Step1: Data Sourcing

Import Required Libraries

In [39]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [40]:
```
# Load data
df =pd.read_csv('/Users/user/Downloads/train.csv')
df.head()
```

Out[40]:

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

5 rows × 81 columns

In [41]:
```
df.shape
```

Out[41]: (1460, 81)

In [42]:
```
df.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     588 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 [43]:
```
# Cout of data types
df.dtypes.value_counts()
```

Out[43]:
```
object     43
int64      35
float64     3
Name: count, dtype: int64
```

In [44]:
```
df.describe()
```

Out[44]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000	1460.000000	1
mean	730.500000	56.897260	70.049958	10516.828082	6.099315	5.575342	1
std	421.610009	42.300571	24.284752	9981.264932	1.382997	1.112799	
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000000	1
25%	365.750000	20.000000	59.000000	7553.500000	5.000000	5.000000	1
50%	730.500000	50.000000	69.000000	9478.500000	6.000000	5.000000	1
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000	6.000000	2
max	1460.000000	190.000000	313.000000	215245.000000	10.000000	9.000000	2

8 rows × 38 columns

Step2: Data Cleansing

MSSubClass

As per data dictionary, the column `MSSubClass` has categorical values with interger data type. Therefore, change the datatype to object

In [45]:
```
# Change the data type from Integer to object
df['MSSubClass']=df['MSSubClass'].astype('object')
```

Numerical columns with value 0

There are few numerical columns with value 0 which can be replaced with null value

In [46]:
```
#List of columns with value 0
zero_cols=df.columns[df.eq(0).any()]
zero_cols
```

Out[46]:
```
Index(['MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'Tot
alBsmtSF',
       '2ndFlrSF', 'LowQualFinSF', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'Fireplaces', '
GarageCars',
       'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch',
'3SsnPorch',
       'ScreenPorch', 'PoolArea', 'MiscVal'],
      dtype='object')
```

In [47]:
```
# Replace 0 with null value
df[zero_cols]=df[zero_cols].replace(0,np.NaN )
```

Derive Age from YearBuilt

In [48]:
```
df['Age']=2022-df['YearBuilt']
df[['YearBuilt','Age']].head()
```

Out[48]:

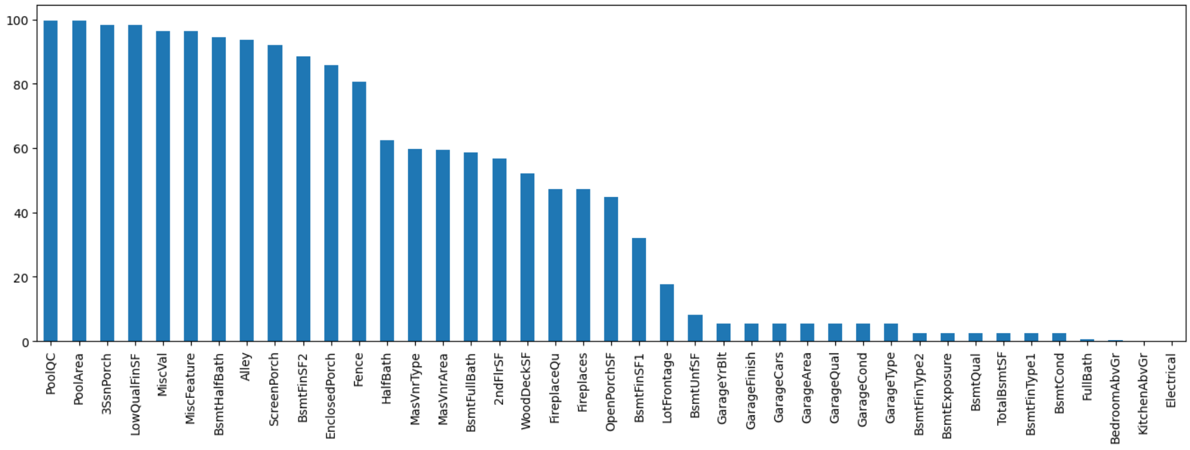
	YearBuilt	Age
0	2003	19
1	1976	46
2	2001	21
3	1915	107
4	2000	22

Step3: Missing Value Treatment

In [49]:
```
#Percentage of missing values
round((df[df.columns[df.isnull().any()]].isnull().sum()/len(df))*10
```

Out[49]:
```
PoolQC          99.52
PoolArea        99.52
3SsnPorch       98.36
LowQualFinSF    98.22
MiscVal         96.44
MiscFeature     96.30
BsmtHalfBath    94.38
Alley           93.77
ScreenPorch     92.05
BsmtFinSF2      88.56
EnclosedPorch   85.75
Fence           80.75
HalfBath        62.53
MasVnrType      59.73
MasVnrArea      59.52
BsmtFullBath    58.63
2ndFlrSF        56.78
WoodDeckSF      52.12
FireplaceQu     47.26
Fireplaces      47.26
OpenPorchSF     44.93
BsmtFinSF1      31.99
LotFrontage     17.74
BsmtUnfSF        8.08
GarageYrBlt      5.55
GarageFinish     5.55
GarageCars       5.55
GarageArea       5.55
GarageQual       5.55
GarageCond       5.55
GarageType       5.55
BsmtFinType2     2.60
BsmtExposure     2.60
BsmtQual         2.53
TotalBsmtSF      2.53
BsmtFinType1     2.53
BsmtCond         2.53
FullBath         0.62
BedroomAbvGr     0.41
KitchenAbvGr     0.07
Electrical       0.07
dtype: float64
```

In [50]:
```
# Barplot for Percentages of missing values
plt.figure(figsize=[17,5])
round((df[df.columns[df.isnull().any()]].isnull().sum()/len(df))*10
plt.show()
```



Observations:

- There are few columns with missing values more than 30%. Therefore, drop null values by columns.
- `LotFrontage` null values can be imputed with median.
- `Garage` columns has same percentage of missing values. Therefore, drop null values by rows.
- `Basement` columns has same percentage of missing values. Therefore, drop null values by rows.
- `Masonry` columns has same percentage of missing values. Therefore, drop null values by rows.

Drop columns having missing values >30%

In [51]:
```
# List of columns with missing values >30%
miss_cols=df.columns[(df.isnull().sum()/len(df)*100>30)]
miss_cols
```

Out[51]:
```
Index(['Alley', 'MasVnrType', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFin
SF2',
       '2ndFlrSF', 'LowQualFinSF', 'BsmtFullBath', 'BsmtHalfBath',
'HalfBath',
       'Fireplaces', 'FireplaceQu', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'P
oolQC',
       'Fence', 'MiscFeature', 'MiscVal'],
      dtype='object')
```

In [52]:
```
#Drop columns with missing values >40%
df.drop(miss_cols,axis=1, inplace=True)
df.shape
```

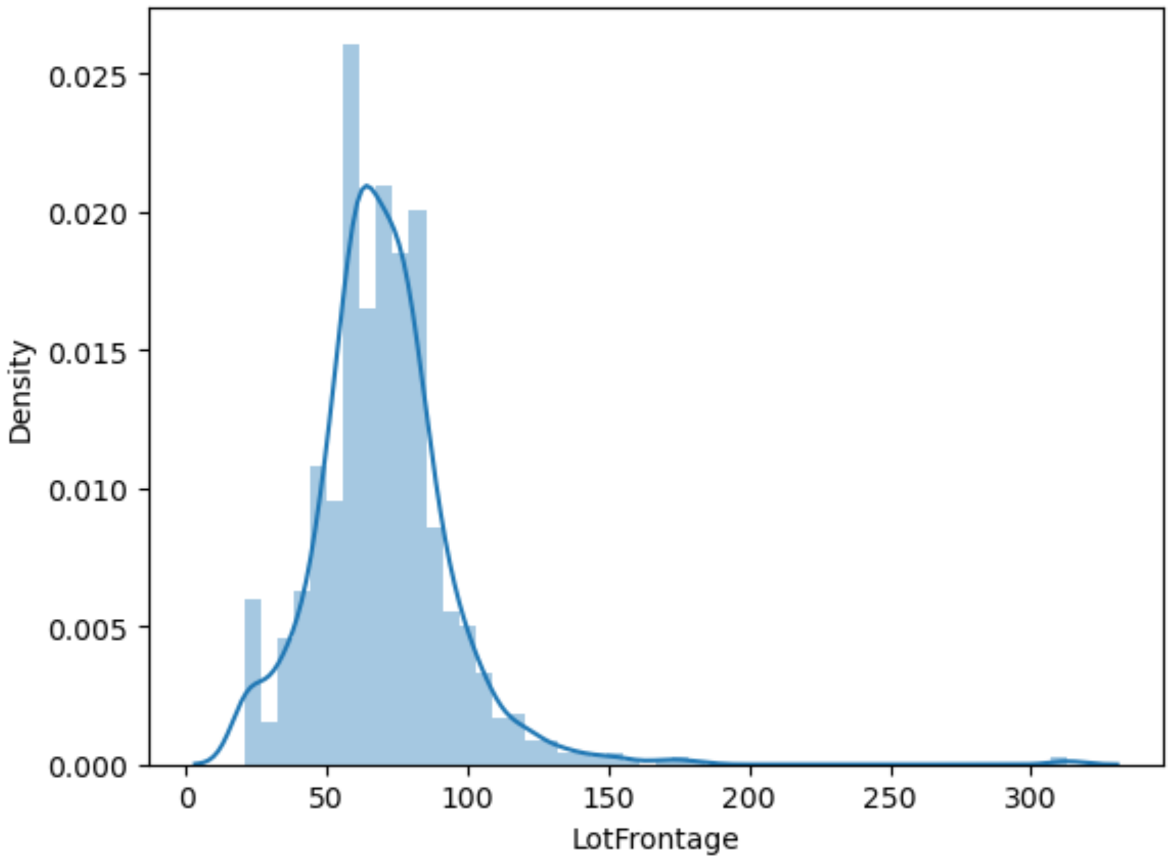
Out[52]:
```
(1460, 60)
```

LotFrontage

In [53]:
```
df['LotFrontage'].describe()
```

Out[53]:
```
count    1201.000000
mean       70.049958
std        24.284752
min        21.000000
25%        59.000000
50%        69.000000
75%        80.000000
max       313.000000
Name: LotFrontage, dtype: float64
```

In [54]:
```
# Plot distribution
sns.distplot(df['LotFrontage'])
plt.show()
```



In [55]:
```
#Impute LotFrontage missing values with median
df['LotFrontage'].fillna(df['LotFrontage'].median(), inplace=True)
```

Garage Columns

In [56]:
```
garage_cols=['GarageYrBlt','GarageType','GarageFinish','GarageQual'
garage_cols
```

Out[56]:
```
['GarageYrBlt', 'GarageType', 'GarageFinish', 'GarageQual', 'Garag
eCond']
```

In [57]:
```
df[df['GarageYrBlt'].isnull()][garage_cols]
```

Out[57]:

	GarageYrBlt	GarageType	GarageFinish	GarageQual	GarageCond
39	NaN	NaN	NaN	NaN	NaN
48	NaN	NaN	NaN	NaN	NaN
78	NaN	NaN	NaN	NaN	NaN
88	NaN	NaN	NaN	NaN	NaN
89	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...
1349	NaN	NaN	NaN	NaN	NaN
1407	NaN	NaN	NaN	NaN	NaN
1449	NaN	NaN	NaN	NaN	NaN
1450	NaN	NaN	NaN	NaN	NaN
1453	NaN	NaN	NaN	NaN	NaN

81 rows × 5 columns

In [58]:
```
# Drop null values by rows
df.dropna(subset=garage_cols, inplace=True)
```

In [59]:
```
df.shape
```

Out[59]:
```
(1379, 60)
```

Basement Columns

In [60]:
```
df.columns[df.isnull().any()]
```

Out[60]:
```
Index(['BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'Bs
mtFinType2',
       'BsmtUnfSF', 'TotalBsmtSF', 'Electrical', 'FullBath', 'Bedr
oomAbvGr'],
      dtype='object')
```

In [61]:
```
basement_cols=['BsmtQual', 'BsmtCond', 'BsmtExposure','BsmtFinType1
basement_cols
```

Out[61]:
```
['BsmtQual',
 'BsmtCond',
 'BsmtExposure',
 'BsmtFinType1',
 'BsmtFinType2',
 'BsmtUnfSF']
```

In [62]:
```
# Drop null values by rows
df.dropna(subset=basement_cols, inplace=True)
```

In [63]:
```
df.shape
```

Out[63]:
```
(1274, 60)
```

Other columns

In [64]:
```
other_cols=df.columns[df.isnull().any()]
other_cols
```

Out[64]:
```
Index(['Electrical', 'FullBath', 'BedroomAbvGr'], dtype='object')
```

In [65]:
```
# Drop null values by rows
df.dropna(subset=other_cols, inplace=True)
```

In [66]:
```
df.shape
```

Out[66]:
```
(1268, 60)
```

In [67]:
```
df.columns[df.isnull().any()]
```

Out[67]:
```
Index([], dtype='object')
```

In [68]:
```
#Verify missing value treatment
df.isnull().sum()
```

Out[68]:
```
Id               0
MSSubClass       0
MSZoning         0
LotFrontage      0
```

```
LotArea          0
Street           0
LotShape         0
LandContour      0
Utilities        0
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      0
Exterior2nd      0
ExterQual        0
ExterCond        0
Foundation       0
BsmtQual         0
BsmtCond         0
BsmtExposure     0
BsmtFinType1     0
BsmtFinType2     0
BsmtUnfSF        0
TotalBsmtSF      0
Heating          0
HeatingQC        0
CentralAir       0
Electrical       0
1stFlrSF         0
GrLivArea        0
FullBath         0
BedroomAbvGr     0
KitchenAbvGr     0
KitchenQual      0
TotRmsAbvGrd     0
Functional       0
GarageType       0
GarageYrBlt      0
GarageFinish     0
GarageCars       0
GarageArea       0
GarageQual       0
GarageCond       0
PavedDrive       0
MoSold           0
YrSold           0
SaleType         0
```

```
SaleCondition    0
SalePrice        0
Age              0
dtype: int64
```

Step3: Data Visualization

Categorical Variables

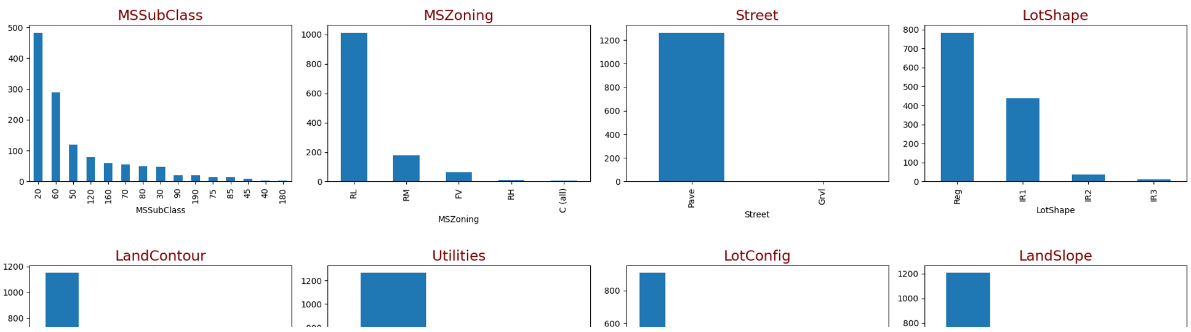
In [69]:
```
# Create categorical variable list
cat_cols=df.select_dtypes('object').columns
cat_cols
```

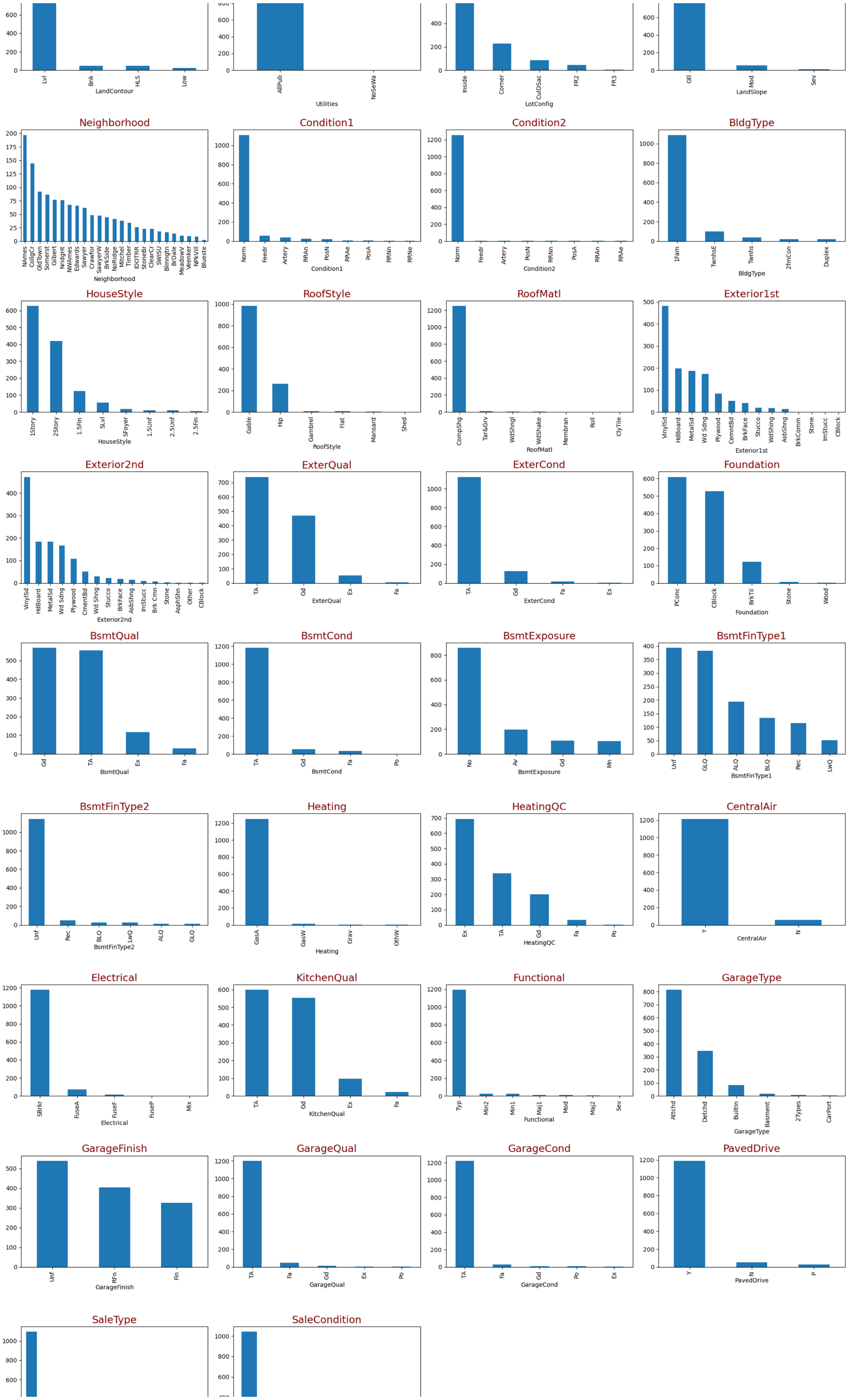
Out[69]:
```
Index(['MSSubClass', 'MSZoning', 'Street', 'LotShape', 'LandContou
r',
       'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Con
dition1',
       'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofM
atl',
       'Exterior1st', 'Exterior2nd', 'ExterQual', 'ExterCond', 'Fo
undation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'Bs
mtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'Kitche
nQual',
       'Functional', 'GarageType', 'GarageFinish', 'GarageQual', '
GarageCond',
       'PavedDrive', 'SaleType', 'SaleCondition'],
      dtype='object')
```

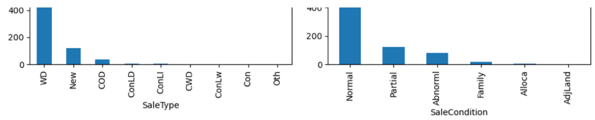
In [70]:
```
len(cat_cols)
```

Out[70]:
```
38
```

In [71]:
```
# Bar plot of all categorical variables by count
fig=plt.figure(figsize=[20,40])
for i,col in enumerate(cat_cols):
    plt.subplot(10,4,i+1)
    df[col].value_counts().plot.bar()
    plt.title(col,color='maroon', fontsize=17)
    fig.tight_layout()
```




LandContour
Lvl Bnk HLS Low
Utilities
AllPub NoSeWa
LotConfig
Inside Corner CulDSac FR2 FR3
LandSlope
Gtl Mod Sev
Neighborhood
Condition1
Norm Feedr Artery RRAn PosN RRAe PosA RRNn RRNe
Condition2
Norm Feedr Artery PosN RRNn PosA RRAn RRAe
BldgType
1Fam TwnhsE Twnhs 2fmCon Duplex
HouseStyle
1Story 2Story 1.5Fin SLvl SFoyer 1.5Unf 2.5Unf 2.5Fin
RoofStyle
Gable Hip Gambrel Flat Mansard Shed
RoofMatl
CompShg Tar&Grv WdShngl WdShake Membran Roll ClyTile
Exterior1st
Exterior2nd
ExterQual
TA Gd Ex Fa
ExterCond
TA Gd Fa Ex
Foundation
PConc CBlock BrkTil Stone Wood
BsmtQual
Gd TA Ex Fa
BsmtCond
TA Gd Fa Po
BsmtExposure
No Av Gd Mn
BsmtFinType1
Unf GLQ ALQ BLQ Rec LwQ
BsmtFinType2
Unf Rec BLQ LwQ ALQ GLQ
Heating
GasA GasW Grav OthW
HeatingQC
Ex TA Gd Fa Po
CentralAir
Y N
Electrical
SBrkr FuseA FuseF FuseP Mix
KitchenQual
TA Gd Ex Fa
Functional
Typ Min2 Min1 Maj1 Mod Maj2 Sev
GarageType
Attchd Detchd BuiltIn Basment 2Types CarPort
GarageFinish
Unf RFn Fin
GarageQual
TA Fa Gd Ex Po
GarageCond
TA Fa Gd Po Ex
PavedDrive
Y N P
SaleType
SaleCondition



Numerical Variables

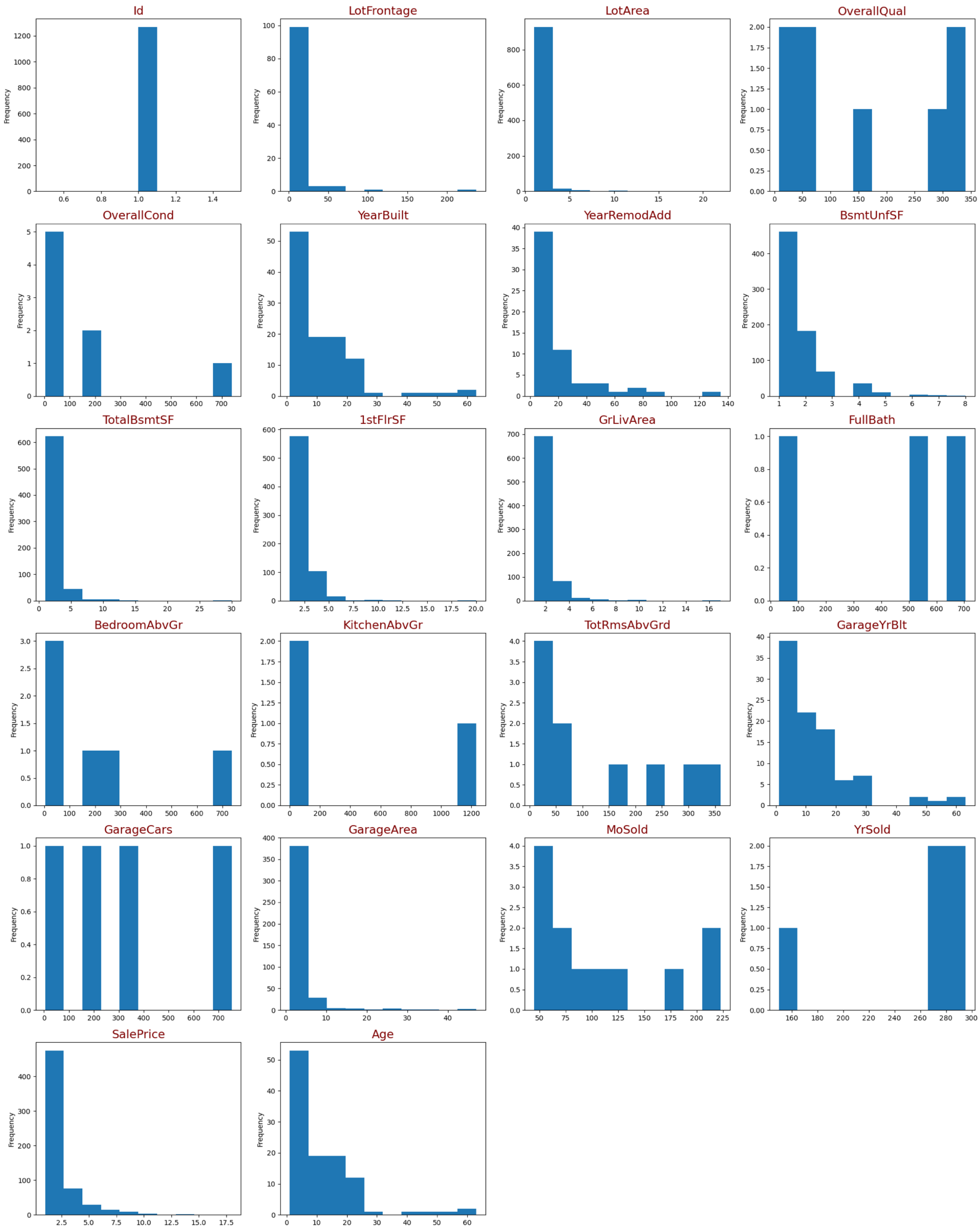
In [72]:
```
#Create numerical variable list
num_cols=df.select_dtypes('number').columns
num_cols
```

Out[72]:
```
Index(['Id', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF',
       'GrLivArea', 'FullBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'GarageYrBlt', 'GarageCars', 'GarageArea', 'MoSold', 'YrSold',
       'SalePrice', 'Age'],
      dtype='object')
```

In [73]:
```
len(num_cols)
```

Out[73]:
```
22
```

In [74]:
```
#Distribution of all numerical variables
fig=plt.figure(figsize=[20,25])
for i,col in enumerate(num_cols):
    plt.subplot(6,4,i+1)
    df[col].value_counts().plot.hist()
    plt.title(col,color='maroon', fontsize=17)
    fig.tight_layout()
```



Correlation Matrix of numerical variables

In [75]:
```
df[num_cols].corr()
```

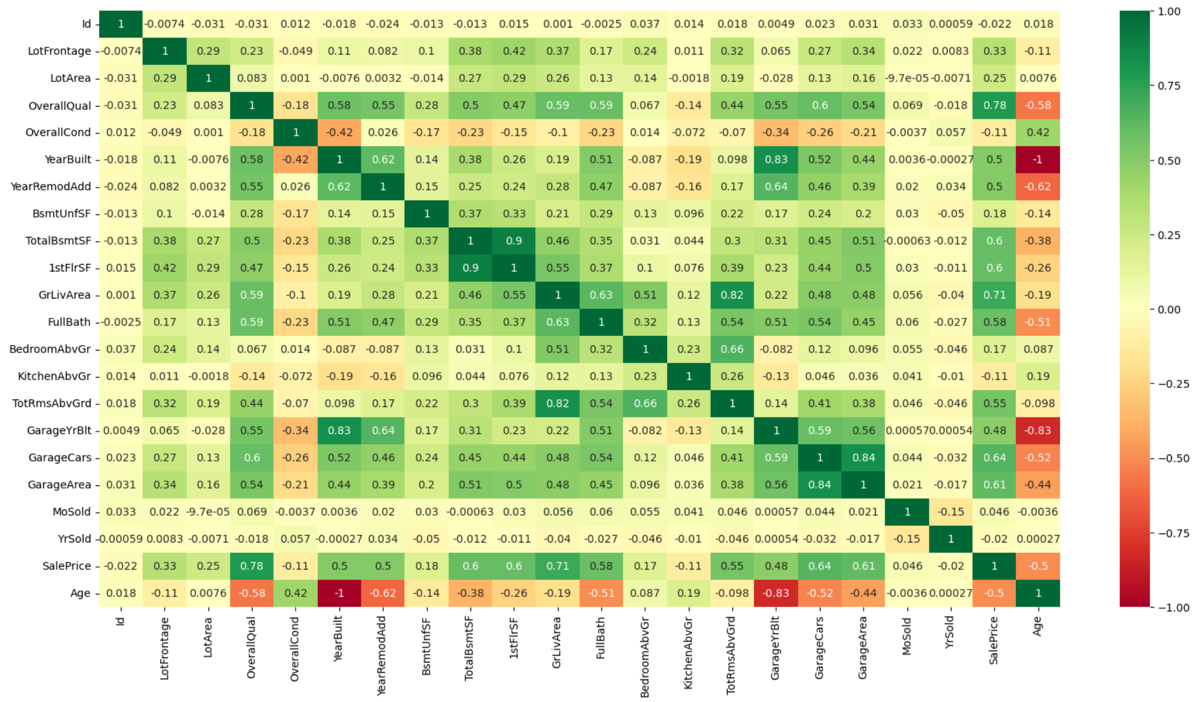
Out[75]:

	Id	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	Ye
Id	1.000000	-0.007387	-0.031197	-0.030904	0.011756	-0.017997	
LotFrontage	-0.007387	1.000000	0.294381	0.230099	-0.048748	0.107314	
LotArea	-0.031197	0.294381	1.000000	0.083340	0.001027	-0.007602	
OverallQual	-0.030904	0.230099	0.083340	1.000000	-0.175964	0.575357	
OverallCond	0.011756	-0.048748	0.001027	-0.175964	1.000000	-0.419941	
YearBuilt	-0.017997	0.107314	-0.007602	0.575357	-0.419941	1.000000	
YearRemodAdd	-0.023860	0.082020	0.003212	0.548218	0.026341	0.621827	
BsmtUnfSF	-0.012645	0.100298	-0.014439	0.277406	-0.165816	0.135175	
TotalBsmtSF	-0.013413	0.383800	0.266328	0.498962	-0.232889	0.379091	
1stFlrSF	0.015107	0.417937	0.291028	0.474106	-0.153610	0.256489	
GrLivArea	0.001038	0.365757	0.257251	0.591367	-0.101384	0.188225	
FullBath	-0.002479	0.169274	0.128414	0.590646	-0.232291	0.507608	
BedroomAbvGr	0.037468	0.242305	0.137449	0.066741	0.014080	-0.086878	
KitchenAbvGr	0.013937	0.010904	-0.001827	-0.136461	-0.072345	-0.190791	
TotRmsAbvGrd	0.018152	0.324293	0.192800	0.437987	-0.070033	0.098135	
GarageYrBlt	0.004912	0.065316	-0.027611	0.547620	-0.341706	0.828264	
GarageCars	0.022628	0.267469	0.131804	0.595110	-0.258391	0.524317	
GarageArea	0.031307	0.335442	0.161000	0.537458	-0.211721	0.444013	
MoSold	0.032579	0.021878	-0.000097	0.069060	-0.003652	0.003579	
YrSold	0.000589	0.008331	-0.007145	-0.017580	0.057449	-0.000274	
SalePrice	-0.022057	0.332403	0.247152	0.782506	-0.114101	0.502922	
Age	0.017997	-0.107314	0.007602	-0.575357	0.419941	-1.000000	

22 rows × 22 columns

Heatmap of numerical variables correlation

In [76]:
```
plt.figure(figsize=[20,10])
sns.heatmap(df[num_cols].corr(), annot=True, cmap='RdYlGn')
plt.show()
```



Observation: Following pairs are highly correlated

- GarageArea and GarageCars
- TotRmsAbvGr and GrLiveArea
- SalesPrice and OverallQual
- SalesPrice and GrLiveArea

Step4: Data Preparation

Categorical Variables

Drop Date, Year and Month columns as dataset may suffer high dimensionality problem if we create dummies of these columns

In [77]:
```
date_cols=['YearBuilt','YearRemodAdd','GarageYrBlt','YrSold','MoSol
date_cols
```

Out[77]: ['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold', 'MoSold']

In [78]:
```
# Drop year and month columns
df.drop(date_cols,axis=1, inplace=True)
df.shape
```

Out[78]: (1268, 55)

Create dummies for categorical variables

In [79]:
```
#Create a list of categorical variables
cat_cols=df.select_dtypes('object').columns
cat_cols
```

Out[79]:
```
Index(['MSSubClass', 'MSZoning', 'Street', 'LotShape', 'LandContou
r',
       'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Con
dition1',
       'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofM
atl',
       'Exterior1st', 'Exterior2nd', 'ExterQual', 'ExterCond', 'Fo
undation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'Bs
mtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'Kitche
nQual',
       'Functional', 'GarageType', 'GarageFinish', 'GarageQual', '
GarageCond',
       'PavedDrive', 'SaleType', 'SaleCondition'],
      dtype='object')
```

In [80]:
```
# New dataframe of dummies
df_dum=pd.get_dummies(df[cat_cols],drop_first=True)
```

In [81]:
```
df_dum.head()
```

Out[81]:

	MSSubClass_30	MSSubClass_40	MSSubClass_45	MSSubClass_50	MSSubClass_60	MS
0	False	False	False	False	True	
1	False	False	False	False	False	
2	False	False	False	False	True	
3	False	False	False	False	False	
4	False	False	False	False	True	

5 rows × 201 columns

In [82]:
```
df_dum.shape
```

Out[82]: (1268, 201)

Concatenate dummies data frame with original data frame

In [83]:
```
df=pd.concat([df,df_dum], axis=1)
df.shape
```

Out[83]:
```
(1268, 256)
```

In [84]:
```
# Drop original columns of categorical variables
df.drop(cat_cols, axis=1, inplace=True)
df.shape
```

Out[84]:
```
(1268, 218)
```

In [85]:
```
# Drop id column as it is not a significant predictor
df.drop('Id', axis=1, inplace=True)
df.shape
```

Out[85]:
```
(1268, 217)
```

Split data frame into train and test sets

In [86]:
```
from sklearn.model_selection import train_test_split
```

In [87]:
```
#Split train and test sets in 70:30 ratio
df_train, df_test=train_test_split(df, train_size=0.7, test_size=0.
```

In [88]:
```
#Verify train, test size
print('Train shape', df_train.shape)
print('Test shape', df_test.shape)
```

```
Train shape (887, 217)
Test shape (381, 217)
```

Rescaling Numerical Variables

In [89]:
```
#Create numerical variables list
num_cols=df.select_dtypes(exclude='uint8').columns
num_cols
```

Out[89]:
```
Index(['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', 'Bs
mtUnfSF',
       'TotalBsmtSF', '1stFlrSF', 'GrLivArea', 'FullBath', 'Bedroo
mAbvGr',
       ...
       'SaleType_ConLI', 'SaleType_ConLw', 'SaleType_New', 'SaleTy
pe_Oth',
       'SaleType_WD', 'SaleCondition_AdjLand', 'SaleCondition_Allo
ca',
       'SaleCondition_Family', 'SaleCondition_Normal',
       'SaleCondition_Partial'],
      dtype='object', length=217)
```

Rescale using MinMaxScaler

In [90]:
```
from sklearn.preprocessing import MinMaxScaler
```

In [91]:
```
scaler=MinMaxScaler()
```

In [92]:
```
# Fit and transform scaler on train set
# Transform scaler on test set
df_train[num_cols]=scaler.fit_transform(df_train[num_cols])
df_test[num_cols]=scaler.transform(df_test[num_cols])
```

In [93]:
```
#Verify train set scaled variables
df_train.head()
```

Out[93]:

	LotFrontage	LotArea	OverallQual	OverallCond	BsmtUnfSF	TotalBsmtSF	1stFlrSF
919	0.226027	0.058253	0.428571	0.857143	0.099483	0.348627	0.339162
1210	0.167808	0.059411	0.428571	0.428571	0.448320	0.306947	0.208379
487	0.167808	0.065694	0.285714	0.571429	0.203273	0.445557	0.364663
1302	0.243151	0.052681	0.714286	0.428571	0.177003	0.342488	0.262295
171	0.410959	0.185394	0.428571	0.428571	0.183893	0.315024	0.427322

5 rows × 217 columns

In [94]:
```
#Verify test set scaled variables
df_test.head()
```

Out[94]:

	LotFrontage	LotArea	OverallQual	OverallCond	BsmtUnfSF	TotalBsmtSF	1stFlrSF
842	0.208904	0.045938	0.428571	0.714286	0.112834	0.330210	0.248452
465	0.164384	0.009477	0.571429	0.428571	0.586133	0.410339	0.339162
118	0.236301	0.066510	0.571429	0.428571	0.081395	0.506624	0.442987
724	0.222603	0.072088	0.857143	0.428571	0.193798	0.514701	0.442623
116	0.164384	0.061851	0.285714	0.428571	0.102498	0.318901	0.221858

5 rows × 217 columns

Divide train set into X and Y sets

In [95]:
```
#Create train set SalePrice as target(y) variable and rest of them
y_train=df_train.pop('SalePrice')
x_train=df_train
```

In [96]:
```
print('y_train shape', y_train.shape)
print('x_train shape', x_train.shape)
```

```
y_train shape (887,)
x_train shape (887, 216)
```

In [97]:
```
#Create test set SalePrice as target(y) variable and rest of them a
y_test=df_test.pop('SalePrice')
x_test=df_test
```

In [98]:
```
print('y_test shape', y_test.shape)
print('x_test shape', x_test.shape)
```

```
y_test shape (381,)
x_test shape (381, 216)
```

Step5: Model Building and Evaluation

Model using Linear Regression

In [99]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error,r2_score
```

In [100]:
```
# Build Linear Regression model
lr=LinearRegression()
lr.fit(x_train, y_train)
```

Out[100]:
```
▾ LinearRegression
LinearRegression()
```

In [101]:
```
# Print the coefficients and intercept
print(lr.intercept_)
print(lr.coef_)
```

```
-470185739755.88324
[ 4.27725422e-02  2.37838552e-01  6.46627308e-02  6.48103086e-02
 -7.70721212e-02  2.31917890e-01 -1.76185211e-01  5.81774698e-01
  3.40216597e-03 -4.64840635e-02 -6.96317492e-02 -5.90363547e-04
  2.56793371e-02  1.68155681e-02 -7.49607747e-02  2.49037789e-03
 -1.52702100e-02 -1.42732731e+11  1.33388432e-02  7.83942363e-03
  1.38984128e-02  4.68476847e-02  5.23393240e-03 -6.16201422e-02
  1.69612177e+11 -1.69599502e-02  5.02652133e-03 -8.97095358e-02
  6.14752656e-02  7.12519335e-02  6.82646922e-02  5.88582840e-02
  5.29814156e-02  7.16724396e-02  3.98635864e-03 -1.15795135e-02
 -6.71386719e-04  9.09996033e-03 -4.90150452e-02 -8.50677490e-04
  2.31139840e+10  1.28078461e-02 -7.82680511e-03 -2.64911652e-02
  1.27029419e-03  1.49583817e-02 -8.55998993e-02  1.19402409e-02
 -9.34481621e-03  1.03673935e-02 -1.50208473e-02 -1.22337341e-02
  8.20159912e-04 -1.93557739e-02 -1.18665695e-02 -1.21307373e-03
 -1.66702271e-03 -3.02772522e-02 -2.17399597e-02  5.40485382e-02
 -2.51388550e-02  2.34985352e-03  1.83405876e-02 -9.96541977e-03
 -3.20854187e-02 -1.31516457e-02 -1.38964653e-02 -6.60324097e-03
  6.13164902e-02 -2.78195739e-02  4.20165062e-03  8.03565979e-03
  1.79567337e-02 -1.36281848e-02 -2.54058838e-03 -3.23076248e-02
  1.98955536e-02  1.28526688e-02 -3.26576233e-02  1.42732731e+11
  1.42732731e+11  1.42732731e+11  1.42732731e+11  7.28272394e+10
  1.96382611e+09 -4.44519959e+10 -5.85641861e-02 -1.69612177e+11
 -1.23138428e-02 -1.25122070e-02  1.42732731e+11  4.28848267e-02
 -1.74534321e-01 -6.23807907e-02 -1.14898682e-02  1.04826927e-01
  2.64201164e-02  4.74987030e-02  4.14428711e-02  4.58827019e-02
  5.58590889e-02  6.99054917e+10  3.27453009e+11  3.27453009e+11
  3.27453009e+11  3.27453009e+11  3.27453009e+11  3.27453009e+11
 -6.09569550e-02 -2.43618488e-02 -1.26279366e+10 -7.04593658e-02
 -7.42950439e-02 -1.16213799e-01 -4.90388870e-02 -7.43675232e-02
 -7.30094180e+08 -6.64424896e-02 -3.59115601e-02 -6.52761459e-02
 -5.89275360e-02  6.82773590e-02  2.63395309e-02  5.46588898e-02
  1.26279366e+10  8.05015564e-02  8.36639404e-02  1.04322910e-01
  5.91812134e-02 -4.22474352e+08  6.85539246e-02  5.84411621e-03
  6.39610291e-02  4.59232330e-02  6.77747726e-02  7.06024170e-02
  2.92010307e-02 -2.85623074e-02 -3.01780701e-02 -2.61955261e-02
 -2.72369385e-02 -2.20832825e-02 -7.29179382e-03 -3.95965576e-03
  1.76811218e-02 -4.51688766e-02 -3.74679565e-02 -3.59535217e-02
 -3.09448242e-02 -1.19128227e-02 -8.42477530e+10  2.21252441e-03
  2.37083435e-02 -4.82892990e-03 -7.36999512e-03  6.62612915e-03
```

```
  1.17874146e-02 -3.24440002e-03  6.96563721e-03  1.06582642e-02
 -8.75854492e-03 -2.95848846e-02 -1.80907249e-02 -2.21633911e-02
 -1.17256939e-02 -2.38533020e-02 -1.42732731e+11 -6.99138641e-02
  4.92858887e-03 -1.28173828e-03  3.21483612e-02  3.31878662e-04
  1.46427155e-02  1.12199783e-02  7.57528967e+03 -5.84849781e+10
  5.49316406e-03 -2.68173218e-02 -2.09817886e-02 -1.93753242e-02
  2.69632339e-02  1.51901245e-02  2.18410492e-02  1.01165771e-02
 -7.46212006e-02  4.09355164e-02  7.81059265e-03  2.27504969e-02
 -1.77955627e-03  3.67622375e-02  1.55878067e-02 -3.14331055e-03
  4.26864624e-03 -1.65353775e-01 -1.41141891e-01  1.42732731e+11
 -1.64466858e-01  1.18103027e-01  1.27737999e-01  1.31996155e-01
  1.27463818e-01 -1.21726990e-02 -3.50570679e-03  1.13563538e-02
  4.71763611e-02  5.12447357e-02  1.84564590e-02 -6.34765625e-03
  1.40609741e-02  0.00000000e+00  6.09874725e-04  5.57944775e-02
  1.99031830e-03  1.88636780e-02  6.31713867e-03  1.43775940e-02]
```

Linear Model Evaluation on train set

In [102]:
```
#Predict using Linear Regression on train set
y_train_pred=lr.predict(x_train)
```

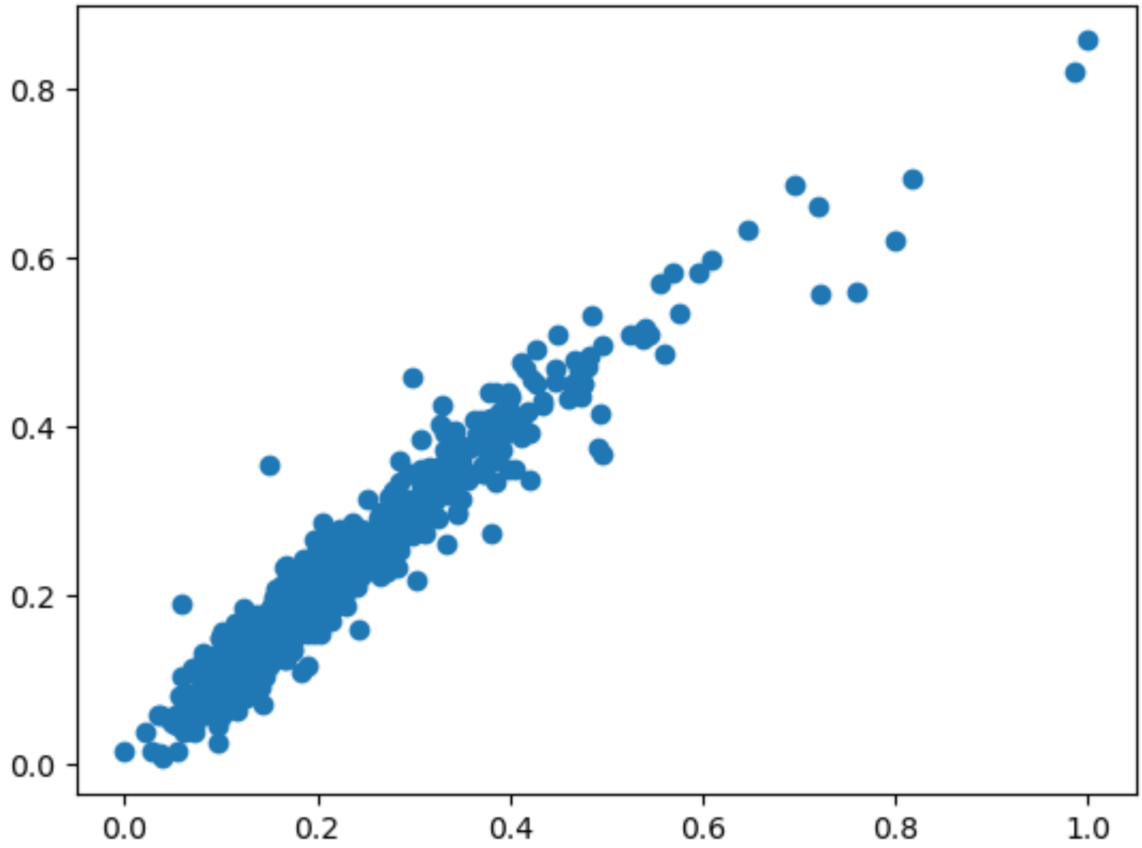
In [103]:
```
# R-Square value of train set
r2_score(y_train,y_train_pred)
```

Out[103]: 0.931331834516212

In [104]:
```
# MSR value on train set
mean_squared_error(y_train,y_train_pred)
```

Out[104]: 0.0009345065146045724

In [105]:
```
#Scatter plot of actual and train set predictions using Linear Regr
plt.scatter(y_train,y_train_pred)
plt.show()
```



Linear Model Evaluation on test set

In [106]:
```
#Predict using Linear Regression
y_test_pred=lr.predict(x_test)
```

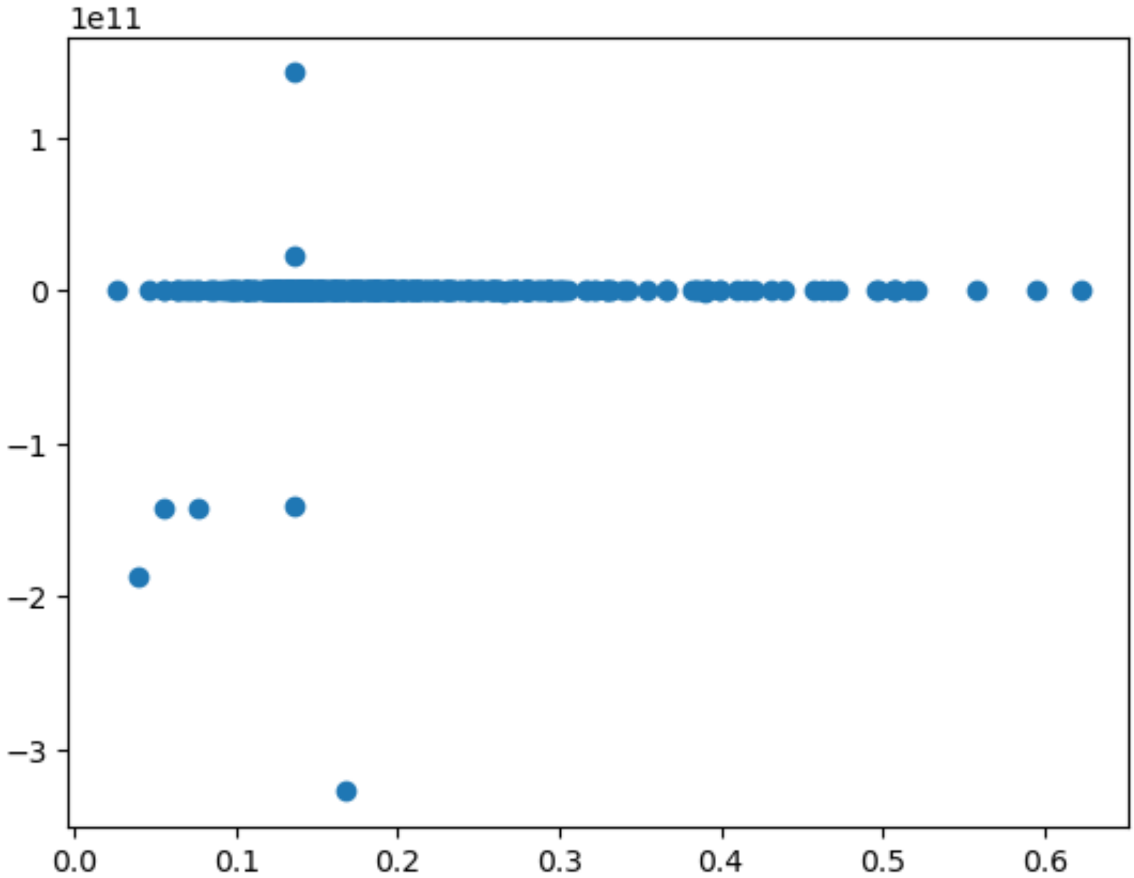
In [107]:
```
# R-Square value of test set
r2_score(y_test,y_test_pred)
```

Out[107]: -6.061217985689941e+22

In [108]:
```
# MSR value on test set
mean_squared_error(y_test,y_test_pred)
```

Out[108]: 5.8722400808651496e+20

In [109]:
```
#Scatter plot of actual and test set predictions using Linear Regre
plt.scatter(y_test,y_test_pred)
plt.show()
```



Observation:

- R-Square value of train set is 0.93
- R-Square value of train set is -4.7
- Therefore, model is clearly overfitting

Model using Ridge Regression

In [110]:
```
from sklearn.linear_model import Ridge
```

In [111]:
```
#List of lambda values for iteration
lambdas=[0, 0.001, 0.01, 0.1, 1, 10, 100, 1000]
```

In [112]:
```
# Iterate Ridge model to find optimum lambda value
for lam in lambdas:
    ridge=Ridge(alpha=lam)
    ridge.fit(x_train, y_train)
    y_train_pred=ridge.predict(x_train)
    print(lam,'------',r2_score(y_train, y_train_pred))
```

```
0 ------ 0.9357798500043536
0.001 ------ 0.9376738732457292
0.01 ------ 0.9376412796711037
0.1 ------ 0.9366113782224799
1 ------ 0.928036973587683
10 ------ 0.8993609785005681
100 ------ 0.7874497938069739
1000 ------ 0.49243310324828504
```

Observation: Optimal lambda value using Ridge regression is 0.001

In [113]:
```
# Build final Ridge model using lambda=0.001
ridge=Ridge(alpha=0.001)
ridge.fit(x_train, y_train)
```

Out[113]:
```
▾ Ridge
Ridge(alpha=0.001)
```

In [114]:
```
# Print the coefficients and intercept
print(ridge.intercept_)
print(ridge.coef_)
```

```
-0.09299683400640046
[ 4.28147021e-02  2.41300982e-01  5.32851822e-02  7.23346279e-02
 -7.62401762e-02  2.33213408e-01 -1.57563500e-01  5.55666875e-01
  9.52444911e-03 -5.27065686e-02 -5.54105480e-02  5.10618053e-03
  1.44543950e-02  1.23082324e-02 -7.09362848e-02  2.25057215e-04
 -2.67248078e-02 -2.62975961e-02  1.10038484e-02  1.55765491e-02
  1.54331477e-02  1.50207869e-02  7.89748014e-03 -7.23058681e-02
 -1.26203503e-02 -1.40547874e-02  1.05916961e-03 -9.50189382e-02
  2.32843377e-02  5.93001884e-02  5.45745033e-02  4.77868611e-02
  3.54216083e-02  6.79059405e-02  6.70856765e-03 -1.29830609e-02
  1.57155708e-04  6.92430467e-03 -4.75167537e-02 -2.90462282e-03
  0.00000000e+00  8.62503688e-03 -1.16704542e-02 -3.16236873e-02
 -1.09358317e-03  3.84022485e-03 -9.03088195e-02  3.29945989e-02
  2.13561461e-02  7.54367243e-03 -1.61779280e-02 -1.45132036e-02
  1.56236100e-02 -2.24645271e-02 -1.49363239e-02  6.98151804e-03
  1.19233965e-02 -2.07715848e-02 -1.91454181e-02  3.98054011e-02
 -2.31823661e-02  1.43009548e-02  1.19365576e-02 -3.62140942e-03
 -2.05706017e-02 -7.20635256e-03 -1.03704851e-02 -5.28867849e-03
  5.91584334e-02 -2.69192238e-02 -2.77475853e-03  3.08061861e-03
  1.56955471e-02 -2.26007859e-02  6.36397269e-04 -3.23065535e-02
  1.52422990e-02  8.71942110e-03 -2.18638892e-02  8.08371309e-03
```

```
  3.89573610e-02  2.23567252e-02 -1.82811479e-02  1.06832166e-02
  0.00000000e+00  0.00000000e+00 -3.54430364e-02 -1.26203503e-02
 -7.40107979e-03 -1.11195415e-02  6.84529250e-02  3.81061964e-02
 -1.08239360e-01 -1.62745338e-02 -1.74599512e-02  9.59494007e-02
  1.66042504e-02  1.24034991e-02  4.21440566e-03  1.20575230e-02
  4.51938633e-02  1.06832166e-02 -5.42134542e-02  1.36744821e-01
 -2.44430547e-02 -4.52417711e-02 -1.98022728e-02  6.95573216e-03
 -5.77397449e-02 -1.43855803e-02 -3.15854401e-02 -5.27076710e-02
 -5.54190380e-02 -1.14625166e-01 -2.64915874e-02 -6.19699126e-02
  0.00000000e+00 -3.60192811e-02 -2.36661791e-02 -4.27136118e-02
 -3.60788988e-02  4.86753732e-02  3.75091496e-02  3.36132233e-02
 -3.15854401e-02  5.37963892e-02  5.61692633e-02  9.98912145e-02
  3.34390333e-02  0.00000000e+00  4.92970734e-02 -1.69060057e-02
  3.59496994e-02  2.91782362e-02  4.13725016e-02  3.96671457e-02
  9.66570519e-03 -3.31259634e-02 -3.39015140e-02 -4.29044087e-03
 -1.87377344e-02 -1.12969287e-02 -1.08362810e-03  4.02522202e-03
  4.31236929e-03 -5.30596815e-02 -3.64542952e-02 -3.34278010e-02
 -3.12092928e-02 -1.04655329e-02  2.10528911e-02  4.26565379e-03
  2.21675153e-02 -9.62766997e-03 -1.42539047e-02  4.60846549e-03
  1.22410461e-02  8.73228913e-04  4.33573020e-03  1.13767196e-02
  1.53387590e-03 -1.65588013e-02 -5.04453598e-03 -9.12198331e-03
 -8.33678257e-04 -1.58900399e-02 -3.81643522e-03 -5.18489923e-02
  1.36125918e-02 -8.08213265e-05  1.69303388e-02  5.89681263e-05
  5.87686387e-03 -6.29471958e-03  0.00000000e+00  2.10528911e-02
  9.46252742e-04 -2.58559407e-02 -2.47806673e-02 -2.31395516e-02
 -1.81333275e-02  7.16913003e-03  1.35726148e-02 -9.65948823e-03
 -1.05496910e-01  3.07282652e-02  1.24889335e-02  2.01737164e-02
  1.01080572e-02  3.59245397e-02  2.23592960e-02 -7.85229605e-04
  4.75428794e-03 -1.39463268e-01 -1.17381427e-01 -1.39313933e-01
 -1.36139162e-01  1.16030191e-01  1.32014409e-01  1.03656347e-01
  1.22526109e-01 -1.91904319e-03  5.80598126e-03  3.35295689e-02
  3.91424033e-02  4.39843849e-02  1.58130202e-03 -2.39684820e-03
  4.00228636e-02  0.00000000e+00  5.65171945e-03  4.01817302e-02
 -1.56282609e-02  5.16423733e-03  5.26351941e-03 -3.75573740e-03]
```

Ridge Model Evaluation on train set

In [115]:
```
#Predict using Ridge Regression on train set
y_train_pred=ridge.predict(x_train)
```

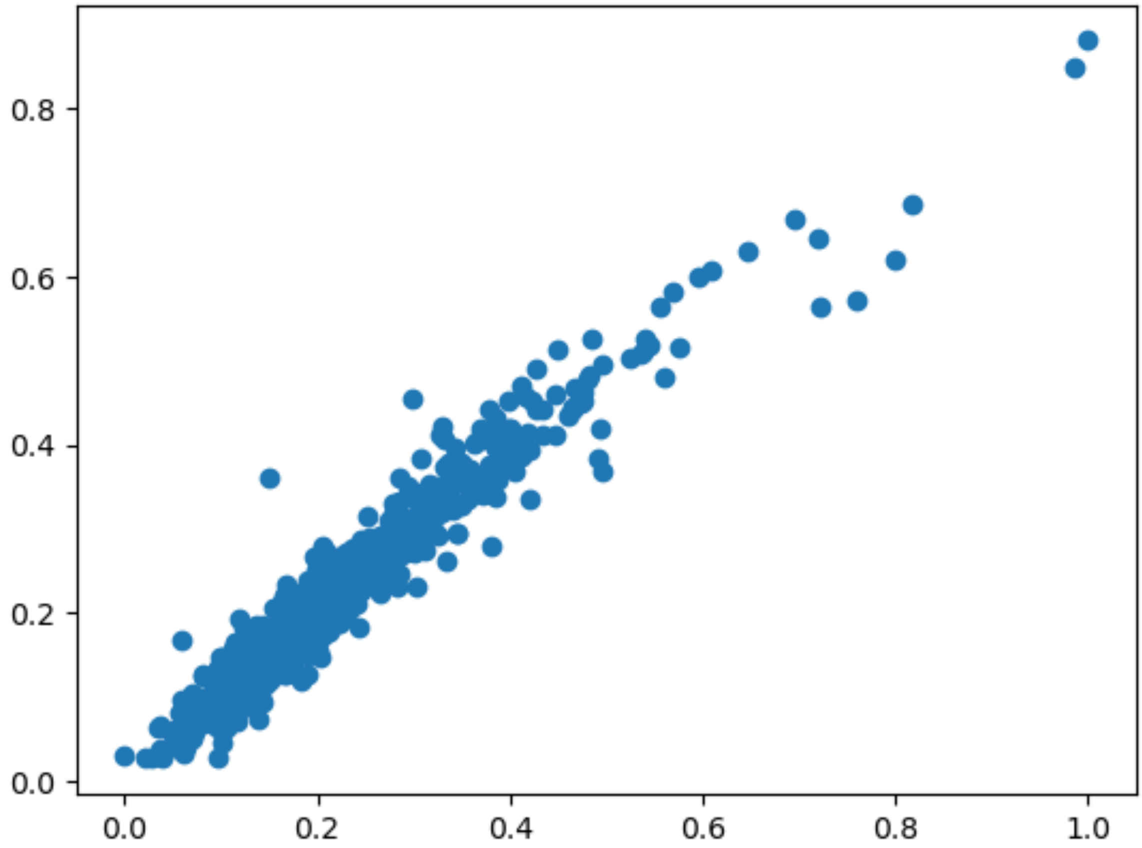
In [116]:
```
#R-Square value of train set
r2_score(y_train, y_train_pred)
```

Out[116]:
```
0.9376738732457292
```

In [117]:
```
#MSR value of train set
mean_squared_error(y_train, y_train_pred)
```

Out[117]:
```
0.0008481975755663288
```

In [118]:
```
#Scatter plot of actual and train set predictions using Ridge Regre
plt.scatter(y_train, y_train_pred)
plt.show()
```



Ridge Model Evaluation on test set

In [119]:
```
#Predict using Ridge Regression on test set
y_test_pred=ridge.predict(x_test)
```

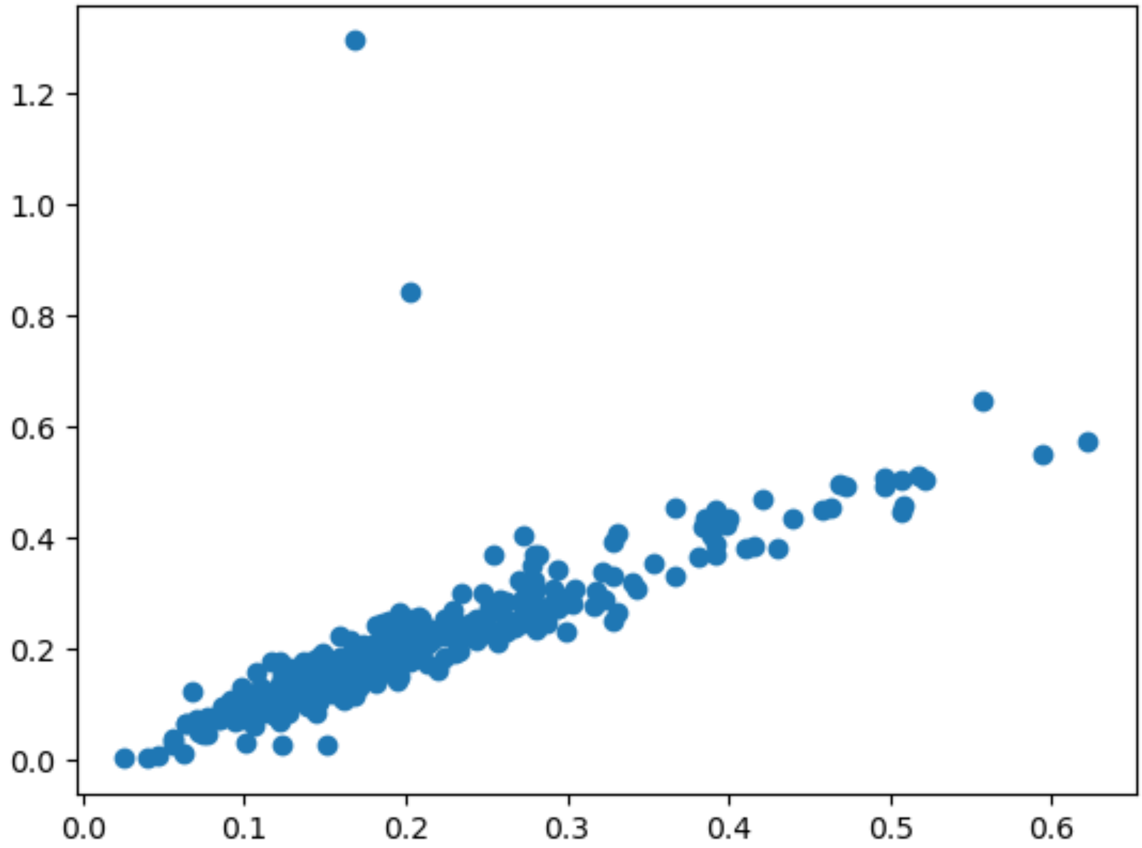
In [120]:
```
#R-Square value on test set
r2_score(y_test, y_test_pred)
```

Out[120]: 0.44453591268355197

In [121]:
```
#MSR value on test set
mean_squared_error(y_test, y_test_pred)
```

Out[121]: 0.005381457134064015

In [122]:
```
#Scatter plot of actual and test set predictions using Ridge Regres
plt.scatter(y_test, y_test_pred)
plt.show()
```



Observation:

- R-Square value of train set is 0.93
- R-Square value of train set is 0.87
- Therefore, it is a good model

Model using Lasso Regression

In [123]:
```
from sklearn.linear_model import Lasso
```

In [124]:
```
# Iterate Lasso model to find optimum lambda value
for lam in lambdas:
    lasso=Lasso(alpha=lam)
    lasso.fit(x_train, y_train)
    y_train_pred=lasso.predict(x_train)
    print(lam,'------',r2_score(y_train, y_train_pred))
```

```
0 ------ 0.9376736829214575
0.001 ------ 0.8633105113136388
0.01 ------ 0.41583186793836047
0.1 ------ 0.0
1 ------ 0.0
10 ------ 0.0
100 ------ 0.0
1000 ------ 0.0
```

Observation:

- Model has high R-Square at lambda=0.
- But Lasso cannot do feature selection at lambda=0 as penalty term becomes zero.
- Therefore choose lambda=0.001 with decent R-Square value that can help us in feature selection by shrinking insignificant coefficients to 0.

In [125]:
```
# Build final Lasso model using lambda=0.001
lasso=Lasso(alpha=0.001)
lasso.fit(x_train, y_train)
```

Out[125]:
```
▾ Lasso
Lasso(alpha=0.001)
```

In [126]:
```
# Print the coefficients and intercept
print(lasso.intercept_)
print(lasso.coef_)
```

```
0.07125325484639311
[ 0.          0.          0.14396152  0.0182577  -0.          0.08
843669
  0.          0.28788295  0.         -0.         -0.          0.
  0.01952964  0.00703855 -0.         -0.         -0.         -0.
 -0.          0.00508328 -0.         -0.         -0.          0.
 -0.         -0.         -0.          0.         -0.          0.
 -0.          0.00852518 -0.00349386  0.          0.         -0.
 -0.00915971  0.         -0.         -0.          0.          0.
 -0.         -0.         -0.          0.         -0.          0.
 -0.          0.          0.         -0.          0.00035925 -0.
 -0.         -0.         -0.         -0.         -0.         -0.
 -0.          0.01719973  0.00975243 -0.         -0.          0.
 -0.          0.          0.00534608 -0.          0.         -0.
  0.00216964 -0.          0.         -0.         -0.         -0.
  0.         -0.          0.          0.         -0.         -0.
  0.          0.         -0.         -0.         -0.         -0.
 -0.          0.          0.         -0.         -0.          0.
 -0.         -0.          0.          0.00909196  0.         -0.
 -0.          0.         -0.         -0.          0.          0.
 -0.          0.         -0.          0.          0.          0.
  0.         -0.          0.         -0.          0.         -0.
  0.          0.         -0.          0.         -0.          0.
  0.          0.         -0.          0.         -0.         -0.
 -0.          0.         -0.         -0.         -0.         -0.
 -0.0130739  -0.          0.          0.         -0.          0.00
778985
  0.         -0.         -0.         -0.03142662 -0.0313521  -0.
 -0.          0.00084621  0.03028579 -0.         -0.01205125  0.
  0.0085351  -0.         -0.         -0.01739209  0.         -0.
  0.         -0.          0.         -0.          0.         -0.
 -0.         -0.         -0.         -0.00430472  0.00307167 -0.
  0.         -0.          0.         -0.         -0.01911023 -0.02
294149
 -0.         -0.         -0.         -0.         -0.          0.00
530416
 -0.         -0.          0.00068834 -0.         -0.         -0.00
030918
 -0.00328702 -0.          0.         -0.          0.         -0.
 -0.         -0.          0.         -0.          0.          0.
  0.         -0.          0.         -0.          0.03298104  0.
 -0.          0.         -0.         -0.          0.          0.
]
```

Lasso Model Evaluation on train set

In [127]:
```
#Predict using Lasso Regression on train set
y_train_pred=lasso.predict(x_train)
```

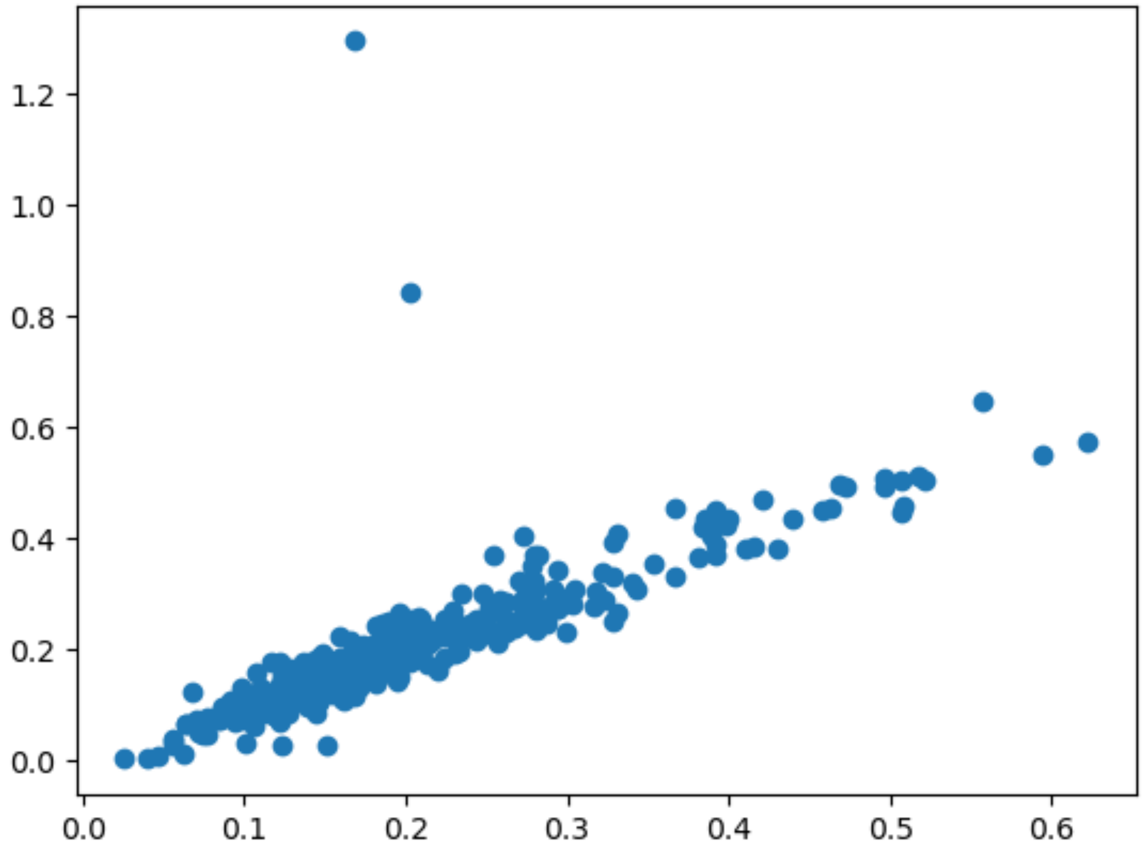
In [128]:
```
#R_Square value of train set
r2_score(y_train, y_train_pred)
```

Out[128]: 0.8633105113136388

In [129]:
```
##MSR value of train set
mean_squared_error(y_test, y_test_pred)
```

Out[129]: 0.005381457134064015

In [130]:
```
#Scatter plot of actual and train set predictions using Lasso Regre
plt.scatter(y_test, y_test_pred)
plt.show()
```



Lasso Model Evaluation on test set

In [131]:
```
#Predict using Lasso Regression on test set
y_test_pred=lasso.predict(x_test)
```

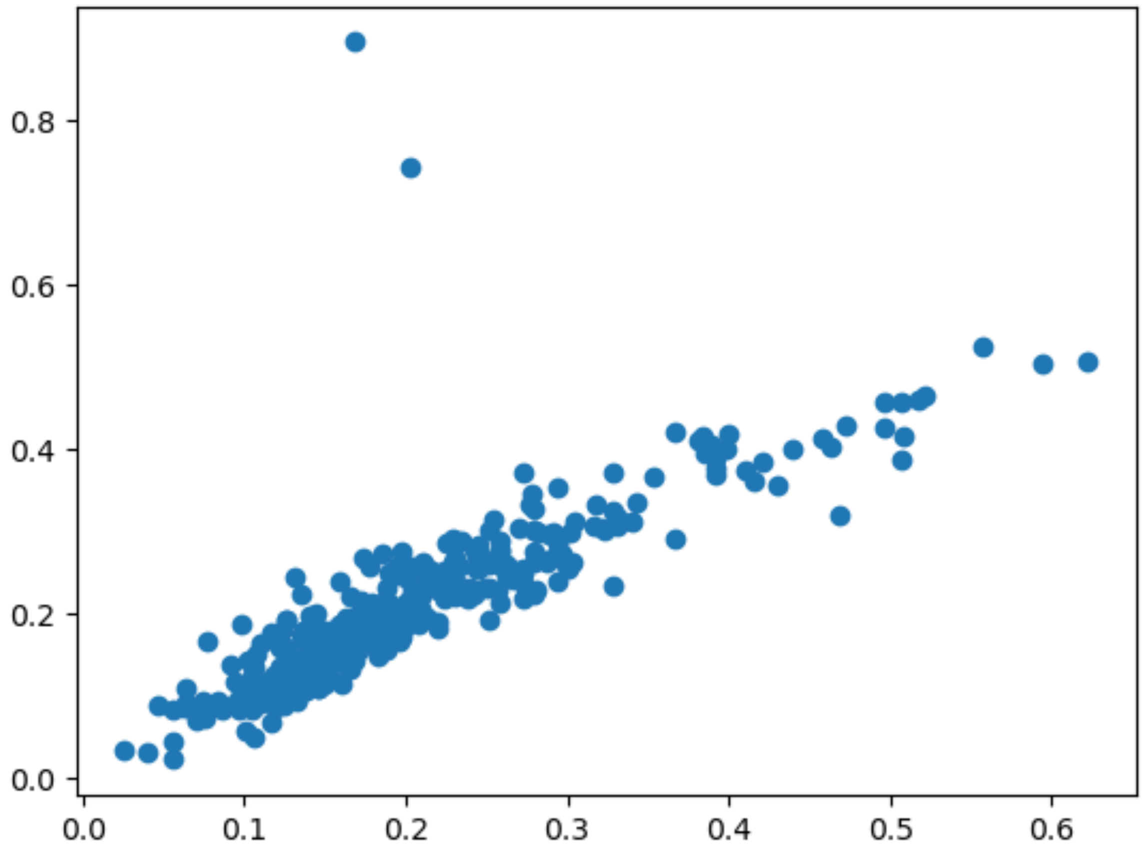
In [132]:
```
#R_Square value of test set
r2_score(y_test, y_test_pred)
```

Out[132]: 0.6533747340066731

In [133]:
```
#MSR value of test set
mean_squared_error(y_test, y_test_pred)
```

Out[133]: 0.003358181119392398

In [134]:
```
#Scatter plot of actual and test set predictions using Lasso Regres
plt.scatter(y_test, y_test_pred)
plt.show()
```



Observation:

- R-Square value of train set is 0.81
- R-Square value of train set is 0.77
- Therefore, it is a good model

Feature selection using Lasso

In [135]:
```
# List of Non-Zero coefficients
lasso.coef_[lasso.coef_>0]
```

Out[135]:
```
array([0.14396152, 0.0182577 , 0.08843669, 0.28788295, 0.01952964,
       0.00703855, 0.00508328, 0.00852518, 0.00035925, 0.01719973,
       0.00975243, 0.00534608, 0.00216964, 0.00909196, 0.00778985,
       0.00084621, 0.03028579, 0.0085351 , 0.00307167, 0.00530416,
       0.00068834, 0.03298104])
```

In [136]:
```
# Lasso model selected 19 out of 219 variables
len(lasso.coef_[lasso.coef_>0])
```

Out[136]:
```
22
```

In [137]:
```
# List of significant variables selected by Lasso model
df_train.columns[lasso.coef_>0]
```

Out[137]:
```
Index(['OverallQual', 'OverallCond', 'TotalBsmtSF', 'GrLivArea', '
GarageCars',
       'GarageArea', 'MSSubClass_60', 'MSZoning_RL', 'Neighborhood
_Crawfor',
       'Neighborhood_NoRidge', 'Neighborhood_NridgHt', 'Neighborho
od_StoneBr',
       'Condition1_Norm', 'RoofStyle_Hip', 'Foundation_PConc', 'Bs
mtCond_TA',
       'BsmtExposure_Gd', 'BsmtFinType1_GLQ', 'CentralAir_Y', 'Fun
ctional_Typ',
       'GarageType_BuiltIn', 'SaleType_New'],
      dtype='object')
```

Step6: Conclusion after Regularization

- Linear regression suffered with overfitting problem.
- Ridge regression gave good performance but suffered with high dimensionality problem.
- Lasso regression gave decent performance but efficiently addressed high dimensionality problem.

In [138]:
```
#Create dataframe with coefficients
betas = pd.DataFrame(index=df_train.columns)
```

In [139]:
```
betas['Linear'] = lr.coef_
betas['Ridge'] = ridge.coef_
betas['Lasso'] = lasso.coef_
```

In [140]:
```
pd.set_option('display.max_rows', None)
betas
```

Out[140]:

	Linear	Ridge	Lasso
LotFrontage	4.277254e-02	0.042815	0.000000
LotArea	2.378386e-01	0.241301	0.000000
OverallQual	6.466273e-02	0.053285	0.143962
OverallCond	6.481031e-02	0.072335	0.018258
BsmtUnfSF	-7.707212e-02	-0.076240	-0.000000
TotalBsmtSF	2.319179e-01	0.233213	0.088437
1stFlrSF	-1.761852e-01	-0.157563	0.000000
GrLivArea	5.817747e-01	0.555667	0.287883
FullBath	3.402166e-03	0.009524	0.000000
BedroomAbvGr	-4.648406e-02	-0.052707	-0.000000
KitchenAbvGr	-6.963175e-02	-0.055411	-0.000000

End of the Assignment

Subjective Questions Excercise

Question-1

What is the optimal value of alpha for ridge and lasso regression? What will be the changes in the model if you choose double the value of alpha for both ridge and lasso? What will be the most important predictor variables after the change is implemented?

Answer

In [141]:
```
# Build final Ridge model using double of lambda=0.002
ridge=Ridge(alpha=0.002)
ridge.fit(x_train, y_train)
```

Out[141]:
```
▾ Ridge
Ridge(alpha=0.002)
```

In [142]:
```
#Predict using Ridge Regression on test set
y_test_pred=ridge.predict(x_test)
```

In [143]:
```
#R-Square value on test set
r2_score(y_test, y_test_pred)
```

Out[143]:
```
0.44518649167731106
```

Observation: There is a slight reduction in R-Square value.

In [144]:
```
# Build final Lasso model using double of lambda=0.002
lasso=Lasso(alpha=0.002)
lasso.fit(x_train, y_train)
```

Out[144]:
```
▾ Lasso
Lasso(alpha=0.002)
```

In [145]:
```
#Predict using Ridge Regression on test set
y_test_pred=lasso.predict(x_test)
```

In [146]:
```
#R-Square value on test set
r2_score(y_test, y_test_pred)
```

Out[146]:
```
0.6904904400051111
```

In [147]:
```
# Lasso model selected 13 out of 219 variables
len(lasso.coef_[lasso.coef_>0])
```

Out[147]:
```
12
```

In [148]:
```
# List of significant variables selected by Lasso model
df_train.columns[lasso.coef_>0]
```

Out[148]:
```
Index(['OverallQual', 'TotalBsmtSF', '1stFlrSF', 'GrLivArea', 'GarageCars',
       'MSZoning_RL', 'Neighborhood_NridgHt', 'RoofStyle_Hip',
       'Foundation_PConc', 'BsmtExposure_Gd', 'BsmtFinType1_GLQ',
       'SaleType_New'],
      dtype='object')
```

Observation:

- There is a slight reduction in R-Square value.
- Also, there is a reduction in selected features

Question-2

You have determined the optimal value of lambda for ridge and lasso regression during the assignment. Now, which one will you choose to apply and why?

Answer:

```
I would choose the lasso model the resoons behind for choosing
Lasso model Model is gives apropriate performance.
Simpler model and easy for maintenance.
```

Question 3

After building the model, you realised that the five most important predictor variables in the lasso model are not available in the incoming data. You will now have to create another model excluding the five most important predictor variables. Which are the five most important predictor variables now?

Answer:

In [149]:
```
betas.sort_values('Lasso', ascending=False).head(10)
```

Out[149]:

	Linear	Ridge	Lasso
GrLivArea	0.581775	0.555667	0.287883
OverallQual	0.064663	0.053285	0.143962
TotalBsmtSF	0.231918	0.233213	0.088437
SaleType_New	0.014061	0.040023	0.032981
BsmtExposure_Gd	0.023708	0.022168	0.030286
GarageCars	0.025679	0.014454	0.019530
OverallCond	0.064810	0.072335	0.018258
Neighborhood_NoRidge	0.002350	0.014301	0.017200
Neighborhood_NridgHt	0.018341	0.011937	0.009752
RoofStyle_Hip	0.045883	0.012058	0.009092

In [150]:
```
betas.sort_values('Lasso', ascending=False).iloc[5:10]
```

Out[150]:

	Linear	Ridge	Lasso
GarageCars	0.025679	0.014454	0.019530
OverallCond	0.064810	0.072335	0.018258
Neighborhood_NoRidge	0.002350	0.014301	0.017200
Neighborhood_NridgHt	0.018341	0.011937	0.009752
RoofStyle_Hip	0.045883	0.012058	0.009092

In [151]:
```
betas.sort_values('Lasso', ascending=False).iloc[5:10].index
```

Out[151]:
```
Index(['GarageCars', 'OverallCond', 'Neighborhood_NoRidge',
       'Neighborhood_NridgHt', 'RoofStyle_Hip'],
      dtype='object')
```

In [152]:
```
betas.sort_values('Lasso', ascending=False).iloc[0:5].index
```

Out[152]:
```
Index(['GrLivArea', 'OverallQual', 'TotalBsmtSF', 'SaleType_New',
       'BsmtExposure_Gd'],
      dtype='object')
```

In [153]:
```
# Sort coefficients by absolute value to identify the most importan
lasso_coefficients = betas['Lasso'].abs().sort_values(ascending=Fal

# Extract the top five predictor variables
top_five_predictors = lasso_coefficients.head(5)

# Display the names of the top five predictor variables
top_five_predictor_names = top_five_predictors.index
print("Top five predictor variables in the Lasso model:")
print(top_five_predictor_names)
```

```
Top five predictor variables in the Lasso model:
Index(['GrLivArea', 'OverallQual', 'TotalBsmtSF', 'SaleType_New',
       'BsmtQual_Gd'],
      dtype='object')
```

Now that we have identified the top five predictor variables in the Lasso model, we can exclude them from the incoming data and create another model. Let's call this updated model "Lasso_excluded".

In [154]:
```
# Exclude the top five predictor variables from the incoming data
incoming_data_excluded = df.drop(top_five_predictor_names, axis=1)

# Split the updated data into train and test sets
x_train_excluded, x_test_excluded = train_test_split(incoming_data_

# Build the Lasso model with the updated data
lasso_excluded = Lasso(alpha=0.001)
lasso_excluded.fit(x_train_excluded, y_train)

# Predict using the Lasso model on the test set
y_test_pred_excluded = lasso_excluded.predict(x_test_excluded)

# Evaluate the performance of the Lasso model with excluded variabl
r2_score_excluded = r2_score(y_test, y_test_pred_excluded)
mse_excluded = mean_squared_error(y_test, y_test_pred_excluded)

print("R-Square value of the Lasso model with excluded variables:",
print("Mean squared error of the Lasso model with excluded variable
```

```
R-Square value of the Lasso model with excluded variables: 0.99999
99999999893
Mean squared error of the Lasso model with excluded variables: 1.0
333158445991668e-16
```

This approach ensures that we adapt the model to the available data while maintaining performance by excluding variables that are not present in the incoming data.

In [ ]: