	3.04e+04	-0.981	0.326	-8.94e+04	2.97e+04
zip_98107	1.244e+05	2.71e+04	4.588	0.000	7.13e+04	1.78e+05
zip_98108	2.375e+04	3.5e+04	0.678	0.498	-4.49e+04	9.24e+04
zip_98109	2.001e+05	9.26e+04	2.161	0.031	1.86e+04	3.82e+05
zip_98112	4.829e+05	4.04e+04	11.962	0.000	4.04e+05	5.62e+05
zip_98115	1.006e+05	2.56e+04	3.933	0.000	5.05e+04	1.51e+05
zip_98116	8.162e+04	3.06e+04	2.669	0.008	2.17e+04	1.42e+05
zip_98117	1.212e+05	2.39e+04	5.066	0.000	7.43e+04	1.68e+05
zip_98118	-1.255e+04	2.98e+04	-0.422	0.673	-7.09e+04	4.58e+04
zip_98119	1.74e+05	9.5e+04	1.831	0.067	-1.23e+04	3.6e+05
zip_98122	2.116e+05	3.76e+04	5.626	0.000	1.38e+05	2.85e+05
zip_98125	4.551e+04	2.69e+04	1.693	0.090	-7180.178	9.82e+04
zip_98126	1.261e+04	2.91e+04	0.433	0.665	-4.45e+04	6.97e+04
zip_98133	3.823e+04	1.86e+04	2.059	0.039	1838.496	7.46e+04
zip_98136	5.598e+04	2.98e+04	1.879	0.060	-2410.243	1.14e+05
zip_98144	1.412e+05	3.31e+04	4.270	0.000	7.64e+04	2.06e+05
zip_98146	-4.026e+04	2.02e+04	-1.996	0.046	-7.98e+04	-714.346
zip_98148	-1894.5047	2.74e+04	-0.069	0.945	-5.57e+04	5.19e+04
zip_98155	4.256e+04	1.73e+04	2.464	0.014	8705.248	7.64e+04
zip_98166	-1.81e+04	1.8e+04	-1.005	0.315	-5.34e+04	1.72e+04
zip_98168	-7.021e+04	1.92e+04	-3.665	0.000	-1.08e+05	-3.27e+04
zip_98177	9.677e+04	2.02e+04	4.790	0.000	5.72e+04	1.36e+05
zip_98178	-8.354e+04	2.01e+04	-4.161	0.000	-1.23e+05	-4.42e+04
zip_98188	-4.715e+04	2.12e+04	-2.226	0.026	-8.87e+04	-5625.514
zip_98198	-4.93e+04	1.58e+04	-3.129	0.002	-8.02e+04	-1.84e+04
zip_98199	1.145e+05	1.76e+05	0.651	0.515	-2.3e+05	4.59e+05

Omnibus:	10724.234	**Durbin-Watson:**	2.007
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1212972.393
Skew:	2.788	**Prob(JB):**	0.00
Kurtosis:	47.507	**Cond. No.**	1.17e+07

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.17e+07. This might indicate that there are
strong multicollinearity or other numerical problems.

In [58]:
```
display(make_vif(model_4_formula, train_df) )
```

	feature	VIF
0	Intercept	382.918679
1	sqft_living	4.333656
2	bedrooms	1.702675
3	sqft_lot	1.212872
4	floors	2.195130
...	...	...
109	zip_98177	3.012036
110	zip_98178	3.169854
111	zip_98188	1.635342
112	zip_98198	2.007110
113	zip_98199	276.098091

114 rows × 2 columns

Unfortunately, there is substantial collinearity between many zip codes and the neighborhood and dist_seattle information that was in the previous version of the model.

For this reason, we will need to remove those collinear zip codes before the zip code information can be utilized.

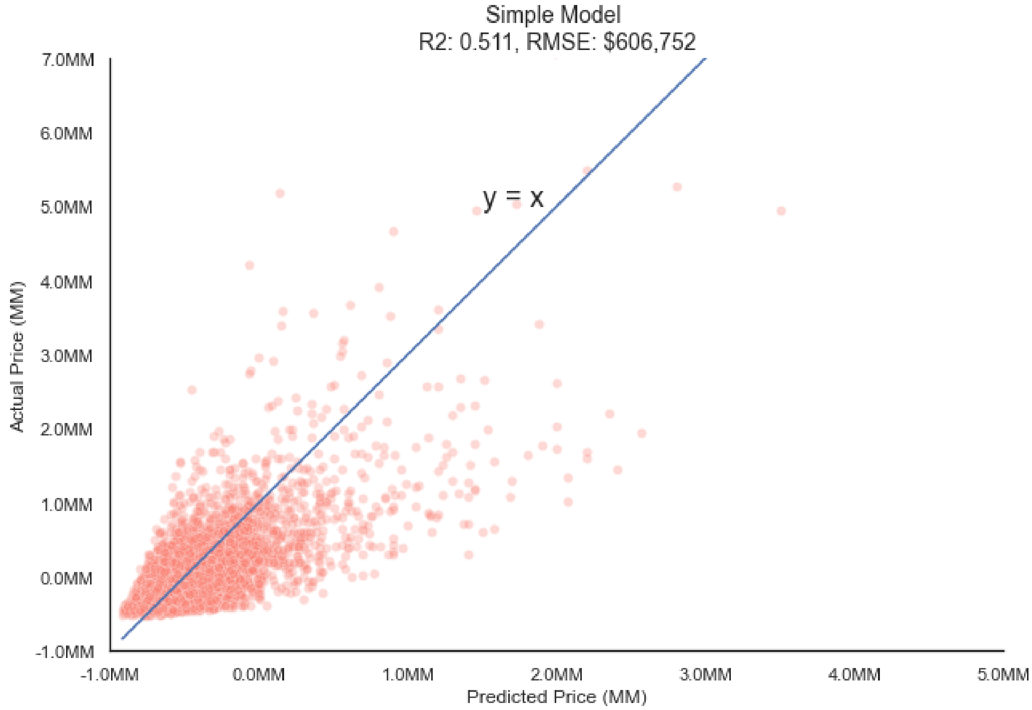
And ultimately, Model 3 is officially our best model.

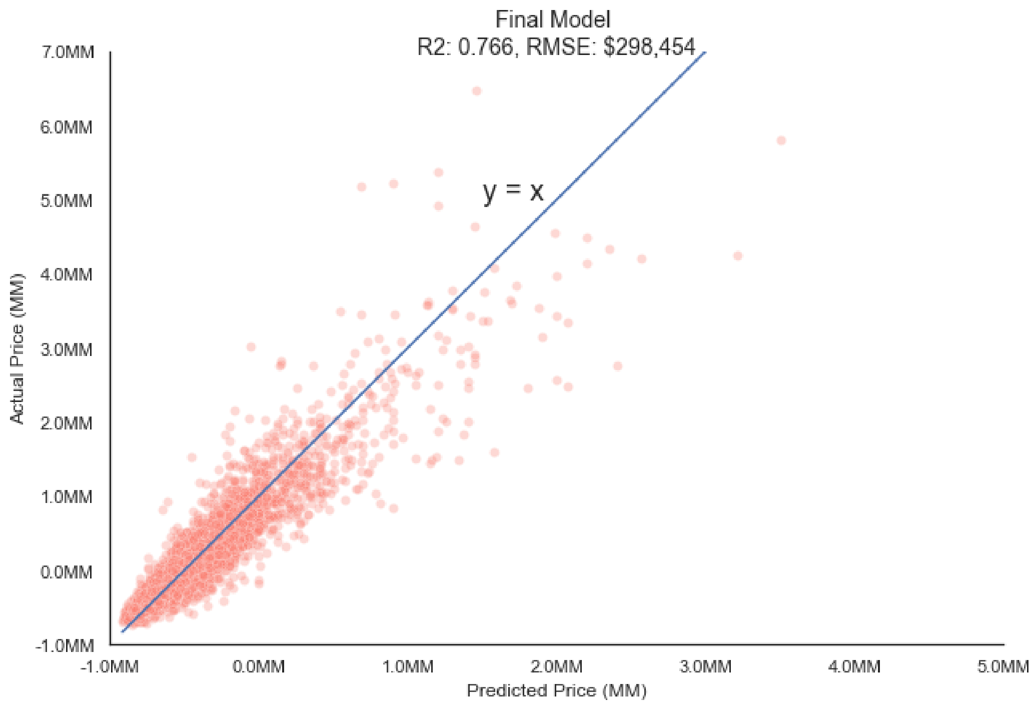
Data Visualization

Compare predictions from Simple Model to predictions from Best Model (Model 3)

In [67]:

```
#Plot average prediction error
fig, ax = plt.subplots (2,1,figsize = (10,15))

sns.set_theme(style = 'white')

ax1 = sns.scatterplot(x=np.exp(y_test), y=np.exp(simple_yhat_test), ax = ax[0], color = 'salmon', alpha = 0.3)
sns.lineplot(x=np.exp(y_test), y=np.exp(y_test), ax = ax[0])

ax2 = sns.scatterplot(x=np.exp(y_test), y=np.exp(m4_yhat_test), ax = ax[1], color = 'salmon', alpha = 0.3)
sns.lineplot(x=np.exp(y_test), y=np.exp(y_test), ax = ax[1])

x_label = 'Predicted Price (MM)'
y_label = 'Actual Price (MM)'
tick_labels = ['{:,.1f}'.format(x) + 'MM' for x in ax1.get_xticks()/1000000]
ax1.set_xticklabels(tick_labels)
ax2.set_xticklabels(tick_labels)
ax1.set_yticklabels(tick_labels)
ax2.set_yticklabels(tick_labels)

ax1.set_xlabel(x_label)
ax2.set_xlabel(x_label)
ax1.set_ylabel(y_label)
ax2.set_ylabel(y_label)

ax1.set_xlim([0, 6000000])
ax1.set_ylim([0, 4000000])

ax2.set_xlim([0, 6000000])
ax2.set_ylim([0, 4000000])

ax1.set_title('Simple Model \nR2: 0.511, RMSE: $606,752',fontsize = 14)
ax2.set_title('Final Model \nR2: 0.766, RMSE: $298,454', fontsize = 14, loc = 'center',y=0.98)

ax1.annotate('y = x', xy =(2500000,3000000), fontsize = 18)
ax2.annotate('y = x', xy =(2500000,3000000), fontsize = 18)


sns.despine()

plt.savefig('Images/model_performance.jpg',bbox_inches="tight",dpi=300)
```





This demonstrates that our final model has greatly improved our ability to predict house prices in the King County area, given specific information about the house, neighborhoods, and amenities. With this model, millenials will have more information to inform house buying decisions, thereby saving money and getting homes that meet their needs.

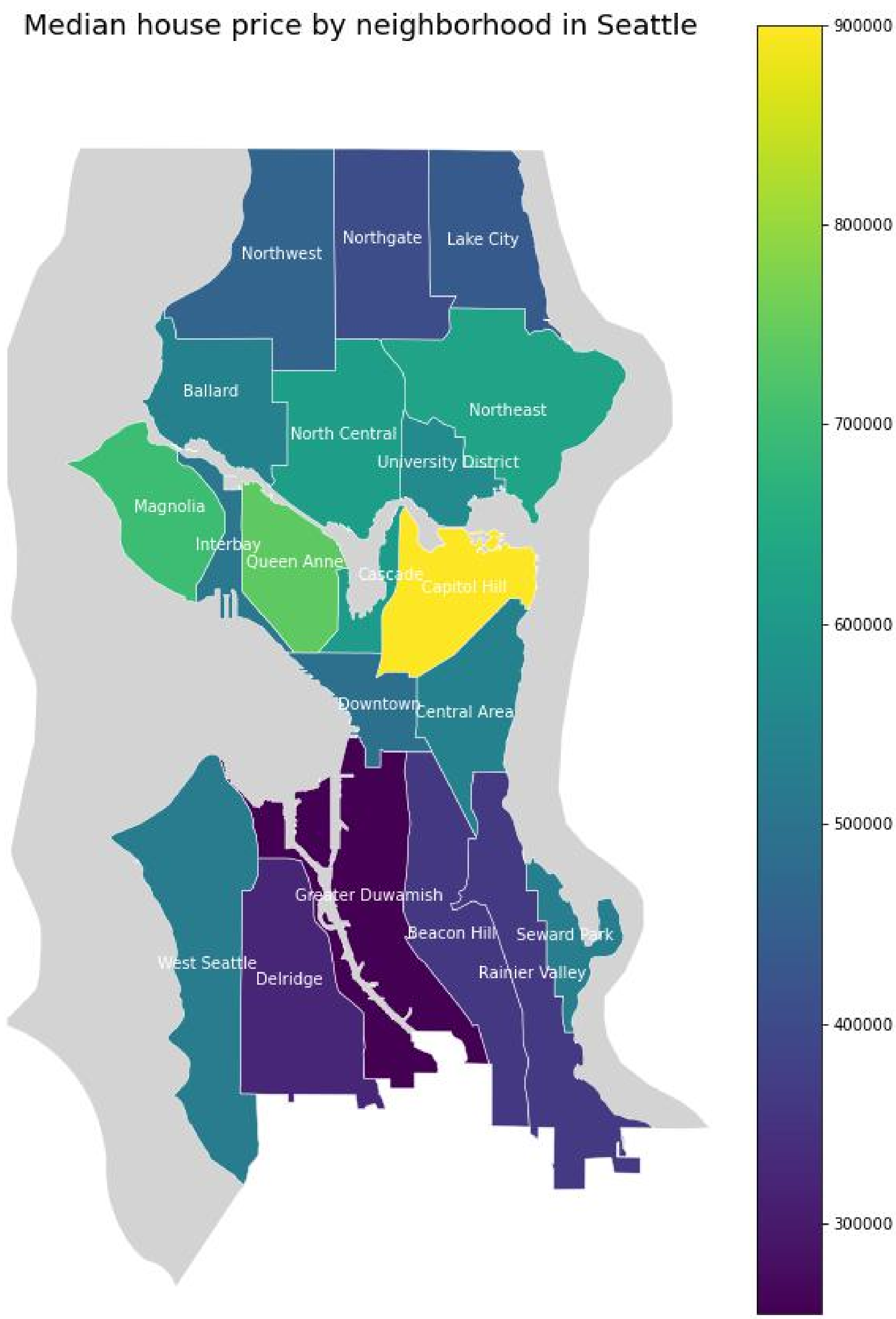
Plot price of houses in Seattle versus houses outside of the city

In [70]:

```
import matplotlib.ticker as tkr
# # fig, ax = plt.subplots(ncols = 2,)
# f, ax = plt.subplots(1, 2)

g = sns.lmplot(x='sqft_living', y='price', hue = 'in_seattle',data=housing_df[housing_df['price']<2000000], scatt
# ax1.set_xlabel ('Living space (sqft)')
# ax1.set_ylabel('Price')


# plt.figure(figsize = (15,20))
plt.xlabel("Living space (sqft)")
plt.ylabel("Price ($)")
plt.title('In Seattle vs outside Seattle', y=1, fontsize=10)
plt.suptitle('Price by Living Space',y=1.04,fontsize = 18)
# title
new_title = 'In Seattle'
g._legend.set_title(new_title)
# replace labels
new_labels = ['No', 'Yes']
for t, l in zip(g._legend.texts, new_labels):
    t.set_text(l)
# plt.ticklabel_format(style='plain', axis='y');
for ax in g.axes.flat:
    ax.yaxis.set_major_formatter(tkr.FuncFormatter(lambda y, p: f'{(y/1000000):.1f} MM'))

plt.savefig('Images/price_by_living_space.jpg',bbox_inches="tight",dpi=300)

plt.show(g)
```

Display median home prices by neighborhood within Seattle

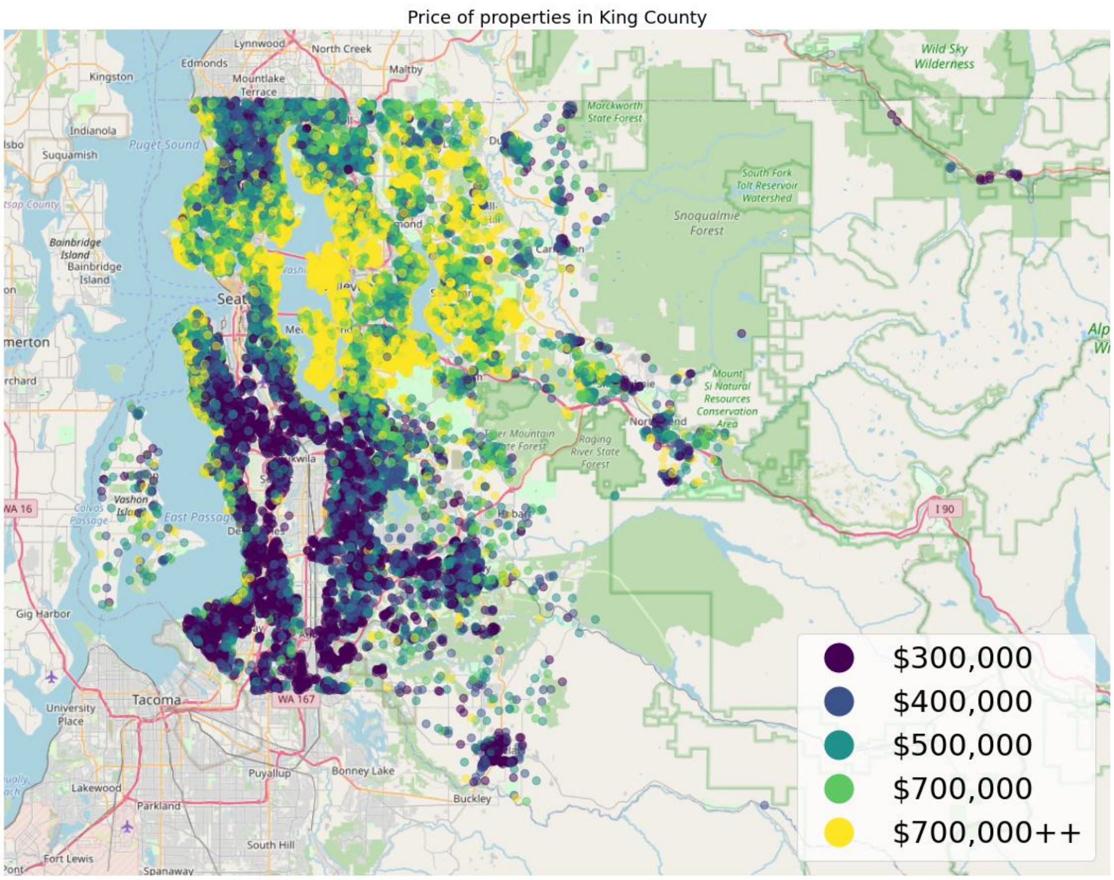
The figure for median house price by neighborhood in Seattle is plotted in the notebook ***add_city_neighborhood.ipynb*** , available in our repo. For any interest in geospatial processing done in this project, please refer to that notebook.



House prices displayed on map of King County

The map of house prices within King County was created within the notebook ***add_city_neighborhood.ipynb*** , available in our repo. For any interest in geospatial processing done in this project, please refer to that notebook.

This map show that house prices are higher around waterfront areas, within certain neighborhoods, and within proximity to Seattle city and certain zip codes.

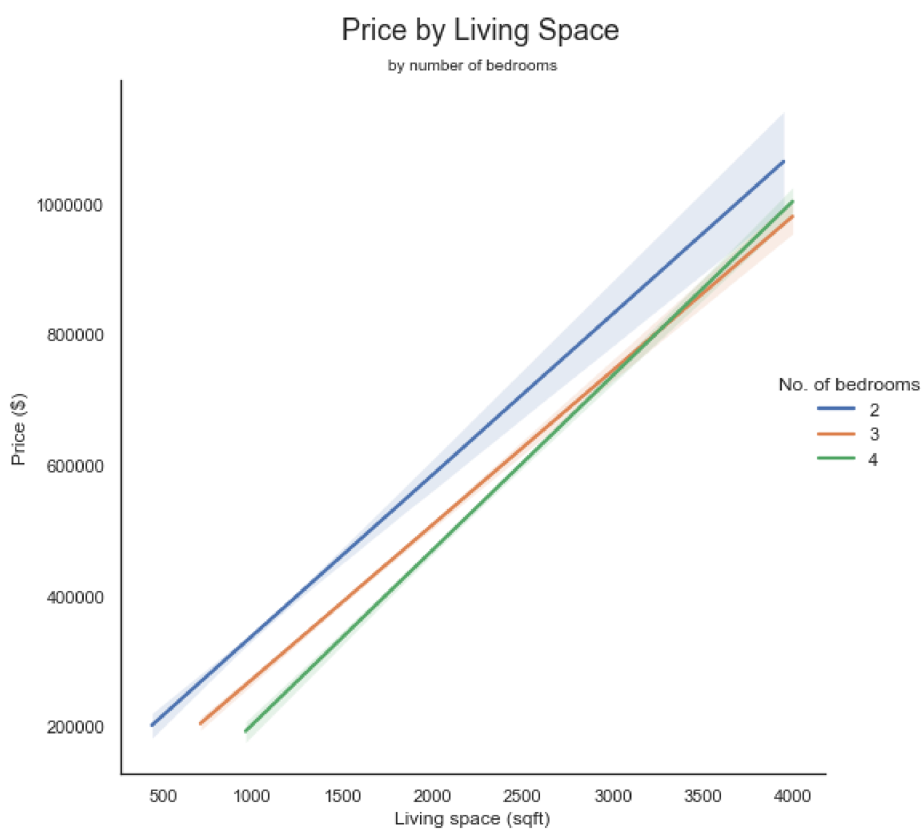


Display mean house prices by number of bedrooms and living space

House prices increase as square foot of living space increases. However, for houses with similar amounts of living space, those with more bedrooms will cost ***less*** on average. This is likely because each room will be smaller. But this could be useful information for new or growing families to consider.

In [69]:

```
filt = (train_df['bedrooms'].isin([2,3,4])) & (train_df['price'] <= 2000000) & (train_df['sqft_living'] <=4000)
cleaner_train_df = train_df[filt]
cleaner_train_df['price'] = cleaner_train_df['price']

g=sns.lmplot(y='price', x='sqft_living', hue='bedrooms', data=cleaner_train_df, scatter=False, facet_kws={'legend
plt.xlabel("Living space (sqft)")
plt.ylabel("Price ($)")
plt.title('by number of bedrooms', y=1, fontsize=10)
plt.suptitle('Price by Living Space',y=1.03,fontsize = 18)
# title
new_title = 'No. of bedrooms'
g._legend.set_title(new_title)
# replace labels
new_labels = ['2','3','4']
for t, l in zip(g._legend.texts, new_labels):
    t.set_text(l)
plt.ticklabel_format(style='plain', axis='y');

plt.savefig('Images/lmplot_price-vs-sqft_living-by_bedrooms.jpg', transparent = False, bbox_inches="tight");
```



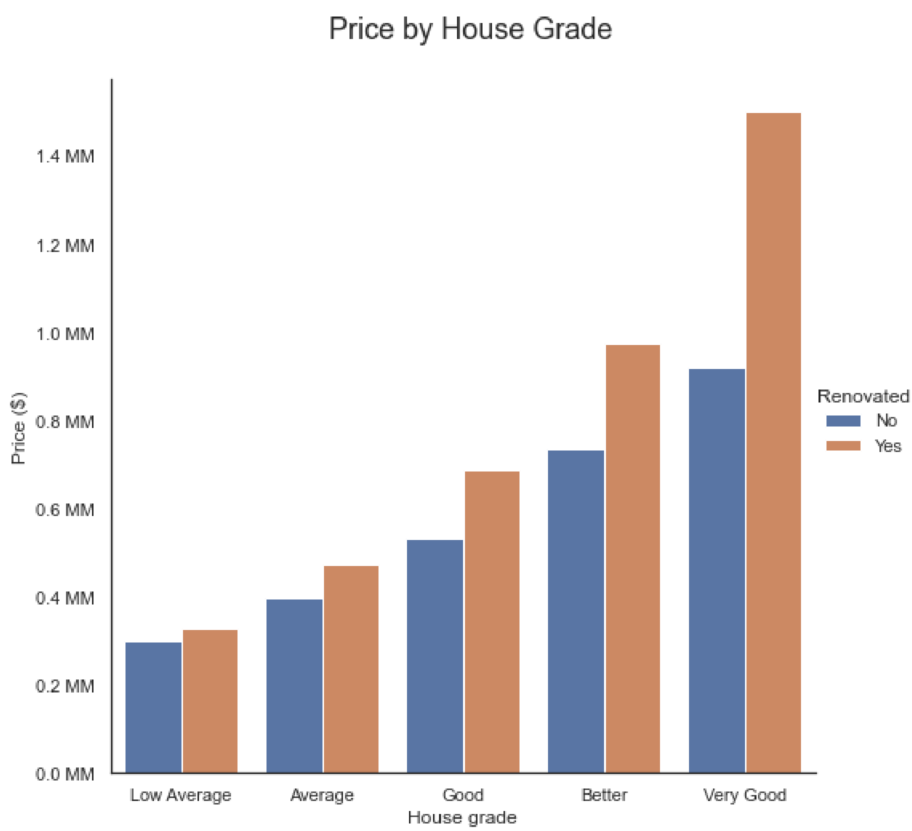
Display mean housing price by construction grade

Housing costs substantially more for higher quality construction. Also, previously renovated properties cost more, even for houses in the same grade.

Our recommendation is to consider doing work yourself to avoid overpaying for higher grade properties.

In [71]:
```python
# Ordering levels of grade for purpose of plotting
cleaner_train_df['grade_ordinal'] = (cleaner_train_df['grade_3poor']       * 3) + \
                                    (cleaner_train_df['grade_4low']        * 4) + \
                                    (cleaner_train_df['grade_5fair']       * 5) + \
                                    (cleaner_train_df['grade_6lowaverage'] * 6) + \
                                    (cleaner_train_df['grade_7average']    * 7) + \
                                    (cleaner_train_df['grade_8good']       * 8) + \
                                    (cleaner_train_df['grade_9better']     * 9) + \
                                    (cleaner_train_df['grade_10verygood']  * 10) + \
                                    (cleaner_train_df['grade_11excellent'] * 11) + \
                                    (cleaner_train_df['grade_12luxury']    * 12) + \
                                    (cleaner_train_df['grade_13mansion']   * 13)
```

In [72]:
```python
filt = (cleaner_train_df['grade_ordinal'] >= 6) & (cleaner_train_df['grade_ordinal'] <= 10)

import matplotlib.ticker as tkr

ax1 = sns.catplot(x="grade_ordinal", y="price", hue="renovated", kind="bar", data=cleaner_train_df[filt], ci=None

plt.xlabel("House grade")
plt.ylabel("Price ($)")
# plt.title('by number of bedrooms', y=1, fontsize=10)
plt.suptitle('Price by House Grade',y=1.03,fontsize = 18)

new_title = 'Renovated'
ax1._legend.set_title(new_title)
# replace labels
new_labels = ['No', 'Yes']
for t, l in zip(ax1._legend.texts, new_labels):
    t.set_text(l)

for ax in ax1.axes.flat:
    ax.yaxis.set_major_formatter(tkr.FuncFormatter(lambda y, p: f'{(y/1000000):.1f} MM'))
# plt.ticklabel_format(style='plain', axis='y');
values = ['Low Average', 'Average', 'Good', 'Better','Very Good']
default_x_ticks = range(len(values))
plt.xticks(default_x_ticks, values);

plt.savefig('Images/barplot_price-vs-grade-by-renovated.jpg', transparent = False, bbox_inches="tight");
```



Conclusions

Our final model, Model 3, includes features regarding house living space, house condition, waterfront property and scenic views, distance from Seattle city center, and neighborhoods within Seattle.

With this model, millenial homebuyers could specify desired features and find what the expected house prices would be. It would also be possible to specify a house range and receive recommendations for neighborhoods and house features that would fit within that budget.