Linear Regression Machine Learning Algorithms

Data Scientist → Linear Regression

Agenda

1. What problem we are solving
2. Geometric Intuition
3. Mathematical Intuition

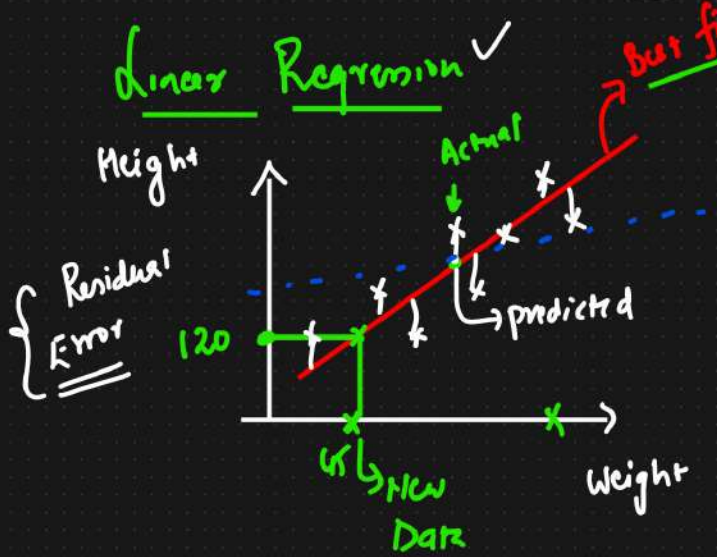
①

- Machine Learning
  - Supervised
    - Regression
    - Classification
  - Unsupervised

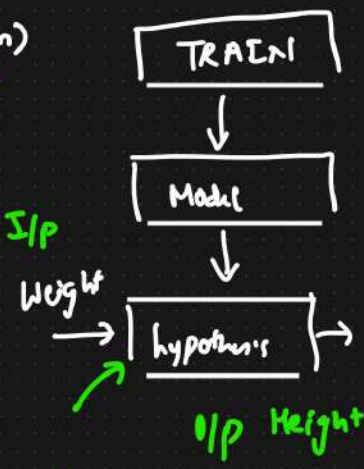
Linear Regression ↓ Regression — Continuous

Aim : To find best fit line — Minimal Error

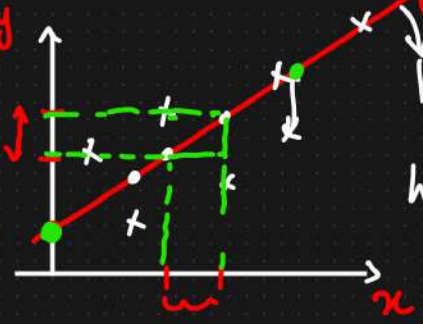
Linear Regression ✓



Weight (kg)	Height (cm)
73	150
63	155
78	170
82	165



Maths {Basic Maths}



$\hat{y} = mx + c$

$h_\theta(x) = \theta_0 + \theta_1 x_1$

$h_\theta(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3 + \cdots \theta_n x_n$

m = Slope or Coefficient

c = Intercept

Andrew NG

House Price Predictions with Exploratory Data Analysis and important Observations

Ask a home buyer to describe their dream house, and they probably won't begin with the height of the basement ceiling or the proximity to an east-west railroad. But in real dataset, it proves that much more influences price negotiations than the number of bedrooms or a white-picket fence.

With 79 explanatory variables describing (almost) every aspect of residential homes in Ames, Iowa, this competition challenges you to predict the final price of each home.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
# To display the entire columns

pd.set_option('display.max_columns', None)
```

In [3]:
```
# Read the dataset

df = pd.read_csv(r"C:\Users\460379\Python Projects ineuron\Python_EDA_Preprocessing\Py
```

In [4]:
```
# Calling the dataset
df
```

Out[4]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	U
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	
...	...	...	...	...	...	...	...	...	...	...
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	Lvl	
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	Lvl	
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	Lvl	
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	Lvl	
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	Lvl	

1460 rows × 81 columns

In [5]:
```
#Chek the number of features in the datasets
df.columns
```

Out[5]:
```
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')
```

In [6]:
```
#Check the number of columns and number of rows in the dataset

df.shape
```

Out[6]:
```
(1460, 81)
```

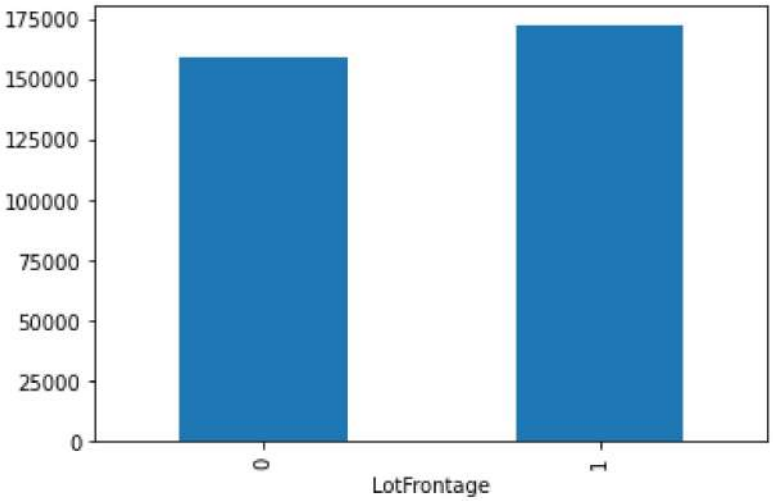
In [7]:
```
# Check for the total missing values in the dataset

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

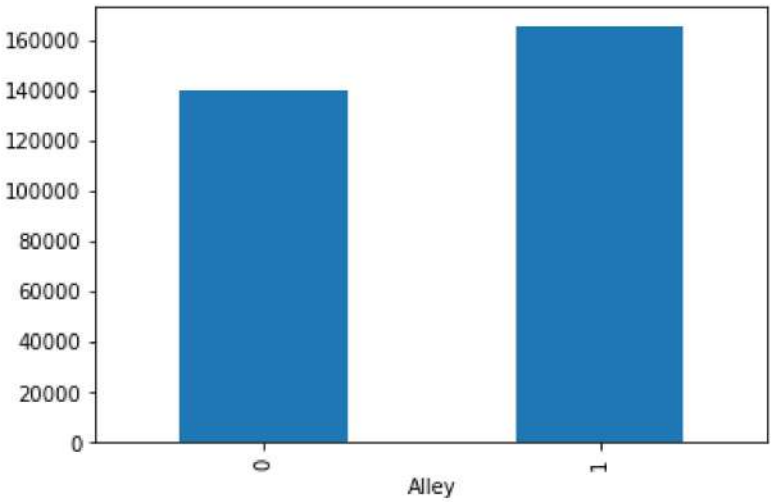
Out[7]:
```
Id               0
MSSubClass       0
MSZoning         0
LotFrontage    259
LotArea          0
                ...
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
Length: 81, dtype: int64
```

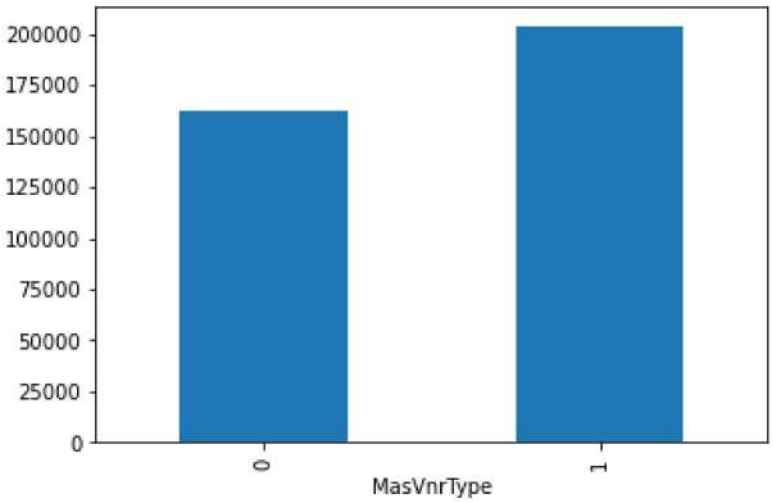
In [8]:
```
# Find the percentage of missing values for all the features in the datasets with deci

feature_with_na = [feature for feature in df.columns if df[feature].isnull().sum()>1]

for feature in feature_with_na:
    print(feature, np.round(df[feature].isnull().mean(),4))
```

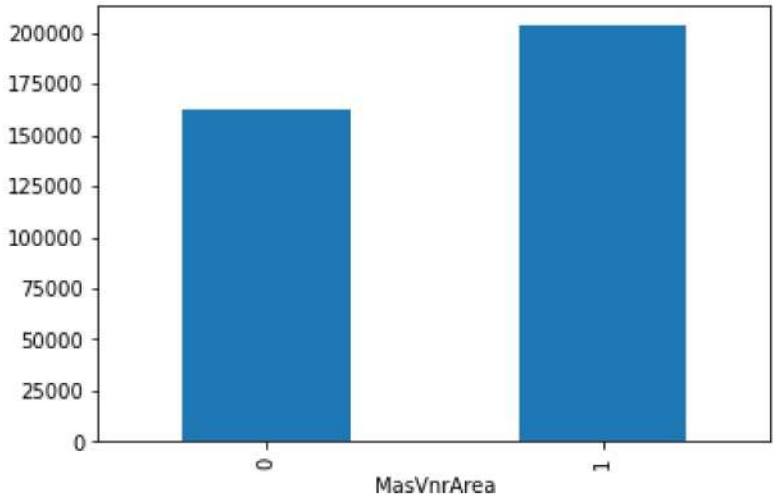
```
LotFrontage 0.1774
Alley 0.9377
MasVnrType 0.0055
MasVnrArea 0.0055
BsmtQual 0.0253
BsmtCond 0.0253
BsmtExposure 0.026
BsmtFinType1 0.0253
BsmtFinType2 0.026
FireplaceQu 0.4726
GarageType 0.0555
GarageYrBlt 0.0555
GarageFinish 0.0555
GarageQual 0.0555
GarageCond 0.0555
PoolQC 0.9952
Fence 0.8075
MiscFeature 0.963
```

In [9]:
```
# Let's plot the missing values of the dataset for all the features

for feature in feature_with_na:
    df1 = df.copy()

    #Lets create a variable which will indicate 1 if the there is null value else 0 if
    df1[feature] = np.where(df1[feature].isnull(), 1, 0)

    #Let's plot it using count plot with median sales price in Y axis and understand i
    df1.groupby(feature)['SalePrice'].median().plot.bar()
    plt.show()
```


175000
150000
125000
100000
75000
50000
25000
0
0
1
LotFrontage


160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
Alley


200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
MasVnrType


200000
175000
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75000
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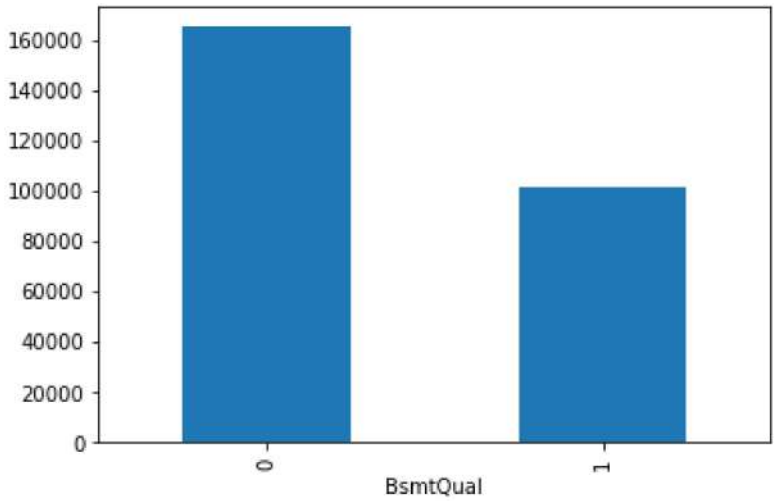
25000
0
0
1
MasVnrArea


160000
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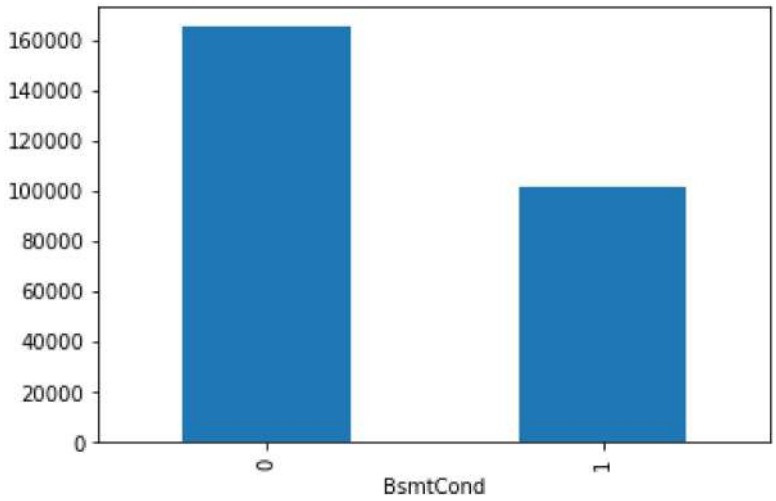
1
BsmtQual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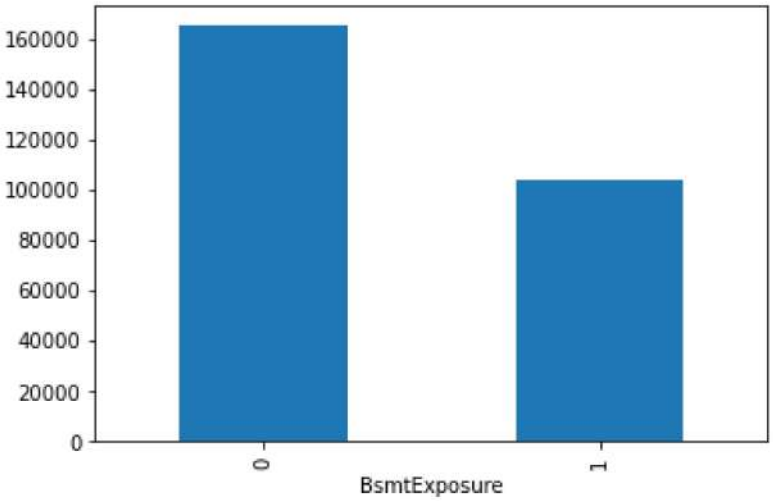
1
BsmtCond


160000
140000
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100000
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60000
40000
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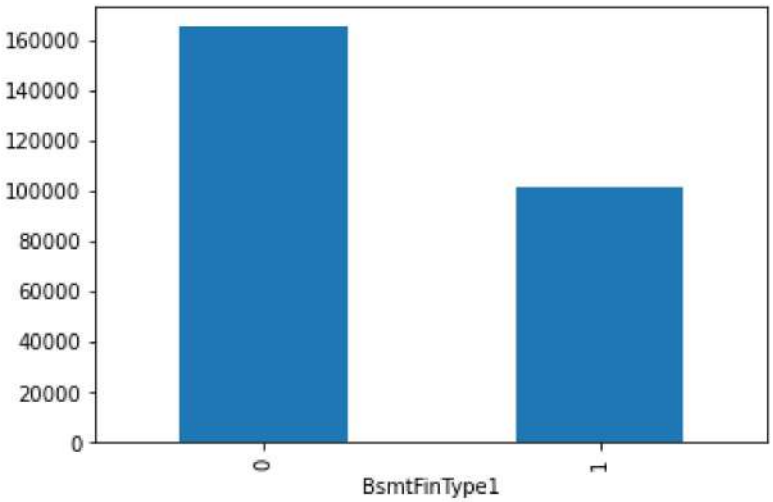
0
0
1
BsmtExposure


160000
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100000
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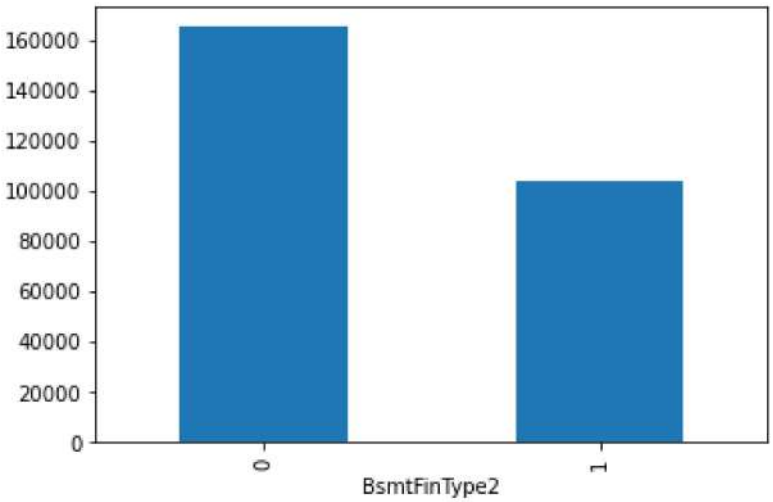
0
0
1
BsmtFinType1


160000
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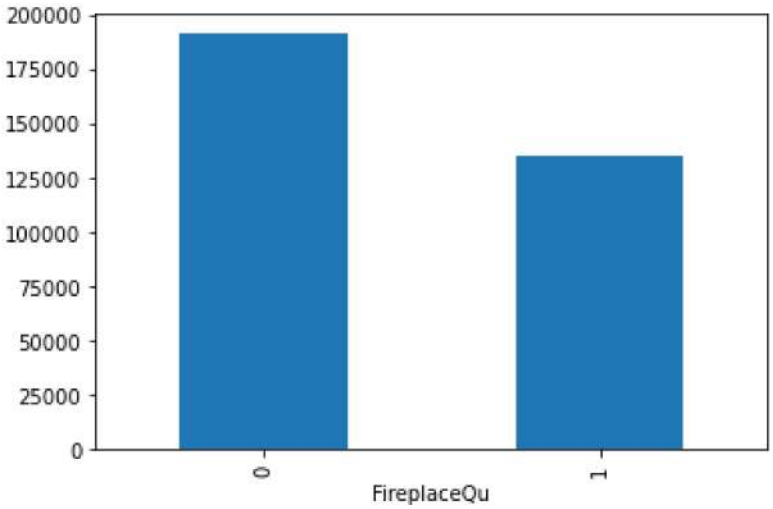
20000
0
0
1
BsmtFinType2


200000
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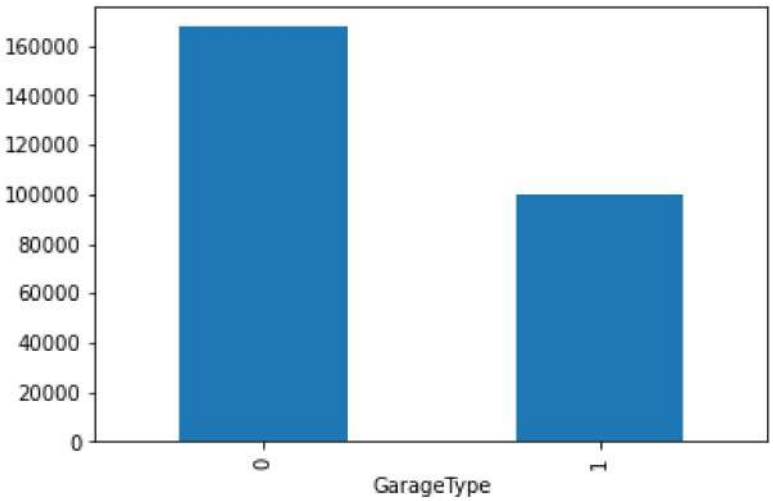
0
1
FireplaceQu


160000
140000
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100000
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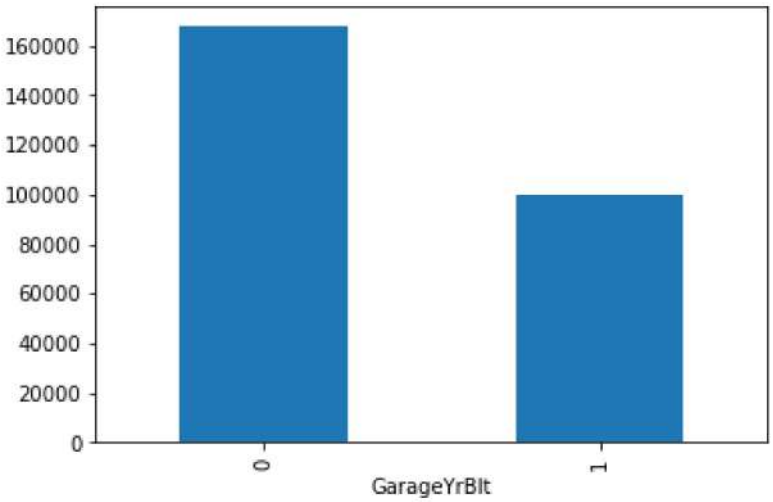
0
0
1
GarageType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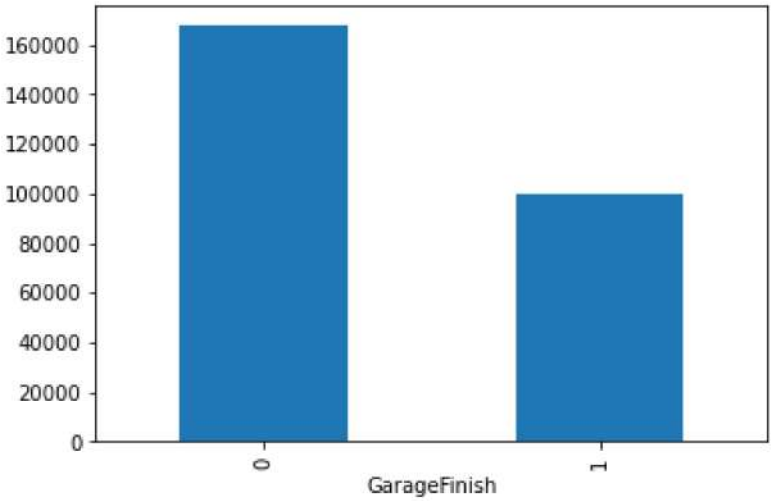
0
1
GarageYrBlt


160000
140000
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100000
80000
60000
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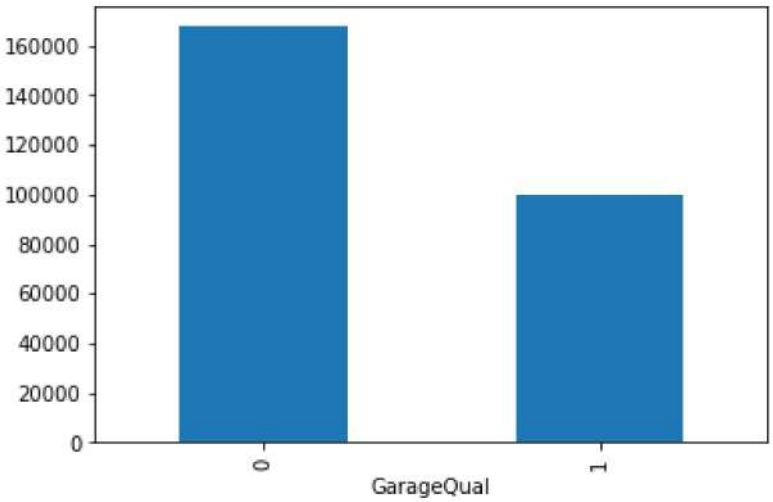
20000
0
0
1
GarageFinish


160000
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100000
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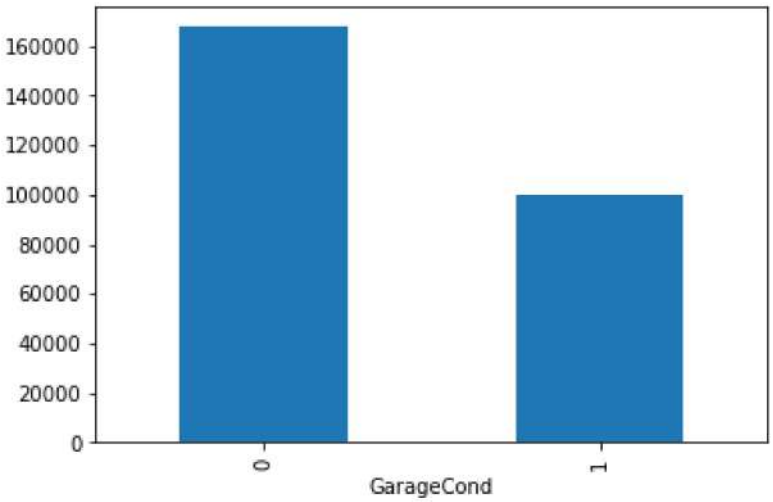
0
0
1
GarageQual


160000
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100000
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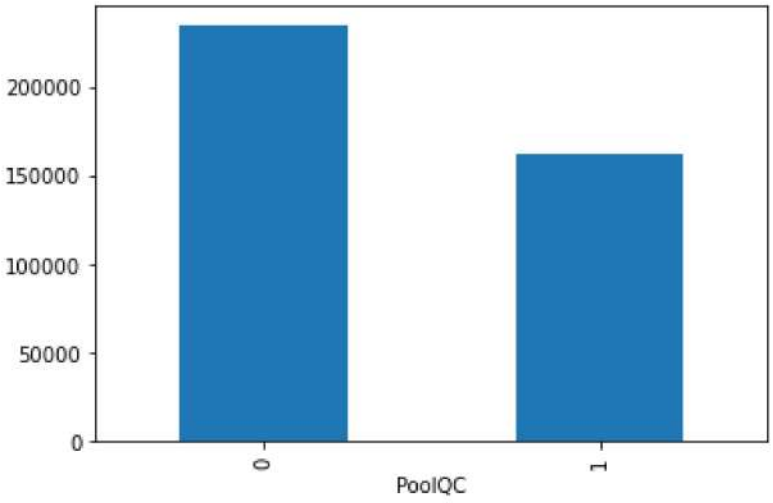
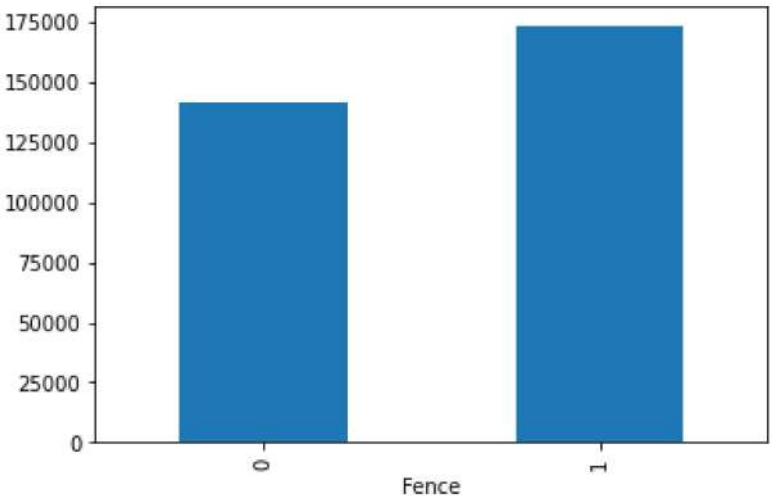
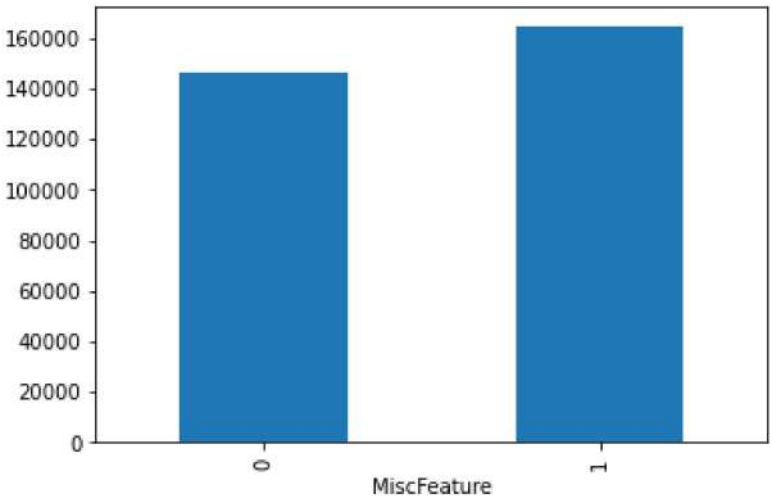
60000
40000
20000
0
0
1
GarageCond







Observation 1 : There are significant impact of features with null values with target variable that is "Sales Price" hence we need to treat these missing values in feature engineering very carefully

In [10]:
```
# Find the categorical features in the dataset

categorical_features = [features for features in df.columns if df[features].dtypes ==
categorical_features
```

Out[10]:
```
['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']
```

In [11]:
```
# Find the numerical features in the dataset

Numerical_features = [features for features in df.columns if df[features].dtypes != 'O
```

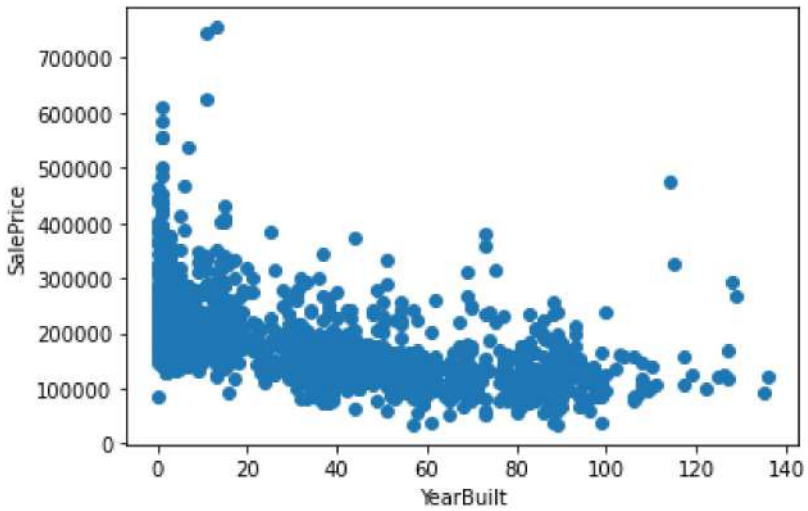
In [12]:
```
# Find the year features in the datasets since there are multiple year features

year_features = [features for features in Numerical_features if 'Year' in features or
year_features
```

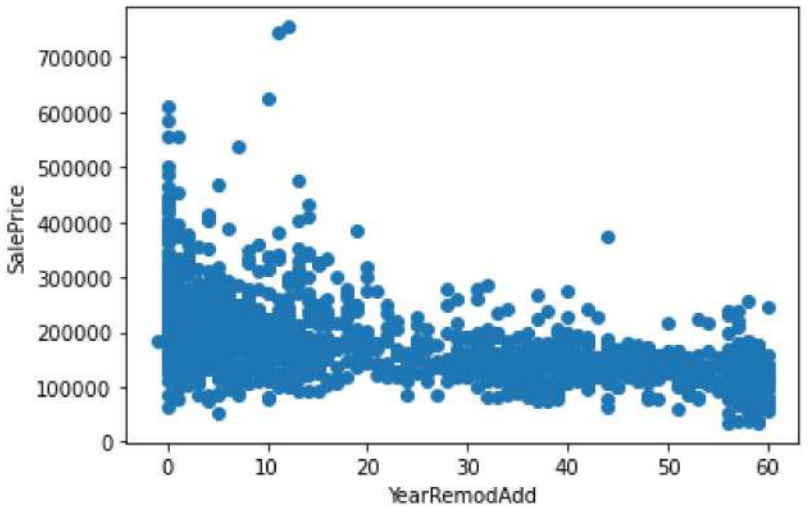
Out[12]:
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

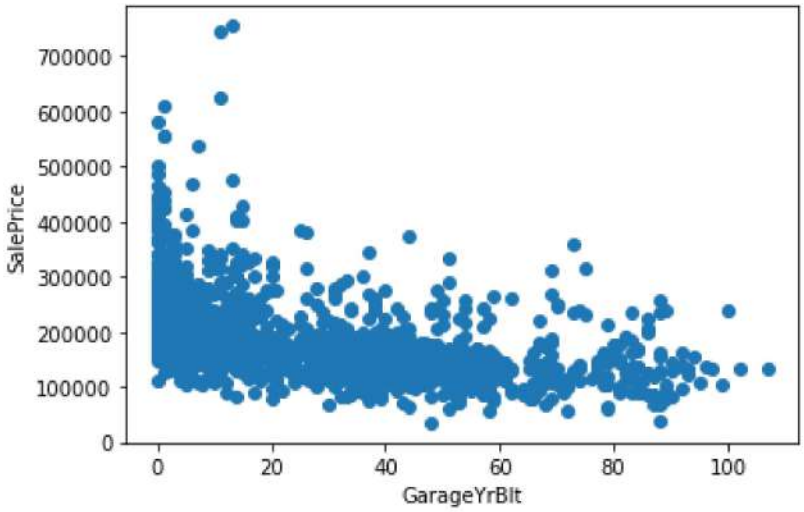
In [13]:
```
# Find the discreet features of the dataset

discreet_features = [features for features in Numerical_features if len(df[features].u
```

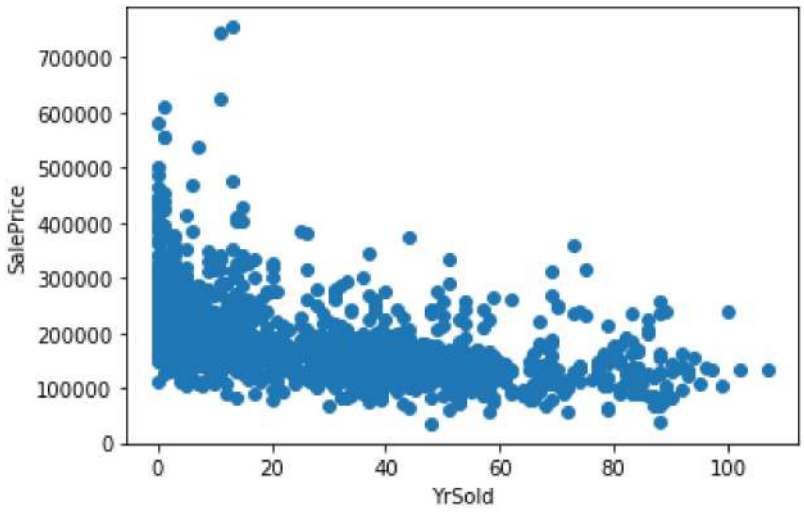
Bivariate Analysis of Year Features v/s Target Variable ("SalePrice")

In [14]:
```
# Perform Bi-variate analysis of "year feature" with target feature using scatter plot

for features in year_features:
    if features != 'YrSold':
        df1 = df.copy()

# Let's capture the difference between the year variables and year the house was sold
        df1[feature] = df1['YrSold']-df1[features]

#Let's plot the difference between year variables and year sold using scatter plot
    plt.scatter(df1[feature], df1['SalePrice'])
    plt.xlabel(features)
    plt.ylabel('SalePrice')
    plt.show()
```





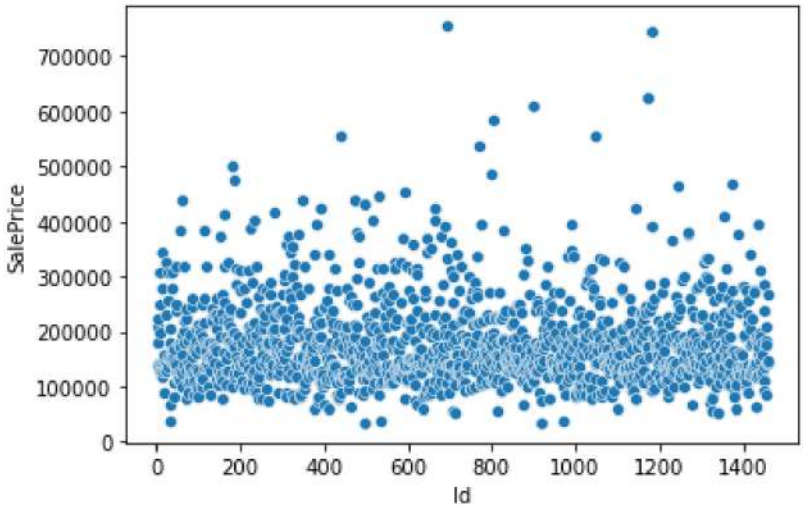


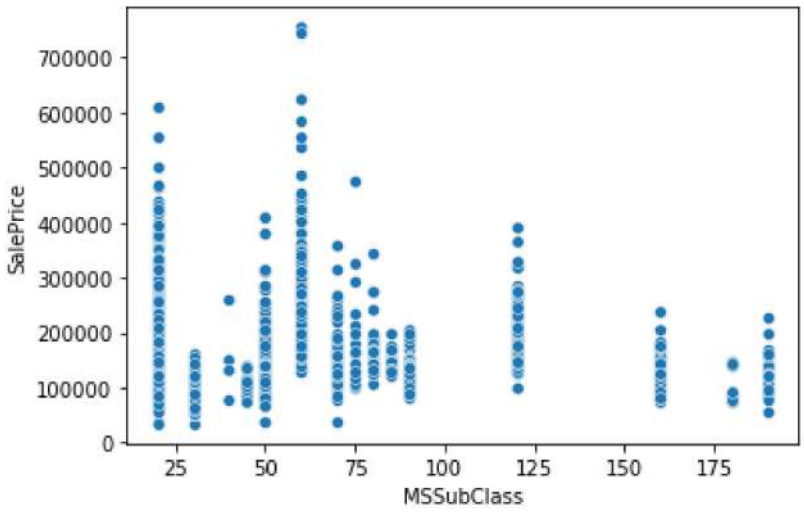


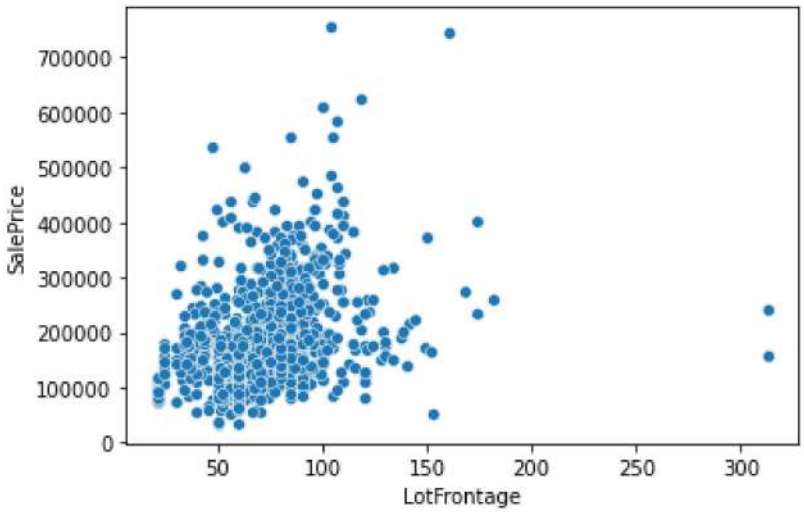
Observation 2 : We see that the "sales price" decreases substantially as the "Yearbuilt", "Yearremodel", "GarageYearBuilt" increases and it decreases faster rate after 20 to 25 years

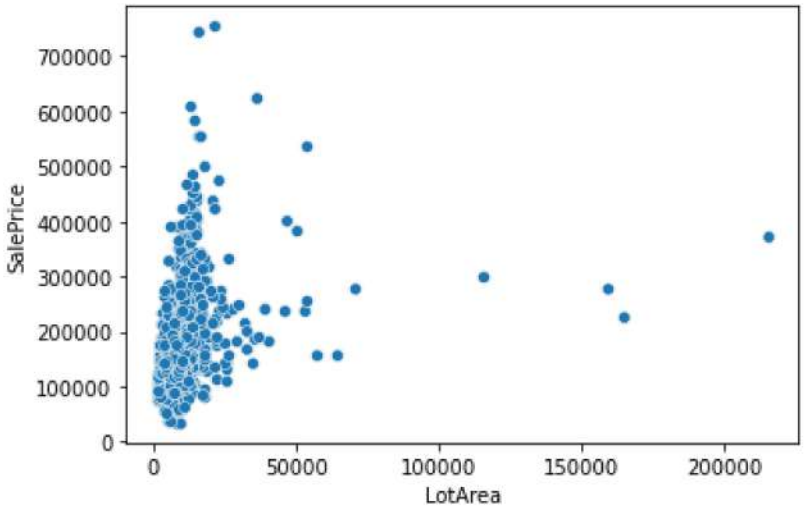
Bivariate Analysis of Numerical Features v/s Target Feature ("SalePrice")

In [15]:
```
# Let's perform Bivariate analysis of Numerical features with Target feature using sca

for features in Numerical_features:
    df1 = df.copy()
    sns.scatterplot(x = features, y = 'SalePrice', data = df1)
    plt.show()
```


SalePrice
Id
0
100000
200000
300000
400000
500000
600000
700000
0
200
400
600
800
1000
1200
1400


SalePrice
MSSubClass
0
100000
200000
300000
400000
500000
600000
700000
25
50
75
100
125
150
175


SalePrice
LotFrontage
0
100000
200000
300000
400000
500000
600000
700000
50
100
150
200
250
300


SalePrice
LotArea
0
100000
200000
300000
400000
500000
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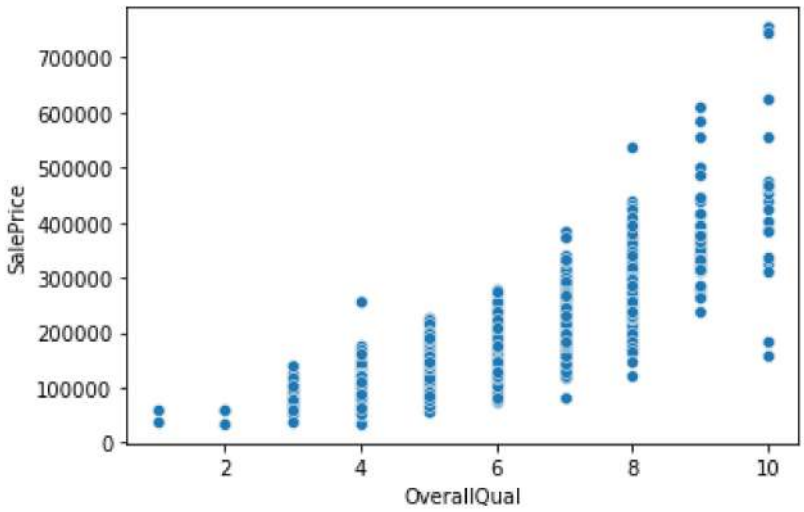
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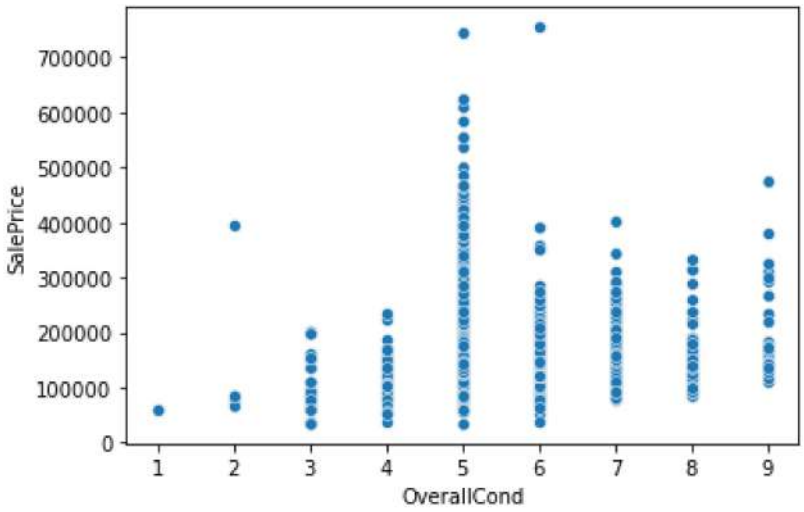
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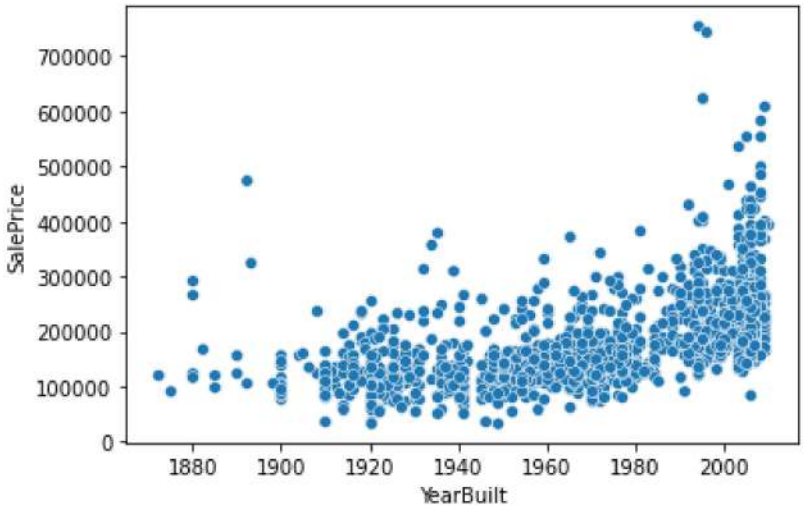
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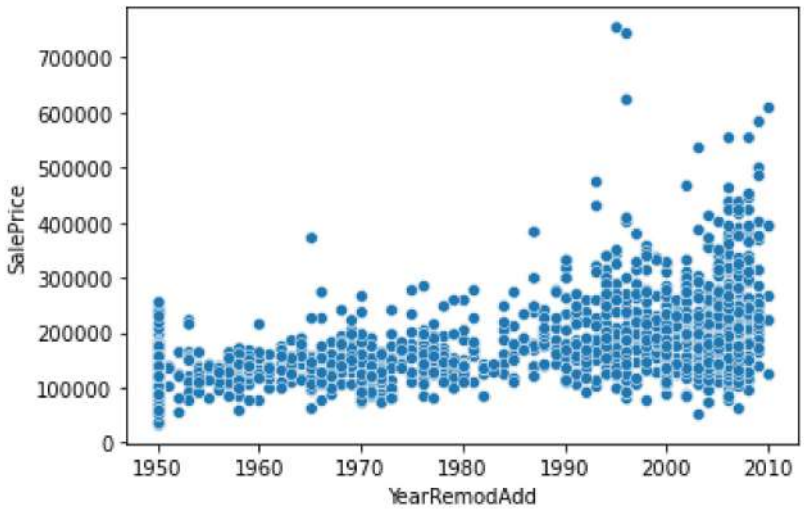
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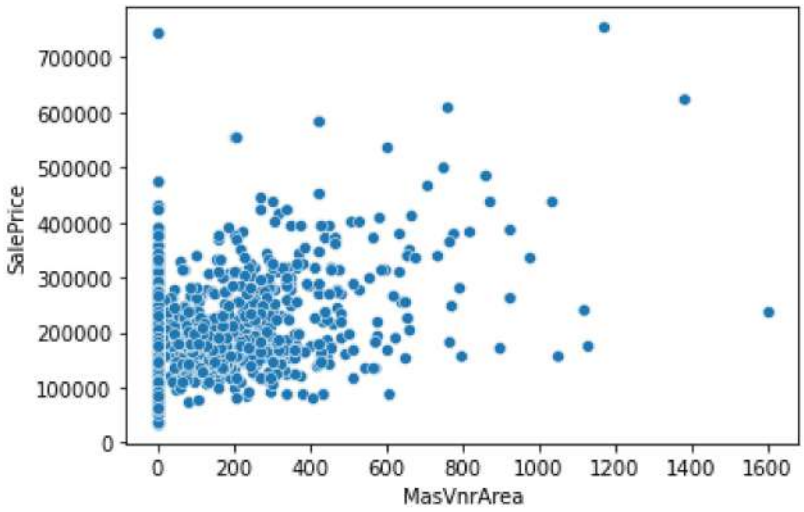
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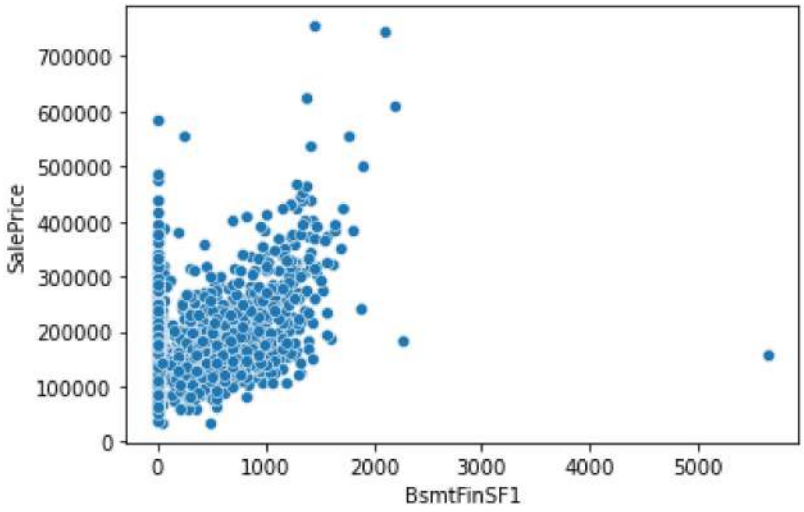
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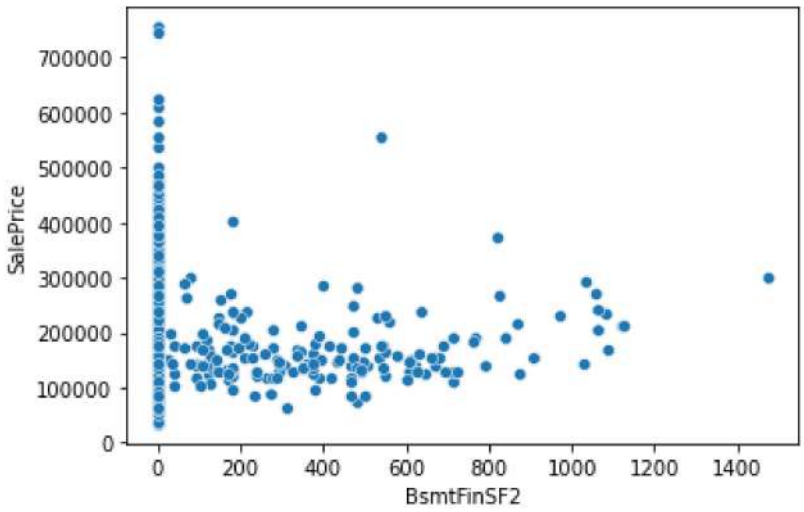
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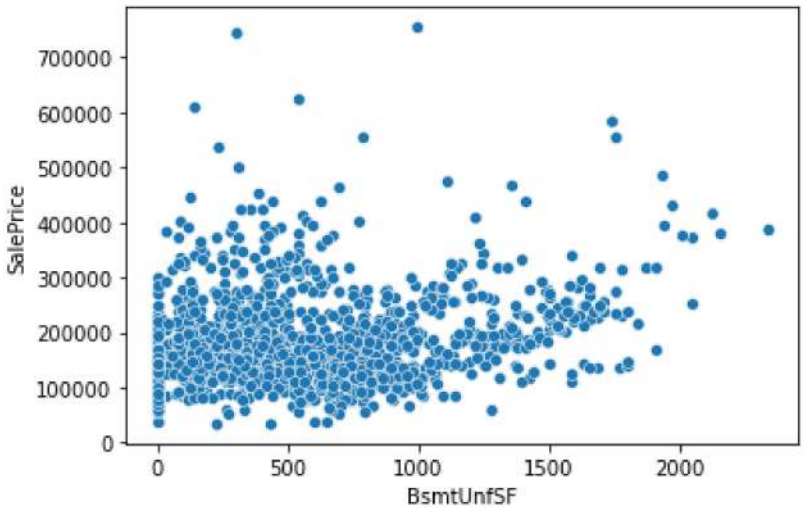
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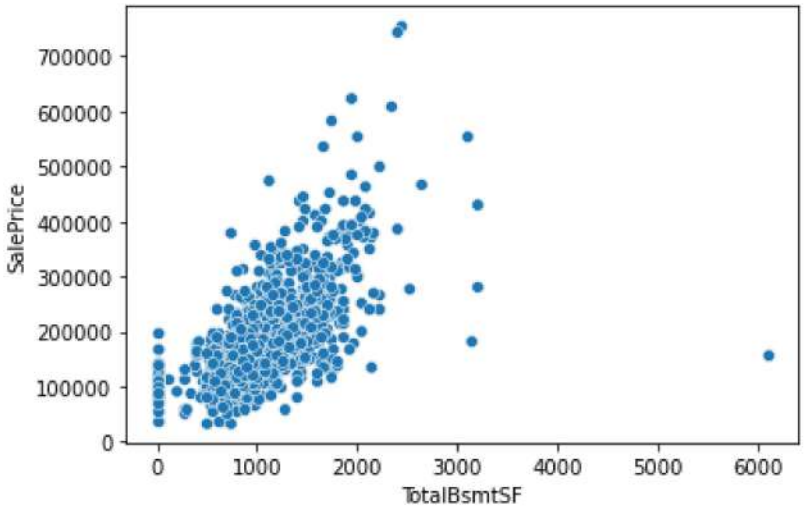
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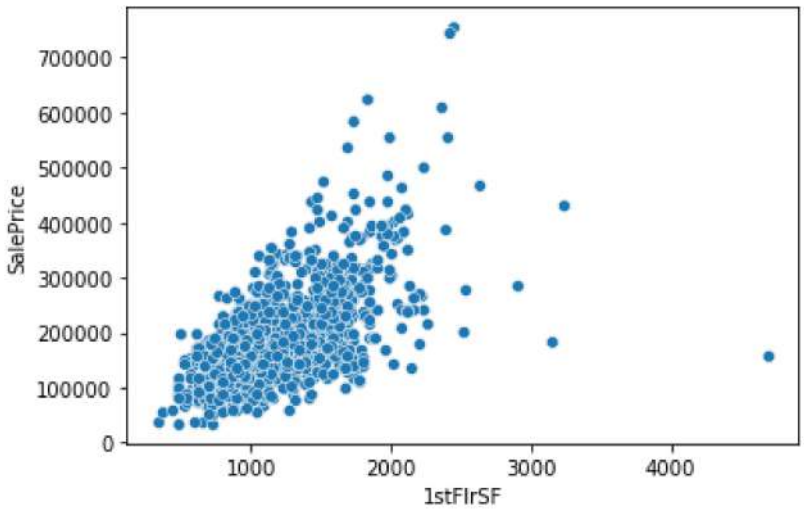
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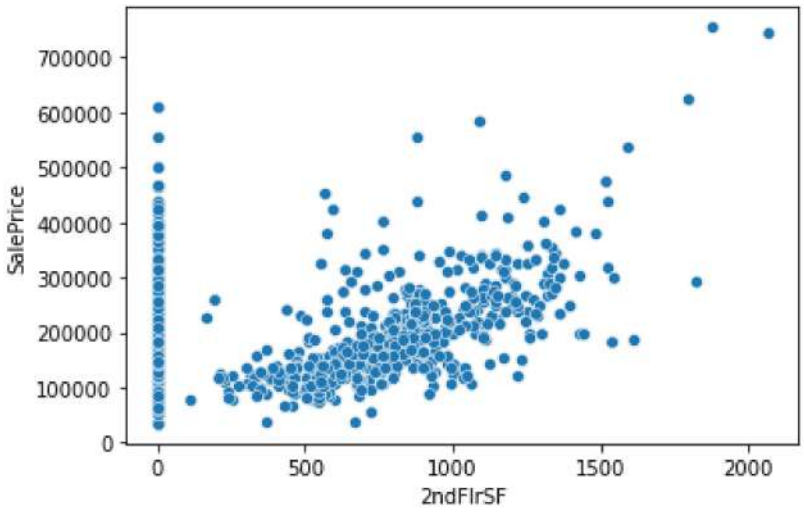
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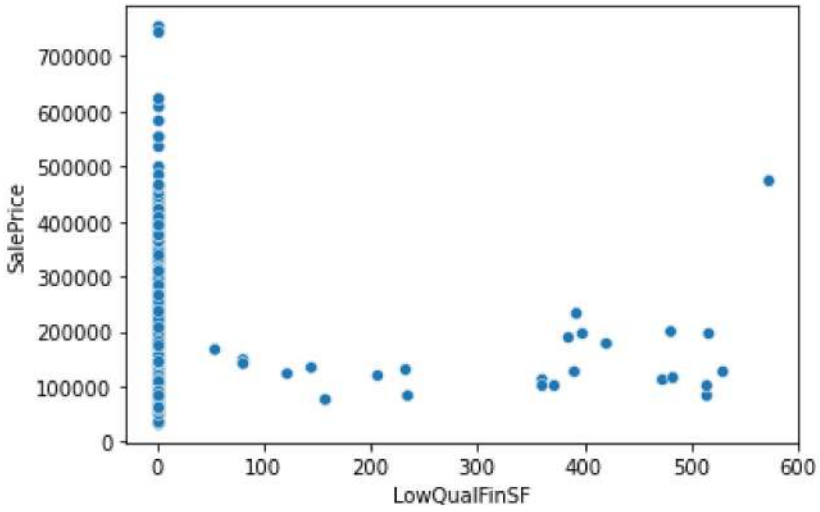
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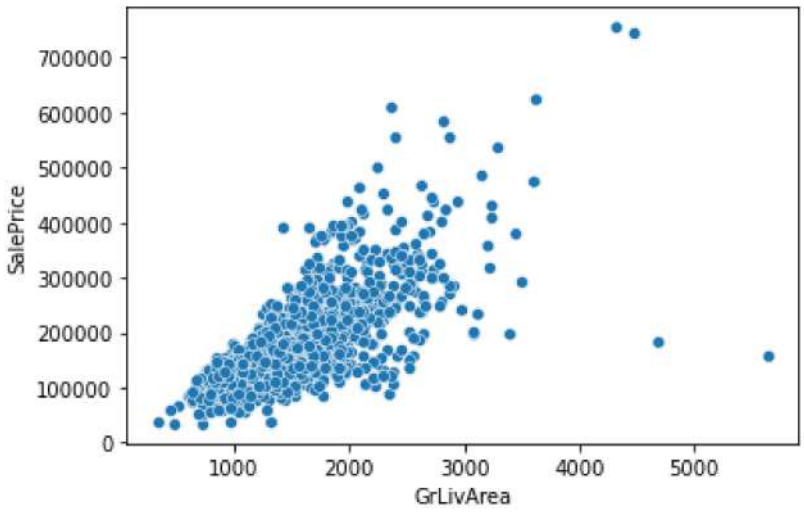
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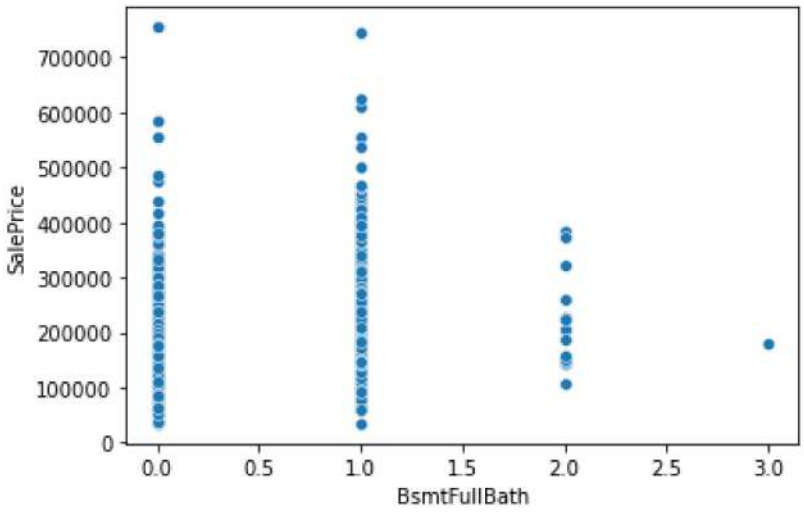
SalePrice
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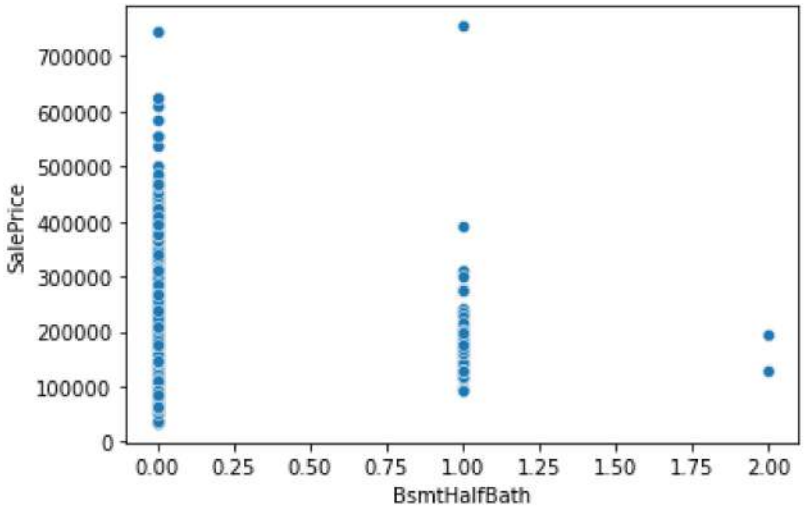
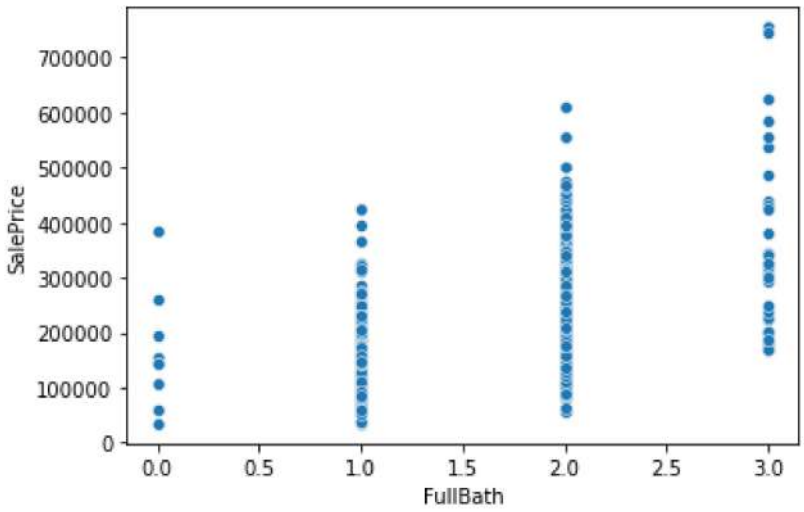
2.5
3.0


SalePrice
BsmtHalfBath


SalePrice
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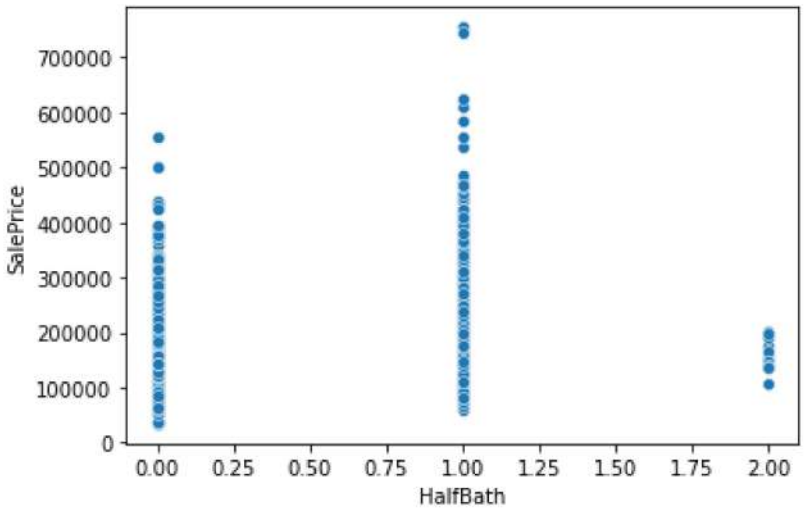
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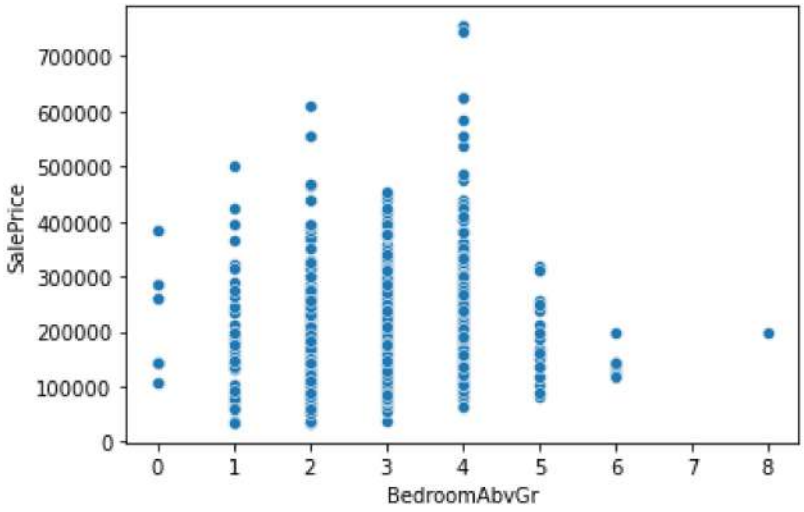
SalePrice
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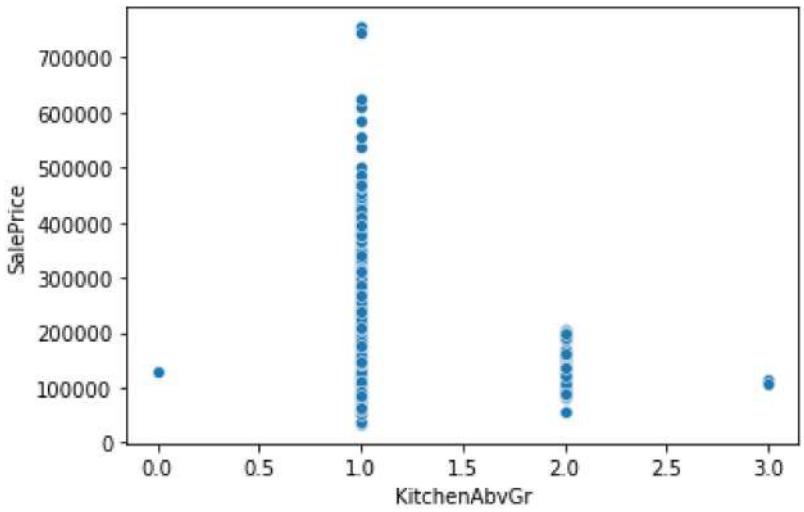
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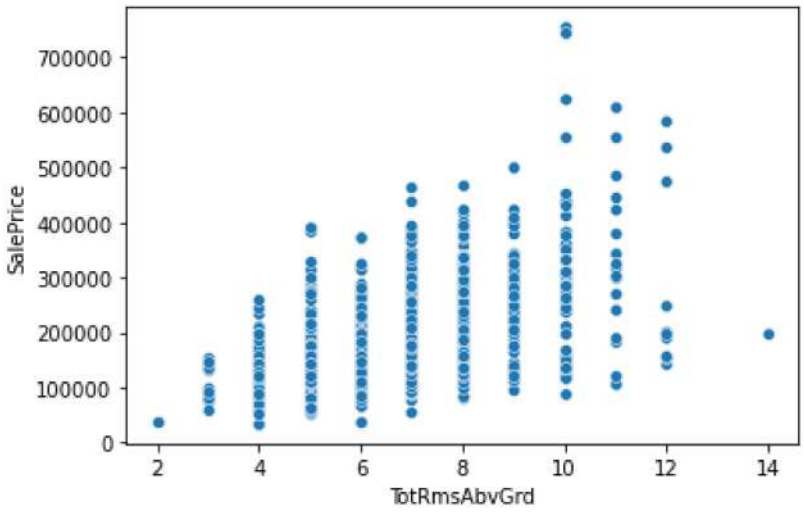
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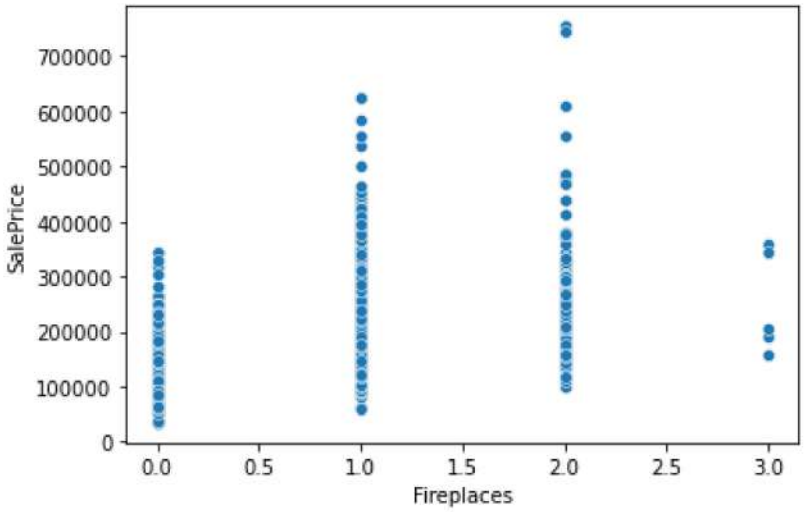
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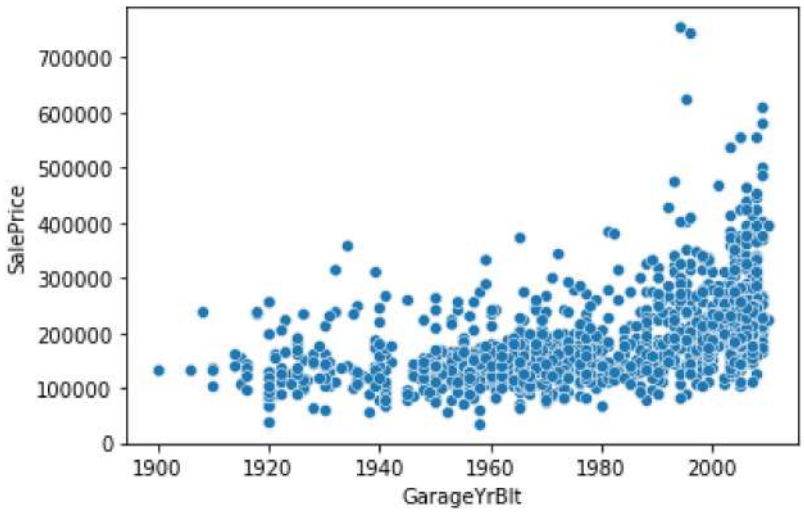
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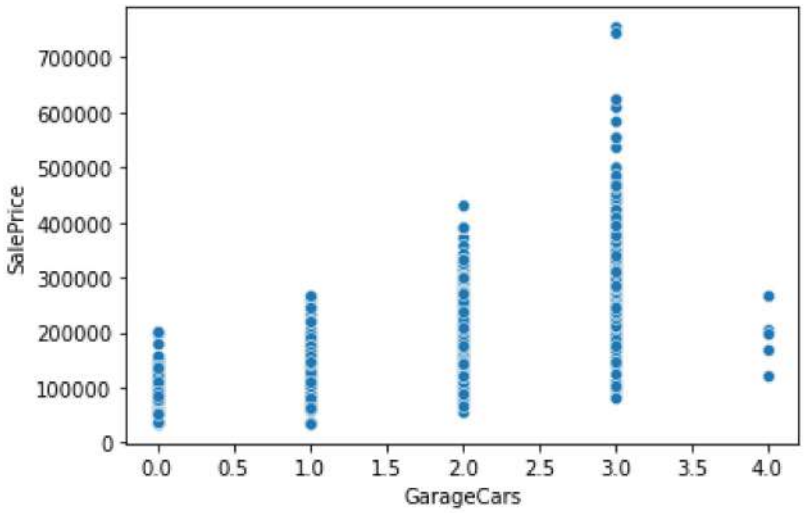
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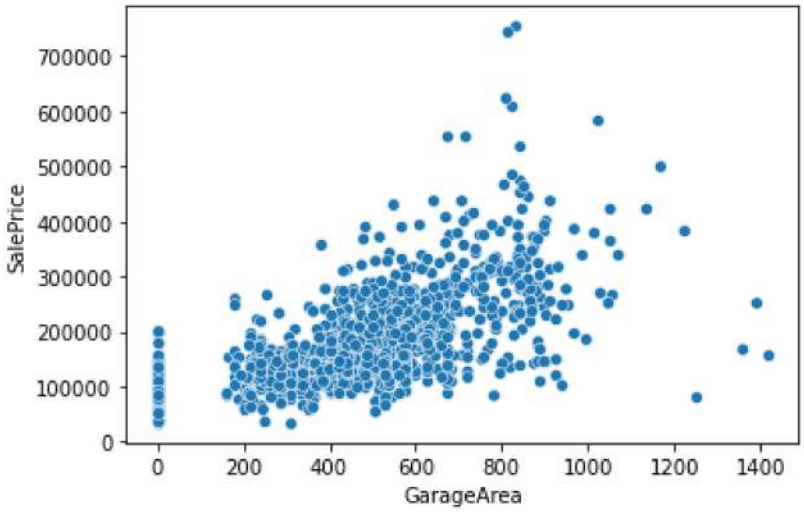
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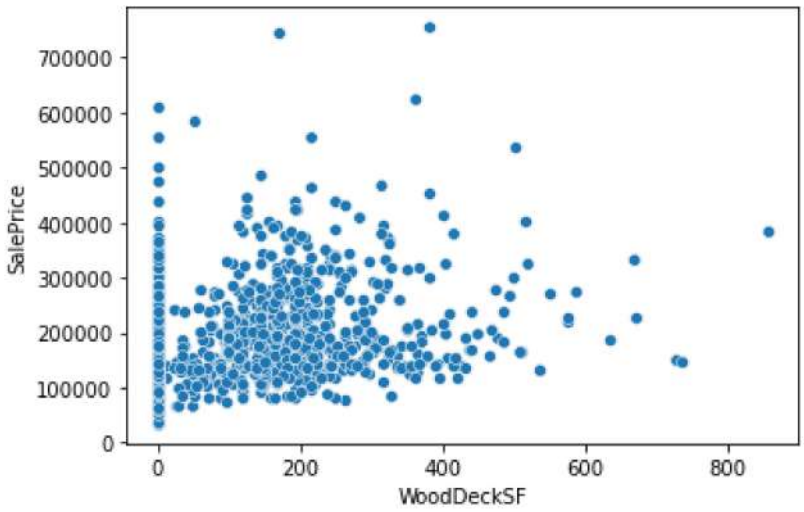
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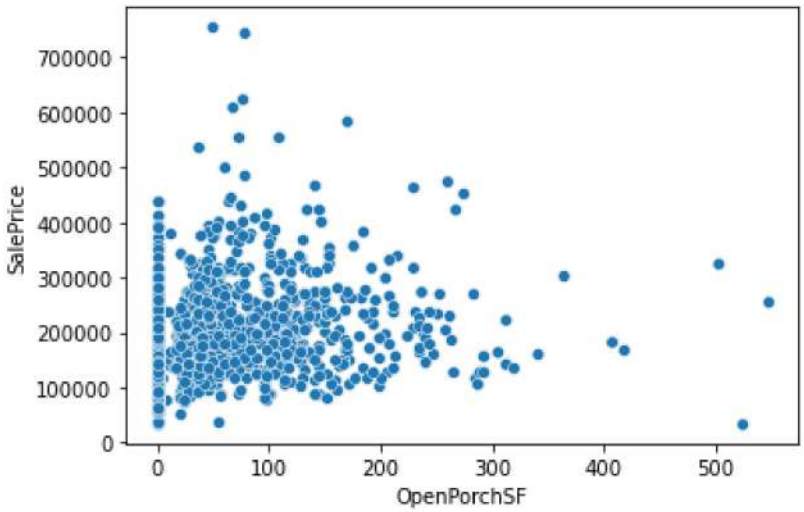
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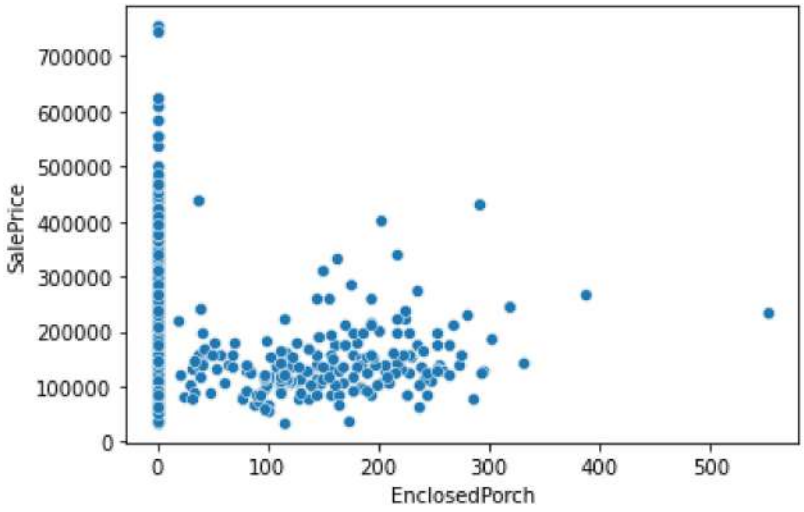
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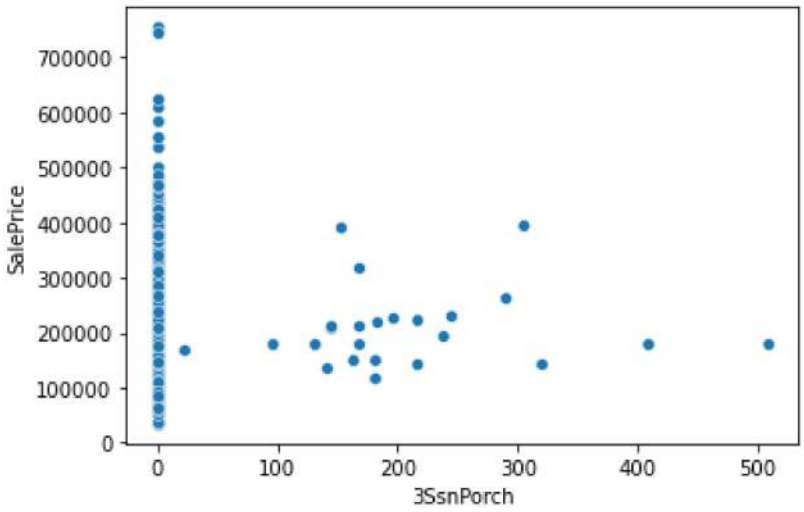
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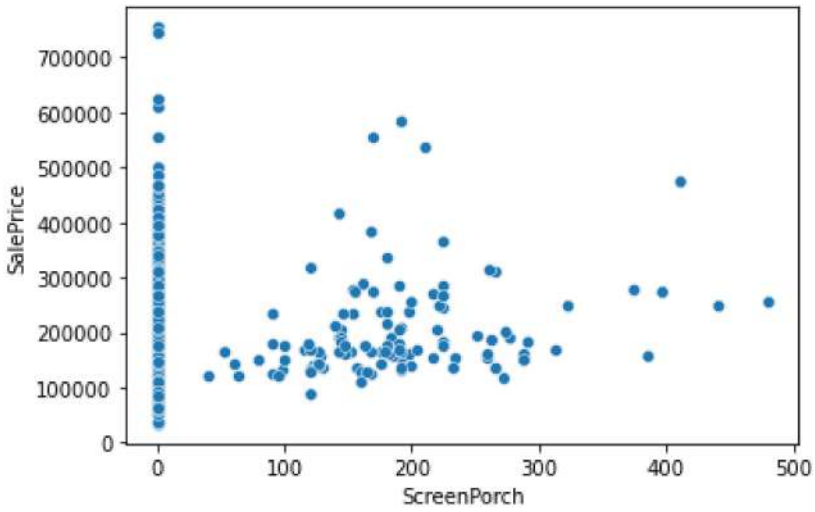
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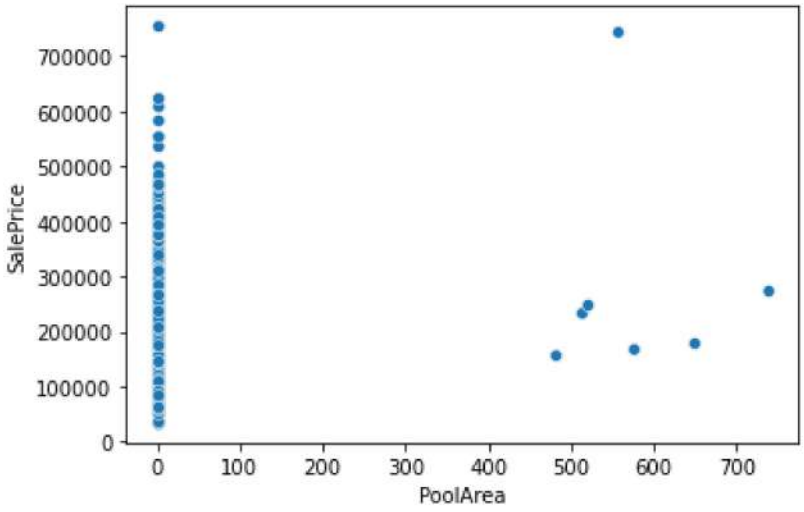
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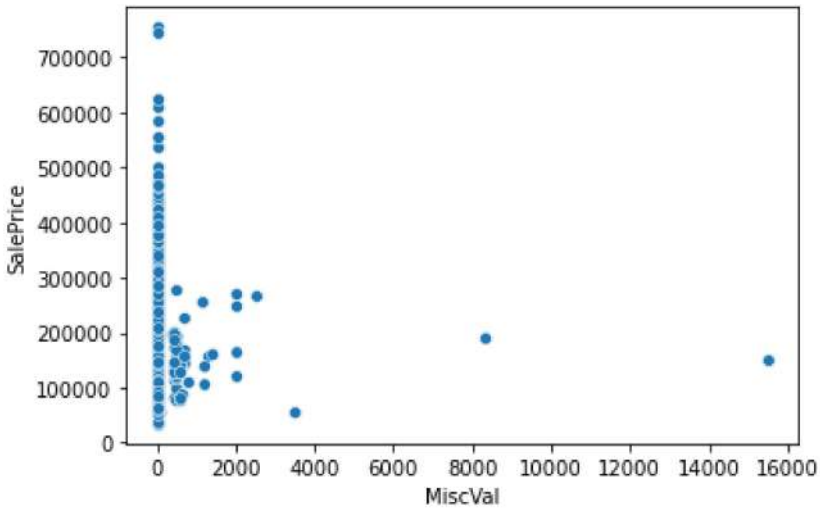
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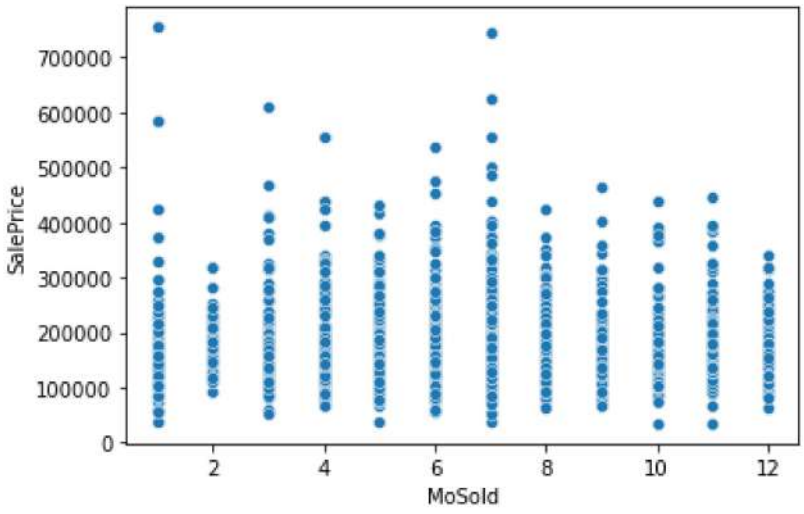
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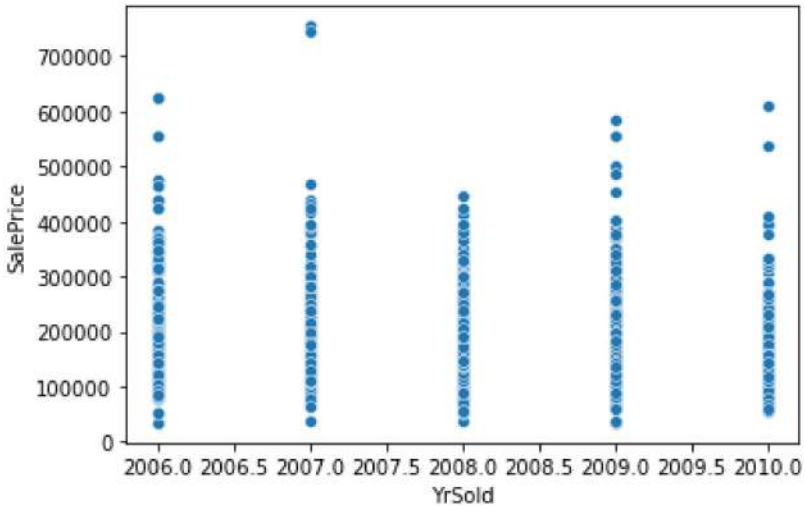
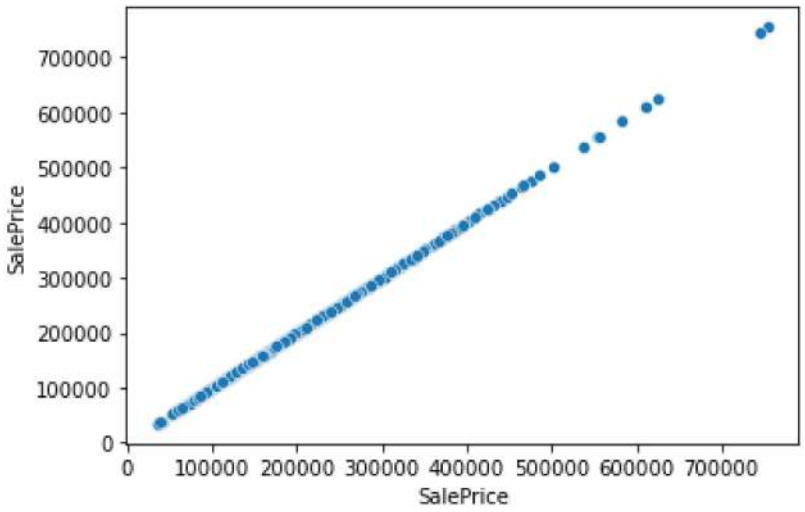
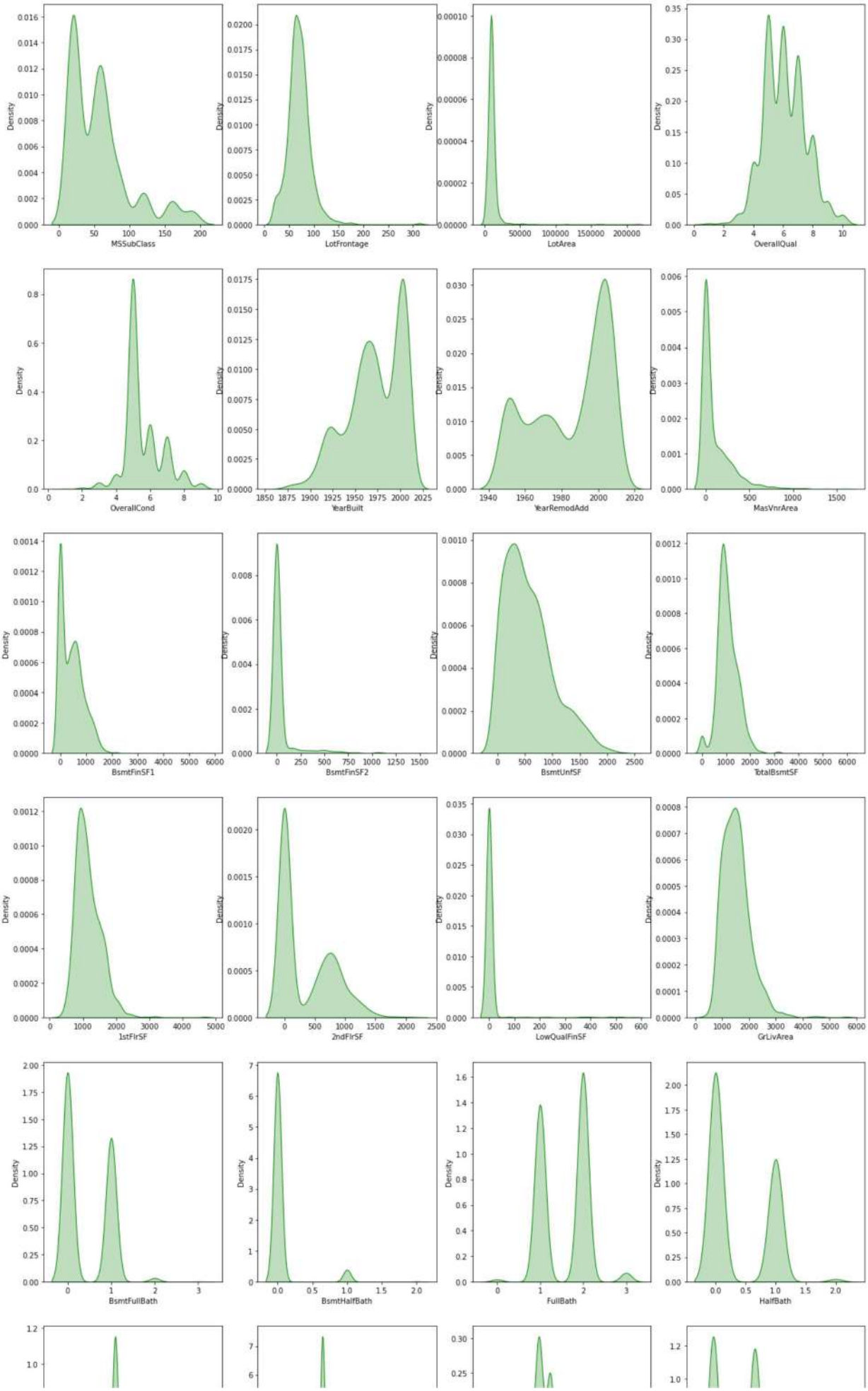
10
12

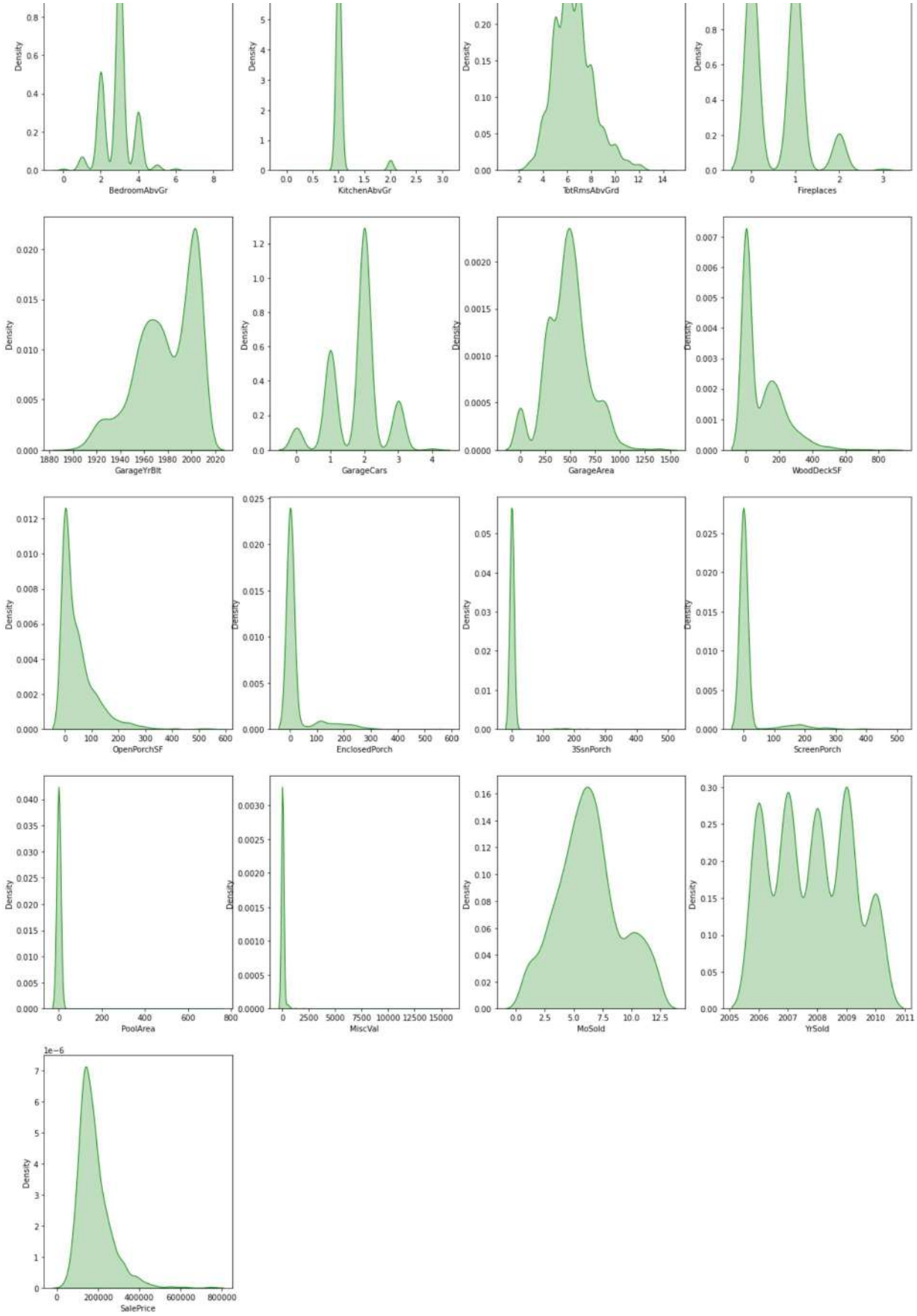




Univariate Analysis of Numerical Features and Discreet Features

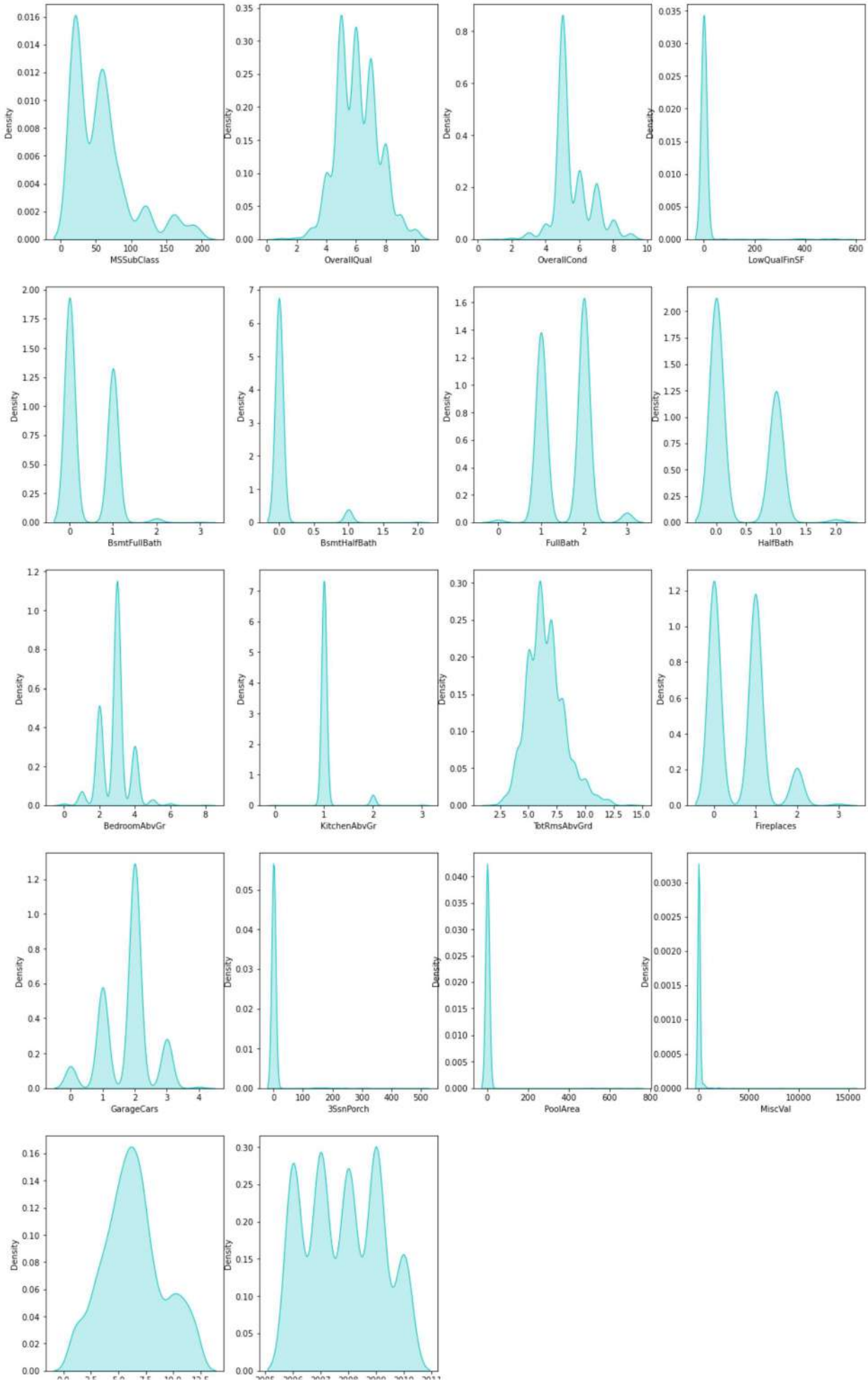
In [16]:
```
# Let's first perform Univariate anaylsis of Numerical features using kdeplot

Numerical_features = [features for features in Numerical_features if features not in '
plt.figure(figsize=(20,65))

for i in range(0, len(Numerical_features)):
    df1 = df.copy()
    plt.subplot(10, 4, i+1)
    sns.kdeplot(x=df1[Numerical_features[i]], shade = True, color = 'g',in_layout = Tr
    plt.xlabel(Numerical_features[i])
```


Density
MSSubClass
LotFrontage
LotArea
OverallQual
OverallCond
YearBuilt
YearRemodAdd
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
LowQualFinSF
GrLivArea
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath



In [17]:
```
# Let's perform univariate analysis of "Discreet features"  using kdeplot
plt.figure(figsize= (18,50))
for i in range(0, len(discreet_features)):
    df1 = df.copy()
    plt.subplot(8, 4, i+1)
```

```
    sns.kdeplot(x= df1[discreet_features[i]],shade = True, color = 'c', in_layout = Tr
```


Density
MSSubClass
OverallQual
OverallCond
LowQualFinSF
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageCars
3SsnPorch
PoolArea
MiscVal

Multivariate Analysis of all House Features with Target Feature "SalePrice" using Correlation and Heatmap

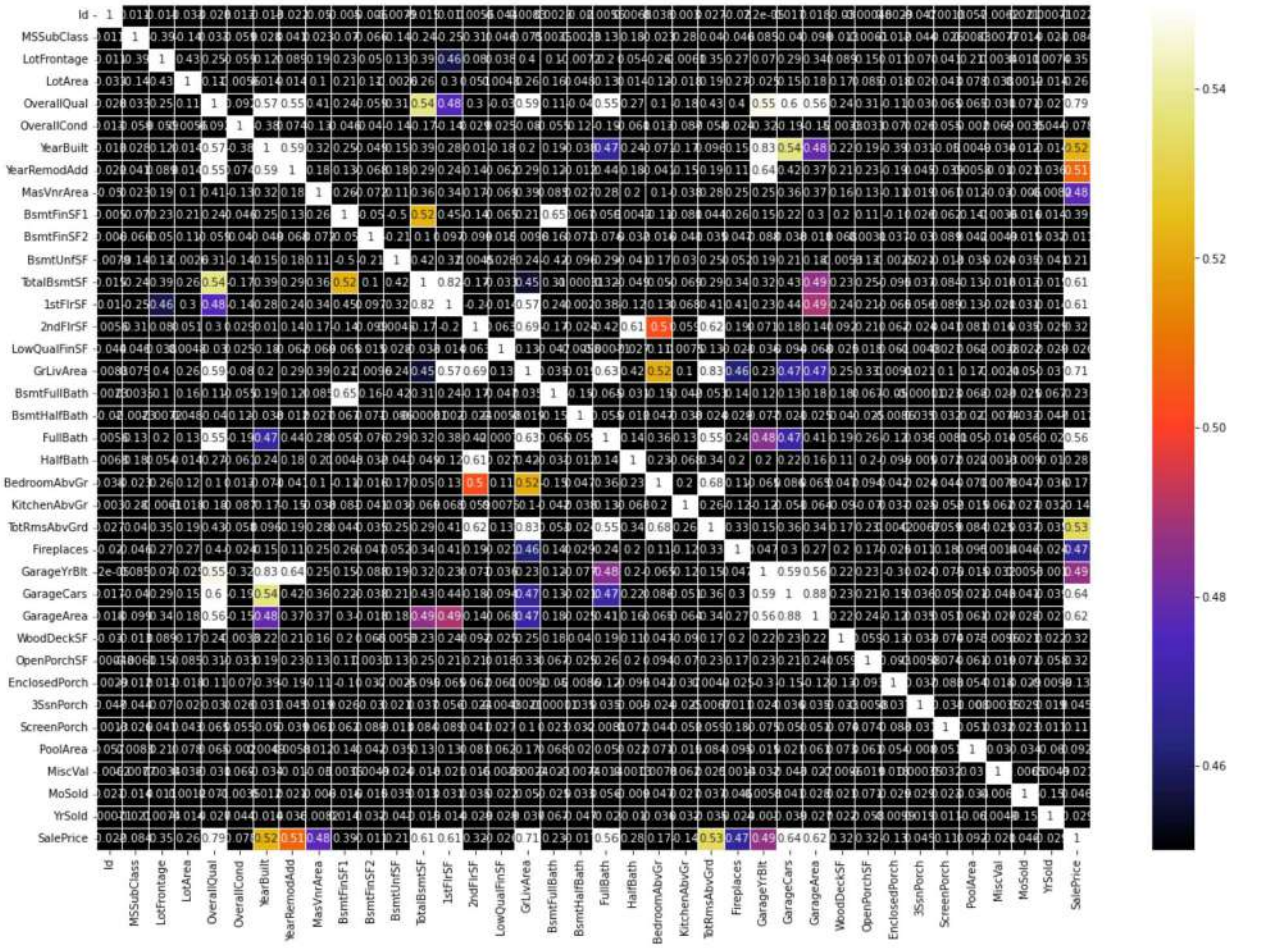
In [18]:
```
# Find the correlation of different numerical features

df.corr()
```

Out[18]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt
Id	1.000000	0.011156	-0.010601	-0.033226	-0.028365	0.012609	-0.012713
MSSubClass	0.011156	1.000000	-0.386347	-0.139781	0.032628	-0.059316	0.027850
LotFrontage	-0.010601	-0.386347	1.000000	0.426095	0.251646	-0.059213	0.123349
LotArea	-0.033226	-0.139781	0.426095	1.000000	0.105806	-0.005636	0.014228
OverallQual	-0.028365	0.032628	0.251646	0.105806	1.000000	-0.091932	0.572323
OverallCond	0.012609	-0.059316	-0.059213	-0.005636	-0.091932	1.000000	-0.375983
YearBuilt	-0.012713	0.027850	0.123349	0.014228	0.572323	-0.375983	1.000000
YearRemodAdd	-0.021998	0.040581	0.088866	0.013788	0.550684	0.073741	0.592855
MasVnrArea	-0.050298	0.022936	0.193458	0.104160	0.411876	-0.128101	0.315707
BsmtFinSF1	-0.005024	-0.069836	0.233633	0.214103	0.239666	-0.046231	0.249503
BsmtFinSF2	-0.005968	-0.065649	0.049900	0.111170	-0.059119	0.040229	-0.049107
BsmtUnfSF	-0.007940	-0.140759	0.132644	-0.002618	0.308159	-0.136841	0.149040
TotalBsmtSF	-0.015415	-0.238518	0.392075	0.260833	0.537808	-0.171098	0.391452
1stFlrSF	0.010496	-0.251758	0.457181	0.299475	0.476224	-0.144203	0.281986
2ndFlrSF	0.005590	0.307886	0.080177	0.050986	0.295493	0.028942	0.010308
LowQualFinSF	-0.044230	0.046474	0.038469	0.004779	-0.030429	0.025494	-0.183784
GrLivArea	0.008273	0.074853	0.402797	0.263116	0.593007	-0.079686	0.199010
BsmtFullBath	0.002289	0.003491	0.100949	0.158155	0.111098	-0.054942	0.187599
BsmtHalfBath	-0.020155	-0.002333	-0.007234	0.048046	-0.040150	0.117821	-0.038162
FullBath	0.005587	0.131608	0.198769	0.126031	0.550600	-0.194149	0.468271
HalfBath	0.006784	0.177354	0.053532	0.014259	0.273458	-0.060769	0.242656
BedroomAbvGr	0.037719	-0.023438	0.263170	0.119690	0.101676	0.012980	-0.070651
KitchenAbvGr	0.002951	0.281721	-0.006069	-0.017784	-0.183882	-0.087001	-0.174800
TotRmsAbvGrd	0.027239	0.040380	0.352096	0.190015	0.427452	-0.057583	0.095589
Fireplaces	-0.019772	-0.045569	0.266639	0.271364	0.396765	-0.023820	0.147716
GarageYrBlt	0.000072	0.085072	0.070250	-0.024947	0.547766	-0.324297	0.825667
GarageCars	0.016570	-0.040110	0.285691	0.154871	0.600671	-0.185758	0.537850
GarageArea	0.017634	-0.098672	0.344997	0.180403	0.562022	-0.151521	0.478954
WoodDeckSF	-0.029643	-0.012579	0.088521	0.171698	0.238923	-0.003334	0.224880
OpenPorchSF	-0.000477	-0.006100	0.151972	0.084774	0.308819	-0.032589	0.188686
EnclosedPorch	0.002889	-0.012037	0.010700	-0.018340	-0.113937	0.070356	-0.387268
3SsnPorch	-0.046635	-0.043825	0.070029	0.020423	0.030371	0.025504	0.031355
ScreenPorch	0.001330	-0.026030	0.041383	0.043160	0.064886	0.054811	-0.050364

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt
PoolArea	0.057044	0.008283	0.206167	0.077672	0.065166	-0.001985	0.004950
MiscVal	-0.006242	-0.007683	0.003368	0.038068	-0.031406	0.068777	-0.034383
MoSold	0.021172	-0.013585	0.011200	0.001205	0.070815	-0.003511	0.012398
YrSold	0.000712	-0.021407	0.007450	-0.014261	-0.027347	0.043950	-0.013618
SalePrice	-0.021917	-0.084284	0.351799	0.263843	0.790982	-0.077856	0.522897

In [19]:
```
# Now, Let's plot the heatmap to find the multicollinearity between different features

plt.figure(figsize = (20, 14))
sns.heatmap(df.corr(), cmap="CMRmap",annot=True, vmin = .5, vmax = .5, linewidth = .5)
plt.show()
```

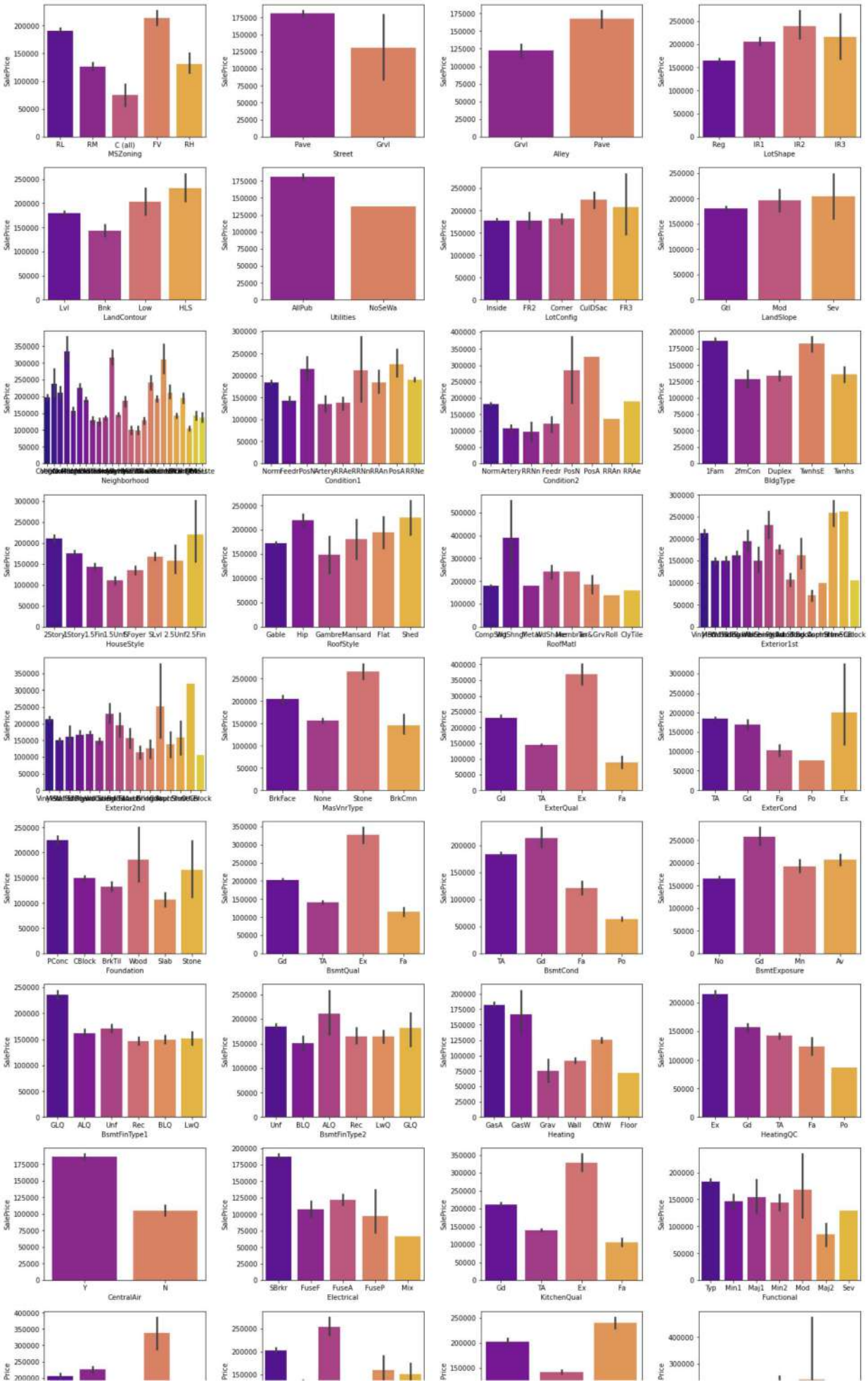


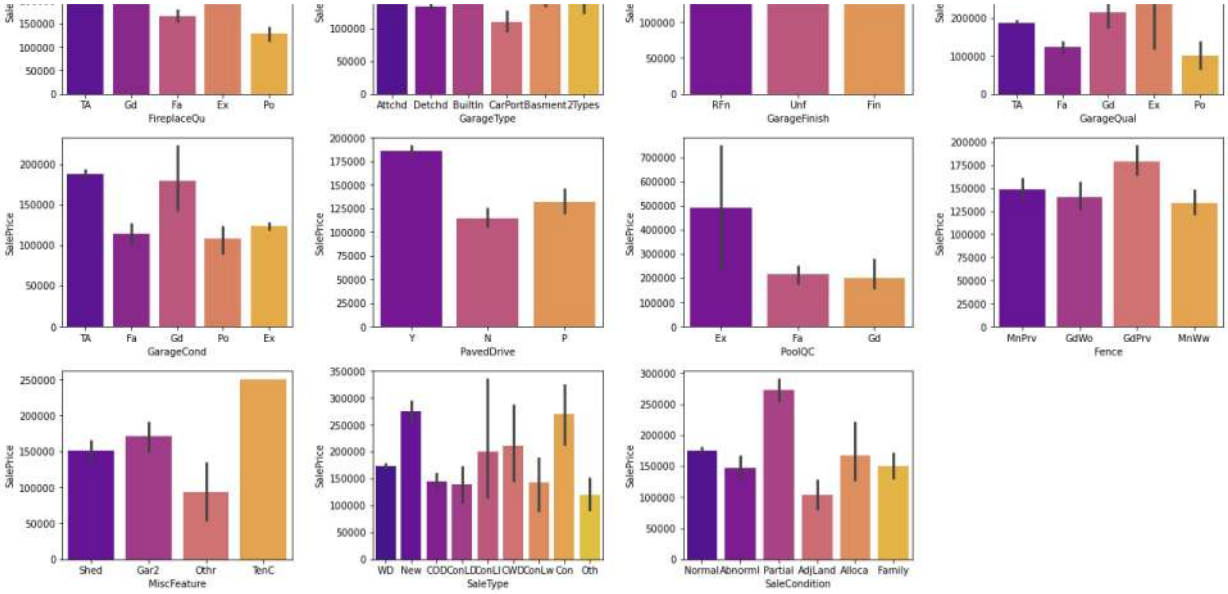
Bivariate Analysis of Categorical Features

In [20]:
```
categorical_features
```

Out[20]:
```
['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']
```

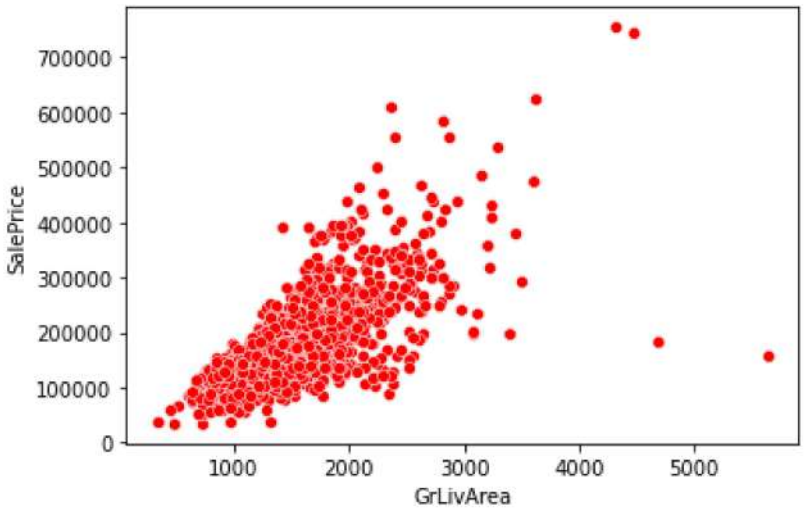
In [21]:
```
# Perform Bivariate analysis of Categorical features with target feature using "Barplo

plt.figure(figsize= (18,50))
for i in range(0, len(categorical_features)):
    df1 = df.copy()
    plt.subplot(15, 4, i+1)
    sns.barplot(x = df1[categorical_features[i]], y ='SalePrice', data = df1, palette
    plt.tight_layout()
```


SalePrice
MSZoning
RL RM C (all) FV RH
Street
Pave Grvl
Alley
Grvl Pave
LotShape
Reg IR1 IR2 IR3
LandContour
Lvl Bnk Low HLS
Utilities
AllPub NoSeWa
LotConfig
Inside FR2 Corner CulDSac FR3
LandSlope
Gtl Mod Sev
Neighborhood
Condition1
Norm Feedr PosN Artery RRAe RRNn RRAn PosA RRNe
Condition2
Norm Artery RRNn Feedr PosN PosA RRAn RRAe
BldgType
1Fam 2fmCon Duplex TwnhsE Twnhs
HouseStyle
2Story 1Story 1.5Fin 1.5Unf SFoyer SLvl 2.5Unf 2.5Fin
RoofStyle
Gable Hip Gambrel Mansard Flat Shed
RoofMatl
Exterior1st
Exterior2nd
MasVnrType
BrkFace None Stone BrkCmn
ExterQual
Gd TA Ex Fa
ExterCond
TA Gd Fa Po Ex
Foundation
PConc CBlock BrkTil Wood Slab Stone
BsmtQual
Gd TA Ex Fa
BsmtCond
TA Gd Fa Po
BsmtExposure
No Gd Mn Av
BsmtFinType1
GLQ ALQ Unf Rec BLQ LwQ
BsmtFinType2
Unf BLQ ALQ Rec LwQ GLQ
Heating
GasA GasW Grav Wall OthW Floor
HeatingQC
Ex Gd TA Fa Po
CentralAir
Y N
Electrical
SBrkr FuseF FuseA FuseP Mix
KitchenQual
Gd TA Ex Fa
Functional
Typ Min1 Maj1 Min2 Mod Maj2 Sev
Price



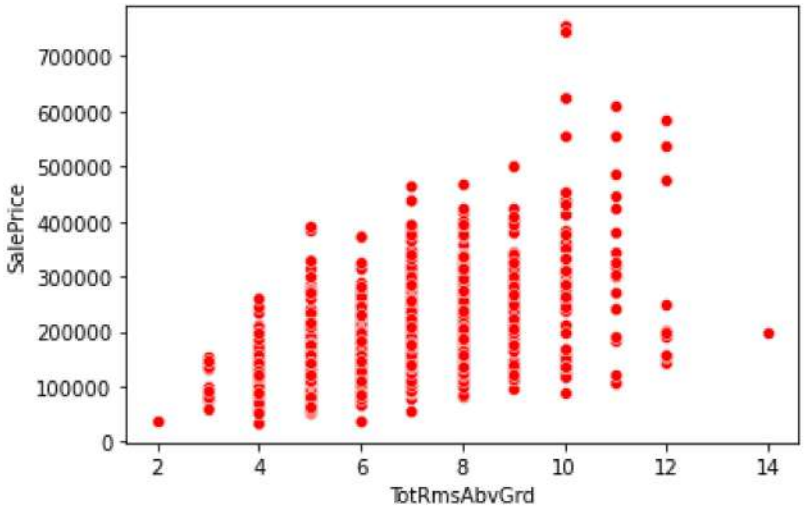
In [22]:
```
# Just checking multicollinear features in order to find out whether or not drop any c

for features in df.columns:
    df1 = df.copy()
sns.scatterplot(x = 'GrLivArea', y = 'SalePrice', data = df1, color = 'r')
```

Out[22]:
```
<AxesSubplot:xlabel='GrLivArea', ylabel='SalePrice'>
```



In [23]:
```
# Just checking multicollinear features in order to find out whether or not drop any c

for features in df.columns:
    df1 = df.copy()
sns.scatterplot(x = 'TotRmsAbvGrd', y = 'SalePrice', data = df1, color = 'r')
```

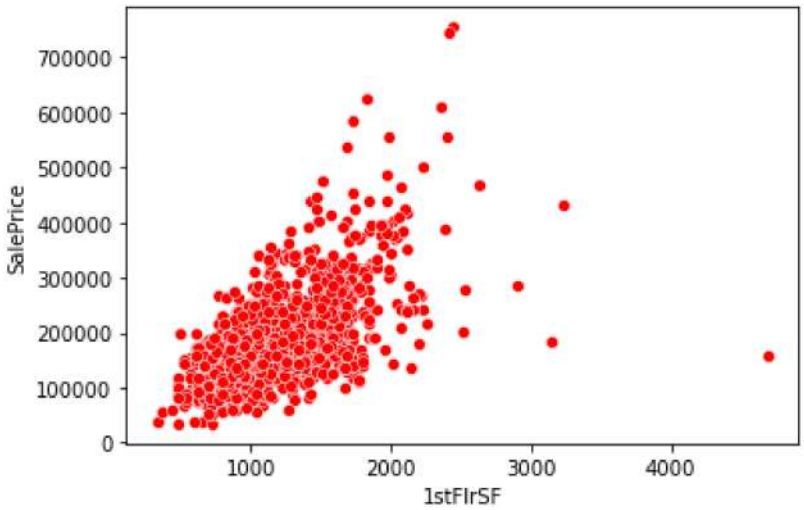
Out[23]:
```
<AxesSubplot:xlabel='TotRmsAbvGrd', ylabel='SalePrice'>
```



Observation : Both "TotRmsAbvGrd" and "GrLivArea" are highly correlated hence any one feature can be dropped

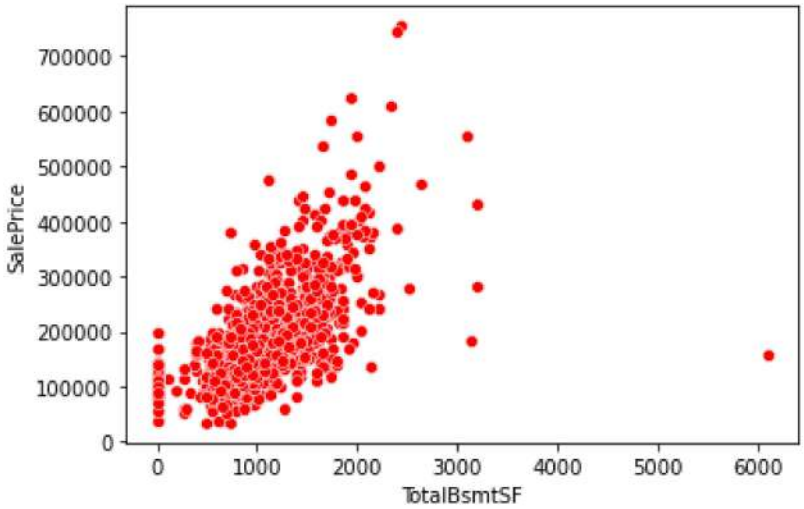
In [24]:
```
# Just checking multicollinear features in order to find out whether or not drop any c

for features in df.columns:
    df1 = df.copy()
sns.scatterplot(x = '1stFlrSF', y = 'SalePrice', data = df1, color = 'r')
```

Out[24]:
```
<AxesSubplot:xlabel='1stFlrSF', ylabel='SalePrice'>
```



In [25]:
```
# Just checking multicollinear features in order to find out whether or not drop any c

for features in df.columns:
    df1 = df.copy()
sns.scatterplot(x = 'TotalBsmtSF', y = 'SalePrice', data = df1, color = 'r')
```

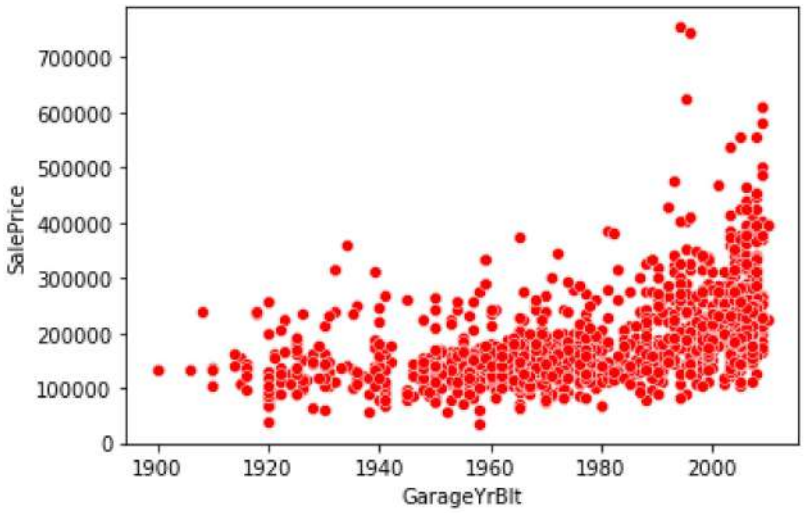
Out[25]:
```
<AxesSubplot:xlabel='TotalBsmtSF', ylabel='SalePrice'>
```



Observation : Both "TotalBsmtSF" and "1stFlrSF" are highly correlated hence any one feature can be dropped

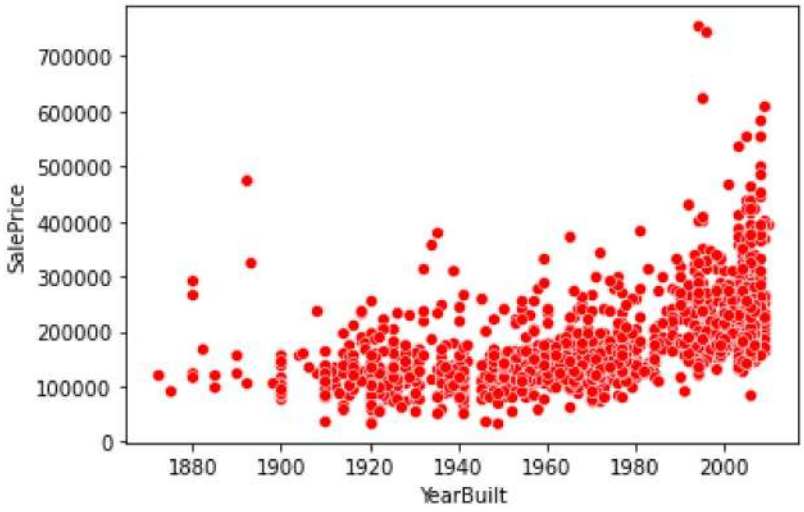
In [26]:
```
# Just checking multicollinear features in order to find out whether or not drop any c

for features in df.columns:
    df1 = df.copy()
sns.scatterplot(x = 'GarageYrBlt', y = 'SalePrice', data = df1, color = 'r')
```

Out[26]:
```
<AxesSubplot:xlabel='GarageYrBlt', ylabel='SalePrice'>
```



In [27]:
```
# Just checking multicollinear features in order to find out whether or not drop any c

for features in df.columns:
    df1 = df.copy()
sns.scatterplot(x = 'YearBuilt', y = 'SalePrice', data = df1, color = 'r')
```

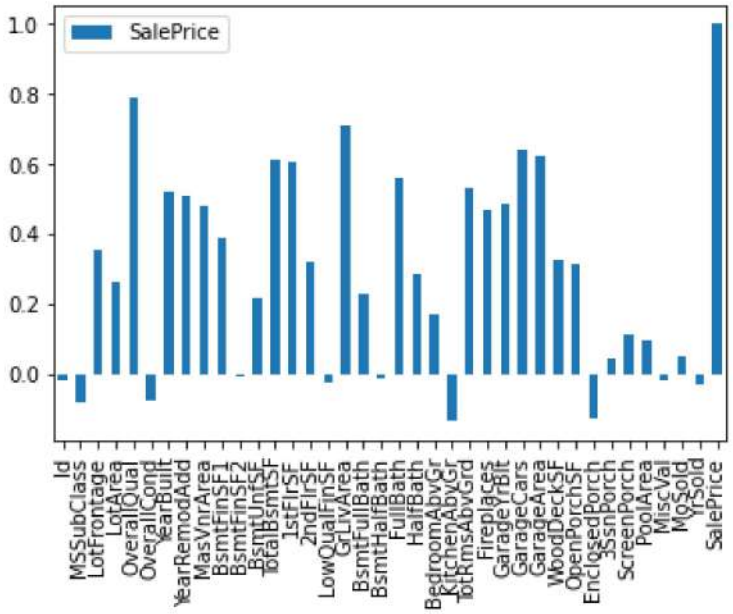
Out[27]:
```
<AxesSubplot:xlabel='YearBuilt', ylabel='SalePrice'>
```



Observation : Both "YearBuilt" and "GarageYrBlt" are highly correlated hence any one feature can be dropped

In [28]:
```
# Peforming mulcollinearity with target feature using bar plot
df.corr()[['SalePrice']].plot(kind = 'bar')
```

Out[28]:
```
<AxesSubplot:>
```



Treatment for Missing Values

In [29]:
```
# Finding the number of missing values in each and every feature of the dataset

features_with_na = [features for features in df.columns if df[features].isnull().sum()

for features in features_with_na:
    df1 = df.copy()
    print(features, np.round(df1[features].isnull().sum(),4))
```

```
LotFrontage 259
Alley 1369
MasVnrType 8
MasVnrArea 8
BsmtQual 37
BsmtCond 37
BsmtExposure 38
BsmtFinType1 37
BsmtFinType2 38
Electrical 1
FireplaceQu 690
GarageType 81
GarageYrBlt 81
GarageFinish 81
GarageQual 81
GarageCond 81
PoolQC 1453
Fence 1179
MiscFeature 1406
```

In [30]:
```
# finding the categories in every feature to derive wheather to use mean, median or mo

df['Electrical'].value_counts()
#df1.columns
```

Out[30]:
```
SBrkr    1334
FuseA      94
FuseF      27
FuseP       3
Mix         1
Name: Electrical, dtype: int64
```

In [31]:
```
# Missing values treatment : used mode to fill the missing values for categorical vari

df['LotFrontage'] = df['LotFrontage'].fillna(df['LotFrontage'].mode()[0])
df['Electrical'] = df['Electrical'].fillna(df['Electrical'].mode()[0])
df['MasVnrType'] = df['MasVnrType'].fillna(df['MasVnrType'].mode()[0])
df['MasVnrArea'] = df['MasVnrArea'].fillna(df['MasVnrArea'].mean())
df['BsmtQual'] = df['BsmtQual'].fillna(df['BsmtQual'].mode()[0])
df['BsmtCond'] = df['BsmtCond'].fillna(df['BsmtCond'].mode()[0])
df['BsmtExposure'] = df['BsmtExposure'].fillna(df['BsmtExposure'].mode()[0])
df['BsmtFinType1'] = df['BsmtFinType1'].fillna(df['BsmtFinType1'].mode()[0])
df['BsmtFinType2'] = df['BsmtFinType2'].fillna(df['BsmtFinType2'].mode()[0])
df['GarageType'] = df['GarageType'].fillna(df['GarageType'].mode()[0])
df['GarageYrBlt'] = df['GarageYrBlt'].fillna(df['GarageYrBlt'].mean())
df['GarageFinish'] = df['GarageFinish'].fillna(df['GarageFinish'].mode()[0])
df['GarageQual'] = df['GarageQual'].fillna(df['GarageQual'].mode()[0])
df['GarageCond'] = df['GarageCond'].fillna(df['GarageCond'].mode()[0])
df['GarageQual'] = df['GarageQual'].fillna(df['GarageQual'].mode()[0])
df['GarageQual'] = df['GarageQual'].fillna(df['GarageQual'].mode()[0])
```

In [32]:
```
# Again, after the missing values treatment validating if there are any more missing v

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

Out[32]:
```
Id              0
MSSubClass      0
MSZoning        0
LotFrontage     0
LotArea         0
               ..
MoSold          0
YrSold          0
SaleType        0
SaleCondition   0
SalePrice       0
Length: 81, dtype: int64
```

In [33]:
```
df.isnull().sum().sum()
```

Out[33]:
```
6097
```

In [34]:
```
# Let's drop the features which has high missing values

df.drop('Alley', axis = 1, inplace = True)
df.drop('Id', axis = 1, inplace = True)
```

In [35]:
```
# Let's drop the features which has high missing values

df.drop('FireplaceQu', axis = 1, inplace = True)
```

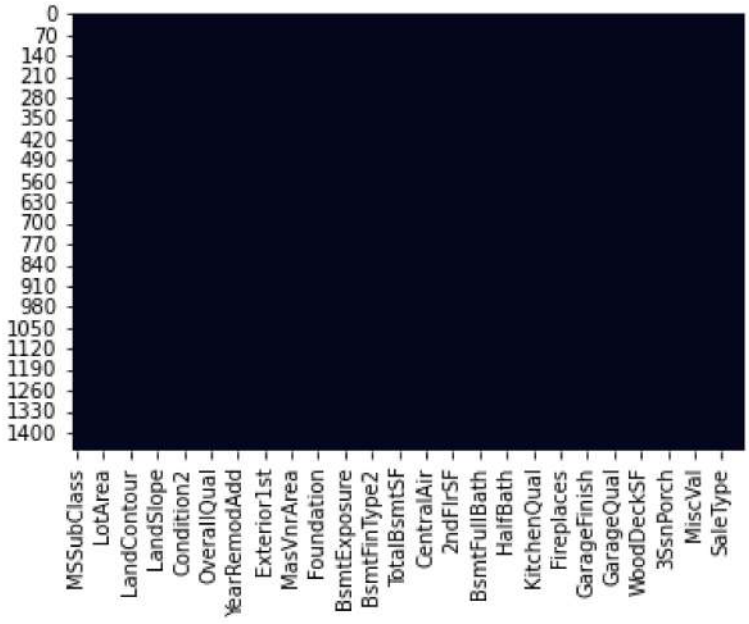
In [36]:
```
# Let's drop the features which has high missing values

df.drop('PoolQC', axis = 1, inplace = True)
```

In [37]:
```
# Let's drop the features which has high missing values

df.drop('Fence', axis = 1, inplace = True)
```

In [38]:
```
# Let's drop the features which has high missing values

df.drop('MiscFeature', axis = 1, inplace = True)
```

In [39]:
```
# Perform plotting to confirm that there are no missing values present in the dataset

sns.heatmap(df.isnull(), cbar = False)
```

Out[39]:
```
<AxesSubplot:>
```



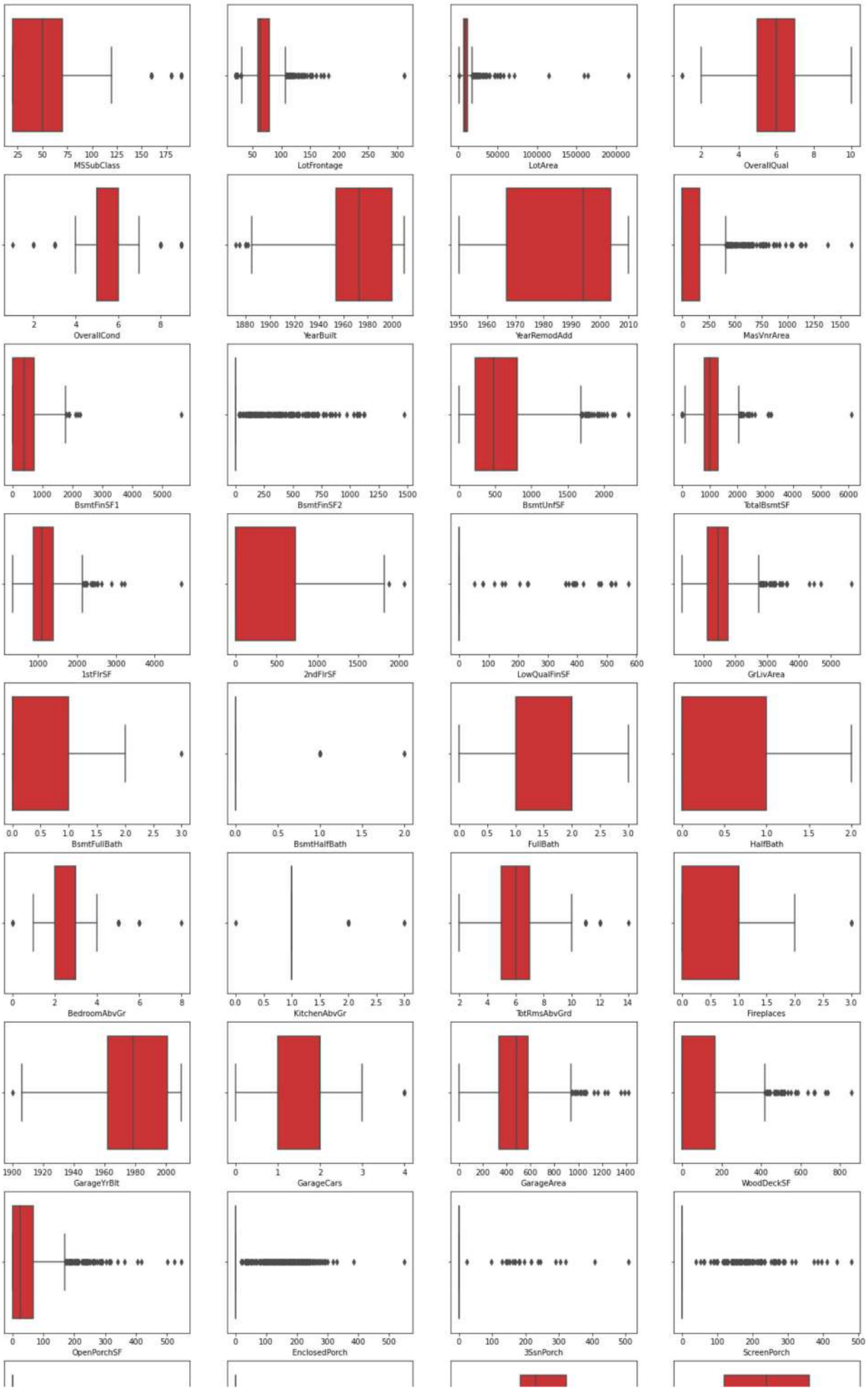
Observation : All the missing values has been treated and there are no null values in the dataset

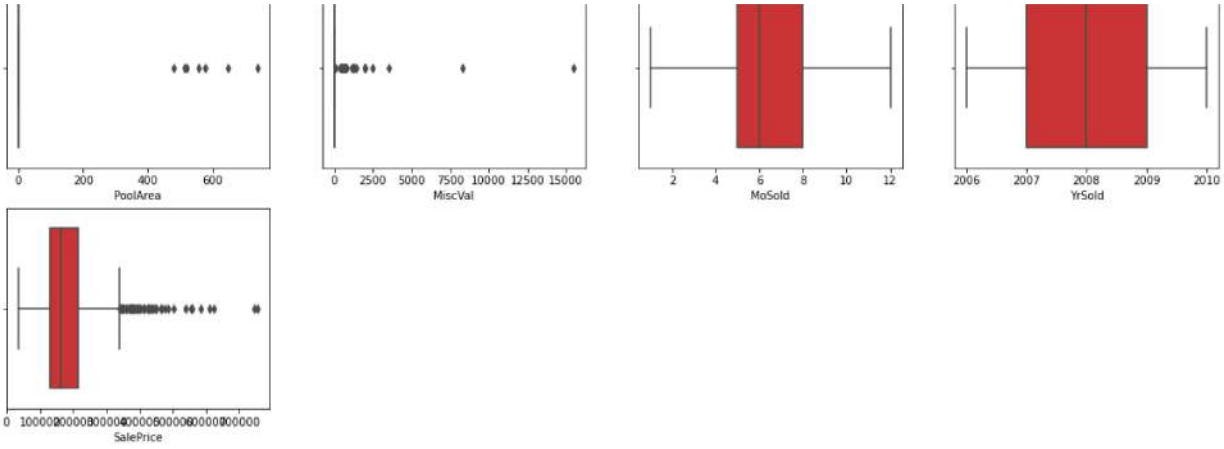
Finding the Outliers for the Numerical features using Boxplot

In [40]:
```
len(Numerical_features)
```

Out[40]:
```
37
```

In [41]:
```
# Finding the Outliers using Boxplot

plt.figure(figsize = (20,40))
for i in range(0, len(Numerical_features)):
    df1 = df.copy()
    plt.subplot(10, 4, i+1)
    sns.boxplot(x = df1[Numerical_features[i]], palette="Set1")
```


MSSubClass
LotFrontage
LotArea
OverallQual
OverallCond
YearBuilt
YearRemodAdd
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
LowQualFinSF
GrLivArea
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageYrBlt
GarageCars
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
3SsnPorch
ScreenPorch



Let use now use 5 Number summary for the Outliers

1. Minimum
2. 25th Percentile
3. Median
4. 75th Percentile
5. Maximum

In [42]:
```
# Finding the Minimum value in numerical features

for features in Numerical_features:
    df1 = df.copy()
    print(features, np.min(df1[features]))
```

```
MSSubClass 20
LotFrontage 21.0
LotArea 1300
OverallQual 1
OverallCond 1
YearBuilt 1872
YearRemodAdd 1950
MasVnrArea 0.0
BsmtFinSF1 0
BsmtFinSF2 0
BsmtUnfSF 0
TotalBsmtSF 0
1stFlrSF 334
2ndFlrSF 0
LowQualFinSF 0
GrLivArea 334
BsmtFullBath 0
BsmtHalfBath 0
FullBath 0
HalfBath 0
BedroomAbvGr 0
KitchenAbvGr 0
TotRmsAbvGrd 2
Fireplaces 0
GarageYrBlt 1900.0
GarageCars 0
GarageArea 0
WoodDeckSF 0
OpenPorchSF 0
EnclosedPorch 0
3SsnPorch 0
ScreenPorch 0
PoolArea 0
MiscVal 0
MoSold 1
YrSold 2006
SalePrice 34900
```

In [43]:

```
# Let's find 25th, 75th Percentile of Numerical features

for features in Numerical_features:
    df1 = df.copy()
    print(features, "Q1 Percentile is : ", np.percentile(df[features], [25]))
    print(features, "Q3 Percentile is : ", np.percentile(df[features], [75]), "\n")
```

```
MSSubClass Q1 Percentile is :  [20.]
MSSubClass Q3 Percentile is :  [70.]

LotFrontage Q1 Percentile is :  [60.]
LotFrontage Q3 Percentile is :  [79.]

LotArea Q1 Percentile is :  [7553.5]
LotArea Q3 Percentile is :  [11601.5]

OverallQual Q1 Percentile is :  [5.]
OverallQual Q3 Percentile is :  [7.]

OverallCond Q1 Percentile is :  [5.]
OverallCond Q3 Percentile is :  [6.]

YearBuilt Q1 Percentile is :  [1954.]
YearBuilt Q3 Percentile is :  [2000.]

YearRemodAdd Q1 Percentile is :  [1967.]
YearRemodAdd Q3 Percentile is :  [2004.]

MasVnrArea Q1 Percentile is :  [0.]
MasVnrArea Q3 Percentile is :  [164.25]

BsmtFinSF1 Q1 Percentile is :  [0.]
BsmtFinSF1 Q3 Percentile is :  [712.25]

BsmtFinSF2 Q1 Percentile is :  [0.]
BsmtFinSF2 Q3 Percentile is :  [0.]

BsmtUnfSF Q1 Percentile is :  [223.]
BsmtUnfSF Q3 Percentile is :  [808.]

TotalBsmtSF Q1 Percentile is :  [795.75]
TotalBsmtSF Q3 Percentile is :  [1298.25]

1stFlrSF Q1 Percentile is :  [882.]
1stFlrSF Q3 Percentile is :  [1391.25]

2ndFlrSF Q1 Percentile is :  [0.]
2ndFlrSF Q3 Percentile is :  [728.]

LowQualFinSF Q1 Percentile is :  [0.]
LowQualFinSF Q3 Percentile is :  [0.]

GrLivArea Q1 Percentile is :  [1129.5]
GrLivArea Q3 Percentile is :  [1776.75]

BsmtFullBath Q1 Percentile is :  [0.]
BsmtFullBath Q3 Percentile is :  [1.]

BsmtHalfBath Q1 Percentile is :  [0.]
BsmtHalfBath Q3 Percentile is :  [0.]

FullBath Q1 Percentile is :  [1.]
FullBath Q3 Percentile is :  [2.]

HalfBath Q1 Percentile is :  [0.]
HalfBath Q3 Percentile is :  [1.]
```

```
BedroomAbvGr Q1 Percentile is :  [2.]
BedroomAbvGr Q3 Percentile is :  [3.]

KitchenAbvGr Q1 Percentile is :  [1.]
KitchenAbvGr Q3 Percentile is :  [1.]

TotRmsAbvGrd Q1 Percentile is :  [5.]
TotRmsAbvGrd Q3 Percentile is :  [7.]

Fireplaces Q1 Percentile is :  [0.]
Fireplaces Q3 Percentile is :  [1.]

GarageYrBlt Q1 Percentile is :  [1962.]
GarageYrBlt Q3 Percentile is :  [2001.]

GarageCars Q1 Percentile is :  [1.]
GarageCars Q3 Percentile is :  [2.]

GarageArea Q1 Percentile is :  [334.5]
GarageArea Q3 Percentile is :  [576.]

WoodDeckSF Q1 Percentile is :  [0.]
WoodDeckSF Q3 Percentile is :  [168.]

OpenPorchSF Q1 Percentile is :  [0.]
OpenPorchSF Q3 Percentile is :  [68.]

EnclosedPorch Q1 Percentile is :  [0.]
EnclosedPorch Q3 Percentile is :  [0.]

3SsnPorch Q1 Percentile is :  [0.]
3SsnPorch Q3 Percentile is :  [0.]

ScreenPorch Q1 Percentile is :  [0.]
ScreenPorch Q3 Percentile is :  [0.]

PoolArea Q1 Percentile is :  [0.]
PoolArea Q3 Percentile is :  [0.]

MiscVal Q1 Percentile is :  [0.]
MiscVal Q3 Percentile is :  [0.]

MoSold Q1 Percentile is :  [5.]
MoSold Q3 Percentile is :  [8.]

YrSold Q1 Percentile is :  [2007.]
YrSold Q3 Percentile is :  [2009.]

SalePrice Q1 Percentile is :  [129975.]
SalePrice Q3 Percentile is :  [214000.]
```

In [44]:

```
# Finding the median of all numerical features

for features in Numerical_features:
    df1 = df.copy()
    print(features, "Median Value is : ", np.median(df1[features]), "\n")
```

```
MSSubClass Median Value is :  50.0

LotFrontage Median Value is :  63.0

LotArea Median Value is :  9478.5

OverallQual Median Value is :  6.0

OverallCond Median Value is :  5.0

YearBuilt Median Value is :  1973.0

YearRemodAdd Median Value is :  1994.0

MasVnrArea Median Value is :  0.0

BsmtFinSF1 Median Value is :  383.5

BsmtFinSF2 Median Value is :  0.0

BsmtUnfSF Median Value is :  477.5

TotalBsmtSF Median Value is :  991.5

1stFlrSF Median Value is :  1087.0

2ndFlrSF Median Value is :  0.0

LowQualFinSF Median Value is :  0.0

GrLivArea Median Value is :  1464.0

BsmtFullBath Median Value is :  0.0

BsmtHalfBath Median Value is :  0.0

FullBath Median Value is :  2.0

HalfBath Median Value is :  0.0

BedroomAbvGr Median Value is :  3.0

KitchenAbvGr Median Value is :  1.0

TotRmsAbvGrd Median Value is :  6.0

Fireplaces Median Value is :  1.0

GarageYrBlt Median Value is :  1978.5061638868744

GarageCars Median Value is :  2.0

GarageArea Median Value is :  480.0

WoodDeckSF Median Value is :  0.0

OpenPorchSF Median Value is :  25.0

EnclosedPorch Median Value is :  0.0
```

```
3SsnPorch Median Value is :  0.0

ScreenPorch Median Value is :  0.0

PoolArea Median Value is :  0.0

MiscVal Median Value is :  0.0

MoSold Median Value is :  6.0

YrSold Median Value is :  2008.0

SalePrice Median Value is :  163000.0
```

In [45]:
```
# Created a function to find the 5 number summary such as q1, q3, IQR, Lower_fence, Hi

def outliers_detection(self):
    df1 = df.copy()
    q1 = self.quantile(0.25)
    q3 = self.quantile(0.75)
    IQR = q3-q1
    lower_fence = q1 - (1.5*IQR)
    higher_fence = q3 + (1.5*IQR)
    return IQR, lower_fence, higher_fence
```

In [46]:
```
# Testing the function on one feature whether it is working fine or not

outliers_detection(df1['BsmtUnfSF'])
```

Out[46]:
```
(585.0, -654.5, 1685.5)
```

In [47]:
```
# Applying the function to call 5 number summary on all the features

for features in Numerical_features:
    df1 = df.copy()
    print(features, outliers_detection(df1[features]))
```

```
MSSubClass (50.0, -55.0, 145.0)
LotFrontage (19.0, 31.5, 107.5)
LotArea (4048.0, 1481.5, 17673.5)
OverallQual (2.0, 2.0, 10.0)
OverallCond (1.0, 3.5, 7.5)
YearBuilt (46.0, 1885.0, 2069.0)
YearRemodAdd (37.0, 1911.5, 2059.5)
MasVnrArea (164.25, -246.375, 410.625)
BsmtFinSF1 (712.25, -1068.375, 1780.625)
BsmtFinSF2 (0.0, 0.0, 0.0)
BsmtUnfSF (585.0, -654.5, 1685.5)
TotalBsmtSF (502.5, 42.0, 2052.0)
1stFlrSF (509.25, 118.125, 2155.125)
2ndFlrSF (728.0, -1092.0, 1820.0)
LowQualFinSF (0.0, 0.0, 0.0)
GrLivArea (647.25, 158.625, 2747.625)
BsmtFullBath (1.0, -1.5, 2.5)
BsmtHalfBath (0.0, 0.0, 0.0)
FullBath (1.0, -0.5, 3.5)
HalfBath (1.0, -1.5, 2.5)
BedroomAbvGr (1.0, 0.5, 4.5)
KitchenAbvGr (0.0, 1.0, 1.0)
TotRmsAbvGrd (2.0, 2.0, 10.0)
Fireplaces (1.0, -1.5, 2.5)
GarageYrBlt (39.0, 1903.5, 2059.5)
GarageCars (1.0, -0.5, 3.5)
GarageArea (241.5, -27.75, 938.25)
WoodDeckSF (168.0, -252.0, 420.0)
OpenPorchSF (68.0, -102.0, 170.0)
EnclosedPorch (0.0, 0.0, 0.0)
3SsnPorch (0.0, 0.0, 0.0)
ScreenPorch (0.0, 0.0, 0.0)
PoolArea (0.0, 0.0, 0.0)
MiscVal (0.0, 0.0, 0.0)
MoSold (3.0, 0.5, 12.5)
YrSold (2.0, 2004.0, 2012.0)
SalePrice (84025.0, 3937.5, 340037.5)
```

In [48]:
```python
# 1st type of outlier function : Created a function to find the outliers above the upp

def outliers_handler_fit(df1,feature_name):
        q1=df1.loc[:,[feature_name]].quantile(0.25)
        q3=df1.loc[:,[feature_name]].quantile(0.75)
        IQR = q3-q1
        lower = q1 - (1.5*IQR)
        upper = q3 + (1.5*IQR)
        df1.loc[df[feature_name]<=lower[0],feature_name]=lower[0]
        df1.loc[df[feature_name]>=upper[0],feature_name]=upper[0]
        return df1
```

In [49]:
```python
# 2nd type of Outlier function : Created a function to find the outliers above the upp


def outlier_treatment(df1, feature_name):
    q1 = df1.loc[:, [feature_name]].quantile(0.25)
    q3 = df1.loc[:, [feature_name]].quantile(0.75)
    IQR = q3-q1
    lower_fence = q1 - (1.5*IQR)
    higher_fence = q3 + (1.5*IQR)
```

```
    return IQR, lower_fence, higher_fence
```

In [50]:
```
outlier_treatment(df1, 'LotFrontage')
```

Out[50]:
```
(LotFrontage    19.0
 dtype: float64,
 LotFrontage    31.5
 dtype: float64,
 LotFrontage    107.5
 dtype: float64)
```

In [51]:
```
# 3rd type of Outlier function : Created a function to find the outliers above the upp


def detect_outliers(col):

    # Finding the IQR

    percentile25 = df1[col].quantile(0.25)

    percentile75 = df1[col].quantile(0.75)

    print('\n ####', col ,'####')

    print("percentile25",percentile25)

    print("percentile75",percentile75)

    iqr = percentile75 - percentile25

    higher_fence = percentile75 + 1.5 * iqr

    lower_fence = percentile25 - 1.5 * iqr

    print("higher_fence",higher_fence)

    print("lower_fence",lower_fence)

    df1.loc[(df1[col]>higher_fence), col]= higher_fence

    df1.loc[(df1[col]<lower_fence), col]= lower_fence

    return df1
```

In [52]:
```
# Applying the function on one of the feature called "LotArea"

detect_outliers('LotArea')
```

```
 #### LotArea ####
percentile25 7553.5
percentile75 11601.5
higher_fence 17673.5
lower_fence 1481.5
```

Out[52]:

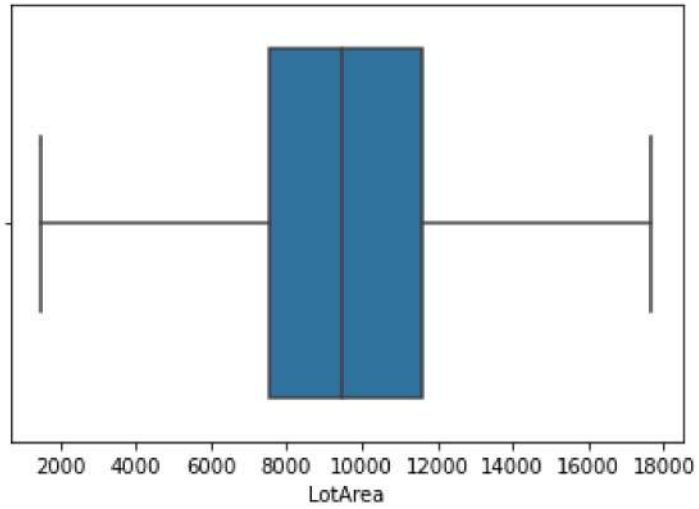
	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotC
0	60	RL	65.0	8450.0	Pave	Reg	Lvl	AllPub	I
1	20	RL	80.0	9600.0	Pave	Reg	Lvl	AllPub	
2	60	RL	68.0	11250.0	Pave	IR1	Lvl	AllPub	I
3	70	RL	60.0	9550.0	Pave	IR1	Lvl	AllPub	C
4	60	RL	84.0	14260.0	Pave	IR1	Lvl	AllPub	
...	...	...	...	...	...	...	...	...	
1455	60	RL	62.0	7917.0	Pave	Reg	Lvl	AllPub	I
1456	20	RL	85.0	13175.0	Pave	Reg	Lvl	AllPub	I
1457	70	RL	66.0	9042.0	Pave	Reg	Lvl	AllPub	I
1458	20	RL	68.0	9717.0	Pave	Reg	Lvl	AllPub	I
1459	20	RL	75.0	9937.0	Pave	Reg	Lvl	AllPub	I

1460 rows × 75 columns

In [53]:
```
# After applying the function on "LotArea", validating the outliers for "LotArea" usir

sns.boxplot(x = df1['LotArea'])
```

Out[53]:
```
<AxesSubplot:xlabel='LotArea'>
```

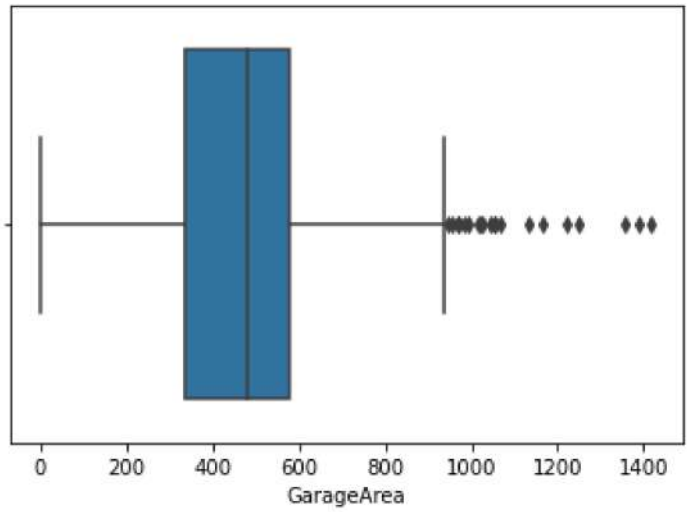


In [54]:
```
# Checking for outliers on feature called "GarageArea" before applying the outlier fur

sns.boxplot(df1['GarageArea'])
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

Out[54]:
```
<AxesSubplot:xlabel='GarageArea'>
```



In [55]:
```
# Now, applied the outlier function

detect_outliers('GarageArea')
```

```
 #### GarageArea ####
percentile25 334.5
percentile75 576.0
higher_fence 938.25
lower_fence -27.75
```

Out[55]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotCo
0	60	RL	65.0	8450.0	Pave	Reg	Lvl	AllPub	I
1	20	RL	80.0	9600.0	Pave	Reg	Lvl	AllPub	
2	60	RL	68.0	11250.0	Pave	IR1	Lvl	AllPub	I
3	70	RL	60.0	9550.0	Pave	IR1	Lvl	AllPub	C
4	60	RL	84.0	14260.0	Pave	IR1	Lvl	AllPub	
...	...	...	...	...	...	...	...	...	
1455	60	RL	62.0	7917.0	Pave	Reg	Lvl	AllPub	I
1456	20	RL	85.0	13175.0	Pave	Reg	Lvl	AllPub	I
1457	70	RL	66.0	9042.0	Pave	Reg	Lvl	AllPub	I
1458	20	RL	68.0	9717.0	Pave	Reg	Lvl	AllPub	I
1459	20	RL	75.0	9937.0	Pave	Reg	Lvl	AllPub	I

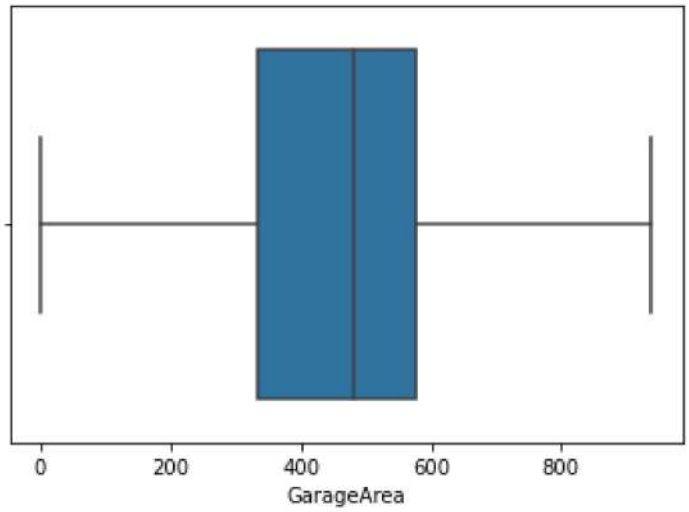
1460 rows × 75 columns

In [56]:
```
# Post applying the outlier function above, validating with the boxplot

sns.boxplot(df1['GarageArea'])
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

Out[56]:
```
<AxesSubplot:xlabel='GarageArea'>
```



In [57]:
```
# Now, In order to manipulate the outliers, applying the functions to each and every f

detect_outliers('OverallQual')
detect_outliers('OverallCond')
detect_outliers('YearBuilt')
detect_outliers('MasVnrArea')
detect_outliers('BsmtFinSF1')
detect_outliers('BsmtFinSF2')
detect_outliers('BsmtUnfSF')
detect_outliers('1stFlrSF')
detect_outliers('2ndFlrSF')
detect_outliers('LowQualFinSF')
detect_outliers('GrLivArea')
detect_outliers('BsmtFullBath')
detect_outliers('BsmtHalfBath')
detect_outliers('BedroomAbvGr')
detect_outliers('KitchenAbvGr')
detect_outliers('TotRmsAbvGrd')
detect_outliers('Fireplaces')
detect_outliers('GarageYrBlt')
detect_outliers('GarageArea')
detect_outliers('WoodDeckSF')
detect_outliers('OpenPorchSF')
detect_outliers('EnclosedPorch')
detect_outliers('3SsnPorch')
detect_outliers('ScreenPorch')
detect_outliers('PoolArea')
detect_outliers('MiscVal')
```

```
 #### OverallQual ####
percentile25 5.0
percentile75 7.0
higher_fence 10.0
lower_fence 2.0

 #### OverallCond ####
percentile25 5.0
percentile75 6.0
higher_fence 7.5
lower_fence 3.5

 #### YearBuilt ####
percentile25 1954.0
percentile75 2000.0
higher_fence 2069.0
lower_fence 1885.0

 #### MasVnrArea ####
percentile25 0.0
percentile75 164.25
higher_fence 410.625
lower_fence -246.375

 #### BsmtFinSF1 ####
percentile25 0.0
percentile75 712.25
higher_fence 1780.625
lower_fence -1068.375

 #### BsmtFinSF2 ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0

 #### BsmtUnfSF ####
percentile25 223.0
percentile75 808.0
higher_fence 1685.5
lower_fence -654.5

 #### 1stFlrSF ####
percentile25 882.0
percentile75 1391.25
higher_fence 2155.125
lower_fence 118.125

 #### 2ndFlrSF ####
percentile25 0.0
percentile75 728.0
higher_fence 1820.0
lower_fence -1092.0

 #### LowQualFinSF ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```

```
 #### GrLivArea ####
percentile25 1129.5
percentile75 1776.75
higher_fence 2747.625
lower_fence 158.625

 #### BsmtFullBath ####
percentile25 0.0
percentile75 1.0
higher_fence 2.5
lower_fence -1.5

 #### BsmtHalfBath ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0

 #### BedroomAbvGr ####
percentile25 2.0
percentile75 3.0
higher_fence 4.5
lower_fence 0.5

 #### KitchenAbvGr ####
percentile25 1.0
percentile75 1.0
higher_fence 1.0
lower_fence 1.0

 #### TotRmsAbvGrd ####
percentile25 5.0
percentile75 7.0
higher_fence 10.0
lower_fence 2.0

 #### Fireplaces ####
percentile25 0.0
percentile75 1.0
higher_fence 2.5
lower_fence -1.5

 #### GarageYrBlt ####
percentile25 1962.0
percentile75 2001.0
higher_fence 2059.5
lower_fence 1903.5

 #### GarageArea ####
percentile25 334.5
percentile75 576.0
higher_fence 938.25
lower_fence -27.75

 #### WoodDeckSF ####
percentile25 0.0
percentile75 168.0
higher_fence 420.0
lower_fence -252.0
```

```
 #### OpenPorchSF ####
percentile25 0.0
percentile75 68.0
higher_fence 170.0
lower_fence -102.0

 #### EnclosedPorch ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0

 #### 3SsnPorch ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0

 #### ScreenPorch ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0

 #### PoolArea ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0

 #### MiscVal ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```

Out[57]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotCo
0	60	RL	65.0	8450.0	Pave	Reg	Lvl	AllPub	I
1	20	RL	80.0	9600.0	Pave	Reg	Lvl	AllPub	
2	60	RL	68.0	11250.0	Pave	IR1	Lvl	AllPub	I
3	70	RL	60.0	9550.0	Pave	IR1	Lvl	AllPub	C
4	60	RL	84.0	14260.0	Pave	IR1	Lvl	AllPub	
...	...	...	...	...	...	...	...	...	
1455	60	RL	62.0	7917.0	Pave	Reg	Lvl	AllPub	I
1456	20	RL	85.0	13175.0	Pave	Reg	Lvl	AllPub	I
1457	70	RL	66.0	9042.0	Pave	Reg	Lvl	AllPub	I
1458	20	RL	68.0	9717.0	Pave	Reg	Lvl	AllPub	I
1459	20	RL	75.0	9937.0	Pave	Reg	Lvl	AllPub	I

1460 rows × 75 columns

In [58]:
```
# Let us find only the numerical feature from my transformed dataset called "df1"

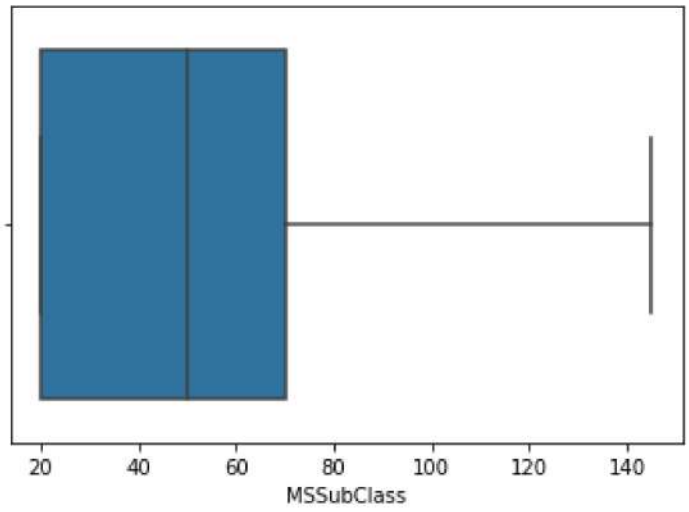
df1.describe().columns
```

Out[58]:
```
Index(['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
       'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
       'MoSold', 'YrSold', 'SalePrice'],
      dtype='object')
```

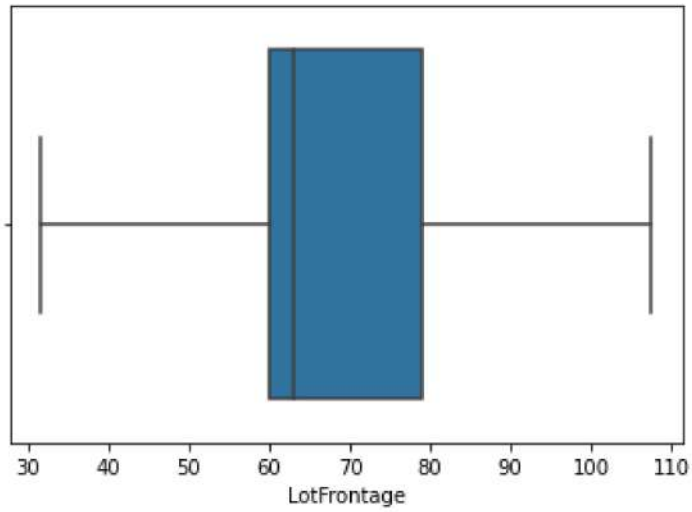
In [59]:
```
# Let us now apply the outlier function for all features and BXplotting the same

for features in df1.describe().columns:
    detect_outliers(features)
    sns.boxplot(df1[features])
    plt.show()
```

```
 #### MSSubClass ####
percentile25 20.0
percentile75 70.0
higher_fence 145.0
lower_fence -55.0
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

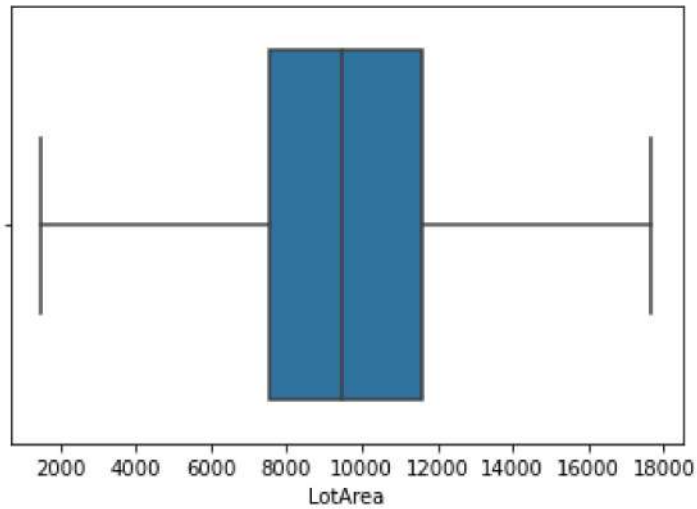



```
 #### LotFrontage ####
percentile25 60.0
percentile75 79.0
higher_fence 107.5
lower_fence 31.5
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

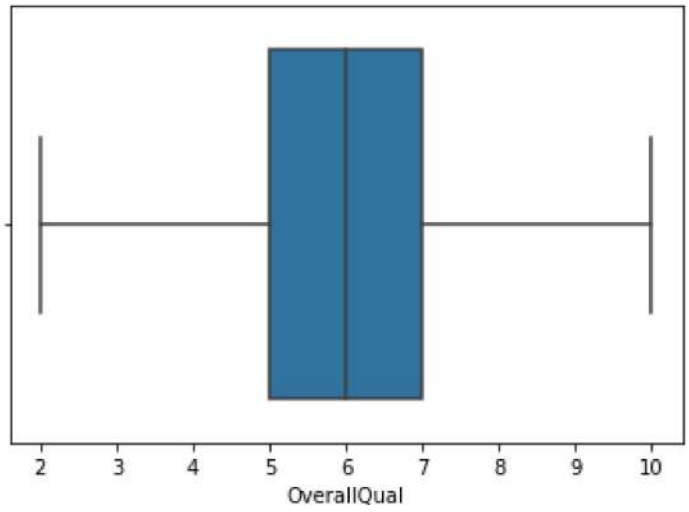



```
 #### LotArea ####
percentile25 7553.5
percentile75 11601.5
higher_fence 17673.5
lower_fence 1481.5
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

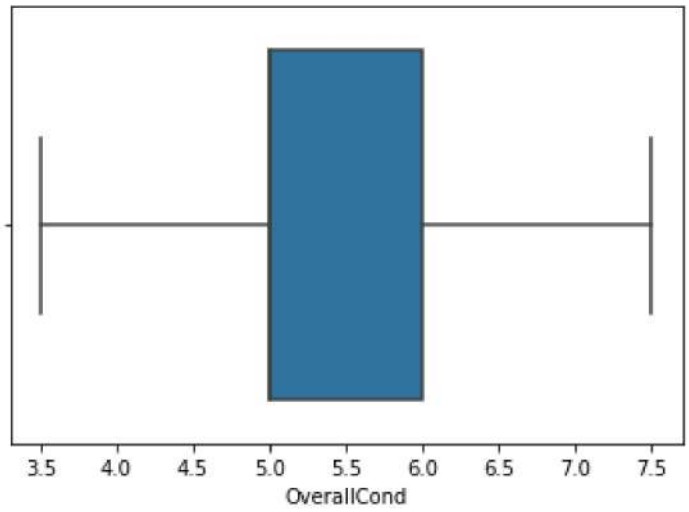



```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
 #### OverallQual ####
percentile25 5.0
percentile75 7.0
higher_fence 10.0
lower_fence 2.0
```



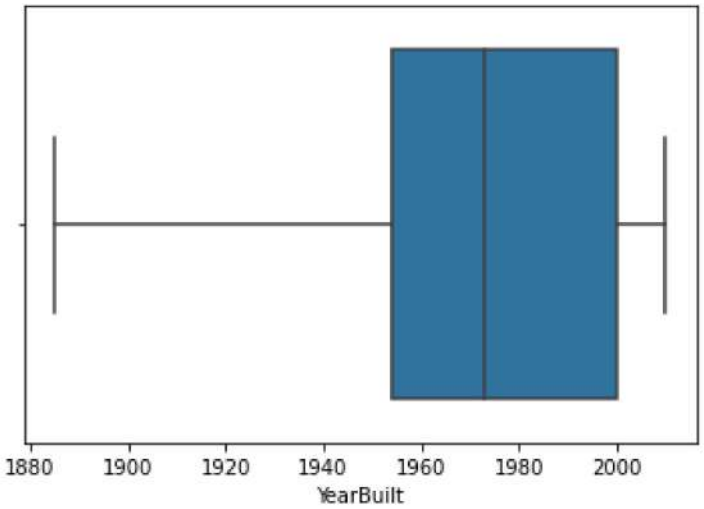

```
 #### OverallCond ####
percentile25 5.0
percentile75 6.0
higher_fence 7.5
lower_fence 3.5
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



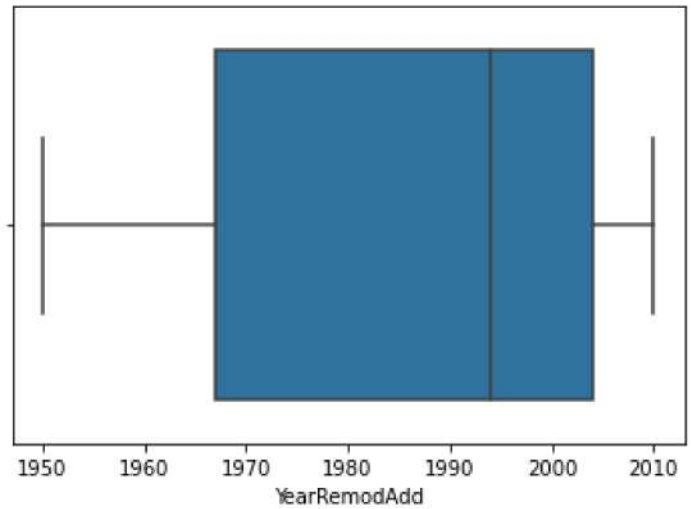

```
 #### YearBuilt ####
percentile25 1954.0
percentile75 2000.0
higher_fence 2069.0
lower_fence 1885.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



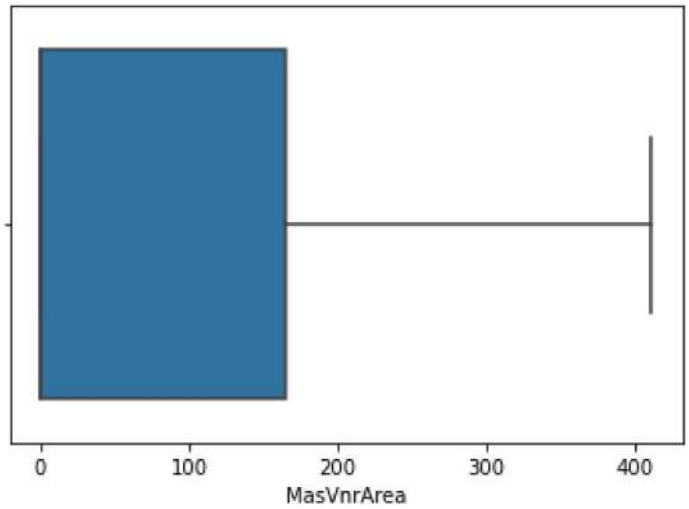

```
 #### YearRemodAdd ####
percentile25 1967.0
percentile75 2004.0
higher_fence 2059.5
lower_fence 1911.5
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



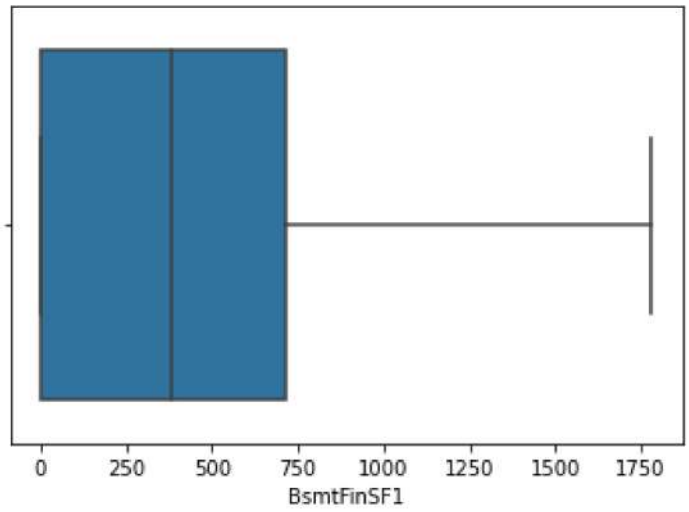

```
 #### MasVnrArea ####
percentile25 0.0
percentile75 164.25
higher_fence 410.625
lower_fence -246.375
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



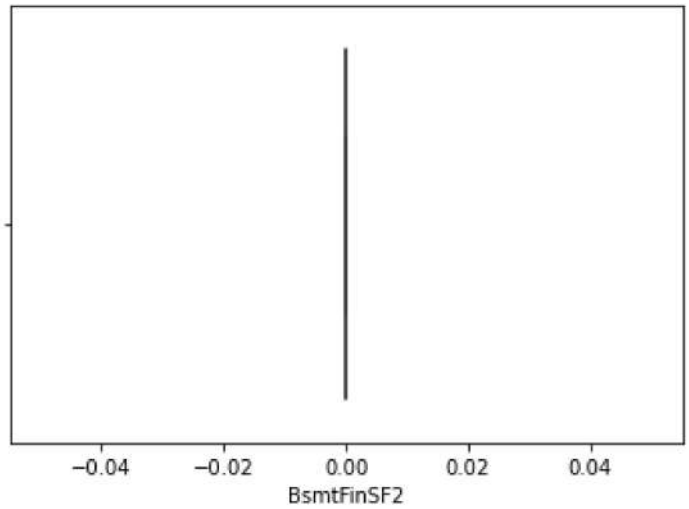

```
 #### BsmtFinSF1 ####
percentile25 0.0
percentile75 712.25
higher_fence 1780.625
lower_fence -1068.375
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



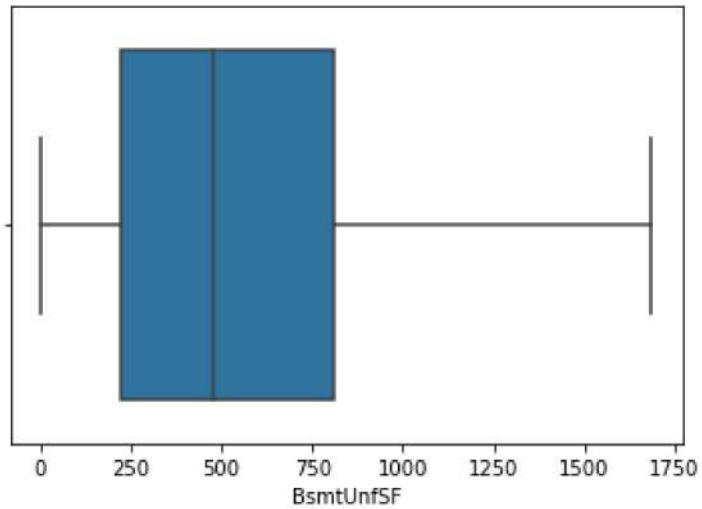

```
 #### BsmtFinSF2 ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



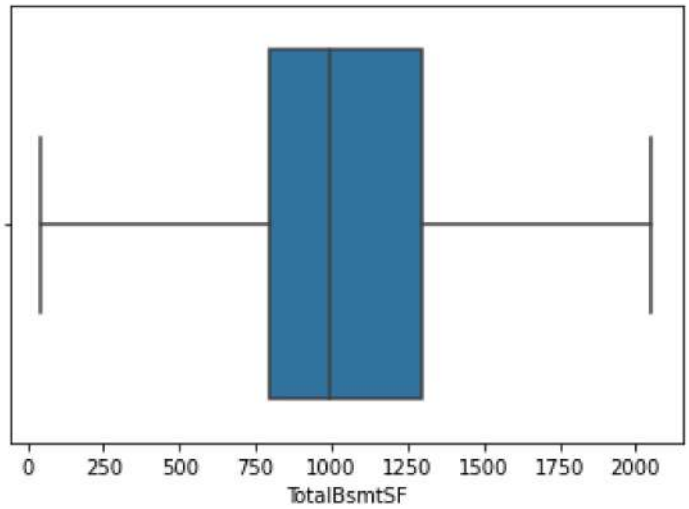

```
#### BsmtUnfSF ####
percentile25 223.0
percentile75 808.0
higher_fence 1685.5
lower_fence -654.5
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



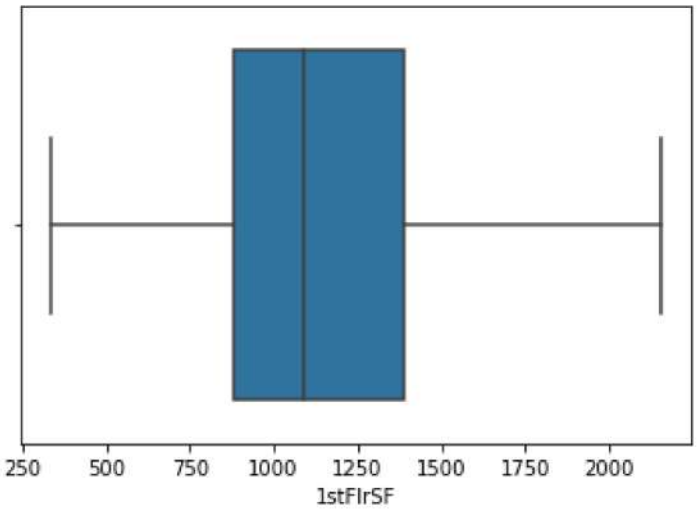

```
#### TotalBsmtSF ####
percentile25 795.75
percentile75 1298.25
higher_fence 2052.0
lower_fence 42.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



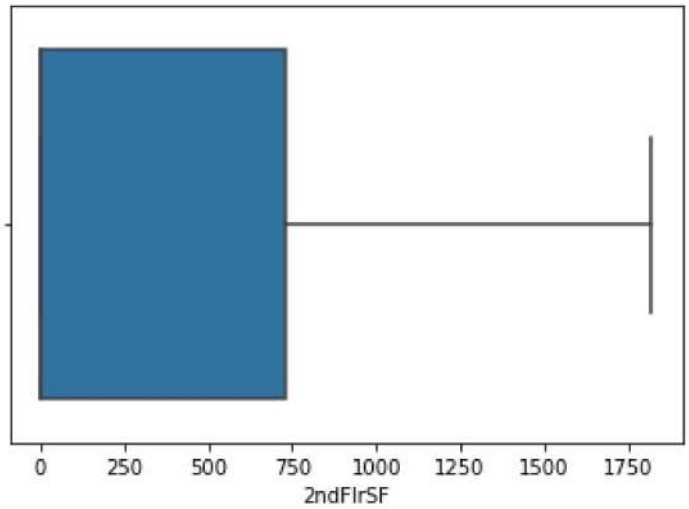

```
#### 1stFlrSF ####
percentile25 882.0
percentile75 1391.25
higher_fence 2155.125
lower_fence 118.125
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



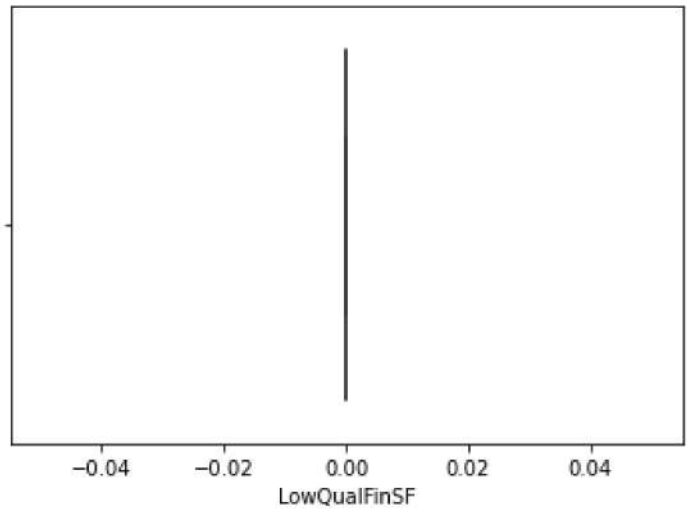

```
#### 2ndFlrSF ####
percentile25 0.0
percentile75 728.0
higher_fence 1820.0
lower_fence -1092.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



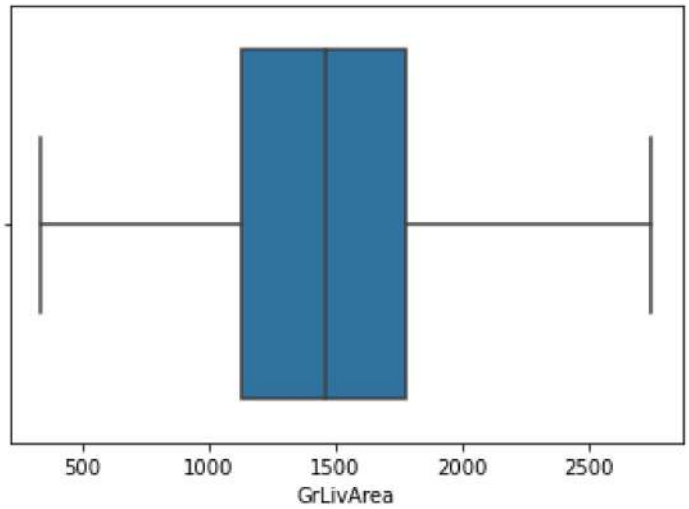

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

```
 #### LowQualFinSF ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```



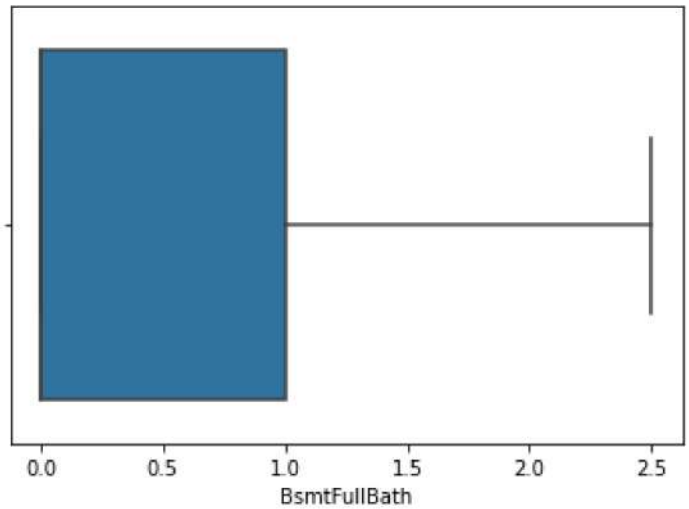

```
 #### GrLivArea ####
percentile25 1129.5
percentile75 1776.75
higher_fence 2747.625
lower_fence 158.625
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



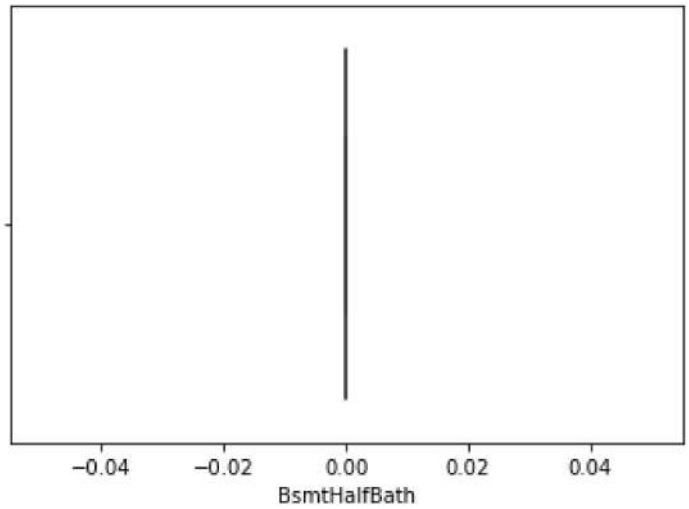

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

```
 #### BsmtFullBath ####
percentile25 0.0
percentile75 1.0
higher_fence 2.5
lower_fence -1.5
```



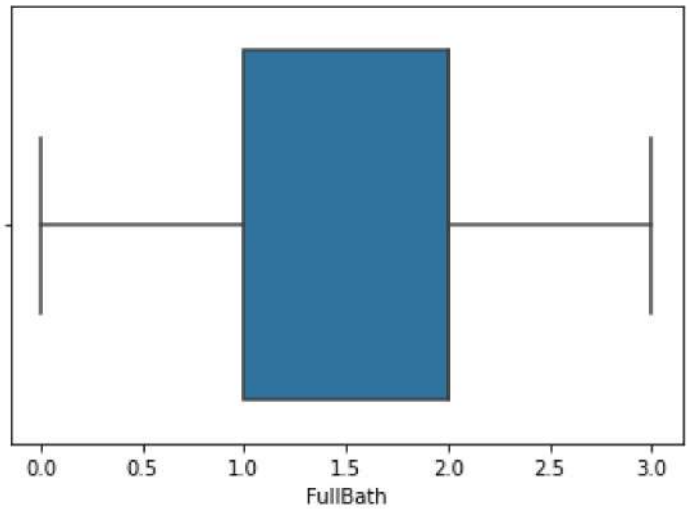

```
 #### BsmtHalfBath ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



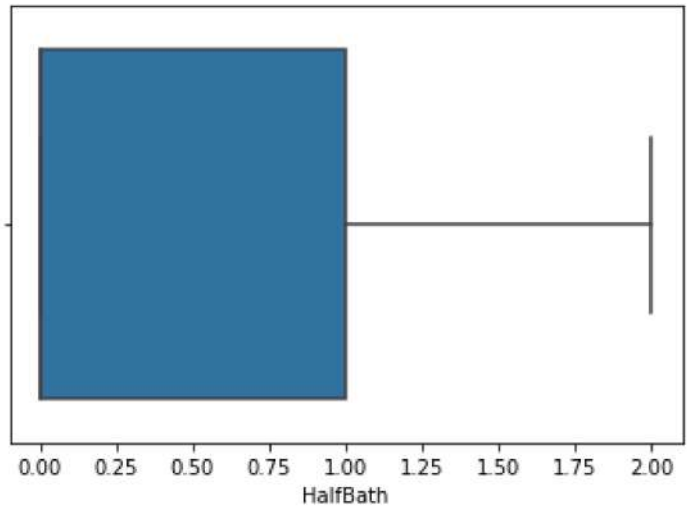

```
#### FullBath ####
percentile25 1.0
percentile75 2.0
higher_fence 3.5
lower_fence -0.5
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

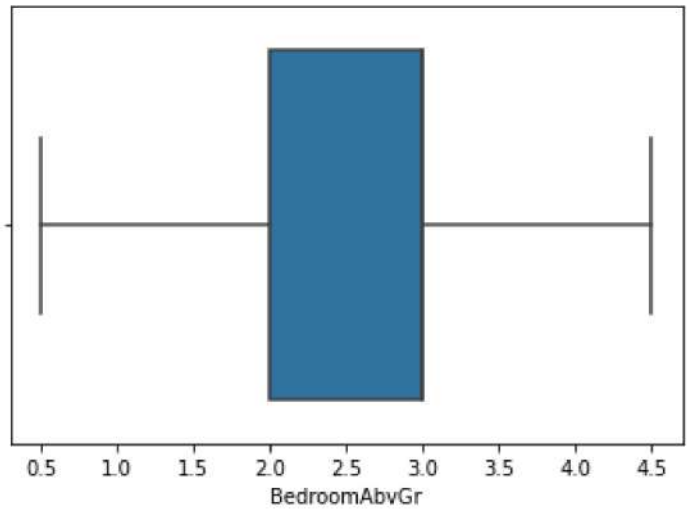



```
#### HalfBath ####
percentile25 0.0
percentile75 1.0
higher_fence 2.5
lower_fence -1.5
```

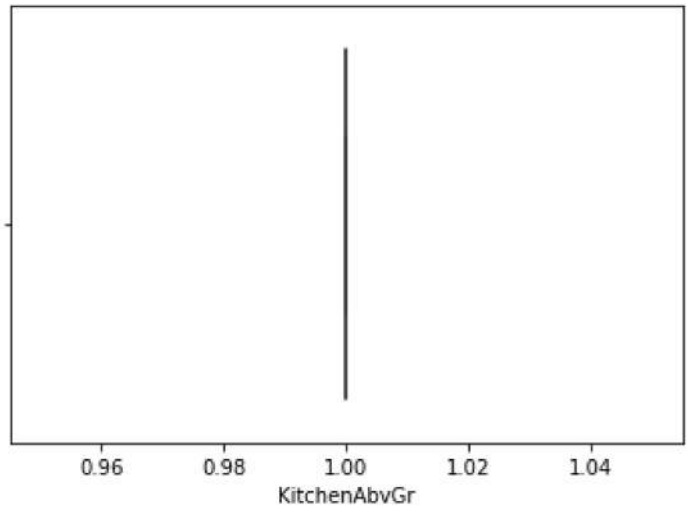
```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```




```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
 #### BedroomAbvGr ####
percentile25 2.0
percentile75 3.0
higher_fence 4.5
lower_fence 0.5
```

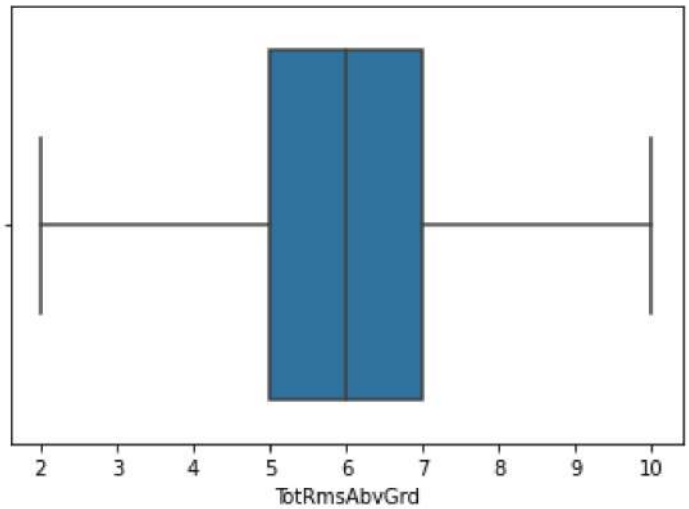



```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
 #### KitchenAbvGr ####
percentile25 1.0
percentile75 1.0
higher_fence 1.0
lower_fence 1.0
```



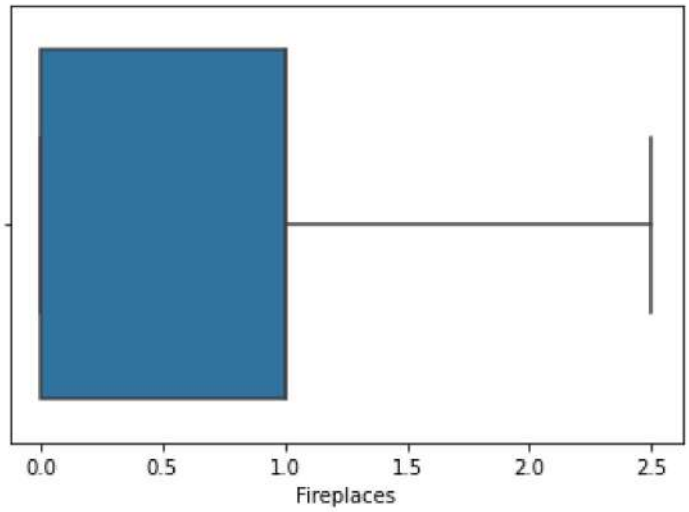

```
#### TotRmsAbvGrd ####
percentile25 5.0
percentile75 7.0
higher_fence 10.0
lower_fence 2.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



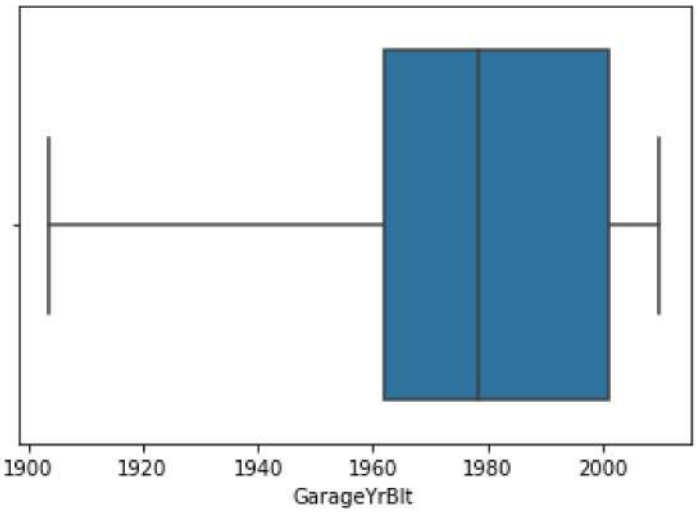

```
#### Fireplaces ####
percentile25 0.0
percentile75 1.0
higher_fence 2.5
lower_fence -1.5
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



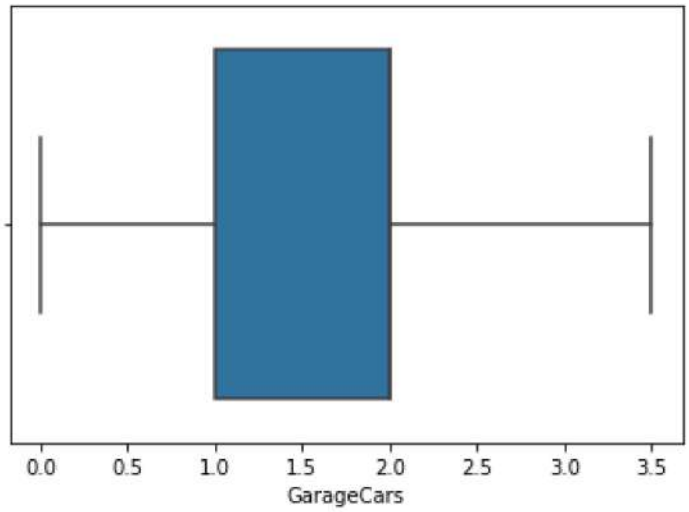

```
 #### GarageYrBlt ####
percentile25 1962.0
percentile75 2001.0
higher_fence 2059.5
lower_fence 1903.5
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

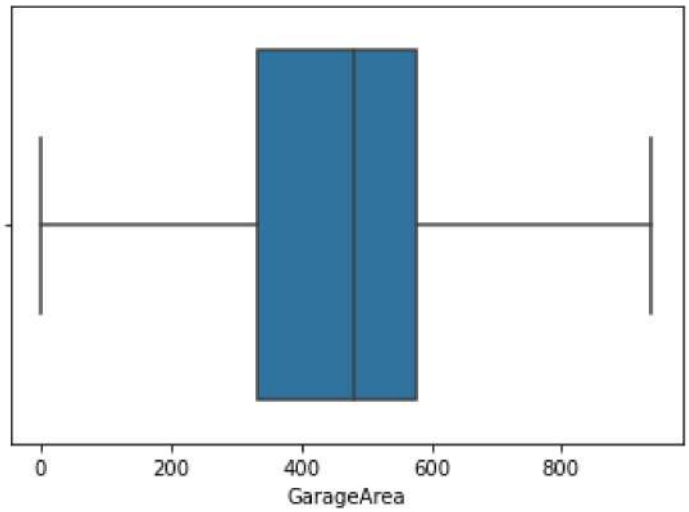



```
 #### GarageCars ####
percentile25 1.0
percentile75 2.0
higher_fence 3.5
lower_fence -0.5
```

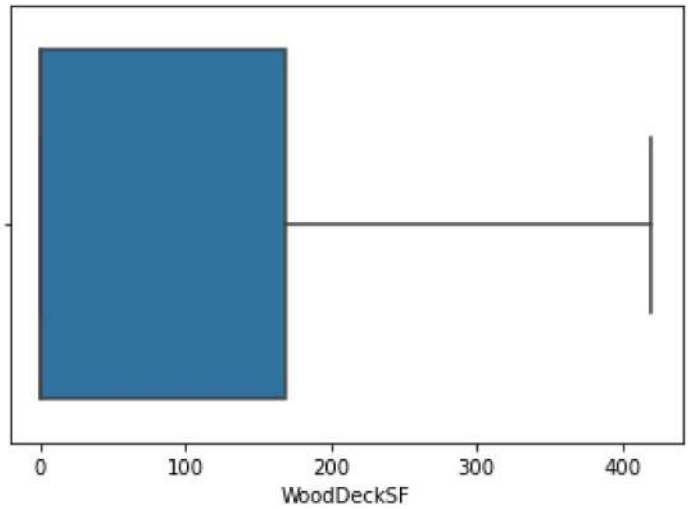
```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```




```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
 #### GarageArea ####
percentile25 334.5
percentile75 576.0
higher_fence 938.25
lower_fence -27.75
```

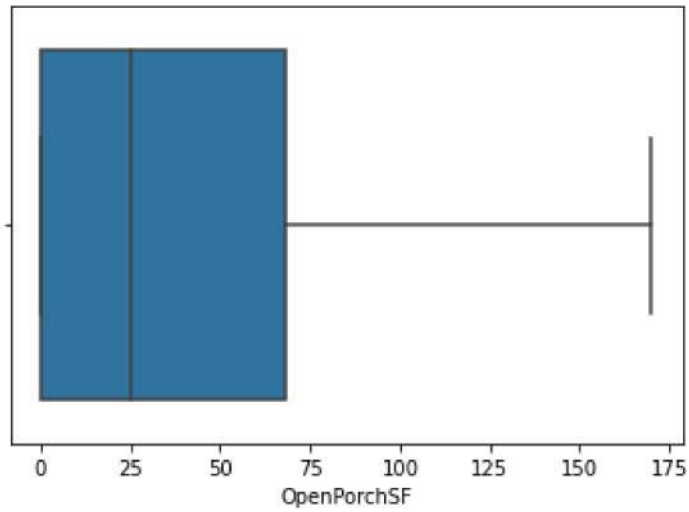



```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
 #### WoodDeckSF ####
percentile25 0.0
percentile75 168.0
higher_fence 420.0
lower_fence -252.0
```



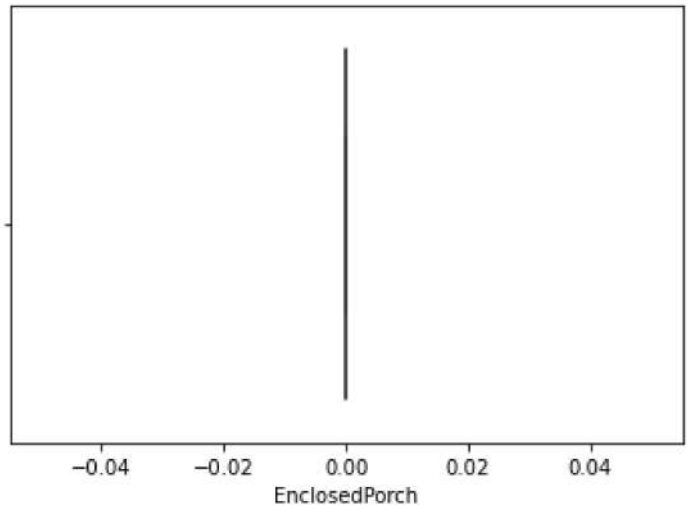

```
 #### OpenPorchSF ####
percentile25 0.0
percentile75 68.0
higher_fence 170.0
lower_fence -102.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



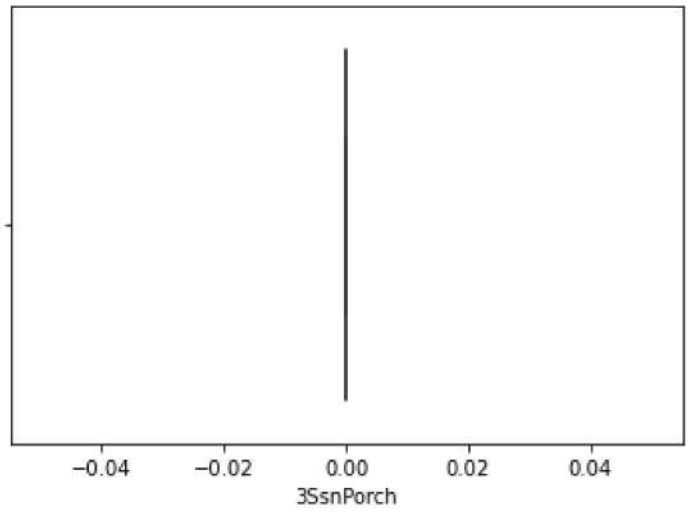

```
 #### EnclosedPorch ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

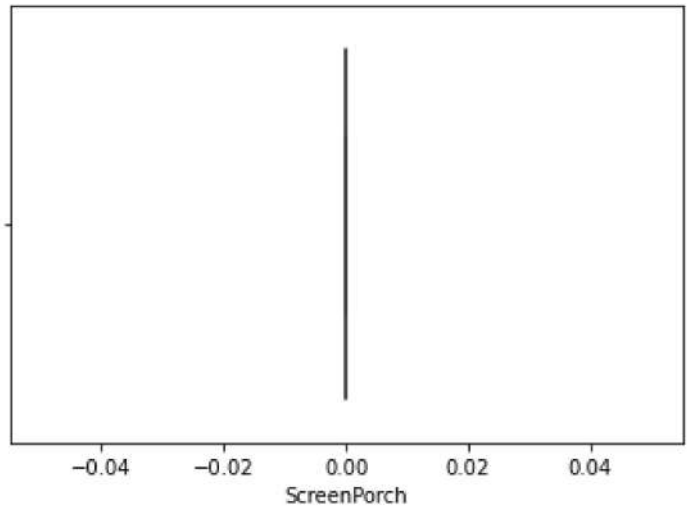



```
 #### 3SsnPorch ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

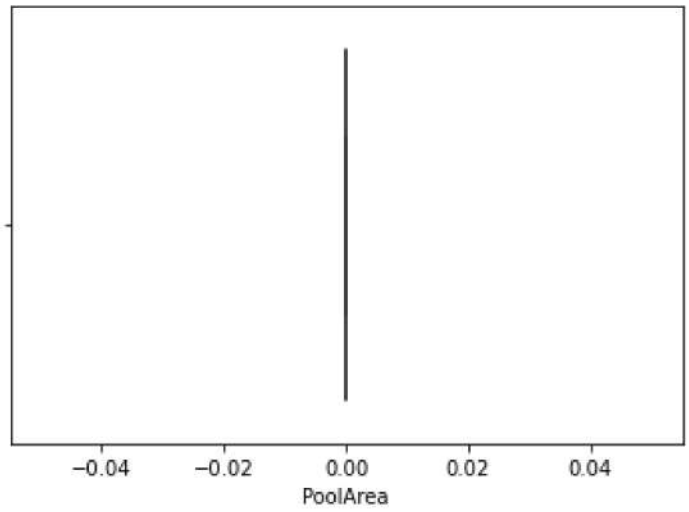



```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
 #### ScreenPorch ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```



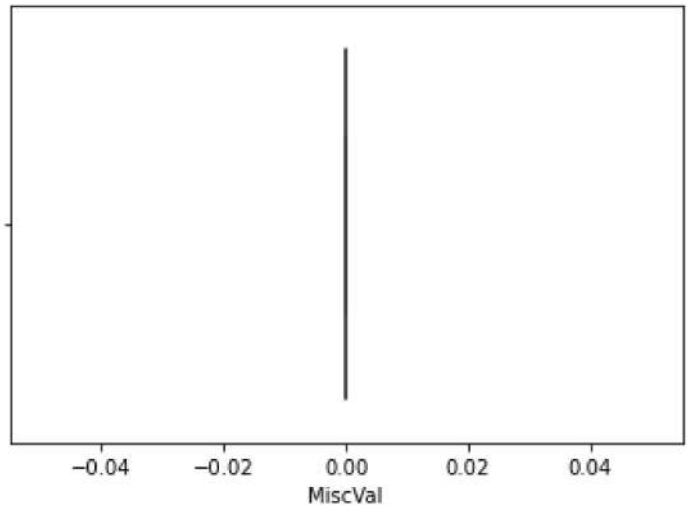

```
#### PoolArea ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



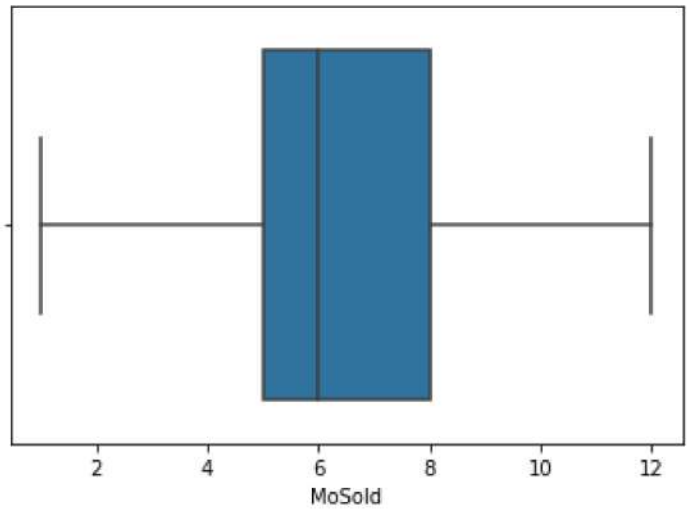

```
#### MiscVal ####
percentile25 0.0
percentile75 0.0
higher_fence 0.0
lower_fence 0.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



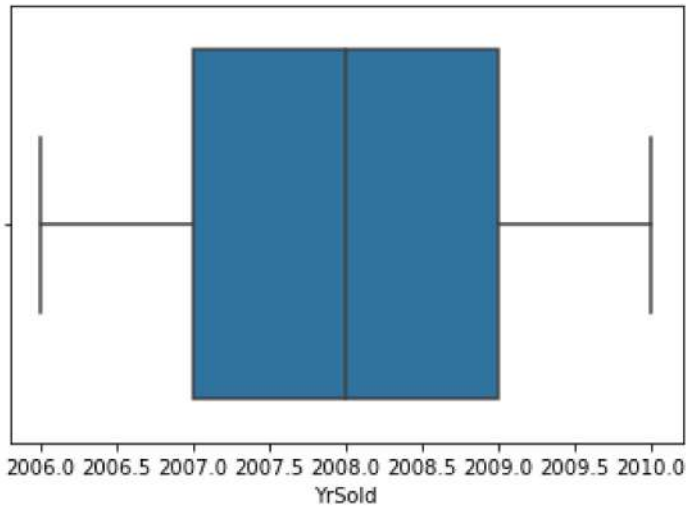

```
 #### MoSold ####
percentile25 5.0
percentile75 8.0
higher_fence 12.5
lower_fence 0.5
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



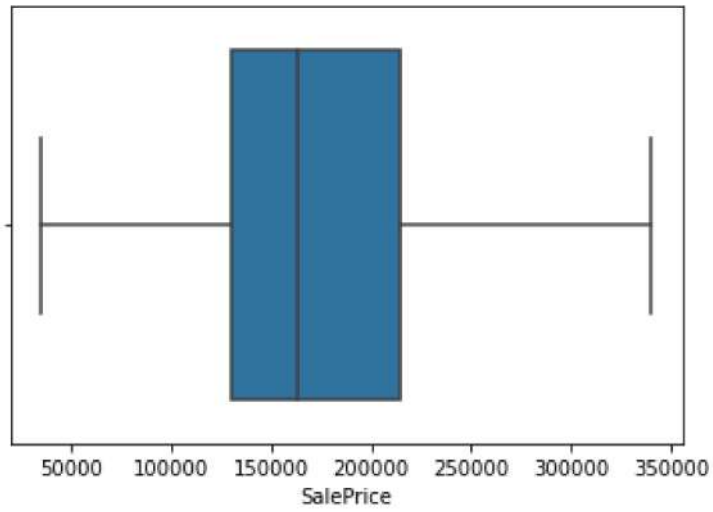

```
 #### YrSold ####
percentile25 2007.0
percentile75 2009.0
higher_fence 2012.0
lower_fence 2004.0
```

```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



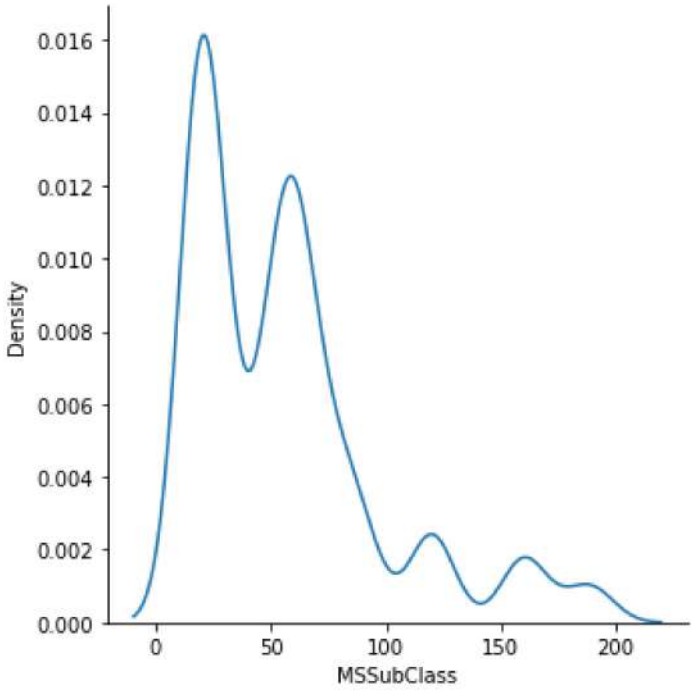

```
 #### SalePrice ####
percentile25 129975.0
percentile75 214000.0
higher_fence 340037.5
lower_fence 3937.5
```

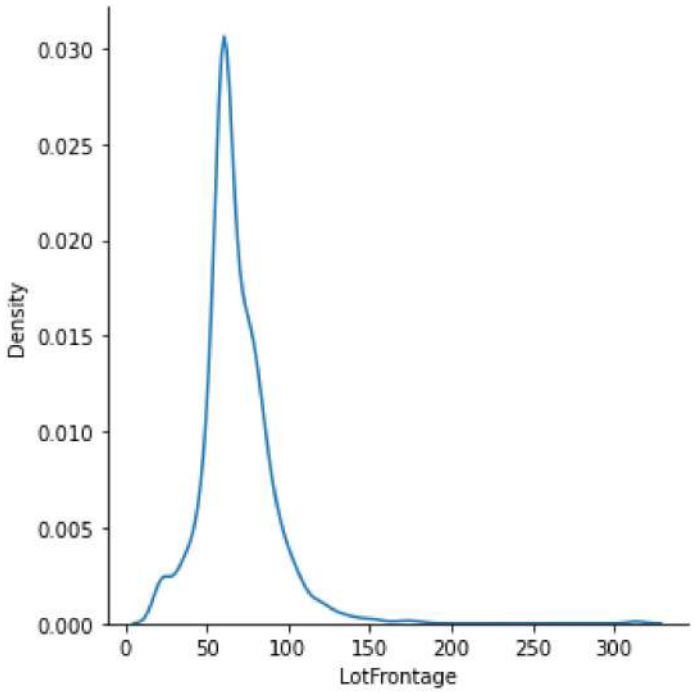
```
C:\Users\460379\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
Pass the following variable as a keyword arg: x. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

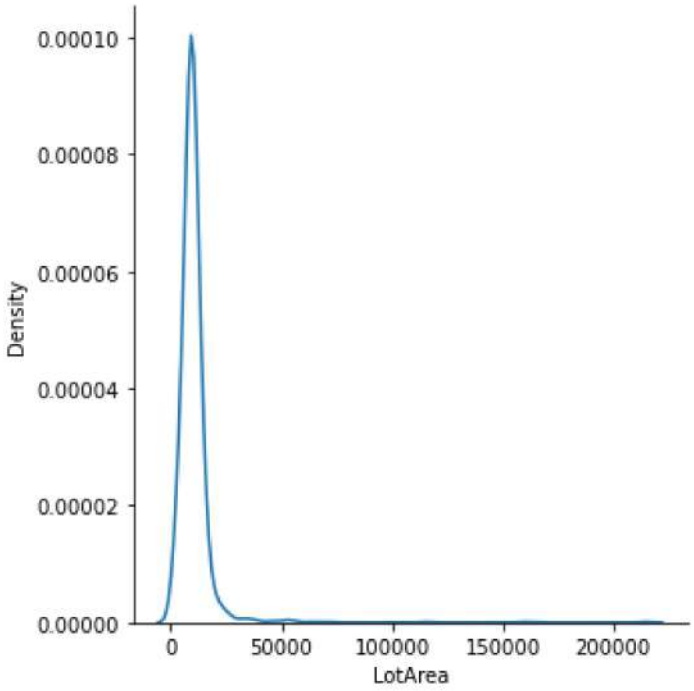


In [60]:
```
#Let us check the distribution plot for all the numerical features

for features in df1.describe().columns:
    df1 = df.copy()
    sns.displot(data = df1, x = df1[features], kind = 'kde')
    plt.show()
```


0.016
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Density
0
50
100
150
200
MSSubClass


0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
0
50
100
150
200
250
300
LotFrontage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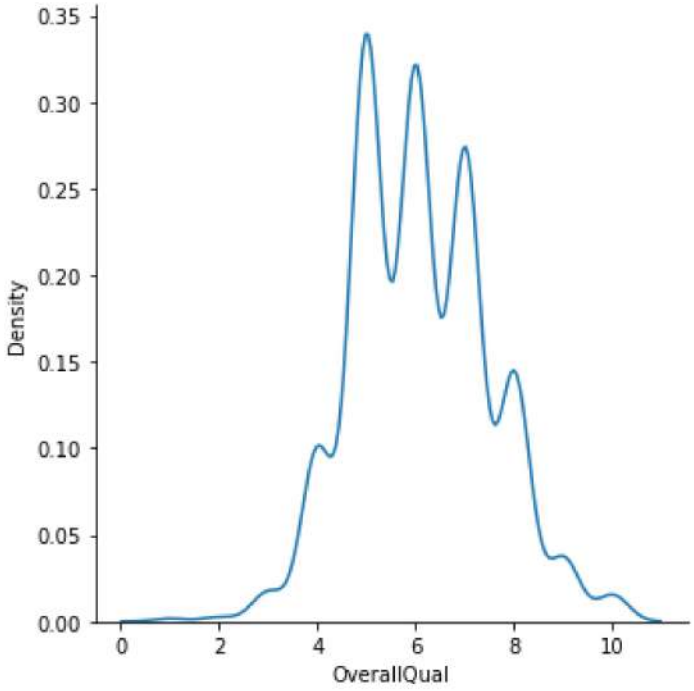
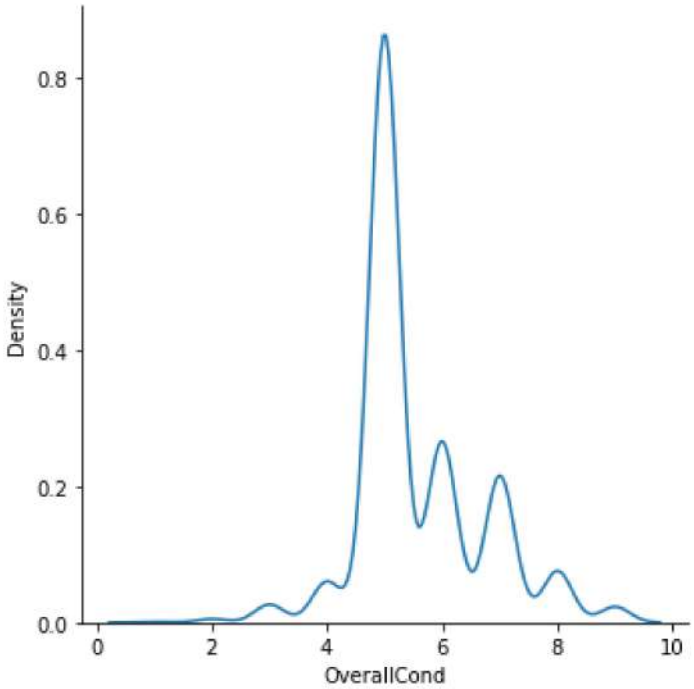
0.00008
0.00006
0.00004
0.00002
0.00000
Density
0
50000
100000
150000
200000
LotArea


0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Density
0
2
4
6
8
10
OverallQual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0.4
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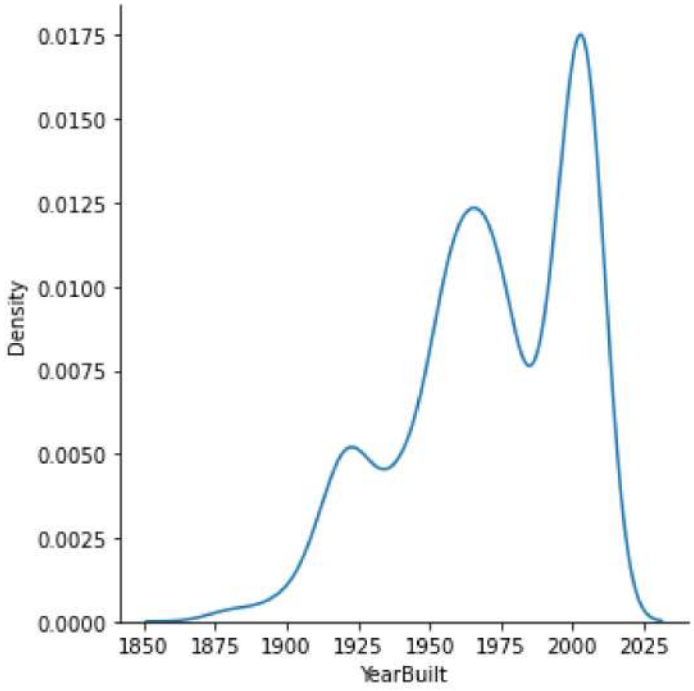
0.8
0
2
4
6
8
10
OverallCond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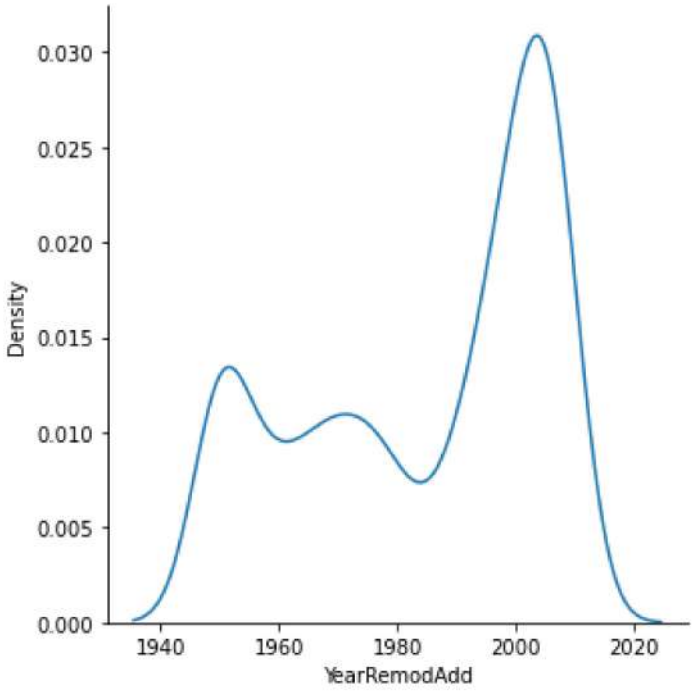
0.0025
0.0050
0.0075
0.0100
0.0125
0.0150
0.0175
1850
1875
1900
1925
1950
1975
2000
2025
YearBuilt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0.025
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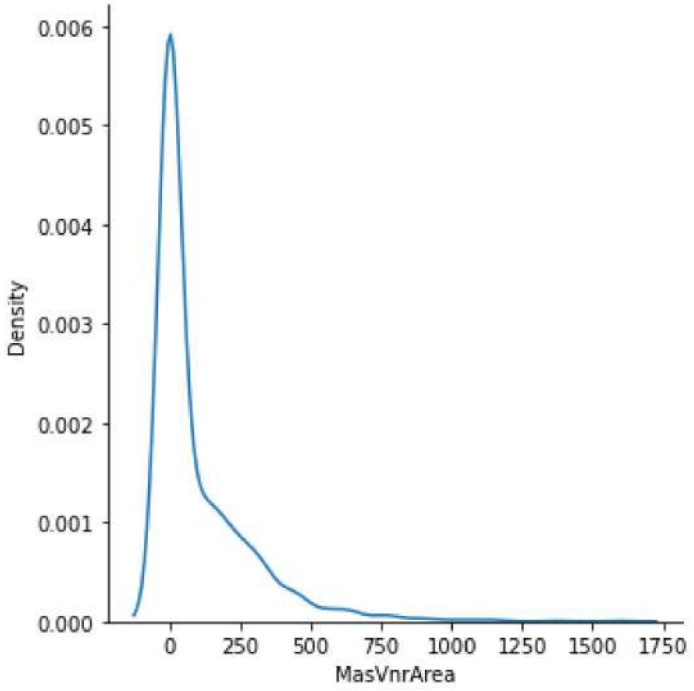
0.010
0.005
0.000
Density
1940
1960
1980
2000
2020
YearRemodAdd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0.005
0.004
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0.001
0.000
Density
0
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750
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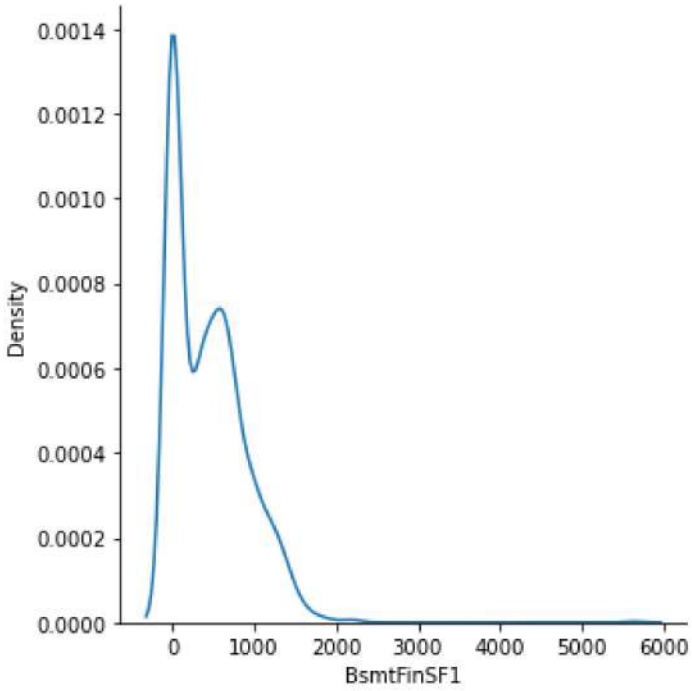
1500
1750
MasVnrArea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0.0012
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0.0004
0.0002
0.0000
Density
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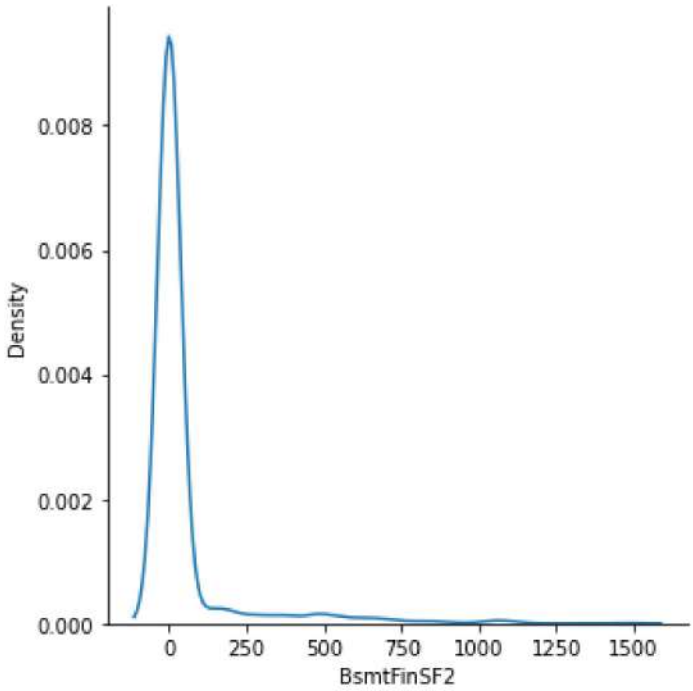
2000
3000
4000
5000
6000
BsmtFinSF1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Density
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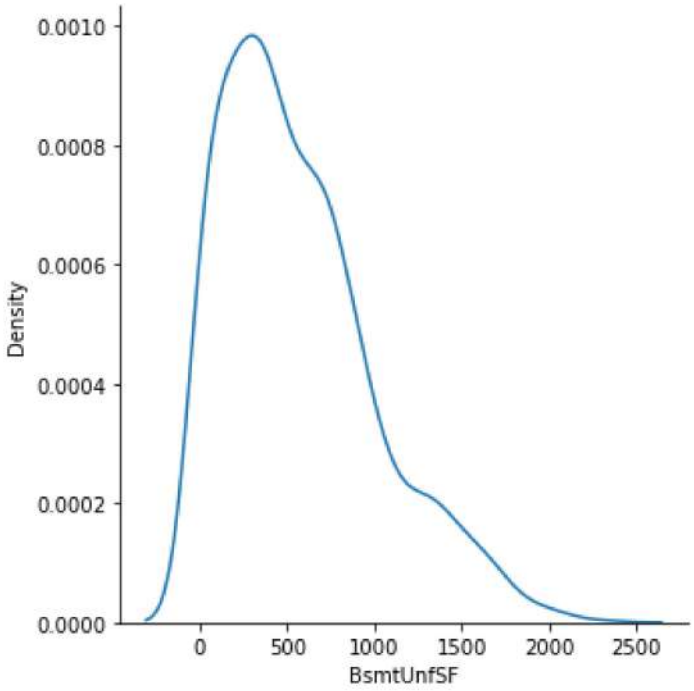
500
750
1000
1250
1500
BsmtFinSF2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Density
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500
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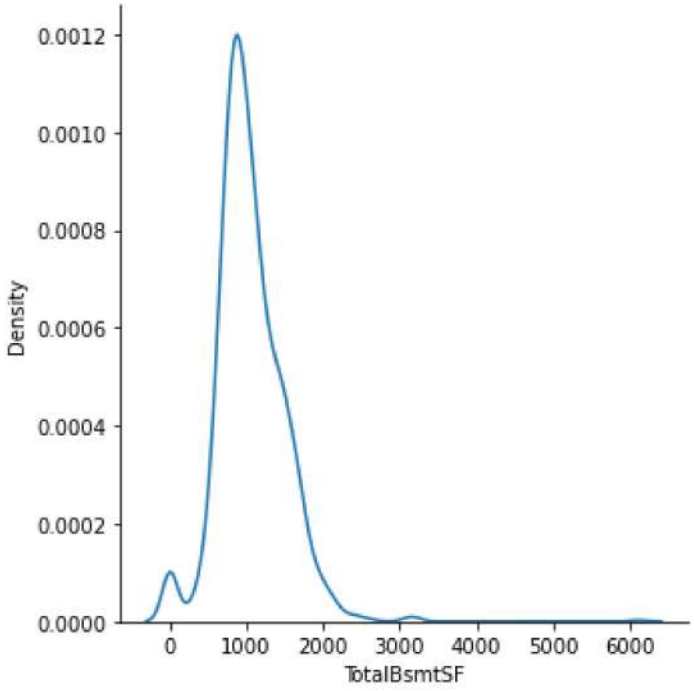
1500
2000
2500
BsmtUnfSF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Density
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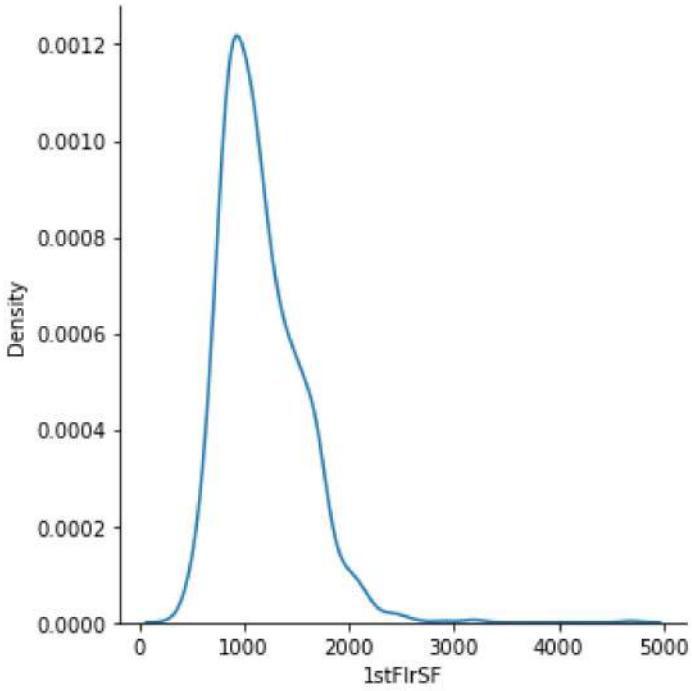
5000
6000
TotalBsmtSF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Density
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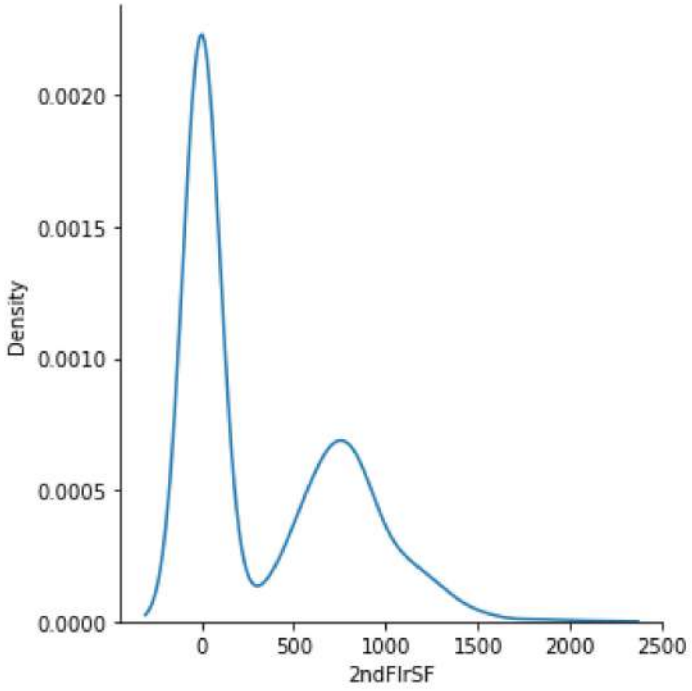
2000
3000
4000
5000
1stFlrSF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1500
2000
2500
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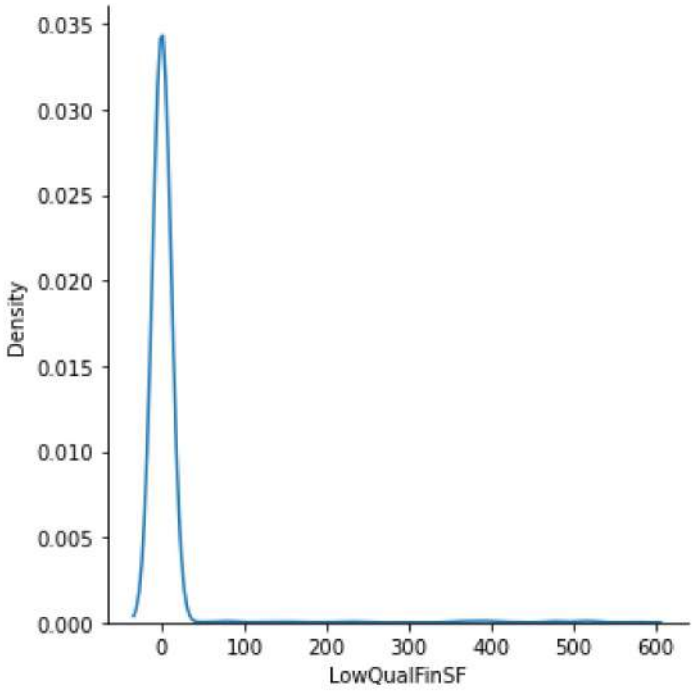
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0.000
Density
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100
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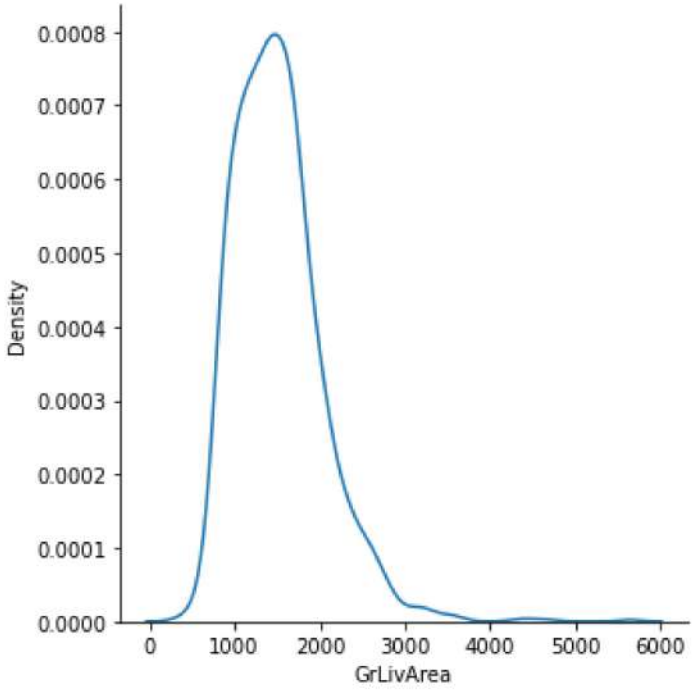
500
600
LowQualFinSF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0.0006
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0.0001
0.0000
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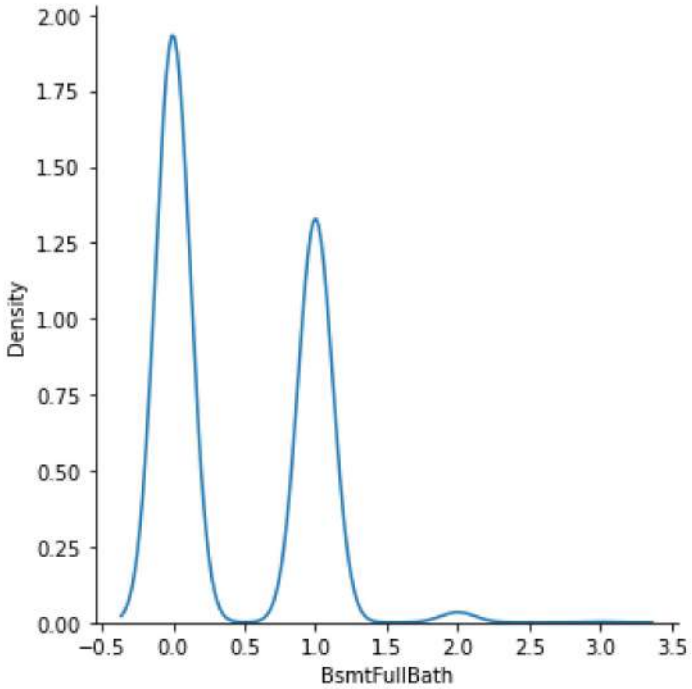
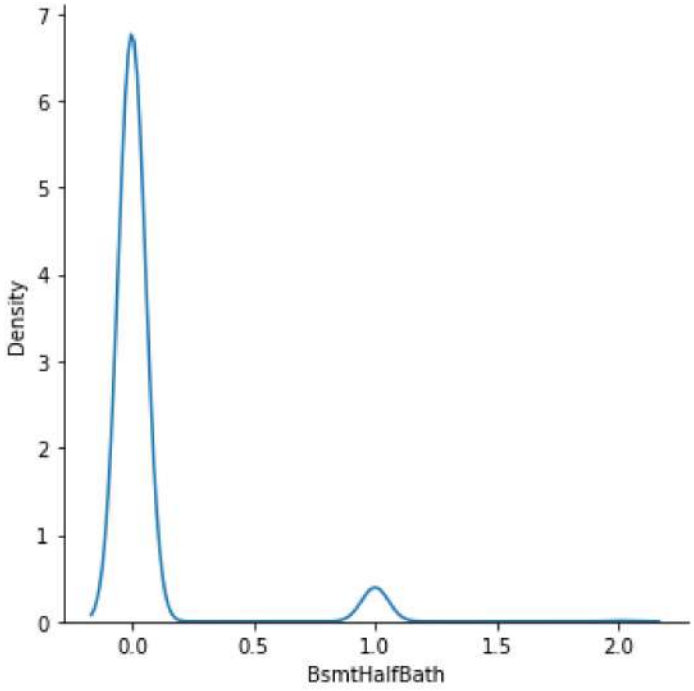
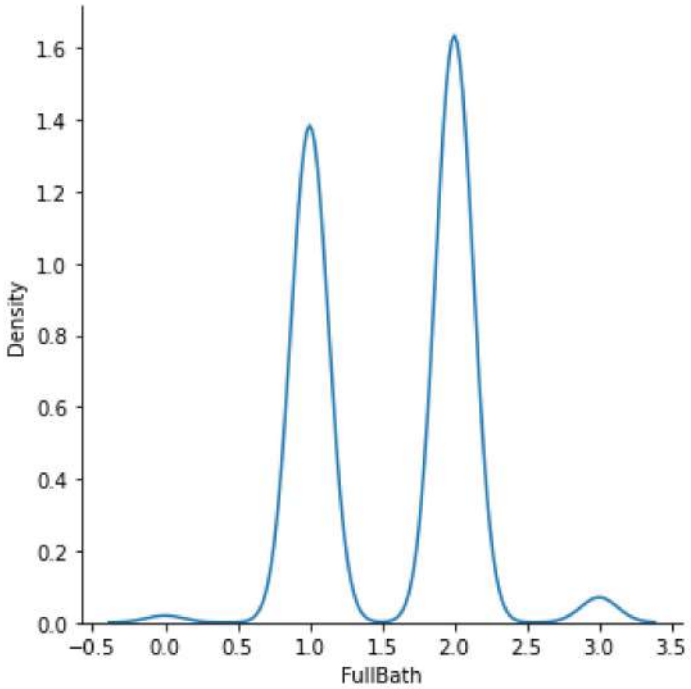
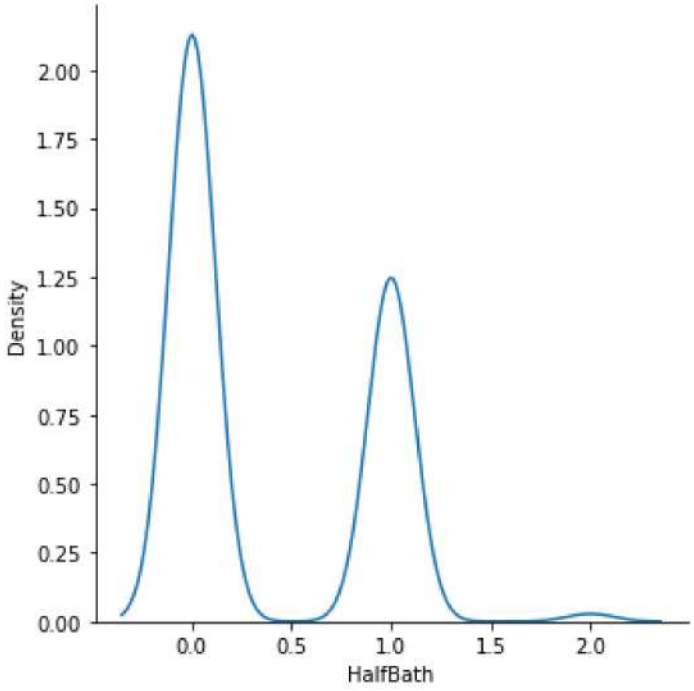
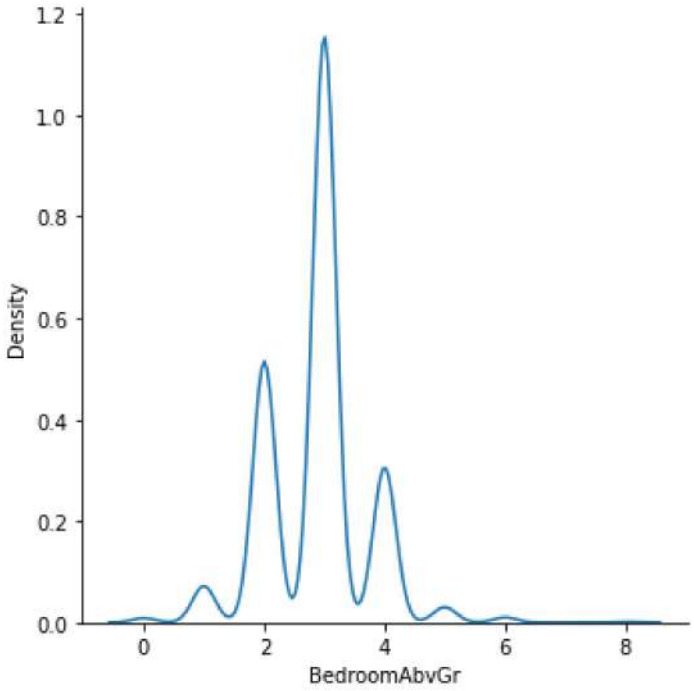
5000
6000
GrLivArea


Density
BsmtFullBath


Density
BsmtHalfBath


Density
FullBath


Density
HalfBath


Density
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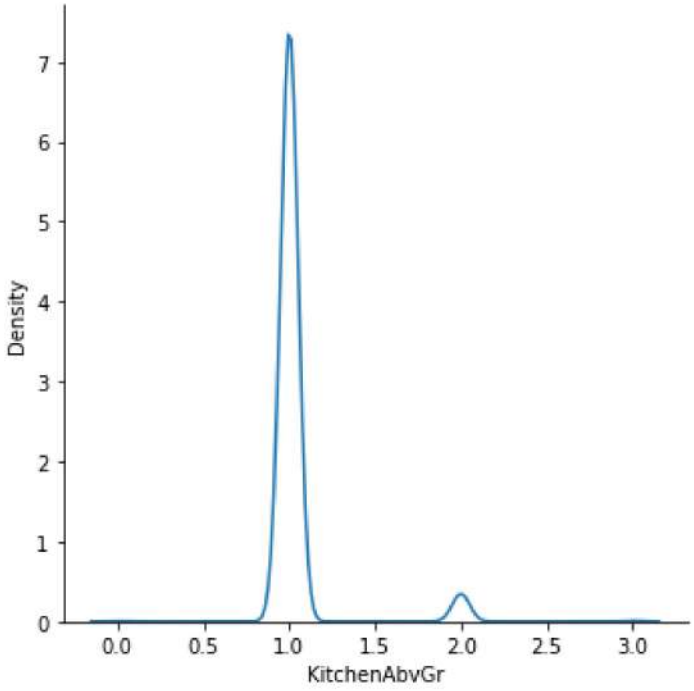
0.6
0.8
1.0
1.2
0
2
4
6
8


Density
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1.0
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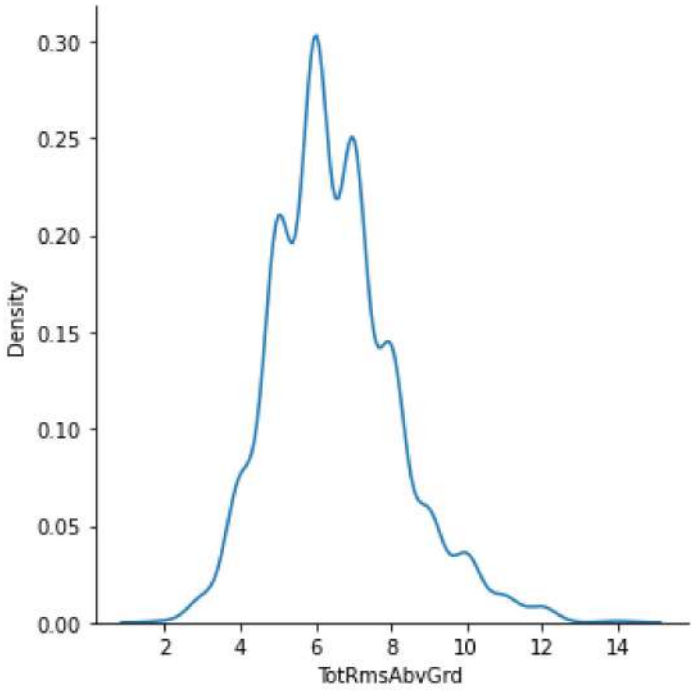
3.0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Density
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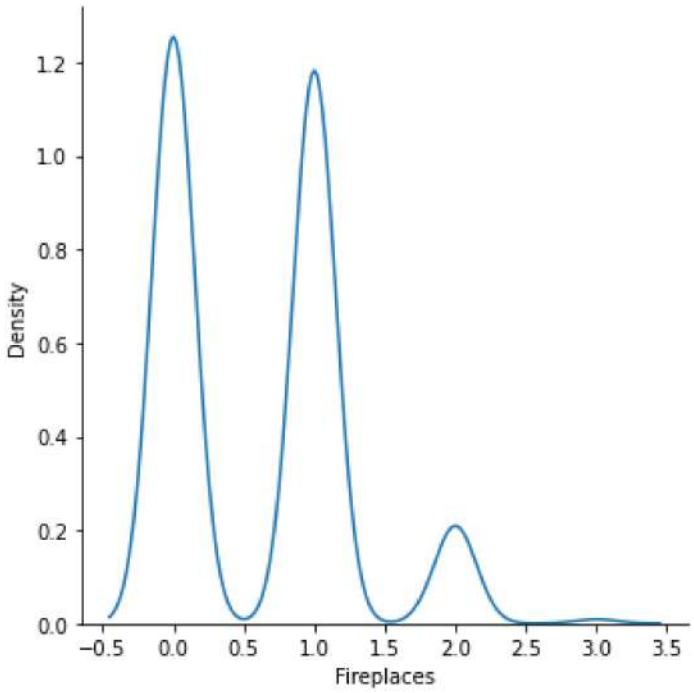
14
TotRmsAbvGrd


1.2
1.0
0.8
0.6
0.4
0.2
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Density
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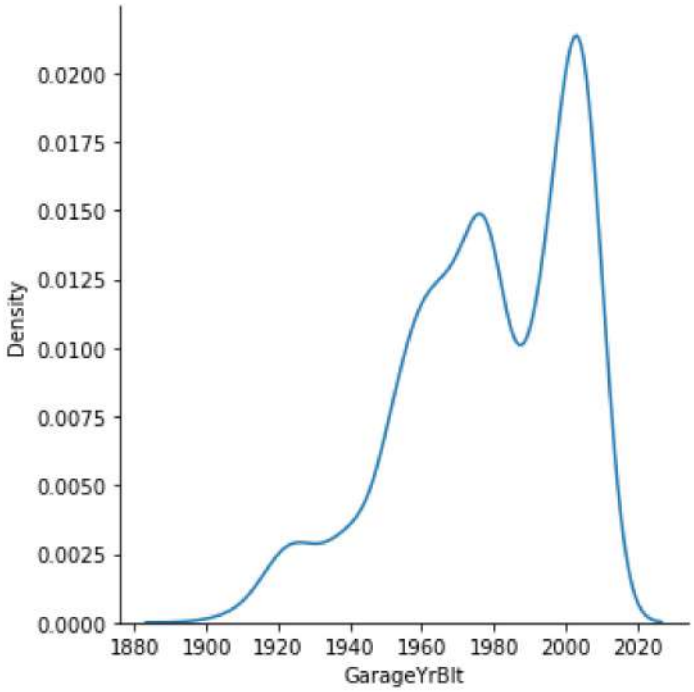
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Fireplaces


0.0200
0.0175
0.0150
0.0125
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0.0075
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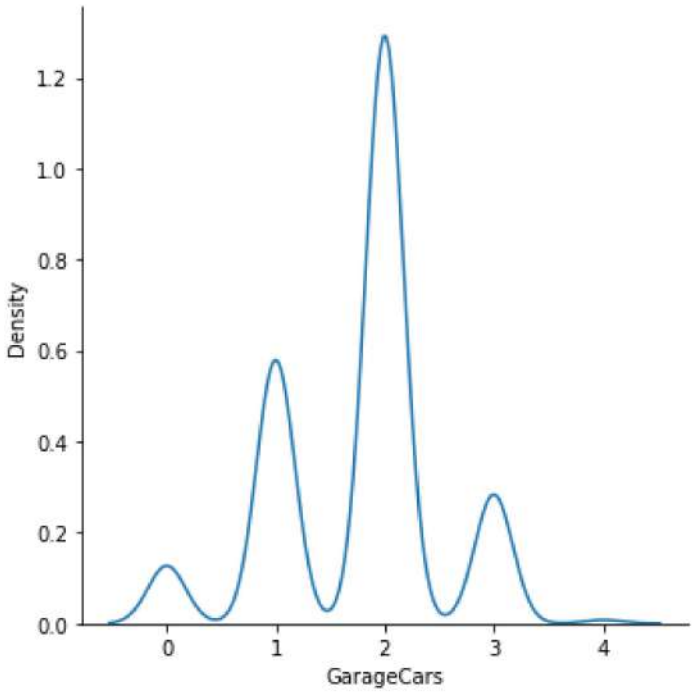
0.0025
0.0000
Density
1880
1900
1920
1940
1960
1980
2000
2020
GarageYrBlt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0.6
0.4
0.2
0.0
Density
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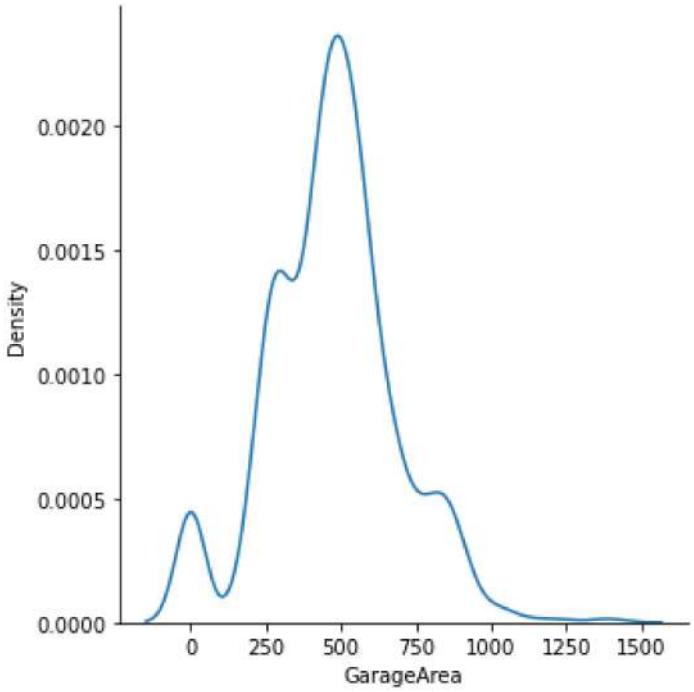
1
2
3
4
GarageCars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0.0000
Density
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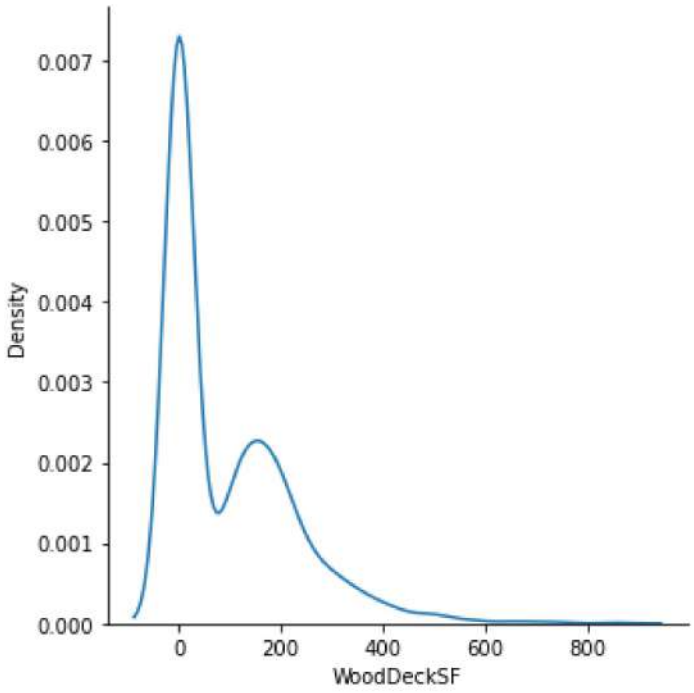
500
750
1000
1250
1500
GarageArea


0.007
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0.005
0.004
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0.002
0.001
0.000
Density
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200
400
600
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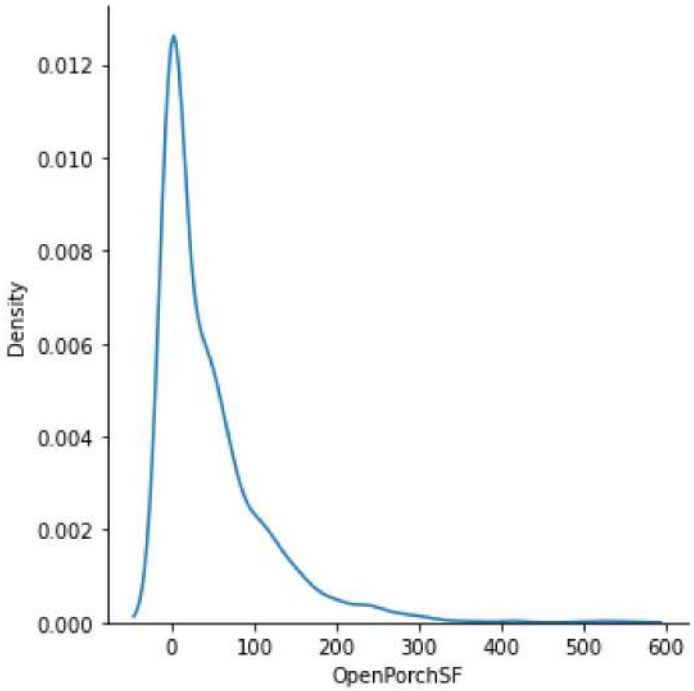
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0.004
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Density
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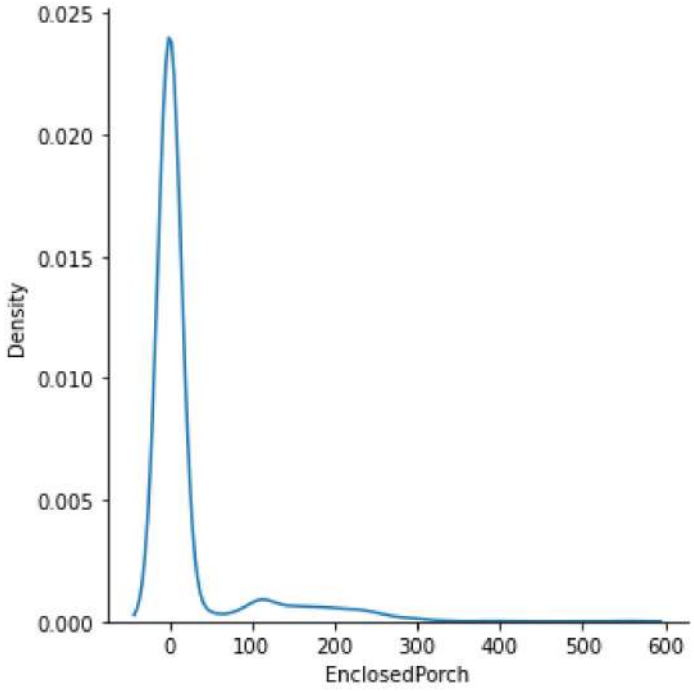
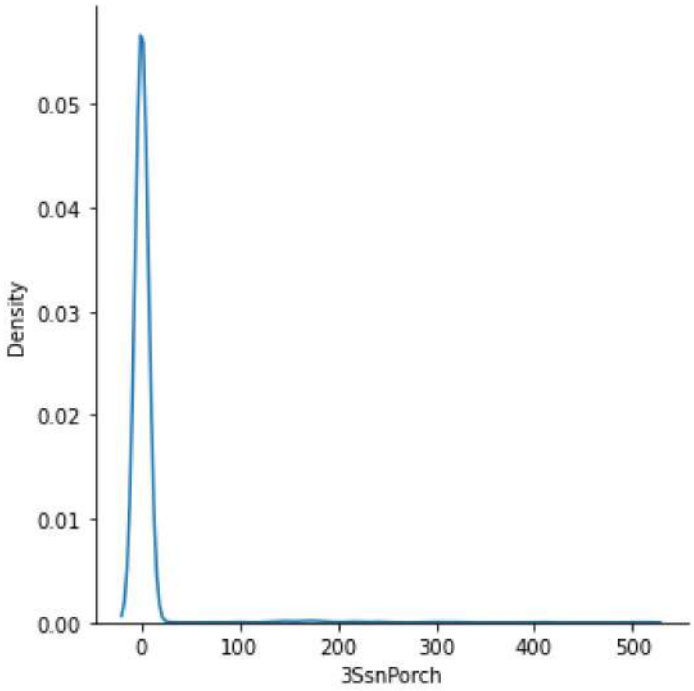
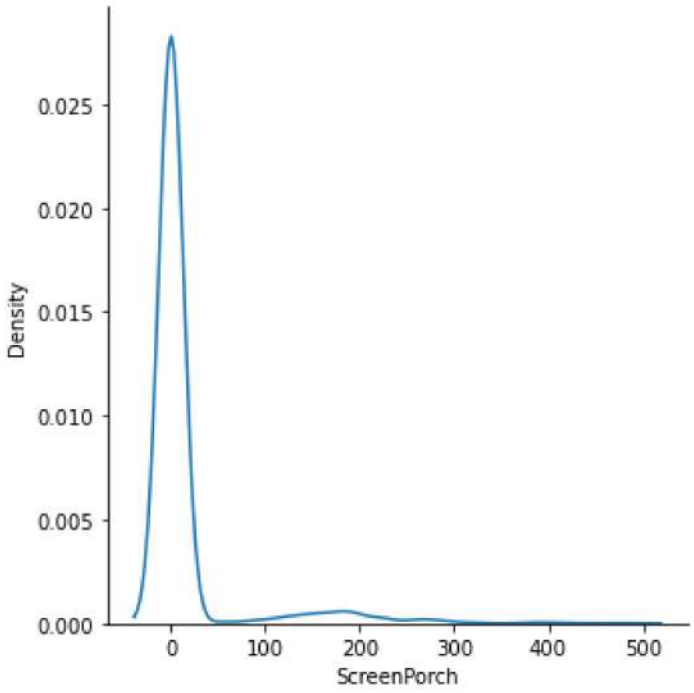
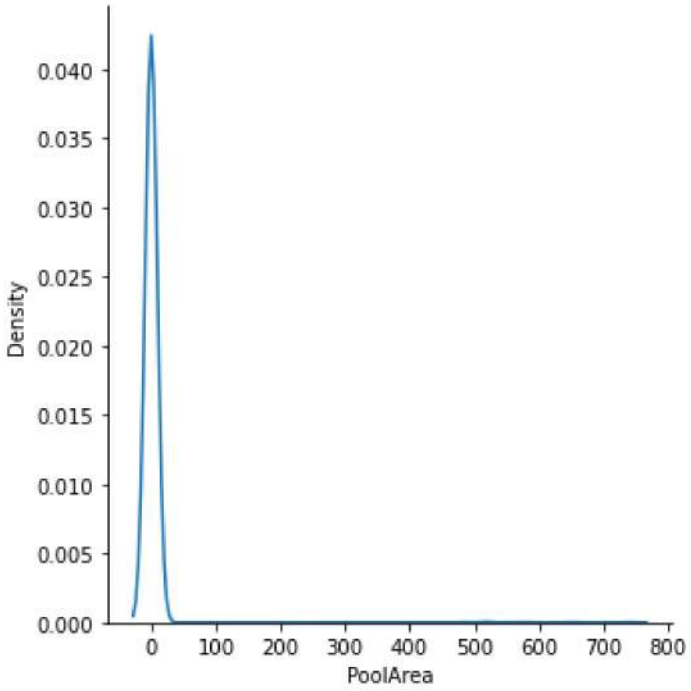
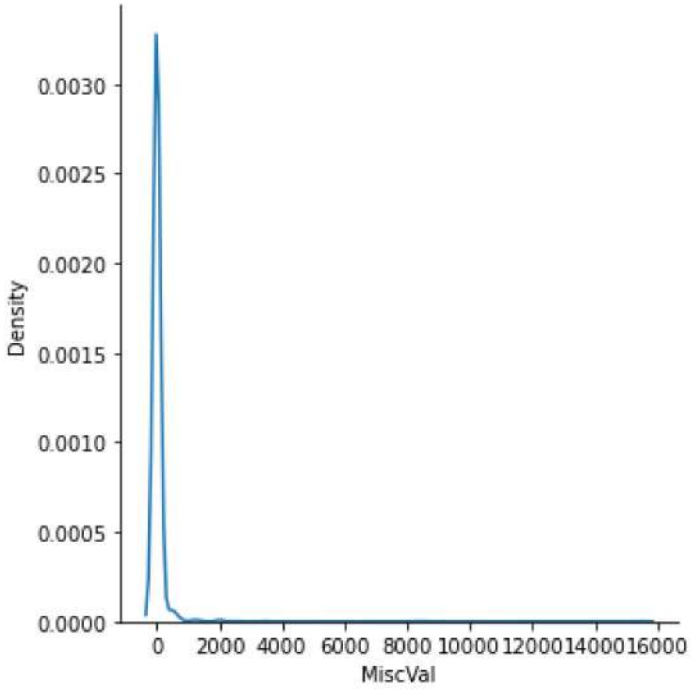
100
200
300
400
500
600
OpenPorchSF

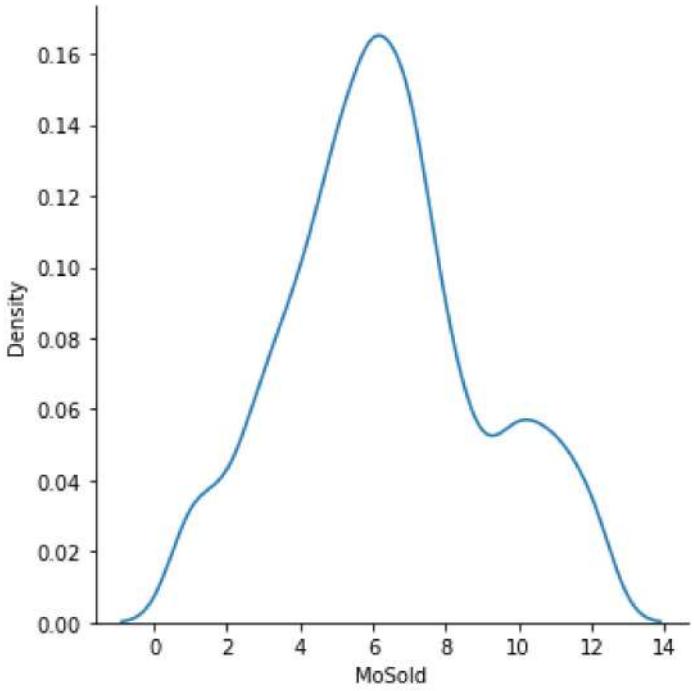

0.025
0.020
0.015
0.010
0.005
0.000
Density
0
100
200
300
400
500
600
EnclosedPorch

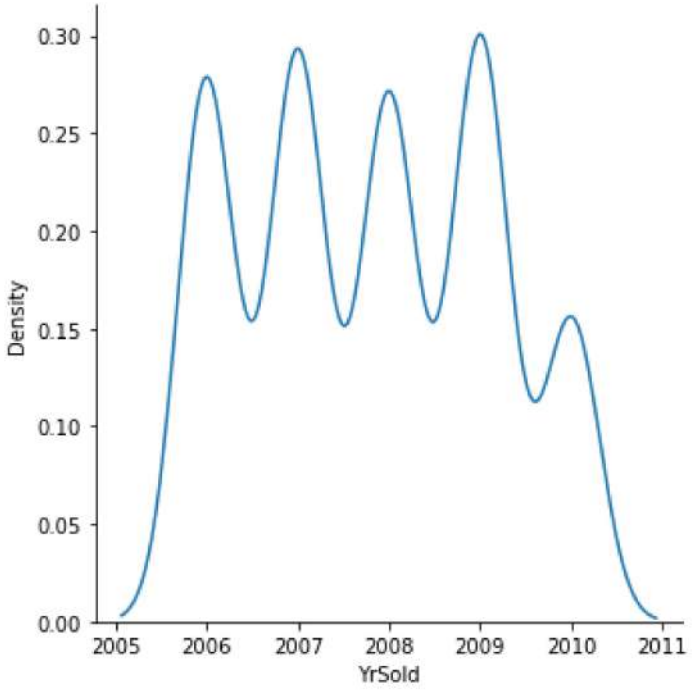

0.05
0.04
0.03
0.02
0.01
0.00
Density
0
100
200
300
400
500
3SsnPorch

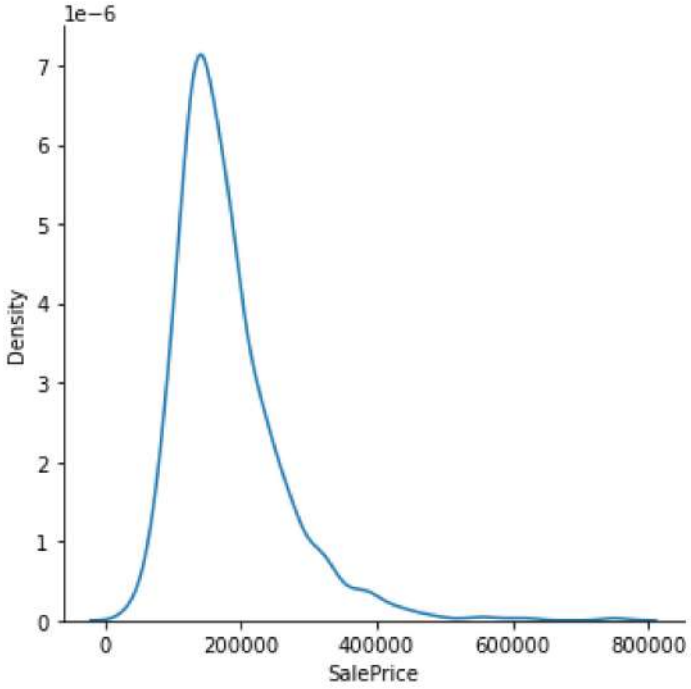

0.025
0.020
0.015
0.010
0.005
0.000
Density
0
100
200
300
400
500
ScreenPorch


0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
0
100
200
300
400
500
600
700
800
PoolArea


0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
Density
0
2000
4000
6000
8000
10000
12000
14000
16000
MiscVal

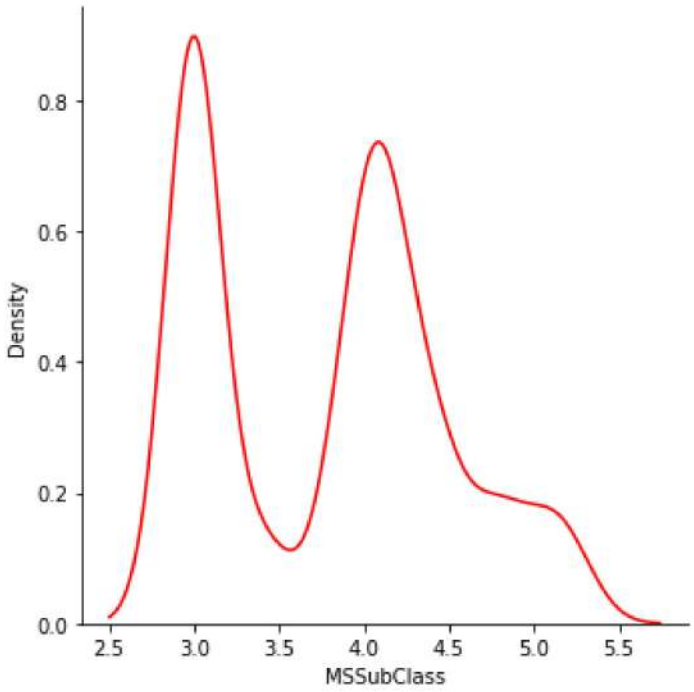

0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Density
0
2
4
6
8
10
12
14
MoSold

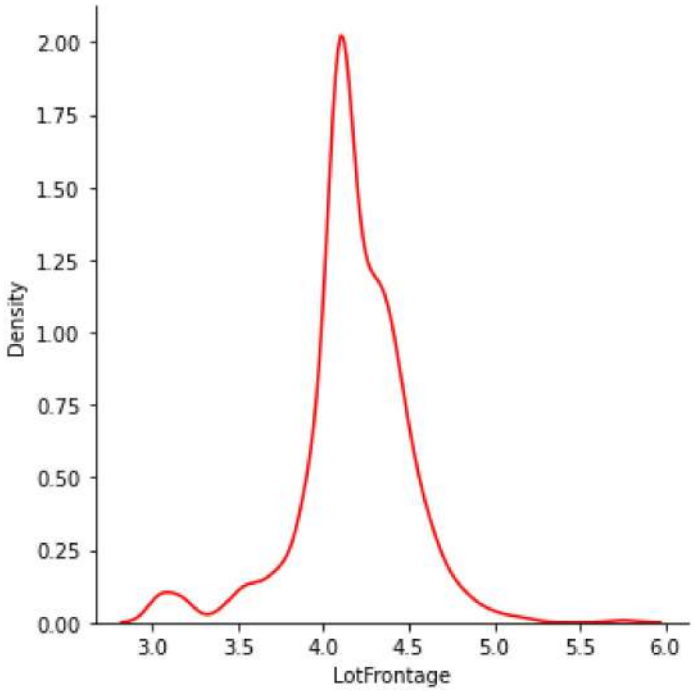

0.30
0.25
0.20
0.15
0.10
0.05
0.00
Density
2005
2006
2007
2008
2009
2010
2011
YrSold

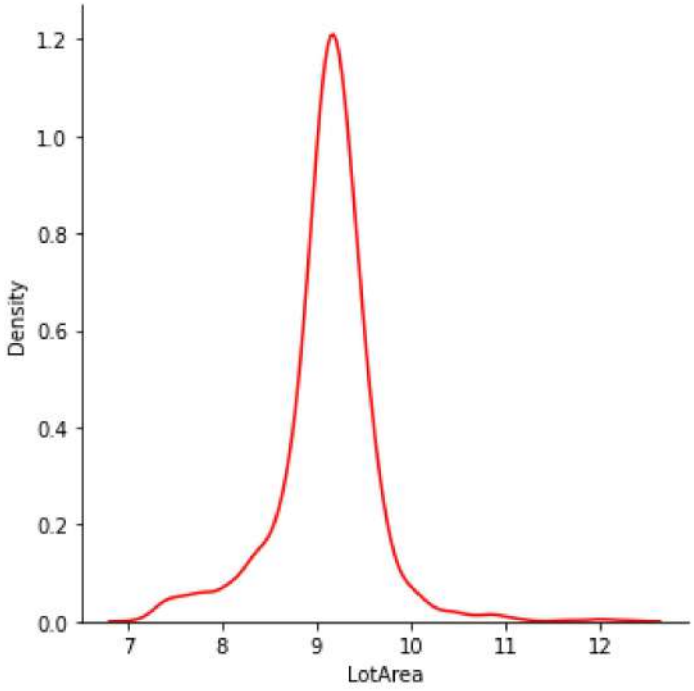


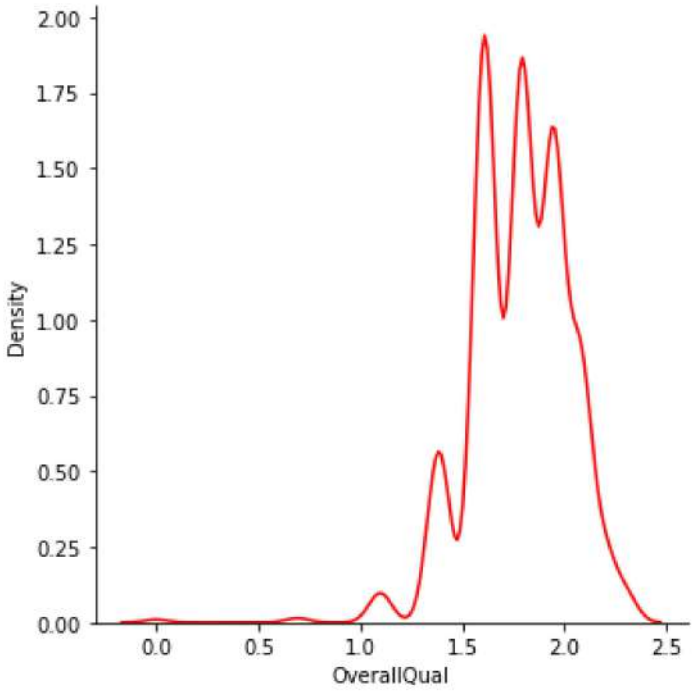
In [61]:
```
# Let us now perform log transformation on all the numerical features except the targe

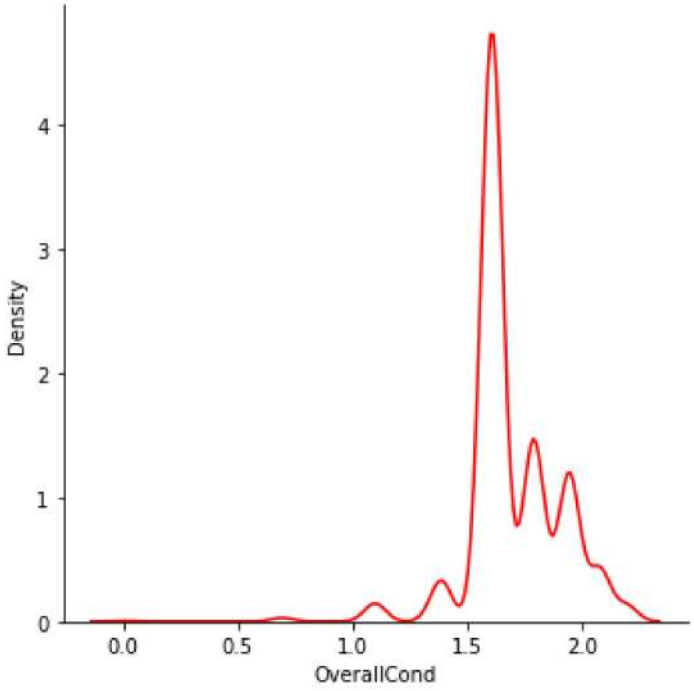
numerical_features = [features for features in Numerical_features if features not in '
for features in numerical_features:
    df1=df.copy()
    #sns.scatterplot(x = np.log(df1[features]), y = 'SalePrice', data=df1)
    sns.displot(data = df1, x = np.log(df1[features]), kind = 'kde', color = 'r')
    plt.show()
```

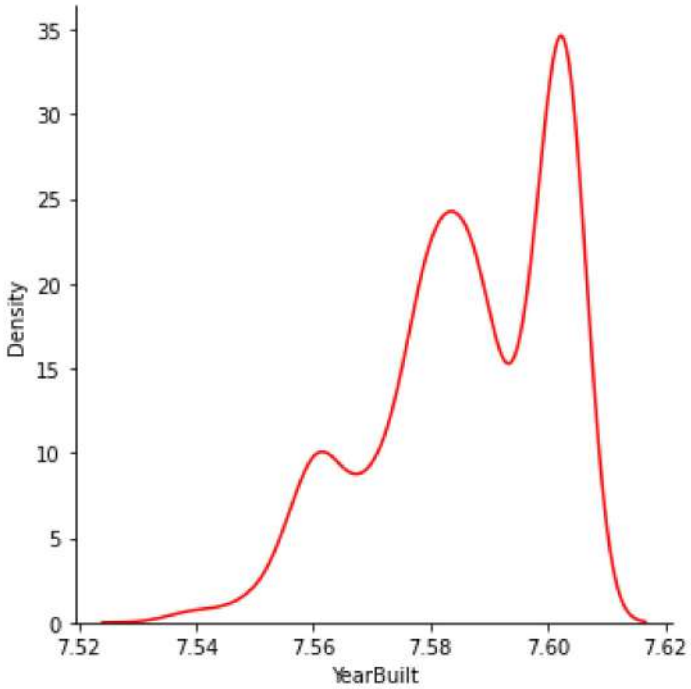


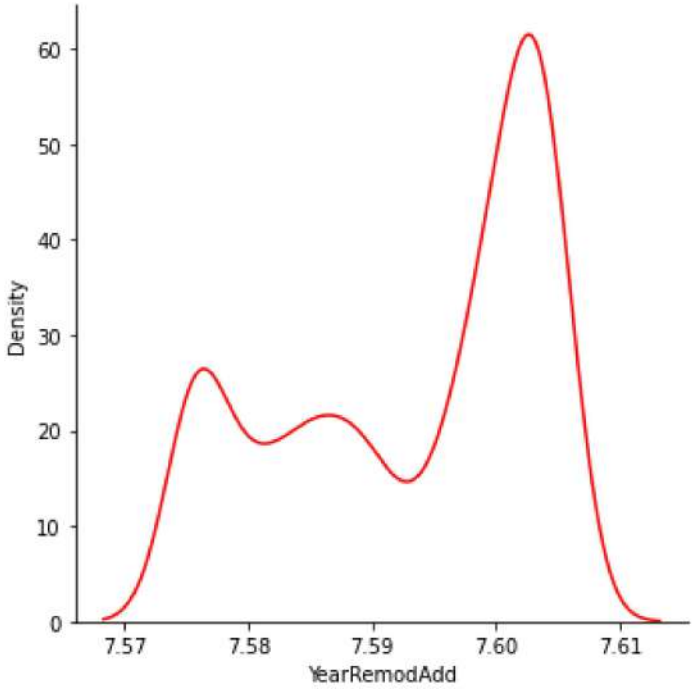

Density
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
3.0
3.5
4.0
4.5
5.0
5.5
6.0
LotFrontage


Density
1.2
1.0
0.8
0.6
0.4
0.2
0.0
7
8
9
10
11
12
LotArea

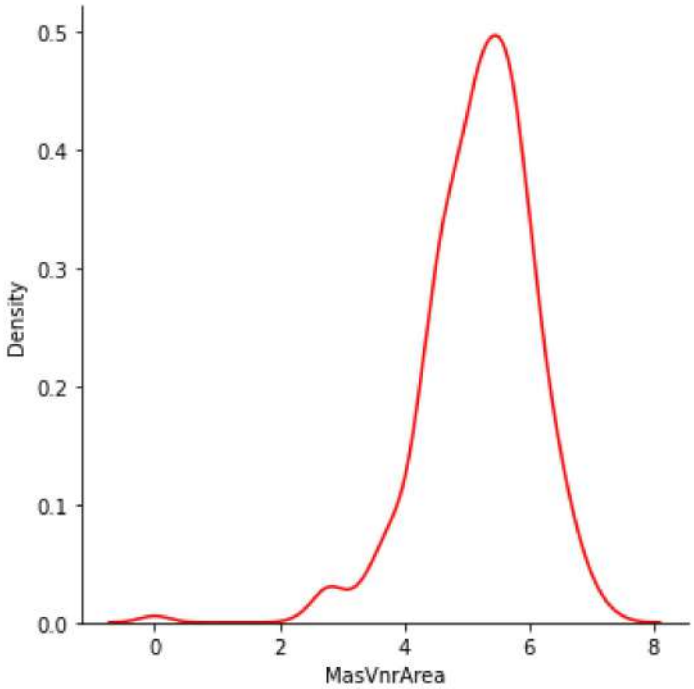

2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Density
0.0
0.5
1.0
1.5
2.0
2.5
OverallQual


4
3
2
1
0
Density
0.0
0.5
1.0
1.5
2.0
OverallCond






```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

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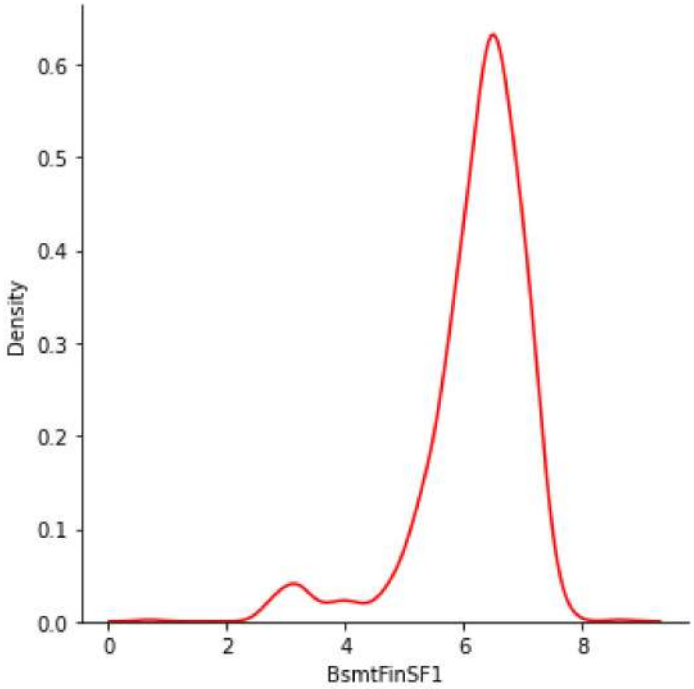
```




```
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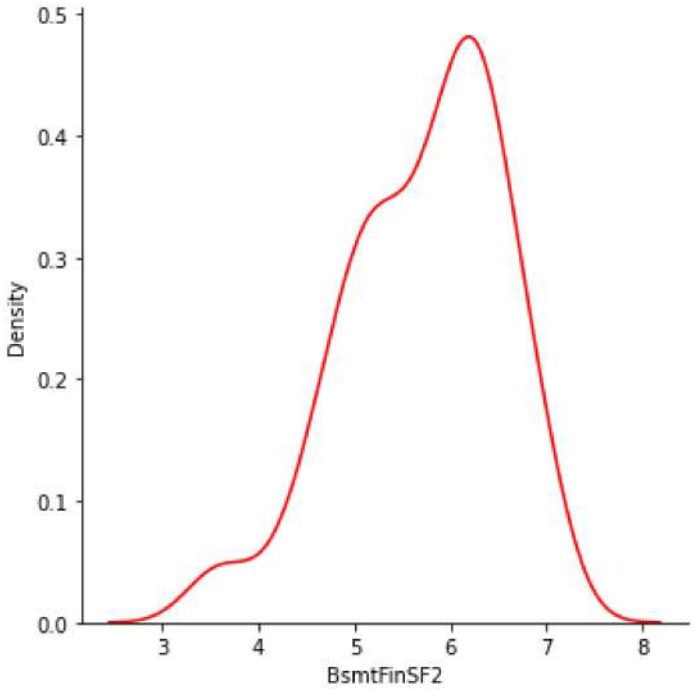


```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
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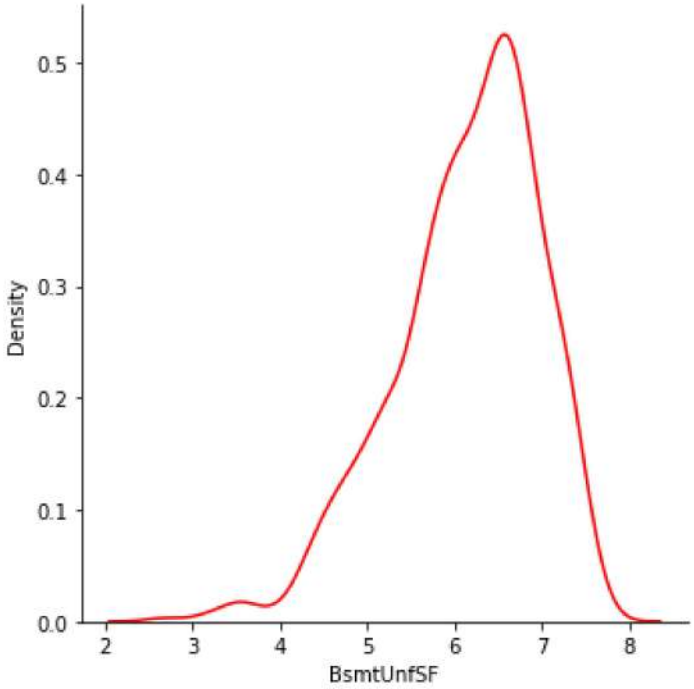
```

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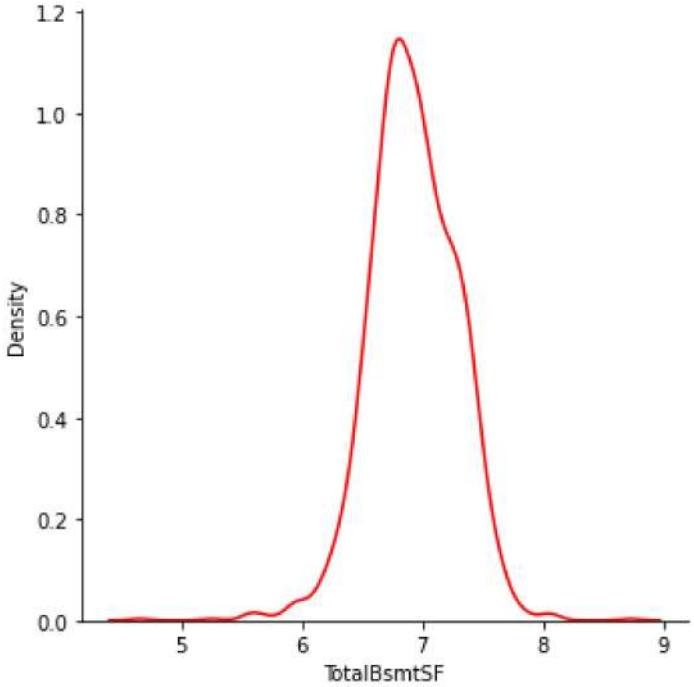

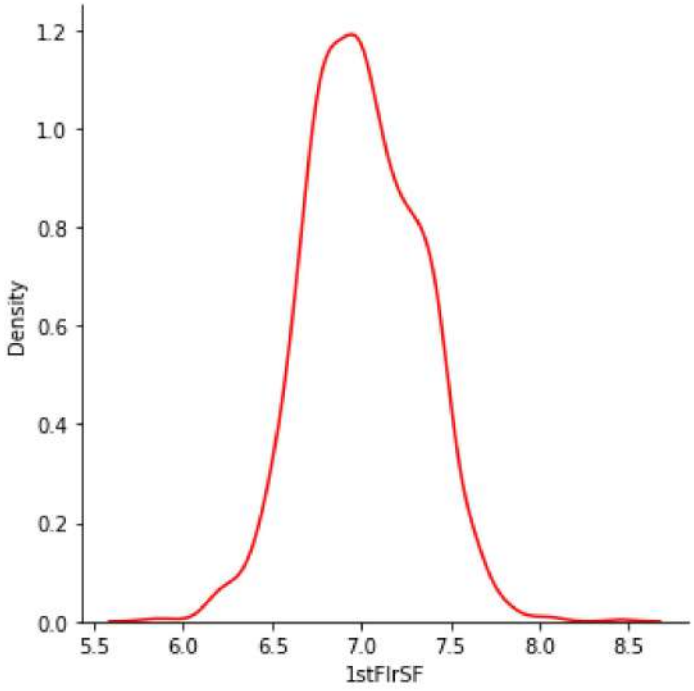


```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
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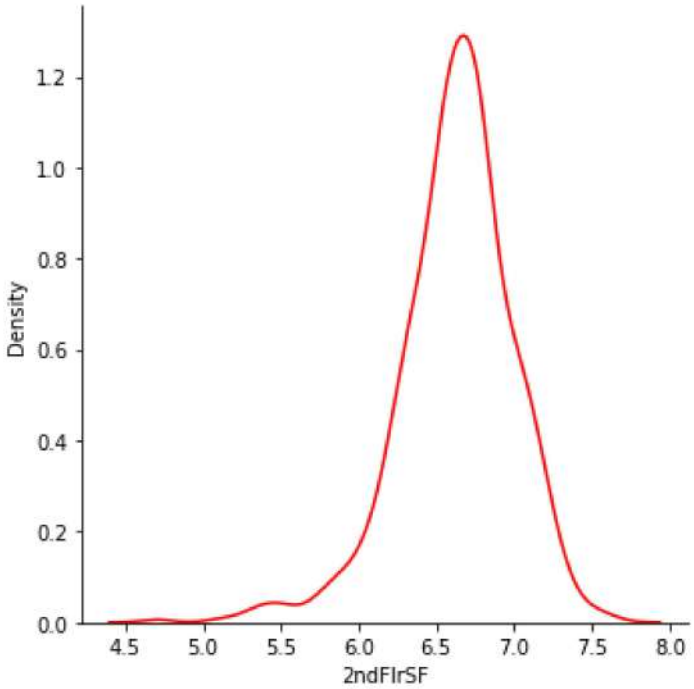
```




```
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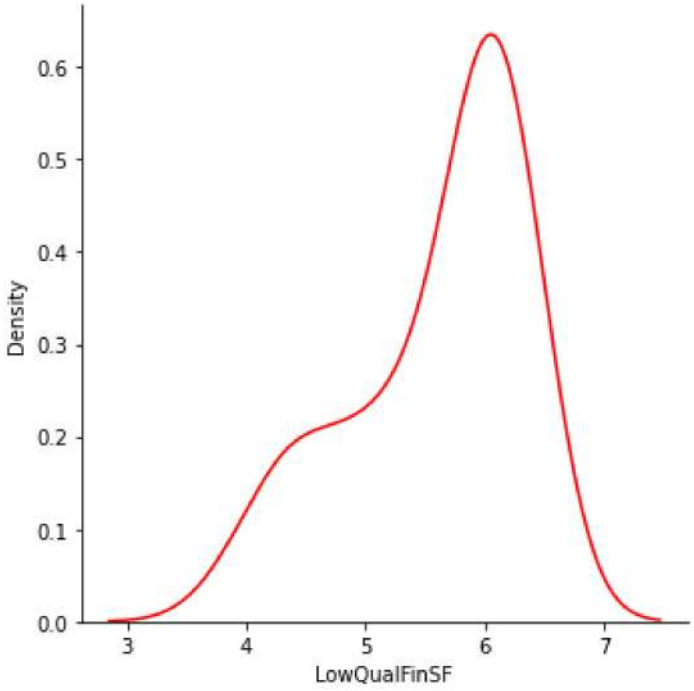
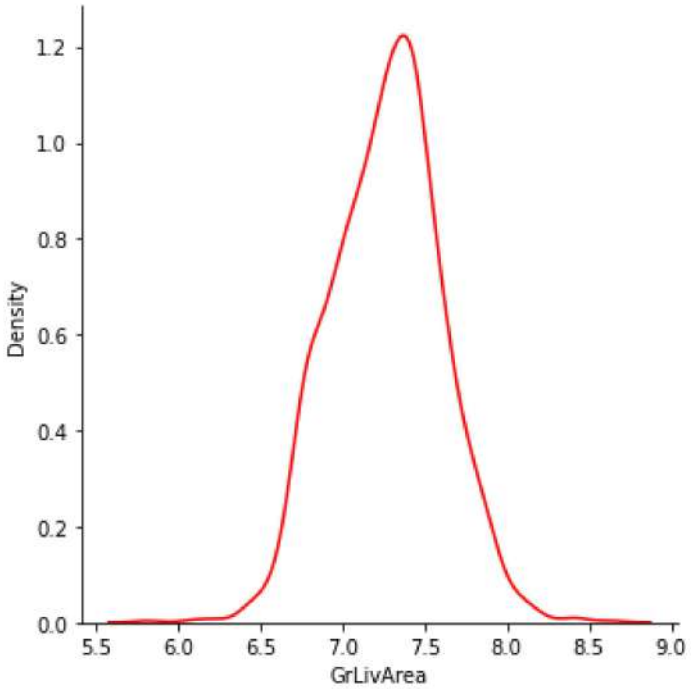
```



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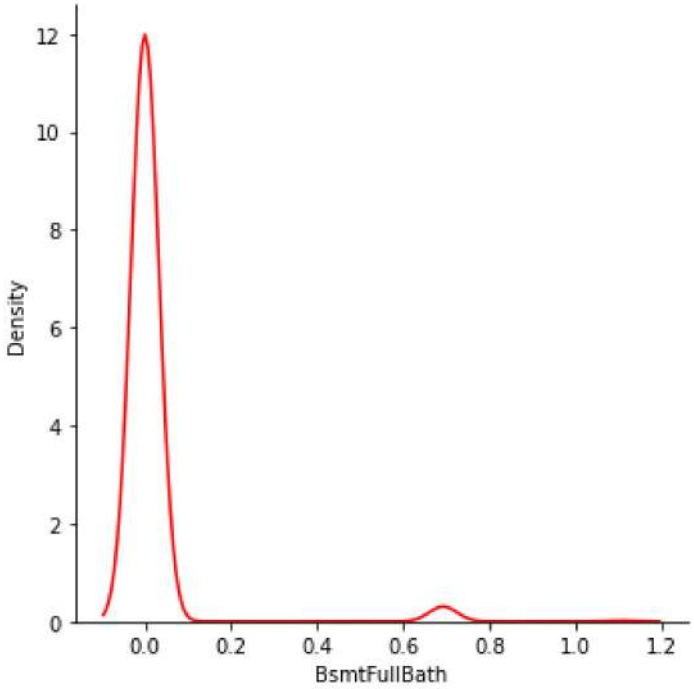


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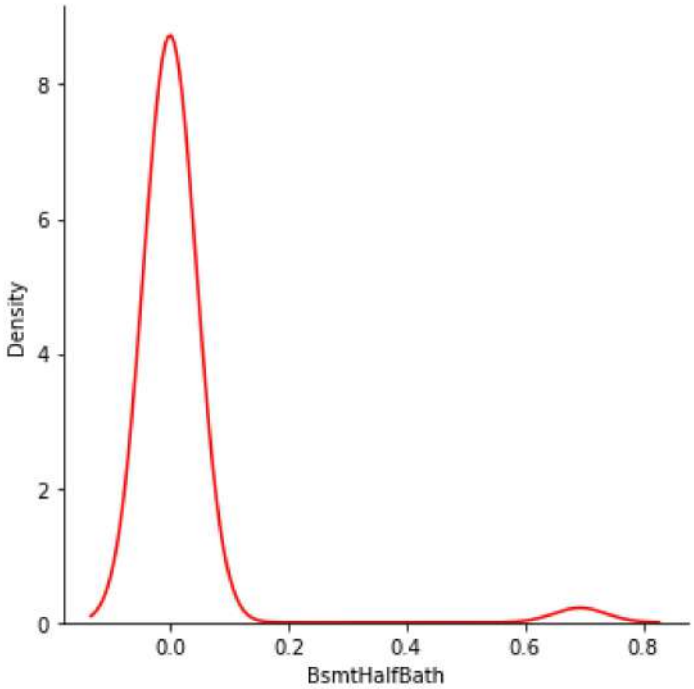


```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
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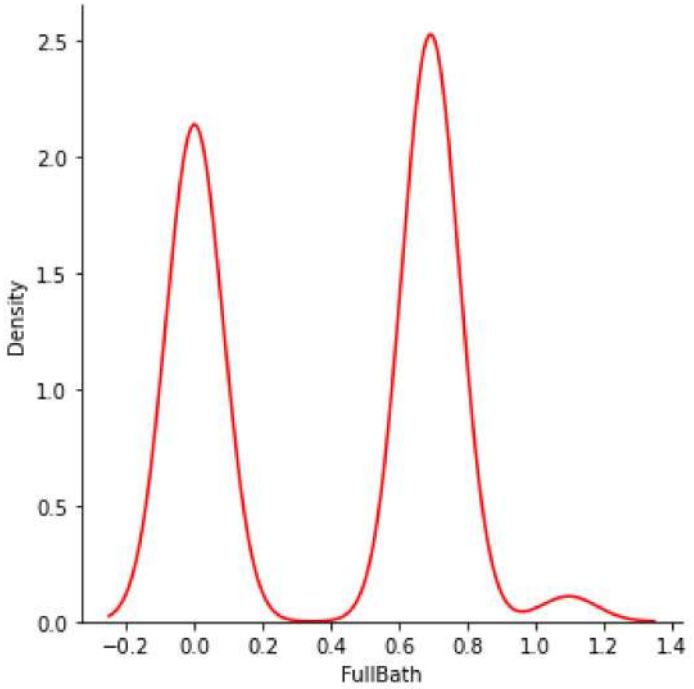
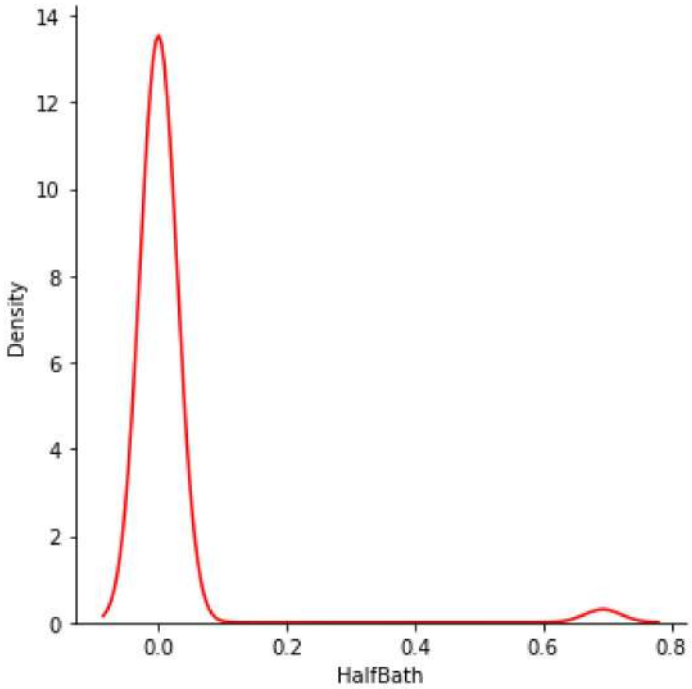
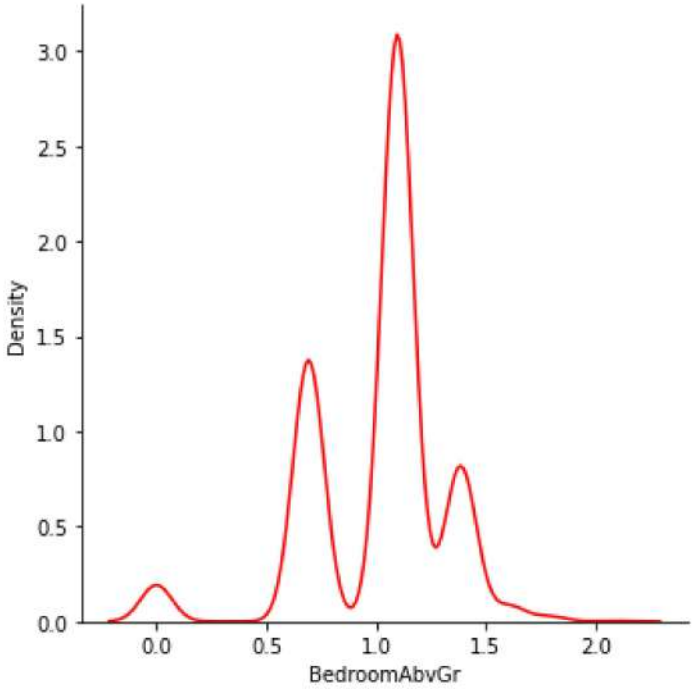
```



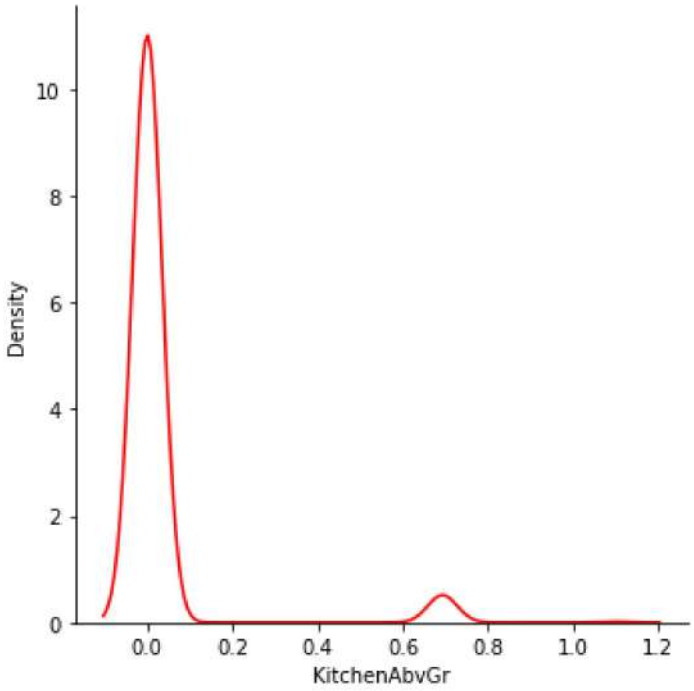

```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

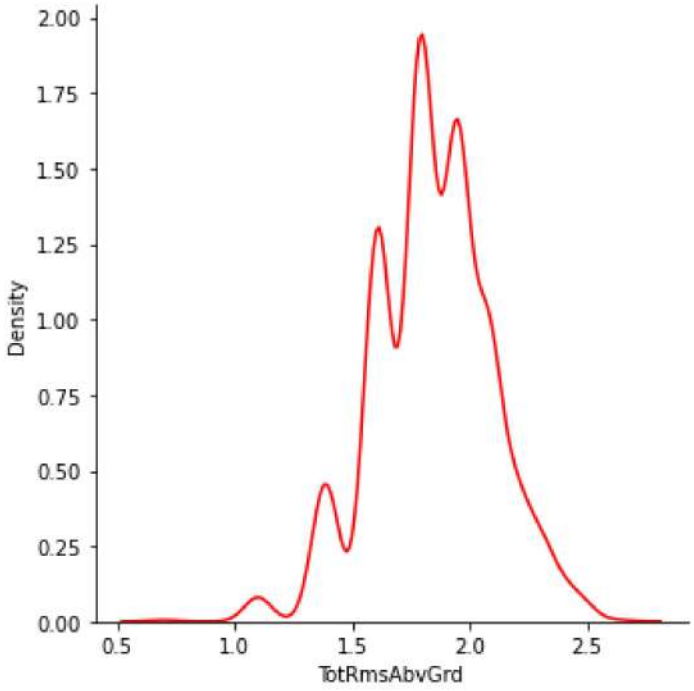



```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```




```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```






```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
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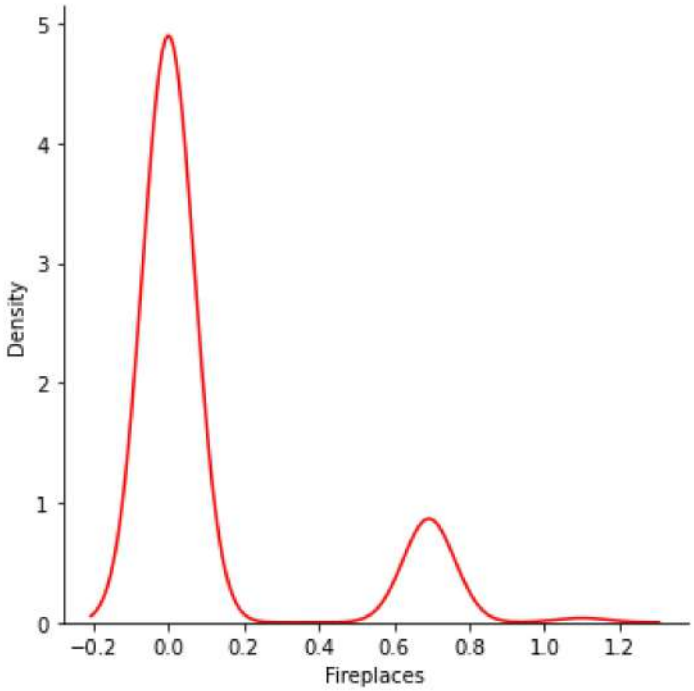
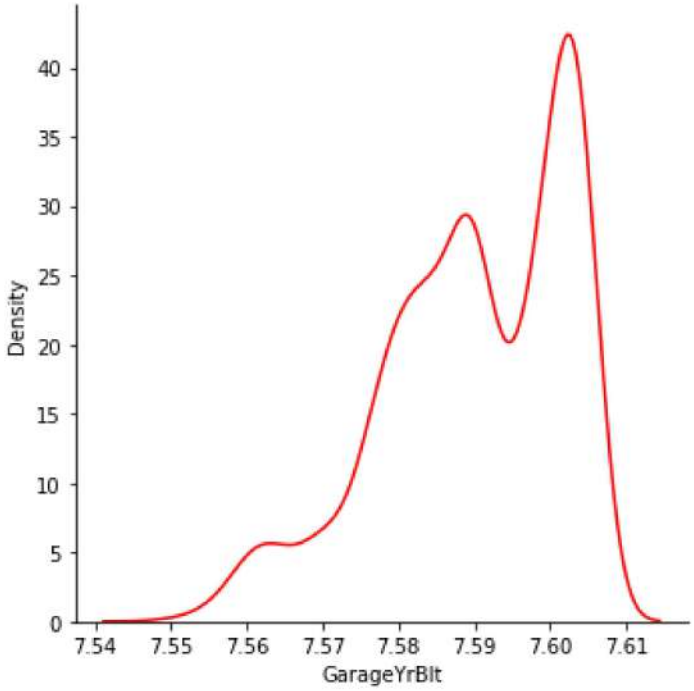
  result = getattr(ufunc, method)(*inputs, **kwargs)
```






```
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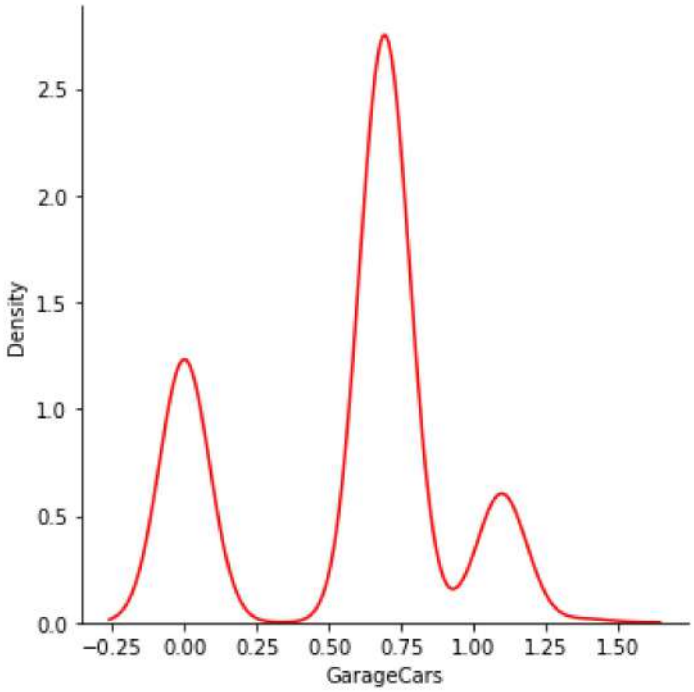
  result = getattr(ufunc, method)(*inputs, **kwargs)
```




```
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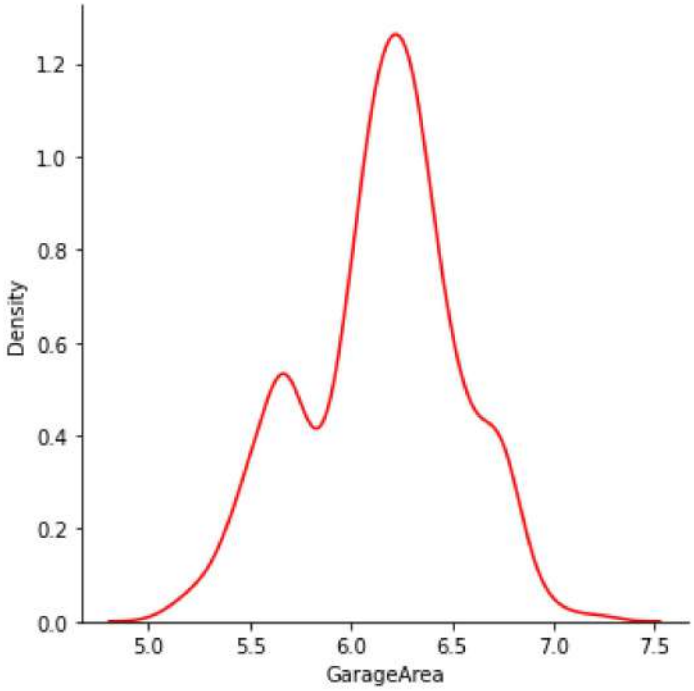
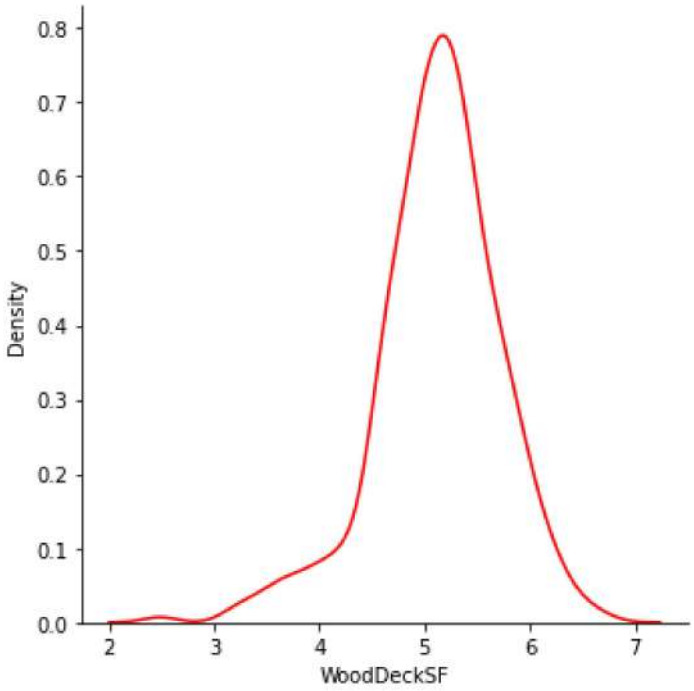
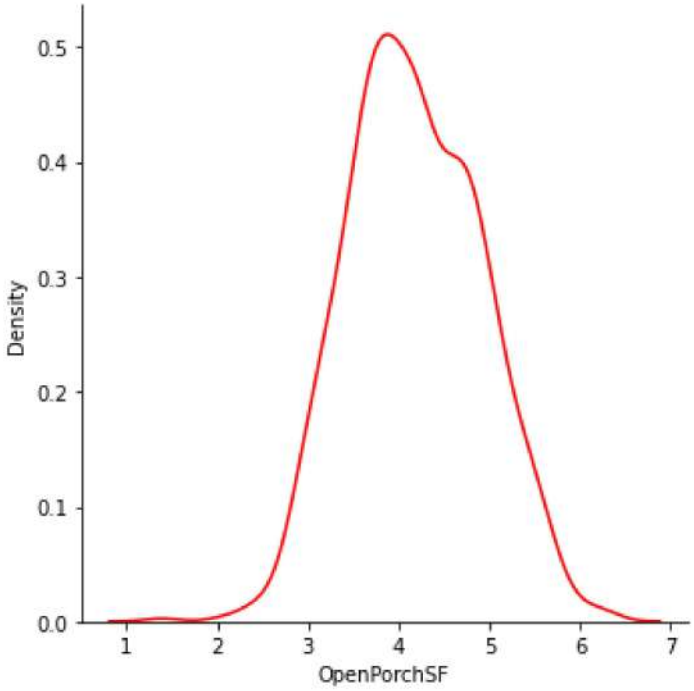
```



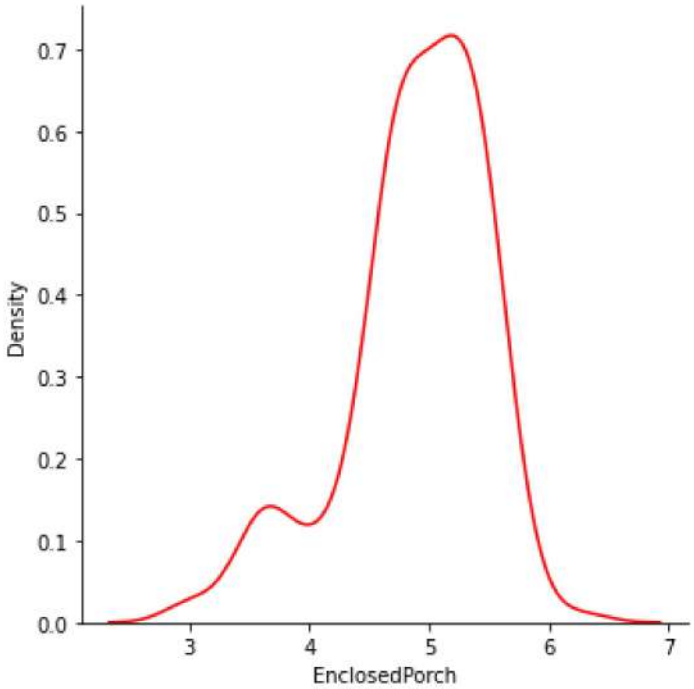

```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```




```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```




```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```




```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
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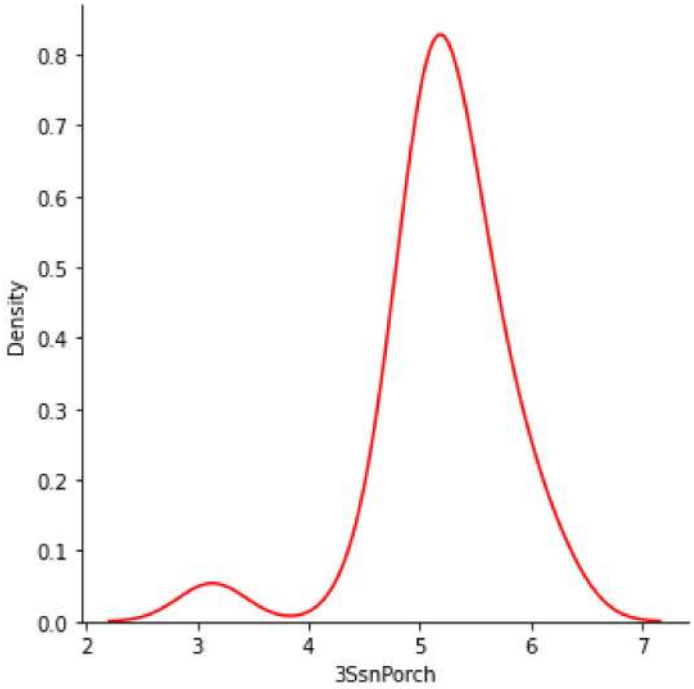
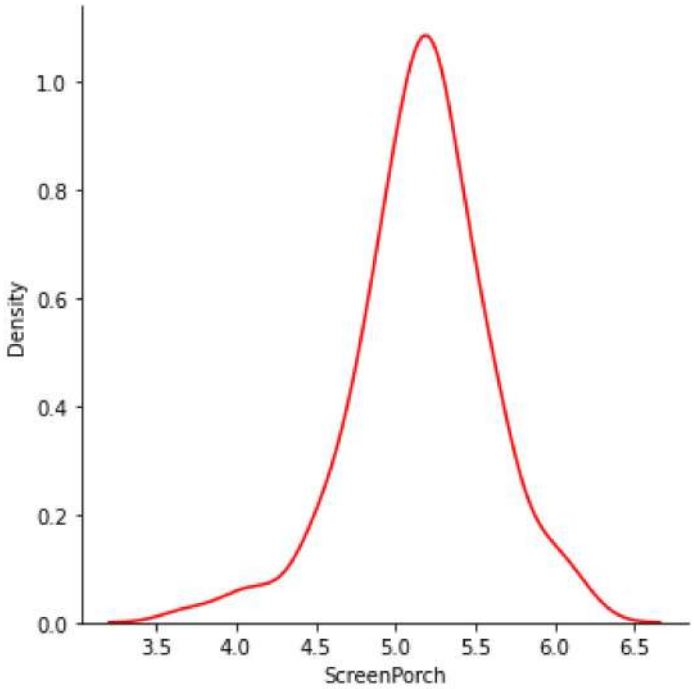
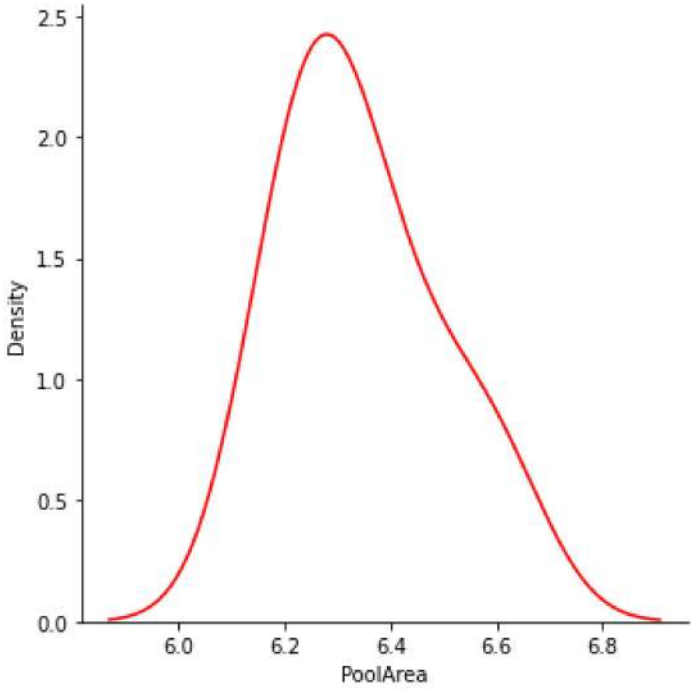
  result = getattr(ufunc, method)(*inputs, **kwargs)
```



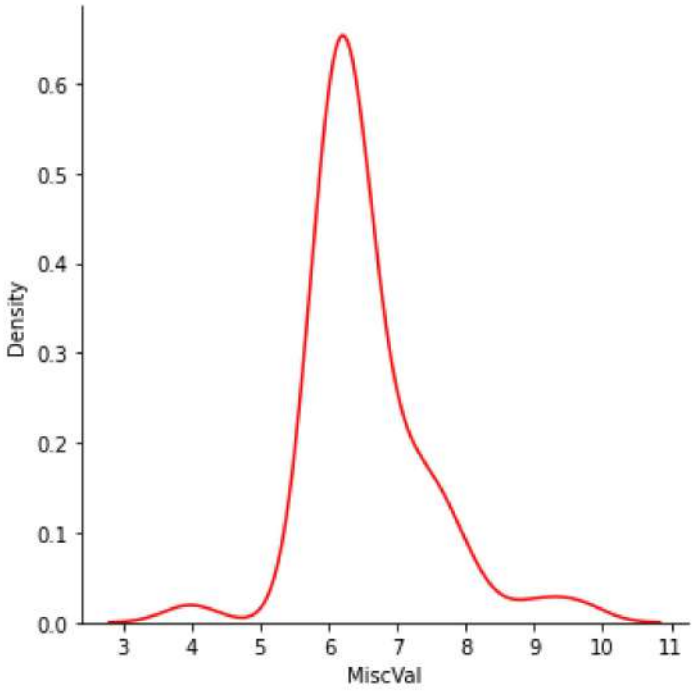

```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

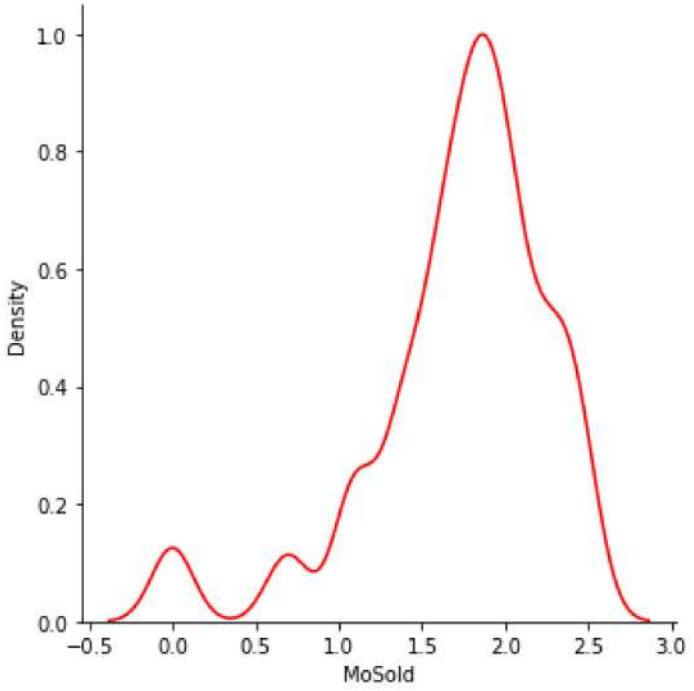


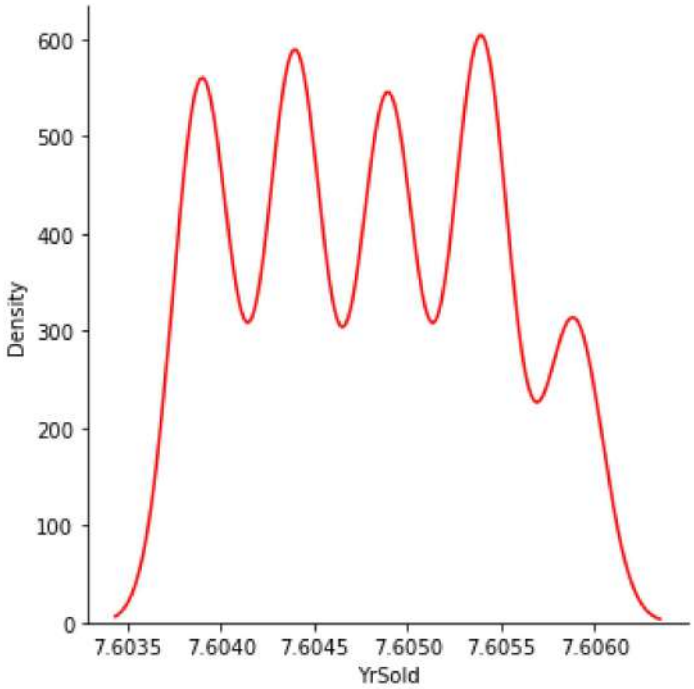

```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```




```
C:\Users\460379\Anaconda3\lib\site-packages\pandas\core\arraylike.py:397: RuntimeWarn
ing: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```


Density
0.0
0.1
0.2
0.3
0.4
0.5
0.6
3
4
5
6
7
8
9
10
11
MiscVal


Density
0.0
0.2
0.4
0.6
0.8
1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
MoSold



In [63]:
```
# We have below categorical features in this variable

categorical_features = [features for features in categorical_features if features not
categorical_features
```

Out[63]:
```
['MSZoning',
 'Street',
 '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',
 'GarageType',
 'GarageFinish',
 'GarageQual',
 'GarageCond',
 'PavedDrive',
 'SaleType',
 'SaleCondition']
```

In [64]:
```
# Let us find the unique values in the categorical features

for features in categorical_features:
    df1 = df.copy()
    print(features, df1[features].unique())
```

```
MSZoning ['RL' 'RM' 'C (all)' 'FV' 'RH']
Street ['Pave' 'Grvl']
LotShape ['Reg' 'IR1' 'IR2' 'IR3']
LandContour ['Lvl' 'Bnk' 'Low' 'HLS']
Utilities ['AllPub' 'NoSeWa']
LotConfig ['Inside' 'FR2' 'Corner' 'CulDSac' 'FR3']
LandSlope ['Gtl' 'Mod' 'Sev']
Neighborhood ['CollgCr' 'Veenker' 'Crawfor' 'NoRidge' 'Mitchel' 'Somerst' 'NWAmes'
 'OldTown' 'BrkSide' 'Sawyer' 'NridgHt' 'NAmes' 'SawyerW' 'IDOTRR'
 'MeadowV' 'Edwards' 'Timber' 'Gilbert' 'StoneBr' 'ClearCr' 'NPkVill'
 'Blmngtn' 'BrDale' 'SWISU' 'Blueste']
Condition1 ['Norm' 'Feedr' 'PosN' 'Artery' 'RRAe' 'RRNn' 'RRAn' 'PosA' 'RRNe']
Condition2 ['Norm' 'Artery' 'RRNn' 'Feedr' 'PosN' 'PosA' 'RRAn' 'RRAe']
BldgType ['1Fam' '2fmCon' 'Duplex' 'TwnhsE' 'Twnhs']
HouseStyle ['2Story' '1Story' '1.5Fin' '1.5Unf' 'SFoyer' 'SLvl' '2.5Unf' '2.5Fin']
RoofStyle ['Gable' 'Hip' 'Gambrel' 'Mansard' 'Flat' 'Shed']
RoofMatl ['CompShg' 'WdShngl' 'Metal' 'WdShake' 'Membran' 'Tar&Grv' 'Roll'
 'ClyTile']
Exterior1st ['VinylSd' 'MetalSd' 'Wd Sdng' 'HdBoard' 'BrkFace' 'WdShing' 'CemntBd'
 'Plywood' 'AsbShng' 'Stucco' 'BrkComm' 'AsphShn' 'Stone' 'ImStucc'
 'CBlock']
Exterior2nd ['VinylSd' 'MetalSd' 'Wd Shng' 'HdBoard' 'Plywood' 'Wd Sdng' 'CmentBd'
 'BrkFace' 'Stucco' 'AsbShng' 'Brk Cmn' 'ImStucc' 'AsphShn' 'Stone'
 'Other' 'CBlock']
MasVnrType ['BrkFace' 'None' 'Stone' 'BrkCmn']
ExterQual ['Gd' 'TA' 'Ex' 'Fa']
ExterCond ['TA' 'Gd' 'Fa' 'Po' 'Ex']
Foundation ['PConc' 'CBlock' 'BrkTil' 'Wood' 'Slab' 'Stone']
BsmtQual ['Gd' 'TA' 'Ex' 'Fa']
BsmtCond ['TA' 'Gd' 'Fa' 'Po']
BsmtExposure ['No' 'Gd' 'Mn' 'Av']
BsmtFinType1 ['GLQ' 'ALQ' 'Unf' 'Rec' 'BLQ' 'LwQ']
BsmtFinType2 ['Unf' 'BLQ' 'ALQ' 'Rec' 'LwQ' 'GLQ']
Heating ['GasA' 'GasW' 'Grav' 'Wall' 'OthW' 'Floor']
HeatingQC ['Ex' 'Gd' 'TA' 'Fa' 'Po']
CentralAir ['Y' 'N']
Electrical ['SBrkr' 'FuseF' 'FuseA' 'FuseP' 'Mix']
KitchenQual ['Gd' 'TA' 'Ex' 'Fa']
Functional ['Typ' 'Min1' 'Maj1' 'Min2' 'Mod' 'Maj2' 'Sev']
GarageType ['Attchd' 'Detchd' 'BuiltIn' 'CarPort' 'Basment' '2Types']
GarageFinish ['RFn' 'Unf' 'Fin']
GarageQual ['TA' 'Fa' 'Gd' 'Ex' 'Po']
GarageCond ['TA' 'Fa' 'Gd' 'Po' 'Ex']
PavedDrive ['Y' 'N' 'P']
SaleType ['WD' 'New' 'COD' 'ConLD' 'ConLI' 'CWD' 'ConLw' 'Con' 'Oth']
SaleCondition ['Normal' 'Abnorml' 'Partial' 'AdjLand' 'Alloca' 'Family']
```

In [65]:
```
# Let us perform encoding technique on categorical features

#for features in categorical_features:
    #df1=df.copy()
    #print(pd.get_dummies(df1[features]))
```

In [66]:
```
#LE = LabelEncoder()
#LE.fit_transform(df1['HouseStyle'])
```

In [67]:
```
#l = []
#for features in categorical_features:
    #l.append(LE.fit_transform(df[features]))
```

```
#df [ ['col1', 'col2']].apply(LabelEncoder ().fit_transform)
```

In [68]:
```
df
```

Out[68]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotC
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	I
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	I
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	C
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	
...	...	...	...	...	...	...	...	...	
1455	60	RL	62.0	7917	Pave	Reg	Lvl	AllPub	I
1456	20	RL	85.0	13175	Pave	Reg	Lvl	AllPub	I
1457	70	RL	66.0	9042	Pave	Reg	Lvl	AllPub	I
1458	20	RL	68.0	9717	Pave	Reg	Lvl	AllPub	I
1459	20	RL	75.0	9937	Pave	Reg	Lvl	AllPub	I

1460 rows × 75 columns

In [69]:
```
#from sklearn.preprocessing import LabelEncoder
#LE = LabelEncoder()
#LE.fit_transform(df['HouseStyle'])
```

In [70]:
```
df
```

Out[70]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotC
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	I
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	I
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	C
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	
...	...	...	...	...	...	...	...	...	
1455	60	RL	62.0	7917	Pave	Reg	Lvl	AllPub	I
1456	20	RL	85.0	13175	Pave	Reg	Lvl	AllPub	I
1457	70	RL	66.0	9042	Pave	Reg	Lvl	AllPub	I
1458	20	RL	68.0	9717	Pave	Reg	Lvl	AllPub	I
1459	20	RL	75.0	9937	Pave	Reg	Lvl	AllPub	I

1460 rows × 75 columns

In [71]:
```
# Let us perform Ordinal encoding technique to different categories of categorical fea

from sklearn.preprocessing import OrdinalEncoder
enc = OrdinalEncoder()
enc.fit_transform(df[categorical_features])
```

Out[71]:
```
array([[3., 1., 3., ..., 2., 8., 4.],
       [3., 1., 3., ..., 2., 8., 4.],
       [3., 1., 0., ..., 2., 8., 4.],
       ...,
       [3., 1., 3., ..., 2., 8., 4.],
       [3., 1., 3., ..., 2., 8., 4.],
       [3., 1., 3., ..., 2., 8., 4.]])
```

In [72]:
```
df[categorical_features] = enc.fit_transform(df[categorical_features])
```

In [73]:
```
df
```

Out[73]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotC
0	60	3.0	65.0	8450	1.0	3.0	3.0	0.0	
1	20	3.0	80.0	9600	1.0	3.0	3.0	0.0	
2	60	3.0	68.0	11250	1.0	0.0	3.0	0.0	
3	70	3.0	60.0	9550	1.0	0.0	3.0	0.0	
4	60	3.0	84.0	14260	1.0	0.0	3.0	0.0	
...	...	...	...	...	...	...	...	...	
1455	60	3.0	62.0	7917	1.0	3.0	3.0	0.0	
1456	20	3.0	85.0	13175	1.0	3.0	3.0	0.0	
1457	70	3.0	66.0	9042	1.0	3.0	3.0	0.0	
1458	20	3.0	68.0	9717	1.0	3.0	3.0	0.0	
1459	20	3.0	75.0	9937	1.0	3.0	3.0	0.0	

1460 rows × 75 columns

In [74]:
```
# Let us now split our independant and dependant feature

X = df.iloc[:,:-1]
y = df["SalePrice"]
```

In [75]:
```
y
```

Out[75]:
```
0       208500
1       181500
2       223500
3       140000
4       250000
         ...
1455    175000
1456    210000
1457    266500
1458    142125
1459    147500
Name: SalePrice, Length: 1460, dtype: int64
```

In [76]:
```
# Lets us now split the data into Train , Test and split

from sklearn.model_selection import train_test_split
X_train, X_test,y_train, y_test = train_test_split(X,y,random_state=10,test_size=0.33)
```

In [77]:
```
# Let us scale the data using standard scaler

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [78]:
```
# Let us perform linear regerssion model

from sklearn import datasets, linear_model, metrics
reg = linear_model.LinearRegression()
reg.fit(X_train, y_train)
```

Out[78]:
```
LinearRegression()
```

In [79]:
```
# regression coefficients
print('Coefficients: ', reg.coef_)
```

```
Coefficients:  [-8.02842258e+03 -1.30415289e+03 -4.45556621e+03  5.06428659e+03
  2.96654302e+03 -1.66404774e+03  3.75024347e+03 -1.87927812e+03
 -7.71131057e+02  2.14522721e+03  3.02670519e+03 -2.80022905e+02
 -2.31866127e+03 -5.92895368e+02 -3.29150333e+03  1.71368114e+04
  4.91738262e+03  4.83601680e+03  3.47105378e+02  1.07906518e+03
  4.27481472e+03 -2.13482189e+03  8.07156514e+02  1.75494124e+03
  5.14577273e+03 -5.65028043e+03  4.07254831e+02  9.14680584e+02
 -8.36776310e+03  3.16458056e+03 -4.29428082e+03 -3.88294283e+03
  8.45520106e+16  1.14452908e+03  2.70086559e+16  7.88208156e+16
 -8.00419400e+16 -6.04294570e+02 -1.27004108e+03  4.35744917e+02
 -9.47544641e+02  1.24043369e+16  1.38119351e+16  1.65550085e+15
 -1.68554285e+16  4.06218558e+03 -2.82834176e+02  9.04550485e+02
 -2.64484819e+03 -1.59031128e+03 -1.61104258e+03 -8.86231157e+03
  4.68499508e+03  2.34642364e+03  2.22431844e+03 -1.68012888e+03
 -5.78573739e+02  1.15063849e+02  9.98676083e+03 -1.27944500e+03
  7.95640322e+01 -5.50338354e+00  6.29555227e+02  2.80547782e+03
 -8.32280714e+02  5.59063905e+02  8.90210730e+02  2.87746676e+03
  5.71580183e+02 -1.95128336e+02 -2.39284632e+02 -1.05202798e+03
 -7.72680934e+02  2.49861534e+03]
```

In [80]:
```
# variance score: 1 means perfect prediction
print('Variance score: {}'.format(reg.score(X_test, y_test)))
```

```
Variance score: 0.8379855358615005
```

In [83]:
```
## PRediction for the test data
reg_pred= reg.predict(X_test)
reg_pred
```

Out[83]:
```
array([169879.67765076, 202836.71882716, 125885.01609103, 139891.32135079,
       304716.02869594, 265353.56040633, 245777.22255767,  93576.42535458,
       192864.13763517, 166663.69315385, 158652.83976643, 170670.35023447,
       264378.67013601, 119384.09826124, 236866.93679072, 186434.98765883,
       270649.1143477 , 134353.67490588, 226032.84589248, 201577.87258518,
       407751.62043951, 118380.82483891, 131569.90571031, 105269.19656937,
       214008.31262086, 173284.05767226, 146299.44406133,  85168.16201312,
       165172.5207528 , 206649.38639147, 114414.98574084, 155973.89501611,
       135962.38222017, 137818.67081111, 137834.96453475,  45456.00345128,
       135504.97408375, 215716.82676451, 322903.44386826, 138016.3994178 ,
       227163.21464488, 122202.9588629 ,  88501.94807457, 205104.98242678,
       221352.76735728, 247930.13875453, 262282.45246748, 137681.03695603,
       126975.77257795, 163320.97619105, 197103.08473885,  16435.859759  ,
       195820.32755503, 116480.62554441, 226108.7922838 , 199903.6423214 ,
       204120.01594796, 187795.61021642, 131312.74642694, 137474.48777328,
       117272.39566832, 232473.5386909 , 129134.10918144, 235013.24927876,
       218957.86962585, 211876.50132565, 232316.01627833, 183000.67981018,
       128731.1880826 , 180614.09320099, 119261.07702254, 114940.76044865,
       123712.79431986, 107642.33868016, 177259.28803245, 251713.30063042,
       225785.64126565,  75790.18926545, 208169.17135339, 202893.73269634,
       274218.35793686, 229917.62781493, 209997.4607751 , 224029.10782987,
       140360.99657375, 136417.84002893, 159714.41627222, 174277.10762714,
       254836.19462764, 150937.89770615, 165247.02905438, 113369.995982  ,
        58528.98889896,  98336.83021594, 275656.1598368 , 169639.22528958,
       169607.88567768, 223367.67535269, 162635.23138661, 259967.97004003,
       232005.54567524, 190448.72444354,  41657.76224074, 116722.98287776,
       111532.65512834, 318378.75992628, 194345.98247319, 206082.11813005,
        78646.64429678, 120208.93763603, 170195.96669325, 218355.37040641,
       168285.82003162, 135048.21670259, 112037.40539995, 133496.74501344,
       339767.34778116, 323005.8281896 , 143691.99783672,  98594.19969554,
       160897.92181307, 341263.23526809, 112364.76601672, 153653.1799585 ,
       288983.0925667 , 174698.88802578, 107954.84719975, 174224.22585663,
       249366.28702768, 184346.07220255, 121073.99058816, 180808.1574266 ,
       171984.39759031, 237549.42408081,  97576.82742378, 219448.33605663,
        36151.29513385, 217555.09406414,  90527.2147213 , 184364.9636153 ,
       215286.38721572, 109332.85206443, 151264.30928943, 347265.15398399,
       196458.97556711,  21933.42023289, 199280.83884741, 173727.61344742,
       282591.71213228, 191956.45058482, 253788.95399869, 207393.82965694,
       221831.61187349, 179802.76159979, 124535.42613024, 126887.68350945,
       152141.96802712, 126912.27847937, 198434.00749318, 376590.94041925,
        47781.57447545, 326479.06459216, 296799.52000468, 183196.24425754,
       169303.61159456, 236553.63526222, 197836.20115921, 213111.35646345,
       301335.73938682, 201099.78019791, 106657.48291983, 234821.41666958,
       124298.33529454, 229972.22792706,  92209.35893438, 188836.52250739,
       136141.56811038, 244108.0788628 , 315797.41679309,  55166.78868923,
       126739.86684723,  98846.10672416, 186620.33465525, 194906.69517479,
        95135.29213178, 397830.64673868, 241274.40472462, 156988.59424564,
       135851.01594277, 129390.27390871, 126832.25914519, 123833.69435619,
       119115.78746293, 156758.40891796, 249475.82806841, 164314.714941  ,
       145039.00156703, 121261.00409869, 247631.91803714, 238977.37266166,
       187202.06050911, 354533.67469218, 175358.66250543, 353297.67846059,
       247875.94634005, 102707.86541992, 173658.28948084, 385735.41728374,
       112168.20313391,  87324.70683671, 100338.44850238,  70730.96234285,
        85808.42459401, 103935.56657238, 172810.17129356, 165706.36321187,
       256163.06396577,  88808.93634258,  31606.54667461, 154721.71039684,
       119981.14105143, 171164.83976643,  82174.82839406, 254024.18646941,
       100414.7041445 , 116425.17429052, 213438.17029173, 161306.34144256,
       293875.6729384 , 112792.19181017, 253852.29165028, 146746.0063159 ,
       136134.77178162, 248811.57606372, 100980.34379884, 114561.19261343,
       244460.61772292, 156012.30457073, 284461.74357532, 115674.73595888,
```

```
131972.68843439, 245699.82296817, 191054.32252336, 318617.613837  ,
366831.98887258, 210065.10178478, 160699.45625221, 271804.563457  ,
157021.45805714, 226986.67833546, 211000.67440996, 212043.90104176,
100399.97804119, 116914.91367969, 149597.58099418, 188637.17657576,
329834.64028511, 115670.03562361, 186291.08505907, 123335.68412916,
 88780.18633932, 198613.14247814, 125696.37827621,  82502.00356511,
128626.89375971,  88703.71985148, 129329.65814117, 119148.59815623,
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```

In [84]:
```
from sklearn.metrics import r2_score
score=r2_score(y_test,reg_pred)
print(score)
```

```
0.8379855358615005
```

In [85]:
```
mae = metrics.mean_absolute_error(y_test, reg_pred)
mse = metrics.mean_squared_error(y_test, reg_pred)
rmse = np.sqrt(mse) # or mse**(0.5)
r2 = metrics.r2_score(y_test, reg_pred)
AR2 = 1 - (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)

print("Results of sklearn.metrics:")
print("MAE:",mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R-Squared:", r2)
print("Adjusted R2:", AR2)
```

```
Results of sklearn.metrics:
MAE: 22003.07853147816
MSE: 1045532579.5643027
RMSE: 32334.696218834386
R-Squared: 0.8379855358615005
Adjusted R2: 0.8085283605635915
```

In [86]:
```
## Ridge
from sklearn.linear_model import Ridge
ridge=Ridge()
```

In [87]:
```
ridge.fit(X_train,y_train)
```

Out[87]:
```
Ridge()
```

In [88]:
```
ridge.predict(X_test)
```

Out[88]:
```
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In [ ]:

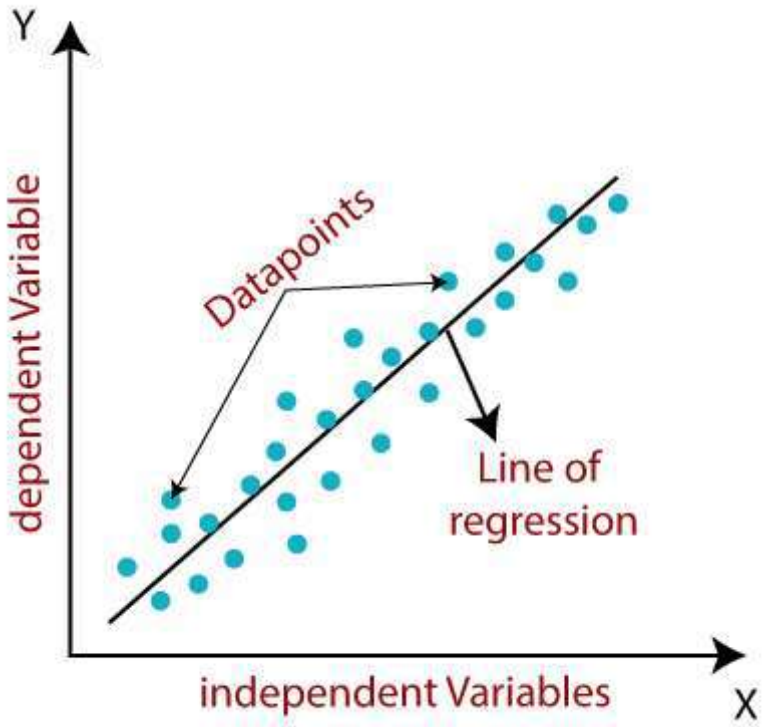
Linear Regression Questions Answers

1. What is Linear Regression

Ans: Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables.

It is mostly used for finding out the relationship between variables and forecasting.

Different regression models differ based on – the kind of relationship between dependent and independent variables they are considering, and the number of independent variables getting used.



Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression. In the figure above, X (input) is the work experience and Y (output) is the salary of a person. The regression line is the best fit line for our model.

Hypothesis function for Linear Regression :

$$y = \theta_1 + \theta_2.x$$

x: input training data (univariate – one input variable(parameter)) y: labels to data (supervised learning)

When training the model – it fits the best line to predict the value of y for a given value of x. The model gets the best regression fit line by finding the best θ1 and θ2 values. θ1: intercept θ2: coefficient of x

Once we find the best θ1 and θ2 values, we get the best fit line. So when we are finally using our model for prediction, it will predict the value of y for the input value of x.

2. How can you calculate error in Linear Regression?

Ans:

Linear regression most often uses mean-square error (MSE) to calculate the error of the model.

MSE is calculated by:

1. measuring the distance of the observed y-values from the predicted y-values at each value of x;
2. squaring each of these distances;
3. calculating the mean of each of the squared distances.

Linear regression fits a line to the data by finding the regression coefficient that results in the smallest MSE.

3. Difference between Loss and Cost function?

Ans:

There is no major difference.

1. When calculating loss we consider only a single data point, then we use the **loss function**.
2. Whereas, when calculating the sum of error for multiple data then we use the **cost function**.

The Most commonly used loss functions are **Mean-squared error** and **Hinge loss**.

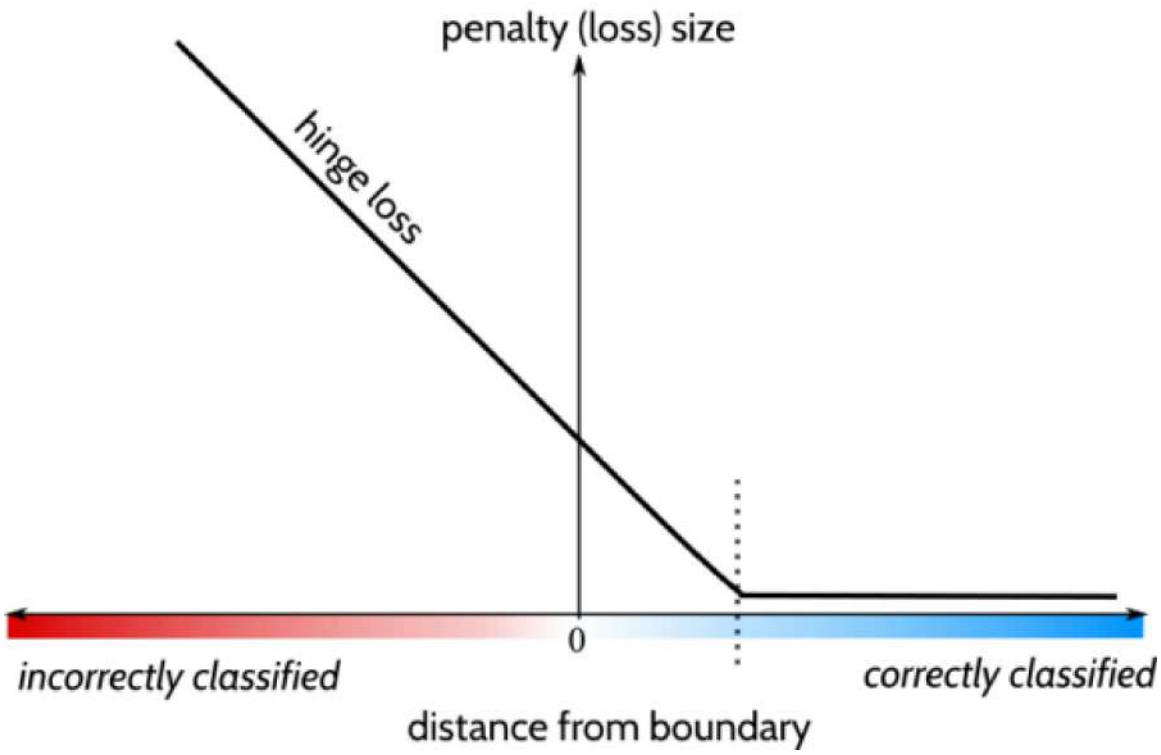
Mean-Squared Error(MSE): we can say how our model predicted values against the actual values.

MSE = √(predicted value - actual value)2

Hinge loss: It is used to train the machine learning classifier, which is

L(y) = max(0,1- yy)

Where y = -1 or 1 indicating two classes and y represents the output form of the classifier. The most common cost function represents the total cost as the sum of the fixed costs and the variable costs in the equation y = mx + b



4. MAE , MSE and RMSE?

Ans:

MAE :

MAE evaluates the absolute distance of the observations (the entries of the dataset) to the predictions on a regression, taking the average over all observations. We use the absolute value of the distances so that negative errors are accounted properly. This is exactly the situation described on the image above.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i^{real} - y_i^{pred}|$$

MSE :

Another way to do so is by squaring the distance, so that the results are positive. This is done by the MSE, and higher errors (or distances) weigh more in the metric than lower ones, due to the nature of the power function.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i^{real} - y_i^{pred})^2$$

RMSE :

A backlash in MSE is the fact that the unit of the metric is also squared, so if the model tries to predict price in US, $the MSE will yield a number with unit (US)^2$ which does not make sense. RMSE is used then to return the MSE error to the original unit by taking the square root of it, while maintaining the property of penalizing higher errors.

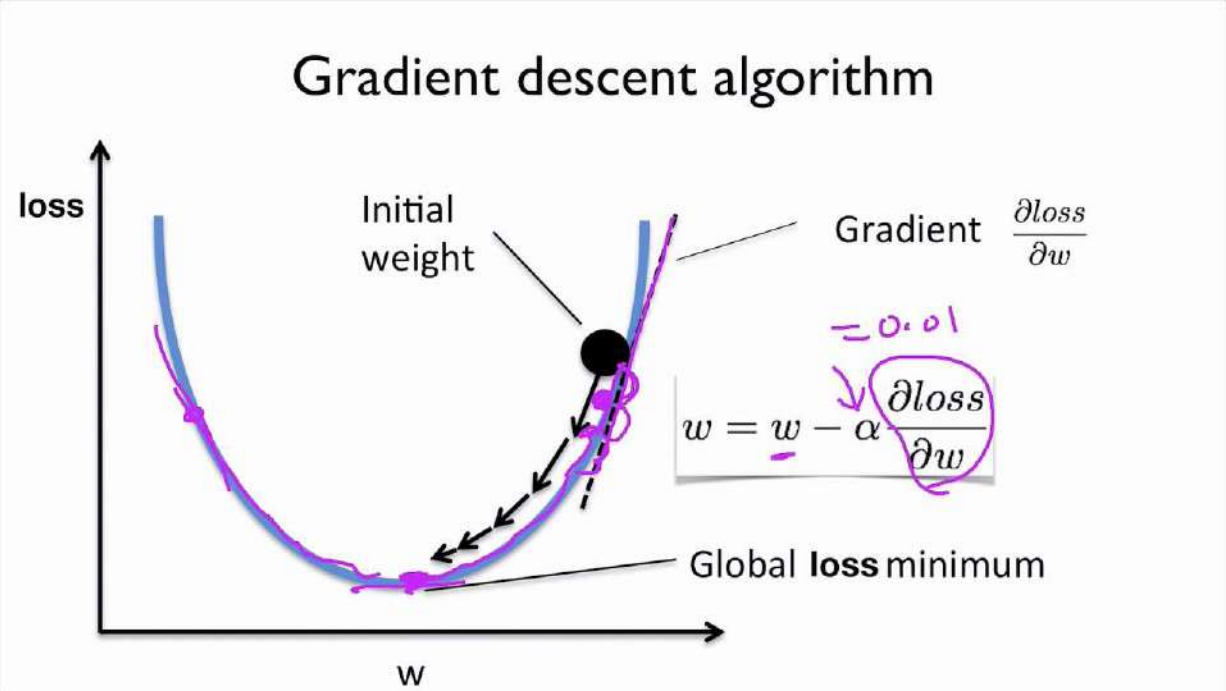
$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^{real} - y_i^{pred})^2}$$

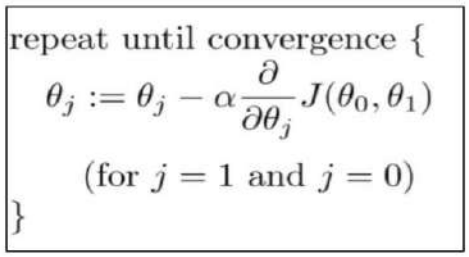
In [ ]:

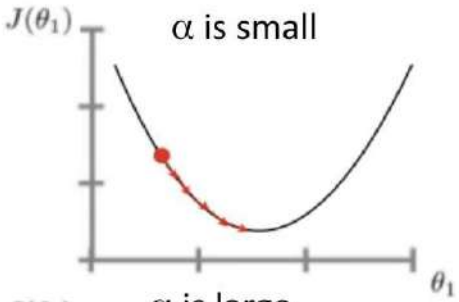
5. Explain how Gradient descent work in Linear Regression ?

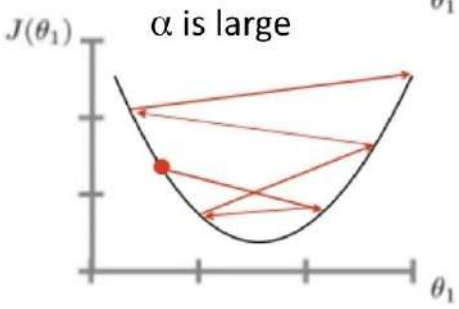
Ans:

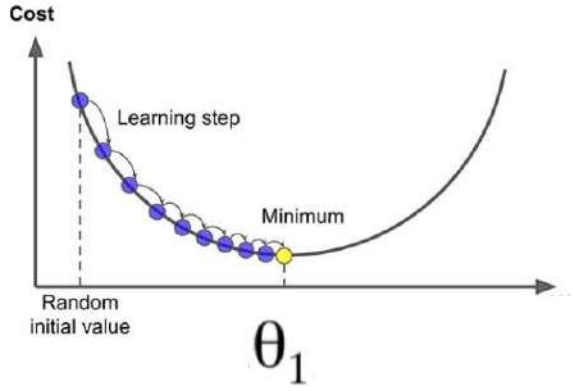
Gradient descent is an algorithm that approaches the least squared regression line via minimizing sum of squared errors through multiple iterations. So far, I've talked about simple linear regression, where you only have 1 independent variable (i.e. one set of x values).











In [3]:
```
def update_weights(m, b, X, Y, learning_rate):
    m_deriv = 0
    b_deriv = 0
    N = len(X)
    for i in range(N):
        # Calculate partial derivatives
        # -2x(y - (mx + b))
        m_deriv += -2*X[i] * (Y[i] - (m*X[i] + b))

        # -2(y - (mx + b))
        b_deriv += -2*(Y[i] - (m*X[i] + b))

    # We subtract because the derivatives point in direction of steepest ascent
    m -= (m_deriv / float(N)) * learning_rate
    b -= (b_deriv / float(N)) * learning_rate

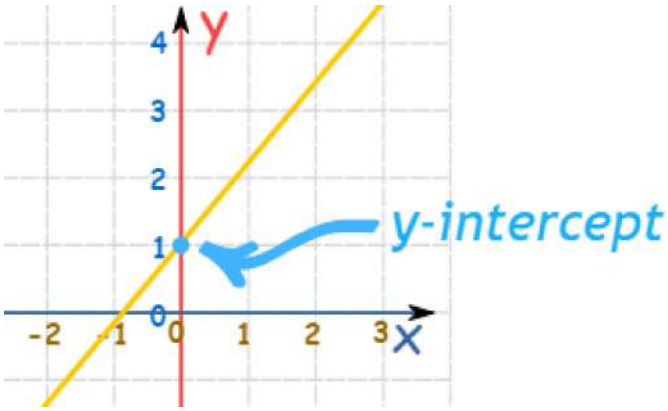
    return m, b
```

In [ ]:
```
```

6. Explain the intercept term means?

Ans:

The intercept (often labeled as constant) is the point where the function crosses the y-axis. In some analysis, the regression model only becomes significant when we remove the intercept, and the regression line reduces to Y = bX + error



7. Write all the assumption for Linear Regression?

Ans:

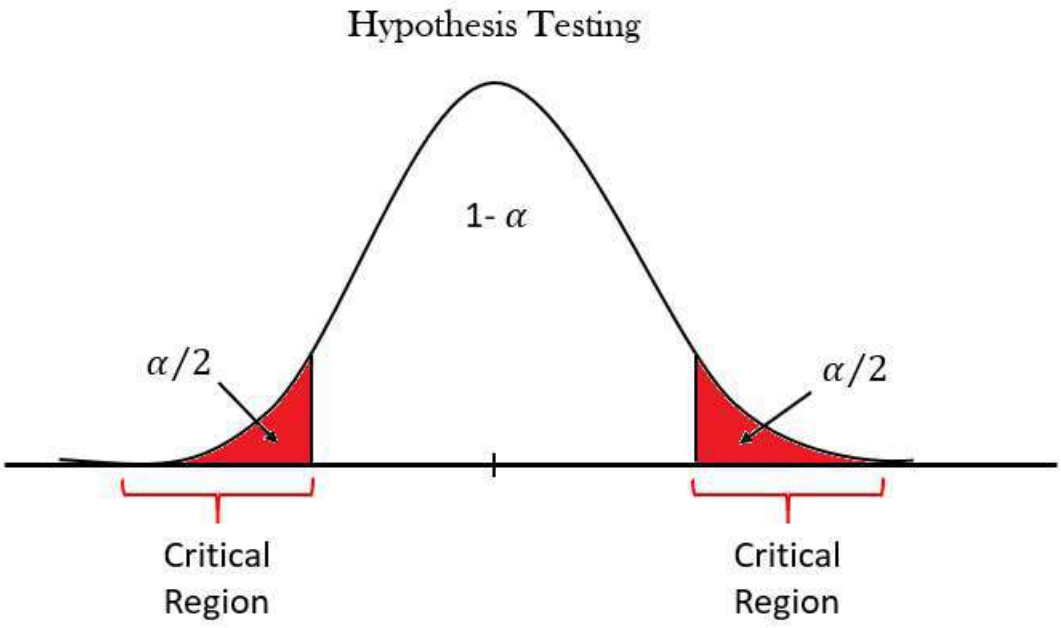
Linear regression is an analysis that assesses whether one or more predictor variables explain the dependent (criterion) variable. The regression has five key assumptions:

1. Linear relationship
2. Multivariate normality
3. No or little multicollinearity
4. No auto-correlation
5. Homoscedasticity

8. How is Hypothesis testing used in Linear Regression?

Ans:

Hypothesis testing is used to confirm if our beta coefficients are significant in a linear regression model. Every time we run the linear regression model, we test if the line is significant or not by checking if the coefficient is significant.



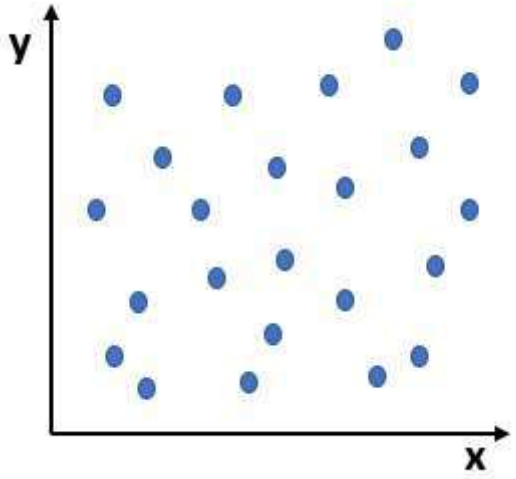
Let us understand it in Simple Linear Regression first.

When we fit a straight line through the data, we get two parameters i.e., the intercept (β_0) and the slope (β_1).

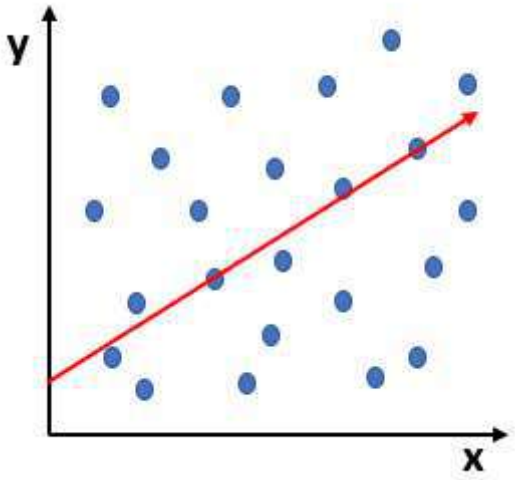
$$y = \beta_0 + \beta_1 x$$

Now, β_0 is not of much importance right now, but there are a few aspects around β_1 which needs to be checked and verified. Suppose we have a dataset for which the scatter plot looks like the following:

Scatter Plot



When we run a linear regression on this dataset in Python, Python will fit a line on the data which looks like the following:



We can clearly see that the data in randomly scattered and doesn't seem to follow linear trend. Python will anyway fit a line through the data using the least squared method. We can see that the fitted line is of no use in this case. Hence, every time we perform linear regression, we need to test whether the fitted line is a significant one or not (in other terms, test whether β_1 is significant or not). We will use Hypothesis Testing on β_1 for the same.

Steps to Perform Hypothesis testing:

1.Set the Hypothesis

2.Set the Significance Level, Criteria for a decision

3.Compute the test statistics

4.Make a decision

9. How would you decide the importance of variable for multivariate regression?

Ans:

1. Variables that are already proven in the literature to be related to the outcome.
2. Variables that can either be considered the cause of the exposure, the outcome, or both.
3. Interaction terms of variables that have large main effects.

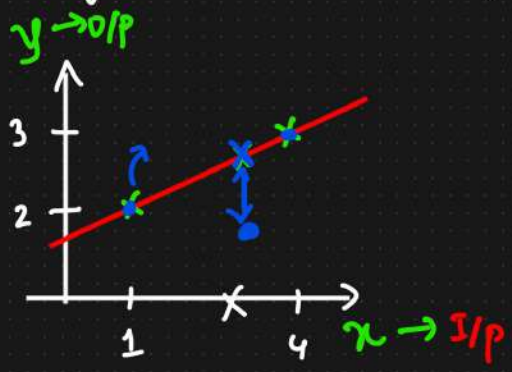
10. What is the difference between R^2 vs adjusted R^2?

Ans:

However, there is one main difference between R^2 and the adjusted R^2:
R^2 assumes that every single variable explains the variation in the dependent variable.
The adjusted R^2 tells you the percentage of variation explained by only the independent variables that actually affect the dependent variable.

In [ ]:

Ridge and Lasso Regression Math Intuition



Training set

x	y
1	2
4	3

⇒ Linear Regression

→ Generalized Model

Model

Overfitting

Train Accuracy = 90% ↓↓

Test Accuracy = 70%

Low Bias

High Variance

Underfitting

Train Accuracy = 60%

Test Data = 62%

High Bias

High Variance

Train Acc = 90%

Test Acc = 89%

Low Bias &

Low Variance

Ridge Regression (l_2 Regularization)

$\lambda = 1$

Cost function → Residual Error

$$= \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x)^{(i)} - y^{(i)}\right)^2 \quad \downarrow\downarrow\downarrow$$

$$\Rightarrow \left(h_\theta(x)^{(i)} - y^{(i)}\right)^2 + \lambda (\text{slope})^2 \quad \text{(penalizing)}$$

$$= 0 + 1(2)^2$$

$$= 4 \quad \downarrow\downarrow\downarrow$$

$y = mx + c$

$\lambda (m^2)$

$$\Rightarrow \{\text{small value}\} + 1(1.3)^2$$

$$\Rightarrow \approx 2.05 \quad \downarrow\downarrow\downarrow$$

$y = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \theta_3 x_3$ (θ_2, θ_3 ↓ small)

① Overfitting is removed

Lasso Regression (l_1 Regularization)

$$\left(h_\theta(x)^{(i)} - y^{(i)}\right)^2 + \lambda |\text{slope}| \quad \downarrow\downarrow\downarrow\downarrow$$

$\lambda |m|$

$\hookrightarrow \lambda |m_1 + m_2 + m_3 + \cdots m_n|$

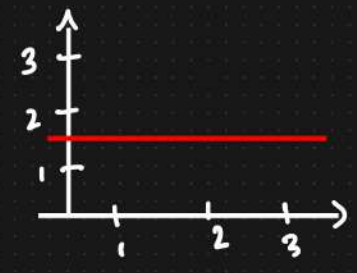
① Overfitting prevent ✓
② Feature selection ✓

Hypothesis {y is a linear function of x}

$\rightarrow h_\theta(x) = \theta_0 + \theta_1 x_1$ (θ_1 → coefficient, θ_0 → intercept)

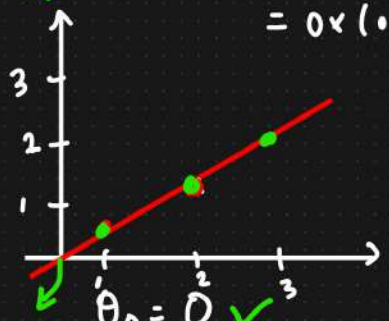
$= 0 \times (0.5)\,1 = 0.5$

$= 0 \times (0.5)\,2 = 1$



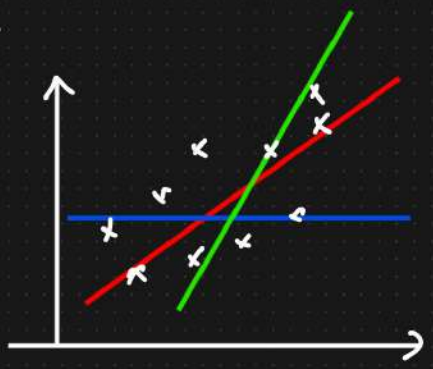
$\theta_0 = 1.5$

$\theta_1 = 0$



$\theta_0 = 0$ ✓

$\theta_1 = 0.5$



$m \rightarrow$ No. of datapoints

Solve {Cost function}

Minimize θ_0, θ_1

$$\sum_{i=1}^{m} \frac{1}{2m} \left(h_\theta(x)^{(i)} - y^{(i)} \right)^2 \downarrow\downarrow$$

$$\frac{\partial}{\partial x}(x^2) = 2x^{2-1} = 2x$$

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x)^{(i)} - y^{(i)} \right)^2 \downarrow\downarrow\downarrow$$

↳ Squared Error Function

Hypothesis

$h_\theta(x) = \theta_1 x_1$

Sets $\theta_0 = 0$

Cost function

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2$$

{When $\theta_1 = 1$} {(1,1), (2,2), (3,3)}

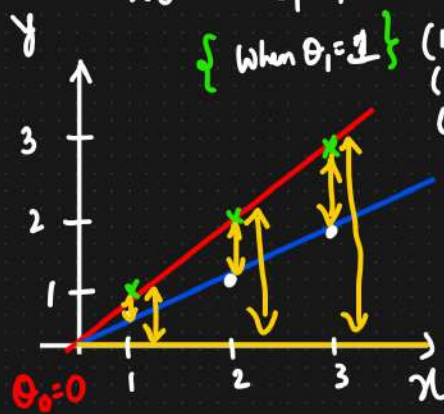
$h_\theta(x) = 1 \times 1$

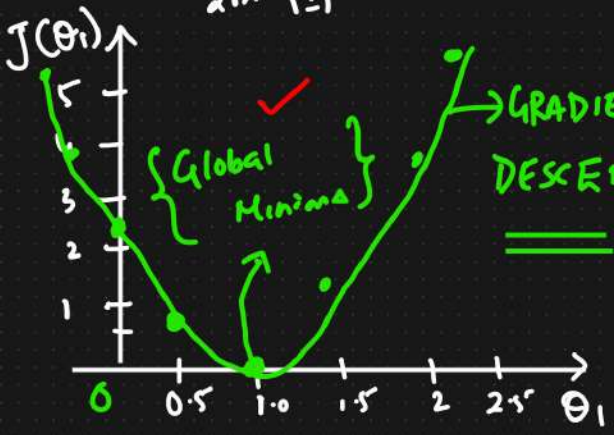
$h_\theta(x) = 1 \times 2$

$h_\theta(x) = 1 \times 3$

When $\theta_1 = 0.5$ =

When $\theta_1 = 0.0$





✓ {Global Minima}

→ GRADIENT DESCENT

$$J(\theta_1) = \frac{1}{2m}\sum_{i=1}^{m}\left(h_\theta(x)^{(i)} - y^{(i)}\right)^2$$ When $\theta_1 = 1$

$$= \frac{1}{6}\left[(0)^2 + (0)^2 + (0)^2\right]$$

$$= 0$$

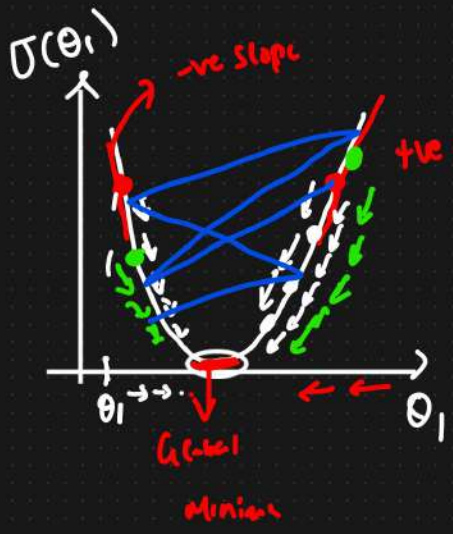
When $\theta_1 = 0.5$

$$J(\theta_1) = \frac{1}{6}\left[(0.5-1)^2 + (1-2)^2 + (1.5-3)^2\right]$$

$$= \frac{1}{6}(3.5) = \approx 0.58$$

$$J(\theta_1) = \frac{1}{6}\left[(0-1)^2 + (0-2)^2 + (0-3)^2\right]$$

$$= \frac{14}{6} \approx 2.3$$



$\theta_1 \rightarrow$ Update $\rightarrow$ find derivation or slope

$\alpha = 1000$

Repeat convergence theorem

{ Learning Rate }

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j}(J(\theta_1))$$ ← Slope

{ $\alpha = 0.01$ }

}

$\theta_1 := \theta_1 - \alpha(+ve)$ } Decrease ✓

$\theta_1 := \theta_1 - \alpha(-ve)$ } Increase ✓ ← Slope

$\theta_1 = \theta_1 +$

Outline

1. Start with θ_0 & θ_1
2. Keep changing θ_0, θ_1 to reduce $J(\theta_0, \theta_1)$ until we reach near global Minima.
3. Convergence Theorem

{

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} (J(\theta_0, \theta_1)$$

$j := 0$ and 1

}