In [32]:
```
# Importing Python Modules/Packages
import pandas as pd
import numpy as np
from pandas.plotting import scatter_matrix
from matplotlib import pyplot as plt
import seaborn as sns
import matplotlib.image as mpimg
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score

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

In [33]:
```
# Loading King County dataset into a DataFrame
```

In [34]:
```
df = pd.read_csv('kc_house_data.csv')
```

In [35]:
```
## Pre-process the Dataset
```

In [36]:
```
# Checking the type of all variables
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   id             21613 non-null  int64  
 1   date           21613 non-null  object 
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64  
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64  
 6   sqft_lot       21613 non-null  int64  
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64  
 9   view           21613 non-null  int64  
 10  condition      21613 non-null  int64  
 11  grade          21613 non-null  int64  
 12  sqft_above     21613 non-null  int64  
 13  sqft_basement  21613 non-null  int64  
 14  yr_built       21613 non-null  int64  
 15  yr_renovated   21613 non-null  int64  
 16  zipcode        21613 non-null  int64  
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64  
 20  sqft_lot15     21613 non-null  int64  
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

In [37]:
```
## We can see the date is in object format, so change it to date format
```

In [38]:
```
#Changing the date format
df.date = pd.to_datetime(df.date)

# Now re-run and check the datatype of a date
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   id             21613 non-null  int64
 1   date           21613 non-null  datetime64[ns]
 2   price          21613 non-null  float64
 3   bedrooms       21613 non-null  int64
 4   bathrooms      21613 non-null  float64
 5   sqft_living    21613 non-null  int64
 6   sqft_lot       21613 non-null  int64
 7   floors         21613 non-null  float64
 8   waterfront     21613 non-null  int64
 9   view           21613 non-null  int64
 10  condition      21613 non-null  int64
 11  grade          21613 non-null  int64
 12  sqft_above     21613 non-null  int64
 13  sqft_basement  21613 non-null  int64
 14  yr_built       21613 non-null  int64
 15  yr_renovated   21613 non-null  int64
 16  zipcode        21613 non-null  int64
 17  lat            21613 non-null  float64
 18  long           21613 non-null  float64
 19  sqft_living15  21613 non-null  int64
 20  sqft_lot15     21613 non-null  int64
dtypes: datetime64[ns](1), float64(5), int64(15)
memory usage: 3.5 MB
```

In [39]:
```
## Now the datatype of date has been changed to datetime
```

In [40]:
```
# Checking for null values in the dataset. If we have any null values we shoulc

df.isnull().sum()
```

Out[40]:

```
id               0
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
grade            0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
zipcode          0
lat              0
long             0
sqft_living15    0
sqft_lot15       0
dtype: int64
```

In [41]:

```
## We can see that there are no null values in the dataset.
```

Perform Exploratory Data Analysis on the Data

In [42]:

```
df.shape
```

Out[42]:

```
(21613, 21)
```

The dataset has a total of 21 columns and 21613 records.

In [43]:

```
# Retrieving the first five records from the data set
df.head(5)
```

Out[43]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfron
0	7129300520	2014-10-13	221900.0	3	1.00	1180	5650	1.0	(
1	6414100192	2014-12-09	538000.0	3	2.25	2570	7242	2.0	(
2	5631500400	2015-02-25	180000.0	2	1.00	770	10000	1.0	(
3	2487200875	2014-12-09	604000.0	4	3.00	1960	5000	1.0	(
4	1954400510	2015-02-18	510000.0	3	2.00	1680	8080	1.0	(

5 rows × 21 columns

In [44]:

```
# Retrieve the summary statistics of the numeric variables of a given data set
df.describe()
```

Out[44]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot
count	2.161300e+04	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04
mean	4.580302e+09	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04
std	2.876566e+09	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04
min	1.000102e+06	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02
25%	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06

In [45]:

```
df.sort_values('price')
```

Out[45]:

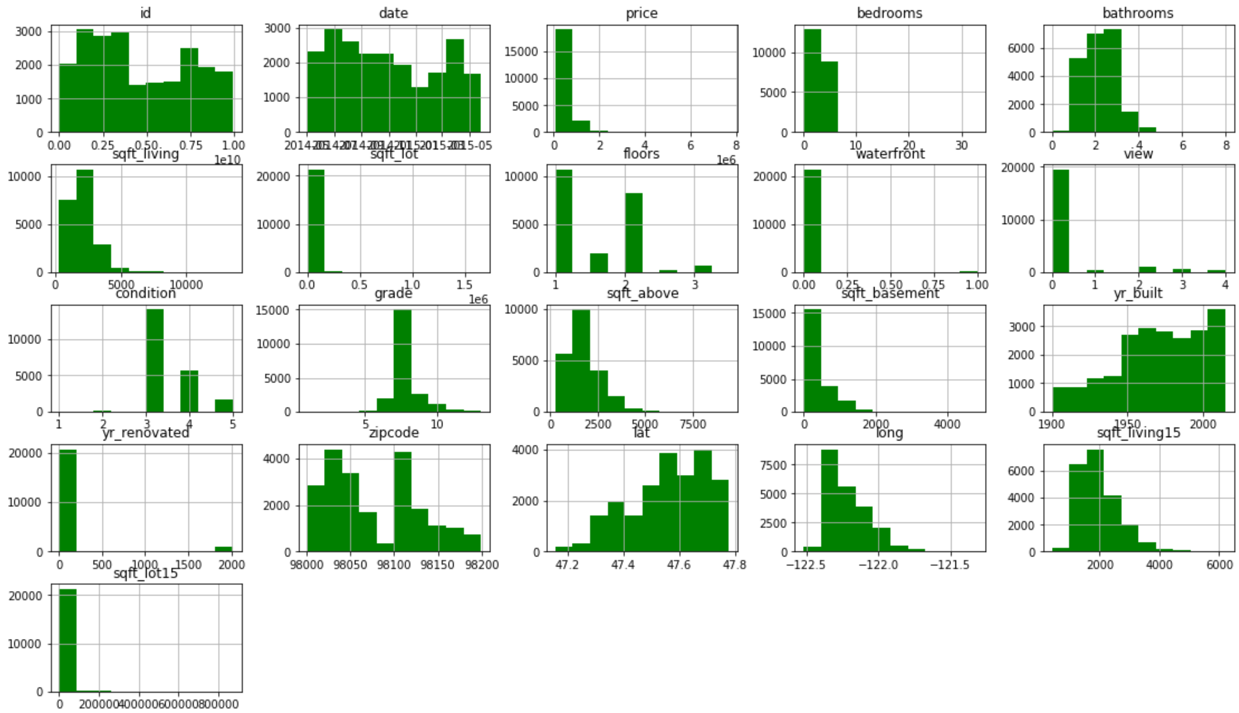
	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	wat
1149	3421079032	2015-02-17	75000.0	1	0.00	670	43377	1.0	
15293	40000362	2014-05-06	78000.0	2	1.00	780	16344	1.0	
465	8658300340	2014-05-23	80000.0	1	0.75	430	5050	1.0	
16198	3028200080	2015-03-24	81000.0	2	1.00	730	9975	1.0	
8274	3883800011	2014-11-05	82000.0	3	1.00	860	10426	1.0	
...	...	...	...	...	...	...	...	...	
1448	8907500070	2015-04-13	5350000.0	5	5.00	8000	23985	2.0	
4411	2470100110	2014-08-04	5570000.0	5	5.75	9200	35069	2.0	
9254	9208900037	2014-09-19	6885000.0	6	7.75	9890	31374	2.0	
3914	9808700762	2014-06-11	7062500.0	5	4.50	10040	37325	2.0	
7252	6762700020	2014-10-13	7700000.0	6	8.00	12050	27600	2.5	

21613 rows × 21 columns

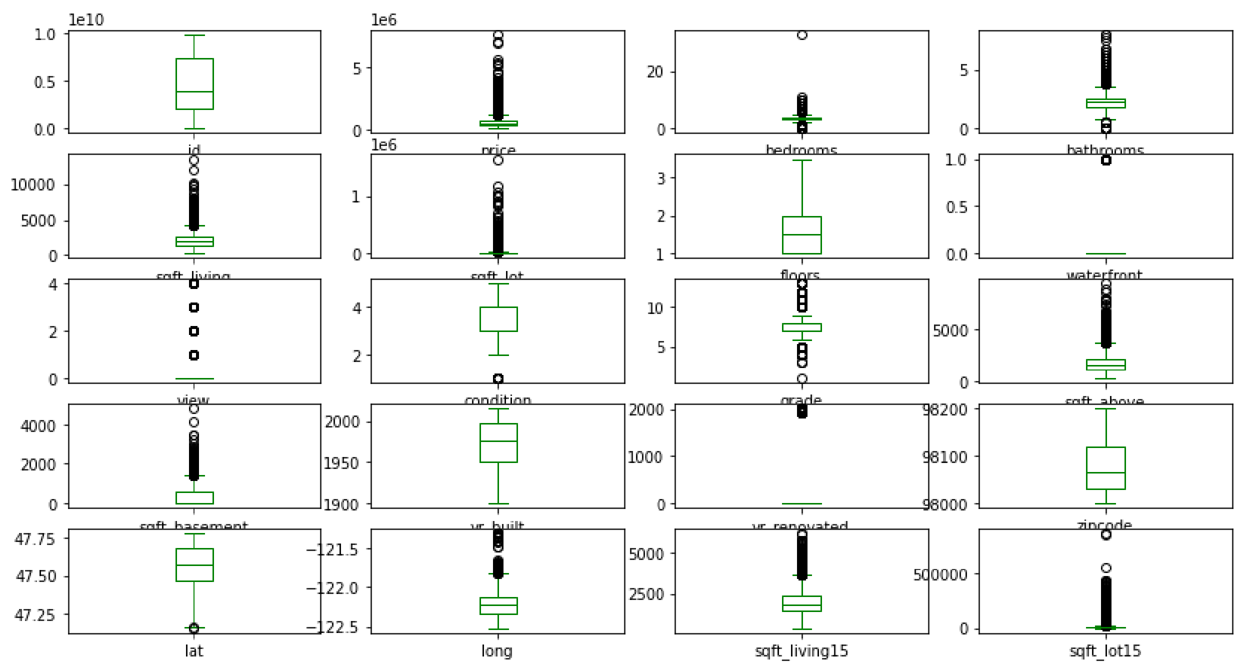
The min price and max price of the houses i.e, 75,000 and 7,700,000

Data Visualization for the Dataset

In [46]:
```
# Histogram for each numeric
df.hist(figsize=(19,11), color="green")
plt.show()
```



In [47]:
```
# Boxplots
df.plot(kind='box', subplots=True, layout=(6, 4),sharex=False, figsize=(14,9),
plt.show()
```



We can see some major outliers in number of bedrooms and bathrooms. We can make an assumption that a residential house will have atleast 1 bedroom and 1 bathroom. And also we can see there are 33 bedrooms in one house, so may be that is a Motel/commercial property. Delete all such records from the datset

In [48]:
```
# Delete records with 0 bedrooms and bathrooms
df = df[df.bedrooms > 0]
df = df[df.bathrooms > 0]

# Delete the record with 33 bedrooms
df = df[df.bedrooms < 33]
df.shape
```

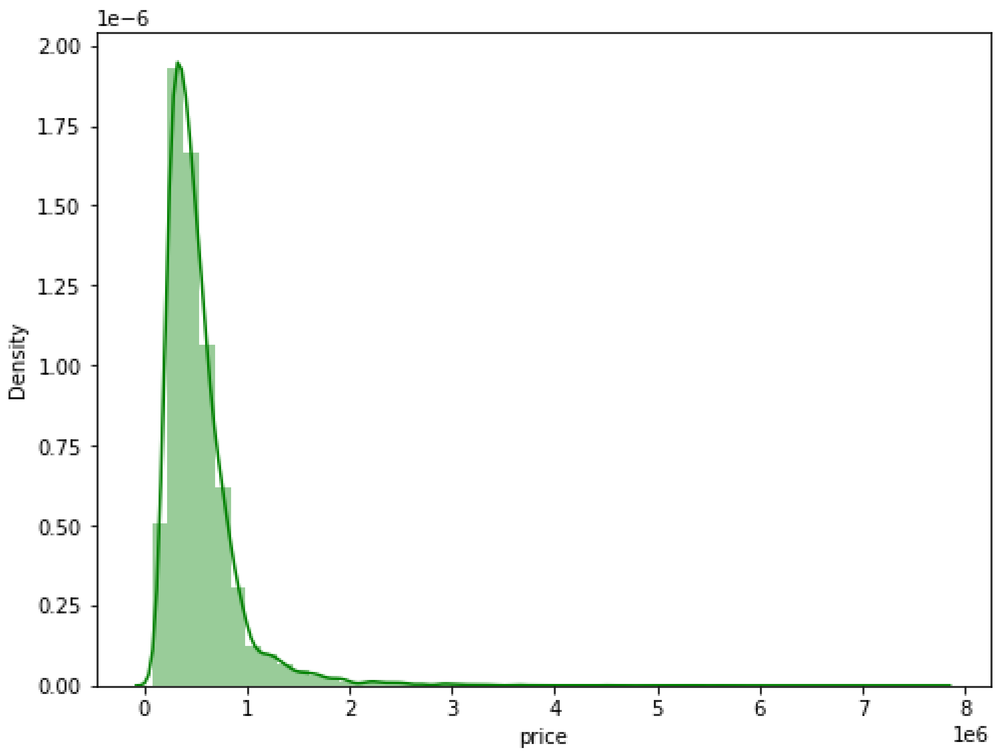
Out[48]:
```
(21596, 21)
```

The datset has 21,596 records after removing the records. So we are still left with enough observations to develop a prediction model

Target Variable : Housing Price distribution

In [49]:
```
plt.figure(figsize = (8,6))
sns.distplot(df['price'], color='green')
```

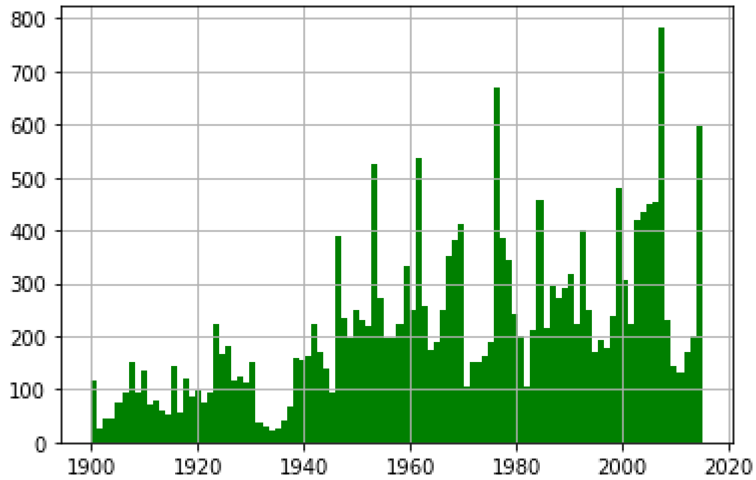
Out[49]:
```
<AxesSubplot:xlabel='price', ylabel='Density'>
```



We can see that most of the houses are within a million dollars, and there are very less number of houses that are more than 2 million

Relation between Price and other Categorical variables

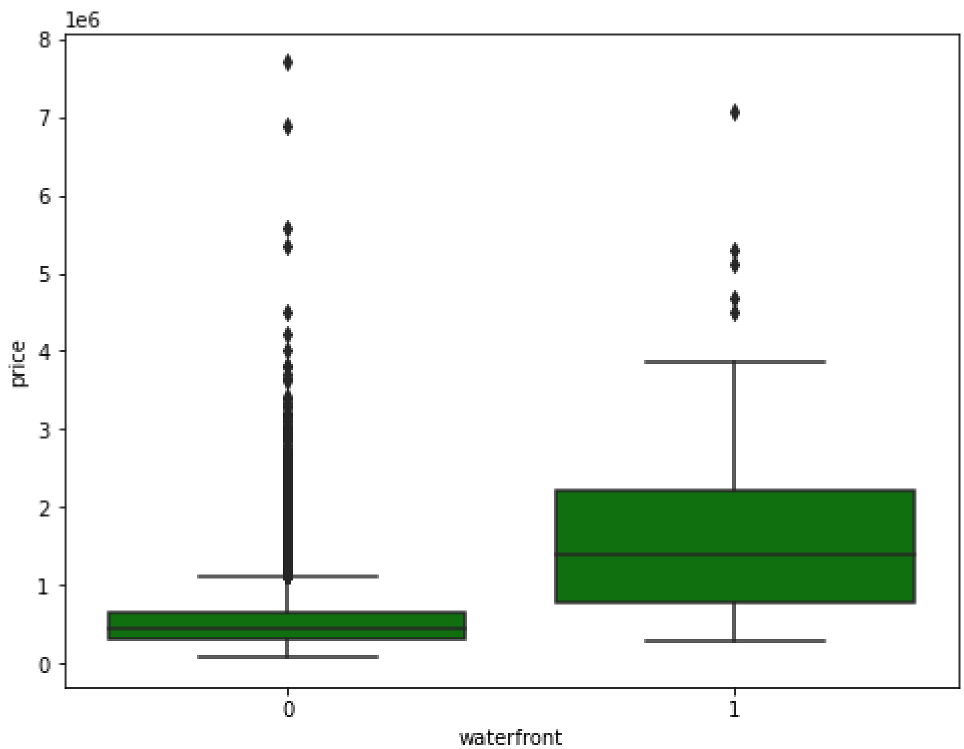
In [50]:
```
# Price of house and Year_built
df['yr_built'].hist(bins = 100, color='green')
plt.show()
```



The houses built after 2000 are more expensive, perhaps because of the realestate boom and the dips in between are may be due to recession.

In [51]:
```
# Price and Waterfront
plt.figure(figsize = (8,6))
sns.boxplot(x='waterfront', y='price', data=df, color='green')
```

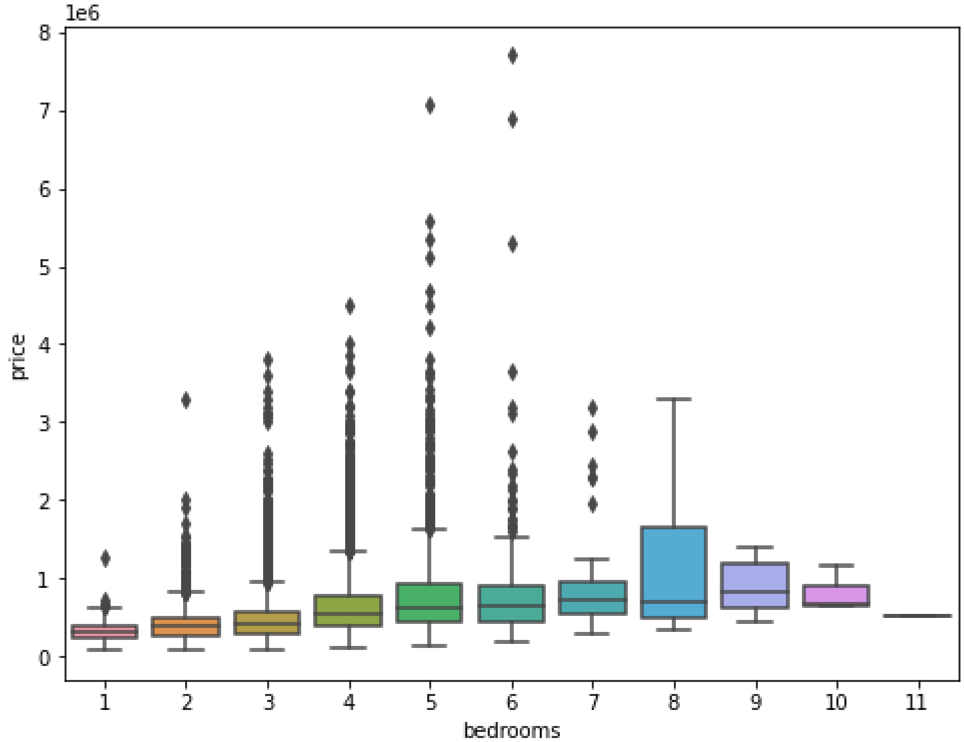
Out[51]: <AxesSubplot:xlabel='waterfront', ylabel='price'>



Waterfront Property comes at a premium

In [52]:
```
# Price and Number of berdooms
plt.figure(figsize = (8,6))
sns.boxplot(x='bedrooms', y='price', data=df)
```

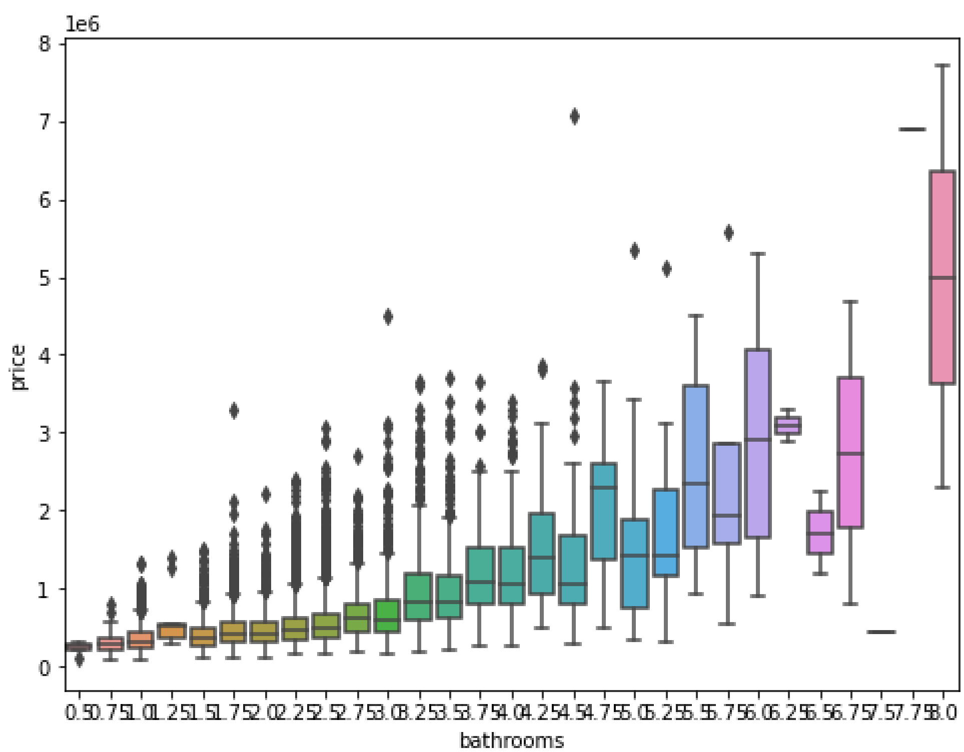
Out[52]: <AxesSubplot:xlabel='bedrooms', ylabel='price'>



There is increase in price with the increase in number of bedrooms

In [53]:
```
# Price and Number of bathrooms
plt.figure(figsize = (8,6))
sns.boxplot(x='bathrooms', y='price', data=df)
```

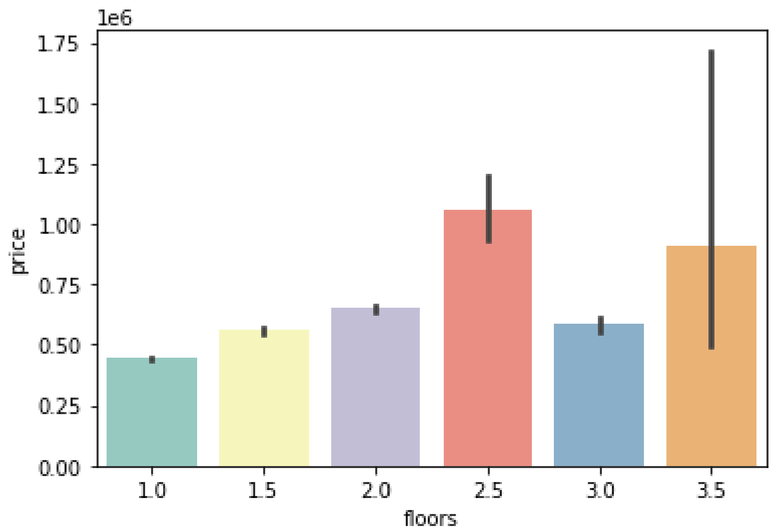
Out[53]: <AxesSubplot:xlabel='bathrooms', ylabel='price'>



there are more number of bathrooms, the house price increases

In [54]:
```
# Price and Number of Floors
sns.barplot(x ='floors', y='price', data = df, palette= 'Set3' )
```

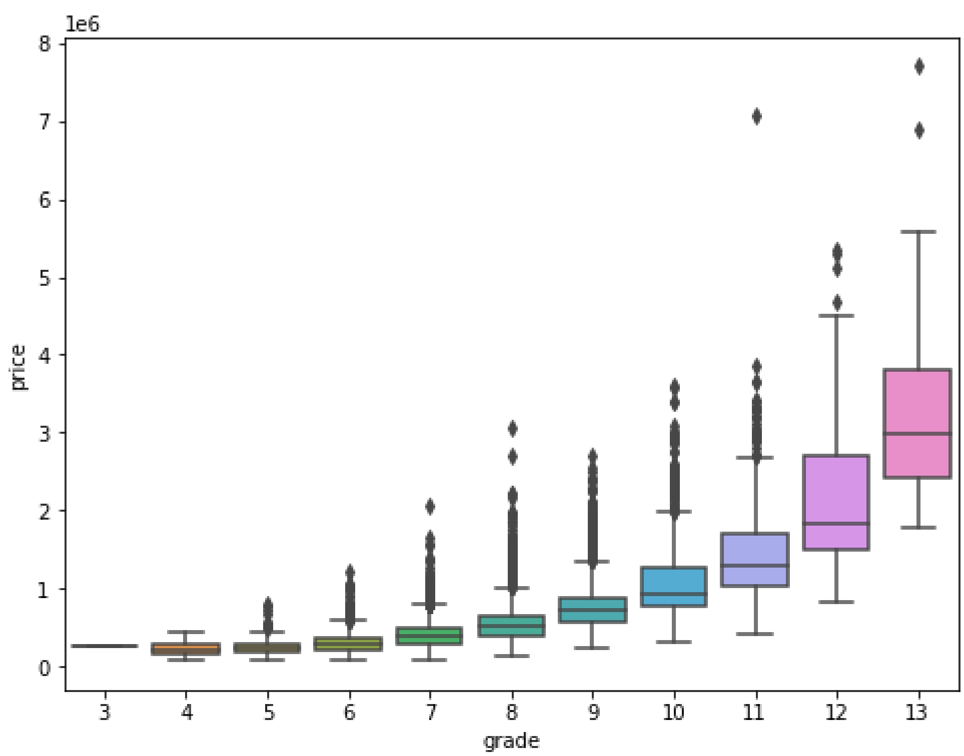
Out[54]:
```
<AxesSubplot:xlabel='floors', ylabel='price'>
```



Houses with 2.5 floors are more expensive

In [55]:
```
# Price and Grade
plt.figure(figsize = (8,6))
sns.boxplot(x='grade', y='price', data=df)
```

Out[55]:
```
<AxesSubplot:xlabel='grade', ylabel='price'>
```

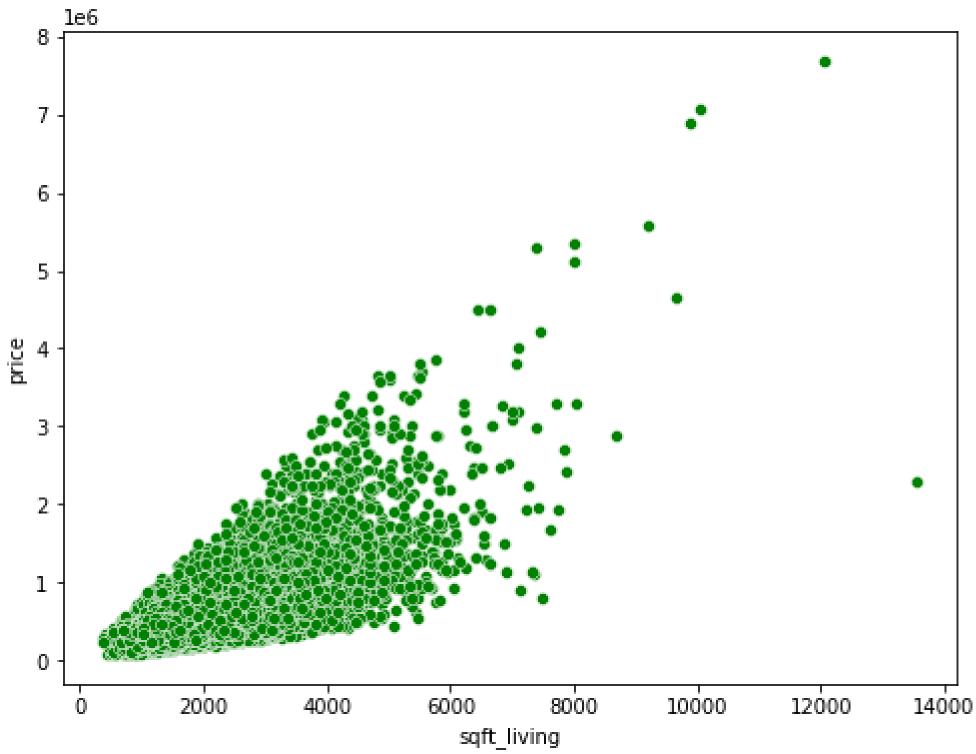


As we can view the good construction quality/grade, the house price increases

In [56]:
```
# Price and Sqft_living area
plt.figure(figsize =(8,6))
```

```
sns.scatterplot(x ='sqft_living', y = 'price', data = df, color='green')
```

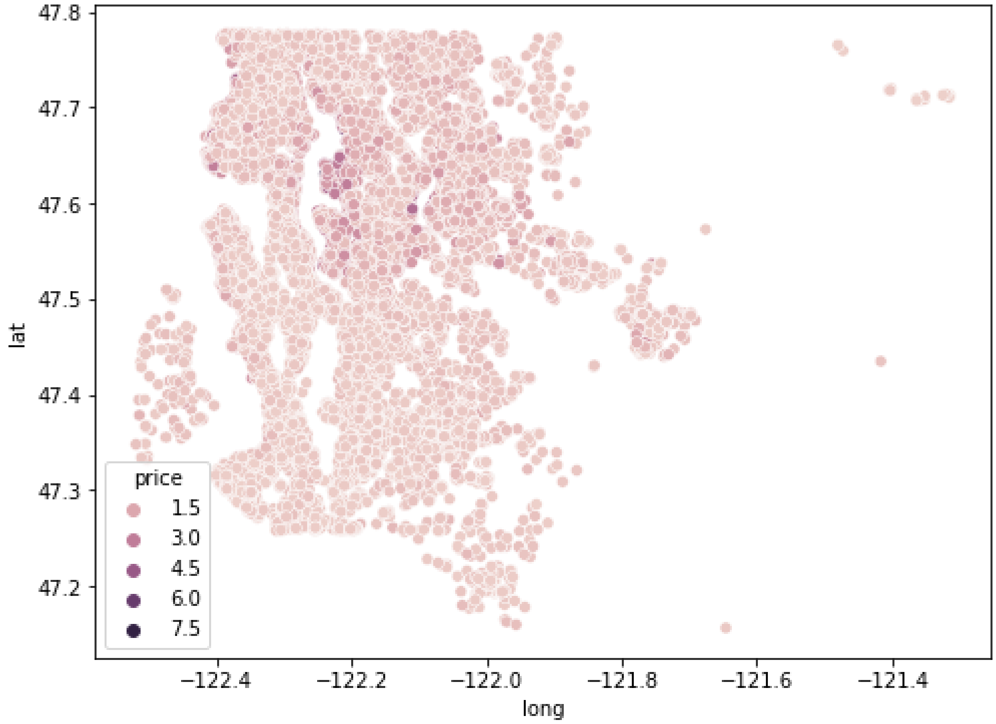
Out[56]: <AxesSubplot:xlabel='sqft_living', ylabel='price'>



The price increases with increse in size of living area. We can see some outliers. For example, there is one house with living area of almost 14,000 sqft for less price (220,000). This may be because the property is in the country area ad not in the city

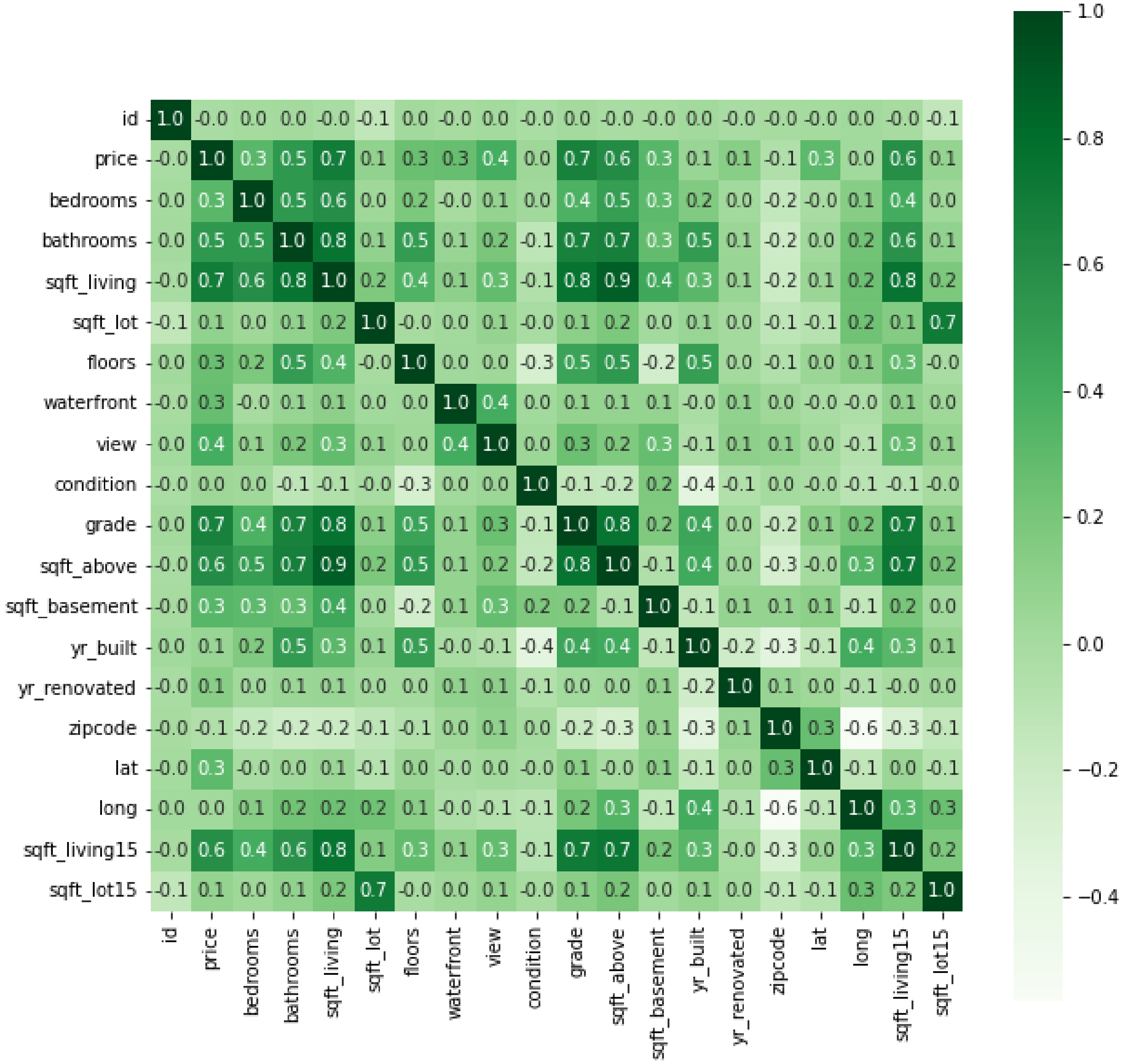
In [57]:
```
plt.figure(figsize =(8,6))
sns.scatterplot(x ='long', y = 'lat', data = df, hue ='price')
```

Out[57]: <AxesSubplot:xlabel='long', ylabel='lat'>



In [58]:
```
# Correlation matrix
corr  = df.corr()
plt.figure(figsize = (10,10))
sns.heatmap(corr, cbar= True, square = True, fmt = '.1f', annot = True, annot_k
```

Out[58]: <AxesSubplot:>



Feature Engineering : Creating new Features

1.Split the Date sold column into month_sold and year_sold. This way we can understand if there are more sales in any particular month of the year

In [59]:
```
# Convert the Date column into month_sold and year_sold.

df['month_sold'] = df['date'].apply(lambda x:x.month)
df['year_sold'] = df['date'].apply(lambda x:x.year)


#Drop original Date column
df.drop(columns=['date'], axis=1, inplace=True)
```

1. Convert the Year built column into 'Age' column that allows better interpretation. For this, we subtracted the actual year built from the latest built year in the dataset('2015') to calculate age of the house.

In [60]:
```
# calculate age of the house as of 2015
```

```
df['age'] = 2015 - df.yr_built

# Drp the original column 'yr_built'
df = df.drop(columns=['yr_built'], axis=1)
```

1. Change the year renovated column into a binary column - '1' for the homes that are renovated within past 10 years or built within the past 5 years(so they dont need renovation yet), and '0' for homes that are not renovated within past 10 years

In [61]:
```
#Fill missing values
df.yr_renovated.fillna(0.0, inplace=True)

#Create renovated column
df['renovated'] = df.year_sold - df.yr_renovated

#Replace any values less than 10 with 1, and any values over 10 with 0
renovated = df.renovated.values
age = df.age.values
values = np.where(renovated <= 10, 1, 0)
df['renovated'] = np.where(age <= 5, 1, values)

#Drop yr_renovated column
df.drop(columns=['yr_renovated'], axis=1, inplace=True)
```

1. Seattle is an important city in King county, where a lot of houses are listed. So for better analysis, calculate distance of the house from specific latitude and longitude points (Seattle downtown). This can be done using geopy module in python

In [63]:
```
from geopy import distance
lat_long = df['lat'].astype(str) + ',' + df['long'].astype(str)
lat_long = list(map(eval, lat_long))

Seattle = (47.6062, -122.3321)
miles = []
for i in lat_long:
    miles.append(round(distance.distance(i, Seattle).miles, 1))

df['distance'] = miles
```

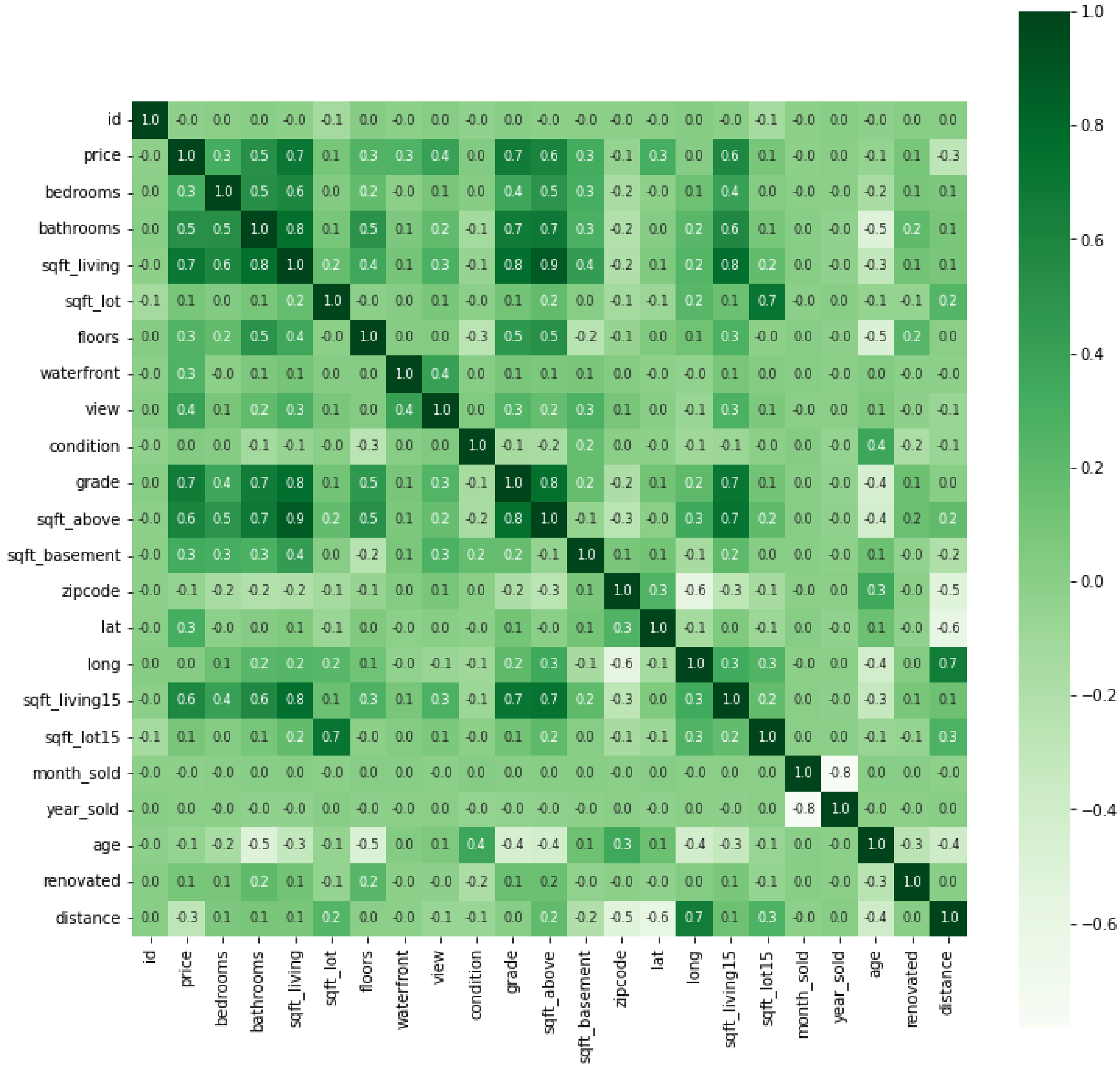
In [64]:
```
df.columns
```

Out[64]:
```
Index(['id', 'price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot',
       'floors', 'waterfront', 'view', 'condition', 'grade', 'sqft_above',
       'sqft_basement', 'zipcode', 'lat', 'long', 'sqft_living15',
       'sqft_lot15', 'month_sold', 'year_sold', 'age', 'renovated',
       'distance'],
      dtype='object')
```

Correlation matrix

In [66]:
```
# Correlation matrix
corr  = df.corr()
plt.figure(figsize = (12,12))
sns.heatmap(corr, cbar= True, square = True, fmt = '.1f', annot = True, annot_k
```

Out[66]:
```
<AxesSubplot:>
```



Feature Selection

By looking at the correlation matrix we can understand which features are important and influence the house price

In [67]:
```
# Drop all unnecessary features
dCol = ['id','zipcode','month_sold','year_sold','lat','long','condition']
df.drop(dCol, axis = 1, inplace = True)

df.columns
```

Out[67]:
```
Index(['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors',
       'waterfront', 'view', 'grade', 'sqft_above', 'sqft_basement',
       'sqft_living15', 'sqft_lot15', 'age', 'renovated', 'distance'],
      dtype='object')
```

In [68]:
```
# Now we have 16 features
df.shape
```

Out[68]:
```
(21596, 16)
```

Separate the dataset into Input and Output arrays

In [69]:
```
X = df.drop(['price'], axis = 1)
Y = df['price']
```

Split Input/Output arrays into Training/Testing Datasets

In [71]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.3, random_
```

Build and Train the model

In [72]:
```
model = LinearRegression()
#model = RandomForestRegressor()
#model = DecisionTreeRegressor()
model.fit(X_train,Y_train)
```

Out[72]:
```
▾ LinearRegression
LinearRegression()
```

Medel Prediction on Trained data

In [74]:
```
Y_predict = model.predict(X_train)
```

Model Evaluation

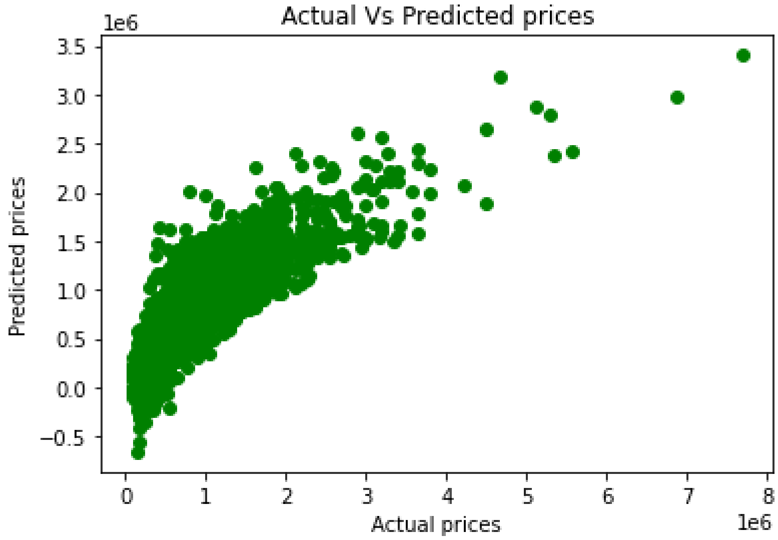
In [75]:
```
# Model Evaluation

print('R^2:',metrics.r2_score(Y_train,Y_predict))
print('MAE:', metrics.mean_absolute_error(Y_train,Y_predict))
print('MSE:', metrics.mean_squared_error(Y_train,Y_predict))
print('RMSE:', np.sqrt(metrics.mean_squared_error(Y_train,Y_predict)))
```

```
R^2: 0.7085481351384417
MAE: 127748.50571488231
MSE: 40239112611.98932
RMSE: 200596.8908333061
```

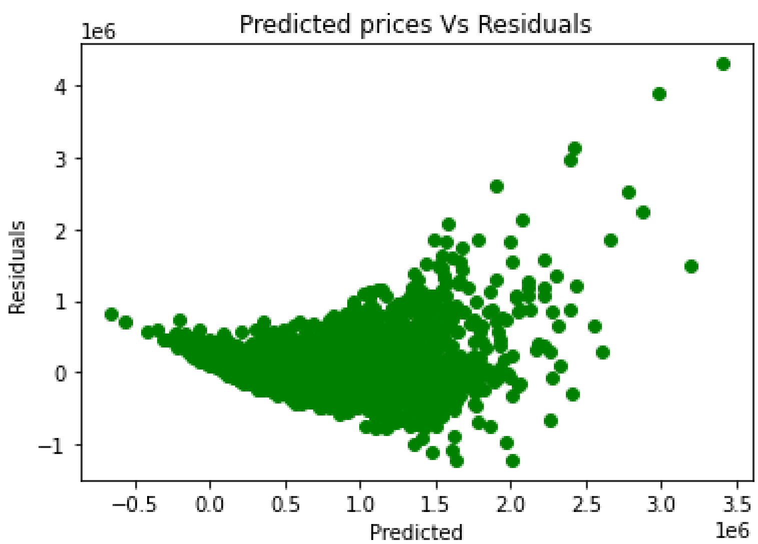
Visualizing the differences between actual and predicted values

In [77]:
```
plt.scatter(Y_train,Y_predict, color='green')
plt.xlabel("Actual prices")
plt.ylabel("Predicted prices")
plt.title("Actual Vs Predicted prices")
plt.show()
```



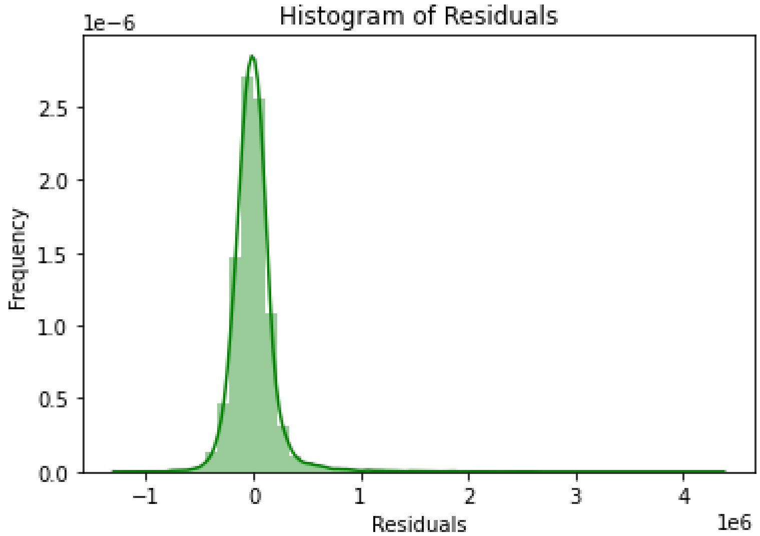
Inspecting residuals

In [78]:
```
# Checking residuals
plt.scatter(Y_predict, Y_train-Y_predict, color='green')
plt.xlabel("Predicted")
plt.ylabel("Residuals")
plt.title("Predicted prices Vs Residuals")
plt.show()
```



Checking Normality of Errors

In [79]:
```
sns.distplot(Y_train-Y_predict, color='green')
plt.xlabel("Residuals")
plt.ylabel("Frequency")
plt.title("Histogram of Residuals")
plt.show()
```



Model Evaluation

In [80]:
```
# Predicting test data with model
Y_test_predict = model.predict(X_test)
```

In [81]:
```
# Model Evaluation
act_model = metrics.r2_score(Y_test, Y_test_predict)

print('R^2:', act_model)
print('MAE:', metrics.mean_absolute_error(Y_test, Y_test_predict))
print('MSE:', metrics.mean_squared_error(Y_test, Y_test_predict))
print('RMSE:', np.sqrt(metrics.mean_squared_error(Y_test, Y_test_predict)))
```

```
R^2: 0.7111081828873791
MAE: 124755.49161087959
MSE: 36728240445.75293
RMSE: 191646.13339630133
```

Let's make a Prediction using the Linaer model

In [82]:
```
# Predict the house price in dollars
# Arbitrary predictors/housing records are used
model.predict([[4,3,3400,7000,2,1,4,3,3000,400,2800,6000,5,0,5.5]])
```

Out[82]:
```
array([1196974.91036818])
```

The Predicted value of the house with the above features is $1,196,975