## Part 1:Predict the price of a house

## importing the libraries

```
In [52]: import pandas as pd
   import numpy as np
   import seaborn as sns
   import matplotlib.pyplot as plt
   from sklearn.metrics import r2_score,mean_absolute_error
   from sklearn.model_selection import train_test_split
   from sklearn.linear_model import LinearRegression,Lasso,Ridge
   from sklearn.tree import DecisionTreeRegressor
   from sklearn.svm import SVR
   from sklearn.ensemble import RandomForestRegressor,AdaBoostRegressor,GradientBoos
   from sklearn.neighbors import KNeighborsRegressor
```

In [2]: df=pd.read\_excel('houseprice.xlsx')
df

#### Out[2]:

Transaction date	House Age	Distance from nearest Metro station (km)	Number of convenience stores	latitude	longitude	Number of bedrooms	House size (sqft)	House price of unit area
2012.916667	32.0	84.87882	10	24.98298	121.54024	1	575	37.9
2012.916667	19.5	306.59470	9	24.98034	121.53951	2	1240	42.2
2013.583333	13.3	561.98450	5	24.98746	121.54391	3	1060	47.3
2013.500000	13.3	561.98450	5	24.98746	121.54391	2	875	54.8
2012.833333	5.0	390.56840	5	24.97937	121.54245	1	491	43.1
2013.000000	13.7	4082.01500	0	24.94155	121.50381	3	803	15.4
2012.666667	5.6	90.45606	9	24.97433	121.54310	2	1278	50.0
2013.250000	18.8	390.96960	7	24.97923	121.53986	1	503	40.6
2013.000000	8.1	104.81010	5	24.96674	121.54067	1	597	52.5
2013.500000	6.5	90.45606	9	24.97433	121.54310	2	1097	63.9
						·		
	2012.916667 2012.916667 2013.583333 2013.500000 2012.8333333 2013.0000000 2012.6666667 2013.2500000 2013.0000000	date     Age       2012.916667     32.0       2012.916667     19.5       2013.583333     13.3       2013.500000     13.3       2012.833333     5.0           2013.000000     13.7       2012.666667     5.6       2013.250000     18.8       2013.000000     8.1	Transaction date         House Age         from nearest Metro station (km)           2012.916667         32.0         84.87882           2012.916667         19.5         306.59470           2013.583333         13.3         561.98450           2012.833333         5.0         390.56840           2013.000000         13.7         4082.01500           2012.666667         5.6         90.45606           2013.250000         18.8         390.96960           2013.000000         8.1         104.81010	Transaction date         House Age         from nearest Metro station (km)         Number of convenience stores           2012.916667         32.0         84.87882         10           2012.916667         19.5         306.59470         9           2013.583333         13.3         561.98450         5           2012.833333         5.0         390.56840         5           2013.000000         13.7         4082.01500         0           2013.250000         18.8         390.96960         7           2013.000000         8.1         104.81010         5	Transaction date date         House Age Age         from nearest Metro station (km)         Number of convenience stores         latitude           2012.916667         32.0         84.87882         10         24.98298           2012.916667         19.5         306.59470         9         24.98034           2013.583333         13.3         561.98450         5         24.98746           2013.500000         13.3         561.98450         5         24.98746           2012.833333         5.0         390.56840         5         24.97937                  2013.000000         13.7         4082.01500         0         24.94155           2012.666667         5.6         90.45606         9         24.97433           2013.250000         18.8         390.96960         7         24.97923           2013.000000         8.1         104.81010         5         24.96674	Transaction date         House Age         If from Metro station (km)         Number of convenience stores         latitude         longitude           2012.916667         32.0         84.87882         10         24.98298         121.54024           2012.916667         19.5         306.59470         9         24.98034         121.53951           2013.583333         13.3         561.98450         5         24.98746         121.54391           2012.8333333         5.0         390.56840         5         24.97937         121.54245                   2013.000000         13.7         4082.01500         0         24.97433         121.54310           2012.666667         5.6         90.45606         9         24.97433         121.54310           2013.250000         18.8         390.96960         7         24.97923         121.53986           2013.000000         8.1         104.81010         5         24.96674         121.54067	Transaction date         House Age         from nearest Metro station (km)         Number of convenience stores         latitude         longitude         Number of bedrooms           2012.916667         32.0         84.87882         10         24.98298         121.54024         1           2012.916667         19.5         306.59470         9         24.98034         121.53951         2           2013.583333         13.3         561.98450         5         24.98746         121.54391         3           2012.833333         5.0         390.56840         5         24.98746         121.54391         2           2013.000000         13.7         4082.01500         3         121.54391         1           2012.666667         5.6         90.45606         9         24.94155         121.50381         3           2013.250000         18.8         390.96960         7         24.97923         121.53986         1           2013.000000         8.1         104.81010         5         24.96674         121.54067         1	Transaction date         House date         Registation (km)         Number of convenience stores         latitude         longitude         Number of bedrooms         House size (sqft)           2012.916667         32.0         84.87882         10         24.98298         121.54024         1         575           2012.916667         19.5         306.59470         9         24.98034         121.53951         2         124           2013.583333         13.3         561.98450         5         24.98746         121.54391         3         1060           2012.833333         5.0         390.56840         5         24.97937         121.54245         1         491           2013.000000         13.7         4082.01500         0         24.94155         121.50381         3         803           2012.666667         5.6         90.45606         9         24.97433         121.50381         3         1278           2013.250000         18.8         390.96960         7         24.97923         121.53060         1         507           2013.000000         8.1         104.81010         5         24.96674         121.54067         1         597

414 rows × 9 columns

```
In [3]: df.shape
Out[3]: (414, 9)
In [4]: df.describe()
```

Out[4]:

	Transaction date	House Age	Distance from nearest Metro station (km)	Number of convenience stores	latitude	longitude	Number of bedrooms	۴
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000	4
mean	2013.148953	17.712560	1083.885689	4.094203	24.969030	121.533361	1.987923	9
std	0.281995	11.392485	1262.109595	2.945562	0.012410	0.015347	0.818875	3
min	2012.666667	0.000000	23.382840	0.000000	24.932070	121.473530	1.000000	4
25%	2012.916667	9.025000	289.324800	1.000000	24.963000	121.528085	1.000000	5
50%	2013.166667	16.100000	492.231300	4.000000	24.971100	121.538630	2.000000	9
75%	2013.416667	28.150000	1454.279000	6.000000	24.977455	121.543305	3.000000	12
max	2013.583333	43.800000	6488.021000	10.000000	25.014590	121.566270	3.000000	15

# In [5]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 414 entries, 0 to 413
Data columns (total 9 columns):

#	Column	Non-Null Count	Dtype
0	Transaction date	414 non-null	float64
1	House Age	414 non-null	float64
2	Distance from nearest Metro station (km)	414 non-null	float64
3	Number of convenience stores	414 non-null	int64
4	latitude	414 non-null	float64
5	longitude	414 non-null	float64
6	Number of bedrooms	414 non-null	int64
7	House size (sqft)	414 non-null	int64
8	House price of unit area	414 non-null	float64

dtypes: float64(6), int64(3)

memory usage: 29.2 KB

## In [6]: df.isnull()

### Out[6]:

	Transaction date	House Age	Distance from nearest Metro station (km)	Number of convenience stores	latitude	longitude	Number of bedrooms	House size (sqft)	House price of unit area
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
	•••		•••						
409	False	False	False	False	False	False	False	False	False
410	False	False	False	False	False	False	False	False	False
411	False	False	False	False	False	False	False	False	False
412	False	False	False	False	False	False	False	False	False
413	False	False	False	False	False	False	False	False	False

414 rows × 9 columns

```
In [7]: df.isnull().sum()
Out[7]: Transaction date
                                                     0
                                                     0
        House Age
        Distance from nearest Metro station (km)
                                                     0
        Number of convenience stores
                                                     0
        latitude
                                                     0
        longitude
                                                     0
        Number of bedrooms
                                                     0
        House size (sqft)
                                                     0
        House price of unit area
        dtype: int64
```

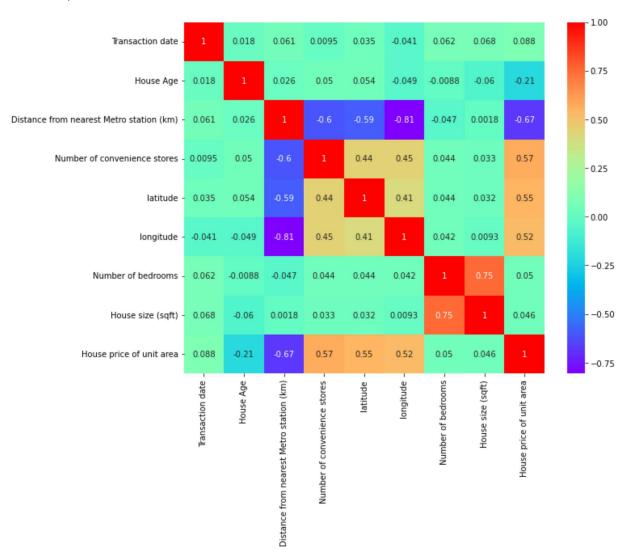
In [8]: df.corr()

Out[8]:

	Transaction date	House Age	Distance from nearest Metro station (km)	Number of convenience stores	latitude	longitude	Number of bedrooms	Н
Transaction date	1.000000	0.017542	0.060880	0.009544	0.035016	-0.041065	0.061985	0.06
House Age	0.017542	1.000000	0.025622	0.049593	0.054420	-0.048520	-0.008756	-0.06
Distance from nearest Metro station (km)	0.060880	0.025622	1.000000	-0.602519	-0.591067	-0.806317	-0.046856	0.00
Number of convenience stores	0.009544	0.049593	-0.602519	1.000000	0.444143	0.449099	0.043638	0.03
latitude	0.035016	0.054420	-0.591067	0.444143	1.000000	0.412924	0.043921	0.03
longitude	-0.041065	-0.048520	-0.806317	0.449099	0.412924	1.000000	0.041680	0.00
Number of bedrooms	0.061985	-0.008756	-0.046856	0.043638	0.043921	0.041680	1.000000	0.75
House size (sqft)	0.068405	-0.060361	0.001795	0.033286	0.031696	0.009322	0.752276	1.00
House price of unit area	0.087529	-0.210567	-0.673613	0.571005	0.546307	0.523287	0.050265	0.04

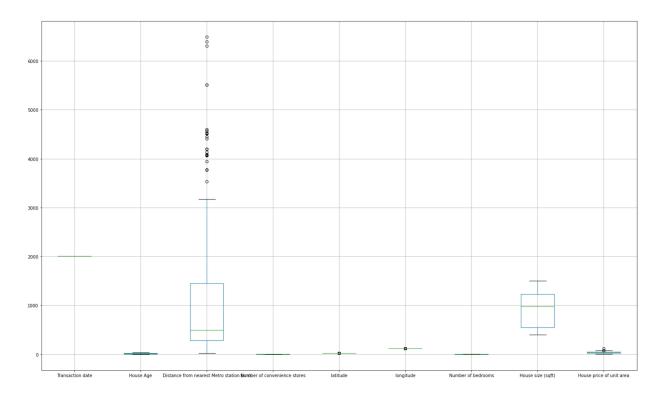
In [9]: plt.figure(figsize=(10,8))
 sns.heatmap(df.corr(),annot=True,cmap='rainbow')

### Out[9]: <AxesSubplot:>



```
In [10]: plt.figure(figsize=(25,15))
df.boxplot()
```

Out[10]: <AxesSubplot:>



From the above box plot we say that the variable 'Distance from nearest metro station' contain many outliers so we drop that columns.

```
In [55]: df1=df.drop(columns=['Distance from nearest Metro station (km)'])
```

```
In [56]: | x=df1.iloc[:,:-1]
           Х
Out[56]:
                  Transaction
                                House
                                                  Number of
                                                                                     Number of
                                                                                                    House
                                                               latitude
                                                                        longitude
                                          convenience stores
                                                                                     bedrooms
                        date
                                  Age
                                                                                                 size (sqft)
                 2012.916667
                                 32.0
                                                              24.98298
                                                          10
                                                                       121.54024
                                                                                             1
                                                                                                      575
                 2012.916667
                                  19.5
                                                              24.98034
                                                                       121.53951
                                                                                             2
                                                                                                     1240
              2 2013.583333
                                                                                             3
                                 13.3
                                                              24.98746 121.54391
                                                                                                     1060
                 2013.500000
                                                                                             2
                                  13.3
                                                              24.98746
                                                                      121.54391
                                                                                                      875
                 2012.833333
                                                              24.97937
                                                                       121.54245
                                                                                             1
                                                                                                      491
                                  5.0
                                   ...
                                                                                                       ...
            409
                 2013.000000
                                  13.7
                                                              24.94155 121.50381
                                                                                             3
                                                                                                      803
            410
                 2012.666667
                                  5.6
                                                              24.97433 121.54310
                                                                                             2
                                                                                                     1278
                 2013.250000
                                  18.8
                                                              24.97923 121.53986
                                                                                             1
                                                                                                      503
            411
                2013.000000
                                  8.1
                                                              24.96674 121.54067
                                                                                                      597
                                                                                             1
            413
                2013.500000
                                  6.5
                                                           9 24.97433 121.54310
                                                                                             2
                                                                                                     1097
           414 rows × 7 columns
In [57]: x.shape
Out[57]: (414, 7)
In [59]: y=df1.iloc[:,-1]
           У
Out[59]: 0
                   37.9
           1
                   42.2
           2
                   47.3
           3
                   54.8
           4
                   43.1
           409
                   15.4
           410
                   50.0
           411
                   40.6
           412
                   52.5
           413
                   63.9
           Name: House price of unit area, Length: 414, dtype: float64
In [60]: | y.shape
```

In [78]: x\_train,x\_test,y\_train,y\_test=train\_test\_split(x,y,test\_size=0.2,random\_state=1000
In [80]: x\_train.shape
Out[80]: (331, 7)

Out[60]: (414,)

```
In [81]: x_test.shape
Out[81]: (83, 7)
In [82]: y_train.shape
Out[82]: (331,)
In [83]: y_test.shape
Out[83]: (83,)
```

```
In [85]:
      k = 42
      models = [LinearRegression(),DecisionTreeRegressor(random state=k),RandomForestRe
              Ridge(random_state=k),SVR(),AdaBoostRegressor(random_state=k),GradientE
      for i in models:
         print(20*'=',i,20*'=')
         model=i
         model.fit(x_train,y_train)
         y_pred=model.predict(x_test)
         print('R^2_Score :',r2_score(y_test,y_pred))
         print('Mean Absolute Error:' , mean_absolute_error(y_test,y_pred))
         print(70*'*')
      ======== LinearRegression() ==========
      R^2 Score : 0.6348333998620814
      Mean Absolute Error: 5.7943206440635295
       ***************************
       ======== DecisionTreeRegressor(random_state=42) ==============
      R^2 Score : 0.6854281647279253
      Mean Absolute Error: 5.353012048192771
       *****************************
       ========== RandomForestRegressor(random_state=42) =============
      R^2 Score : 0.8417226447318275
      Mean Absolute Error: 3.7600602409638544
       **************************
       ========== Lasso(random state=42) ================
      R^2 Score : 0.4988391733969735
      Mean Absolute Error: 7.039104412989815
       ************************
      R^2 Score : 0.5246295588465157
      Mean Absolute Error: 6.933806861827341
      R^2_Score : -0.010565565070761673
      Mean Absolute Error: 9.821697854756335
       *************************
       ========= AdaBoostRegressor(random state=42) ================
      R^2 Score : 0.7241076656036954
      Mean Absolute Error: 4.999809487777276
       **********************************
      R^2 Score : 0.8396747073035247
      Mean Absolute Error: 3.8748143010645912
```

So here we can see that Random Forest has mininum mean\_absolute\_error and highest accuracy so we can say that this is a best model for our problem statment.