PredictAPrice

As a property seller in Manhattan, what are factors that affect what you should price at?

Datasets

We used NYC.gov's Rolling Sales data from the last 12 months, and 2 Zillow datasets: one showing all median prices and one of all square footage of properties sold. Both are in the year 2018. We merged all datasets together into a main dataframe.

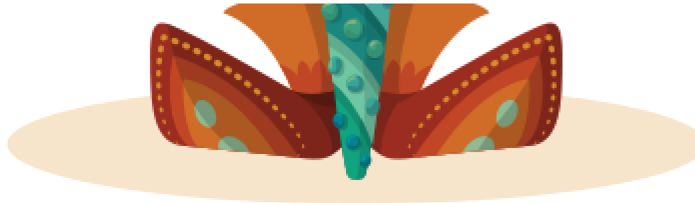
Data Cleaning

We filtered out all 0 value rows and extreme outliers.

Transforming Data

When we plotted out our graphs, the normal distribution was postively skewed. We log transformed the data and the graph read much better.

Checking Features for Usability



Import all libraries

In [1]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
from sklearn import datasets, linear_model
from sklearn.model_selection import train_test_split
from sklearn import metrics

from scipy import stats
from scipy.stats import skew,norm
from scipy.stats.stats import pearsonr


from sklearn.linear_model import LinearRegression

import statsmodels.api as sm
import statsmodels.formula.api as smf
import scipy.stats as stats
import statsmodels.stats.api as sms
import seaborn as sns


import matplotlib


# from sklearn.cross_validation import train_test_split
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn import metrics
```

Access and Filter necessary info from 3 Real Estate datasets

In [26]:
```
#combined Rolling Sales Manhattan excel sheets for years 2016-2018
data=pd.read_excel("rollingsales_manhattan.xls", skiprows=1)

##Filter 0 values and very extreme outliers
data = data[data['SALE_PRICE'] > 100]
data = data[data['SALE_PRICE'] < 250000000]
data=data[data['GROSS SQUARE FEET'] > 100]

#List of Columns pre-filtering
data.columns=['BOROUGH', 'NEIGHBORHOOD', 'BUILDING_CLASS_CATEGORY',
       'TAX_CLASS_AT_PRESENT', 'BLOCK', 'LOT', 'EASE-MENT',
       'BUILDING_CLASS_AT_PRESENT', 'ADDRESS', 'APARTMENT_NUMBER', 'ZIP_CODE',
       'RESIDENTIAL_UNITS', 'COMMERCIAL_UNITS', 'TOTAL_UNITS',
       'LAND_SQUARE_FEET', 'GROSS_SQUARE_FEET', 'YEAR_BUILT',
       'TAX_CLASS_AT_TIME_OF_SALE', 'BUILDING_CLASS_AT_TIME_OF_SALE',
       'SALE_PRICE', 'SALE_DATE']

#Pull Sq ft data from Zillow Median Square Footage Excel File
zillow_squarefootage=pd.read_excel("Zip_MedianListingPricePerSqft_AllHomes.xls")
zillow_squarefootage=zillow_squarefootage.loc[:,["RegionName","2018-10"]]
zillow_squarefootage['ZIP_CODE']=zillow_squarefootage['RegionName']
zillow_squarefootage['ZillowSquareFootage']=zillow_squarefootage['2018-10']

#Pull Median Price data from Zillow Median Price Excel File
zillow_median_listing=pd.read_excel("Zip_MedianListingPrice_AllHomes.xls")
zillow_median_listing=zillow_median_listing.loc[:,["RegionName","2018-10"]]
zillow_median_listing['ZIP_CODE']=zillow_median_listing['RegionName']
zillow_median_listing['ZillowMedianPrice']=zillow_median_listing['2018-10']

#Merge Zillow data together
new_df2= zillow_squarefootage.merge(zillow_median_listing, how = 'inner', on = ['ZIP_CODE'])
# new_df3=new_df2.merge(average_by_zip_2018, how = 'inner', on = ['ZIP_CODE'])

#Merge merged Zillow data with main excel Rolling Sales Data
new_df3= data.merge(new_df2, how = 'inner', on = ['ZIP_CODE'])
new_df=new_df3.copy()
new_df=new_df.drop(columns=['RegionName_y', 'RegionName_x',"2018-10_x","2018-10_y"])
new_df.columns
```

```
Out[26]: Index(['BOROUGH', 'NEIGHBORHOOD', 'BUILDING_CLASS_CATEGORY',
               'TAX_CLASS_AT_PRESENT', 'BLOCK', 'LOT', 'EASE-MENT',
               'BUILDING_CLASS_AT_PRESENT', 'ADDRESS', 'APARTMENT_NUMBER', 'ZIP_CODE',
               'RESIDENTIAL_UNITS', 'COMMERCIAL_UNITS', 'TOTAL_UNITS',
               'LAND_SQUARE_FEET', 'GROSS_SQUARE_FEET', 'YEAR_BUILT',
               'TAX_CLASS_AT_TIME_OF_SALE', 'BUILDING_CLASS_AT_TIME_OF_SALE',
               'SALE_PRICE', 'SALE_DATE', 'ZillowSquareFootage', 'ZillowMedianPrice'],
              dtype='object')
```

```
In [27]: new_df.head()
```

Out[27]:

	BOROUGH	NEIGHBORHOOD	BUILDING_CLASS_CATEGORY	TAX_CLASS_AT_PRESENT	BLOCK	LOT	EASE-MENT	BUILDINC
0	1	CLINTON	08 RENTALS - ELEVATOR APARTMENTS	2	1071	42		D6
1	1	CLINTON	29 COMMERCIAL GARAGES	4	1076	1		G8
2	1	MIDTOWN WEST	21 OFFICE BUILDINGS	4	1263	56		O5
3	1	CLINTON	26 OTHER HOTELS	4	1076	57		H3
4	1	CLINTON	07 RENTALS - WALKUP APARTMENTS	2	1055	55		C4

5 rows × 23 columns

Data Cleaning and Deciding what features to use

In [28]:
```
#Change the datatype of Zillow Median Price and Square Footage from Float to Integer
new_df['ZillowMedianPrice'] = new_df['ZillowMedianPrice'].astype(int)
new_df['ZillowSquareFootage'] = new_df['ZillowSquareFootage'].astype(int)

#Set target (Y value) = sales price / #Set features (X values) = all columns (will drop all unecessar
y)
target=new_df[["SALE_PRICE"]]
features= new_df

#Drop unecessary features, maybe drop both Zillow data columns
features=features.drop(columns=["SALE_DATE",'BOROUGH',
       'TAX_CLASS_AT_PRESENT', 'BLOCK', 'LOT', 'EASE-MENT',
       'BUILDING_CLASS_AT_PRESENT', 'ADDRESS', 'APARTMENT_NUMBER',
        'TOTAL_UNITS',
       'TAX_CLASS_AT_TIME_OF_SALE', 'BUILDING_CLASS_AT_TIME_OF_SALE',
      'SALE_PRICE','ZillowSquareFootage', 'ZillowMedianPrice',])

##Data Cleaning
#Strip duplicate BUILDING CLASS CATEGORY and NEIGHBORHOOD categories
features["BUILDING_CLASS_CATEGORY"]=features["BUILDING_CLASS_CATEGORY"].str.strip()
features["BUILDING_CLASS_CATEGORY"]=features["BUILDING_CLASS_CATEGORY"].str.replace(' ', '')
features["NEIGHBORHOOD"]=features["NEIGHBORHOOD"].str.strip()
features["NEIGHBORHOOD"]=features["NEIGHBORHOOD"].str.replace(' ', '')

#Set Category Variables
cat_vars=features[['BUILDING_CLASS_CATEGORY',"NEIGHBORHOOD","ZIP_CODE"]]
```

In [29]:
```
features.head()
```

Out[29]:

	NEIGHBORHOOD	BUILDING_CLASS_CATEGORY	ZIP_CODE	RESIDENTIAL_UNITS	COMMERCIAL_UNITS	LAND_SQUAR
0	CLINTON	08RENTALS-ELEVATORAPARTMENTS	10036	375	5	24100
1	CLINTON	29COMMERCIALGARAGES	10036	0	2	30125
2	MIDTOWNWEST	21OFFICEBUILDINGS	10036	0	61	8234
3	CLINTON	26OTHERHOTELS	10036	0	1	5021
4	CLINTON	07RENTALS-WALKUPAPARTMENTS	10036	20	0	2510

Change Category Variables to Dummy Variables

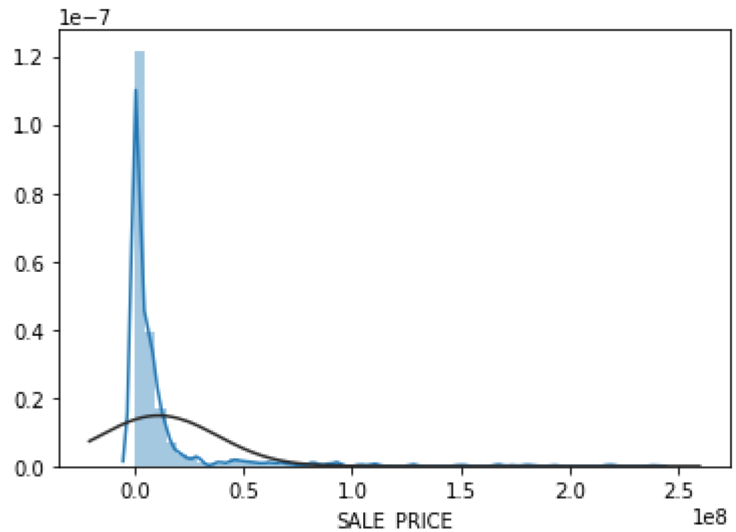
In [31]:
```
for var in cat_vars:
    cat_list='var'+'_'+var
    cat_list = pd.get_dummies(features[var], prefix=var)#,drop_first=True)
    data1=features.join(cat_list)
    features=data1
data_vars=features.columns.values.tolist()
to_keep=[i for i in data_vars if i not in cat_vars]
features=features[to_keep]
```

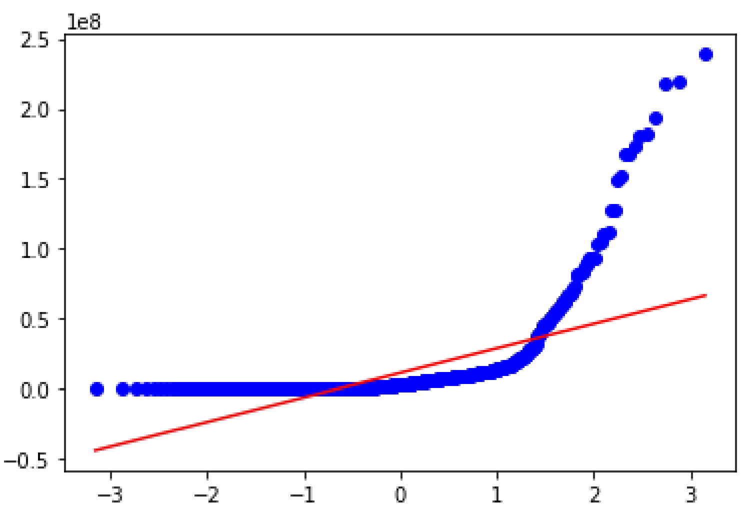
Graph out Sale Price Distribution

In [32]:
```
new_df["SALE_PRICE"].describe()
sns.distplot(new_df.SALE_PRICE,fit=norm);
plt.ylabel =('Frequency')
plt.title = ('SalePrice Distribution');
#Get the fitted parameters used by the function
(mu, sigma) = norm.fit(new_df["SALE_PRICE"]);
#QQ plot
fig = plt.figure()
res = stats.probplot(new_df["SALE_PRICE"], plot=plt)
# plt.show()
print("skewness: %f" % new_df["SALE_PRICE"].skew())
print("kurtosis: %f" % new_df["SALE_PRICE"].kurt())
```

```
/Users/chrischung/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Us
ing a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead
of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
skewness: 4.750264
kurtosis: 26.823504
```



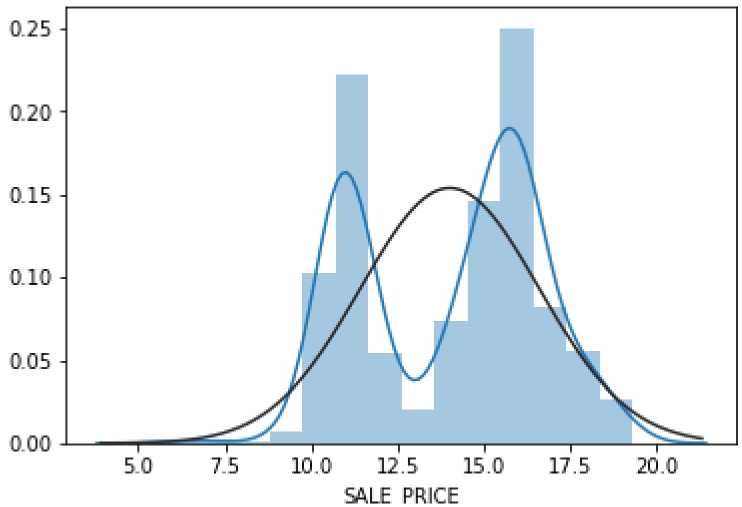


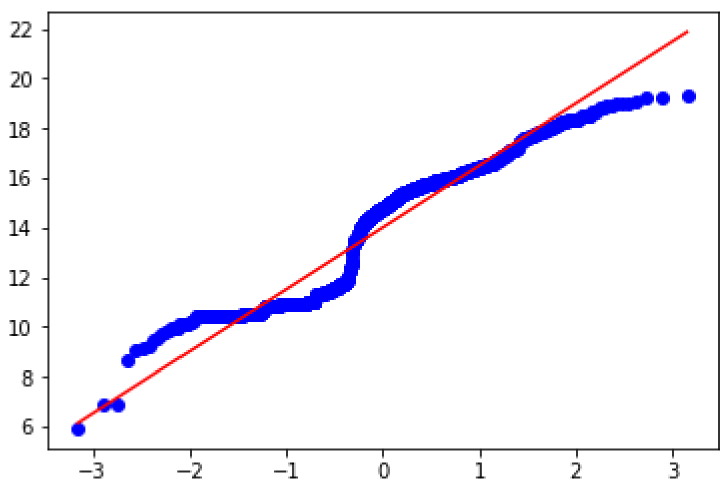
Transform Data

In [33]:
```
#notes
#Plotted the distribution of the SALE_PRICE and normal probability graph which is used to identify su
bstantive departures from normality. This includes identifying outliers, skewness and kurtosis. Used
 the QQ-plot
#log transform the target
new_df["SALE_PRICE"] = np.log1p(new_df["SALE_PRICE"])

#Kernel Density plot
sns.distplot(new_df.SALE_PRICE,fit=norm);
plt.ylabel=('Frequency')
plt.title=('SalePrice distribution');
#Get the fitted parameters used by the function
(mu,sigma)= norm.fit(new_df["SALE_PRICE"]);
#QQ plot
fig =plt.figure()
res =stats. probplot(new_df["SALE_PRICE"], plot=plt)
plt.show()
```

```
/Users/chrischung/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Us
ing a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead
of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



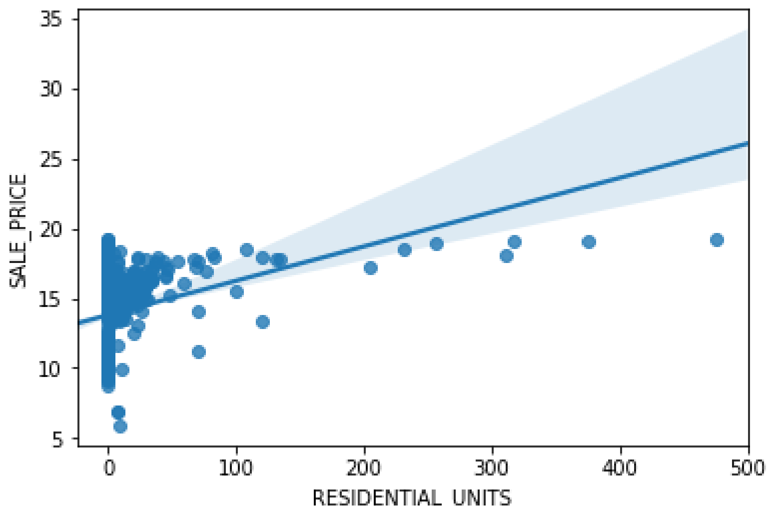


Step 1: Checking for Linearity using Scatterplots

In [34]:
```
sns.regplot(y=new_df.SALE_PRICE, x=new_df['RESIDENTIAL_UNITS'], data=new_df, fit_reg = True)
```

```
/Users/chrischung/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Us
ing a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead
of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

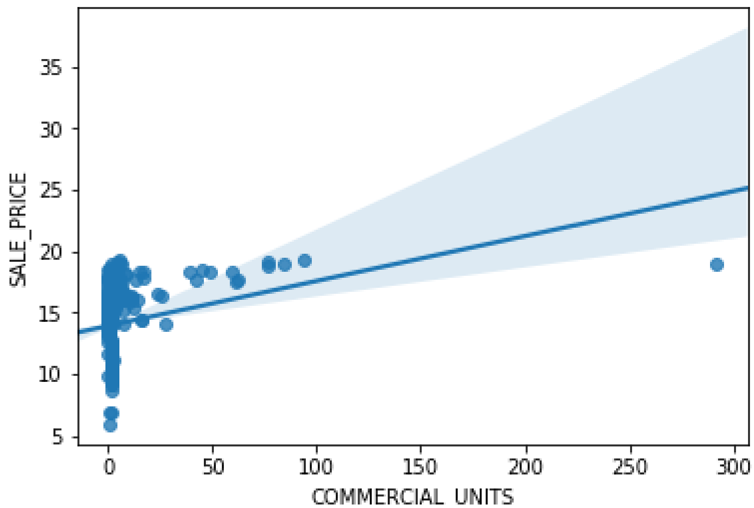
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2953d438>



In [35]:
```
sns.regplot(y=new_df.SALE_PRICE, x=new_df['COMMERCIAL_UNITS'], data=new_df, fit_reg = True)
```

```
/Users/chrischung/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

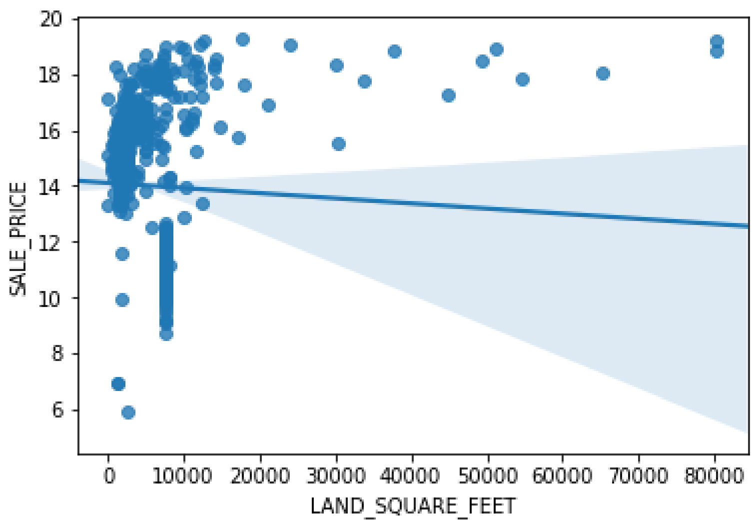
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1c295253c8>



In [36]:
```
sns.regplot(y=new_df.SALE_PRICE, x=new_df['LAND_SQUARE_FEET'], data=new_df, fit_reg = True)
```

```
/Users/chrischung/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Us
ing a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead
of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which
will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

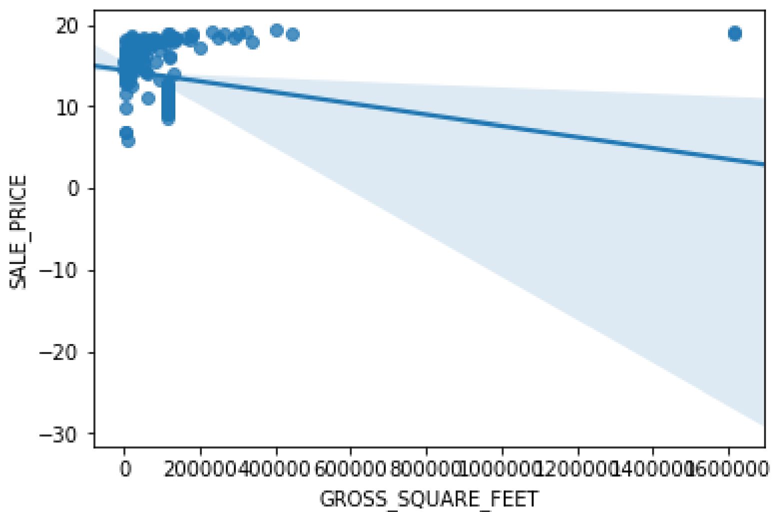
Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2964a518>



In [37]:
```
sns.regplot(y=new_df.SALE_PRICE, x=new_df['GROSS_SQUARE_FEET'], data=new_df, fit_reg = True)
```

```
/Users/chrischung/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

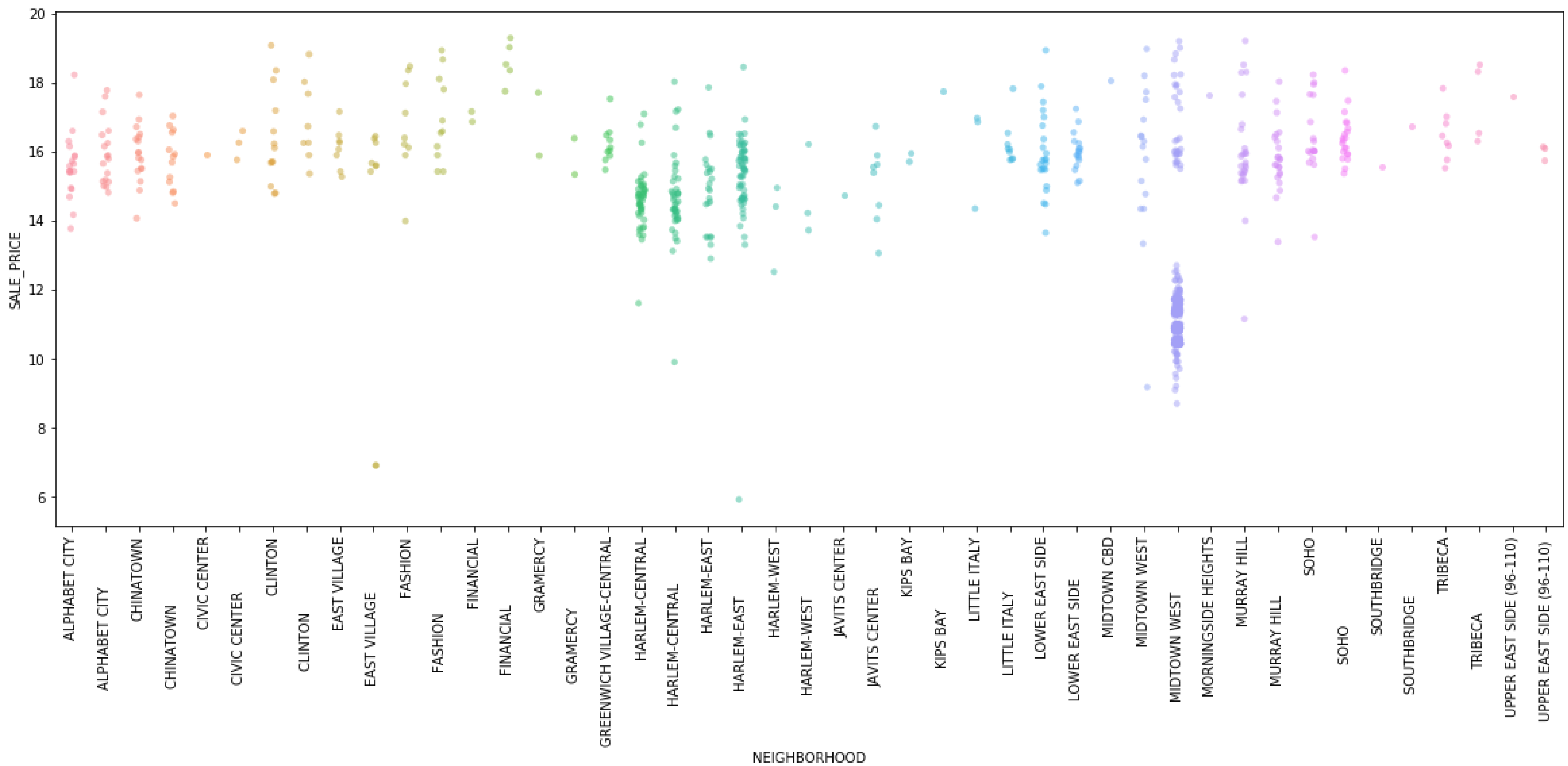
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2962e5f8>



Graph showing the distribution of prices by neighborhoood

In [38]:
```
plt.figure(figsize=(20,7))
sns.stripplot(x = new_df.NEIGHBORHOOD, y = new_df.SALE_PRICE,
              order = np.sort(new_df.NEIGHBORHOOD.unique()),
              jitter=0.1, alpha=0.5)
plt.xticks(rotation=90)
```

Out[38]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44]),
 <a list of 45 Text xticklabel objects>)
```



Distribution of square footage and sale price

In [39]:
```
plt.figure(figsize=(12,7))
sns.stripplot(x = new_df.GROSS_SQUARE_FEET, y = new_df.SALE_PRICE,
              order = np.sort(new_df.GROSS_SQUARE_FEET),
              jitter=0.1, alpha=0.5)
plt.xticks(rotation=45)
```

```
Out[39]: (array([  0,   1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  12,
                  13,  14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  25,
                  26,  27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  38,
                  39,  40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  51,
                  52,  53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  64,
                  65,  66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  76,  77,
                  78,  79,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,
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                 442, 443, 444, 445, 446, 447, 448, 449, 450, 451, 452, 453, 454,
                 455, 456, 457, 458, 459, 460, 461, 462, 463, 464, 465, 466, 467,
                 468, 469, 470, 471, 472, 473, 474, 475, 476, 477, 478, 479, 480,
                 481, 482, 483, 484, 485, 486, 487, 488, 489, 490, 491, 492, 493,
                 494, 495, 496, 497, 498, 499, 500, 501, 502, 503, 504, 505, 506,
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                 520, 521, 522, 523, 524, 525, 526, 527, 528, 529, 530, 531, 532,
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                 546, 547, 548, 549, 550, 551, 552, 553, 554, 555, 556, 557, 558,
```

```
        559, 560, 561, 562, 563, 564, 565, 566, 567, 568, 569, 570, 571,
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        715, 716, 717, 718, 719, 720, 721, 722, 723, 724, 725, 726, 727,
        728, 729, 730, 731, 732, 733, 734, 735, 736, 737, 738, 739, 740,
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        806, 807, 808, 809, 810, 811, 812, 813, 814, 815, 816, 817, 818,
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        832, 833, 834, 835, 836, 837, 838, 839, 840, 841, 842, 843, 844,
        845, 846, 847, 848, 849, 850, 851, 852, 853, 854, 855, 856, 857,
        858, 859, 860, 861, 862, 863, 864, 865]),
 <a list of 866 Text xticklabel objects>)
```
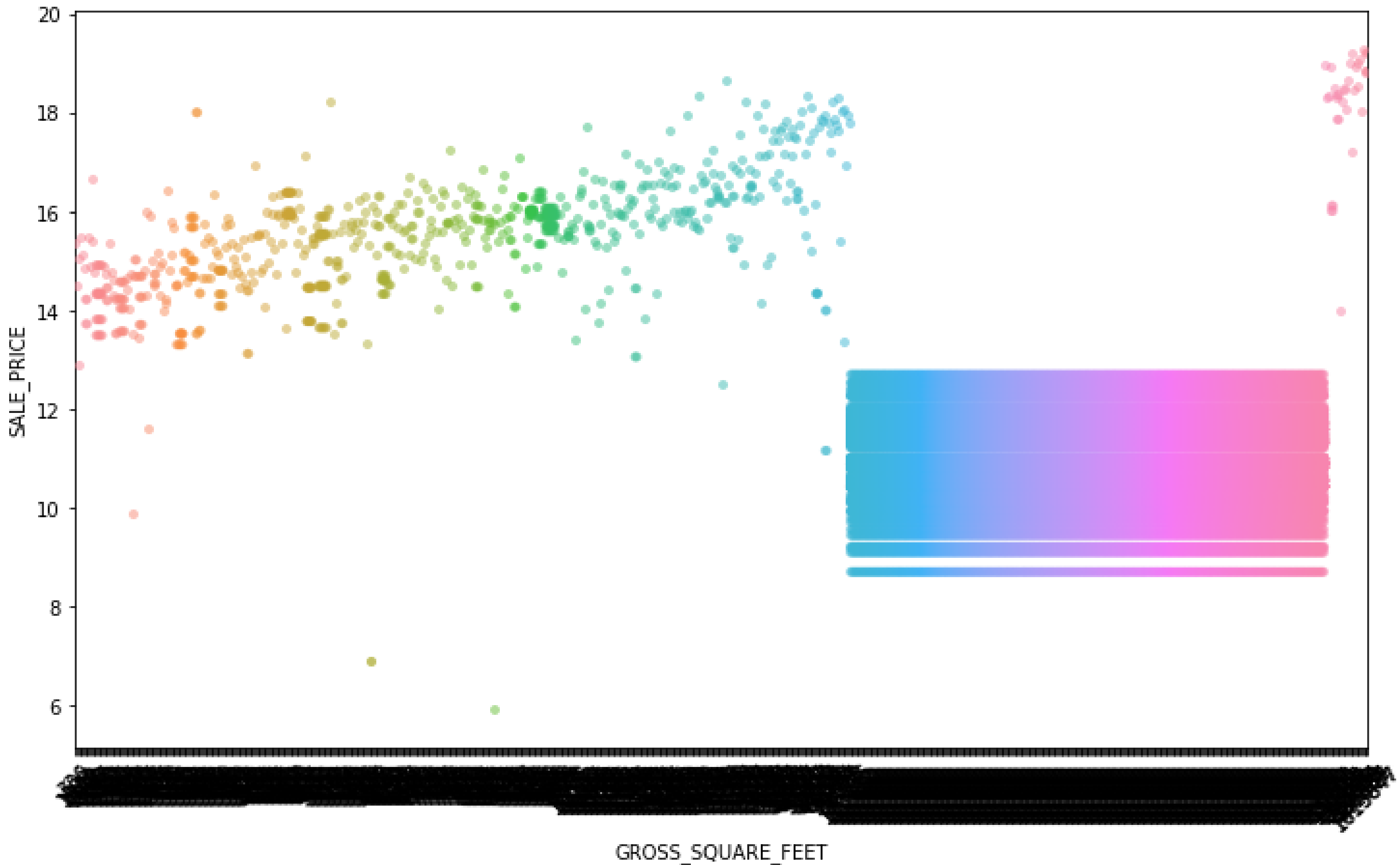
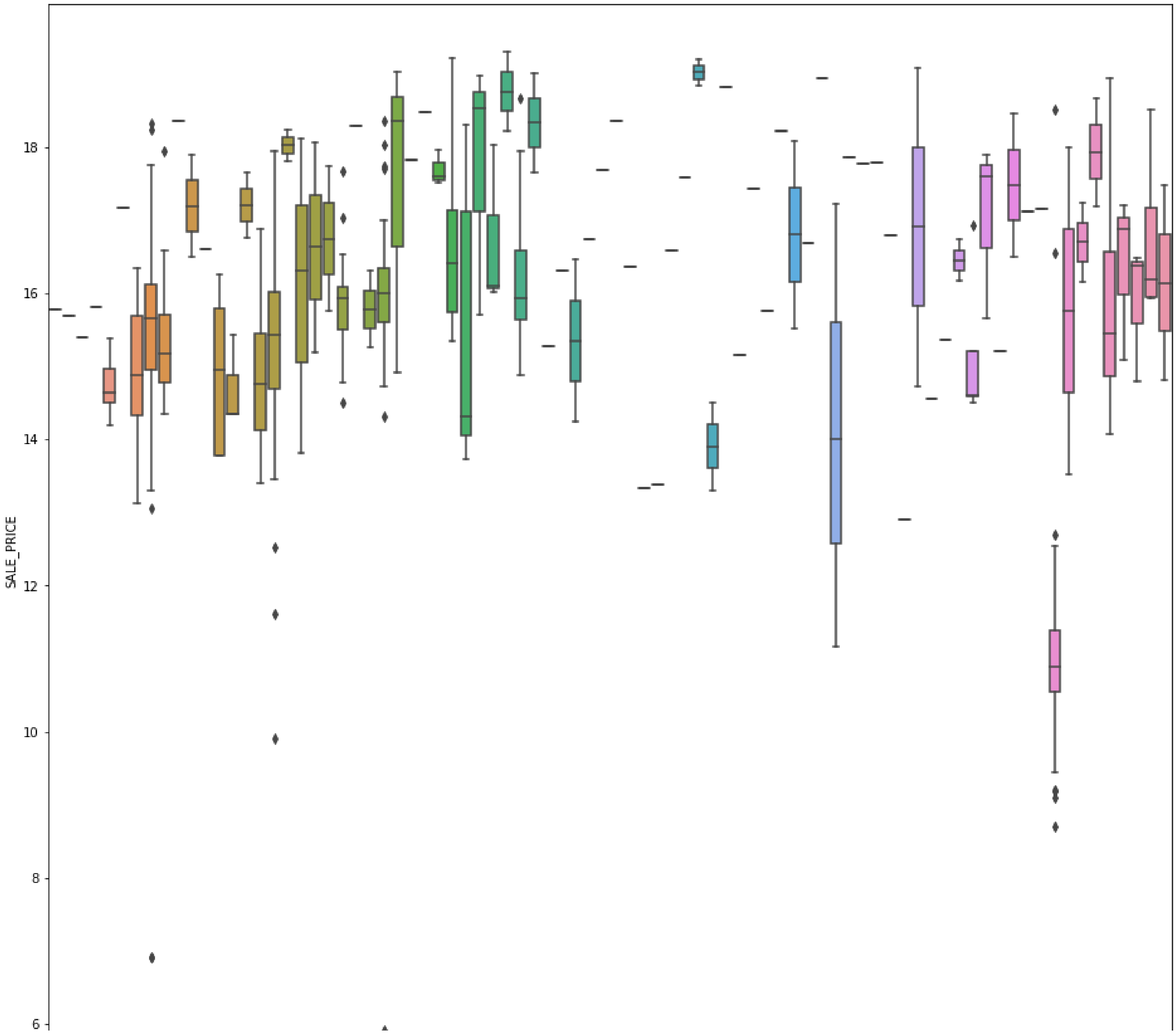
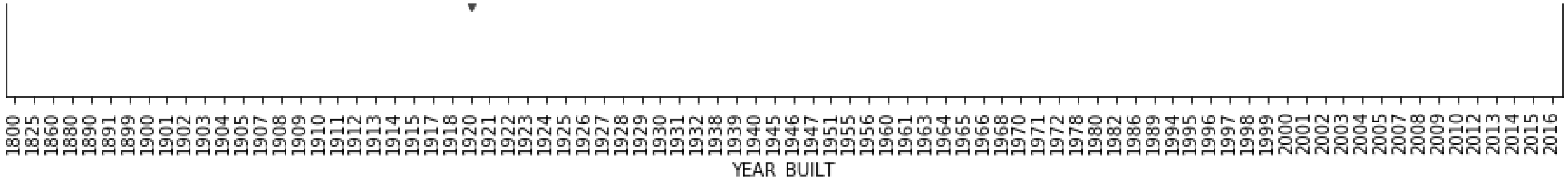



Distribution of homes built by year

In [40]:
```
var  = 'YEAR_BUILT'
data= pd.concat([new_df['SALE_PRICE'], new_df[var]], axis =1)
f, ax = plt.subplots(figsize=(16, 16))
fig = sns.boxplot(x=var, y=new_df['SALE_PRICE'], data=data)
fig.axis(ymin=5)
plt.xticks(rotation=90);
plt.show();
```


SALE_PRICE
18
16
14
12
10
8
6



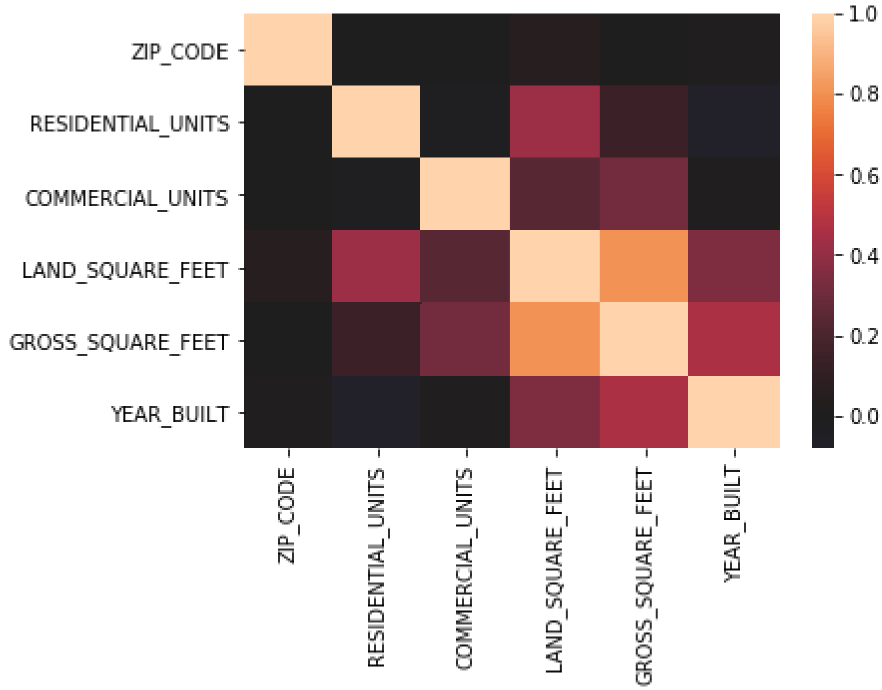
Correlation of Features

In [45]:
```
features.corr() >.75
```

Out[45]:

	ZIP_CODE	RESIDENTIAL_UNITS	COMMERCIAL_UNITS	LAND_SQUARE_FEET	GROSS_SQUARE_F
ZIP_CODE	True	False	False	False	False
RESIDENTIAL_UNITS	False	True	False	False	False
COMMERCIAL_UNITS	False	False	True	False	False
LAND_SQUARE_FEET	False	False	False	True	True
GROSS_SQUARE_FEET	False	False	False	True	True
YEAR_BUILT	False	False	False	False	False

In [47]:
```
import seaborn as sns
sns.heatmap(features.corr(), center=0);
```



Regression Info Below

Features described first

In [41]:
```
features.describe()
```

Out[41]:

	RESIDENTIAL_UNITS	COMMERCIAL_UNITS	LAND_SQUARE_FEET	GROSS_SQUARE_FEET	YEAR_BUILT	BUILDING
count	866.000000	866.000000	866.000000	8.660000e+02	866.000000	866.00000
mean	9.247113	2.975751	5549.627021	5.932070e+04	1952.683603	0.032333
std	31.859502	12.372564	6301.376164	9.459625e+04	48.081714	0.176984
min	0.000000	0.000000	0.000000	3.360000e+02	1800.000000	0.000000
25%	0.000000	1.000000	2124.250000	6.251500e+03	1910.000000	0.000000
50%	0.000000	2.000000	4966.500000	2.035950e+04	1925.000000	0.000000
75%	8.000000	2.000000	7532.000000	1.128500e+05	2007.000000	0.000000
max	476.000000	292.000000	80333.000000	1.613847e+06	2016.000000	1.000000

8 rows × 65 columns

Of the 5 original features used [RESIDENTIAL_UNITS, COMMERCIAL_UNITS, LAND_SQUARE_FEET, GROSS_SQUARE_FEET and YEAR_BUILT], only the LAND_SQUARE_FEET had a P value above 0.05. Its value was 0.219

R^2 total using 4 features = 0.727

In [42]:
```
# GROSS_SQUARE_FEET:0.645
# Residential Units: 0.071
# COMMERCIAL_UNITS :0.098
# LAND_SQUARE_FEET:0.534
# YEAR_BUILT:0.000
#ZillowSquareFootage:0.006... pvalue of 0.024
#ZillowMedianPrice0.012...pvalue of 0.001
#ALL WITH ZILLOW: 0.729

m7 = ols('SALE_PRICE ~RESIDENTIAL_UNITS+COMMERCIAL_UNITS+GROSS_SQUARE_FEET+YEAR_BUILT',new_df).fit()
print(m7.summary())
m1 = ols('SALE_PRICE ~GROSS_SQUARE_FEET',new_df).fit()
print(m1.summary())
# m2 = ols('SALE_PRICE ~RESIDENTIAL_UNITS ',new_df).fit()
# print(m2.summary())
# m3 = ols('SALE_PRICE ~COMMERCIAL_UNITS ',new_df).fit()
# print(m3.summary())
# m4 = ols('SALE_PRICE ~LAND_SQUARE_FEET ',new_df).fit()
# print(m4.summary())
m5 = ols('SALE_PRICE ~GROSS_SQUARE_FEET ',new_df).fit()
print(m1.summary())
# m6 = ols('SALE_PRICE ~YEAR_BUILT ',new_df).fit()
# print(m6.summary())


#####regression for zillow items below
# m8 = ols('SALE_PRICE ~ZillowSquareFootage ',new_df).fit()
# print(m8.summary())
# m9 = ols('SALE_PRICE ~ZillowMedianPrice ',new_df).fit()
# print(m9.summary())
# m10 = ols('SALE_PRICE ~RESIDENTIAL_UNITS+ZillowSquareFootage+ZillowMedianPrice+COMMERCIAL_UNITS+LAN
D_SQUARE_FEET+GROSS_SQUARE_FEET+YEAR_BUILT ',new_df).fit()
# print(m10.summary())

1- (RSS/TSS)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             SALE_PRICE   R-squared:                       0.602
Model:                            OLS   Adj. R-squared:                  0.601
Method:                 Least Squares   F-statistic:                     326.2
Date:                Fri, 07 Dec 2018   Prob (F-statistic):          8.86e-171
Time:                        13:33:48   Log-Likelihood:                -1653.8
No. Observations:                 866   AIC:                             3318.
Df Residuals:                     861   BIC:                             3341.
Df Model:                           4
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept            84.9087      2.607     32.565      0.000      79.791      90.026
RESIDENTIAL_UNITS     0.0208      0.002     11.541      0.000       0.017       0.024
COMMERCIAL_UNITS      0.0424      0.005      8.798      0.000       0.033       0.052
GROSS_SQUARE_FEET -1.034e-06   7.26e-07     -1.423      0.155   -2.46e-06    3.92e-07
YEAR_BUILT           -0.0364      0.001    -27.134      0.000      -0.039      -0.034
==============================================================================
Omnibus:                      138.842   Durbin-Watson:                   1.210
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1003.100
Skew:                           0.503   Prob(JB):                    1.51e-218
Kurtosis:                       8.176   Cond. No.                     5.23e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.23e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
                            OLS Regression Results
==============================================================================
Dep. Variable:             SALE_PRICE   R-squared:                       0.061
Model:                            OLS   Adj. R-squared:                  0.060
Method:                 Least Squares   F-statistic:                     56.30
Date:                Fri, 07 Dec 2018   Prob (F-statistic):           1.55e-13
Time:                        13:33:48   Log-Likelihood:                -2025.9
No. Observations:                 866   AIC:                             4056.
Df Residuals:                     864   BIC:                             4065.
Df Model:                           1
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
```

```
------------------------------------------------------------------------------------
Intercept            14.4053      0.101    142.878      0.000      14.207      14.603
GROSS_SQUARE_FEET -6.778e-06   9.03e-07     -7.503      0.000   -8.55e-06      -5e-06
==============================================================================
Omnibus:                       99.204   Durbin-Watson:                   0.360
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              276.513
Skew:                           0.587   Prob(JB):                     9.03e-61
Kurtosis:                       5.507   Cond. No.                     1.32e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.32e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
                            OLS Regression Results
==============================================================================
Dep. Variable:             SALE_PRICE   R-squared:                       0.061
Model:                            OLS   Adj. R-squared:                  0.060
Method:                 Least Squares   F-statistic:                     56.30
Date:                Fri, 07 Dec 2018   Prob (F-statistic):           1.55e-13
Time:                        13:33:48   Log-Likelihood:                -2025.9
No. Observations:                 866   AIC:                             4056.
Df Residuals:                     864   BIC:                             4065.
Df Model:                           1
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept            14.4053      0.101    142.878      0.000      14.207      14.603
GROSS_SQUARE_FEET -6.778e-06   9.03e-07     -7.503      0.000   -8.55e-06      -5e-06
==============================================================================
Omnibus:                       99.204   Durbin-Watson:                   0.360
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              276.513
Skew:                           0.587   Prob(JB):                     9.03e-61
Kurtosis:                       5.507   Cond. No.                     1.32e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.32e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [43]:
```
reg = LinearRegression()
```

In [22]:
```
new_df
```

Out[22]:

	BOROUGH	NEIGHBORHOOD	BUILDING_CLASS_CATEGORY	TAX_CLASS_AT_PRESENT	BLOCK	LOT	EASE-MENT	BUILDI
0	1	CLINTON	08 RENTALS - ELEVATOR APARTMENTS	2	1071	42		D6
1	1	CLINTON	29 COMMERCIAL GARAGES	4	1076	1		G8
2	1	MIDTOWN WEST	21 OFFICE BUILDINGS	4	1263	56		O5
3	1	CLINTON	26 OTHER HOTELS	4	1076	57		H3
4	1	CLINTON	07 RENTALS - WALKUP APARTMENTS	2	1055	55		C4
5	1	MIDTOWN WEST	22 STORE BUILDINGS	4	1034	31		K4
6	1	CLINTON	07 RENTALS - WALKUP APARTMENTS	2	1053	6		C4
7	1	CLINTON	07 RENTALS - WALKUP APARTMENTS	2A	1058	113		C3
8	1	MIDTOWN WEST	22 STORE BUILDINGS	4	1263	55		K9
9	1	MIDTOWN WEST	22 STORE BUILDINGS	4	1263	21		K2
10	1	MIDTOWN WEST	22 STORE BUILDINGS	4	999	11		K4
11	1	CLINTON	02 TWO FAMILY DWELLINGS	1	1053	55		S2

	BOROUGH	NEIGHBORHOOD	BUILDING_CLASS_CATEGORY	TAX_CLASS_AT_PRESENT	BLOCK	LOT	EASE-MENT	BUILDI
12	1	MIDTOWN WEST	38 ASYLUMS AND HOMES	4	1039	123		N9
13	1	CLINTON	29 COMMERCIAL GARAGES	4	1095	24		G2
14	1	CLINTON	37 RELIGIOUS FACILITIES	4	1053	59		M4
15	1	MIDTOWN WEST	07 RENTALS - WALKUP APARTMENTS	2	1036	45		C7
16	1	MIDTOWN WEST	21 OFFICE BUILDINGS	4	1260	1		O4
17	1	MIDTOWN WEST	21 OFFICE BUILDINGS	4	1260	64		O6
18	1	MIDTOWN WEST	21 OFFICE BUILDINGS	4	1263	1		O5
19	1	MIDTOWN WEST	22 STORE BUILDINGS	4	1001	11		K9
20	1	MIDTOWN WEST	25 LUXURY HOTELS	4	1260	56		H2
21	1	MIDTOWN WEST	29 COMMERCIAL GARAGES	4	1263	45		G1
22	1	LOWER EAST SIDE	08 RENTALS - ELEVATOR APARTMENTS	2	246	1		D6
23	1	LOWER EAST SIDE	08 RENTALS - ELEVATOR APARTMENTS	2	283	24		D7

	BOROUGH	NEIGHBORHOOD	BUILDING_CLASS_CATEGORY	TAX_CLASS_AT_PRESENT	BLOCK	LOT	EASE-MENT	BUILDI
24	1	LOWER EAST SIDE	08 RENTALS - ELEVATOR APARTMENTS	2	343	68		D6
25	1	LOWER EAST SIDE	08 RENTALS - ELEVATOR APARTMENTS	2	350	69		D1
26	1	CHINATOWN	07 RENTALS - WALKUP APARTMENTS	2	277	2		C7
27	1	LOWER EAST SIDE	21 OFFICE BUILDINGS	4	424	6		O6
28	1	LOWER EAST SIDE	07 RENTALS - WALKUP APARTMENTS	2	411	42		C7
29	1	CHINATOWN	07 RENTALS - WALKUP APARTMENTS	2	280	10		C7
...	...	...	...	...	...	...	...	...
836	1	GREENWICH VILLAGE-CENTRAL	23 LOFT BUILDINGS	4	529	62		L3
837	1	SOHO	08 RENTALS - ELEVATOR APARTMENTS	2	488	8		D1
838	1	LITTLE ITALY	07 RENTALS - WALKUP APARTMENTS	2	507	10		C7
839	1	LITTLE ITALY	07 RENTALS - WALKUP APARTMENTS	2	507	1		C7

	BOROUGH	NEIGHBORHOOD	BUILDING_CLASS_CATEGORY	TAX_CLASS_AT_PRESENT	BLOCK	LOT	EASE-MENT	BUILDI
840	1	GREENWICH VILLAGE-CENTRAL	07 RENTALS - WALKUP APARTMENTS	2B	537	11		C7
841	1	LITTLE ITALY	01 ONE FAMILY DWELLINGS	1	494	22		A7
842	1	GREENWICH VILLAGE-CENTRAL	07 RENTALS - WALKUP APARTMENTS	2B	543	67		C5
843	1	GREENWICH VILLAGE-CENTRAL	07 RENTALS - WALKUP APARTMENTS	2A	531	39		C3
844	1	SOHO	22 STORE BUILDINGS	4	499	15		K9
845	1	GREENWICH VILLAGE-CENTRAL	03 THREE FAMILY DWELLINGS	1	526	45		C0
846	1	GREENWICH VILLAGE-CENTRAL	01 ONE FAMILY DWELLINGS	1	525	34		S1
847	1	GREENWICH VILLAGE-CENTRAL	01 ONE FAMILY DWELLINGS	1	526	51		A4
848	1	GREENWICH VILLAGE-CENTRAL	02 TWO FAMILY DWELLINGS	1	542	46		S2
849	1	GREENWICH VILLAGE-CENTRAL	14 RENTALS - 4-10 UNIT	2A	526	61		S4

	BOROUGH	NEIGHBORHOOD	BUILDING_CLASS_CATEGORY	TAX_CLASS_AT_PRESENT	BLOCK	LOT	EASE-MENT	BUILDI
850	1	GREENWICH VILLAGE-CENTRAL	23 LOFT BUILDINGS	4	525	31		L9
851	1	LITTLE ITALY	07 RENTALS - WALKUP APARTMENTS	2	494	28		C7
852	1	LITTLE ITALY	07 RENTALS - WALKUP APARTMENTS	2	508	42		C7
853	1	LITTLE ITALY	07 RENTALS - WALKUP APARTMENTS	2B	508	43		C7
854	1	LITTLE ITALY	07 RENTALS - WALKUP APARTMENTS	2	510	26		C7
855	1	SOHO	07 RENTALS - WALKUP APARTMENTS	2	489	36		C7
856	1	SOHO	07 RENTALS - WALKUP APARTMENTS	2B	496	35		C7
857	1	SOHO	14 RENTALS - 4-10 UNIT	2A	520	79		S5
858	1	SOHO	41 TAX CLASS 4 - OTHER	4	511	19		O2
859	1	SOHO	41 TAX CLASS 4 - OTHER	4	513	28		K2
860	1	FINANCIAL	08 RENTALS - ELEVATOR APARTMENTS	2A	79	26		D5

	BOROUGH	NEIGHBORHOOD	BUILDING_CLASS_CATEGORY	TAX_CLASS_AT_PRESENT	BLOCK	LOT	EASE-MENT	BUILDI
861	1	SOUTHBRIDGE	14 RENTALS - 4-10 UNIT	2A	90	23		S5
862	1	FINANCIAL	26 OTHER HOTELS	4	78	20		H8
863	1	SOUTHBRIDGE	08 RENTALS - ELEVATOR APARTMENTS	2	92	3		D5
864	1	CIVIC CENTER	14 RENTALS - 4-10 UNIT	2B	145	10		S9
865	1	CIVIC CENTER	23 LOFT BUILDINGS	4	136	20		L8

866 rows × 23 columns

In [44]:
```
train1= features # can change to scaled_features or features to test regresion model with or without
 categorical values
labels=target
```

In [45]:
```
x_train , x_test , y_train , y_test = train_test_split(train1 , labels , test_size = 0.20,random_stat
e =30)
```

In [83]:
```
lm = LinearRegression()
lm.fit(x_train,y_train)

# evaluation using r-square

lm.score(x_train,y_train)
# x_test
```

Out[83]: 0.7317281102976905

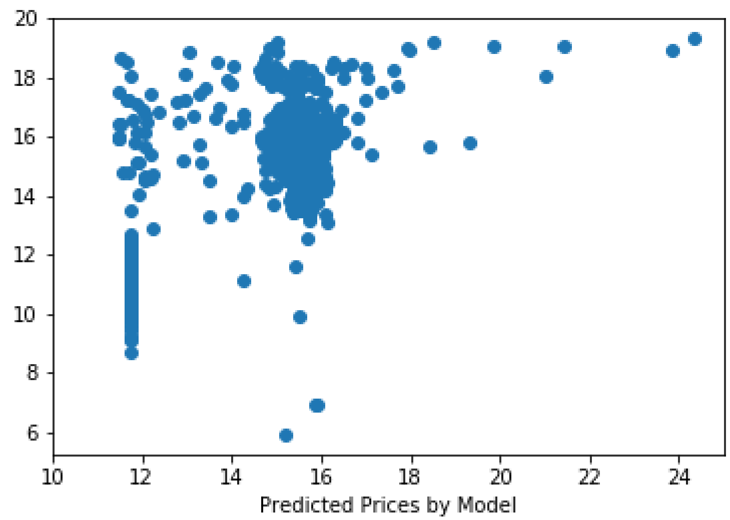
We create a scatterplot between the predicted prices, (where m is the fitted model) and the original prices.

A perfect model would get us a scatterplot where all the data lies on the 45 degree line.

Data shows we are more accurate when we hit prices around 160 million

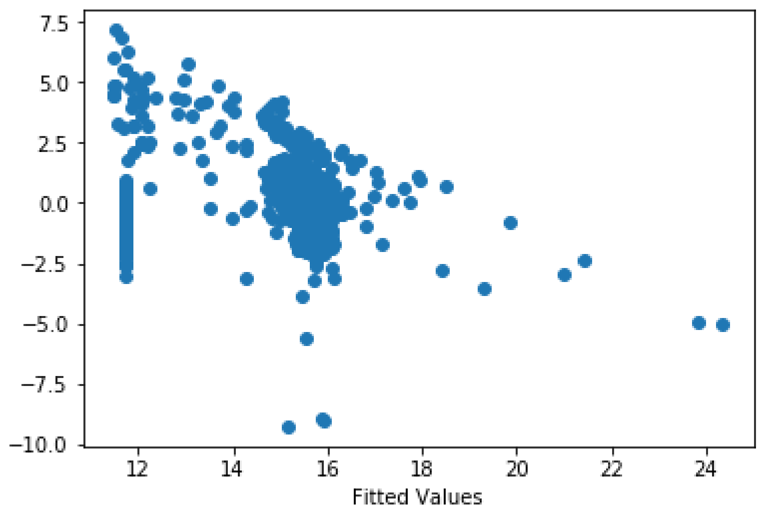
In [52]:
```
import matplotlib.pyplot as plt
```

In [63]:
```
predicted_prices = m7.fittedvalues

plt.scatter(predicted_prices, new_df.SALE_PRICE)
plt.xlabel("Predicted Prices by Model")
plt.ylabel='Original Prices'
plt.title='Predictions vs. Original Prices'
plt.xlim((10,25))
plt.show()
```



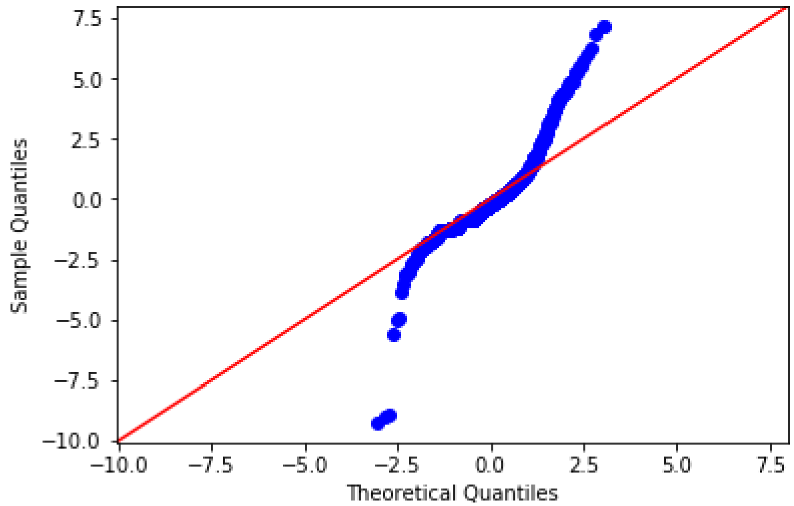
In [57]:
```
x = m7.fittedvalues
y = m7.resid
plt.scatter(x, y)

plt.xlabel("Fitted Values")
# plt.ylabel("Residual")
# plt.title("Fitted Values vs. Residuals")

## the model is predicting heteroskedastically,
because we are overpredicting the price when the actual price is low and underpredicting when it is h
igh
```

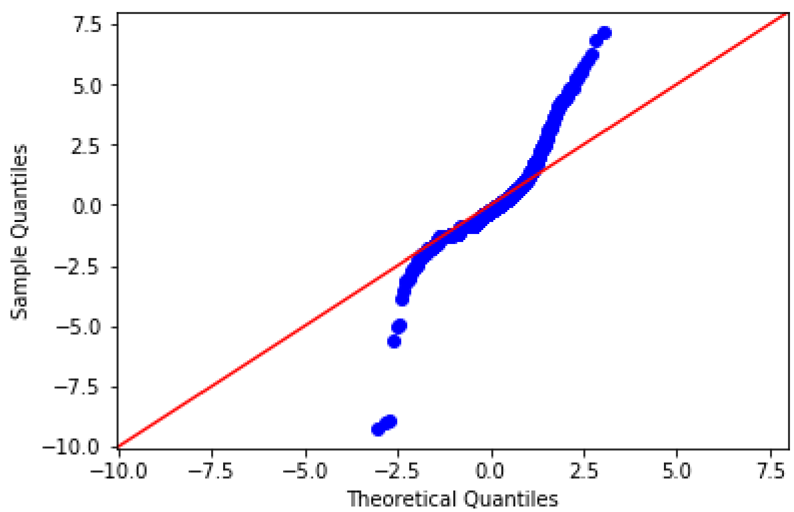
Out[57]: Text(0.5,0,'Fitted Values')



In [64]:
```
sm.qqplot(m7.resid,line='45')
```

Out[64]:





In [82]:
```
np.sqrt(metrics.mean_squared_error(y_test, y_pred))/np.std(y_train)
```

Out[82]:
```
SALE_PRICE    0.502126
dtype: float64
```

In [67]:
```
reg.fit(x_train,y_train)
reg.score(x_test,y_test)
#highest score with all variables (2110) is .79
```

Out[67]: 0.7250078942974605

In [69]:
```
y_pred = lm.predict(x_test) #from seans ridge nad lasso slides

print('MSE:', metrics.mean_squared_error(y_test, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
MSE: 184264415698494.62
RMSE: 13574402.959191047
```

Overall Metrics

- Root Mean Square Error : 13574402.959191047

In [28]:
```
from sklearn.metrics import median_absolute_error
median_absolute_error(y_test, y_pred)
# sklearn.metrics.median_absolute_error(y_true, y_pred)[source]
```

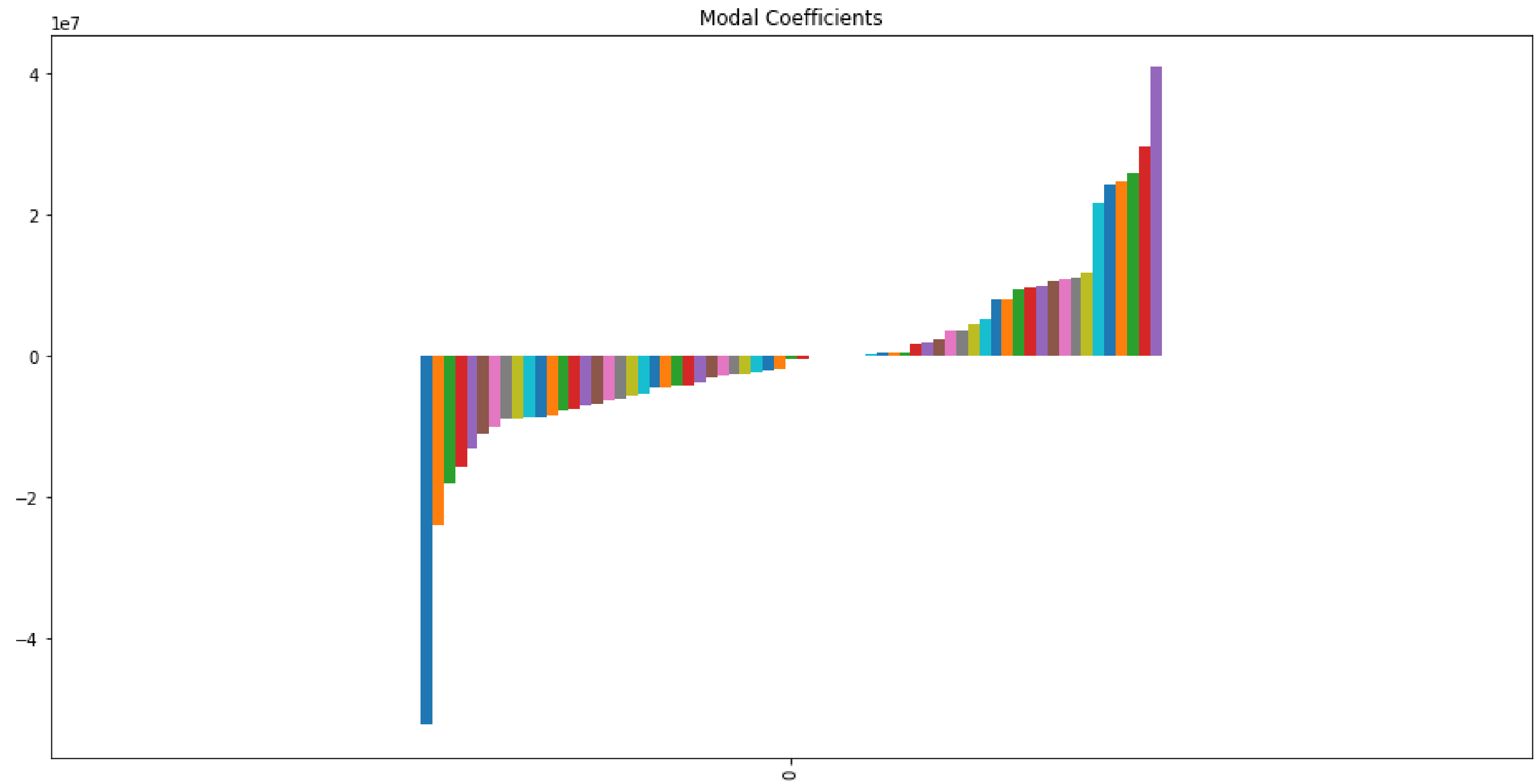
Out[28]: 1585151.4366711155

Next Steps

- Regularization (with Lasso and Ridge)
- Determine why our predictions are heteroskedastic.

In [29]:
```
coef = pd.DataFrame(data=lm.coef_, columns=x_train.columns ) #takes co-effficent and pairs up with co
lumns, and looks at

model_coef = coef.T.sort_values(by=0).T

model_coef.plot(kind='bar', title='Modal Coefficients', legend=False, figsize=(16,8))
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x1c24c92b00>



In [30]:
```
y_test.std()
```

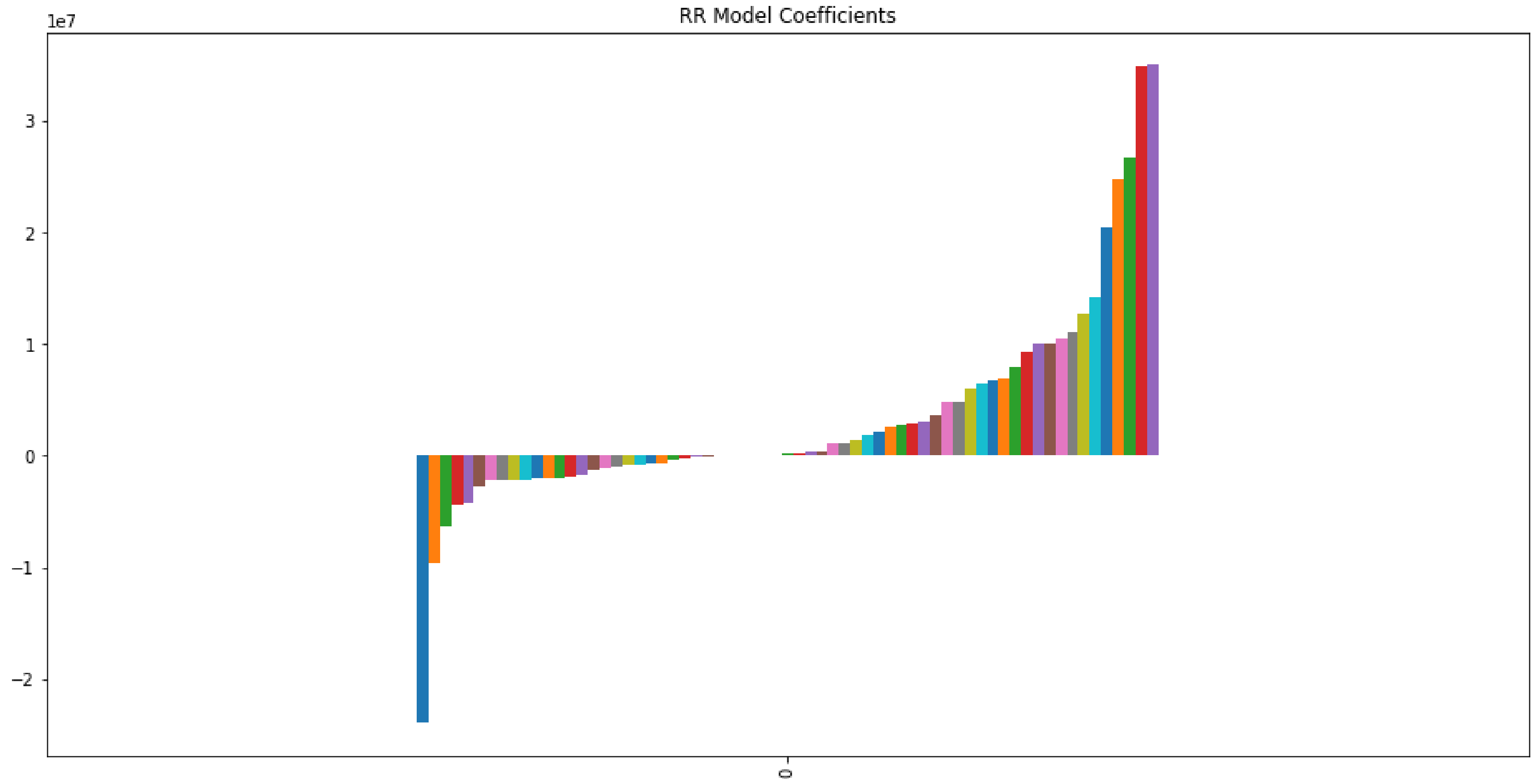
Out[30]:
```
SALE_PRICE    2.596045e+07
dtype: float64
```

In [31]:

```
X_train=x_train #***
X_test=x_test
ridgeReg = Ridge(alpha=.50, normalize=True)

ridgeReg.fit(X_train,y_train)

y_pred = ridgeReg.predict(X_test)

#calculating mse

print('MSE:', metrics.mean_squared_error(y_test, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred))/ y_test.std())
coef = pd.DataFrame(data=ridgeReg.coef_, columns=X_train.columns )

model_coef = coef.T.sort_values(by=0).T

model_coef.plot(kind='bar', title='RR Model Coefficients', legend=False, figsize=(16,8))
```

```
MSE: 247987123402372.03
RMSE: 15747606.91033314
SALE_PRICE    0.6066
dtype: float64
```

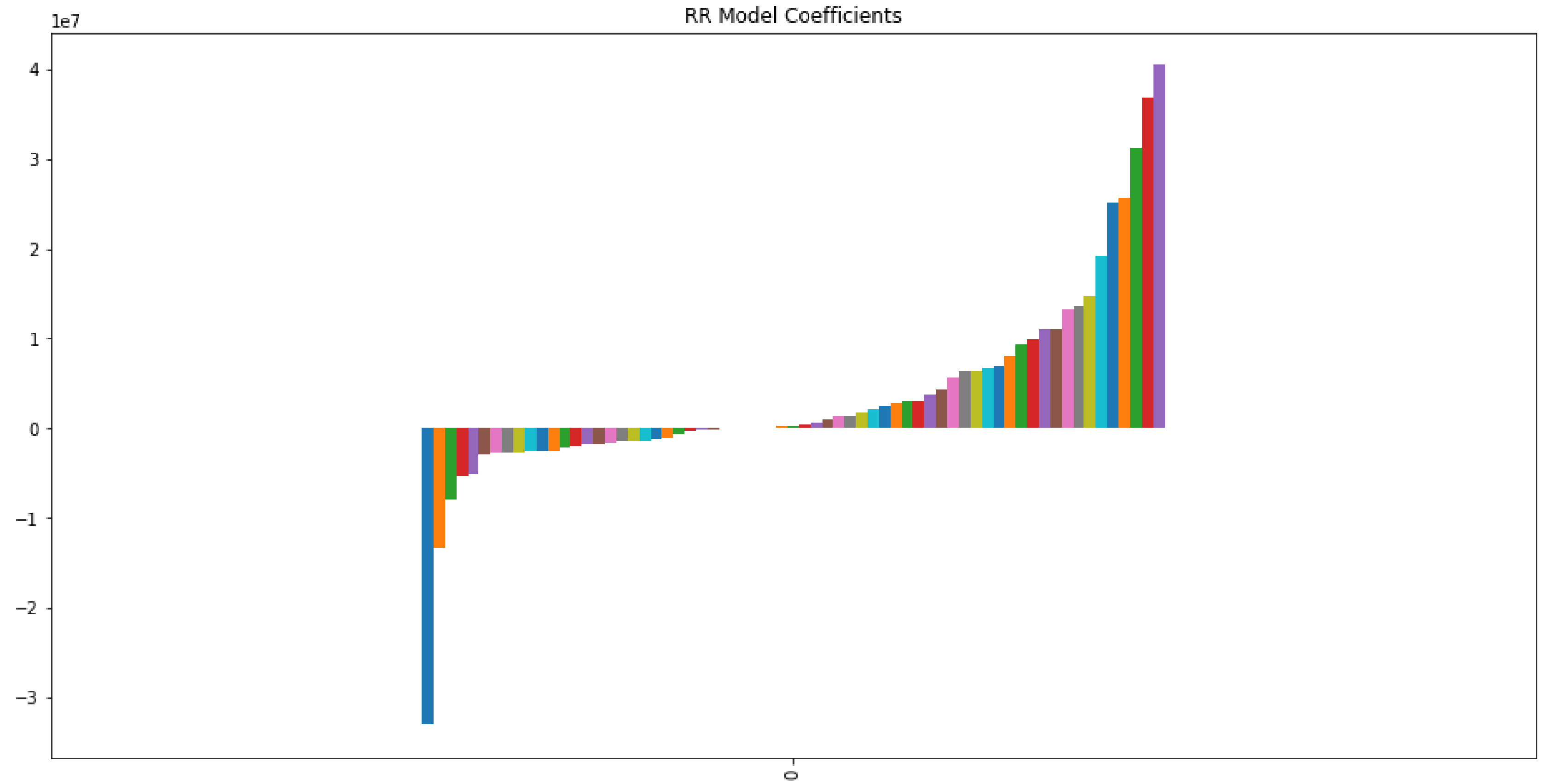
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x1c260557f0>



In [32]:
```
#Identifing Outliers
X_train=x_train #***
X_test=x_test
ridgeReg = Ridge(alpha=.20, normalize=True)

ridgeReg.fit(X_train,y_train)

y_pred = ridgeReg.predict(X_test)

#calculating mse

print('MSE:', metrics.mean_squared_error(y_test, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred))/ y_test.std())
coef = pd.DataFrame(data=ridgeReg.coef_, columns=X_train.columns )

model_coef = coef.T.sort_values(by=0).T

model_coef.plot(kind='bar', title='RR Model Coefficients', legend=False, figsize=(16,8))
```

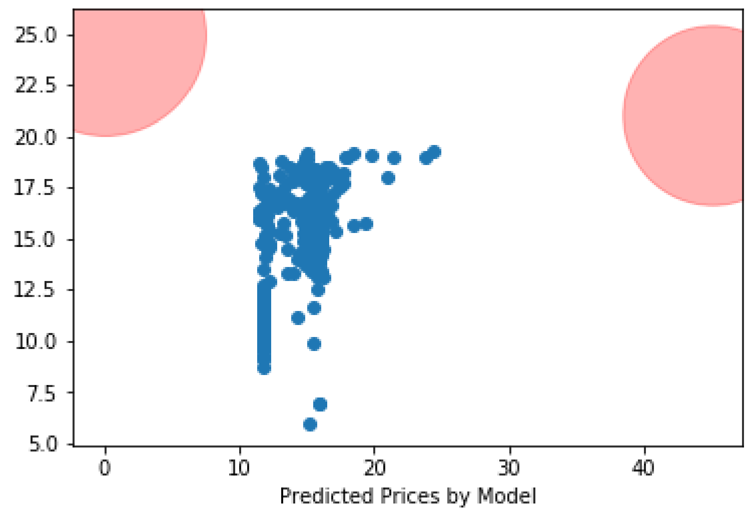
```
MSE: 218642713567700.6
RMSE: 14786572.069540005
SALE_PRICE    0.569581
dtype: float64
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2617dc50>



In [33]:
```
plt.scatter(-0, 25, s=10000, alpha=0.3, c = 'r' )
plt.scatter(45, 21, s=8000, alpha=0.3, c = 'r' )


predicted_prices = m7.fittedvalues

plt.xlabel("Predicted Prices by Model")
# plt.ylabel()
# plt.title("Predictions vs. Original Prices")
plt.scatter(predicted_prices, new_df.SALE_PRICE)
```

Out[33]: <matplotlib.collections.PathCollection at 0x1c26e057f0>

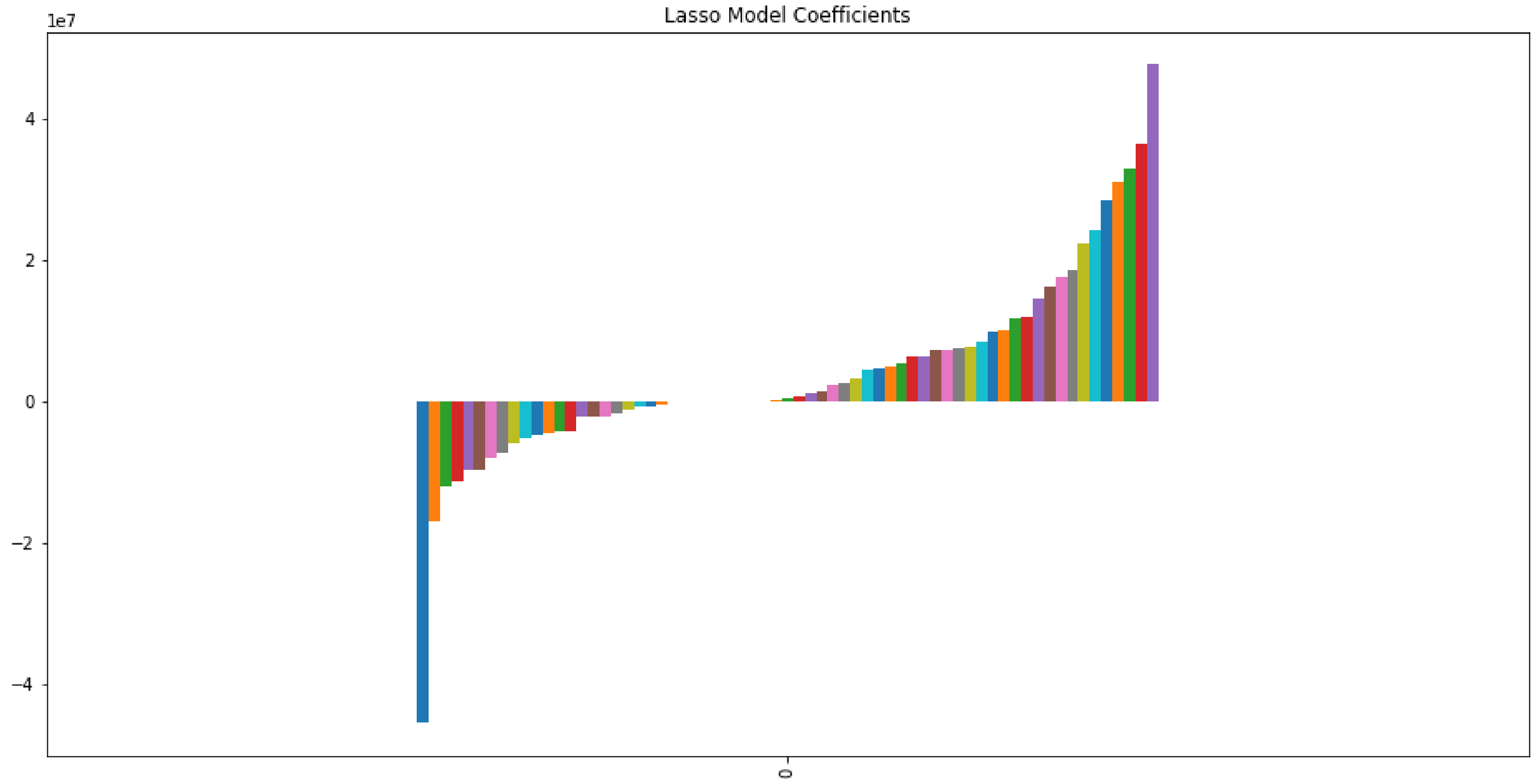


In [34]:
```
#***Lasso regression not only helps in reducing over-fitting but it can help us in feature selection.
from sklearn.linear_model import Lasso


lassoReg = Lasso(alpha=50, normalize=True)

lassoReg.fit(X_train,y_train)

y_pred = lassoReg.predict(X_test)

#calculating mse

print('MSE:', metrics.mean_squared_error(y_test, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred))/ y_test.std())



coef = pd.DataFrame(data=lassoReg.coef_, index=X_train.columns )
model_coef = coef.sort_values(by=0).T

model_coef.plot(kind='bar', title='Lasso Model Coefficients', legend=False, figsize=(16,8))
```

```
/Users/chrischung/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/coordinate_descent.py:4
91: ConvergenceWarning: Objective did not converge. You might want to increase the number of iterati
ons. Fitting data with very small alpha may cause precision problems.
  ConvergenceWarning)
```

```
MSE: 184445775930621.6
RMSE: 13581081.544951476
SALE_PRICE    0.523145
dtype: float64
```

```
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1c262c1828>
```



In [35]:
```
from sklearn.feature_selection import RFE
rfe = RFE(lm, n_features_to_select=10)
rfe.fit(features_selected_train,y_train)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-35-22d8e31e57c9> in <module>()
      1 from sklearn.feature_selection import RFE
      2 rfe = RFE(lm, n_features_to_select=10)
----> 3 rfe.fit(features_selected_train,y_train)

NameError: name 'features_selected_train' is not defined
```

In [ ]:
```
plt.style.use('fivethirtyeight')
plt.figure(figsize=(12,8))
sns.distplot(new_df.SALE_PRICE, bins = 25)
plt.ticklabel_format(style='sci', axis='x', scilimits=(0,1))
plt.xlabel("House Sales Price in USD")
plt.ylabel("Number of Houses")
plt.title("House Sales Price Distribution")
```

In [ ]:
```
# x_test
```

In [ ]:
```
from sklearn import preprocessing
from sklearn import pipeline

scaler = preprocessing.StandardScaler()
X_test=x_test#[['RESIDENTIAL_UNITS', 'COMMERCIAL_UNITS', 'LAND_SQUARE_FEET','GROSS_SQUARE_FEET', 'YEA
R_BUILT']]
X_test1=x_test#[['RESIDENTIAL_UNITS', 'COMMERCIAL_UNITS', 'LAND_SQUARE_FEET','GROSS_SQUARE_FEET', 'YE
AR_BUILT',"BUILDING_CLASS_CATEGORY_01ONEFAMILYDWELLINGS"]]
X_test1=x_test[['RESIDENTIAL_UNITS', 'COMMERCIAL_UNITS', 'LAND_SQUARE_FEET','GROSS_SQUARE_FEET', 'YEA
R_BUILT',"BUILDING_CLASS_CATEGORY_01ONEFAMILYDWELLINGS"]]
X_train=x_train
```

In [ ]:
```
scaler.fit(features.iloc[:,:-1])
```

In [ ]:
```
len(X_test1.columns[:-1])
len(X_test1.iloc[:,:-1])
X_test1.columns.shape
```

In [ ]:
```
scaler.fit(X_train.iloc[:,:-1])
features_scaled_train = pd.DataFrame(scaler.transform(X_train.iloc[:,:-1]), columns=X_train.columns[:
-1], index=X_train.index)

features_scaled_train.head()
```

In [ ]:
```
features_scaled_test = pd.DataFrame(scaler.transform(X_test.iloc[:,:-1]), columns=X_test.columns[:-1
], index=X_test.index)

features_scaled_test.head()
```

In [ ]:
```
poly = preprocessing.PolynomialFeatures(degree=2, interaction_only=False, include_bias=False)
features_64_train = pd.DataFrame(poly.fit_transform(features_scaled_train), columns=poly.get_feature_
names(features_scaled_train.columns))
features_64_train.head()
```

In [ ]:
```
pd.set_option('display.max_columns', 100)
features_64_train.head()
features_64_test = pd.DataFrame(poly.fit_transform(features_scaled_test), columns=poly.get_feature_na
mes(features_scaled_test.columns))
features_64_test.head()
```

In [ ]:
```
***
```

In [ ]:
```
from sklearn.feature_selection import VarianceThreshold
thresholder = VarianceThreshold(threshold=.5)

def variance_threshold_selector(data, threshold=0.5):
    selector = VarianceThreshold(threshold)
    selector.fit(data)
    return data[data.columns[selector.get_support(indices=True)]]
```

In [ ]:
```
features_selected_train = variance_threshold_selector(features_64_train)
# features_selected_train = variance_threshold_selector(features_64_train)
```

In [ ]:
```
features_selected_train.head()
```

In [ ]:
```
import seaborn as sns

sns.set(style="white")


# Compute the correlation matrix
corr = features_selected_train.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

In [ ]:
```
# Create correlation matrix
corr_matrix = features_selected_train.corr().abs()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))

# Find index of feature columns with correlation greater than 0.95
to_drop = [column for column in upper.columns if any(upper[column] > 0.95)]
```

In [ ]:
```
upper
```

In [ ]:
```
features_selected_train.drop(columns=to_drop, inplace=True)
```

In [ ]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_regression, mutual_info_regression
```

In [ ]:
```
def information_selector(X, y, scoring, k=5):
    selector = SelectKBest(score_func=scoring, k=k)
    selector.fit(X, y)
    return X[X.columns[selector.get_support(indices=True)]]
test = SelectKBest(score_func=mutual_info_regression, k=30)
fit = test.fit(features_selected_train, y_train)
```

In [ ]:
```
features_selected_train[features_selected_train.columns[fit.get_support(indices=True)]].head()
```

In [ ]:
```
features_selected_train = information_selector(features_selected_train, y_train, mutual_info_regressi
on, k=30)
```

In [ ]:
```
# fit a model
lm = linear_model.LinearRegression()
model = lm.fit(features_selected_train, y_train)
```

In [ ]:
```
features_selected_test = features_64_test[features_selected_train.columns]
y_pred = lm.predict(features_selected_test)

print(metrics.mean_absolute_error(y_test, y_pred))
print(metrics.mean_squared_error(y_test, y_pred))
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

In [ ]:
```
from sklearn.feature_selection import RFE
rfe = RFE(lm, n_features_to_select=10)
rfe.fit(features_selected_train,y_train)
```

In [ ]:
```
def ranking(ranks, names, order=1):

    ranks = map(lambda x: (x,2), ranks)
    return list(sorted(zip(ranks, names),reverse=True))
```

In [ ]:
```
rankings = ranking(np.abs(lm.coef_), features_selected_train.columns)
```

In [ ]:
```
rankings[:15]
```

In [ ]:
```
[item[1] for item in rankings[0:15]]
```

In [ ]:
```
final_columns = [item[1] for item in rankings[0:15]]
```

In [ ]:
```
lm = linear_model.LinearRegression()
model = lm.fit(features_selected_train[final_columns], y_train)
```

In [ ]:
```
features_selected_test = features_64_test[final_columns]
y_pred = lm.predict(features_selected_test)

print(metrics.mean_absolute_error(y_test, y_pred))
print(metrics.mean_squared_error(y_test, y_pred))
print(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

In [ ]:
```
# Get numerical feature importances
importances = list(rf.feature_importances_)
# List of tuples with variable and importance
feature_importances = [(feature, round(importance, 2)) for feature, importance in zip(feature_list, i
mportances)]
# Sort the feature importances by most important first
feature_importances = sorted(feature_importances, key = lambda x: x[1], reverse = True)
# Print out the feature and importances
[print('Variable: {:20} Importance: {}'.format(*pair)) for pair in feature_importances];
```

In [ ]:
```
### Module 2 Projects

Projects are designed to review the material we covered in Module 2:

* cleaning data with numpy and pandas
* probability and combinatorics
* probability distributions
* hypothesis testing
* simple linear regression
* multiple linear regression
* cross validation and the bias/variance tradeoff

Ask a main question with which you can use a regression to answer. The other topics we learned in Mod
ule 2 can be used as further justification for your answers to subsequent questions.

Sample Questions:

* What best determines the final auction price of an item?
* What are the key factors in determining a country's happiness level?
* Is there a way we can predict the spread of a football game?


### Data
* You must have at least 4 different features in your models (independent variables) with at least on
e target (dependent variable).
* Your data must contain at least one categorical feature and at least one numerical feature
* **BONUS**: Challenge yourself to obtain a unique dataset (either from webscraping or querying APIs)

### The Deliverables

1. ** A well documented Jupyter Notebook** containing any code you've written for this project, comme
nts explaining it, and graphical visualizations.

## Requirements

#### Organization/Code Cleanliness

* The notebook should be well organized, easy to follow,  and code should be commented where appropri
ate.
    * Level Up: The notebook contains well-formatted, professional looking markdown cells explaining
any substantial code. All functions have docstrings that act as professional-quality documentation
* The notebook is written for a technical audiences with a way to both understand your approach and r
```

```
eproduce your results. The target audience for this deliverable is other data scientists looking to v
alidate your findings.

#### Visualizations & EDA (Exploratory Data Analysis)

* Your project contains at least 4 _meaningful_ data visualizations, with corresponding interpretatio
ns. All visualizations are well labeled with axes labels, a title, and a legend (when appropriate)
* You pose at least 3 meaningful questions and answer them through EDA.  These questions should be we
ll labeled and easy to identify inside the notebook.
    * **Level Up**: Each question is clearly answered with a visualization that makes the answer easy
to understand.
* Your notebook should contain 1 - 2 paragraphs briefly explaining your approach to this project.


#### Model Quality/Approach

* Your model should not include any predictors with p-values greater than .05 (unless you can justify
)
* Your model should have cross-validation and account for the bias-variance tradeoff
* Your notebook shows an iterative approach to modeling, and details the parameters and results of th
e model at each iteration.
    * **Level Up**: Whenever necessary, you briefly explain the changes made from one iteration to th
e next, and why you made these choices.
* You provide at least 1 paragraph explaining your final model.
```