Exploration of the King County Housing Dataset

My goal in this notebook is to provide plauseable insight into ways a homeowner can make renovations to their current home in order to make it more attactive to buyers and/or sell for a high price.

Let's first import some tools and take our first look at the dataset

In [288]:

```
#All the imports that we may or may not need
import pandas as pd
pd.set_option('display.max_columns', 50)
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score, mean_squared_error
%matplotlib inline
#The data
df = pd.read_csv("data/kc_house_data.csv")
df.head(5)
```

Out[288]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	grade	s
0	7129300520	10/13/2014	221900.0	3	1.00	1180	5650	1.0	NaN	0.0	3	7	
1	6414100192	12/9/2014	538000.0	3	2.25	2570	7242	2.0	0.0	0.0	3	7	
2	5631500400	2/25/2015	180000.0	2	1.00	770	10000	1.0	0.0	0.0	3	6	
3	2487200875	12/9/2014	604000.0	4	3.00	1960	5000	1.0	0.0	0.0	5	7	
4	1954400510	2/18/2015	510000.0	3	2.00	1680	8080	1.0	0.0	0.0	3	8	

In [289]:

```
df.corr().price.sort_values(ascending=False)
```

Out[289]:

```
price            1.000000
sqft_living      0.701917
grade            0.667951
sqft_above       0.605368
sqft_living15    0.585241
bathrooms        0.525906
view             0.395734
bedrooms         0.308787
lat              0.306692
waterfront       0.276295
floors           0.256804
yr_renovated     0.129599
sqft_lot         0.089876
sqft_lot15       0.082845
yr_built         0.053953
condition        0.036056
long             0.022036
```

```
id              -0.016772
zipcode         -0.053402
Name: price, dtype: float64
```

Model 1

1.a Cleaning and Prepping the data

Sweet. Now that we can get a good look at what we're working with we will start to clean the data a bit to get it ready for modeling. First, we can already start to eliminate some columns that are irrelevant. Here's what we can get rid of:

- **id - the specific id of the house doesn't matter, we just need the data from it to make a model**
- **date - like id, date sold doesn't matter, we just need the data about the house to make a model**
- **view - this is not about the view from the house but how many times it had been view. Not particularly useful**
- **zipcode - this is only helpful if we have information about how safe the neighborhood is. We do not so we will ignore this one**
- **lat - latitude of the house isn't quite as useful as an address**
- **long - like with lat, longitude of a house isn't quite as useful as an address**
- **sqft_living15 - The square footage of interior housing living space for the nearest 15 neighbors. Not useful**
- **sqft_lot15 - The square footage of the land lots of the nearest 15 neighbors. Not useful**

In [290]:

```
# Remove the above mentioned columns
df.drop(['id', 'date', 'view', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15'],
axis=1, inplace=True)
# Sanity Check
dfListDrop = list(df.columns)
dfListDrop
```

Out[290]:

```
['price',
 'bedrooms',
 'bathrooms',
 'sqft_living',
 'sqft_lot',
 'floors',
 'waterfront',
 'condition',
 'grade',
 'sqft_above',
 'sqft_basement',
 'yr_built',
 'yr_renovated']
```

Awesome! Now, let's take a look at our data and see if any columns have NaN (missing) values that might get in the way.

In [291]:

```
df.isna().sum()
```

Out[291]:

```
price               0
bedrooms            0
bathrooms           0
sqft_living         0
sqft_lot            0
floors              0
waterfront       2376
condition           0
grade               0
sqft_above          0
```

```
sqft_basement       0
yr_built            0
yr_renovated     3842
dtype: int64
```

Okay, it looks like we have a couple. Let's take a closer look...

In [292]:

```
print(df['waterfront'].value_counts())
print('column "waterfront" has', df['waterfront'].isna().sum(), 'NaN values')
```

```
0.0    19075
1.0      146
Name: waterfront, dtype: int64
column "waterfront" has 2376 NaN values
```

In [293]:

```
print(df['yr_renovated'].value_counts())
print('column "yr_renovated" has', df['yr_renovated'].isna().sum(), 'NaN values')
```

```
0.0       17011
2014.0       73
2003.0       31
2013.0       31
2007.0       30
          ...
1946.0        1
1959.0        1
1971.0        1
1951.0        1
1954.0        1
Name: yr_renovated, Length: 70, dtype: int64
column "yr_renovated" has 3842 NaN values
```

When it comes to 'waterfront' it looks like the values are 1 or 0 indicating a 'yes' or 'no' as to whether or not it has a waterfront view. Since there isn't much data here to begin with, and we want as many results as posible, we'll simply replace NaN values with a 0 to assume those homes don't have a waterfront view.

In [294]:

```
# Fill NaN values with 0
df['waterfront'] = df['waterfront'].fillna(0)
```

In [295]:

```
# Sanity Check
print(df['waterfront'].value_counts())
print('column "waterfront" has', df['waterfront'].isna().sum(), 'NaN values')
```

```
0.0    21451
1.0      146
Name: waterfront, dtype: int64
column "waterfront" has 0 NaN values
```

As far as 'yr_renovated' the values are either meant to have a year for when it was rennovated or a 0 for if it wasn't renovated. Like the with 'waterfront' we have to assume that NaN values in this case just haven't been renovated at all.

In [296]:

```
df['yr_renovated'] = df['yr_renovated'].fillna(0)

print(df['yr_renovated'].value_counts())
print('column "yr_renovated" has', df['yr_renovated'].isna().sum(), 'NaN values')
```

```
0.0       20853
2014.0       73
```

```
2003.0        31
2013.0        31
2007.0        30
          ...
1946.0         1
1959.0         1
1971.0         1
1951.0         1
1954.0         1
Name: yr_renovated, Length: 70, dtype: int64
column "yr_renovated" has 0 NaN values
```

Success! Lastly, let's check to make sure all of our columns are either a float or int as our program wont know what to do with anything else

Column 'sqft_basement' is an object. Let's see why...

In [297]:

```
df.sqft_basement.value_counts()
```

Out[297]:

```
0.0       12826
?           454
600.0       217
500.0       209
700.0       208
          ...
1024.0        1
935.0         1
602.0         1
506.0         1
946.0         1
Name: sqft_basement, Length: 304, dtype: int64
```

There is a '?' somewhere in our dataset. That's not a number so it wont convert away from a string to a float or int. And since we can't just *pReTEnD* that the house *dOEsN't* have a basement when it truely might, we can't just zero these values out an ignore it because it would skew our data too much. We're going to have to remove these rows entirely. This shouldn't hit the data too hard since there are plent more rows to spare.

In [298]:

```
# This code removes all rows that have a '?' value in the basement column
index_names = df[ df['sqft_basement'] == '?' ].index
df.drop(index_names, inplace = True)

# I've already explored this data a bit a know that the rest
# of the data shows up as an object but converts to a float without any fuss
df['sqft_basement'] = df['sqft_basement'].astype(float)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21143 entries, 0 to 21596
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   price          21143 non-null  float64
 1   bedrooms       21143 non-null  int64  
 2   bathrooms      21143 non-null  float64
 3   sqft_living    21143 non-null  int64  
 4   sqft_lot       21143 non-null  int64  
 5   floors         21143 non-null  float64
 6   waterfront     21143 non-null  float64
 7   condition      21143 non-null  int64  
 8   grade          21143 non-null  int64  
 9   sqft_above     21143 non-null  int64  
 10  sqft_basement  21143 non-null  float64
 11  yr_built       21143 non-null  int64  
 12  yr_renovated   21143 non-null  float64
```

```
dtypes: float64(6), int64(7)
memory usage: 2.3 MB
```

Finally, we can start taking a first look at our total dataset and modeling our first substandard model.

1.b Buildiing the Model

In [299]:

```
#creating a column of every feature that is NOT 'price'
xCols = [c for c in df.columns.to_list() if c not in ['price']]

x = df[xCols]
y = df['price']
```

In [300]:

```
stdScaled = StandardScaler()
```

In [301]:

```
xTrain, xTest, yTrain, yTest = train_test_split(
    x, y, test_size=0.33, random_state=42)
```

In [302]:

```
# this is just a sanity check that our test and train
# data equals the whole length of our data frame
print(len(x))
print(xTrain.shape)
print(xTest.shape)
print(len(xTrain + xTest) == len(x))
```

```
21143
(14165, 12)
(6978, 12)
True
```

In [303]:

```
xTrainScaled = stdScaled.fit_transform(xTrain)
xTestScaled = stdScaled.transform(xTest)

lr = LinearRegression()
lr.fit(xTrainScaled, yTrain)

yPredTrain = lr.predict(xTrainScaled)
yPredTest = lr.predict(xTestScaled)

print(f"Train Score: {r2_score(yTrain, yPredTrain)}")
print(f"Test Score: {r2_score(yTest, yPredTest)}")
print('-----')
print(f"Train Score: {mean_squared_error(yTrain, yPredTrain, squared=False)}")
print(f"Test Score: {mean_squared_error(yTest, yPredTest, squared=False)}")
```

```
Train Score: 0.6471207231814522
Test Score: 0.6444879405509031
-----
Train Score: 218076.31453394078
Test Score: 220609.8437281631
```

1.c Assessing the Damage

Oof. Our model is about $220,000 off and accounts for only 64 percent of our data. Not good. What are we missing? Let's try running this again with different scalers.

In [304]:

```
# Model again but with Min Max Scaler
minMaxScaled = MinMaxScaler()

xTrainScaled = minMaxScaled.fit_transform(xTrain)
xTestScaled = minMaxScaled.transform(xTest)

lr = LinearRegression()
lr.fit(xTrainScaled, yTrain)

yPredTrain = lr.predict(xTrainScaled)
yPredTest = lr.predict(xTestScaled)

print(f"Train Score: {r2_score(yTrain, yPredTrain)}")
print(f"Test Score: {r2_score(yTest, yPredTest)}")
print('-----')
print(f"Train Score: {mean_squared_error(yTrain, yPredTrain, squared=False)}")
print(f"Test Score: {mean_squared_error(yTest, yPredTest, squared=False)}")
```

```
Train Score: 0.6471207231814522
Test Score: 0.6444879405509031
-----
Train Score: 218076.3145339408
Test Score: 220609.8437281631
```

In [305]:

```
# Model again but with Robust Scaler
robScaled = RobustScaler()

xTrainScaled = robScaled.fit_transform(xTrain)
xTestScaled = robScaled.transform(xTest)

lr = LinearRegression()
lr.fit(xTrainScaled, yTrain)

yPredTrain = lr.predict(xTrainScaled)
yPredTest = lr.predict(xTestScaled)

print(f"Train R2 Score: {r2_score(yTrain, yPredTrain)}")
print(f"Test R2 Score: {r2_score(yTest, yPredTest)}")
print('-----')
print(f"Dollar Value Variance (Train): {mean_squared_error(yTrain, yPredTrain, squared=Fa
lse)}")
print(f"Dollar Value Variance (Test): {mean_squared_error(yTest, yPredTest, squared=False
)}")
```

```
Train R2 Score: 0.6471207231814522
Test R2 Score: 0.6444879405509026
-----
Dollar Value Variance (Train): 218076.31453394078
Dollar Value Variance (Test): 220609.84372816325
```

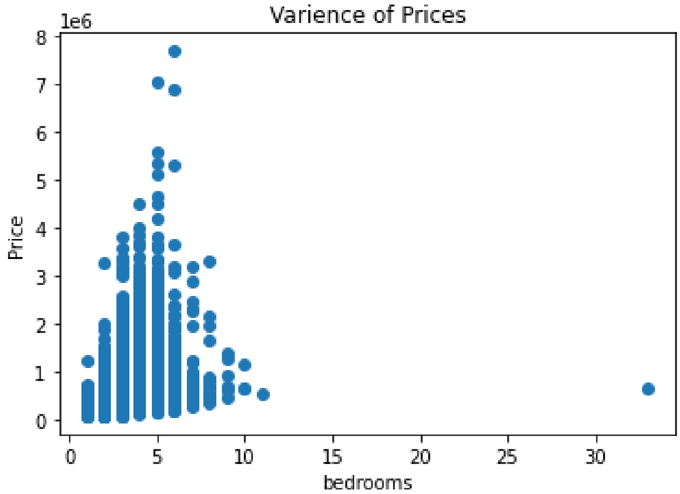
No difference at all. Bummer. But also not unexpected. Let's try something else. How about taking a look at our data in a series of scatter plots for a visual.

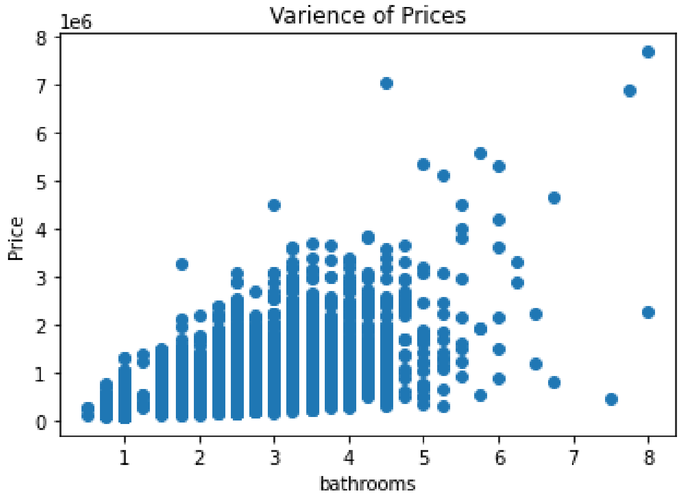
In [306]:

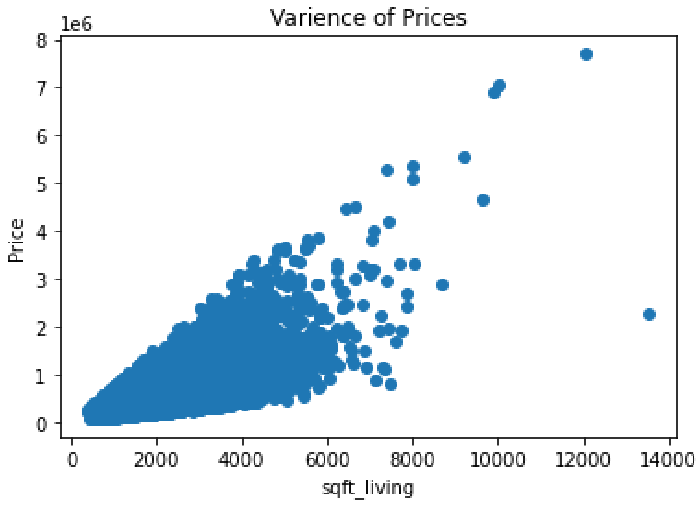
```
X = df[xCols]
lr = LinearRegression()
lr.fit(X, y)

yPred = lr.predict(X)

print(f"Train Score: {r2_score(y, yPred)}")
print('-----')
print(f"Dolar Value Variance: {mean_squared_error(y, yPred, squared=False)}")

for x in xCols:
    plt.scatter(df[x], df['price'])
    plt.title(f'Plot of Price against {x}')
```

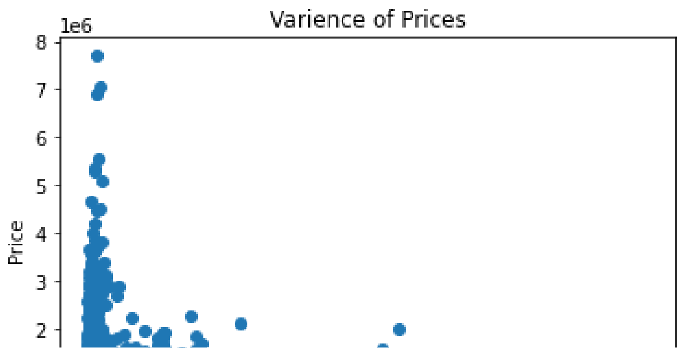
```
    plt.xlabel(x)
    plt.ylabel('Price')
    plt.title('Varience of Prices')
    plt.show()
```

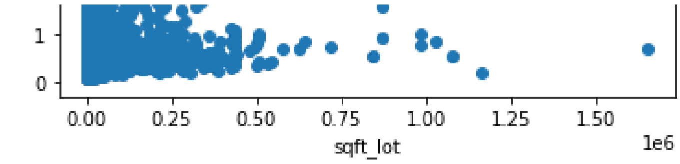
```
Train Score: 0.6465316078832293
-----
Dolar Value Variance: 218827.2578722521
```

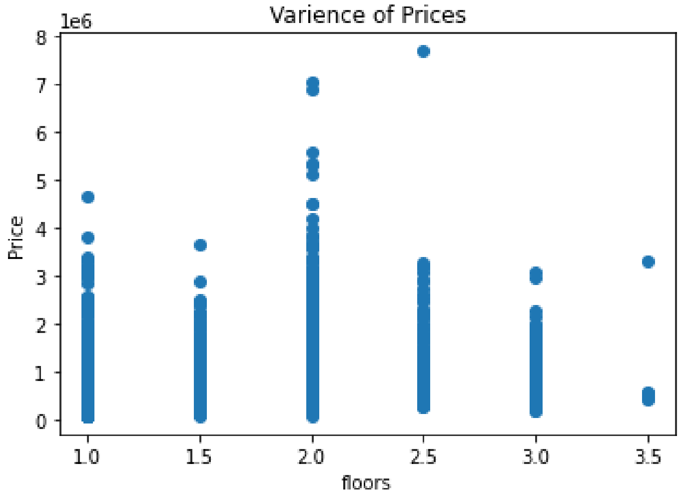


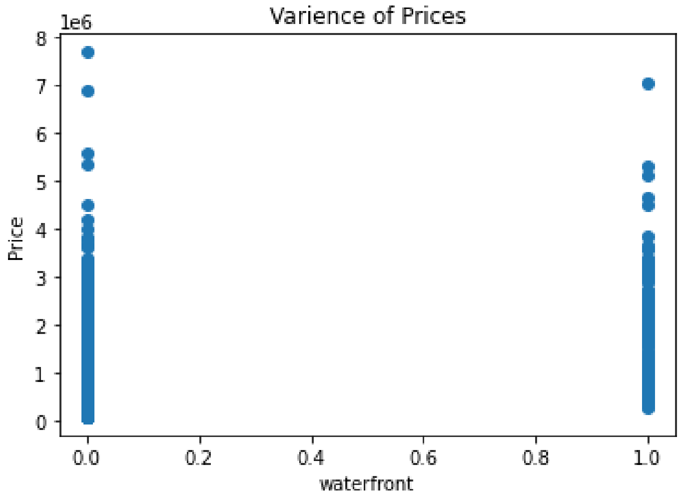


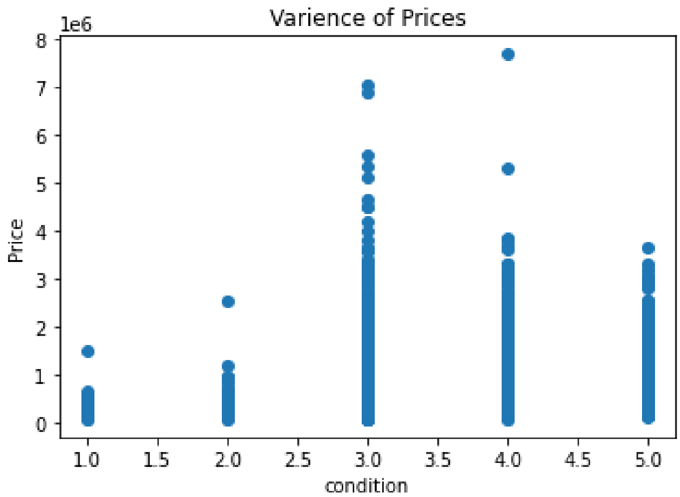


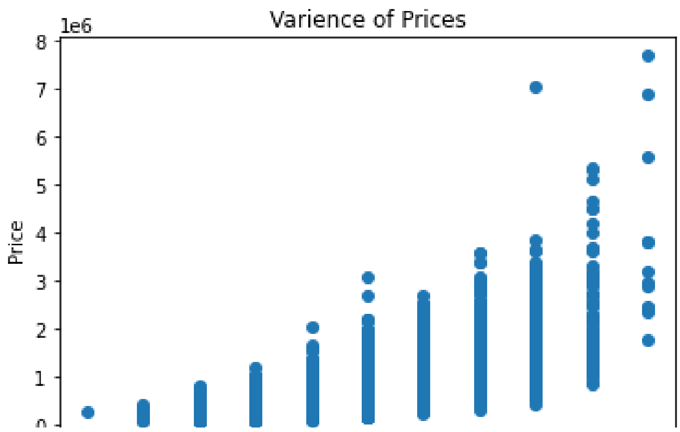


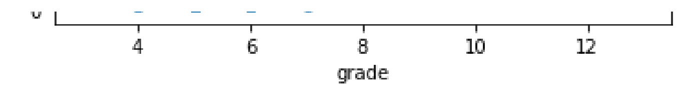

1
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1e6
sqft_lot

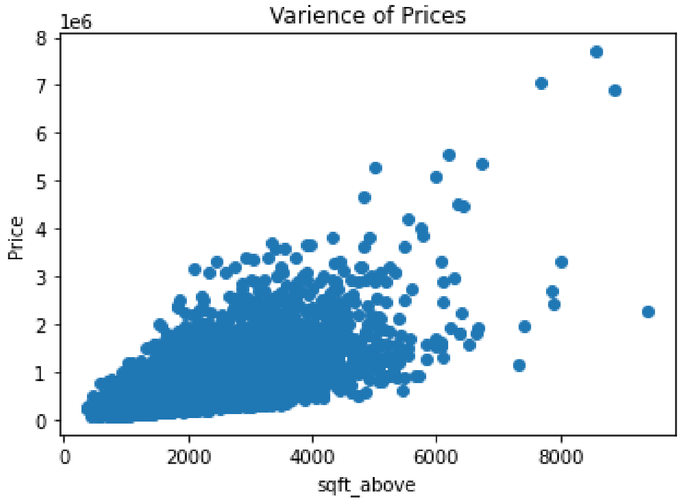

Varience of Prices
1e6
Price
0
1
2
3
4
5
6
7
8
1.0
1.5
2.0
2.5
3.0
3.5
floors

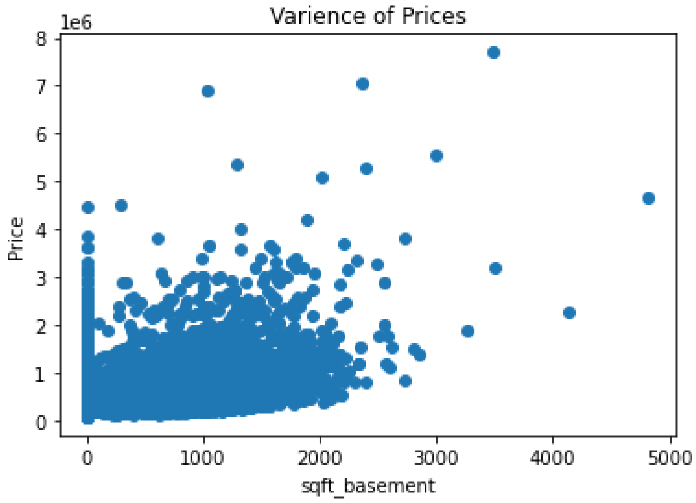

Varience of Prices
1e6
Price
0
1
2
3
4
5
6
7
8
0.0
0.2
0.4
0.6
0.8
1.0
waterfront

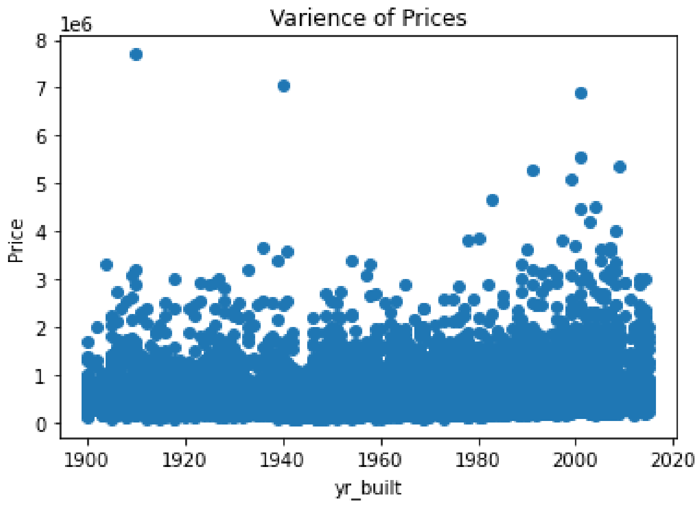

Varience of Prices
1e6
Price
0
1
2
3
4
5
6
7
8
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
condition

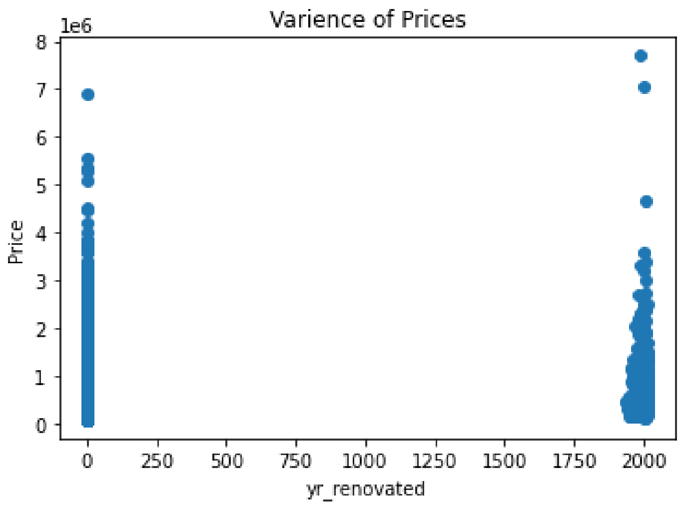

Varience of Prices
1e6
Price
1
2
3
4
5
6
7
8


4
6
8
10
12
grade


Varience of Prices
1e6
Price
sqft_above


Varience of Prices
1e6
Price
sqft_basement


Varience of Prices
1e6
Price
yr_built


Varience of Prices
1e6
Price
yr_renovated

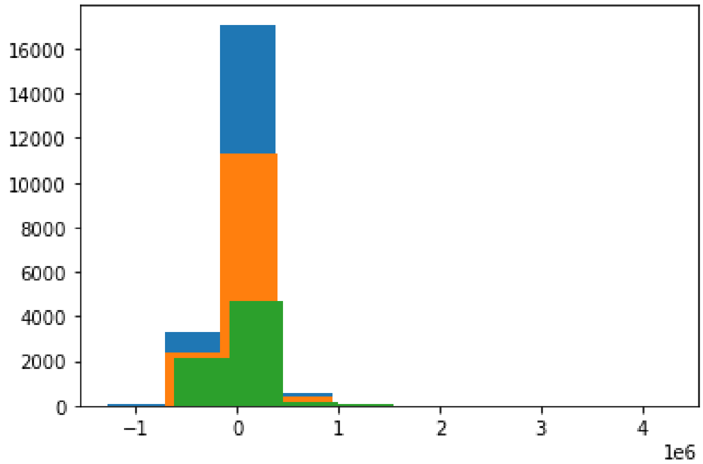
Okay, we're seeing a lot of outliers in out data. Let's check a few more plots and see what else we can see.

In [307]:

```
trainResiduals = yTrain-yPredTrain
testResiduals = yTest-yPredTest
residuals = y-yPred
```

In [308]:

```
plt.hist(residuals)
plt.hist(trainResiduals)
plt.hist(testResiduals)
# plt.savefig('baselineModelNormalize')
```

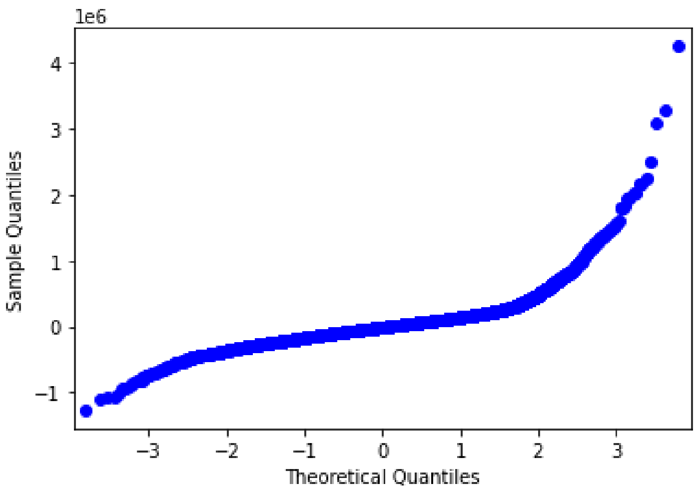


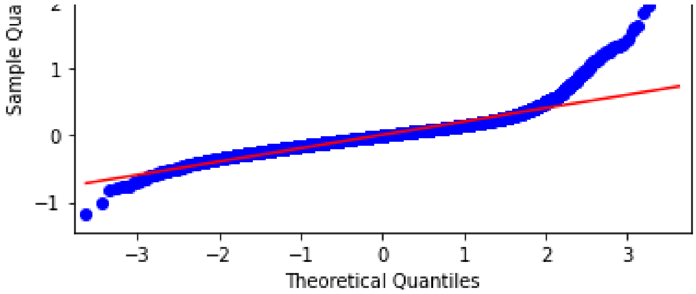
Okay, that's some reasuring info. A LARGE majority of the residual data points we're seeing tends to fall very close to the mean. And those that do exist end to exist on the low end with a few on the exreme high end. So removing the outliers from our data wont take away very many values.

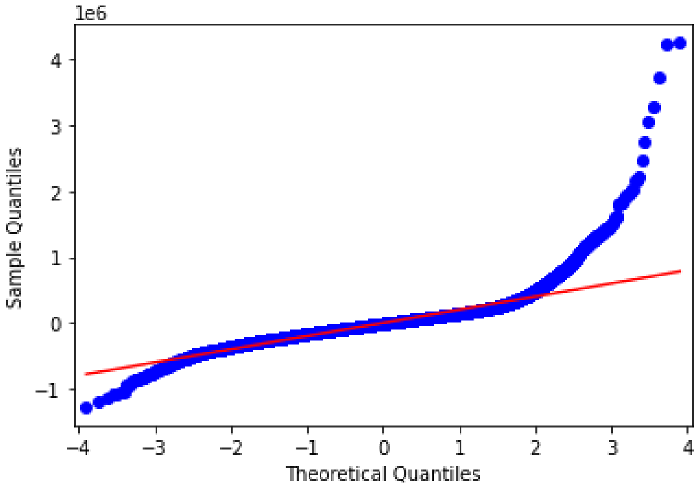
In [309]:

```
fig = sm.qqplot(trainResiduals, line = 'r')
fig2 = sm.qqplot(testResiduals, line = 'r')
fig3 = sm.qqplot(residuals, line = 'r')
```

```
C:\Users\jpake\anaconda3\envs\learn-env\lib\site-packages\numpy\linalg\linalg.py:1872: Ru
ntimeWarning: invalid value encountered in greater
  return count_nonzero(S > tol, axis=-1)
```



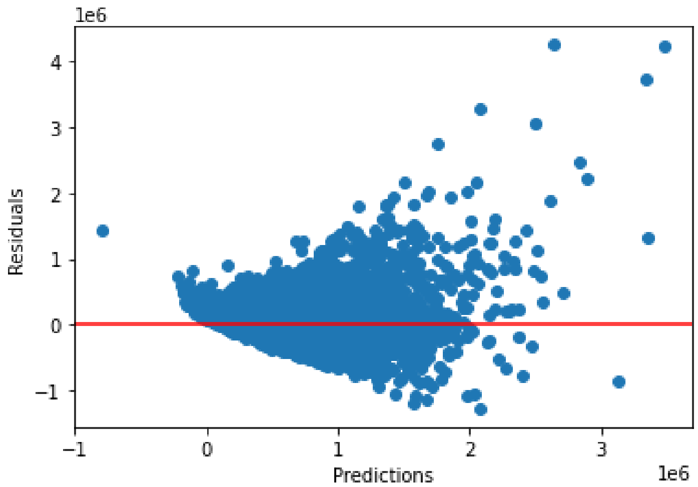




Here we can see the effect those outliers are having. Our trend seems to take a sharp turn up and meters off.

In [310]:

```
lr = LinearRegression()
lr.fit(X, y)

yPred = lr.predict(X)

plt.scatter(yPred, residuals)
plt.axhline(y=0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.show()
```



Ouch. This model shows out predictions seem to be extremely scattered. Good news is that they seem to collect in one spot. Bad news is that the spot is about the size and shape of the Big Island of Hawai'i.

Model 2

Cleaning the Data

Okay! Let's try this again but armed with the new knowledge from our assessment of Model 1. Just like last time,

we'll impoprt our data so we have a fresh model and clean it again. Why don't we go through some of our models and trim off outliers while we're at at?

In [311]:

```
# Importing the Data, freshhhhhh
df = pd.read_csv("data/kc_house_data.csv")

# Maximum Effort Data Cleaning
df.drop(['id', 'date', 'view', 'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15'],
axis=1, inplace=True)
df['waterfront'] = df['waterfront'].fillna(0)
df['yr_renovated'] = df['yr_renovated'].fillna(0)
index_names = df[ df['sqft_basement'] == '?' ].index
df.drop(index_names, inplace = True)
df['sqft_basement'] = df['sqft_basement'].astype(float)

# Data Haircut
df=df[(df['bedrooms'] < 7)]
df=df[(df['bathrooms'] <= 4) & (df['bathrooms'] != 1.25) & (df['bathrooms'] != 0.5)]
df=df[(df['sqft_living'] < 5000)]
df=df[(df['sqft_lot'] < 20000)]
df=df[(df['floors'] <= 3)]
df=df[(df['condition'] > 2)]
df=df[(df['grade'] > 3) & (df['grade'] < 12) & (df['grade'] != 4)]
df=df[(df['sqft_above'] < 6000)]
df=df[(df['sqft_basement'] < 2000)]
df=df[(df['price'] < 2000000)]
```

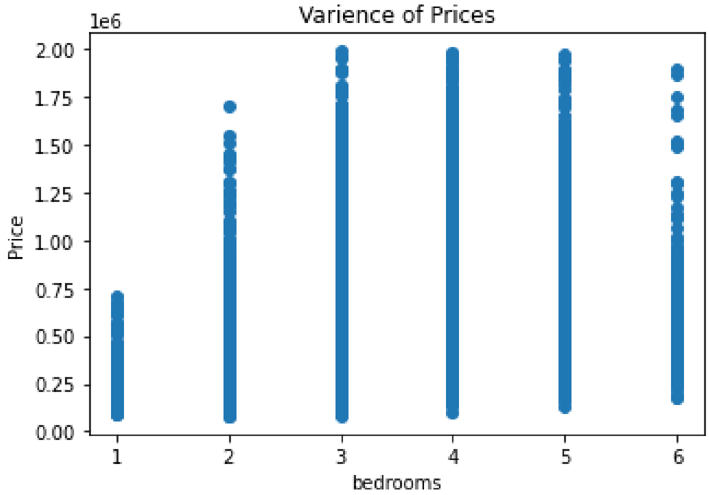
In [312]:

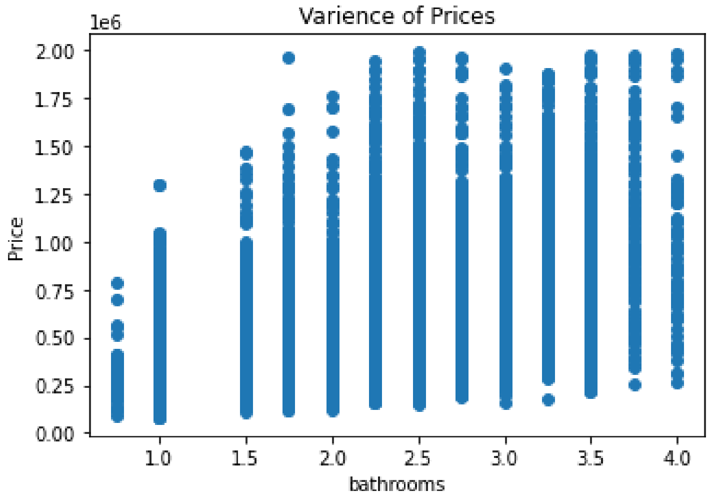
```
# run the model again
xCols = [c for c in df.columns.to_list() if c not in ['price']]
x = df[xCols]
y = df['price']

xTrain, xTest, yTrain, yTest = train_test_split(
    x, y, test_size=0.33, random_state=42)

xTrainScaled = stdScaled.fit_transform(xTrain)
xTestScaled = stdScaled.transform(xTest)

lr = LinearRegression()
lr.fit(xTrainScaled, yTrain)

yPredTrain = lr.predict(xTrainScaled)
yPredTest = lr.predict(xTestScaled)

print(f"Train Score: {r2_score(yTrain, yPredTrain)}")
print(f"Test Score: {r2_score(yTest, yPredTest)}")
print('-----')
print(f"Train Score: {mean_squared_error(yTrain, yPredTrain, squared=False)}")
print(f"Test Score: {mean_squared_error(yTest, yPredTest, squared=False)}")
```

```
Train Score: 0.6093776441118106
Test Score: 0.6033114943854014
-----
Train Score: 164840.90418478948
Test Score: 169668.27224539465
```

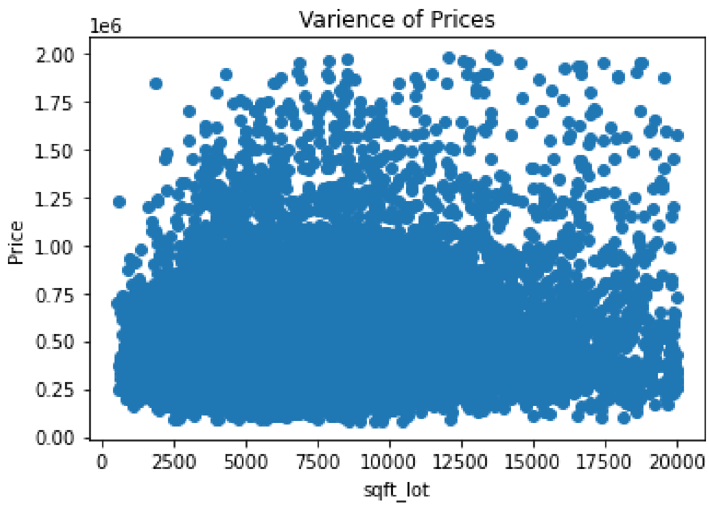
In [313]:

```
# Run the plots, again
for x in xCols:
    plt.scatter(df[x], df['price'])
    plt.title(f'Plot of Price against {x}')
    plt.xlabel(x)
    plt.ylabel('Price')
    plt.title('Varience of Prices')
    plt.show()
```

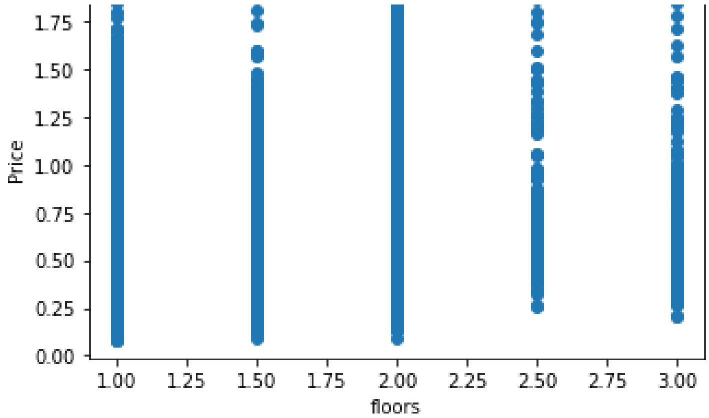

Varience of Prices
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
1
2
3
4
5
6
bedrooms


Varience of Prices
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
1.0
1.5
2.0
2.5
3.0
3.5
4.0
bathrooms

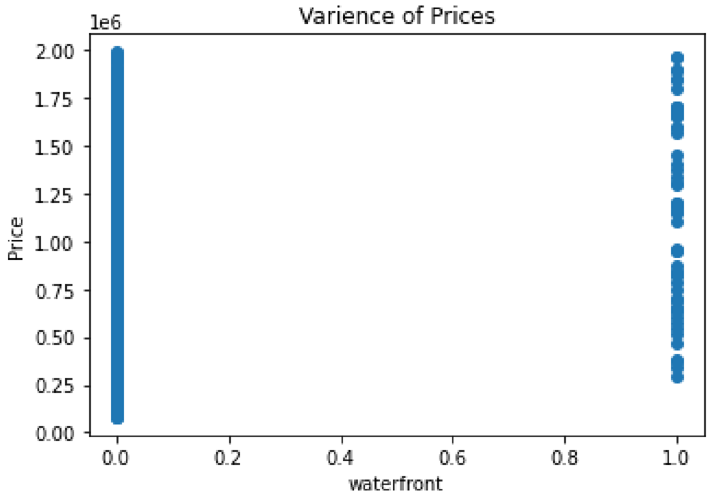

Varience of Prices
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
1000
2000
3000
4000
5000
sqft_living


Varience of Prices
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
0
2500
5000
7500
10000
12500
15000
17500
20000
sqft_lot

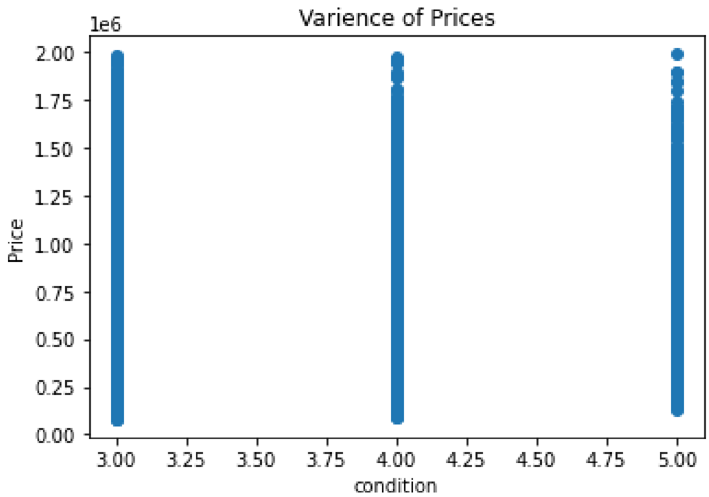

Varience of Prices
1e6
2.00



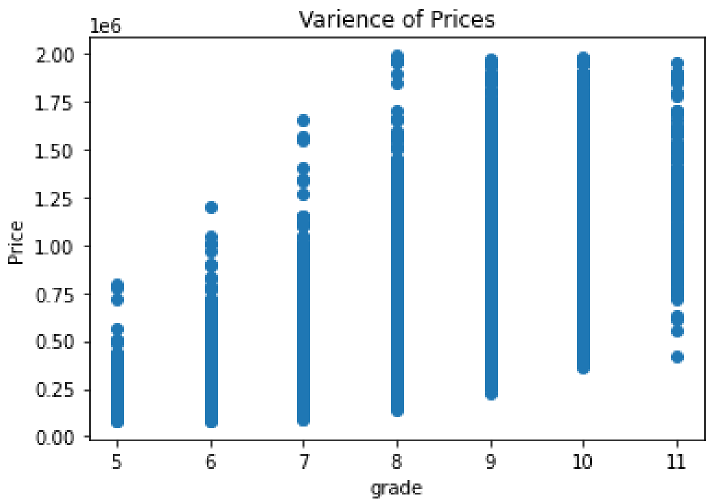
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
floors



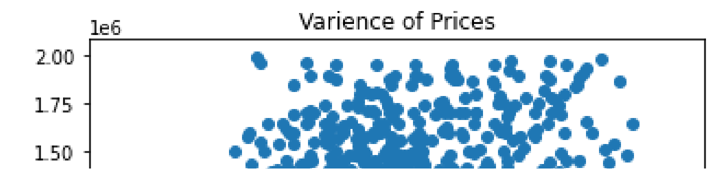
Varience of Prices
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
0.0
0.2
0.4
0.6
0.8
1.0
waterfront



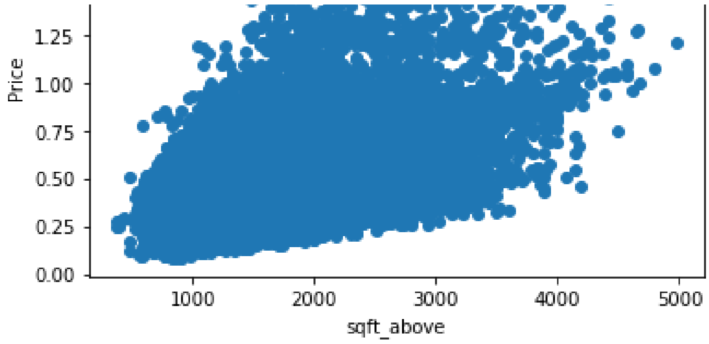
Varience of Prices
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
3.00
3.25
3.50
3.75
4.00
4.25
4.50
4.75
5.00
condition

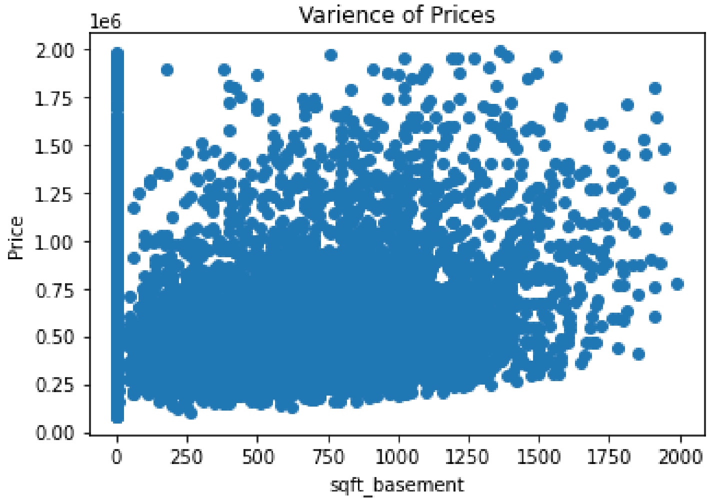


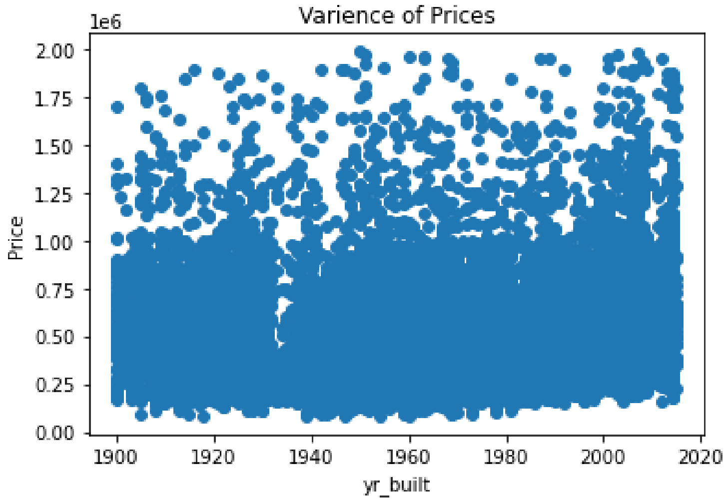
Varience of Prices
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Price
5
6
7
8
9
10
11
grade

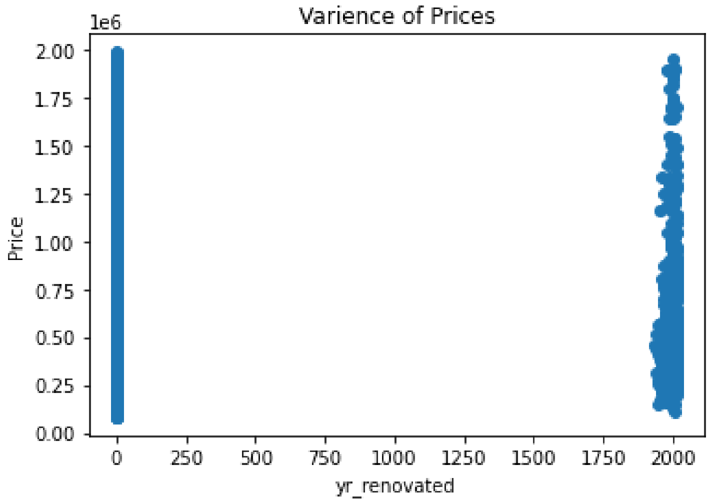


Varience of Prices
1e6
2.00
1.75
1.50





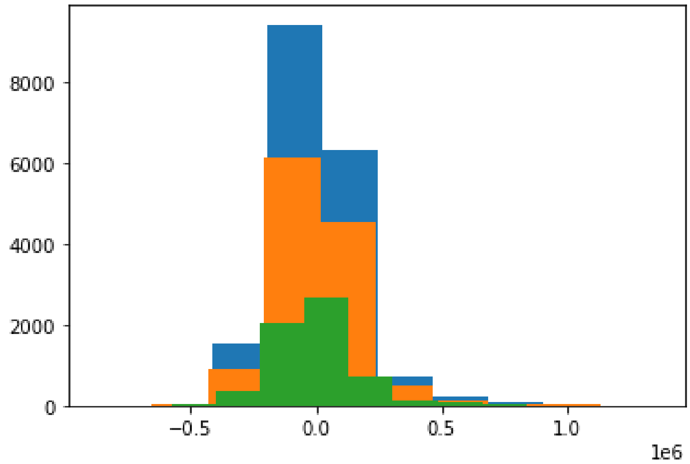




In [314]:

```
X = df[xCols]
lr = LinearRegression()
lr.fit(X, y)

yPred = lr.predict(X)
```

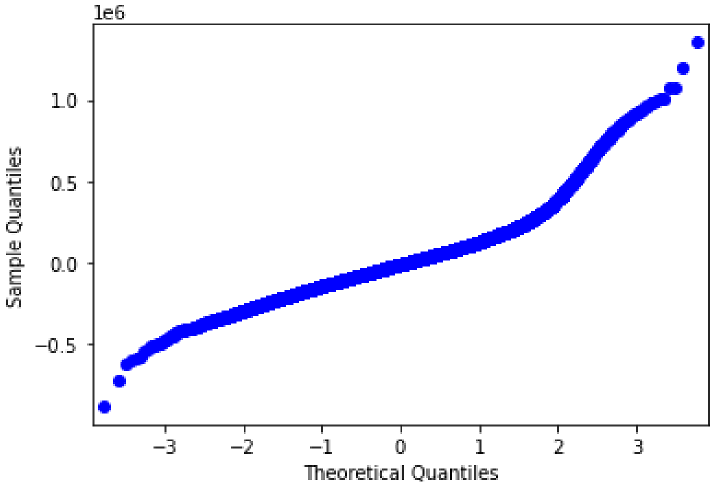
```
trainResiduals = yTrain-yPredTrain
testResiduals = yTest-yPredTest
residuals = y-yPred

plt.hist(residuals)
plt.hist(trainResiduals)
plt.hist(testResiduals)
# plt.savefig('Model2Normalize')
```

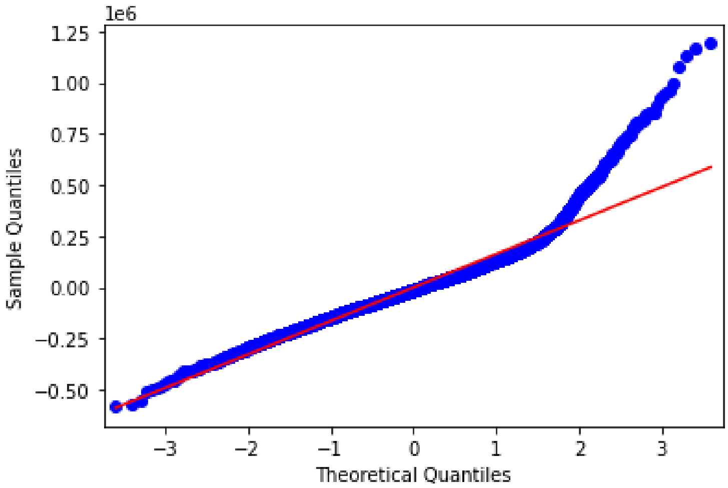


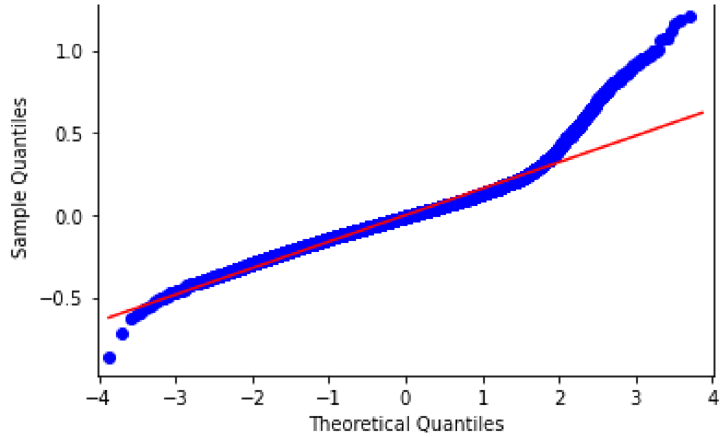
In [315]:

```
fig = sm.qqplot(trainResiduals, line = 'r')
fig2 = sm.qqplot(testResiduals, line = 'r')
fig3 = sm.qqplot(residuals, line = 'r')
```

```
C:\Users\jpake\anaconda3\envs\learn-env\lib\site-packages\numpy\linalg\linalg.py:1872: Ru
ntimeWarning: invalid value encountered in greater
  return count_nonzero(S > tol, axis=-1)
```

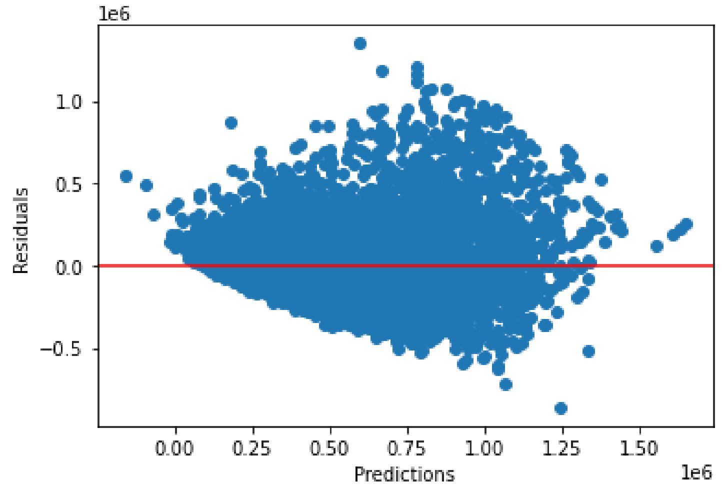






In [316]:

```
plt.scatter(yPred, residuals)
plt.axhline(y=0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.show()
```



Alright, after fiddling with the data for a long while I've somehow made the model worse. Let's take a step back and reevaluate. Perhaps there's some useful data in what we removed earlier. Let's add some of it back in and see how Our results change purely on that.

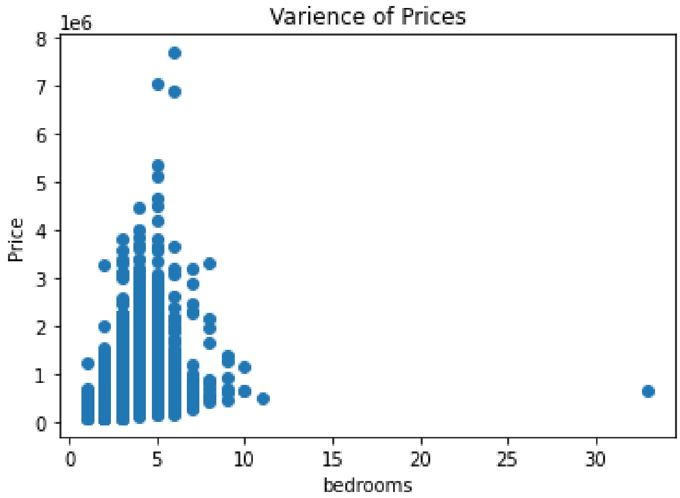
Model 3

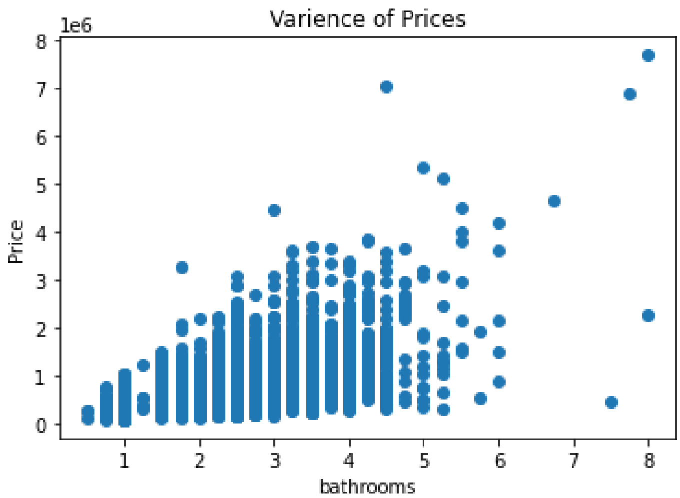
In [317]:

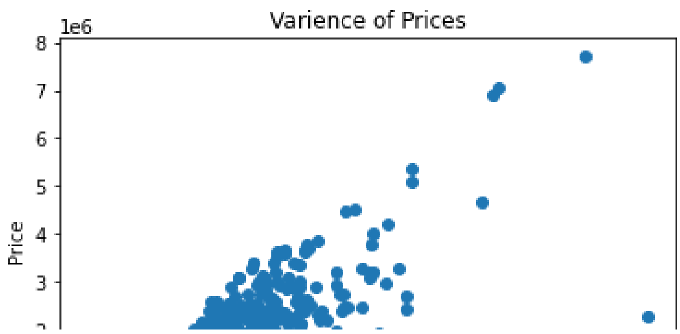
```
df = pd.read_csv("data/kc_house_data.csv")
# Changes to the list of dropped columns
# Only removed 2 columns ('id' & 'date') this time.
df.drop(['id', 'date'], axis=1, inplace=True)
df = df.dropna()
index_names = df[ df['sqft_basement'] == '?' ].index
df.drop(index_names, inplace = True)
df['sqft_basement'] = df['sqft_basement'].astype(float)

xCols = [c for c in df.columns.to_list() if c not in ['price']]
x = df[xCols]
y = df['price']

xTrain, xTest, yTrain, yTest = train_test_split(
    x, y, test_size=0.33, random_state=42)

xTrainScaled = stdScaled.fit_transform(xTrain)
xTestScaled = stdScaled.transform(xTest)

lr = LinearRegression()
```

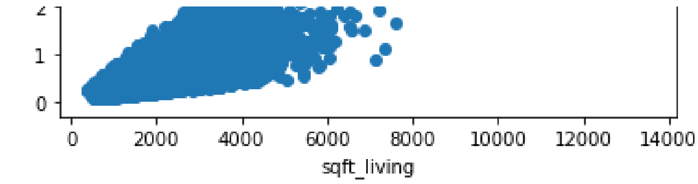
```
lr.fit(xTrainScaled, yTrain)

yPredTrain = lr.predict(xTrainScaled)
yPredTest = lr.predict(xTestScaled)

print(f"Train R2 Score: {r2_score(yTrain, yPredTrain)}")
print(f"Test R2 Score: {r2_score(yTest, yPredTest)}")
print('-----')
print(f"Dollar Value Variance (Train): {mean_squared_error(yTrain, yPredTrain, squared=False)}")
print(f"Dollar Value Variance (Test): {mean_squared_error(yTest, yPredTest, squared=False)}")

for x in xCols:
    plt.scatter(df[x], df['price'])
    plt.title(f'Plot of Price against {x}')
    plt.xlabel(x)
    plt.ylabel('Price')
    plt.title('Varience of Prices')
    plt.show()
```

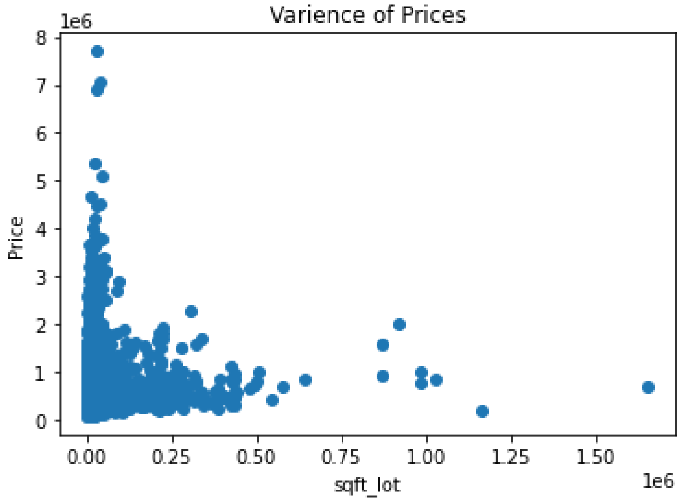
```
Train R2 Score: 0.6961840815077176
Test R2 Score: 0.7101463584756225
-----
Dollar Value Variance (Train): 204582.10359046079
Dollar Value Variance (Test): 202821.66803727273
```

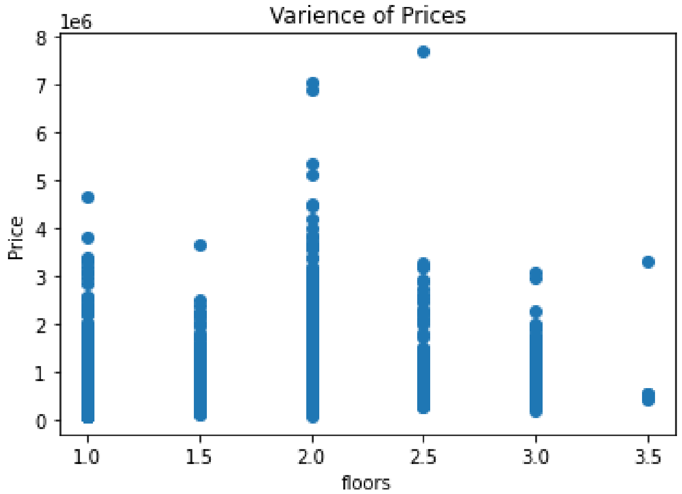


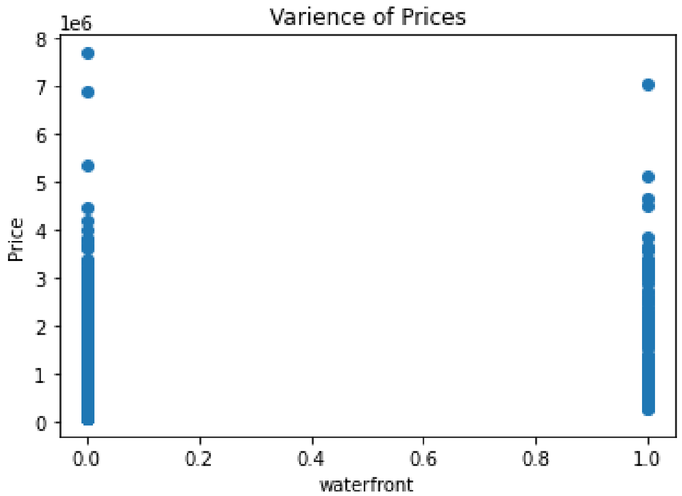


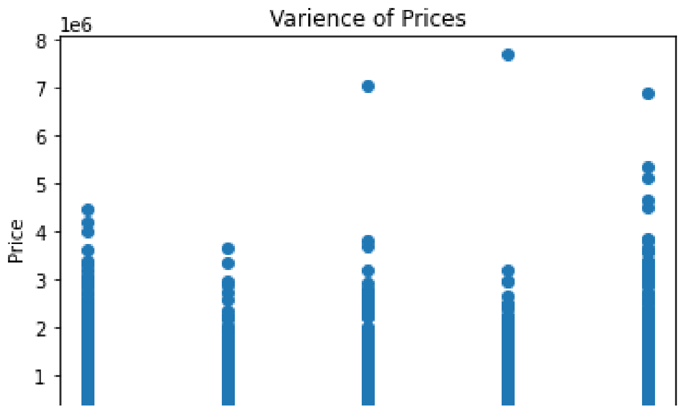


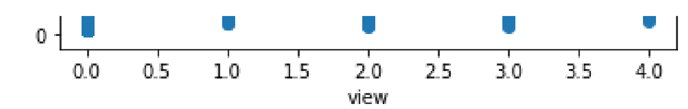

0 2000 4000 6000 8000 10000 12000 14000
sqft_living


Varience of Prices
1e6
Price
sqft_lot
1e6

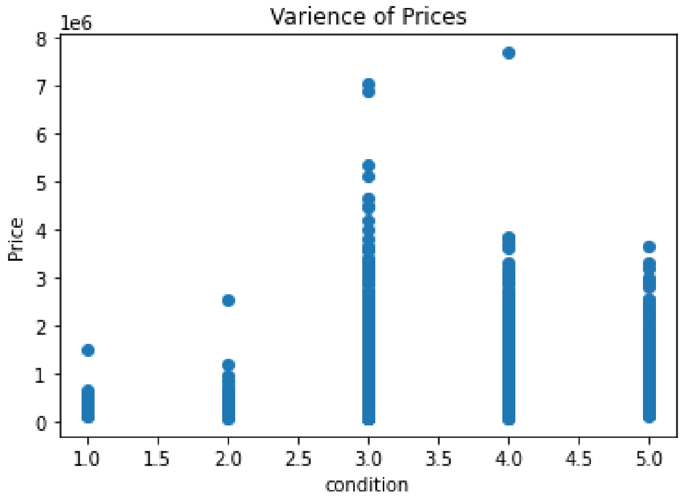

Varience of Prices
1e6
Price
1.0 1.5 2.0 2.5 3.0 3.5
floors


Varience of Prices
1e6
Price
0.0 0.2 0.4 0.6 0.8 1.0
waterfront

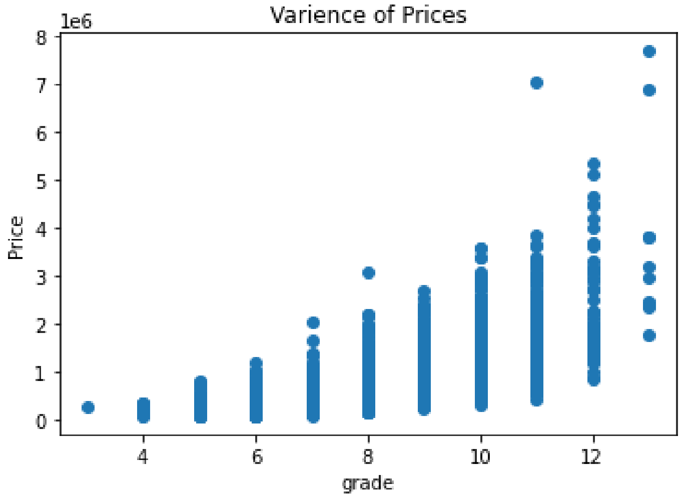

Varience of Prices
1e6
Price



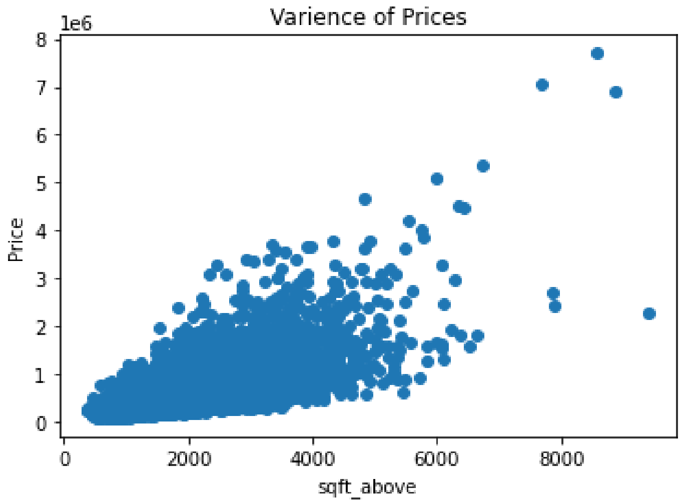
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
view



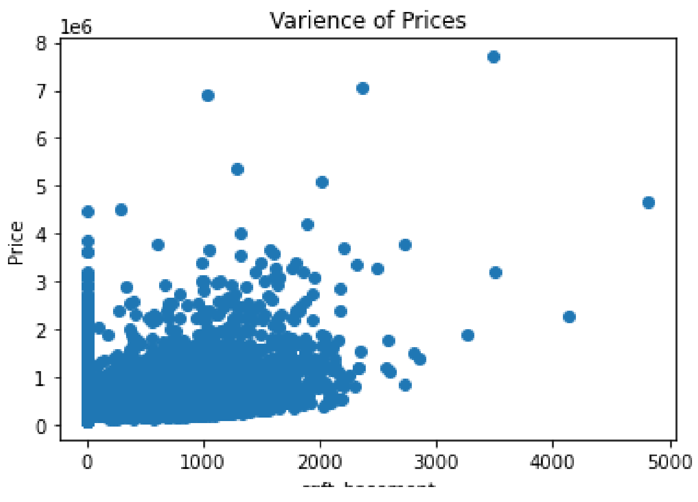
Varience of Prices
1e6
Price
condition



Varience of Prices
1e6
Price
grade

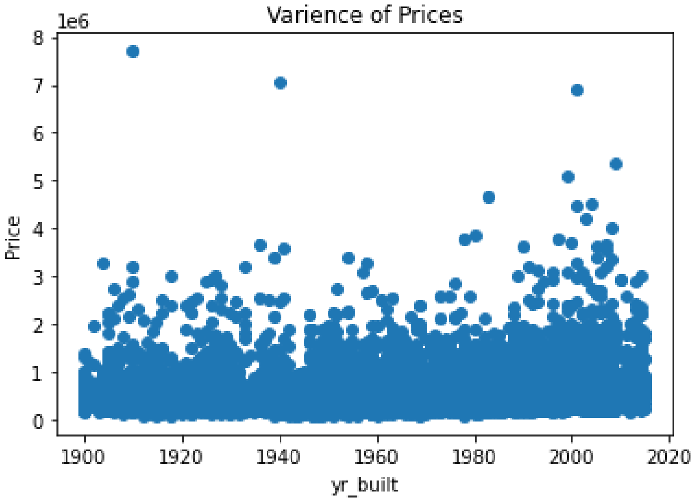


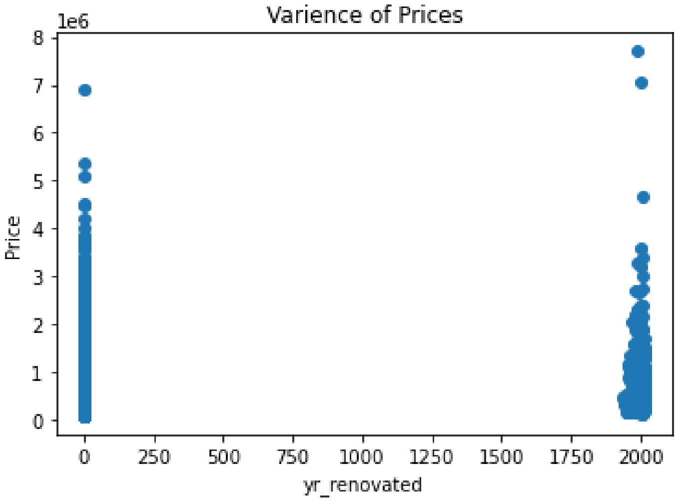
Varience of Prices
1e6
Price
sqft_above

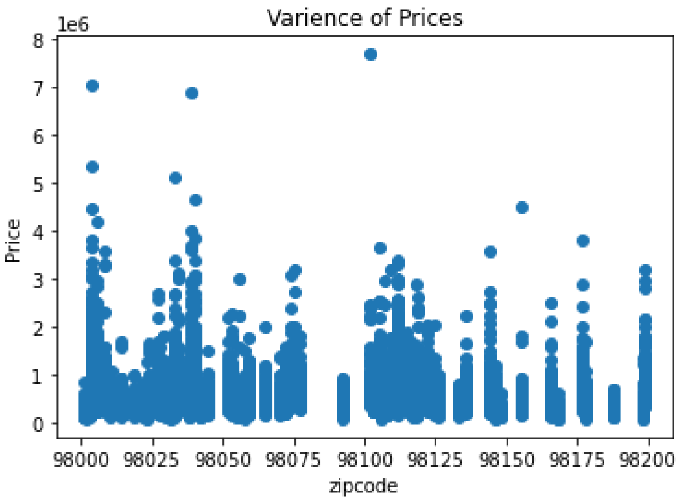


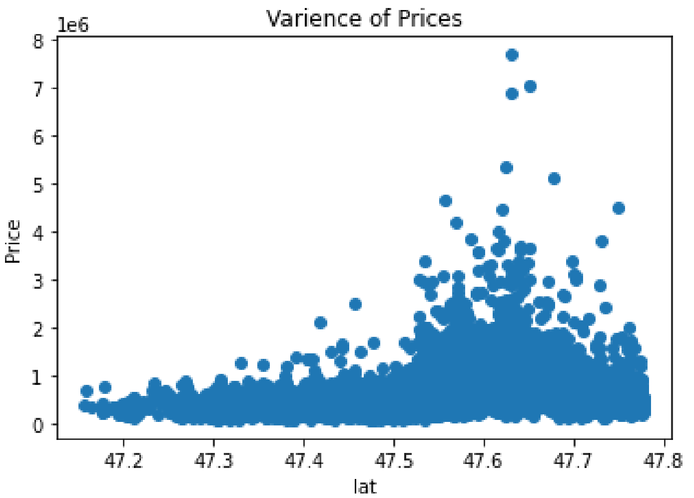
Varience of Prices
1e6
Price

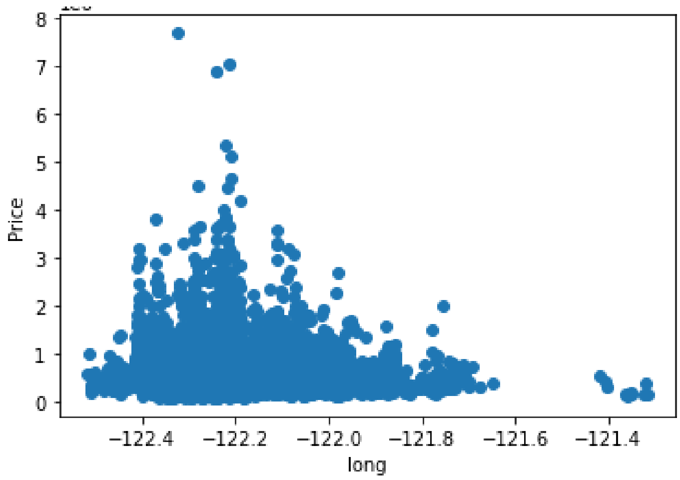
sqft_basement

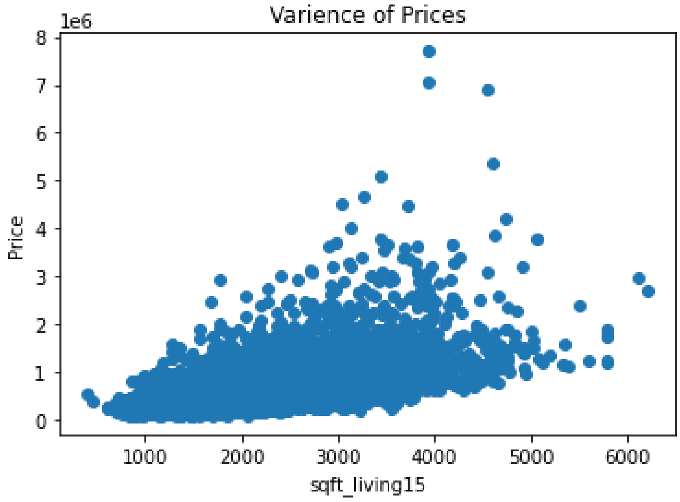


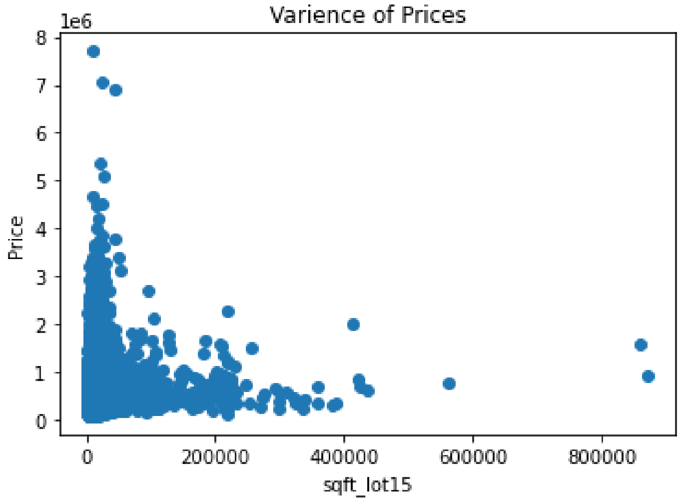










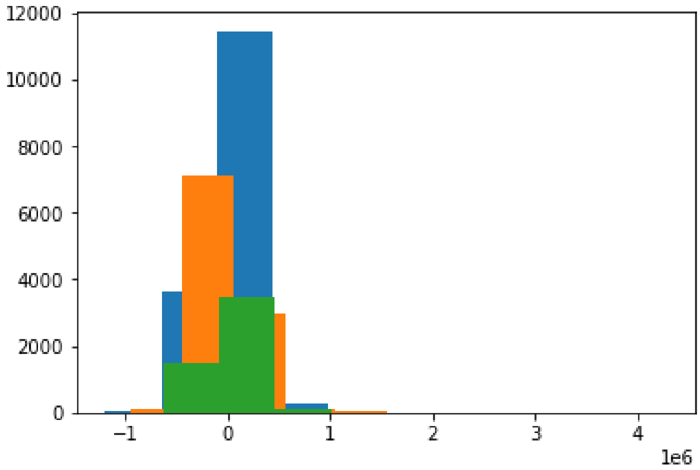


Oo! Oo! Oo! Progress! We're seeing pregress. We've jumped from 64 to 70 percent and a small decrease in the Dollar Varience. Still not great but we're making progress in thr right direction. Let's check out plots.

In [318]:

```
xCols = [c for c in df.columns.to_list() if c not in ['price']]
x = df[xCols]
y = df['price']

trainResiduals = yTrain-yPredTrain
testResiduals = yTest-yPredTest
lr = LinearRegression()
lr.fit(x, y)

yPred = lr.predict(x)
residuals = y-yPred

plt.hist(residuals)
plt.hist(trainResiduals)
```

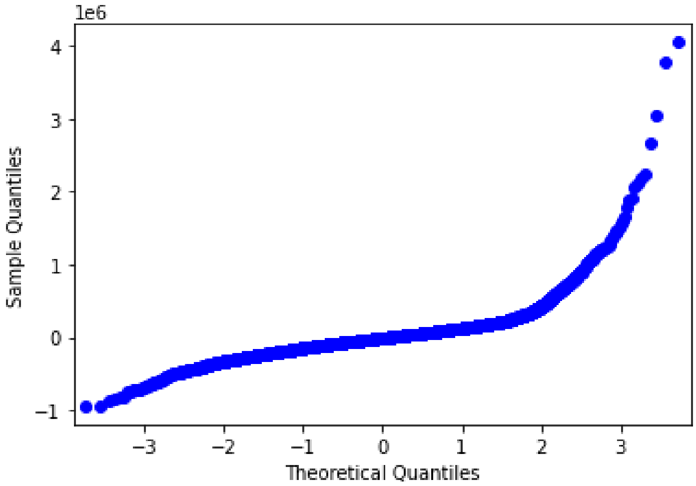
```
plt.hist(testResiduals)
# plt.savefig('Model3Normalize')
```

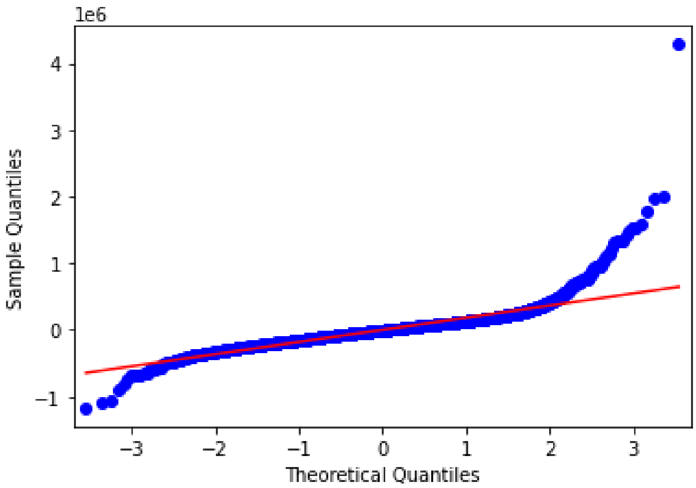


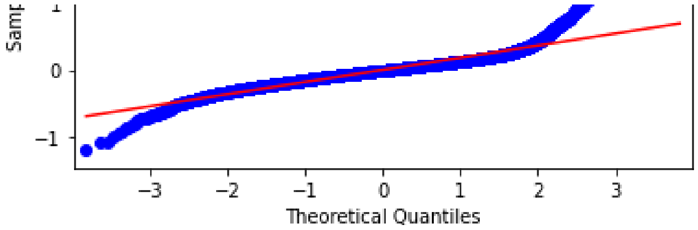
In [319]:

```
fig = sm.qqplot(trainResiduals, line = 'r')
fig2 = sm.qqplot(testResiduals, line = 'r')
fig3 = sm.qqplot(residuals, line = 'r')
```

```
C:\Users\jpake\anaconda3\envs\learn-env\lib\site-packages\numpy\linalg\linalg.py:1872: Ru
ntimeWarning: invalid value encountered in greater
  return count_nonzero(S > tol, axis=-1)
```

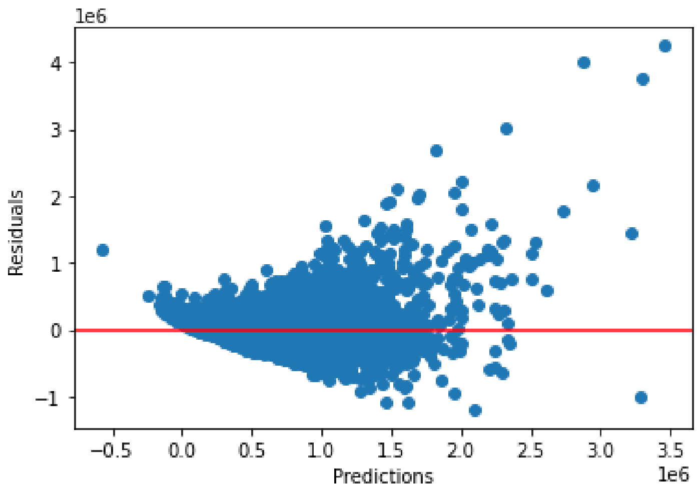






In [320]:

```
plt.scatter(yPred, residuals)
plt.axhline(y=0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.show()
```



Nothing has really changed, but that was expected. We haven't trimmed the data on this one. Let's do that and see if we can't make more improvements. Practically just a combination of Models 2 & 3.

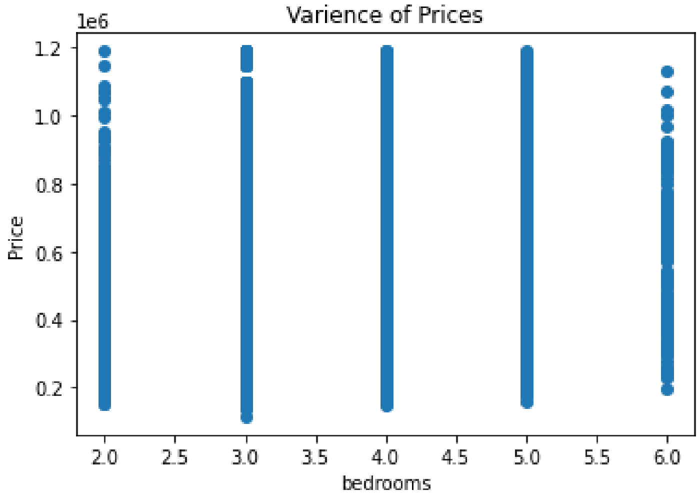
Model 4

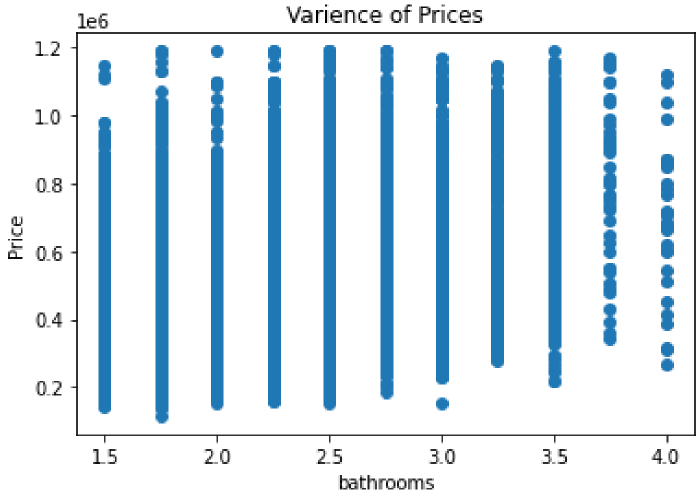
In [321]:

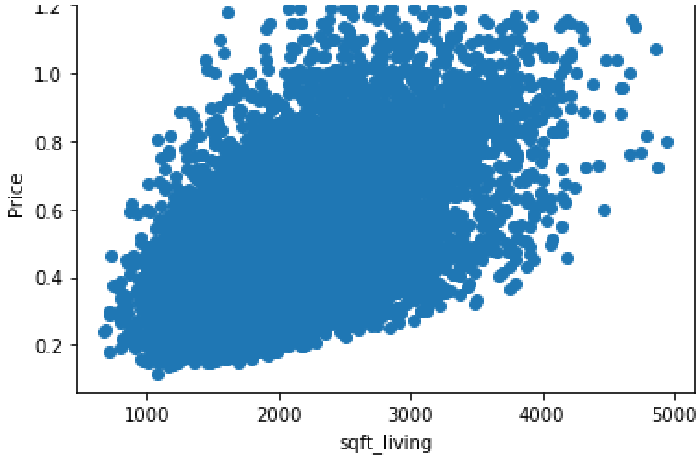
```
df = pd.read_csv("data/kc_house_data.csv")
# Keeping column list from model 3
df.drop(['id', 'date'], axis=1, inplace=True)
df = df.dropna()
index_names = df[ df['sqft_basement'] == '?' ].index
df.drop(index_names, inplace = True)
df['sqft_basement'] = df['sqft_basement'].astype(float)

# Cleaing from model 2 (but edited a bit)
df=df[(df['bedrooms'] < 7) & (df['bedrooms'] != 1)]
df=df[(df['bathrooms'] <= 4) & (df['bathrooms'] != 1.25) & (df['bathrooms'] > 1)]
df=df[(df['sqft_living'] < 5000)]
df=df[(df['sqft_lot'] < 20000)]
df=df[(df['floors'] <= 3)]
df=df[(df['condition'] > 2)]
df=df[(df['grade'] > 3) & (df['grade'] < 12) & (df['grade'] != 4)]
df=df[(df['sqft_above'] < 6000)]
df=df[(df['sqft_basement'] < 2000)]
df=df[(df['price'] < 1200000) & (df['price'] > 100000)]

# New data cleaning for new columns
df=df[(df['long'] < -121.8) & (df['long'] > -122.4)]
df=df[(df['lat'] > 47.25)]
df=df[(df['sqft_living15'] < 4000)]
df=df[(df['sqft_lot15'] < 20000)]

xCols = [c for c in df.columns.to_list() if c not in ['price']]
x = df[xCols]
```

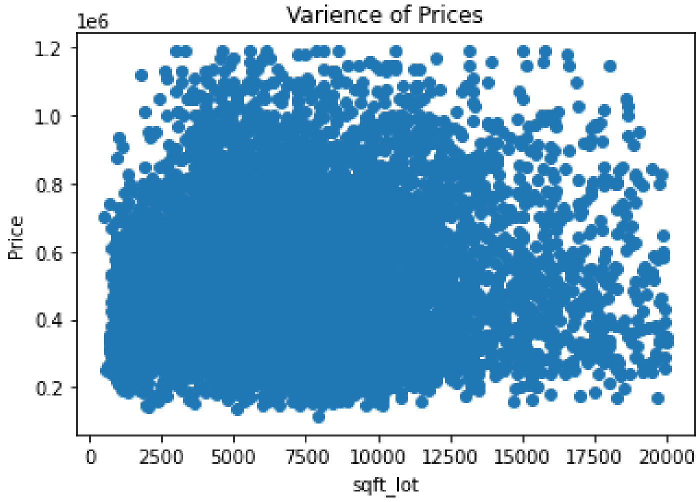
```
y = df['price']

xTrain, xTest, yTrain, yTest = train_test_split(
    x, y, test_size=0.33, random_state=42)

xTrainScaled = stdScaled.fit_transform(xTrain)
xTestScaled = stdScaled.transform(xTest)

lr = LinearRegression()
lr.fit(xTrainScaled, yTrain)

yPredTrain = lr.predict(xTrainScaled)
yPredTest = lr.predict(xTestScaled)

print(f"Train R2 Score: {r2_score(yTrain, yPredTrain)}")
print(f"Test R2 Score: {r2_score(yTest, yPredTest)}")
print('-----')
print(f"Dollar Value Variance (Train): {mean_squared_error(yTrain, yPredTrain, squared=Fa
lse)}")
print(f"Dollar Value Variance (Test): {mean_squared_error(yTest, yPredTest, squared=False
)}")

for x in xCols:
    plt.scatter(df[x], df['price'])
    plt.title(f'Plot of Price against {x}')
    plt.xlabel(x)
    plt.ylabel('Price')
    plt.title('Varience of Prices')
    plt.show()
```

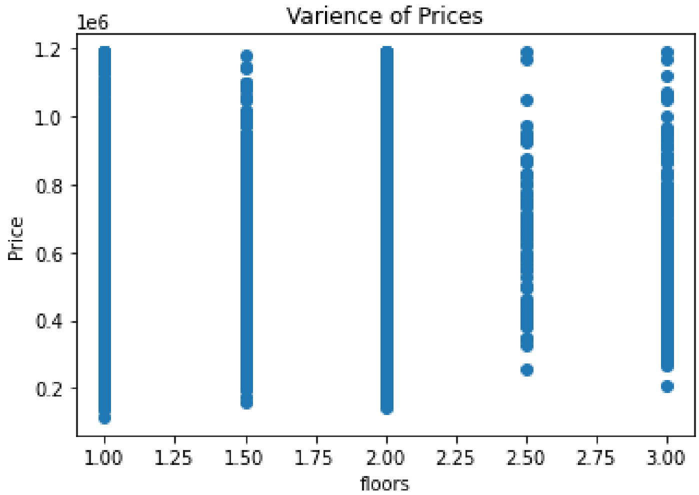
```
Train R2 Score: 0.6936703591900614
Test R2 Score: 0.6756440070126208
-----
Dollar Value Variance (Train): 114395.19879776801
Dollar Value Variance (Test): 117124.95926191621
```

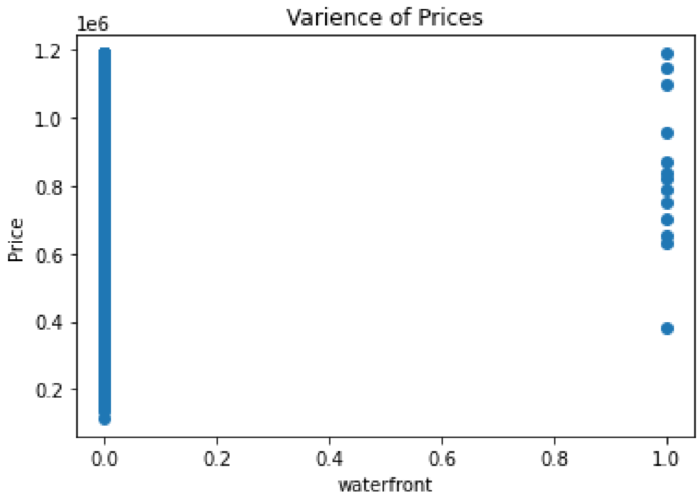




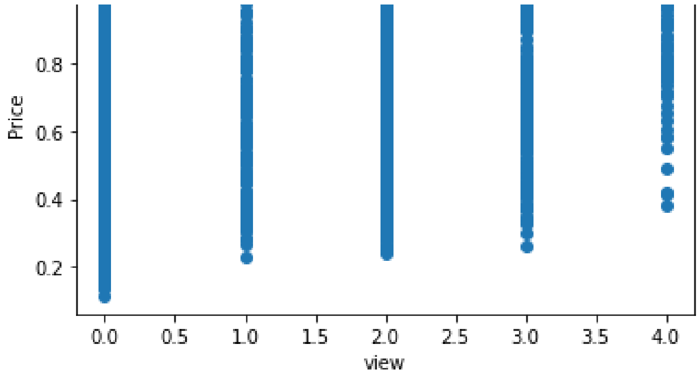

Price
sqft_living

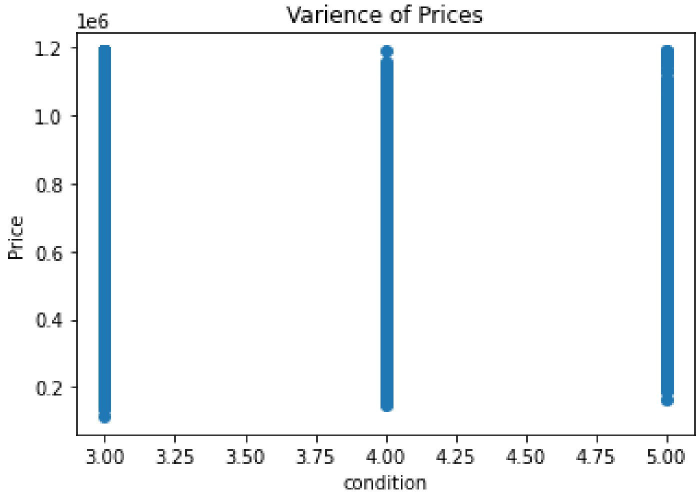

Varience of Prices
1e6
Price
sqft_lot

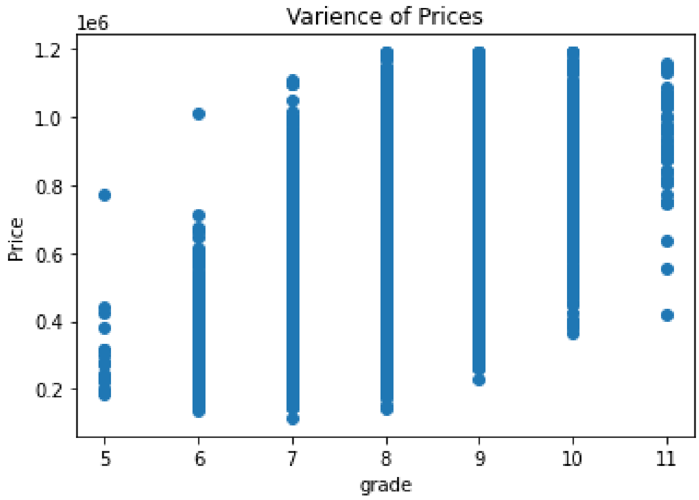

Varience of Prices
1e6
Price
floors

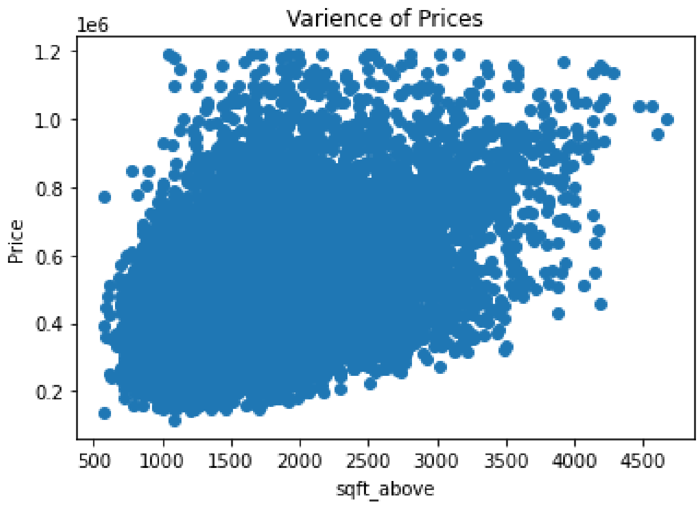

Varience of Prices
1e6
Price
waterfront

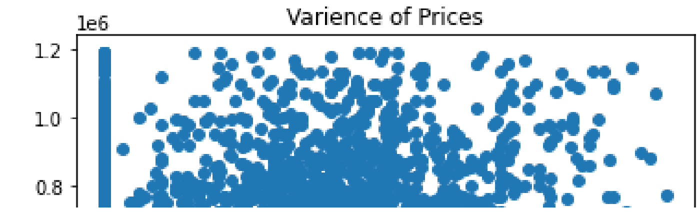

Varience of Prices
1e6

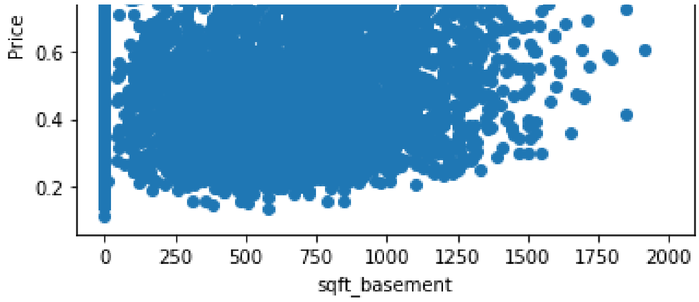

Price
0.2
0.4
0.6
0.8
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
view

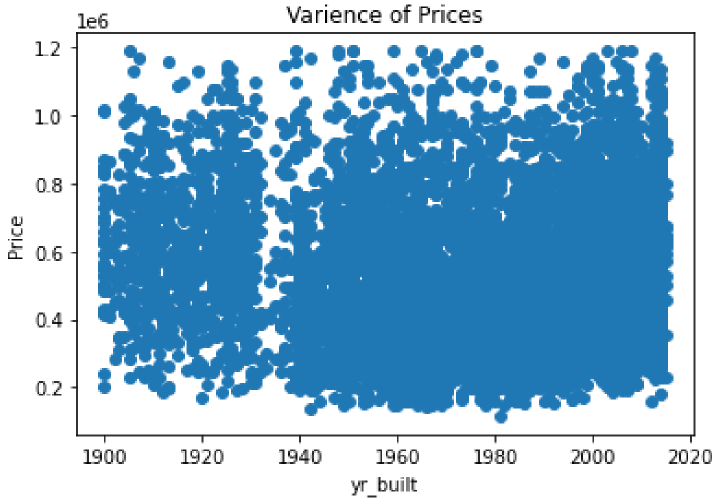

Varience of Prices
1e6
Price
0.2
0.4
0.6
0.8
1.0
1.2
3.00
3.25
3.50
3.75
4.00
4.25
4.50
4.75
5.00
condition

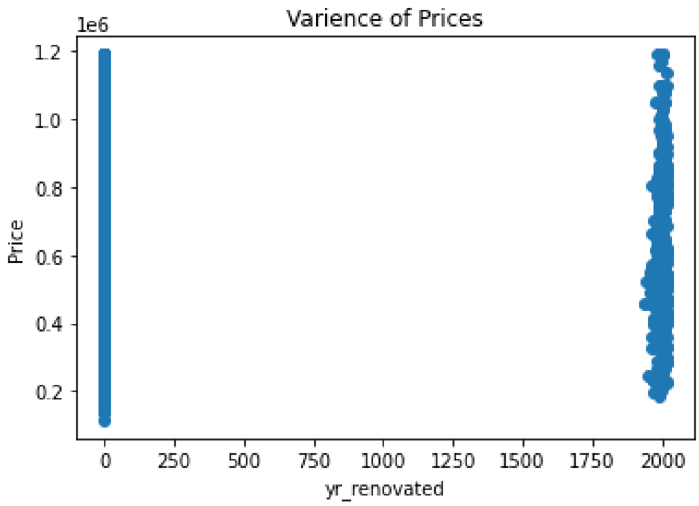

Varience of Prices
1e6
Price
0.2
0.4
0.6
0.8
1.0
1.2
5
6
7
8
9
10
11
grade

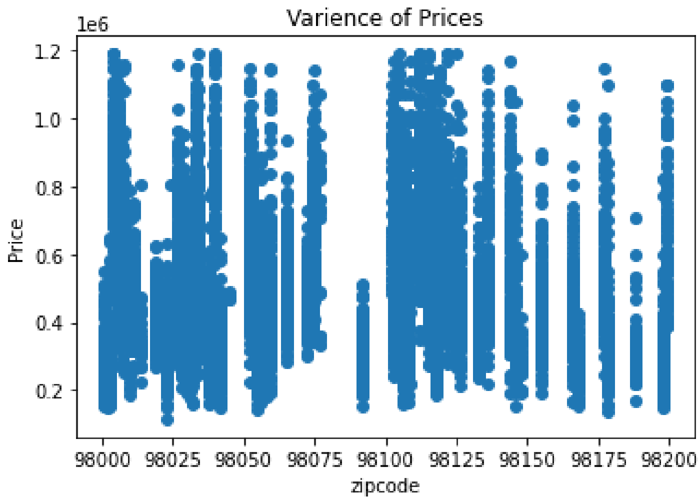

Varience of Prices
1e6
Price
0.2
0.4
0.6
0.8
1.0
1.2
500
1000
1500
2000
2500
3000
3500
4000
4500
sqft_above

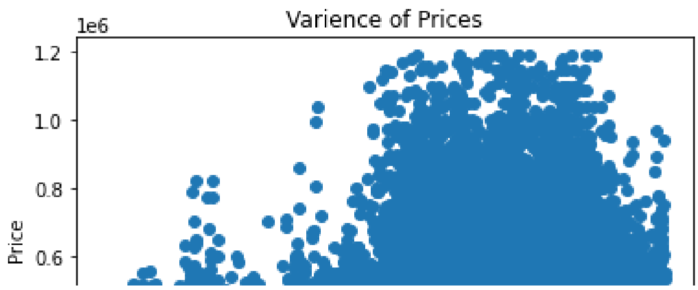

Varience of Prices
1e6
0.8
1.0
1.2

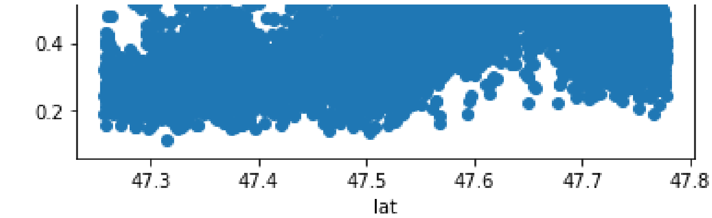

Price
0.2
0.4
0.6
0 250 500 750 1000 1250 1500 1750 2000
sqft_basement

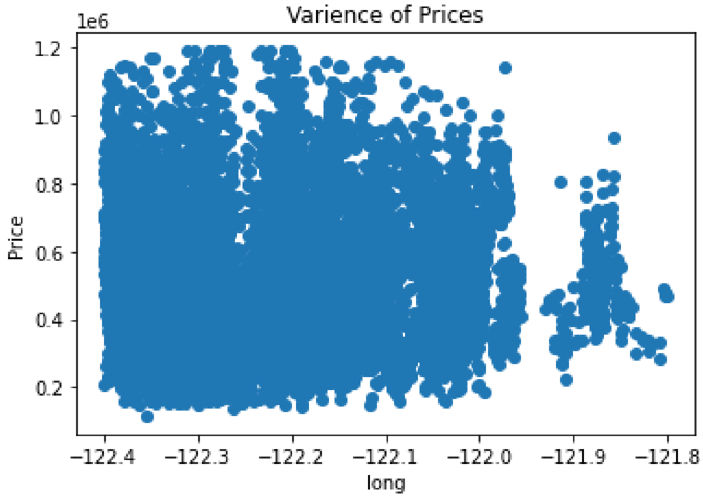

Varience of Prices
1e6
Price
0.2
0.4
0.6
0.8
1.0
1.2
1900 1920 1940 1960 1980 2000 2020
yr_built

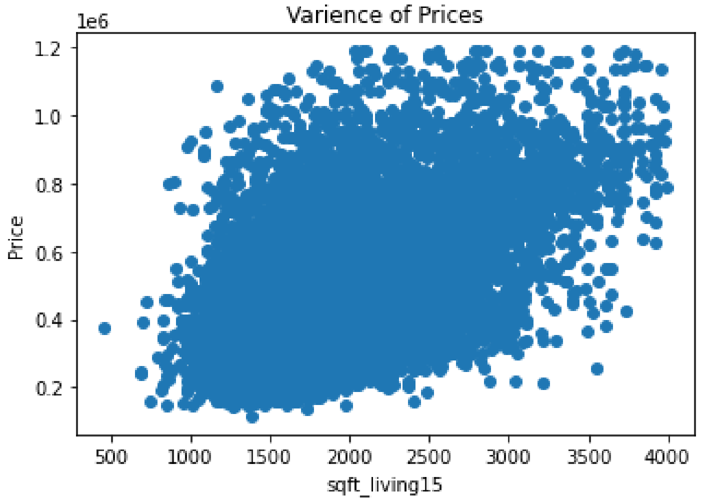

Varience of Prices
1e6
Price
0.2
0.4
0.6
0.8
1.0
1.2
0 250 500 750 1000 1250 1500 1750 2000
yr_renovated

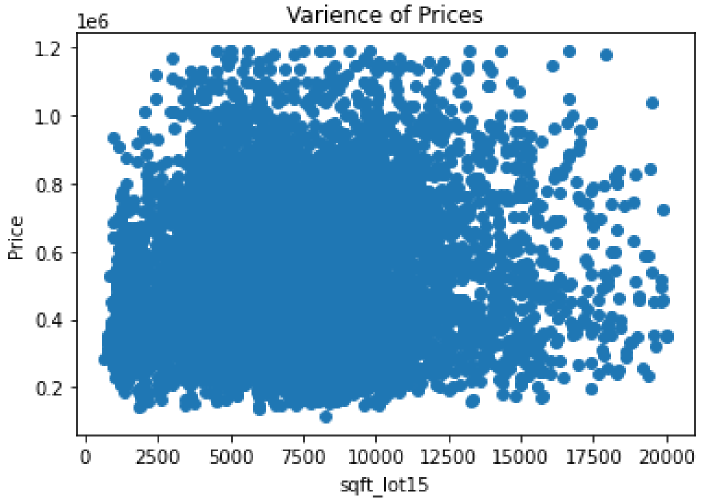

Varience of Prices
1e6
Price
0.2
0.4
0.6
0.8
1.0
1.2
98000 98025 98050 98075 98100 98125 98150 98175 98200
zipcode


Varience of Prices
1e6
Price
0.6
0.8
1.0
1.2





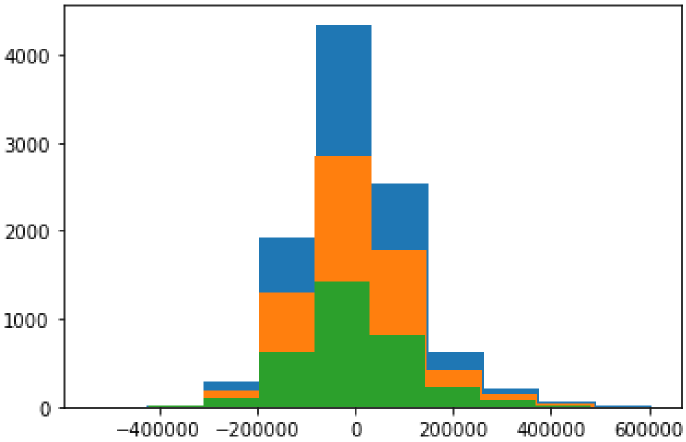




In [322]:

```
xCols = [c for c in df.columns.to_list() if c not in ['price']]
x = df[xCols]
y = df['price']

trainResiduals = yTrain-yPredTrain
testResiduals = yTest-yPredTest
lr = LinearRegression()
lr.fit(x, y)
```

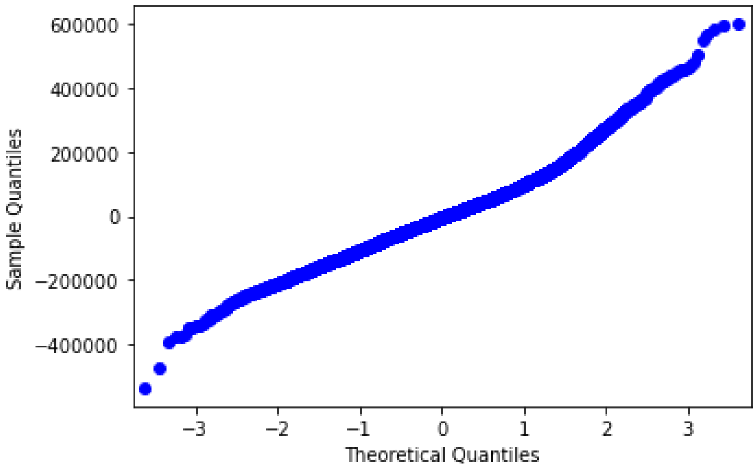
```
yPred = lr.predict(x)
residuals = y-yPred

plt.hist(residuals)
plt.hist(trainResiduals)
plt.hist(testResiduals)
# plt.savefig('Model4Normalize')
```

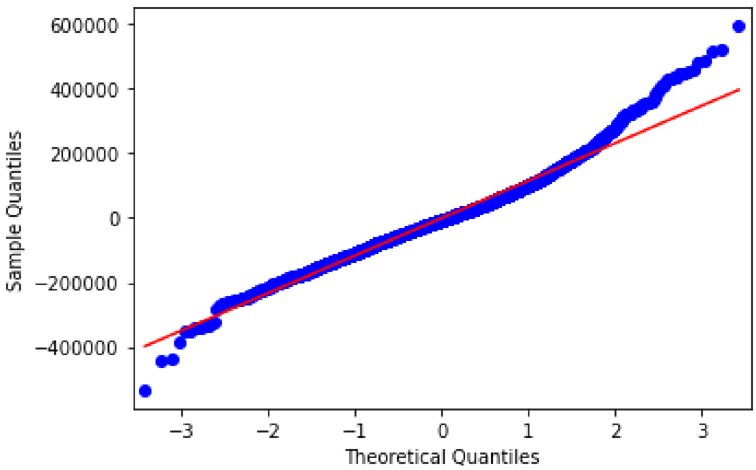


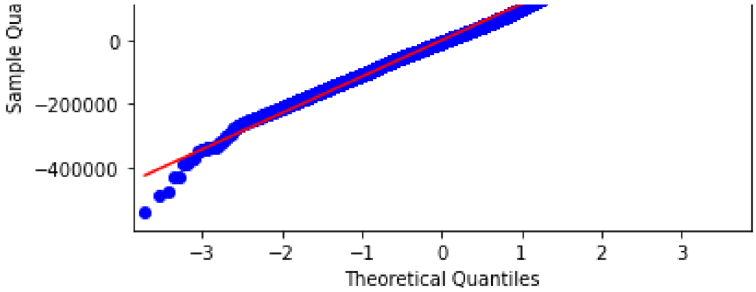
In [323]:

```
fig = sm.qqplot(trainResiduals, line = 'r')
fig2 = sm.qqplot(testResiduals, line = 'r')
fig3 = sm.qqplot(residuals, line = 'r')
```

```
C:\Users\jpake\anaconda3\envs\learn-env\lib\site-packages\numpy\linalg\linalg.py:1872: Ru
ntimeWarning: invalid value encountered in greater
  return count_nonzero(S > tol, axis=-1)
```

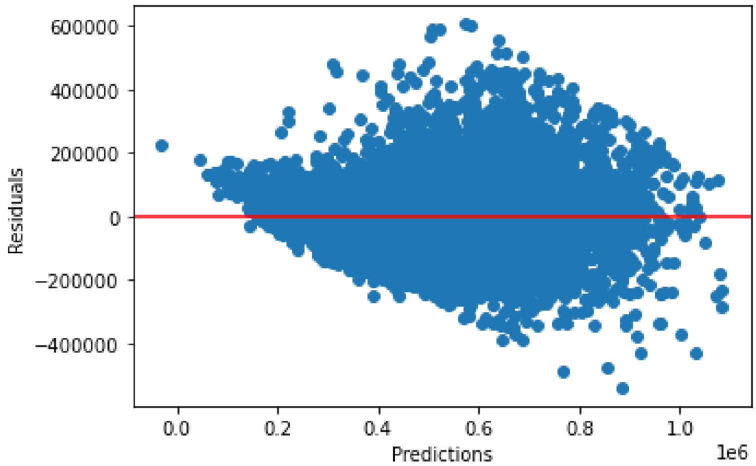






In [324]:

```
plt.scatter(yPred, residuals)
plt.axhline(y=0, color = 'red', label = '0')
plt.xlabel('Predictions')
plt.ylabel('Residuals')
plt.show()
```



This is good. Not amazing but better than what we had. We now have about a 30% variance on our predictions and parameters on what kinda of housing fits within that prediction. homes have have

- **between 2 and 7 bedrooms**
- **between 1 and 4 bathrooms but NOT 1.25 bathrooms**
- **a living space of less than 5,000 sqare feet**
- **a lot of less than 20,000 square feet**
- **3 or less floors**
- **weather or not it has a waterfront view**
- **how many people have viewed it in an open house**
- **a condition rating of greater than 2**
- **a grade rating between 3 and 12 but NOT 4**
- **a second floor of less than 6,000 square feet**
- **a basement of less than 2,000 square feet**
- **year it was built**
- **year it was renovated**
- **zipcode**
- **a longitude aproximately between -121.8 and -122.4**
- **a latitude aproximately between 47.3 amd 47.8**
- **nearest 15 neighbors with a living space of less than 4000**
- **nearest 15 neighbors with a lot space of less than 4000**

In [325]:

```
df.describe()
```

Out[325]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	
count	1.001500e+04	10015.000000	10015.000000	10015.000000	10015.000000	10015.000000	10015.000000	10015.000000	100

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
mean	4.976459e+05	3.484873	2.279406	2092.746580	7311.090764	1.565352	0.001298	0.157863
std	2.063680e+05	0.786181	0.503021	652.129974	3687.378191	0.554587	0.036007	0.611244
min	1.150000e+05	2.000000	1.500000	680.000000	520.000000	1.000000	0.000000	0.000000
25%	3.350000e+05	3.000000	1.750000	1600.000000	4782.500000	1.000000	0.000000	0.000000
50%	4.550000e+05	3.000000	2.250000	2000.000000	7205.000000	1.500000	0.000000	0.000000
75%	6.250000e+05	4.000000	2.500000	2492.500000	9417.000000	2.000000	0.000000	0.000000
max	1.190000e+06	6.000000	4.000000	4940.000000	19998.000000	3.000000	1.000000	4.000000