Data Analysis with Kings County House Sales Price

1. Introduction

I use the dataset 'House Sales in King County, USA' from Kaggle. This dataset is about house sales status in Kings County for 1 year from 2014 to 2015. The dataset includes 21 columns as below.

[1] id- Unique ID for each home sold
[2] date- Date of the home sale
[3] price- Price of each home sold
[4] bedrooms- Number of bedrooms
[5] bathrooms- Number of bathrooms (.5= a room with a toilet but no shower)
[6] sqft_living - Sq. ft. of the apts interior living space
[7] sqft_lot- Sq. ft. of the land space
[8] floors- Number of floors
[9] waterfront- A variable for whether the apartment was overlooking the waterfront or not
[10] view -Index from 0 to 4 describing the property view.
[11] condition -Index from 1 to 5 describing the condition of the apartment
[12] grade- Index from 1 to 13 in construction and design
[13] sqft_above- Sq. ft. of the interior housing space above ground level
[14] sqft_basement- Sq. ft. of the interior housing space above ground level
[15] yr_built- The year the house was initially built
[16] yr_renovated- The year of the house's last renovation
[17] zipcode- area zipcode of the house
[18] lat- Lattitude
[19] long- Longitude
[20] sqft_living15- Sq. ft. of interior housing living space for the nearest 15 neighbors
[21] sqft_lot15- Sq. ft. of the land lots of the nearest 15 neighbors

I want to see this dataset in various perspectives. For example, where is the most expensive area, which factors are more effective to price. I imagine which information is more important if I were a person who are searching for a place. I consider built year because usually people prefer recent built house to old house. Also, I sort out zip code by grade and density, so a person can easily find out a place whether they like high graded and crowded area or not. Finally, I do some linear regression with the most five correlated factors for price and see how the price factor is well explained by those factors.

2. Imported Module List

- pandas
- matplotlib.pyplot
- from pandas.tools.plotting import scatter_matrix
- csv
- re
- from sklearn.cross_validation import train_test_split
- from sklearn.linear_model import LinearRegression
- import numpy
- from sklearn.metrics import mean_absolute_error

3. Description

1.Draw histogram, scatter_matrix to get correlation between other factors and price factor and later do a linear regression with the most five correlated factors for price. Test this model how well explained for price and predict.

2.Find out which part of Kings County has most expensive area with drawing sacatter_plot with latitude and longitude.

3.Make a function if put an id, you can get the built year

4. Make a program for finding out area(zip code) following grade and density.

In [1]:
```
try:
    f = open('kc_house_data.csv','r')
    print('file is found')

except IOError:
    print("File not found.")
```

```
file is found
```

In [35]:
```
#Data load
import pandas as pd
data = pd.read_csv('kc_house_data.csv')
data.head()
```

Out[35]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	0	0
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	0	0
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	0	0
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	0	0
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	0	0

5 rows × 21 columns

In [36]:
```
#Drop unimprtant columns : waterfront, view,, year of renovated

data.drop(data.columns[[8,9,15]], axis=1, inplace=True)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 18 columns):
id               21613 non-null int64
date             21613 non-null object
price            21613 non-null float64
bedrooms         21613 non-null int64
bathrooms        21613 non-null float64
sqft_living      21613 non-null int64
sqft_lot         21613 non-null int64
floors           21613 non-null float64
condition        21613 non-null int64
grade            21613 non-null int64
sqft_above       21613 non-null int64
sqft_basement    21613 non-null int64
yr_built         21613 non-null int64
zipcode          21613 non-null int64
lat              21613 non-null float64
long             21613 non-null float64
sqft_living15    21613 non-null int64
sqft_lot15       21613 non-null int64
dtypes: float64(5), int64(12), object(1)
memory usage: 3.0+ MB
```

In [37]:
```
# Maximum and minmum of date it is range from May 2th 2014 to May27 2015 about 1 year

data.date.min(), data.date.max()
```

Out[37]: ('20140502T000000', '20150527T000000')

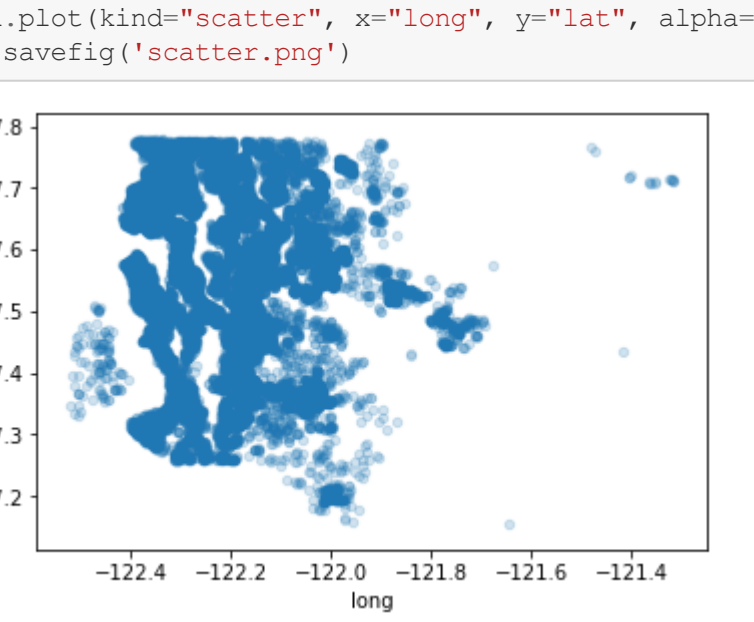
In [38]:
```
data.describe()
```

Out[38]:

	id	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	
count	2.161300e+04	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000	216
mean	4.580302e+09	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04	1.494309	3.4
std	2.876566e+09	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04	0.539989	0.6
min	1.000102e+06	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02	1.000000	1.0
25%	2.123049e+09	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000	3.0
50%	3.904930e+09	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000	3.0
75%	7.308900e+09	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000	4.0
max	9.900000e+09	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000	5.0

In [41]:
```
# Draw a scatter plot to find out where is the most expecsive area.

%matplotlib inline
import matplotlib.pyplot as plt
data.plot(kind="scatter", x="long", y="lat", alpha=0.2)
plt.savefig('scatter.png')
```

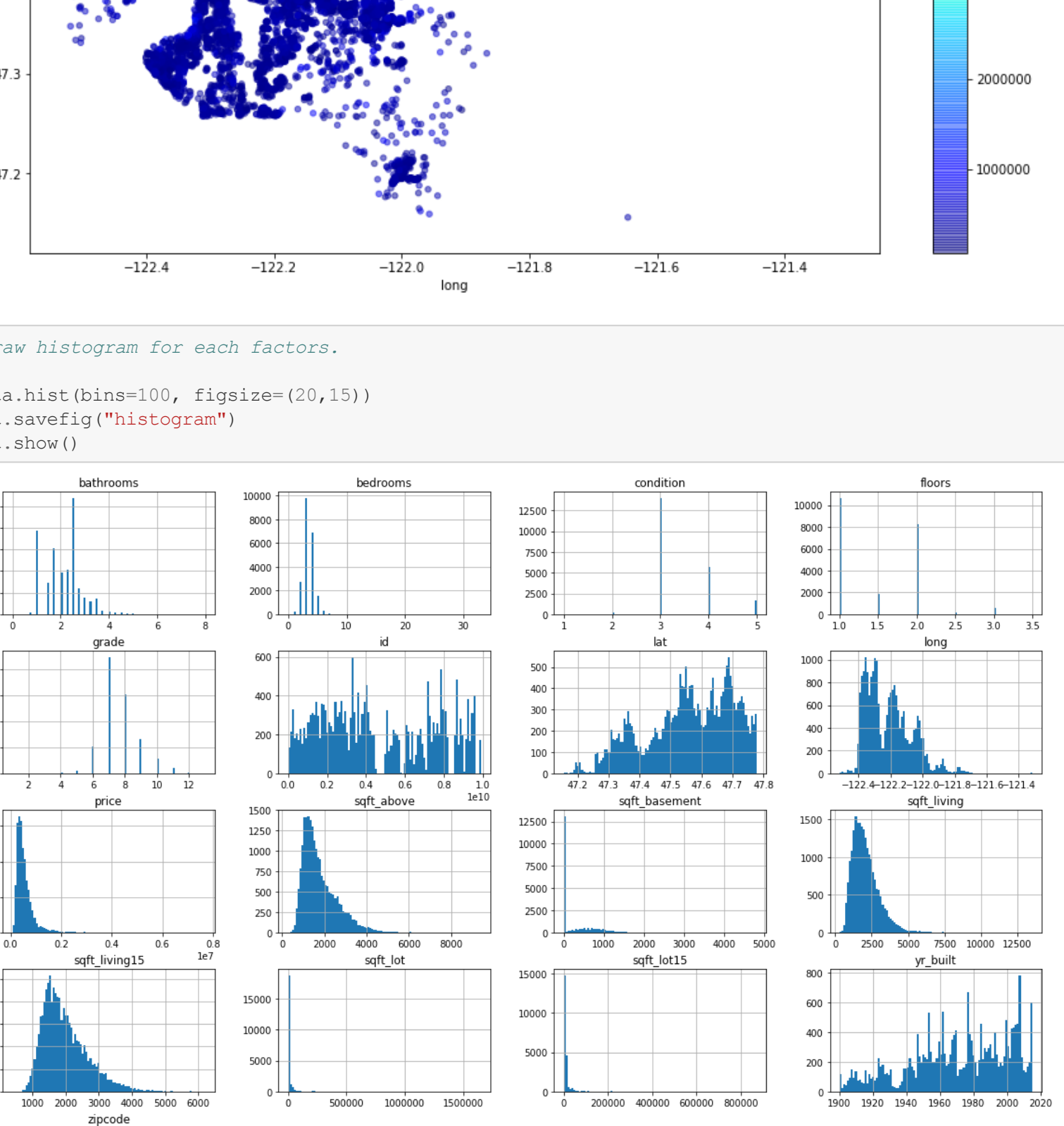


In [42]:
```
# The most expensive area is North West part of KIngs County.

data.plot(kind="scatter", x="long", y="lat", alpha=0.5, figsize=(15,10), c="price", cmap=plt.get_cma
p("jet"), colorbar=True, sharex=False)
plt.savefig('coloredByPrice.png')
```

In [43]:
```
#Draw histogram for each factors.

data.hist(bins=100, figsize=(20,15))
plt.savefig("histogram")
plt.show()
```



In [44]:
```
# Find out wich factor is highly corelated with price.

correlation = data.corr()
correlation["price"].sort_values(ascending=False)
```

Out[44]:
```
price            1.000000
sqft_living      0.702035
grade            0.667434
sqft_above       0.605567
sqft_living15    0.585379
bathrooms        0.525138
sqft_basement    0.323816
bedrooms         0.308350
lat              0.307003
floors           0.256794
sqft_lot         0.089661
sqft_lot15       0.082447
yr_built         0.054012
condition        0.036362
long             0.021626
id              -0.016762
zipcode         -0.053203
Name: price, dtype: float64
```

In [56]:
```
# Draw matrix to test relations show line.

from pandas.tools.plotting import scatter_matrix
factors = ["price", "sqft_living", "grade", "sqft_above","sqft_living15","bathrooms"]
scatter_matrix(data[factors], figsize=(15, 10))
plt.savefig('scatter_matrix.png')
```

```
C:\Users\byunh\Anaconda3\lib\site-packages\ipykernel_launcher.py:5: FutureWarning: 'pandas.tool
s.plotting.scatter_matrix' is deprecated, import 'pandas.plotting.scatter_matrix' instead.
  """
```

In [46]:
```
#Built year is not significant factor but still important for people who searching a place.
#Check minium to maximun built year.

data.yr_built.min(), data.yr_built.max()
```

Out[46]: (1900, 2015)

In [47]:
```
#Make a dictionary for pair of id and  yr_built columns

import csv

with open('kc_house_data.csv', mode='r') as infile:
    reader = csv.reader(infile)
    with open('new_column.csv', mode='w') as outfile:
        writer = csv.writer(outfile)
        yearbuilt = {rows[0]:rows[14] for rows in reader}
```

In [48]:
```
#If input id as key, get the year of built as value.

print(yearbuilt['1432701230'])
```

```
1959
```

In [49]:
```
# Check zipcode, if there is invalid zipcode. It should start with 9.

import re

count1 = 0
count2 = 0

zipcode_check = re.compile(r'(9\d)')

for i in data['zipcode']:

    if zipcode_check.search(str(i)):
        count1 += 1
    else:
        count2 += 1

print('The number of valid zipcode is %d' %count1)
print("The number of invalid zipcode is %d " %count2)
```

```
The number of valid zipcode is 21613
The number of invalid zipcode is 0
```

In [50]:
```
#The number of zipcode is 70

len(data['zipcode'].value_counts())
```

Out[50]: 70

In [51]:
```
#Zipcode grouped by grade and density

dens = data.groupby('zipcode').count()['grade']
mean = data.groupby('zipcode').mean()['grade']
group = pd.concat([dens, mean], axis=1)
group['zipcode'] = group.index
group.columns = ['density', 'grade','zipcode']
group.describe()
```

Out[51]:

	density	grade	zipcode
count	70.000000	70.000000	70.000000
mean	308.757143	7.664549	98077.300000
std	142.267296	0.611821	56.622408
min	50.000000	6.509294	98001.000000
25%	204.500000	7.261202	98029.250000
50%	282.500000	7.536861	98067.500000
75%	409.000000	8.016916	98117.750000
max	602.000000	9.560000	98199.000000

In [20]:
```
#Find out values by each group

group1 = group[group.grade < 7.536861]
group1.index
```

Out[20]:
```
Int64Index([98001, 98002, 98010, 98014, 98019, 98022, 98024, 98030, 98031,
            98032, 98034, 98042, 98055, 98056, 98070, 98103, 98106, 98107,
            98108, 98115, 98117, 98118, 98125, 98126, 98133, 98136, 98144,
            98146, 98148, 98155, 98166, 98168, 98178, 98188, 98198],
           dtype='int64', name='zipcode')
```

In [21]:
```
temp= group[group.grade >= 7.536861]
group2 = temp[temp.density <282.500000]
group2.index
```

Out[21]:
```
Int64Index([98003, 98005, 98007, 98011, 98039, 98040, 98045, 98072, 98077,
            98102, 98105, 98109, 98112, 98119, 98177],
           dtype='int64', name='zipcode')
```

In [23]:
```
group3 = temp[temp.density >=282.500000]
group3.index
```

Out[23]:
```
Int64Index([98004, 98006, 98008, 98023, 98027, 98028, 98029, 98033, 98038,
            98052, 98053, 98058, 98059, 98065, 98074, 98075, 98092, 98116,
            98122, 98199],
           dtype='int64', name='zipcode')
```

In [24]:
```
#Make a function. if you put a zip code, you can get one of three groups.

def find_group(x):
    if x in group1.index:
        return 'low grade area'
    elif x in group2.index:
        return 'high grade and low density area'
    else:
        return 'high grade and high density area'

data['group'] = data.zipcode.apply(find_group)
```

In [25]:
```
find_group(98004)
```

Out[25]: 'high grade and high density area'

In [26]:
```
find_group(98005)
```

Out[26]: 'high grade and low density area'

In [27]:
```
find_group(98118)
```

Out[27]: 'low grade area'

In [ ]:
```
#for index, row in data.iterrows():
#    print (row["zipcode"], row["group"])
```

In [ ]:
```
#Linear Regression and predict

#Except those high cofficient variables(sqft_living, grade,sqft_above , sqft_living15 ,bathrooms)
#drop other variables for liniear regression
#also remove newly added'group' column
```

In [28]:
```
data.head()
```

Out[28]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	condition	grade
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	3	7
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	3	7
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	3	6
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	5	7
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	3	8

In [29]:
```
data.drop(data.columns[[0,1, 3, 6, 7, 8, 11, 12, 13, 14, 15, 17,18 ]], axis=1, inplace=True)
data.head()
```

Out[29]:

	price	bathrooms	sqft_living	grade	sqft_above	sqft_living15
0	221900.0	1.00	1180	7	1180	1340
1	538000.0	2.25	2570	7	2170	1690
2	180000.0	1.00	770	6	770	2720
3	604000.0	3.00	1960	7	1050	1360
4	510000.0	2.00	1680	8	1680	1800

In [52]:
```
# linear regresstion with those five factors for price factor

X = data[['bathrooms', 'sqft_living', 'grade', 'sqft_above', 'sqft_living15']]
Y = data['price']
```

In [53]:
```
from sklearn.cross_validation import train_test_split

Xtrain, Xtest, Ytrain, Ytest = train_test_split(X, Y, test_size=0.2, random_state=0)

from sklearn.linear_model import LinearRegression
reg = LinearRegression()
reg.fit(Xtrain, Ytrain)
```

Out[53]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)

In [54]:
```
# Get R squared

predict= reg.predict(Xtest)
print(' R squared is %.4f' % reg.score(Xtest, Ytest))
```

```
 R squared is 0.5491
```

In [55]:
```
# Get Root mean squared error (RMSE)

import numpy as np
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(predict, Ytest)
rmse = np.sqrt(mse)
print('RMSE is %.4f' % rmse)
```

```
RMSE is 231575.4823
```

4. Conclusion

First, I find out which part of Kings County shows more expensive house price. I draw a scatter plot with latitude and longitude according price. The result shows that The North West part is most expensive area.

Second, I expect the built year is highly related to house price but as the result of correlation, it is not significant. It 's minimal as 0.054012. The five significant factors for price are following.

sqft_living 0.702035,
grade 0.667434,
sqft_above 0.605567,
sqft_living15 0.585379,
bathrooms 0.525138.
But built year is still one of the most perspective factors when people considering buying a house even it is not significant for price factor. So, I made a program if you put a specific zip code, you can get built year.

Third, I make a program to get zip code by grade and density. Usually, people consider grade of house and how many neighbors live near their house. So, I divide 3 sections to low grade, high grade & high density, and high grade & low density. If I were a house buyer, I would like to live high grade and not crowed area. As I expected the result shows that low grade area has the largest zip code, and high grade & high density area is second and high grade and low density is the least. This is explained well by high demand to low supply.

Forth, I do some linear regression with the most five correlated factors for price factor and predict price. The result of linear regression R squired is 0.5491. Price factor can be moderately explained by around 55% with those five factors.(sqft_living, grade, sqft_above, sqft_living15, bathrooms). RMSE is 231575.4823. This means that linear model can predict each house price in the test set within $231575 of the real price.