Introduction to Data Science

Regression Dataset 2

House Prices

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Overview

There is always a supply and demand in the housing sector and predicting the price of the house at the right amount is very crucial. If the price of the house is stated low than the market value, people will tend to lose the gain they could have made. Similary, if a house is priced high, there is less likely chance of selling the house or getting any buyer. Thus, pricing the house correctly is very important.

Objective

Predict the price of the house based on the most important feature

About the Dataset

The dataset consists of house prices from King County an area in the US State of Washington, this data also covers Seattle.

The dataset was obtained from Kaggle

The dataset contains 21 fields out of which the first field is an id field and the second field is the price of houses being sold. The description of each field is as follows:

1. **id** : ID of the house.
2. **date** : Date of the house being sold.
3. **price** : Price of the house being sold.
4. **bedrooms** : No. of bedrooms in the house.
5. **bathrooms** : No. of bathrooms in the house.
6. **sqft_living** : The square foot area of the living space of the house.
7. **sqft_lot** : The square foot area of the entire land.
8. **floors** : No. of floors in the house.
9. **waterfront** : If a view of the waterfront is present or not.
10. **view** : Number of views. (1 indicates worn out property and 5 excellent)
11. **condition** : Condition of the house. (Based on King County grading system - 1 poor and 13 excellent)
12. **grade** : Grade of the house.
13. **sqft_above** : The square foot area apart from the basement.
14. **sqft_basement** : The square foot area of the basement.
15. **yr_built** : The year of house built.
16. **yr_renovated** : The year when house is renovated.
17. **zipcode** : Zipcode.
18. **lat** : Latitutde co-ordinates of the house.
19. **long** : Longitude co-ordinates of the house.
20. **sqftliving15** : Living room area in 2015.
21. **sqftlot15** : The lot size area in 2015.

In [1]:
```
# All the required libraries are imported here.
import numpy as np
import pandas as pd
from pandas.plotting import scatter_matrix

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split, GridSearchCV, RepeatedStratifiedKFold
from sklearn.linear_model import LinearRegression, RidgeClassifier, LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, mean_squared_error
from sklearn.feature_selection import SelectKBest, chi2

import math

from scipy import stats

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
#Describing the size, shape and dimension of the dataset.
house_data = pd.read_csv('house_data.csv')
print("The total size of the dataset is {} bytes.".format(house_data.size))
print("There are {} number of records and {} number of fields with a {} shape.".format(house_data.shape[0], house_data.shape[1], house_data.shape))
print("The dataset has a {} dimensional structure.".format(house_data.ndim))
```

```
The total size of the dataset is 453873 bytes.
There are 21613 number of records and 21 number of fields with a (21613, 21) shape.
The dataset has a 2 dimensional structure.
```

In [3]:
```
print("The top 5 records of the dataset are: \n{}".format(house_data.head()))
```

```
The top 5 records of the dataset are:
           id             date     price  bedrooms  bathrooms  sqft_living  \
0  7129300520  20141013T000000  221900.0         3       1.00         1180
1  6414100192  20141209T000000  538000.0         3       2.25         2570
2  5631500400  20150225T000000  180000.0         2       1.00          770
3  2487200875  20141209T000000  604000.0         4       3.00         1960
4  1954400510  20150218T000000  510000.0         3       2.00         1680

   sqft_lot  floors  waterfront  view  ...  grade  sqft_above  sqft_basement  \
0      5650     1.0           0     0  ...      7        1180              0
1      7242     2.0           0     0  ...      7        2170            400
2     10000     1.0           0     0  ...      6         770              0
3      5000     1.0           0     0  ...      7        1050            910
4      8080     1.0           0     0  ...      8        1680              0

   yr_built  yr_renovated  zipcode      lat     long  sqft_living15  \
0      1955             0    98178  47.5112 -122.257           1340
1      1951          1991    98125  47.7210 -122.319           1690
2      1933             0    98028  47.7379 -122.233           2720
3      1965             0    98136  47.5208 -122.393           1360
4      1987             0    98074  47.6168 -122.045           1800

   sqft_lot15
0        5650
1        7639
2        8062
3        5000
4        7503

[5 rows x 21 columns]
```

In [4]:
```
print(house_data[house_data['id'] == 6021501535])
```

```
            id             date     price  bedrooms  bathrooms  sqft_living  \
93  6021501535  20140725T000000  430000.0         3        1.5         1580
94  6021501535  20141223T000000  700000.0         3        1.5         1580

    sqft_lot  floors  waterfront  view  ...  grade  sqft_above  sqft_basement  \
93      5000     1.0           0     0  ...      8        1290            290
94      5000     1.0           0     0  ...      8        1290            290

    yr_built  yr_renovated  zipcode     lat     long  sqft_living15  \
93      1939             0    98117  47.687 -122.386           1570
94      1939             0    98117  47.687 -122.386           1570

    sqft_lot15
93        4500
94        4500

[2 rows x 21 columns]
```

Here, is a sample record of a house that was sold in different dates and prices but the data records the house twice. We will remove the duplicates and keep the latest transactions. To do that, we need to find and remove the duplicates.

We will find the duplicate records based on id, bedrooms, bathrooms, sqft_living, sqft_lot, zipcode, lat and longitude.

In [5]:
```
print("There are {} number of duplicate values in the dataset. "
      .format(house_data.duplicated(subset=['id', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'zipcode', 'lat', 'long']).sum()))
```

```
There are 177 number of duplicate values in the dataset.
```

In [6]:
```
print("The list of duplicate values are as follows: \n")
house_data.loc[house_data.duplicated(subset=['id', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'zipcode', 'lat', 'long'], keep=False), :]
```

```
The list of duplicate values are as follows:
```

Out[6]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built	yr_renovated	zipcode	lat	long	sq
93	6021501535	20140725T000000	430000.0	3	1.50	1580	5000	1.0	0	0	...	8	1290	290	1939	0	98117	47.6870	-122.386	
94	6021501535	20141223T000000	700000.0	3	1.50	1580	5000	1.0	0	0	...	8	1290	290	1939	0	98117	47.6870	-122.386	
313	4139480200	20140618T000000	1384000.0	4	3.25	4290	12103	1.0	0	3	...	11	2690	1600	1997	0	98006	47.5503	-122.102	
314	4139480200	20141209T000000	1400000.0	4	3.25	4290	12103	1.0	0	3	...	11	2690	1600	1997	0	98006	47.5503	-122.102	
324	7520000520	20140905T000000	232000.0	2	1.00	1240	12092	1.0	0	0	...	6	960	280	1922	1984	98146	47.4957	-122.352	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
20670	8564860270	20150330T000000	502000.0	4	2.50	2680	5539	2.0	0	0	...	8	2680	0	2013	0	98045	47.4759	-121.734	
20779	6300000226	20140626T000000	240000.0	4	1.00	1200	2171	1.5	0	0	...	7	1200	0	1933	0	98133	47.7076	-122.342	
20780	6300000226	20150504T000000	380000.0	4	1.00	1200	2171	1.5	0	0	...	7	1200	0	1933	0	98133	47.7076	-122.342	
21580	7853420110	20141003T000000	594866.0	3	3.00	2780	6000	2.0	0	0	...	9	2780	0	2013	0	98065	47.5184	-121.886	
21581	7853420110	20150504T000000	625000.0	3	3.00	2780	6000	2.0	0	0	...	9	2780	0	2013	0	98065	47.5184	-121.886	

353 rows × 21 columns

In [7]:
```
#Now deleting the first occurence of the duplicate values.
house_data = house_data.drop_duplicates(subset=['id', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'zipcode', 'lat', 'long'], keep='last')
```

In [8]:
```
#Printing the data types
print("The datatype of the dataset are: \n{}".format(house_data.dtypes))
```

```
The datatype of the dataset are:
id                 int64
date              object
price            float64
bedrooms           int64
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
grade              int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
zipcode            int64
lat              float64
long             float64
sqft_living15      int64
sqft_lot15         int64
dtype: object
```

We can see that the date value is of type object. Since, we know date will not play much part in predicting the price of the house, we can either drop the field or leave it as it is.

In [9]:
```
#Statistical description of the data
print(house_data.describe().T)
```

```
                 count          mean           std           min  \
id             21436.0  4.580765e+09  2.876590e+09  1.000102e+06
price          21436.0  5.416500e+05  3.673149e+05  7.500000e+04
bedrooms       21436.0  3.371571e+00  9.292047e-01  0.000000e+00
bathrooms      21436.0  2.117349e+00  7.699128e-01  0.000000e+00
sqft_living    21436.0  2.082705e+03  9.191465e+02  2.900000e+02
sqft_lot       21436.0  1.513564e+04  4.153862e+04  5.200000e+02
floors         21436.0  1.496198e+00  5.403884e-01  1.000000e+00
waterfront     21436.0  7.604031e-03  8.687095e-02  0.000000e+00
view           21436.0  2.351185e-01  7.670921e-01  0.000000e+00
condition      21436.0  3.410384e+00  6.502354e-01  1.000000e+00
grade          21436.0  7.661737e+00  1.174256e+00  1.000000e+00
sqft_above     21436.0  1.790960e+03  8.290265e+02  2.900000e+02
sqft_basement  21436.0  2.917445e+02  4.427820e+02  0.000000e+00
yr_built       21436.0  1.971098e+03  2.938528e+01  1.900000e+03
yr_renovated   21436.0  8.472980e+01  4.024310e+02  0.000000e+00
zipcode        21436.0  9.807786e+04  5.346937e+01  9.800100e+04
lat            21436.0  4.756016e+01  1.386013e-01  4.715590e+01
long           21436.0 -1.222137e+02  1.408960e-01 -1.225190e+02
sqft_living15  21436.0  1.988314e+03  6.856991e+02  3.990000e+02
sqft_lot15     21436.0  1.278596e+04  2.737547e+04  6.510000e+02

                        25%           50%           75%           max
id             2.123700e+09  3.904921e+09  7.308675e+09  9.900000e+09
price          3.248660e+05  4.500000e+05  6.450000e+05  7.700000e+06
bedrooms       3.000000e+00  3.000000e+00  4.000000e+00  3.300000e+01
bathrooms      1.750000e+00  2.250000e+00  2.500000e+00  8.000000e+00
sqft_living    1.430000e+03  1.920000e+03  2.550000e+03  1.354000e+04
sqft_lot       5.040000e+03  7.614000e+03  1.069625e+04  1.651359e+06
floors         1.000000e+00  1.500000e+00  2.000000e+00  3.500000e+00
waterfront     0.000000e+00  0.000000e+00  0.000000e+00  1.000000e+00
view           0.000000e+00  0.000000e+00  0.000000e+00  4.000000e+00
condition      3.000000e+00  3.000000e+00  4.000000e+00  5.000000e+00
grade          7.000000e+00  7.000000e+00  8.000000e+00  1.300000e+01
sqft_above     1.200000e+03  1.560000e+03  2.220000e+03  9.410000e+03
sqft_basement  0.000000e+00  0.000000e+00  5.600000e+02  4.820000e+03
yr_built       1.952000e+03  1.975000e+03  1.997000e+03  2.015000e+03
yr_renovated   0.000000e+00  0.000000e+00  0.000000e+00  2.015000e+03
zipcode        9.803300e+04  9.806500e+04  9.811700e+04  9.819900e+04
lat            4.747110e+01  4.757200e+01  4.767800e+01  4.777760e+01
long          -1.223280e+02 -1.222300e+02 -1.221240e+02 -1.213150e+02
sqft_living15  1.490000e+03  1.840000e+03  2.370000e+03  6.210000e+03
sqft_lot15     5.100000e+03  7.620000e+03  1.008725e+04  8.712000e+05
```

Now, since the id field is unique we can create that as an index column as the field does not make any contribution on linear regression or classification.

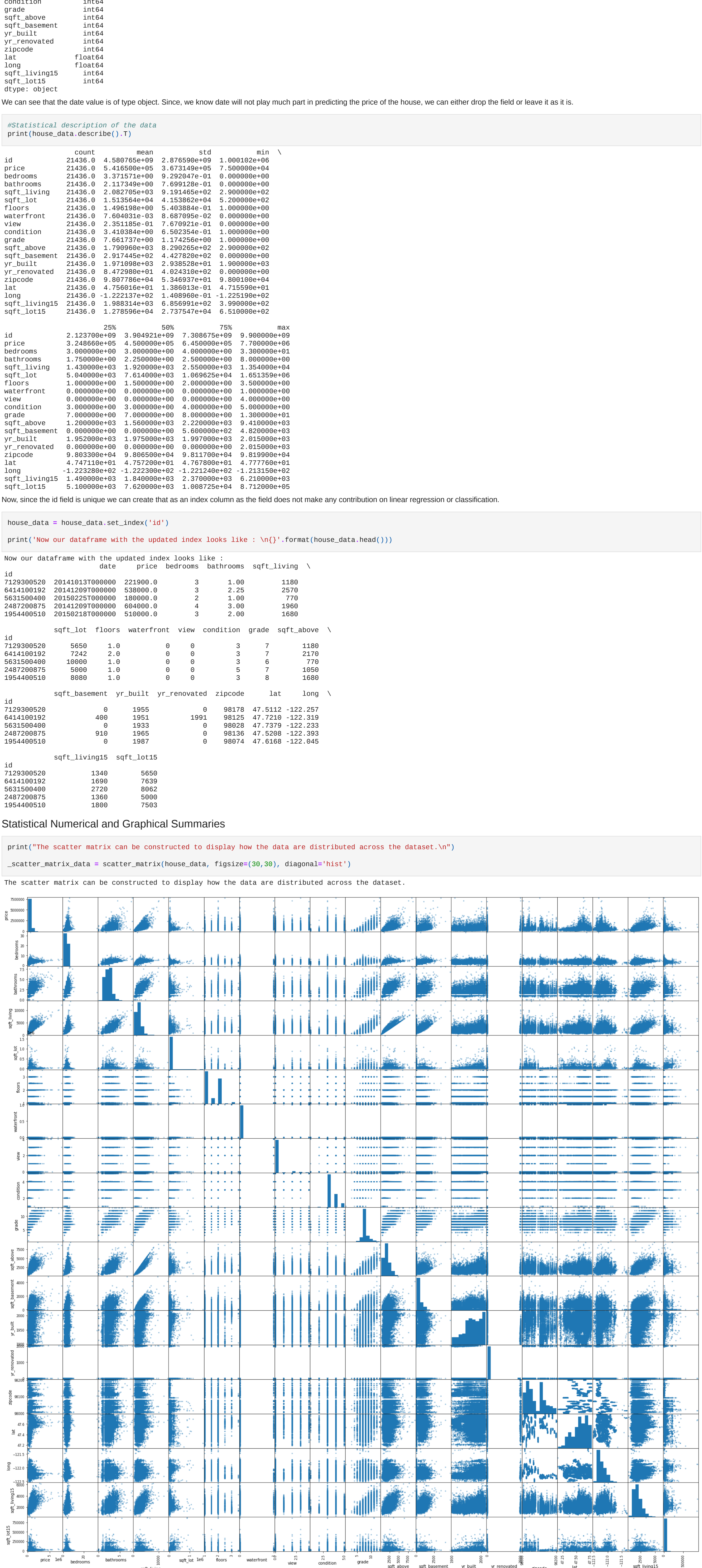
In [10]:
```
house_data = house_data.set_index('id')

print('Now our dataframe with the updated index looks like : \n{}'.format(house_data.head()))
```

```
Now our dataframe with the updated index looks like :
                       date     price  bedrooms  bathrooms  sqft_living  \
id
7129300520  20141013T000000  221900.0         3       1.00         1180
6414100192  20141209T000000  538000.0         3       2.25         2570
5631500400  20150225T000000  180000.0         2       1.00          770
2487200875  20141209T000000  604000.0         4       3.00         1960
1954400510  20150218T000000  510000.0         3       2.00         1680

            sqft_lot  floors  waterfront  view  condition  grade  sqft_above  \
id
7129300520      5650     1.0           0     0          3      7        1180
6414100192      7242     2.0           0     0          3      7        2170
5631500400     10000     1.0           0     0          3      6         770
2487200875      5000     1.0           0     0          5      7        1050
1954400510      8080     1.0           0     0          3      8        1680

            sqft_basement  yr_built  yr_renovated  zipcode      lat     long  \
id
7129300520              0      1955             0    98178  47.5112 -122.257
6414100192            400      1951          1991    98125  47.7210 -122.319
5631500400              0      1933             0    98028  47.7379 -122.233
2487200875            910      1965             0    98136  47.5208 -122.393
1954400510              0      1987             0    98074  47.6168 -122.045

            sqft_living15  sqft_lot15
id
7129300520           1340        5650
6414100192           1690        7639
5631500400           2720        8062
2487200875           1360        5000
1954400510           1800        7503
```

Statistical Numerical and Graphical Summaries

In [11]:
```
print("The scatter matrix can be constructed to display how the data are distributed across the dataset.\n")

_scatter_matrix_data = scatter_matrix(house_data, figsize=(30,30), diagonal='hist')
```

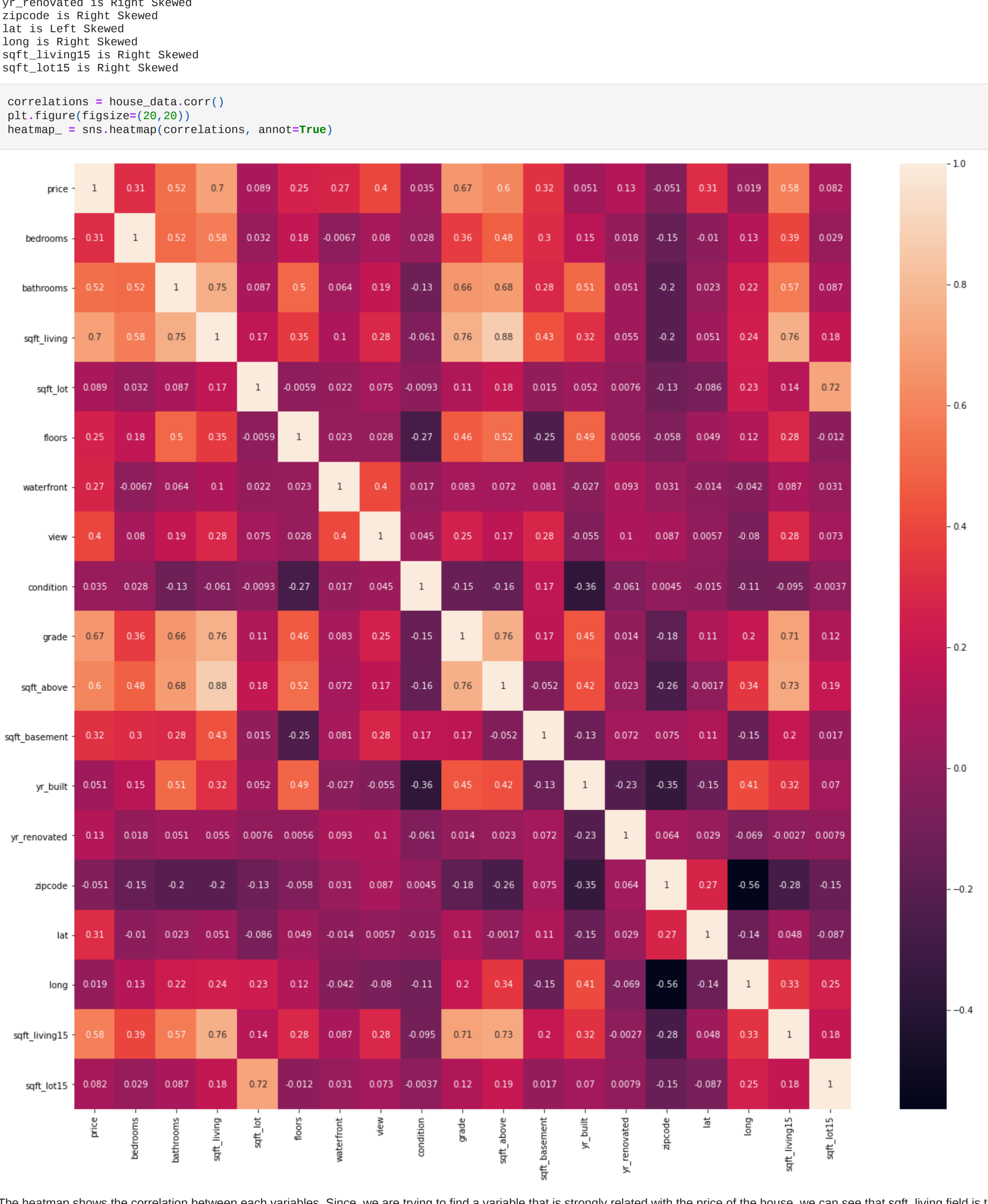
```
The scatter matrix can be constructed to display how the data are distributed across the dataset.
```



In [12]:
```
print("From the above graph while considering the histograms diagonally we can see that most of the fields are right skewed. \
    \nWhereas from the scatter plot we can see there are few outliers in the dataset. \
    \nBelow is the list of all the keys of the dataset and determines whether they are normally distributed or skewed. \n")

#Removing the date field from the dataset.
house_data = house_data[['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront'
                         , 'view', 'condition', 'grade', 'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated',
                         'zipcode', 'lat', 'long', 'sqft_living15', 'sqft_lot15']]
for data_keys in house_data.keys():
      skewness = house_data[data_keys].skew()
      if skewness > 0:
          print(data_keys, "is Right Skewed")
      elif skewness <0:
          print(data_keys, "is Left Skewed")
      else:
          print(data_keys, "is Normally Distributed")
```

```
From the above graph while considering the histograms diagonally we can see that most of the fields are right skewed.
Whereas from the scatter plot we can see there are few outliers in the dataset.
Below is the list of all the keys of the dataset and determines whether they are normally distributed or skewed.

price is Right Skewed
bedrooms is Right Skewed
bathrooms is Right Skewed
sqft_living is Right Skewed
sqft_lot is Right Skewed
floors is Right Skewed
waterfront is Right Skewed
view is Right Skewed
condition is Right Skewed
grade is Right Skewed
sqft_above is Right Skewed
sqft_basement is Right Skewed
yr_built is Left Skewed
yr_renovated is Right Skewed
zipcode is Right Skewed
lat is Left Skewed
long is Right Skewed
sqft_living15 is Right Skewed
sqft_lot15 is Right Skewed
```

In [13]:
```
correlations = house_data.corr()
plt.figure(figsize=(20,20))
heatmap_ = sns.heatmap(correlations, annot=True)
```



The heatmap shows the correlation between each variables. Since, we are trying to find a variable that is strongly related with the price of the house, we can see that sqft_living field is the most strongly correlated with the price of the house. After sqft_living, the grade and the sqft_above are more strongly related to the price.

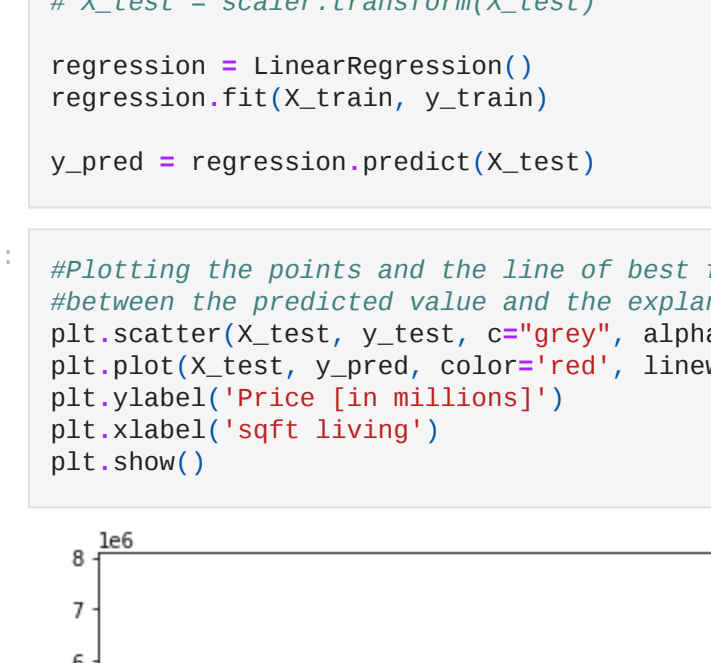
We will choose sqft_living to predict the price of the house. With this finding we can also say that the larger the sqft of the house the higher the price of the house is to be estimated. Which is true, but as all association does not imply causation, we cannot neglect other factors such as sqft_above, the grade of the house, number of bathrooms and bedrooms and other fiels, as they could play vital role in determining the prices.

We will only find the correlation between the price of the house and the sqft_living of the house in this dataset.

Algorithm Implementation and Statistical Tests

In [14]:
```
#Linear Regression between sqft_living and price.
sqft_data = house_data[['sqft_living']]
price_data = house_data[['price']]

X_train, X_test, y_train, y_test = train_test_split(sqft_data, price_data, test_size=0.25)

# scaler = MinMaxScaler()
# scaler.fit(X_train)

# X_train = scaler.transform(X_train)
# X_test = scaler.transform(X_test)

regression = LinearRegression()
regression.fit(X_train, y_train)

y_pred = regression.predict(X_test)
```

In [15]:
```
#Plotting the points and the line of best fits. Here the scatter plot is plotted between sqft_living and price of the house and the best line of fit is created by plott
#between the predicted value and the explanatory variable values.
plt.scatter(X_test, y_test, c="grey", alpha=0.5)
plt.plot(X_test, y_pred, color='red', linewidth=2)
plt.ylabel('Price [in millions]')
plt.xlabel('sqft living')
plt.show()
```



In [16]:
```
print("Thus, the line of best fit for the above can be found using : \n y = {} + {} x. \n".format(regression.intercept_, regression.coef_[0]))

mse = mean_squared_error(y_test, y_pred)
print("Where the Slope is {} and the y intercept is {} \n\
with mean squared error of {} and \nroot mean squared error of {}"
      .format(regression.coef_[0], regression.intercept_, mse, math.sqrt(mse)))
```

```
Thus, the line of best fit for the above can be found using :
 y = [-44025.93903058] + [281.47743554] x.

Where the Slope is [281.47743554] and the y intercept is [-44025.93903058]
with mean squared error of 69880439595.75397 and
root mean squared error of 264349.08661796805
```

In [17]:
```
pearson_coef, p_value = stats.pearsonr(sqft_data['sqft_living'], price_data['price'])
print("The Pearson coefficient of the variables is r = {}".format(pearson_coef))
```

```
The Pearson coefficient of the variables is r = 0.7014132305241632
```

Thus, from the above calculation we can see that with increase in 1 square foot, there is an increase of 280.316 in price.

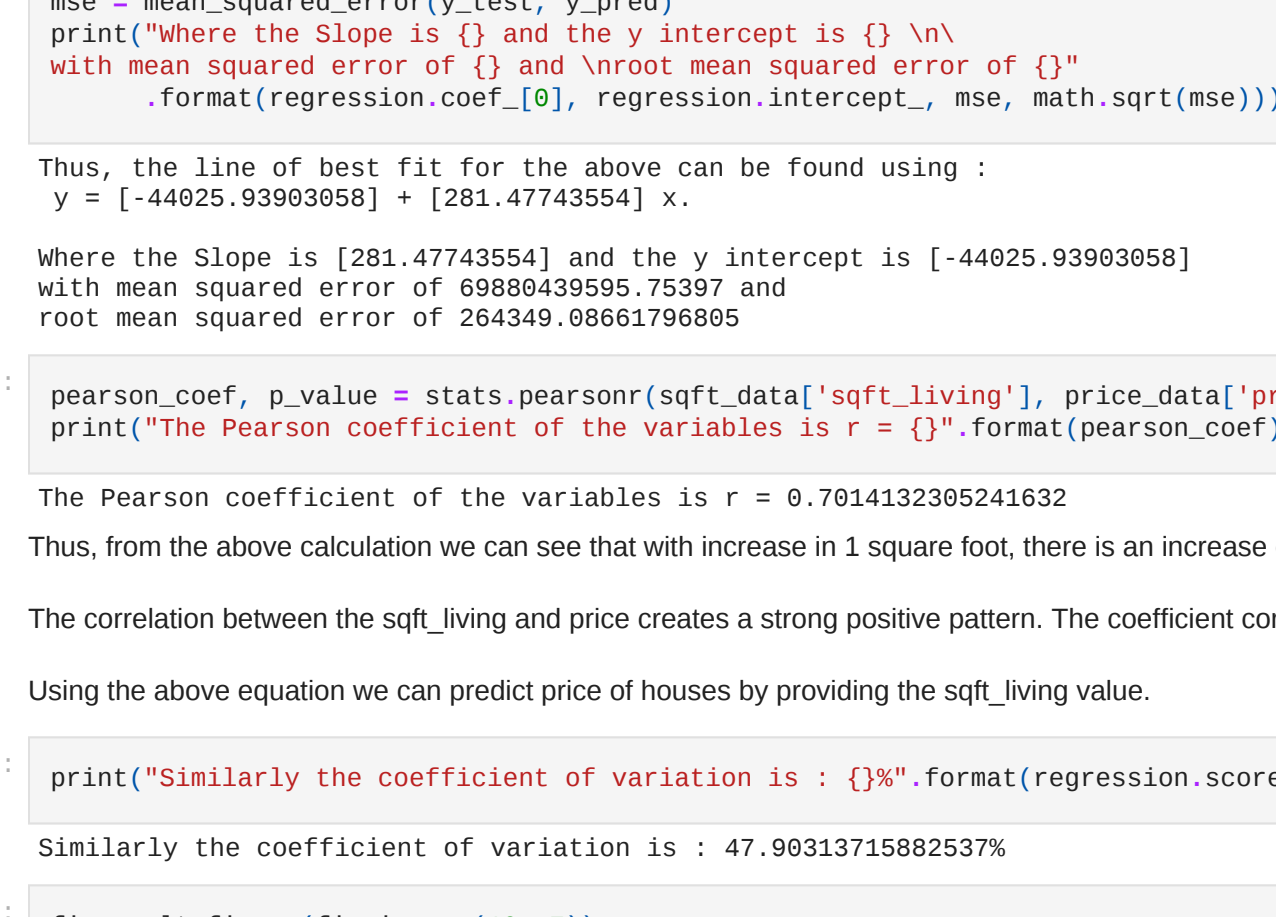
The correlation between the sqft_living and price creates a strong positive pattern. The coefficient correlation between the variables is 0.701.

Using the above equation we can predict price of houses by providing the sqft_living value.

In [18]:
```
print("Similarly the coefficient of variation is : {}%".format(regression.score(X_test, y_test)*100))
```

```
Similarly the coefficient of variation is : 47.90313715882537%
```

In [19]:
```
fig = plt.figure(figsize = (10, 7))
sns.residplot(sqft_data['sqft_living'], price_data['price'], color='magenta')

# title and labels
plt.title('Residual plot', size=24)
plt.xlabel('Sqft_living', size=18)
plt.ylabel('Price', size=18);
```



The residual plot created above looks like it leans more toward Homoscedastic as the residual plot shows homogeneous spread out of the plot and are uniformly distributed about x-axis.

In [20]:
```
print('To predict a price of a house with 2570 of sqft_living, we can use the above equation. \nThe predicted price of the house would be:\n')
x = 2570
print('The equation is given by : y = {} + ({}) * {}'.format(regression.intercept_, (regression.coef_[0]), x))
print('y = {}\n'.format(regression.intercept_ + (regression.coef_[0]) * x))
print("Thus the price of the house can be put up as : ${}".format(regression.intercept_ + (regression.coef_[0]) * x))
```

```
To predict a price of a house with 2570 of sqft_living, we can use the above equation.
The predicted price of the house would be:

The equation is given by : y = [-44025.93903058] + ([281.47743554]) * 2570
y = [679371.07031926]

Thus the price of the house can be put up as : $[679371.07031926]
```

Performance Improvement

From the above we can see that we are able to obtain coefficient of variation of 48%. Let us see if we could find better score using the multi-linear regression.

In [21]:
```
#Considering most of the features to find the top features that helps to determine the price.
#Removing few features as the algorithm does not consider negative numbers.
X = house_data[['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront', 'view', 'condition'
                , 'grade', 'sqft_above', 'sqft_basement', 'yr_built', 'yr_renovated', 'zipcode']]
y = house_data['price']

select_k_best = SelectKBest(score_func=chi2, k=10)

best_result = select_k_best.fit(X, y)

scores = pd.DataFrame(best_result.scores_)
columns = pd.DataFrame(X.columns)

feature_scores = pd.concat([columns, scores], axis=1)
feature_scores.columns = ['Field', 'Score']

print(feature_scores.nlargest(10, 'Score'))
```

```
            Field         Score
3        sqft_lot  3.936220e+08
12   yr_renovated  9.228790e+06
2     sqft_living  5.450062e+06
9      sqft_above  4.398121e+06
10  sqft_basement  4.374270e+06
6            view  1.917994e+04
5      waterfront  8.116336e+03
1       bathrooms  2.691092e+03
8           grade  2.360518e+03
11       yr_built  2.087580e+03
```

In [25]:
```
# Defining the dataset for Logistic Regression.
predictor_data = house_data[['sqft_lot', 'yr_renovated', 'sqft_living']]
target_data = house_data['price']

X_train, X_test, y_train, y_test = train_test_split(predictor_data, target_data)

# Data normalization
scaler = MinMaxScaler()
scaler.fit_transform(X_train)

X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

# Defining models and parameters for our grid search
regression = LogisticRegression(n_jobs=-1)
solvers = ['newton-cg', 'lbfgs']
c = [0.01, 0.1]
# solvers = ['newton-cg', 'lbfgs', 'liblinear']
# c = [0.01, 0.1]

param_grid = dict(solver=solvers,C=c)
# Creating a Repeated Stratifier KFold with 10 splits and 2 repeats for the cross-validator
cv = RepeatedStratifiedKFold(n_splits=5, n_repeats=2, random_state=1)

# Parameterizing the grid search
grid_search = GridSearchCV(estimator=regression, param_grid=param_grid, n_jobs=-1, cv=cv, scoring='accuracy',error_score=0)
grid_result = grid_search.fit(X_train, np.ravel(y_train))

# summarize results
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

The result is obtained as below. The result is copied after executing the above code in Google Colab:

Best: 0.008483 using {'C': 0.1, 'solver': 'newton-cg'}
0.008205 (0.000282) with: {'C': 0.01, 'solver': 'newton-cg'}
0.008205 (0.000282) with: {'C': 0.01, 'solver': 'lbfgs'}
0.008483 (0.000462) with: {'C': 0.1, 'solver': 'newton-cg'}
0.008483 (0.000462) with: {'C': 0.1, 'solver': 'lbfgs'}

In [26]:
```
# Defining the dataset for Logistic Regression.
predictor_data = house_data[['sqft_lot', 'yr_renovated', 'sqft_living']]
target_data = house_data['price']

X_train, X_test, y_train, y_test = train_test_split(predictor_data, target_data)

# Data normalization
scaler = MinMaxScaler()
scaler.fit_transform(X_train)

X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)

# Defining models and parameters for our grid search
regression = LogisticRegression(n_jobs=-1, C=0.1, solver='newton-cg')
regression.fit(X_train, y_train)

y_pred = regression.predict(X_test)
```

In [28]:
```
print("Thus, the line of best fit for the above can be found using : \n y = {} + {} x. \n".format(regression.intercept_, regression.coef_[0]))

mse = mean_squared_error(y_test, y_pred)
print("Where the Slope is {} and the y intercept is {} \n\
with mean squared error of {} and \nroot mean squared error of {}"
      .format(regression.coef_[0], regression.intercept_, mse, math.sqrt(mse)))
```

```
Thus, the line of best fit for the above can be found using :
 y = [-0.70172825 -0.70182603 -0.70146252 ... -0.70921109 -0.71114961
 -0.71775034] + [ 0.00170372 -0.00426096 -0.01067159] x.

Where the Slope is [ 0.00170372 -0.00426096 -0.01067159] and the y intercept is [-0.70172825 -0.70182603 -0.70146252 ... -0.70921109 -0.71114961
 -0.71775034]
with mean squared error of 146476276489.88504 and
root mean squared error of 382722.19231432746
```

In [48]:
```
print("Similarly the coefficient of variation is : {}%".format(regression.score(X_test, y_test)*100))
```

```
Similarly the coefficient of variation is : 0.6157865273371897%
```

Conclusion

Thus we can conclude that the price of the house increases with the increase in the square foot of the living area. We saw both the variables presented a positive strong correlation. With the line of best fit that was obtained through the linear regression, we are able to predict the price of a house with any given square foot.

However, there are some other lurking variables due to which the coefficient of variation between the price and the sqft of living does not give us a high accuracy. Other variables such as number of bedrooms and bathrooms and the grade of the house are also important in determining the price of the house.

In [ ]: