lab1_61340500032

April 11, 2021

0.1 3. Exploring data tables with Pandas

1. Use Pandas to read the house prices data. How many columns and rows are there in this dataset?
2. The first step I usually do is to use commands like pandas.head() to print a few rows of data. Look around what kind of features are available and read data description.txt for more info. Try to understand as much as you can. Pick three features you think will be good predictors of house prices and explain what they are.
3. How many unique conditions are there in SaleCondition? Use Pandas to find out how many samples are labeled with each condition. What do you learn from doing this?
4. Select one variable you picked in b., do you want to know something more about that variable? Use Pandas to answer your own question and de- scribe what you did shortly here.

[43]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from sklearn import preprocessing
```

[44]:
```
dataset = pd.read_csv('train.csv') # load training set as dataframe
```

[45]:
```
# 3a) Find number of rows, columns
print("This dataframe has %d rows and %d columns"% dataset.shape)
```

```
This dataframe has 1460 rows and 81 columns
```

[46]:
```
# 3b) Look around & pick 3 features
dataset.head()
picked_features = ["LotArea", "YearBuilt", "SaleCondition"]
# x1 = dataset.loc[:,"LotArea"]
# x2 = dataset.loc[:,"YearBuilt"]
# x3 = dataset.loc[:,"SaleCondition"]
```

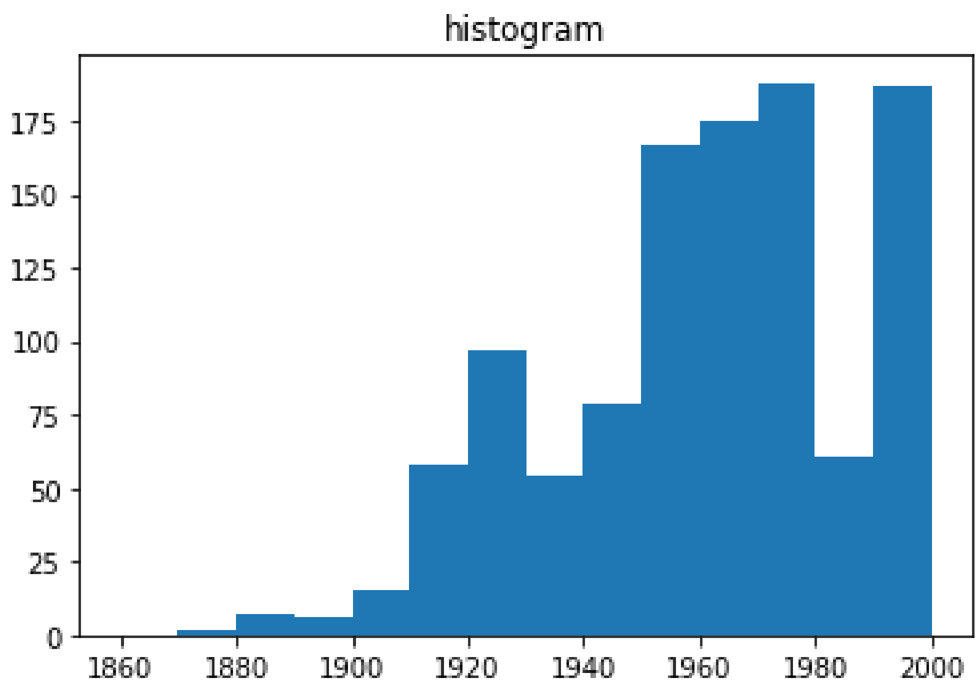
[47]:
```
# 3c) How many type of Sale Condition
n = dataset['SaleCondition'].nunique()
print("There %d unique conditions in SaleCondition."%(n))
print(dataset['SaleCondition'].value_counts())
```

```
There 6 unique conditions in SaleCondition.
Normal     1198
```

```
Partial      125
Abnorml      101
Family        20
Alloca        12
AdjLand        4
Name: SaleCondition, dtype: int64
```

[48]:
```python
# 3d) Select one variable from 3b) & visualize something
#      3 features -> LotArea, YearBuilt, SaleCondition (    :                 )
print(dataset['YearBuilt'].value_counts())

plt.hist(dataset['YearBuilt'], bins = np.arange(1860, 2010, 10))
plt.title("histogram")
plt.show()
```

```
2006    67
2005    64
2004    54
2007    49
2003    45
        ..
1906     1
1911     1
1913     1
1917     1
1872     1
Name: YearBuilt, Length: 112, dtype: int64
```

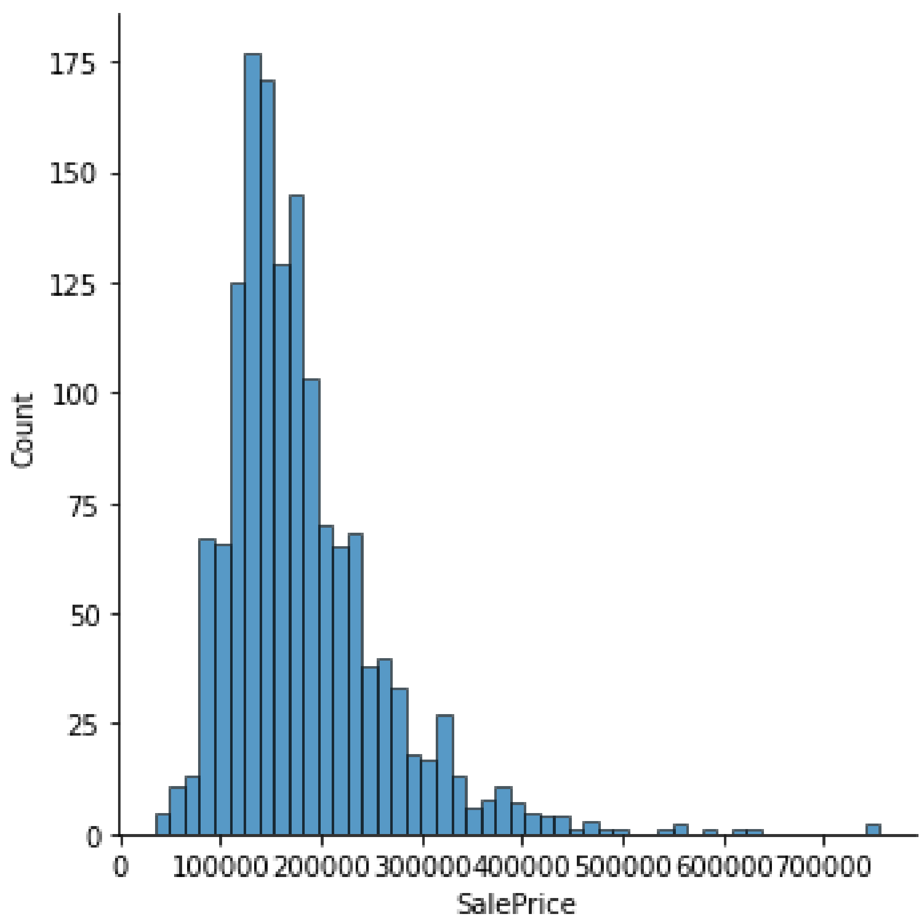


0.2 4. Learning to explore data with Seaborn

1. Let us first look at the variable we want to predict SalePrice. Use Seaborn to plot histogram of sale prices. What do you notice in the histogram?
2. Plot the histogram of the LotArea variable. What do you notice in the histogram?
3. Use Seaborn to plot LotArea in the x-axis and SalePrice on the y-axis. Try plotting log(LotArea) versus log(SalePrice) and see if the plot looks better.

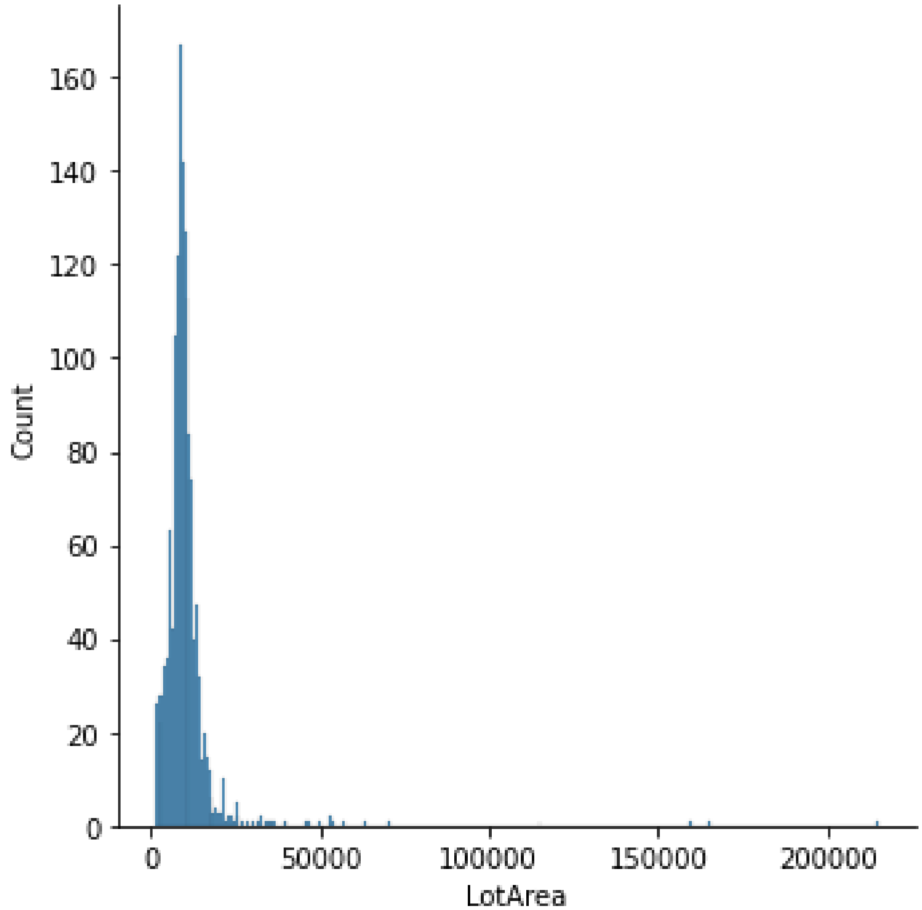
[49]:
```
# 4a) Look at dependence variable "SalePrice"
sns.displot(dataset, x="SalePrice") # Plot histogram of "SalePrice"
```

[49]:
```
<seaborn.axisgrid.FacetGrid at 0x7efd7e300128>
```



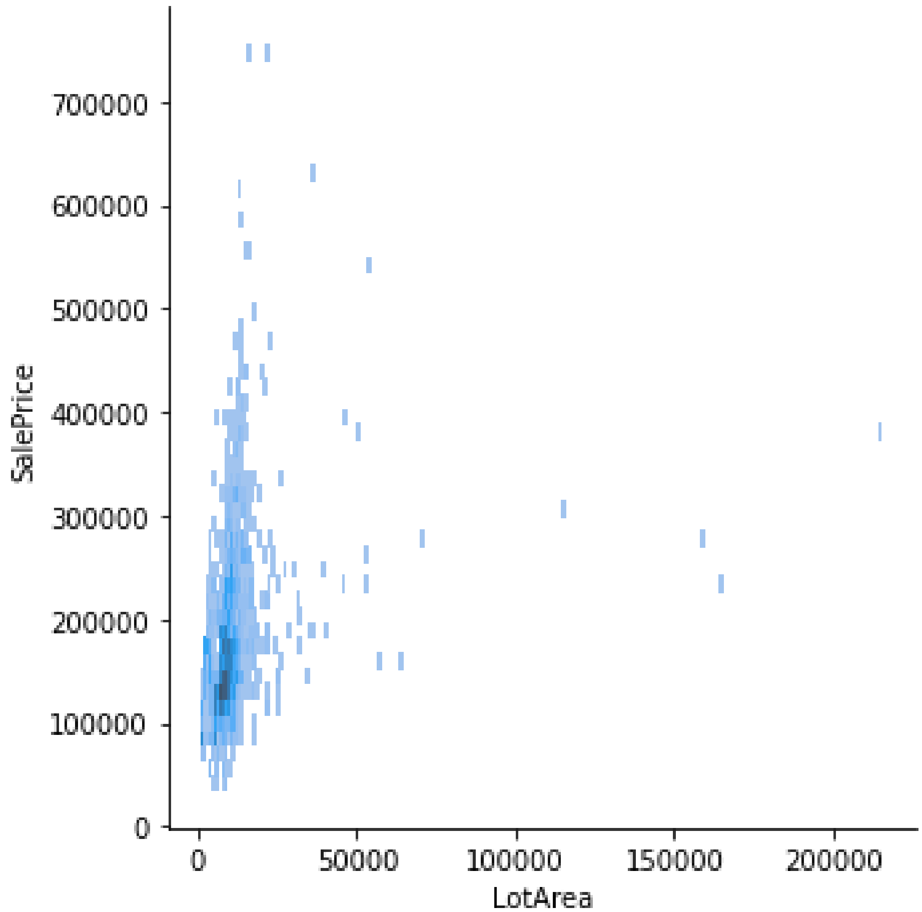
[50]:
```
# 4b) Plot histogram of "LotArea" variable
sns.displot(dataset, x="LotArea") # Plot histogram of "LotArea"
```

[50]: <seaborn.axisgrid.FacetGrid at 0x7efd7c601518>



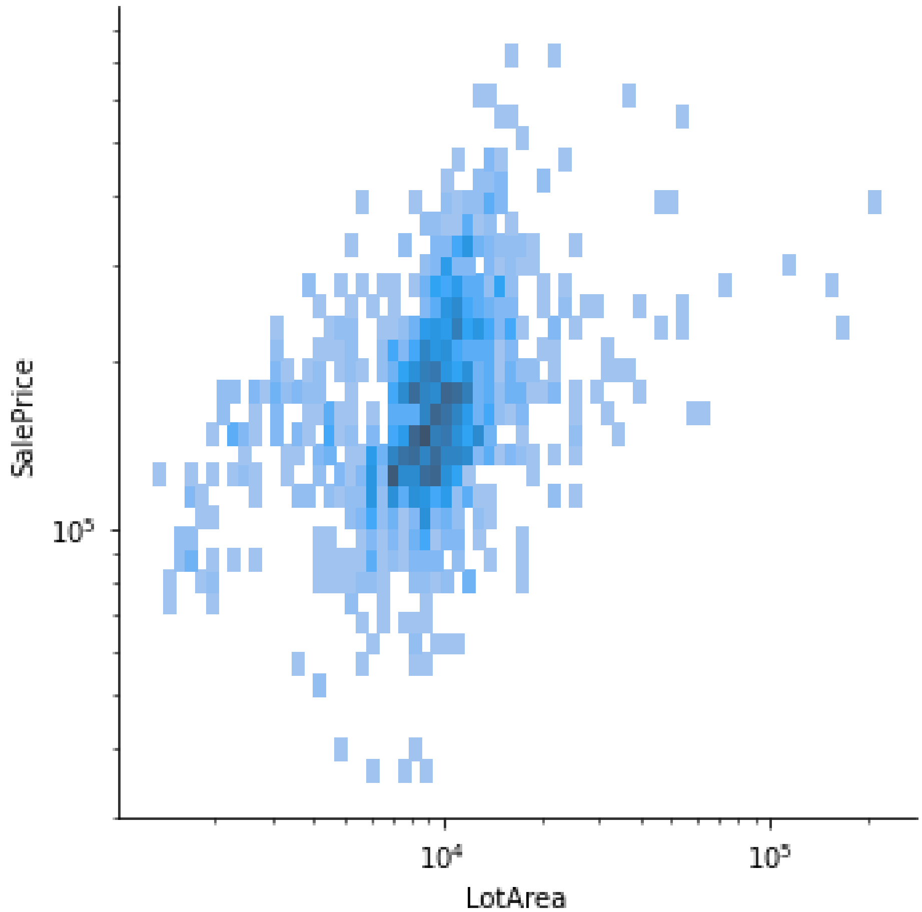
[51]:
```
# 4c) Plot LotArea in X-axis, SalePrice in Y-Axis
sns.displot(dataset, x="LotArea", y="SalePrice")
```

[51]: <seaborn.axisgrid.FacetGrid at 0x7efd7c5ae780>



[52]:
```
# 4d) Plot LotArea in X-axis, SalePrice in Y-Axis in log scale
sns.displot(dataset, x="LotArea", y="SalePrice", log_scale=True)
```

[52]: <seaborn.axisgrid.FacetGrid at 0x7efd7d4954a8>



0.3 5. Dealing with missing values

1. Suppose we want to start the first step of house price modeling by exploring the relationship between four variables: MSSubClass, LotArea, LotFrontage and SalePrice. I have done some exploring and found out that LotFrontage has a lot of missing values, so you need to fix it.
2. LotFrontage is the width of the front side of the property. Use Pandas to find out how many of the houses in our database is missing LotFrontage value.
3. Use Pandas to replace NaN values with another number. Since we are just exploring and not modeling yet, you can simply replace NaN with zeros for now.

[53]:
```
# 5a) LotFrontage
n_missing = dataset['LotFrontage'].isna().sum()
print("There are %d missing cells in column LotFrontage."%(n_missing))
```

```
There are 259 missing cells in column LotFrontage.
```

[54]:
```
# 5b)     Nan     0
from sklearn.impute import SimpleImputer
```

```
imputer = SimpleImputer(missing_values = np.nan, strategy = 'constant',␣
↪fill_value=0) # ['mean', 'median', 'most_frequent', 'constant']
dataset['LotFrontage'] = imputer.fit_transform(np.
↪asarray(dataset['LotFrontage']).reshape(-1, 1))
n_missing = dataset['LotFrontage'].isna().sum()
print("There are %d missing cells in column LotFrontage."%(n_missing))
```

```
There are 0 missing cells in column LotFrontage.
```

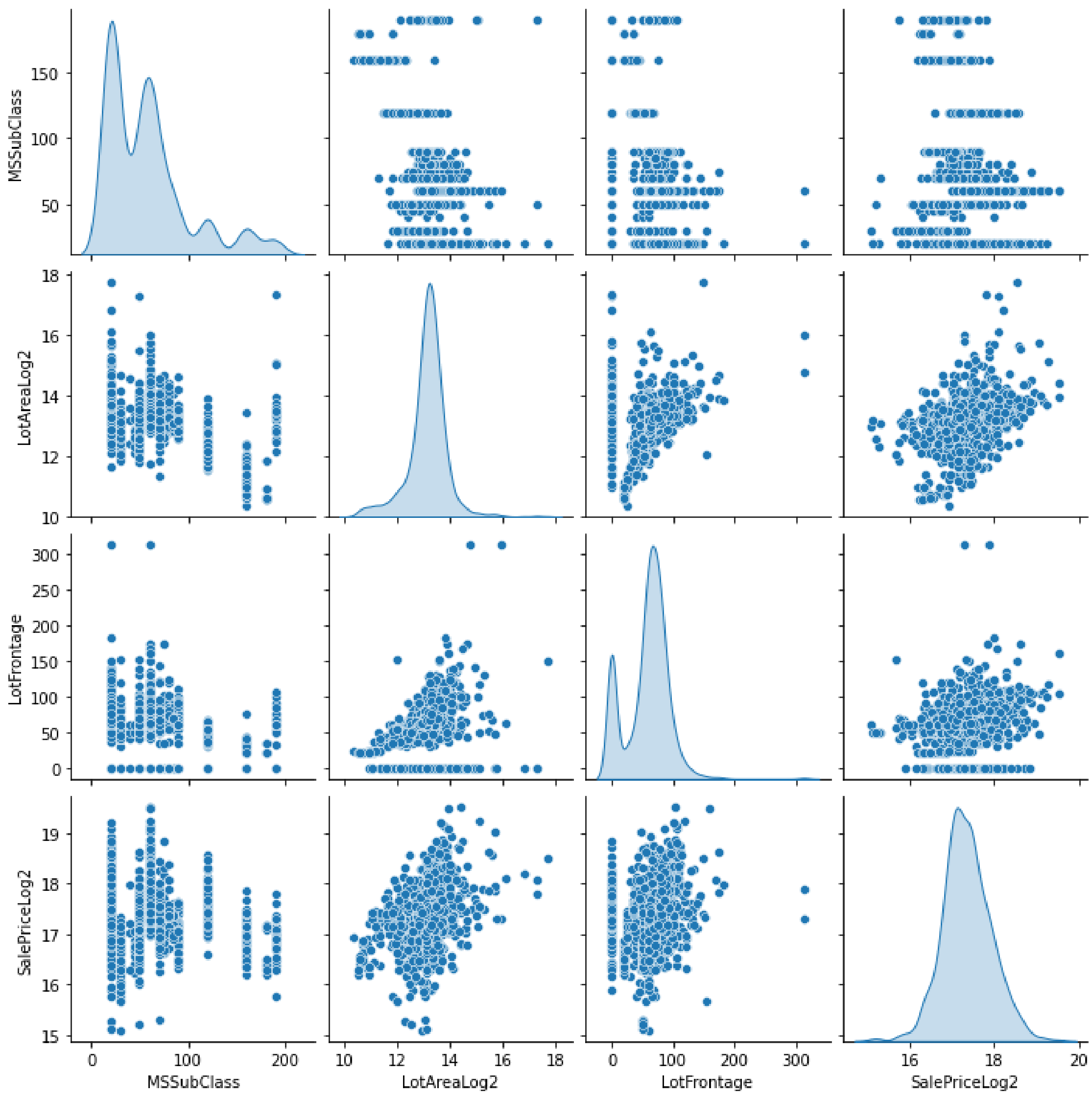
0.4 6. Correlations between multiple variables

One incredible feature of Seaborn is the ability to create correlation grid with pairplot function. We want to create one single plot that show us how all variables are correlated. 1. First, you need to create a data table with four columns: MSSubClass, LotArea (with log function applied), LotFrontage (missing values replaced) and SalePrice (with log function applied). 2. Then, use pairplot to create a grid of correlation plots. What do you observe from this plot?

[55]:
```
# 6a) Create table with four columns: MSSubClass, log(LotArea),␣
↪log(LotFrontage), log(SalePrice)
dataset['LotAreaLog2'] = np.log2(dataset['LotArea'])
dataset['SalePriceLog2'] = np.log2(dataset['SalePrice'])

new_dataframe = dataset[['MSSubClass', 'LotAreaLog2', 'LotFrontage',␣
↪'SalePriceLog2']].copy()
# new_dataframe = dataset.filter(['MSSubClass', 'LotAreaLog2',␣
↪'LotFrontageLog2', 'SalePrice'], axis=1) # Alternative way
```

[56]:
```
#6b) Use pairplot to create grid of coorelation plots
sns.pairplot(new_dataframe, diag_kind='kde')
```

[56]:
```
<seaborn.axisgrid.PairGrid at 0x7efd7d488b38>
```



0.5 7. Data Preparation

Let's prepare train.csv for model training

1. Pick columns that are numeric data and plot distributions of those data (with Seaborn). If you find a column with skewed distribution you will write a script to transform that column with a log function. Then standardize them.
2. For categorical variables, we will simply transform categorical data into numeric data by using function `pandas.get dummies()`.
3. Split data into x and y. The variable x contains all the house features except the SalePrice. y contains only the SalePrice.

[57]:
```
from scipy.stats import skew
# 7) Get rid of negative, zero values
def shift_negative(X): return X-(min(X)-1)
```

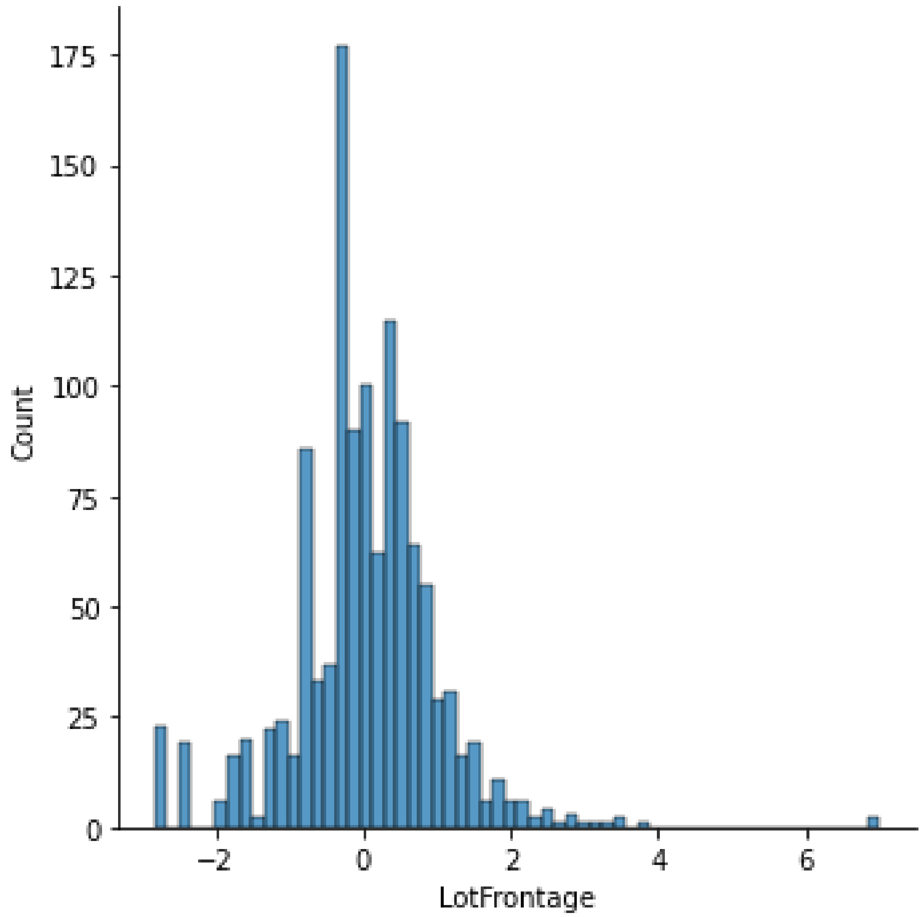
[58]:
```
# 7a) read training data using pandas.read_csv()
dataset = pd.read_csv('train.csv') # load training set
new_dataframe = pd.DataFrame().reindex_like(dataset)
new_dataframe.pop('SalePrice')
```

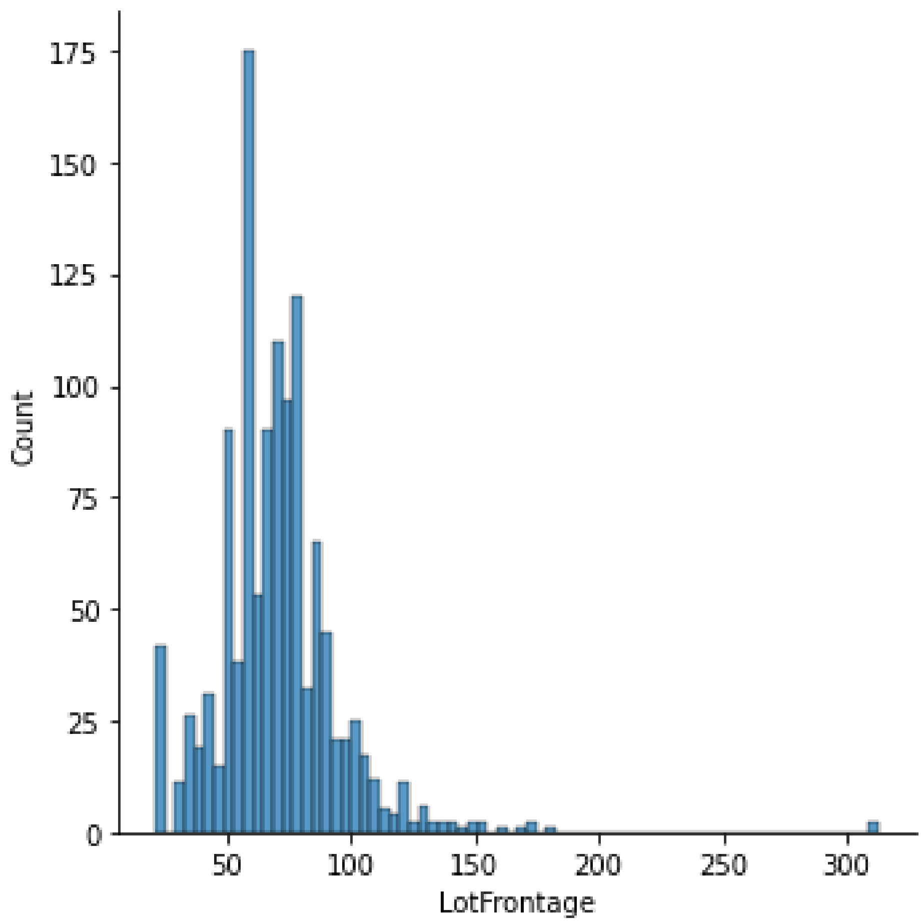
[58]:
```
0      NaN
1      NaN
2      NaN
3      NaN
4      NaN
        ..
1455   NaN
1456   NaN
1457   NaN
1458   NaN
1459   NaN
Name: SalePrice, Length: 1460, dtype: float64
```

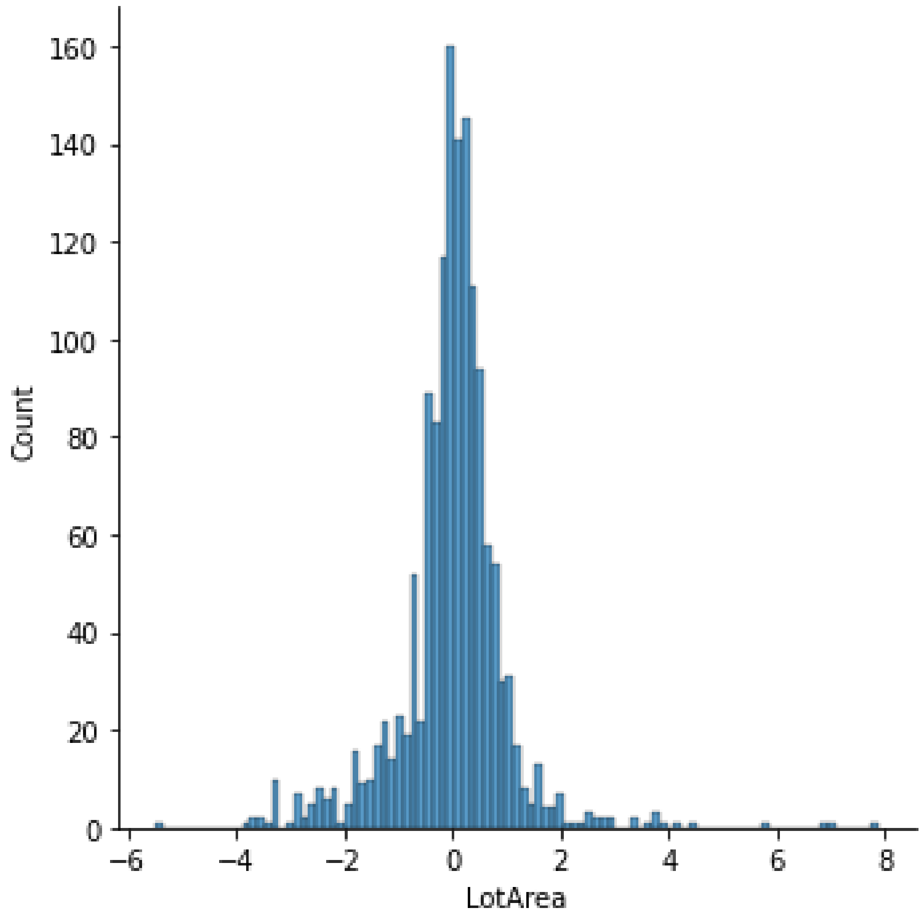
[59]:
```
# 7b) Pick numerical columns & transform with log() or boxcox() to standardize␣
 ↪them
#      data_description.txt   columns                   categorical data      ␣
 ↪dataset.._get_numeric_data().columns

numerical_features = ['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']
categorical_features = ['MSSubClass', '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']
PT_list = {}
SS_list = {}
for feature in numerical_features:
    # sns.displot(dataset, x=feature) # Plot original
```

```
    if skew(dataset[feature] , nan_policy = "omit") > 0.3:
        pt = preprocessing.PowerTransformer(method='box-cox', standardize=True)␣
↪# Boxcox
        PT_list[feature]= pt
        new_dataframe[feature] = pt.fit_transform(np.
↪asarray(shift_negative(dataset[feature])).reshape(-1, 1))
        sns.displot(new_dataframe[feature]) # Plot after shift to positive and␣
↪applied boxcox
    else:
        scaler = preprocessing.StandardScaler()
        new_dataframe[feature] = scaler.fit_transform(np.
↪asarray(shift_negative(dataset[feature])).reshape(-1, 1))
        SS_list[feature] = scaler
    sns.displot(dataset[feature]) # Plot after standartized
```

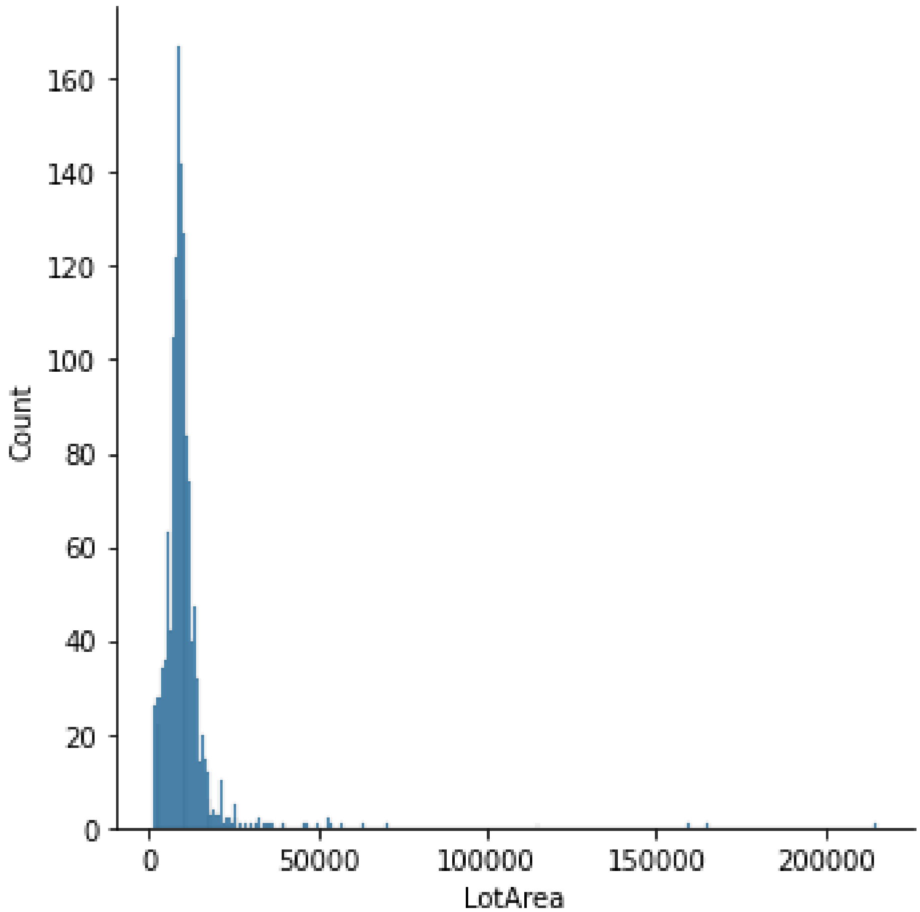
```
/home/teera/.virtualenvs/cv/lib/python3.6/site-packages/seaborn/axisgrid.py:392:
RuntimeWarning: More than 20 figures have been opened. Figures created through
the pyplot interface (`matplotlib.pyplot.figure`) are retained until explicitly
closed and may consume too much memory. (To control this warning, see the
rcParam `figure.max_open_warning`).
  fig, axes = plt.subplots(nrow, ncol, **kwargs)
```

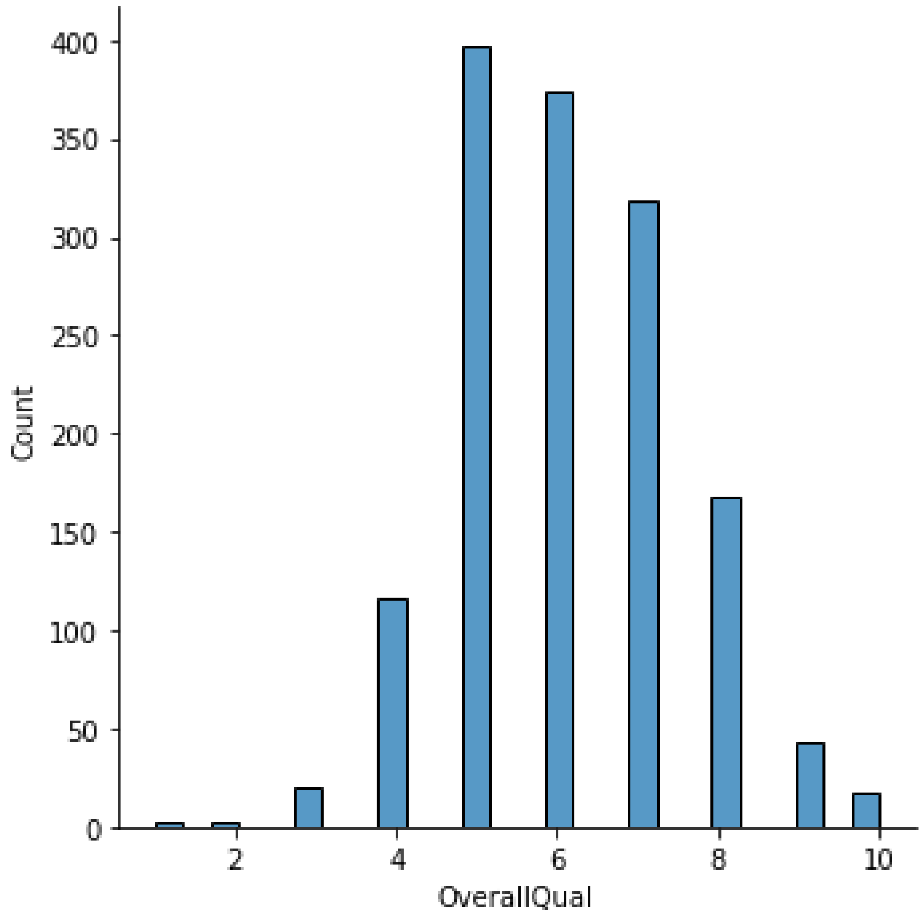

175
150
125
100
75
50
25
0
Count
−2
0
2
4
6
LotFrontage

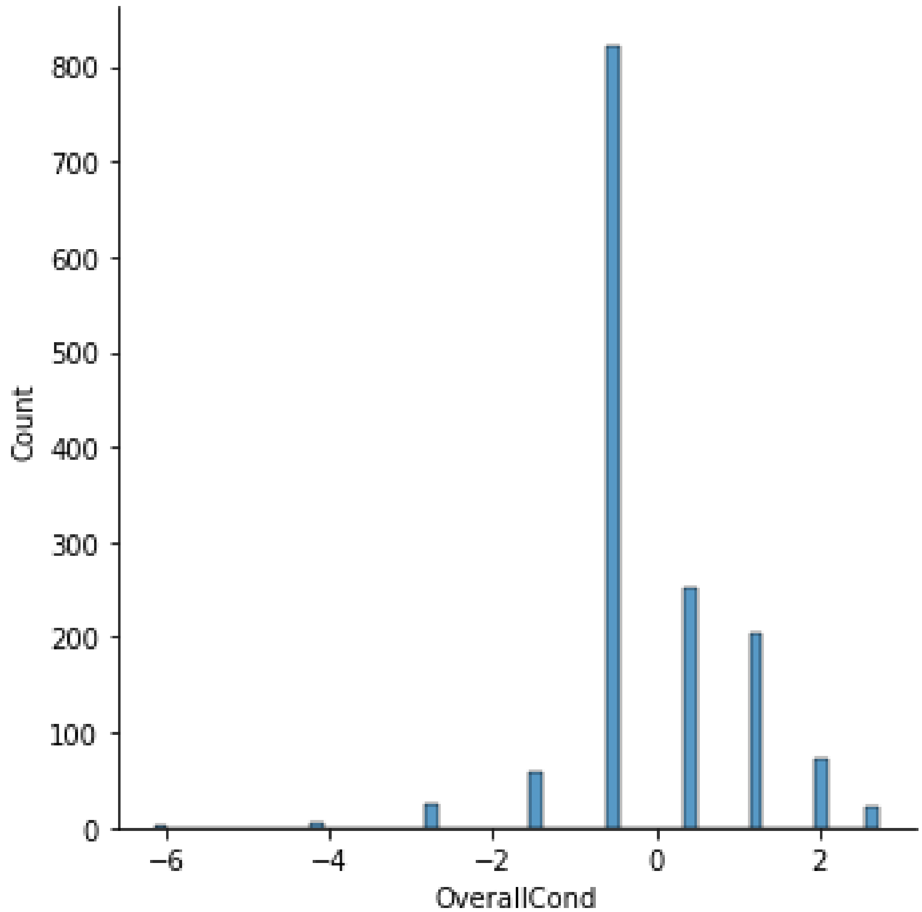

175
150
125
100
75
50
25
0
Count
50
100
150
200
250
300
LotFrontage

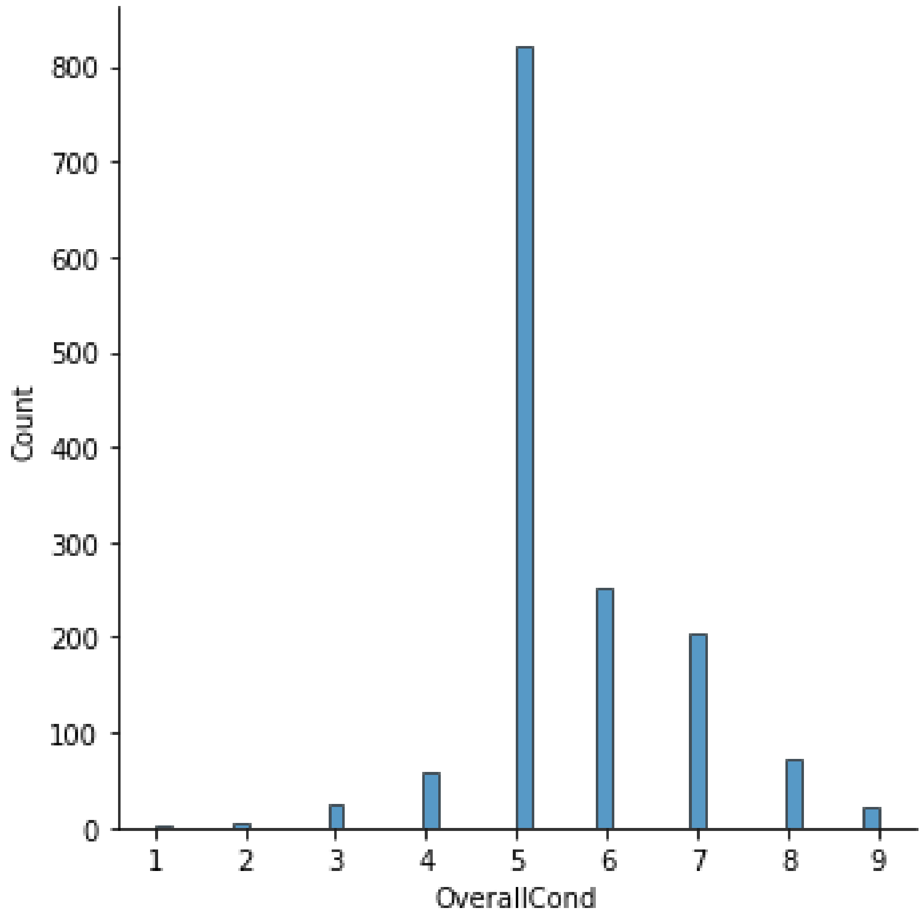


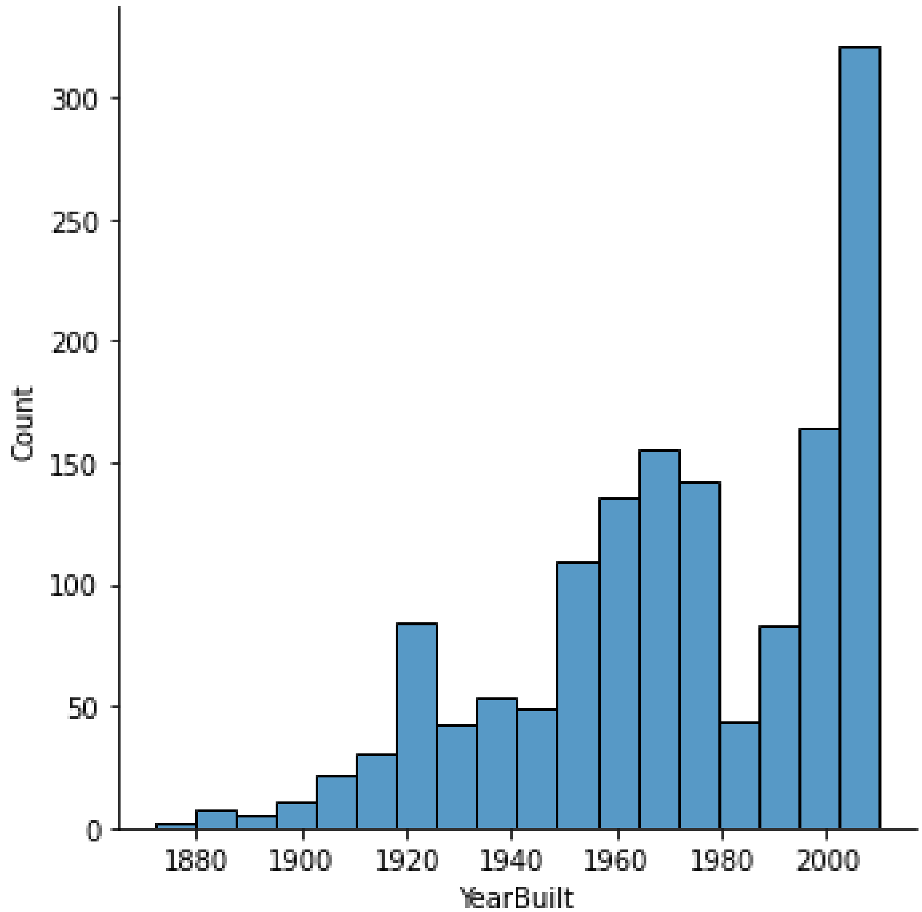
160
140
120
100
80
60
40
20
0
Count
−6
−4
−2
0
2
4
6
8
LotArea

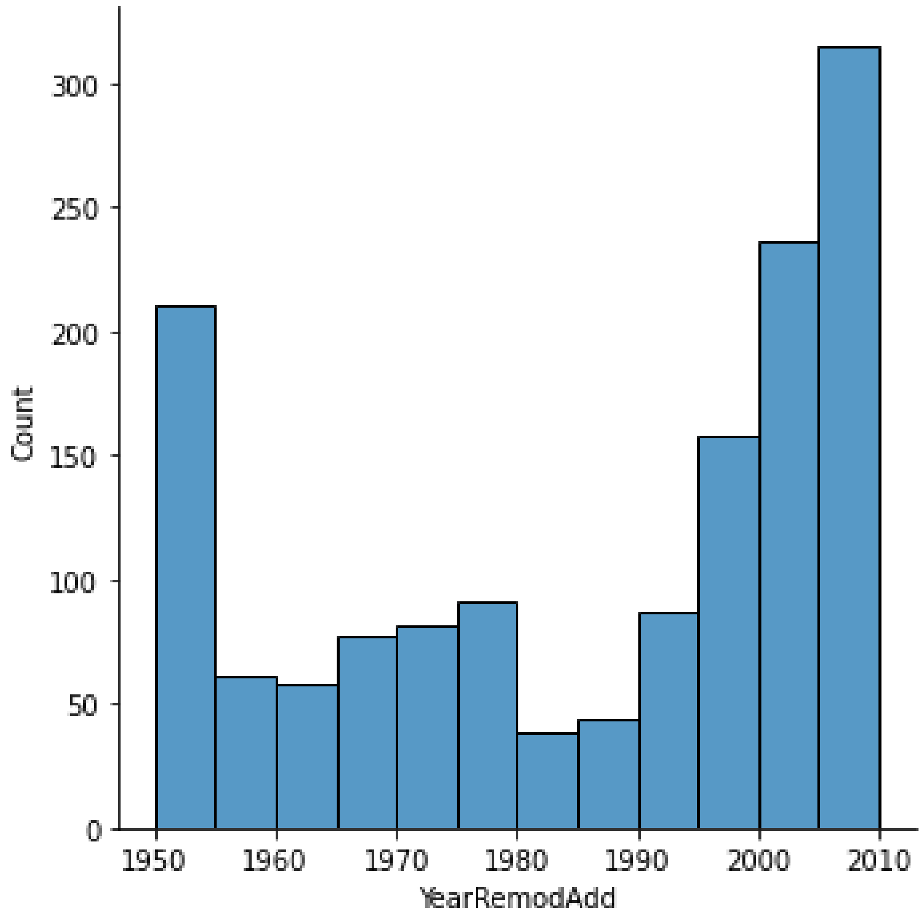

Count
0
20
40
60
80
100
120
140
160
0
50000
100000
150000
200000
LotArea

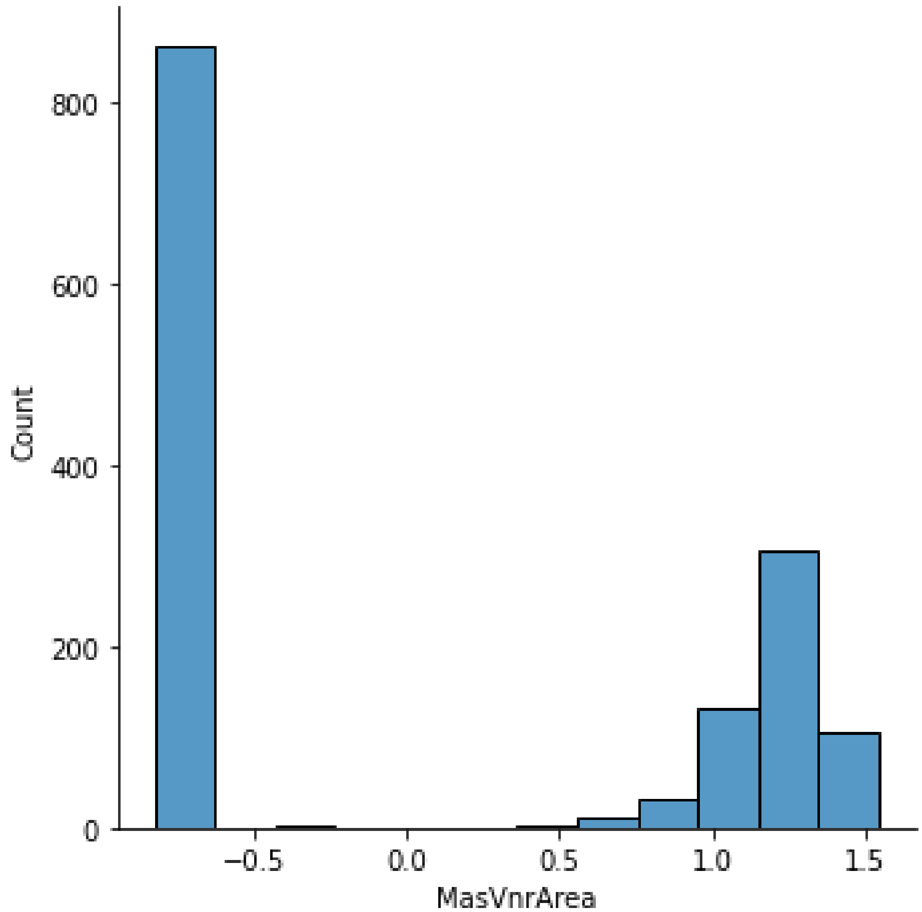

400
350
300
250
200
150
100
50
0
Count
2
4
6
8
10
OverallQual

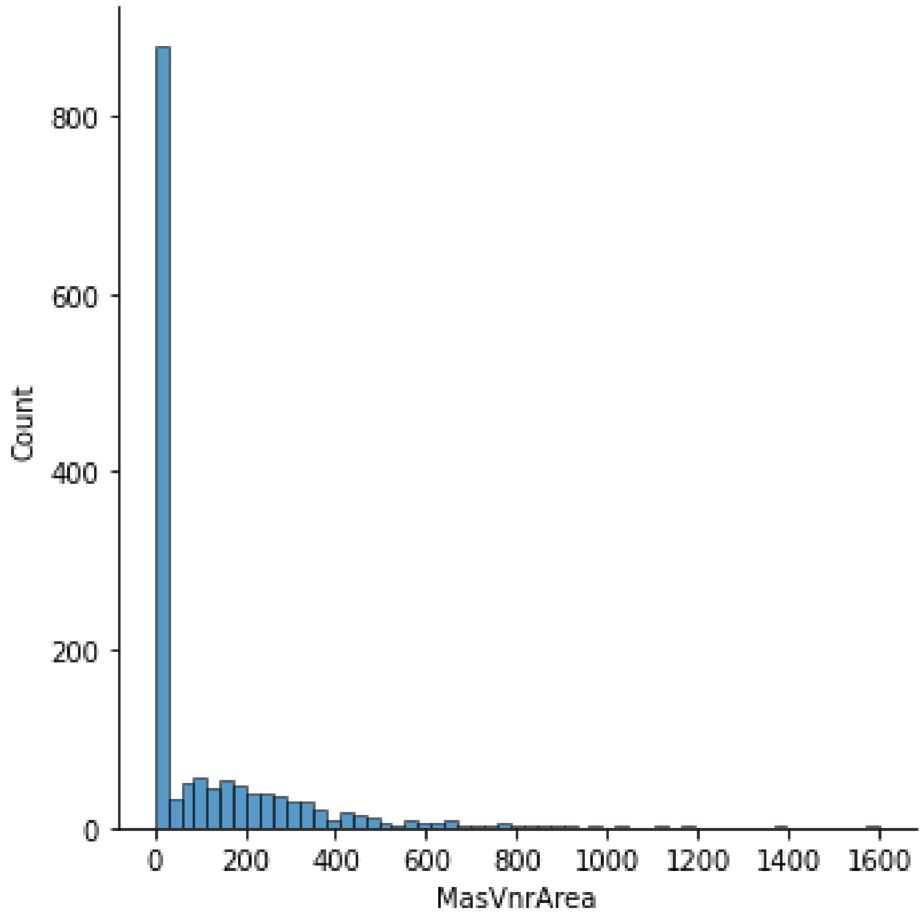

Count
800
700
600
500
400
300
200
100
0
−6
−4
−2
0
2
OverallCond


800
700
600
500
400
300
200
100
0
Count
1
2
3
4
5
6
7
8
9
OverallCond

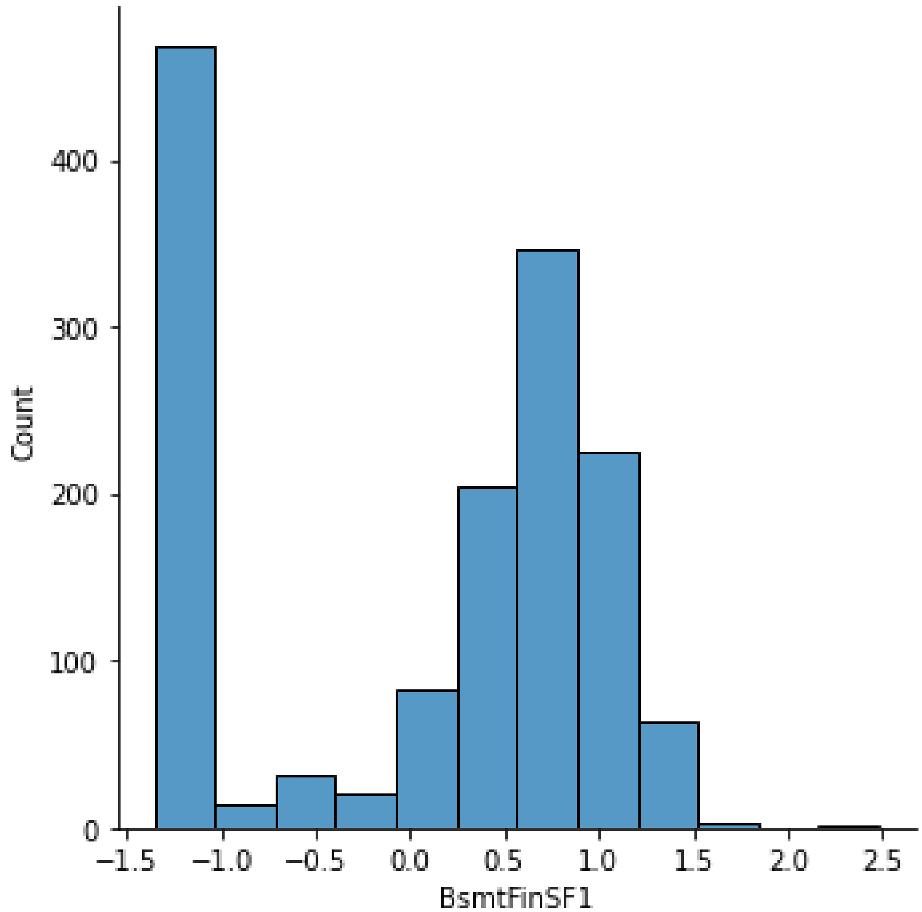

300
250
200
150
100
50
0
Count
1880
1900
1920
1940
1960
1980
2000
YearBuilt

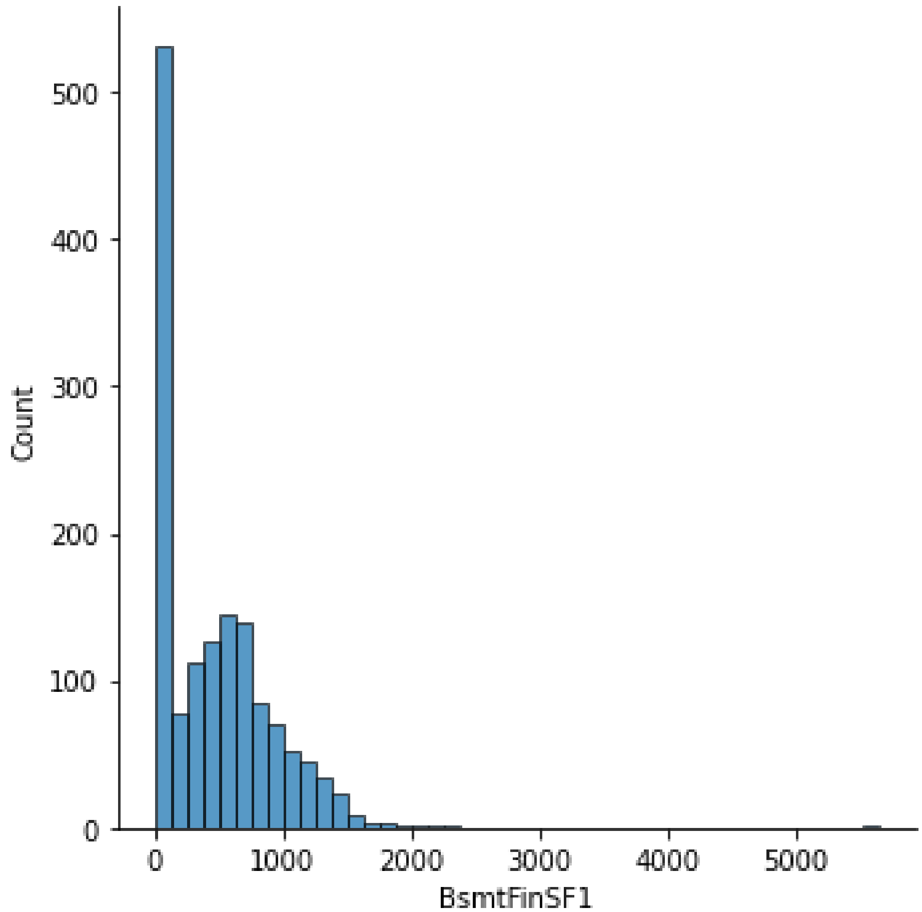

300
250
200
150
100
50
0
Count
1950
1960
1970
1980
1990
2000
2010
YearRemodAdd

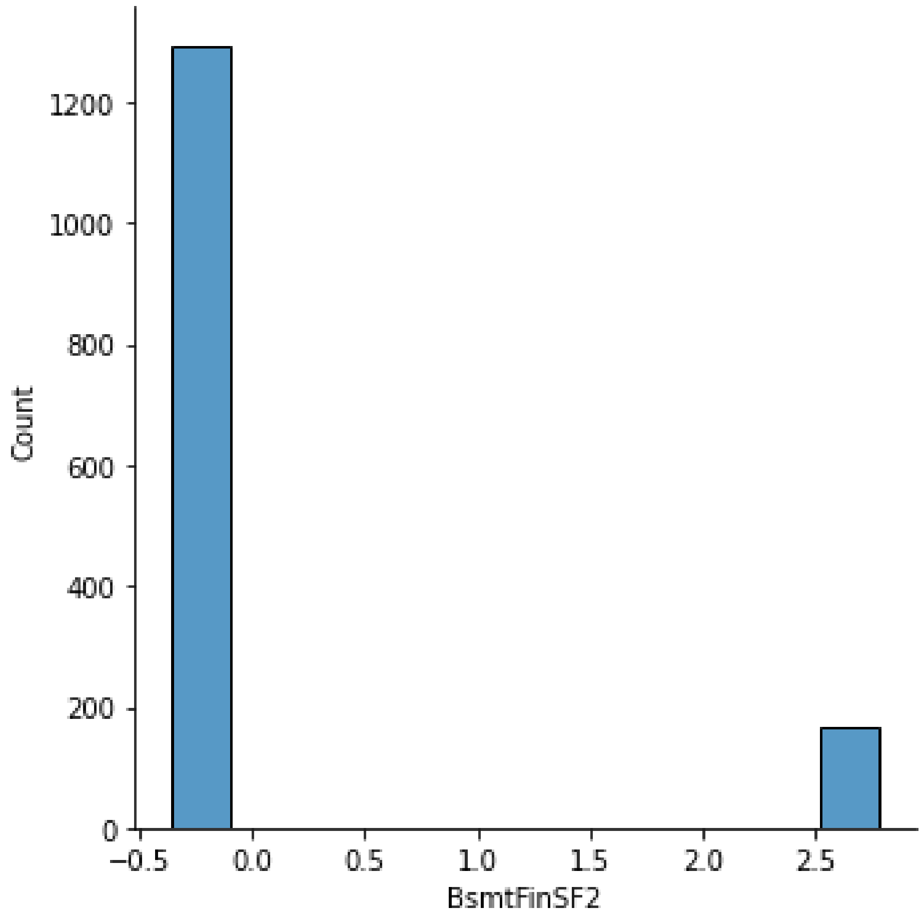

800
600
400
200
0
Count
−0.5
0.0
0.5
1.0
1.5
MasVnrArea



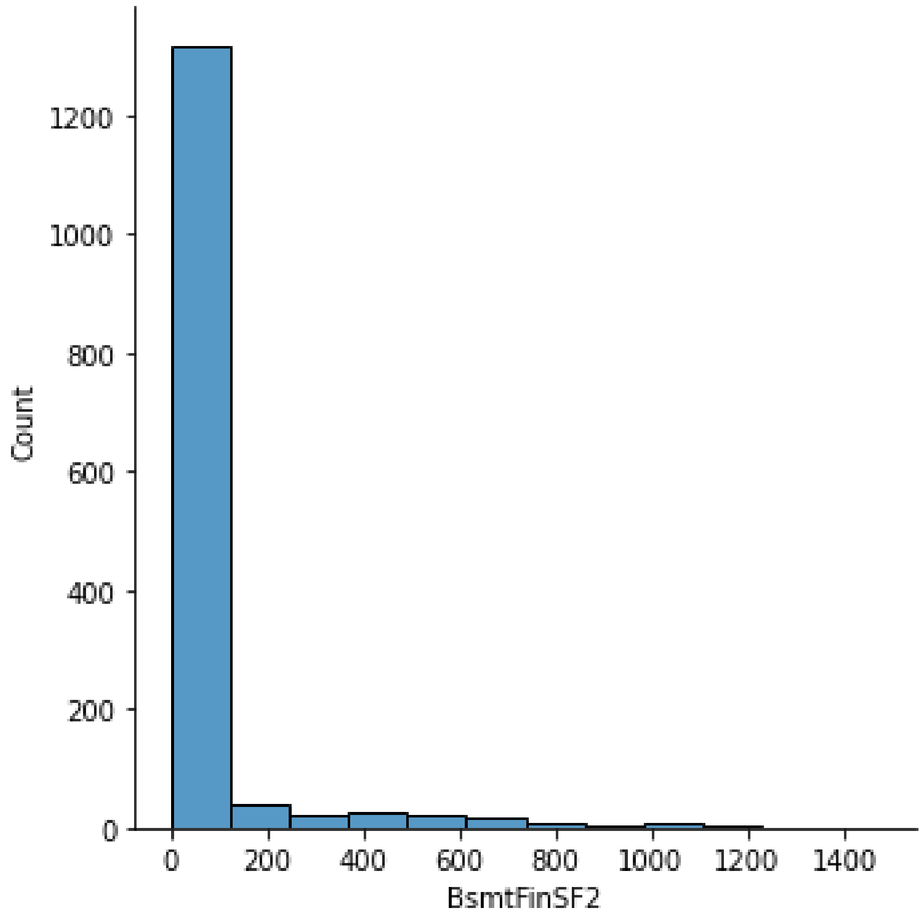
800
600
400
200
0
Count
0
200
400
600
800
1000
1200
1400
1600
MasVnrArea


400
300
200
100
0
Count
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
BsmtFinSF1

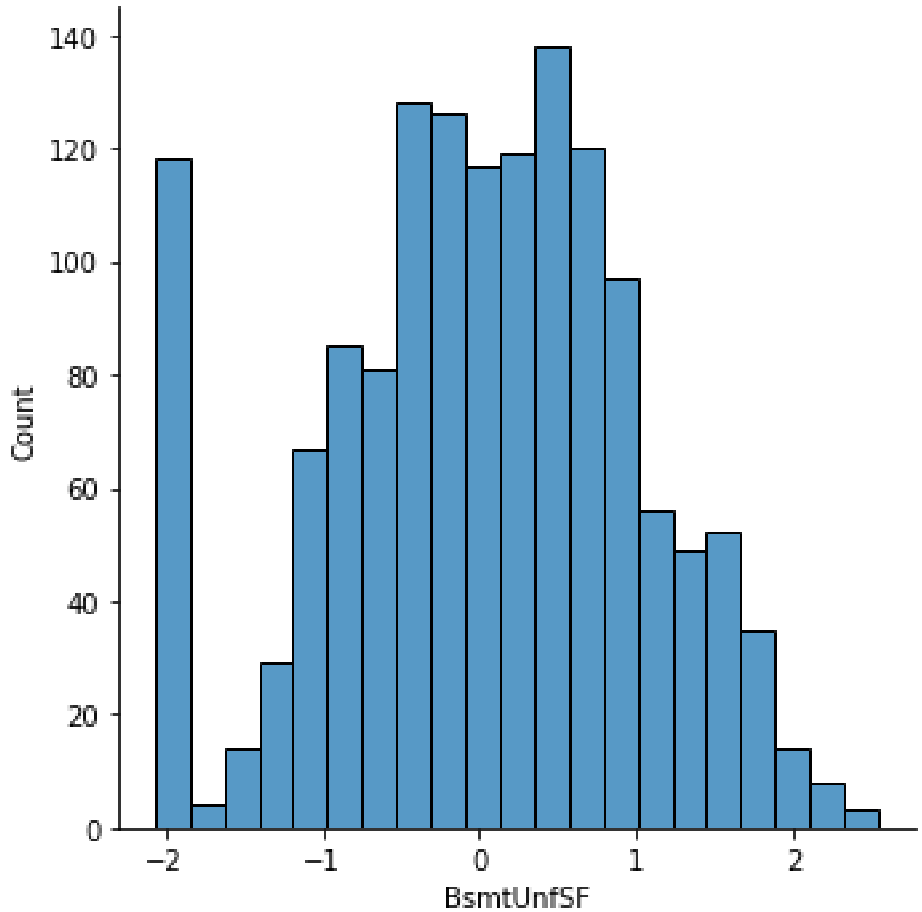

500
400
300
200
100
0
Count
0
1000
2000
3000
4000
5000
BsmtFinSF1



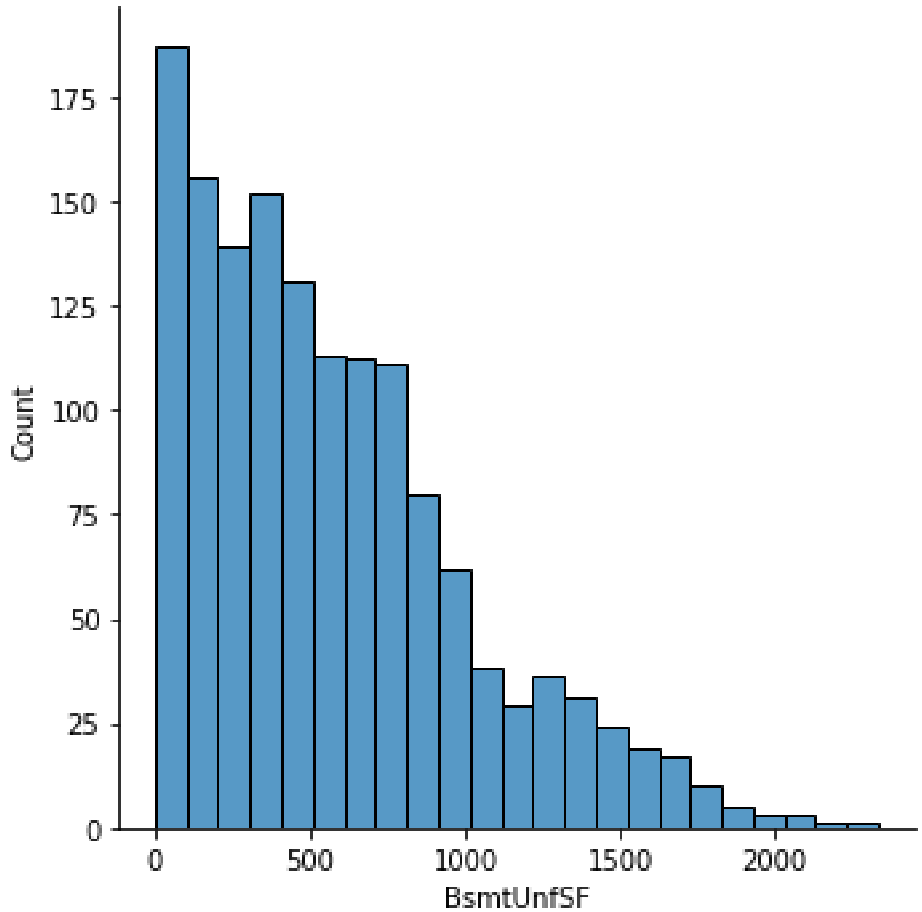
Count
1200
1000
800
600
400
200
0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
BsmtFinSF2

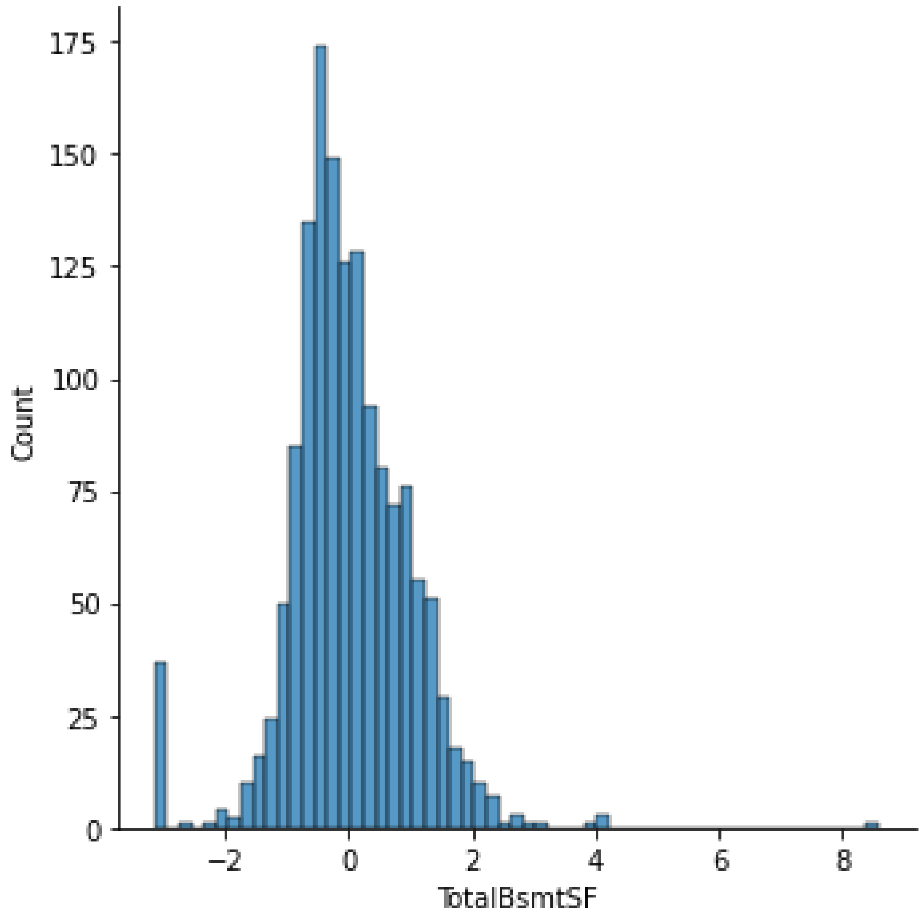


Count
0
200
400
600
800
1000
1200
0
200
400
600
800
1000
1200
1400
BsmtFinSF2

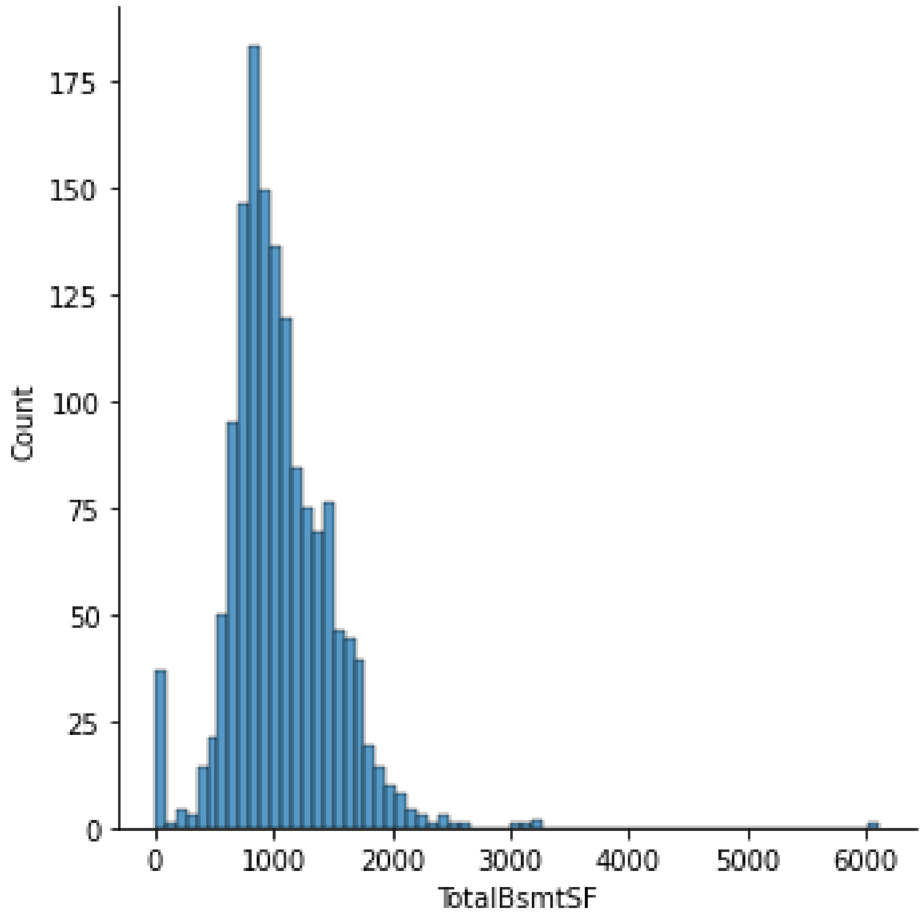


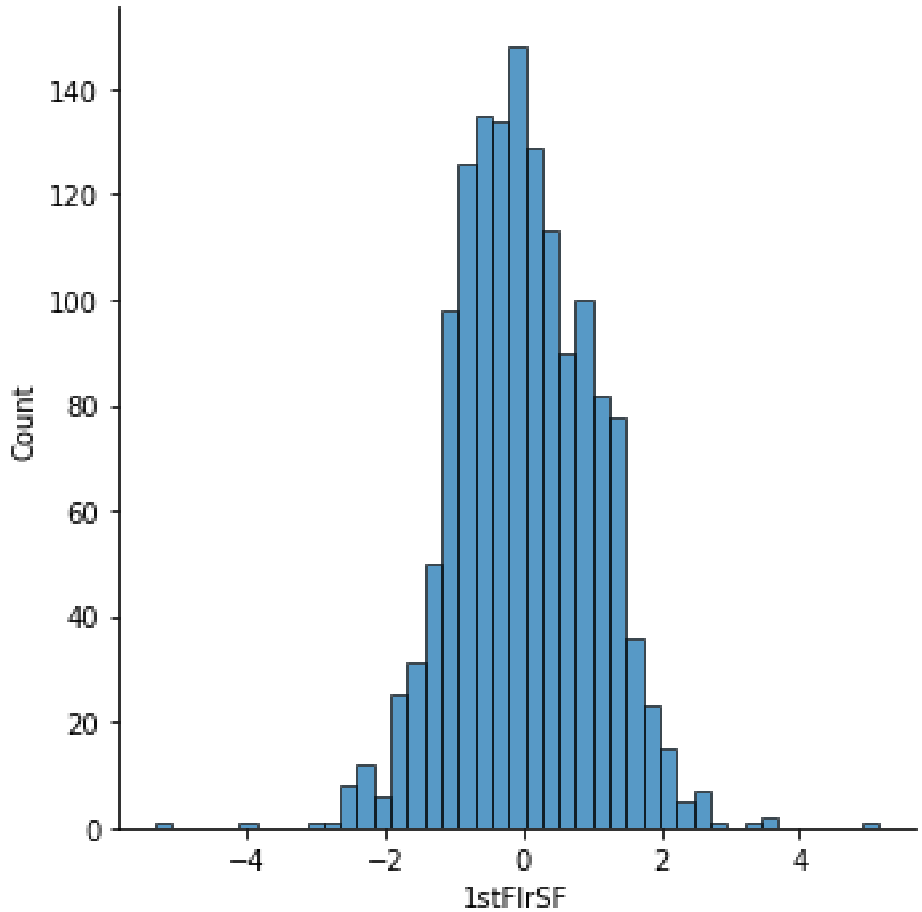
140
120
100
80
60
40
20
0
Count
−2
−1
0
1
2
BsmtUnfSF

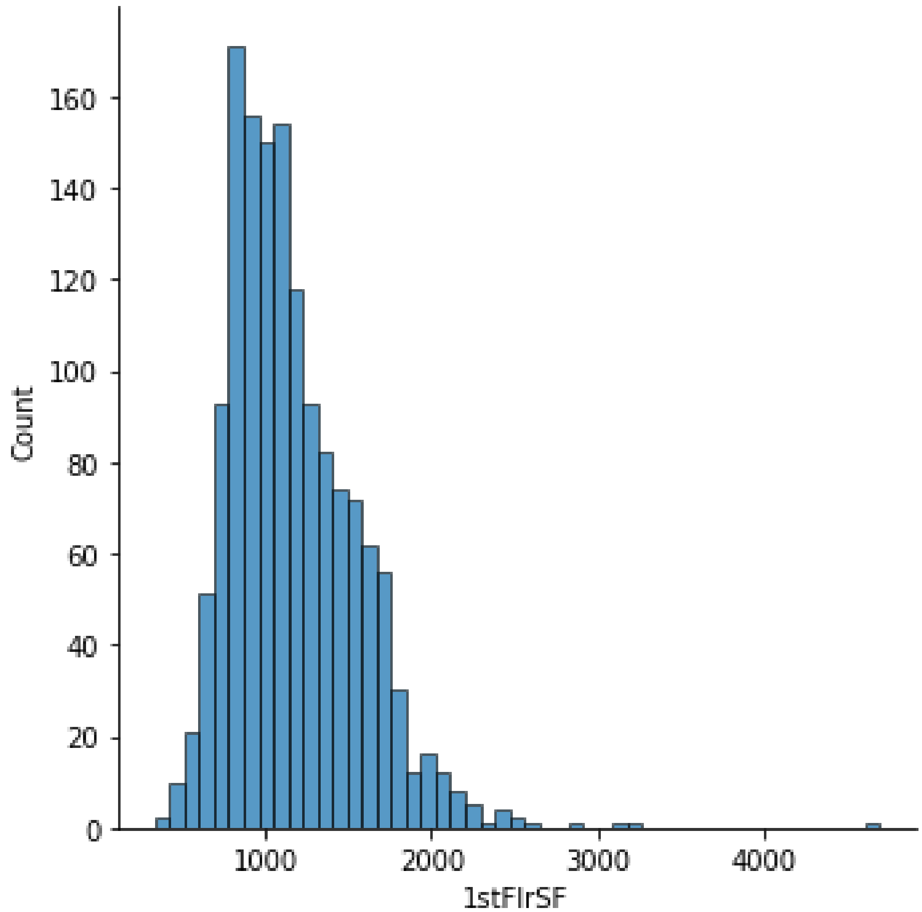

175
150
125
100
75
50
25
0
Count
0
500
1000
1500
2000
BsmtUnfSF



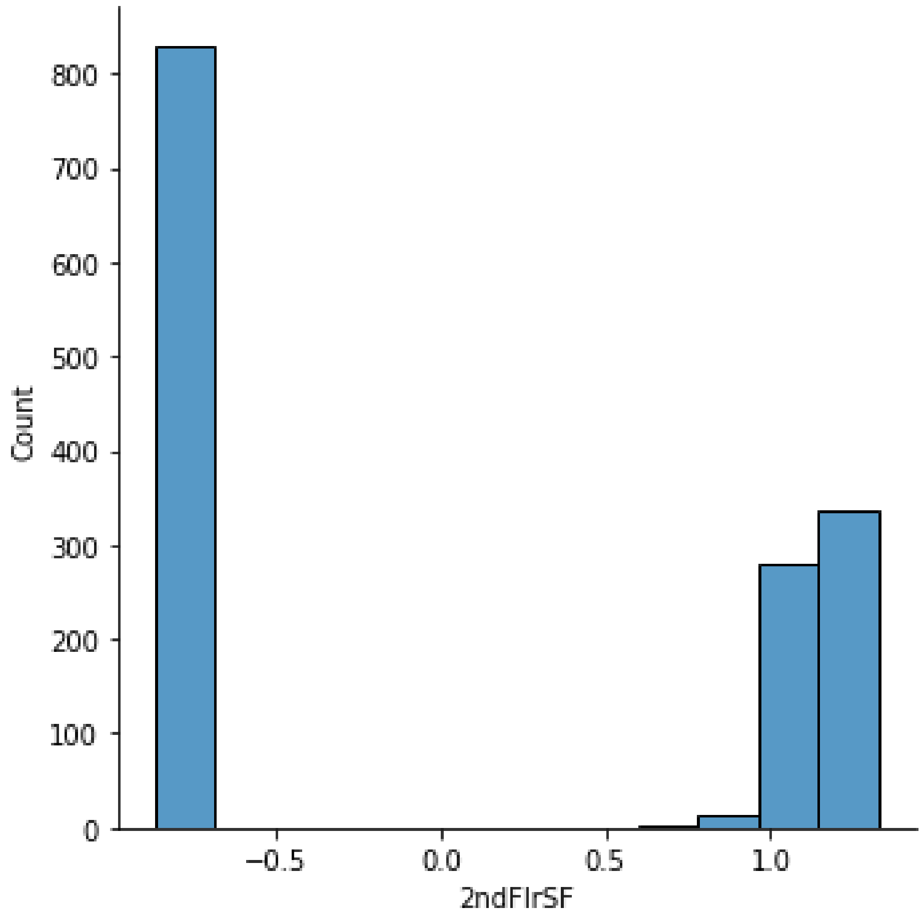
175
150
125
100
75
50
25
0
Count
−2
0
2
4
6
8
TotalBsmtSF

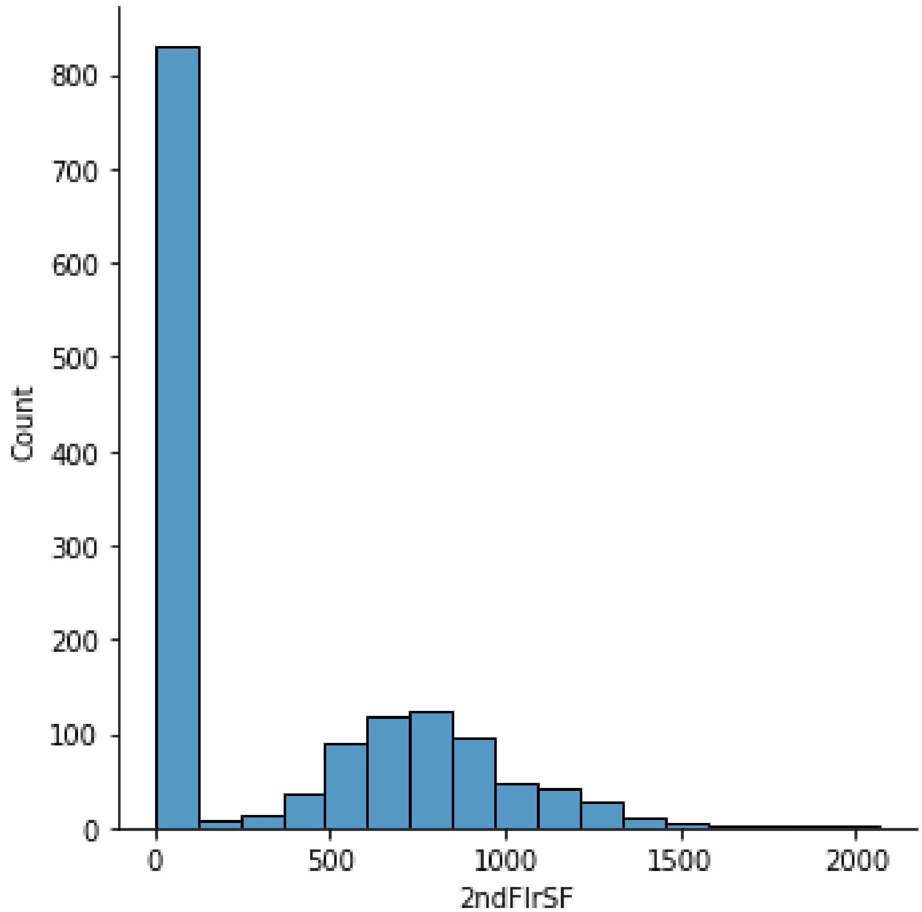

175
150
125
100
75
50
25
0
Count
0
1000
2000
3000
4000
5000
6000
TotalBsmtSF


Count
0
20
40
60
80
100
120
140
−4
−2
0
2
4
1stFlrSF

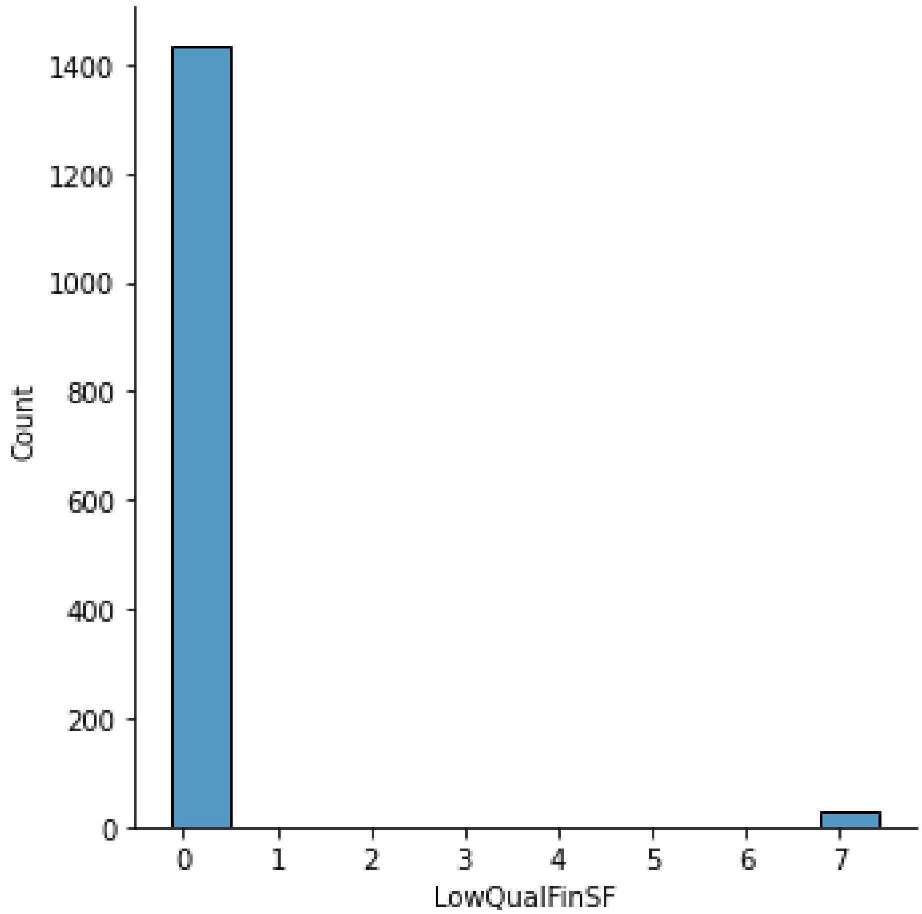


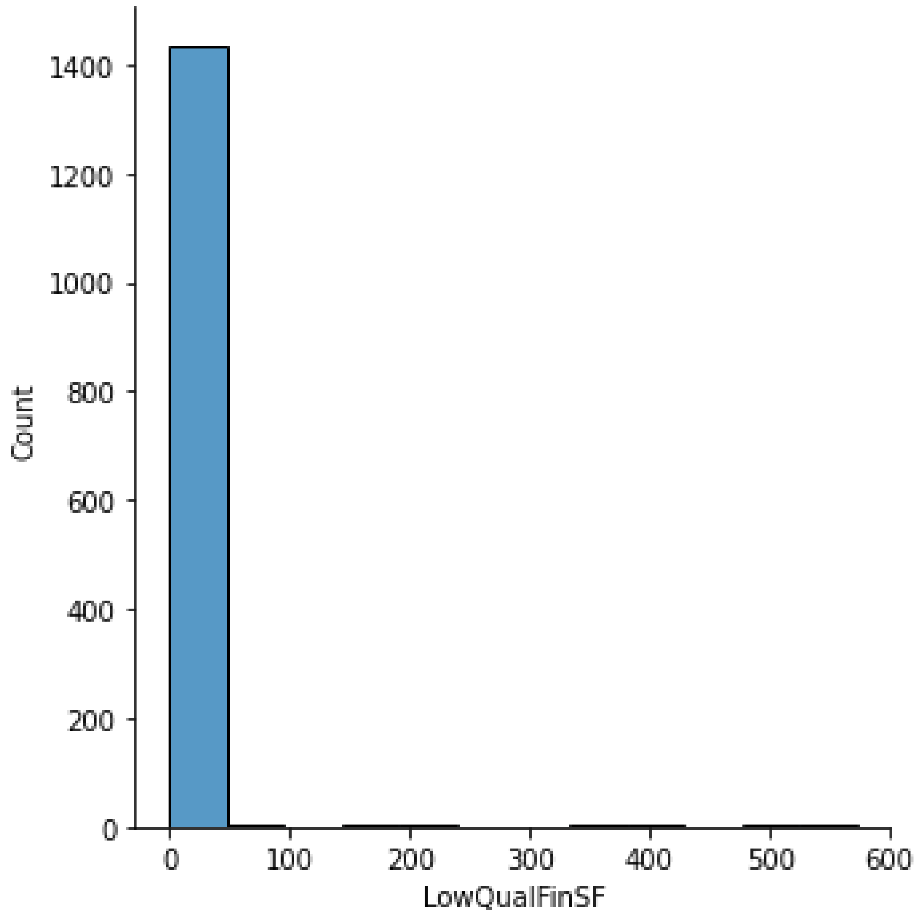
160
140
120
100
80
60
40
20
0
Count
1000
2000
3000
4000
1stFlrSF


800
700
600
500
400
300
200
100
0
Count
−0.5
0.0
0.5
1.0
2ndFlrSF

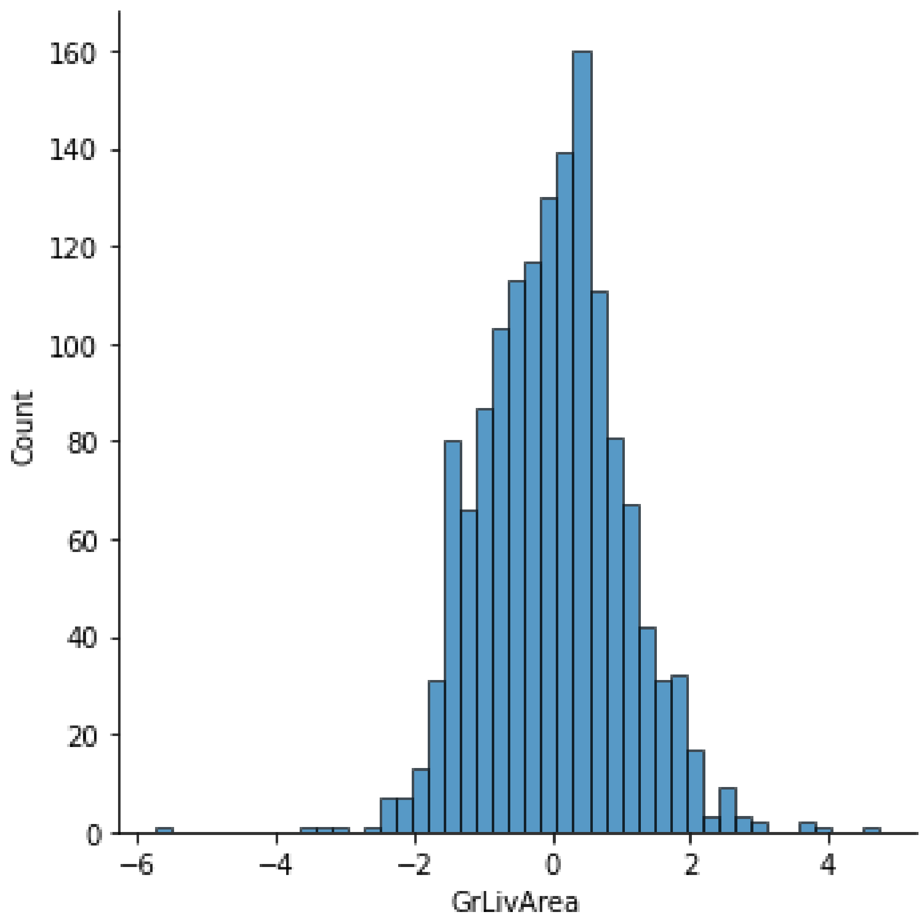


800
700
600
500
400
300
200
100
0
Count
0
500
1000
1500
2000
2ndFlrSF

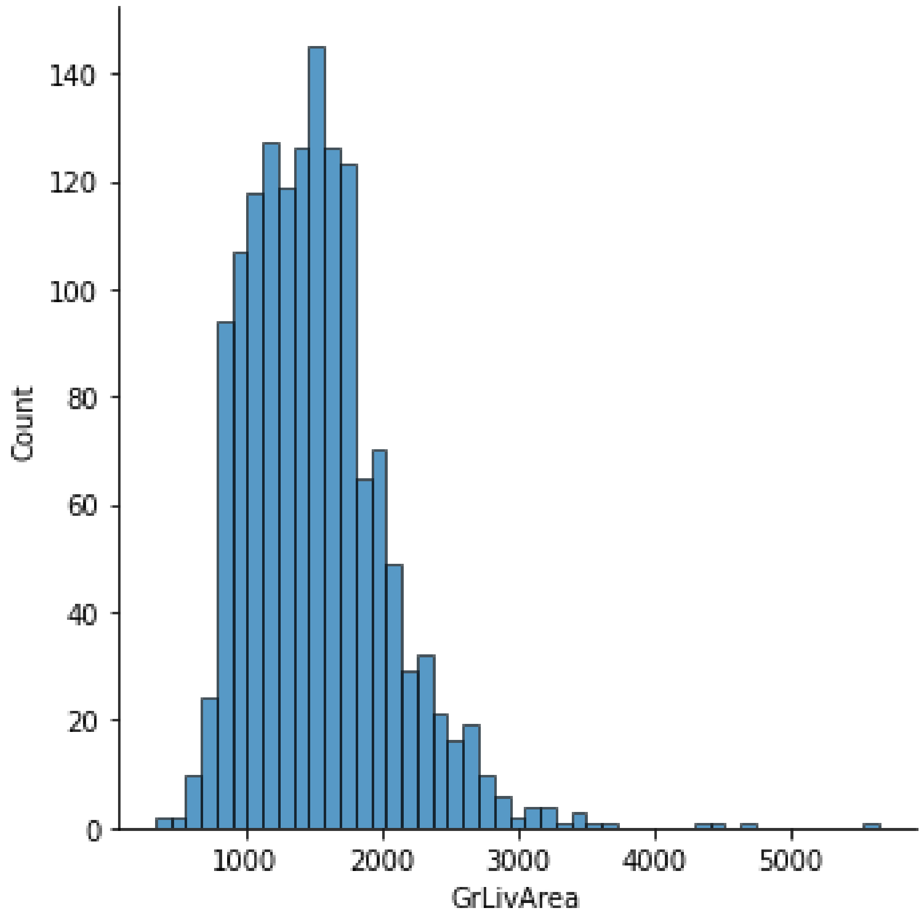

1400
1200
1000
800
600
400
200
0
Count
0
1
2
3
4
5
6
7
LowQualFinSF



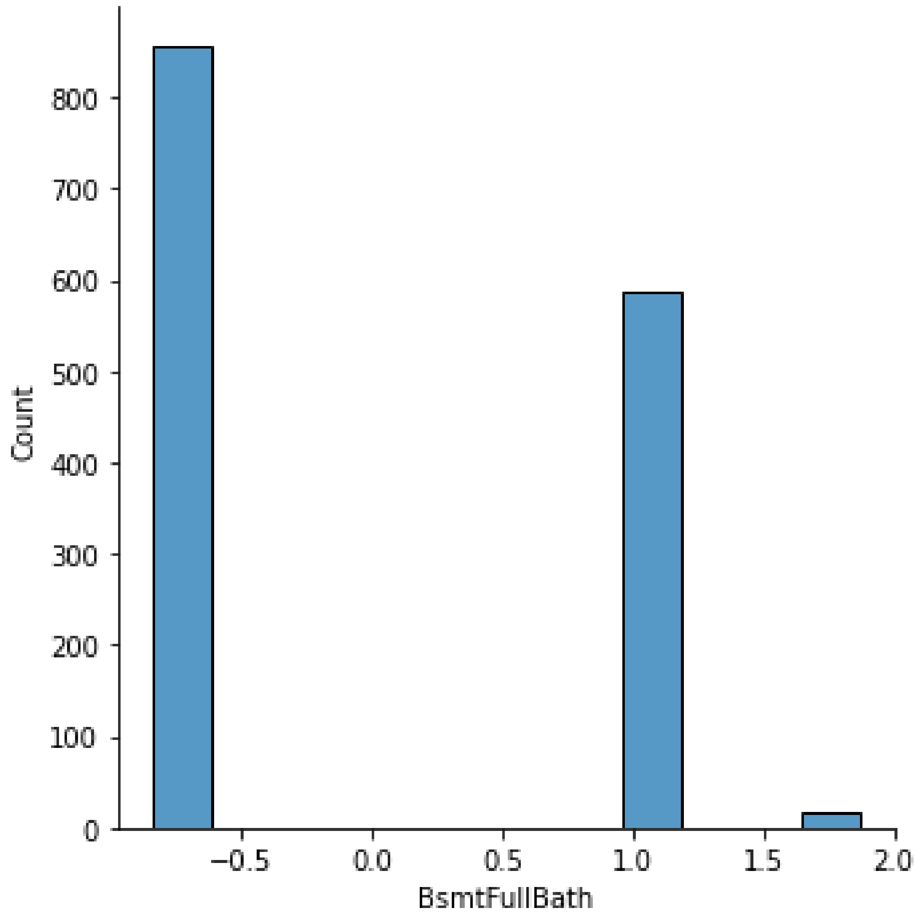
1400
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
600
LowQualFinSF



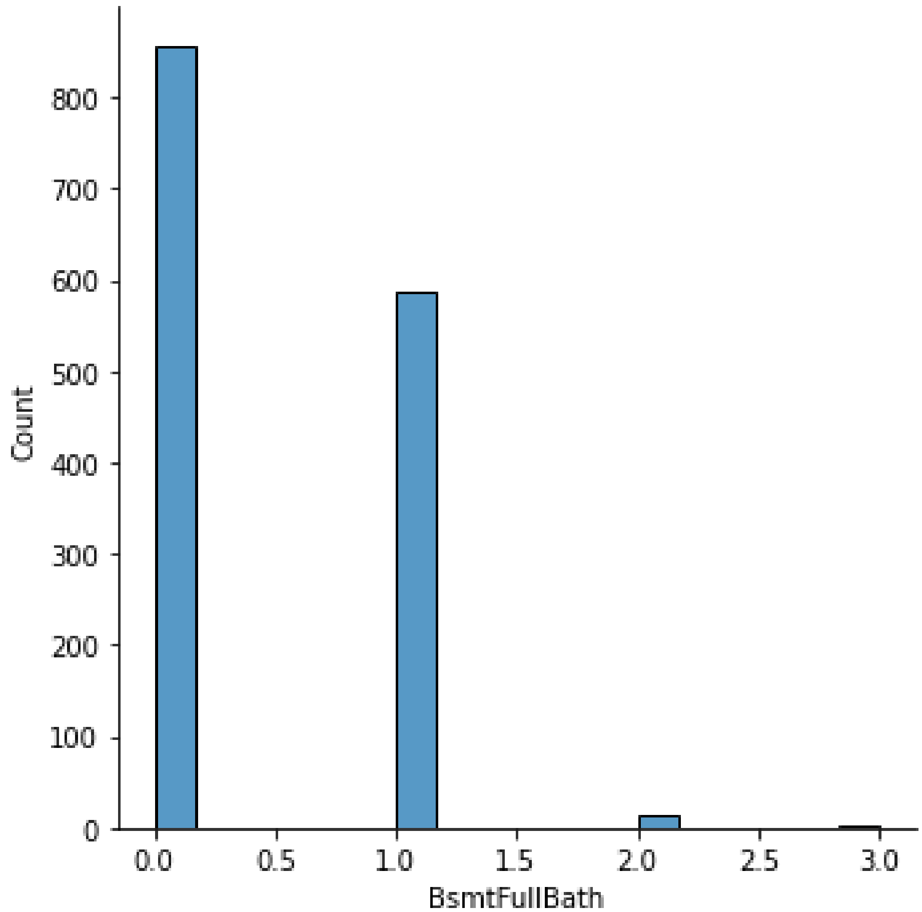
160
140
120
100
80
60
40
20
0
Count
−6
−4
−2
0
2
4
GrLivArea

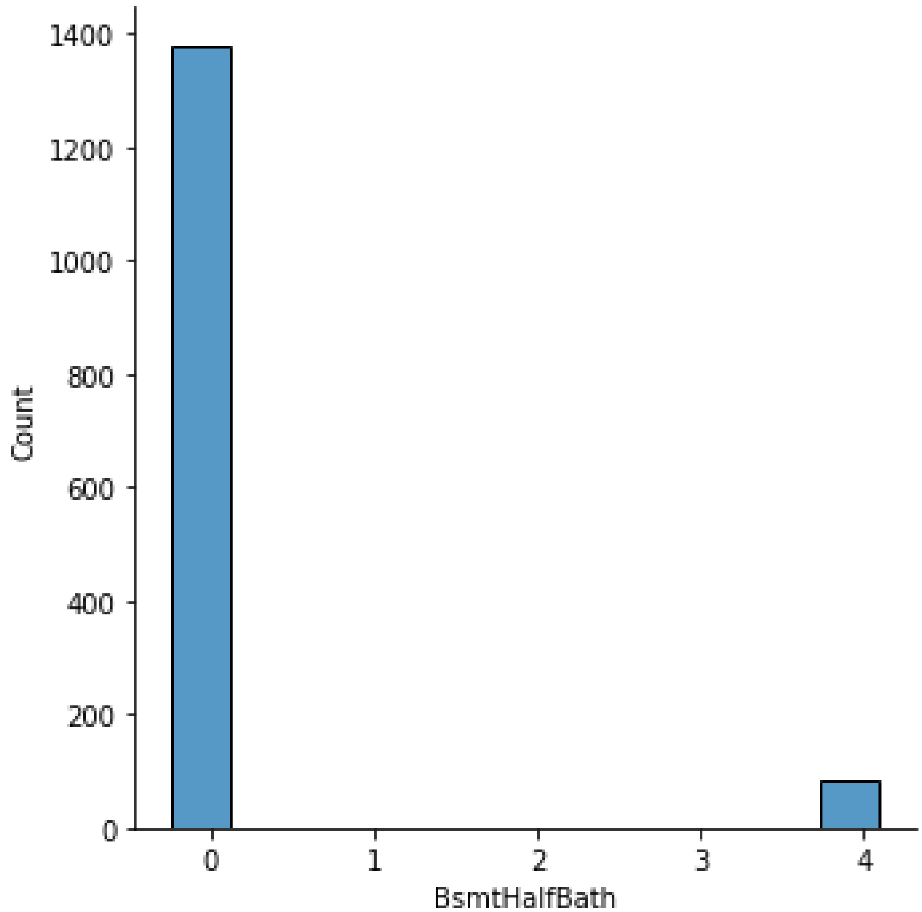


140
120
100
80
60
40
20
0
Count
1000
2000
3000
4000
5000
GrLivArea

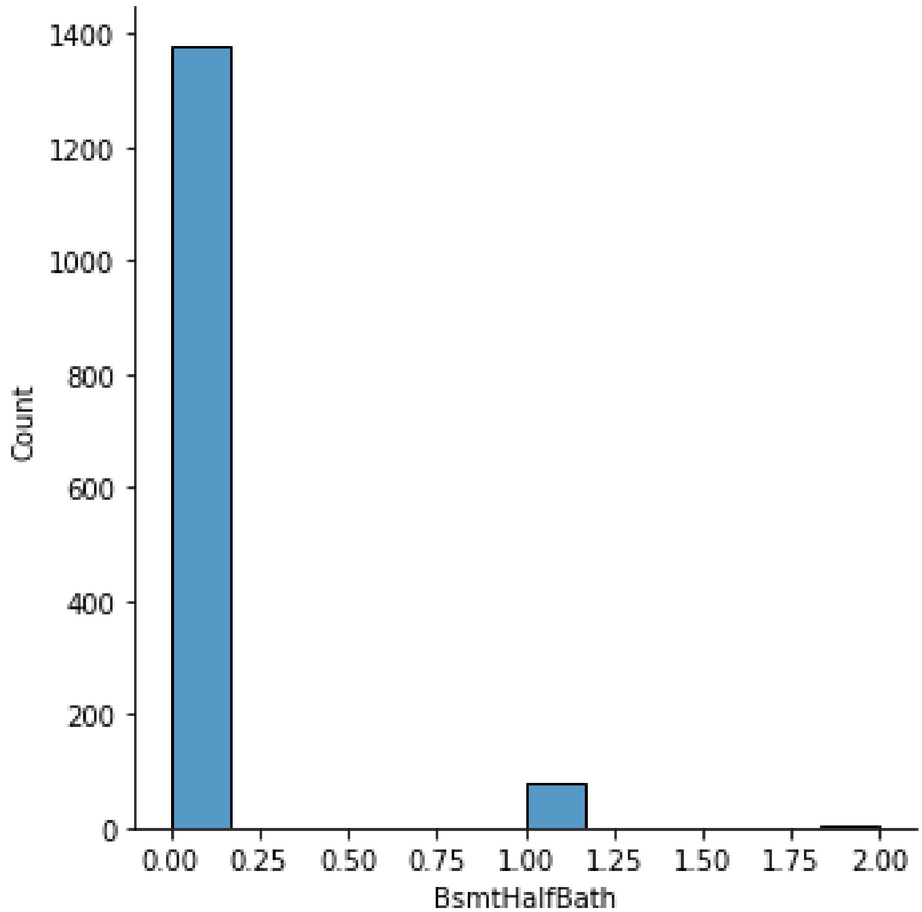


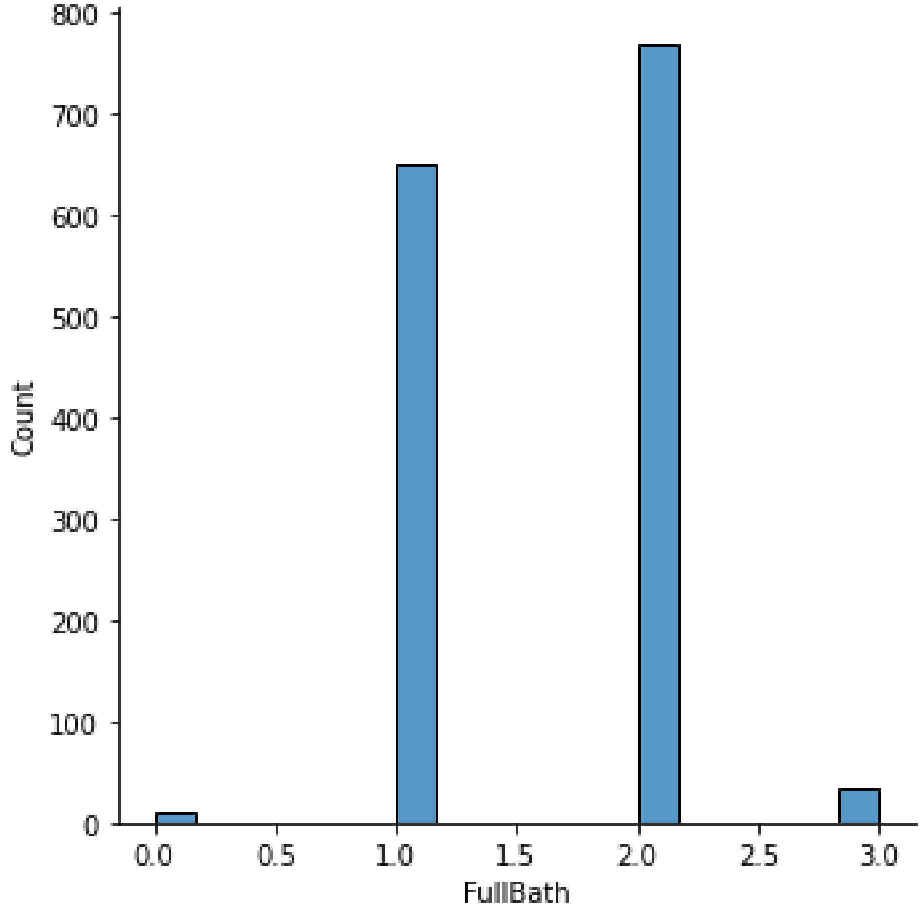
Count
800
700
600
500
400
300
200
100
0
−0.5
0.0
0.5
1.0
1.5
2.0
BsmtFullBath

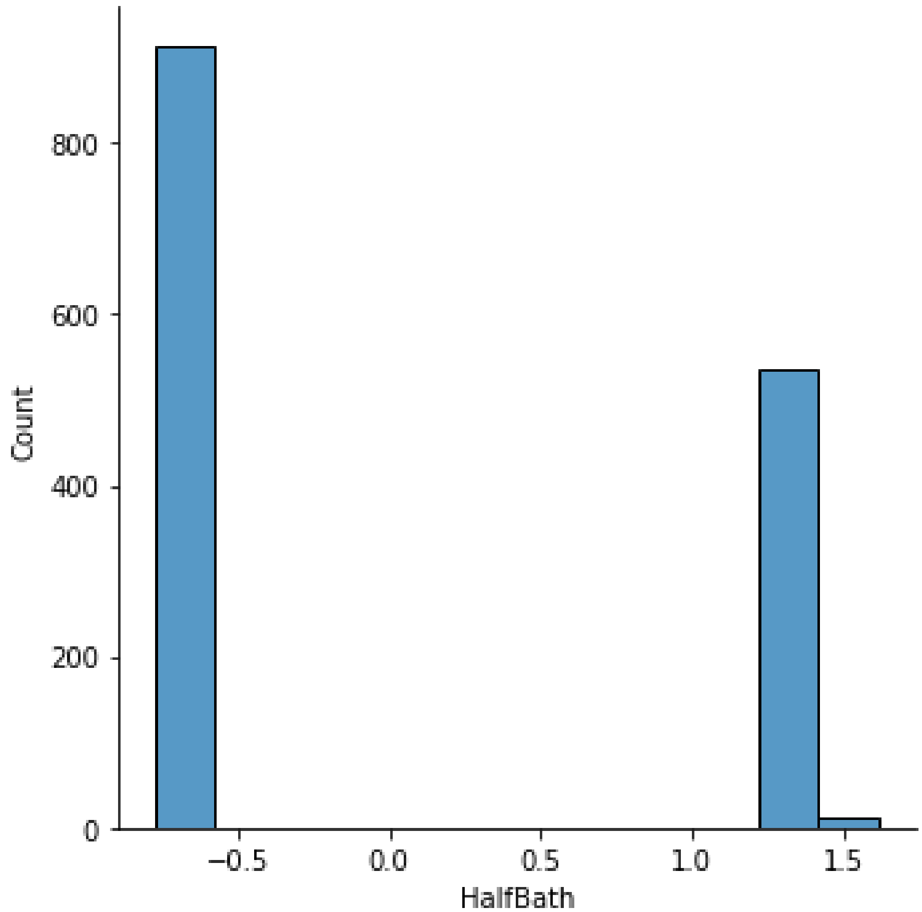

800
700
600
500
400
300
200
100
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
BsmtFullBath

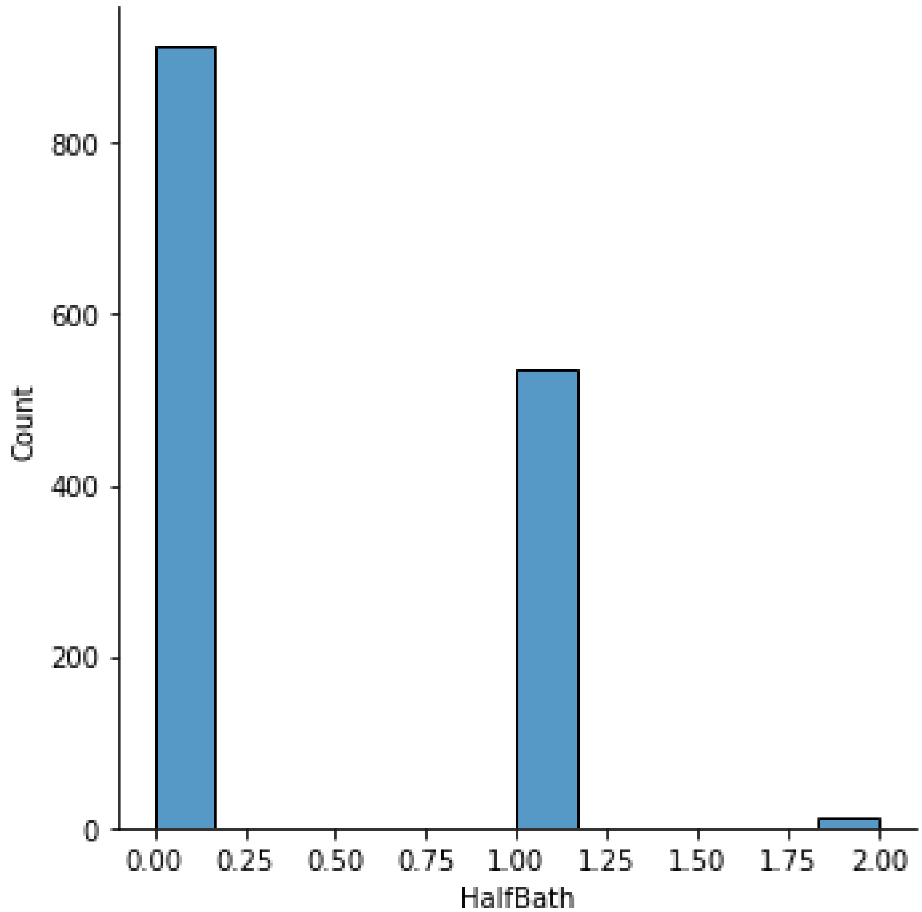


1400
1200
1000
800
600
400
200
0
Count
0
1
2
3
4
BsmtHalfBath

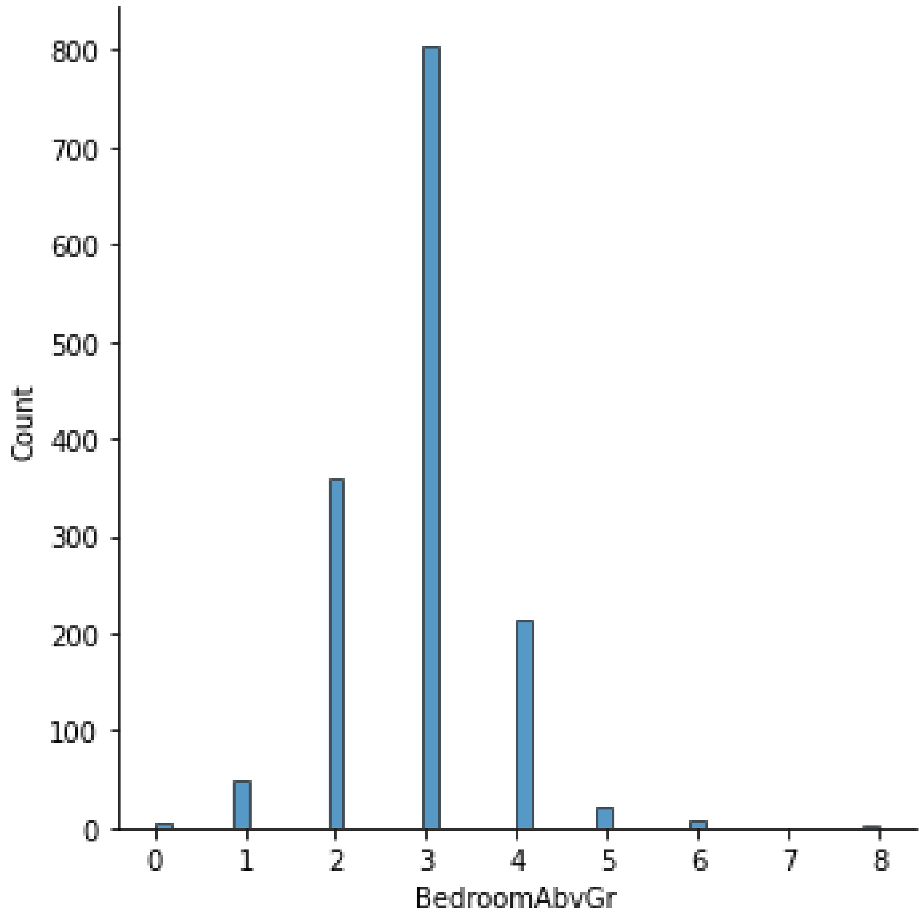

1400
1200
1000
800
600
400
200
0
Count
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
BsmtHalfBath


800
700
600
500
400
300
200
100
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
FullBath

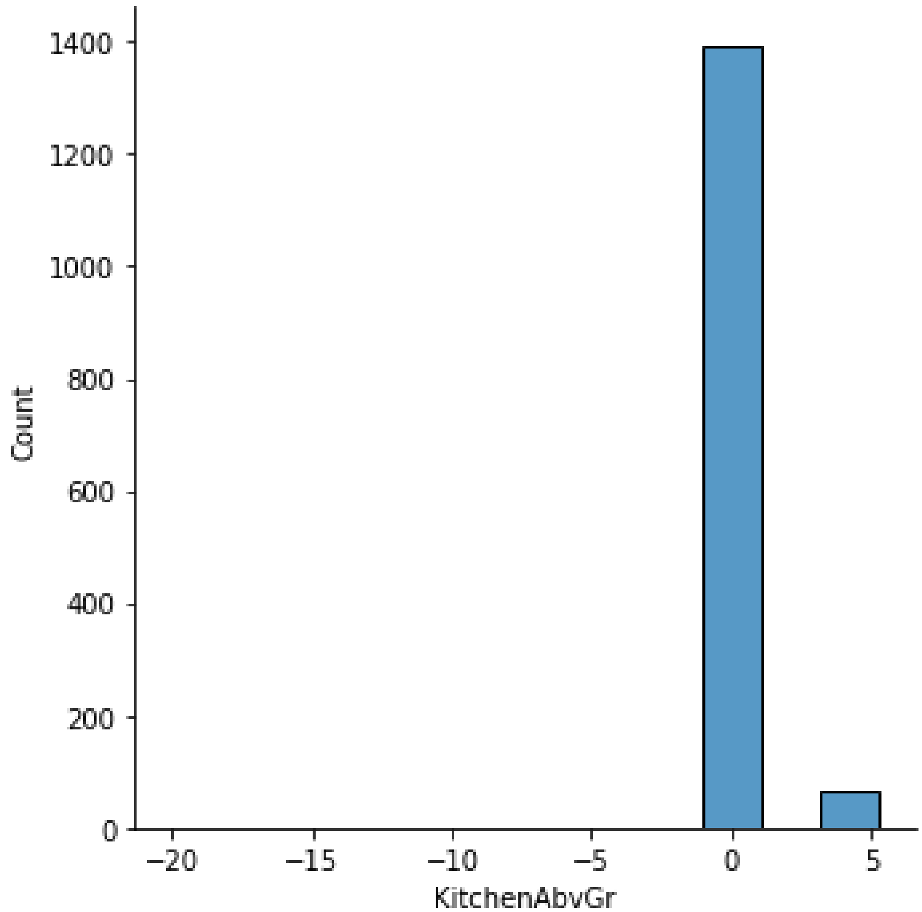

800
600
400
200
0
Count
−0.5
0.0
0.5
1.0
1.5
HalfBath

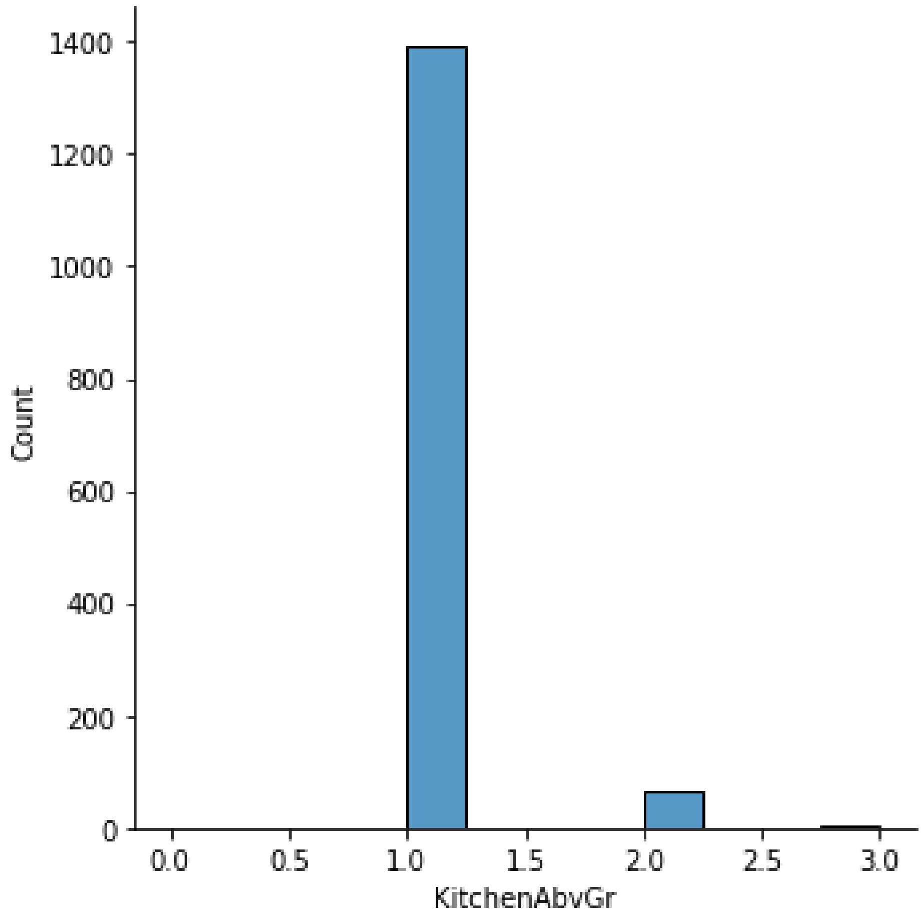


800
600
400
200
0
Count
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
HalfBath

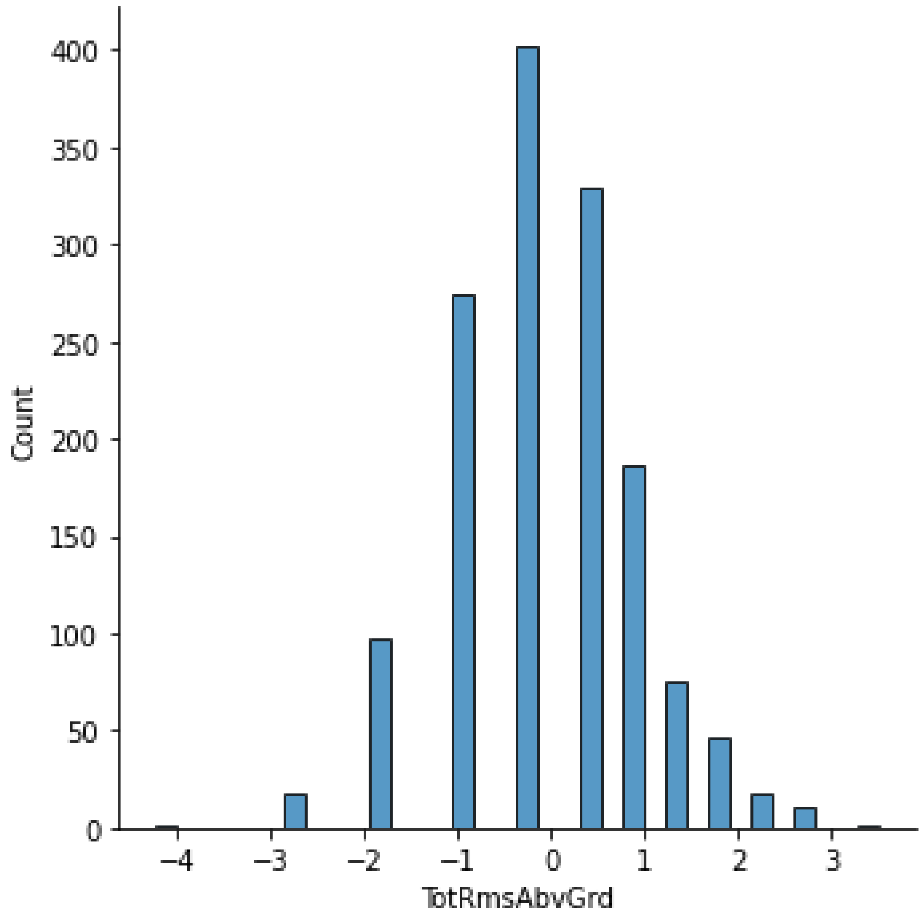


800
700
600
500
400
300
200
100
0
Count
0
1
2
3
4
5
6
7
8
BedroomAbvGr

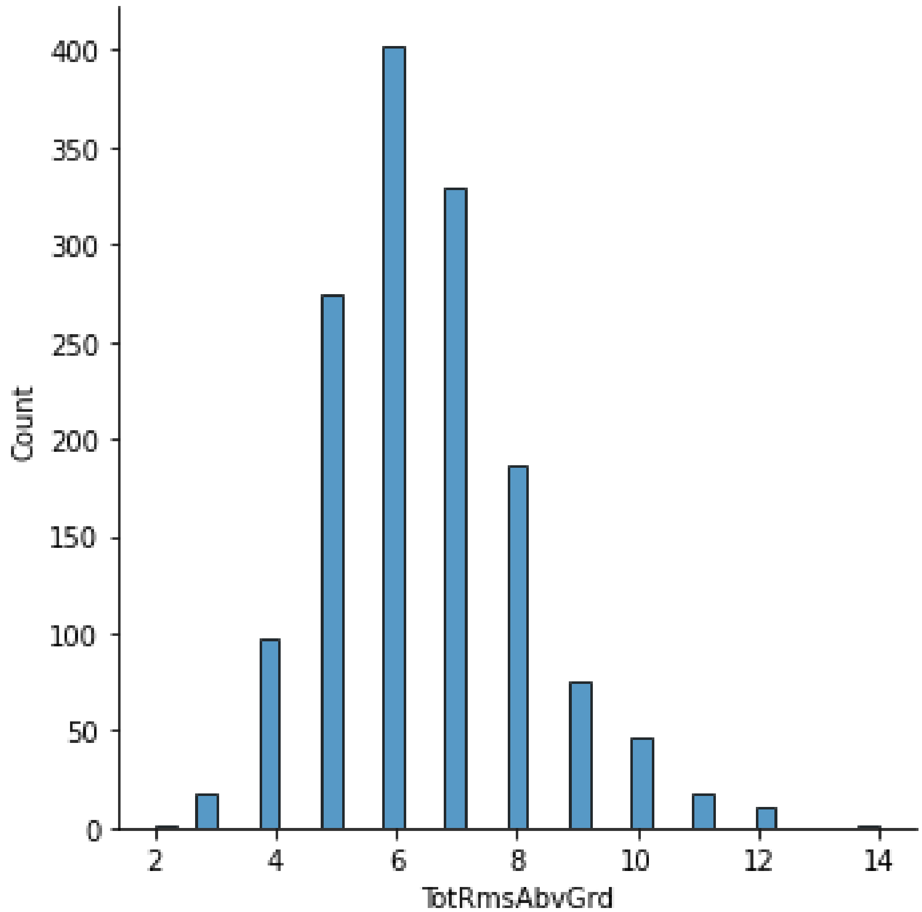

1400
1200
1000
800
600
400
200
0
Count
−20
−15
−10
−5
0
5
KitchenAbvGr

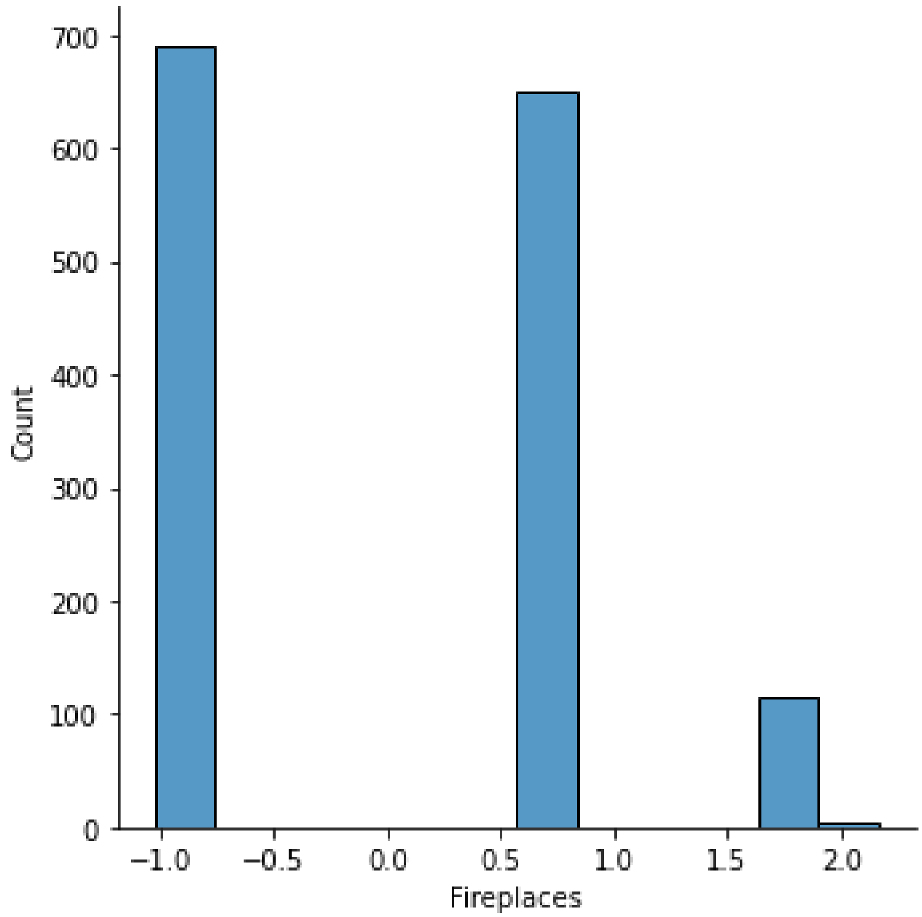


1400
1200
1000
800
600
400
200
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
KitchenAbvGr

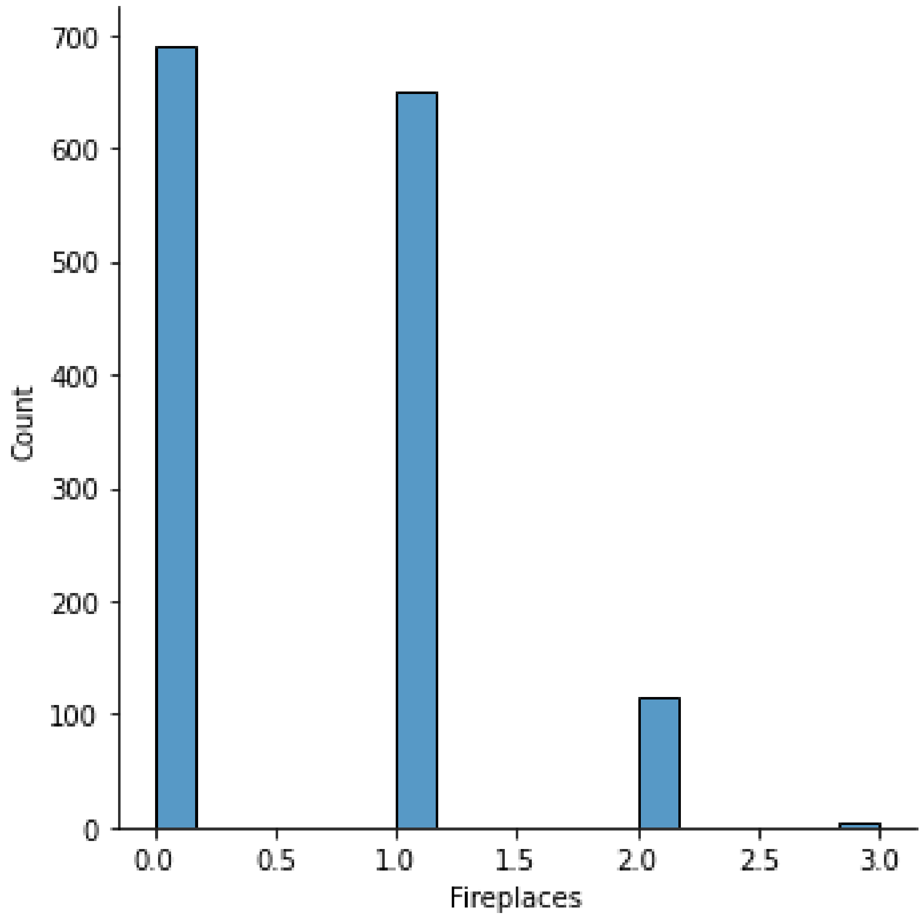


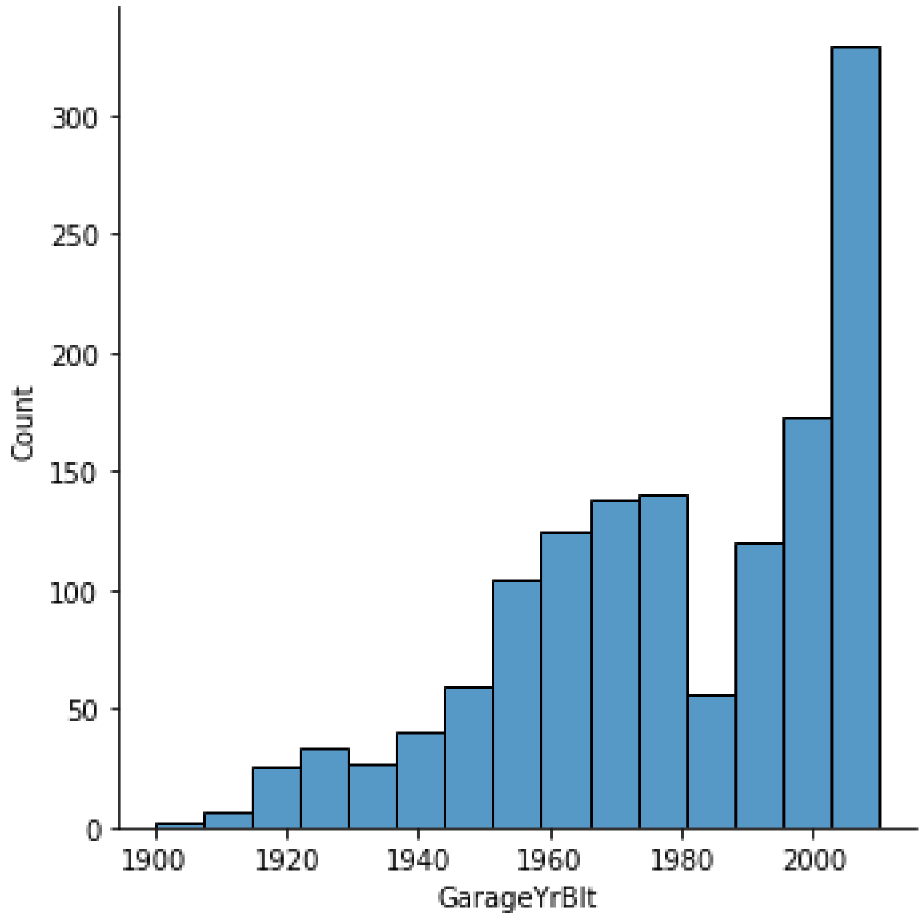
400
350
300
250
200
150
100
50
0
Count
−4
−3
−2
−1
0
1
2
3
TotRmsAbvGrd


400
350
300
250
200
150
100
50
0
Count
2
4
6
8
10
12
14
TotRmsAbvGrd

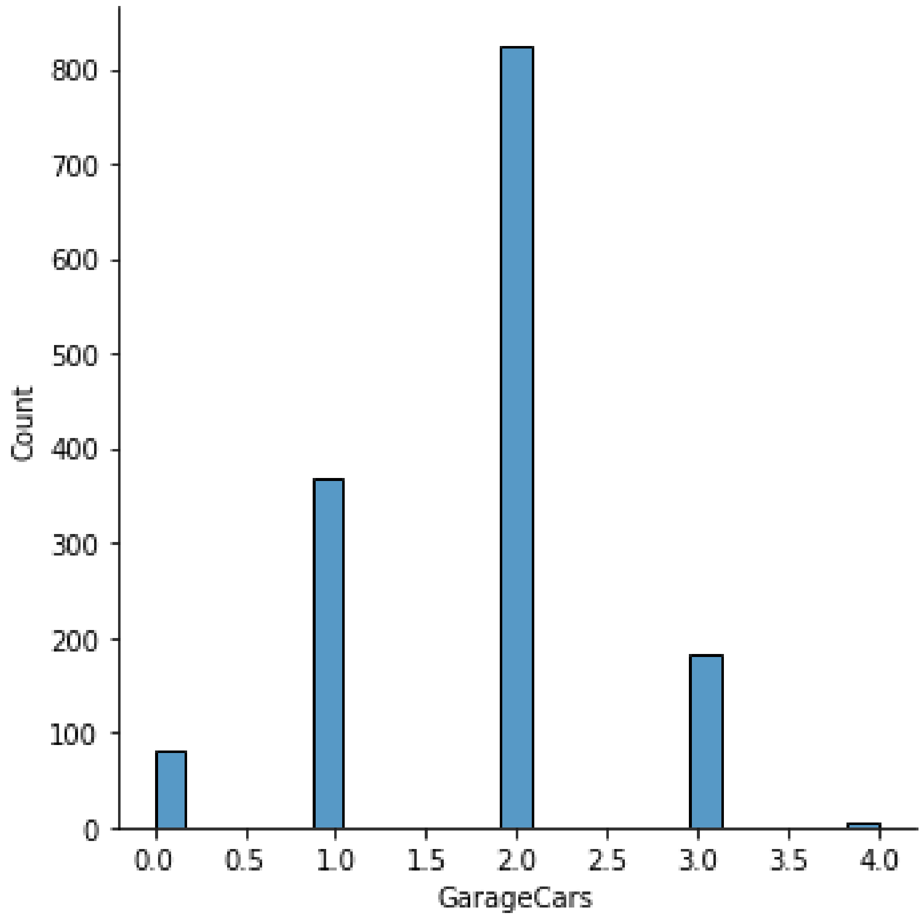


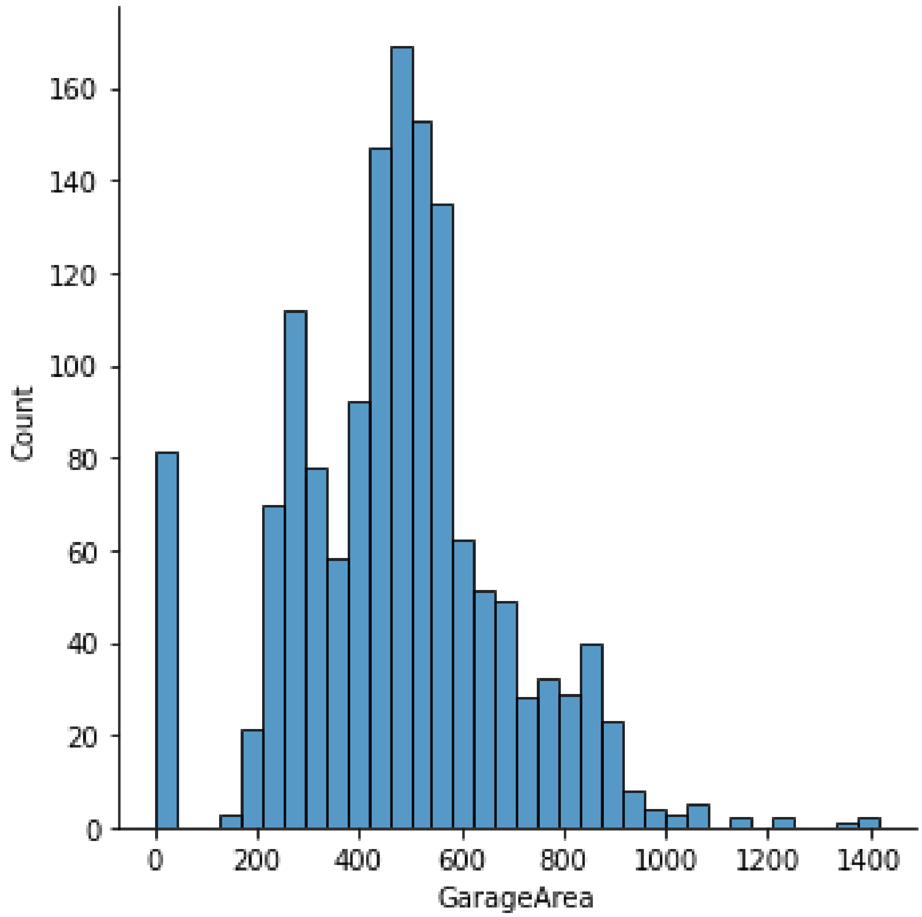
700
600
500
400
300
200
100
0
Count
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Fireplaces

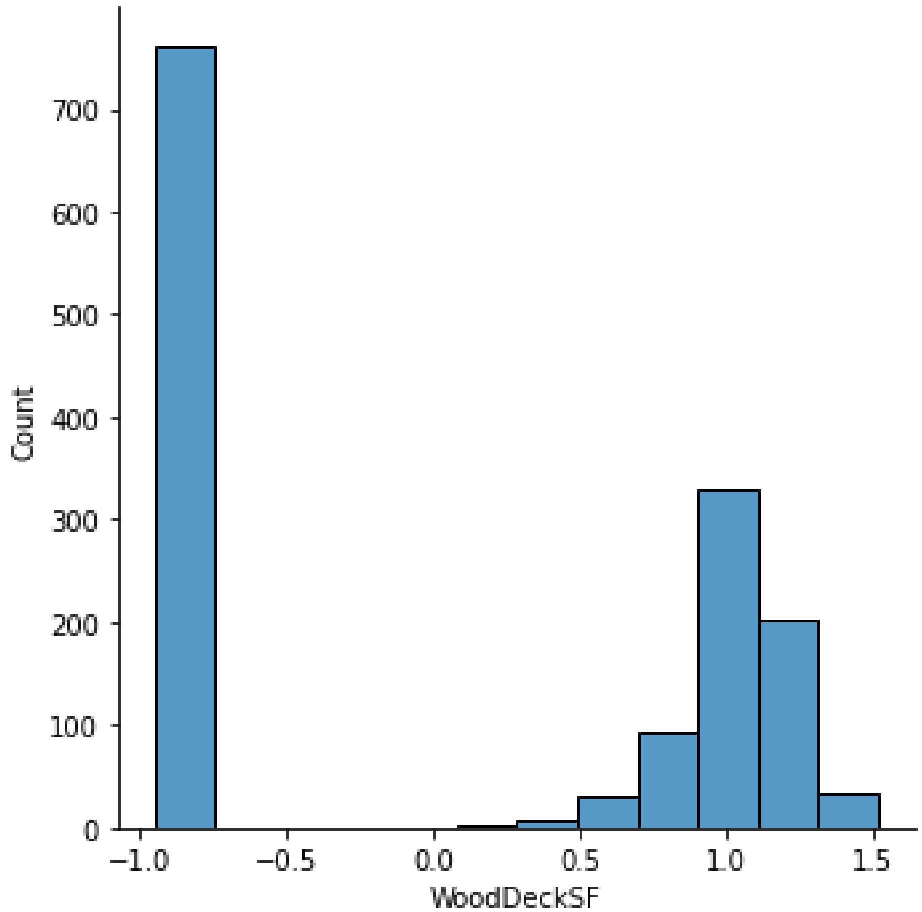

700
600
500
400
300
200
100
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Fireplaces



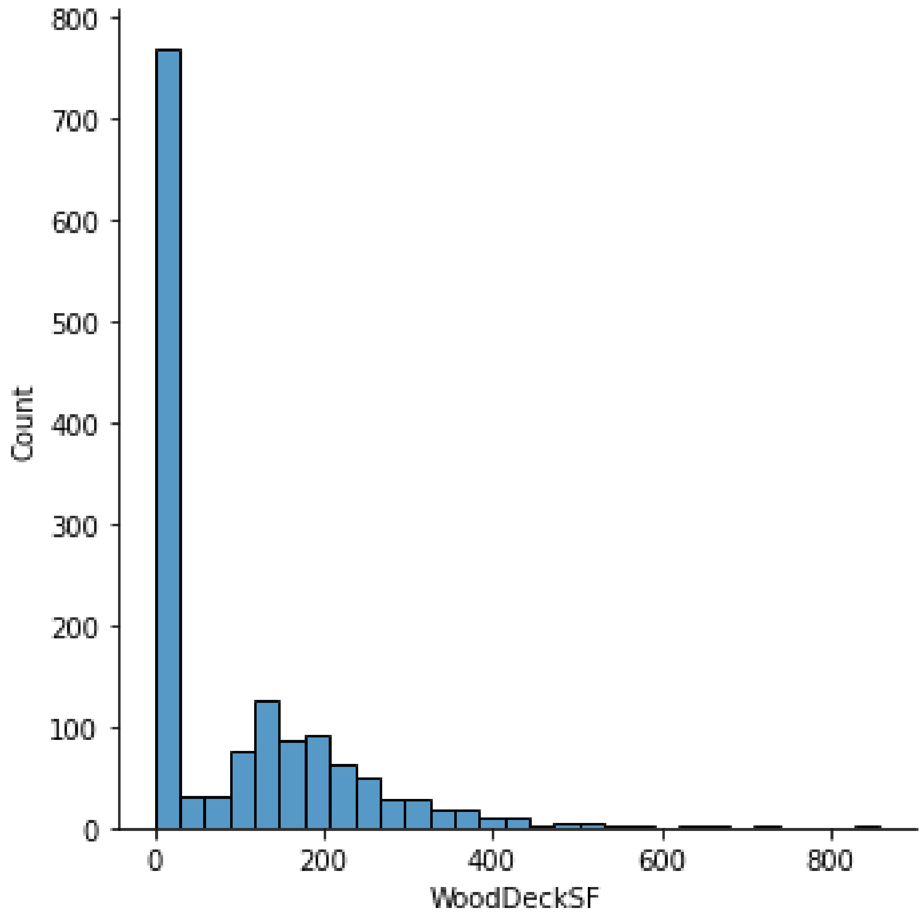
300
250
200
150
100
50
0
Count
1900
1920
1940
1960
1980
2000
GarageYrBlt

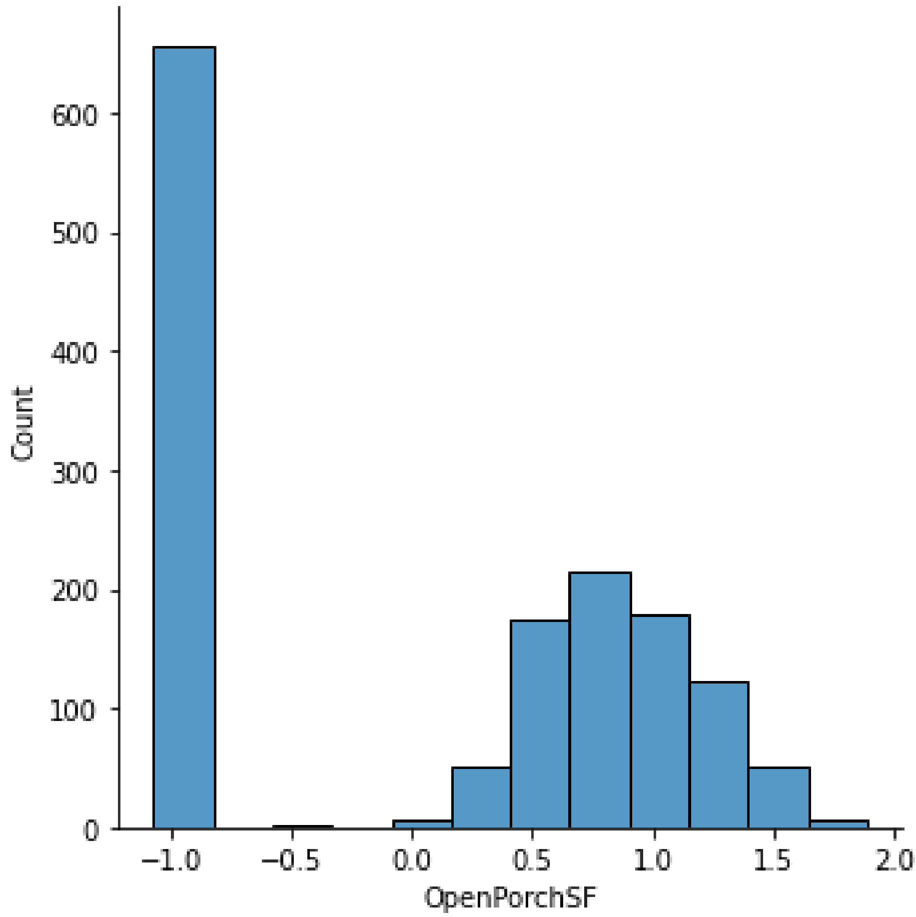

800
700
600
500
400
300
200
100
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
GarageCars

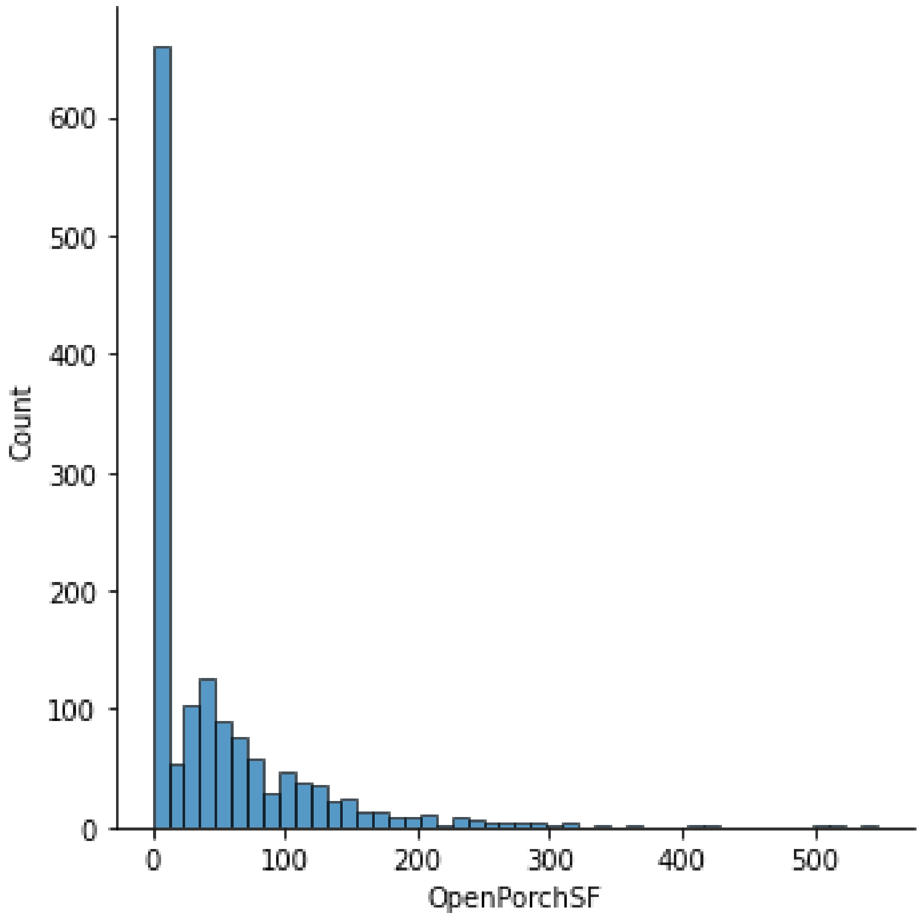

160
140
120
100
80
60
40
20
0
Count
0
200
400
600
800
1000
1200
1400
GarageArea

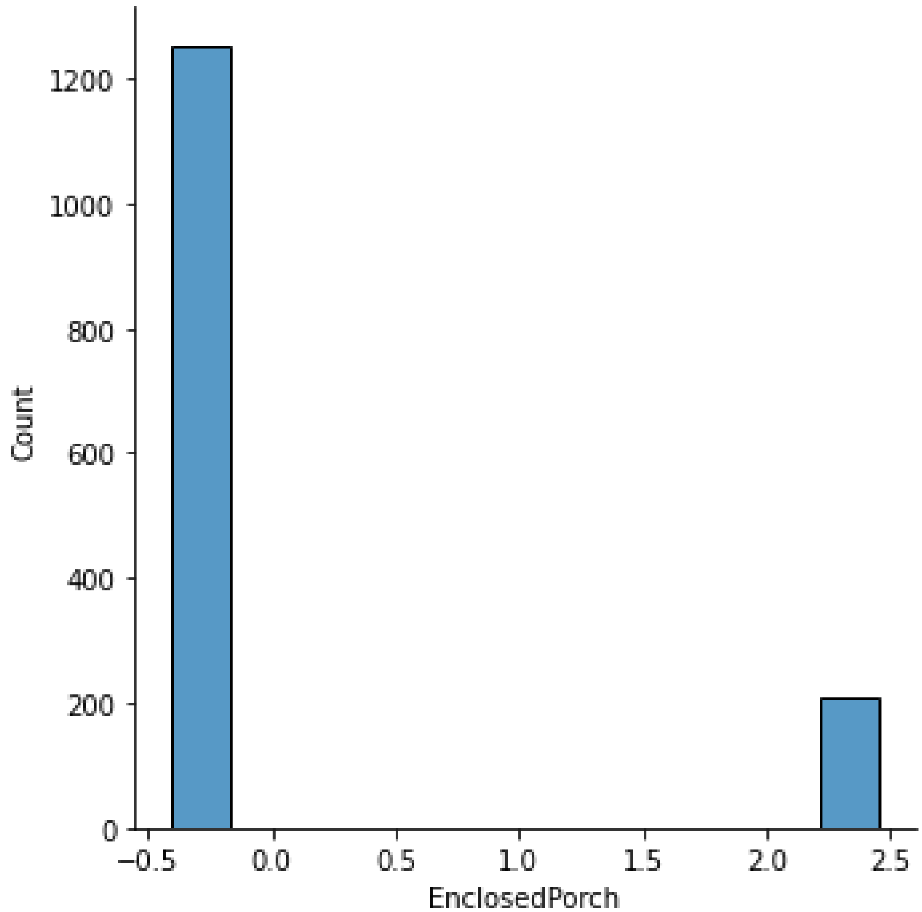


Count
0
100
200
300
400
500
600
700
−1.0
−0.5
0.0
0.5
1.0
1.5
WoodDeckSF

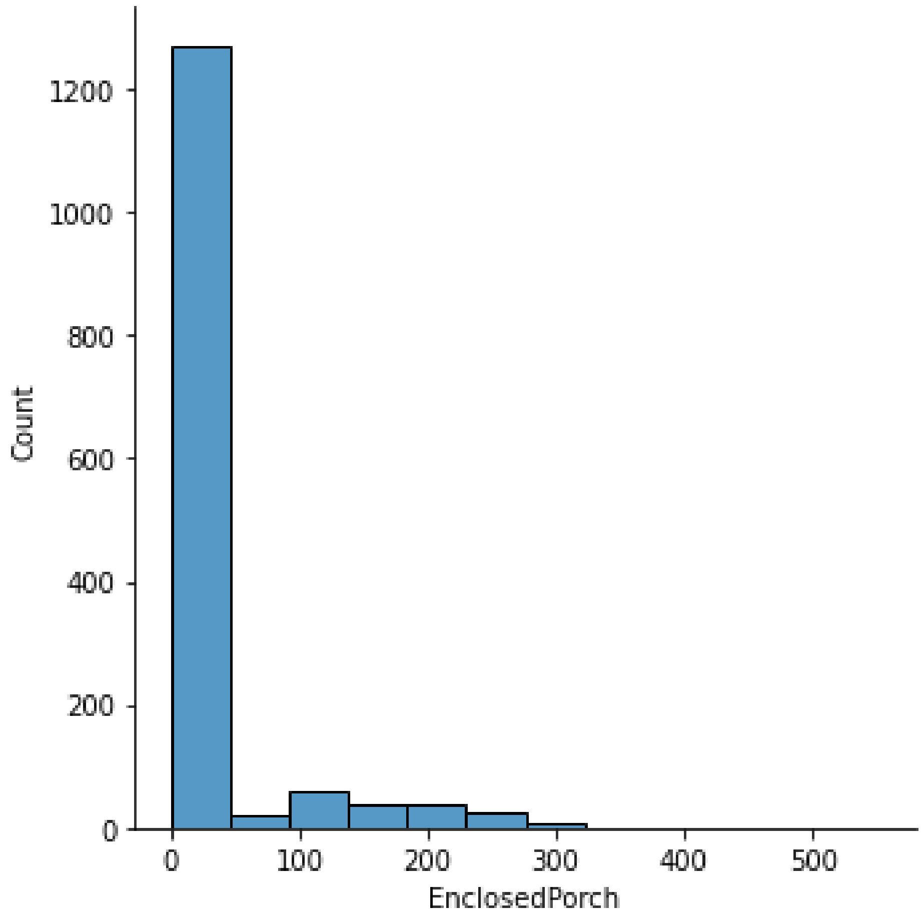

800
700
600
500
400
300
200
100
0
Count
0
200
400
600
800
WoodDeckSF

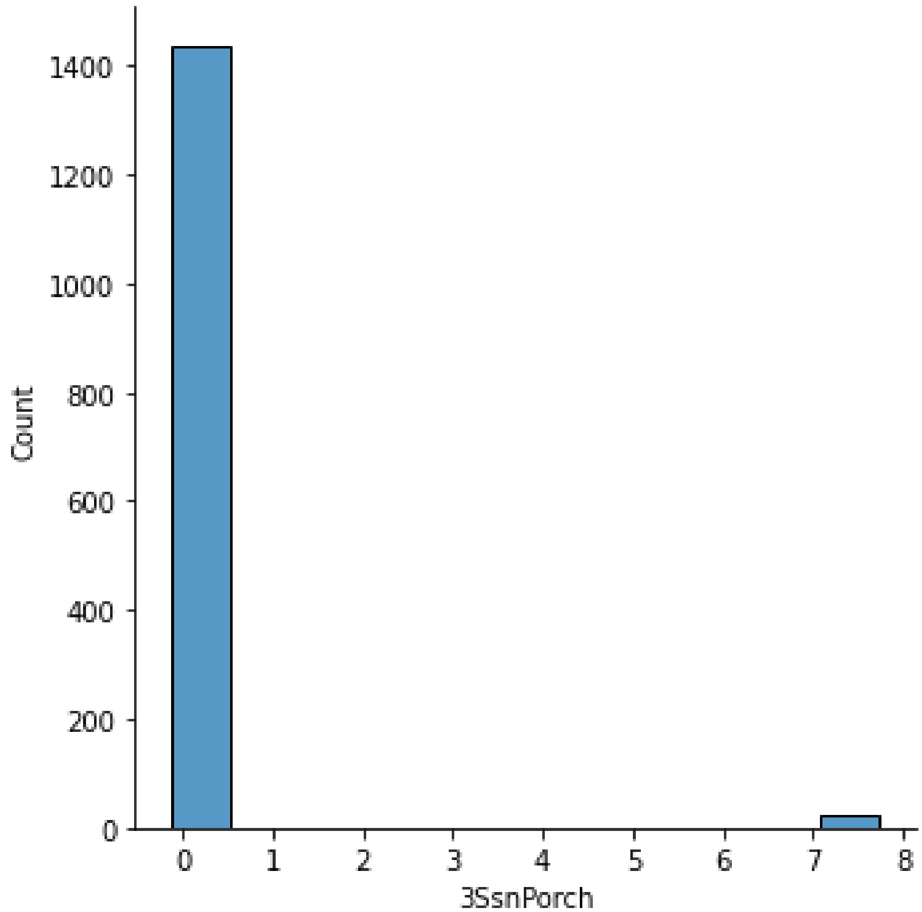

Count
0
100
200
300
400
500
600
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
OpenPorchSF

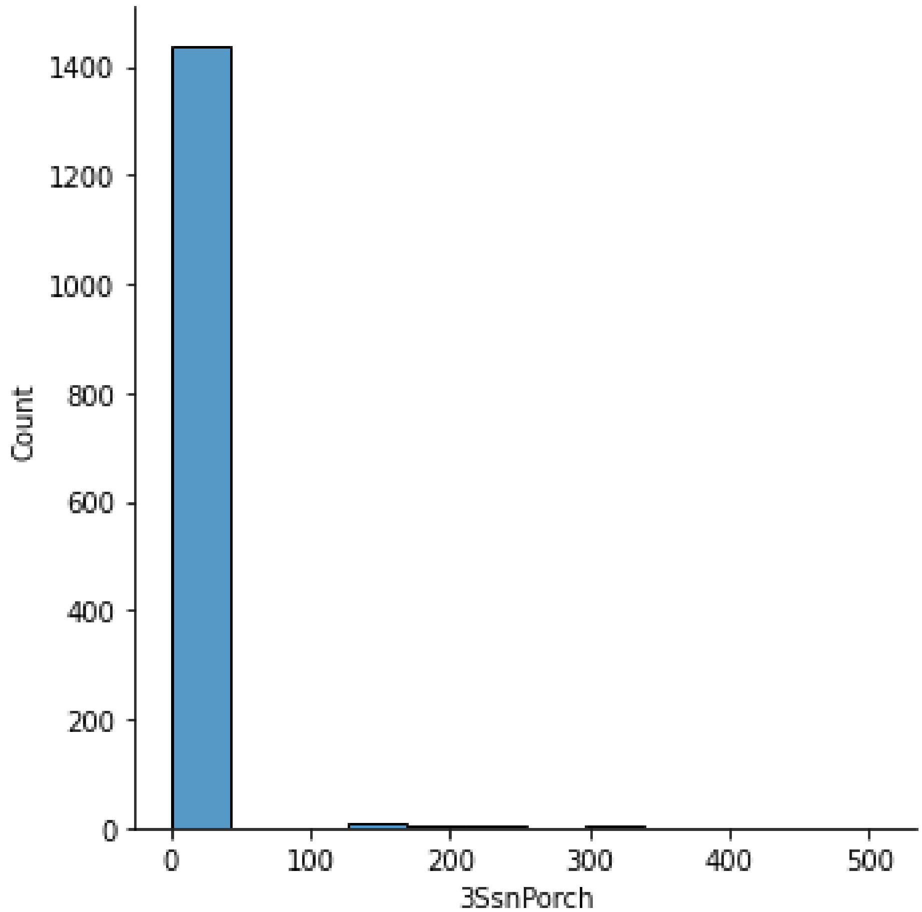

Count
600
500
400
300
200
100
0
0
100
200
300
400
500
OpenPorchSF

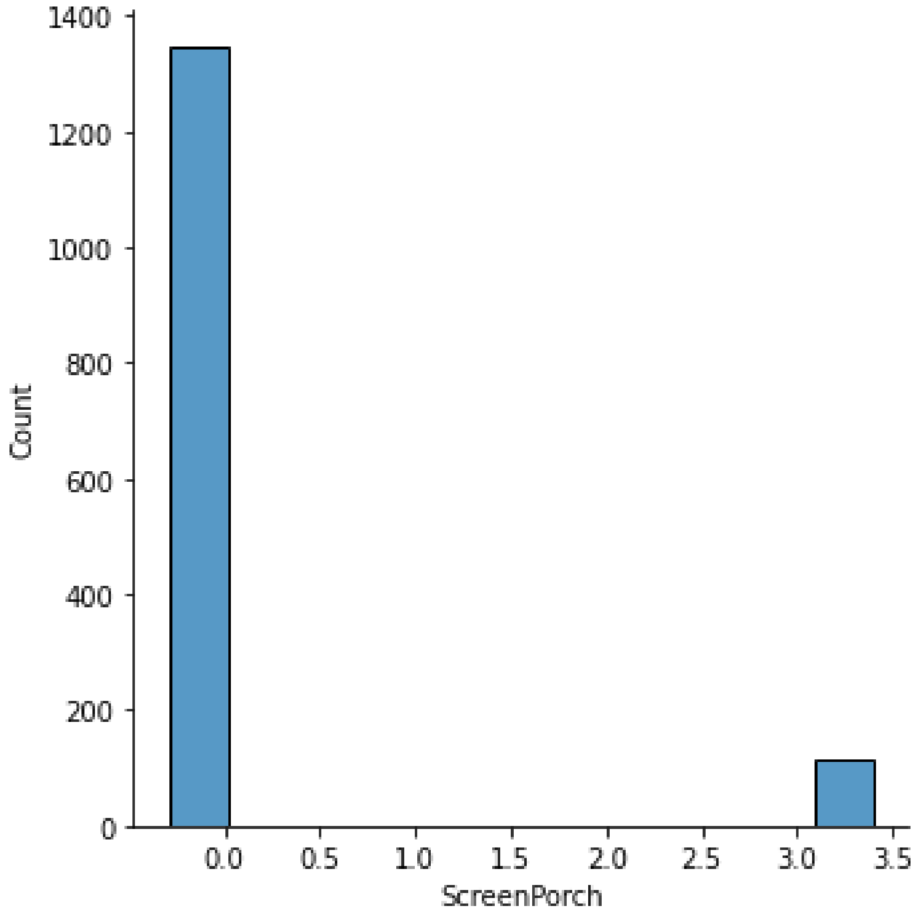


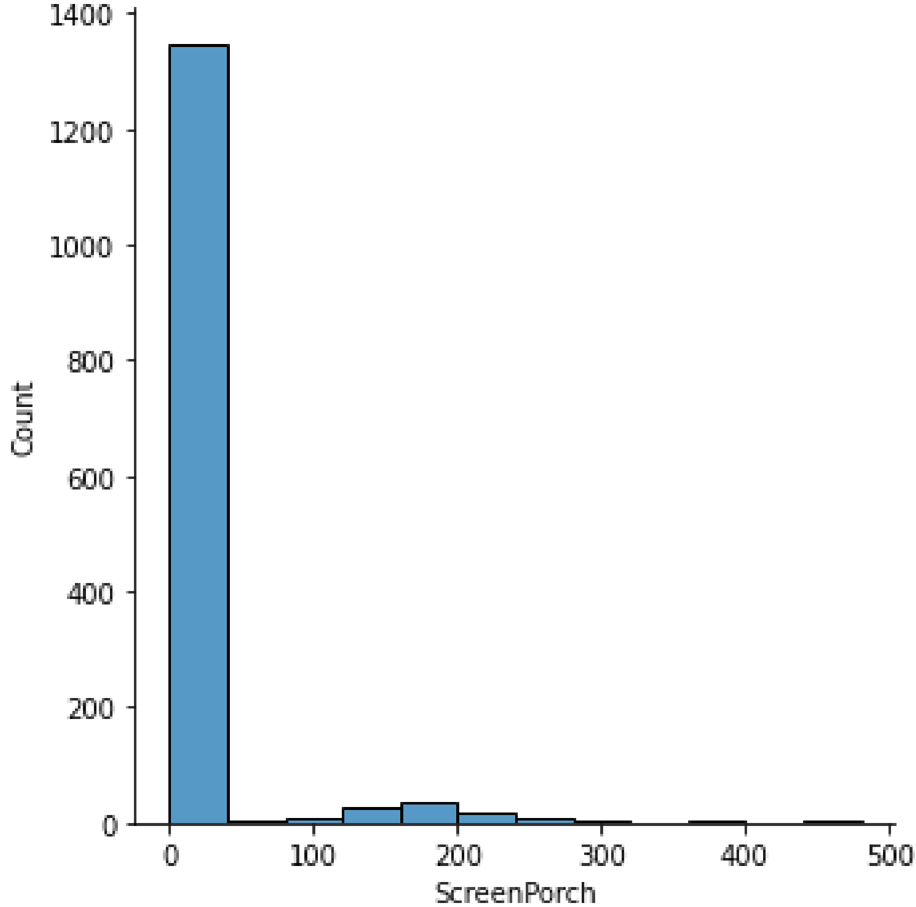
1200
1000
800
600
400
200
0
Count
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
EnclosedPorch

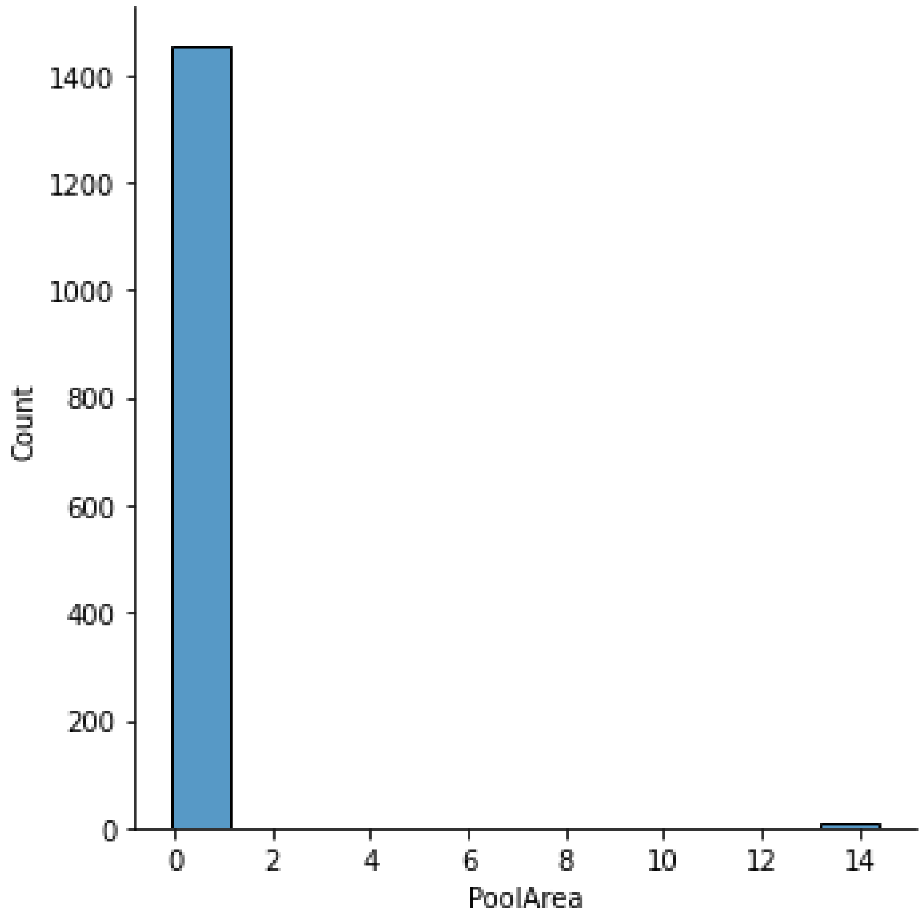

1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
EnclosedPorch


1400
1200
1000
800
600
400
200
0
Count
0
1
2
3
4
5
6
7
8
3SsnPorch

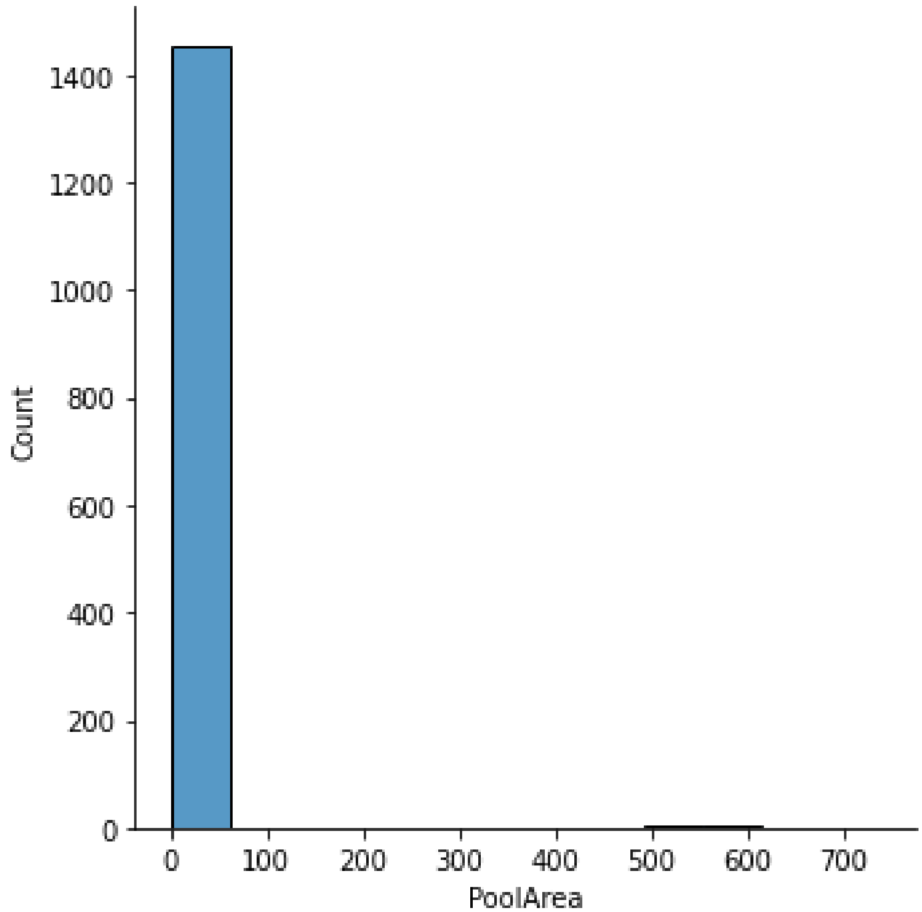

1400
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
3SsnPorch

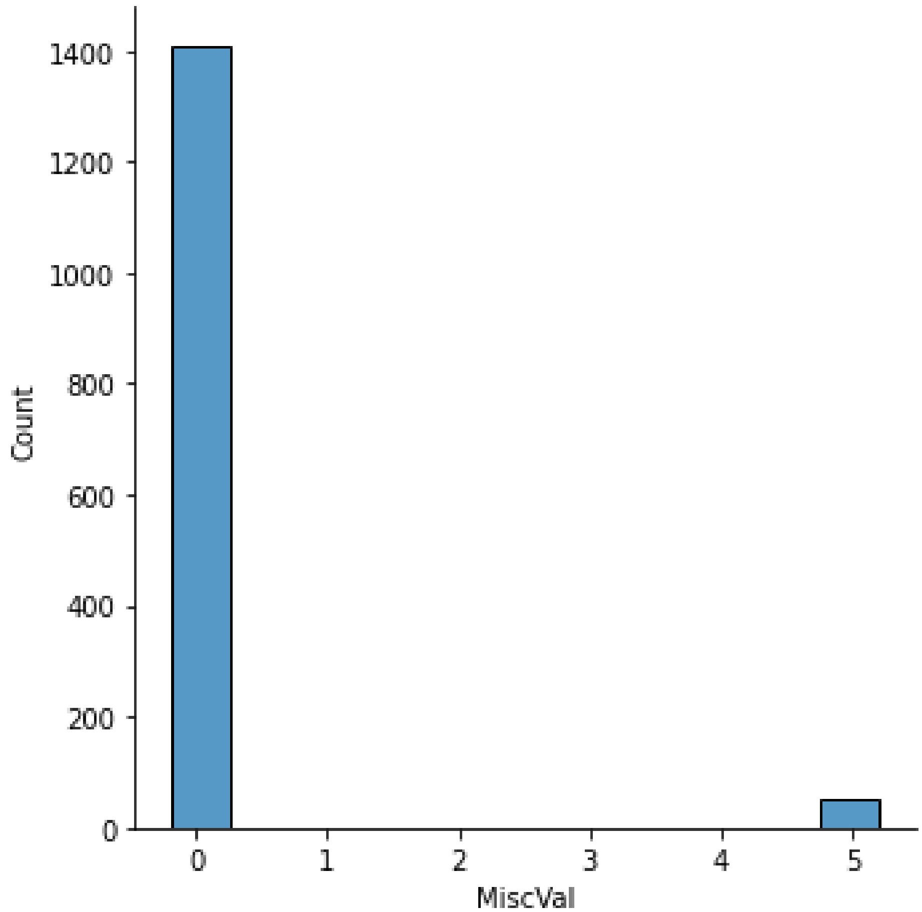

1400
1200
1000
800
600
400
200
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
ScreenPorch

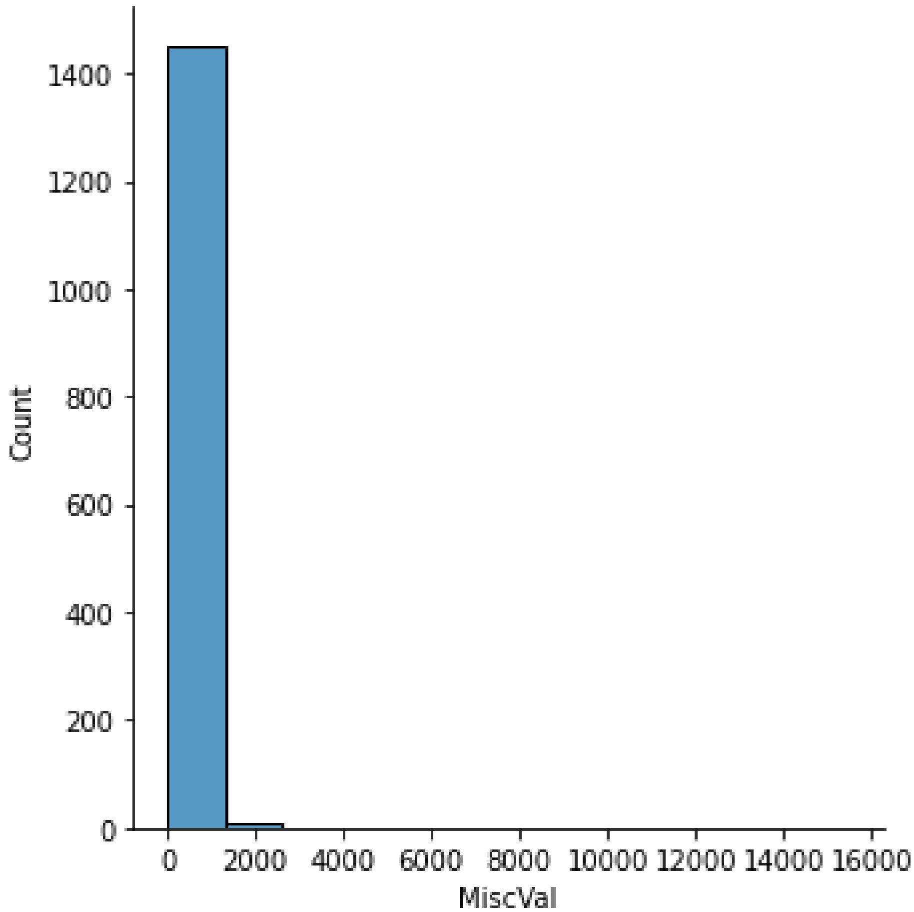

1400
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
ScreenPorch



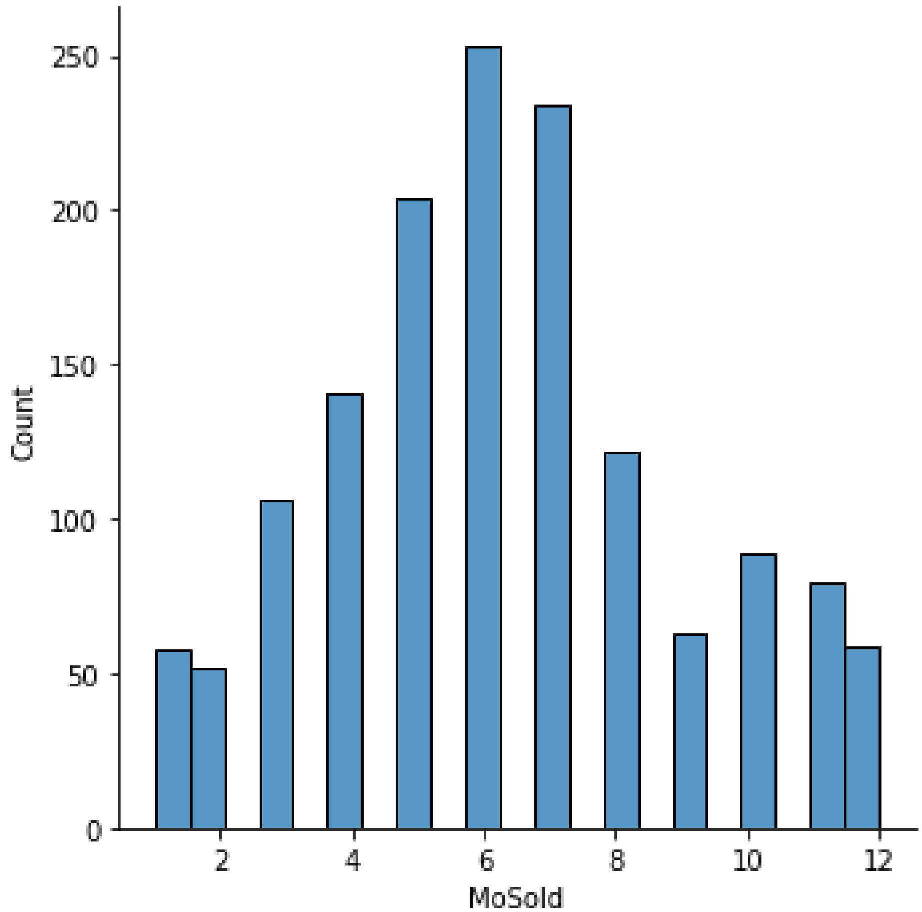
1400
1200
1000
800
600
400
200
0
Count
0
2
4
6
8
10
12
14
PoolArea


1400
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
600
700
PoolArea

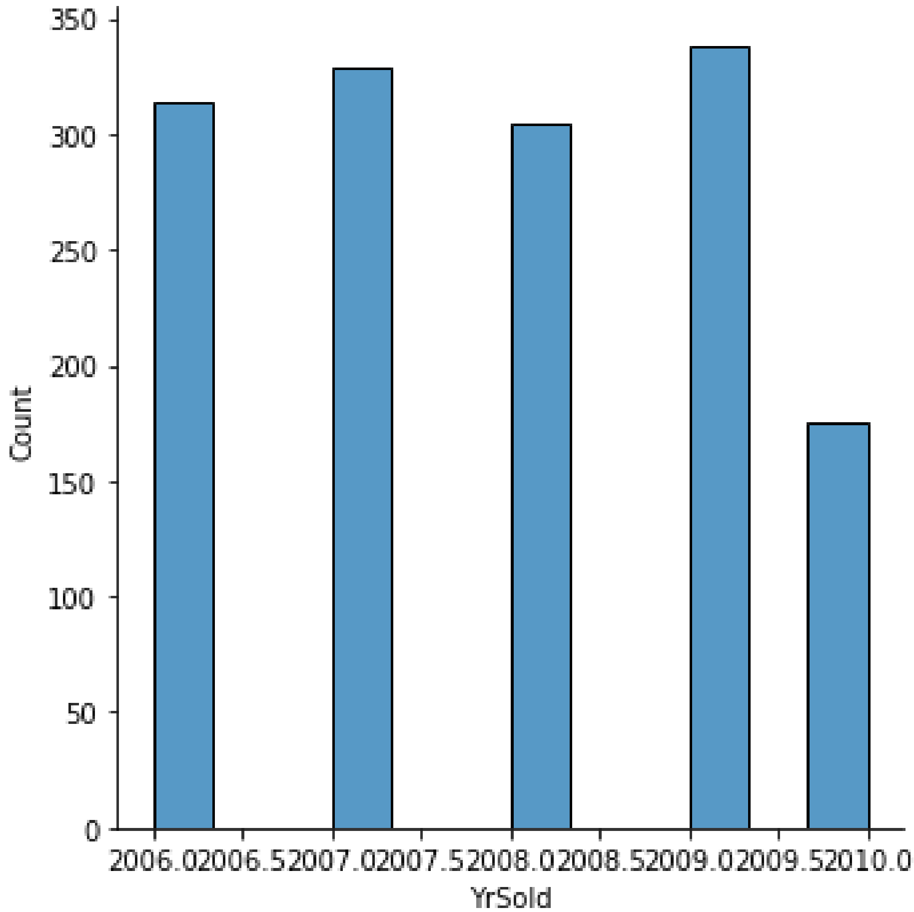

1400
1200
1000
800
600
400
200
0
Count
0
1
2
3
4
5
MiscVal



1400
1200
1000
800
600
400
200
0
Count
0
2000
4000
6000
8000
10000
12000
14000
16000
MiscVal



Count
MoSold
0
50
100
150
200
250
2
4
6
8
10
12



[60]:
```
# 7c) Perform one-hot encoding on categorical features
new_dataframe.pop('Id')
for feature in categorical_features:
    # n = dataset[feature].nunique()
    # if n==2: #Avoiding Dummy Variable Trap for 2 categories (When using␣
↪multiple Linear Regression)
    #     onehot = pd.get_dummies(dataset[feature], dummy_na=True,␣
↪prefix=feature, prefix_sep='-').iloc[:, 0]
    # else:
    #     onehot = pd.get_dummies(dataset[feature], dummy_na=True,␣
↪prefix=feature, prefix_sep='-') # Act as missing data is another categories
    onehot = pd.get_dummies(dataset[feature], dummy_na=True, prefix=feature,␣
↪prefix_sep='-') # Act as missing data is another categories         Nan      ␣
↪
    new_dataframe.pop(feature) #Remove original column
    new_dataframe = pd.concat([new_dataframe, onehot], axis=1)
    # dataset.merge(onehot, left_on=feature) # Insert next to original column
```

```
    # dataset.drop(feature,axis = 1) # remove old categorical column
```

[61]:
```
# 7d) Fill nNan with mean of that column
new_dataframe = new_dataframe.fillna(new_dataframe.mean())
```

[62]:
```
# 7e) Split independent & dependent variables
y_train = dataset['SalePrice'].fillna(dataset['SalePrice'].mean())
X_train = new_dataframe
```

0.6 8. Let us first fit a very simple linear regression model, just to see what we get.

1. Use import LinearRegression from sklearn.linear model and use function `fit()` to fit the model.
2. Use function `predict()` to get house price predictions from the model (let's call the predicted house prices yhat).
3. Plot `y` against `yhat` to see how good your predictions are.

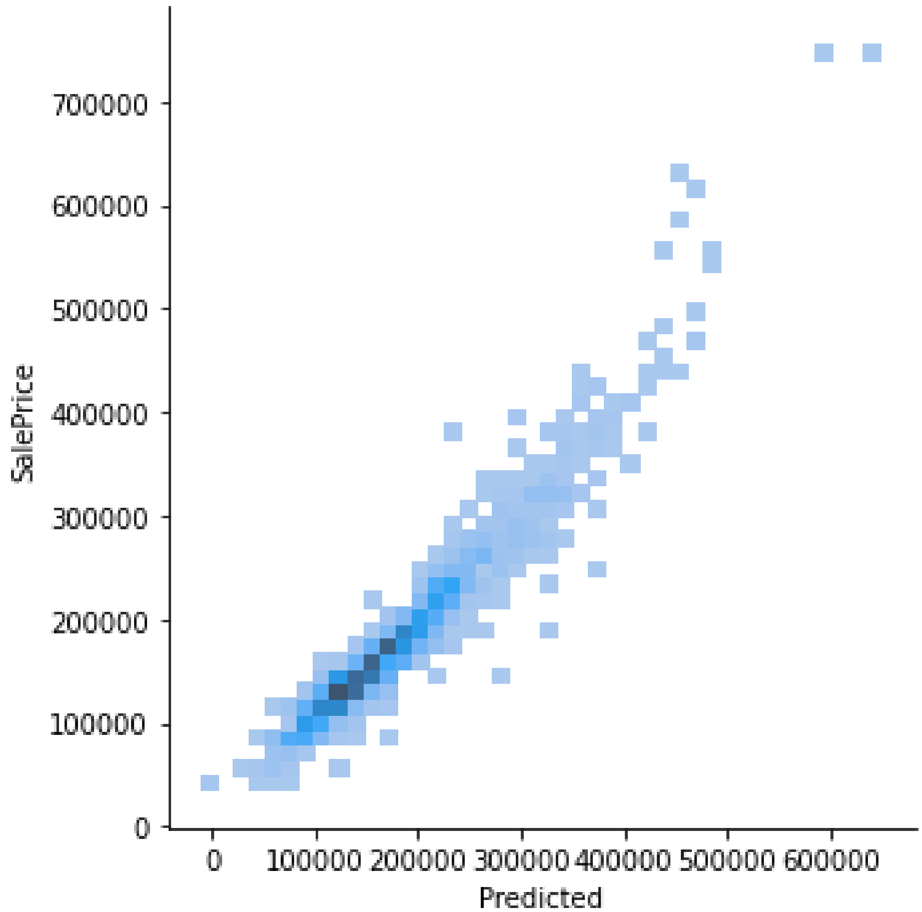
[63]:
```
# 8a) Import & Fit
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

[63]:
```
LinearRegression()
```

[64]:
```
# 8b) Predict
yhat = pd.DataFrame(regressor.predict(X_train))
yhat.columns = ['Predicted'] # Rename predicted column
```

[65]:
```
# 8c) Plot y(real) against yhat
concatned = pd.concat([y_train, yhat], axis=1)
sns.displot(concatned, x='Predicted', y='SalePrice')
```

[65]:
```
<seaborn.axisgrid.FacetGrid at 0x7efd7bad2e10>
```



0.7 9. Assessing Your Model

According to Kaggle's official rule on this problem, they use root mean square errors (rmse) to judge the accuracy of our model. This error computes the dif- ference between the log of actual house prices and the log of predicted house price. Find the mean and squareroot them.

We want to see how we compare to other machine learning contestants on Kag- gle so let us compute our rmse. Luckily, sklearn has done most of the work for you by providing mean square error function. You can use it by importing the function from sklearn.metrics. Then, you can compute mean square error and take a squareroot to get rmse.

What's the rmse of your current model? Check out Kaggle Leaderboard for this problem to see how your number measures up with the other contestants.

[66]:
```
# 9a) Calculate RMSE
from sklearn.metrics import mean_squared_error
rmse = mean_squared_error(y_train, yhat, squared=False)
print("Got RMSE(Root Mean Square Errors) = %f"%(rmse))
mse = mean_squared_error(y_train, yhat)
```

```
print("Got MSE(Mean Square Errors) = %f"%(mse))
```

```
Got RMSE(Root Mean Square Errors) = 21792.171285
Got MSE(Mean Square Errors) = 474898729.321918
```

0.8 10. Cross Validation

As we discussed earlier, don't brag about your model's accuracy until you have performed cross validation. Let us check cross-validated performance to avoid embarrassment.

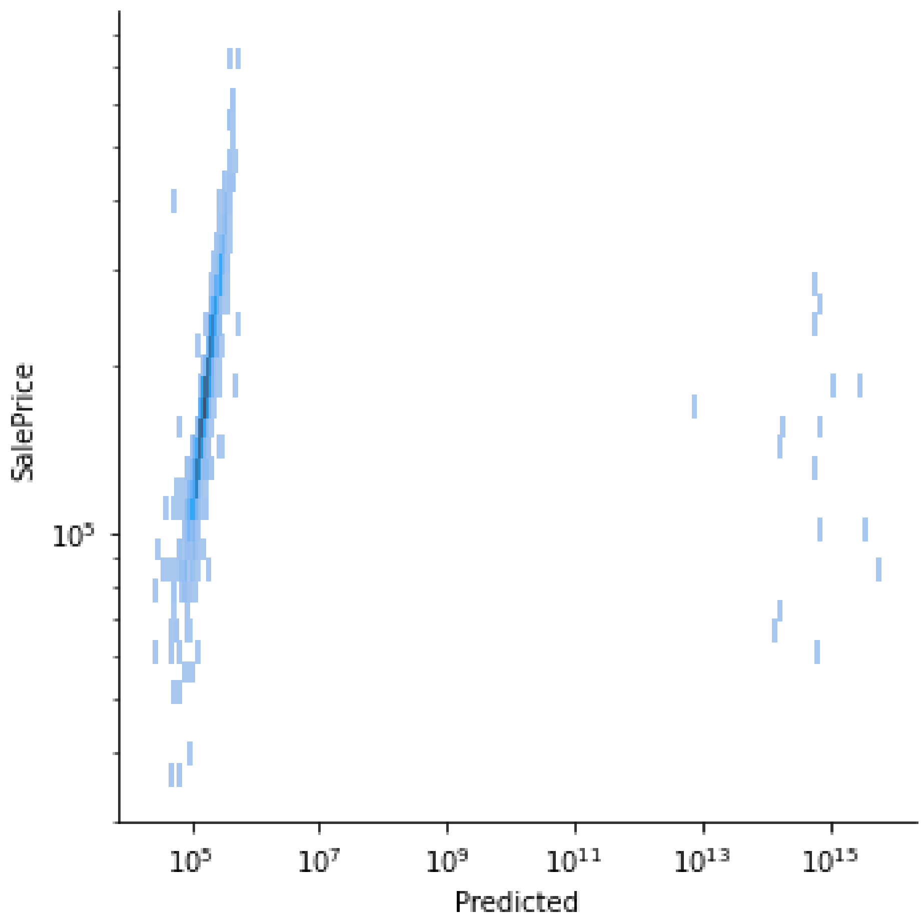
Luckily, scikit learn has done most of the work for us once again. You can use the function `cross_val_predict()` to train the model with cross validation method and output the predictions.

What's the rmse of your cross-validated model? Discuss what you observe in your results here. You may try plotting this new yhat with y to get better insights about this question.

[67]:
```
from sklearn.model_selection import cross_val_predict
yhat = pd.DataFrame(cross_val_predict(regressor, X_train, y_train, cv=10))
yhat.columns = ['Predicted'] # Rename predicted column
concatned = pd.concat([y_train, yhat], axis=1)
sns.displot(concatned, x='Predicted', y='SalePrice', log_scale=True)
rmse = mean_squared_error(y_train, yhat, squared=False)
print("Got RMSE(Root Mean Square Errors) = %f"%(rmse))
mse = mean_squared_error(y_train, yhat)
print("Got MSE(Mean Square Errors) = %f"%(mse))
```

```
/home/teera/.virtualenvs/cv/lib/python3.6/site-
packages/pandas/core/series.py:726: RuntimeWarning: invalid value encountered in
log10
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

```
Got RMSE(Root Mean Square Errors) = 211064251192948.687500
Got MSE(Mean Square Errors) = 44548118131640137560384077824.000000
```



Predicted Data RMSE predict

0.9 11 (Optional) Fit Better Models

There are other models you can fit that will perform better than linear regres- sion. For example, you can fit linear regression with L2 regularization. This class of models has a street name of ‘Ridge Regression’ and sklearn simply called them Ridge. As we learned last time, this model will fight overfitting problem. Furthermore, you can try linear regression with L1 regularization (street name Lasso Regression or Lasso in sklearn). Try these models and see how you com- pare with other Kagglers now. You can write about your findings below.

[67]:
```

```

[67]:
```

```