Property Price Prediction

Using Machine Learning Algorithms

Background

The dataset contains the property information of Beijing, China for the period of 2011 to 2017. It includes URL, ID, Lng, Lat, CommunityID, TradeTime, DOM(days on market), Followers, Total price, Price, Square, Living Room, number of Drawing room, Kitchen and Bathroom, Building Type, Construction time, renovation condition, building structure, Ladder ratio(which is the proportion between number of residents on the same floor and number of elevator of ladder. It describes how many ladders a resident has on average), elevator, Property rights for five years （It's related to China's restricted purchase of houses policy), Subway, District, Community average price. Most of the data were traded in 2011-2017, some of them were traded in Jan 2018, and some even earlier(2010,2009).

Data Source

This dataset has been taken from Kaggle.com. Data originally fetched from Lianjia.com.

Kaggle URL: https://www.kaggle.com/ruiqurm/lianjia

Lianjia URL: https://bj.lianjia.com/chengjiao

About Dataset

Column Name	Description
url	the url which fetches the data
id	the id of transaction
Lng and Lat	coordinates, using the BD09 protocol.
Cid	community id
tradeTime	the time of transaction
DOM	active days on market
followers	the number of people follow the transaction.
totalPrice	the total price
price	the average price by square
square	the square of house
livingRoom	the number of living room
drawingRoom	the number of drawing room
kitchen	the number of kitchen
bathroom	the number of bathroom
floor	the height of the house.

buildingType	including tower (1), bungalow (2), combination of plate and tower (3), plate (4)
constructionTime	the time of construction
renovationCondition	including others (1), rough (2), Simplicity (3), hardcover (4)
buildingStructure	including unknown (1), mixed (2), brick and wood (3), brick and concrete (4), steel (5) and steel-concrete composite (6).
ladderRatio	the proportion between number of residents on the same floor and number of elevators of ladder. It describes how many ladders a resident has on average.
elevator	Available (1) or elevator not available(0)
fiveYearsProperty	owner has the property for less than 5 years (0) or has the property for more than 5 years (1)

Data Cleaning & Pre-processing

Most of the columns have invalid characters and irrelevant data which must be treated first before moving to Statistical Analysis. Initially, the unnecessary variables are dropped as it is not required to perform machine learning algorithms. Variable DOM has the greatest number of null values, that is 50% of the value is null which in turn is not required for the analysis. Hence, the DOM column is dropped. Variables such as Living Room, Drawing Room, Bathroom, Construction Time, Building Type, Building Structure have few invalid data which are corrected later. Floor type has been split into Floor type and Floor number. As a final step on Data cleaning, most of the columns which had the null values have been updated with their Mode values and few columns updated with their Average.

Descriptive Data Analysis

Creating detailed numerical summary to do descriptive data analysis.

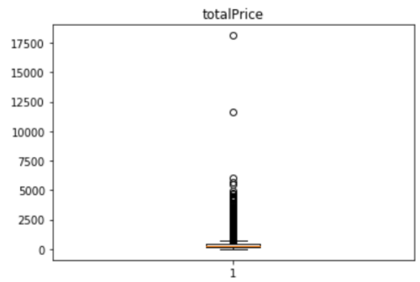
	Lng	Lat	tradeTime	followers	totalPrice	price	square	livingRoom
count	318851	318851	318851	318851	318851	318851	318851	318851
mean	116.4184594	39.94959061	2014.78394	16.7315078	349.030201	43530.4364	83.2405967	2.01036848
std	0.112054302	0.091982547	1.65659078	34.2091847	230.780778	21709.0242	37.2346609	0.77678348
min	116.072514	39.62703	2002	0	0.1	1	6.9	0
25%	116.344985	39.8932	2013	0	205	28050	57.9	1
50%	116.41678	39.934527	2015	5	294	38737	74.26	2
75%	116.477581	40.003018	2016	18	425.5	53819.5	98.71	2
max	116.732378	40.252758	2018	1143	18130	156250	1745.5	9

	drawingRoon	kitchen	bathRoom	buildingType	renovationC	buildingStru	ladderRatio	elevator
count	318851	318851	318851	318851	318851	318851	318851	318851
mean	1.171932972	0.994599358	1.18810353	3.01643087	2.60641177	4.45111353	63.1648604	0.57709714
std	0.52226411	0.109608912	0.43752592	1.26802255	1.31160757	1.90157098	25068.5061	0.49402105
min	0	0	0	1	1	1	0	0
25%	1	1	1	1	1	2	0.25	0
50%	1	1	1	4	3	6	0.333	1
75%	1	1	1	4	4	6	0.5	1
max	5	4	7	4	4	6	10009400	1

Outliers

It has been observed from the boxplot that the totalPrice has the Outlier. Hence, those outliers are replaced with the Average.

In [174]:
```
# Box Plot totalPrice
plt.boxplot(dataset['totalPrice'])
plt.title('totalPrice')
plt.show()
```

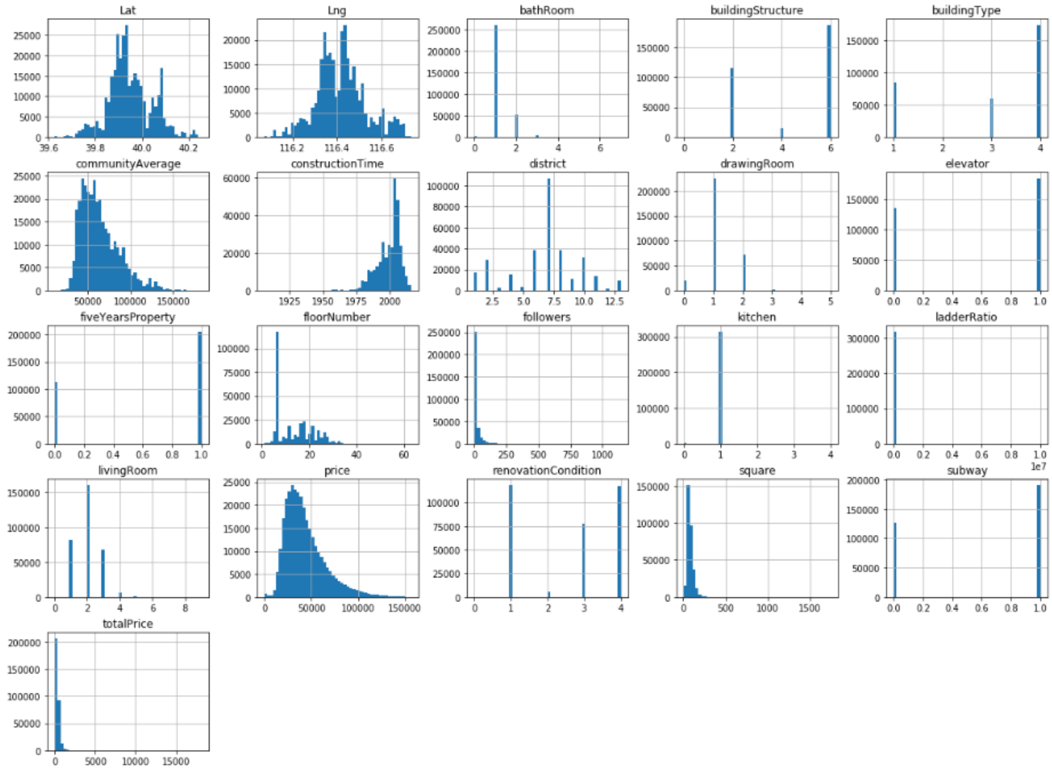


Exploratory Data Analysis

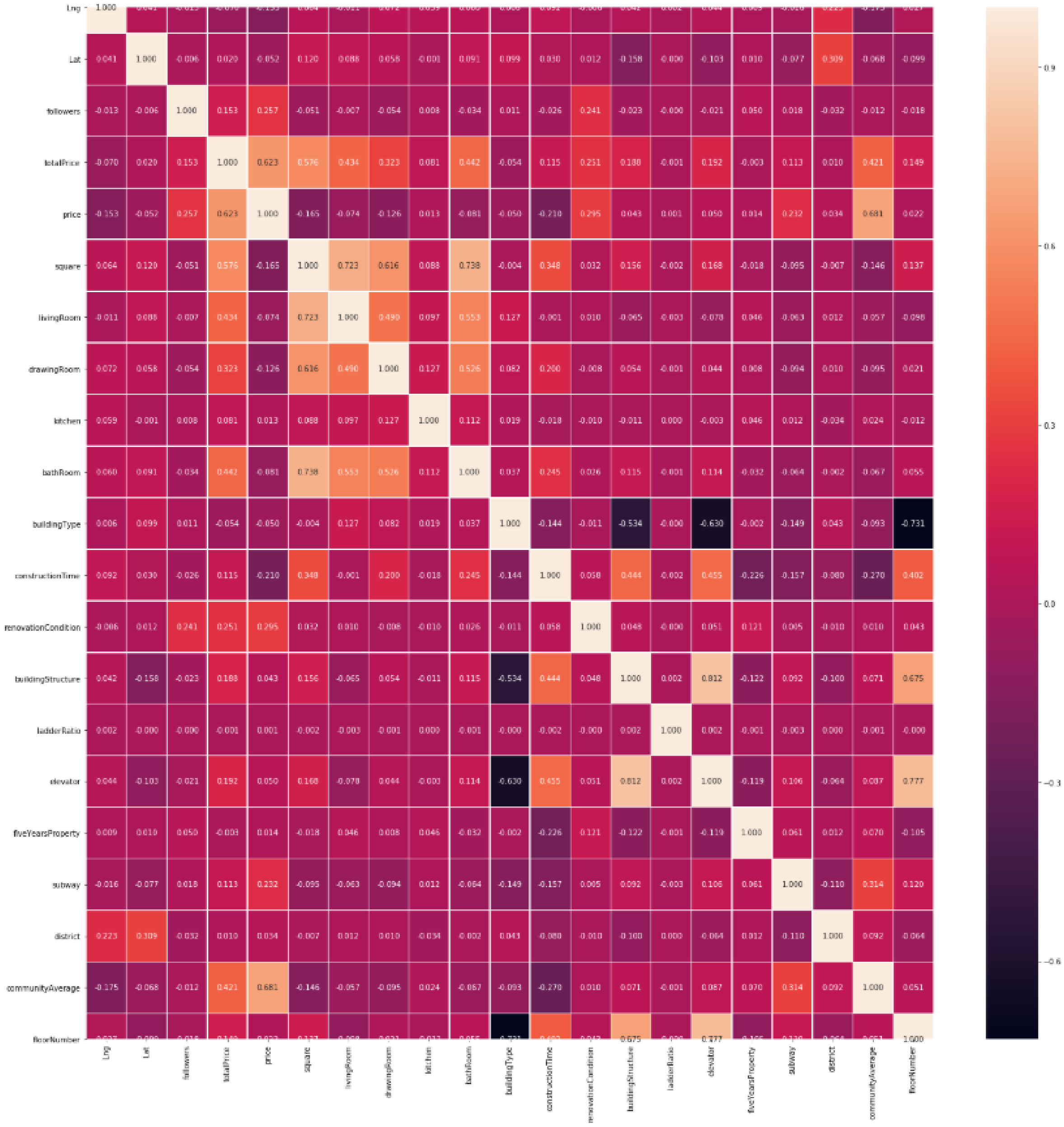
Creating Histograms and Correlation Matrices.

Histograms:

In [18]:
```
#Histograms for each column
dataset.hist(bins=50, figsize=(20,15))
plt.show()
```



Correlation Heat Map:



Feature Selection

Feature Selection is one of the core concepts in machine learning which hugely impacts the performance of the model. The data features that are used to train the machine learning models have a huge influence on the performance which is achieved. From the Correlation matrices and heat map, below features are selected to be removed from the dataset.

['Lng', 'Lat', 'kitchen', 'buildingType', 'ladderRatio', 'fiveYearsProperty', 'price']

Machine Learning Model Development

Machine-learning algorithms use statistics to find patterns in massive amounts of data. The purpose of this project is to predict the property price and (to be added) from the House price in Beijing dataset. There are quite a few number of Machine learning algorithms available. Since Price feature is a continuous variable, regression algorithms would be the perfect match. So, this project has been developed with both Linear and Non-linear Machine learning algorithms. Main objective is to attain the highest possible accuracy of prediction.

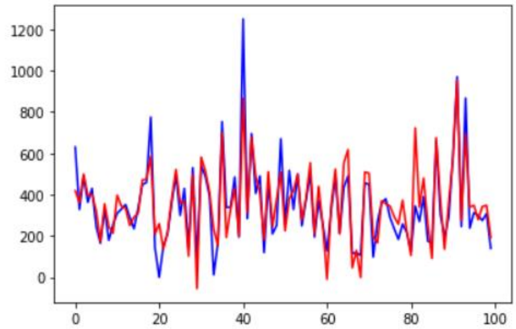
Note: Below Models are for Total Price Prediction

Multi-Linear Regression Model:

Multi Linear Regression Model an obtained accuracy of 80%.

```
Accuracy:  0.8081718234464055
```

```
# Plotting Test data vs Predicted Data
plt.plot(y_test[:100], color = 'blue')
plt.plot(y_pred[:100], color = 'red')
plt.show()
```

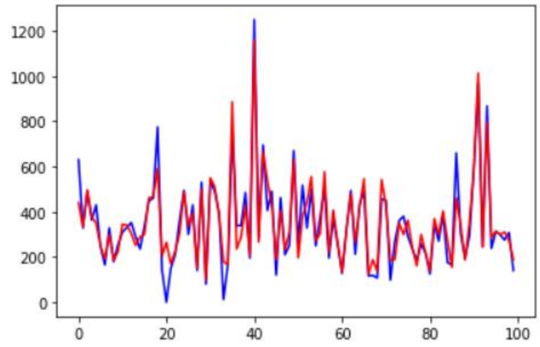


Random Forest Regression Model:

Random Forest Regression Model obtained the accuracy level of 91% which is significantly higher than the Multi linear regression model.

```
Accuracy:  0.9103582877555013
```

```
# Plotting Test data vs Predicted Data
plt.plot(y_test[:100], color = 'blue')
plt.plot(y_pred[:100], color = 'red')
plt.show()
```



Rather than creating each model one by one, Pipeline method from scikit-learn can be used. Pipelines are set up with the fit/transform/predict functionality, so that it can fit the whole pipeline to the training data and transform the test data without having to do it individually every time.

Model Selection:

Using Pipeline method and creating Support Vector Regression, Decision Tree Regression, Random Forest Regression and XgBoost Models and evaluation.

```
Support Vector Regression Test Accuracy: 0.7880154354787211
Decision Tree Regression Test Accuracy: 0.8523314480946618
Random Forest Regression Test Accuracy: 0.9269710134397035
XgBoost Test Accuracy: 0.9254096946611579

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Best Regressor -  Random Forest Regression
Best Score -  0.9269710134397035
Wall time: 8min 41s
```

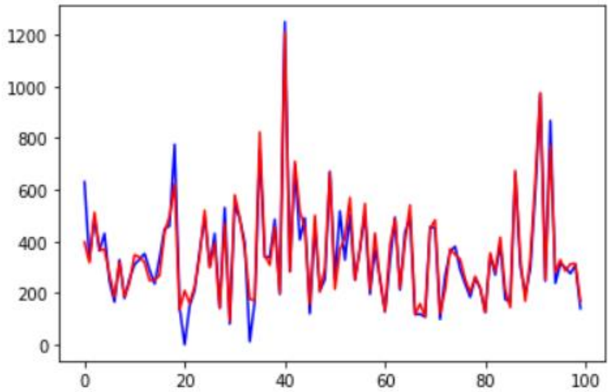
From the above, it is clear that the Random Forest Regression could be the best model for the dataset. However, XGBoost Model’s accuracy is almost same as Random Forest Regression.

XGBoost Model:

Since the XGBoost Model also has the higher accuracy, fine tuning some of its parameters obtained the accuracy of 93% which is slightly increased from the Random Forest Regression Model.

```
Accuracy:  0.9316550942094334
```

```python
# Plotting Test data vs Predicted Data
plt.plot(y_test[:100], color = 'blue')
plt.plot(y_pred[:100], color = 'red')
plt.show()
```



Square Prediction

With the same dataset, variable square is also predicted using Multi-Linear Regression, Random Forest Regression and XGBoost Models. Below table shows accuracies obtained from the models.

Model	Accuracy
Multi-Linear Regression Model	85 %
Random Forest Regression Model	86 %
XGBoost Model	93 %

Conclusion

XGBoost Model is the best one across all the regression models for this dataset. This model obtained 93% of accuracy for both of the Total Price and Square variable predictions.

References

1. https://www.udemy.com/course/machinelearning/
2. https://scikit-learn.org/stable/modules/generated/sklearn.pipeline.Pipeline.html
3. https://stackoverflow.com/questions/42929997/how-to-replace-non-integer-values-in-a-pandas-dataframe
4. https://matplotlib.org/tutorials/introductory/pyplot.html
5. https://www.kaggle.com/gemartin/load-data-reduce-memory-usage