House-Prices

June 23, 2025

[65]:
```
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

The aim of the project is to build a model for predicting the sale price of residential buildings based on the characteristics of the property.

The project covers the full cycle of data analytics:

data exploration and cleaning,

handling missing values and outliers,

visualization of price distribution and key features,

feature selection and transformation (feature engineering),

training LinearRegression and RandomForestRegressor models,

comparison of results and formation of predictions on the test data set.

[66]:
```
test = pd.read_csv("D:/ProjectsKaggle/house/test.csv")
train = pd.read_csv("D:/ProjectsKaggle/house/train.csv")
sample = pd.read_csv("D:/ProjectsKaggle/house/sample_submission.csv")
pd.set_option('display.max_columns', None)
```

Number of rows and columns

[67]:
```
train.shape
```

[67]:
```
(1460, 81)
```

All rows and columns

[68]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
```

```
1   MSSubClass     1460 non-null   int64
2   MSZoning       1460 non-null   object
3   LotFrontage    1201 non-null   float64
4   LotArea        1460 non-null   int64
5   Street         1460 non-null   object
6   Alley          91 non-null     object
7   LotShape       1460 non-null   object
8   LandContour    1460 non-null   object
9   Utilities      1460 non-null   object
10  LotConfig      1460 non-null   object
11  LandSlope      1460 non-null   object
12  Neighborhood   1460 non-null   object
13  Condition1     1460 non-null   object
14  Condition2     1460 non-null   object
15  BldgType       1460 non-null   object
16  HouseStyle     1460 non-null   object
17  OverallQual    1460 non-null   int64
18  OverallCond    1460 non-null   int64
19  YearBuilt      1460 non-null   int64
20  YearRemodAdd   1460 non-null   int64
21  RoofStyle      1460 non-null   object
22  RoofMatl       1460 non-null   object
23  Exterior1st    1460 non-null   object
24  Exterior2nd    1460 non-null   object
25  MasVnrType     588 non-null    object
26  MasVnrArea     1452 non-null   float64
27  ExterQual      1460 non-null   object
28  ExterCond      1460 non-null   object
29  Foundation     1460 non-null   object
30  BsmtQual       1423 non-null   object
31  BsmtCond       1423 non-null   object
32  BsmtExposure   1422 non-null   object
33  BsmtFinType1   1423 non-null   object
34  BsmtFinSF1     1460 non-null   int64
35  BsmtFinType2   1422 non-null   object
36  BsmtFinSF2     1460 non-null   int64
37  BsmtUnfSF      1460 non-null   int64
38  TotalBsmtSF    1460 non-null   int64
39  Heating        1460 non-null   object
40  HeatingQC      1460 non-null   object
41  CentralAir     1460 non-null   object
42  Electrical     1459 non-null   object
43  1stFlrSF       1460 non-null   int64
44  2ndFlrSF       1460 non-null   int64
45  LowQualFinSF   1460 non-null   int64
46  GrLivArea      1460 non-null   int64
47  BsmtFullBath   1460 non-null   int64
48  BsmtHalfBath   1460 non-null   int64
```

```
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

Descriptive statistics for quantitative columns for train

[69]:
```
train.describe()
```

[69]:

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

	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1
count	1460.000000	1460.000000	1460.000000	1452.000000	1460.000000
mean	5.575342	1971.267808	1984.865753	103.685262	443.639726
std	1.112799	30.202904	20.645407	181.066207	456.098091
min	1.000000	1872.000000	1950.000000	0.000000	0.000000
25%	5.000000	1954.000000	1967.000000	0.000000	0.000000
50%	5.000000	1973.000000	1994.000000	0.000000	383.500000
75%	6.000000	2000.000000	2004.000000	166.000000	712.250000
max	9.000000	2010.000000	2010.000000	1600.000000	5644.000000

	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stFlrSF	2ndFlrSF
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	46.549315	567.240411	1057.429452	1162.626712	346.992466
std	161.319273	441.866955	438.705324	386.587738	436.528436
min	0.000000	0.000000	0.000000	334.000000	0.000000
25%	0.000000	223.000000	795.750000	882.000000	0.000000
50%	0.000000	477.500000	991.500000	1087.000000	0.000000
75%	0.000000	808.000000	1298.250000	1391.250000	728.000000
max	1474.000000	2336.000000	6110.000000	4692.000000	2065.000000

	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	5.844521	1515.463699	0.425342	0.057534	1.565068
std	48.623081	525.480383	0.518911	0.238753	0.550916
min	0.000000	334.000000	0.000000	0.000000	0.000000
25%	0.000000	1129.500000	0.000000	0.000000	1.000000
50%	0.000000	1464.000000	0.000000	0.000000	2.000000
75%	0.000000	1776.750000	1.000000	0.000000	2.000000
max	572.000000	5642.000000	3.000000	2.000000	3.000000

	HalfBath	BedroomAbvGr	KitchenAbvGr	TotRmsAbvGrd	Fireplaces
count	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	0.382877	2.866438	1.046575	6.517808	0.613014
std	0.502885	0.815778	0.220338	1.625393	0.644666
min	0.000000	0.000000	0.000000	2.000000	0.000000
25%	0.000000	2.000000	1.000000	5.000000	0.000000
50%	0.000000	3.000000	1.000000	6.000000	1.000000
75%	1.000000	3.000000	1.000000	7.000000	1.000000
max	2.000000	8.000000	3.000000	14.000000	3.000000

	GarageYrBlt	GarageCars	GarageArea	WoodDeckSF	OpenPorchSF
count	1379.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	1978.506164	1.767123	472.980137	94.244521	46.660274
std	24.689725	0.747315	213.804841	125.338794	66.256028
min	1900.000000	0.000000	0.000000	0.000000	0.000000
25%	1961.000000	1.000000	334.500000	0.000000	0.000000

```
50%    1980.000000     2.000000   480.000000     0.000000    25.000000
75%    2002.000000     2.000000   576.000000   168.000000    68.000000
max    2010.000000     4.000000  1418.000000   857.000000   547.000000

       EnclosedPorch    3SsnPorch  ScreenPorch     PoolArea       MiscVal  \
count    1460.000000  1460.000000  1460.000000  1460.000000   1460.000000
mean       21.954110     3.409589    15.060959     2.758904     43.489041
std        61.119149    29.317331    55.757415    40.177307    496.123024
min         0.000000     0.000000     0.000000     0.000000      0.000000
25%         0.000000     0.000000     0.000000     0.000000      0.000000
50%         0.000000     0.000000     0.000000     0.000000      0.000000
75%         0.000000     0.000000     0.000000     0.000000      0.000000
max       552.000000   508.000000   480.000000   738.000000  15500.000000

             MoSold       YrSold      SalePrice
count   1460.000000  1460.000000    1460.000000
mean       6.321918  2007.815753  180921.195890
std        2.703626     1.328095   79442.502883
min        1.000000  2006.000000   34900.000000
25%        5.000000  2007.000000  129975.000000
50%        6.000000  2008.000000  163000.000000
75%        8.000000  2009.000000  214000.000000
max       12.000000  2010.000000  755000.000000
```

All missing values in columns

We create a DF that has 3 columns. The first is the number of missing values, the second is the percentage of missing values, and the third is the data types.

missing_values - Shows the number of missing values

missing_percentage - Shows in percentage how many values are missing in a column

missing_data - creating DF

[70]:
```
missing_values = train.isnull().sum().sort_values(ascending=False)
missing_percentage = (train.isnull().sum() / len(train) * 100).
 ↪sort_values(ascending=False)
missing_type = train.dtypes
missing_data = pd.concat([missing_values, missing_percentage, missing_type],␣
 ↪axis=1, keys=["Total Missing for train", "Percentage for train", "Type for␣
 ↪train"])
```

Missing Value Columns for train

[71]:
```
missing_data[missing_data["Total Missing for train"] > 0]
```

[71]:
```
              Total Missing for train  Percentage for train Type for train
PoolQC                           1453             99.520548         object
MiscFeature                      1406             96.301370         object
```

Alley	1369	93.767123	object
Fence	1179	80.753425	object
MasVnrType	872	59.726027	object
FireplaceQu	690	47.260274	object
LotFrontage	259	17.739726	float64
GarageQual	81	5.547945	object
GarageFinish	81	5.547945	object
GarageType	81	5.547945	object
GarageYrBlt	81	5.547945	float64
GarageCond	81	5.547945	object
BsmtFinType2	38	2.602740	object
BsmtExposure	38	2.602740	object
BsmtCond	37	2.534247	object
BsmtQual	37	2.534247	object
BsmtFinType1	37	2.534247	object
MasVnrArea	8	0.547945	float64
Electrical	1	0.068493	object

Descriptive statistics for quantitative columns for test

[72]:
```
test.describe()
missing_values_test = test.isnull().sum().sort_values(ascending=False)
missing_percentage_test = (test.isnull().sum() / len(test) * 100).
 ↪sort_values(ascending=False)
missing_type_test = test.dtypes
missing_data_test = pd.concat([missing_values_test, missing_percentage_test,␣
 ↪missing_type_test], axis=1, keys=["Total Missing for test", "Percentage for␣
 ↪test", "Type for test"])
```

Missing Value Columns for test

[73]:
```
missing_data_test[missing_data_test["Total Missing for test"] > 0]
```

[73]:

	Total Missing for test	Percentage for test	Type for test
PoolQC	1456	99.794380	object
MiscFeature	1408	96.504455	object
Alley	1352	92.666210	object
Fence	1169	80.123372	object
MasVnrType	894	61.274846	object
FireplaceQu	730	50.034270	object
LotFrontage	227	15.558602	float64
GarageYrBlt	78	5.346127	float64
GarageCond	78	5.346127	object
GarageFinish	78	5.346127	object
GarageQual	78	5.346127	object
GarageType	76	5.209047	object
BsmtCond	45	3.084304	object
BsmtQual	44	3.015764	object

```
BsmtExposure          44          3.015764       object
BsmtFinType1          42          2.878684       object
BsmtFinType2          42          2.878684       object
MasVnrArea            15          1.028101      float64
MSZoning               4          0.274160       object
BsmtHalfBath           2          0.137080      float64
Utilities              2          0.137080       object
Functional             2          0.137080       object
BsmtFullBath           2          0.137080      float64
BsmtFinSF1             1          0.068540      float64
Exterior1st            1          0.068540       object
TotalBsmtSF            1          0.068540      float64
BsmtUnfSF              1          0.068540      float64
BsmtFinSF2             1          0.068540      float64
SaleType               1          0.068540       object
KitchenQual            1          0.068540       object
GarageCars             1          0.068540      float64
GarageArea             1          0.068540      float64
Exterior2nd            1          0.068540       object
```

Replacing empty values with mode and mean values for train

[74]:
```
mode_columns_train = ["GarageQual", "GarageFinish", "GarageType", "GarageCond",
                      "BsmtFinType2", "BsmtExposure", "BsmtCond", "BsmtQual",␣
 ↪"BsmtFinType1", "Electrical"]
for column in mode_columns_train:
    train[column] = train[column].fillna(train[column].mode()[0])

mean_columns_train = ["MasVnrArea", "GarageYrBlt"]
for column in mean_columns_train:
    train[column] = train[column].fillna(train[column].mean())
```

Saving statistics from train

[75]:
```
train_modes = {col: train[col].mode()[0] for col in mode_columns_train}
train_means = {col: train[col].mean() for col in mean_columns_train}
```

Replacing empty values with mode and mean values for test

[76]:
```
mode_columns_test = ["GarageQual", "GarageFinish", "GarageType", "GarageCond",␣
 ↪"Utilities", "Functional", "Exterior1st", "Exterior2nd",
                      "BsmtFinType2", "BsmtExposure", "BsmtCond", "BsmtQual",␣
 ↪"BsmtFinType1", "MSZoning", "SaleType", "KitchenQual"]
for column in mode_columns_test:
    if column in test.columns:
        test[column] = test[column].fillna(train_modes.get(column, test[column].
 ↪mode()[0]))
```

For test we use the mean value or mode, where the gaps are 10%<x<25%

[77]:
```
mean_columns_test = ["MasVnrArea", "GarageYrBlt", "BsmtHalfBath",␣
 ↪"BsmtFullBath", "BsmtFinSF1", "TotalBsmtSF", "BsmtUnfSF", "BsmtFinSF2",
                     "GarageCars", "GarageArea", "LotFrontage"]
for column in mean_columns_test:
    test[column] = train[column].fillna(train[column].mean())
for column in mean_columns_test:
    if column in test.columns:
        fill_value = train_means.get(column, test[column].mean())
        test[column] = test[column].fillna(fill_value)
```

Using interpolation to replace empty values where gaps are 10%<x<25%

[78]:
```
train["LotFrontage"] = train["LotFrontage"].interpolate()
```

Removing empty values that have a gap value greater than 45% for train

[79]:
```
drop_columns_train = ["PoolQC", "MiscFeature", "Alley", "Fence", "MasVnrType",␣
 ↪"FireplaceQu"]
train = train.drop(columns=drop_columns_train)
```

Removing empty values that have a skip value greater than 45% for test

[80]:
```
drop_columns_test = ["PoolQC", "MiscFeature", "Alley", "Fence", "MasVnrType",␣
 ↪"FireplaceQu"]
test = test.drop(columns=drop_columns_test)
```

Let's see if there are any duplicate lines for train

[81]:
```
train.duplicated().sum()
```

[81]:
```
np.int64(0)
```

Let's see if there are any duplicate lines for test

[82]:
```
test.duplicated().sum()
```

[82]:
```
np.int64(0)
```

Statistics for SalePrice

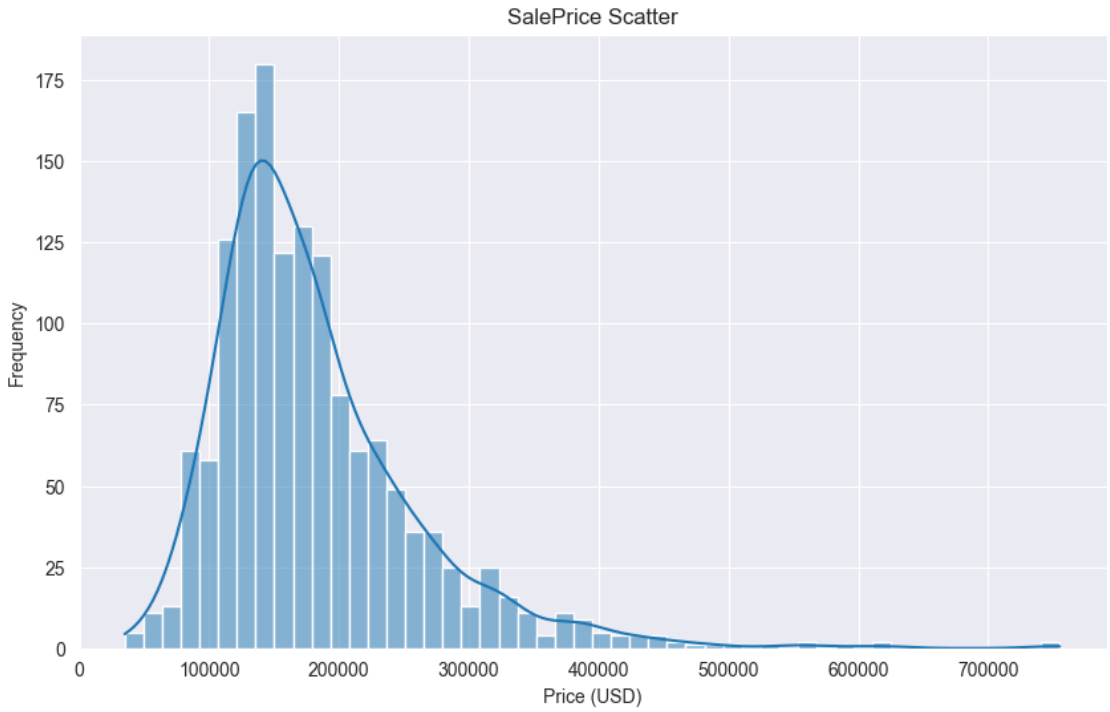
[83]:
```
train["SalePrice"].describe()
```

[83]:
```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
```

```
50%       163000.000000
75%       214000.000000
max       755000.000000
Name: SalePrice, dtype: float64
```

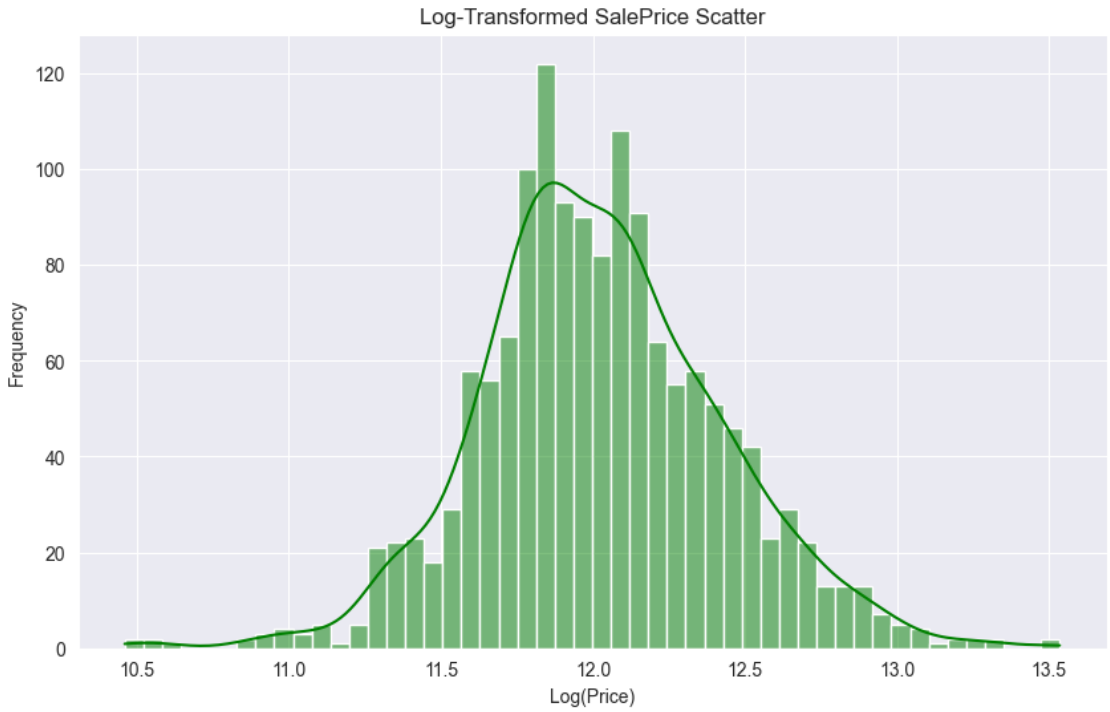
Graph without normalization

[84]:
```
plt.figure(figsize=(10, 6))
sns.histplot(train['SalePrice'], kde=True, bins=50)
plt.title("SalePrice Scatter")
plt.xlabel("Price (USD)")
plt.ylabel("Frequency")
plt.show()
```



Normalization. Logarithmization.

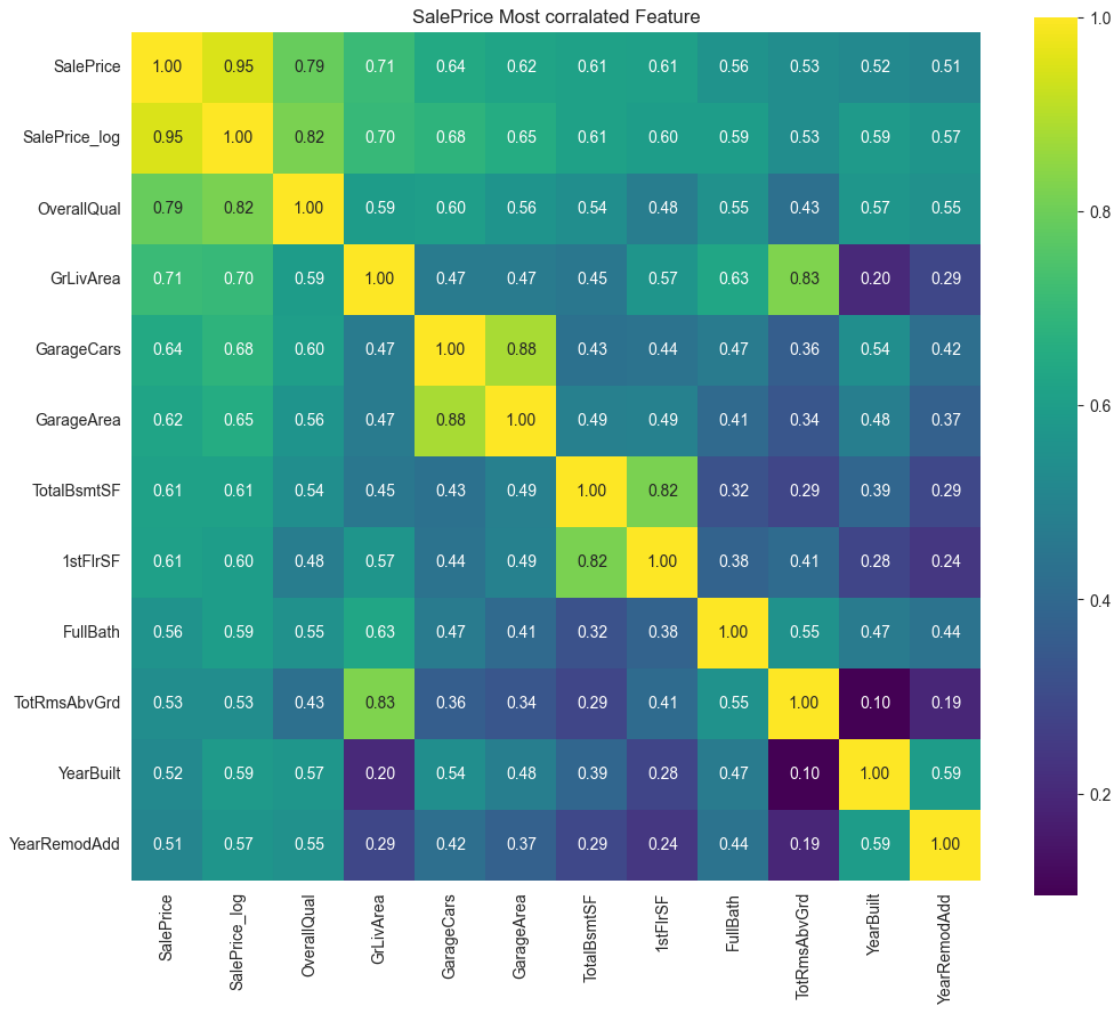
[85]:
```
train["SalePrice_log"] = np.log1p(train["SalePrice"])
plt.figure(figsize=(10, 6))
sns.histplot(train['SalePrice_log'], kde=True, bins=50, color='green')
plt.title("Log-Transformed SalePrice Scatter")
plt.xlabel("Log(Price)")
plt.ylabel("Frequency")
plt.show()
```



After normalization, it can be seen that the data is centered, which will improve the performance of the model.

Creating a heat map to find correlation

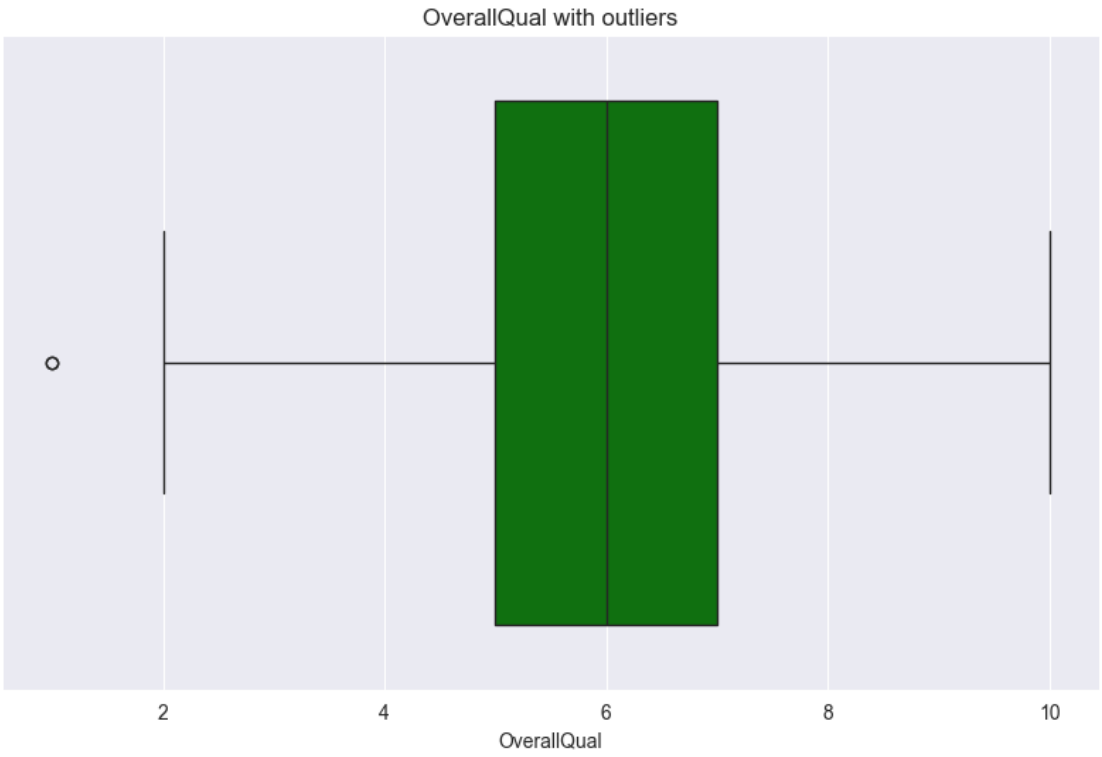
[86]:
```
numerical_cols = train.select_dtypes(include=["int64", "float64"]).columns.
 ↪tolist()
numerical_cols

corr_matrix = train[numerical_cols].corr()
k = 12
corr_top15 = corr_matrix.nlargest(k, "SalePrice")["SalePrice"].index
cm = np.corrcoef(train[corr_top15].values.T)

plt.figure(figsize=(12, 10))
sns.heatmap(cm, annot=True, square=True, fmt=".2f",
            annot_kws={"size": 10}, yticklabels=corr_top15.values,␣
 ↪xticklabels=corr_top15.values,
            cmap="viridis")
plt.title("SalePrice Most  orralated Feature")
plt.show()
```

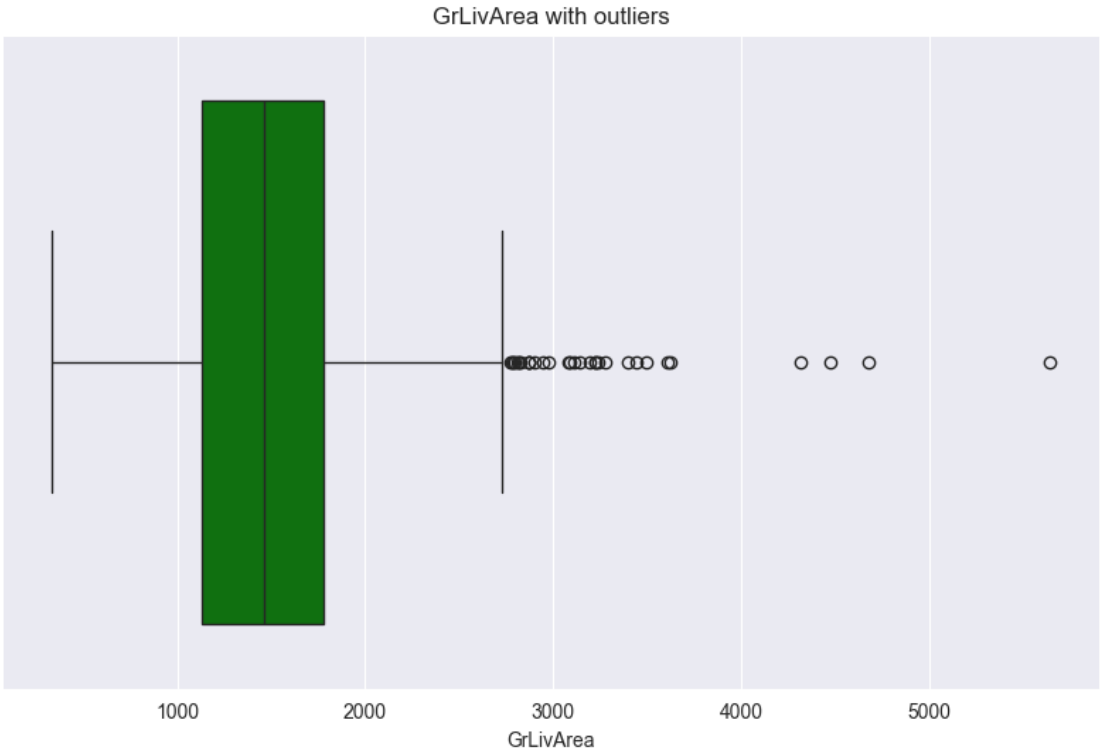


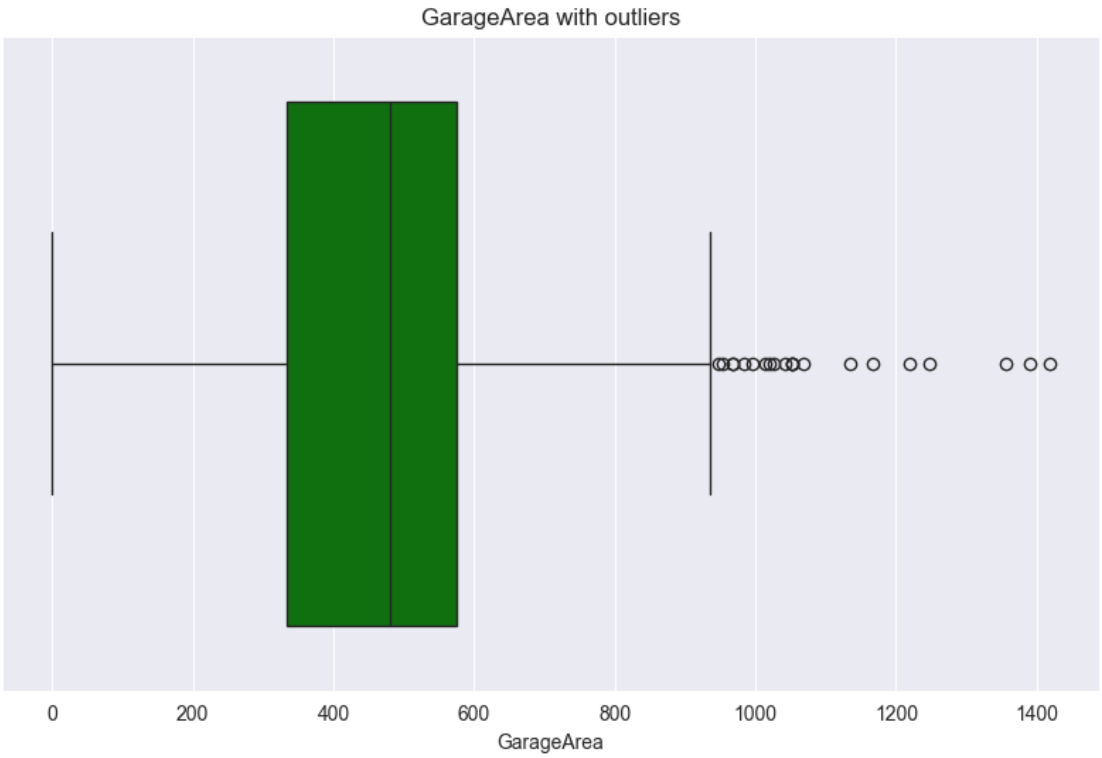
Identifying outliers for train

First, you need to plot a graph and make sure that there are a lot of emissions and they are not necessary. For example, a house can really be expensive.

[87]:
```
plt.figure(figsize = (10,6))
sns.boxplot(x = train["OverallQual"], color = "green")
plt.title("OverallQual with outliers")
plt.show()
plt.figure(figsize = (10,6))
sns.boxplot(x = train["GrLivArea"], color = "green")
plt.title("GrLivArea with outliers")
plt.show()
plt.figure(figsize = (10,6))
sns.boxplot(x = train["GarageArea"], color = "green")
plt.title("GarageArea with outliers")
plt.show()
```

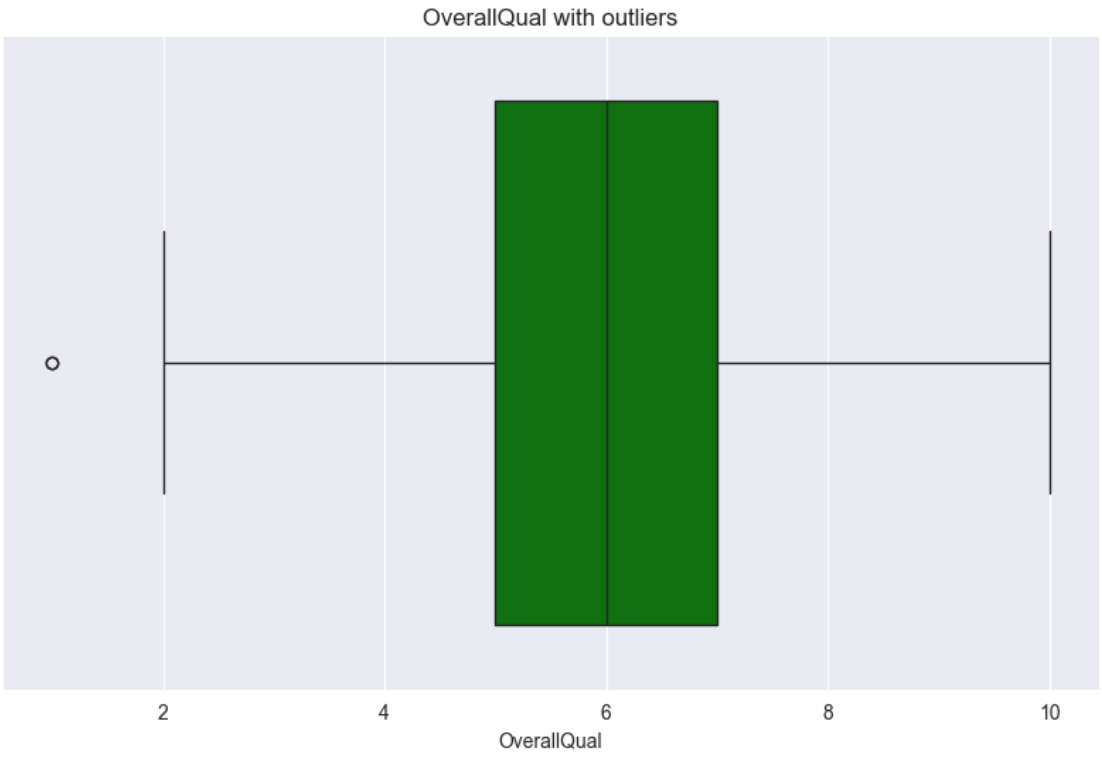

OverallQual with outliers
2
4
6
8
10
OverallQual

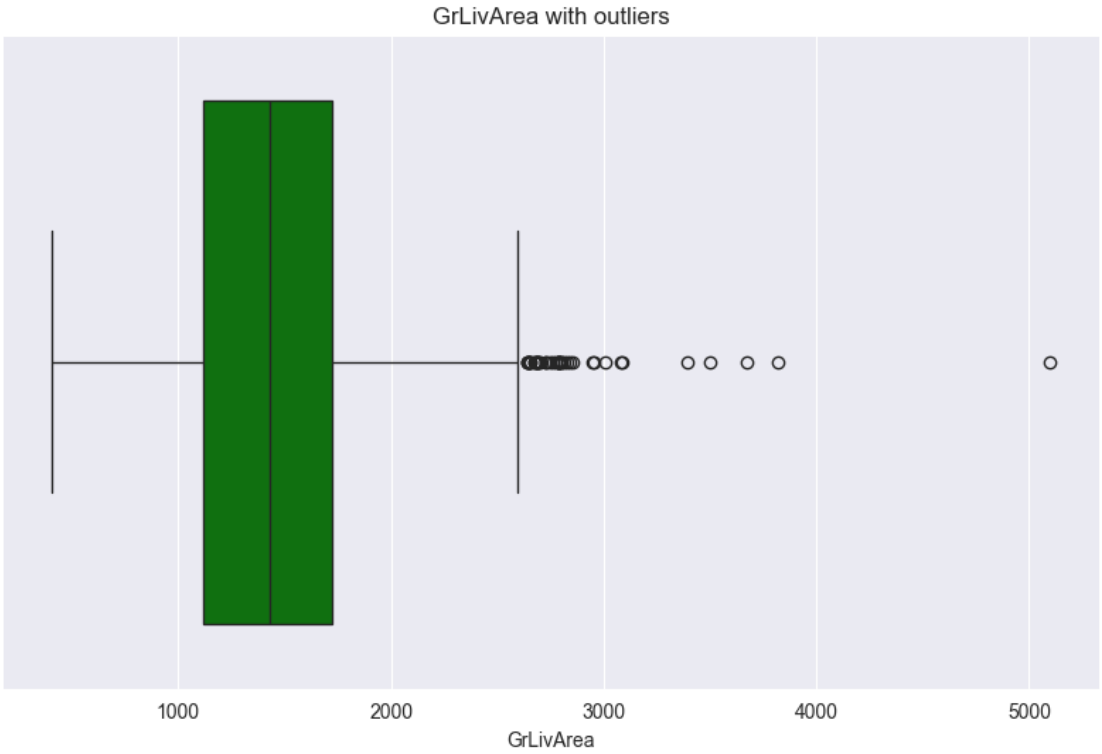

GrLivArea with outliers
1000
2000
3000
4000
5000
GrLivArea

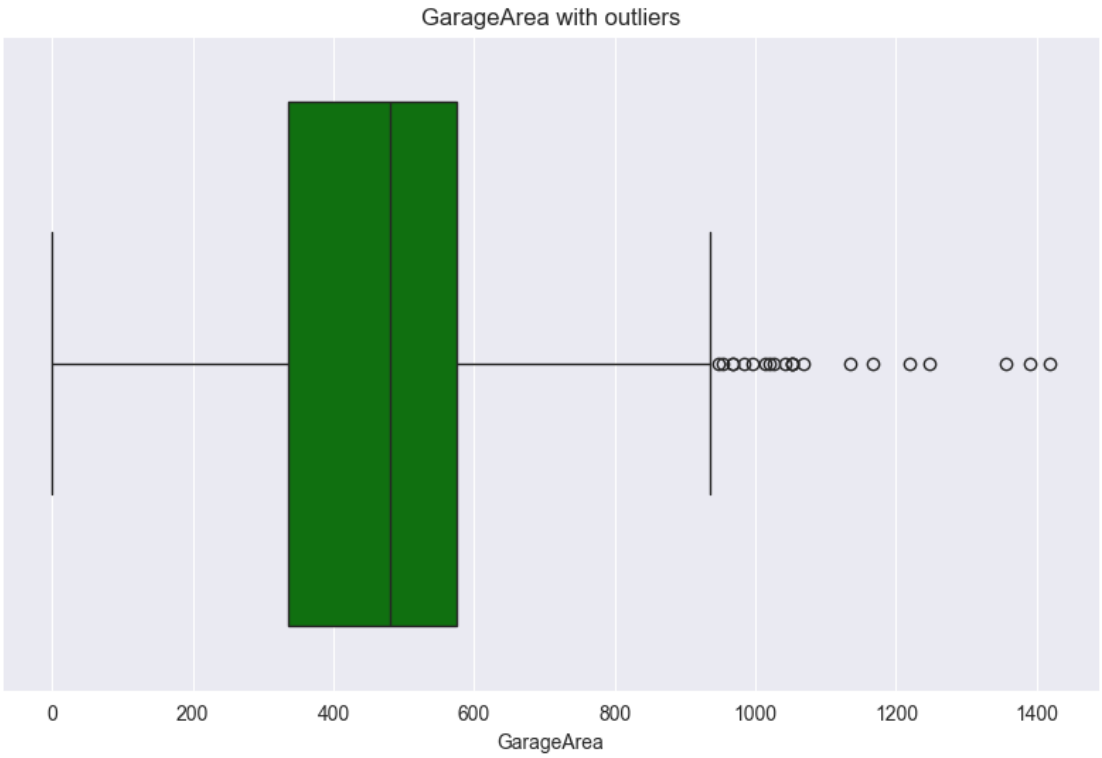


Identifying outliers for test

[88]:
```
plt.figure(figsize = (10,6))
sns.boxplot(x = test["OverallQual"], color = "green")
plt.title("OverallQual with outliers")
plt.show()
plt.figure(figsize = (10,6))
sns.boxplot(x = test["GrLivArea"], color = "green")
plt.title("GrLivArea with outliers")
plt.show()
plt.figure(figsize = (10,6))
sns.boxplot(x = test["GarageArea"], color = "green")
plt.title("GarageArea with outliers")
plt.show()
```

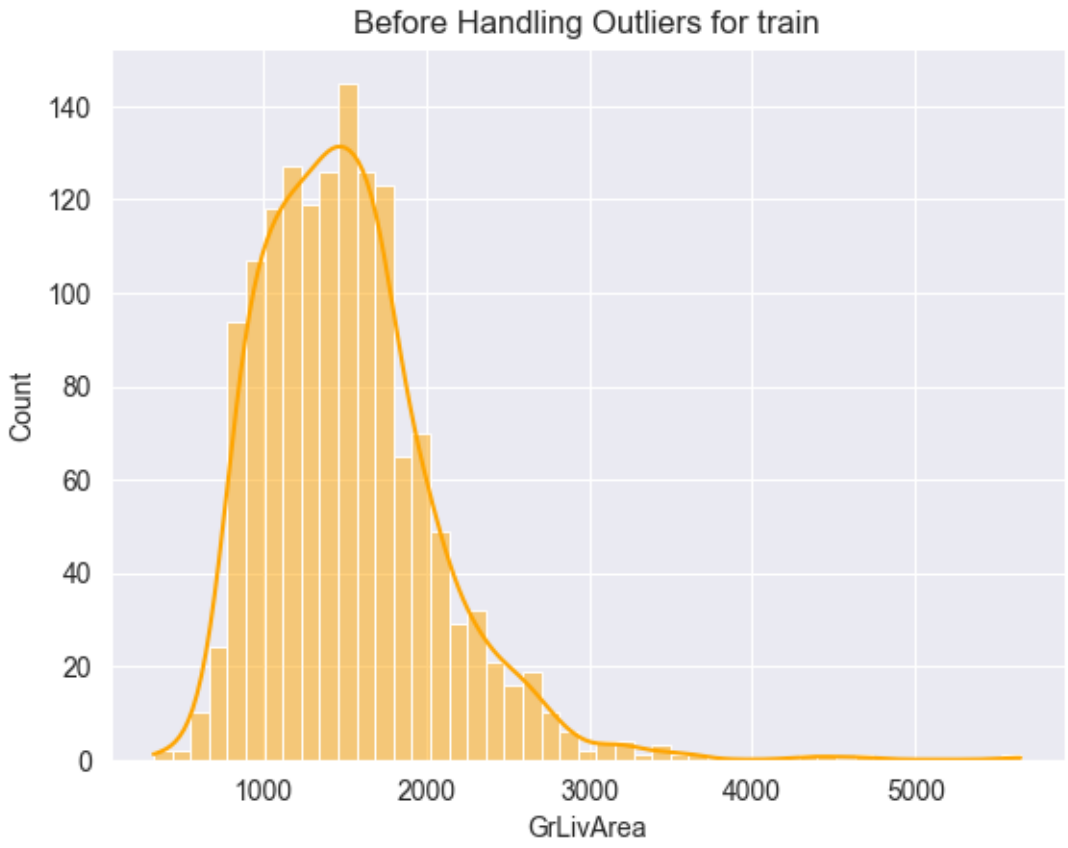

OverallQual with outliers
2
4
6
8
10
OverallQual


GrLivArea with outliers
1000
2000
3000
4000
5000
GrLivArea



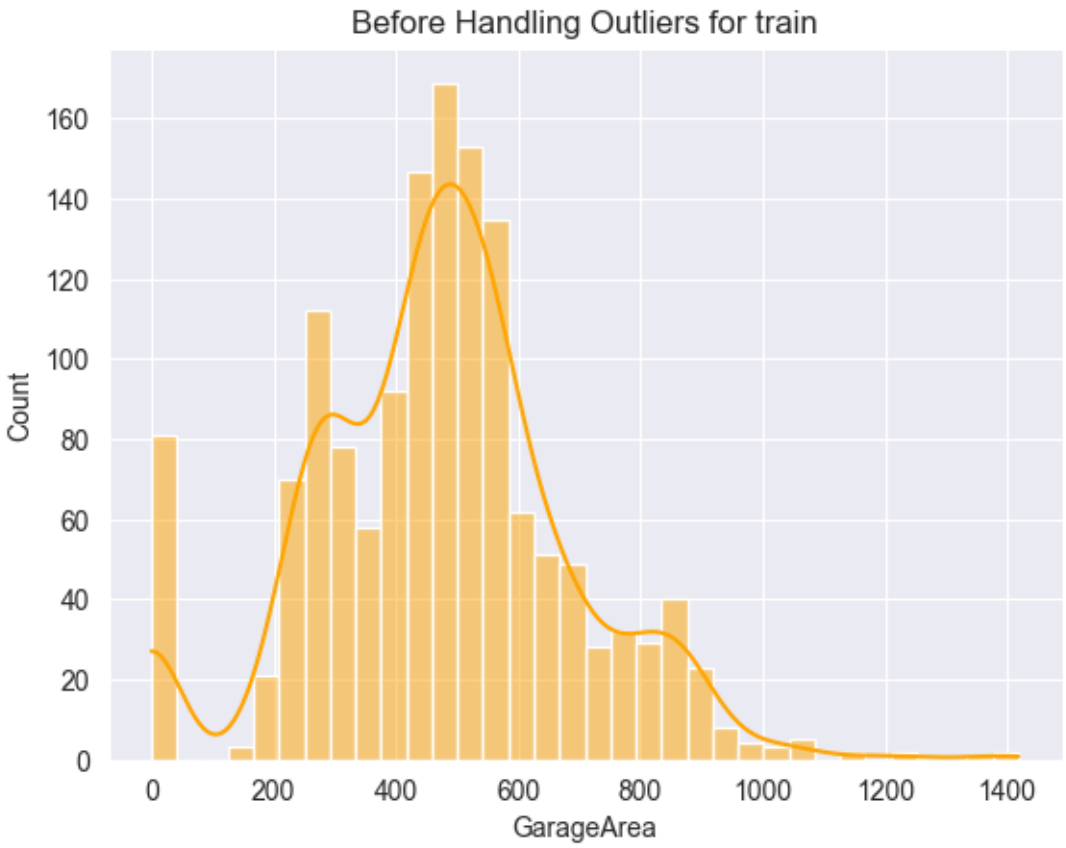
Histogram before outliers for GrLivArea for train

[89]:
```
sns.histplot(train['GrLivArea'], kde=True, color='orange')
plt.title("Before Handling Outliers for train")
plt.show()
```



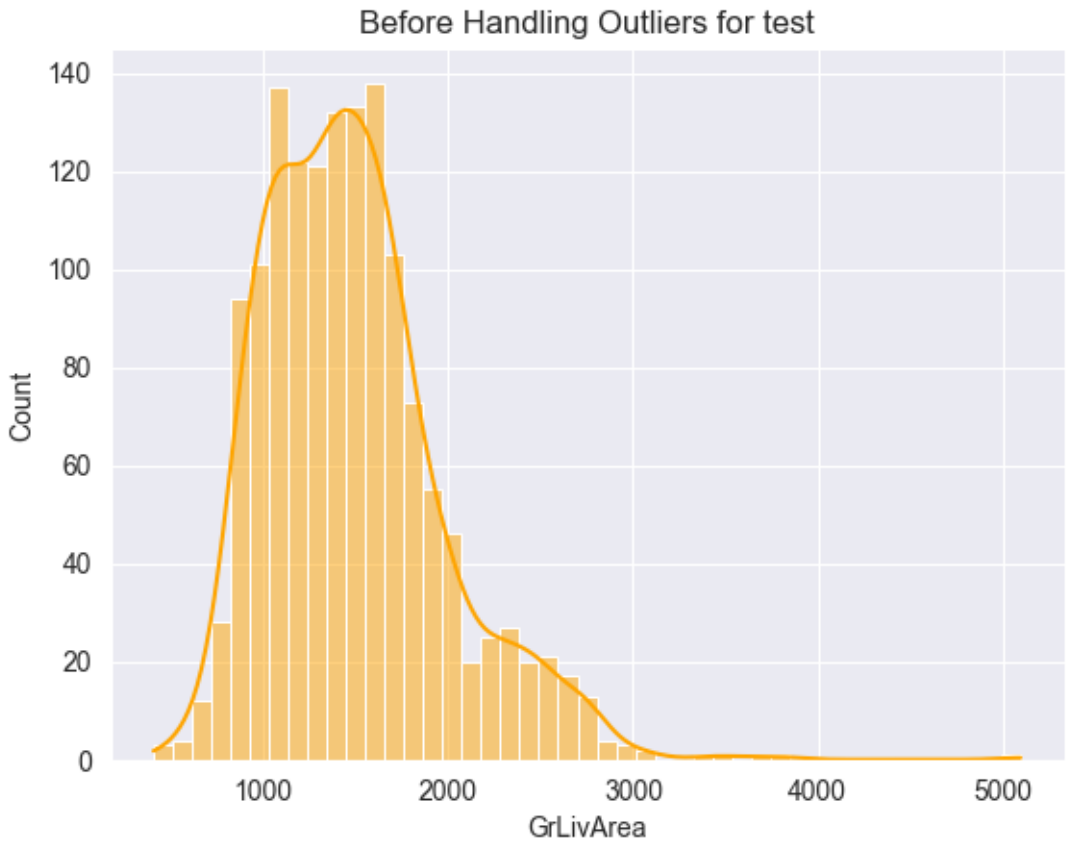
Histogram before outliers for GarageArea for train

[90]:
```
sns.histplot(train['GarageArea'], kde=True, color='orange')
plt.title("Before Handling Outliers for train")
plt.show()
```



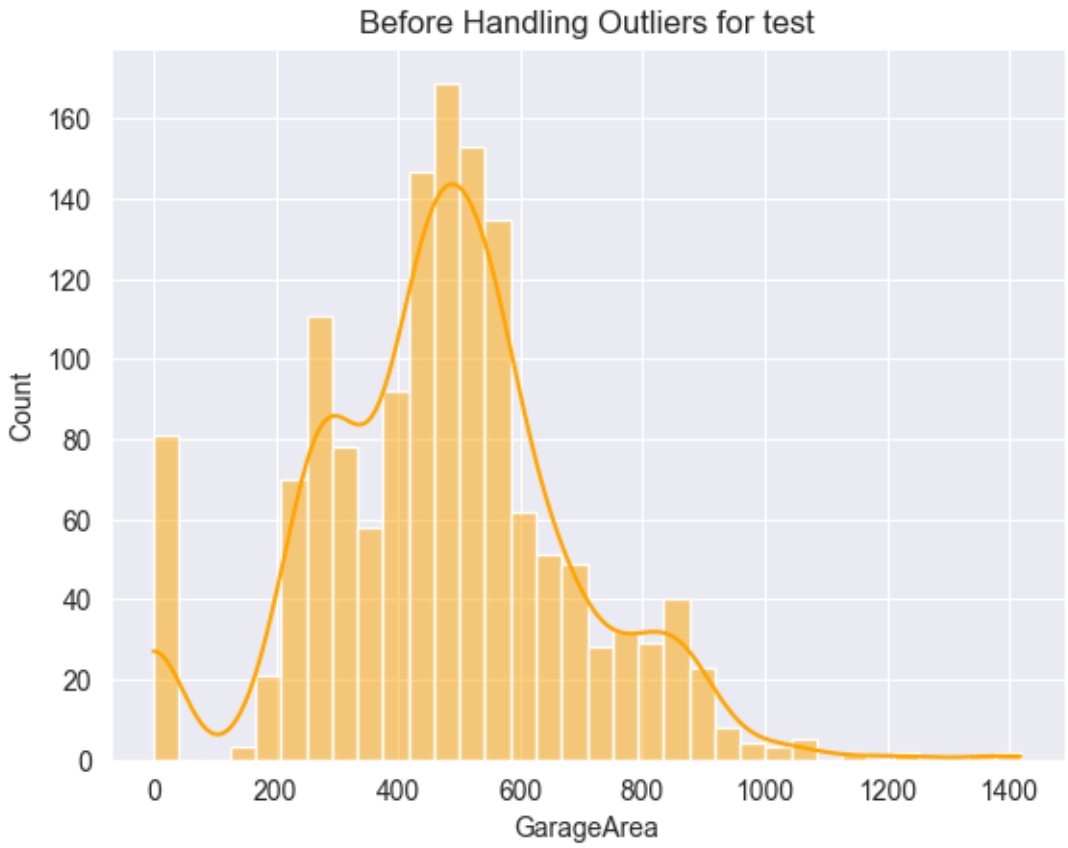
Histogram before outliers for GrLivArea for test

[91]:
```
sns.histplot(test['GrLivArea'], kde=True, color='orange')
plt.title("Before Handling Outliers for test")
plt.show()
```



Histogram before outliers for GarageArea for test

[92]:
```
sns.histplot(test['GarageArea'], kde=True, color='orange')
plt.title("Before Handling Outliers for test")
plt.show()
```



IQR method for data that has many outliers for train

If the values go beyond lower_bound = Q1 - 1.5 * IQR and upper_bound = Q3 + 1.5 * IQR - these are outliers

[93]:
```
Q1 = train["GrLivArea"].quantile(0.25)
Q3 = train["GrLivArea"].quantile(0.75)
IQR = Q3 - Q1
train = train[(train["GrLivArea"] >= Q1 - 1.5*IQR) & (train["GrLivArea"] <= Q3␣
 ↪+ 1.5*IQR)]

Q1 = train["GarageArea"].quantile(0.25)
Q3 = train["GarageArea"].quantile(0.75)
IQR = Q3 - Q1
train = train[(train["GarageArea"] >= Q1 - 1.5*IQR) & (train["GarageArea"] <=␣
 ↪Q3 + 1.5*IQR)]
```

IQR method for data that have many outliers for test

[94]:
```
test["GrLivArea"] = test["GrLivArea"].clip(lower=Q1 - 1.5*IQR, upper=Q3 + 1.
 ↪5*IQR)
```

Resetting indices for train

[95]:
```
train = train.reset_index(drop=True)
```

Resetting indices for test

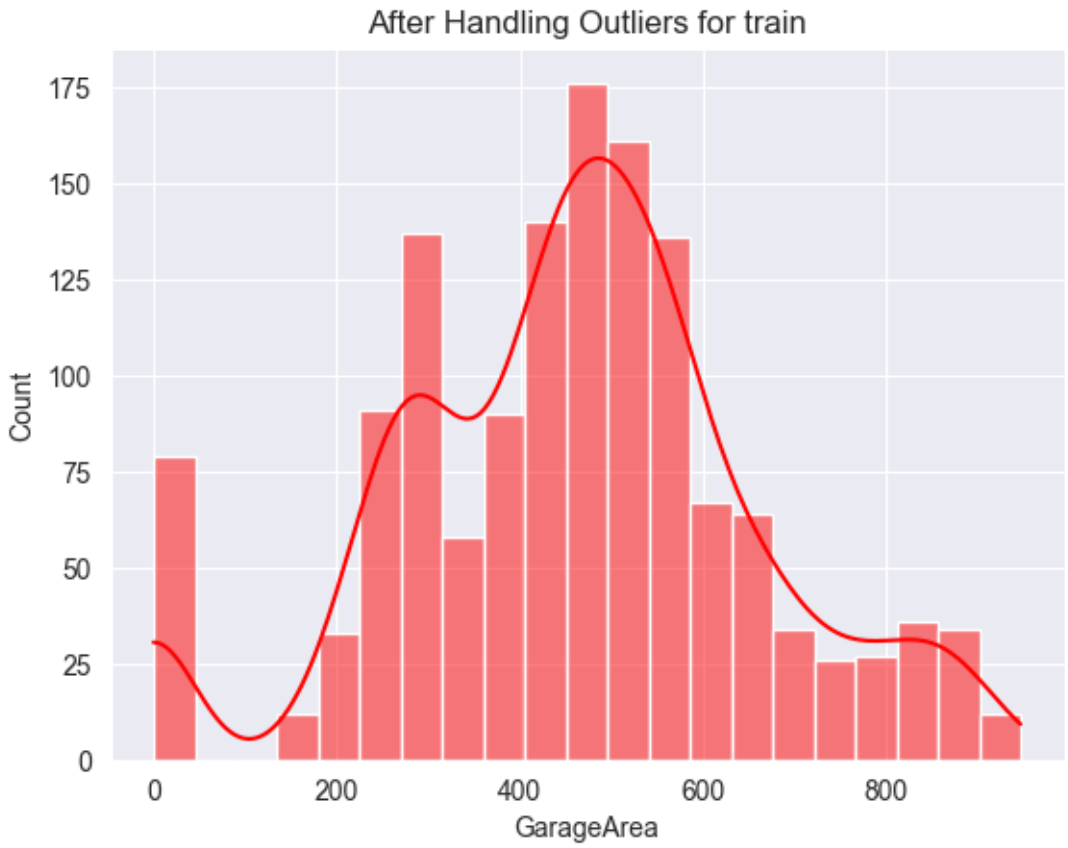
[96]:
```
test = test.reset_index(drop=True)
```

Histogram without outliers for GrLivArea for train

[97]:
```
sns.histplot(train["GrLivArea"], kde=True, color='red')
plt.title("After Handling Outliers for train")
plt.show()
```

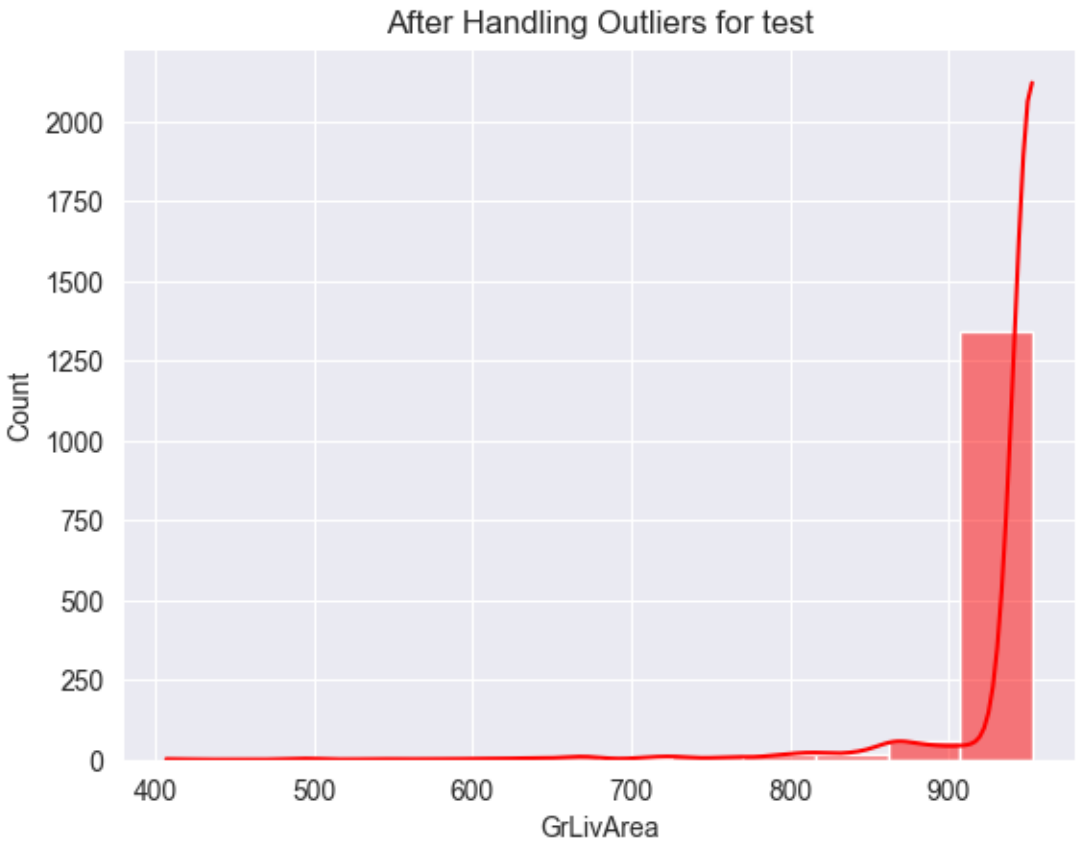
Outlier-free histogram for GarageArea for train

[98]:
```
sns.histplot(train["GarageArea"], kde=True, color='red')
plt.title("After Handling Outliers for train")
plt.show()
```



Histogram without outliers for GrLivArea for test

[99]:
```
sns.histplot(test["GrLivArea"], kde=True, color='red')
plt.title("After Handling Outliers for test")
plt.show()
```



Histogram without outliers for GarageArea for test

[100]:
```
sns.histplot(test["GarageArea"], kde=True, color='red')
plt.title("After Handling Outliers for test")
plt.show()
```

Using Categorical Data for Analysis. Neighborhood for train

Data processing

[101]:
```
train["Neighborhood"] = train["Neighborhood"].str.lower().str.strip()
```

One-hot encoding

[102]:
```
df_encoded = pd.get_dummies(train, columns=["Neighborhood"], drop_first=True)
neighborhood_columns = [col for col in df_encoded.columns if col.
 ↪startswith('Neighborhood_')]
df_encoded.head()
```

[102]:

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

	Utilities	LotConfig	LandSlope	Condition1	Condition2	BldgType	HouseStyle	\

```
0    AllPub    Inside       Gtl       Norm       Norm     1Fam     2Story
1    AllPub       FR2       Gtl      Feedr       Norm     1Fam     1Story
2    AllPub    Inside       Gtl       Norm       Norm     1Fam     2Story
3    AllPub    Corner       Gtl       Norm       Norm     1Fam     2Story
4    AllPub       FR2       Gtl       Norm       Norm     1Fam     2Story

   OverallQual  OverallCond  YearBuilt  YearRemodAdd RoofStyle RoofMatl  \
0            7            5       2003          2003     Gable  CompShg
1            6            8       1976          1976     Gable  CompShg
2            7            5       2001          2002     Gable  CompShg
3            7            5       1915          1970     Gable  CompShg
4            8            5       2000          2000     Gable  CompShg

  Exterior1st Exterior2nd  MasVnrArea ExterQual ExterCond Foundation BsmtQual  \
0     VinylSd     VinylSd       196.0        Gd        TA      PConc       Gd
1     MetalSd     MetalSd         0.0        TA        TA     CBlock       Gd
2     VinylSd     VinylSd       162.0        Gd        TA      PConc       Gd
3     Wd Sdng     Wd Shng         0.0        TA        TA     BrkTil       TA
4     VinylSd     VinylSd       350.0        Gd        TA      PConc       Gd

  BsmtCond BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
0       TA           No          GLQ         706          Unf           0
1       TA           Gd          ALQ         978          Unf           0
2       TA           Mn          GLQ         486          Unf           0
3       Gd           No          ALQ         216          Unf           0
4       TA           Av          GLQ         655          Unf           0

   BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  1stFlrSF  \
0         150          856    GasA        Ex          Y      SBrkr       856
1         284         1262    GasA        Ex          Y      SBrkr      1262
2         434          920    GasA        Ex          Y      SBrkr       920
3         540          756    GasA        Gd          Y      SBrkr       961
4         490         1145    GasA        Ex          Y      SBrkr      1145

   2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  \
0       854             0       1710             1             0         2
1         0             0       1262             0             1         2
2       866             0       1786             1             0         2
3       756             0       1717             1             0         1
4      1053             0       2198             1             0         2

   HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  \
0         1             3             1          Gd             8        Typ
1         0             3             1          TA             6        Typ
2         1             3             1          Gd             6        Typ
3         0             3             1          Gd             7        Typ
4         1             4             1          Gd             9        Typ
```

```
   Fireplaces GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea  \
0           0     Attchd       2003.0          RFn           2         548
1           1     Attchd       1976.0          RFn           2         460
2           1     Attchd       2001.0          RFn           2         608
3           1     Detchd       1998.0          Unf           3         642
4           1     Attchd       2000.0          RFn           3         836

  GarageQual GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  \
0         TA         TA          Y           0           61              0
1         TA         TA          Y         298            0              0
2         TA         TA          Y           0           42              0
3         TA         TA          Y           0           35            272
4         TA         TA          Y         192           84              0

   3SsnPorch  ScreenPorch  PoolArea  MiscVal  MoSold  YrSold SaleType  \
0          0            0         0        0       2    2008       WD
1          0            0         0        0       5    2007       WD
2          0            0         0        0       9    2008       WD
3          0            0         0        0       2    2006       WD
4          0            0         0        0      12    2008       WD

  SaleCondition  SalePrice  SalePrice_log  Neighborhood_blueste  \
0        Normal     208500      12.247699                 False
1        Normal     181500      12.109016                 False
2        Normal     223500      12.317171                 False
3       Abnorml     140000      11.849405                 False
4        Normal     250000      12.429220                 False

   Neighborhood_brdale  Neighborhood_brkside  Neighborhood_clearcr  \
0                False                 False                 False
1                False                 False                 False
2                False                 False                 False
3                False                 False                 False
4                False                 False                 False

   Neighborhood_collgcr  Neighborhood_crawfor  Neighborhood_edwards  \
0                  True                 False                 False
1                 False                 False                 False
2                  True                 False                 False
3                 False                  True                 False
4                 False                 False                 False

   Neighborhood_gilbert  Neighborhood_idotrr  Neighborhood_meadowv  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
```

```
3                 False                False                 False
4                 False                False                 False

   Neighborhood_mitchel  Neighborhood_names  Neighborhood_noridge  \
0                 False               False                 False
1                 False               False                 False
2                 False               False                 False
3                 False               False                 False
4                 False               False                  True

   Neighborhood_npkvill  Neighborhood_nridght  Neighborhood_nwames  \
0                 False                 False                False
1                 False                 False                False
2                 False                 False                False
3                 False                 False                False
4                 False                 False                False

   Neighborhood_oldtown  Neighborhood_sawyer  Neighborhood_sawyerw  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Neighborhood_somerst  Neighborhood_stonebr  Neighborhood_swisu  \
0                 False                 False               False
1                 False                 False               False
2                 False                 False               False
3                 False                 False               False
4                 False                 False               False

   Neighborhood_timber  Neighborhood_veenker
0                False                False
1                False                 True
2                False                False
3                False                False
4                False                False
```

Using Categorical Data for Analysis. Neighborhood for test

[103]:
```
test["Neighborhood"] = test["Neighborhood"].str.lower().str.strip()
```

One-hot encoding

[104]:
```
df_encoded_t = pd.get_dummies(test, columns=["Neighborhood"], drop_first=True)
for col in neighborhood_columns:
    if col not in df_encoded_t.columns:
        df_encoded_t[col] = 0
```

```
df_encoded_t.head()
```

[104]:

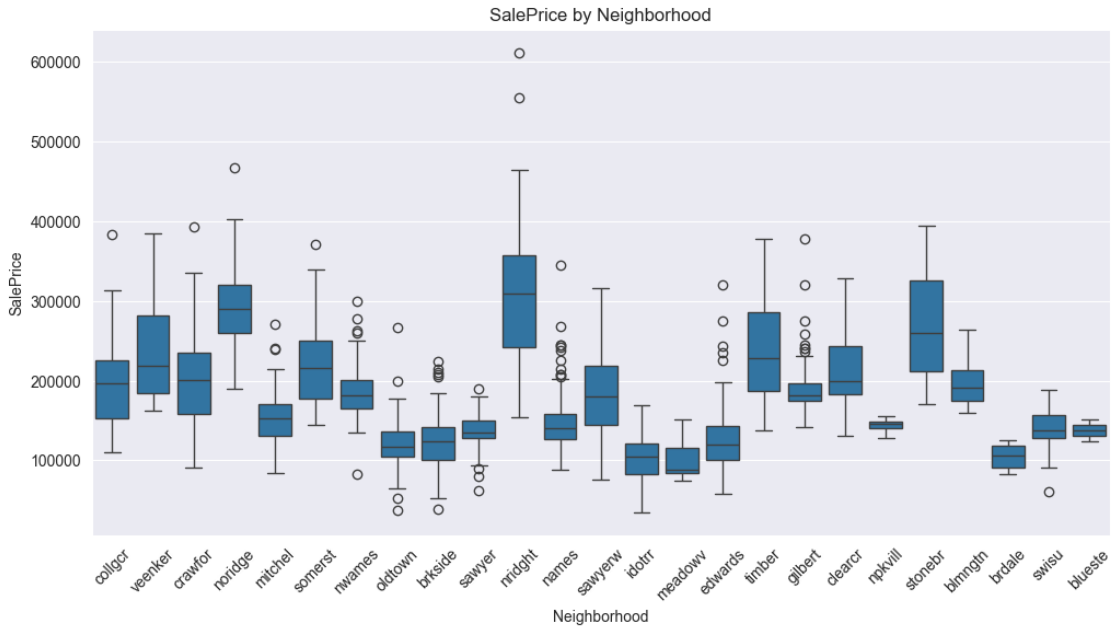
```
     Id  MSSubClass MSZoning  LotFrontage  LotArea Street LotShape  \
0  1461          20       RH         65.0    11622   Pave      Reg
1  1462          20       RL         80.0    14267   Pave      IR1
2  1463          60       RL         68.0    13830   Pave      IR1
3  1464          60       RL         60.0     9978   Pave      IR1
4  1465         120       RL         84.0     5005   Pave      IR1

  LandContour Utilities LotConfig LandSlope Condition1 Condition2 BldgType  \
0         Lvl    AllPub    Inside       Gtl      Feedr       Norm     1Fam
1         Lvl    AllPub    Corner       Gtl       Norm       Norm     1Fam
2         Lvl    AllPub    Inside       Gtl       Norm       Norm     1Fam
3         Lvl    AllPub    Inside       Gtl       Norm       Norm     1Fam
4         HLS    AllPub    Inside       Gtl       Norm       Norm   TwnhsE

  HouseStyle  OverallQual  OverallCond  YearBuilt  YearRemodAdd RoofStyle  \
0     1Story            5            6       1961          1961     Gable
1     1Story            6            6       1958          1958       Hip
2     2Story            5            5       1997          1998     Gable
3     2Story            6            6       1998          1998     Gable
4     1Story            8            5       1992          1992     Gable

  RoofMatl Exterior1st Exterior2nd  MasVnrArea ExterQual ExterCond Foundation  \
0  CompShg     VinylSd     VinylSd       196.0        TA        TA     CBlock
1  CompShg     Wd Sdng     Wd Sdng         0.0        TA        TA     CBlock
2  CompShg     VinylSd     VinylSd       162.0        TA        TA      PConc
3  CompShg     VinylSd     VinylSd         0.0        TA        TA      PConc
4  CompShg     HdBoard     HdBoard       350.0        Gd        TA      PConc

  BsmtQual BsmtCond BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  \
0       TA       TA           No          Rec         706          LwQ
1       TA       TA           No          ALQ         978          Unf
2       Gd       TA           No          GLQ         486          Unf
3       TA       TA           No          GLQ         216          Unf
4       Gd       TA           No          ALQ         655          Unf

   BsmtFinSF2  BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  \
0           0        150          856    GasA        TA          Y      SBrkr
1           0        284         1262    GasA        TA          Y      SBrkr
2           0        434          920    GasA        Gd          Y      SBrkr
3           0        540          756    GasA        Ex          Y      SBrkr
4           0        490         1145    GasA        Ex          Y      SBrkr

   1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  \
0       896         0             0      896.0             1             0
1      1329         0             0      952.5             0             1
```

```
2       928       701             0      952.5             1             0
3       926       678             0      952.5             1             0
4      1280         0             0      952.5             1             0

   FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  TotRmsAbvGrd  \
0         1         0             2             1          TA             5
1         1         1             3             1          Gd             6
2         2         1             3             1          TA             6
3         2         1             3             1          Gd             7
4         2         0             2             1          Gd             5

  Functional  Fireplaces GarageType  GarageYrBlt GarageFinish  GarageCars  \
0        Typ           0     Attchd       2003.0          Unf           2
1        Typ           0     Attchd       1976.0          Unf           2
2        Typ           1     Attchd       2001.0          Fin           2
3        Typ           1     Attchd       1998.0          Fin           3
4        Typ           0     Attchd       2000.0          RFn           3

   GarageArea GarageQual GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  \
0         548         TA         TA          Y         140            0
1         460         TA         TA          Y         393           36
2         608         TA         TA          Y         212           34
3         642         TA         TA          Y         360           36
4         836         TA         TA          Y           0           82

   EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea  MiscVal  MoSold  YrSold  \
0              0          0          120         0        0       6    2010
1              0          0            0         0    12500       6    2010
2              0          0            0         0        0       3    2010
3              0          0            0         0        0       6    2010
4              0          0          144         0        0       1    2010

  SaleType SaleCondition  Neighborhood_blueste  Neighborhood_brdale  \
0       WD        Normal                 False                False
1       WD        Normal                 False                False
2       WD        Normal                 False                False
3       WD        Normal                 False                False
4       WD        Normal                 False                False

   Neighborhood_brkside  Neighborhood_clearcr  Neighborhood_collgcr  \
0                 False                 False                 False
1                 False                 False                 False
2                 False                 False                 False
3                 False                 False                 False
4                 False                 False                 False

   Neighborhood_crawfor  Neighborhood_edwards  Neighborhood_gilbert  \
```

```
0                False                False                False
1                False                False                False
2                False                False                 True
3                False                False                 True
4                False                False                False

   Neighborhood_idotrr  Neighborhood_meadowv  Neighborhood_mitchel  \
0                False                 False                 False
1                False                 False                 False
2                False                 False                 False
3                False                 False                 False
4                False                 False                 False

   Neighborhood_names  Neighborhood_noridge  Neighborhood_npkvill  \
0                True                 False                 False
1                True                 False                 False
2               False                 False                 False
3               False                 False                 False
4               False                 False                 False

   Neighborhood_nridght  Neighborhood_nwames  Neighborhood_oldtown  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Neighborhood_sawyer  Neighborhood_sawyerw  Neighborhood_somerst  \
0                False                 False                 False
1                False                 False                 False
2                False                 False                 False
3                False                 False                 False
4                False                 False                 False

   Neighborhood_stonebr  Neighborhood_swisu  Neighborhood_timber  \
0                 False               False                False
1                 False               False                False
2                 False               False                False
3                 False               False                False
4                  True               False                False

   Neighborhood_veenker
0                 False
1                 False
2                 False
3                 False
4                 False
```

In which area are houses more expensive?

[105]:
```
plt.figure(figsize=(12,6))
sns.boxplot(x="Neighborhood", y='SalePrice', data=train)
plt.xticks(rotation=45)
plt.title("SalePrice by Neighborhood")
plt.show()
```



Creating a new df for the model for train

[106]:
```
numeric_features = train[["OverallQual", "GrLivArea", "GarageArea"]]
neighborhood_features = df_encoded.filter(regex='^Neighborhood_')
all_features = pd.concat([numeric_features, neighborhood_features], axis=1)
all_features.head()
```

[106]:

	OverallQual	GrLivArea	GarageArea	Neighborhood_blueste	Neighborhood_brdale	Neighborhood_brkside	Neighborhood_clearcr
0	7	1710	548	False	False	False	False
1	6	1262	460	False	False	False	False
2	7	1786	608	False	False	False	False
3	7	1717	642	False	False	False	False
4	8	2198	836	False			

```
4                False                 False                 False

   Neighborhood_collgcr  Neighborhood_crawfor  Neighborhood_edwards  \
0                  True                 False                 False
1                 False                 False                 False
2                  True                 False                 False
3                 False                  True                 False
4                 False                 False                 False

   Neighborhood_gilbert  Neighborhood_idotrr  Neighborhood_meadowv  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Neighborhood_mitchel  Neighborhood_names  Neighborhood_noridge  \
0                 False               False                 False
1                 False               False                 False
2                 False               False                 False
3                 False               False                 False
4                 False               False                  True

   Neighborhood_npkvill  Neighborhood_nridght  Neighborhood_nwames  \
0                 False                 False                 False
1                 False                 False                 False
2                 False                 False                 False
3                 False                 False                 False
4                 False                 False                 False

   Neighborhood_oldtown  Neighborhood_sawyer  Neighborhood_sawyerw  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Neighborhood_somerst  Neighborhood_stonebr  Neighborhood_swisu  \
0                 False                 False               False
1                 False                 False               False
2                 False                 False               False
3                 False                 False               False
4                 False                 False               False

   Neighborhood_timber  Neighborhood_veenker
0                False                 False
1                False                  True
```

```
2                False                 False
3                False                 False
4                False                 False
```

Creating a new df for the model for test

[107]:
```
numeric_features_t = test[["OverallQual", "GrLivArea", "GarageArea"]]
neighborhood_features_t = df_encoded_t.filter(regex='^Neighborhood_')
all_features_t = pd.concat([numeric_features_t, neighborhood_features_t],␣
 ↪axis=1)
all_features_t.head()
```

[107]:
```
   OverallQual  GrLivArea  GarageArea  Neighborhood_blueste  \
0            5      896.0         548                 False
1            6      952.5         460                 False
2            5      952.5         608                 False
3            6      952.5         642                 False
4            8      952.5         836                 False

   Neighborhood_brdale  Neighborhood_brkside  Neighborhood_clearcr  \
0                False                 False                 False
1                False                 False                 False
2                False                 False                 False
3                False                 False                 False
4                False                 False                 False

   Neighborhood_collgcr  Neighborhood_crawfor  Neighborhood_edwards  \
0                 False                 False                 False
1                 False                 False                 False
2                 False                 False                 False
3                 False                 False                 False
4                 False                 False                 False

   Neighborhood_gilbert  Neighborhood_idotrr  Neighborhood_meadowv  \
0                 False                False                 False
1                 False                False                 False
2                  True                False                 False
3                  True                False                 False
4                 False                False                 False

   Neighborhood_mitchel  Neighborhood_names  Neighborhood_noridge  \
0                 False                True                 False
1                 False                True                 False
2                 False               False                 False
3                 False               False                 False
4                 False               False                 False
```

```
   Neighborhood_npkvill  Neighborhood_nridght  Neighborhood_nwames  \
0                 False                 False                False
1                 False                 False                False
2                 False                 False                False
3                 False                 False                False
4                 False                 False                False

   Neighborhood_oldtown  Neighborhood_sawyer  Neighborhood_sawyerw  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Neighborhood_somerst  Neighborhood_stonebr  Neighborhood_swisu  \
0                 False                 False               False
1                 False                 False               False
2                 False                 False               False
3                 False                 False               False
4                 False                  True               False

   Neighborhood_timber  Neighborhood_veenker
0                False                 False
1                False                 False
2                False                 False
3                False                 False
4                False                 False
```

Column alignment

[108]:
```
all_features_t = all_features_t[all_features.columns]
all_features_t.head()
```

[108]:
```
   OverallQual  GrLivArea  GarageArea  Neighborhood_blueste  \
0            5      896.0         548                 False
1            6      952.5         460                 False
2            5      952.5         608                 False
3            6      952.5         642                 False
4            8      952.5         836                 False

   Neighborhood_brdale  Neighborhood_brkside  Neighborhood_clearcr  \
0                False                 False                 False
1                False                 False                 False
2                False                 False                 False
3                False                 False                 False
4                False                 False                 False
```

```
   Neighborhood_collgcr  Neighborhood_crawfor  Neighborhood_edwards  \
0                 False                 False                 False
1                 False                 False                 False
2                 False                 False                 False
3                 False                 False                 False
4                 False                 False                 False

   Neighborhood_gilbert  Neighborhood_idotrr  Neighborhood_meadowv  \
0                 False                False                 False
1                 False                False                 False
2                  True                False                 False
3                  True                False                 False
4                 False                False                 False

   Neighborhood_mitchel  Neighborhood_names  Neighborhood_noridge  \
0                 False                True                 False
1                 False                True                 False
2                 False               False                 False
3                 False               False                 False
4                 False               False                 False

   Neighborhood_npkvill  Neighborhood_nridght  Neighborhood_nwames  \
0                 False                 False                 False
1                 False                 False                 False
2                 False                 False                 False
3                 False                 False                 False
4                 False                 False                 False

   Neighborhood_oldtown  Neighborhood_sawyer  Neighborhood_sawyerw  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Neighborhood_somerst  Neighborhood_stonebr  Neighborhood_swisu  \
0                 False                 False               False
1                 False                 False               False
2                 False                 False               False
3                 False                 False               False
4                 False                  True               False

   Neighborhood_timber  Neighborhood_veenker
0                False                 False
1                False                 False
2                False                 False
3                False                 False
```

```
4                False                 False
```

[109]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(all_features,␣
 ↪train["SalePrice_log"], test_size = 0.2, random_state = 42)
```

Model training

[110]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

Linear

[111]:
```
lr = LinearRegression()
lr.fit(x_train, y_train)
y_pred_lr = lr.predict(x_test)
print("RandomForestRegressor")
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(x_train, y_train)
y_pred_rf = rf.predict(x_test)
```

```
RandomForestRegressor
```

RandomForestRegressor

[112]:
```
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(x_train, y_train)
y_pred_rf = rf.predict(x_test)
```

Metrics for linear regression. Log

[113]:
```
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
r2_lr = r2_score(y_test, y_pred_lr)
print("RMSE", rmse_lr)
print("R2", r2_lr)
```

```
RMSE 0.1463222517662175
R2 0.8545311112781473
```

Metrics for RandomForestRegressor. Log”

[114]:
```
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))
r2_rf = r2_score(y_test, y_pred_rf)
print("RMSE", rmse_rf)
print("R2", r2_rf)
```

```
RMSE 0.16610166259201772
R2 0.8125448707213268
```

[115]:
```
y_test_original = np.expm1(y_test)
```

Metrics for linear regression.

[116]:
```
y_pred_lr_original = np.expm1(y_pred_lr)
rmse_lr_original = np.sqrt(mean_squared_error(y_test_original,␣
 ↪y_pred_lr_original))
r2_lr_original = r2_score(y_test_original, y_pred_lr_original)
print("RMSE", rmse_lr_original)
print("R2", r2_lr_original)
```

```
RMSE 25192.78468715876
R2 0.8642775976515636
```

Metrics for RandomForestRegressor.

[117]:
```
y_pred_rf_original = np.expm1(y_pred_rf)
rmse_rf_original = np.sqrt(mean_squared_error(y_test_original,␣
 ↪y_pred_rf_original))
r2_rf_original = r2_score(y_test_original, y_pred_rf_original)
print("RMSE", rmse_rf_original)
print("R2", r2_rf_original)
```

```
RMSE 28244.19693371522
R2 0.8294083969402922
```

Cross-validation. Mean. Standard deviation. Linear model

[118]:
```
from sklearn.model_selection import cross_val_score
scores_lr = cross_val_score(lr, all_features, train["SalePrice_log"], cv = 3)
mean_lr = scores_lr.mean()
std_lr = scores_lr.std()
print("Average RMSE", mean_lr, "Standard Deviation", std_lr)
```

```
Average RMSE 0.8232581658688632 Standard Deviation 0.009078693545882305
```

Cross-validation. Average. Standard Deviation. Random Forest

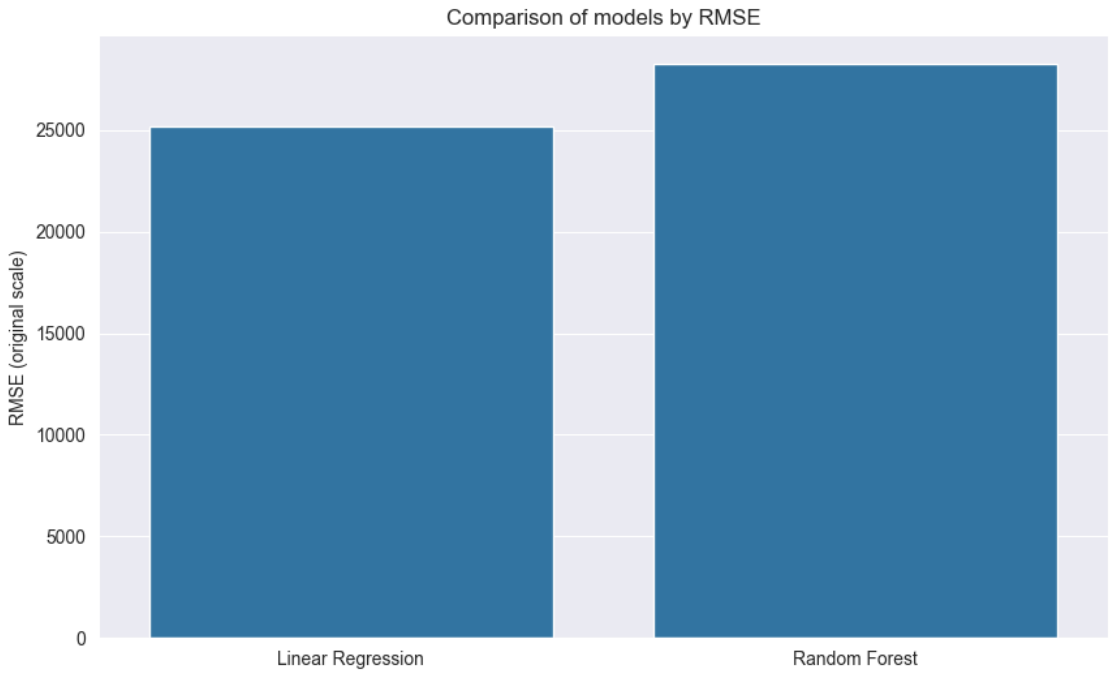
[119]:
```
scores_rf = cross_val_score(rf, all_features, train["SalePrice_log"], cv=3)
rmse_scores_rf = -scores_rf
mean_rf = rmse_scores_rf.mean()
std_rf = rmse_scores_rf.std()
print("Average RMSE:" , mean_rf, "Standard Deviation", std_rf)
```

```
Average RMSE: -0.7900592851372817 Standard Deviation 0.0051711900287019375
```

Comparison of models

[120]:
```
models = ["Linear Regression", "Random Forest"]
rmse_values = [rmse_lr_original, rmse_rf_original]
```

[121]:
```
plt.figure(figsize=(10, 6))
sns.barplot(x=models, y=rmse_values)
plt.title("Comparison of models by RMSE")
plt.ylabel("RMSE (original scale)")
plt.show()
```



Train the best model on all data

[122]:
```
best_model = RandomForestRegressor(n_estimators=100, random_state=42)
best_model.fit(all_features, train["SalePrice_log"])
```

[122]:
```
RandomForestRegressor(random_state=42)
```

Predictions for test data

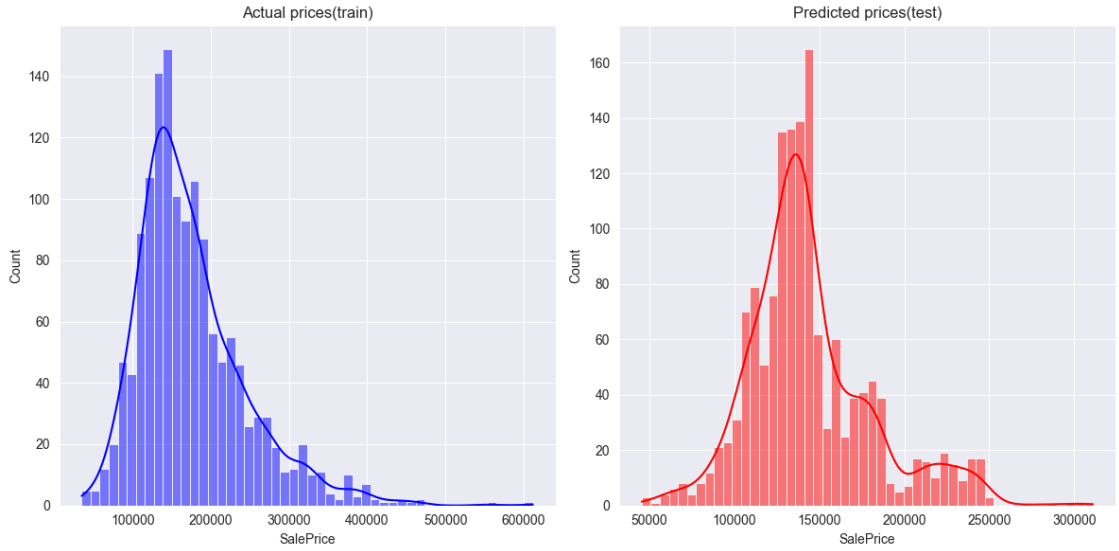
[123]:
```
test_predictions_log = best_model.predict(all_features_t)
test_predictions = np.expm1(test_predictions_log)
```

Creating a file

[124]:
```
submission = pd.DataFrame({
    "Id": test["Id"],
    "SalePrice": test_predictions
})
submission.to_csv('D:/ProjectsKaggle/house/submission.csv', index=False)
```

Visualization of Predictions

[125]:
```
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
sns.histplot(train["SalePrice"], bins=50, kde=True, color="blue")
plt.title("Actual prices(train)")

plt.subplot(1, 2, 2)
sns.histplot(submission["SalePrice"], bins=50, kde=True, color="red")
plt.title("Predicted prices(test)")

plt.tight_layout()
plt.show()


plt.savefig('figure_name.png', dpi=300, bbox_inches='tight')
```




```
<Figure size 640x480 with 0 Axes>
```

Conclusion:

Preliminary analysis showed a high degree of influence of the OverallQual, GrLivArea and GarageArea features on the final sale price

The target variable (SalePrice) was normalized using logarithm, which improved the distribution and increased the accuracy of the model.

Outliers were identified and removed using the IQR method, which helped reduce the impact of extreme values on model training.

Using two models to identify the best result.

Cross-validation confirmed that linear regression has less variation in metric values across folds than random forest.

The final model (RandomForest) was further trained on the entire training set and used to predict prices on the test set.

The project was completed with partial use of open sources (Kaggle/ChatGPT/StackOverflow) and my own analysis.