House Price Prediction using Machine Learning in Python

PHASE-1 DOCUMENT SUBMISSION

PROJECT: Problem definition at design thinking

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ABSTRACT:

PROJECT DESCRIPTION:

A. Problem Statement

Thousands of houses are sold everyday. There are some questions every buyer asks himself like: What is the actual price that this house deserves? Am I paying a fair price?

B. Best Possible Solutions

- Housing Expert
- Intuition About House
- Using Machine Learning

C. Introduction About Project

House Price prediction are very stressful work as we have to consider different things while buying a house like the structure and the rooms kitchen parking space and gardens. People don’t know about the factor which influence the house price. But by using the Machine learning we can easily find the house which is to be prefect for us and helps to predict the price accurately.

Housing Price Prediction In Beijing

Installation Guide

1. Clone or Fork the Project
2. Create a Virtual Enviroment
3. go to same virtual enviroment and write below cmd
4. pip install -r requirements.txt

Project Highlights

1. Research Paper
2. User Friendly
3. Accuracy
4. Open Source

Table Of Content

6. Model Creation
7. Model Deployment
8. Model Conclusion
9. Project Innovation
10. Limitation And Next Step
11. Working Project Video

D. Tools and Libraries

Tools:
a.Python
b.Jupyter Notebook
c. Flask
d. HTML
e. CSS
f. JS
g. Heroku
h. GitHub

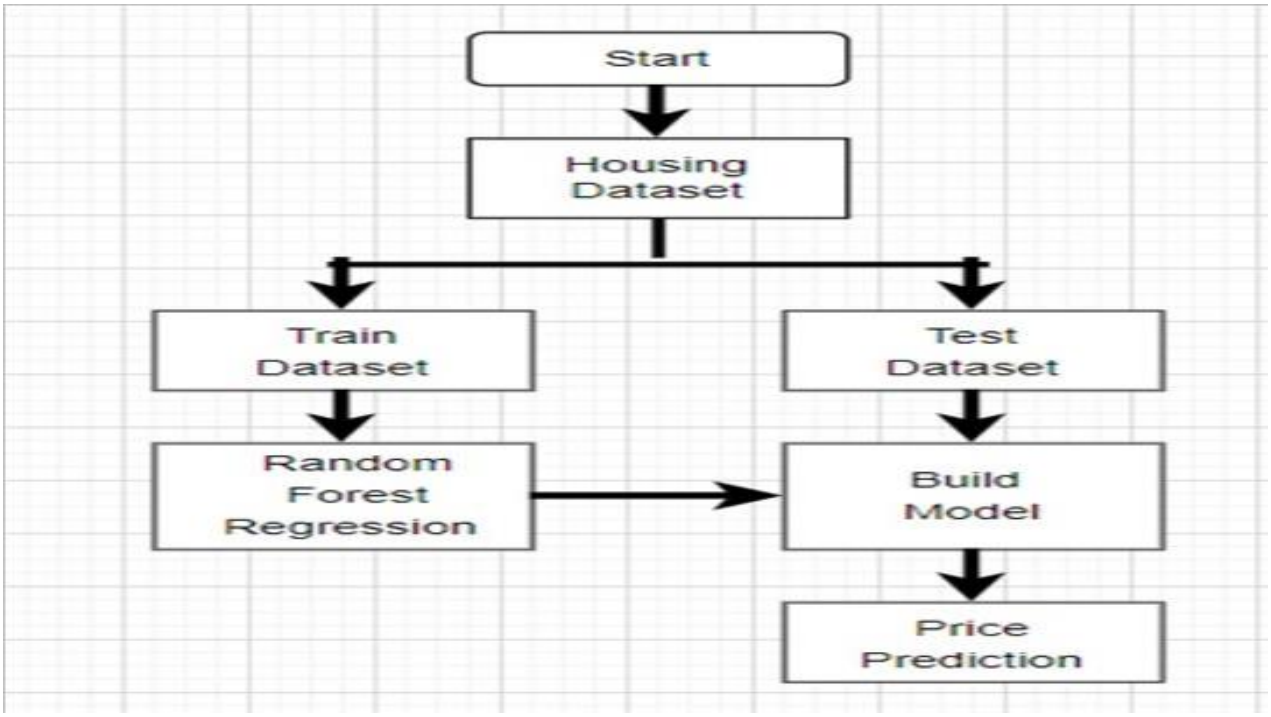
Libraries:
a.Pandas
b.Scikit Learn
c.Numpy
d.Seaborn
e.Matpoltlib

2. Data Collection

For this project we used the data that is available on Kaggle. There are 26 columns and 318851 Rows. These are the major point about the data set.
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.
total Price: the total price
price: the average price by square
square: the square of house
living Room: the number of living room
drawing Room: the number of drawing room
kitchen: the number of kitchen
bathroom the number of bathroom
floor: the height of the house. I will turn the Chinese characters to English in the next version.
building Type: including tower(1) , bungalow(2), combination of plate and tower(3), plate(4).
construction Time: the time of construction
renovation Condition: including other(1), rough(2),Simplicity(3), hardcover(4)
building Structure: including unknow(1), mixed(2), brick and wood(3), brick and concrete(4),steel(5) and steel-concrete composite (6).
ladder Ratio: the proportion between number of residents on the same floor and number of elevator of ladder. It describes how many ladders a resident have on average.
elevator: have (1) or not have elevator(0)
fiveYearsProperty: if the owner have the property for less than 5 years.

3. Generic Flow Of Project:



4. EDA:

Index(['url', 'id', 'Lng', 'Lat', 'Cid', 'tradeTime', 'DOM', 'followers', 'totalPrice', 'price', 'square', 'livingRoom', 'drawingRoom', 'kitchen', 'bathRoom' 'floor', 'buildingType', 'constructionTime', ' renovationCondition', 'buildingStructure', 'ladderRatio', 'elevator', 'five YearsProperty', 'subway', 'district', 'communityAverage'], dtype='object')

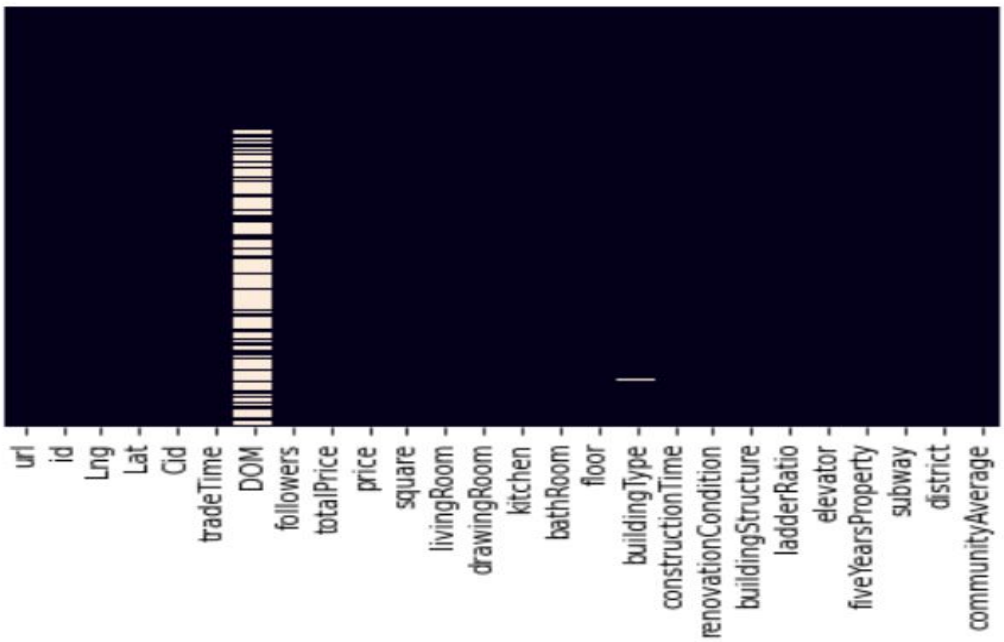
A.Data Cleaning

we have 26 columns ,from these we don't want some column(i.e. url,id,cid) then we will perform data cleaning wich involve following steps. our target variable is totalPrice

a. Impute/Remove missing values or Null values (NaN)
b. Remove unnecessary and corrupted data.
c. Date/Text parsing if required.

```
url                        0
id                         0
Lng                        0
Lat                        0
Cid                        0
tradeTime                  0
DOM                   157977
followers                  0
totalPrice                 0
price                      0
square                     0
livingRoom                 0
drawingRoom                0
kitchen                    0
bathRoom                   0
floor                      0
buildingType            2021
constructionTime           0
renovationCondition        0
buildingStructure          0
ladderRatio                0
elevator                  32
fiveYearsProperty         32
subway                    32
district                   0
communityAverage         463
dtype: int64
```

we handle NAN value using appropriate solutions.



DOM Column have more than 50% value are missing it's better to delete that column

```
data.floor.unique()
#so,floor have a chinese character...
```

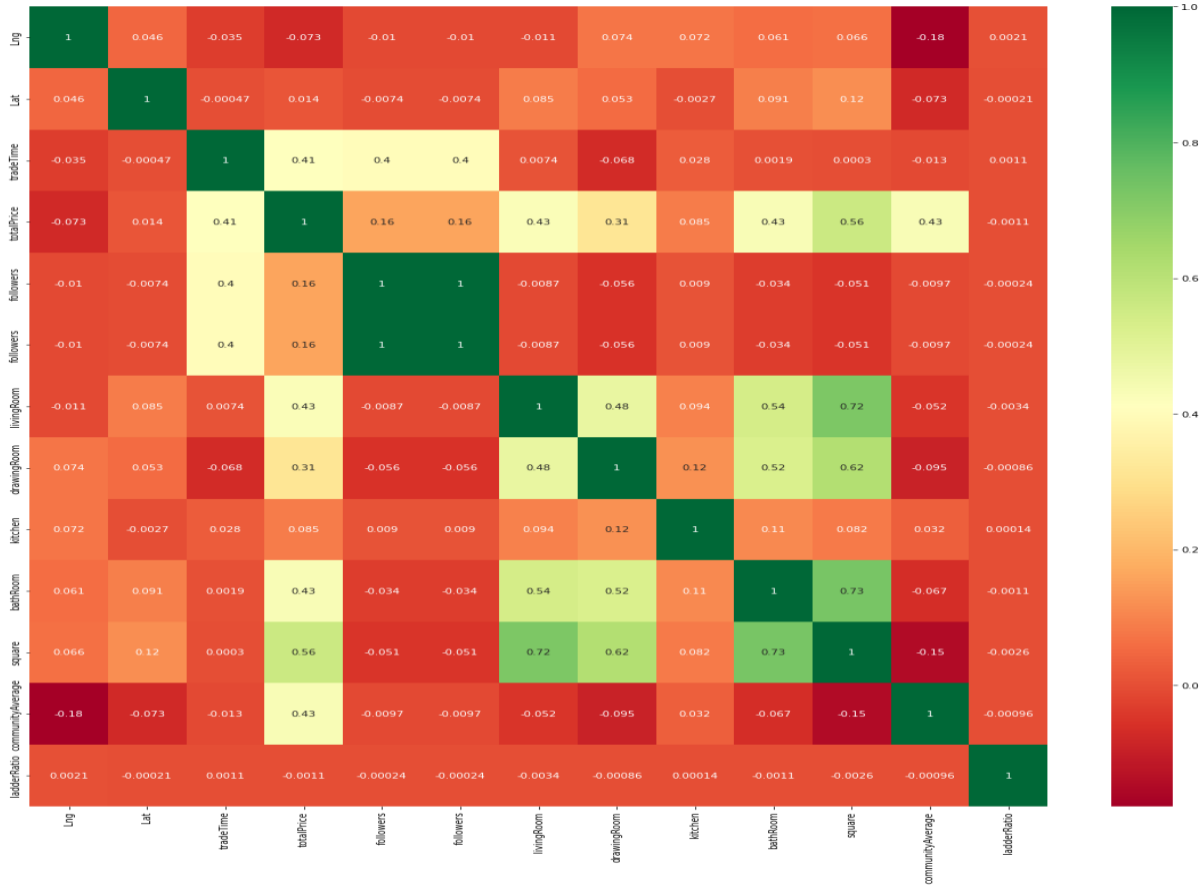
```
array(['高 26', '高 22', '中 4', '底 21', '中 6', '中 8', '高 6', '高 10', '中 23',
       '底 11', '底 3', '高 24', '低 23', '中 19', '高 18', '低 25', '中 12',
       '中 14', '中 30', '中 27', '中 5', '低 18', '底 28', '中 11', '低 9',
       '顶 7', '顶 27', '低 6', '中 17', '顶 6', '中 24', '中 15', '底 5', '中 29',
       '顶 19', '顶 5', '中 9', '低 22', '顶 18', '低 16', '高 13', '高 9',
       '高 17', '底 6', '中 28', '低 26', '底 15', '高 16', '底 2', '低 7',
       '中 13', '低 33', '底 14', '高 15', '底 4', '顶 11', '中 32', '顶 16',
       '底 18', '顶 17', '低 14', '低 10', '底 20', '高 12', '低 31', '低 30',
       '低 19', '低 12', '中 10', '中 16', '顶 20', '底 19', '中 31', '低 13',
       '底 10', '高 25', '中 21', '中 20', '高 20', '低 21', '低 24', '顶 4',
```

some column have unique character. we solve these problem using split method and create seprate column for unique character.

We also have a categorical data we handle such kind of data using dummies variable concept. following are the columns which have categorical data.

a. renovationCondition
b. buildingStructure
c. buildingType
d. district

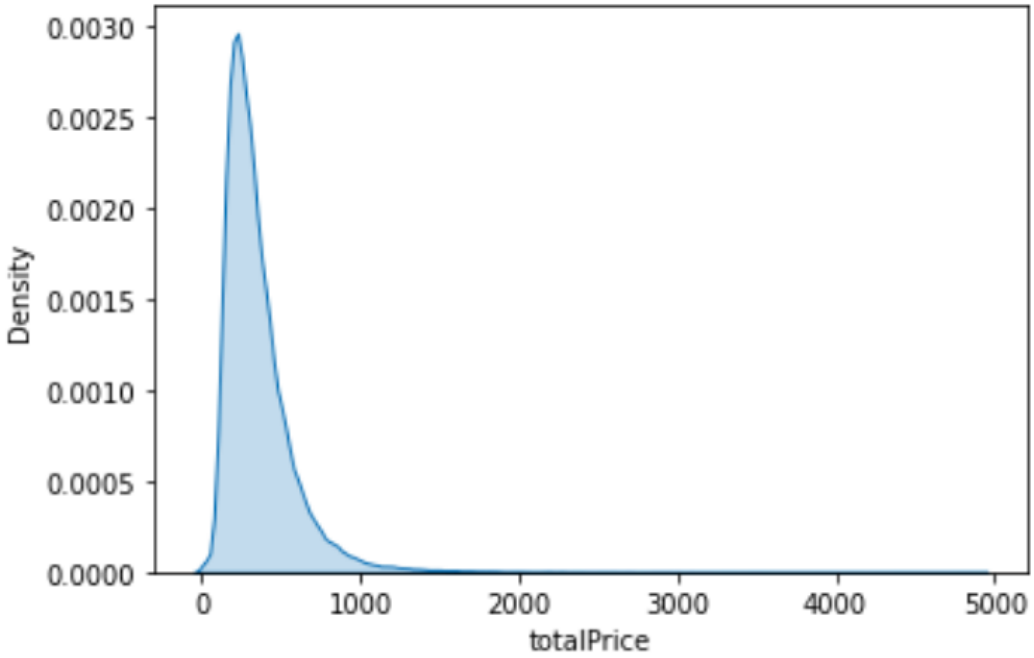
e. elevator
f. floor_type



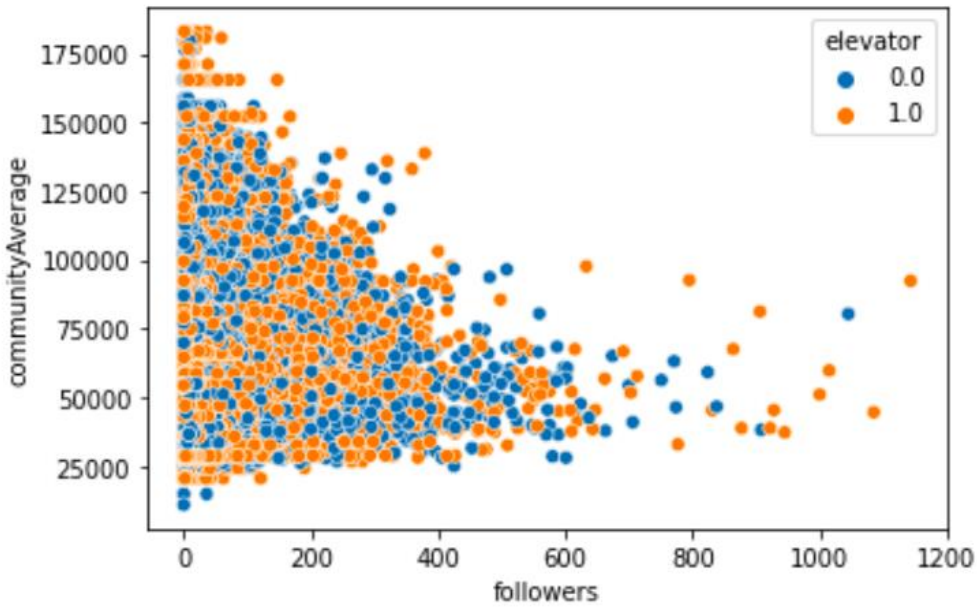
Summary of the Heat-Map

a. totalPrice is highly corellated with community average, square, bathroom, Livingroom and Trde Time.

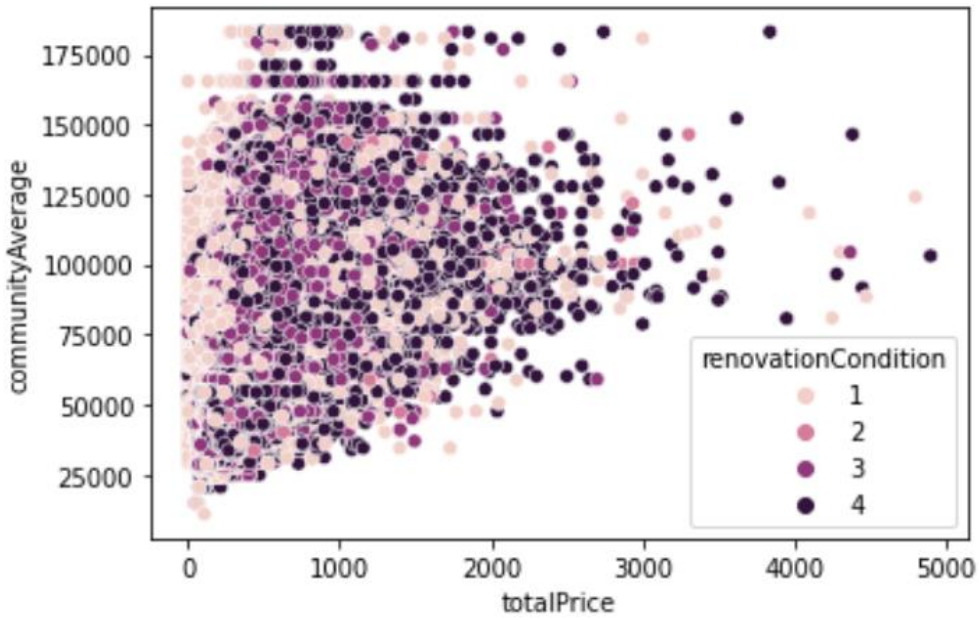
b. total price is highly negative corellated with ladderRatio,lat and lng.



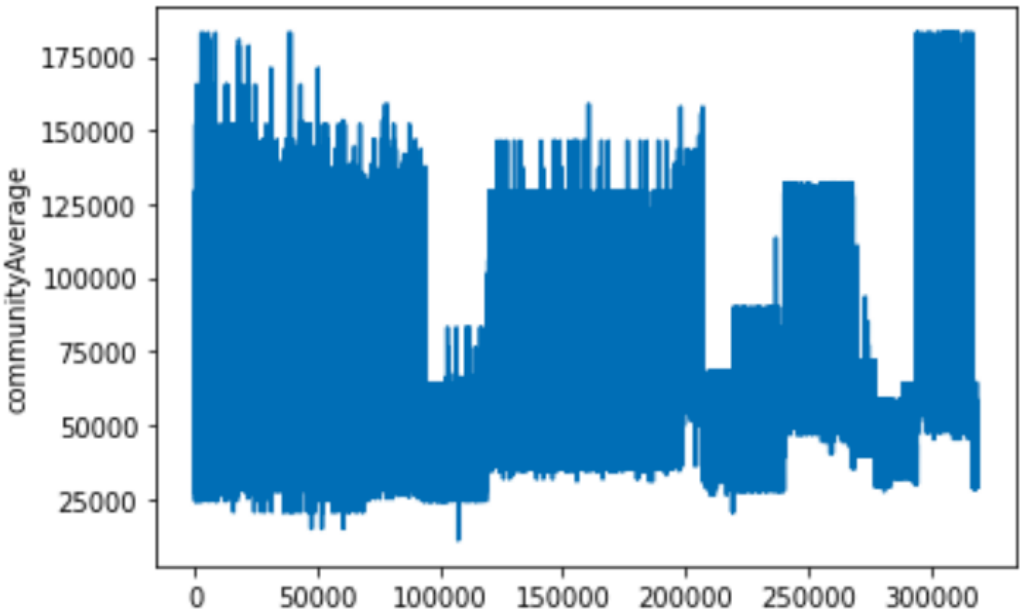
Summary of the Density Plot
a. most of the output features is lies between 0-2500



Summary of Scatterplot
a. Most of the House Followers 0-400.



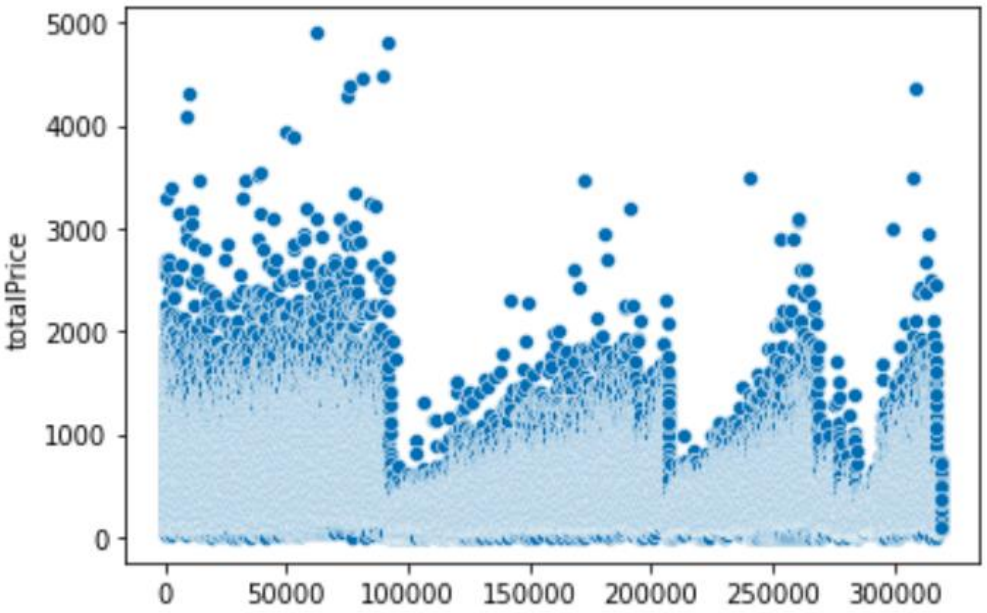
Summary of Scatterplot with respect to renovation Condition
a. most of the expensive houses have Hardcover as a renovation condition



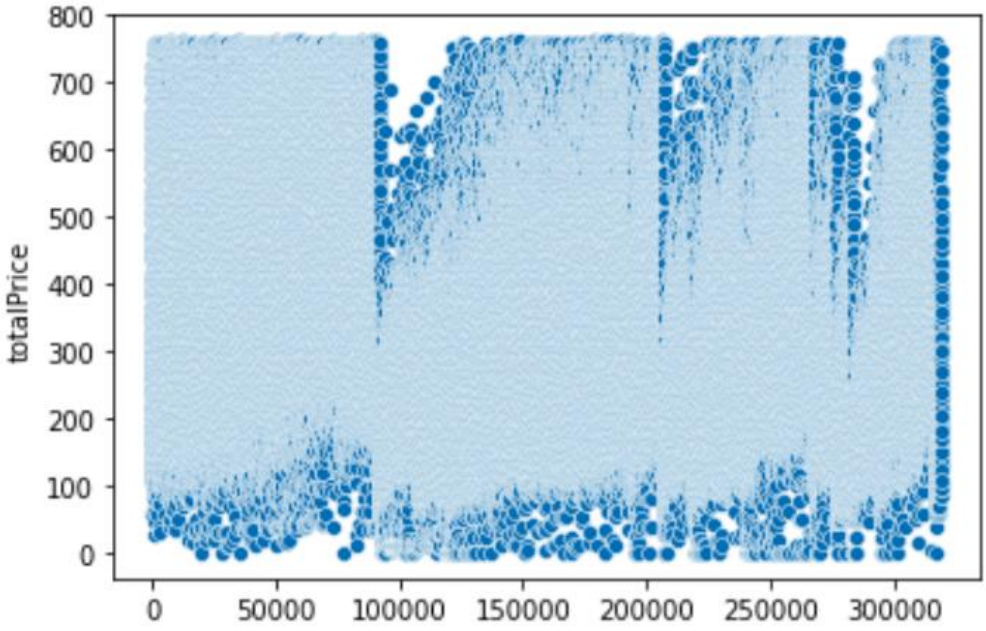
Summary of lineplot
a. Most of the peoples average are lies in 12500-150000 ...

B. Feature Engineering

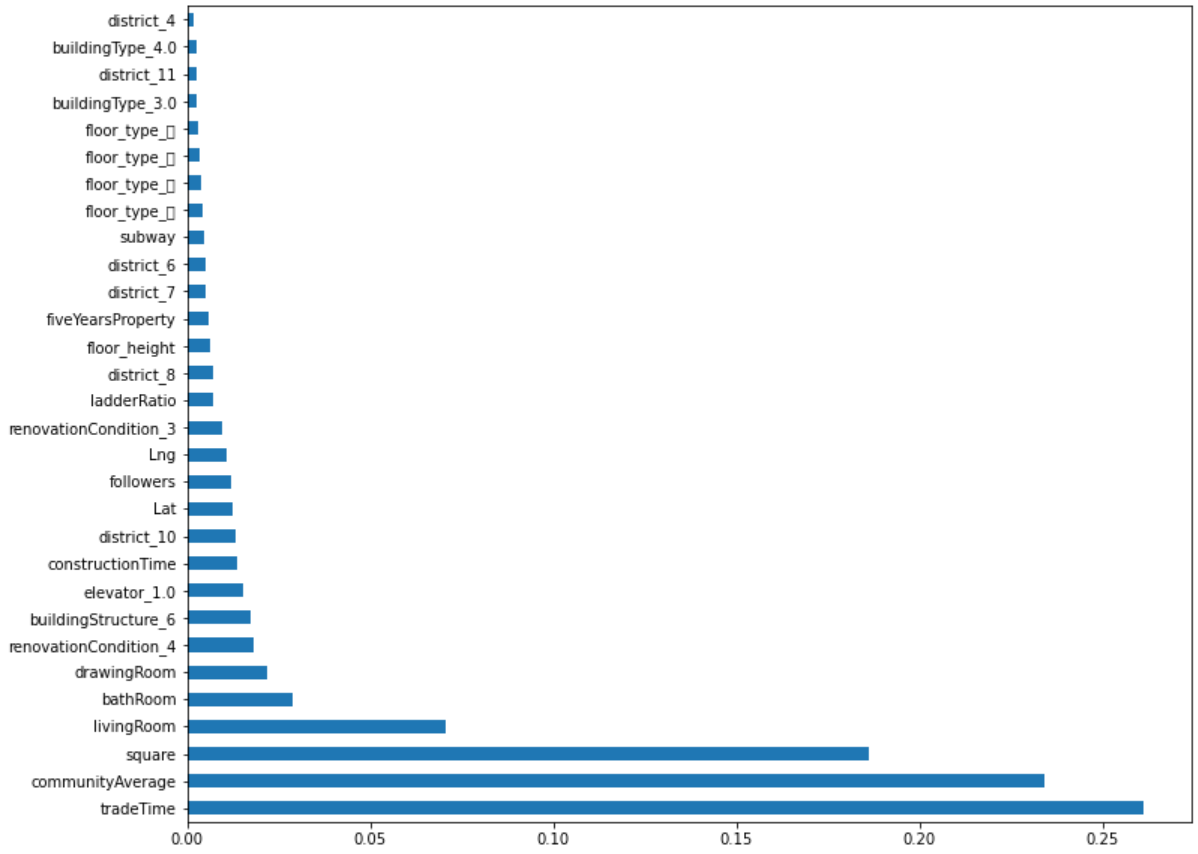
we found outlier in our data ..



from the above figure we can notice that we have an outlier present in our dataset.
for outlier we can use IQR method and after using IQR method. Now, our data looks fine.



using the feature engineering we got out top 30 features with respect to totalPrice .



So, these are the top 20 features for our model
a. tradeTime
b. CommunityAverage
c. square
d. livingRoom
e. bathRoom
f. drawingRoom
g. renovationCondition
h. buildingStructure
i. elevator
j. constructionTime
k. Followers

C. Data Normalization

Normalization (min-max Normalization)
In this approach we scale down the feature in between 0 to 1

we have numerical column where we can apply min-max Normalization.

col_for_normalization= ['Lng', 'Lat', 'followers', 'square', 'livingRoom', 'drawingRoom', 'kitchen', 'bathRoom', 'ladderRatio', 'fiveYears Property', 'subway', 'communityAverage', 'floor_height']

5. Choosing Best ML Model

List of the model that we can use for our problem
a. Linear Regression model
b. KNN Model
c. Decision Tree
d. Random Forest

By using Linear Regression we got: Training data accuracy 0.7574698746154127 Testing data accuracy 0.7576318049777959

Using the linearRegression we got only 75 % accuracy.

print (rfm.score (X_train,y_train)) print (rfm.score (X_test,y_test))

0.9848032043888097

0.895634280563376

Using the Random Forest we got 98 % accuracy on train data and 89 % on test data .so,we can consider Random Forest as a Best Algorithm for this problem.

6. Model Creation

So, using a Random Forest we got good accuracy , we can Hyperparameter tuning for best accuracy.

Algorithm that can be used for Hyperparameter tuning are :-

a. GridSearchCV
b. RandomizedSearchCV
c. Bayesian Optimization-Automate Hyperparameter Tuning (Hyperopt)
d. Sequential model-based optimization

e. Optuna-Automate Hyperparameter Tuning
f. Genetic Algorithm

Main parameters used by Random Forest Algorithm are :-

a. n_estimators ---> The number of trees in the forest.
b. criterion--->{"mse", "mae"}-->The function to measure the quality of a split
c. max_features--->{"auto", "sqrt", "log2"}--> The number of features to consider when looking for the best split:

So, After Hyperparameter Tuning we got 90 % accuracy on test data and 94 % accuracy on train data.

print (rfm.score (X_train, y_train))

print (rfm.score (X_test, y_test))

[Parallel (n_jobs=12)]: Using backend ThreadingBackend with 12 concurrent workers.

[Parallel (n_jobs=12)]: Done 17 tasks | elapsed 0.2s

[Parallel (n_jobs=12)]: Done 120 out of 120 | elapsed: 0.9s finished

[Parallel (n_jobs=12)]: Using backend ThreadingBackend with 12 concurrent workers.

[Parallel (n_jobs=12)]: Done 17 tasks elapsed: 0.1s

0.944283757229526

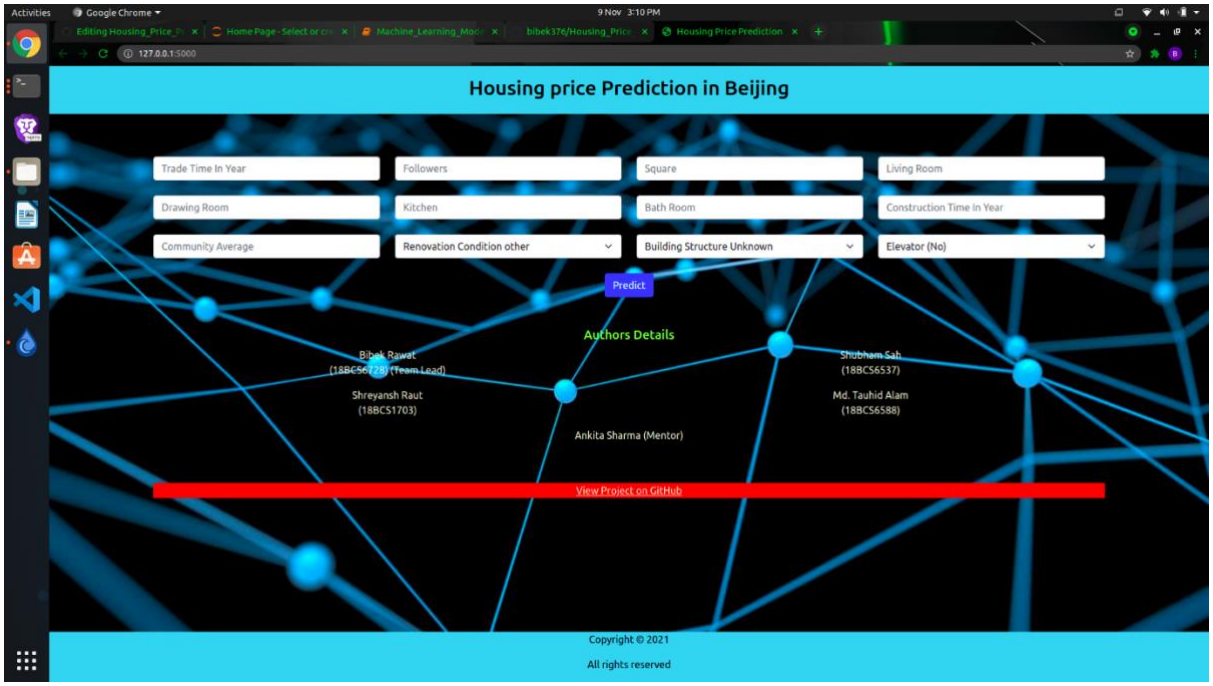
0.8966624691850038

[Parallel (n_jobs=12)]: Done 120 out of 120 | elapsed: 0.4s finished

Now, Accuracy of model seems to be very good .so we can save the model using pickle.

7. Model Deployment

After creating model, we integrate that model with beautiful UI. for the UI part we used HTML, CSS, JS and Flask



8. Model Conclusion

Model predict 90% accurately on test data and 94% accurately on train data .

9. Project Innovation

a. Easy to use
b. open source
c. Best accuracy
d. GUI Based Application

10. Limitation And Next Step

Limitation are :-
a. Mobile Application
b. Accuracy can be improve
c. Model Size is heavy(~310 mb)
d. Feature is limited

Next Step are :-
a. we will work on mobile application
b. we will reduce the size of model using PCA .

11. Working Project Video

PYTHON PROGRAMMING:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import pandas as pdd

# Loading the dataset
data_h = pdd.read_csv('kc_house_data.csv')

# Selecting the features and target variable
Features1 = ['bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'zipcode']
target = 'price'
X1 = data_h[features1]
y1 = data_h[target]
```

```
# We will perform the data splitting into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X1, y1, test_size=0.2,
random_state=42)


# instance of the Linear Regression model creation
model = LinearRegression()


# Training the model
model.fit(X_train, y_train)


# Making predictions on the test set
y_pred = model.predict(X_test)


# Evaluating the model
score = model.score(X_test, y_test)
print("Model R^2 Score:", score)
# Predicting the price of a new house
new_house = pdd.DataFrame({'bedrooms': [2], 'bathrooms': [2.5], 'sqft_living':
[600], 'sqft_lot': [600], 'floors': [2], 'zipcode': [98008]})
predicted_price = model.predict(new_house)
print("Predicted Price:", predicted_price[0])
```

OUTPUT:

Model R^2 Score: 0.5152176902631012

Predicted Price: 121215.61449578404

CONCLUSION:

In conclusion, using machine learning in Python is a powerful tool for predicting house prices. By gathering and cleaning data, visualizing patterns, and training and evaluating our models, we can make informed decisions in the dynamic world of real estate.

By leveraging advanced algorithms and data analysis, we can make accurate predictions and inform decision-making processes. This approach empowers buyers, sellers, and investors to make informed choices in a dynamic and competitive market, ultimately maximizing their opportunities and outcomes.