

Import Libraries

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import calendar
from pandas.api.types import CategoricalDtype
from sklearn.preprocessing import StandardScaler
```

Data Loading

```
In [ ]: train_data_path=r"train.csv"
test_data_path=r"test.csv"

df_train=pd.read_csv(train_data_path)
df_test=pd.read_csv(test_data_path)

print(df_train.shape)
print(df_test.shape)
```

(1460, 81)
(1459, 80)

Data Analysis

```
In [3]: pd.set_option('display.max_columns',None) #to display all columns
pd.set_option('display.max_rows',None) #to display all rows
```

```
In [4]: df_train.head()
```

```
Out[4]:   Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape Lan
0  1        60      RL     65.0    8450  Pave  NaN    Reg
1  2        20      RL     80.0    9600  Pave  NaN    Reg
2  3        60      RL     68.0   11250  Pave  NaN    IR1
3  4        70      RL     60.0    9550  Pave  NaN    IR1
4  5        60      RL     84.0   14260  Pave  NaN    IR1
```

```
In [5]: df_test.head()
```

Out [5]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	Lan
0	1461	20	RH	80.0	11622	Pave	NaN	Reg	
1	1462	20	RL	81.0	14267	Pave	NaN	IR1	
2	1463	60	RL	74.0	13830	Pave	NaN	IR1	
3	1464	60	RL	78.0	9978	Pave	NaN	IR1	
4	1465	120	RL	43.0	5005	Pave	NaN	IR1	

data integration

In [6]:

```
df=pd.concat((df_train,df_test))
temp_df=df
print(df.shape)
```

(2919, 81)

In [7]:

```
df.head()
```

Out [7]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	Lan
0	1	60	RL	65.0	8450	Pave	NaN	Reg	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	

In [8]:

```
df.tail()
```

Out [8]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	Lan
1454	2915	160	RM	21.0	1936	Pave	NaN	Reg	
1455	2916	160	RM	21.0	1894	Pave	NaN	Reg	
1456	2917	20	RL	160.0	20000	Pave	NaN	Reg	
1457	2918	85	RL	62.0	10441	Pave	NaN	Reg	
1458	2919	60	RL	74.0	9627	Pave	NaN	Reg	

Exploratory data analysis

In [9]:

```
df.info()
```

<class 'pandas.core.frame.DataFrame'>

Int64Index: 2919 entries, 0 to 1458				
Data columns (total 81 columns):				
#	Column	Non-Null Count	Dtype	
0	Id	2919	non-null	int64
1	MSSubClass	2919	non-null	int64
2	MSZoning	2915	non-null	object
3	LotFrontage	2433	non-null	float64
4	LotArea	2919	non-null	int64
5	Street	2919	non-null	object
6	Alley	198	non-null	object
7	LotShape	2919	non-null	object
8	LandContour	2919	non-null	object
9	Utilities	2917	non-null	object
10	LotConfig	2919	non-null	object
11	LandSlope	2919	non-null	object
12	Neighborhood	2919	non-null	object
13	Condition1	2919	non-null	object
14	Condition2	2919	non-null	object
15	BldgType	2919	non-null	object
16	HouseStyle	2919	non-null	object
17	OverallQual	2919	non-null	int64
18	OverallCond	2919	non-null	int64
19	YearBuilt	2919	non-null	int64
20	YearRemodAdd	2919	non-null	int64
21	RoofStyle	2919	non-null	object
22	RoofMatl	2919	non-null	object
23	Exterior1st	2918	non-null	object
24	Exterior2nd	2918	non-null	object
25	MasVnrType	2895	non-null	object
26	MasVnrArea	2896	non-null	float64
27	ExterQual	2919	non-null	object
28	ExterCond	2919	non-null	object
29	Foundation	2919	non-null	object
30	BsmtQual	2838	non-null	object
31	BsmtCond	2837	non-null	object
32	BsmtExposure	2837	non-null	object
33	BsmtFinType1	2840	non-null	object
34	BsmtFinSF1	2918	non-null	float64
35	BsmtFinType2	2839	non-null	object
36	BsmtFinSF2	2918	non-null	float64
37	BsmtUnfSF	2918	non-null	float64
38	TotalBsmtSF	2918	non-null	float64
39	Heating	2919	non-null	object
40	HeatingQC	2919	non-null	object
41	CentralAir	2919	non-null	object
42	Electrical	2918	non-null	object
43	1stFlrSF	2919	non-null	int64
44	2ndFlrSF	2919	non-null	int64
45	LowQualFinSF	2919	non-null	int64
46	GrLivArea	2919	non-null	int64
47	BsmtFullBath	2917	non-null	float64
48	BsmtHalfBath	2917	non-null	float64

```
49  FullBath      2919 non-null    int64
50  HalfBath      2919 non-null    int64
51  BedroomAbvGr  2919 non-null    int64
52  KitchenAbvGr  2919 non-null    int64
53  KitchenQual   2918 non-null    object
54  TotRmsAbvGrd  2919 non-null    int64
55  Functional    2917 non-null    object
56  Fireplaces    2919 non-null    int64
57  FireplaceQu   1499 non-null    object
58  GarageType    2762 non-null    object
59  GarageYrBlt   2760 non-null    float64
60  GarageFinish   2760 non-null    object
61  GarageCars    2918 non-null    float64
62  GarageArea    2918 non-null    float64
63  GarageQual   2760 non-null    object
64  GarageCond    2760 non-null    object
65  PavedDrive   2919 non-null    object
66  WoodDeckSF   2919 non-null    int64
67  OpenPorchSF  2919 non-null    int64
68  EnclosedPorch 2919 non-null    int64
69  3SsnPorch    2919 non-null    int64
70  ScreenPorch   2919 non-null    int64
71  PoolArea     2919 non-null    int64
72  PoolQC       10 non-null     object
73  Fence         571 non-null    object
74  MiscFeature   105 non-null    object
75  MiscVal      2919 non-null    int64
76  MoSold       2919 non-null    int64
77  YrSold       2919 non-null    int64
78  SaleType     2918 non-null    object
79  SaleCondition 2919 non-null    object
80  SalePrice    1460 non-null    float64
dtypes: float64(12), int64(26), object(43)
memory usage: 1.8+ MB
```

In [10]: `df.describe()`

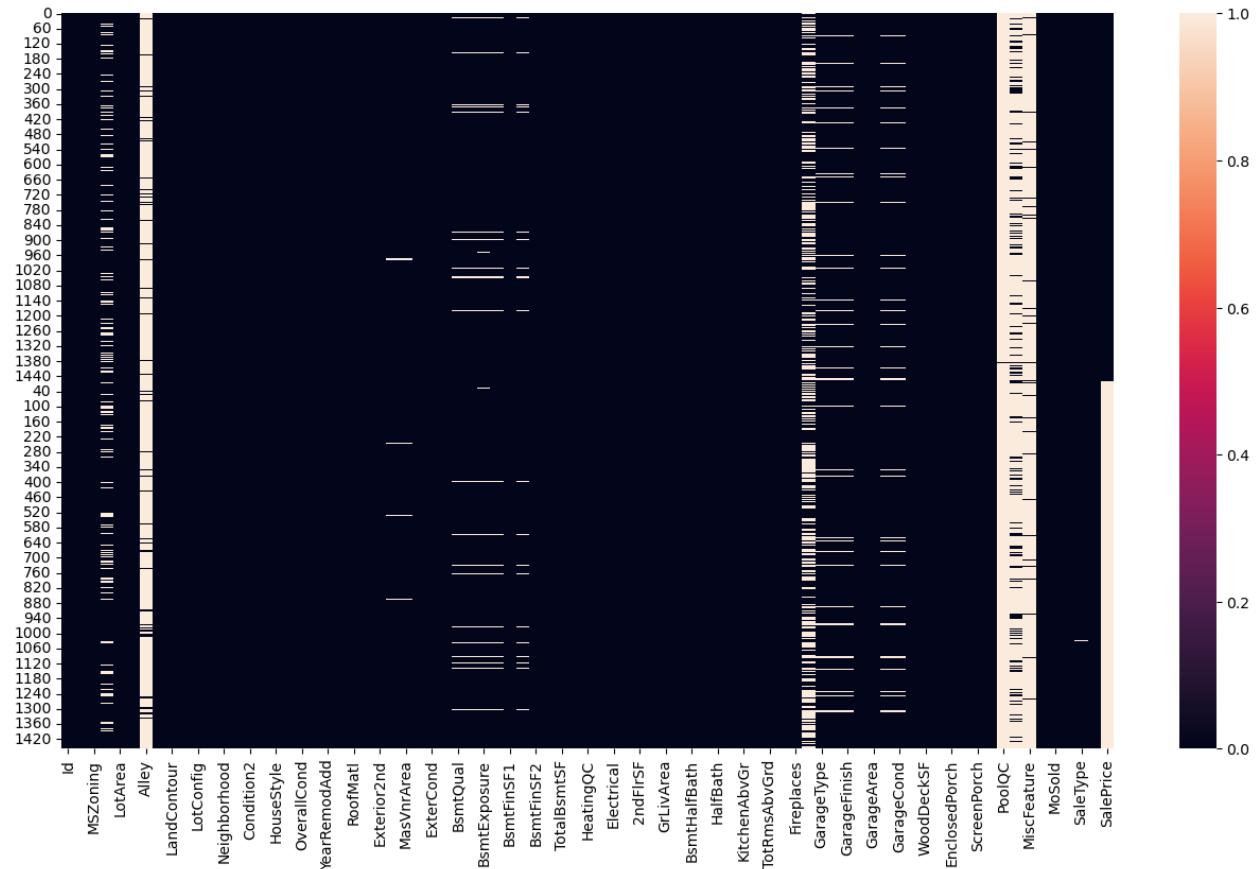
	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond
count	2919.000000	2919.000000	2433.000000	2919.000000	2919.000000	2919.000000
mean	1460.000000	57.137718	69.305795	10168.114080	6.089072	5.885000
std	842.787043	42.517628	23.344905	7886.996359	1.409947	1.409947
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000000
25%	730.500000	20.000000	59.000000	7478.000000	5.000000	5.000000
50%	1460.000000	50.000000	68.000000	9453.000000	6.000000	6.000000
75%	2189.500000	70.000000	80.000000	11570.000000	7.000000	7.000000
max	2919.000000	190.000000	313.000000	215245.000000	10.000000	9.000000

```
In [11]: int_feature=df.select_dtypes(include=['int64']).columns
In [12]: float_feature=df.select_dtypes(include=['float64']).columns
In [13]: cat_feature=df.select_dtypes(include=['object']).columns
```

visualizing missing value

```
In [14]: plt.figure(figsize=(16,9))
sns.heatmap(df.isnull())
```

Out[14]: <AxesSubplot: >



```
In [15]: # set index as is column
df=df.set_index("Id")
```

get the null value percentage for every feature

```
In [16]: null_count=df.isnull().sum()
null_count
```

```
Out[16]: MSSubClass      0
MSZoning        4
LotFrontage     486
LotArea         0
```

Street	0
Alley	2721
LotShape	0
LandContour	0
Utilities	2
LotConfig	0
LandSlope	0
Neighborhood	0
Condition1	0
Condition2	0
BldgType	0
HouseStyle	0
OverallQual	0
OverallCond	0
YearBuilt	0
YearRemodAdd	0
RoofStyle	0
RoofMatl	0
Exterior1st	1
Exterior2nd	1
MasVnrType	24
MasVnrArea	23
ExterQual	0
ExterCond	0
Foundation	0
BsmtQual	81
BsmtCond	82
BsmtExposure	82
BsmtFinType1	79
BsmtFinSF1	1
BsmtFinType2	80
BsmtFinSF2	1
BsmtUnfSF	1
TotalBsmtSF	1
Heating	0
HeatingQC	0
CentralAir	0
Electrical	1
1stFlrSF	0
2ndFlrSF	0
LowQualFinSF	0
GrLivArea	0
BsmtFullBath	2
BsmtHalfBath	2
FullBath	0
HalfBath	0
BedroomAbvGr	0
KitchenAbvGr	0
KitchenQual	1
TotRmsAbvGrd	0
Functional	2
Fireplaces	0
FireplaceQu	1420

```
GarageType      157
GarageYrBlt    159
GarageFinish    159
GarageCars       1
GarageArea       1
GarageQual     159
GarageCond     159
PavedDrive      0
WoodDeckSF      0
OpenPorchSF     0
EnclosedPorch   0
3SsnPorch       0
ScreenPorch     0
PoolArea        0
PoolQC         2909
Fence          2348
MiscFeature    2814
MiscVal         0
MoSold          0
YrSold          0
SaleType         1
SaleCondition   0
SalePrice      1459
dtype: int64
```

```
In [17]: null_percent=df.isnull().sum()/df.shape[0]*100
null_percent
```

```
Out[17]: MSSubClass      0.000000
MSZoning        0.137033
LotFrontage     16.649538
LotArea         0.000000
Street          0.000000
Alley           93.216855
LotShape         0.000000
LandContour     0.000000
Utilities       0.068517
LotConfig        0.000000
LandSlope        0.000000
Neighborhood    0.000000
Condition1      0.000000
Condition2      0.000000
BldgType        0.000000
HouseStyle       0.000000
OverallQual     0.000000
OverallCond     0.000000
YearBuilt       0.000000
YearRemodAdd    0.000000
RoofStyle        0.000000
RoofMatl        0.000000
Exterior1st     0.034258
Exterior2nd     0.034258
MasVnrType      0.822199
MasVnrArea      0.787941
```

ExterQual	0.000000
ExterCond	0.000000
Foundation	0.000000
BsmtQual	2.774923
BsmtCond	2.809181
BsmtExposure	2.809181
BsmtFinType1	2.706406
BsmtFinSF1	0.034258
BsmtFinType2	2.740665
BsmtFinSF2	0.034258
BsmtUnfSF	0.034258
TotalBsmtSF	0.034258
Heating	0.000000
HeatingQC	0.000000
CentralAir	0.000000
Electrical	0.034258
1stFlrSF	0.000000
2ndFlrSF	0.000000
LowQualFinSF	0.000000
GrLivArea	0.000000
BsmtFullBath	0.068517
BsmtHalfBath	0.068517
FullBath	0.000000
HalfBath	0.000000
BedroomAbvGr	0.000000
KitchenAbvGr	0.000000
KitchenQual	0.034258
TotRmsAbvGrd	0.000000
Functional	0.068517
Fireplaces	0.000000
FireplaceQu	48.646797
GarageType	5.378554
GarageYrBlt	5.447071
GarageFinish	5.447071
GarageCars	0.034258
GarageArea	0.034258
GarageQual	5.447071
GarageCond	5.447071
PavedDrive	0.000000
WoodDeckSF	0.000000
OpenPorchSF	0.000000
EnclosedPorch	0.000000
3SsnPorch	0.000000
ScreenPorch	0.000000
PoolArea	0.000000
PoolQC	99.657417
Fence	80.438506
MiscFeature	96.402878
MiscVal	0.000000
MoSold	0.000000
YrSold	0.000000
SaleType	0.034258
SaleCondition	0.000000

```
SalePrice      49.982871  
dtype: float64
```

drop column/features

```
In [18]: """ as per domain knowldge we will not drop this featurre rather we add s  
miss_value_50_perc=null_percent[null_percent>50]  
miss_value_50_perc
```

```
Out[18]: Alley      93.216855  
PoolQC     99.657417  
Fence      80.438506  
MiscFeature 96.402878  
dtype: float64
```

```
In [19]: """ as per domain knowldge we will not drop this featurre rather we add s  
miss_value_20_50_perc=null_percent[(null_percent>20)& (null_percent<51)]  
miss_value_20_50_perc
```

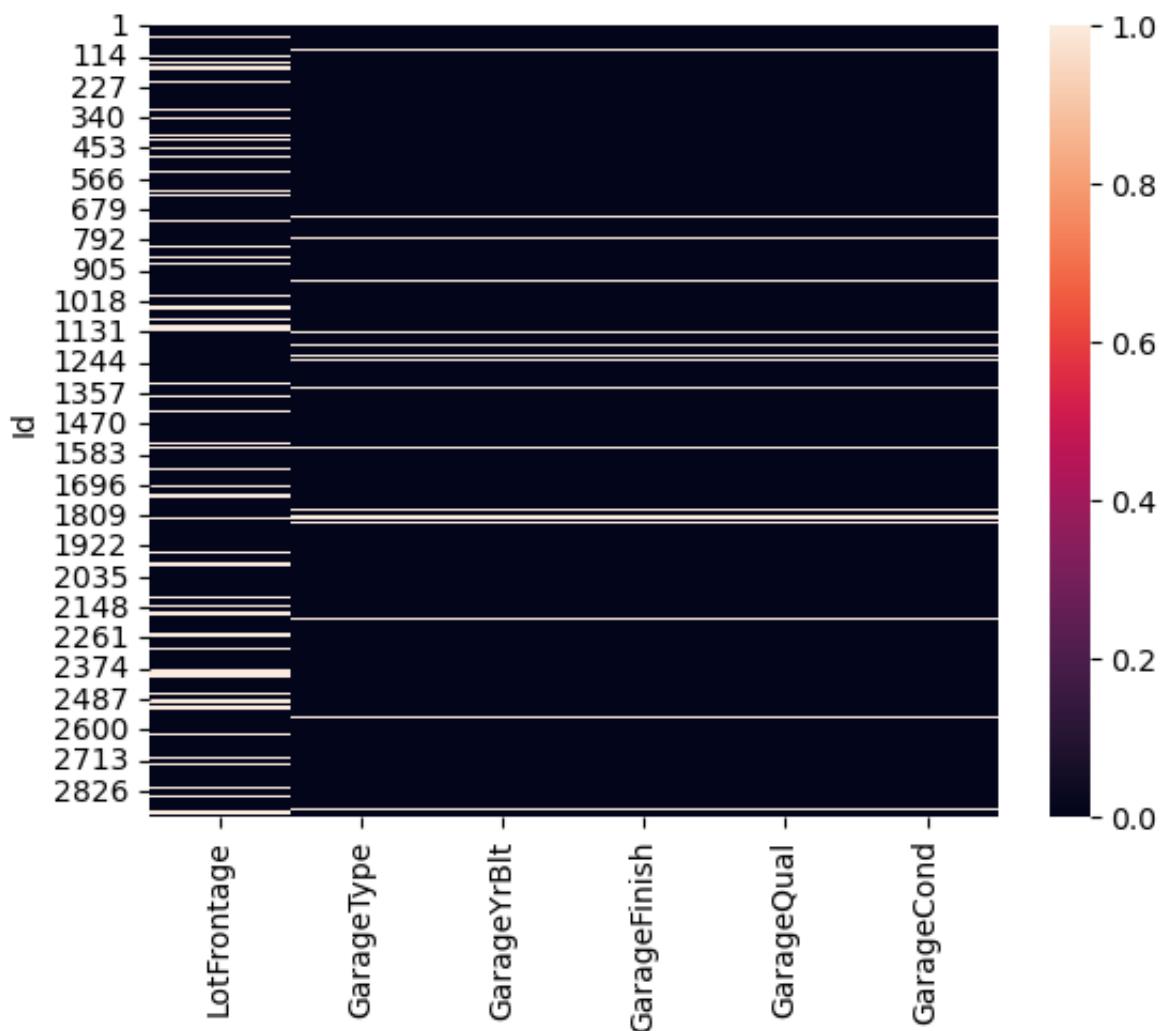
```
Out[19]: FireplaceQu    48.646797  
SalePrice      49.982871  
dtype: float64
```

```
In [20]: miss_value_5_20_perc=null_percent[(null_percent>5)& (null_percent<21)]  
miss_value_5_20_perc
```

```
Out[20]: LotFrontage    16.649538  
GarageType      5.378554  
GarageYrBlt     5.447071  
GarageFinish     5.447071  
GarageQual      5.447071  
GarageCond      5.447071  
dtype: float64
```

```
In [21]: sns.heatmap(df[miss_value_5_20_perc.keys()].isnull())
```

```
Out[21]: <AxesSubplot: ylabel='Id'>
```



```
In [22]: ## as per observation we will not drop any feature from data set
```

missing value imputation

```
In [23]: missing_value_feat=null_percent[null_percent>0]
print("Total missing value feature=",len(missing_value_feat))
missing_value_feat
```

```
Total missing value feature= 35
```

```
Out[23]: MSZoning      0.137033
          LotFrontage   16.649538
          Alley         93.216855
          Utilities     0.068517
          Exterior1st   0.034258
          Exterior2nd   0.034258
          MasVnrType    0.822199
          MasVnrArea    0.787941
          BsmtQual      2.774923
          BsmtCond      2.809181
          BsmtExposure   2.809181
          BsmtFinType1   2.706406
          BsmtFinSF1     0.034258
          BsmtFinType2   2.740665
          BsmtFinSF2     0.034258
          BsmtUnfSF      0.034258
          TotalBsmtSF    0.034258
          Electrical     0.034258
          BsmtFullBath   0.068517
          BsmtHalfBath   0.068517
          KitchenQual    0.034258
          Functional     0.068517
          FireplaceQu    48.646797
          GarageType      5.378554
          GarageYrBlt    5.447071
          GarageFinish    5.447071
          GarageCars      0.034258
          GarageArea      0.034258
          GarageQual      5.447071
          GarageCond      5.447071
          PoolQC          99.657417
          Fence           80.438506
          MiscFeature     96.402878
          SaleType        0.034258
          SalePrice       49.982871
          dtype: float64
```

```
In [24]: cat_na_feat=missing_value_feat[missing_value_feat.keys().isin(cat_feature)
print("total number of categorical missing feature", len(cat_na_feat))
cat_na_feat
```

```
total number of categorical missing feature 23
```

```
Out[24]: MSZoning      0.137033
          Alley        93.216855
          Utilities    0.068517
          Exterior1st  0.034258
          Exterior2nd  0.034258
          MasVnrType   0.822199
          BsmtQual     2.774923
          BsmtCond     2.809181
          BsmtExposure 2.809181
          BsmtFinType1 2.706406
          BsmtFinType2  2.740665
          Electrical    0.034258
          KitchenQual   0.034258
          Functional    0.068517
          FireplaceQu   48.646797
          GarageType    5.378554
          GarageFinish   5.447071
          GarageQual    5.447071
          GarageCond    5.447071
          PoolQC        99.657417
          Fence         80.438506
          MiscFeature   96.402878
          SaleType      0.034258
          dtype: float64
```

```
In [25]: int_na_feat=missing_value_feat[missing_value_feat.keys().isin(int_feature)
print("total number of int missing feature",len(int_na_feat))
int_na_feat
```

```
total number of int missing feature 0
```

```
Out[25]: Series([], dtype: float64)
```

```
In [26]: float_na_feat=missing_value_feat[missing_value_feat.keys().isin(float_fea
print("total number of float missing feature",len(float_na_feat))
float_na_feat
```

```
total number of float missing feature 12
```

```
Out[26]: LotFrontage    16.649538
          MasVnrArea    0.787941
          BsmtFinSF1   0.034258
          BsmtFinSF2   0.034258
          BsmtUnfSF    0.034258
          TotalBsmtSF  0.034258
          BsmtFullBath 0.068517
          BsmtHalfBath 0.068517
          GarageYrBlt   5.447071
          GarageCars    0.034258
          GarageArea    0.034258
          SalePrice     49.982871
          dtype: float64
```

```
In [27]: ## function to visualize data feature before and after imputation of missi
def plot_data(df, df_new, feature):
```

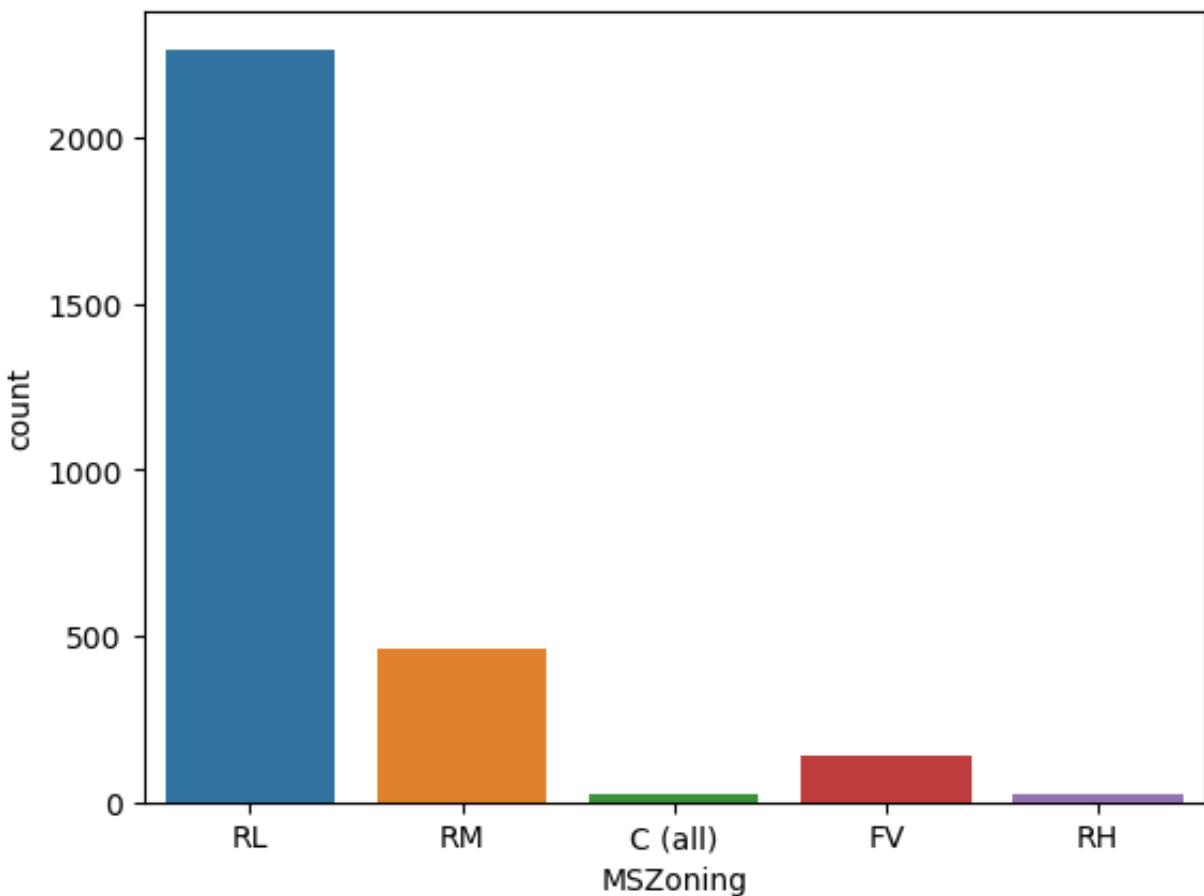
```
plt.subplot(121)
sns.countplot(x=feature, data=df)
plt.title("Before Imputation")
plt.subplot(122)
sns.countplot(x=feature, data=df_new)
plt.title("After Imputation")
plt.show()
```

In [28]: *### handling MSZoning=0.137033*

```
df["MSZoning"].value_counts()

# count plot in graph form
sns.countplot(x=df["MSZoning"])
```

Out[28]: <AxesSubplot: xlabel='MSZoning', ylabel='count'>



In [29]: *## backing up original data frame*

```
df_mvi=df.copy()
```

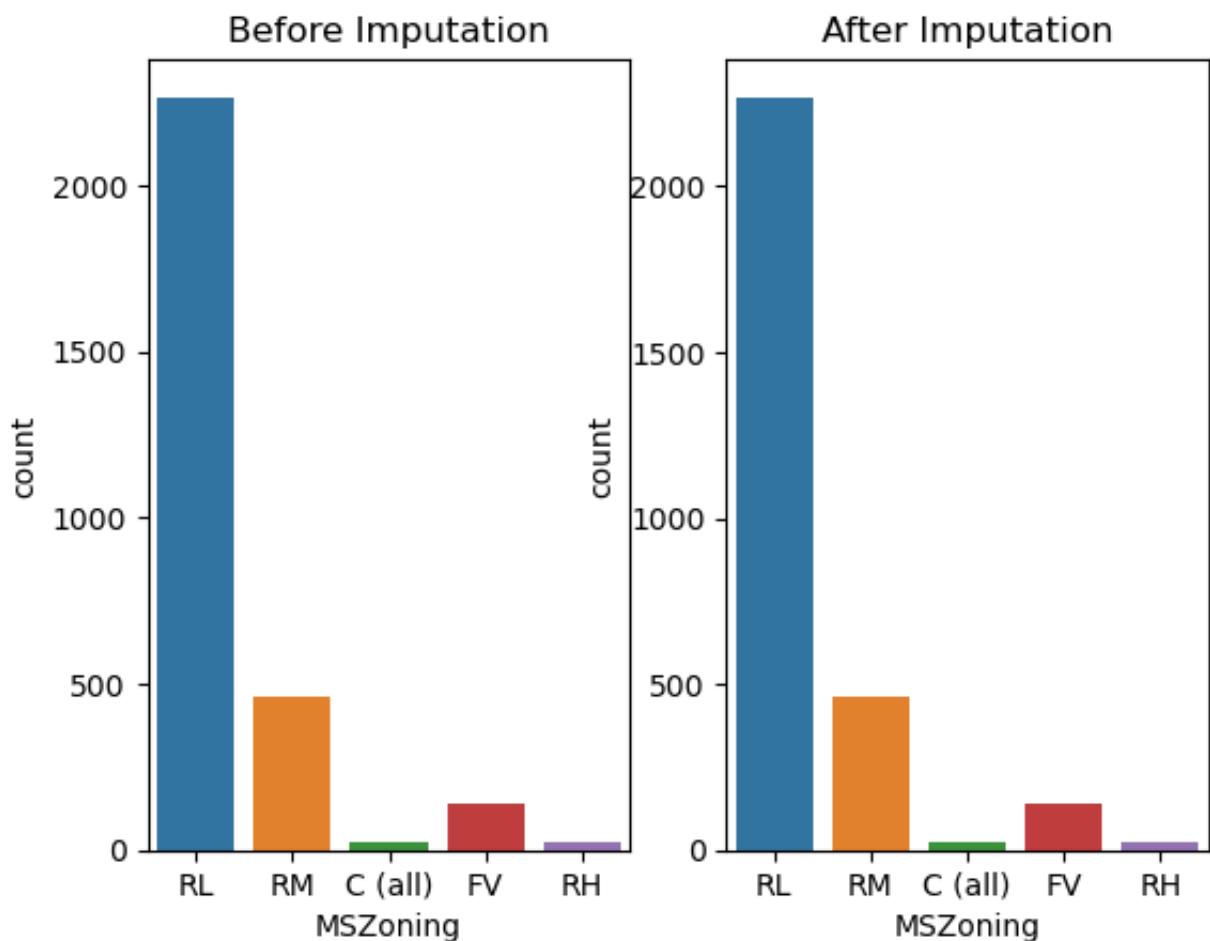
In [30]: *# as we can see here RL is the mode for this feature*

```
mszoning_mode=df["MSZoning"].mode()[0]
mszoning_mode
df_mvi["MSZoning"].replace(np.nan,mszoning_mode,inplace=True)
# now check do we have any missing value
df_mvi["MSZoning"].isnull().sum()
```

```
Out[30]: 0
```

```
In [ ]:
```

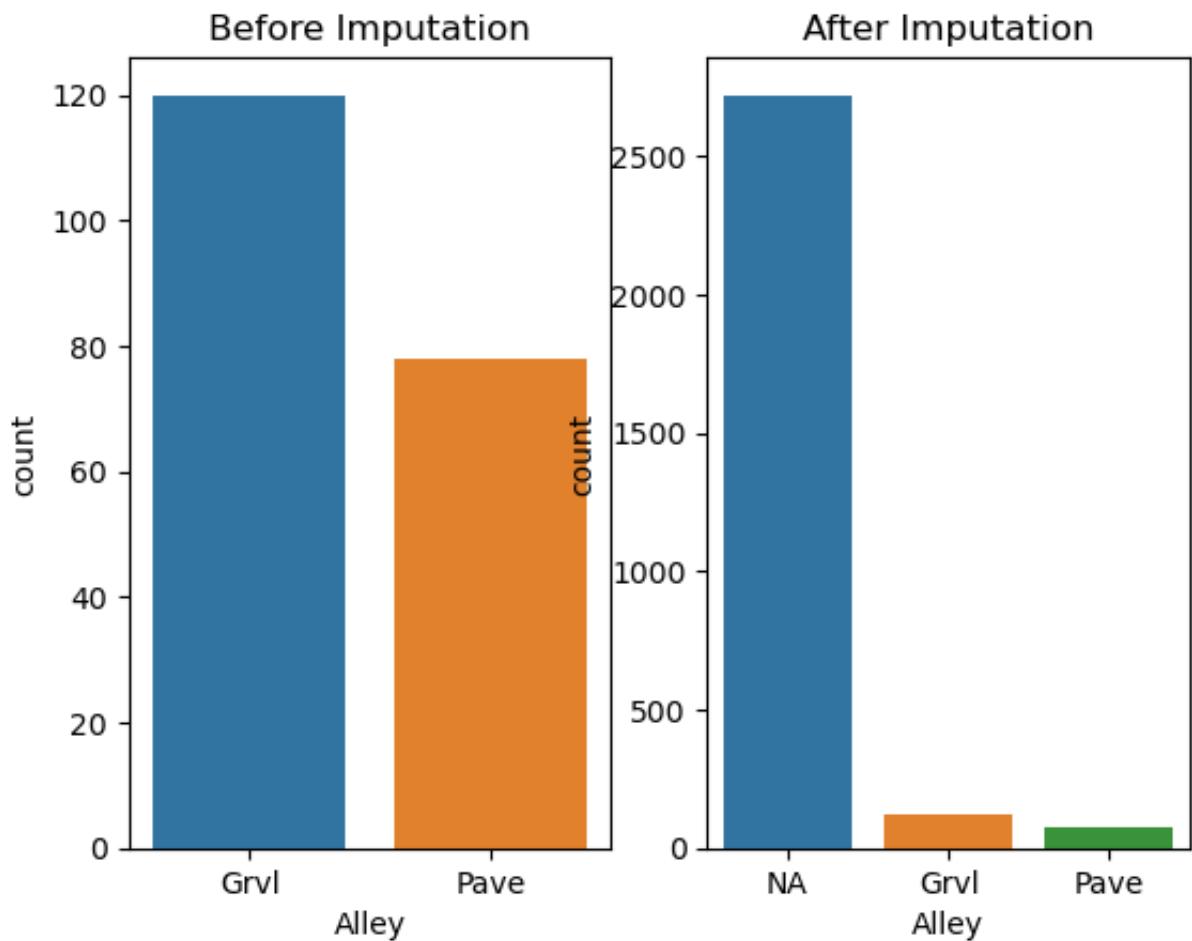
```
In [31]: #compare before and after imputation
feature="MSZoning"
plot_data(df,df_mvi,feature)
```



```
In [32]: ## handleing alley = 93.216855
```

```
df_mvi["Alley"].value_counts()
alley_cont="NA"
df_mvi["Alley"].replace(np.nan,alley_cont,inplace=True) # replace missing
df_mvi["Alley"].isnull().sum()

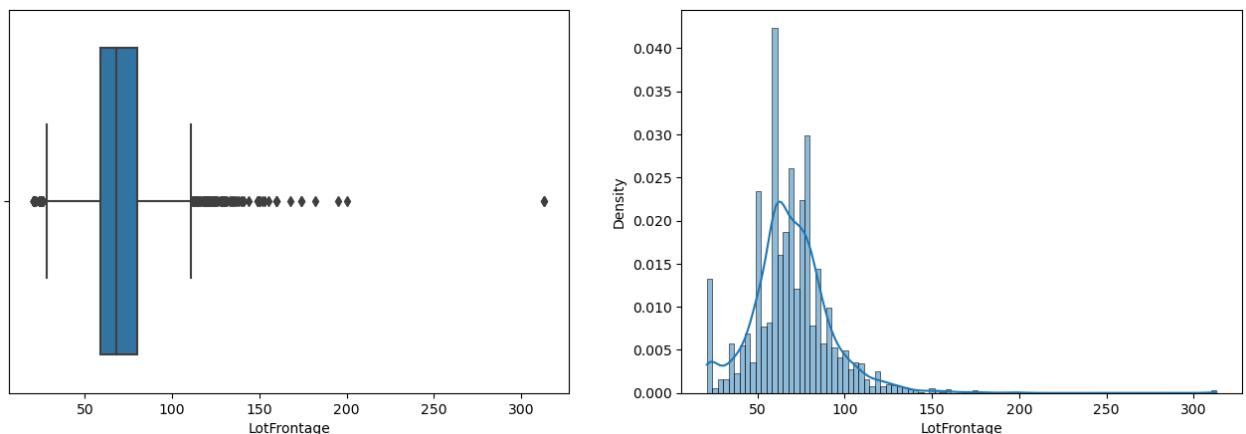
# compare before and after imputation
plot_data(df,df_mvi,"Alley")
```



```
In [33]: #LotFrontage=16.649538
```

```
def boxHistPlot(df, feature, figsize=(16,5)):
    plt.figure(figsize=figsize)
    plt.subplot(121)
    sns.boxplot(x=feature, data=df)
    plt.subplot(122)
    sns.histplot(x=feature, data=df, stat="density", kde=True)
    plt.show()
```

```
In [34]: boxHistPlot(df,"LotFrontage")
```



```
In [35]: lotfrontage_mean=df["LotFrontage"].mean()
```

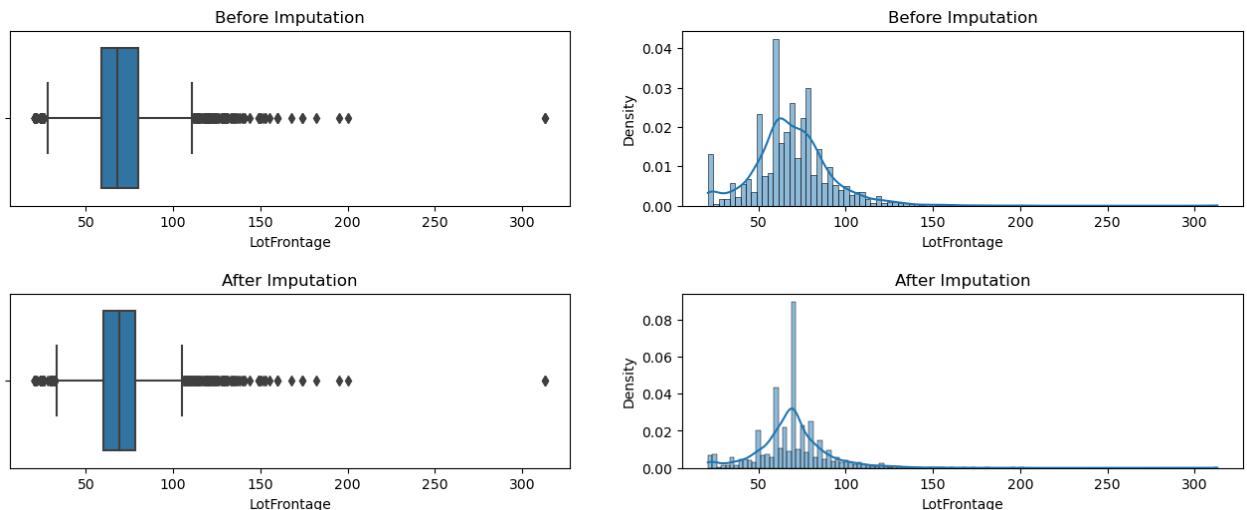
```
# lotfrontage_mean
df_mvi["LotFrontage"].replace(np.nan, lotfrontage_mean, inplace=True)
df_mvi["LotFrontage"].isnull().sum()
```

Out[35]: 0

In [36]: # compare old and new box hist plot after imputation

```
def oldNewBoxHistPlot(df, df_new, feature, figsize=(16,5)):
    plt.figure(figsize=figsize)
    plt.subplot(221)
    sns.boxplot(x=feature, data=df)
    plt.title("Before Imputation")
    plt.subplot(222)
    sns.histplot(x=feature, data=df, stat="density", kde=True)
    plt.title("Before Imputation")
    plt.figure(figsize=figsize)
    plt.subplot(223)
    sns.boxplot(x=feature, data=df_new)
    plt.title("After Imputation")
    plt.subplot(224)
    sns.histplot(x=feature, data=df_new, stat="density", kde=True)
    plt.title("After Imputation")
    plt.show()
```

```
oldNewBoxHistPlot(df, df_mvi, "LotFrontage")
```



In [37]: ## handling utility

```
df["Utilities"].value_counts()
utility_const=df["Utilities"].mode()[0]
df_mvi["Utilities"].replace(np.nan,utility_const,inplace=True)
df_mvi["Utilities"].isnull().sum()
```

Out[37]: 0

In [38]: # Exterior1st 0.034258

```
# Exterior2nd 0.034258
```

```
# both are object type
```

```
print(df["Exterior1st"].value_counts())
print("----")
print(df["Exterior2nd"].value_counts())
```

```
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
Name: Exterior1st, dtype: int64
----
```

```
VinylSd    1014
MetalSd     447
HdBoard    406
Wd Sdng    391
Plywood     270
CmentBd    126
Wd Shng     81
BrkFace      47
Stucco       47
AsbShng     38
Brk Cmn     22
ImStucc     15
Stone         6
AsphShn      4
CBlock        3
Other         1
Name: Exterior2nd, dtype: int64
```

```
In [39]: exterior_1_const=df["Exterior1st"].mode()[0]
df_mvi["Exterior1st"].replace(np.nan,exterior_1_const,inplace=True)
df_mvi["Exterior1st"].isnull().sum()
```

```
Out[39]: 0
```

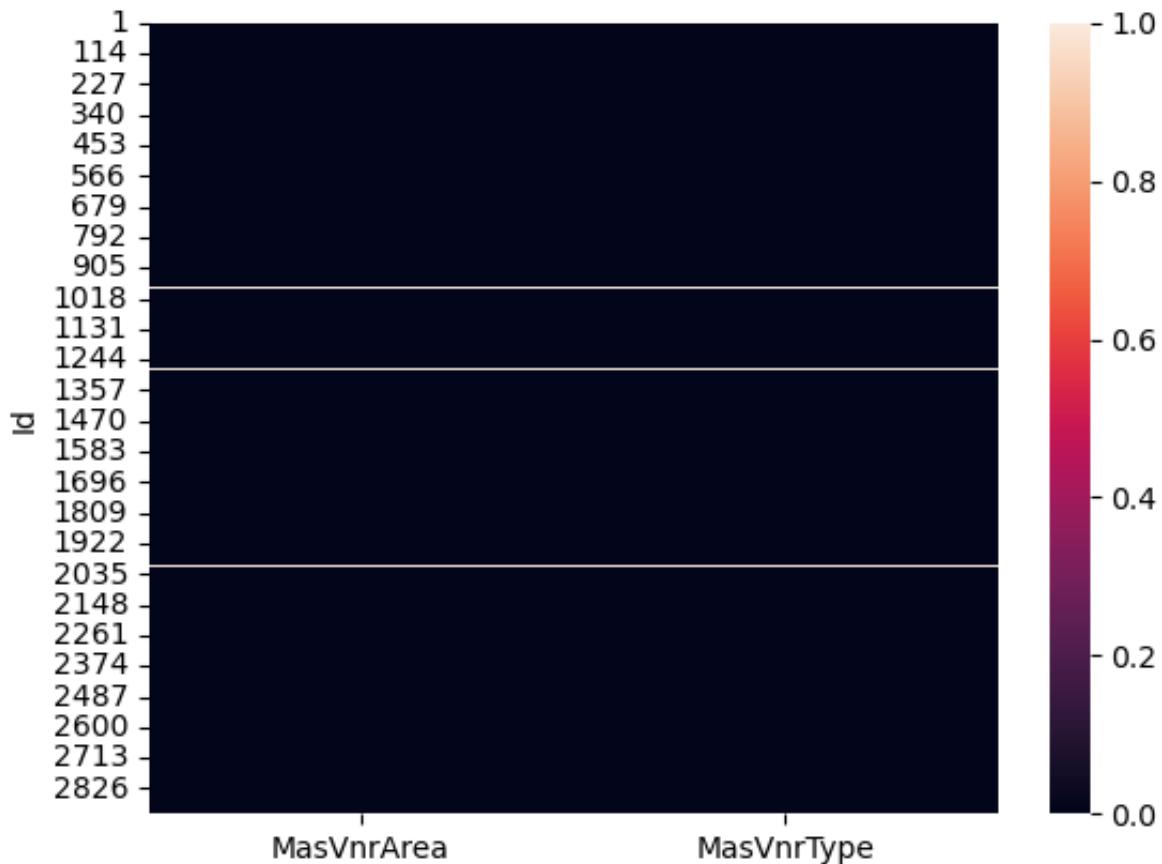
```
In [40]: exterior_2_const=df["Exterior2nd"].mode()[0]
df_mvi["Exterior2nd"].replace(np.nan,exterior_2_const,inplace=True)
df_mvi["Exterior2nd"].isnull().sum()
```

```
Out[40]: 0
```

```
In [41]: # MasVnrType      0.822199
# MasVnrArea      0.787941
```

```
sns.heatmap(df[["MasVnrArea", "MasVnrType"]].isnull())
```

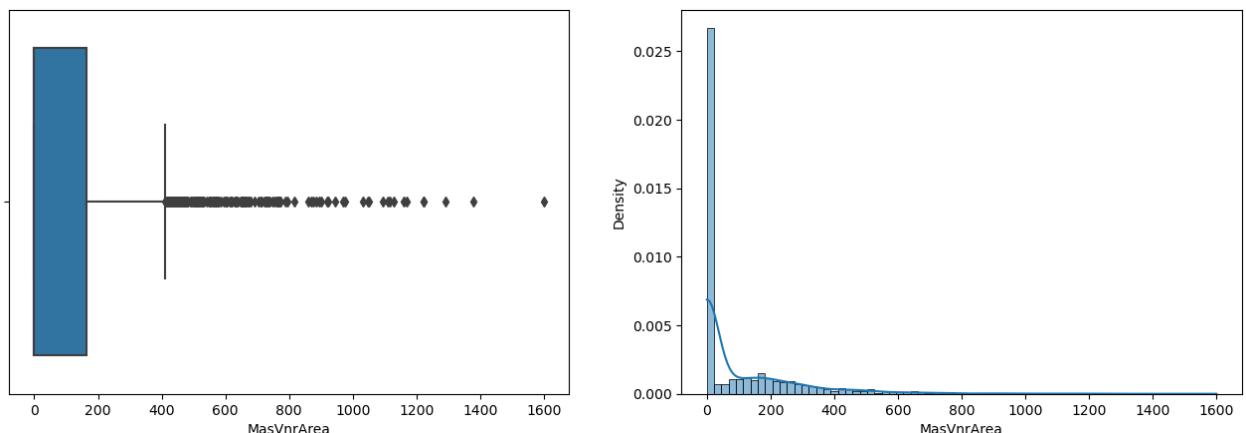
Out[41]: <AxesSubplot: ylabel='Id'>



```
In [42]: mas_vnr_type_const=df["MasVnrType"].mode()[0]
df_mvi["MasVnrType"].replace(np.nan,mas_vnr_type_const,inplace=True)
df_mvi["MasVnrType"].isnull().sum()
```

Out[42]: 0

In [43]: boxHistPlot(df, "MasVnrArea")



```
In [44]: mas_vnr_area_const=0# as we can see the mode is 0 in above plots
df_mvi["MasVnrArea"].replace(np.nan,mas_vnr_area_const,inplace=True)
```

```
df_mvi["MasVnrArea"].isnull().sum()
```

Out[44]: 0

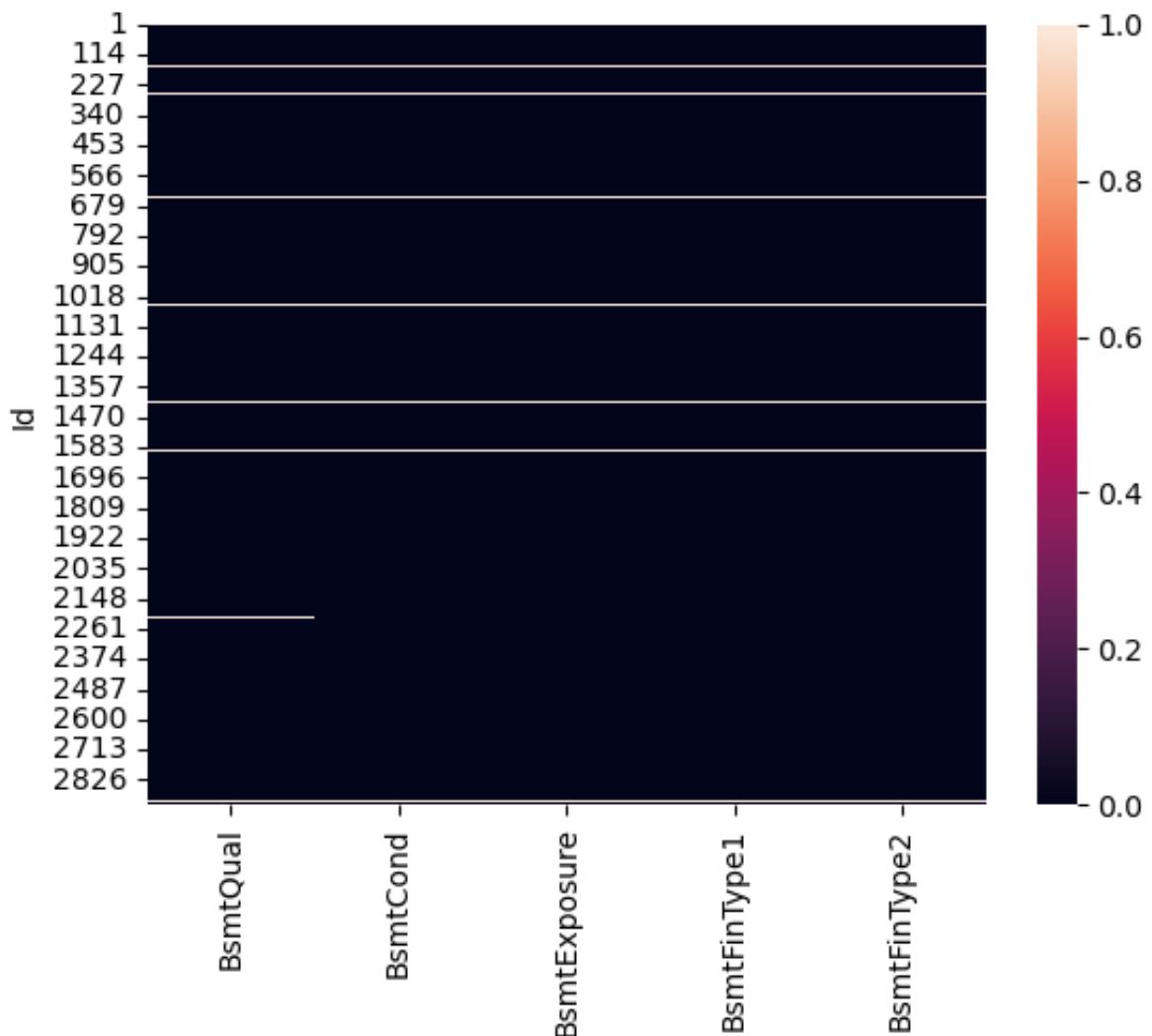
```
In [45]: ### handleing basement
## categarical
# BsmtQual      2.774923
# BsmtCond      2.809181
# BsmtExposure   2.809181
# BsmtFinType1   2.706406
# BsmtFinType2   2.740665

## numerical
# BsmtFinSF1     0.034258
# BsmtFinSF2     0.034258
# BsmtUnfSF      0.034258
# TotalBsmtSF    0.034258
# BsmtFullBath    0.068517
# BsmtHalfBath    0.068517

cat_bsmt_feat=["BsmtQual","BsmtCond","BsmtExposure","BsmtFinType1","BsmtF
num_bsmt_feat=["BsmtFinSF1","BsmtFinSF2","BsmtUnfSF","TotalBsmtSF","BsmtF

sns.heatmap(df[cat_bsmt_feat].isnull()) # check missing values in categor
for feat in cat_bsmt_feat:
    print(df[feat].value_counts())
    print("----")
```

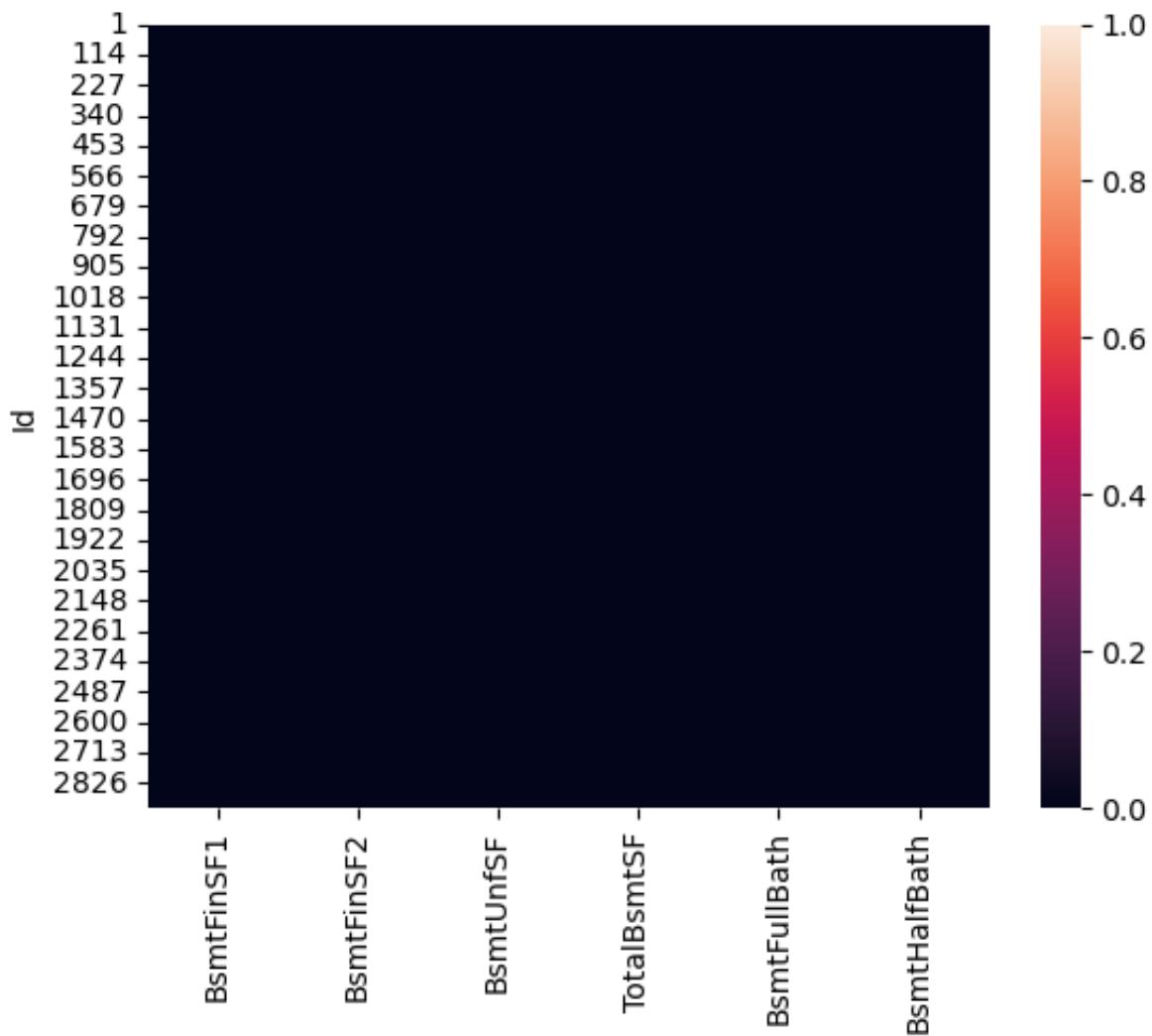
```
TA      1283
Gd      1209
Ex      258
Fa      88
Name: BsmtQual, dtype: int64
-----
TA      2606
Gd      122
Fa      104
Po      5
Name: BsmtCond, dtype: int64
-----
No     1904
Av     418
Gd     276
Mn     239
Name: BsmtExposure, dtype: int64
-----
Unf    851
GLQ    849
ALQ    429
Rec    288
BLQ    269
LwQ    154
Name: BsmtFinType1, dtype: int64
-----
Unf    2493
Rec    105
LwQ    87
BLQ    68
ALQ    52
GLQ    34
Name: BsmtFinType2, dtype: int64
-----
```



```
In [46]: bsmt_cont="NA"  
for feat in cat_bsmt_feat:  
    df_mvi[feat].replace(np.nan,bsmt_cont,inplace=True)
```

```
In [47]: sns.heatmap(df[num_bsmt_feat].isnull()) # check missing values in numeric
```

```
Out[47]: <AxesSubplot: ylabel='Id'>
```



```
In [48]: # analysing basement feature
df_bsmt=df[cat_bsmt_feat+num_bsmt_feat]
df_bsmt[df_bsmt.isnull().any(axis=1)]
```

```
Out[48]:      BsmtQual BsmtCond BsmtExposure BsmtFinType1 BsmtFinType2 BsmtFin
```

Id	BsmtQual	BsmtCond	BsmtExposure	BsmtFinType1	BsmtFinType2	BsmtFin
18	NaN	NaN	NaN	NaN	NaN	NaN
40	NaN	NaN	NaN	NaN	NaN	NaN
91	NaN	NaN	NaN	NaN	NaN	NaN
103	NaN	NaN	NaN	NaN	NaN	NaN
157	NaN	NaN	NaN	NaN	NaN	NaN
183	NaN	NaN	NaN	NaN	NaN	NaN
260	NaN	NaN	NaN	NaN	NaN	NaN
333	Gd	TA	No	GLQ	NaN	11
343	NaN	NaN	NaN	NaN	NaN	NaN

363	NaN	NaN	NaN	NaN	NaN
372	NaN	NaN	NaN	NaN	NaN
393	NaN	NaN	NaN	NaN	NaN
521	NaN	NaN	NaN	NaN	NaN
533	NaN	NaN	NaN	NaN	NaN
534	NaN	NaN	NaN	NaN	NaN
554	NaN	NaN	NaN	NaN	NaN
647	NaN	NaN	NaN	NaN	NaN
706	NaN	NaN	NaN	NaN	NaN
737	NaN	NaN	NaN	NaN	NaN
750	NaN	NaN	NaN	NaN	NaN
779	NaN	NaN	NaN	NaN	NaN
869	NaN	NaN	NaN	NaN	NaN
895	NaN	NaN	NaN	NaN	NaN
898	NaN	NaN	NaN	NaN	NaN
949	Gd	TA	NaN	Unf	Unf
985	NaN	NaN	NaN	NaN	NaN
1001	NaN	NaN	NaN	NaN	NaN
1012	NaN	NaN	NaN	NaN	NaN
1036	NaN	NaN	NaN	NaN	NaN
1046	NaN	NaN	NaN	NaN	NaN
1049	NaN	NaN	NaN	NaN	NaN
1050	NaN	NaN	NaN	NaN	NaN
1091	NaN	NaN	NaN	NaN	NaN
1180	NaN	NaN	NaN	NaN	NaN
1217	NaN	NaN	NaN	NaN	NaN
1219	NaN	NaN	NaN	NaN	NaN
1233	NaN	NaN	NaN	NaN	NaN
1322	NaN	NaN	NaN	NaN	NaN
1413	NaN	NaN	NaN	NaN	NaN
1488	Gd	TA	NaN	Unf	Unf
1586	NaN	NaN	NaN	NaN	NaN

1594	NaN	NaN	NaN	NaN	NaN	
1730	NaN	NaN	NaN	NaN	NaN	
1779	NaN	NaN	NaN	NaN	NaN	
1815	NaN	NaN	NaN	NaN	NaN	
1848	NaN	NaN	NaN	NaN	NaN	
1849	NaN	NaN	NaN	NaN	NaN	
1857	NaN	NaN	NaN	NaN	NaN	
1858	NaN	NaN	NaN	NaN	NaN	
1859	NaN	NaN	NaN	NaN	NaN	
1861	NaN	NaN	NaN	NaN	NaN	
1916	NaN	NaN	NaN	NaN	NaN	
2041	Gd	NaN	Mn	GLQ	Rec	10
2051	NaN	NaN	NaN	NaN	NaN	
2067	NaN	NaN	NaN	NaN	NaN	
2069	NaN	NaN	NaN	NaN	NaN	
2121	NaN	NaN	NaN	NaN	NaN	
2123	NaN	NaN	NaN	NaN	NaN	
2186	TA	NaN	No	BLQ	Unf	10
2189	NaN	NaN	NaN	NaN	NaN	
2190	NaN	NaN	NaN	NaN	NaN	
2191	NaN	NaN	NaN	NaN	NaN	
2194	NaN	NaN	NaN	NaN	NaN	
2217	NaN	NaN	NaN	NaN	NaN	
2218	NaN	Fa	No	Unf	Unf	
2219	NaN	TA	No	Unf	Unf	
2225	NaN	NaN	NaN	NaN	NaN	
2349	Gd	TA	NaN	Unf	Unf	
2388	NaN	NaN	NaN	NaN	NaN	
2436	NaN	NaN	NaN	NaN	NaN	
2453	NaN	NaN	NaN	NaN	NaN	
2454	NaN	NaN	NaN	NaN	NaN	

2491	NaN	NaN	NaN	NaN	NaN
2499	NaN	NaN	NaN	NaN	NaN
2525	TA	NaN	Av	ALQ	Unf
2548	NaN	NaN	NaN	NaN	NaN
2553	NaN	NaN	NaN	NaN	NaN
2565	NaN	NaN	NaN	NaN	NaN
2579	NaN	NaN	NaN	NaN	NaN
2600	NaN	NaN	NaN	NaN	NaN
2703	NaN	NaN	NaN	NaN	NaN
2764	NaN	NaN	NaN	NaN	NaN
2767	NaN	NaN	NaN	NaN	NaN
2804	NaN	NaN	NaN	NaN	NaN
2805	NaN	NaN	NaN	NaN	NaN
2825	NaN	NaN	NaN	NaN	NaN
2892	NaN	NaN	NaN	NaN	NaN
2905	NaN	NaN	NaN	NaN	NaN

```
In [49]: bsmt_num=0
for feat in num_bsmt_feat:
    df_mvi[feat].replace(np.nan,bsmt_num,inplace=True)
```

```
In [50]: # Electrical      0.034258 -- KitchenQual      0.034258
df["Electrical"].value_counts()
```

```
Out[50]: SBrkr    2671
FuseA     188
FuseF     50
FuseP      8
Mix       1
Name: Electrical, dtype: int64
```

```
In [51]: df["KitchenQual"].value_counts()
```

```
Out[51]: TA     1492
Gd     1151
Ex      205
Fa      70
Name: KitchenQual, dtype: int64
```

```
In [52]: df_ekk=df[["Electrical","KitchenQual","KitchenAbvGr"]]
df_ekk[df_ekk.isnull().any(axis=1)]
```

Out[52]: Electrical KitchenQual KitchenAbvGr

Id			
1380	NaN	Gd	1
1556	SBrkr	NaN	1

In [53]: electrical_mode=df["Electrical"].mode()[0]
df_mvi["Electrical"].replace(np.nan,electrical_mode,inplace=True)
df_mvi["Electrical"].isnull().sum()

Out[53]: 0

In [54]: kitchenqual_mode=df["KitchenQual"].mode()[0]
df_mvi["KitchenQual"].replace(np.nan,kitchenqual_mode,inplace=True)
df_mvi["KitchenQual"].isnull().sum()

Out[54]: 0

In [55]: # Functional 0.068517 - mode
FireplacesQu 48.646797 - NA
PoolQC 99.657417 - NA
Fence 80.438506 - NA
MiscFeature 96.402878 - NA
SaleType 0.034258 - mode

In [56]: print(df["Functional"].value_counts())
print("----")
print(df["FireplaceQu"].value_counts())
print("----")
print(df["PoolQC"].value_counts())
print("----")
print(df["Fence"].value_counts())
print("----")
print(df["MiscFeature"].value_counts())
print("----")
print(df["SaleType"].value_counts())
print("----")

```
Typ      2717
Min2     70
Min1     65
Mod      35
Maj1     19
Maj2      9
Sev      2
Name: Functional, dtype: int64
-----
Gd      744
TA      592
Fa      74
Po      46
Ex      43
Name: FireplaceQu, dtype: int64
-----
Ex      4
Gd      4
Fa      2
Name: PoolQC, dtype: int64
-----
MnPrv    329
GdPrv    118
GdWo     112
MnWw     12
Name: Fence, dtype: int64
-----
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
Name: SaleType, dtype: int64
-----
```

```
In [57]: functional_mode=df["Functional"].mode()[0]
df_mvi["Functional"].replace(np.nan,functional_mode,inplace=True)
df_mvi["Functional"].isnull().sum()
```

```
Out[57]: 0
```

```
In [58]: saletype_mode=df["SaleType"].mode()[0]
df_mvi["SaleType"].replace(np.nan,saletype_mode,inplace=True)
```

```
df_mvi["SaleType"].isnull().sum()
```

Out[58]: 0

```
In [59]: other_cat_feat=["FireplaceQu","PoolQC","Fence","MiscFeature"]
```

```
other_cat_const="NA"
for feat in other_cat_feat:
    df_mvi[feat].replace(np.nan,other_cat_const,inplace=True)

for feat in other_cat_feat:
    print(df_mvi[feat].isnull().sum())
    print("----")
```

```
0
-----
0
-----
0
-----
0
-----
```

```
In [60]: # cat
```

```
# GarageType      5.378554 - NA
# GarageFinish    5.447071 - NA
# GarageQual      5.447071 - NA
# GarageCond      5.447071 - NA

# num
# GarageYrBlt    5.447071
# GarageCars       0.034258
# GarageArea       0.034258
```

```
In [61]: cat_garage_feat=["GarageType","GarageFinish","GarageQual","GarageCond"]
num_garage_feat=["GarageYrBlt","GarageCars","GarageArea"]
```

```
for feat in cat_garage_feat:
    print(df[feat].value_counts())
    print("----")

for feat in num_garage_feat:
    print(df[feat].value_counts())
    print("----")
```

```
Attchd      1723
Detchd      779
BuiltIn     186
Basment     36
2Types      23
CarPort     15
Name: GarageType, dtype: int64
-----
Unf        1230
```

```
RFn      811
Fin      719
Name: GarageFinish, dtype: int64
-----
TA      2604
Fa      124
Gd      24
Po      5
Ex      3
Name: GarageQual, dtype: int64
-----
TA      2654
Fa      74
Gd      15
Po      14
Ex      3
Name: GarageCond, dtype: int64
-----
2005.0    142
2006.0    115
2007.0    115
2004.0    99
2003.0    92
1977.0    66
2008.0    61
1998.0    58
2000.0    55
1999.0    54
2002.0    53
1950.0    51
1976.0    50
1993.0    49
1968.0    48
1997.0    44
1958.0    42
1978.0    41
1956.0    41
2001.0    41
1996.0    40
1994.0    39
1966.0    39
1960.0    37
1954.0    37
1967.0    36
1959.0    36
1964.0    35
1974.0    35
1979.0    35
1995.0    35
1962.0    35
1963.0    34
1957.0    34
1965.0    34
```

1920.0	33
1969.0	32
1970.0	32
1980.0	32
1961.0	31
2009.0	29
1973.0	29
1975.0	28
1992.0	27
1972.0	27
1930.0	27
1990.0	26
1940.0	25
1955.0	24
1971.0	24
1953.0	23
1939.0	21
1988.0	20
1984.0	19
1948.0	19
1989.0	19
1987.0	18
1985.0	18
1991.0	17
1951.0	17
1952.0	16
1926.0	15
1925.0	15
1981.0	15
1949.0	14
1941.0	14
1986.0	12
1938.0	11
1983.0	11
1910.0	10
1945.0	10
1946.0	9
1982.0	9
1924.0	8
1935.0	8
1922.0	8
1936.0	7
1928.0	7
1915.0	7
1916.0	6
1937.0	6
1900.0	6
1923.0	6
1942.0	6
1921.0	5
1947.0	5
2010.0	5
1927.0	5

```
1932.0      4  
1934.0      4  
1931.0      4  
1918.0      3  
1914.0      2  
1929.0      2  
1917.0      2  
1895.0      1  
1943.0      1  
2207.0      1  
1908.0      1  
1896.0      1  
1933.0      1  
1906.0      1  
1919.0      1  
Name: GarageYrBlt, dtype: int64
```

2.0 1594
1.0 776
3.0 374
0.0 157
4.0 16
5.0 1

```
Name: GarageCars, dtype: int64
```

0.0 157
576.0 97
440.0 96
240.0 69
484.0 68
528.0 65
400.0 58
480.0 54
264.0 51
288.0 50
308.0 48
280.0 30
420.0 29
336.0 29
672.0 23
462.0 23
216.0 23
384.0 21
504.0 21
506.0 21
286.0 20
312.0 19
624.0 17
525.0 17
352.0 17
495.0 17
550.0 17
360.0 16

180.0	16
564.0	16
300.0	16
572.0	15
460.0	14
588.0	14
660.0	14
390.0	14
540.0	14
478.0	14
520.0	13
539.0	12
297.0	12
720.0	11
252.0	11
432.0	11
472.0	11
200.0	11
470.0	11
502.0	10
294.0	10
450.0	10
461.0	10
530.0	9
482.0	9
434.0	9
578.0	9
473.0	9
542.0	9
492.0	9
529.0	9
441.0	9
490.0	9
396.0	9
474.0	9
270.0	9
552.0	8
648.0	8
527.0	8
430.0	8
431.0	8
299.0	8
451.0	8
546.0	8
676.0	8
560.0	7
512.0	7
380.0	7
616.0	7
393.0	7
392.0	7
880.0	7
610.0	7

315.0	7
410.0	7
870.0	6
840.0	6
625.0	6
388.0	6
516.0	6
786.0	6
784.0	6
500.0	6
256.0	6
642.0	6
670.0	6
486.0	6
544.0	6
575.0	6
452.0	6
320.0	6
338.0	6
600.0	6
632.0	6
250.0	6
864.0	6
541.0	5
626.0	5
498.0	5
615.0	5
438.0	5
260.0	5
437.0	5
570.0	5
463.0	5
531.0	5
820.0	5
398.0	5
429.0	5
621.0	5
319.0	5
758.0	5
275.0	5
225.0	5
650.0	5
515.0	5
612.0	5
483.0	5
517.0	5
551.0	5
521.0	5
534.0	5
433.0	5
577.0	5
608.0	5
678.0	5

467.0	5
532.0	5
656.0	5
850.0	5
511.0	5
583.0	5
596.0	5
442.0	5
834.0	5
402.0	5
522.0	5
379.0	4
836.0	4
496.0	4
370.0	4
477.0	4
350.0	4
418.0	4
342.0	4
730.0	4
776.0	4
281.0	4
436.0	4
746.0	4
220.0	4
888.0	4
364.0	4
580.0	4
795.0	4
792.0	4
487.0	4
598.0	4
471.0	4
499.0	4
628.0	4
586.0	4
368.0	4
416.0	4
556.0	4
305.0	4
330.0	4
253.0	4
666.0	4
276.0	4
644.0	4
210.0	4
246.0	4
627.0	4
736.0	4
810.0	4
774.0	4
397.0	4
205.0	4

816.0	4
630.0	4
900.0	3
228.0	3
508.0	3
874.0	3
878.0	3
668.0	3
768.0	3
686.0	3
619.0	3
574.0	3
409.0	3
444.0	3
756.0	3
788.0	3
796.0	3
614.0	3
510.0	3
554.0	3
160.0	3
403.0	3
704.0	3
326.0	3
567.0	3
779.0	3
928.0	3
466.0	3
230.0	3
234.0	3
324.0	3
871.0	3
322.0	3
844.0	3
591.0	3
215.0	3
318.0	3
868.0	3
884.0	3
649.0	3
538.0	3
658.0	3
692.0	3
524.0	3
457.0	3
195.0	3
454.0	3
856.0	3
497.0	3
750.0	3
732.0	3
453.0	3
435.0	3

273.0	3
476.0	3
366.0	3
684.0	3
852.0	3
565.0	3
826.0	3
691.0	3
468.0	3
636.0	3
932.0	3
456.0	3
505.0	3
513.0	3
569.0	3
304.0	3
846.0	3
501.0	3
514.0	3
592.0	3
754.0	3
301.0	3
566.0	3
231.0	3
751.0	2
555.0	2
925.0	2
690.0	2
533.0	2
631.0	2
365.0	2
728.0	2
310.0	2
488.0	2
724.0	2
814.0	2
725.0	2
355.0	2
663.0	2
640.0	2
738.0	2
543.0	2
371.0	2
647.0	2
523.0	2
331.0	2
224.0	2
638.0	2
597.0	2
479.0	2
579.0	2
287.0	2
343.0	2

896.0	2
812.0	2
936.0	2
828.0	2
714.0	2
712.0	2
701.0	2
372.0	2
620.0	2
561.0	2
162.0	2
357.0	2
394.0	2
622.0	2
313.0	2
762.0	2
782.0	2
518.0	2
662.0	2
351.0	2
582.0	2
722.0	2
885.0	2
920.0	2
489.0	2
944.0	2
938.0	2
545.0	2
780.0	2
404.0	2
905.0	2
912.0	2
399.0	2
1052.0	2
464.0	2
311.0	2
748.0	2
548.0	2
968.0	2
894.0	2
386.0	2
590.0	2
866.0	2
683.0	2
447.0	2
271.0	2
839.0	2
680.0	2
711.0	2
772.0	2
282.0	2
685.0	2
702.0	2

898.0	2
606.0	2
843.0	2
594.0	2
573.0	2
641.0	2
509.0	2
493.0	2
296.0	2
617.0	2
422.0	2
427.0	2
908.0	2
706.0	2
721.0	2
164.0	2
603.0	2
292.0	2
765.0	2
558.0	2
645.0	2
408.0	2
283.0	2
349.0	2
789.0	2
605.0	2
618.0	2
865.0	2
675.0	2
682.0	2
412.0	2
895.0	2
423.0	2
818.0	2
481.0	2
389.0	2
924.0	2
303.0	2
726.0	2
831.0	2
494.0	2
800.0	2
439.0	2
249.0	1
266.0	1
904.0	1
207.0	1
811.0	1
1138.0	1
316.0	1
340.0	1
226.0	1
405.0	1

1184.0	1
1348.0	1
740.0	1
325.0	1
869.0	1
1314.0	1
1231.0	1
687.0	1
1150.0	1
557.0	1
698.0	1
715.0	1
428.0	1
1166.0	1
295.0	1
307.0	1
401.0	1
783.0	1
851.0	1
766.0	1
469.0	1
787.0	1
267.0	1
1488.0	1
1003.0	1
613.0	1
369.0	1
599.0	1
1154.0	1
100.0	1
571.0	1
1041.0	1
963.0	1
443.0	1
773.0	1
485.0	1
1085.0	1
899.0	1
959.0	1
803.0	1
760.0	1
584.0	1
449.0	1
688.0	1
568.0	1
353.0	1
791.0	1
1008.0	1
378.0	1
258.0	1
848.0	1
317.0	1
646.0	1

265.0	1
609.0	1
853.0	1
890.0	1
242.0	1
806.0	1
344.0	1
356.0	1
185.0	1
892.0	1
257.0	1
729.0	1
1110.0	1
585.0	1
1040.0	1
1174.0	1
916.0	1
876.0	1
933.0	1
747.0	1
1092.0	1
859.0	1
744.0	1
1105.0	1
293.0	1
1200.0	1
184.0	1
374.0	1
217.0	1
323.0	1
332.0	1
674.0	1
667.0	1
700.0	1
907.0	1
406.0	1
832.0	1
1134.0	1
1248.0	1
1043.0	1
254.0	1
719.0	1
862.0	1
562.0	1
749.0	1
261.0	1
842.0	1
1390.0	1
306.0	1
889.0	1
830.0	1
807.0	1
358.0	1

186.0	1
693.0	1
426.0	1
813.0	1
995.0	1
757.0	1
1356.0	1
459.0	1
367.0	1
716.0	1
739.0	1
290.0	1
665.0	1
611.0	1
425.0	1
1220.0	1
595.0	1
857.0	1
902.0	1
1020.0	1
455.0	1
414.0	1
354.0	1
602.0	1
327.0	1
284.0	1
833.0	1
601.0	1
841.0	1
689.0	1
808.0	1
752.0	1
255.0	1
424.0	1
824.0	1
328.0	1
983.0	1
475.0	1
858.0	1
954.0	1
549.0	1
927.0	1
535.0	1
263.0	1
375.0	1
363.0	1
209.0	1
1017.0	1
671.0	1
741.0	1
581.0	1
345.0	1
1053.0	1

```
413.0      1
458.0      1
694.0      1
886.0      1
949.0      1
673.0      1
309.0      1
815.0      1
623.0      1
972.0      1
984.0      1
604.0      1
845.0      1
559.0      1
465.0      1
713.0      1
962.0      1
958.0      1
708.0      1
526.0      1
1014.0     1
753.0      1
1418.0     1
213.0      1
198.0      1
860.0      1
248.0      1
696.0      1
825.0      1
947.0      1
373.0      1
770.0      1
639.0      1
377.0      1
804.0      1
244.0      1
208.0      1
445.0      1
189.0      1
1069.0     1
872.0      1
923.0      1
192.0      1
1025.0     1
272.0      1
Name: GarageArea, dtype: int64
```

```
In [62]: cat_garage_cont="NA"
for feat in cat_garage_feat:
    df_mvi[feat].replace(np.nan,cat_garage_cont,inplace=True)

num_garage_val=0
for feat in num_garage_feat:
```

```
df_mvi[feat].replace(np.nan, num_garage_val, inplace=True)
```

```
In [63]: # df_mvi[cat_garage_feat].isnull().sum()  
# df_mvi[num_garage_feat].isnull().sum()
```

Feature Transformation

Numerical to Categorical

```
In [64]: ## MSSubClass, YearBuilt, YearRemodAdd, GarageYrBlt, MoSold, YrSold  
for_num_con = ["MSSubClass", "YearBuilt", "YearRemodAdd", "GarageYrBlt", "MoSold"]  
for feat in for_num_con:  
    print(f"{feat}: data type = {df_mvi[feat].dtype}")
```

```
MSSubClass: data type = int64  
YearBuilt: data type = int64  
YearRemodAdd: data type = int64  
GarageYrBlt: data type = float64  
MoSold: data type = int64  
YrSold: data type = int64
```

```
In [65]: df_mvi["MoSold"] = df_mvi["MoSold"].apply(lambda x: calendar.month_abbr[x])
```

```
In [66]: for feat in for_num_con:  
    df_mvi[feat] = df_mvi[feat].astype(str)
```

```
In [67]: for feat in for_num_con:  
    print(f"{feat}: data type = {df_mvi[feat].dtype}")
```

```
MSSubClass: data type = object  
YearBuilt: data type = object  
YearRemodAdd: data type = object  
GarageYrBlt: data type = object  
MoSold: data type = object  
YrSold: data type = object
```

Categorial into Numerical(ordinal objects)

```
In [68]: ordinal_end_var=[  
    "ExterQual",  
    "ExterCond",  
    "BsmtQual",  
    "BsmtCond",  
    "BsmtExposure",  
    "BsmtFinType1",  
    "BsmtFinType2",  
    "HeatingQC",  
    "KitchenQual",  
    "FireplaceQu",  
    "GarageQual",
```

```
"GarageCond",
"PoolQC",
"Functional",
"GarageFinish",
"PavedDrive",
"Utilities",
]
print(len(ordinal_end_var))
```

17

```
In [69]: df_mvi["ExterQual"] = df_mvi["ExterQual"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["ExterCond"] = df_mvi["ExterCond"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["BsmtQual"] = df_mvi["BsmtQual"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["BsmtCond"] = df_mvi["BsmtCond"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["BsmtExposure"] = df_mvi["BsmtExposure"].astype(CategoricalDtype(categories=["N", "L", "M", "F", "P"], ordered=True))
df_mvi["BsmtFinType1"] = df_mvi["BsmtFinType1"].astype(CategoricalDtype(categories=["Unf", "Fls", "Lwsl", "Gd", "Av"], ordered=True))
df_mvi["BsmtFinType2"] = df_mvi["BsmtFinType2"].astype(CategoricalDtype(categories=["Unf", "Fls", "Lwsl", "Gd", "Av"], ordered=True))
df_mvi["HeatingQC"] = df_mvi["HeatingQC"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["KitchenQual"] = df_mvi["KitchenQual"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["FireplaceQu"] = df_mvi["FireplaceQu"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["GarageQual"] = df_mvi["GarageQual"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["GarageCond"] = df_mvi["GarageCond"].astype(CategoricalDtype(categories=["Po", "Fa", "TA", "Gd", "Ex"], ordered=True))
df_mvi["PoolQC"] = df_mvi["PoolQC"].astype(CategoricalDtype(categories=["NA", "Gd", "Fa", "Po"], ordered=True))
df_mvi["Functional"] = df_mvi["Functional"].astype(CategoricalDtype(categories=["Sal", "Sev", "Mod", "Min", "Typ"], ordered=True))
df_mvi["GarageFinish"] = df_mvi["GarageFinish"].astype(CategoricalDtype(categories=["Unf", "Fls", "Lwsl", "Gd", "Av"], ordered=True))
df_mvi["PavedDrive"] = df_mvi["PavedDrive"].astype(CategoricalDtype(categories=["N", "Y"], ordered=True))
df_mvi["Utilities"] = df_mvi["Utilities"].astype(CategoricalDtype(categories=["NoSewr", "AllPub", "NoAllPub", "NoSewr"], ordered=True))
```

```
In [70]: df_mvi.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2919 entries, 1 to 2919
Data columns (total 80 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   MSSubClass        2919 non-null   object 
 1   MSZoning          2919 non-null   object 
 2   LotFrontage       2919 non-null   float64
 3   LotArea           2919 non-null   int64  
 4   Street            2919 non-null   object 
 5   Alley              2919 non-null   object 
 6   LotShape           2919 non-null   object 
 7   LandContour        2919 non-null   object 
 8   Utilities          2919 non-null   int8   
 9   LotConfig          2919 non-null   object 
 10  LandSlope          2919 non-null   object 
 11  Neighborhood       2919 non-null   object 
 12  Condition1         2919 non-null   object 
 13  Condition2         2919 non-null   object 
 14  BldgType           2919 non-null   object 
 15  HouseStyle          2919 non-null   object 
 16  OverallQual        2919 non-null   int64  
 17  OverallCond        2919 non-null   int64
```

18	YearBuilt	2919	non-null	object
19	YearRemodAdd	2919	non-null	object
20	RoofStyle	2919	non-null	object
21	RoofMatl	2919	non-null	object
22	Exterior1st	2919	non-null	object
23	Exterior2nd	2919	non-null	object
24	MasVnrType	2919	non-null	object
25	MasVnrArea	2919	non-null	float64
26	ExterQual	2919	non-null	int8
27	ExterCond	2919	non-null	int8
28	Foundation	2919	non-null	object
29	BsmtQual	2919	non-null	int8
30	BsmtCond	2919	non-null	int8
31	BsmtExposure	2919	non-null	int8
32	BsmtFinType1	2919	non-null	int8
33	BsmtFinSF1	2919	non-null	float64
34	BsmtFinType2	2919	non-null	int8
35	BsmtFinSF2	2919	non-null	float64
36	BsmtUnfSF	2919	non-null	float64
37	TotalBsmtSF	2919	non-null	float64
38	Heating	2919	non-null	object
39	HeatingQC	2919	non-null	int8
40	CentralAir	2919	non-null	object
41	Electrical	2919	non-null	object
42	1stFlrSF	2919	non-null	int64
43	2ndFlrSF	2919	non-null	int64
44	LowQualFinSF	2919	non-null	int64
45	GrLivArea	2919	non-null	int64
46	BsmtFullBath	2919	non-null	float64
47	BsmtHalfBath	2919	non-null	float64
48	FullBath	2919	non-null	int64
49	HalfBath	2919	non-null	int64
50	BedroomAbvGr	2919	non-null	int64
51	KitchenAbvGr	2919	non-null	int64
52	KitchenQual	2919	non-null	int8
53	TotRmsAbvGrd	2919	non-null	int64
54	Functional	2919	non-null	int8
55	Fireplaces	2919	non-null	int64
56	FireplaceQu	2919	non-null	int8
57	GarageType	2919	non-null	object
58	GarageYrBlt	2919	non-null	object
59	GarageFinish	2919	non-null	int8
60	GarageCars	2919	non-null	float64
61	GarageArea	2919	non-null	float64
62	GarageQual	2919	non-null	int8
63	GarageCond	2919	non-null	int8
64	PavedDrive	2919	non-null	int8
65	WoodDeckSF	2919	non-null	int64
66	OpenPorchSF	2919	non-null	int64
67	EnclosedPorch	2919	non-null	int64
68	3SsnPorch	2919	non-null	int64
69	ScreenPorch	2919	non-null	int64
70	PoolArea	2919	non-null	int64

```

71 PoolQC      2919 non-null    int8
72 Fence        2919 non-null    object
73 MiscFeature  2919 non-null    object
74 MiscVal      2919 non-null    int64
75 MoSold       2919 non-null    object
76 YrSold       2919 non-null    object
77 SaleType     2919 non-null    object
78 SaleCondition 2919 non-null    object
79 SalePrice    1460 non-null    float64
dtypes: float64(11), int64(20), int8(17), object(32)
memory usage: 1.5+ MB

```

In [71]: # df_mvi["ExterQual"]

Categorial into Numerical(nominal objects)

In [72]: df_encod=df_mvi.copy()

```

object_features=df_encod.select_dtypes(include="object").columns.to_list()
print(object_features)

```

```

['MSSubClass', 'MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'YearBuilt', 'YearRemodAdd', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'Foundation', 'Heating', 'CentralAir', 'Electrical', 'GarageType', 'GarageYrBlt', 'Fence', 'MiscFeature', 'MoSold', 'YrSold', 'SaleType', 'SaleCondition']

```

In [73]: df_encod[object_features].head(2)

	MSSubClass	MSZoning	Street	Alley	LotShape	LandContour	LotConfig	LandSlope
Id								
1	60	RL	Pave	NA	Reg		Lvl	Inside
2	20	RL	Pave	NA	Reg		Lvl	FR2

```

In [74]: print("before",df_encod.shape)
df_encod=pd.get_dummies(df_encod,
                        columns=object_features,
                        prefix=object_features,
                        drop_first=True)
print("after",df_encod.shape)

```

```

before (2919, 80)
after (2919, 513)

```

In [75]: df_encod.head(2)

Out[75]:

	LotFrontage	LotArea	Utilities	OverallQual	OverallCond	MasVnrArea	ExterQua
Id							
1	65.0	8450	3	7	5	196.0	
2	80.0	9600	3	6	8	0.0	

Split data

In [76]:

```
len_train=df_train.shape[0]
len_train
```

Out[76]:

```
1460
```

In [77]:

```
X_train=df_encod[:len_train].drop("SalePrice",axis=1)
y_train=df_encod[:len_train]["SalePrice"]
X_test=df_encod[len_train: ].drop("SalePrice",axis=1)

print("Shape of X_train",X_train.shape)
print("Shape of y_train",y_train.shape)
print("Shape of X_test",X_test.shape)
```

```
Shape of X_train (1460, 512)
Shape of y_train (1460,)
Shape of X_test (1459, 512)
```

In [78]:

```
sc = StandardScaler()

sc.fit(X_train) # it will learn about mean and std variance
X_train=sc.transform(X_train)
X_test=sc.transform(X_test)
```

Cross Validation and Model Selection

In [79]:

```
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.gaussian_process import GaussianProcessRegressor
from sklearn.tree import DecisionTreeRegressor

from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor

from sklearn.neural_network import MLPRegressor

from xgboost import XGBRegressor
```

```
In [80]: svr = SVR()
lr = LinearRegression()
sgdr = SGDRegressor()
knn = KNeighborsRegressor()
gpr = GaussianProcessRegressor()
dtr = DecisionTreeRegressor()
rfr = RandomForestRegressor()
gbr = GradientBoostingRegressor()
xgbr = XGBRegressor()

mlpr = MLPRegressor()
```

```
In [81]: models = {"a": ["LinearRegression", lr],
                 "b": ["SVR", svr],
                 "c": ["SGDRegressor", sgdr],
                 "d": ["KNeighborsRegressor", knn],
                 "e": ["GaussianProcessRegressor", gpr],
                 "f": ["DecisionTreeRegressor", dtr],
                 "g": ["GradientBoostingRegressor", gbr],
                 "h": ["RandomForestRegressor", rfr],
                 "i": ["XGBRegressor", xgbr],
                 "j": ["MLPRegressor", mlpr],
             }      # Create a dictionary to store the results
```

```
In [82]: from sklearn.model_selection import cross_val_score, KFold
from sklearn.metrics import make_scorer, r2_score

def test_model(model, X_train=X_train, y_train=y_train):
    cv = KFold(n_splits=7, random_state=45, shuffle=True)
    r2 = make_scorer(r2_score)
    r2_val_score = cross_val_score(model, X_train, y_train, cv=cv, scoring='r2')
    score = [r2_val_score.mean()]
    return score
```

```
In [83]: models_score = []
for model in models:
    print("Model Name: ", models[model][0])
    score = test_model(models[model][1], X_train, y_train)
    print("Score of Model:", score)
    print("-----")
    models_score.append([models[model][0], score])
```

```
Model Name: LinearRegression
Score of Model: [-1.2722448407974715e+24]
-----
Model Name: SVR
Score of Model: [-0.052133548352104216]
-----
Model Name: SGDRegressor
Score of Model: [-6043.376589984432]
-----
Model Name: KNeighborsRegressor
Score of Model: [0.5585925623107102]
-----
Model Name: GaussianProcessRegressor
Score of Model: [-5.398916312612151]
-----
Model Name: DecisionTreeRegressor
Score of Model: [0.7008206494020515]
-----
Model Name: GradientBoostingRegressor
Score of Model: [0.8715666756167462]
-----
Model Name: RandomForestRegressor
Score of Model: [0.8457476035359204]
-----
Model Name: XGBRegressor
Score of Model: [0.8582487612757063]
-----
Model Name: MLPRegressor
c:\Users\nirde\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:684: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
    warnings.warn(
c:\Users\nirde\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:684: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
    warnings.warn(
c:\Users\nirde\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:684: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
    warnings.warn(
c:\Users\nirde\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:684: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
    warnings.warn(
c:\Users\nirde\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:684: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
    warnings.warn(
c:\Users\nirde\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:684: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.
```

```
Score of Model: [-4.852157124690591]
```

```
c:\Users\nirde\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:684: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and the optimization hasn't converged yet.  
warnings.warn(
```

```
In [84]: models_score
```

```
Out[84]: [['LinearRegression', [-1.2722448407974715e+24]],  
           ['SVR', [-0.052133548352104216]],  
           ['SGDRegressor', [-6043.376589984432]],  
           ['KNeighborsRegressor', [0.5585925623107102]],  
           ['GaussianProcessRegressor', [-5.398916312612151]],  
           ['DecisionTreeRegressor', [0.7008206494020515]],  
           ['GradientBoostingRegressor', [0.8715666756167462]],  
           ['RandomForestRegressor', [0.8457476035359204]],  
           ['XGBRegressor', [0.8582487612757063]],  
           ['MLPRegressor', [-4.852157124690591]]]
```

Model Training

```
In [85]: gbr.fit(X_train,y_train)
```

```
Out[85]: ▾ GradientBoostingRegressor  
GradientBoostingRegressor()
```

```
In [86]: y_pred=gbr.predict(X_test)
```

```
In [87]: # y_pred # is a numpy array hence we gonna convert it into dataframe  
y_pred=pd.concat([df_test['Id'],pd.DataFrame(y_pred,columns=['SalePrice'])]  
y_pred
```

```
Out[87]:
```

	Id	SalePrice
0	1461	122103.500909
1	1462	155398.306856
2	1463	175032.391922
3	1464	180116.442684
4	1465	204131.608740
5	1466	170930.824326
6	1467	157931.059686
7	1468	159943.505730
8	1469	190038.522001

9	1470	129854.392427
10	1471	200965.020774
11	1472	95461.489798
12	1473	95677.490047
13	1474	154819.496462
14	1475	137990.081928
15	1476	407464.266211
16	1477	277826.803080
17	1478	311162.185967
18	1479	286536.780138
19	1480	484967.859526
20	1481	319955.713640
21	1482	213799.485481
22	1483	165842.688843
23	1484	174316.540813
24	1485	175527.486372
25	1486	193866.191964
26	1487	350948.923099
27	1488	239107.506370
28	1489	200610.223162
29	1490	222909.030296
30	1491	190933.714005
31	1492	89257.865711
32	1493	188818.811478
33	1494	292143.047463
34	1495	301955.268491
35	1496	235919.708953
36	1497	182223.884972
37	1498	165683.328424
38	1499	167733.284069
39	1500	146715.310659
40	1501	165761.689504

41	1502	159338.955452
42	1503	290292.318318
43	1504	228485.048420
44	1505	213225.858751
45	1506	191678.968133
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1262	2723	145575.825905
1263	2724	130455.416018
1264	2725	132839.329707
1265	2726	141879.253836
1266	2727	180093.927092
1267	2728	166319.061480
1268	2729	151944.398559

1269	2730	141852.730709
1270	2731	134019.341310
1271	2732	128565.101317
1272	2733	154547.796104
1273	2734	157030.342938
1274	2735	138607.196576
1275	2736	143803.218195
1276	2737	122772.754375
1277	2738	139701.562058
1278	2739	161585.442242
1279	2740	136999.903080
1280	2741	147771.728268
1281	2742	145094.936797
1282	2743	142484.358922
1283	2744	148637.563701
1284	2745	143022.074618
1285	2746	143197.413301
1286	2747	161416.436657
1287	2748	120763.220077
1288	2749	130114.399214
1289	2750	139151.002706
1290	2751	138521.257288
1291	2752	216267.858226
1292	2753	149711.324974
1293	2754	215269.882938
1294	2755	126947.672571
1295	2756	101024.887233
1296	2757	72059.708609
1297	2758	88090.892202
1298	2759	151376.187730
1299	2760	132069.624440
1300	2761	143749.377606

1301	2762	143363.563916
1302	2763	183224.167044
1303	2764	166975.183665
1304	2765	270562.588959
1305	2766	132180.243031
1306	2767	83095.611824
1307	2768	138769.091878
1308	2769	133478.760237
1309	2770	155493.055312
1310	2771	115858.462673
1311	2772	120952.930458
1312	2773	145645.785504
1313	2774	133218.601428
1314	2775	111860.980952
1315	2776	142109.140016
1316	2777	153323.140683
1317	2778	126296.315071
1318	2779	137382.280783
1319	2780	99079.542143
1320	2781	99218.646103
1321	2782	96188.834980
1322	2783	104622.668433
1323	2784	127638.637128
1324	2785	135010.005472
1325	2786	80413.458786
1326	2787	121722.982415
1327	2788	80076.865084
1328	2789	183072.158559
1329	2790	90446.604580
1330	2791	110782.563497
1331	2792	66260.823710

1332	2793	165545.440050
1333	2794	105800.504428
1334	2795	114848.869321
1335	2796	99469.208755
1336	2797	191732.963886
1337	2798	110059.991420
1338	2799	111004.351926
1339	2800	79822.397495
1340	2801	112135.148774
1341	2802	140088.851416
1342	2803	166436.874598
1343	2804	151140.157198
1344	2805	106458.747976
1345	2806	85852.447328
1346	2807	161618.683749
1347	2808	148263.690743
1348	2809	137698.580262
1349	2810	135934.149222
1350	2811	162192.853713
1351	2812	144075.532885
1352	2813	176411.547371
1353	2814	167900.394699
1354	2815	102941.694881
1355	2816	223355.183109
1356	2817	153279.491193
1357	2818	134346.272503
1358	2819	184879.883815
1359	2820	135108.614761
1360	2821	100769.428695
1361	2822	190735.250371
1362	2823	226249.299484
1363	2824	178863.935650

1364	2825	157607.025989
1365	2826	131424.569711
1366	2827	136489.686972
1367	2828	224031.060327
1368	2829	202130.441377
1369	2830	235795.554918
1370	2831	183598.935732
1371	2832	246968.870803
1372	2833	304737.984603
1373	2834	210989.171318
1374	2835	207695.396828
1375	2836	187495.111599
1376	2837	164006.884718
1377	2838	143821.792286
1378	2839	178160.136132
1379	2840	193334.037724
1380	2841	203646.684602
1381	2842	219963.198816
1382	2843	145502.080201
1383	2844	139243.229353
1384	2845	119891.369739
1385	2846	205282.401587
1386	2847	191817.605914
1387	2848	219330.003836
1388	2849	201628.564364
1389	2850	287453.756854
1390	2851	236153.003061
1391	2852	223822.038215
1392	2853	230806.007405
1393	2854	142859.687416
1394	2855	201349.810671

1395	2856	202114.156817
1396	2857	187495.111599
1397	2858	210576.541508
1398	2859	125912.299923
1399	2860	128566.466755
1400	2861	130563.062325
1401	2862	195874.344536
1402	2863	132624.343778
1403	2864	250350.190115
1404	2865	140279.367259
1405	2866	149483.694981
1406	2867	100005.348742
1407	2868	104469.426224
1408	2869	105381.748515
1409	2870	138689.208714
1410	2871	91474.882384
1411	2872	51279.113382
1412	2873	108749.867332
1413	2874	128949.150407
1414	2875	110661.371033
1415	2876	170860.457861
1416	2877	140183.545417
1417	2878	184586.320687
1418	2879	139457.453874
1419	2880	98317.244197
1420	2881	166197.191030
1421	2882	167619.188677
1422	2883	194880.087035
1423	2884	207346.301791
1424	2885	188415.936454
1425	2886	223820.252844
1426	2887	99800.643271

1427	2888	137083.060890
1428	2889	57468.737035
1429	2890	86359.654738
1430	2891	138192.797032
1431	2892	69975.788043
1432	2893	98985.136419
1433	2894	73002.725122
1434	2895	294782.721766
1435	2896	289467.797250
1436	2897	196104.573949
1437	2898	154903.073955
1438	2899	229527.501384
1439	2900	152508.873443
1440	2901	221113.034781
1441	2902	180440.037247
1442	2903	341872.755824
1443	2904	374666.965953
1444	2905	94257.508999
1445	2906	210456.160406
1446	2907	117604.511717
1447	2908	131626.796280
1448	2909	154793.593428
1449	2910	90602.729709
1450	2911	79959.397309
1451	2912	143212.583712
1452	2913	87766.124948
1453	2914	75954.975933
1454	2915	82324.315442
1455	2916	84298.677180
1456	2917	167620.942720
1457	2918	123952.178061

```
1458 2919 217032.206363
```

```
In [88]: y_pred.to_csv("\House Price Prediction\ML_Model\data_set\submission.csv",
```

```
In [89]: #storing model in pickle file
import pickle

with open('gbr.pkl','wb') as f:
    pickle.dump(gbr,f)
```