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The objective of this project is to predict the price of a house, on the basis of given features provided.

The following dataset has been used for this project :

https://www.kaggle.com/datasets/harshsingh1112/house-price-prediction-codestring

```
import pandas as pd
import numpy as np
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import preprocessing
from sklearn import utils
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.datasets import make_regression
from sklearn.linear_model import RidgeCV
```

Section 1 : Exploratory Data Analysis and pre-processing

We will read the dataset, analyse the values, identify useful variables, and clean the data as required.

```
pricedata=pd.read_csv("data.csv")
pricedata.head()

                  date      price  bedrooms  bathrooms  sqft_living
sqft_lot  \
0  2014-05-02 00:00:00   313000.0       3.0       1.50         1340
7912
1  2014-05-02 00:00:00  2384000.0       5.0       2.50         3650
9050
2  2014-05-02 00:00:00   342000.0       3.0       2.00         1930
11947
3  2014-05-02 00:00:00   420000.0       3.0       2.25         2000
8030
4  2014-05-02 00:00:00   550000.0       4.0       2.50         1940
10500

   floors  waterfront  view  condition  sqft_above  sqft_basement
yr_built  \
0     1.5           0     0          3        1340              0
1955
1     2.0           0     4          5        3370            280
1921
```

```
2     1.0           0     0          4       1930             0
1966
3     1.0           0     0          4       1000          1000
1963
4     1.0           0     0          4       1140           800
1976

   yr_renovated                    street       city  statezip country

0          2005      18810 Densmore Ave N  Shoreline  WA 98133     USA

1             0           709 W Blaine St    Seattle  WA 98119     USA

2             0  26206-26214 143rd Ave SE       Kent  WA 98042     USA

3             0           857 170th Pl NE   Bellevue  WA 98008     USA

4          1992         9105 170th Ave NE    Redmond  WA 98052     USA
```

Clearly, 'price' can be the target variable, so we can prefer regression techniques.

To check the data types for each column :

```
pricedata.dtypes

date              object
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
```

To summarise the entire dataset values, first for numerical values

```
pricedata.describe()
```

```
                price     bedrooms    bathrooms   sqft_living
sqft_lot  \
count  4.600000e+03  4600.000000  4600.000000   4600.000000
4.600000e+03
mean   5.519630e+05     3.400870     2.160815   2139.346957
1.485252e+04
std    5.638347e+05     0.908848     0.783781    963.206916
3.588444e+04
min    0.000000e+00     0.000000     0.000000    370.000000
6.380000e+02
25%    3.228750e+05     3.000000     1.750000   1460.000000
5.000750e+03
50%    4.609435e+05     3.000000     2.250000   1980.000000
7.683000e+03
75%    6.549625e+05     4.000000     2.500000   2620.000000
1.100125e+04
max    2.659000e+07     9.000000     8.000000  13540.000000
1.074218e+06

            floors   waterfront         view    condition   sqft_above
\
count  4600.000000  4600.000000  4600.000000  4600.000000  4600.000000

mean      1.512065     0.007174     0.240652     3.451739  1827.265435

std       0.538288     0.084404     0.778405     0.677230   862.168977

min       1.000000     0.000000     0.000000     1.000000   370.000000

25%       1.000000     0.000000     0.000000     3.000000  1190.000000

50%       1.500000     0.000000     0.000000     3.000000  1590.000000

75%       2.000000     0.000000     0.000000     4.000000  2300.000000

max       3.500000     1.000000     4.000000     5.000000  9410.000000


       sqft_basement     yr_built  yr_renovated
count    4600.000000  4600.000000   4600.000000
mean      312.081522  1970.786304    808.608261
std       464.137228    29.731848    979.414536
min         0.000000  1900.000000      0.000000
25%         0.000000  1951.000000      0.000000
50%         0.000000  1976.000000      0.000000
75%       610.000000  1997.000000   1999.000000
max      4820.000000  2014.000000   2014.000000
```

and for catergorical values :

```
pricedata.describe(include="object")
```

```
                       date                   street     city   statezip
country
count                  4600                     4600     4600       4600
4600
unique                   70                     4525       44         77
1
top     2014-06-23 00:00:00  2520 Mulberry Walk NE  Seattle   WA 98103
USA
freq                    142                        4     1573        148
4600
```

Checking for null data:

```
pricedata.isnull().sum()
```

```
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
street           0
city             0
statezip         0
country          0
dtype: int64
```

The dataset has no null values.

```
pricedata.columns
```

```
Index(['date', 'price', 'bedrooms', 'bathrooms', 'sqft_living',
'sqft_lot',
       'floors', 'waterfront', 'view', 'condition', 'sqft_above',
       'sqft_basement', 'yr_built', 'yr_renovated', 'street', 'city',
       'statezip', 'country'],
      dtype='object')
```

To find correlation among attributes, using Pearson coefficent (gives values between +1 and -1) :

```python
pricedata.corr(method='pearson')
```

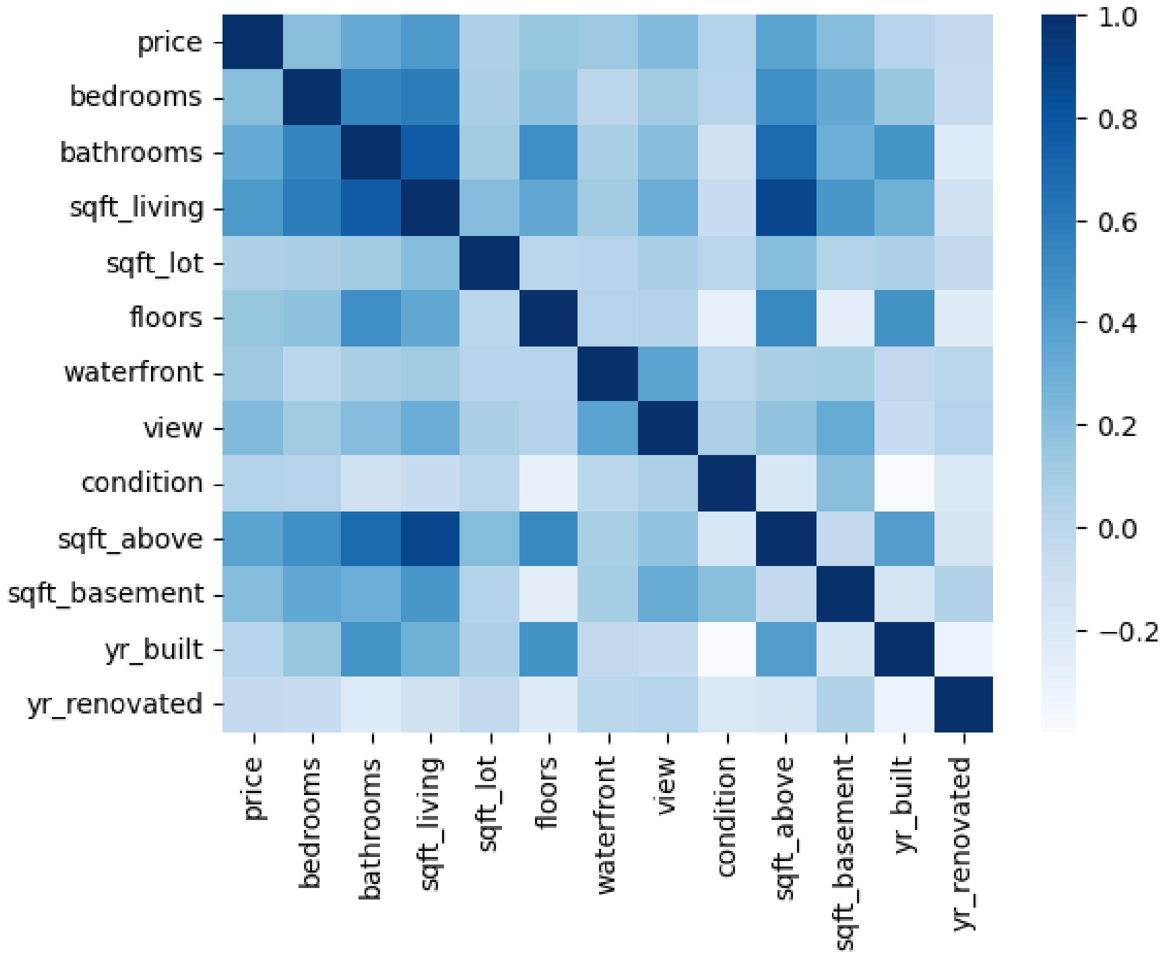
```
C:\Users\Asus\AppData\Local\Temp\ipykernel_24448\3456885043.py:1:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  pricedata.corr(method='pearson')
```

```
                  price  bedrooms  bathrooms  sqft_living  sqft_lot
floors  \
price          1.000000  0.200336   0.327110     0.430410  0.050451
0.151461
bedrooms       0.200336  1.000000   0.545920     0.594884  0.068819
0.177895
bathrooms      0.327110  0.545920   1.000000     0.761154  0.107837
0.486428
sqft_living    0.430410  0.594884   0.761154     1.000000  0.210538
0.344850
sqft_lot       0.050451  0.068819   0.107837     0.210538  1.000000
0.003750
floors         0.151461  0.177895   0.486428     0.344850  0.003750
1.000000
waterfront     0.135648 -0.003483   0.076232     0.117616  0.017241
0.022024
view           0.228504  0.111028   0.211960     0.311009  0.073907
0.031211
condition      0.034915  0.025080  -0.119994    -0.062826  0.000558 -
0.275013
sqft_above     0.367570  0.484705   0.689918     0.876443  0.216455
0.522814
sqft_basement  0.210427  0.334165   0.298020     0.447206  0.034842 -
0.255510
yr_built       0.021857  0.142461   0.463498     0.287775  0.050706
0.467481
yr_renovated  -0.028774 -0.061082  -0.215886    -0.122817 -0.022730 -
0.233996

               waterfront      view  condition  sqft_above
sqft_basement  \
price            0.135648  0.228504   0.034915    0.367570
0.210427
bedrooms        -0.003483  0.111028   0.025080    0.484705
0.334165
bathrooms        0.076232  0.211960  -0.119994    0.689918
0.298020
sqft_living      0.117616  0.311009  -0.062826    0.876443
0.447206
sqft_lot         0.017241  0.073907   0.000558    0.216455
0.034842
```

```
floors            0.022024  0.031211  -0.275013    0.522814       -
0.255510
waterfront        1.000000  0.360935   0.000352    0.078911
0.097501
view              0.360935  1.000000   0.063077    0.174327
0.321602
condition         0.000352  0.063077   1.000000   -0.178196
0.200632
sqft_above        0.078911  0.174327  -0.178196    1.000000       -
0.038723
sqft_basement     0.097501  0.321602   0.200632   -0.038723
1.000000
yr_built         -0.023563 -0.064465  -0.399698    0.408535       -
0.161675
yr_renovated      0.008625  0.022967  -0.186818   -0.160426
0.043125

               yr_built  yr_renovated
price          0.021857     -0.028774
bedrooms       0.142461     -0.061082
bathrooms      0.463498     -0.215886
sqft_living    0.287775     -0.122817
sqft_lot       0.050706     -0.022730
floors         0.467481     -0.233996
waterfront    -0.023563      0.008625
view          -0.064465      0.022967
condition     -0.399698     -0.186818
sqft_above     0.408535     -0.160426
sqft_basement -0.161675      0.043125
yr_built       1.000000     -0.321342
yr_renovated  -0.321342      1.000000
```

```
sns.heatmap(pricedata.corr(),cmap="Blues")
```

```
C:\Users\Asus\AppData\Local\Temp\ipykernel_24448\606827974.py:1:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  sns.heatmap(pricedata.corr(),cmap="Blues")

<AxesSubplot: >
```



From the dataset, the target variable being 'price', we have to select numerical and categorical variables to accurately predict it without any noise.

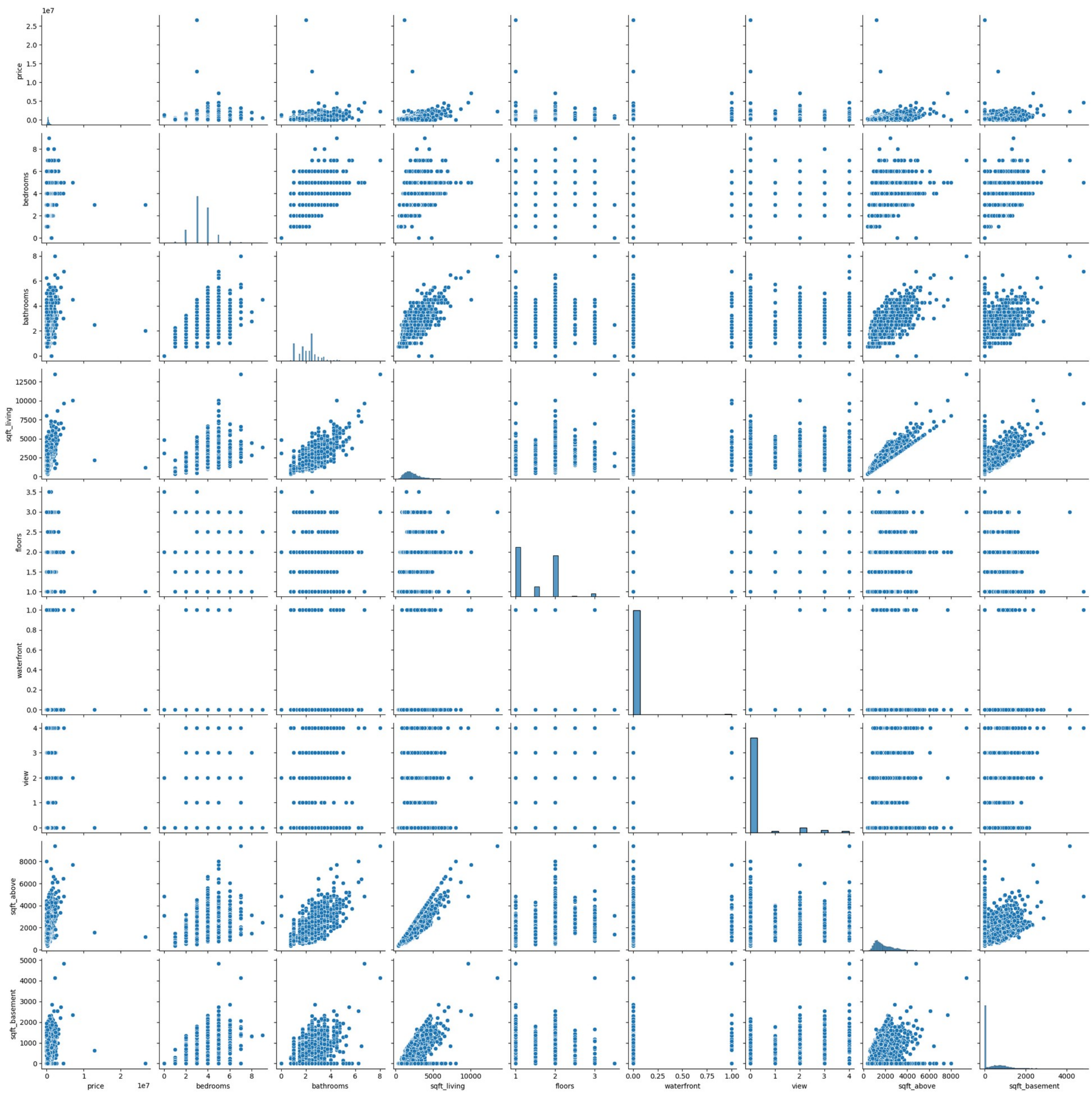
For the numerical variables, we will consider the given Pearson correlation value, and keeping in mind the current values, we will select those above +0.20 and below -0.50. This is obtained by :

```
numeric_vars = list(pricedata.corr()["price"][(pricedata.corr()
["price"]>0.10) | (pricedata.corr()["price"]<-0.50)].index)

print(numeric_vars)

['price', 'bedrooms', 'bathrooms', 'sqft_living', 'floors',
'waterfront', 'view', 'sqft_above', 'sqft_basement']

C:\Users\Asus\AppData\Local\Temp\ipykernel_24448\3787433713.py:1:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only
valid columns or specify the value of numeric_only to silence this
warning.
  numeric_vars = list(pricedata.corr()["price"][(pricedata.corr()
["price"]>0.10) | (pricedata.corr()["price"]<-0.50)].index)
```

To show correlation between all selected numeric variables :

```
sns.pairplot(pricedata[numeric_vars])
```

```
<seaborn.axisgrid.PairGrid at 0x1f4b1d12790>
```



To examine categorical variables :

```
cat_vars=[x for x in dict(pricedata.dtypes) if pricedata.dtypes[x]
=='object']
cat_data=pricedata[cat_vars]
cat_data.describe(include='object')
```

```
                        date                   street     city  statezip
country
count                   4600                     4600     4600      4600
4600
unique                    70                     4525       44        77
1
top      2014-06-23 00:00:00  2520 Mulberry Walk NE  Seattle  WA 98103
USA
freq                     142                        4     1573       148
4600
```

The date,street and streetzip columns are seemingly irrelevant, and so, can be removed.

```
cat_vars.remove('date')
cat_vars.remove('street')
cat_vars.remove('statezip')
```

Now, we will prepare the data for training/testing.

All relevant numeric and categorical attributes are taken in a new dataframe.

```
relevantdata= pricedata.copy()

relevant_cols= numeric_vars + cat_vars

relevantdata1=relevantdata[relevant_cols]
```

The categorical values must be converted to numerical in order to proceed further.

get_dummies method was tried but lead to problems.

pd.factorise() has been implemented to convert it.

```
relevantdata1['city']=pd.factorize(relevantdata1['city'])[0]
relevantdata1['country']=pd.factorize(relevantdata1['country'])[0]

C:\Users\Asus\AppData\Local\Temp\ipykernel_24448\2924767697.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  relevantdata1['city']=pd.factorize(relevantdata1['city'])[0]
C:\Users\Asus\AppData\Local\Temp\ipykernel_24448\2924767697.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  relevantdata1['country']=pd.factorize(relevantdata1['country'])[0]
```

Now, all values must be standardised.

StandardScaler() removes the mean and scales each feature/variable to unit variance.

The idea behind the StandardScaler is that variables that are measured at different scales do not contribute equally to the fit of the model and the learning function of the model and could end up creating a bias.

```
relevantdata1.drop_duplicates(inplace=True)

scaler=StandardScaler()

relevantdata1[relevant_cols]=scaler.fit_transform(relevantdata1[releva
nt_cols])

C:\Users\Asus\AppData\Local\Temp\ipykernel_24448\4021453304.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  relevantdata1.drop_duplicates(inplace=True)
C:\Users\Asus\AppData\Local\Temp\ipykernel_24448\4021453304.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy

relevantdata1[relevant_cols]=scaler.fit_transform(relevantdata1[releva
nt_cols])
```

The matrix so achieved must be converted back to a dataframe :

```
relevantdata=pd.DataFrame(relevantdata1,columns=relevant_cols)

relevantdata

         price  bedrooms  bathrooms  sqft_living   floors  waterfront
\
0    -0.423868 -0.442787  -0.844542    -0.831280 -0.02146   -0.085051
```

```
1      3.247746  1.759168   0.431784     1.567581  0.90882   -0.085051
2     -0.372455 -0.442787  -0.206379    -0.218584 -0.95174   -0.085051
3     -0.234171 -0.442787   0.112703    -0.145891 -0.95174   -0.085051
4     -0.003698  0.658191   0.431784    -0.208199 -0.95174   -0.085051
...         ...       ...        ...          ...      ...         ...
4595  -0.432437 -0.442787  -0.525460    -0.654740 -0.95174   -0.085051
4596  -0.031473 -0.442787   0.431784    -0.706664  0.90882   -0.085051
4597  -0.239660 -0.442787   0.431784     0.902962  0.90882   -0.085051
4598  -0.618175  0.658191  -0.206379    -0.052429 -0.95174   -0.085051
4599  -0.587682 -0.442787   0.431784    -0.675510  0.90882   -0.085051

          view  sqft_above  sqft_basement      city  country
0    -0.309379   -0.566104      -0.672995 -0.933590      0.0
1     4.827368    1.788480      -0.069839 -0.824459      0.0
2    -0.309379    0.118233      -0.672995 -0.715327      0.0
3    -0.309379   -0.960468       1.481133 -0.606196      0.0
4    -0.309379   -0.798083       1.050307 -0.497065      0.0
...        ...         ...            ...       ...      ...
4595 -0.309379   -0.368922      -0.672995 -0.824459      0.0
4596 -0.309379   -0.426917      -0.672995 -0.606196      0.0
4597 -0.309379    1.370918      -0.672995  1.030775      0.0
4598 -0.309379   -0.879275       1.524216 -0.824459      0.0
4599 -0.309379   -0.392120      -0.672995  1.576433      0.0

[4595 rows x 11 columns]
```

Section 2 : Model Training and Testing

The dataset is split into the input values and the target variable 'price' :

```
x1=relevantdata.drop('price',axis=1)

y=relevantdata[['price']]
```

Now, we will split it into training and testing data :

```
tr_x,tst_x,tr_y,tst_y=train_test_split(x1,y)
```

We will now apply a variety of models :

1. Linear Regression

```
lin=LinearRegression()
lin.fit(tr_x,tr_y)
predictions=lin.predict(tst_x)
```

The score obtained :

```
print("Score",lin.score(tst_x,tst_y))

Score 0.5048151977185034
```

1. Ridge Regression with Leave-One-Out Cross Validation

```
lin_ridgecv=RidgeCV()
lin_ridgecv.fit(tr_x,tr_y)
predictions1=lin_ridgecv.predict(tst_x)
```

The score obtained :

```
print("Score :",lin_ridgecv.score(tst_x,tst_y))

Score : 0.5135770851610719
```

1. Random Forest Regressor

```
regressor = RandomForestRegressor(max_depth=3, random_state=0)
regressor.fit(tr_x,tr_y)
predictions2=regressor.predict(tst_x)

C:\Users\Asus\AppData\Local\Temp\ipykernel_24448\2031978905.py:2:
DataConversionWarning: A column-vector y was passed when a 1d array
was expected. Please change the shape of y to (n_samples,), for
example using ravel().
  regressor.fit(tr_x,tr_y)
```

The score obtained is :

```
print("Score :",regressor.score(tst_x,tst_y))

Score : 0.48485826273103083
```