House Prices data taken from kaggle

problem statement

Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. But this playground competition's dataset proves that much more influences price negotiations than the number of bedrooms or a white-picket fence.With 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa, this competition challenges you to predict the final price of each home.

The three data sets collected from kaggle are train, test, and submissions. data sets for training and testing

I predicted the values using machine learning techniques.

import the libraries we'll need to make our predictions

In [187...
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

establishing a connection between my jupiter notebook and the file

In [188...
```
import io
%cd "D:\phython\house-prices-advanced-regression-techniques"
```

```
D:\phython\house-prices-advanced-regression-techniques
```

Importing the data from the train and the test

In [358...
```
housetrain=pd.read_csv("train.csv")
```

In [359...
```
housetest=pd.read_csv("test.csv")
```

EDA(exploratory data anlaysis)

In [360...
```
# exploratory data anlaysis done on train data.
```

In [363...
```
housetrain.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     1452 non-null   object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
 29  Foundation     1460 non-null   object 
 30  BsmtQual       1423 non-null   object 
 31  BsmtCond       1423 non-null   object 
 32  BsmtExposure   1422 non-null   object 
 33  BsmtFinType1   1423 non-null   object 
 34  BsmtFinSF1     1460 non-null   int64  
 35  BsmtFinType2   1422 non-null   object 
 36  BsmtFinSF2     1460 non-null   int64  
 37  BsmtUnfSF      1460 non-null   int64  
 38  TotalBsmtSF    1460 non-null   int64  
 39  Heating        1460 non-null   object 
 40  HeatingQC      1460 non-null   object 
 41  CentralAir     1460 non-null   object 
 42  Electrical     1459 non-null   object 
 43  1stFlrSF       1460 non-null   int64  
 44  2ndFlrSF       1460 non-null   int64  
 45  LowQualFinSF   1460 non-null   int64  
 46  GrLivArea      1460 non-null   int64  
 47  BsmtFullBath   1460 non-null   int64  
 48  BsmtHalfBath   1460 non-null   int64  
 49  FullBath       1460 non-null   int64  
 50  HalfBath       1460 non-null   int64  
 51  BedroomAbvGr   1460 non-null   int64  
 52  KitchenAbvGr   1460 non-null   int64  
 53  KitchenQual    1460 non-null   object 
 54  TotRmsAbvGrd   1460 non-null   int64  
 55  Functional     1460 non-null   object 
 56  Fireplaces     1460 non-null   int64  
 57  FireplaceQu    770 non-null    object 
 58  GarageType     1379 non-null   object 
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object 
 61  GarageCars     1460 non-null   int64  
 62  GarageArea     1460 non-null   int64  
 63  GarageQual     1379 non-null   object 
 64  GarageCond     1379 non-null   object 
 65  PavedDrive     1460 non-null   object 
 66  WoodDeckSF     1460 non-null   int64  
 67  OpenPorchSF    1460 non-null   int64  
 68  EnclosedPorch  1460 non-null   int64  
 69  3SsnPorch      1460 non-null   int64  
 70  ScreenPorch    1460 non-null   int64  
 71  PoolArea       1460 non-null   int64  
 72  PoolQC         7 non-null      object 
 73  Fence          281 non-null    object 
 74  MiscFeature    54 non-null     object 
 75  MiscVal        1460 non-null   int64  
 76  MoSold         1460 non-null   int64  
 77  YrSold         1460 non-null   int64  
 78  SaleType       1460 non-null   object 
 79  SaleCondition  1460 non-null   object 
 80  SalePrice      1460 non-null   int64  
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

In [364…
```
housetrain.MSZoning.value_counts()
```
Out[364]:
```
RL         1151
RM          218
FV           65
RH           16
C (all)      10
Name: MSZoning, dtype: int64
```
In [365…
```
housetrain.Street.value_counts()
```
Out[365]:
```
Pave    1454
Grvl       6
Name: Street, dtype: int64
```
In [366…
```
housetrain.Alley.value_counts()
```
Out[366]:
```
Grvl    50
Pave    41
Name: Alley, dtype: int64
```
In [367…
```
housetrain.SalePrice.mean()
```
Out[367]:
```
180921.19589041095
```
In [368…
```
housetrain.SalePrice.median()
```
Out[368]:
```
163000.0
```
In [369…
```
housetrain.GarageType.value_counts()
```
Out[369]:
```
Attchd     870
Detchd     387
BuiltIn     88
Basment     19
CarPort      9
2Types       6
Name: GarageType, dtype: int64
```
In [370…
```
housetrain.GarageFinish.value_counts()
```
Out[370]:
```
Unf    605
RFn    422
Fin    352
Name: GarageFinish, dtype: int64
```
In [371…
```
housetrain.SalePrice.groupby(housetrain.GarageFinish).mean()
```
Out[371]:
```
GarageFinish
Fin    240052.690341
RFn    202068.869668
Unf    142156.423140
Name: SalePrice, dtype: float64
```
In [372…
```
housetrain.SalePrice.groupby(housetrain.GarageFinish).median()
```
Out[372]:
```
GarageFinish
Fin    215000.0
RFn    190000.0
Unf    135000.0
Name: SalePrice, dtype: float64
```
In [373…
```
housetrain.SalePrice.groupby(housetrain.GarageType).median()
```
Out[373]:
```
GarageType
2Types     159000.0
Attchd     185000.0
Basment    148000.0
BuiltIn    227500.0
CarPort    108000.0
Detchd     129500.0
Name: SalePrice, dtype: float64
```
In [374…
```
housetrain.SalePrice.groupby(housetrain.GarageType).median()
```
Out[374]:
```
GarageType
2Types     159000.0
Attchd     185000.0
Basment    148000.0
BuiltIn    227500.0
CarPort    108000.0
Detchd     129500.0
Name: SalePrice, dtype: float64
```
In [375…
```
housetrain.SalePrice.groupby(housetrain.GarageType).mean()
```

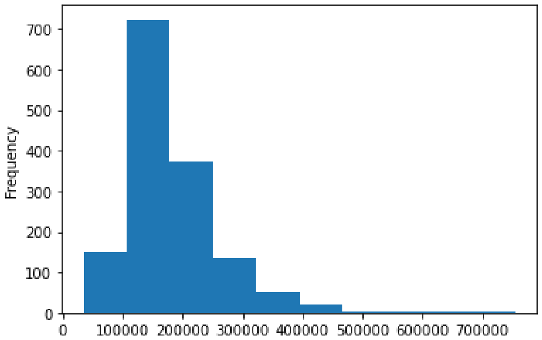
Out[375]:
```
GarageType
2Types      151283.333333
Attchd      202892.656322
Basment     160570.684211
BuiltIn     254751.738636
CarPort     109962.111111
Detchd      134091.162791
Name: SalePrice, dtype: float64
```

In [376…
```
housetrain.SalePrice.groupby(housetrain.GarageType).mean()
```

Out[376]:
```
GarageType
2Types      151283.333333
Attchd      202892.656322
Basment     160570.684211
BuiltIn     254751.738636
CarPort     109962.111111
Detchd      134091.162791
Name: SalePrice, dtype: float64
```

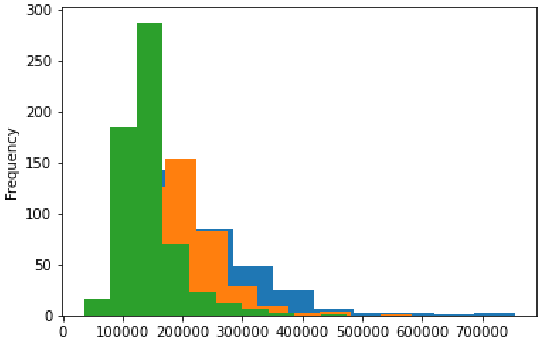
In [538…
```
housetrain.SalePrice.plot(kind='hist')
```

Out[538]: <AxesSubplot:ylabel='Frequency'>



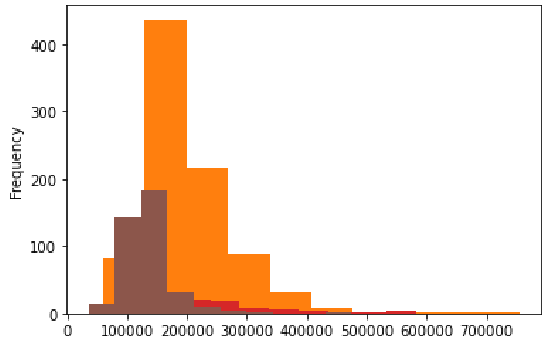
In [539…
```
housetrain.SalePrice.groupby(housetrain.GarageFinish).plot(kind='hist')
```

Out[539]:
```
GarageFinish
Fin     AxesSubplot(0.125,0.125;0.775x0.755)
RFn     AxesSubplot(0.125,0.125;0.775x0.755)
Unf     AxesSubplot(0.125,0.125;0.775x0.755)
Name: SalePrice, dtype: object
```



In [540…
```
housetrain.SalePrice.groupby(housetrain.GarageType).plot(kind='hist')
```

Out[540]:
```
GarageType
2Types      AxesSubplot(0.125,0.125;0.775x0.755)
Attchd      AxesSubplot(0.125,0.125;0.775x0.755)
Basment     AxesSubplot(0.125,0.125;0.775x0.755)
BuiltIn     AxesSubplot(0.125,0.125;0.775x0.755)
CarPort     AxesSubplot(0.125,0.125;0.775x0.755)
Detchd      AxesSubplot(0.125,0.125;0.775x0.755)
Name: SalePrice, dtype: object
```



In [378…

```
# Using shape to understand the data observations and variables
print(housetrain.shape)
print(housetest.shape)
```

```
(1460, 81)
(1459, 80)
```

In [379…

```
housetrain.isnull().sum().sort_values(ascending=False).head(50)
```

Out[379]:

```
PoolQC           1453
MiscFeature      1406
Alley            1369
Fence            1179
FireplaceQu       690
LotFrontage       259
GarageYrBlt        81
GarageCond         81
GarageType         81
GarageFinish       81
GarageQual         81
BsmtFinType2       38
BsmtExposure       38
BsmtQual           37
BsmtCond           37
BsmtFinType1       37
MasVnrArea          8
MasVnrType          8
Electrical          1
Id                  0
Functional          0
Fireplaces          0
KitchenQual         0
KitchenAbvGr        0
BedroomAbvGr        0
HalfBath            0
FullBath            0
BsmtHalfBath        0
TotRmsAbvGrd        0
GarageCars          0
GrLivArea           0
GarageArea          0
PavedDrive          0
WoodDeckSF          0
OpenPorchSF         0
EnclosedPorch       0
3SsnPorch           0
ScreenPorch         0
PoolArea            0
MiscVal             0
MoSold              0
YrSold              0
SaleType            0
SaleCondition       0
```

```
BsmtFullBath        0
HeatingQC           0
LowQualFinSF        0
LandSlope           0
OverallQual         0
HouseStyle          0
dtype: int64
```

In [380…

```
# Added Dependent variable to test Data for Row wise Concatenation
housetest['SalePrice']='test'
```

combining the test and training data into a single file Row wise Concatenation

In [381…

```
# Row wise concatenation
combinedf=pd.concat([housetrain,housetest],axis=0)
```

separating the numeric columns from the object columns

In [382…

```
# Split data into ObjectColumns and NumericColumns
objectcolumns=combinedf.select_dtypes(include=['object'])
numericcolumns=combinedf.select_dtypes(include=np.number)
```

In [383…

```
# to know the observation and variables.
print(objectcolumns.shape)
print(numericcolumns.shape)
```

```
(2919, 44)
(2919, 37)
```

examining null values

In [384…

```
objectcolumns.isnull().sum().sort_values(ascending=False)
```

Out[384]:

```
PoolQC           2909
MiscFeature      2814
Alley            2721
Fence            2348
FireplaceQu      1420
GarageCond        159
GarageQual        159
GarageFinish      159
GarageType        157
BsmtCond           82
BsmtExposure       82
BsmtQual           81
BsmtFinType2       80
BsmtFinType1       79
MasVnrType         24
MSZoning            4
Utilities           2
Functional          2
Exterior2nd         1
Electrical          1
SaleType            1
Exterior1st         1
KitchenQual         1
RoofStyle           0
Neighborhood        0
SaleCondition       0
ExterQual           0
LotShape            0
LandContour         0
ExterCond           0
PavedDrive          0
LotConfig           0
LandSlope           0
Condition1          0
HouseStyle          0
Condition2          0
Foundation          0
RoofMatl            0
Street              0
CentralAir          0
HeatingQC           0
Heating             0
BldgType            0
```

```
SalePrice          0
dtype: int64
```

I'm seperating these data since certain variables are categorical values with large number of missing vales.

In [385…
```
# Since variables - PoolQC,MiscFeature,Alley,Fence, FireplaceQu has morethan
# 50% NA or missing values - impute with word 'missing'
missingcols=['PoolQC','MiscFeature','Alley','Fence','FireplaceQu']
```

The missing columns include enormous amounts of missing data, thus I'm replacing missing observations with missing data.

In [386…
```
for col in missingcols:
    objectcolumns[col]=objectcolumns[col].fillna("missing")
```

Creating a for loop to find duplicate categorical values in a dataset

In [387…
```
for col in objectcolumns.columns:
    freq=objectcolumns[col].value_counts(dropna=False)
    print(freq)
```

```
RL         2265
RM          460
FV          139
RH           26
C (all)      25
NaN           4
Name: MSZoning, dtype: int64
Pave    2907
Grvl      12
Name: Street, dtype: int64
missing    2721
Grvl        120
Pave         78
Name: Alley, dtype: int64
Reg    1859
IR1     968
IR2      76
IR3      16
Name: LotShape, dtype: int64
Lvl    2622
HLS     120
Bnk     117
Low      60
Name: LandContour, dtype: int64
AllPub    2916
NaN          2
NoSeWa       1
Name: Utilities, dtype: int64
Inside     2133
Corner      511
CulDSac     176
FR2          85
FR3          14
Name: LotConfig, dtype: int64
Gtl    2778
Mod     125
Sev      16
Name: LandSlope, dtype: int64
NAmes      443
CollgCr    267
OldTown    239
Edwards    194
Somerst    182
NridgHt    166
```

```
Gilbert    165
Sawyer     151
NWAmes     131
SawyerW    125
Mitchel    114
BrkSide    108
Crawfor    103
IDOTRR      93
Timber      72
NoRidge     71
StoneBr     51
SWISU       48
ClearCr     44
MeadowV     37
BrDale      30
Blmngtn     28
Veenker     24
NPkVill     23
Blueste     10
Name: Neighborhood, dtype: int64
Norm      2511
Feedr      164
Artery      92
RRAn        50
PosN        39
RRAe        28
PosA        20
RRNn         9
RRNe         6
Name: Condition1, dtype: int64
Norm      2889
Feedr       13
Artery       5
PosN         4
PosA         4
RRNn         2
RRAn         1
RRAe         1
Name: Condition2, dtype: int64
1Fam      2425
TwnhsE     227
Duplex     109
Twnhs       96
2fmCon      62
```

```
Name: BldgType, dtype: int64
1Story    1471
2Story     872
1.5Fin     314
SLvl       128
SFoyer      83
2.5Unf      24
1.5Unf      19
2.5Fin       8
Name: HouseStyle, dtype: int64
Gable      2310
Hip         551
Gambrel      22
Flat         20
Mansard      11
Shed          5
Name: RoofStyle, dtype: int64
CompShg    2876
Tar&Grv      23
WdShake       9
WdShngl       7
Metal         1
Membran       1
Roll          1
ClyTile       1
Name: RoofMatl, dtype: int64
VinylSd    1025
MetalSd     450
HdBoard     442
Wd Sdng     411
Plywood     221
CemntBd     126
BrkFace      87
WdShing      56
AsbShng      44
Stucco       43
BrkComm       6
AsphShn       2
Stone         2
CBlock        2
ImStucc       1
NaN           1
Name: Exterior1st, dtype: int64
VinylSd    1014
```

```
MetalSd     447
HdBoard     406
Wd Sdng     391
Plywood     270
CmentBd     126
Wd Shng      81
Stucco       47
BrkFace      47
AsbShng      38
Brk Cmn      22
ImStucc      15
Stone         6
AsphShn       4
CBlock        3
Other         1
NaN           1
Name: Exterior2nd, dtype: int64
None       1742
BrkFace     879
Stone       249
BrkCmn       25
NaN          24
Name: MasVnrType, dtype: int64
TA    1798
Gd     979
Ex     107
Fa      35
Name: ExterQual, dtype: int64
TA    2538
Gd     299
Fa      67
Ex      12
Po       3
Name: ExterCond, dtype: int64
PConc     1308
CBlock    1235
BrkTil     311
Slab        49
Stone       11
Wood         5
Name: Foundation, dtype: int64
TA     1283
Gd     1209
Ex      258
```

```
Fa       88
NaN      81
Name: BsmtQual, dtype: int64
TA     2606
Gd      122
Fa      104
NaN      82
Po        5
Name: BsmtCond, dtype: int64
No     1904
Av      418
Gd      276
Mn      239
NaN      82
Name: BsmtExposure, dtype: int64
Unf    851
GLQ    849
ALQ    429
Rec    288
BLQ    269
LwQ    154
NaN     79
Name: BsmtFinType1, dtype: int64
Unf    2493
Rec     105
LwQ      87
NaN      80
BLQ      68
ALQ      52
GLQ      34
Name: BsmtFinType2, dtype: int64
GasA     2874
GasW       27
Grav        9
Wall        6
OthW        2
Floor       1
Name: Heating, dtype: int64
Ex    1493
TA     857
Gd     474
Fa      92
Po       3
Name: HeatingQC, dtype: int64
```

```
Y    2723
N     196
Name: CentralAir, dtype: int64
SBrkr    2671
FuseA     188
FuseF      50
FuseP       8
Mix         1
NaN         1
Name: Electrical, dtype: int64
TA     1492
Gd     1151
Ex      205
Fa       70
NaN       1
Name: KitchenQual, dtype: int64
Typ     2717
Min2      70
Min1      65
Mod       35
Maj1      19
Maj2       9
Sev        2
NaN        2
Name: Functional, dtype: int64
missing    1420
Gd          744
TA          592
Fa           74
Po           46
Ex           43
Name: FireplaceQu, dtype: int64
Attchd     1723
Detchd      779
BuiltIn     186
NaN         157
Basment      36
2Types       23
CarPort      15
Name: GarageType, dtype: int64
Unf    1230
RFn     811
Fin     719
NaN     159
```

```
Name: GarageFinish, dtype: int64
TA     2604
NaN     159
Fa      124
Gd       24
Po        5
Ex        3
Name: GarageQual, dtype: int64
TA     2654
NaN     159
Fa       74
Gd       15
Po       14
Ex        3
Name: GarageCond, dtype: int64
Y    2641
N     216
P      62
Name: PavedDrive, dtype: int64
missing    2909
Ex            4
Gd            4
Fa            2
Name: PoolQC, dtype: int64
missing    2348
MnPrv       329
GdPrv       118
GdWo        112
MnWw         12
Name: Fence, dtype: int64
missing    2814
Shed         95
Gar2          5
Othr          4
TenC          1
Name: MiscFeature, dtype: int64
WD       2525
New       239
COD        87
ConLD      26
CWD        12
ConLI       9
ConLw       8
Oth         7
```

```
Con          5
NaN          1
Name: SaleType, dtype: int64
Normal     2402
Partial     245
Abnorml     190
Family       46
Alloca       24
AdjLand      12
Name: SaleCondition, dtype: int64
test      1459
140000      20
135000      17
145000      14
155000      14
          ...
202665       1
164900       1
181500       1
289000       1
208300       1
Name: SalePrice, Length: 664, dtype: int64
```

Because the sales price is a dependent variable (int data type) in the object, converting the file to numeric data is necessary.

In [388…
```
numericcolumns['SalePrice']=objectcolumns.SalePrice
```

In [389…
```
numericcolumns.SalePrice.tail()
```

Out[389]:
```
1454    test
1455    test
1456    test
1457    test
1458    test
Name: SalePrice, dtype: object
```

In [390…
```
# droping the dependent variable from the objectcolumns
```

In [391…
```
objectcolumns=objectcolumns.drop('SalePrice',axis=1)
```

Using the simple imputer technique to impute the data's missing values

In [392…
```
from sklearn.impute import SimpleImputer
```

In [393…
```
# for categorical data imputation using the simple imputer we use strategy=most_frequent
# for numerical data imputation using the simple imputer  we use strategy=mean,median
```

In [394…
```
imputer=SimpleImputer(strategy="most_frequent")
```

In [395…
```
objectcolumnsimputed=imputer.fit_transform(objectcolumns)
```

In [396…
```
#  after imputation the objectcolumnsimputed data type is changed so we are changing the objectcolumnsimputed data type
```

In [397…
```
objectcolumnsimputed=pd.DataFrame(objectcolumnsimputed,
                                  columns=objectcolumns.columns)
```

In [400…
```
numericcolumns.YrSold=2022-numericcolumns.YrSold
```

In [401…
```
numericcolumns.YrSold
```

Out[401]:
```
0       14
1       15
2       14
3       16
4       14
        ..
1454    16
1455    16
1456    16
1457    16
1458    16
Name: YrSold, Length: 2919, dtype: int64
```

In [402…
```
# separating the categorical data from the numerical data
```

In [403…
```
categorycolumns=numericcolumns[['OverallQual','OverallCond', 'YearBuilt',
```

```
                                'YearRemodAdd','GarageYrBlt','MoSold']]
```

In [404…
```
numericcolumns=numericcolumns.drop(['OverallQual','OverallCond', 'YearBuilt',
                                'YearRemodAdd','GarageYrBlt','MoSold'],axis=1)
```

In [405…
```
print(objectcolumnsimputed.shape)
print(categorycolumns.shape)
print(numericcolumns.shape)
```

```
(2919, 43)
(2919, 6)
(2919, 32)
```

In [406…
```
#  here i am using the manual imputation to impute the missing data  from the numeric columns
```

In [407…
```
numericcolumns.LotFrontage=numericcolumns.LotFrontage.fillna(
numericcolumns.LotFrontage.median())
```

In [408…
```
for col in numericcolumns.columns.drop('SalePrice'):
    numericcolumns[col]=numericcolumns[col].fillna(
        numericcolumns[col].median())
```

In [409…
```
categorycolumnsimputed=imputer.fit_transform(categorycolumns)
```

In [410…
```
categorycolumnsimputed=pd.DataFrame(categorycolumnsimputed,
                                   columns=categorycolumns.columns)
```

In [411…
```
# importing the lable encoder to convert the categorical data into binary coded form
```

In [412…
```
from sklearn.preprocessing import LabelEncoder
```

In [413…
```
le=LabelEncoder()
```

In [414…
```
objectcolumnsdummy=objectcolumnsimputed.apply(le.fit_transform)
```

In [415…
```
categorycolumnsdummy=categorycolumnsimputed.apply(le.fit_transform)
```

In [416…
```
numericcolumns=numericcolumns.reset_index(drop=True)
```

In [417…
```
objectcolumnsdummy=objectcolumnsdummy.reset_index(drop=True)
```

In [418…
```
categorycolumnsdummy=categorycolumnsdummy.reset_index(drop=True)
```

In [419…
```
combinedfclean=pd.concat([numericcolumns,objectcolumnsdummy,
                          categorycolumnsdummy],axis=1)
```

finding a correlation for the numeric columns

In [420…
```
numericcolumns.corr()
```

Out[420]:

	Id	MSSubClass	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stFlrSF	...	Garage(
Id	1.000000	0.008931	-0.024710	-0.040746	-0.026737	-0.016988	0.018170	-0.014509	-0.024960	-0.008678	...	-0.010
MSSubClass	0.008931	1.000000	-0.389469	-0.201730	0.006309	-0.064254	-0.072431	-0.125913	-0.219893	-0.248641	...	-0.046
LotFrontage	-0.024710	-0.389469	1.000000	0.361426	0.200474	0.201697	0.040330	0.106921	0.330765	0.423217	...	0.290
LotArea	-0.040746	-0.201730	0.361426	1.000000	0.124728	0.194050	0.084107	0.021400	0.254150	0.332460	...	0.180
MasVnrArea	-0.026737	0.006309	0.200474	0.124728	1.000000	0.301427	-0.014580	0.087991	0.393662	0.392367	...	0.357
BsmtFinSF1	-0.016988	-0.064254	0.201697	0.194050	0.301427	1.000000	-0.055028	-0.477387	0.536471	0.458091	...	0.255
BsmtFinSF2	0.018170	-0.072431	0.040330	0.084107	-0.014580	-0.055028	1.000000	-0.238215	0.089423	0.084389	...	-0.014
BsmtUnfSF	-0.014509	-0.125913	0.106921	0.021400	0.087991	-0.477387	-0.238215	1.000000	0.412291	0.296623	...	0.180
TotalBsmtSF	-0.024960	-0.219893	0.330765	0.254150	0.393662	0.536471	0.089423	0.412291	1.000000	0.801638	...	0.437
1stFlrSF	-0.008678	-0.248641	0.423217	0.332460	0.392367	0.458091	0.084389	0.296623	0.801638	1.000000	...	0.440
2ndFlrSF	-0.022252	0.309309	0.023249	0.031515	0.119377	-0.162240	-0.097654	-0.000318	-0.205605	-0.249823	...	0.182
LowQualFinSF	-0.037816	0.026482	0.005142	0.000554	-0.057380	-0.066022	-0.004913	0.046920	-0.023354	-0.012704	...	-0.067
GrLivArea	-0.029046	0.071677	0.348304	0.284519	0.400088	0.211682	-0.017747	0.234017	0.445223	0.562538	...	0.489
BsmtFullBath	-0.000318	0.010436	0.100502	0.126671	0.141141	0.638911	0.162957	-0.398054	0.325939	0.257950	...	0.161
BsmtHalfBath	0.010243	-0.001728	-0.023879	0.025838	0.016204	0.078443	0.099530	-0.106960	0.012600	0.010462	...	-0.033
FullBath	-0.009946	0.139140	0.163745	0.125826	0.254085	0.081566	-0.075314	0.273231	0.327751	0.373077	...	0.480
HalfBath	-0.015358	0.178750	0.034010	0.034244	0.187685	-0.007269	-0.032368	-0.035744	-0.055676	-0.104141	...	0.234
BedroomAbvGr	0.003074	-0.008796	0.212073	0.132801	0.078213	-0.113468	-0.031111	0.183300	0.053433	0.108418	...	0.092
KitchenAbvGr	-0.011702	0.260155	0.004911	-0.020854	-0.051118	-0.086342	-0.037758	0.065001	-0.038948	0.076071	...	-0.037
TotRmsAbvGrd	-0.029368	0.040509	0.320571	0.213802	0.277103	0.052204	-0.048245	0.247514	0.282082	0.391782	...	0.358
Fireplaces	-0.035236	-0.055151	0.231731	0.261185	0.273129	0.293095	0.065707	0.004881	0.332948	0.407545	...	0.321
GarageCars	-0.010066	-0.046564	0.290631	0.180415	0.357659	0.255510	-0.014753	0.180067	0.437900	0.440452	...	1.000
GarageArea	-0.008847	-0.103389	0.338014	0.213249	0.370945	0.310454	0.003225	0.164435	0.486021	0.491979	...	0.889
WoodDeckSF	-0.007056	-0.017654	0.104364	0.158045	0.166606	0.223511	0.098462	-0.039244	0.229614	0.227347	...	0.240
OpenPorchSF	0.009960	-0.015923	0.151789	0.104797	0.140880	0.124191	-0.005805	0.119804	0.245533	0.238502	...	0.203
EnclosedPorch	0.021609	-0.020867	0.011039	0.020974	-0.110614	-0.099690	0.032775	0.005032	-0.085490	-0.065796	...	-0.132
3SsnPorch	-0.046538	-0.037529	0.024882	0.015995	0.014059	0.050914	-0.023268	-0.005803	0.037897	0.044086	...	0.023
ScreenPorch	0.022208	-0.049181	0.069352	0.054375	0.066392	0.096837	0.063329	-0.049136	0.075376	0.098381	...	0.043
PoolArea	0.014332	-0.003080	0.161025	0.093708	0.004791	0.084465	0.044530	-0.032268	0.072219	0.121900	...	0.030
MiscVal	0.008244	-0.028867	0.035161	0.069029	0.045156	0.093300	-0.005130	-0.010486	0.084005	0.093062	...	-0.016
YrSold	0.256050	0.015028	0.007562	0.024234	0.017654	-0.022547	-0.008867	0.038026	0.011192	0.013442	...	0.022

31 rows × 31 columns

In [421…
```
# Split Data into train and test
housetraindf=combinedfclean[combinedfclean.SalePrice!='test']
housetestdf=combinedfclean[combinedfclean.SalePrice=='test']
```

In [422…
```
print(housetraindf.shape)
print(housetestdf.shape)
```

```
(1460, 81)
(1459, 81)
```

In [423…
```
housetestdf=housetestdf.drop('SalePrice',axis=1)
```

In [424…
```
# here id is a uniquie so i am deleting the variable from the data
```

In [425…
```
housetestdf=housetestdf.drop('Id',axis=1)
```

In [426…
```
y=housetraindf.SalePrice
X=housetraindf.drop(['SalePrice','Id'],axis=1)
```

In [427…
```
y=y.astype('float64')
```

In [428…
```
y.skew()
```

Out[428]: 1.8828757597682129

In [429...
```
y.kurt()
```

Out[429]: 6.536281860064529

after completion of my EDA and the data preprocessing

hypothesis testing

In [430...
```
# On the test data set, hypothesis testing is performed
# There are three different methods of hypothesis testing.
```

In [432...
```
# ttest.
# The ttest is used to compare two variables where one is numeric and the other is a categorical variable with two levels.
# perform hypothesis testing between street and the sales price
```

In [433...
```
housetrain.SalePrice.groupby(housetrain.Street).mean()
```

Out[433]:
```
Street
Grvl    130190.500000
Pave    181130.538514
Name: SalePrice, dtype: float64
```

In [434...
```
housetrain.SalePrice.groupby(housetrain.Street).var()
```

Out[434]:
```
Street
Grvl    4.283212e+09
Pave    6.311762e+09
Name: SalePrice, dtype: float64
```

In [435...
```
sg=housetrain[housetrain.Street=='Grvl']
```

In [436...
```
sp=housetrain[housetrain.Street=='Pave']
```

In [437...
```
from scipy.stats import ttest_ind
```

In [438...
```
ttest_ind(sg.SalePrice,sp.SalePrice,equal_var=False)
```

Out[438]: Ttest_indResult(statistic=-1.9007878559110067, pvalue=0.11504797250476277)

In [439...
```
# here p value is pvalue=0.11504797250476277 .
#  here p value is greater than 0.05 so failed to reject null hypothesis .
# null their is significant difference .
# alter their is no significant difference .
#  failed to reject null hypothesis testing .
```

In [440...
```
# anova test.
# Anova is used to compare two variables, one of which is numeric and the other is a categorical variable with two levels.
# perform hypothesis testing between PavedDrive and the sales price
```

In [441...
```
housetrain.SalePrice.groupby(housetrain.PavedDrive).mean()
```

Out[441]:
```
PavedDrive
N    115039.122222
P    132330.000000
Y    186433.973881
Name: SalePrice, dtype: float64
```

In [442...
```
housetrain.PavedDrive.value_counts()
```

Out[442]:
```
Y    1340
N      90
P      30
Name: PavedDrive, dtype: int64
```

In [443...
```
y1=housetrain[housetrain.PavedDrive=='Y']
n=housetrain[housetrain.PavedDrive=='N']
p=housetrain[housetrain.PavedDrive=='P']
```

In [444...
```
from scipy.stats import f_oneway
```

In [445...
```
f_oneway(y1.SalePrice,n.SalePrice,p.SalePrice)
# here p value is pvalue=1.803568890651533e-18 .
# null their is no significant difference .
# alter their is significant difference .
# reject null hypothesis testing .
```

Out[445]: F_onewayResult(statistic=42.02417941762533, pvalue=1.803568890651533e-18)

In [446…
```
# chisquaretest.
# For both categorical and continuous variables, the chisquare test is used .
# perform hypothesis testing between Fence and the MiscFeature .
```

In [447…
```
housetrain.Fence.value_counts()
```

Out[447]:
```
MnPrv    157
GdPrv     59
GdWo      54
MnWw      11
Name: Fence, dtype: int64
```

In [448…
```
housetrain.MiscFeature.value_counts()
```

Out[448]:
```
Shed    49
Gar2     2
Othr     2
TenC     1
Name: MiscFeature, dtype: int64
```

In [449…
```
pd.crosstab(housetrain.Fence,housetrain.MiscFeature)
```

Out[449]:

MiscFeature	Shed	TenC
Fence		
GdPrv	5	0
GdWo	4	0
MnPrv	13	1
MnWw	1	0

In [450…
```
from scipy.stats import chi2_contingency
```

In [451…
```
chi2_contingency(pd.crosstab(housetrain.Fence,housetrain.MiscFeature))
```

Out[451]:
```
(0.7453416149068322,
 0.8624908016956859,
 3,
 array([[ 4.79166667,  0.20833333],
        [ 3.83333333,  0.16666667],
        [13.41666667,  0.58333333],
        [ 0.95833333,  0.04166667]]))
```

In [452…
```
# here p value is pvalue=0.8624908016956859.
# null their is no significant difference .
# alter their is significant difference .
# failed to reject null hypothesis testing .
```

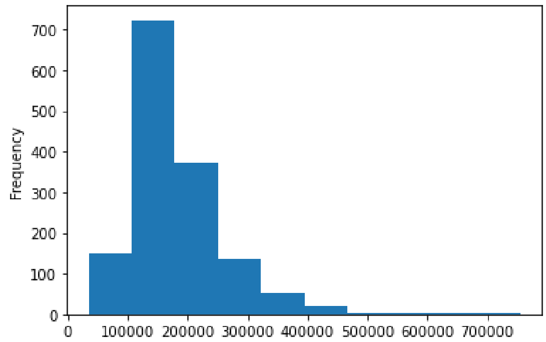
sutudy of dependent variable

In [453…
```
#  her the dependent variable is in numeric continues  and  it is in normal distribution from
# having a outliers in the maximum side (as per the box plot of my dependent variable )
# the dependet variable conatins positive  skewness and positive kurtosis
#  for postive skewness in the dependent variable we use Logarthemic Transformation
```

In [454…
```
# Create Histogram, boxplot and density curve for dependent variabe y
```

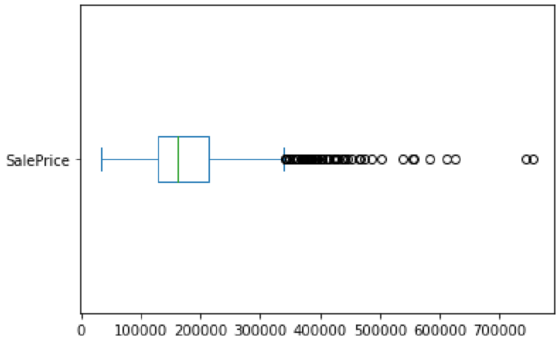
In [455…
```
y.plot(kind='hist')
```

Out[455]:
```
<AxesSubplot:ylabel='Frequency'>
```



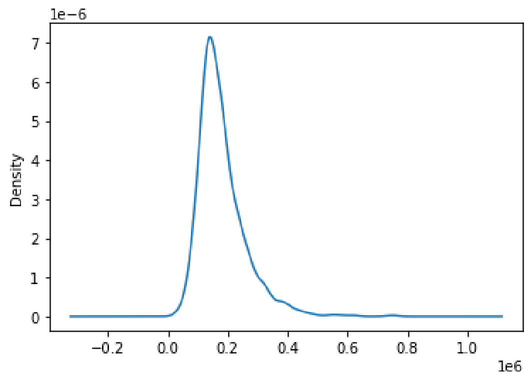
In [456…
```
y.plot(kind='box',vert=False)
```

Out[456]: <AxesSubplot:>



In [457…
```
y.plot(kind='density')
```

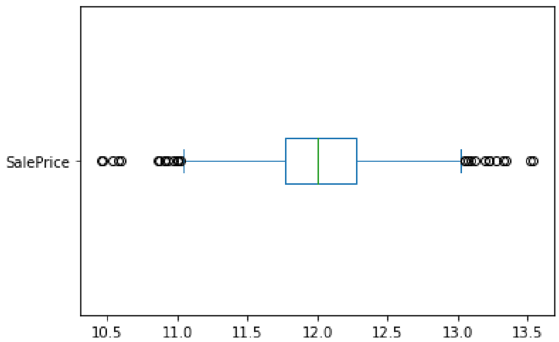
Out[457]: <AxesSubplot:ylabel='Density'>



In [458…
```
# Positive Skewness - Logarthemic Transformation

np.log(y).plot(kind='box',vert=False)
```

Out[458]: <AxesSubplot:>



here the dependent variable is in numeric form continues and it is in

the normal distribution form .

so i used to perform the regression machine learning techiniques

In [459…
```
# under regression models in machine learning
# 1.Linear regression
# 2.decission treee
# 3.Random forest regression
# 4.gradient bossting regression
```

linear regression¶

In [460…
```
from sklearn.linear_model import LinearRegression
```

In [461…
```
reg=LinearRegression()
```

In [462…
```
regmodel=reg.fit(X,y)
```

In [463…
```
regmodel.score(X,y) # R Square 0.60 - 0.95
```

Out[463]:
```
0.8545634224507179
```

In [464…
```
regtestpredict=regmodel.predict(housetestdf)
```

In [465…
```
regtestpredict
```

Out[465]:
```
array([106189.76326881, 156987.78817192, 167242.08767411, ...,
       143662.33304422, 115297.31625419, 242815.16584994])
```

In [466…
```
lertr=regmodel.predict(X)
```

In [467…
```
regres=y-lertr
```

In [468…
```
np.sqrt(np.mean(regres**2))
```

Out[468]:
```
30285.933156831714
```

In [469…
```
#pd.DataFrame(regtestpredict).to_csv("reg.csv") # write test predictions -csv
```

Impact of Logarthmic Transformation in linear regression

In [470…
```
regmodel2=reg.fit(X,np.log(y))
```

In [471…
```
regmodel2.score(X,np.log(y))
```

Out[471]:
```
0.8878960435064192
```

In [472…
```
lertrlog=regmodel2.predict(X)
```

In [473…
```
lertrlog=np.exp(lertrlog)
```

In [474…
```
regreslog=y-lertrlog
```

In [475…
```
np.sqrt(np.mean(regreslog**2))
```

Out[475]:
```
31849.80642221831
```

In [476…
```
reglogpredict=regmodel2.predict(housetestdf)
```

In [477…
```
np.exp(reglogpredict)
```

Out[477]:
```
array([116427.50595598, 156670.35705991, 166136.43801705, ...,
       153094.51135758, 116083.49210687, 241087.06424904])
```

In [478…
```
#pd.DataFrame(np.exp(reglogpredict)).to_csv("reglog.csv")
```

decision tree regressor

In [479…
```
from sklearn.tree import DecisionTreeRegressor
```

In [480...
```
tree=DecisionTreeRegressor(max_depth=6)
```

In [481...
```
treemodel=tree.fit(X,y)
```

In [482...
```
treemodel.score(X,y)
```

Out[482]:
```
0.9062567454058851
```

In [483...
```
tretrore=treemodel.predict(X)
```

In [484...
```
treres=y-tretrore
```

In [485...
```
np.sqrt(np.mean(treres**2))
```

Out[485]:
```
24314.993070689074
```

In [486...
```
treepredict=treemodel.predict(housetestdf)
```

In [487...
```
treepredict
```

Out[487]:
```
array([128881.04487179, 141044.80645161, 177793.80203046, ...,
       141044.80645161, 109902.06097561, 195035.71428571])
```

In [488...
```
#pd.DataFrame(treepredict).to_csv("tree.csv")
```

Impact of Logarthmic Transformation in decision tree regressor

In [489...
```
dctreelog=tree.fit(X,np.log(y))
```

In [490...
```
dctreelog.score(X,np.log(y))
```

Out[490]:
```
0.8865720049066539
```

In [491...
```
dctrepretr=dctreelog.predict(X)
```

In [492...
```
dtrestr=y-dctrepretr
```

In [493...
```
np.sqrt(np.mean(dtrestr**2))
```

Out[493]:
```
197572.42461482942
```

In [494...
```
treepredictlog=dctreelog.predict(housetestdf)
```

In [495...
```
treepredictlog=np.exp(treepredictlog)
```

In [496...
```
#pd.DataFrame(treepredictlog).to_csv('dttreelog.csv')
```

decision tree polt tree

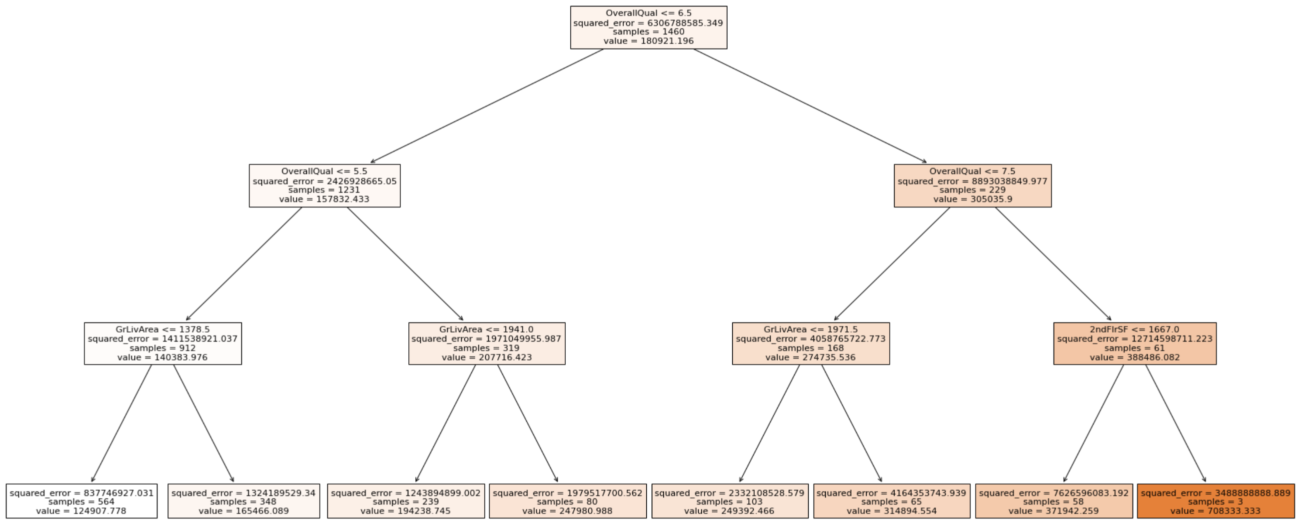
In [497...
```
from sklearn.tree import plot_tree
```

In [498...
```
tree2=DecisionTreeRegressor(max_depth=3)
```

In [499...
```
tree2model=tree2.fit(X,y)
```

In [500...
```
plt.figure(figsize=(30,15))
plot_tree(tree2model,feature_names=X.columns,filled=True)
```

Out[500]:
```
[Text(0.5, 0.875, 'OverallQual <= 6.5\nsquared_error = 6306788585.349\nsamples = 1460\nvalue = 180921.196'),
 Text(0.25, 0.625, 'OverallQual <= 5.5\nsquared_error = 2426928665.05\nsamples = 1231\nvalue = 157832.433'),
 Text(0.125, 0.375, 'GrLivArea <= 1378.5\nsquared_error = 1411538921.037\nsamples = 912\nvalue = 140383.976'),
 Text(0.0625, 0.125, 'squared_error = 837746927.031\nsamples = 564\nvalue = 124907.778'),
 Text(0.1875, 0.125, 'squared_error = 1324189529.34\nsamples = 348\nvalue = 165466.089'),
 Text(0.375, 0.375, 'GrLivArea <= 1941.0\nsquared_error = 1971049955.987\nsamples = 319\nvalue = 207716.423'),
 Text(0.3125, 0.125, 'squared_error = 1243894899.002\nsamples = 239\nvalue = 194238.745'),
 Text(0.4375, 0.125, 'squared_error = 1979517700.562\nsamples = 80\nvalue = 247980.988'),
 Text(0.75, 0.625, 'OverallQual <= 7.5\nsquared_error = 8893038849.977\nsamples = 229\nvalue = 305035.9'),
 Text(0.625, 0.375, 'GrLivArea <= 1971.5\nsquared_error = 4058765722.773\nsamples = 168\nvalue = 274735.536'),
 Text(0.5625, 0.125, 'squared_error = 2332108528.579\nsamples = 103\nvalue = 249392.466'),
 Text(0.6875, 0.125, 'squared_error = 4164353743.939\nsamples = 65\nvalue = 314894.554'),
 Text(0.875, 0.375, '2ndFlrSF <= 1667.0\nsquared_error = 12714598711.223\nsamples = 61\nvalue = 388486.082'),
 Text(0.8125, 0.125, 'squared_error = 7626596083.192\nsamples = 58\nvalue = 371942.259'),
 Text(0.9375, 0.125, 'squared_error = 3488888888.889\nsamples = 3\nvalue = 708333.333')]
```



Random forest regression

In [501...
```
# for  bagging method  we use randorm forest regression in python
```

In [502...
```
from sklearn.ensemble import RandomForestRegressor
```

In [503...
```
RF=RandomForestRegressor(n_estimators=3000)
```

In [504...
```
RFmodel=RF.fit(X,y)
```

In [505...
```
RFmodel.score(X,y)
```

Out[505]:
```
0.982346173267018
```

In [506...
```
rfmodelpre=RFmodel.predict(X)
```

In [507...
```
rfress=y-rfmodelpre
```

In [508...
```
np.sqrt(np.mean(rfress**2))
```

Out[508]:
```
10551.727485454909
```

In [509...
```
RFpredict=RFmodel.predict(housetestdf)
```

In [510...
```
RFpredict
```

Out[510]:
```
array([126096.38666667, 154679.43966667, 180108.87133333, ...,
       151793.379     , 115044.689     , 227318.90566667])
```

In [511...
```
#pd.DataFrame(RFpredict).to_csv("RF.csv")
```

Impact of Logarthmic Transformation in Random forest regression

In [512...
```
RFmodellog=RF.fit(X,np.log(y))
```

In [513...
```
RFmodellog.score(X,np.log(y))
```

Out[513]:
```
0.9834567001817225
```

In [514...
```
rfmodelprelog=RFmodellog.predict(X)
```

In [515...
```
rfmodelprelog=np.exp(rfmodelprelog)
```

In [516...
```
rfresslog=y-rfmodelprelog
```

In [517...
```
np.sqrt(np.mean(rfresslog**2))
```

Out[517]:
```
10795.058177442188
```

In [518…
```
RFpredictlog=RFmodellog.predict(housetestdf)
```
In [519…
```
RFpredictlog=np.exp(RFpredictlog)
```
In [520…
```
#pd.DataFrame(RFpredictlog).to_csv("RFlog.csv")
```

GradientBoostingRegressor

In [521…
```
# for  bosting method  we use  GradientBoostingRegressor in python
```
In [522…
```
from sklearn.ensemble import GradientBoostingRegressor
```
In [523…
```
gbm=GradientBoostingRegressor(n_estimators=5000)
```
In [524…
```
gbmmodel=gbm.fit(X,y)
```
In [525…
```
gbmmodel.score(X,y)
```
Out[525]:
```
0.9999986515738404
```
In [526…
```
gbmpredict=gbmmodel.predict(housetestdf)
```
In [527…
```
gbmpredict
```
Out[527]:
```
array([114008.68613965, 166205.49685935, 190916.05024479, ...,
       163683.74826769, 107503.90879008, 235733.40704988])
```
In [528…
```
#pd.DataFrame(gbmpredict).to_csv("gbm1.csv")
```

Impact of Logarthmic Transformation in GradientBoostingRegressor

In [529…
```
gbm1=GradientBoostingRegressor(n_estimators=991,max_depth=3)
```
In [530…
```
gbmo=gbm1.fit(X,np.log(y))
```
In [531…
```
gbmo.score(X,np.log(y))
```
Out[531]:
```
0.9970237140610402
```
In [532…
```
gbmpredict1=gbmo.predict(housetestdf)
```
In [533…
```
gbmpredict1=np.exp(gbmpredict1)
```
In [534…
```
pd.DataFrame(gbmpredict1).to_csv("gbmlog991adjusted.csv")
```

I started updating the expected values of test data in the kaggle after I finished my model predictions.

The logarithmic transformation of the dependant variable in the gradient bosting approach provides me the best score, according to my Kaggle score.

In [535…
```
kaggle=pd.read_csv('kaggle prediction file.csv')
```
In [536…
```
kaggle
```

Out[536]:

	model	score
0	linear regg	0.356720
1	linear log regg	0.141730
2	dectree with maxdepth	0.206190
3	dctree norml	0.209730
4	dttree log	0.207070
5	dtree treemaxdepth is 6	0.210710
6	random forest	0.146640
7	rf on 3000	0.145910
8	gbm 3000	0.132724
9	gbm5000	0.137960
10	new5000gbm	0.137910
11	bgmnew	0.137270
12	gbmlog1000withmaxdepth3	0.132880
13	gbmlog5000	0.133750
14	gbmlog900	0.133360
15	gbm990	0.132280
16	gbm991	0.132140
17	gbm992	0.132640
18	gbmlog995	0.132720
19	gbmlog899	0.133120

In [537…

```
min(kaggle.score)
```

Out[537]:

```
0.13214
```

In Kaggle, I received a rank of 1074 for an rmse of 0.13214, and the gradient bosting approach provided me with the highest score.

In [543…

```
# tottally updated one
```