Final_Notebook

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0.1 Phase 2 Final Project Submission

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Business Problem

The mortgage department at Bentley & Co. Bank of Seattle is looking for an additional method of appraising the value of homes. They currently hire an appraisal management company, and will continue to do so. However, as independant appraisals can be costly and take time, Bentley & Co. Bank is looking for a tool that can estimate the value of a house cheaply and quickly.

This will be useful for obtaining a ballpark estimate of the value of a home before an appraisal can be performed. In addition, it will be useful for estimating the price impact of any renovations performed on a house Bentley & Co. Bank has an interest in without any additional appraisals.

This tool must meet two criteria to be of use to Bentley & Co. Bank:

The tool must be capable of accurately predicting the price of a house provided information about the house.

The tool must provide insight into what factors impact the price of a house the most.

Goals

Bentley Bank & Co. can use the models created in this notebook to: * Generate a range of prices that the price of a given house can be expected to fall within. * Predict the price impact of any physical changes to a home.

Imports & Important Functions

[1]:
```
# Import necessary modules

import warnings
import pandas as pd
import numpy as np
import seaborn as sns
import math
import matplotlib.pyplot as plt
import statsmodels.api as sm
import scipy.stats as stats
```

```
from datetime import datetime as dt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.linear_model import LinearRegression

# Set important global options
%matplotlib inline
plt.style.use('seaborn')
warnings.filterwarnings("ignore")
pd.options.display.float_format = '{:.3f}'.format
```

I made the following function to answer my business problem. It uses the best model to get a range of prices for any given house.

[2]:
```
# This can not be run until the model sm_best is created in memory
def predict_interval(house,confidence=0.001):
    # Calculates predicted value and confidence interval of specified alpha
    prediction = np.exp(sm_best.get_prediction(house).predicted_mean[0])
    conf_interval = np.exp(sm_best.get_prediction(house).
 ↪conf_int(alpha=confidence)[0])

    # Formats everything nicely
    pred_statement = f'This house has a predicted value of ${math.
 ↪trunc(prediction)}.'
    interval_statement = (f'A safe value for this house would fall between '
        f'${math.trunc(conf_interval[0])} and ${math.trunc(conf_interval[1])}.')

    print(pred_statement)
    print(interval_statement)
    return(prediction)

# This can not be run until the model sm_best is created in memory
#predict_interval(X_test_best.iloc[42]);
```

I prefer SKLearn to statsmodels so I created a helper function to extract all of the relevant information from an SKLearn regression.

[3]:
```
# The following function returns the results of a sklearn model
def model_summary(model,train_X,test_X,train_y,test_y):
    #Evaluates the model on training data
    train_r2 = model.score(train_X,train_y)
    train_mae = mean_absolute_error(train_y,model.predict(train_X))
    train_mse = mean_squared_error(train_y,model.predict(train_X))
    train_rmse = mean_squared_error(train_y,model.
 ↪predict(train_X),squared=False)

    #Evaluates the model on test data
```

```
    test_r2 = model.score(test_X,test_y)
    test_mae = mean_absolute_error(test_y,model.predict(test_X))
    test_mse = mean_squared_error(test_y,model.predict(test_X))
    test_rmse = mean_squared_error(test_y,model.predict(test_X),squared=False)

    # Prepare the results to be added to a dataframe
    labels = ['Train R2','Train Mean Abs Err','Train Mean Sq Err','Train Root␣
↪Mean Sq Err',
            'Test R2','Test Mean Abs Err','Test Mean Sq Err','Test Root Mean Sq␣
↪Err']
    results = [train_r2,train_mae,train_mse,train_rmse,
            test_r2,test_mae,test_mse,test_rmse]

    #Return the results as pandas dataframes
    dfr = pd.DataFrame(results,index=labels,columns=['Values'])
    coefficients = pd.DataFrame(model.coef_,index=train_X.
↪columns,columns=['Values'])
    return dfr,coefficients
```

Data Understanding

The data provided in 'kc_house_data.csv' contains information on 21 thousand homes sold in the King County, WA area between 2014 and 2015.

The data provided in 'zips.csv' contains a list of zipcodes and the corresponding city for each zipcode in King County, WA.

I began by loading each dataset into dataframes, dropping most of the columns suggested by the project description, and merging the two datasets together by the zipcode column.

[4]:
```
# Homes contains data on home sales, zipcodes is for encoding cities later
homes = pd.read_csv('data/kc_house_data.csv')
zipcodes = pd.read_csv('data/zips.csv')

# Columns suggested to drop by project description
cols_to_drop = (['id','date','sqft_above','sqft_basement',
                'lat','long','sqft_living15','sqft_lot15'])
homes = homes.drop(cols_to_drop,axis=1)

# Exchange the zipcode column for a city column based on zipcode
homes = homes.merge(zipcodes,how='left',on='zipcode').drop('zipcode',axis=1)

# Overview of the data
homes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21597 entries, 0 to 21596
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
```

```
---  ------        --------------  -----
 0   price         21597 non-null  float64
 1   bedrooms      21597 non-null  int64
 2   bathrooms     21597 non-null  float64
 3   sqft_living   21597 non-null  int64
 4   sqft_lot      21597 non-null  int64
 5   floors        21597 non-null  float64
 6   waterfront    19221 non-null  object
 7   view          21534 non-null  object
 8   condition     21597 non-null  object
 9   grade         21597 non-null  object
 10  yr_built      21597 non-null  int64
 11  yr_renovated  17755 non-null  float64
 12  city          21597 non-null  object
dtypes: float64(4), int64(4), object(5)
memory usage: 2.3+ MB
```

[5]:
```
# Quick statistics on the data
homes.describe()
```

[5]:
```
             price  bedrooms  bathrooms  sqft_living    sqft_lot    floors  \
count    21597.000 21597.000  21597.000    21597.000   21597.000 21597.000
mean    540296.574     3.373      2.116     2080.322   15099.409     1.494
std     367368.140     0.926      0.769      918.106   41412.637     0.540
min      78000.000     1.000      0.500      370.000     520.000     1.000
25%     322000.000     3.000      1.750     1430.000    5040.000     1.000
50%     450000.000     3.000      2.250     1910.000    7618.000     1.500
75%     645000.000     4.000      2.500     2550.000   10685.000     2.000
max    7700000.000    33.000      8.000    13540.000 1651359.000     3.500

       yr_built  yr_renovated
count 21597.000     17755.000
mean   1971.000        83.637
std      29.375       399.946
min    1900.000         0.000
25%    1951.000         0.000
50%    1975.000         0.000
75%    1997.000         0.000
max    2015.000      2015.000
```

[6]:
```
# Quick overview of the data
homes.head()
```

[6]:
```
       price  bedrooms  bathrooms  sqft_living  sqft_lot  floors waterfront  \
0 221900.000         3      1.000         1180      5650   1.000        NaN
1 538000.000         3      2.250         2570      7242   2.000         NO
2 180000.000         2      1.000          770     10000   1.000         NO
3 604000.000         4      3.000         1960      5000   1.000         NO
```

```
4 510000.000          3      2.000          1680      8080    1.000          NO

   view  condition           grade  yr_built  yr_renovated       city
0  NONE    Average       7 Average      1955         0.000    Seattle
1  NONE    Average       7 Average      1951      1991.000    Seattle
2  NONE    Average   6 Low Average      1933           nan    Kenmore
3  NONE  Very Good       7 Average      1965         0.000    Seattle
4  NONE    Average          8 Good      1987         0.000  Sammamish
```

Data Cleanup & Pre-processing

Not too much looks weird here, but the homes.describe() shows that at least one home has 33 bedrooms. Let's investigate this further.

[7]:
```
homes[homes.bedrooms > 8]
```

[7]:
```
             price  bedrooms  bathrooms  sqft_living  sqft_lot  floors  \
4092    599999.000         9      4.500         3830      6988   2.500
4231    700000.000         9      3.000         3680      4400   2.000
6073   1280000.000         9      4.500         3650      5000   2.000
8537    450000.000         9      7.500         4050      6504   2.000
8748    520000.000        11      3.000         3000      4960   2.000
13301 1150000.000        10      5.250         4590     10920   1.000
15147   650000.000        10      2.000         3610     11914   2.000
15856   640000.000        33      1.750         1620      6000   1.000
16830 1400000.000         9      4.000         4620      5508   2.500
18428   934000.000         9      3.000         2820      4480   2.000
19239   660000.000        10      3.000         2920      3745   2.000

      waterfront     view  condition          grade  yr_built  yr_renovated  \
4092          NO     NONE    Average      7 Average      1938         0.000
4231          NO     NONE    Average      7 Average      1908         0.000
6073          NO     NONE    Average         8 Good      1915      2010.000
8537          NO     NONE    Average      7 Average      1996         0.000
8748          NO     NONE    Average      7 Average      1918      1999.000
13301         NO  AVERAGE    Average       9 Better      2008         0.000
15147         NO     NONE       Good      7 Average      1958         0.000
15856         NO     NONE  Very Good      7 Average      1947         0.000
16830         NO     NONE    Average   11 Excellent      1915         0.000
18428         NO     NONE    Average      7 Average      1918         0.000
19239         NO     NONE       Good      7 Average      1913         0.000

          city
4092   Seattle
4231   Seattle
6073   Seattle
8537   Seattle
8748   Seattle
```

```
13301   Bellevue
15147   Bellevue
15856    Seattle
16830    Seattle
18428    Seattle
19239    Seattle
```

The 33 bedroom house only has 1600 sq. ft. of living space. I will assume this is a data entry issue and impute the median value of 3 bedrooms on this home.

[8]:
```
homes.loc[homes.bedrooms > 20,'bedrooms'] = 3
```

Waterfronts seems to have some missing values. I will impute the mode "NO" for the missing values, and then map the values No to 0 and Yes to 1 so this feature can be used in my model.

[9]:
```
waterfront_rule = {'NO':0,'YES':1}
waterfronts = homes.waterfront.fillna('NO').map(waterfront_rule)
homes.waterfront = waterfronts
```

Views also seems to have some missing values. I will impute the mode "NONE" for the missing values. In order to get this column to work with my model, I will take the values from worst to best and map them to the numbers 0 through 4.

[10]:
```
view_rule = {'NONE':0,'FAIR':1,'AVERAGE':2,'GOOD':3,'EXCELLENT':4}
views = homes.view.fillna('NONE').map(view_rule)
homes.view = views
```

Condition is very similar to view, but without any missing values to impute. In order to get this column to work with my model, I will take the values from worst to best and map them to the numbers 0 through 4.

[11]:
```
condition_rule = {'Poor':0,'Fair':1,'Average':2,'Good':3,'Very Good':4}
conditions = homes.condition.map(condition_rule)
homes.condition = conditions
```

Grade already has a numerical rating in the column, so I will extract that number for use in my model.

[12]:
```
# Numerical rating is the part of grade before the space
grades = homes.grade.apply(lambda x: int(x.split()[0]))
homes.grade = grades
```

I decided to engineer a feature called since_reno which is the number of years since the last renovation. If the home had an NA value for year renovated, I assumed the home had not been renovated and used the year built as the renovation date. I used a helper function since_reno to calculate this feature.

[13]:
```
homes.yr_renovated.fillna(0,inplace=True)

def since_reno(home):
```

```
    # Use the year built if the house has not been renovated
    if home.yr_renovated < home.yr_built:
        return dt.today().year - home.yr_built
    else:
        return dt.today().year - home.yr_renovated

homes['since_reno'] = homes.apply(lambda x:since_reno(x),axis=1)
homes.drop('yr_renovated',inplace=True,axis=1)
```

I decided to drop the year built in favor of the home's age. This probably won't affect the model but is easier to read.

[14]:
```
homes['age'] = dt.today().year - homes['yr_built']
homes.drop('yr_built',inplace=True,axis=1)
```

City is a categorical feature, so I had to one-hot-encode it so it would work with my model. I did not merge cities back into my main dataset yet so the visualizations will be easier to see.

[15]:
```
cities = pd.get_dummies(homes.city,prefix='city',sparse=False,drop_first=True)
# Grouped cities is created for plotting purposes later
grouped_cities = homes.copy().groupby('city')
homes.drop('city',inplace=True,axis=1)
cities.head()
```

[15]:
```
   city_Bellevue  city_Black_Diamond  city_Bothell  city_Carnation  \
0              0                   0             0               0
1              0                   0             0               0
2              0                   0             0               0
3              0                   0             0               0
4              0                   0             0               0

   city_Duvall  city_Enumclaw  city_Fall_City  city_Federal_Way  \
0            0              0               0                 0
1            0              0               0                 0
2            0              0               0                 0
3            0              0               0                 0
4            0              0               0                 0

   city_Issaquah  city_Kenmore  …  city_Medina  city_Mercer_Island  \
0              0             0  …            0                   0
1              0             0  …            0                   0
2              0             1  …            0                   0
3              0             0  …            0                   0
4              0             0  …            0                   0

   city_North_Bend  city_Redmond  city_Renton  city_Sammamish  city_Seattle  \
0                0             0            0               0             1
1                0             0            0               0             1
```

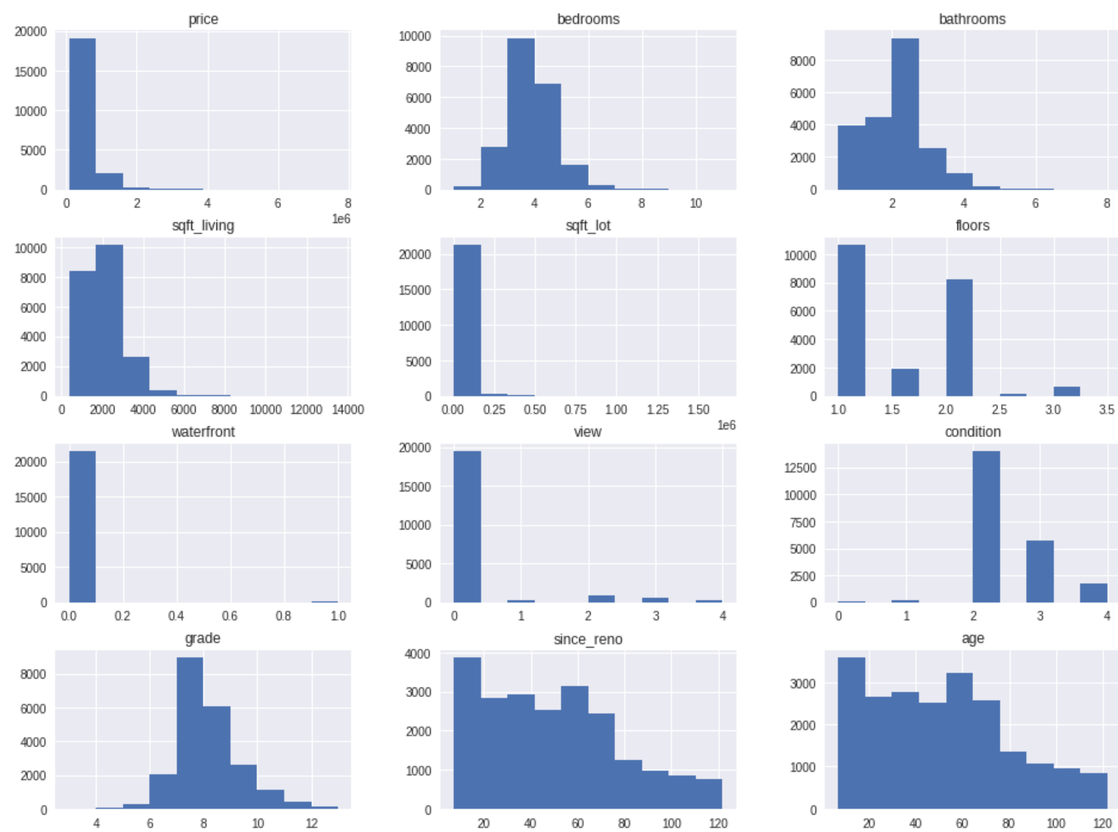
```
2                 0             0            0               0             0
3                 0             0            0               0             1
4                 0             0            0               1             0

   city_Snoqualmie  city_Vashon  city_Woodinville
0                0            0                 0
1                0            0                 0
2                0            0                 0
3                0            0                 0
4                0            0                 0

[5 rows x 23 columns]
```

Exploratory Data Analysis

Distrobutions

This plot shows how each numeric variable in the homes dataframe is distributed. Age and Since_reno seem to be very similar. Price and both sqft columns seem to be good candidates for log transformations.

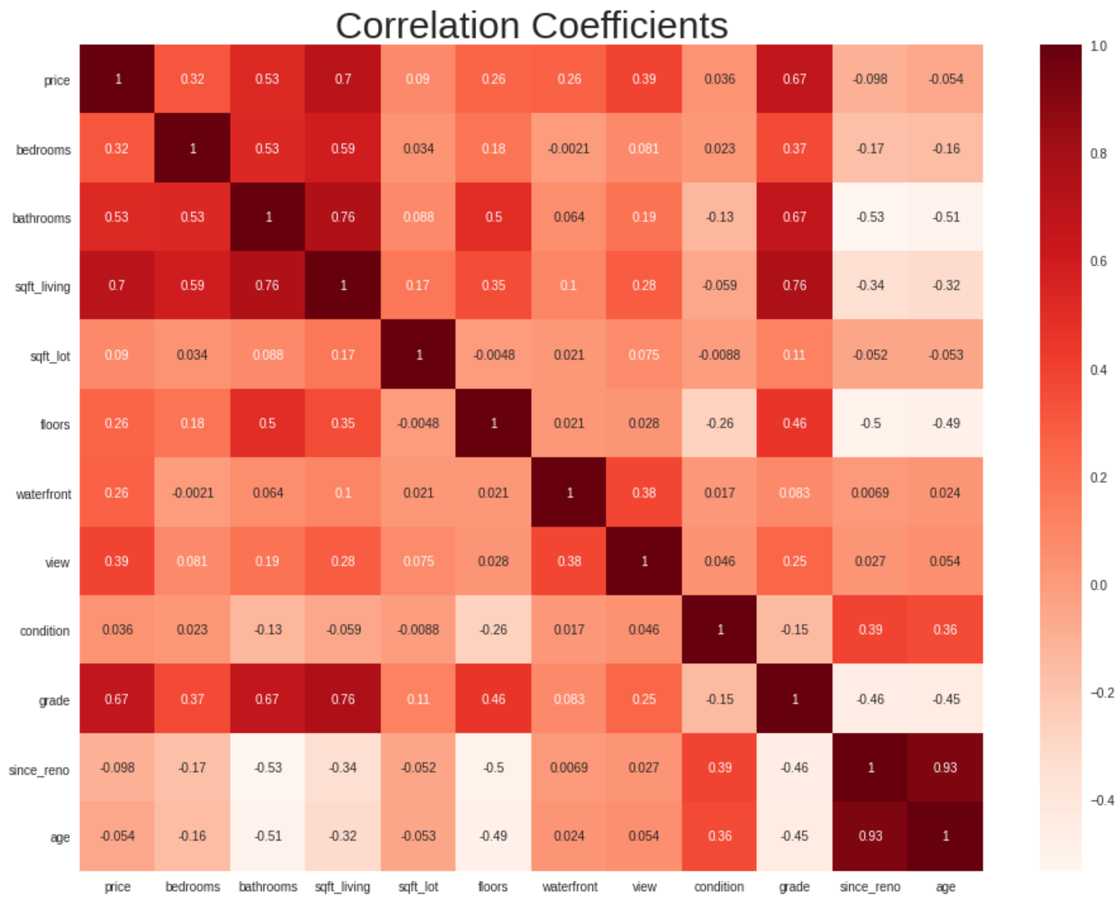
[16]:
```python
pd.plotting.hist_frame(homes,figsize=(16,12));
```



Correlations

Just a standard correlation coefficient matrix.

[17]:
```python
fig,ax = plt.subplots(figsize = (16,12))
ax.set_title('Correlation Coefficients',fontsize=30);
sns.heatmap(homes.corr(),annot=True,ax=ax,cmap='Reds');
ax.set_yticklabels(homes.columns,rotation=0);
```

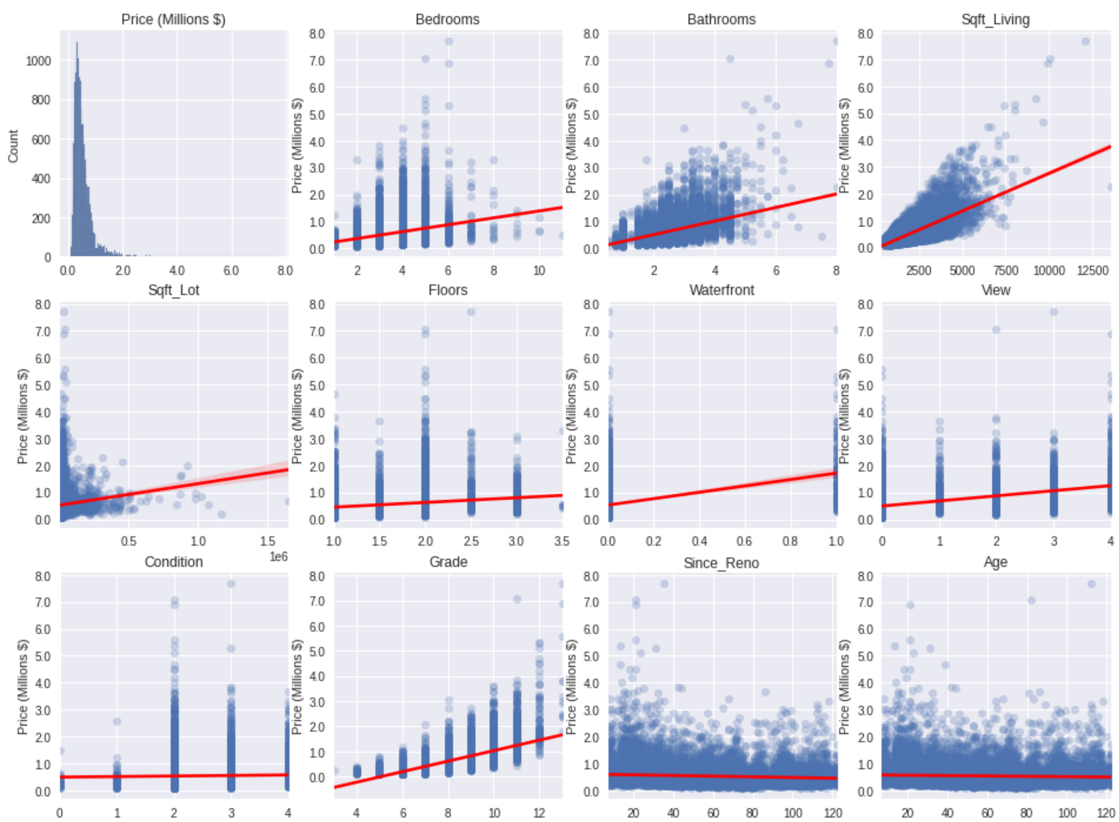


Regression Plots

This takes a year and a half to run. This helps to visualize which variables have linear relationships with price.

[18]:
```python
fig,ax = plt.subplots(3,4,figsize=(16,12))
for idx,row in enumerate(ax):
    for idx2,col in enumerate(row):
        y_val = homes.columns.values[(4*idx) + idx2]

        # Make a histogram for the price column
        if y_val == 'price':
```

```
            sns.histplot(homes.price,ax=col)
            col.set_title('Price (Millions $)')
            col.set_xticklabels(col.get_xticks()/1000000)
            col.set_xlabel('')
        # Make a scatter plot for all of the other columns
        else:
            sns.
↪regplot(y='price',x=y_val,data=homes,ax=col,scatter_kws={'alpha':0.25},
                        line_kws={"color": "red"})
            col.set_title(y_val.title())
            col.set_yticklabels(col.get_yticks()/1000000)
            col.set_xlabel('')
            col.set_ylabel('Price (Millions $)')
```

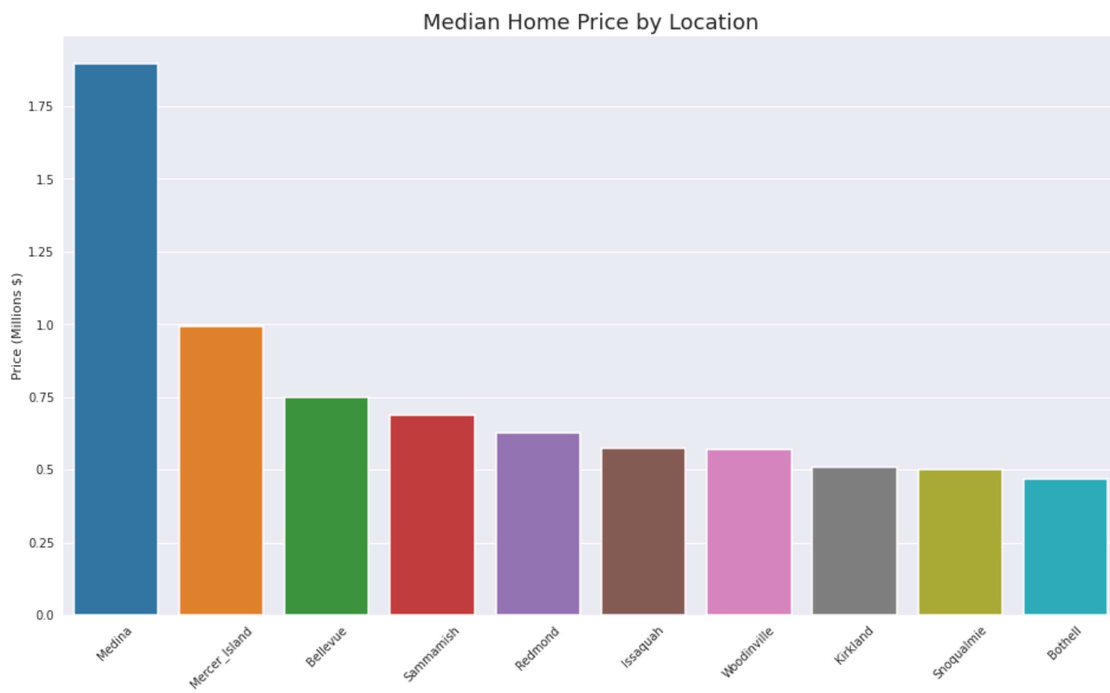


Median Price by Location

Location has a huge impact on the price of a home, but has been left out of the plots so far.

[19]:
```
# Reshaping the data and taking only the first 10 cities for visibility
grouped_cities = pd.DataFrame(grouped_cities['price'].agg(np.median).
 ↪sort_values(ascending=False)[:10]).T
fig,ax = plt.subplots(figsize = (16,9))
```

```
sns.set_theme(context='talk');
sns.barplot(data = grouped_cities,palette='tab10')
ax.set_xticklabels(grouped_cities.columns.values[:10], rotation = 45);
ax.set_yticklabels(ax.get_yticks()/1000000);
ax.set_title('Median Home Price by Location');
ax.set_ylabel('Price (Millions $)');
ax.set_xlabel('');
```



Models

I start here by adding the encoded location data back to the main dataframe. This was kept separate earlier to keep the plots clean.

[20]:
```
# Plotting is done so we can bring the encoded cities data back
homes = pd.concat([homes,cities],axis=1)
```

Basic Model

This is a very basic linear regression model that only used sqft_living to predict the price.

[21]:
```
X_basic = homes[['sqft_living']]
y_basic = homes.price

#Scaling the data so the coefficients are comparable
scaler_basic = StandardScaler()
X_scaled_basic = scaler_basic.fit_transform(X=X_basic,y=y_basic)
```

```
X_scaled_basic = pd.DataFrame(X_scaled_basic,columns=X_basic.columns)

X_scaled_basic = sm.add_constant(X_scaled_basic)

# Perform a train test split with the default size
# Random seed e = 2.71828
X_train_basic, X_test_basic, y_train_basic, y_test_basic\
     = train_test_split(X_scaled_basic,y_basic,random_state=271828)

# Create and fit linear regression and get summary
basic_regression = LinearRegression().fit(X_train_basic,y_train_basic)
basic_summary = model_summary(basic_regression,
                                                              ␣
 ↪X_train_basic,X_test_basic,y_train_basic,y_test_basic)
# Print summary statistics
basic_summary[0]
```

[21]:

	Values
Train R2	0.488
Train Mean Abs Err	175043.731
Train Mean Sq Err	70579154795.151
Train Root Mean Sq Err	265667.376
Test R2	0.509
Test Mean Abs Err	171258.475
Test Mean Sq Err	62125867519.457
Test Root Mean Sq Err	249250.612

[22]:
```
# Print coefficients
basic_summary[1].sort_values(by='Values',ascending=False)
```

[22]:

	Values
sqft_living	259302.560
const	0.000

An R2 of around 0.5 for both train and test is not great and the RMSE is around $250,000. This means the model is off by a quarter of a million dollars on average. Not good!

Slightly Better Model

This is a better linear regression model that uses all of the available predictors to predict the housing price.

[23]:
```
X_mid = homes.drop('price',axis=1)
y_mid = homes.price

scaler_mid = StandardScaler()
X_scaled_mid = scaler_mid.fit_transform(X=X_mid,y=y_mid)
X_scaled_mid = pd.DataFrame(X_scaled_mid,columns=X_mid.columns)
```

```
X_scaled_mid = sm.add_constant(X_scaled_mid)

# Perform a train test split with the default size
# Random seed e = 2.71828
X_train_mid, X_test_mid, y_train_mid, y_test_mid\
     = train_test_split(X_scaled_mid,y_mid,random_state=271828)

# Create and fit linear regression and get summary
mid_regression = LinearRegression().fit(X_train_mid,y_train_mid)
mid_summary = model_summary(mid_regression,
                              X_train_mid,X_test_mid,y_train_mid,y_test_mid)
# Print summary statistics
mid_summary[0]
```

[23]:

	Values
Train R2	0.728
Train Mean Abs Err	120343.656
Train Mean Sq Err	37499863867.808
Train Root Mean Sq Err	193648.816
Test R2	0.762
Test Mean Abs Err	116574.837
Test Mean Sq Err	30129105775.133
Test Root Mean Sq Err	173577.377

[24]:

```
# Print coefficients
mid_summary[1].sort_values(by='Values',ascending=False)
```

[24]:

	Values
sqft_living	161404.841
grade	113241.238
city_Seattle	95183.422
age	87532.790
city_Bellevue	85803.122
city_Medina	58767.617
city_Kirkland	53127.830
city_Mercer_Island	50847.110
waterfront	49556.441
city_Redmond	42439.396
view	33166.125
bathrooms	27850.444
city_Issaquah	27576.336
city_Sammamish	27002.028
city_Woodinville	17728.645
city_Renton	17404.948
floors	16619.022
condition	15046.525
city_Kenmore	13027.638

```
city_Snoqualmie     11390.561
city_Bothell        10575.870
city_Fall_City       9652.928
city_North_Bend      9453.148
city_Duvall          8351.466
city_Carnation       7983.642
city_Maple_Valley    6111.203
city_Black_Diamond   5347.325
city_Kent            2827.747
sqft_lot             2045.366
const                  -0.000
city_Enumclaw        -125.125
city_Vashon          -223.728
city_Federal_Way    -5959.077
since_reno         -17860.985
bedrooms           -37013.718
```

An R2 value of between 0.728 and 0.762 is pretty alright for this model. We even got the RMSE down to between $193,000 and $173,000. This is about $60,000 better than the previous model. We can still do better though.

Best I Could Do

This is the best linear regression model I could make that uses some of the available predictors to predict the housing price. It differs from the previous models in that I transform some of the data before I use it to make a prediction.

[25]:
```
# These two features did not provide significant value in the previous model
homes.drop('sqft_lot',inplace=True,axis=1)
homes.drop('since_reno',inplace=True,axis=1)

# These predictors appear to be log normally distributed
homes.price = homes.price.apply(np.log)
homes.sqft_living = homes.sqft_living.apply(np.log)
```

[26]:
```
X_best = homes.drop('price',axis=1)
y_best = homes.price

# Scaling the data this time
#scaler_best = StandardScaler()
#X_scaled_best = scaler_best.fit_transform(X=X_best,y=y_best)
#X_scaled_best = pd.DataFrame(X_scaled_best,columns=X_best.columns)

X_best = sm.add_constant(X_best)

# Perform a train test split with the default size
# Random seed e = 2.71828
X_train_best, X_test_best, y_train_best, y_test_best\
     = train_test_split(X_best,y_best,random_state=271828)
```

```python
# Create and fit linear regression and get summary
best_regression = LinearRegression().fit(X_train_best,y_train_best)
best_summary = model_summary(best_regression,
                              X_train_best,X_test_best,y_train_best,y_test_best)

# Print summary statistics
best_summary[0]
```

[26]:

	Values
Train R2	0.779
Train Mean Abs Err	0.187
Train Mean Sq Err	0.062
Train Root Mean Sq Err	0.248
Test R2	0.783
Test Mean Abs Err	0.183
Test Mean Sq Err	0.059
Test Root Mean Sq Err	0.244

[27]:
```python
# Print coefficients
best_summary[1].sort_values(by='Values',ascending=False)
```

[27]:

	Values
city_Medina	1.178
city_Mercer_Island	0.777
city_Bellevue	0.685
city_Kirkland	0.594
city_Redmond	0.582
city_Sammamish	0.499
city_Issaquah	0.481
city_Fall_City	0.465
city_Seattle	0.464
city_Woodinville	0.444
sqft_living	0.423
city_Bothell	0.410
city_Snoqualmie	0.406
city_Kenmore	0.383
city_Vashon	0.339
city_Carnation	0.338
waterfront	0.330
city_Duvall	0.328
city_North_Bend	0.328
city_Black_Diamond	0.272
city_Renton	0.230
city_Maple_Valley	0.171
grade	0.171
floors	0.081

```
bathrooms          0.064
view               0.054
condition          0.053
city_Enumclaw      0.048
city_Kent          0.038
age                0.004
const              0.000
bedrooms          -0.036
city_Federal_Way  -0.045
```

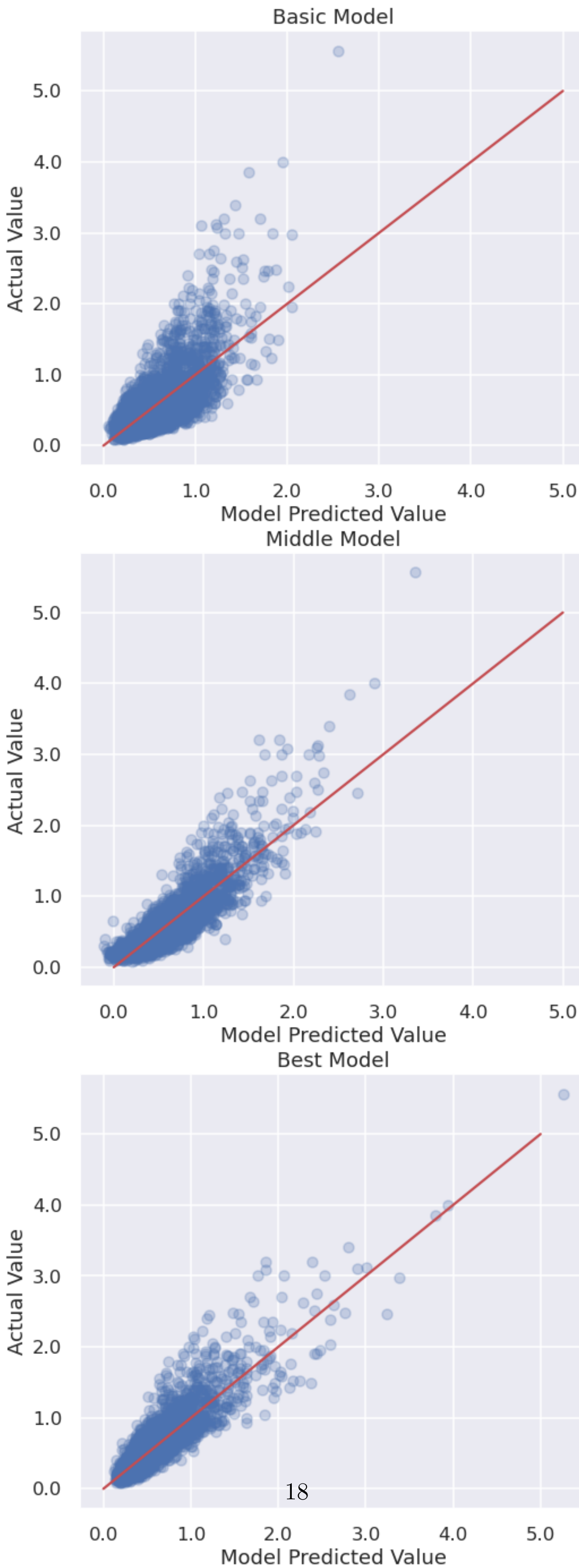
This model got an R2 value between 0.779 and 0.783 which is pretty good. The rest of the factors are not super easy to interpret though because this model is predicting the natural log of the price of the house instead of the price directly. You can inverse the log to get good price predictions from this model, but it is less useful in analyzing the effects of each variable than the lase model.

Comparing Model Predictions

The following graphs show the predictive power of each model. The ideal model would just show the line y=x where the predictions from the model are exactly the same as the actual home prices.

[28]:
```python
y_x = np.linspace(0,5e6,100)

# Generating predictions for each model
basic_pred = basic_regression.predict(X_test_basic)
mid_pred = mid_regression.predict(X_test_mid)
# This model predicts the log so we need to exponentiate
best_pred = np.exp(best_regression.predict(X_test_best))

fig,(ax1,ax2,ax3) = plt.subplots(3,figsize = (8,24))

# Plot for the basic model
ax1.scatter(basic_pred,y_test_basic,alpha=0.25)
ax1.plot(y_x,y_x,color='r')
ax1.set_title('Basic Model')

# Plot for the middle model
ax2.scatter(mid_pred,y_test_mid,alpha=0.25)
ax2.plot(y_x,y_x,color='r')
ax2.set_title('Middle Model')

# Plot for the third model
# This model predicts the log so we need to exponentiate
ax3.scatter(best_pred,np.exp(y_test_best),alpha=0.25)
ax3.plot(y_x,y_x,color='r')
ax3.set_title('Best Model')

for ax in [ax1,ax2,ax3]:
    ax.set_xlabel('Model Predicted Value');
```

```
    ax.set_ylabel('Actual Value')
    ax.set_yticklabels(ax.get_yticks()/1000000);
    ax.set_xticklabels(ax.get_xticks()/1000000);
```


Basic Model
Actual Value
Model Predicted Value
0.0
1.0
2.0
3.0
4.0
5.0
Middle Model
Actual Value
Model Predicted Value
0.0
1.0
2.0
3.0
4.0
5.0
Best Model
Actual Value
Model Predicted Value
0.0
1.0
2.0
3.0
4.0
5.0

Using Statsmodels

Statsmodels shows mostly the same information as the SKLearn models. It was mostly used for the confidence interval function at the top of this notebook and statistical information on my coefficients.

[29]:
```
# Generate the regressions using the same data as from SKLearn
sm_basic = sm.OLS(y_train_basic,X_train_basic).fit()
sm_mid = sm.OLS(y_train_mid,X_train_mid).fit()
sm_best = sm.OLS(y_train_best,X_train_best).fit()
```

Basic Model

[30]:
```
sm_basic.summary()
```

[30]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.488
Model:                            OLS   Adj. R-squared:                  0.488
Method:                 Least Squares   F-statistic:                 1.541e+04
Date:                Wed, 23 Feb 2022   Prob (F-statistic):               0.00
Time:                        09:54:00   Log-Likelihood:            -2.2528e+05
No. Observations:               16197   AIC:                         4.506e+05
Df Residuals:                   16195   BIC:                         4.506e+05
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
const        5.406e+05   2087.606    258.967      0.000    5.37e+05    5.45e+05
sqft_living  2.593e+05   2088.744    124.143      0.000    2.55e+05    2.63e+05
==============================================================================
Omnibus:                    11598.301   Durbin-Watson:                   2.008
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           486196.505
Skew:                           2.965   Prob(JB):                         0.00
Kurtosis:                      29.178   Cond. No.                         1.00
==============================================================================

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

Slightly Better Model

[31]:
```python
sm_mid.summary()
```

[31]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.728
Model:                            OLS   Adj. R-squared:                  0.727
Method:                 Least Squares   F-statistic:                     1271.
Date:                Wed, 23 Feb 2022   Prob (F-statistic):               0.00
Time:                        09:54:00   Log-Likelihood:            -2.2016e+05
No. Observations:               16197   AIC:                         4.404e+05
Df Residuals:                   16162   BIC:                         4.407e+05
Df Model:                          34
Covariance Type:            nonrobust
================================================================================
======
                      coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
const            5.404e+05   1523.539    354.689      0.000     5.37e+05
5.43e+05
bedrooms        -3.701e+04   2008.667    -18.427      0.000     -4.1e+04
-3.31e+04
bathrooms        2.785e+04   2771.829     10.048      0.000     2.24e+04
3.33e+04
sqft_living      1.614e+05   3192.868     50.552      0.000     1.55e+05
1.68e+05
sqft_lot         2045.3660   1623.792      1.260      0.208    -1137.447
5228.179
floors           1.662e+04   1986.635      8.365      0.000     1.27e+04
2.05e+04
waterfront       4.956e+04   1657.552     29.897      0.000     4.63e+04
5.28e+04
view             3.317e+04   1770.952     18.728      0.000     2.97e+04
3.66e+04
condition        1.505e+04   1711.802      8.790      0.000     1.17e+04
1.84e+04
grade            1.132e+05   2716.668     41.684      0.000     1.08e+05
1.19e+05
since_reno      -1.786e+04   4196.327     -4.256      0.000    -2.61e+04
-9635.720
age              8.753e+04   4176.321     20.959      0.000     7.93e+04
9.57e+04
city_Bellevue     8.58e+04   2398.625     35.772      0.000     8.11e+04
9.05e+04
```

```
city_Black_Diamond  5347.3252   1585.655      3.372      0.001    2239.265
8455.386
city_Bothell        1.058e+04   1637.897      6.457      0.000    7365.411
1.38e+04
city_Carnation      7983.6422   1640.045      4.868      0.000    4768.973
1.12e+04
city_Duvall         8351.4665   1659.447      5.033      0.000    5098.766
1.16e+04
city_Enumclaw       -125.1253   1728.488     -0.072      0.942   -3513.154
3262.904
city_Fall_City      9652.9279   1648.583      5.855      0.000    6421.523
1.29e+04
city_Federal_Way   -5959.0769   2022.277     -2.947      0.003   -9922.963
-1995.190
city_Issaquah       2.758e+04   2043.705     13.493      0.000    2.36e+04
3.16e+04
city_Kenmore        1.303e+04   1791.541      7.272      0.000    9516.020
1.65e+04
city_Kent           2827.7468   2247.717      1.258      0.208   -1578.027
7233.521
city_Kirkland       5.313e+04   2165.408     24.535      0.000    4.89e+04
5.74e+04
city_Maple_Valley   6111.2027   1931.416      3.164      0.002    2325.414
9896.991
city_Medina         5.877e+04   1583.538     37.112      0.000    5.57e+04
6.19e+04
city_Mercer_Island  5.085e+04   1744.843     29.141      0.000    4.74e+04
5.43e+04
city_North_Bend     9453.1477   1699.063      5.564      0.000    6122.796
1.28e+04
city_Redmond        4.244e+04   2165.701     19.596      0.000    3.82e+04
4.67e+04
city_Renton          1.74e+04   2431.316      7.159      0.000    1.26e+04
2.22e+04
city_Sammamish        2.7e+04   2099.489     12.861      0.000    2.29e+04
3.11e+04
city_Seattle        9.518e+04   3980.495     23.912      0.000    8.74e+04
1.03e+05
city_Snoqualmie     1.139e+04   1775.716      6.415      0.000    7909.960
1.49e+04
city_Vashon         -223.7276   1612.040     -0.139      0.890   -3383.505
2936.050
city_Woodinville    1.773e+04   1894.929      9.356      0.000     1.4e+04
2.14e+04
==============================================================================
Omnibus:                    14326.831   Durbin-Watson:                   2.013
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          1794755.841
```

```
Skew:                           3.732   Prob(JB):                         0.00
Kurtosis:                      54.026   Cond. No.                         9.16
==============================================================================

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

Best Model

[32]:
```python
sm_best.summary()
```

[32]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.779
Model:                            OLS   Adj. R-squared:                  0.778
Method:                 Least Squares   F-statistic:                     1777.
Date:                Wed, 23 Feb 2022   Prob (F-statistic):               0.00
Time:                        09:54:00   Log-Likelihood:                -411.31
No. Observations:               16197   AIC:                             888.6
Df Residuals:                   16164   BIC:                             1142.
Df Model:                          32
Covariance Type:            nonrobust
================================================================================
======
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
------
const                 7.6879      0.057    135.386      0.000       7.577
7.799
bedrooms             -0.0358      0.003    -12.111      0.000      -0.042
-0.030
bathrooms             0.0637      0.005     14.067      0.000       0.055
0.073
sqft_living           0.4230      0.010     43.799      0.000       0.404
0.442
floors                0.0806      0.005     17.150      0.000       0.071
0.090
waterfront            0.3302      0.026     12.753      0.000       0.279
0.381
view                  0.0536      0.003     18.141      0.000       0.048
0.059
condition             0.0529      0.003     15.939      0.000       0.046
0.059
```

grade	0.1706	0.003	58.986	0.000	0.165	0.176
age	0.0036	0.000	36.188	0.000	0.003	0.004
city_Bellevue	0.6855	0.012	55.113	0.000	0.661	0.710
city_Black_Diamond	0.2720	0.030	9.103	0.000	0.213	0.331
city_Bothell	0.4096	0.022	18.464	0.000	0.366	0.453
city_Carnation	0.3381	0.028	12.292	0.000	0.284	0.392
city_Duvall	0.3282	0.023	14.421	0.000	0.284	0.373
city_Enumclaw	0.0481	0.021	2.254	0.024	0.006	0.090
city_Fall_City	0.4650	0.035	13.454	0.000	0.397	0.533
city_Federal_Way	-0.0453	0.014	-3.263	0.001	-0.073	-0.018
city_Issaquah	0.4814	0.014	33.283	0.000	0.453	0.510
city_Kenmore	0.3835	0.020	19.000	0.000	0.344	0.423
city_Kent	0.0378	0.013	3.004	0.003	0.013	0.062
city_Kirkland	0.5937	0.013	44.513	0.000	0.568	0.620
city_Maple_Valley	0.1708	0.015	11.237	0.000	0.141	0.201
city_Medina	1.1781	0.042	27.907	0.000	1.095	1.261
city_Mercer_Island	0.7767	0.020	39.461	0.000	0.738	0.815
city_North_Bend	0.3278	0.022	15.155	0.000	0.285	0.370
city_Redmond	0.5822	0.013	43.598	0.000	0.556	0.608
city_Renton	0.2298	0.012	19.313	0.000	0.207	0.253
city_Sammamish	0.4987	0.014	35.041	0.000	0.471	0.527
city_Seattle	0.4642	0.010	44.935	0.000	0.444	0.484
city_Snoqualmie	0.4057	0.019	21.145	0.000	0.368	0.443
city_Vashon	0.3392	0.028	12.159	0.000	0.285	

```
0.394
city_Woodinville       0.4441      0.017     26.746      0.000       0.412
0.477
==============================================================================
Omnibus:                      532.166   Durbin-Watson:                   2.012
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1272.602
Skew:                          -0.162   Prob(JB):                    4.55e-277
Kurtosis:                       4.335   Cond. No.                     1.80e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.8e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

Model Validation

There are three assumptions made when using a linear regression model.

Linearity: Is there a linear relationship between the target and the predictors?

We looked at this during the exploratory data analysis.

Normality: Are the residuals of the model normally distributed?

We will look at this below.

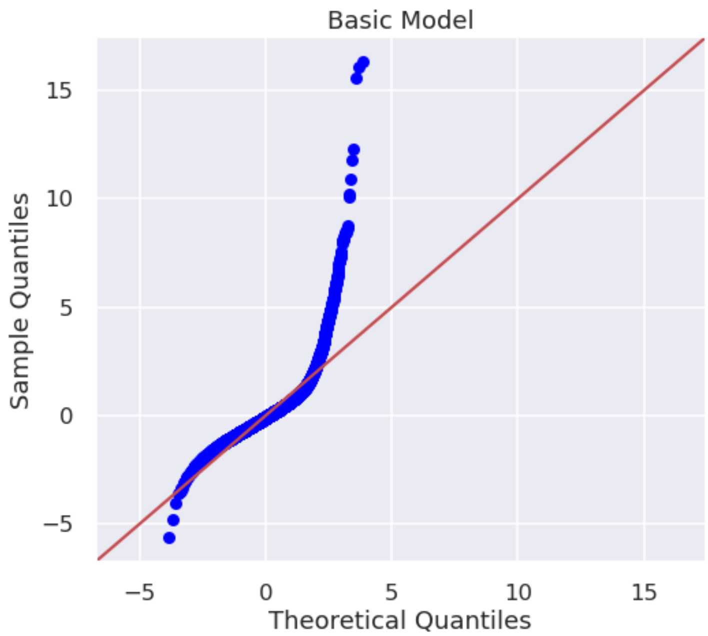
Homoscedasticity: Does the variance of the residuals change based on the value of the target?

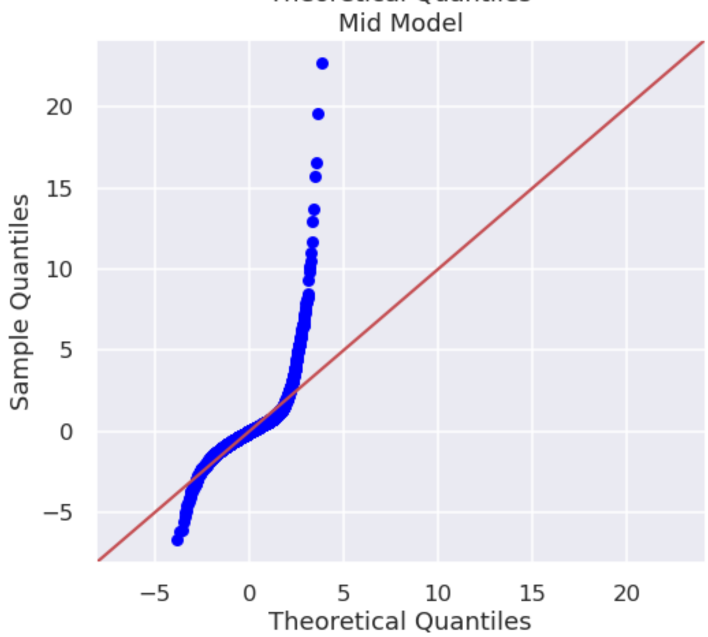
It does appear that the residuals variance increases as price increases. I am not sure if this is statistically significant because I was unable to get the code for the Goldfeld-Quandt test working.

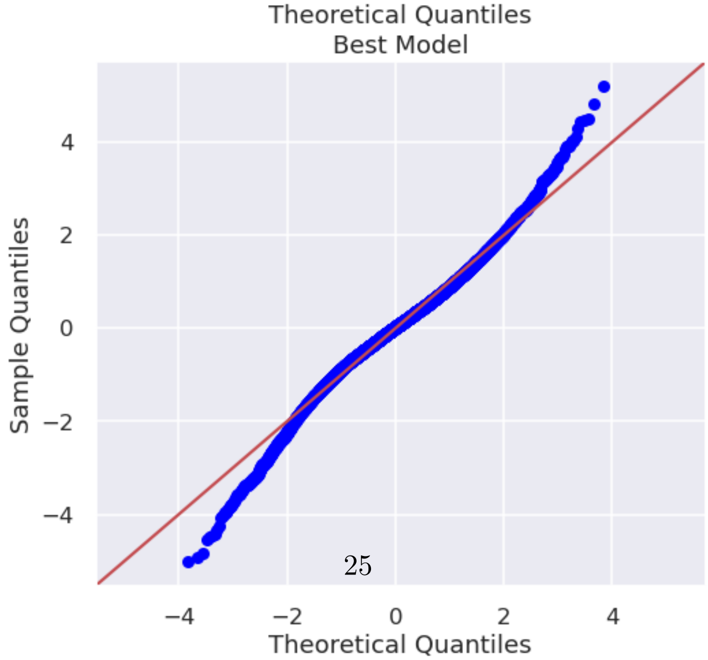
Normality

The basic and medium models perform poorly in terms of normality of the residuals. The best model's residuals are pretty normally distributed however, only really deviating at the tails.

[33]:
```
fig,(ax1,ax2,ax3) = plt.subplots(3,figsize = (8,24));

# Generate the three qq-plots
sm.graphics.qqplot(sm_basic.resid,dist=stats.norm, line='45', fit=True, ax =␣
↪ax1)
ax1.set_title('Basic Model');

sm.graphics.qqplot(sm_mid.resid,dist=stats.norm, line='45', fit=True, ax = ax2)
ax2.set_title('Mid Model');

sm.graphics.qqplot(sm_best.resid,dist=stats.norm, line='45', fit=True, ax = ax3)
ax3.set_title('Best Model');
```


Basic Model
Sample Quantiles
Theoretical Quantiles
15
10
5
0
−5
−5
0
5
10
15


Mid Model
Sample Quantiles
Theoretical Quantiles
20
15
10
5
0
−5
−5
0
5
10
15
20


Best Model
Sample Quantiles
Theoretical Quantiles
4
2
0
−2
−4
−4
−2
0
2
4

Homoscedasticity

None of the models satisfy this assumption. The variance of the residuals increases with price for all three models.

[34]:
```
fig,(ax1,ax2,ax3) = plt.subplots(3,figsize = (8,24));

# Generate the three qq-plots
sns.scatterplot(y_test_basic,-basic_pred + y_test_basic,ax=ax1,alpha=0.6)
ax1.axhline(0,color='red')
ax1.set_title('Basic Model');

sns.scatterplot(y_test_mid,-mid_pred + y_test_mid,ax=ax2,alpha=0.6)
ax2.axhline(0,color='red')
ax2.set_title('Mid Model');

sns.scatterplot(np.exp(y_test_best),-best_pred + np.
 ↪exp(y_test_best),ax=ax3,alpha=0.6)
ax3.axhline(0,color='red')
ax3.set_title('Best Model');

for ax in [ax1,ax2,ax3]:
    ax.set_xlabel('Price (Millions $)');
    ax.set_ylabel('Model Error (Millions $)')
    ax.set_yticklabels(ax.get_yticks()/1000000);
    ax.set_xticklabels(ax.get_xticks()/1000000);
```

Basic Model
Model Error (Millions $)
3.0
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
0.0
1.0
2.0
3.0
4.0
5.0
Price (Millions $)
Mid Model
Model Error (Millions $)
2.0
1.5
1.0
0.5
0.0
-0.5
0.0
1.0
2.0
3.0
4.0
5.0
Price (Millions $)
Best Model
Model Error (Millions $)
1.0
0.5
0.0
-0.5
0.0
1.0
2.0
3.0
4.0
5.0
Price (Millions $)

Results

We were successful in creating a model that Bentley & Co. Bank can use to predict the price of a home given information about its features.

A linear regression model was appropriate for predicting home price using the provided dataset.

78 Percent of the variance in home price can be explained by the selected home features in the best model.

The following features proved to be the most important when predicting the price of a home:

Location

Grade

Living Area Square-Footage

I recommend that Bentley & Co. Bank use the best model for quick-and-dirty estimates of home price before a professional appraisal can be performed.

I recommend that Bentley & Co. Bank use the best model to estimate the price impact of renovations on homes it has an interest in when an additional appraisal is not appropriate.

An example price prediction is shown below.

[35]:
```
# Predict a random house from the test set's price
predict_interval(X_test_best.iloc[42],confidence=0.001);
```

```
This house has a predicted value of $663648.
A safe value for this house would fall between $640175 and $687982.
```