House Price Prediction

We are going to use the house price prediction dataset to build a prediction model and explore the ways to predict the house price.

Data source: https://www.kaggle.com/shree1992/housedata

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Import and learn about Data

In [191…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import statsmodels.formula.api as smf

url = 'https://raw.githubusercontent.com/say0602/data_bootcamp_final_project/main/data.
df = pd.read_csv(url,header=0, index_col=0)
df.head(5)
```

Out[191…

date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	s
2014-05-02 00:00:00	313000.0	3.0	1.50	1340	7912	1.5	0	0	3	
2014-05-02 00:00:00	2384000.0	5.0	2.50	3650	9050	2.0	0	4	5	
2014-05-02 00:00:00	342000.0	3.0	2.00	1930	11947	1.0	0	0	4	
2014-05-02 00:00:00	420000.0	3.0	2.25	2000	8030	1.0	0	0	4	
2014-05-02 00:00:00	550000.0	4.0	2.50	1940	10500	1.0	0	0	4	

In [192…

```
df.isnull().values.any()
```

Out[192…

```
False
```

In [193…

```
df.dtypes
```

Out[193…

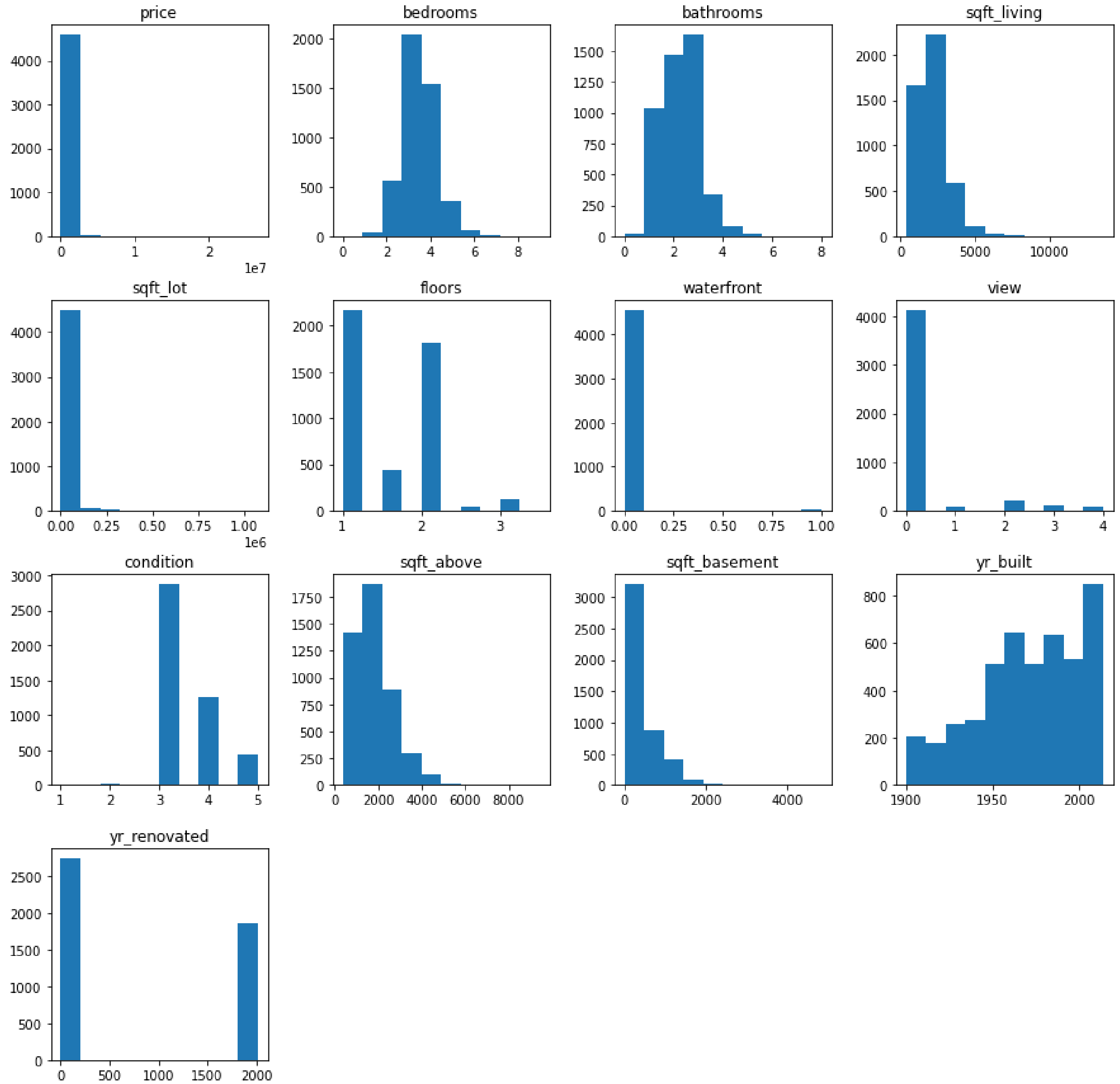
```
price            float64
bedrooms         float64
```

```
bathrooms        float64
sqft_living        int64
sqft_lot           int64
floors           float64
waterfront         int64
view               int64
condition          int64
sqft_above         int64
sqft_basement      int64
yr_built           int64
yr_renovated       int64
street            object
city              object
statezip          object
country           object
dtype: object
```

In [194…

```
fig, ax = plt.subplots(figsize=(15, 15))
df.hist(ax=ax, grid=False)
plt.show()
```

```
<ipython-input-194-e7551949585a>:2: UserWarning: To output multiple subplots, the figure
containing the passed axes is being cleared
  df.hist(ax=ax, grid=False)
```



In [195…

```
df.describe()
```

Out[195…

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterf
count	4.600000e+03	4600.000000	4600.000000	4600.000000	4.600000e+03	4600.000000	4600.000
mean	5.519630e+05	3.400870	2.160815	2139.346957	1.485252e+04	1.512065	0.007
std	5.638347e+05	0.908848	0.783781	963.206916	3.588444e+04	0.538288	0.084
min	0.000000e+00	0.000000	0.000000	370.000000	6.380000e+02	1.000000	0.000
25%	3.228750e+05	3.000000	1.750000	1460.000000	5.000750e+03	1.000000	0.000
50%	4.609435e+05	3.000000	2.250000	1980.000000	7.683000e+03	1.500000	0.000
75%	6.549625e+05	4.000000	2.500000	2620.000000	1.100125e+04	2.000000	0.000
max	2.659000e+07	9.000000	8.000000	13540.000000	1.074218e+06	3.500000	1.000

Although there is no Null value here, the mimimum value of the price is 0, which doesn't help

us for price prediction. So we are going to drop rows with 0 price house.

In [196…
```
df = df[df['price']>0].reset_index(drop=True)
```

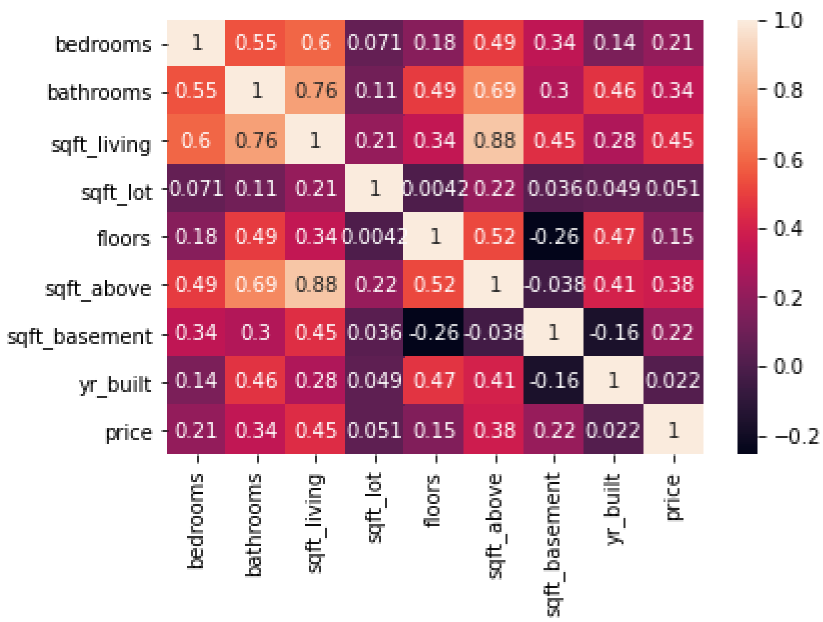
In [197…
```
df.describe()
```

Out[197…

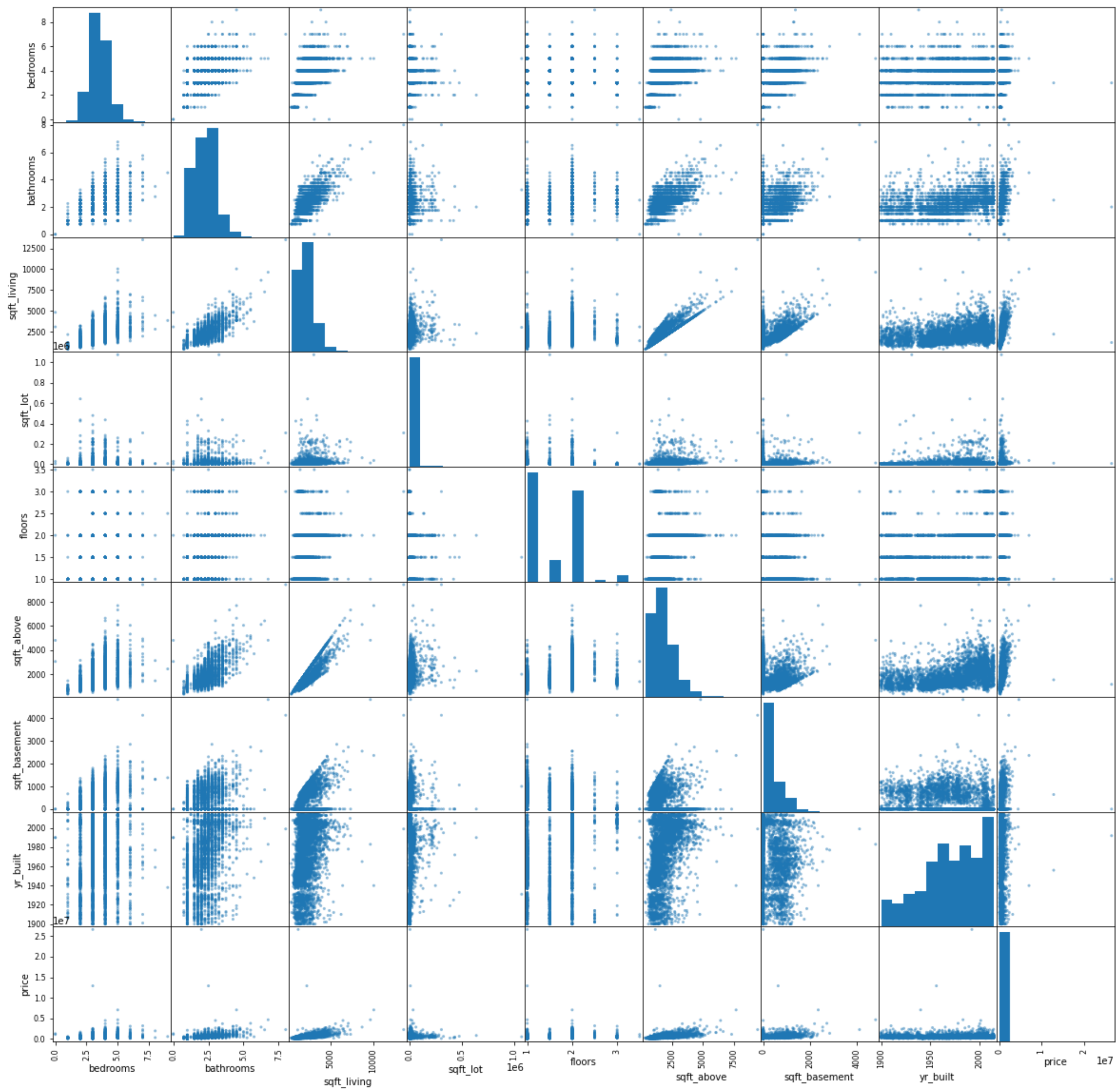
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterf
count	4.551000e+03	4551.000000	4551.000000	4551.000000	4.551000e+03	4551.000000	4551.000
mean	5.579059e+05	3.394639	2.155021	2132.372226	1.483528e+04	1.512195	0.006
std	5.639299e+05	0.904595	0.776351	955.949708	3.596408e+04	0.538531	0.080
min	7.800000e+03	0.000000	0.000000	370.000000	6.380000e+02	1.000000	0.000
25%	3.262643e+05	3.000000	1.750000	1460.000000	5.000000e+03	1.000000	0.000
50%	4.650000e+05	3.000000	2.250000	1970.000000	7.680000e+03	1.500000	0.000
75%	6.575000e+05	4.000000	2.500000	2610.000000	1.097800e+04	2.000000	0.000
max	2.659000e+07	9.000000	8.000000	13540.000000	1.074218e+06	3.500000	1.000

Let's look into correlation between variables.

In [198…
```
import seaborn as sns

new_df = df[['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'sqft_above'

#X = df['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'View', 'Conditio
#Y = df['price']

correlation_mat = new_df.corr()
sns.heatmap(correlation_mat, annot = True)
plt.show()
```



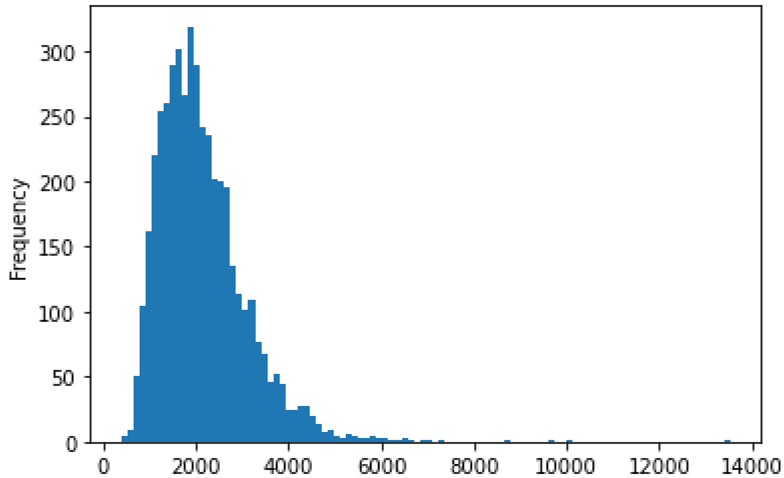
In [199…
```
from pandas.plotting._misc import scatter_matrix
scatter_plots = scatter_matrix(new_df,figsize=(20,20))
```



We decided to choose one variable, sqft_living to predict the price of the house. Next, we looked into how this variable looks.

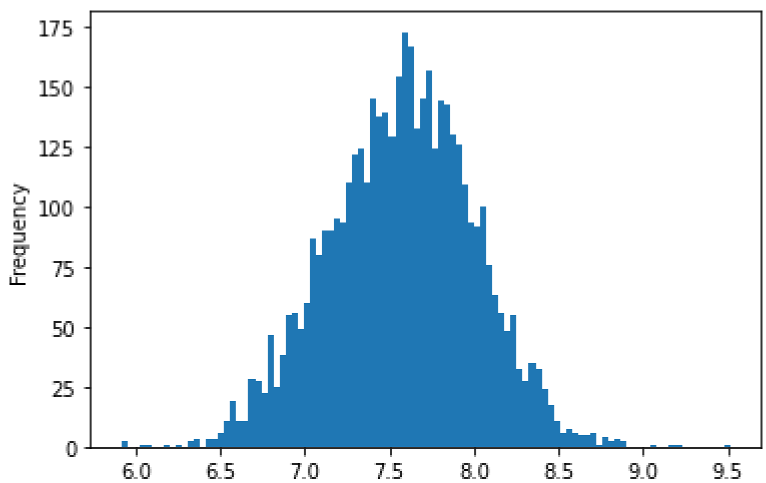
In [200…
```
df['sqft_living'].plot.hist(bins=100)
```

Out[200…
```
<AxesSubplot:ylabel='Frequency'>
```



In [201…
```
np.log(df['sqft_living']).plot.hist(bins=100)
```

Out[201… <AxesSubplot:ylabel='Frequency'>



In [202…
```
#Because original data is highly skewed, we decided to use a logged sqft_living
df['lnsqft'] = np.log(df['sqft_living'])
```

Create prediction models

Here, we are going to create two different models (KNN classifier and random forest) and compare their performances.

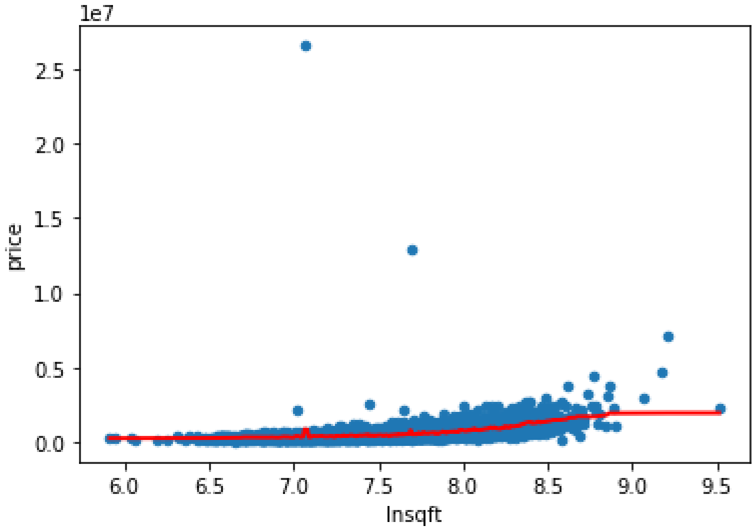
1) KNN classifier

In [203…
```
from sklearn.neighbors import KNeighborsRegressor as knn
```

In [204…
```
sklearn_knn = knn(n_neighbors=50).fit(X=df[['lnsqft']],y=df['price'])
print(sklearn_knn.score(X=df[['lnsqft']],y=df['price']))
df.plot.scatter(x='lnsqft',y='price')
df['yhat_knn'] = sklearn_knn.predict(df[['lnsqft']])
df.sort_values('lnsqft').set_index('lnsqft')['yhat_knn'].plot(color='r',lw=2)
```

```
0.2134084571361341
```

Out[204… <AxesSubplot:xlabel='lnsqft', ylabel='price'>



In [205…
```
from sklearn.model_selection import train_test_split
len(train_test_split(df[['lnsqft']],df['price']))
```

Out[205… 4

In [206…
```
X_train, X_test, y_train, y_test = train_test_split(df[['lnsqft']],df['price'],test_siz
```

In [207…
```
print(len(X_train),len(X_test),len(X_train)/len(df))
```

```
3413 1138 0.7499450670182377
```

In [208…
```
sklearn_knn = knn(n_neighbors=50).fit(X_train,y_train)
sklearn_knn.score(X_test,y_test)
```

Out[208… 0.1868237932243707

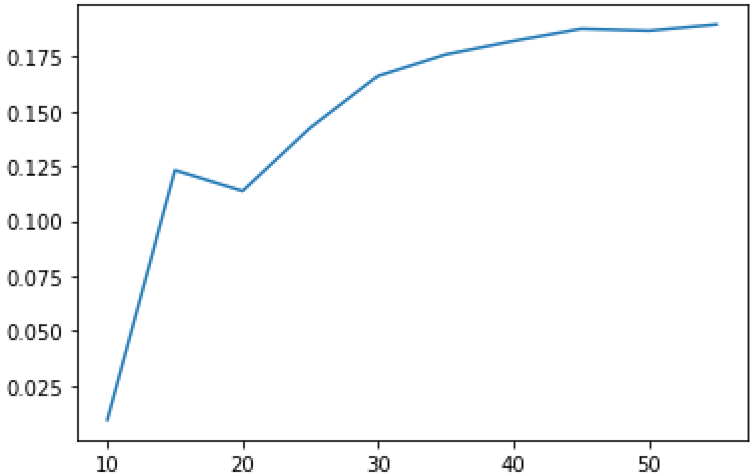
In [209…
```
scores = pd.Series()
for i in range(10,60,5):
    scores.loc[i] = knn(n_neighbors=i).fit(X_train,y_train).score(X_test,y_test)
scores

#the optimal number is 50
```

```
<ipython-input-209-32ede8232b33>:1: DeprecationWarning: The default dtype for empty Seri
es will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly
to silence this warning.
  scores = pd.Series()
```

Out[209…
```
10    0.009455
15    0.123168
20    0.113711
25    0.142566
30    0.166265
35    0.176022
40    0.182192
45    0.187712
50    0.186824
55    0.189700
dtype: float64
```

In [210…
```
scores.plot()
```

Out[210… <AxesSubplot:>



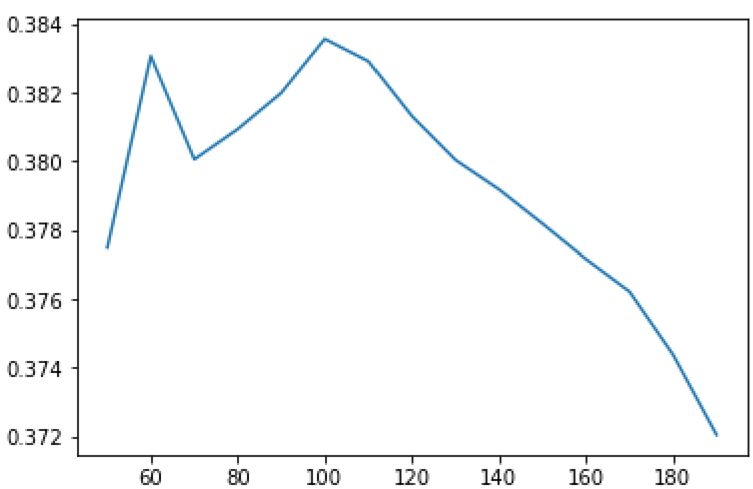
In [211…
```
from sklearn.model_selection import cross_val_score
cross_val_score(knn(n_neighbors=50),X=df[['lnsqft']],y=df['price'],cv=5).mean()
```

Out[211… 0.377488473704888

In [212…
```
scores = pd.Series()
for i in range(50,200,10):
    scores.loc[i] = cross_val_score(knn(n_neighbors=i),df[['lnsqft']],df['price'],cv=5)

scores.plot()
```

```
<ipython-input-212-9630c93d1d5a>:1: DeprecationWarning: The default dtype for empty Seri
es will be 'object' instead of 'float64' in a future version. Specify a dtype explicitly
to silence this warning.
  scores = pd.Series()
```

Out[212… <AxesSubplot:>



In [213…
```
scores.max()
```

Out[213… 0.3835572715507913

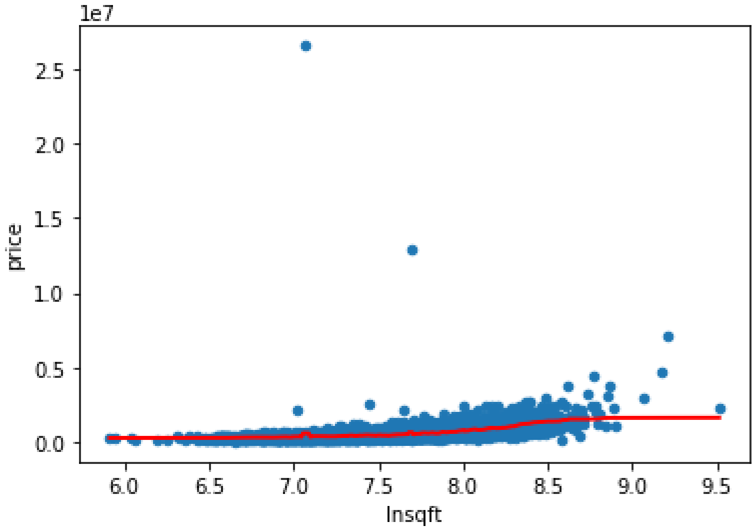
In [214…
```
scores.idxmax()
```

Out[214… 100

In [215…
```
df['yhat_knn'] = knn(n_neighbors=100).fit(df[['lnsqft']],df['price']).predict(df[['lnsq
```

```
df.plot.scatter(x='lnsqft',y='price')
df.sort_values('lnsqft').set_index('lnsqft')['yhat_knn'].plot(color='r',lw=2)
```

Out[215… <AxesSubplot:xlabel='lnsqft', ylabel='price'>



2) Random Forest

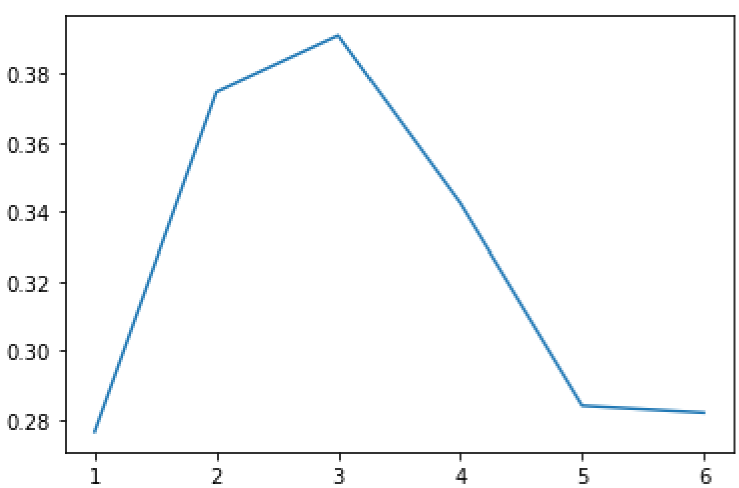
In [216…
```
from sklearn.ensemble import RandomForestRegressor as rf
```

In [217…
```
%%time
scores_rf = pd.Series()
for i in range(1,7,1):
    scores_rf.loc[i] = cross_val_score(rf(n_estimators=100,max_depth=i),df[['lnsqft']],
```

```
<timed exec>:1: DeprecationWarning: The default dtype for empty Series will be 'object'
instead of 'float64' in a future version. Specify a dtype explicitly to silence this war
ning.
Wall time: 5.99 s
```

In [218…
```
scores_rf.plot()
```

Out[218… <AxesSubplot:>

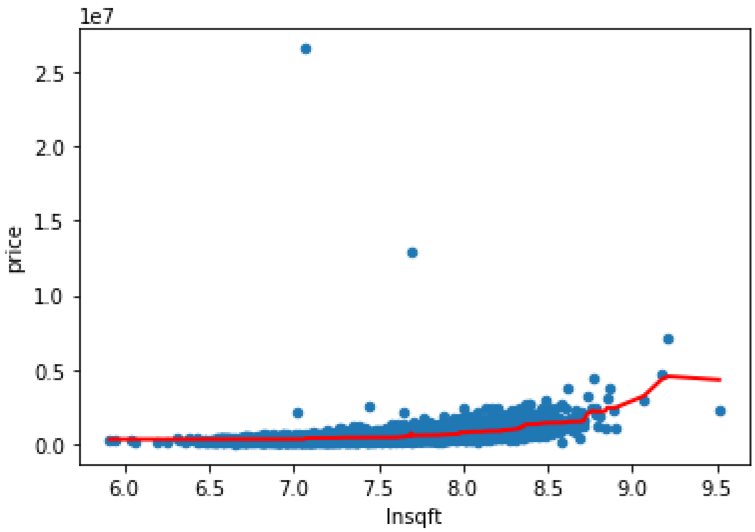


In [219…
```
scores_rf.idxmax()
```

Out[219… 3

In [220…
```
df['yhat_rf'] = rf(n_estimators=100,max_depth=3).fit(df[['lnsqft']],df['price']).predic
df.plot.scatter(x='lnsqft',y='price')
df.sort_values('lnsqft').set_index('lnsqft')['yhat_rf'].plot(color='r',lw=2)
```

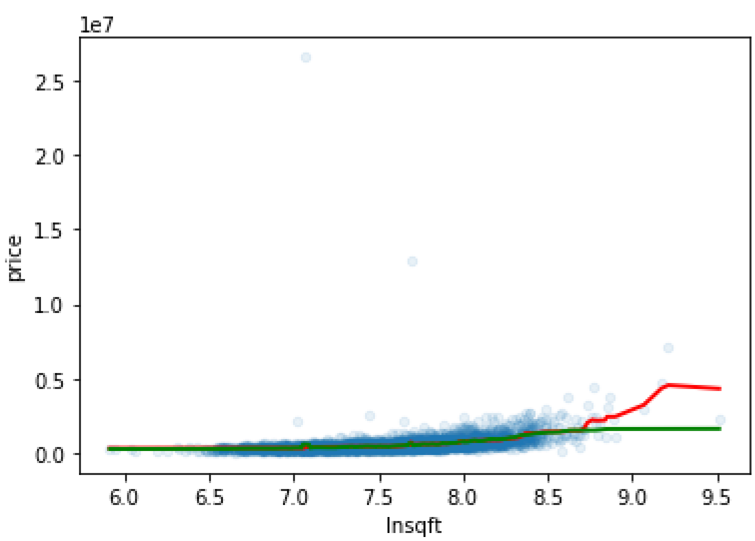
Out[220… <AxesSubplot:xlabel='lnsqft', ylabel='price'>



Model Comparison

In [221…
```
df.plot.scatter(x='lnsqft',y='price',alpha=.1)
df.sort_values('lnsqft').set_index('lnsqft')['yhat_rf'].plot(color='r',lw=2)
df.sort_values('lnsqft').set_index('lnsqft')['yhat_knn'].plot(color='g',lw=2)
```

Out[221… <AxesSubplot:xlabel='lnsqft', ylabel='price'>



In [222…
```
rf(n_estimators=100,max_depth=3).fit(df[['lnsqft']],df['price']).score(df[['lnsqft']],d
```

Out[222… 0.22744328247326706

In [223…
```
knn(n_neighbors=100).fit(df[['lnsqft']],df['price']).score(df[['lnsqft']],df['price'])
```

Out[223… 0.19947158875695736

In [224…

```
df[['yhat_knn','yhat_rf','price']].corr()**2
```

Out[224…

	yhat_knn	yhat_rf	price
yhat_knn	1.000000	0.870516	0.201321
yhat_rf	0.870516	1.000000	0.226059
price	0.201321	0.226059	1.000000

Since the random forest model shows the higher r-squared score than the KNN model, our final model selection would be the random forest model.