

## Import Libraries

```
In [ ]: import random
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
from matplotlib import *
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score
from sklearn.linear_model import Ridge
from sklearn.linear_model import RidgeCV
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import RepeatedKFold
from sklearn.feature_selection import f_regression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
```

Read the database

```
In [ ]: df=pd.read_csv('C:/Users/Asus/Desktop/HOME/train.csv')
df.head()
```

```
Out[ ]:
```

	<b>Id</b>	<b>MSSubClass</b>	<b>MSZoning</b>	<b>LotFrontage</b>	<b>LotArea</b>	<b>Street</b>	<b>Alley</b>	<b>LotShape</b>	<b>LandContour</b>	<b>Utilities</b>
<b>0</b>	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub
<b>1</b>	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub
<b>2</b>	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub
<b>3</b>	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub
<b>4</b>	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub

5 rows × 81 columns



```
In [ ]: 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

```

Check Null values for Numerical features and replacing if less than 70% or removing column if more than 70%

```

In [ ]: for col in df.columns:
        if df[col].dtype != 'object':
            num_null=df[col].isnull().sum()
            percent_num_null=round((num_null/1460)*100,2)
            if percent_num_null > 0.01:
                print(col,":",percent_num_null," %")

```

```

LotFrontage : 17.74 %
MasVnrArea  : 0.55 %
GarageYrBlt : 5.55 %

```

```

In [ ]: for col in df.columns:
        if df[col].dtype != 'object':
            num_fill=df[col].fillna(df[col].mean(),inplace=True)

```

verifying null values as 0% of numerical feature after applying 'Fillna' to the features

```

In [ ]: for col in df.columns:
        if df[col].dtype != 'object':
            num_null=df[col].isnull().sum()
            percent_num_null=round((num_null/1460)*100,2)
            if percent_num_null == 0.00:
                print(col,":",percent_num_null," %")

```

```

Id : 0.0 %
MSSubClass : 0.0 %
LotFrontage : 0.0 %
LotArea : 0.0 %
OverallQual : 0.0 %
OverallCond : 0.0 %
YearBuilt : 0.0 %
YearRemodAdd : 0.0 %
MasVnrArea : 0.0 %
BsmtFinSF1 : 0.0 %
BsmtFinSF2 : 0.0 %
BsmtUnfSF : 0.0 %
TotalBsmtSF : 0.0 %
1stFlrSF : 0.0 %
2ndFlrSF : 0.0 %
LowQualFinSF : 0.0 %
GrLivArea : 0.0 %
BsmtFullBath : 0.0 %
BsmtHalfBath : 0.0 %
FullBath : 0.0 %
HalfBath : 0.0 %
BedroomAbvGr : 0.0 %
KitchenAbvGr : 0.0 %
TotRmsAbvGrd : 0.0 %
Fireplaces : 0.0 %
GarageYrBlt : 0.0 %
GarageCars : 0.0 %
GarageArea : 0.0 %
WoodDeckSF : 0.0 %
OpenPorchSF : 0.0 %
EnclosedPorch : 0.0 %
3SsnPorch : 0.0 %
ScreenPorch : 0.0 %
PoolArea : 0.0 %
MiscVal : 0.0 %
MoSold : 0.0 %
YrSold : 0.0 %
SalePrice : 0.0 %

```

Check Null values for Categorical features and replacing if less than 70% or removing column if more than 70%

```

In [ ]: for col in df.columns:
        if df[col].dtype == 'object':
            cat_null=df[col].isnull().sum()
            percent_cat_null=round((cat_null/1460)*100,2)
            if percent_cat_null >= 70:
                print(col,":",percent_cat_null," %")

```

```

Alley : 93.77 %
PoolQC : 99.52 %
Fence : 80.75 %
MiscFeature : 96.3 %

```

Dropping Null Values above 70% from categorical features

```

In [ ]: df.drop('Alley',axis=1,inplace=True)
df.drop('PoolQC',axis=1,inplace=True)
df.drop('Fence',axis=1,inplace=True)
df.drop('MiscFeature',axis=1,inplace=True)

```

Filling null values with 'bfill' for categorical features

```
In [ ]: for col in df.columns:
        if df[col].dtype == 'object':
            df[col].bfill(inplace=True)
```

Verifying null values for categorical features

```
In [ ]: for col in df.columns:
        if df[col].dtype == 'object':
            cat_null=df[col].isnull().sum()
            percent_cat_null=round((cat_null/1460)*100,2)
            print(col,":",percent_cat_null," %")
```

```
MSZoning : 0.0 %
Street : 0.0 %
LotShape : 0.0 %
LandContour : 0.0 %
Utilities : 0.0 %
LotConfig : 0.0 %
LandSlope : 0.0 %
Neighborhood : 0.0 %
Condition1 : 0.0 %
Condition2 : 0.0 %
BldgType : 0.0 %
HouseStyle : 0.0 %
RoofStyle : 0.0 %
RoofMatl : 0.0 %
Exterior1st : 0.0 %
Exterior2nd : 0.0 %
MasVnrType : 0.21 %
ExterQual : 0.0 %
ExterCond : 0.0 %
Foundation : 0.0 %
BsmtQual : 0.0 %
BsmtCond : 0.0 %
BsmtExposure : 0.0 %
BsmtFinType1 : 0.0 %
BsmtFinType2 : 0.0 %
Heating : 0.0 %
HeatingQC : 0.0 %
CentralAir : 0.0 %
Electrical : 0.0 %
KitchenQual : 0.0 %
Functional : 0.0 %
FireplaceQu : 0.14 %
GarageType : 0.0 %
GarageFinish : 0.0 %
GarageQual : 0.0 %
GarageCond : 0.0 %
PavedDrive : 0.0 %
SaleType : 0.0 %
SaleCondition : 0.0 %
```

```
In [ ]: df.drop('MasVnrType',axis=1,inplace=True)
df.drop('FireplaceQu',axis=1,inplace=True)
```

Checking Outliers for the data by plotting BoxPlot of every Numeric feature

```
In [ ]: numerical_columns=[i for i in df.columns if df[i].dtype != 'object']
```

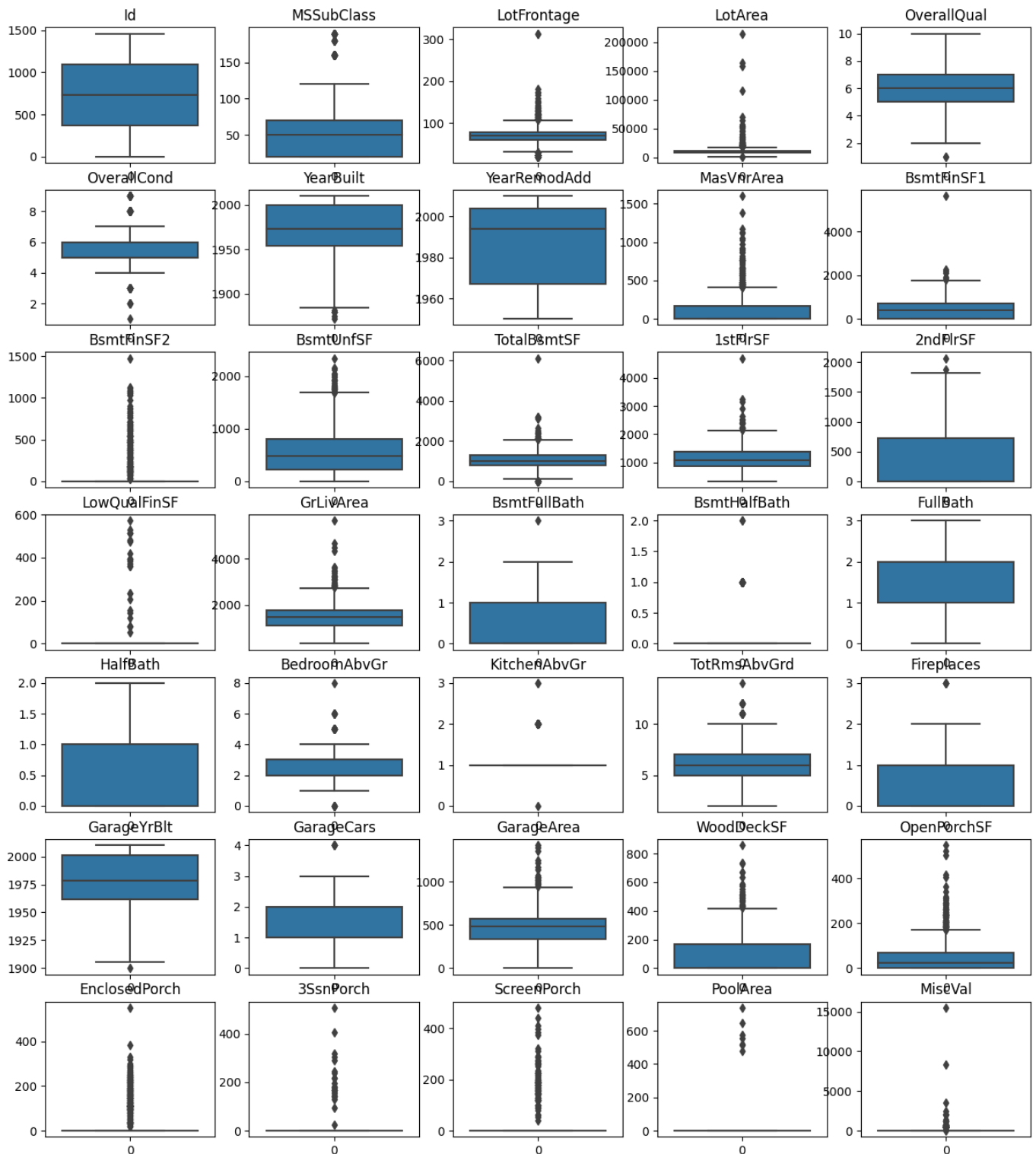
Checking outliers with Boxplot

```
In [ ]: fig, ax = plt.subplots(7,5,figsize=(15, 17))
count = 0
```

```

for i in range(7):
    for j in range(5):
        sns.boxplot(df[numerical_columns[count]],ax=ax[i][j])
        ax[i][j].set_title(numerical_columns[count])
        count = count + 1

```



Function for replacing outliers

```

In [ ]: def check_out(numerical_columns):
        Q1=df[numerical_columns].quantile(0.25)
        Q3=df[numerical_columns].quantile(0.75)
        IQR=Q3-Q1
        up_whisk=Q3+(1.5*IQR)
        low_whisk=Q1-(1.5*IQR)
        return up_whisk, low_whisk

```

```

In [ ]: for i in numerical_columns:
        a,b=check_out(i)
        df.loc[df[i]>a,i]=a

```

```
df.loc[df[i]<b,i]=b
```

Code to remove the columns whose values contains mostly 0

```
In [ ]: for i in numerical_columns:
        a = dict(df[i].value_counts())
        b = list(a.values())
        if(b[0]==1460):
            df.drop(columns=i, inplace=True)
```

```
In [ ]: df.columns
```

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

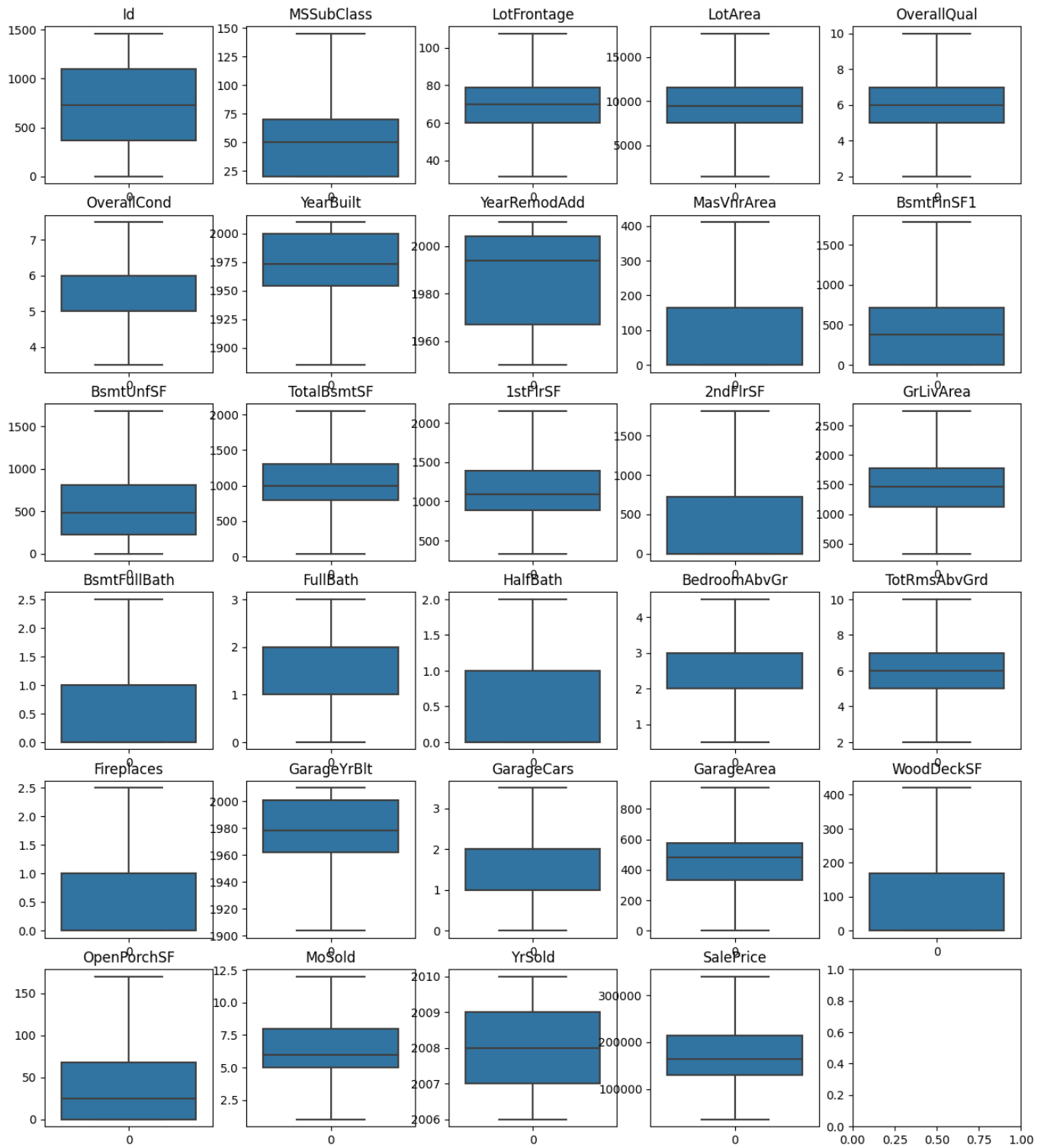
Seperating numeric columns from the new columns list after removing the columns with 0 value

```
In [ ]: numeric_columns = [i for i in df.columns if df[i].dtype != 'object']
        len(numeric_columns)
```

```
Out[ ]: 29
```

Again Checking final boxplot for outliers

```
In [ ]: fig, ax = plt.subplots(6,5,figsize=(15, 17))
        count = 0
        for i in range(6):
            for j in range(5):
                sns.boxplot(df[numeric_columns[count]],ax=ax[i][j])
                ax[i][j].set_title(numeric_columns[count])
                count = count + 1
            if count == 29:
                break
```



## Data Visualization

Removing/Dropping unnecessary columns to avoid false model fitting and visualization

```
In [ ]: df.drop('MSSubClass',axis=1,inplace=True)
df.drop('BsmtExposure',axis=1,inplace=True)
df.drop('BsmtFinType1',axis=1,inplace=True)
df.drop('BsmtFinSF1',axis=1,inplace=True)
df.drop('BsmtFinType2',axis=1,inplace=True)
df.drop('BsmtUnfSF',axis=1,inplace=True)
df.drop('HeatingQC',axis=1,inplace=True)
df.drop('BsmtFullBath',axis=1,inplace=True)
df.drop('GarageFinish',axis=1,inplace=True)
df.drop('WoodDeckSF',axis=1,inplace=True)
```



```
In [ ]: df.drop('LandContour',axis=1,inplace=True)
df.drop('Utilities',axis=1,inplace=True)
df.drop('LotConfig',axis=1,inplace=True)
df.drop('LandSlope',axis=1,inplace=True)
```

```
In [ ]: df.drop('Exterior1st',axis=1,inplace=True)
df.drop('Exterior2nd',axis=1,inplace=True)
df.drop('ExterQual',axis=1,inplace=True)
```

```
In [ ]: df.drop('YearRemodAdd',axis=1,inplace=True)
df.drop('Functional',axis=1,inplace=True)
df.drop('GarageCars',axis=1,inplace=True)
df.drop('GarageQual',axis=1,inplace=True)
df.drop('PavedDrive',axis=1,inplace=True)
```

```
In [ ]: df.drop('LotFrontage',axis=1,inplace=True)
```

```
In [ ]: df.drop('OverallQual',axis=1,inplace=True)
```

```
In [ ]: df.drop('RoofStyle',axis=1,inplace=True)
```

```
In [ ]: df.drop('RoofMatl',axis=1,inplace=True)
df.drop('BsmtQual',axis=1,inplace=True)
```

Checking out reduced columns size

```
In [ ]: df.columns
```

```
Out[ ]: Index(['Id', 'MSZoning', 'LotArea', 'Street', 'LotShape', 'Neighborhood',
              'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'OverallCond',
              'YearBuilt', 'MasVnrArea', 'ExterCond', 'Foundation', 'BsmtCond',
              'TotalBsmtSF', 'Heating', 'CentralAir', 'Electrical', '1stFlrSF',
              '2ndFlrSF', 'GrLivArea', 'FullBath', 'HalfBath', 'BedroomAbvGr',
              'KitchenQual', 'TotRmsAbvGrd', 'Fireplaces', 'GarageType',
              'GarageYrBlt', 'GarageArea', 'GarageCond', 'OpenPorchSF', 'MoSold',
              'YrSold', 'SaleType', 'SaleCondition', 'SalePrice'],
              dtype='object')
```

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

```
Out[ ]: (1460, 39)
```

Pie Charts

```
In [ ]: fig,ax=plt.subplots(2,2,figsize=(20,10))
label=['RL','RM','FV','RH','C (all)']
ax[0][0].pie(df['MSZoning'].value_counts(),labels=label,autopct='%.1f%%')
ax[0][0].set_title('Distribution of region wise property')
ax[0][0].legend(loc='upper right')

label=df['HouseStyle'].unique()
ax[0][1].pie(df['HouseStyle'].value_counts(),labels=label,autopct='%.1f%%')
ax[0][1].set_title('Distribution of porperty based on property style')
ax[0][1].legend(loc='upper left')

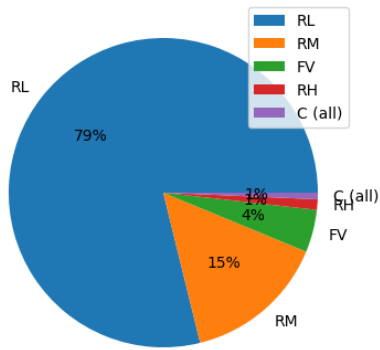
label=df['HalfBath'].unique()
ax[1][0].pie(df['HalfBath'].value_counts(),labels=label,autopct='%.1f%%')
ax[1][0].set_title('No. of Half Bathroom in a property ')
ax[1][0].legend(loc='upper right')

label=df['FullBath'].unique()
ax[1][1].pie(df['FullBath'].value_counts(),labels=label,autopct='%.1f%%')
```

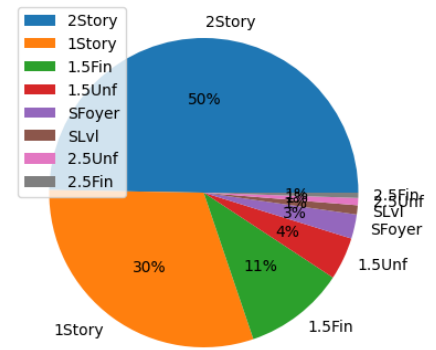
```
ax[1][1].set_title('No. of Full Bathroom in a property ')
ax[1][1].legend(loc='upper left')

plt.show()
```

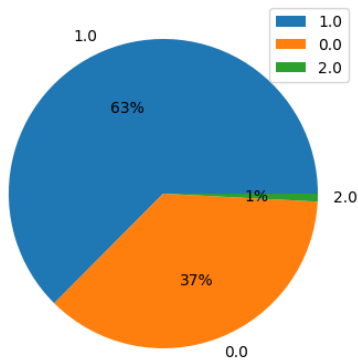
Distribution of region wise property



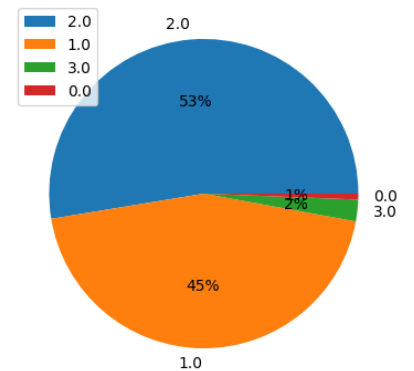
Distribution of property based on property style



No. of Half Bathroom in a property



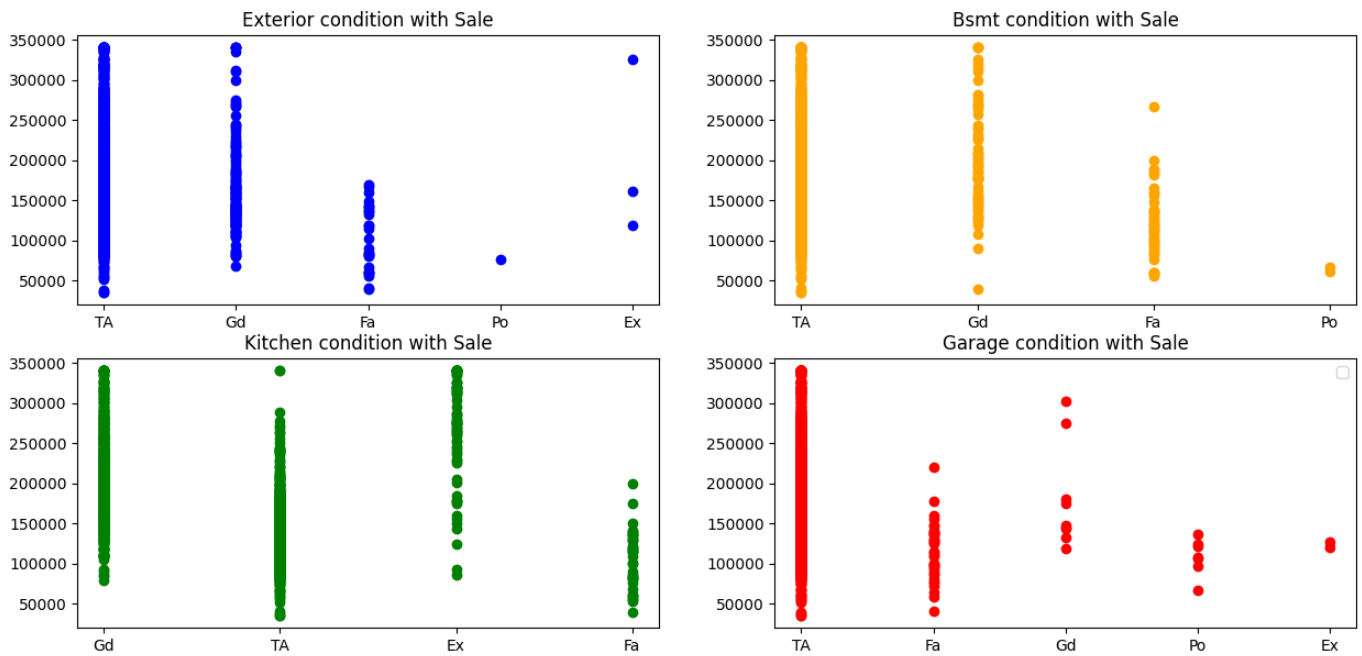
No. of Full Bathroom in a property



## Scatter Plots

```
In [ ]: fig,ax=plt.subplots(2,2,figsize=(15,7))
ax[0][0].scatter(y=df['SalePrice'],x=df['ExterCond'],color='Blue')
ax[0][0].set_title('Exterior condition with Sale')
ax[0][1].scatter(y=df['SalePrice'],x=df['BsmtCond'],color='Orange')
ax[0][1].set_title('Bsmt condition with Sale')
ax[1][0].scatter(y=df['SalePrice'],x=df['KitchenQual'],color='green')
ax[1][0].set_title('Kitchen condition with Sale')
ax[1][1].scatter(y=df['SalePrice'],x=df['GarageCond'],color='red')
ax[1][1].set_title('Garage condition with Sale')
plt.legend()
plt.show()
```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



```
In [ ]: fig,ax=plt.subplots(2,2,figsize=(20,10))

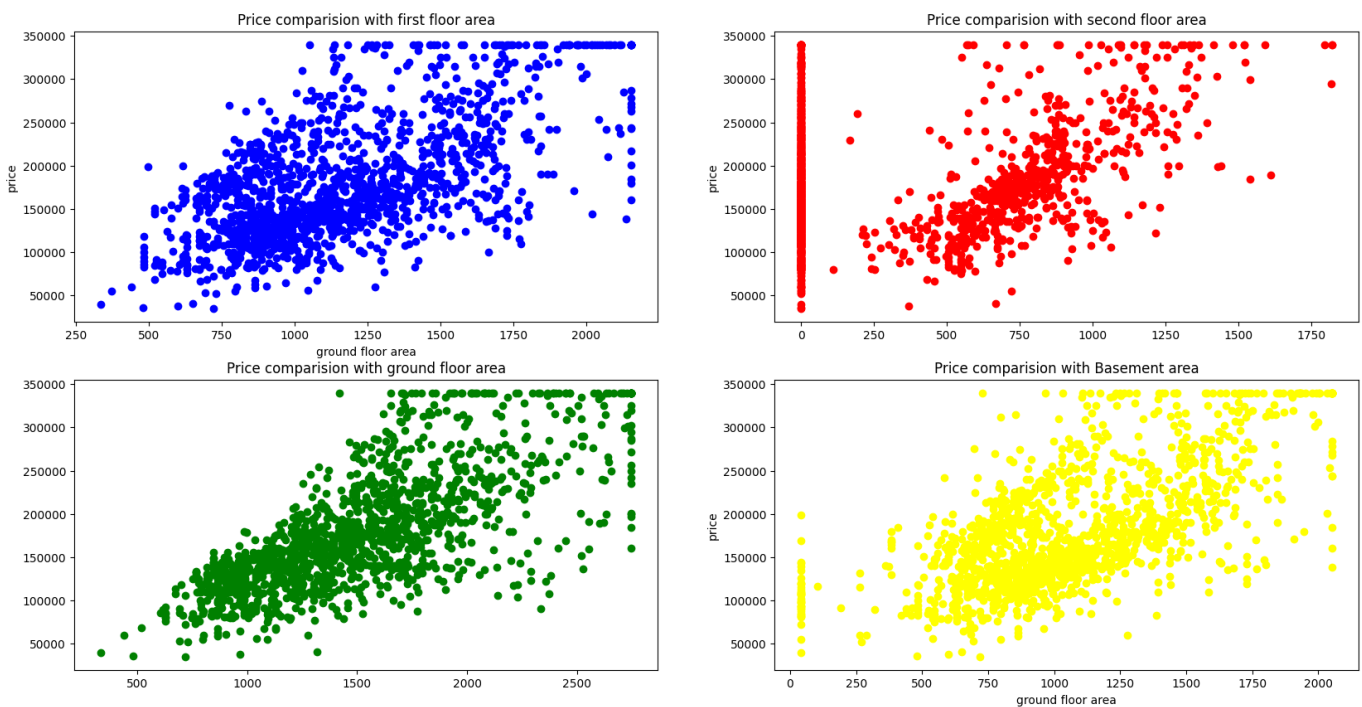
ax[0][0].scatter(x=df['1stFlrSF'],y=df['SalePrice'],color='Blue')
ax[0][0].set_title('Price comparision with first floor area')
ax[0][0].set_xlabel('first floor area')
ax[0][0].set_ylabel('price')

ax[0][1].scatter(x=df['2ndFlrSF'],y=df['SalePrice'],color='red')
ax[0][1].set_title('Price comparision with second floor area')
ax[0][1].set_xlabel('second floor area')
ax[0][1].set_ylabel('price')

ax[1][0].scatter(x=df['GrLivArea'],y=df['SalePrice'],color='green')
ax[1][0].set_title('Price comparision with ground floor area')
ax[1][0].set_xlabel('ground floor area')
ax[1][0].set_ylabel('price')

ax[1][1].scatter(x=df['TotalBsmtSF'],y=df['SalePrice'],color='Yellow')
ax[1][1].set_title('Price comparision with Basement area')
ax[1][1].set_xlabel('ground floor area')
ax[1][1].set_ylabel('price')
```

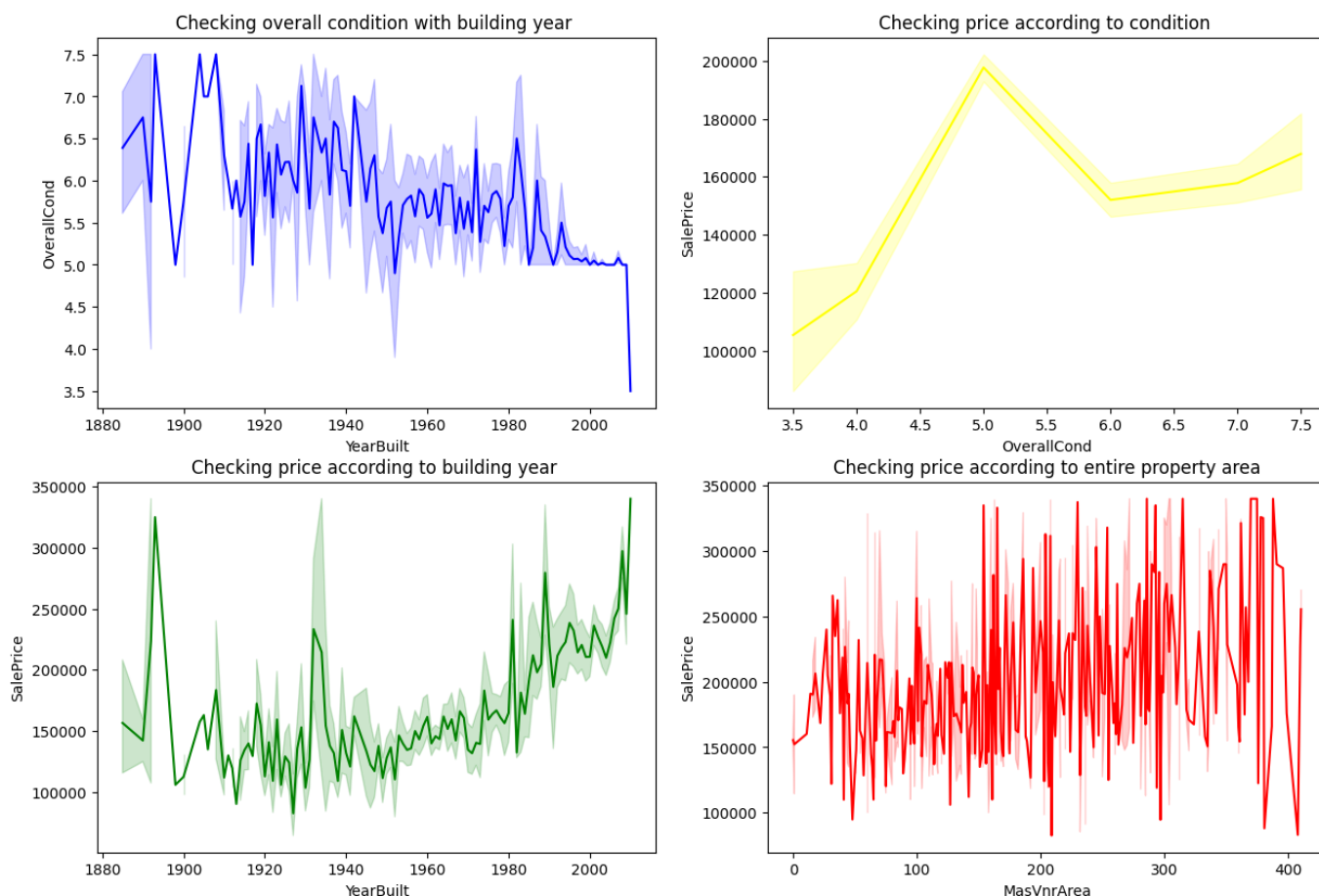
```
Out[ ]: Text(0, 0.5, 'price')
```



## Line Graphs

```
In [ ]: fig,ax=plt.subplots(2,2,figsize=(15,10))
sns.lineplot(x=df['YearBuilt'],y=df['OverallCond'],color='Blue',ax=ax[0][0])
ax[0][0].set_title('Checking overall condition with building year ')
sns.lineplot(x=df['OverallCond'],y=df['SalePrice'],color='yellow',ax=ax[0][1])
ax[0][1].set_title('Checking price according to condition ')
sns.lineplot(x=df['YearBuilt'],y=df['SalePrice'],color='Green',ax=ax[1][0])
ax[1][0].set_title('Checking price according to building year ')
sns.lineplot(x=df['MasVnrArea'],y=df['SalePrice'],color='red',ax=ax[1][1])
ax[1][1].set_title('Checking price according to entire property area')
```

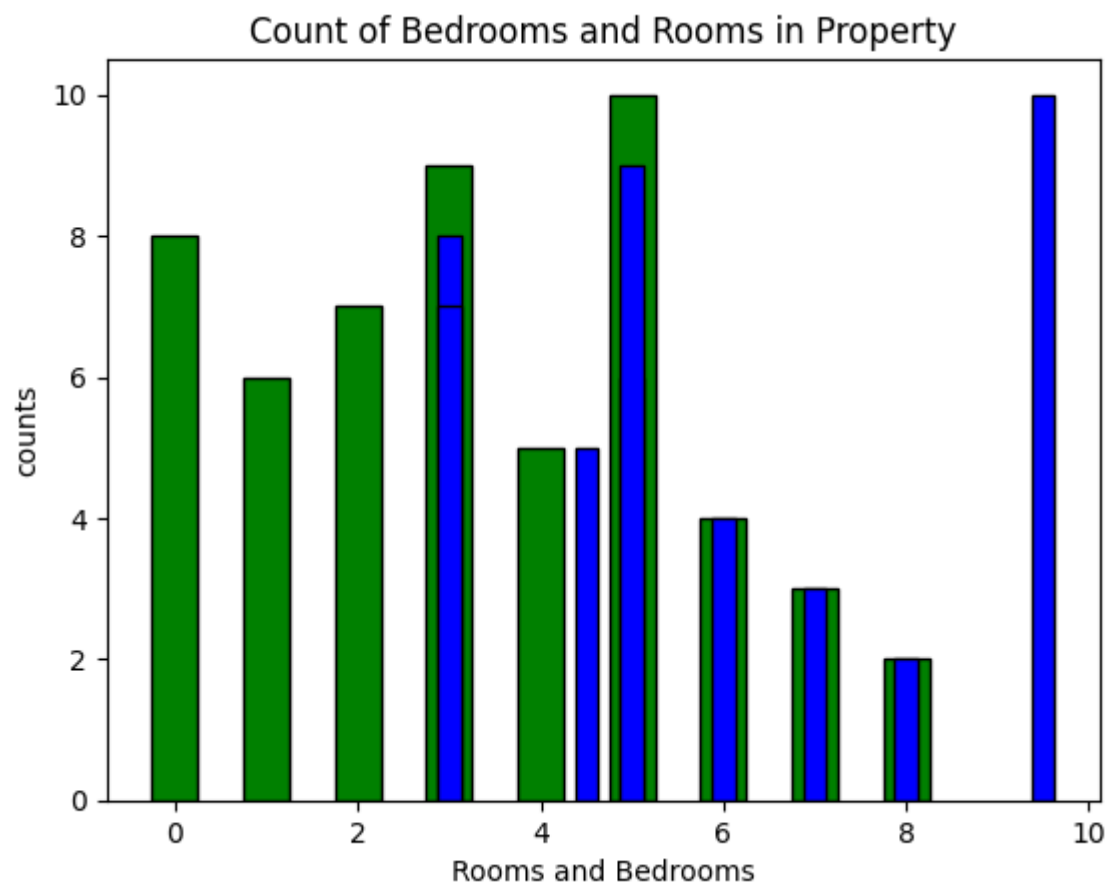
Out[ ]: Text(0.5, 1.0, 'Checking price according to entire property area')



## Bar Graphs

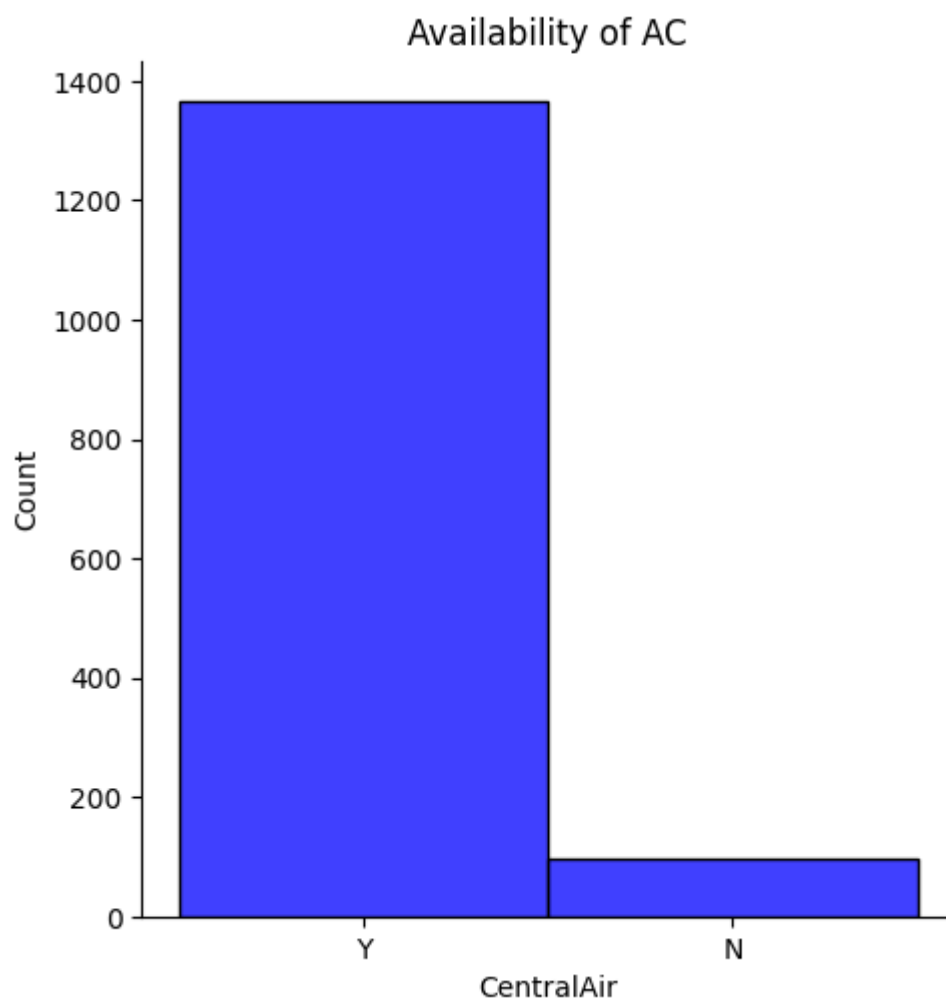
```
In [ ]: rooms=df['TotRmsAbvGrd'].unique()
bedrooms=df['BedroomAbvGr'].unique()
bedrooms = np.pad(bedrooms, (0, len(rooms) - len(bedrooms)), 'constant')
n=9
r=np.arange(n)
plt.bar(r, rooms, color = 'g',width = 0.50, edgecolor = 'black')
plt.bar(r + bedrooms, rooms, color = 'b',width = 0.25, edgecolor = 'black')
plt.xlabel('Rooms and Bedrooms')
plt.ylabel('counts')
plt.title('Count of Bedrooms and Rooms in Property')
```

Out[ ]: Text(0.5, 1.0, 'Count of Bedrooms and Rooms in Property')



```
In [ ]: sns.displot(df['CentralAir'],color='b')  
plt.title('Availability of AC')
```

```
Out[ ]: Text(0.5, 1.0, 'Availability of AC')
```



Normalization

## Normlization of Numerical columns and categorical columns in dataset

```
In [ ]: for col in df.columns:
        if (df[col].dtype != 'object'):
            # For numerical dataset
            number=df[col]
            reshaped_data=number.values.reshape(-1,1)
            scaler=MinMaxScaler()
            scaled_data=scaler.fit_transform(reshaped_data)
            scaled_df=pd.DataFrame(scaled_data)
            df[col]=scaled_df
        else:
            # for categorical dataset
            category=df[col]
            reshaped_data=category.values.reshape(-1,1)
            scaler=LabelEncoder()
            scaled_data=scaler.fit_transform(reshaped_data)
            scaled_df=pd.DataFrame(scaled_data)
            df[col]=scaled_df
```

[illegible]

```

\_label.py:114: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
c:\Users\Asus\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\preprocessing\_label.py:114: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
c:\Users\Asus\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\preprocessing\_label.py:114: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)

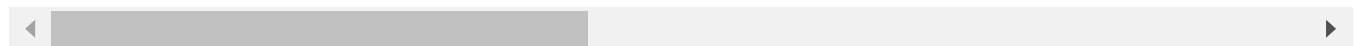
```

```
In [ ]: df.head()
```

```
Out[ ]:
```

	Id	MSZoning	LotArea	Street	LotShape	Neighborhood	Condition1	Condition2	BldgType
0	0.000000	3	0.430367	1	3	5	2	2	C
1	0.000685	3	0.501390	1	3	24	1	2	C
2	0.001371	3	0.603292	1	0	5	2	2	C
3	0.002056	3	0.498302	1	0	6	2	2	C
4	0.002742	3	0.789186	1	0	15	2	2	C

5 rows × 39 columns



Analyzing Correlation in Dataset through HeatMap

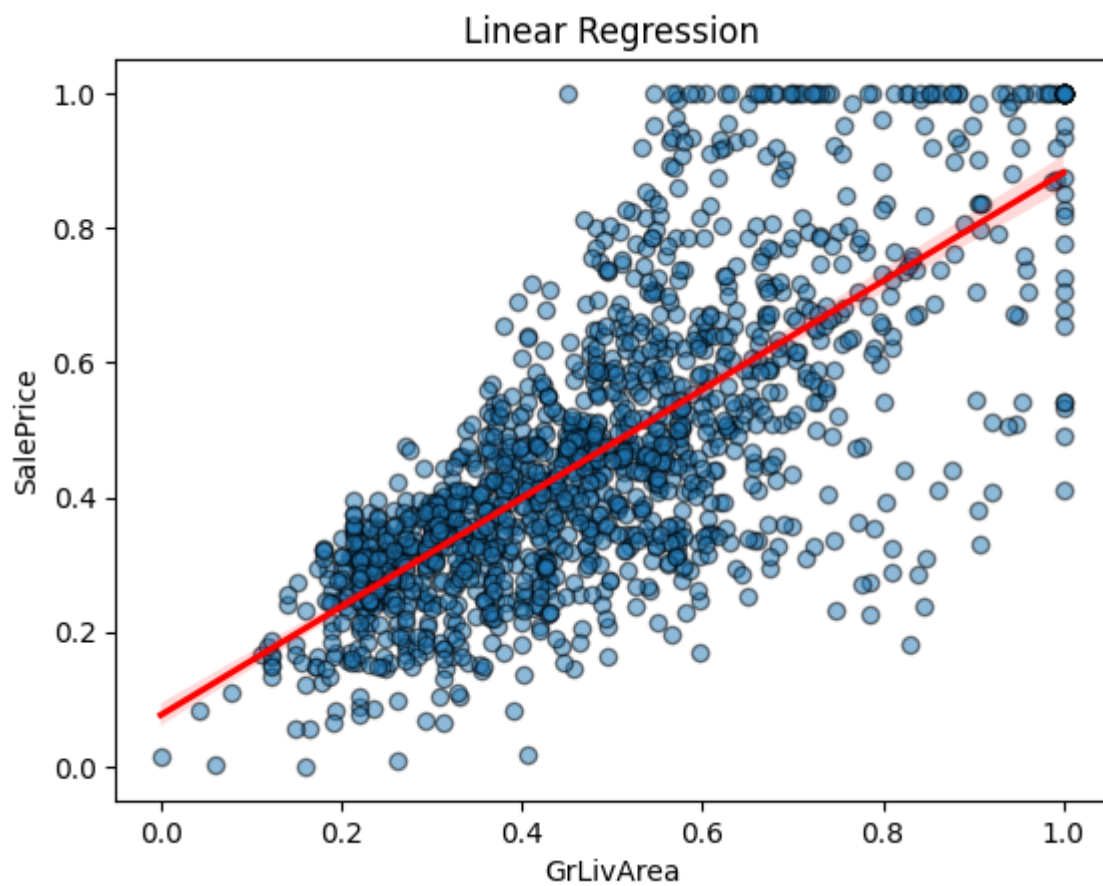
Linear Regression Model

```
In [ ]: x=df['GrLivArea']
y=df['SalePrice']
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.6,random_state=10)
x_train=x_train.values.reshape(-1,1)
y_train=y_train.values.reshape(-1,1)
x_test=x_test.values.reshape(-1,1)
y_test=y_test.values.reshape(-1,1)
model=LinearRegression()
linear=model.fit(x_train,y_train)
prediction=linear.predict(x_test)
```

```
In [ ]: sns.regplot(x='GrLivArea',y='SalePrice',data=df,line_kws={'color':'RED'}, scatter_kws={'alpha':0.1})
plt.title('Linear Regression')
```

```
Out[ ]: Text(0.5, 1.0, 'Linear Regression')
```





```
In [ ]: linear_accuracy=linear.score(x_test,y_test)
        print(linear_accuracy)
```

0.5574204006567671

Multiple Linear Regression Model

```
In [ ]: x=df[['LotArea','YearBuilt','TotalBsmtSF','1stFlrSF','2ndFlrSF','GrLivArea','KitchenQual','Ga
y=df['SalePrice']
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.70,random_state=1)
model=LinearRegression()
Mlinear=model.fit(x_train,y_train)
prediction=Mlinear.predict(x_test)
```

```
In [ ]: multiple_accuracy=Mlinear.score(x_test,y_test)
        print(multiple_accuracy)
```

0.8398349472057939

Polynomial Regression Model

```
In [ ]: x=df['GrLivArea'].values.reshape(-1,1)
y=df['SalePrice']
poly = PolynomialFeatures(degree=5,include_bias=False)
x_poly = poly.fit_transform(x)
plinear=poly.fit(x_poly, y)
model= LinearRegression()
plinear=model.fit(x_poly, y)
prediction=model.predict(x_poly)
```

```
In [ ]: polynomial_accuracy=plinear.score(x_poly,y)
        print(polynomial_accuracy)
```

0.5353363380347977

Logistic Regression Model

```
In [ ]: x=df['Street']
y=df['SaleType']
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.70,random_state=1)
x_train=x_train.values.reshape(-1,1)
x_test=x_test.values.reshape(-1,1)
y_train=y_train.values.reshape(-1,1)
y_test=y_test.values.reshape(-1,1)
model=LogisticRegression()
loglinear=model.fit(x_train,y_train)
prediction=model.predict(x_test)
```

c:\Users\Asus\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\utils\validation.py:1184: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n\_samples, ), for example using ravel().

```
y = column_or_1d(y, warn=True)
```

```
In [ ]: logistic_accuracy=loglinear.score(x_test,y_test)
```

Ridge Regression Model

```
In [ ]: x=df['GrLivArea']
y=df['SalePrice']
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.7,random_state=1)
x_train=x_train.values.reshape(-1,1)
x_test=x_test.values.reshape(-1,1)
y_train=y_train.values.reshape(-1,1)
y_test=y_test.values.reshape(-1,1)
cv = RepeatedKfold(n_splits=10, n_repeats=3, random_state=1)
model=RidgeCV(alphas=(1,2,0.01),cv=cv)
ridgeReg=model.fit(x_test,y_test)
prediction=model.predict(x_test)
```

```
In [ ]: ridge_accuracy=ridgeReg.score(x_test,y_test)
```

The Final R2 Score Comparison

```
In [ ]: print('The R2-Score value obtained by Linear Regression Model: ',linear_accuracy)
print('The R2-Score value obtained by Multi-linear Regression Model: ',multiple_accuracy)
print('The R2-Score value obtained by polynomial Regression Model: ',polynomial_accuracy)
print('The R2-Score value obtained by Logistic Regression Model: ',logistic_accuracy)
print('The R2-Score value obtained by Ridge Regression Model: ',ridge_accuracy)
```

The R2-Score value obtained by Linear Regression Model: 0.5574204006567671  
The R2-Score value obtained by Multi-linear Regression Model: 0.8398349472057939  
The R2-Score value obtained by polynomial Regression Model: 0.5353363380347977  
The R2-Score value obtained by Logistic Regression Model: 0.8656036446469249  
The R2-Score value obtained by Ridge Regression Model: 0.5322770689496097