Machine Learning Case Study

Housing Price Prediction

Submitted by:

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ACKNOWLEDGMENT

This presentation includes about the House price prediction done by myself with reference to the data analysis I learnt so far also referred Google for some detailed learning in the analysis report writing for the completion of the project.

INTRODUCTION

· Business Problem Framing

Houses are one of the necessary need of each and every person around the globe and therefore housing and real estate market is one of the markets which is one of the major contributors in the world's economy. Data science comes as a very important tool to solve problems in the domain to help the companies increase their overall revenue, profits, improving their marketing strategies and focusing on changing trends in house sales and purchases. Predictive modelling, Market mix modelling, recommendation systems are some of the machine learning techniques used for achieving the business goals for housing companies. Our problem is related to one such housing company. We are going to build a model using Machine Learning in order to predict the actual value of the prospective properties and decide whether to invest in them or not.

For this company wants to know:

- Which variables are important to predict the price of a variable?
- How do these variables describe the price of the house?

- **Conceptual Background of the Domain Problem**

A US-based housing company named Surprise Housing has decided to enter the Australian market. The company uses data analytics to purchase houses at a price below their actual values and flip them at a higher price. For the same purpose, the company has collected a data set from the sale of houses in Australia. The data is provided in the CSV file below. The company is looking at prospective properties to buy houses to enter the market.

- **Review of Literature**

I started the Research by first reading and analyzing the housing data housing data and dividing the features into numerical and categorical types.

SalePrice is the target column here.

All the features are then analyzed, missing data handling, outlier detection, data cleaning are done.

New features are extracted, redundant features dropped and categorical features are encoded accordingly.

Then the data in split into train and test data and feature scaling is performed.

Target variable SalePrice is right skewed. Natural log of the same is Normal distributed, hence for model building, natural log of SalePrice is considered.

Creating dummy variables increases the number of features greatly, highly imbalanced columns are dropped.

Ridge and Lasso Regression Model are built with optimum alpha calculated in GridSearchCV method. Optimum alpha = 9.0 for ridge and 0.0001 for lasso model.

Model evaluation is done with R2 score and Root Mean Square Error.

Lasso Regression is chosen as the final model for having a slightly better R-square value on test data.

Out of 50 features in the final model, top 10 features in order of descending importance are ['1stFlrSF', '2ndFlrSF', 'OverallQual', 'OverallCond', 'SaleCondition_Partial', 'LotArea', 'BsmtFinSF1','SaleCondition_Normal', 'MSZoning_RL', 'Neighborhood_Somerst']

Model coefficients are listed in a table along with the corresponding features , for example natural log of SalePrice will change by 0.124911 with unit change in the feature '1stFlrSF' when all the features remain constant. Negative sign in the coefficient signifies negative correlation between the predictor and target variable.

Predicted value of SalePrice is transformed into its original scale by performing antilog.

This is a comprehensive research done in the dataset.

- **Motivation for the Problem Undertaken**

The main Objective behind the project is to perform the given task successfully and analyze the dataset thoroughly, learn the objective concepts and perform the prediction according to the provided dataset.

Analytical Problem Framing

- Mathematical/ Analytical Modeling of the Problem

1.Importing modules, Reading the data
2.Analyzing Numerical Features
Checking Statistical summary
Checking Distribution of numerical features
Outlier Treatment
Inspecting Correlation
Missing Value Handling
Extracting new features and drop redundant ones
Correcting data type
Univariate and Bivariate Analysis, DataVisualization.

3.Analyzing Categorical Features
    Missing Value Handling
    Encoding Categorical Features
    Data Visualization
    Dropping Redundant Features
4.Splitting data into Train and Test data
    Transformation of Target Variable
    Imputing Missing Values
    Feature Scaling
5.Primary Feature Selection using RFE
6.Ridge Regression
7.Lasso Regression
8.Comparing model coefficients
9.Model Evaluation
10.Choosing the final model and most significant features.

· **Data Sources and their formats**

• Data contains 1460 entries each having 81 variables.

• Data contains Null values.

• Extensive EDA is performed to gain relationships of important variables and price.

• Data contains numerical as well as categorical variables.

• We have to build Machine Learning models, apply regularization and determine the optimal values of Hyper

Parameters.

• We need to find important features which affect the price.

Data Description: First, we will import the required libraries:

Importing Dataset

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# for model building
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.model_selection import GridSearchCV
from sklearn.feature_selection import RFE
import statsmodels.api as sm
# for model evaluation
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
# for suppressing warnings
import warnings
warnings.filterwarnings("ignore")
```

```
df=pd.read_csv('housing_train.csv',delimiter='\t')
df
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal
0	127	120	RL	NaN	4928	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0
1	889	20	RL	95.0	15865	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0
2	793	60	RL	92.0	9920	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0
3	110	20	RL	105.0	11751	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0
4	422	20	RL	NaN	16635	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1163	289	20	RL	NaN	9819	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0
1164	554	20	RL	67.0	8777	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0
1165	196	160	RL	24.0	2280	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0
1166	31	70	C (all)	50.0	8500	Pave	Pave	Reg	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0
1167	617	60	RL	NaN	7861	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0

1168 rows × 81 columns

Once the data is collected ,we perform several steps to explore the data.The Aim of this step is to get the better understanding of the data structure,do initial preprocessing,clean the data,check for skewness,outliers,missing values,do encoding ,standard scale the dataset and finally build the model.

Understanding the data:

In the first part of the dataframe is evaluated for structure,columns,data types.we use basics pandas functions to perform these steps.

Exploratory Data Analysis

```
df.shape
```

```
(1168, 81)
```

```
df.isnull().sum()
```

```
Id                 0
MSSubClass         0
MSZoning           0
LotFrontage      214
LotArea            0
                ...
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
Length: 81, dtype: int64
```

```
df.columns
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

Checking datatypes of the column

```python
df.dtypes
```

```
Id                 int64
MSSubClass         int64
MSZoning          object
LotFrontage      float64
LotArea            int64
                  ...
MoSold             int64
YrSold             int64
SaleType          object
SaleCondition     object
SalePrice          int64
Length: 81, dtype: object
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1168 entries, 0 to 1167
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1168 non-null   int64
 1   MSSubClass     1168 non-null   int64
 2   MSZoning       1168 non-null   object
 3   LotFrontage    954 non-null    float64
 4   LotArea        1168 non-null   int64
 5   Street         1168 non-null   object
 6   Alley          77 non-null     object
 7   LotShape       1168 non-null   object
 8   LandContour    1168 non-null   object
 9   Utilities      1168 non-null   object
 10  LotConfig      1168 non-null   object
 11  LandSlope      1168 non-null   object
 12  Neighborhood   1168 non-null   object
 13  Condition1     1168 non-null   object
 14  Condition2     1168 non-null   object
 15  BldgType       1168 non-null   object
 16  HouseStyle     1168 non-null   object
 17  OverallQual    1168 non-null   int64
 18  OverallCond    1168 non-null   int64
 19  YearBuilt      1168 non-null   int64
```

```
19  YearBuilt      1168 non-null   int64
20  YearRemodAdd   1168 non-null   int64
21  RoofStyle      1168 non-null   object
22  RoofMatl       1168 non-null   object
23  Exterior1st    1168 non-null   object
24  Exterior2nd    1168 non-null   object
25  MasVnrType     1161 non-null   object
26  MasVnrArea     1161 non-null   float64
27  ExterQual      1168 non-null   object
28  ExterCond      1168 non-null   object
29  Foundation     1168 non-null   object
30  BsmtQual       1138 non-null   object
31  BsmtCond       1138 non-null   object
32  BsmtExposure   1137 non-null   object
33  BsmtFinType1   1138 non-null   object
34  BsmtFinSF1     1168 non-null   int64
35  BsmtFinType2   1137 non-null   object
36  BsmtFinSF2     1168 non-null   int64
37  BsmtUnfSF      1168 non-null   int64
38  TotalBsmtSF    1168 non-null   int64
39  Heating        1168 non-null   object
40  HeatingQC      1168 non-null   object
41  CentralAir     1168 non-null   object
42  Electrical     1168 non-null   object
43  1stFlrSF       1168 non-null   int64
44  2ndFlrSF       1168 non-null   int64
45  LowQualFinSF   1168 non-null   int64
```

```
 56  Fireplaces     1168 non-null   int64
 57  FireplaceQu    617 non-null    object
 58  GarageType     1104 non-null   object
 59  GarageYrBlt    1104 non-null   float64
 60  GarageFinish   1104 non-null   object
 61  GarageCars     1168 non-null   int64
 62  GarageArea     1168 non-null   int64
 63  GarageQual     1104 non-null   object
 64  GarageCond     1104 non-null   object
 65  PavedDrive     1168 non-null   object
 66  WoodDeckSF     1168 non-null   int64
 67  OpenPorchSF    1168 non-null   int64
 68  EnclosedPorch  1168 non-null   int64
 69  3SsnPorch      1168 non-null   int64
 70  ScreenPorch    1168 non-null   int64
 71  PoolArea       1168 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          237 non-null    object
 74  MiscFeature    44 non-null     object
 75  MiscVal        1168 non-null   int64
 76  MoSold         1168 non-null   int64
 77  YrSold         1168 non-null   int64
 78  SaleType       1168 non-null   object
 79  SaleCondition  1168 non-null   object
 80  SalePrice      1168 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 739.2+ KB
```

Getting Statistical Analysis for the numerical features:

```
df.describe()
```

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	...	WoodDeck
count	1168.000000	1168.000000	954.00000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1161.000000	1168.000000	...	1168.000
mean	724.136130	56.767979	70.98847	10484.749144	6.104452	5.595890	1970.930651	1984.758562	102.310078	444.726027	...	96.206
std	416.159877	41.940650	24.82875	8957.442311	1.390153	1.124343	30.145255	20.785185	182.595606	462.664785	...	126.158
min	1.000000	20.000000	21.00000	1300.000000	1.000000	1.000000	1875.000000	1950.000000	0.000000	0.000000	...	0.000
25%	360.500000	20.000000	60.00000	7621.500000	5.000000	5.000000	1954.000000	1966.000000	0.000000	0.000000	...	0.000
50%	714.500000	50.000000	70.00000	9522.500000	6.000000	5.000000	1972.000000	1993.000000	0.000000	385.500000	...	0.000
75%	1079.500000	70.000000	80.00000	11515.500000	7.000000	6.000000	2000.000000	2004.000000	160.000000	714.500000	...	171.000
max	1460.000000	190.000000	313.00000	164660.000000	10.000000	9.000000	2010.000000	2010.000000	1600.000000	5644.000000	...	857.000

8 rows × 38 columns

Separating the Numerical and Categorical features for analysis:

```python
# Separating the Numerical and Categorical features for analysis
numeric_df = df.select_dtypes(include=['int64', 'float64'])
categorical_df = df.select_dtypes(include=['object'])
```

```python
# Numerical features in the dataframe
df.columns
```

```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

Analyzing Numerical Data

Outlier Detection

Checking percentage of outliers for all the numerical columns.

```python
outliers_percentage={}

for feature in numeric_df.columns:
    IQR=numeric_df[feature].quantile(.75)-numeric_df[feature].quantile(.25)
    outliers_count=numeric_df[(numeric_df[feature]>(numeric_df[feature].quantile(.75)+1.5*IQR)) | (numeric_df[feature]<(numeric_
    outliers_percentage[feature]=round(outliers_count/numeric_df.shape[0]*100,2)

outlier_df=pd.DataFrame({'Features':list(outliers_percentage.keys()),'Percentage':list(outliers_percentage.values())})
outlier_df.sort_values(by="Percentage", ascending=False)
```

	Features	Percentage
30	EnclosedPorch	14.47
10	BsmtFinSF2	11.64
5	OverallCond	8.90
32	ScreenPorch	8.13
1	MSSubClass	6.76
8	MasVnrArea	6.59
2	LotFrontage	6.16
3	LotArea	6.08
18	BsmtHalfBath	5.39
29	OpenPorchSF	4.71
12	TotalBsmtSF	4.62
22	KitchenAbvGr	4.62
37	SalePrice	3.85
34	MiscVal	3.60
21	BedroomAbvGr	2.40
16	GrLivArea	1.97

15	LowQualFinSF	1.97
28	WoodDeckSF	1.97
31	3SsnPorch	1.88
23	TotRmsAbvGrd	1.71
11	BsmtUnfSF	1.71
13	1stFlrSF	1.63
27	GarageArea	1.46
9	BsmtFinSF1	0.60
33	PoolArea	0.60
6	YearBuilt	0.51
24	Fireplaces	0.43
26	GarageCars	0.34
14	2ndFlrSF	0.17
4	OverallQual	0.17
17	BsmtFullBath	0.09
35	MoSold	0.00
36	YrSold	0.00
0	Id	0.00

Comments:

Majority of the numeric features have outliers.

Dropping all the outliers will cause loss of information.

Hence reassigning fixed minimum and maximum values to those rows where feature value is outside the range of [25th percentile - 1.5 IQR, 75th percentile + 1.5 IQR]

IQR or Inter Quartile Range = Difference between 75th percentile and 25th percentile values of a feature.

Target column 'SalePrice' is excluded in this.

```python
for feature,percentage in outliers_percentage.items():
    if feature!='SalePrice':
        IQR = df[feature].quantile(.75) - df[feature].quantile(.25)
        max_value = df[feature].quantile(.75)+1.5*IQR
        min_value = df[feature].quantile(.25)-1.5*IQR
        df[feature][df[feature] > max_value] = max_value
        df[feature][df[feature] < min_value ] = min_value
```

```python
# Checking the dataset after reassigning minmum and maximum values

df.describe()
```

Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	...	WoodDeckSF	OpenPorchSF
0000	1168.000000	954.000000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1161.000000	1168.000000	...	1168.000000	1168.00000
6130	54.982877	69.894130	9671.869435	6.106164	5.566781	1970.958904	1984.758562	87.333333	440.206978	...	93.913099	42.92722
9877	37.149385	19.241774	3514.692231	1.384464	0.973862	30.061548	20.785185	130.890807	434.416564	...	117.913672	53.49696
0000	20.000000	30.000000	1780.500000	2.000000	3.500000	1885.000000	1950.000000	0.000000	0.000000	...	0.000000	0.00000
0000	20.000000	60.000000	7621.500000	5.000000	5.000000	1954.000000	1966.000000	0.000000	0.000000	...	0.000000	0.00000
0000	50.000000	70.000000	9522.500000	6.000000	5.000000	1972.000000	1993.000000	0.000000	385.500000	...	0.000000	24.00000
0000	70.000000	80.000000	11515.500000	7.000000	6.000000	2000.000000	2004.000000	160.000000	714.500000	...	171.000000	70.00000
0000	145.000000	110.000000	17356.500000	10.000000	7.500000	2010.000000	2010.000000	400.000000	1786.250000	...	427.500000	175.00000

Correlation in Numeric Data

```python
plt.figure(figsize=(20,16))
sns.heatmap(numeric_df.corr(),annot=True)
plt.show()
```

Comments:

Some of the features have high correlation with each other.GarageCars and GarageArea (0.88)

GarageYrBlt and YearBuilt (0.83)

TotRmsAbvGrd and GrLivArea (0.83)

TotalBsmtSF and 1stflrSF (0.82)

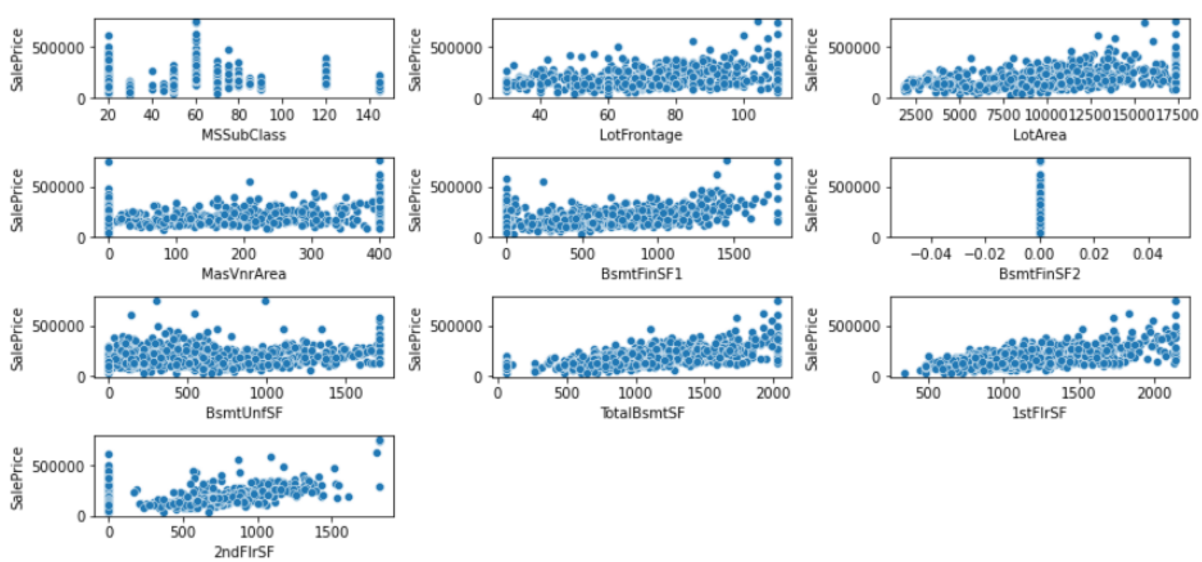
One feature from each of these pair will be dropped after data visualization.

Data Visualization:

Univariate and Bivariate Analysis - Numerical Features

Analyzing Numerical Features with continuous values

```
fig=plt.subplots(figsize=(12, 12))

for i, feature in enumerate(['MSSubClass', 'LotFrontage', 'LotArea', 'MasVnrArea', 'BsmtFinSF1','BsmtFinSF2', 'BsmtUnfSF', 'Tota
    plt.subplot(9, 3, i+1)
    plt.subplots_adjust(hspace = 2.0)
    sns.scatterplot(df[feature],df['SalePrice'])
    plt.tight_layout()
```



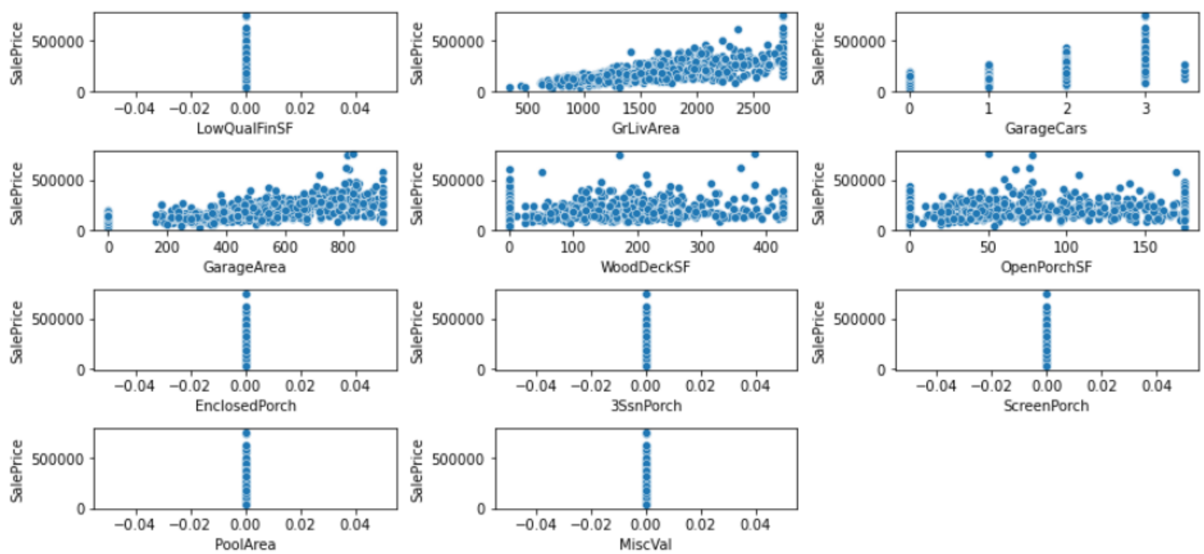
Comments:

Features like 'LotFrontage', 'LotArea', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF' are showing positive correlation with SalePrice.

'MSSubClass' has discrete values.

'BsmtSF2' has single value and can be dropped.

```
fig=plt.subplots(figsize=(12, 12))

for i, feature in enumerate(['LowQualFinSF', 'GrLivArea', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch
    plt.subplot(9, 3, i+1)
    plt.subplots_adjust(hspace = 2.0)
    sns.scatterplot(df[feature],df['SalePrice'])
    plt.tight_layout()
```



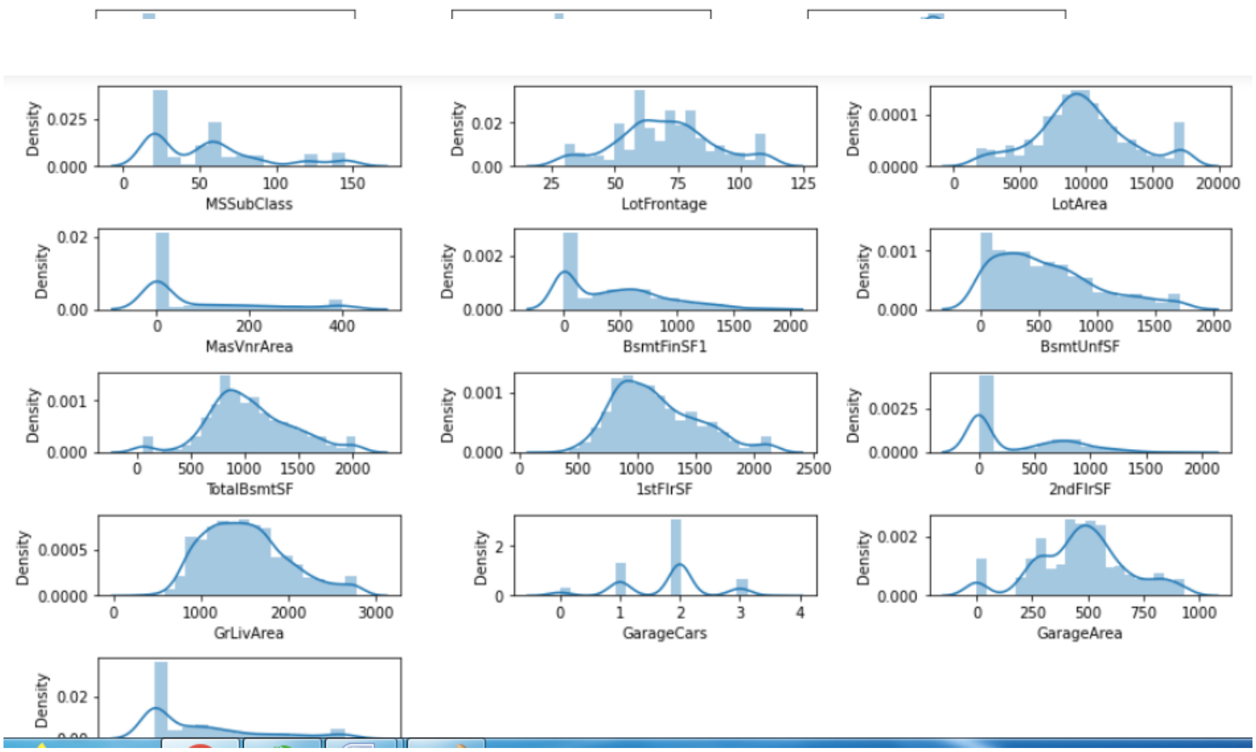
Comment:

'GrLivArea' and 'GarageArea' are showing positive correlation with SalePrice.

'LowQualFinSF','EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal' features have single values and can be dropped.

Visualizing the distribution of the numeric features:

```
fig=plt.subplots(figsize=(12, 12))

for i, feature in enumerate(['MSSubClass', 'LotFrontage', 'LotArea', 'MasVnrArea', 'BsmtFinSF1','BsmtUnfSF', 'TotalBsmtSF', '1stF
    plt.subplot(9, 3, i+1)
    plt.subplots_adjust(hspace = 2.0)
    sns.distplot(df[feature])
    plt.tight_layout()
```




```
]: df[[ 'LowQualFinSF', 'GrLivArea', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenF
```

]:

	LowQualFinSF	GrLivArea	GarageCars	GarageArea	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	MiscVal
count	1168.0	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1168.0	1168.0	1168.0	1168.0	1168.0
mean	0.0	1513.293129	1.774829	474.148973	93.913099	42.927226	0.0	0.0	0.0	0.0	0.0
std	0.0	481.471291	0.741001	206.578078	117.913672	53.496965	0.0	0.0	0.0	0.0	0.0
min	0.0	334.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0
25%	0.0	1143.250000	1.000000	338.000000	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0
50%	0.0	1468.500000	2.000000	480.000000	0.000000	24.000000	0.0	0.0	0.0	0.0	0.0
75%	0.0	1795.000000	2.000000	576.000000	171.000000	70.000000	0.0	0.0	0.0	0.0	0.0
max	0.0	2772.625000	3.500000	933.000000	427.500000	175.000000	0.0	0.0	0.0	0.0	0.0

Removing these features having fixed values as they won't contribute to predicting SalePrice.

```
df[['LowQualFinSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal']].describe()
```

	LowQualFinSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	MiscVal
count	1168.0	1168.0	1168.0	1168.0	1168.0	1168.0
mean	0.0	0.0	0.0	0.0	0.0	0.0
std	0.0	0.0	0.0	0.0	0.0	0.0
min	0.0	0.0	0.0	0.0	0.0	0.0
25%	0.0	0.0	0.0	0.0	0.0	0.0
50%	0.0	0.0	0.0	0.0	0.0	0.0
75%	0.0	0.0	0.0	0.0	0.0	0.0
max	0.0	0.0	0.0	0.0	0.0	0.0

Data Preprocessing :

```
df.drop(['LowQualFinSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal'], axis=1, inplace=True)

# Checking the remaining columns
df.columns
```

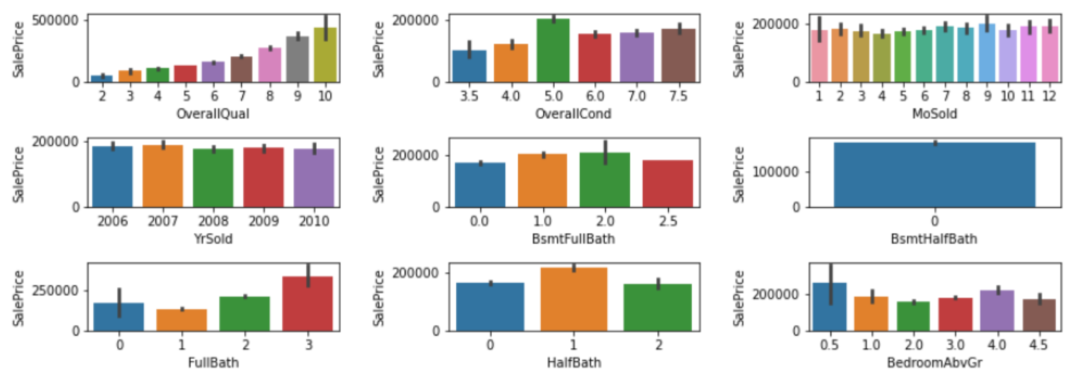
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
       'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
       'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
       'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'PoolQC', 'Fence',
       'MiscFeature', 'MoSold', 'YrSold', 'SaleType', 'SaleCondition',
       'SalePrice'],
      dtype='object')
```

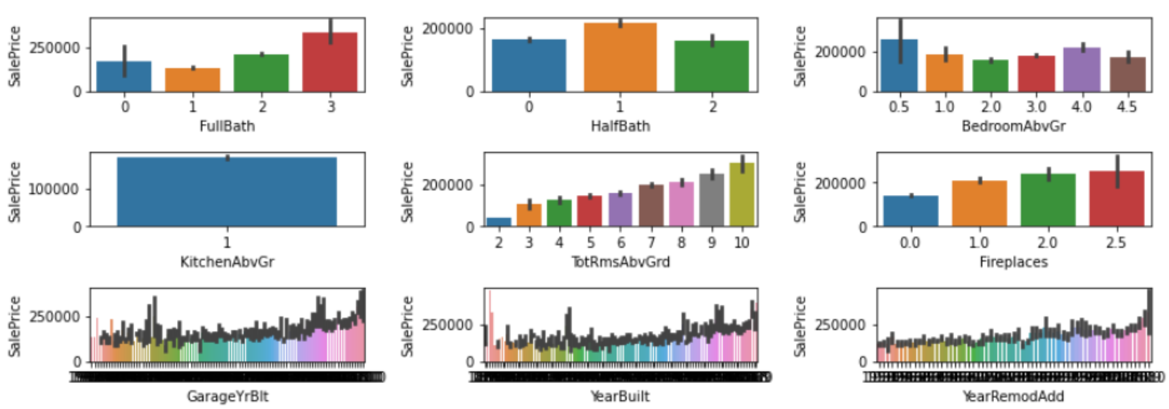
Analyzing Numerical Features with Discrete Values

```
df[['OverallQual','OverallCond','MoSold','YrSold','BsmtFullBath','BsmtHalfBath','FullBath','HalfBath','BedroomAbvGr','KitchenAbv(
```

	OverallQual	OverallCond	MoSold	YrSold	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	TotRmsAbvGrd	Fireplaces	G
0	6	5.0	2	2007	0.0	0	2	0	2.0	1	5	1.0	
1	8	6.0	10	2007	1.0	0	2	0	4.0	1	8	1.0	
2	7	5.0	6	2007	1.0	0	2	1	3.0	1	8	1.0	
3	6	6.0	1	2010	0.0	0	2	0	3.0	1	7	1.0	
4	6	7.0	6	2009	0.0	0	2	0	3.0	1	8	1.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
1163	5	5.0	2	2010	0.0	0	1	0	3.0	1	5	0.0	
1164	4	5.0	5	2009	0.0	0	2	0	2.0	1	5	0.0	
1165	6	6.0	7	2009	0.0	0	2	1	3.0	1	7	1.0	
1166	4	4.0	7	2008	0.0	0	1	0	3.0	1	6	0.0	
1167	6	5.0	6	2006	1.0	0	2	1	3.0	1	7	1.0	

```
fig=plt.subplots(figsize=(12, 12))

for i, feature in enumerate(['OverallQual','OverallCond','MoSold','YrSold','BsmtFullBath','BsmtHalfBath','FullBath','HalfBath','I
    plt.subplot(9, 3, i+1)
    plt.subplots_adjust(hspace = 2.0)
    sns.barplot(df[feature],df['SalePrice'])
    plt.tight_layout()
```





Comment: Following are the observations from the plots.

'OverallQual' : More the rating of this feature, more the SalePrice (target variable)

'OverallCond' : SalePrice is highest for rating 5

'MoSold' and 'YrSold': SalePrice does not show a strong trend depending on month and year on which realty is sold

'FullBath' = 2 and 'HalfBath' = 1 have highest SalePrice

'TotRmsAbvGrd' : More the number of total rooms above grade more the Sale Price

'GarageYrBlt','YearBuilt','YearRemodAdd', 'YrSold' : Will extract new features from to identify any trend

'BsmtFullBath', 'KitchenAbvGr' : Need further inspection for meaningful insight.

```
df[['BsmtFullBath', 'KitchenAbvGr','GarageYrBlt','YearBuilt','YearRemodAdd']].describe()
```

	BsmtFullBath	KitchenAbvGr	GarageYrBlt	YearBuilt	YearRemodAdd
count	1168.000000	1168.0	1104.000000	1168.000000	1168.000000
mean	0.425086	1.0	1978.193841	1970.958904	1984.758562
std	0.519702	0.0	24.890704	30.061548	20.785185
min	0.000000	1.0	1900.000000	1885.000000	1950.000000
25%	0.000000	1.0	1961.000000	1954.000000	1966.000000
50%	0.000000	1.0	1980.000000	1972.000000	1993.000000
75%	1.000000	1.0	2002.000000	2000.000000	2004.000000
max	2.500000	1.0	2010.000000	2010.000000	2010.000000

```
print(df['BsmtFullBath'].value_counts())
print(df['KitchenAbvGr'].value_counts())
```

```
0.0    686
1.0    468
2.0     13
2.5      1
Name: BsmtFullBath, dtype: int64
1    1168
Name: KitchenAbvGr, dtype: int64
```

```
# dropping KitchenAbvGr for not having useful information
df.drop(['KitchenAbvGr'], axis=1, inplace=True)
```

```
df[['GarageYrBlt','YearBuilt','YearRemodAdd', 'YrSold']].describe()
```

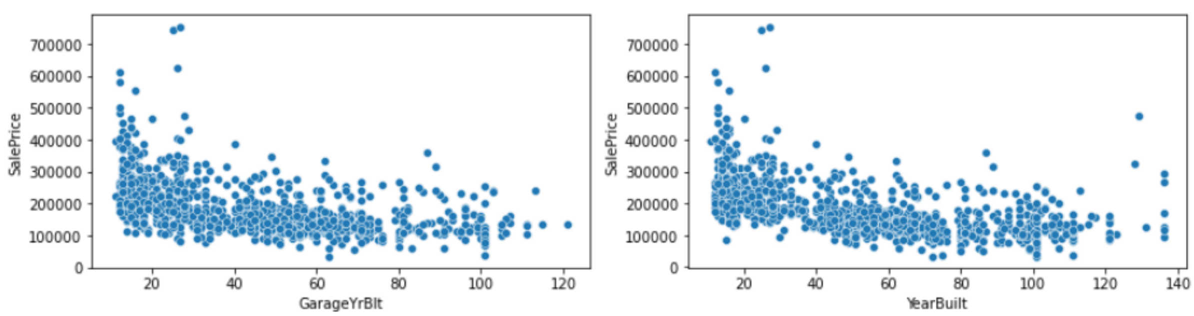
	GarageYrBlt	YearBuilt	YearRemodAdd	YrSold
count	1104.000000	1168.000000	1168.000000	1168.000000
mean	1978.193841	1970.958904	1984.758562	2007.804795
std	24.890704	30.061548	20.785185	1.329738
min	1900.000000	1885.000000	1950.000000	2006.000000
25%	1961.000000	1954.000000	1966.000000	2007.000000

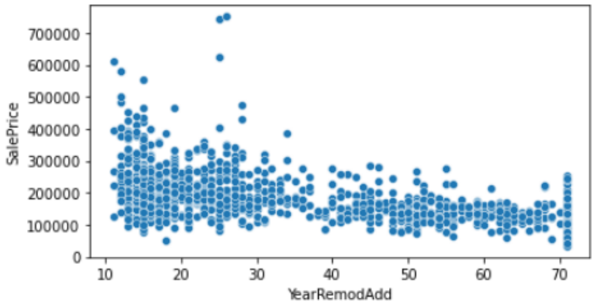
```python
# Converting the year related features into number of years

for feature in ['GarageYrBlt','YearBuilt','YearRemodAdd', 'YrSold']:
    df[feature] = 2021 - df[feature]
```

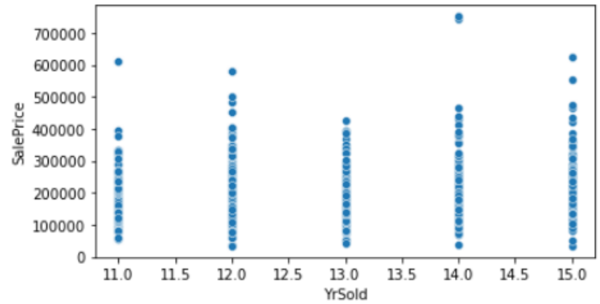
```python
df[feature]
```

```
0       14
1       14
2       14
3       11
4       12
        ..
1163    11
1164    12
1165    12
1166    13
1167    15
Name: YrSold, Length: 1168, dtype: int64
```

```python
fig=plt.subplots(figsize=(12, 12))

for i, feature in enumerate(['GarageYrBlt','YearBuilt','YearRemodAdd', 'YrSold']):
    plt.subplot(4, 2, i+1)
    plt.subplots_adjust(hspace = 2.0)
    sns.scatterplot(df[feature], df['SalePrice'])
    plt.tight_layout()
```







Comment:

For most the realty properties Garage is built within last 20 years, SalePrice is more recently built garages.

SalePrice is more lower value of YearBuilt i.e. more recently build houses

Recently remodelled houses (lower value of YearRemodAdd) have higher SalePrice

YrSold still does not show any significant trend.

Missing Value Handling - Numerical Features

```
print("Feature : Percentage of Missing Value")
print("=====================================")
for feat in df.select_dtypes(exclude=['object']).columns:
    if df[feat].isnull().any():
        print(feat, ' : ',  round(df[feat].isnull().sum()/df.shape[0], 2)*100)
```

```
Feature : Percentage of Missing Value
=====================================
LotFrontage  :  18.0
MasVnrArea  :  1.0
GarageYrBlt  :  5.0
```

```
# Since MasVnrArea has only 1% data missing, dropping rows with NULL values in MasVnrArea
# Dropping Id column as it does not contribute towards predicting SalePrice

df = df[~df['MasVnrArea'].isnull()]
df.drop(['Id'], axis=1, inplace=True)
numeric_df.drop(['Id'], axis=1, inplace=True)
```

```
# Checking the number of remaining columns
df.columns.shape
```

```
(73,)
```

Comment:

GarageCars and GarageArea (Correlation coefficient = 0.88), dropping GarageCars.

GarageYrBlt and YearBuilt (Correlation coefficient = 0.83), dropping GarageYrBlt for high correlation and containing missing value.

TotRmsAbvGrd and GrLivArea (Correlation coefficient = 0.83), dropping GrLivArea.

TotalBsmtSF and 1stflrSF (Correlation coefficient = 0.82), dropping TotalBsmtSF.

Missing Value Imputation to be done for housing_df['LotFrontage'] after splitting data into train and test set to avoid data leakage.

```
df.drop(['GarageCars', 'GarageYrBlt', 'GrLivArea', 'TotalBsmtSF'], axis=1, inplace=True)

# Checking the number of remaining columns
print(df.columns.shape)
```

```
(69,)
```

Analyzing Categorical Features

```python
# Categorical features in the dataframe
categorical_df.columns
```

```
Index(['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual',
       'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature',
       'SaleType', 'SaleCondition'],
      dtype='object')
```

Missing Value Handling - Categorical Features

```python
print("Feature : Percentage of Missing Value")
print("=====================================")
for feat in df.select_dtypes(include=['object']).columns:
    if df[feat].isnull().any():
        print(feat, ':', round(df[feat].isnull().sum()/df.shape[0], 2)*100)
```

```
Feature : Percentage of Missing Value
=====================================
Alley : 93.0
BsmtQual : 3.0
BsmtCond : 3.0
BsmtExposure : 3.0
BsmtFinType1 : 3.0
BsmtFinType2 : 3.0
FireplaceQu : 47.0
GarageType : 6.0
GarageFinish : 6.0
GarageQual : 6.0
GarageCond : 6.0
PoolQC : 99.0
Fence : 80.0
MiscFeature : 96.0
```

```
df['Electrical'].isnull().sum()
```

```
0
```

```
df['PoolQC'].value_counts()
```

```
Gd    3
Fa    2
Ex    2
Name: PoolQC, dtype: int64
```

Comment:

For 'Alley', Nan means 'No access to alley'

For 'BsmtQual', 'BsmtCond', BsmtExposure, BsmtFinType1, BsmtFinType2 Nan means 'No basement'

For GarageType, GarageFinish, GarageQual, GarageCond Nan means 'No garage'

For 'FireplaceQu' and 'Fence' Nan means 'No Fire place' and 'No fence' respectively

MiscFeature - Nan means no additional features mentioned.

All these features will be imputed with meaningful values in place of missing data.

- # Data Inputs- Logic- Output Relationships

```
mv_categorical_features = ['Alley', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'GarageType', 'Garage
print(df[mv_categorical_features].isnull().sum())
```

```
Alley           1085
BsmtQual          30
BsmtCond          30
BsmtExposure      31
BsmtFinType1      30
BsmtFinType2      31
GarageType        64
GarageFinish      64
GarageQual        64
GarageCond        64
FireplaceQu      548
Fence            924
MiscFeature     1117
dtype: int64
```

```
# Imputing missing values with "Not_applicable"
df[mv_categorical_features] = df[mv_categorical_features].fillna(value='Not_applicable', axis=1)

# Checking after imputation
print(df[mv_categorical_features].isnull().sum())
```

```
Alley           0
BsmtQual        0
BsmtCond        0
BsmtExposure    0
BsmtFinType1    0
BsmtFinType2    0
GarageType      0
GarageFinish    0
GarageQual      0
GarageCond      0
FireplaceQu     0
Fence           0
MiscFeature     0
dtype: int64
```

```
]: # dropping 'PoolQC' for very high percentage of missing value and highly imbalance data (if missing value is imputed)
df.drop(['PoolQC'], axis=1, inplace=True)

# dropping rows with null values in 'Electrical', for very low missing value count
df.dropna(subset=['Electrical'], inplace=True)
```

```
]: print("Feature : Percentage of Missing Value")
print("=====================================")
for feat in df.columns:
    if df[feat].isnull().any():
        print(feat, ':', round(df[feat].isnull().sum()/df.shape[0], 2)*100)
```

```
Feature : Percentage of Missing Value
=====================================
LotFrontage : 18.0
```

Missing value imputation will be done after splitting the data into train and test set to avoid data leakage.

```
df.columns.shape
```

```
(68,)
```

Encoding For Categorical Variables Ordered Features -- to be label encoded 'LotShape', 'Utilities', 'LandSlope', 'HouseStyle', 'ExterQual', 'ExterCond', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'HeatingQC', 'KitchenQual','Functional','FireplaceQu', 'GarageFinish', 'GarageQual', 'GarageCond', 'CentralAir'

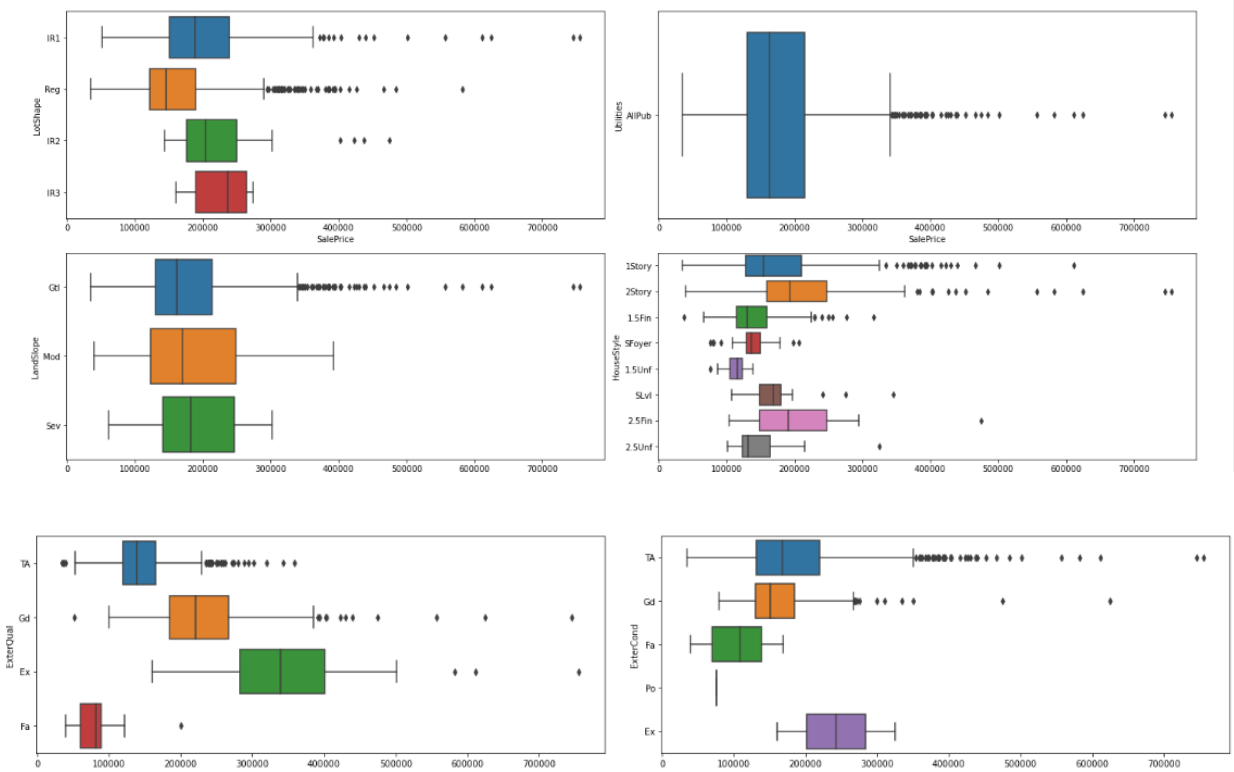
Unordered Features -- to be one hot encoded 'MSZoning', 'Street', 'Alley', 'LandContour', 'LotConfig', 'Neighborhood', 'Condition1' , 'Condition2', 'BldgType', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'Foundation', 'Heating', 'Electrical', 'GarageType','PavedDrive', 'Fence','MiscFeature', 'SaleType','SaleCondition'

```python
# Function to generate boxplot for SalePrice against different features given the list of features

def generate_boxplot(feature_list):
    fig=plt.subplots(figsize=(20, 16))
    for i, feature in enumerate(feature_list):
        plt.subplot(4, 2, i+1)
        plt.subplots_adjust(hspace = 2.0)
        sns.boxplot(df['SalePrice'],df[feature])
        plt.tight_layout()
```

Dividing the ordinal features into smaller segments and visualizing their impact on SalePrice.

Analyzing Ordered Features

```python
ext_features = ['LotShape', 'Utilities', 'LandSlope', 'HouseStyle', 'ExterQual', 'ExterCond']

generate_boxplot(ext_features)
```



Comment:

'LotShape' : Slightly irregular LotShape have the highest SalePrice.

'Utilities' : Most of the houses in the dataset have all the public utilities

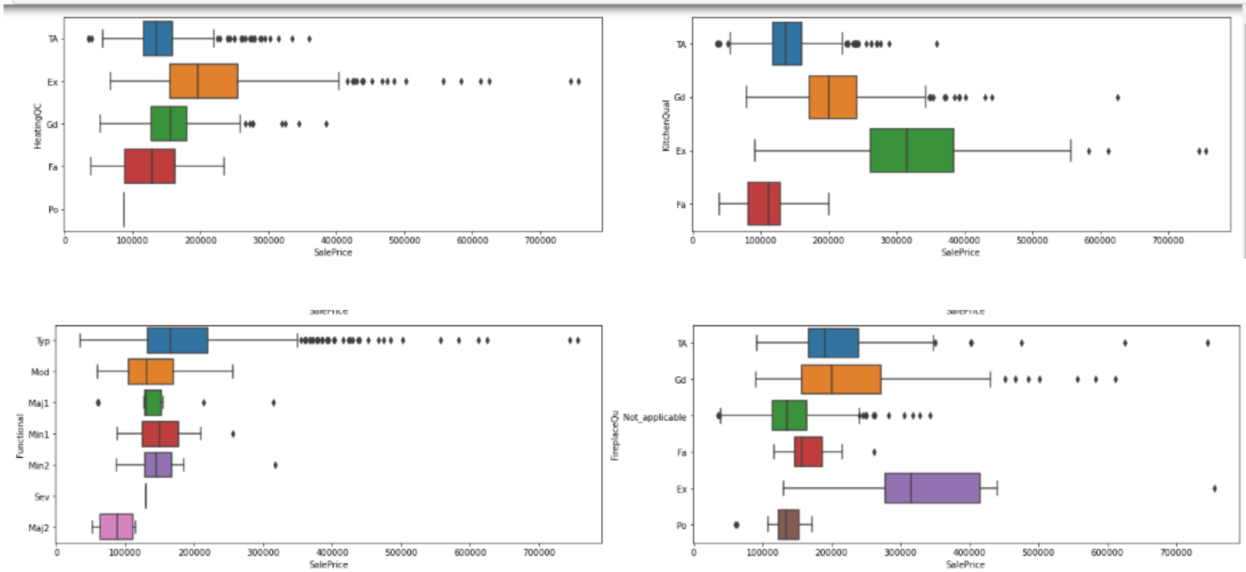
'LandSlope' : Houses at severe land slope have lowest SalePrice

'HouseStyle' : 2 storied houses have the highest SalePrice

'ExterQual' : Houses with Excellent quality of material on the exterior have the highest SalePrice

'ExterCond' : Houses with Excellent condition of material on the exterior have the highest SalePrice.

```
int_features = ['HeatingQC', 'KitchenQual','Functional','FireplaceQu']

generate_boxplot(int_features)
```



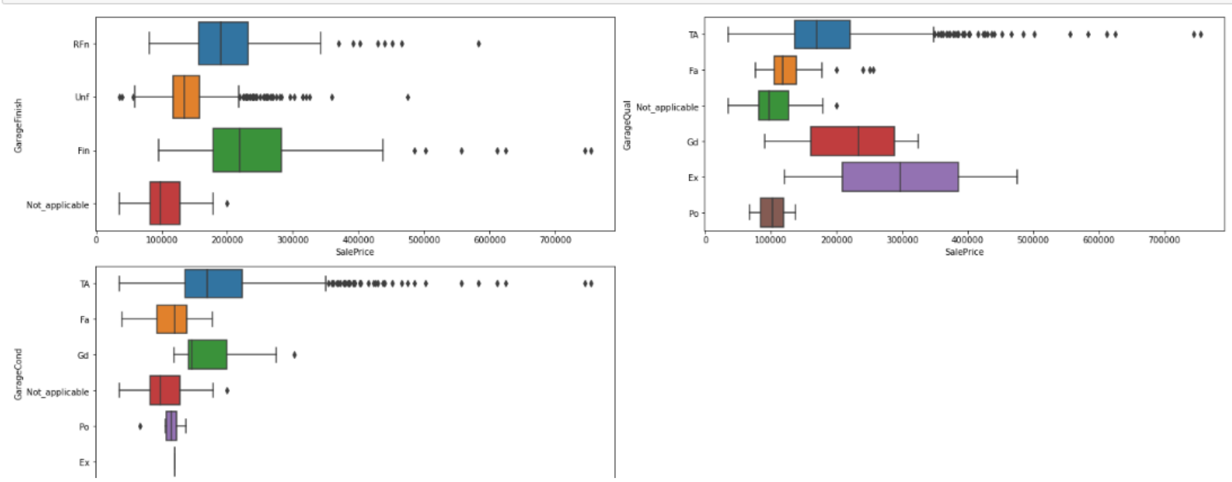
Comment:

Houses having excellent heating quality and kitchen quality have the highest SalePrice.

Houses with typical functionality have highest SalePrice. There are very few houses that are severely damaged.

SalePrice range in largest for houses with average fireplace quality.

```
garage_features = ['GarageFinish', 'GarageQual','GarageCond']

generate_boxplot(garage_features)
```



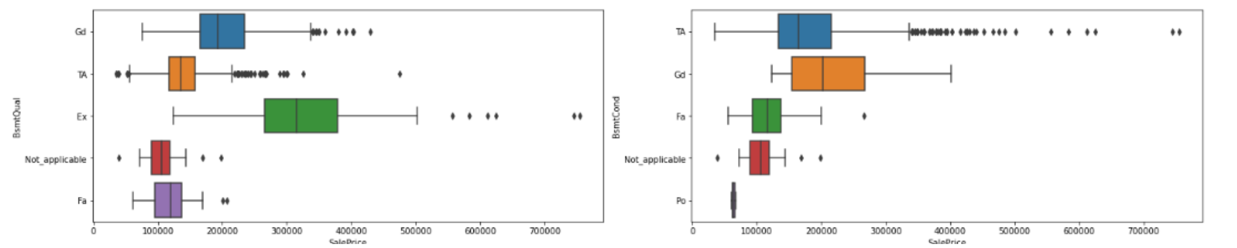
Comment:

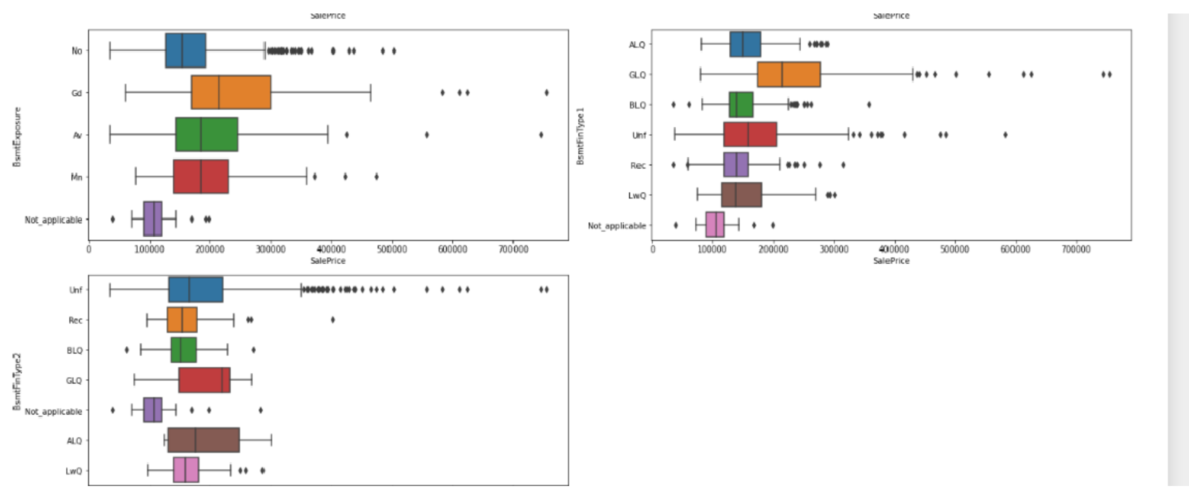
SalePrice is highest where garage is finished.

The range of SalePrice is widest for Typical/Average Garage quality and condition.

There are very few houses with excellect condition of garage.

```python
basement_features = ['BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2']

generate_boxplot(basement_features)
```





Comment:

Houses with excellent quality basement have the highest SalePrice.

Housing with good living quarters (BsmtFinType1= GLQ) have highest SalePrice

A lot of houses have unfinished basment or no basement (label = Not_applicable)

Encoding Categorical Features ¶

```
df['LotShape'] = df['LotShape'].map({'IR1':0,'IR2':1,'IR3':2,'Reg':3})
df['Utilities'] = df['Utilities'].map({'AllPub':3, 'NoSewr':2, 'NoSeWa':1, 'ELO':0})
df['LandSlope'] = df['LandSlope'].map({'Gtl':0,'Mod':1,'Sev':2})
df['HouseStyle'] = df['HouseStyle'].map({'1Story':0, '1.5Unf':1, '1.5Fin':2,  '2Story' :3, '2.5Unf':4, '2.5Fin':5, 'SFoyer':6, 'S
df['ExterQual'] = df['ExterQual'].map({'Po':0,'Fa':1,'TA':2,'Gd':3,'Ex':4})
df['ExterCond'] = df['ExterCond'].map({'Po':0,'Fa':1,'TA':2,'Gd':3,'Ex':4})
df['BsmtQual'] = df['BsmtQual'].map({'Not_applicable':0,'Po':1,'Fa':2,'TA':3,'Gd':4,'Ex':5})
df['BsmtCond'] = df['BsmtCond'].map({'Not_applicable':0,'Po':1,'Fa':2,'TA':3,'Gd':4,'Ex':5})
df['BsmtExposure'] = df['BsmtExposure'].map({'Not_applicable':0,'No':1,'Mn':2,'Av':3,'Gd':4})
df['BsmtFinType1'] = df['BsmtFinType1'].map({'Not_applicable':0,'Unf':1,'LwQ':2,'Rec':3,'BLQ':4,'ALQ':5,'GLQ':6})
df['BsmtFinType2'] = df['BsmtFinType2'].map({'Not_applicable':0,'Unf':1,'LwQ':2,'Rec':3,'BLQ':4,'ALQ':5,'GLQ':6})
df['HeatingQC'] = df['HeatingQC'].map({'Po':0,'Fa':1,'TA':2,'Gd':3,'Ex':4})
df['CentralAir'] = df['CentralAir'].map({'N':0,'Y':1})
df['KitchenQual'] = df['KitchenQual'].map({'Po':0,'Fa':1,'TA':2,'Gd':3,'Ex':4})
df['GarageFinish'] = df['GarageFinish'].map({'Not_applicable':0,'Unf':1,'RFn':2,'Fin':3})
df['GarageQual'] = df['GarageQual'].map({'Not_applicable':0,'Po':1,'Fa':2,'TA':3,'Gd':4,'Ex':5})
df['GarageCond'] = df['GarageCond'].map({'Not_applicable':0,'Po':1,'Fa':2,'TA':3,'Gd':4,'Ex':5})
df['Functional'] = df['Functional'].map({'Typ':0, 'Min1':1, 'Min2':2, 'Mod':3, 'Maj1':4, 'Maj2':5, 'Sev':6, 'Sal':7})
df['FireplaceQu'] = df['FireplaceQu'].map({'Not_applicable':0,'Po':1,'Fa':2,'TA':3,'Gd':4,'Ex':5})
```

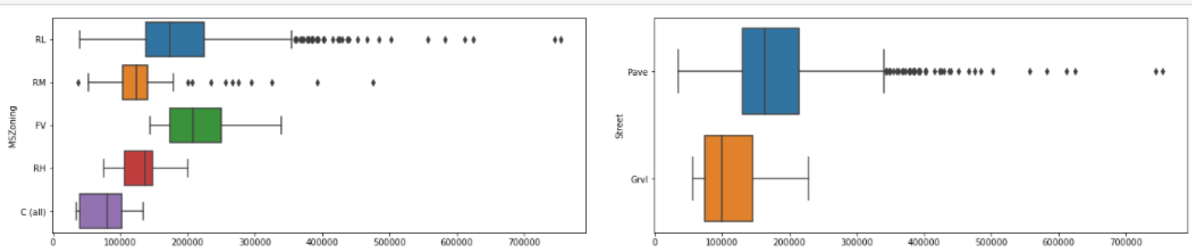
```
# Checking the features after encoding

df[['LotShape', 'Utilities', 'LandSlope', 'HouseStyle', 'ExterQual', 'ExterCond', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtF
```

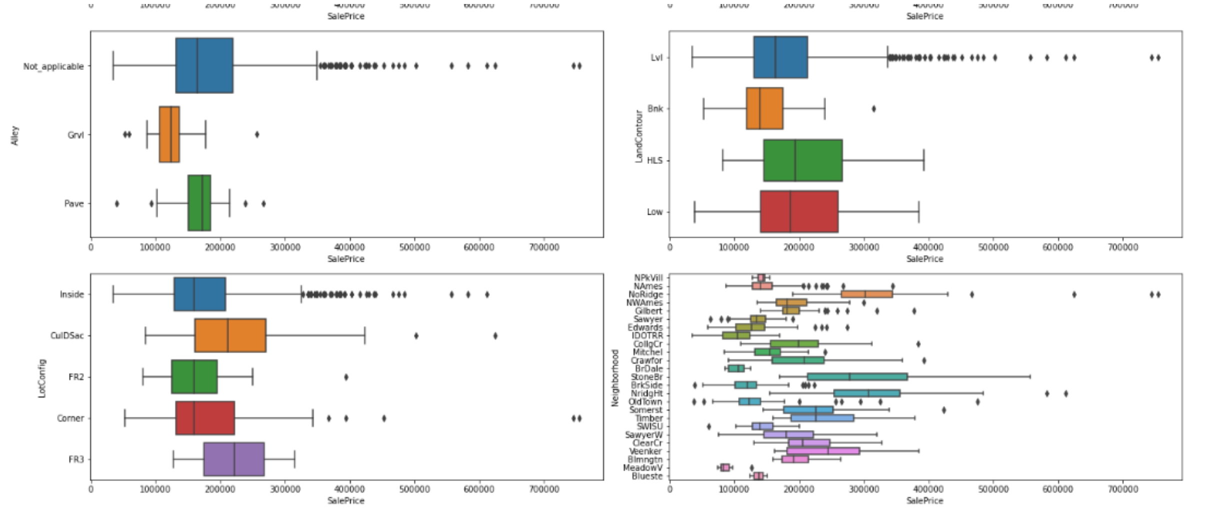
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1161 entries, 0 to 1167
Data columns (total 18 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   LotShape      1161 non-null   int64
 1   Utilities     1161 non-null   int64
 2   LandSlope     1161 non-null   int64
 3   HouseStyle    1161 non-null   int64
 4   ExterQual     1161 non-null   int64
 5   ExterCond     1161 non-null   int64
 6   BsmtQual      1161 non-null   int64
 7   BsmtCond      1161 non-null   int64
 8   BsmtExposure  1161 non-null   int64
 9   BsmtFinType1  1161 non-null   int64
 10  BsmtFinType2  1161 non-null   int64
 11  HeatingQC     1161 non-null   int64
 12  KitchenQual   1161 non-null   int64
 13  Functional    1161 non-null   int64
 14  FireplaceQu   1161 non-null   int64
 15  GarageFinish  1161 non-null   int64
```

Analyzing Unordered Featues

```
unordered_features = ['MSZoning', 'Street', 'Alley', 'LandContour', 'LotConfig', 'Neighborhood', 'Condition1' , 'Condition2',
'BldgType', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'Foundation', 'Heating', 'Electrical', 'GarageTy
```

```
generate_boxplot(['MSZoning', 'Street', 'Alley', 'LandContour', 'LotConfig', 'Neighborhood'])
```





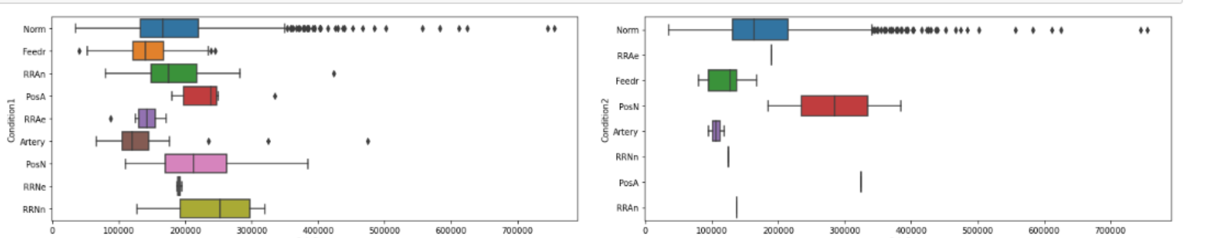
Comment:

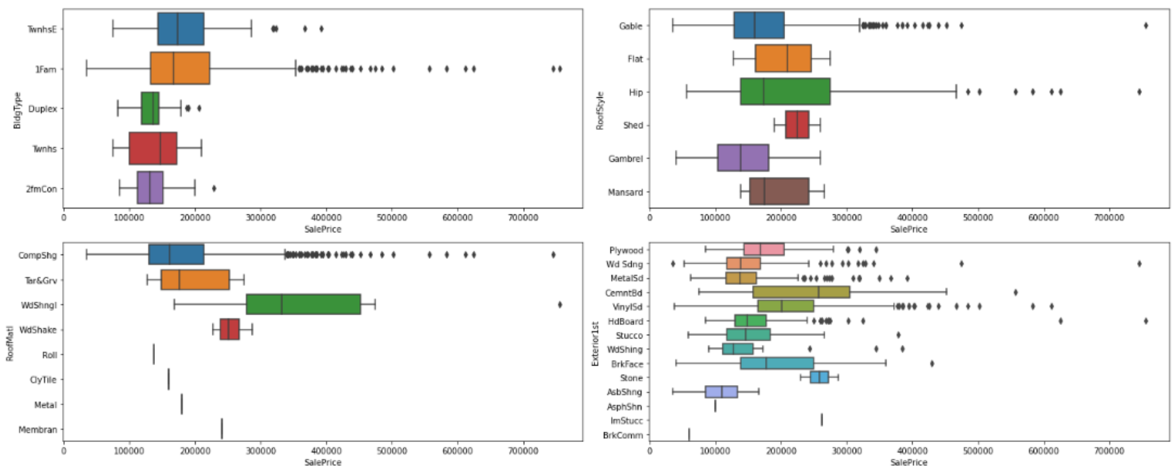
Most of the houses do not have alley.

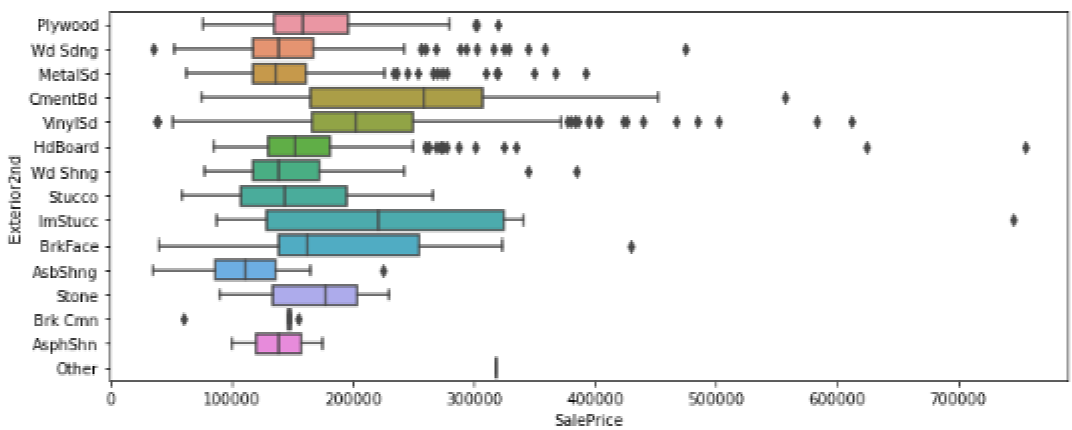
Neighborhood has a lot of labels, using one hot encoding directly would lead to high number of additional columns

Houses classified as MSZoning = RL or Residential Low density have the highest SalePrice.

```
generate_boxplot(['Condition1' , 'Condition2', 'BldgType', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd'])
```





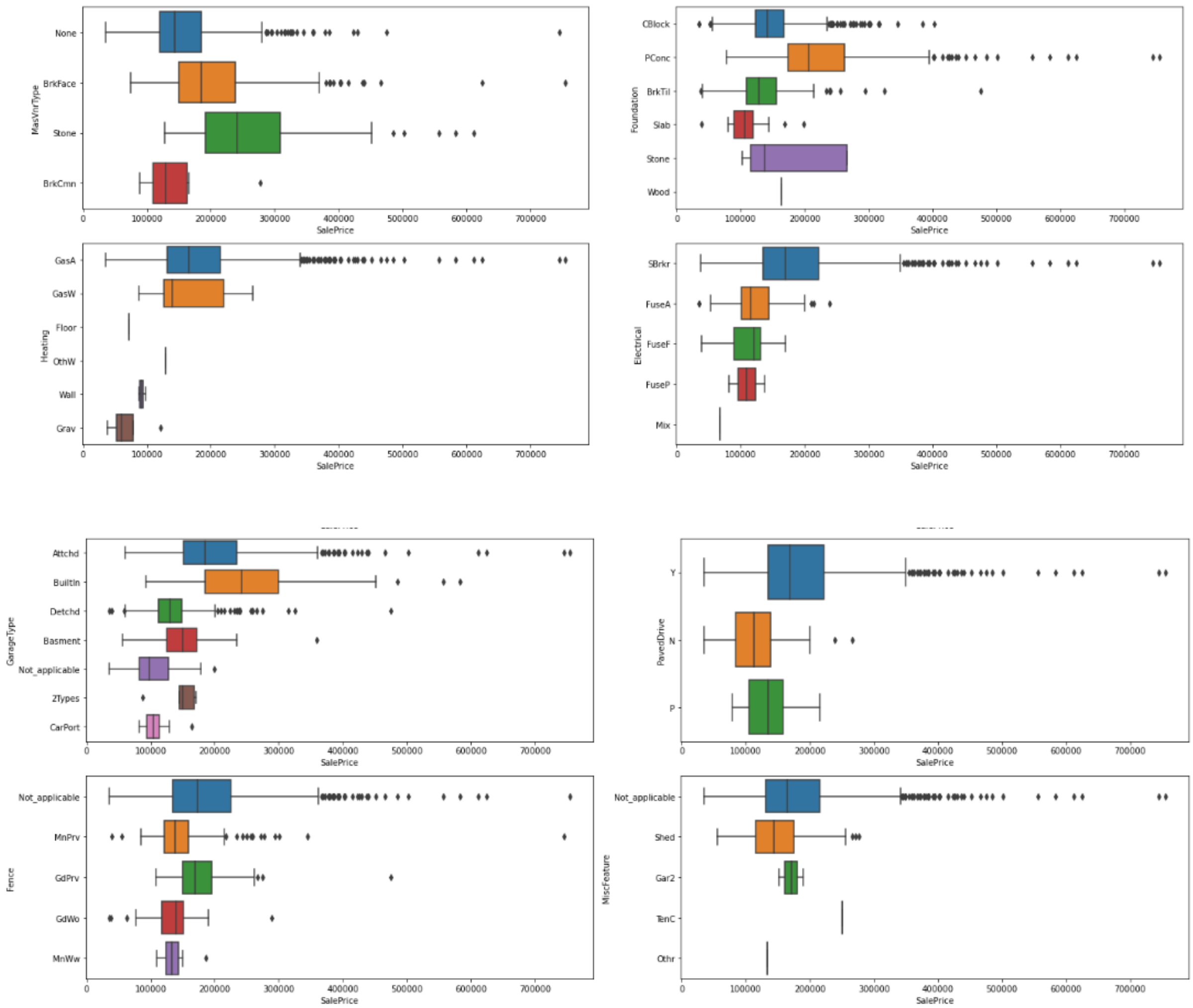


Comment:

Normal Condition (Condition1 = Norm and Condition2 = Norm) Houses are likely to have high SalePrice.

Features like 'RoofMatl', 'Exterior1st', 'Exterior2nd' have some labels with very few data, this labels cannot contribute in predicting Sale Price.

```
generate_boxplot(['MasVnrType', 'Foundation', 'Heating', 'Electrical', 'GarageType','PavedDrive', 'Fence','MiscFeature'])
```



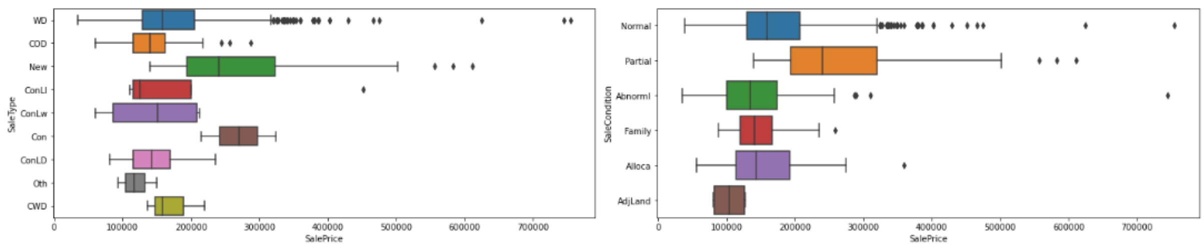
Comment:

Houses with foundation of poured concrete (Foundation = PConc) and/or Electrical with Standard Circuit Breaker and/or Heating type = GasA have the highest price

Houses with attached and built-in garage have high SalePrice

Most of the houses do not have fence (Fence= Not_applicable).

```
generate_boxplot(['SaleType','SaleCondition'])
```



Comment:

Most of the houses are newly built, houses with warranty deed have high SalePrice.

Sale condition = Normal leads to high SalePrice.

Encoding Categorical Variables

```
dummy_df = pd.get_dummies(df[unordered_features], drop_first=True)
```

```
dummy_df.shape
```

```
(1161, 142)
```

Comment:

Adding 144 features to the existing dataset will make the model very complex.

From the above boxplots, for some categorical features only label is dominating over others.

In dummy_df any label having same value in 95% or more rows will be dropped, as those new features are highly imbalanced.

```python
dummies_to_drop = []
for feat in dummy_df.columns:
    if dummy_df[feat].value_counts()[0]/dummy_df.shape[0] >= 0.95:
        dummies_to_drop.append(feat)

print(dummies_to_drop)
print(len(dummies_to_drop))
```

```
['MSZoning_FV', 'MSZoning_RH', 'Alley_Pave', 'LandContour_HLS', 'LandContour_Low', 'LotConfig_FR2', 'LotConfig_FR3', 'Neighborh
ood_Blueste', 'Neighborhood_BrDale', 'Neighborhood_BrkSide', 'Neighborhood_ClearCr', 'Neighborhood_Crawfor', 'Neighborhood_IDOT
RR', 'Neighborhood_MeadowV', 'Neighborhood_Mitchel', 'Neighborhood_NPkVill', 'Neighborhood_NoRidge', 'Neighborhood_SWISU', 'Nei
ghborhood_SawyerW', 'Neighborhood_StoneBr', 'Neighborhood_Timber', 'Neighborhood_Veenker', 'Condition1_PosA', 'Condition1_Pos
N', 'Condition1_RRAe', 'Condition1_RRAn', 'Condition1_RRNe', 'Condition1_RRNn', 'Condition2_Feedr', 'Condition2_PosA', 'Conditi
on2_PosN', 'Condition2_RRAe', 'Condition2_RRAn', 'Condition2_RRNn', 'BldgType_2fmCon', 'BldgType_Duplex', 'BldgType_Twnhs', 'Ro
ofStyle_Gambrel', 'RoofStyle_Mansard', 'RoofStyle_Shed', 'RoofMatl_Membran', 'RoofMatl_Metal', 'RoofMatl_Roll', 'RoofMatl_Tar&G
rv', 'RoofMatl_WdShake', 'RoofMatl_WdShngl', 'Exterior1st_AsphShn', 'Exterior1st_BrkComm', 'Exterior1st_BrkFace', 'Exterior1st_
CemntBd', 'Exterior1st_ImStucc', 'Exterior1st_Stone', 'Exterior1st_Stucco', 'Exterior1st_WdShing', 'Exterior2nd_AsphShn', 'Exte
rior2nd_Brk Cmn', 'Exterior2nd_BrkFace', 'Exterior2nd_CmentBd', 'Exterior2nd_ImStucc', 'Exterior2nd_Other', 'Exterior2nd_Ston
e', 'Exterior2nd_Stucco', 'Exterior2nd_Wd Shng', 'Foundation_Slab', 'Foundation_Stone', 'Foundation_Wood', 'Heating_GasW', 'Hea
ting_Grav', 'Heating_OthW', 'Heating_Wall', 'Electrical_FuseF', 'Electrical_FuseP', 'Electrical_Mix', 'GarageType_Basment', 'Ga
rageType_CarPort', 'PavedDrive_P', 'Fence_GdWo', 'Fence_MnWw', 'MiscFeature_Othr', 'MiscFeature_Shed', 'MiscFeature_TenC', 'Sal
eType_CWD', 'SaleType_Con', 'SaleType_ConLD', 'SaleType_ConLI', 'SaleType_ConLw', 'SaleType_Oth', 'SaleCondition_AdjLand', 'Sal
eCondition_Alloca', 'SaleCondition_Family']
90
```

```
# Dropping the highly imbalanced dummy variables

dummy_df = dummy_df.drop(dummies_to_drop, axis=1)

print(dummy_df.shape)
```

(1161, 52)

```
df.shape
```

(1161, 68)

```
# Adding the dummy variables to the original dataframe
df = pd.concat([df,dummy_df],axis=1)

# Dropping the redundant columns
df = df.drop(unordered_features,axis=1)
```

```
df.shape
```

(1161, 97)

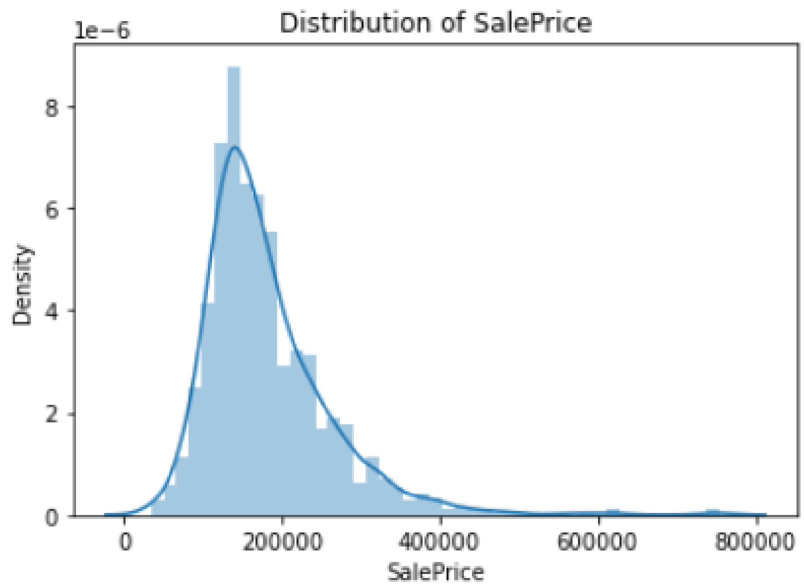
Splitting into Train and Test Data

```
X = df.drop(['SalePrice'], axis=1)
X.head()
```

	MSSubClass	LotFrontage	LotArea	LotShape	Utilities	LandSlope	HouseStyle	OverallQual	OverallCond	YearBuilt	...	GarageType_Detchd	GarageType_No
0	120	NaN	4928.0	0	3	0	0	6	5.0	45	...	0	
1	20	95.0	15865.0	0	3	1	0	8	6.0	51	...	0	
2	60	92.0	9920.0	0	3	0	3	7	5.0	25	...	0	
3	20	105.0	11751.0	0	3	0	0	6	6.0	44	...	0	
4	20	NaN	16635.0	0	3	0	0	6	7.0	44	...	0	

5 rows × 96 columns

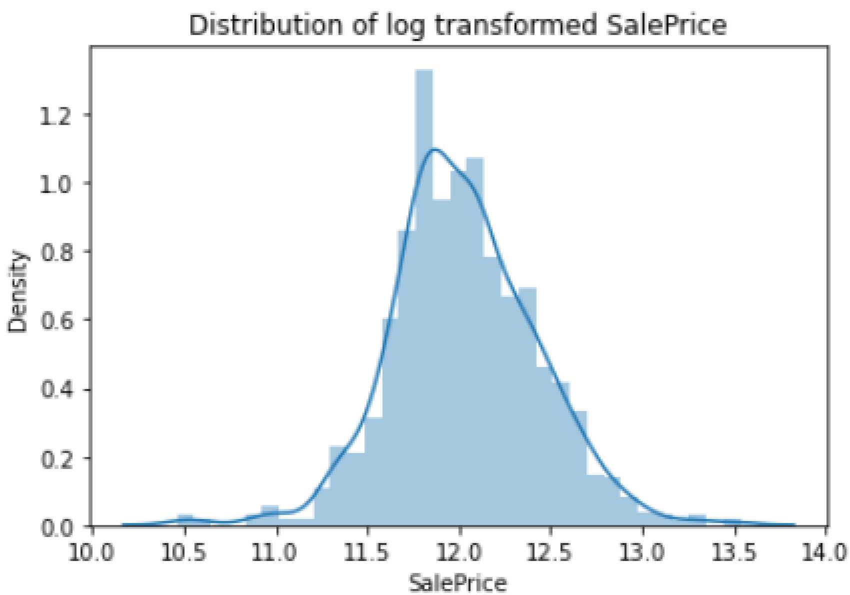
```python
# Checking the distribution of target variable, SalePrice

plt.title('Distribution of SalePrice')
sns.distplot(df['SalePrice'])
plt.show()
```



Comment:

Since SalePrice is highly right skewed, checking the distribution of transformed SalePrice.

```python
sns.distplot(np.log(df['SalePrice']))
plt.title('Distribution of log transformed SalePrice')
plt.show()
```




```python
# log transformed SalePrice is normally distributed, hence transformed data will be used for model building

y = np.log(df['SalePrice'])
print(y)
```

```
0       11.759786
1       12.498742
2       12.505399
3       12.154779
4       12.278393
          ...
1163    11.711776
1164    11.589887
1165    11.908340
1166    10.596635
1167    12.118334
Name: SalePrice, Length: 1161, dtype: float64
```

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=101)
```

```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(928, 96)
(233, 96)
(928,)
(233,)
```

```
X['LotFrontage'].isnull().any()
```

```
True
```

```
# Imputing missing value of LotFrontage after splitting training and test set to prevent data leakage.

si = SimpleImputer(missing_values=np.nan, strategy='mean')
si.fit(X_train[['LotFrontage']])
```

```
SimpleImputer()
```

```
X_train[['LotFrontage']] = si.transform(X_train[['LotFrontage']])
```

```

X_test[['LotFrontage']] = si.transform(X_test[['LotFrontage']])
```

Model Development and Evaluation

Identification of possible problem-solving approaches (methods)

Feature Scaling

```
X_train.values
```

```
array([[6.0000e+01, 6.9000e+01, 9.5880e+03, ..., 0.0000e+00, 0.0000e+00,
        1.0000e+00],
       [6.0000e+01, 7.3000e+01, 8.7600e+03, ..., 0.0000e+00, 0.0000e+00,
        1.0000e+00],
       [2.0000e+01, 1.1000e+02, 1.4442e+04, ..., 1.0000e+00, 1.0000e+00,
        0.0000e+00],
       ...,
       [5.0000e+01, 6.0000e+01, 1.0410e+04, ..., 1.0000e+00, 1.0000e+00,
        0.0000e+00],
       [1.2000e+02, 4.0000e+01, 4.6710e+03, ..., 1.0000e+00, 1.0000e+00,
        0.0000e+00],
       [2.0000e+01, 8.0000e+01, 1.2984e+04, ..., 1.0000e+00, 1.0000e+00,
        0.0000e+00]])
```

```
ss = StandardScaler()
ss.fit(X_train)
```

```
StandardScaler()
```

```
X_tr_scaled = pd.DataFrame(data=ss.transform(X_train), columns=X_train.columns)
X_te_scaled = pd.DataFrame(data=ss.transform(X_test), columns=X_test.columns)
```

```
# Checking the features after

print(X_tr_scaled) # train data
print(X_te_scaled) # test data
```

```
     MSSubClass  LotFrontage   LotArea  LotShape  Utilities  LandSlope  \
0      0.120692    -0.048336 -0.016668 -1.374625        0.0  -0.220360
1      0.120692     0.179162 -0.252924  0.750281        0.0  -0.220360
2     -0.945998     2.283521  1.368343  0.750281        0.0  -0.220360
3      0.120692     0.577284  0.169370  0.750281        0.0  -0.220360
4     -0.945998     1.146030  1.275038 -1.374625        0.0  -0.220360
..          ...          ...       ...       ...        ...        ...
923    2.387410    -0.560207  0.064652  0.750281        0.0  -0.220360
924    2.387410     0.000000  2.199948  0.750281        0.0   3.245634
925   -0.145980    -0.560207  0.217876  0.750281        0.0  -0.220360
926    1.720728    -1.697698 -1.419655 -1.374625        0.0  -0.220360
927   -0.945998     0.577284  0.952326  0.750281        0.0  -0.220360

     HouseStyle  OverallQual  OverallCond  YearBuilt  ...  GarageType_Detchd  \
0      0.683176     1.380450    -0.571288  -1.203520  ...          -0.598925
1      0.683176     0.657913    -0.571288  -1.170113  ...          -0.598925
2     -0.868180    -0.064623     1.495595   0.466835  ...          -0.598925
3      0.683176     1.380450    -0.571288  -1.136706  ...          -0.598925
```

Initial Feature Selection with RFE

```
# Given the number of features = n, the functions prints and returns top n features selected by RFE

def top_n_features(n):
    top_n_cols = []

    linear_m = LinearRegression()
    linear_m.fit(X_tr_scaled, y_train)
    rfe = RFE(linear_m, n)
    rfe = rfe.fit(X_tr_scaled, y_train)

    print("Top %d features : " %n)
    rfe_ranking = list(zip(X_tr_scaled.columns,rfe.support_,rfe.ranking_))

    for i in rfe_ranking:
        if i[1]:
            top_n_cols.append(i[0])
    print(top_n_cols)
    return top_n_cols
```

```python
# Checking top 45, 50 and 55 features
top_45 = top_n_features(45)
top_50 = top_n_features(50)
top_55 = top_n_features(55)
```

```
Top 45 features :
['MSSubClass', 'LotArea', 'Utilities', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'BsmtCond', 'BsmtExposure',
'BsmtFinSF1', 'HeatingQC', 'CentralAir', '1stFlrSF', '2ndFlrSF', 'BsmtFullBath', 'FullBath', 'HalfBath', 'KitchenQual', 'Functi
onal', 'FireplaceQu', 'GarageFinish', 'GarageArea', 'GarageCond', 'MSZoning_RL', 'LotConfig_CulDSac', 'Neighborhood_Edwards',
'Neighborhood_NridgHt', 'Neighborhood_Somerst', 'Condition1_Norm', 'Condition2_Norm', 'BldgType_TwnhsE', 'Exterior1st_Wd Sdng',
'Exterior2nd_Wd Sdng', 'MasVnrType_BrkFace', 'MasVnrType_None', 'MasVnrType_Stone', 'Foundation_PConc', 'Electrical_SBrkr', 'Ga
rageType_Attchd', 'GarageType_Detchd', 'GarageType_Not_applicable', 'Fence_MnPrv', 'Fence_Not_applicable', 'SaleType_New', 'Sal
eCondition_Normal']
Top 50 features :
['MSSubClass', 'LotArea', 'Utilities', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'BsmtCond', 'BsmtExposure',
'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinSF2', 'HeatingQC', 'CentralAir', '1stFlrSF', '2ndFlrSF', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath', 'HalfBath', 'KitchenQual', 'Functional', 'FireplaceQu', 'GarageFinish', 'GarageArea', 'GarageCond', 'MSZoning_RL',
'LotConfig_CulDSac', 'Neighborhood_Edwards', 'Neighborhood_NridgHt', 'Neighborhood_Somerst', 'Condition1_Norm', 'Condition2_Nor
m', 'BldgType_TwnhsE', 'Exterior1st_HdBoard', 'Exterior1st_Wd Sdng', 'Exterior2nd_HdBoard', 'Exterior2nd_Wd Sdng', 'MasVnrType_
BrkFace', 'MasVnrType_None', 'MasVnrType_Stone', 'Foundation_PConc', 'Electrical_SBrkr', 'GarageType_Attchd', 'GarageType_Detch
d', 'GarageType_Not_applicable', 'Fence_MnPrv', 'Fence_Not_applicable', 'SaleType_New', 'SaleCondition_Normal']
Top 55 features :
['MSSubClass', 'LotArea', 'Utilities', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'BsmtCond', 'BsmtExposure',
'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinSF2', 'HeatingQC', 'CentralAir', '1stFlrSF', '2ndFlrSF', 'BsmtFullBath', 'BsmtHalfBath',
'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenQual', 'TotRmsAbvGrd', 'Functional', 'FireplaceQu', 'GarageFinish', 'GarageAre
a', 'GarageCond', 'OpenPorchSF', 'MSZoning_RL', 'LotConfig_CulDSac', 'Neighborhood_Edwards', 'Neighborhood_NAmes', 'Neighborhoo
d NWAmes', 'Neighborhood NridgHt', 'Neighborhood Somerst', 'Condition1 Norm', 'Condition2 Norm', 'BldgType TwnhsE', 'Exterior1s
```

]:
```python
# Given the training data and list of features, this will provide the statistical summary of the model
# This will be used to check adjusted R-square value for top 45, 50 and 55 features

def build_regressor(X_train,y_train,cols):
    X_train_ols = sm.add_constant(X_train[cols])
    lin_reg = sm.OLS(y_train.values.reshape(-1,1), X_train_ols).fit()
    print(lin_reg.summary())
```

]:
```python
build_regressor(X_tr_scaled,y_train,top_45)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.904
Model:                            OLS   Adj. R-squared:                  0.899
Method:                 Least Squares   F-statistic:                     189.3
Date:                Sat, 11 Sep 2021   Prob (F-statistic):               0.00
Time:                        15:44:02   Log-Likelihood:                 637.73
No. Observations:                 928   AIC:                            -1185.
Df Residuals:                     883   BIC:                            -968.0
Df Model:                          44
Covariance Type:            nonrobust
==============================================================================================
```

```
build_regressor(X_tr_scaled,y_train,top_50)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.905
Model:                            OLS   Adj. R-squared:                  0.900
Method:                 Least Squares   F-statistic:                     177.9
Date:                Sat, 11 Sep 2021   Prob (F-statistic):               0.00
Time:                        15:44:49   Log-Likelihood:                 640.81
No. Observations:                 928   AIC:                            -1186.
Df Residuals:                     880   BIC:                            -953.6
Df Model:                          47
Covariance Type:            nonrobust
==============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------
const                      12.0233      0.004   2940.311      0.000      12.015      12.031
MSSubClass                 -0.0159      0.007     -2.449      0.015      -0.029      -0.003
LotArea                     0.0303      0.006      4.976      0.000       0.018       0.042
Utilities               -2.759e-17    2.9e-17     -0.951      0.342   -8.45e-17    2.93e-17
OverallQual                 0.0789      0.008      9.841      0.000       0.063       0.095
OverallCond                 0.0409      0.006      7.412      0.000       0.030       0.052
YearBuilt                  -0.0246      0.010     -2.533      0.011      -0.044      -0.006
YearRemodAdd               -0.0182      0.007     -2.655      0.008      -0.032      -0.005
```

```
build_regressor(X_tr_scaled,y_train,top_55)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.906
Model:                            OLS   Adj. R-squared:                  0.900
Method:                 Least Squares   F-statistic:                     161.9
Date:                Sat, 11 Sep 2021   Prob (F-statistic):               0.00
Time:                        15:45:01   Log-Likelihood:                 646.19
No. Observations:                 928   AIC:                            -1186.
Df Residuals:                     875   BIC:                            -930.2
Df Model:                          52
Covariance Type:            nonrobust
==============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------------
const                      12.0233      0.004   2949.012      0.000      12.015      12.031
MSSubClass                 -0.0156      0.007     -2.387      0.017      -0.028      -0.003
LotArea                     0.0301      0.006      4.932      0.000       0.018       0.042
Utilities                 2.36e-17   1.39e-17      1.701      0.089   -3.62e-18    5.08e-17
OverallQual                 0.0790      0.008      9.868      0.000       0.063       0.095
OverallCond                 0.0428      0.006      7.682      0.000       0.032       0.054
YearBuilt                  -0.0252      0.010     -2.597      0.010      -0.044      -0.006
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The smallest eigenvalue is 3.64e-29. This might indicate that there are

strong multicollinearity problems or that the design matrix is singular.

Comment:
By inspecting adjusted R-square value of linear regression model with top 45, top 50 and top 55 features, top 50 features seem to be optimum as models with 50 and 55 features have the same adjusted R-squared value on the training data.

- **Testing of Identified Approaches (Algorithms)**

```
X_train_rfe = X_tr_scaled[top_50]
X_test_rfe = X_te_scaled[top_50]
```

```
# Reusable Code Block for Cross-validation, Model Building and Model Evaluation

def build_model(X_train, y_train, X_test, params, model='ridge'):
  if model == 'ridge':
    estimator_model = Ridge()
  else:
    estimator_model = Lasso()
  model_cv = GridSearchCV(estimator = estimator_model,
                          param_grid = params,
                          scoring= 'neg_mean_absolute_error',
                          cv = 5,
                          return_train_score=True,
                          verbose = 1)
  model_cv.fit(X_train, y_train)
  alpha = model_cv.best_params_["alpha"]
  print("Optimum alpha for %s is %f" %(model, alpha))
  final_model = model_cv.best_estimator_

  final_model.fit(X_train, y_train)
  y_train_pred = final_model.predict(X_train)
  y_test_pred = final_model.predict(X_test)

  # Model Evaluation
```

```
  # Model Evaluation
  print(model," Regression with ",alpha)
  print("==================================")
  print('R2 score (train) : ',r2_score(y_train,y_train_pred))
  print('R2 score (test) : ',r2_score(y_test,y_test_pred))
  print('RMSE (train) : ', np.sqrt(mean_squared_error(y_train, y_train_pred)))
  print('RMSE (test) : ', np.sqrt(mean_squared_error(y_test, y_test_pred)))

  return final_model, y_test_pred
```

Ridge Regression

```
In [88]: params = {'alpha': [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0,
                   9.0, 10.0, 20, 50, 100, 500, 1000 ]}

         ridge_final_model, y_test_predicted = build_model(X_train_rfe, y_train, X_test_rfe, params, model='ridge')
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
Optimum alpha for ridge is 20.000000
ridge  Regression with  20
===================================
R2 score (train) :  0.9043182431621672
R2 score (test) :  0.8895257621556744
RMSE (train) :  0.12159066631396581
RMSE (test) :  0.13692171167192044
[Parallel(n_jobs=1)]: Done 135 out of 135 | elapsed:    1.9s finished
```

Comment: Ridge Regression model was able to achieve R2 score of 0.88 on test data i.e. 88% of the variance in test data can be explained by the model.

Root Mean Square Error = 0.1369 on test data, that means the prediction made by the model can off by 0.1369 unit.

Lasso Regression

```
params = {'alpha': [0.000001, 0.00001,0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 500, 1000, 10000]}

lasso_final_model, y_test_predicted = build_model(X_train_rfe, y_train, X_test_rfe, params, model='lasso')
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
Optimum alpha for lasso is 0.001000
lasso  Regression with  0.001
===================================
R2 score (train) :  0.9037844937307499
R2 score (test) :  0.8913203632784276
RMSE (train) :  0.12192933428438224
RMSE (test) :  0.13580504433333074
[Parallel(n_jobs=1)]: Done  60 out of  60 | elapsed:    1.1s finished
```

- ## Run and Evaluate selected models

Comparing Model Coefficients¶

]:
```
model_coefficients = pd.DataFrame(index=X_test_rfe.columns)
model_coefficients.rows = X_test_rfe.columns

model_coefficients['Ridge (alpha=9.0)'] = ridge_final_model.coef_
model_coefficients['Lasso (alpha=0.0001)'] = lasso_final_model.coef_
pd.set_option('display.max_rows', None)
model_coefficients
```

]:

	Ridge (alpha=9.0)	Lasso (alpha=0.0001)
MSSubClass	-0.013995	-0.011786
LotArea	0.031863	0.029625
Utilities	0.000000	0.000000
OverallQual	0.078729	0.082145
OverallCond	0.039758	0.040644
YearBuilt	-0.020523	-0.024540
YearRemodAdd	-0.018367	-0.017193
BsmtCond	0.016292	0.015516
BsmtExposure	0.012143	0.010770

:
```
# Converting the predictions to its original scale (anti log)

test_prediction = np.round(np.exp(y_test_predicted)).astype(int)
print(test_prediction[:5])
```

```
[112914 138600 115910 149355 418861]
```

·Key Metrics for success in solving problem under consideration:

Final Model

Lasso Regression produced slightly R2 score on test data than Ridge Regression. Choosing Lasso as the final model.

```
# 50 features ordered by feature importance in Lasso Regression

model_coefficients[['Lasso (alpha=0.0001)']].sort_values(by='Lasso (alpha=0.0001)', ascending=False)
```

	Lasso (alpha=0.0001)
1stFlrSF	0.125864
2ndFlrSF	0.101592
OverallQual	0.082145
OverallCond	0.040644
MSZoning_RL	0.030336
LotArea	0.029625
Neighborhood_Somerst	0.029245

```
model_coefficients[['Lasso (alpha=0.0001)']].sort_values(by='Lasso (alpha=0.0001)', ascending=False).index[:10]
```

```
Index(['1stFlrSF', '2ndFlrSF', 'OverallQual', 'OverallCond', 'MSZoning_RL',
       'LotArea', 'Neighborhood_Somerst', 'Condition1_Norm', 'BsmtFinSF1',
       'GarageArea'],
      dtype='object')
```

- ## Interpretation of the Results

Summary:

First the housing data is read and analyzed dividing the features into numerical and categorical types.

SalePrice is the target column here.

All the features are then analyzed, missing data handling, outlier detection, data cleaning are done. Trend of SalePrice is observed for change in individual features.

New features are extracted, redundant features dropped and categorical features are encoded accordingly.

Then the data in split into train and test data and feature scaling is performed.

Target variable SalePrice is right skewed. Natural log of the same is Normal distributed, hence for model building, natural log of SalePrice is considered.

Creating dummy variables increased the number of features greatly, highly imbalanced columns are dropped.

Top 50 features are selected through RFE and adjusted R-square. 50 features : ['MSSubClass', 'LotArea', 'LandSlope', 'OverallQual', 'OverallCond', 'YearBuilt', 'BsmtQual', 'BsmtExposure', 'BsmtFinSF1', 'BsmtUnfSF', 'HeatingQC', 'CentralAir', '1stFlrSF', '2ndFlrSF', 'BsmtFullBath', 'HalfBath', 'KitchenQual', 'Functional', 'Fireplaces', 'GarageFinish', 'GarageArea', 'GarageQual', 'OpenPorchSF', 'MSZoning_RL', 'Street_Pave', 'LotConfig_CulDSac', 'Neighborhood_Edwards', 'Neighborhood_NAmes', 'Neighborhood_NWAmes', 'Neighborhood_NridgHt', 'Neighborhood_Somerst', 'Condition1_Feedr', 'Condition1_Norm', 'Condition2_Norm', 'BldgType_TwnhsE', 'RoofStyle_Gable', 'RoofStyle_Hip', 'Exterior1st_HdBoard', 'Exterior1st_Wd Sdng', 'Exterior2nd_HdBoard', 'Exterior2nd_Wd Sdng', 'MasVnrType_BrkFace', 'MasVnrType_None', 'MasVnrType_Stone', 'Foundation_PConc', 'Heating_GasA', 'GarageType_Not_applicable', 'PavedDrive_Y', 'SaleCondition_Normal', 'SaleCondition_Partial']

Ridge and Lasso Regression Model are built with optimum alpha calculated in GridSearchCV method. Optimum alpha = 9.0 for ridge and 0.0001 for lasso model.

Model evaluation is done with R2 score and Root Mean Square Error.

Lasso Regression is chosen as final model for having slightly better R-square value on test data.

Out of 50 features in the final model, top 10 features in order of descending importance are ['1stFlrSF', '2ndFlrSF', 'OverallQual', 'OverallCond', 'SaleCondition_Partial', 'LotArea', 'BsmtFinSF1','SaleCondition_Normal', 'MSZoning_RL', 'Neighborhood_Somerst']

Model coefficients are listed in a table along with the corresponding features , for example natural log of SalePrice will change by 0.124911 with unit change in the feature '1stFlrSF' when all the features remain constant. Negative sign in the coefficient signifies negative correlation between the predictor and target variable.

Predicted value of SalePrice is tranformed into its original scale by performing antilog.

CONCLUSION

Model Building

```
]: ridge_model = Ridge(alpha=18.0)
   ridge_model.fit(X_train_rfe, y_train)

   # Predicting
   y_train_pred = ridge_model.predict(X_train_rfe)
   y_test_pred = ridge_model.predict(X_test_rfe)

   print("Model Evaluation : Ridge Regression, alpha=18.0")
   print('R2 score (train) : ',round(r2_score(y_train,y_train_pred), 4))
   print('R2 score (test) : ',round(r2_score(y_test,y_test_pred), 4))
   print('RMSE (train) : ', round(np.sqrt(mean_squared_error(y_train, y_train_pred)), 4))
   print('RMSE (test) : ', round(np.sqrt(mean_squared_error(y_test, y_test_pred)), 4))
```

```
Model Evaluation : Ridge Regression, alpha=18.0
R2 score (train) :  0.9044
R2 score (test) :  0.8897
RMSE (train) :  0.1215
RMSE (test) :  0.1368
```

```
lasso_model = Lasso(alpha=0.0002)
lasso_model.fit(X_train_rfe, y_train)
y_train_pred = lasso_model.predict(X_train_rfe)
y_test_pred = lasso_model.predict(X_test_rfe)

print("Model Evaluation : Lasso Regression, alpha=0.0002")
print('R2 score (train) : ',round(r2_score(y_train,y_train_pred), 4))
print('R2 score (test) : ',round(r2_score(y_test,y_test_pred), 4))
print('RMSE (train) : ', round(np.sqrt(mean_squared_error(y_train, y_train_pred)), 4))
print('RMSE (test) : ', round(np.sqrt(mean_squared_error(y_test, y_test_pred)), 4))
```

```
Model Evaluation : Lasso Regression, alpha=0.0002
R2 score (train) :  0.9047
R2 score (test) :  0.8913
RMSE (train) :  0.1214
RMSE (test) :  0.1358
```

```
model_coefficients['Ridge (alpha = 18.0)'] = ridge_model.coef_
model_coefficients['Lasso (alpha = 0.0002)'] = lasso_model.coef_
pd.set_option('display.max_rows', None)
model_coefficients
```

	Ridge (alpha=9.0)	Lasso (alpha=0.0001)	Ridge (alpha = 18.0)	Lasso (alpha = 0.0002)
MSSubClass	-0.013995	-0.011786	-0.014154	-0.014921
LotArea	0.031863	0.029625	0.031727	0.030139
Utilities	0.000000	0.000000	0.000000	0.000000
OverallQual	0.078729	0.082145	0.078781	0.079602
OverallCond	0.039758	0.040644	0.039877	0.040945
YearBuilt	-0.020523	-0.024540	-0.020858	-0.024607
YearRemodAdd	-0.018367	-0.017193	-0.018343	-0.017974
BsmtCond	0.016292	0.015516	0.016291	0.016118
BsmtExposure	0.012143	0.010770	0.012169	0.012174
BsmtFinType1	0.009467	0.009594	0.009456	0.009414
BsmtFinSF1	0.024810	0.024894	0.024739	0.024120
BsmtFinSF2	0.000000	0.000000	0.000000	0.000000
HeatingQC	0.013147	0.012817	0.013112	0.012775
CentralAir	0.014595	0.013950	0.014592	0.014382
1stFlrSF	0.118539	0.125864	0.119341	0.127273
2ndFlrSF	0.096363	0.101592	0.097397	0.107167

:
```
model_coefficients.sort_values(by='Lasso (alpha = 0.0002)', ascending=False).head(1)
```

:

	Ridge (alpha=9.0)	Lasso (alpha=0.0001)	Ridge (alpha = 18.0)	Lasso (alpha = 0.0002)
1stFlrSF	0.118539	0.125864	0.119341	0.127273

:
```
model_coefficients.sort_values(by='Ridge (alpha = 18.0)', ascending=False).head(1)
```

:

	Ridge (alpha=9.0)	Lasso (alpha=0.0001)	Ridge (alpha = 18.0)	Lasso (alpha = 0.0002)
1stFlrSF	0.118539	0.125864	0.119341	0.127273

:
```
# Top 5 featues in Lasso final model

model_coefficients.sort_values(by='Lasso (alpha=0.0001)', ascending=False).head(5)
```

:

	Ridge (alpha=9.0)	Lasso (alpha=0.0001)	Ridge (alpha = 18.0)	Lasso (alpha = 0.0002)
1stFlrSF	0.118539	0.125864	0.119341	0.127273
2ndFlrSF	0.096363	0.101592	0.097397	0.107167
OverallQual	0.078729	0.082145	0.078781	0.079602
OverallCond	0.039758	0.040644	0.039877	0.040945

```
X_train_new = X_train_rfe.drop(['1stFlrSF', '2ndFlrSF', 'OverallQual', 'OverallCond', 'SaleCondition_Normal'], axis=1)
```

```
X_test_new = X_test_rfe.drop(['1stFlrSF', '2ndFlrSF', 'OverallQual', 'OverallCond', 'SaleCondition_Normal'], axis=1)
```

```
alpha = 0.0001
lasso_model = Lasso(alpha=alpha)
lasso_model.fit(X_train_new, y_train)
y_train_pred = lasso_model.predict(X_train_new)
y_test_pred = lasso_model.predict(X_test_new)
```

```
lasso_model.coef_
```

```
array([-0.01250212,  0.06081117,  0.        ,  0.03374579, -0.04282206,
        0.02806455,  0.01948429,  0.00123001,  0.04627592,  0.        ,
        0.01730744,  0.02043862,  0.01430715,  0.        ,  0.10060322,
        0.04928814,  0.05611037, -0.01846189,  0.06071655,  0.01452197,
        0.0522451 ,  0.03244774,  0.02647395,  0.01445796, -0.02665003,
        0.02045071,  0.02398737,  0.02082199,  0.01024634,  0.00919277,
       -0.01519461, -0.01965894,  0.0079257 ,  0.02519173,  0.03955275,
        0.01701565,  0.02440478,  0.02272969, -0.01510877,  0.00872045,
        0.00954478,  0.02771228,  0.01349331,  0.01164613,  0.01030034])
```

```
model_coeff = pd.DataFrame(index=X_test_new.columns)
model_coeff.rows = X_test_new.columns
model_coeff['Lasso'] = lasso_model.coef_
model_coeff.sort_values(by='Lasso', ascending=False).head(5)
```

	Lasso
FullBath	0.100603
LotArea	0.060811
FireplaceQu	0.060717
KitchenQual	0.056110
GarageArea	0.052245