House Price Advanced Regression Techniques

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Welcome to my Jupyter Notebook dedicated to the analysis and prediction of house prices using advanced regression techniques. In this notebook, I will walk you through a comprehensive data analysis and machine learning project aimed at predicting house prices based on various features.

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Introduction

In the realm of real estate, accurately predicting house prices is of utmost importance for both buyers and sellers. This project focuses on using advanced regression techniques to develop a robust predictive model that can estimate house prices based on a multitude of factors.

The dataset we will be working with contains a wide range of features, including information about the properties, their location, and other relevant attributes. By leveraging various data science tools and techniques, we aim to create a model that provides accurate price estimates.

Data Exploration

Before diving into model building, it's essential to understand our data thoroughly. In this section, we will explore the dataset, visualize key insights, and gain insights into the relationships between different variables.

Data Fields

- **SalePrice**: the property's sale price in dollars. This is the target variable that you're trying to predict.
- **MSSubClass**: The building class
- **MSZoning**: The general zoning classification
- **LotFrontage**: Linear feet of street connected to property
- **LotArea**: Lot size in square feet
- **Street**: Type of road access
- **Alley**: Type of alley access
- **LotShape**: General shape of property
- **LandContour**: Flatness of the property
- **Utilities**: Type of utilities available
- **LotConfig**: Lot configuration
- **LandSlope**: Slope of property
- **Neighborhood**: Physical locations within Ames city limits
- **Condition1**: Proximity to main road or railroad
- **Condition2**: Proximity to main road or railroad (if a second is present)
- **BldgType**: Type of dwelling
- **HouseStyle**: Style of dwelling
- **OverallQual**: Overall material and finish quality
- **OverallCond**: Overall condition rating
- **YearBuilt**: Original construction date
- **YearRemodAdd**: Remodel date
- **RoofStyle**: Type of roof
- **RoofMatl**: Roof material
- **Exterior1st**: Exterior covering on house
- **Exterior2nd**: Exterior covering on house (if more than one material)
- **MasVnrType**: Masonry veneer type
- **MasVnrArea**: Masonry veneer area in square feet
- **ExterQual**: Exterior material quality
- **ExterCond**: Present condition of the material on the exterior
- **Foundation**: Type of foundation
- **BsmtQual**: Height of the basement
- **BsmtCond**: General condition of the basement
- **BsmtExposure**: Walkout or garden level basement walls
- **BsmtFinType1**: Quality of basement finished area
- **BsmtFinSF1**: Type 1 finished square feet
- **BsmtFinType2**: Quality of second finished area (if present)
- **BsmtFinSF2**: Type 2 finished square feet
- **BsmtUnfSF**: Unfinished square feet of basement area
- **TotalBsmtSF**: Total square feet of basement area

- **TotalBsmtSF**: Total square feet of basement area
- **Heating**: Type of heating
- **HeatingQC**: Heating quality and condition
- **CentralAir**: Central air conditioning
- **Electrical**: Electrical system
- **1stFlrSF**: First Floor square feet
- **2ndFlrSF**: Second floor square feet
- **LowQualFinSF**: Low quality finished square feet (all floors)
- **GrLivArea**: Above grade (ground) living area square feet
- **BsmtFullBath**: Basement full bathrooms
- **BsmtHalfBath**: Basement half bathrooms
- **FullBath**: Full bathrooms above grade
- **HalfBath**: Half baths above grade
- **Bedroom**: Number of bedrooms above basement level
- **Kitchen**: Number of kitchens
- **KitchenQual**: Kitchen quality
- **TotRmsAbvGrd**: Total rooms above grade (does not include bathrooms)
- **Functional**: Home functionality rating
- **Fireplaces**: Number of fireplaces
- **FireplaceQu**: Fireplace quality
- **GarageType**: Garage location
- **GarageYrBlt**: Year garage was built
- **GarageFinish**: Interior finish of the garage
- **GarageCars**: Size of garage in car capacity
- **GarageArea**: Size of garage in square feet
- **GarageQual**: Garage quality
- **GarageCond**: Garage condition
- **PavedDrive**: Paved driveway
- **WoodDeckSF**: Wood deck area in square feet
- **OpenPorchSF**: Open porch area in square feet
- **EnclosedPorch**: Enclosed porch area in square feet
- **3SsnPorch**: Three-season porch area in square feet
- **ScreenPorch**: Screen porch area in square feet
- **PoolArea**: Pool area in square feet
- **PoolQC**: Pool quality
- **Fence**: Fence quality
- **MiscFeature**: Miscellaneous feature not covered in other categories
- **MiscVal**: Value of miscellaneous feature
- **MoSold**: Month Sold
- **YrSold**: Year Sold
- **SaleType**: Type of sale
- **SaleCondition**: Condition of sale

Import Librabry

In [186…
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

%reload_ext autoreload
%autoreload 2
# will add libraries as an when needed

from sklearn.preprocessing import OrdinalEncoder
```

In [2]:
```
import plotly.express as px
from plotly.subplots import make_subplots
import plotly.graph_objs as go
```

In [3]:
```
pd.set_option('display.max_columns', 200)
pd.set_option('display.max_rows', 200)
```

In [4]:
```
df=pd.read_csv('train.csv')
test=pd.read_csv('test.csv')
print(f"Full DataSet Shape is : {df.shape}")
print(f"Full Test DataSet Shape is : {test.shape}")
```

```
Full DataSet Shape is : (1460, 81)
Full Test DataSet Shape is : (1459, 80)
```

Data Pre_profiling

In [5]:
```
import pandas_profiling as pp
```

Please Remove # if you are running the profiling first time

In [6]:
```
# profile = pp.ProfileReport(df)
# profile.to_file('Advanced_House_price_prediction_profile.html')
```

Data Preprocessing

Data preprocessing is a critical step in any machine learning project. Here, we will clean the data, handle missing values, and transform variables to ensure they are suitable for model training.

In [7]:
```
df.head(10)
```

Out[7]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilit
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllF
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllF
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllF
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllF
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllF
5	6	50	RL	85.0	14115	Pave	NaN	IR1	Lvl	AllF
6	7	20	RL	75.0	10084	Pave	NaN	Reg	Lvl	AllF
7	8	60	RL	NaN	10382	Pave	NaN	IR1	Lvl	AllF
8	9	50	RM	51.0	6120	Pave	NaN	Reg	Lvl	AllF
9	10	190	RL	50.0	7420	Pave	NaN	Reg	Lvl	AllF

- Dropped Id columns from dataset

In [8]:
```
df.drop(columns=(['Id']), inplace=True)
```

In [9]:
```
df.head(2)
```

Out[9]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
0	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub
1	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub

In [10]:
```
df.describe().T
```

Out[10]:

	count	mean	std	min	25%	50%	75%	
MSSubClass	1460.0	56.897260	42.300571	20.0	20.00	50.0	70.00	1
LotFrontage	1201.0	70.049958	24.284752	21.0	59.00	69.0	80.00	3
LotArea	1460.0	10516.828082	9981.264932	1300.0	7553.50	9478.5	11601.50	2152
OverallQual	1460.0	6.099315	1.382997	1.0	5.00	6.0	7.00	
OverallCond	1460.0	5.575342	1.112799	1.0	5.00	5.0	6.00	
YearBuilt	1460.0	1971.267808	30.202904	1872.0	1954.00	1973.0	2000.00	20
YearRemodAdd	1460.0	1984.865753	20.645407	1950.0	1967.00	1994.0	2004.00	20
MasVnrArea	1452.0	103.685262	181.066207	0.0	0.00	0.0	166.00	16
BsmtFinSF1	1460.0	443.639726	456.098091	0.0	0.00	383.5	712.25	56
BsmtFinSF2	1460.0	46.549315	161.319273	0.0	0.00	0.0	0.00	14
BsmtUnfSF	1460.0	567.240411	441.866955	0.0	223.00	477.5	808.00	23
TotalBsmtSF	1460.0	1057.429452	438.705324	0.0	795.75	991.5	1298.25	61
1stFlrSF	1460.0	1162.626712	386.587738	334.0	882.00	1087.0	1391.25	46
2ndFlrSF	1460.0	346.992466	436.528436	0.0	0.00	0.0	728.00	20
LowQualFinSF	1460.0	5.844521	48.623081	0.0	0.00	0.0	0.00	5
GrLivArea	1460.0	1515.463699	525.480383	334.0	1129.50	1464.0	1776.75	56
BsmtFullBath	1460.0	0.425342	0.518911	0.0	0.00	0.0	1.00	
BsmtHalfBath	1460.0	0.057534	0.238753	0.0	0.00	0.0	0.00	
FullBath	1460.0	1.565068	0.550916	0.0	1.00	2.0	2.00	
HalfBath	1460.0	0.382877	0.502885	0.0	0.00	0.0	1.00	
BedroomAbvGr	1460.0	2.866438	0.815778	0.0	2.00	3.0	3.00	
KitchenAbvGr	1460.0	1.046575	0.220338	0.0	1.00	1.0	1.00	
TotRmsAbvGrd	1460.0	6.517808	1.625393	2.0	5.00	6.0	7.00	
Fireplaces	1460.0	0.613014	0.644666	0.0	0.00	1.0	1.00	
GarageYrBlt	1379.0	1978.506164	24.689725	1900.0	1961.00	1980.0	2002.00	20
GarageCars	1460.0	1.767123	0.747315	0.0	1.00	2.0	2.00	
GarageArea	1460.0	472.980137	213.804841	0.0	334.50	480.0	576.00	14
WoodDeckSF	1460.0	94.244521	125.338794	0.0	0.00	0.0	168.00	8
OpenPorchSF	1460.0	46.660274	66.256028	0.0	0.00	25.0	68.00	5
EnclosedPorch	1460.0	21.954110	61.119149	0.0	0.00	0.0	0.00	5
3SsnPorch	1460.0	3.409589	29.317331	0.0	0.00	0.0	0.00	5
ScreenPorch	1460.0	15.060959	55.757415	0.0	0.00	0.0	0.00	4
PoolArea	1460.0	2.758904	40.177307	0.0	0.00	0.0	0.00	7

	count	mean	std	min	25%	50%	75%	
MiscVal	1460.0	43.489041	496.123024	0.0	0.00	0.0	0.00	15
MoSold	1460.0	6.321918	2.703626	1.0	5.00	6.0	8.00	
YrSold	1460.0	2007.815753	1.328095	2006.0	2007.00	2008.0	2009.00	2(
SalePrice	1460.0	180921.195890	79442.502883	34900.0	129975.00	163000.0	214000.00	755(

In [11]:
```
df.drop_duplicates(inplace=True)
```

In [12]:
```
missing=df.isnull().sum()
lendf=len(df)
perc=(missing/lendf)*100
#print(perc)
col_nam=[]
for i, j in perc.items():
    if j >=40:
        col_nam.append(i)
print(f"List of Columsn has less more than 40% missing values: \t {col_nam} ")
df.drop(columns=(col_nam), inplace=True)
df.shape
```

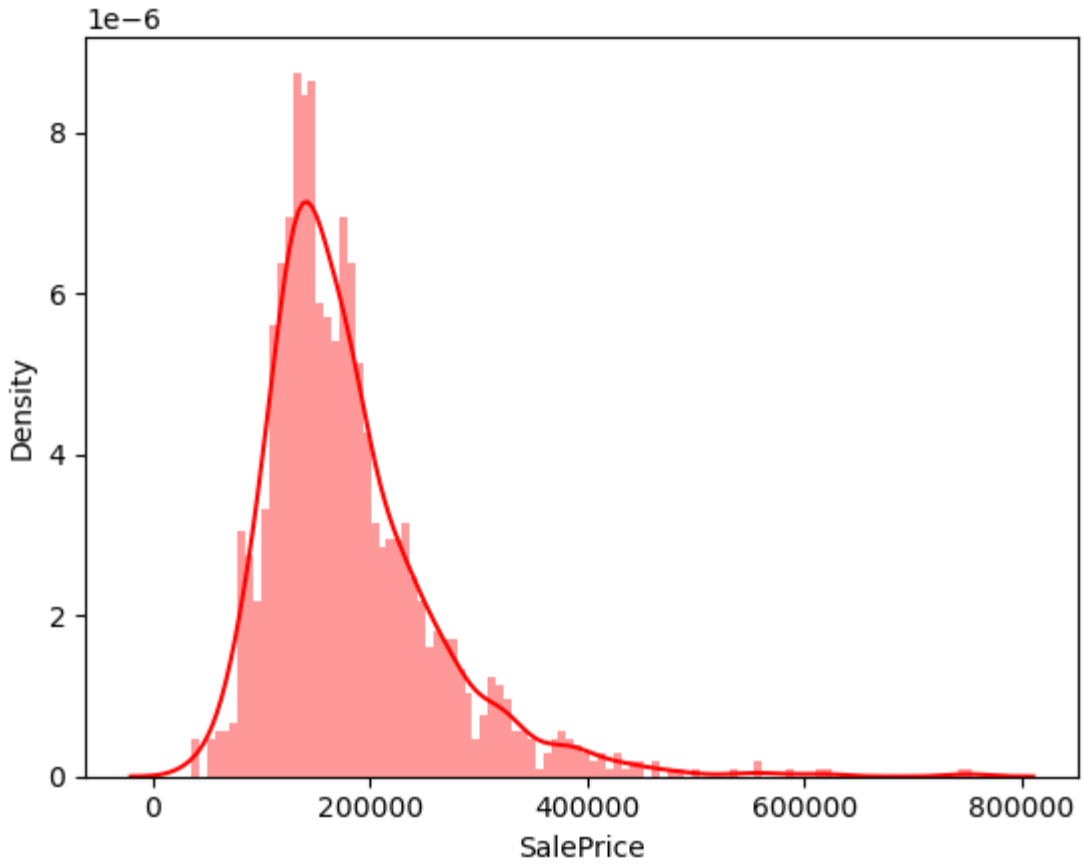
```
List of Columsn has less more than 40% missing values:   ['Alley', 'FireplaceQu', '
PoolQC', 'Fence', 'MiscFeature']
```

Out[12]:
```
(1460, 75)
```

Target Variable Distribution

In [13]:
```
print(df['SalePrice'].describe())
sns.distplot(df['SalePrice'], hist_kws={'alpha': 0.4}, bins=100, color='r' )
plt.show()
```

```
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
```



- Data seperation using Dtypes

In [14]:
```
df.dtypes.unique()
```

Out[14]:
```
array([dtype('int64'), dtype('O'), dtype('float64')], dtype=object)
```

In [15]:
```
df_num=df.select_dtypes(include=['int64', 'float64'])
```

In [16]:
```
df_num.head()
```

Out[16]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVn
0	60	65.0	8450	7	5	2003	2003	
1	20	80.0	9600	6	8	1976	1976	
2	60	68.0	11250	7	5	2001	2002	
3	70	60.0	9550	7	5	1915	1970	
4	60	84.0	14260	8	5	2000	2000	

In [17]:
```
df_cat=df.select_dtypes('O')
df_cat.head(2)
```

Out[17]:

	MSZoning	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Cor
0	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	
1	RL	Pave	Reg	Lvl	AllPub	FR2	Gtl	Veenker	

- Fill missing values

In [18]:
```
df.isnull().sum()
```

Out[18]:

MSSubClass	0
MSZoning	0
LotFrontage	259
LotArea	0
Street	0
LotShape	0
LandContour	0
Utilities	0
LotConfig	0
LandSlope	0
Neighborhood	0
Condition1	0
Condition2	0
BldgType	0
HouseStyle	0
OverallQual	0
OverallCond	0
YearBuilt	0
YearRemodAdd	0
RoofStyle	0
RoofMatl	0
Exterior1st	0
Exterior2nd	0
MasVnrType	8
MasVnrArea	8
ExterQual	0
ExterCond	0
Foundation	0
BsmtQual	37
BsmtCond	37
BsmtExposure	38
BsmtFinType1	37
BsmtFinSF1	0
BsmtFinType2	38
BsmtFinSF2	0
BsmtUnfSF	0
TotalBsmtSF	0
Heating	0
HeatingQC	0
CentralAir	0
Electrical	1
1stFlrSF	0
2ndFlrSF	0
LowQualFinSF	0
GrLivArea	0
BsmtFullBath	0
BsmtHalfBath	0
FullBath	0
HalfBath	0
BedroomAbvGr	0
KitchenAbvGr	0
KitchenQual	0
TotRmsAbvGrd	0
Functional	0
Fireplaces	0
GarageType	81
GarageYrBlt	81
GarageFinish	81
GarageCars	0

```
GarageArea         0
GarageQual        81
GarageCond        81
PavedDrive         0
WoodDeckSF         0
OpenPorchSF        0
EnclosedPorch      0
3SsnPorch          0
ScreenPorch        0
PoolArea           0
MiscVal            0
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
dtype: int64
```

In [19]:
```
backup=df.copy()
```

In [20]:
```
filled_df = df.fillna(df.mode().iloc[0])
```

In [21]:
```
filled_df.isnull().sum()
```

Out[21]:

MSSubClass	0
MSZoning	0
LotFrontage	0
LotArea	0
Street	0
LotShape	0
LandContour	0
Utilities	0
LotConfig	0
LandSlope	0
Neighborhood	0
Condition1	0
Condition2	0
BldgType	0
HouseStyle	0
OverallQual	0
OverallCond	0
YearBuilt	0
YearRemodAdd	0
RoofStyle	0
RoofMatl	0
Exterior1st	0
Exterior2nd	0
MasVnrType	0
MasVnrArea	0
ExterQual	0
ExterCond	0
Foundation	0
BsmtQual	0
BsmtCond	0
BsmtExposure	0
BsmtFinType1	0
BsmtFinSF1	0
BsmtFinType2	0
BsmtFinSF2	0
BsmtUnfSF	0
TotalBsmtSF	0
Heating	0
HeatingQC	0
CentralAir	0
Electrical	0
1stFlrSF	0
2ndFlrSF	0
LowQualFinSF	0
GrLivArea	0
BsmtFullBath	0
BsmtHalfBath	0
FullBath	0
HalfBath	0
BedroomAbvGr	0
KitchenAbvGr	0
KitchenQual	0
TotRmsAbvGrd	0
Functional	0
Fireplaces	0
GarageType	0
GarageYrBlt	0
GarageFinish	0
GarageCars	0

```
GarageArea       0
GarageQual       0
GarageCond       0
PavedDrive       0
WoodDeckSF       0
OpenPorchSF      0
EnclosedPorch    0
3SsnPorch        0
ScreenPorch      0
PoolArea         0
MiscVal          0
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
dtype: int64
```

- will work on numeric columns

In [22]:
```
df_num.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 0 to 1459
Data columns (total 37 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MSSubClass     1460 non-null   int64  
 1   LotFrontage    1201 non-null   float64
 2   LotArea        1460 non-null   int64  
 3   OverallQual    1460 non-null   int64  
 4   OverallCond    1460 non-null   int64  
 5   YearBuilt      1460 non-null   int64  
 6   YearRemodAdd   1460 non-null   int64  
 7   MasVnrArea     1452 non-null   float64
 8   BsmtFinSF1     1460 non-null   int64  
 9   BsmtFinSF2     1460 non-null   int64  
 10  BsmtUnfSF      1460 non-null   int64  
 11  TotalBsmtSF    1460 non-null   int64  
 12  1stFlrSF       1460 non-null   int64  
 13  2ndFlrSF       1460 non-null   int64  
 14  LowQualFinSF   1460 non-null   int64  
 15  GrLivArea      1460 non-null   int64  
 16  BsmtFullBath   1460 non-null   int64  
 17  BsmtHalfBath   1460 non-null   int64  
 18  FullBath       1460 non-null   int64  
 19  HalfBath       1460 non-null   int64  
 20  BedroomAbvGr   1460 non-null   int64  
 21  KitchenAbvGr   1460 non-null   int64  
 22  TotRmsAbvGrd   1460 non-null   int64  
 23  Fireplaces     1460 non-null   int64  
 24  GarageYrBlt    1379 non-null   float64
 25  GarageCars     1460 non-null   int64  
 26  GarageArea     1460 non-null   int64  
 27  WoodDeckSF     1460 non-null   int64  
 28  OpenPorchSF    1460 non-null   int64  
 29  EnclosedPorch  1460 non-null   int64  
 30  3SsnPorch      1460 non-null   int64  
 31  ScreenPorch    1460 non-null   int64  
 32  PoolArea       1460 non-null   int64  
 33  MiscVal        1460 non-null   int64  
 34  MoSold         1460 non-null   int64  
 35  YrSold         1460 non-null   int64  
 36  SalePrice      1460 non-null   int64  
dtypes: float64(3), int64(34)
memory usage: 433.4 KB
```

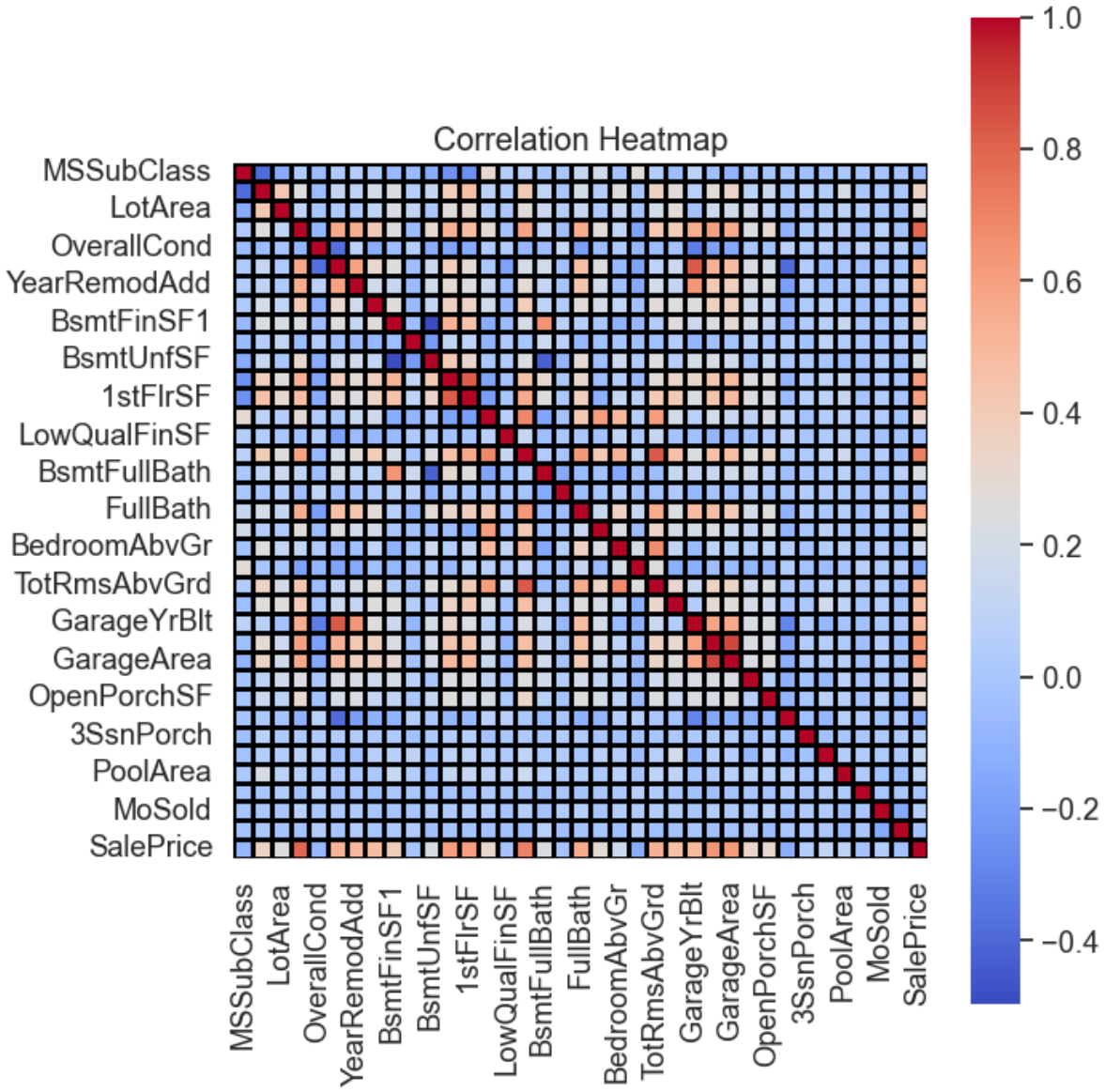
In [23]:
```
df_num.corr()
```

Out[23]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRen
MSSubClass	1.000000	-0.386347	-0.139781	0.032628	-0.059316	0.027850	0
LotFrontage	-0.386347	1.000000	0.426095	0.251646	-0.059213	0.123349	0
LotArea	-0.139781	0.426095	1.000000	0.105806	-0.005636	0.014228	0
OverallQual	0.032628	0.251646	0.105806	1.000000	-0.091932	0.572323	0
OverallCond	-0.059316	-0.059213	-0.005636	-0.091932	1.000000	-0.375983	0
YearBuilt	0.027850	0.123349	0.014228	0.572323	-0.375983	1.000000	0
YearRemodAdd	0.040581	0.088866	0.013788	0.550684	0.073741	0.592855	1
MasVnrArea	0.022936	0.193458	0.104160	0.411876	-0.128101	0.315707	0
BsmtFinSF1	-0.069836	0.233633	0.214103	0.239666	-0.046231	0.249503	0
BsmtFinSF2	-0.065649	0.049900	0.111170	-0.059119	0.040229	-0.049107	-0
BsmtUnfSF	-0.140759	0.132644	-0.002618	0.308159	-0.136841	0.149040	0
TotalBsmtSF	-0.238518	0.392075	0.260833	0.537808	-0.171098	0.391452	0
1stFlrSF	-0.251758	0.457181	0.299475	0.476224	-0.144203	0.281986	0
2ndFlrSF	0.307886	0.080177	0.050986	0.295493	0.028942	0.010308	0
LowQualFinSF	0.046474	0.038469	0.004779	-0.030429	0.025494	-0.183784	-0
GrLivArea	0.074853	0.402797	0.263116	0.593007	-0.079686	0.199010	0
BsmtFullBath	0.003491	0.100949	0.158155	0.111098	-0.054942	0.187599	0
BsmtHalfBath	-0.002333	-0.007234	0.048046	-0.040150	0.117821	-0.038162	-0
FullBath	0.131608	0.198769	0.126031	0.550600	-0.194149	0.468271	0
HalfBath	0.177354	0.053532	0.014259	0.273458	-0.060769	0.242656	0
BedroomAbvGr	-0.023438	0.263170	0.119690	0.101676	0.012980	-0.070651	-0
KitchenAbvGr	0.281721	-0.006069	-0.017784	-0.183882	-0.087001	-0.174800	-0
TotRmsAbvGrd	0.040380	0.352096	0.190015	0.427452	-0.057583	0.095589	0
Fireplaces	-0.045569	0.266639	0.271364	0.396765	-0.023820	0.147716	0
GarageYrBlt	0.085072	0.070250	-0.024947	0.547766	-0.324297	0.825667	0
GarageCars	-0.040110	0.285691	0.154871	0.600671	-0.185758	0.537850	0
GarageArea	-0.098672	0.344997	0.180403	0.562022	-0.151521	0.478954	0
WoodDeckSF	-0.012579	0.088521	0.171698	0.238923	-0.003334	0.224880	0
OpenPorchSF	-0.006100	0.151972	0.084774	0.308819	-0.032589	0.188686	0
EnclosedPorch	-0.012037	0.010700	-0.018340	-0.113937	0.070356	-0.387268	-0
3SsnPorch	-0.043825	0.070029	0.020423	0.030371	0.025504	0.031355	0
ScreenPorch	-0.026030	0.041383	0.043160	0.064886	0.054811	-0.050364	-0
PoolArea	0.008283	0.206167	0.077672	0.065166	-0.001985	0.004950	0

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRen
MiscVal	-0.007683	0.003368	0.038068	-0.031406	0.068777	-0.034383	-0
MoSold	-0.013585	0.011200	0.001205	0.070815	-0.003511	0.012398	0
YrSold	-0.021407	0.007450	-0.014261	-0.027347	0.043950	-0.013618	0
SalePrice	-0.084284	0.351799	0.263843	0.790982	-0.077856	0.522897	0

In [24]:
```
cormat=df_num.corr()
paper=plt.figure(figsize=(7,8))
sns.set(font_scale=1.2)
sns.heatmap(cormat, cmap="coolwarm", cbar=True, linewidths=1, linecolor='black', vm
plt.title("Correlation Heatmap")
plt.show()
```



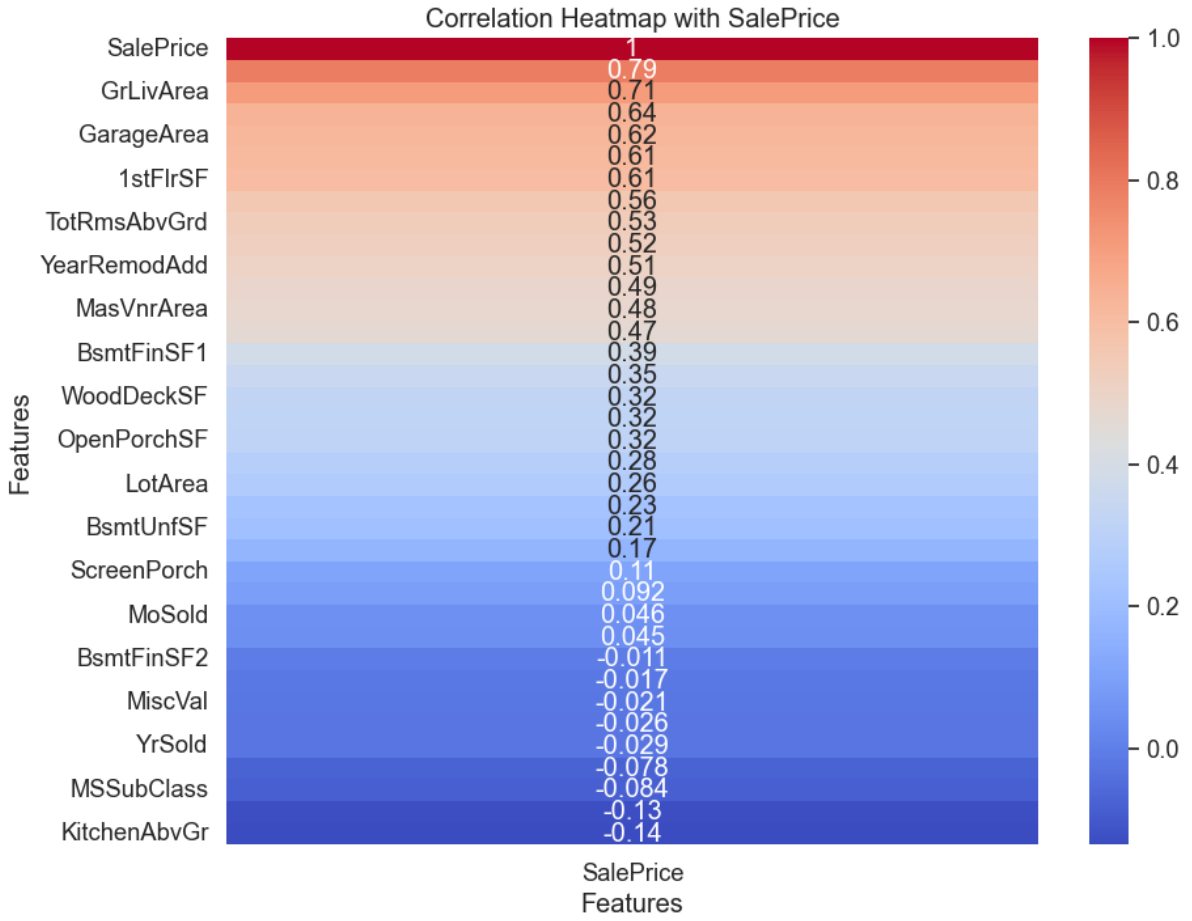
In [25]:
```
df_num.hist(figsize=(16, 20), bins=50, xlabelsize=8, ylabelsize=8, color='Red')
plt.show()
```

In [26]:
```
df_num_corr=df_num.corr()['SalePrice'][:-1]
best_num_features=df_num_corr[abs(df_num_corr)>0.4].sort_values(ascending=False)
```

In [27]:
```
print(f"There Are {len(best_num_features)} Best Features with SalePrice \n\n{best_n
```

```
There Are 13 Best Features with SalePrice

OverallQual     0.790982
GrLivArea       0.708624
GarageCars      0.640409
GarageArea      0.623431
TotalBsmtSF     0.613581
1stFlrSF        0.605852
FullBath        0.560664
TotRmsAbvGrd    0.533723
YearBuilt       0.522897
YearRemodAdd    0.507101
GarageYrBlt     0.486362
MasVnrArea      0.477493
Fireplaces      0.466929
Name: SalePrice, dtype: float64
```

In [28]:
```
correlation_matrix=df_num.corr()
salespricecorr=correlation_matrix["SalePrice"].sort_values(ascending=False)
salepricecorr_df=pd.DataFrame(salespricecorr)
plt.figure(figsize=(10, 8))
sns.heatmap(salepricecorr_df, annot=True, cmap="coolwarm", cbar=True)
plt.xlabel('Features')
plt.ylabel('Features')
plt.title('Correlation Heatmap with SalePrice')
plt.show()
```



In [29]:
```
best_num_features.index
```

Out[29]:
```
Index(['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF',
       '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd',
       'GarageYrBlt', 'MasVnrArea', 'Fireplaces'],
      dtype='object')
```

In [30]:
```
best_num_featurelist= ['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'Tot
       '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd',
       'GarageYrBlt', 'MasVnrArea', 'Fireplaces','SalePrice']
df_best_num_feature=df.loc[:,best_num_featurelist].copy()
```

In [31]:
```
df_best_num_feature
```

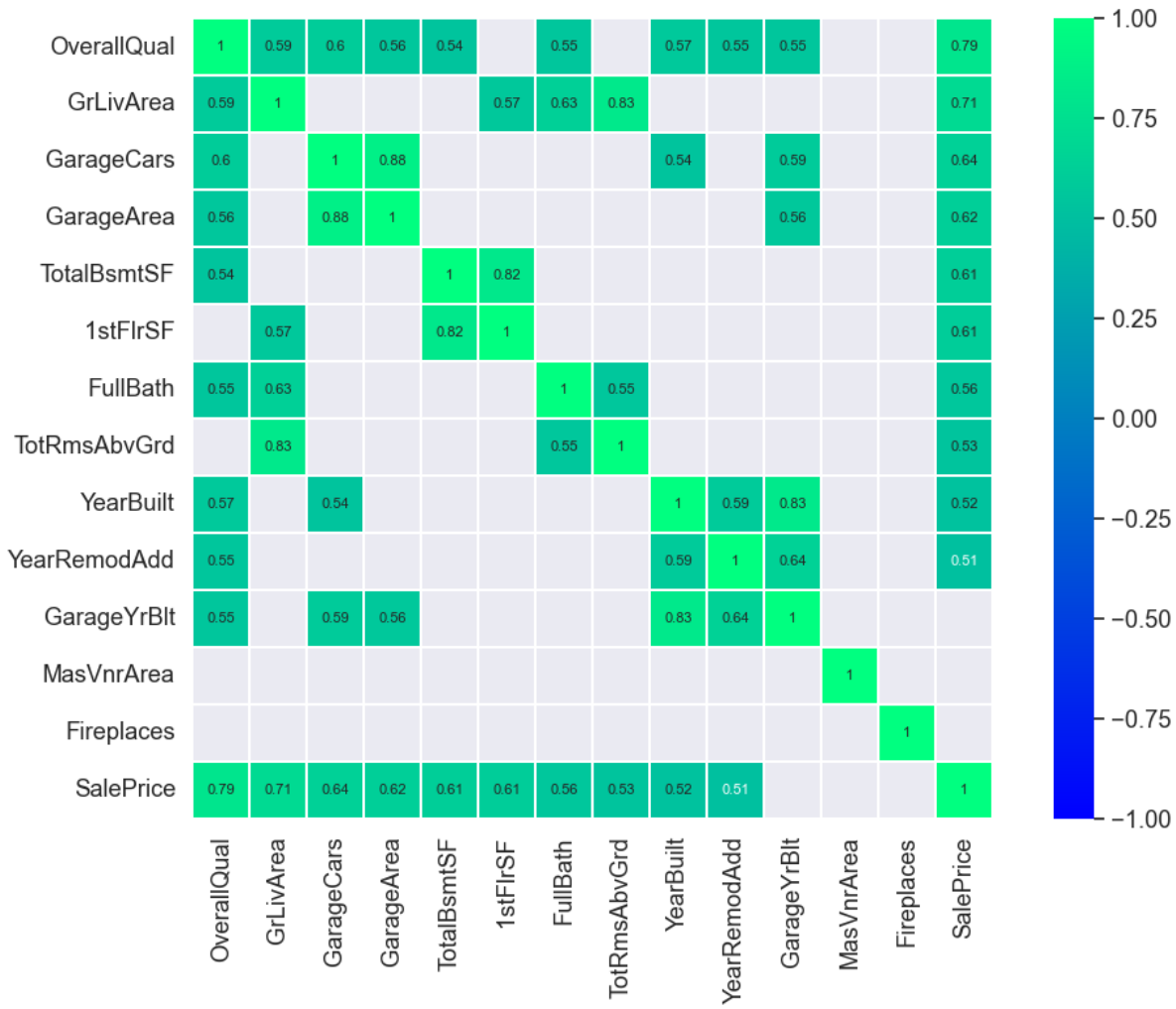
Out[31]:

	OverallQual	GrLivArea	GarageCars	GarageArea	TotalBsmtSF	1stFlrSF	FullBath	TotRmsAb
0	7	1710	2	548	856	856	2	
1	6	1262	2	460	1262	1262	2	
2	7	1786	2	608	920	920	2	
3	7	1717	3	642	756	961	1	
4	8	2198	3	836	1145	1145	2	
...	...	...	...	...	...	...	...	
1455	6	1647	2	460	953	953	2	
1456	6	2073	2	500	1542	2073	2	
1457	7	2340	1	252	1152	1188	2	
1458	5	1078	1	240	1078	1078	1	
1459	5	1256	1	276	1256	1256	1	

1460 rows × 14 columns

Feature to Feature Relationship

In [32]:
```
corr=df_best_num_feature.corr()
paper=plt.figure(figsize=(12,8))
sns.heatmap(corr[(corr>=0.5) |(corr<= -0.4)] ,
            cmap='winter', vmax=1.0, vmin=-1.0, linewidths=0.1,
            annot=True, annot_kws={"size": 8}, square=True)

plt.show()
```

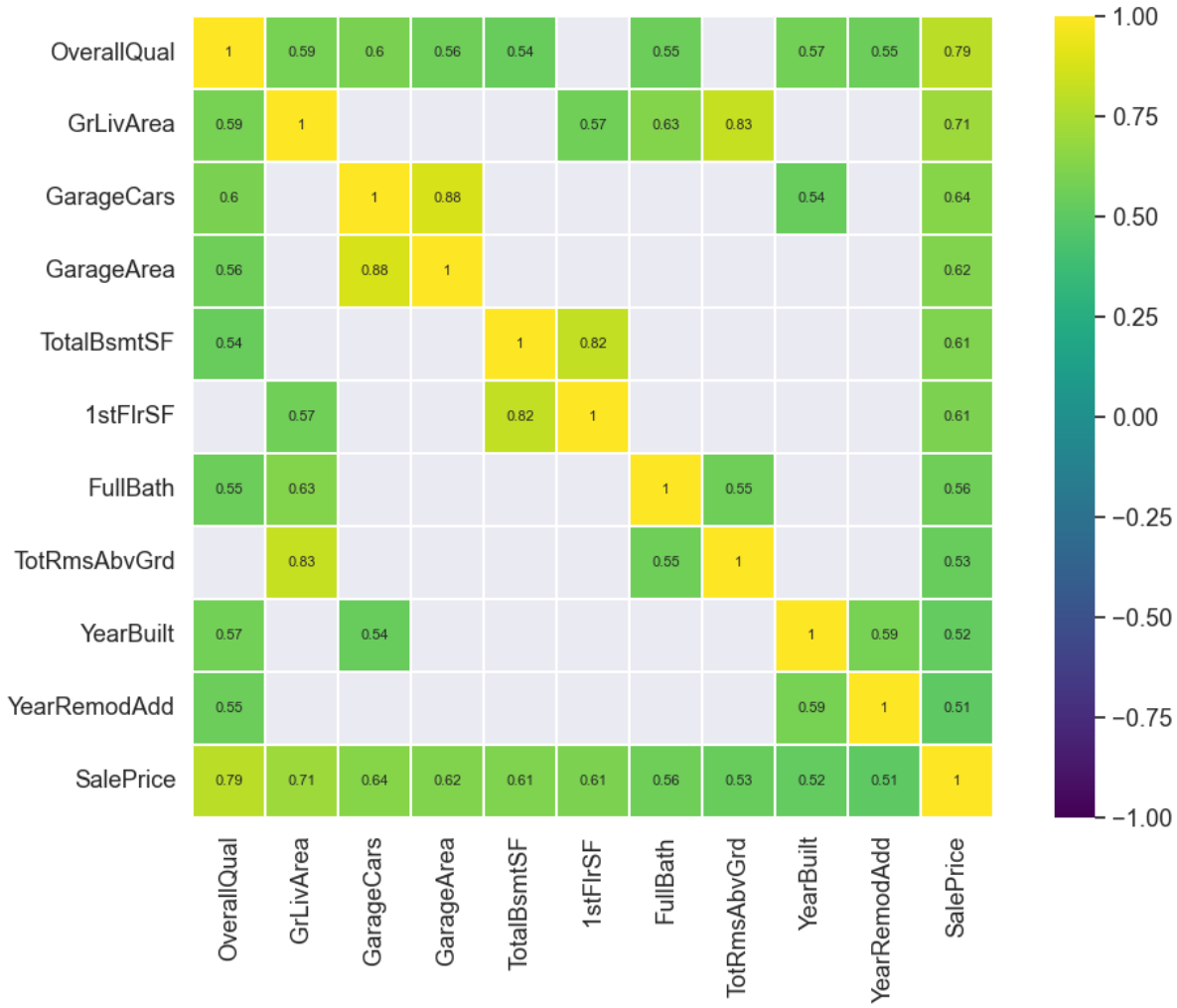


In [33]:
```
df_best_num_feature = df_best_num_feature.drop(['GarageYrBlt', 'MasVnrArea', 'Firep
```

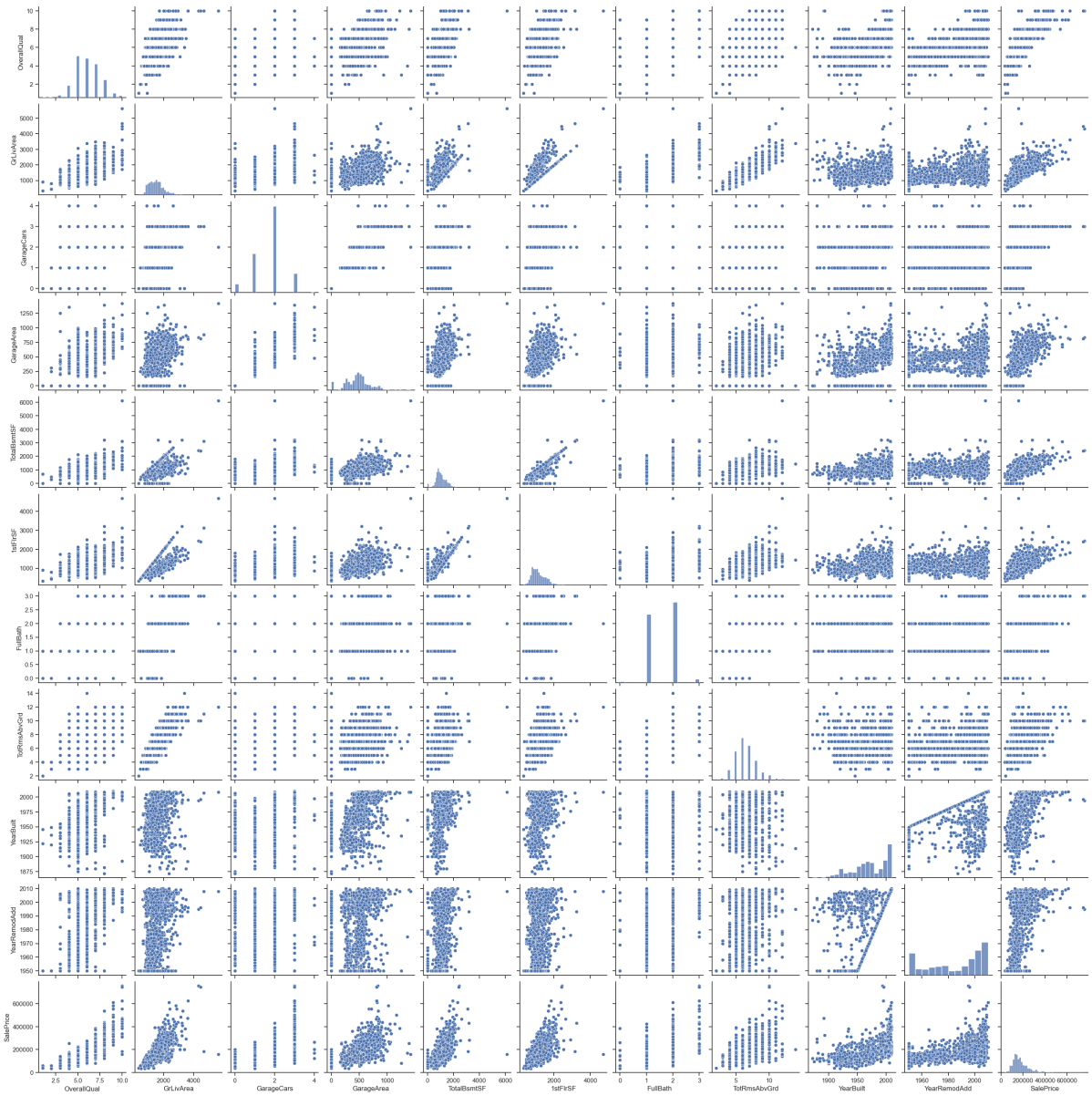
In [34]:
```
df_best_num_feature.columns
```

Out[34]:
```
Index(['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF',
       '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd',
       'SalePrice'],
      dtype='object')
```

In [35]:
```
corr=df_best_num_feature.corr()
paper=plt.figure(figsize=(12,8))
sns.heatmap(corr[(corr>=0.5) |(corr<= -0.4)] ,
            cmap='viridis', vmax=1.0, vmin=-1.0, linewidths=0.1,
            annot=True, annot_kws={"size": 8}, square=True)

plt.show()
```



In [36]:
```
sns.set(style="ticks")
sns.pairplot(df_best_num_feature)

plt.show()
```



In [37]:
```
df_best_num_feature.isnull().sum()
```

Out[37]:
```
OverallQual     0
GrLivArea       0
GarageCars      0
GarageArea      0
TotalBsmtSF     0
1stFlrSF        0
FullBath        0
TotRmsAbvGrd    0
YearBuilt       0
YearRemodAdd    0
SalePrice       0
dtype: int64
```

Working on Categorical Data

In [38]:
```
df_cat.head()
```

Out[38]:

	MSZoning	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Cor
0	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	
1	RL	Pave	Reg	Lvl	AllPub	FR2	Gtl	Veenker	
2	RL	Pave	IR1	Lvl	AllPub	Inside	Gtl	CollgCr	
3	RL	Pave	IR1	Lvl	AllPub	Corner	Gtl	Crawfor	
4	RL	Pave	IR1	Lvl	AllPub	FR2	Gtl	NoRidge	

In [39]:
```
df_cat.nunique()
```

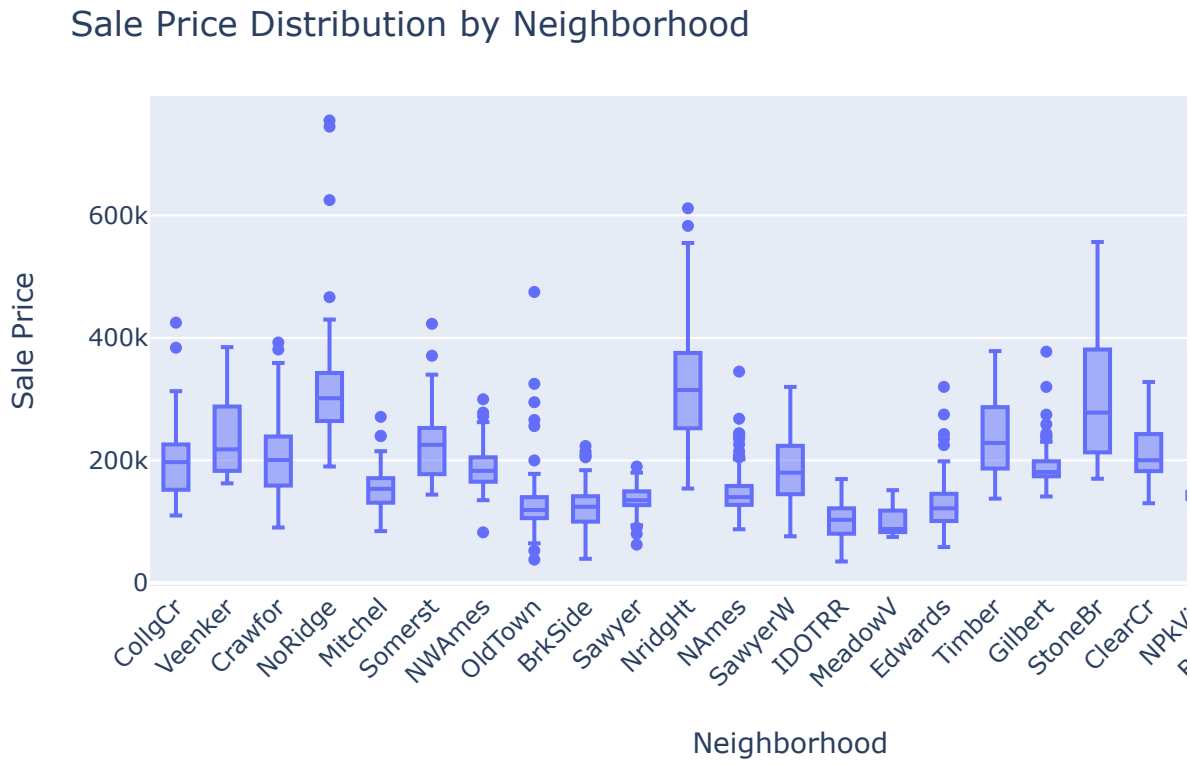
Out[39]:
```
MSZoning          5
Street            2
LotShape          4
LandContour       4
Utilities         2
LotConfig         5
LandSlope         3
Neighborhood     25
Condition1        9
Condition2        8
BldgType          5
HouseStyle        8
RoofStyle         6
RoofMatl          8
Exterior1st      15
Exterior2nd      16
MasVnrType        4
ExterQual         4
ExterCond         5
Foundation        6
BsmtQual          4
BsmtCond          4
BsmtExposure      4
BsmtFinType1      6
BsmtFinType2      6
Heating           6
HeatingQC         5
CentralAir        2
Electrical        5
KitchenQual       4
Functional        7
GarageType        6
GarageFinish      3
GarageQual        5
GarageCond        5
PavedDrive        3
SaleType          9
SaleCondition     6
dtype: int64
```

In [40]:
```
df_cat['Neighborhood'].value_counts()
```

Out[40]:
```
NAmes      225
CollgCr    150
OldTown    113
Edwards    100
Somerst     86
Gilbert     79
NridgHt     77
Sawyer      74
NWAmes      73
SawyerW     59
BrkSide     58
Crawfor     51
Mitchel     49
NoRidge     41
Timber      38
IDOTRR      37
ClearCr     28
StoneBr     25
SWISU       25
MeadowV     17
Blmngtn     17
BrDale      16
Veenker     11
NPkVill      9
Blueste      2
Name: Neighborhood, dtype: int64
```

- This column contains various neighborhood names, which makes it a categorical variable. Categorical variables consist of distinct categories (in this case, neighborhood names) without any inherent order.
- To manage the potential challenge of high dimensionality, we will opt to remove this column from our analysis

In [41]:
```
import plotly.express as px


fig = px.box(df, x='Neighborhood', y=df['SalePrice'])

fig.update_layout(
    title='Sale Price Distribution by Neighborhood',
    xaxis=dict(title='Neighborhood'),
    yaxis=dict(title='Sale Price'),
    xaxis_tickangle=-45,
    width=800,
    height=400,
)

fig.show()
```



In [42]:
```
df_cat.drop(columns=['Neighborhood'], inplace = True)
```

In [43]:
```
df_cat.nunique()
```

Out[43]:
```
MSZoning          5
Street            2
LotShape          4
LandContour       4
Utilities         2
LotConfig         5
LandSlope         3
Condition1        9
Condition2        8
BldgType          5
HouseStyle        8
RoofStyle         6
RoofMatl          8
Exterior1st      15
Exterior2nd      16
MasVnrType        4
ExterQual         4
ExterCond         5
Foundation        6
BsmtQual          4
BsmtCond          4
BsmtExposure      4
BsmtFinType1      6
BsmtFinType2      6
Heating           6
HeatingQC         5
CentralAir        2
Electrical        5
KitchenQual       4
Functional        7
GarageType        6
GarageFinish      3
GarageQual        5
GarageCond        5
PavedDrive        3
SaleType          9
SaleCondition     6
dtype: int64
```

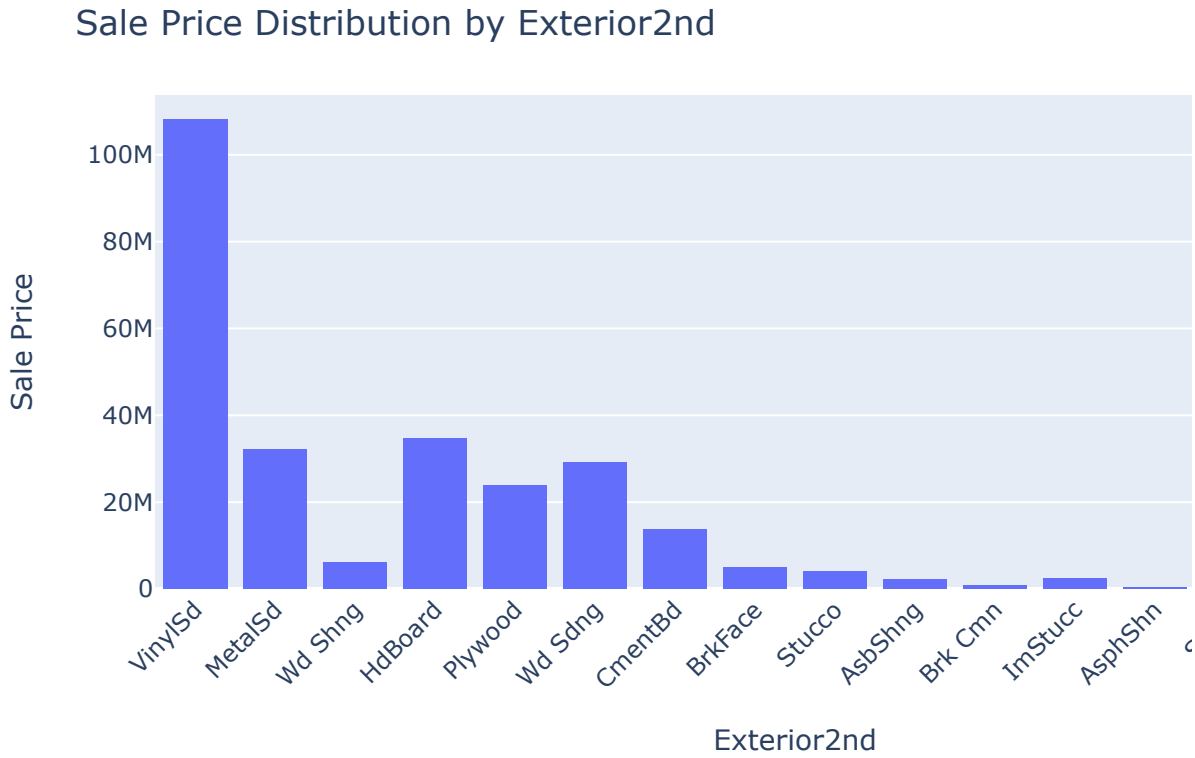
In [44]:
```
df_cat['Exterior1st'].value_counts()
```

Out[44]:
```
VinylSd    515
HdBoard    222
MetalSd    220
Wd Sdng    206
Plywood    108
CemntBd     61
BrkFace     50
WdShing     26
Stucco      25
AsbShng     20
BrkComm      2
Stone        2
AsphShn      1
ImStucc      1
CBlock       1
Name: Exterior1st, dtype: int64
```

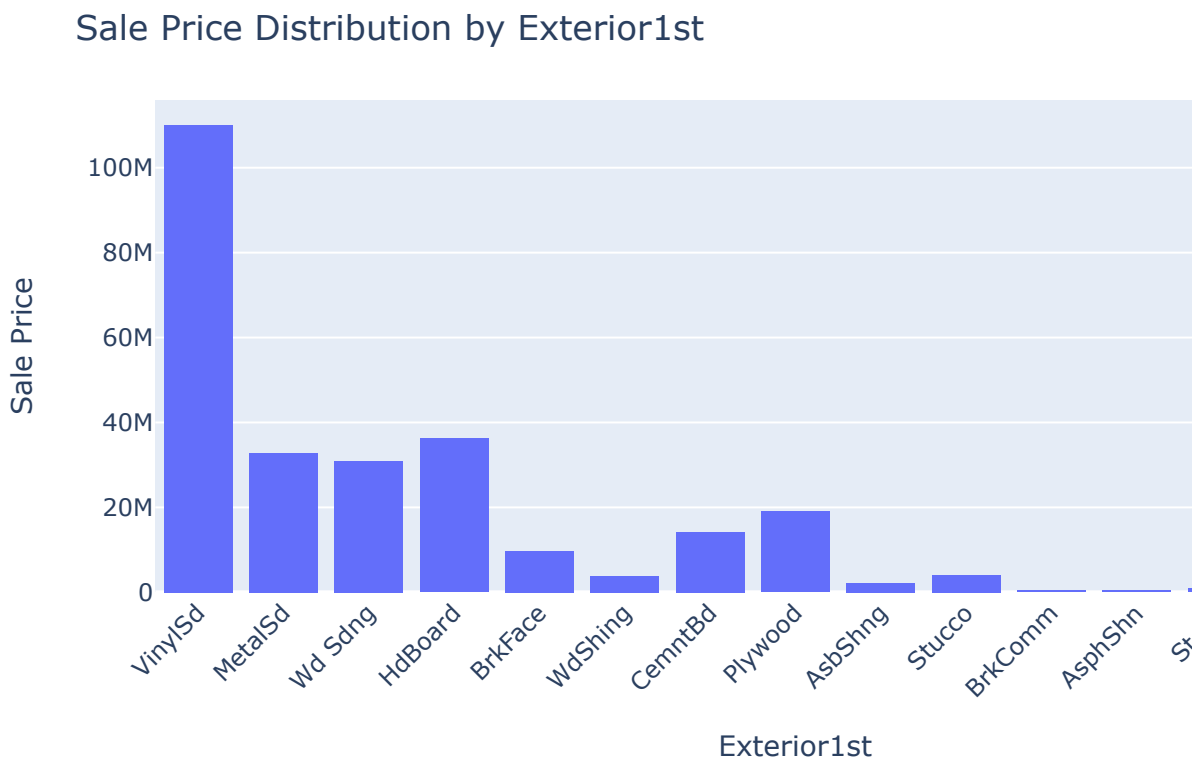
In [45]:
```
df_cat['Exterior2nd'].value_counts()
```

Out[45]:
```
VinylSd    504
MetalSd    214
HdBoard    207
Wd Sdng    197
Plywood    142
CmentBd     60
Wd Shng     38
Stucco      26
BrkFace     25
AsbShng     20
ImStucc     10
Brk Cmn      7
Stone        5
AsphShn      3
Other        1
CBlock       1
Name: Exterior2nd, dtype: int64
```

In [46]:
```
fig = px.histogram(df_cat, x='Exterior2nd', y=df['SalePrice'])

fig.update_layout(
    title='Sale Price Distribution by Exterior2nd',
    xaxis=dict(title='Exterior2nd'),
    yaxis=dict(title='Sale Price'),
    xaxis_tickangle=-45,
    width=800,
    height=400,
)

fig.show()
```



In [47]:
```
fig = px.histogram(df_cat, x='Exterior1st', y=df['SalePrice'])

fig.update_layout(
    title='Sale Price Distribution by Exterior1st',
    xaxis=dict(title='Exterior1st'),
    yaxis=dict(title='Sale Price'),
    xaxis_tickangle=-45,
    width=800,
    height=400,
)

fig.show()
```



In [48]:
```
for material in df_cat['Exterior1st'].unique():
    df_cat[f'Has_{material}_Exterior'] = (df_cat['Exterior1st'] == material) | (df_

df_cat.drop(['Exterior1st', 'Exterior2nd'], axis=1, inplace=True)
```

In [ ]:
```

```

In [49]:
```
for column in df_cat.columns:
    if df_cat[column].nunique() == 2:
        print(df_cat[column].value_counts())
```

```
Pave    1454
Grvl       6
Name: Street, dtype: int64
AllPub    1459
NoSeWa       1
Name: Utilities, dtype: int64
Y    1365
N      95
Name: CentralAir, dtype: int64
False    943
True     517
Name: Has_VinylSd_Exterior, dtype: int64
False    1238
True      222
Name: Has_MetalSd_Exterior, dtype: int64
False    1234
True      226
Name: Has_Wd Sdng_Exterior, dtype: int64
False    1224
True      236
Name: Has_HdBoard_Exterior, dtype: int64
False    1409
True       51
Name: Has_BrkFace_Exterior, dtype: int64
False    1434
True       26
Name: Has_WdShing_Exterior, dtype: int64
False    1399
True       61
Name: Has_CemntBd_Exterior, dtype: int64
False    1306
True      154
Name: Has_Plywood_Exterior, dtype: int64
False    1437
True       23
Name: Has_AsbShng_Exterior, dtype: int64
False    1429
True       31
Name: Has_Stucco_Exterior, dtype: int64
False    1458
True        2
Name: Has_BrkComm_Exterior, dtype: int64
False    1457
True        3
Name: Has_AsphShn_Exterior, dtype: int64
False    1454
True        6
Name: Has_Stone_Exterior, dtype: int64
False    1450
True       10
Name: Has_ImStucc_Exterior, dtype: int64
False    1459
True        1
Name: Has_CBlock_Exterior, dtype: int64
```

In [50]:
```
# Create an empty list to store column names
selected_columns = []

# Loop through the categorical columns
for column in df_cat.columns:
    # Check if the column is binary (unique values equal to 2)
    if df_cat[column].nunique() == 2:
        # Print the value counts for binary columns
        value_counts = df_cat[column].value_counts()
        print(f"Column: {column}")
        print(value_counts)

        # Check if the value count of the most common category is less than 50
        if value_counts.iloc[1] < 50:
            selected_columns.append(column)

# Print the selected columns
print("Selected Columns:", selected_columns)
```

```
Column: Street
Pave    1454
Grvl       6
Name: Street, dtype: int64
Column: Utilities
AllPub    1459
NoSeWa       1
Name: Utilities, dtype: int64
Column: CentralAir
Y    1365
N      95
Name: CentralAir, dtype: int64
Column: Has_VinylSd_Exterior
False    943
True     517
Name: Has_VinylSd_Exterior, dtype: int64
Column: Has_MetalSd_Exterior
False    1238
True      222
Name: Has_MetalSd_Exterior, dtype: int64
Column: Has_Wd Sdng_Exterior
False    1234
True      226
Name: Has_Wd Sdng_Exterior, dtype: int64
Column: Has_HdBoard_Exterior
False    1224
True      236
Name: Has_HdBoard_Exterior, dtype: int64
Column: Has_BrkFace_Exterior
False    1409
True       51
Name: Has_BrkFace_Exterior, dtype: int64
Column: Has_WdShing_Exterior
False    1434
True       26
Name: Has_WdShing_Exterior, dtype: int64
Column: Has_CemntBd_Exterior
False    1399
True       61
Name: Has_CemntBd_Exterior, dtype: int64
Column: Has_Plywood_Exterior
False    1306
True      154
Name: Has_Plywood_Exterior, dtype: int64
Column: Has_AsbShng_Exterior
False    1437
True       23
Name: Has_AsbShng_Exterior, dtype: int64
Column: Has_Stucco_Exterior
False    1429
True       31
Name: Has_Stucco_Exterior, dtype: int64
Column: Has_BrkComm_Exterior
False    1458
True        2
Name: Has_BrkComm_Exterior, dtype: int64
Column: Has_AsphShn_Exterior
False    1457
True        3
```

```
Name: Has_AsphShn_Exterior, dtype: int64
Column: Has_Stone_Exterior
False    1454
True        6
Name: Has_Stone_Exterior, dtype: int64
Column: Has_ImStucc_Exterior
False    1450
True       10
Name: Has_ImStucc_Exterior, dtype: int64
Column: Has_CBlock_Exterior
False    1459
True        1
Name: Has_CBlock_Exterior, dtype: int64
Selected Columns: ['Street', 'Utilities', 'Has_WdShing_Exterior', 'Has_AsbShng_Exte
rior', 'Has_Stucco_Exterior', 'Has_BrkComm_Exterior', 'Has_AsphShn_Exterior', 'Has_
Stone_Exterior', 'Has_ImStucc_Exterior', 'Has_CBlock_Exterior']
```

In [51]:
```
for i in df_cat[selected_columns]:
    print(df_cat[i].value_counts())
```

```
Pave    1454
Grvl       6
Name: Street, dtype: int64
AllPub    1459
NoSeWa       1
Name: Utilities, dtype: int64
False    1434
True       26
Name: Has_WdShing_Exterior, dtype: int64
False    1437
True       23
Name: Has_AsbShng_Exterior, dtype: int64
False    1429
True       31
Name: Has_Stucco_Exterior, dtype: int64
False    1458
True        2
Name: Has_BrkComm_Exterior, dtype: int64
False    1457
True        3
Name: Has_AsphShn_Exterior, dtype: int64
False    1454
True        6
Name: Has_Stone_Exterior, dtype: int64
False    1450
True       10
Name: Has_ImStucc_Exterior, dtype: int64
False    1459
True        1
Name: Has_CBlock_Exterior, dtype: int64
```

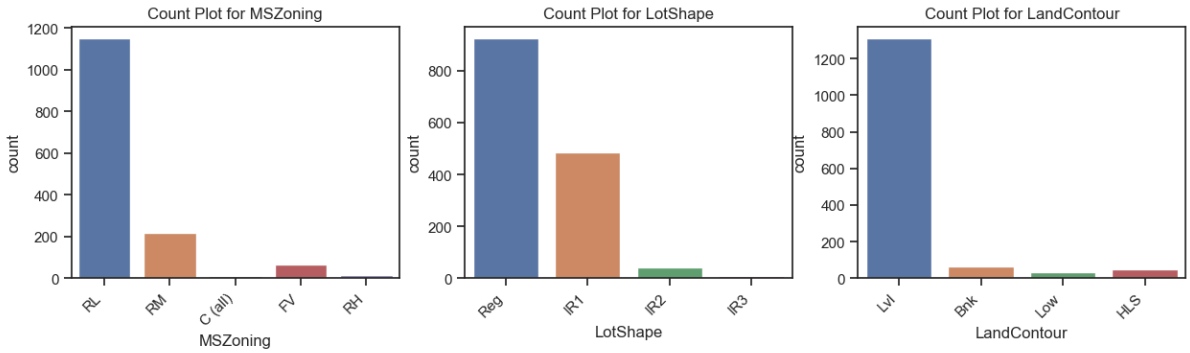
- will drop Selected_columns where most of the values are false

In [52]:
```
df_cat.drop(columns=(selected_columns), inplace = True)
```

In [53]:
```
df_cat.shape
```

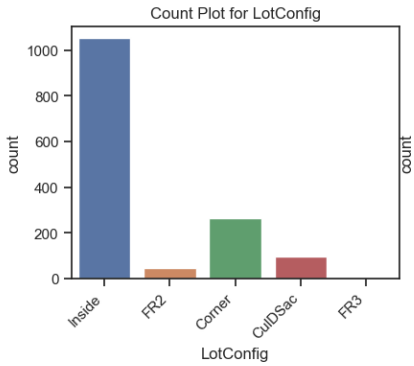
Out[53]: (1460, 40)

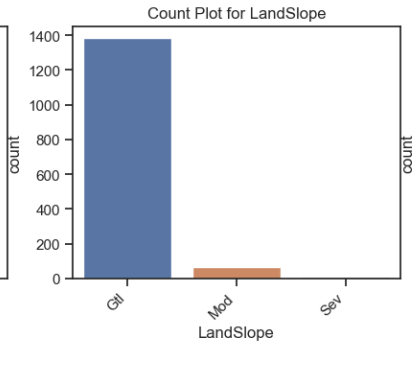
In [54]:
```
# Assuming you have a DataFrame df_cat with 40 categorical columns

# Calculate the number of rows needed
num_rows = (len(df_cat.columns) + 2) // 3  # Ceiling division to ensure enough rows

# Create subplots
fig, axes = plt.subplots(num_rows, 3, figsize=(15, 5 * num_rows))
plt.subplots_adjust(hspace=0.5)  # Adjust vertical spacing

# Loop through categorical columns and create count plots
for i, column in enumerate(df_cat.columns):
    row_idx = i // 3
    col_idx = i % 3
    ax = axes[row_idx, col_idx]

    sns.countplot(data=df_cat, x=column, ax=ax)
    ax.set_title(f'Count Plot for {column}')
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, horizontalalignment='righ

# Remove any empty subplots
for i in range(len(df_cat.columns), num_rows * 3):
    fig.delaxes(axes.flatten()[i])

plt.show()
```

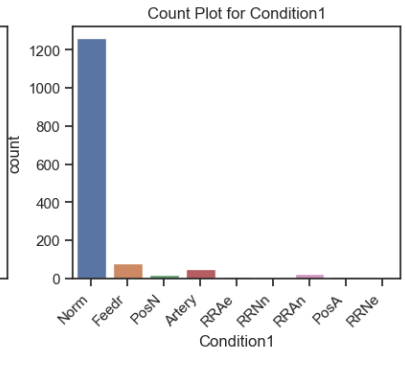

Count Plot for MSZoning
count
MSZoning
RL
RM
C (all)
FV
RH

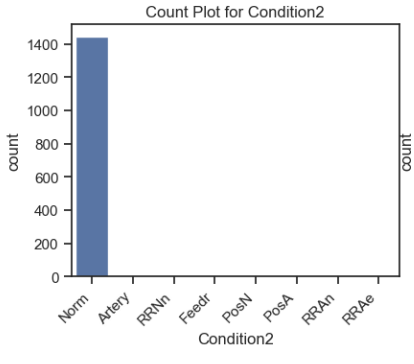
Count Plot for LotShape
count
LotShape
Reg
IR1
IR2
IR3

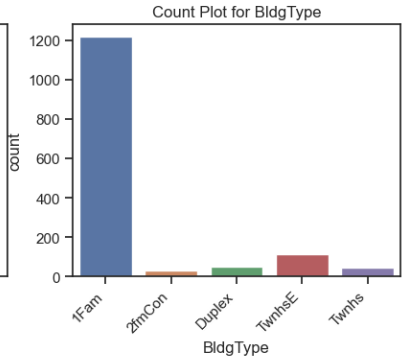
Count Plot for LandContour
count
LandContour
Lvl
Bnk
Low
HLS

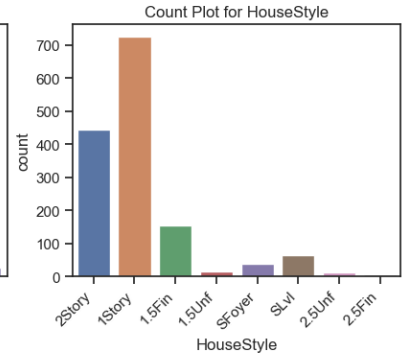

Count Plot for LotConfig
count
LotConfig
Inside
FR2
Corner
CulDSac
FR3

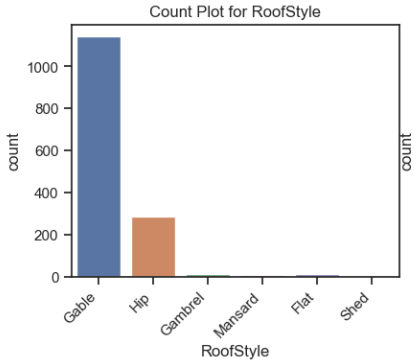

Count Plot for LandSlope
count
LandSlope
Gtl
Mod
Sev

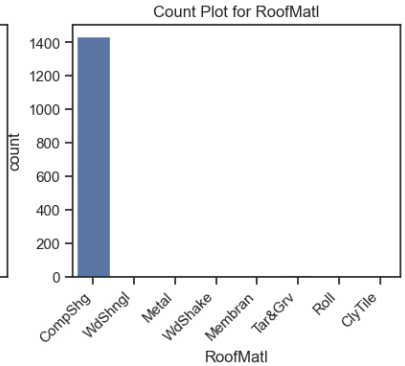

Count Plot for Condition1
count
Condition1
Norm
Feedr
PosN
Artery
RRAe
RRNn
RRAn
PosA
RRNe

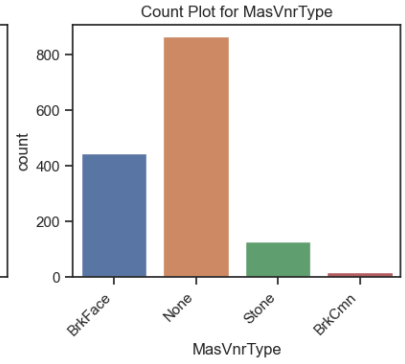

Count Plot for Condition2
count
Condition2
Norm
Artery
RRNn
Feedr
PosN
PosA
RRAn
RRAe

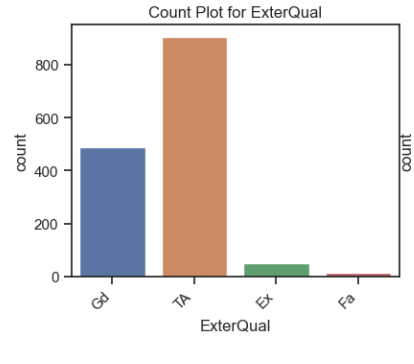

Count Plot for BldgType
count
BldgType
1Fam
2fmCon
Duplex
TwnhsE
Twnhs

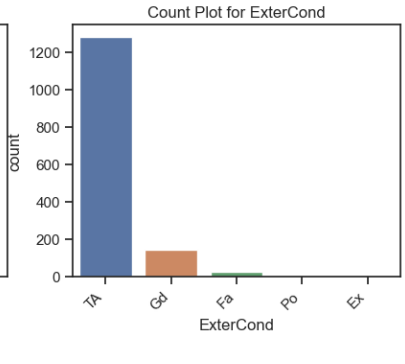

Count Plot for HouseStyle
count
HouseStyle
2Story
1Story
1.5Fin
1.5Unf
SFoyer
SLvl
2.5Unf
2.5Fin

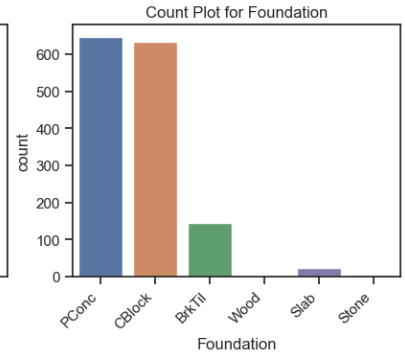

Count Plot for RoofStyle
count
RoofStyle
Gable
Hip
Gambrel
Mansard
Flat
Shed

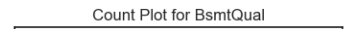

Count Plot for RoofMatl
count
RoofMatl
CompShg
WdShngl
Metal
WdShake
Membran
Tar&Grv
Roll
ClyTile

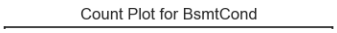

Count Plot for MasVnrType
count
MasVnrType
BrkFace
None
Stone
BrkCmn

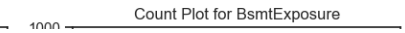

Count Plot for ExterQual
count
ExterQual
Gd
TA
Ex
Fa

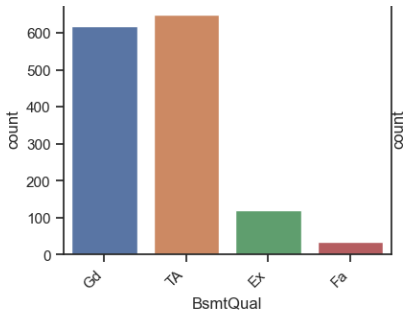

Count Plot for ExterCond
count
ExterCond
TA
Gd
Fa
Po
Ex

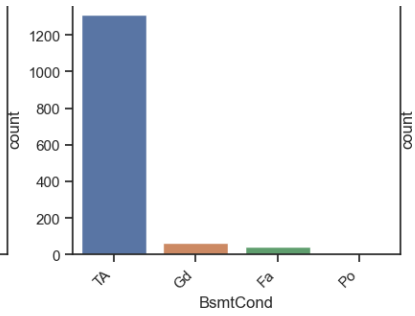

Count Plot for Foundation
count
Foundation
PConc
CBlock
BrkTil
Wood
Slab
Stone

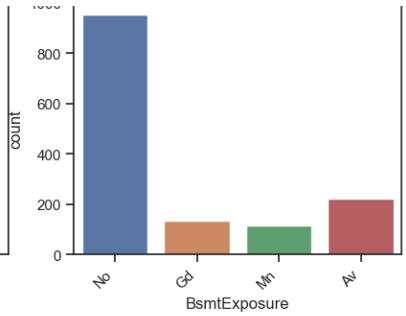

Count Plot for BsmtQual

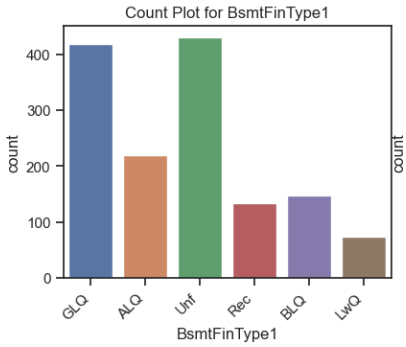

Count Plot for BsmtCond

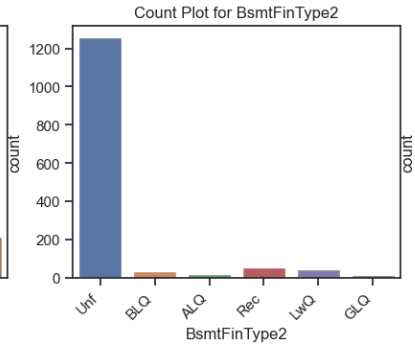

Count Plot for BsmtExposure

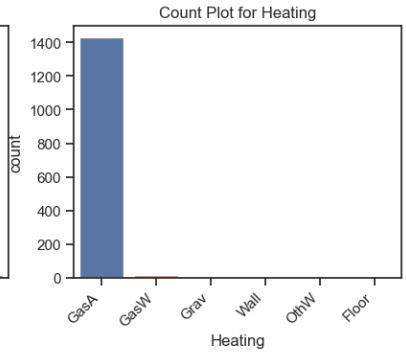

count
BsmtQual
Gd
TA
Ex
Fa

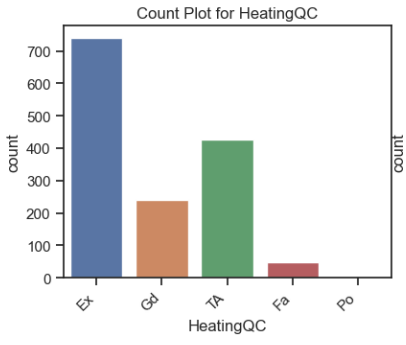

count
BsmtCond
TA
Gd
Fa
Po

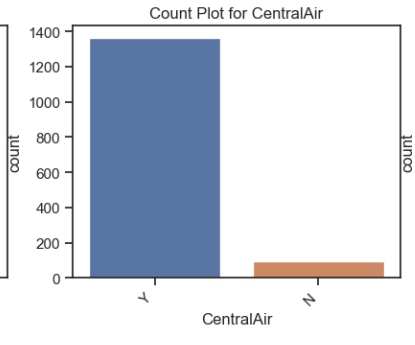

count
BsmtExposure
No
Gd
Mn
Av

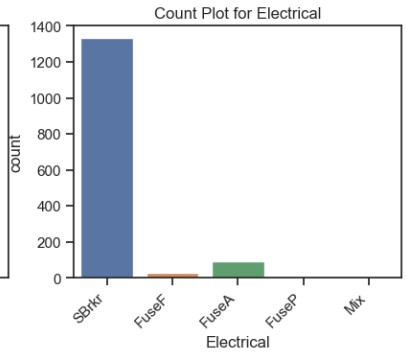

Count Plot for BsmtFinType1
count
BsmtFinType1
GLQ
ALQ
Unf
Rec
BLQ
LwQ

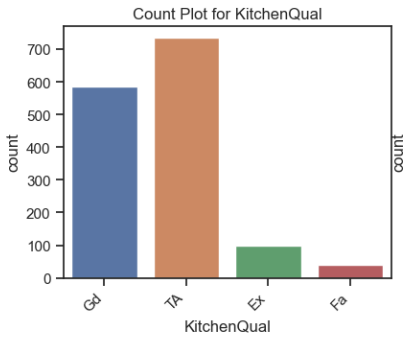

Count Plot for BsmtFinType2
count
BsmtFinType2
Unf
BLQ
ALQ
Rec
LwQ
GLQ

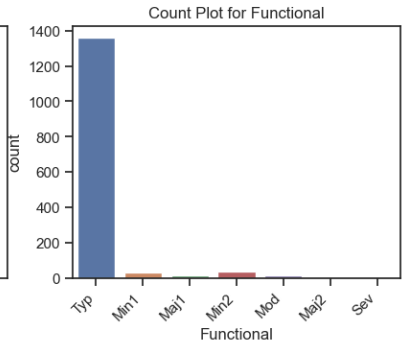

Count Plot for Heating
count
Heating
GasA
GasW
Grav
Wall
OthW
Floor

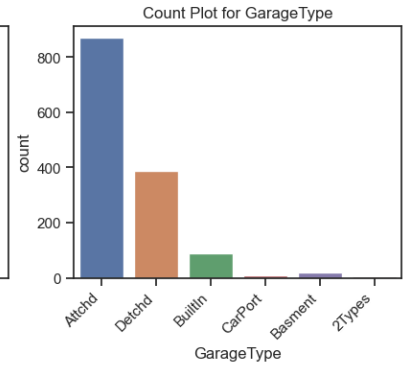

Count Plot for HeatingQC
count
HeatingQC
Ex
Gd
TA
Fa
Po

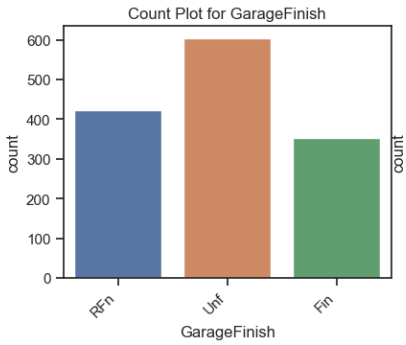

Count Plot for CentralAir
count
CentralAir
Y
N

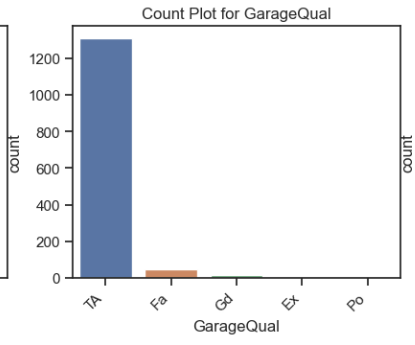

Count Plot for Electrical
count
Electrical
SBrkr
FuseF
FuseA
FuseP
Mix

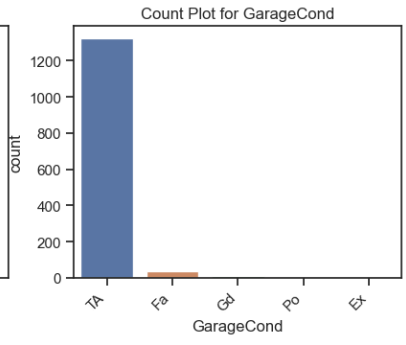

Count Plot for KitchenQual
count
KitchenQual
Gd
TA
Ex
Fa

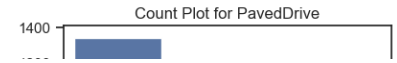

Count Plot for Functional
count
Functional
Typ
Min1
Maj1
Min2
Mod
Maj2
Sev

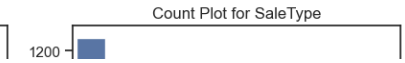

Count Plot for GarageType
count
GarageType
Attchd
Detchd
BuiltIn
CarPort
Basment
2Types

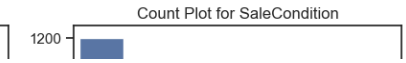

Count Plot for GarageFinish
count
GarageFinish
RFn
Unf
Fin

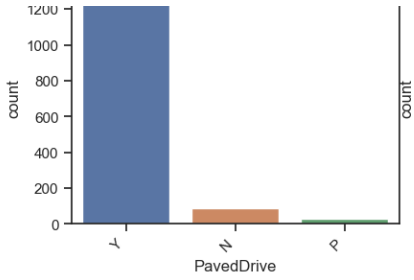

Count Plot for GarageQual
count
GarageQual
TA
Fa
Gd
Ex
Po

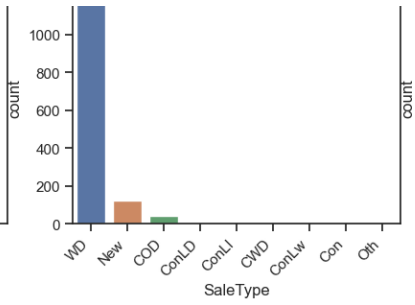

Count Plot for GarageCond
count
GarageCond
TA
Fa
Gd
Po
Ex

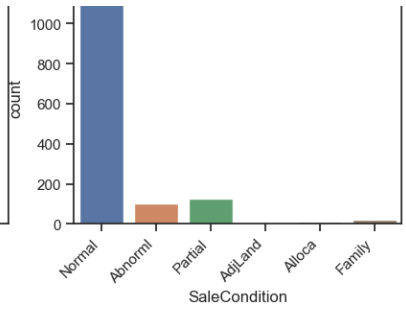

Count Plot for PavedDrive

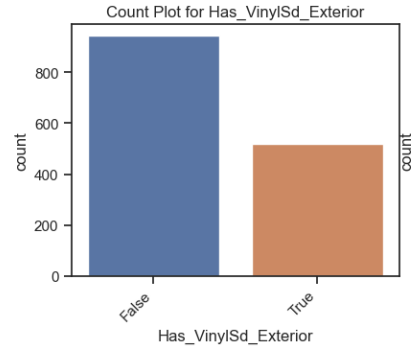

Count Plot for SaleType

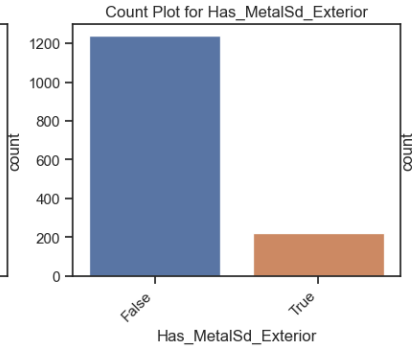

Count Plot for SaleCondition

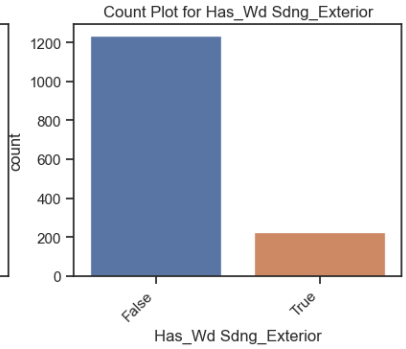


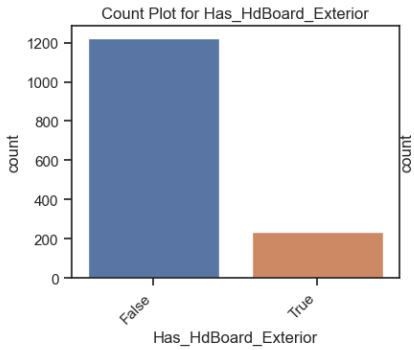


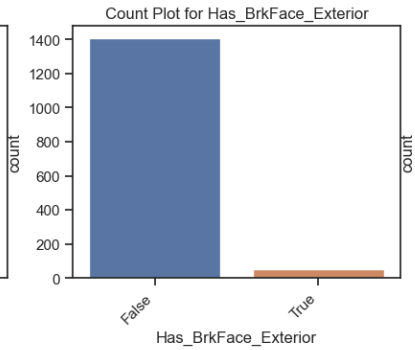


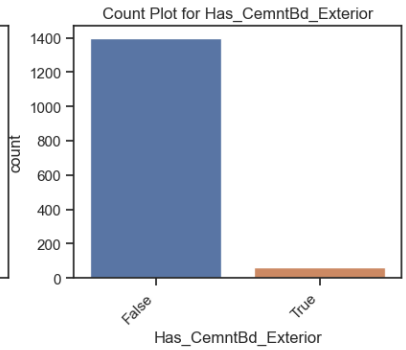


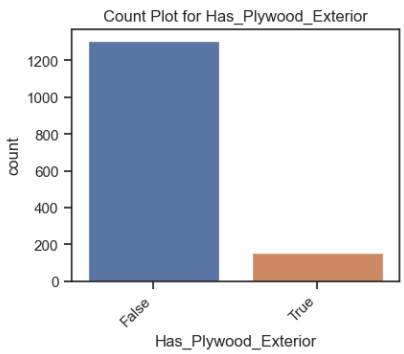












In [55]:
```
df_cat.isnull().sum()
```

Out[55]:
```
MSZoning                0
LotShape                0
LandContour             0
LotConfig               0
LandSlope               0
Condition1              0
Condition2              0
BldgType                0
HouseStyle              0
RoofStyle               0
RoofMatl                0
MasVnrType              8
ExterQual               0
ExterCond               0
Foundation              0
BsmtQual               37
BsmtCond               37
BsmtExposure           38
BsmtFinType1           37
BsmtFinType2           38
Heating                 0
HeatingQC               0
CentralAir              0
Electrical              1
KitchenQual             0
Functional              0
GarageType             81
GarageFinish           81
GarageQual             81
GarageCond             81
PavedDrive              0
SaleType                0
SaleCondition           0
Has_VinylSd_Exterior    0
Has_MetalSd_Exterior    0
Has_Wd Sdng_Exterior    0
Has_HdBoard_Exterior    0
Has_BrkFace_Exterior    0
Has_CemntBd_Exterior    0
Has_Plywood_Exterior    0
dtype: int64
```

In [56]:
```
cat_filled_df = df_cat.fillna(df_cat.mode().iloc[0])
```

In [57]:
```
cat_filled_df.isnull().sum()
```

Out[57]:
```
MSZoning               0
LotShape               0
LandContour            0
LotConfig              0
LandSlope              0
Condition1             0
Condition2             0
BldgType               0
HouseStyle             0
RoofStyle              0
RoofMatl               0
MasVnrType             0
ExterQual              0
ExterCond              0
Foundation             0
BsmtQual               0
BsmtCond               0
BsmtExposure           0
BsmtFinType1           0
BsmtFinType2           0
Heating                0
HeatingQC              0
CentralAir             0
Electrical             0
KitchenQual            0
Functional             0
GarageType             0
GarageFinish           0
GarageQual             0
GarageCond             0
PavedDrive             0
SaleType               0
SaleCondition          0
Has_VinylSd_Exterior   0
Has_MetalSd_Exterior   0
Has_Wd Sdng_Exterior   0
Has_HdBoard_Exterior   0
Has_BrkFace_Exterior   0
Has_CemntBd_Exterior   0
Has_Plywood_Exterior   0
dtype: int64
```

In [58]:
```
# Assuming df_categorical is your DataFrame with categorical columns
threshold = 0.70  # Define the threshold (70% in this case)

# Calculate the percentage of the most frequent category in each column
category_counts = df_cat.apply(lambda col: col.value_counts().max() / len(col))

# Filter columns where the most frequent category exceeds the threshold
unrelevant_columns = category_counts[category_counts > threshold].index
relevant_columns = category_counts[category_counts < threshold].index
```

In [59]:
```
print(df_cat[unrelevant_columns].shape)
print(df_cat[relevant_columns].shape)
print(f"Numerical {df_best_num_feature.shape}")
```

```
(1460, 27)
(1460, 13)
Numerical (1460, 11)
```

In [60]:
```
unrelevant_col= df_cat[unrelevant_columns]
```

In [61]:
```
relevant_columns=df_cat[relevant_columns]
```

In [62]:
```
for col in unrelevant_col:
    print(unrelevant_col[col].value_counts())
```

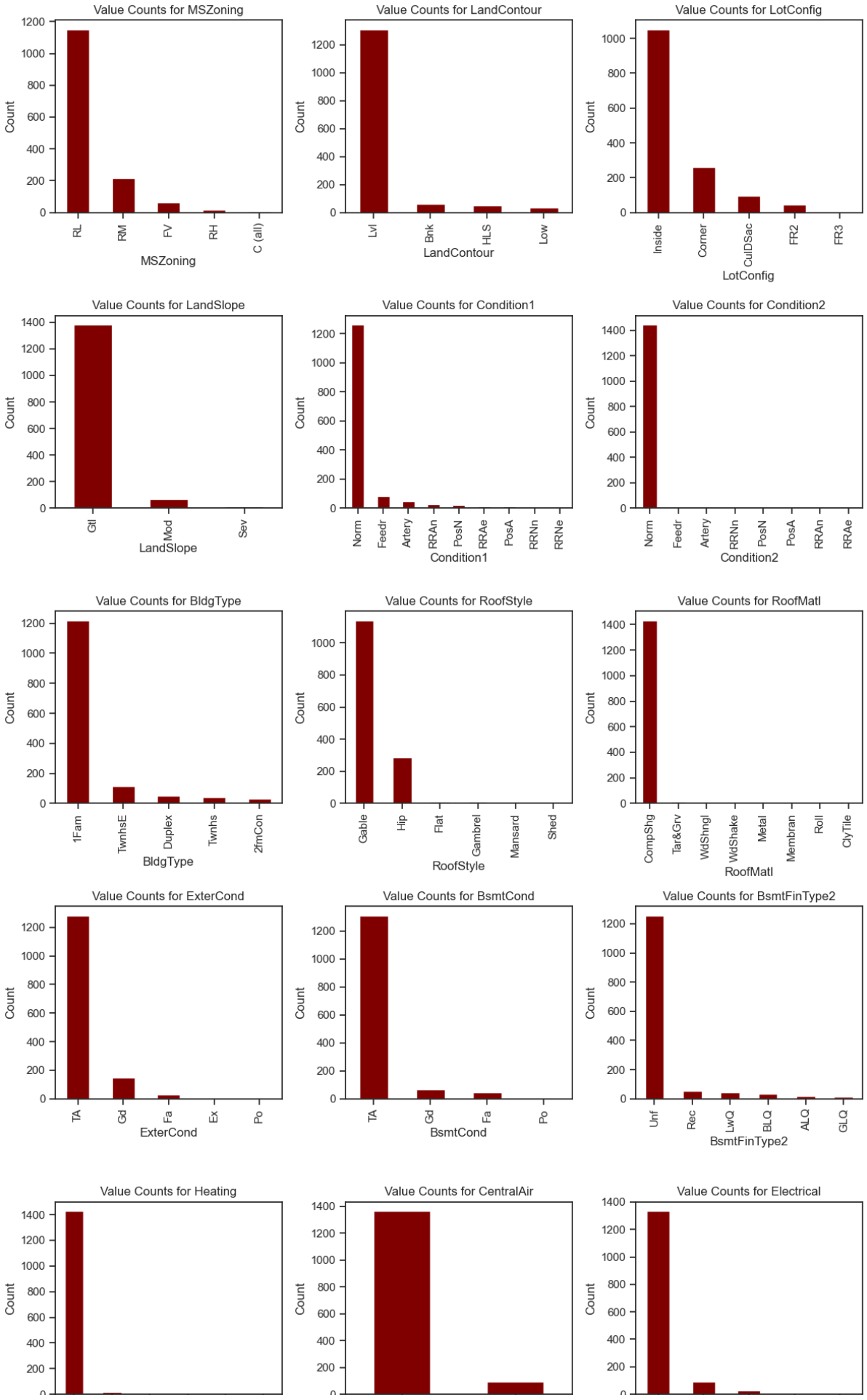
```
RL         1151
RM          218
FV           65
RH           16
C (all)      10
Name: MSZoning, dtype: int64
Lvl    1311
Bnk      63
HLS      50
Low      36
Name: LandContour, dtype: int64
Inside     1052
Corner      263
CulDSac      94
FR2          47
FR3           4
Name: LotConfig, dtype: int64
Gtl    1382
Mod      65
Sev      13
Name: LandSlope, dtype: int64
Norm      1260
Feedr       81
Artery      48
RRAn        26
PosN        19
RRAe        11
PosA         8
RRNn         5
RRNe         2
Name: Condition1, dtype: int64
Norm      1445
Feedr        6
Artery       2
RRNn         2
PosN         2
PosA         1
RRAn         1
RRAe         1
Name: Condition2, dtype: int64
1Fam      1220
TwnhsE     114
Duplex      52
Twnhs       43
2fmCon      31
Name: BldgType, dtype: int64
Gable      1141
Hip         286
Flat         13
Gambrel      11
Mansard       7
Shed          2
Name: RoofStyle, dtype: int64
CompShg    1434
Tar&Grv      11
WdShngl       6
WdShake       5
Metal         1
Membran       1
```

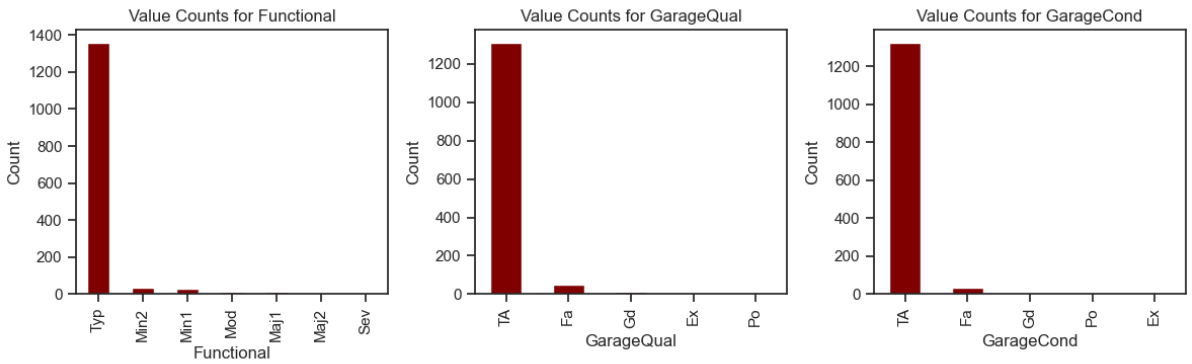
```
Roll          1
ClyTile       1
Name: RoofMatl, dtype: int64
TA    1282
Gd     146
Fa      28
Ex       3
Po       1
Name: ExterCond, dtype: int64
TA    1311
Gd      65
Fa      45
Po       2
Name: BsmtCond, dtype: int64
Unf    1256
Rec      54
LwQ      46
BLQ      33
ALQ      19
GLQ      14
Name: BsmtFinType2, dtype: int64
GasA     1428
GasW       18
Grav        7
Wall        4
OthW        2
Floor       1
Name: Heating, dtype: int64
Y    1365
N      95
Name: CentralAir, dtype: int64
SBrkr    1334
FuseA      94
FuseF      27
FuseP       3
Mix         1
Name: Electrical, dtype: int64
Typ     1360
Min2      34
Min1      31
Mod       15
Maj1      14
Maj2       5
Sev        1
Name: Functional, dtype: int64
TA    1311
Fa      48
Gd      14
Ex       3
Po       3
Name: GarageQual, dtype: int64
TA    1326
Fa      35
Gd       9
Po       7
Ex       2
Name: GarageCond, dtype: int64
Y    1340
N      90
```

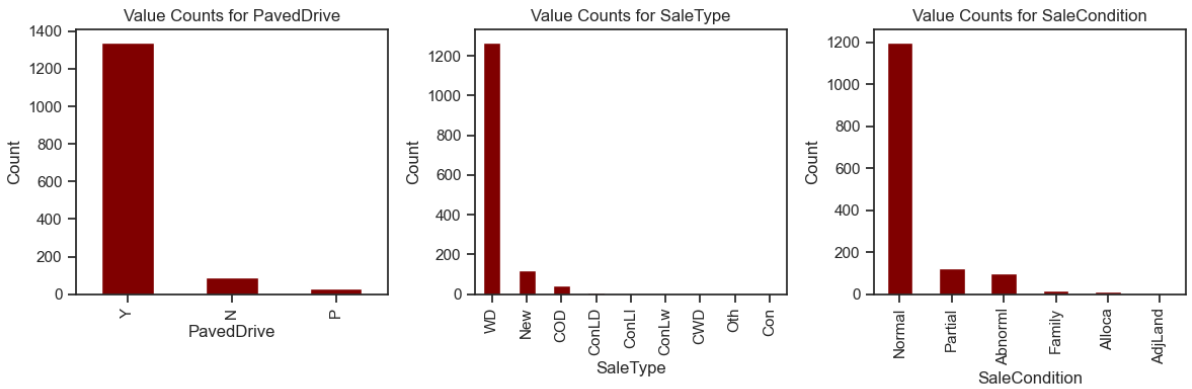
```
P      30
Name: PavedDrive, dtype: int64
WD       1267
New       122
COD        43
ConLD       9
ConLI       5
ConLw       5
CWD         4
Oth         3
Con         2
Name: SaleType, dtype: int64
Normal     1198
Partial     125
Abnorml     101
Family       20
Alloca       12
AdjLand       4
Name: SaleCondition, dtype: int64
False    1238
True      222
Name: Has_MetalSd_Exterior, dtype: int64
False    1234
True      226
Name: Has_Wd Sdng_Exterior, dtype: int64
False    1224
True      236
Name: Has_HdBoard_Exterior, dtype: int64
False    1409
True       51
Name: Has_BrkFace_Exterior, dtype: int64
False    1399
True       61
Name: Has_CemntBd_Exterior, dtype: int64
False    1306
True      154
Name: Has_Plywood_Exterior, dtype: int64
```

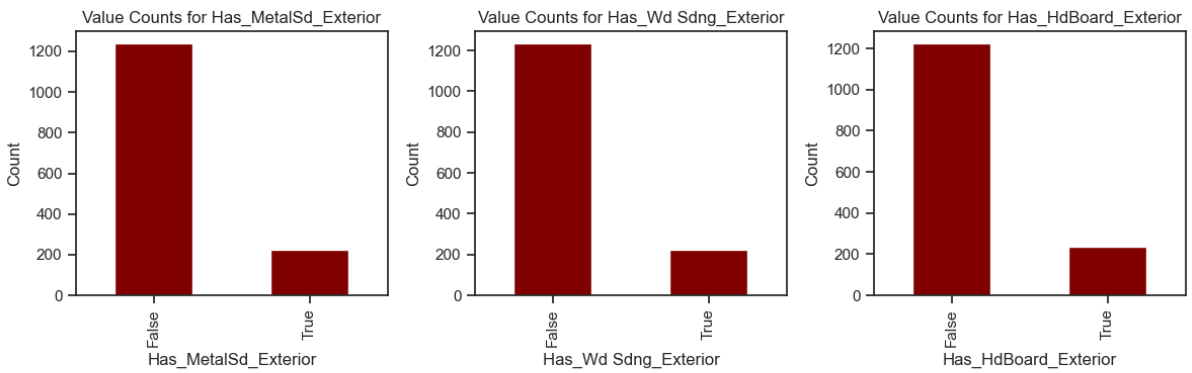
In [63]:
```
num_plots=len(unrelevant_col.columns)
num_plots_per_row=3
num_row=(num_plots+num_plots_per_row-1)//3
print(num_plots, num_row)

#create Subplots

fig ,axes = plt.subplots(num_row, num_plots_per_row, figsize=(12,4 * num_row ))
axes = axes.flatten()

for i, column in enumerate(unrelevant_col):
    counts = df_cat[column].value_counts()

    # Create a bar plot on the current subplot
    counts.plot(kind='bar', color='Maroon', ax=axes[i])

    # Set labels and title
    axes[i].set_xlabel(column)
    axes[i].set_ylabel('Count')
    axes[i].set_title(f'Value Counts for {column}')

for i in range(num_plots, num_row * num_plots_per_row):
    fig.delaxes(axes[i])

fig.tight_layout()
plt.show()
```

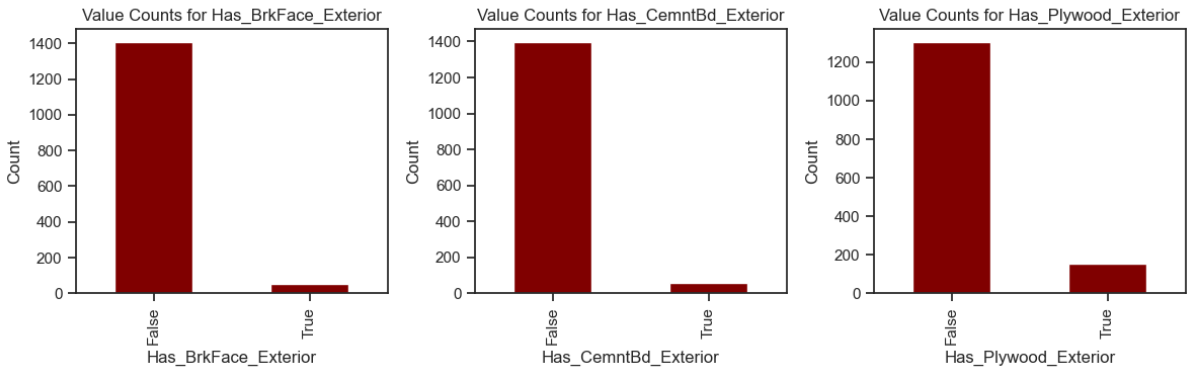
```
27 9
```


Value Counts for MSZoning
Count
MSZoning
RL
RM
FV
RH
C (all)
Value Counts for LandContour
LandContour
Lvl
Bnk
HLS
Low
Value Counts for LotConfig
LotConfig
Inside
Corner
CulDSac
FR2
FR3
Value Counts for LandSlope
LandSlope
Gtl
Mod
Sev
Value Counts for Condition1
Condition1
Norm
Feedr
Artery
RRAn
PosN
RRAe
PosA
RRNn
RRNe
Value Counts for Condition2
Condition2
Norm
Feedr
Artery
RRNn
PosN
PosA
RRAn
RRAe
Value Counts for BldgType
BldgType
1Fam
TwnhsE
Duplex
Twnhs
2fmCon
Value Counts for RoofStyle
RoofStyle
Gable
Hip
Flat
Gambrel
Mansard
Shed
Value Counts for RoofMatl
RoofMatl
CompShg
Tar&Grv
WdShngl
WdShake
Metal
Membran
Roll
ClyTile
Value Counts for ExterCond
ExterCond
TA
Gd
Fa
Ex
Po
Value Counts for BsmtCond
BsmtCond
TA
Gd
Fa
Po
Value Counts for BsmtFinType2
BsmtFinType2
Unf
Rec
LwQ
BLQ
ALQ
GLQ
Value Counts for Heating
Value Counts for CentralAir
Value Counts for Electrical









In [64]:
```
for col in relevant_columns:
    print(relevant_columns[col].value_counts())
```

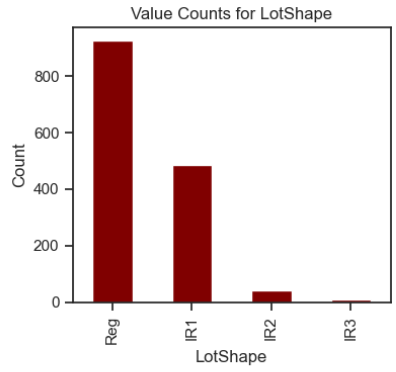
```
Reg    925
IR1    484
IR2     41
IR3     10
Name: LotShape, dtype: int64
1Story    726
2Story    445
1.5Fin    154
SLvl       65
SFoyer     37
1.5Unf     14
2.5Unf     11
2.5Fin      8
Name: HouseStyle, dtype: int64
None       864
BrkFace    445
Stone      128
BrkCmn      15
Name: MasVnrType, dtype: int64
TA    906
Gd    488
Ex     52
Fa     14
Name: ExterQual, dtype: int64
PConc     647
CBlock    634
BrkTil    146
Slab       24
Stone       6
Wood        3
Name: Foundation, dtype: int64
TA    649
Gd    618
Ex    121
Fa     35
Name: BsmtQual, dtype: int64
No    953
Av    221
Gd    134
Mn    114
Name: BsmtExposure, dtype: int64
Unf    430
GLQ    418
ALQ    220
BLQ    148
Rec    133
LwQ     74
Name: BsmtFinType1, dtype: int64
Ex    741
TA    428
Gd    241
Fa     49
Po      1
Name: HeatingQC, dtype: int64
TA    735
Gd    586
Ex    100
Fa     39
Name: KitchenQual, dtype: int64
```

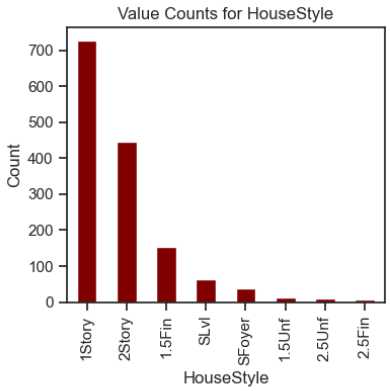
```
Attchd     870
Detchd     387
BuiltIn     88
Basment     19
CarPort      9
2Types       6
Name: GarageType, dtype: int64
Unf    605
RFn    422
Fin    352
Name: GarageFinish, dtype: int64
False    943
True     517
Name: Has_VinylSd_Exterior, dtype: int64
```

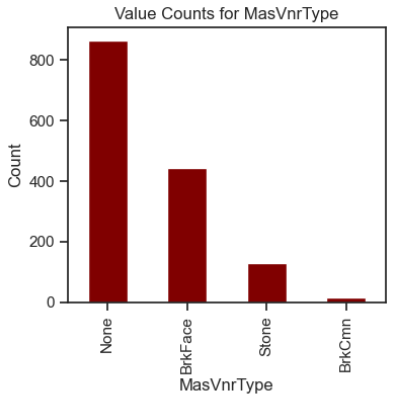
In [65]:

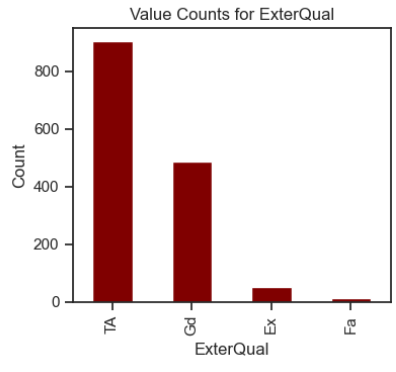
```
num_plots=13
num_plots_per_row=3
num_row=(num_plots+num_plots_per_row-1)//3
print(num_plots, num_row)

#create Subplots

fig ,axes = plt.subplots(num_row, num_plots_per_row, figsize=(12,4 * num_row ))
axes = axes.flatten()

for i, column in enumerate(relevant_columns):
    counts = df_cat[column].value_counts()

    # Create a bar plot on the current subplot
    counts.plot(kind='bar', color='Maroon', ax=axes[i])

    # Set labels and title
    axes[i].set_xlabel(column)
    axes[i].set_ylabel('Count')
    axes[i].set_title(f'Value Counts for {column}')

for i in range(num_plots, num_row * num_plots_per_row):
    fig.delaxes(axes[i])

fig.tight_layout()
plt.show()
```

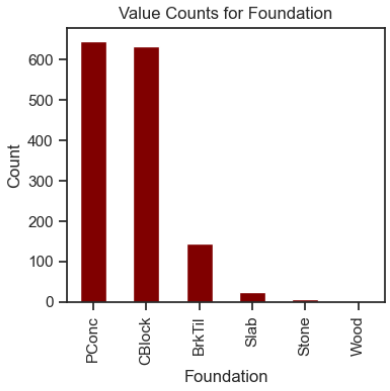
```
13 5
```

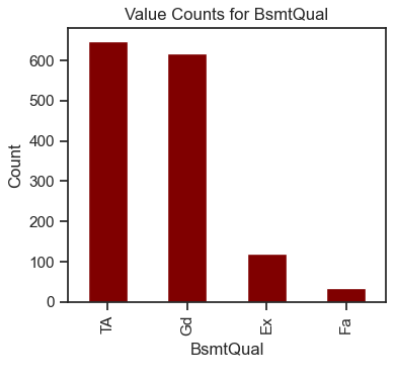

Value Counts for LotShape
Count
LotShape
Reg
IR1
IR2
IR3

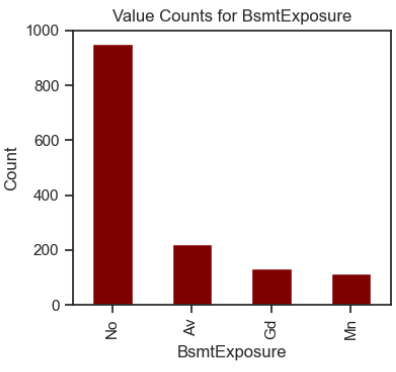

Value Counts for HouseStyle
Count
HouseStyle
1Story
2Story
1.5Fin
SLvl
SFoyer
1.5Unf
2.5Unf
2.5Fin

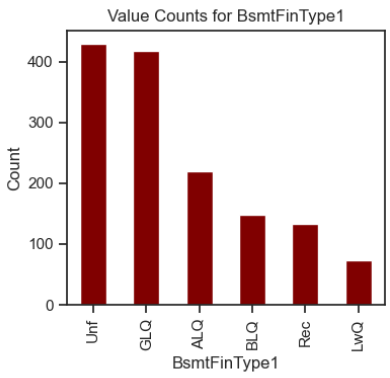

Value Counts for MasVnrType
Count
MasVnrType
None
BrkFace
Stone
BrkCmn

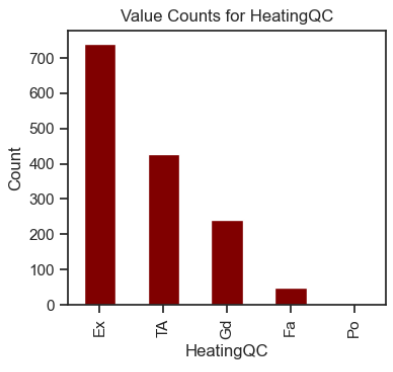

Value Counts for ExterQual
Count
ExterQual
TA
Gd
Ex
Fa

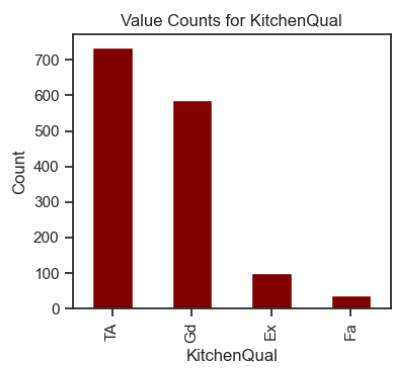

Value Counts for Foundation
Count
Foundation
PConc
CBlock
BrkTil
Slab
Stone
Wood

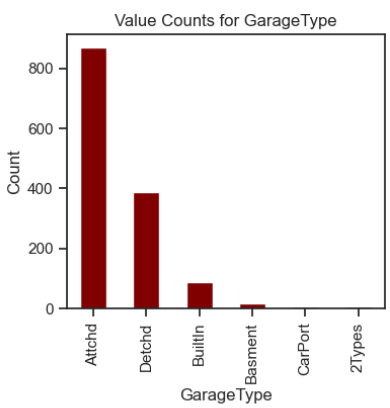

Value Counts for BsmtQual
Count
BsmtQual
TA
Gd
Ex
Fa

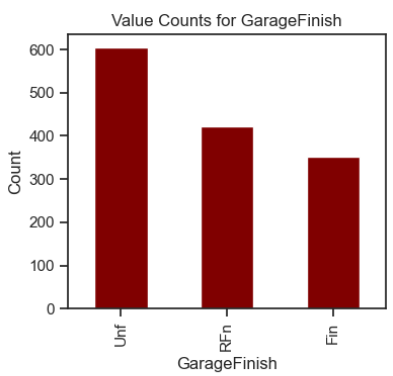

Value Counts for BsmtExposure
Count
BsmtExposure
No
Av
Gd
Mn

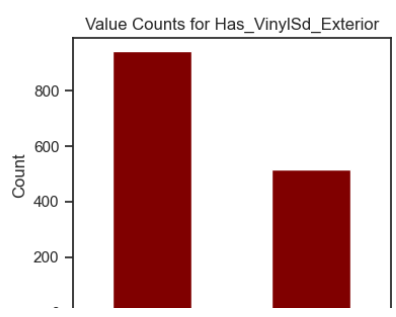

Value Counts for BsmtFinType1
Count
BsmtFinType1
Unf
GLQ
ALQ
BLQ
Rec
LwQ


Value Counts for HeatingQC
Count
HeatingQC
Ex
TA
Gd
Fa
Po


Value Counts for KitchenQual
Count
KitchenQual
TA
Gd
Ex
Fa


Value Counts for GarageType
Count
GarageType
Attchd
Detchd
BuiltIn
Basment
CarPort
2Types


Value Counts for GarageFinish
Count
GarageFinish
Unf
RFn
Fin


Value Counts for Has_VinylSd_Exterior
Count

Feature Engineering

Feature engineering is the art of creating new features from existing ones or selecting the most relevant features for model training. In this section, we will engineer meaningful features to improve our model's performance.

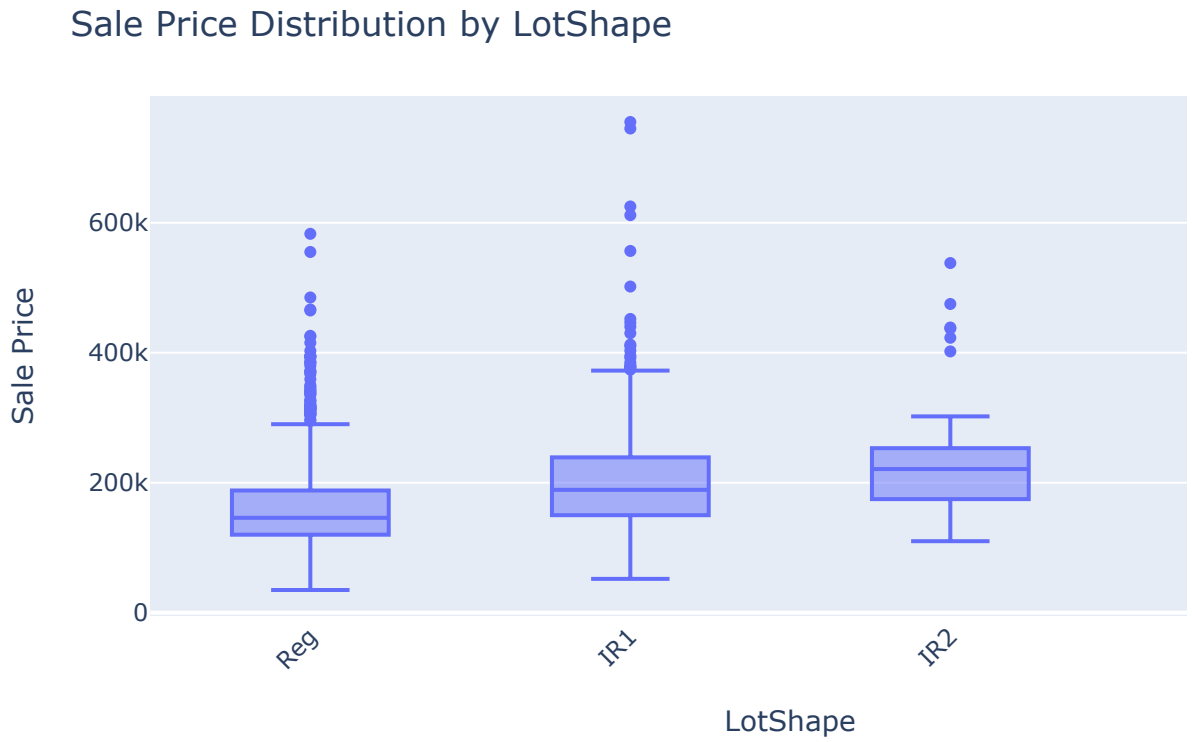
In [66]:
```
df1 = pd.concat([relevant_columns, df_best_num_feature],axis=1)
```

In [67]:
```
df1.head()
```

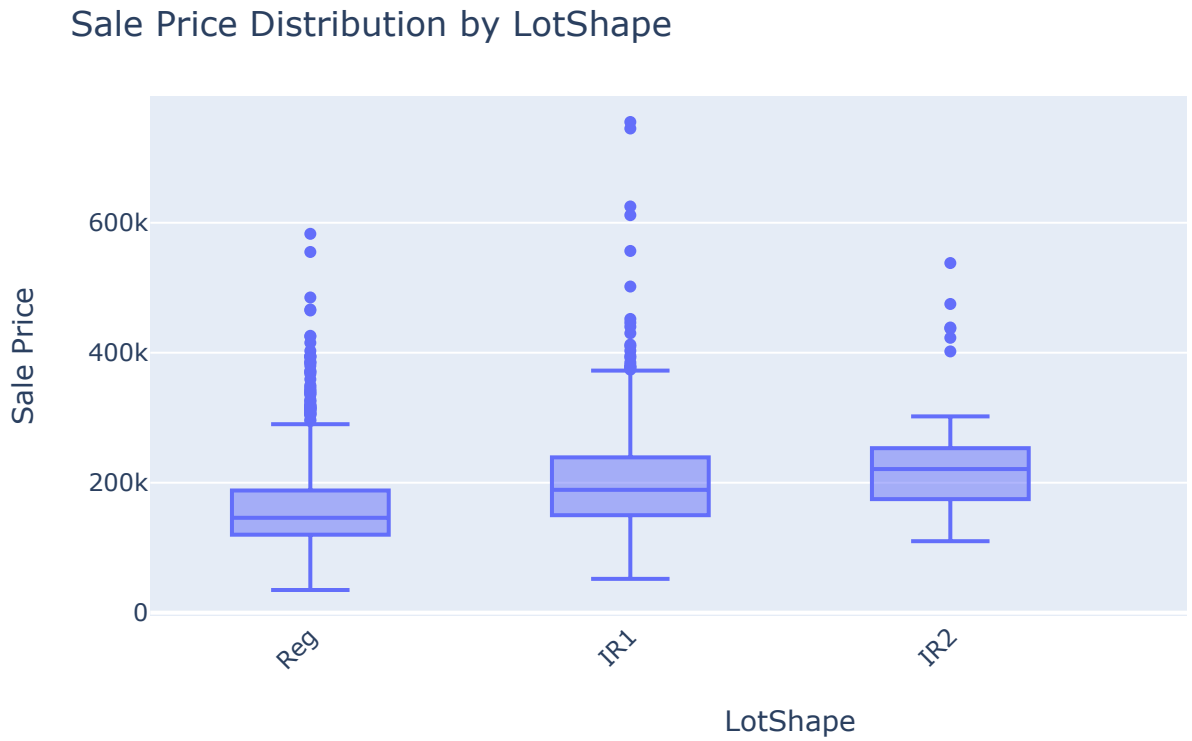
Out[67]:

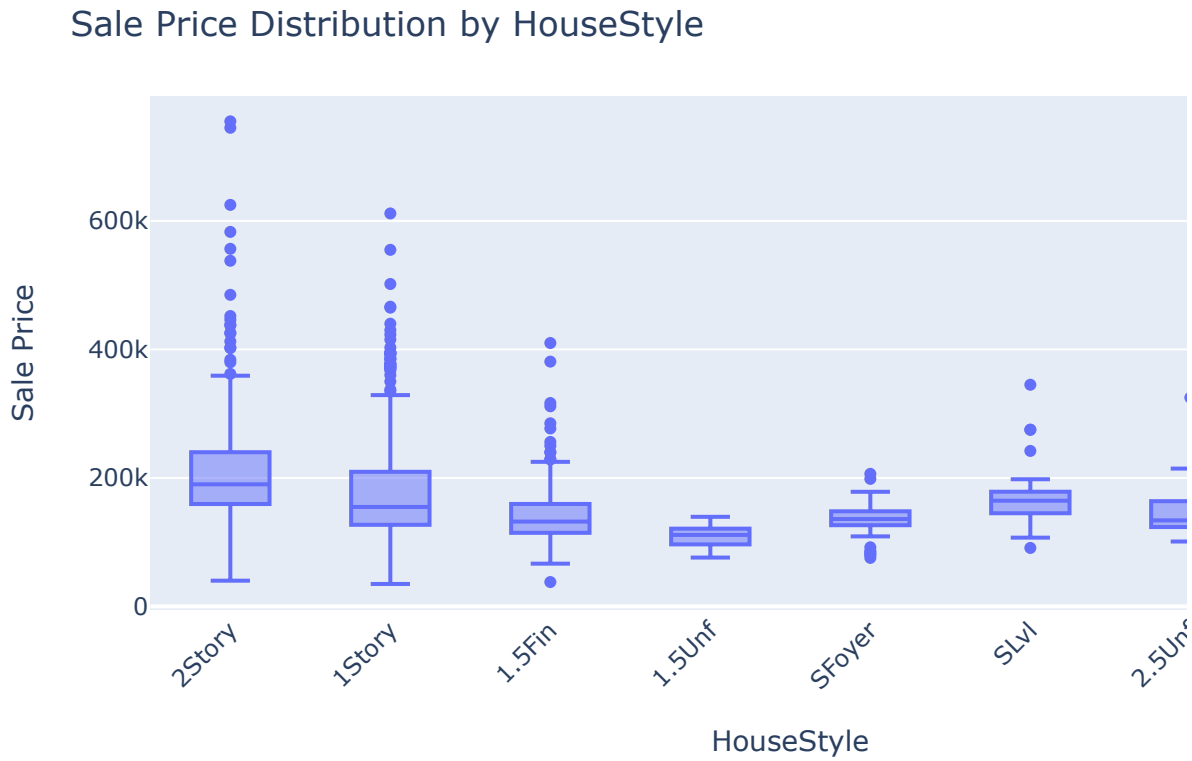
	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFin1
0	Reg	2Story	BrkFace	Gd	PConc	Gd	No	
1	Reg	1Story	None	TA	CBlock	Gd	Gd	
2	IR1	2Story	BrkFace	Gd	PConc	Gd	Mn	
3	IR1	2Story	None	TA	BrkTil	TA	No	
4	IR1	2Story	BrkFace	Gd	PConc	Gd	Av	

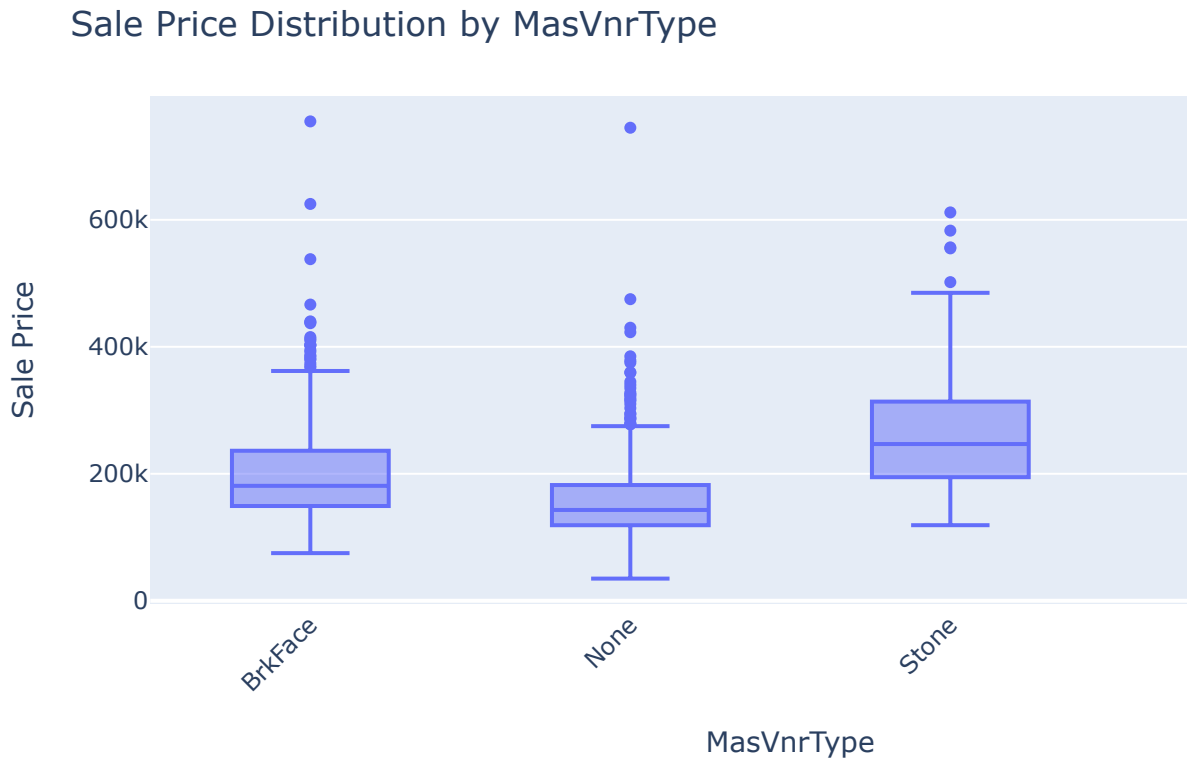
In [68]:
```
fig =px.box(df1, x='LotShape', y='SalePrice')
fig.update_layout(
    title='Sale Price Distribution by LotShape',
    xaxis=dict(title='LotShape'),
    yaxis=dict(title='Sale Price'),
    xaxis_tickangle=-45,
    width=800,
    height=400,
)
fig.show()
```

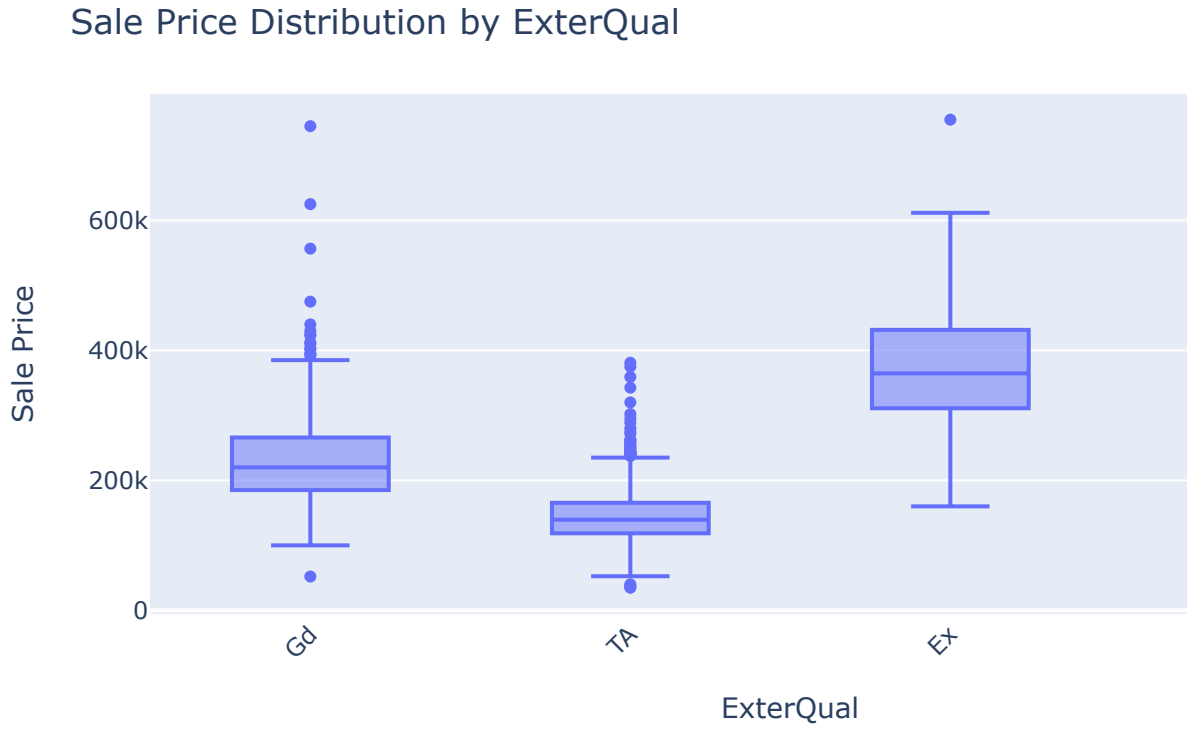


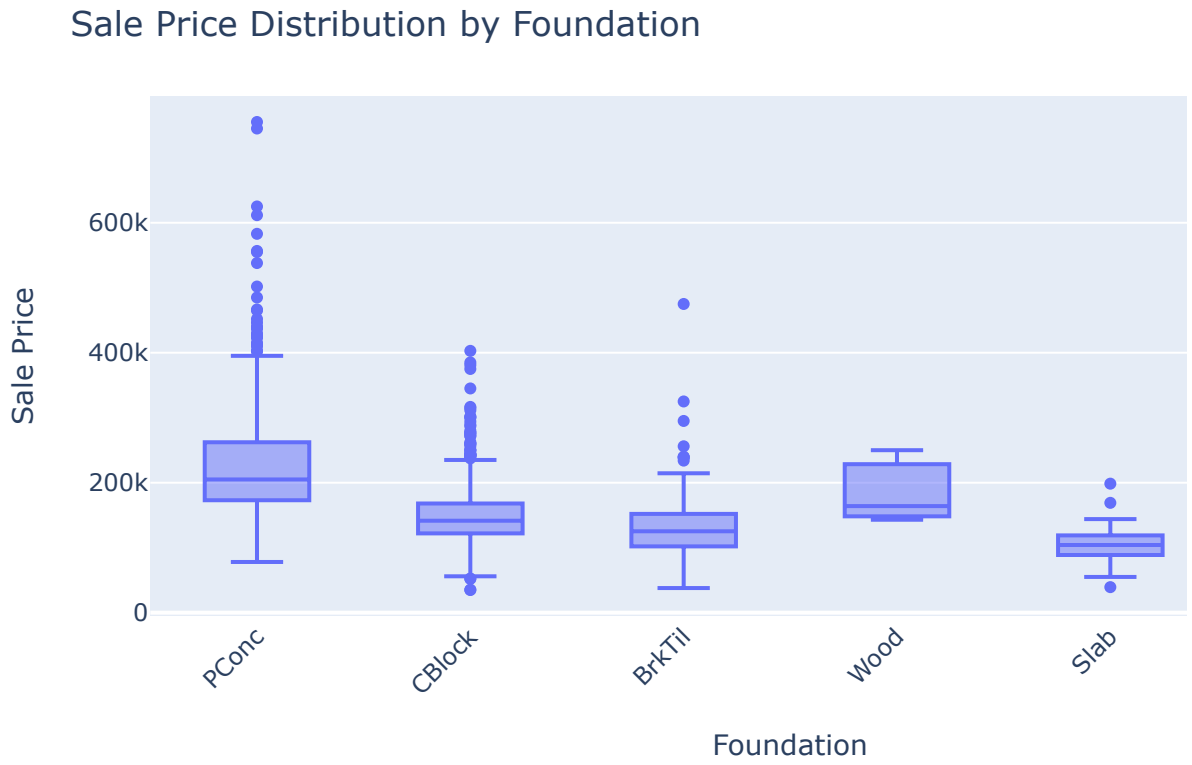
In [69]:
```
for column in df1.columns:
    if column == 'GrLivArea':
        break
    fig = px.box(df1, x=df1[column], y='SalePrice')
    fig.update_layout(
        title=f'Sale Price Distribution by {column}',
        xaxis=dict(title=column),
        yaxis=dict(title='Sale Price'),
        xaxis_tickangle=-45,
        width=800,
        height=400,
    )
    fig.show()
plt.tight_layout()
plt.show()
```

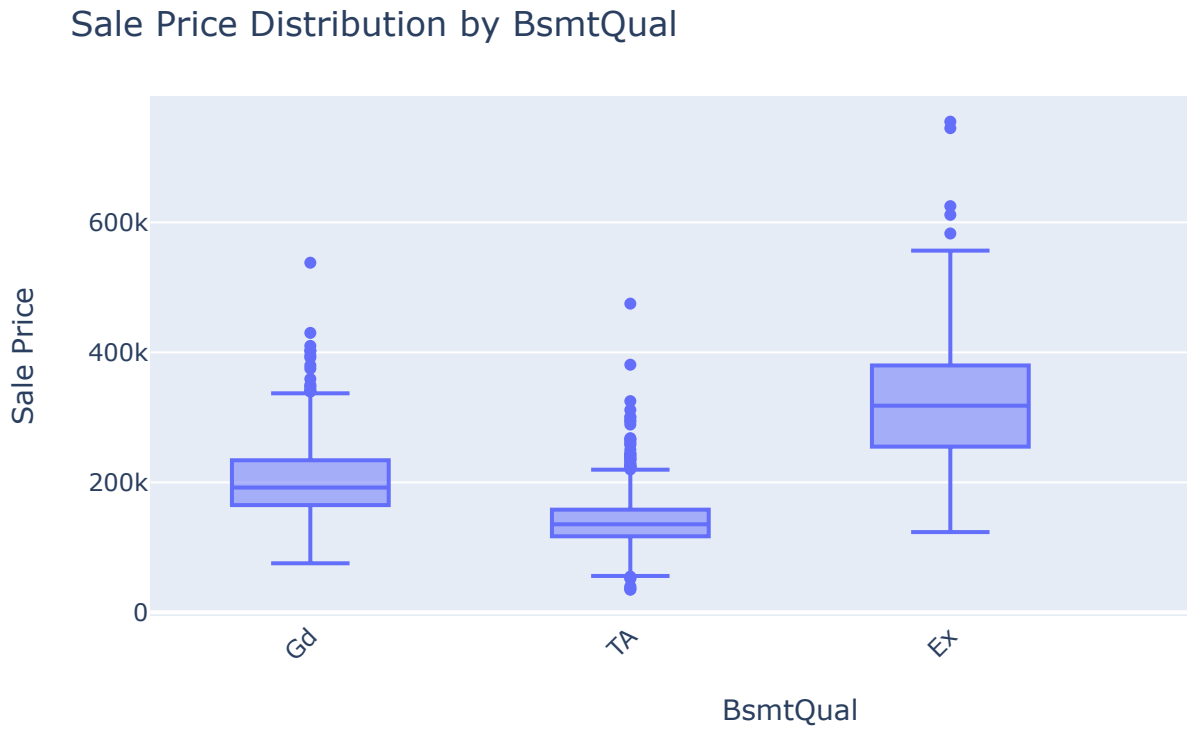

Sale Price Distribution by LotShape
Sale Price
600k
400k
200k
0
Reg
IR1
IR2
LotShape

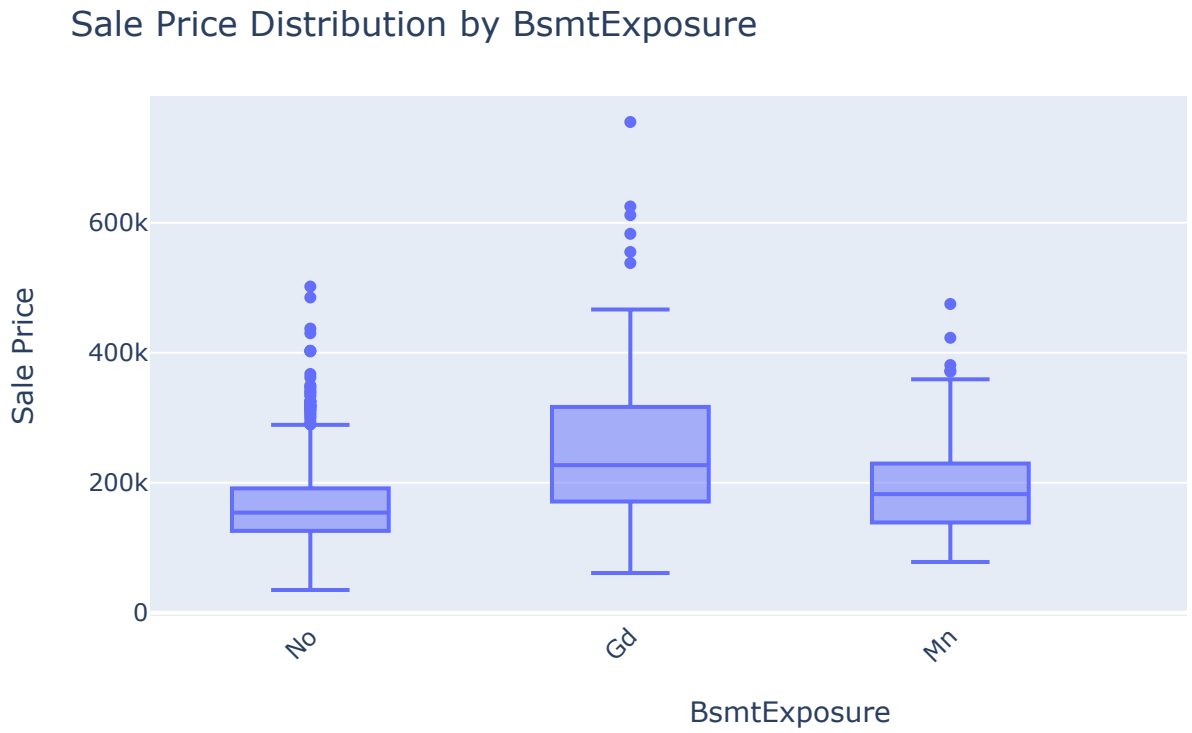

Sale Price Distribution by HouseStyle
Sale Price
600k
400k
200k
0
2Story
1Story
1.5Fin
1.5Unf
SFoyer
SLvl
HouseStyle

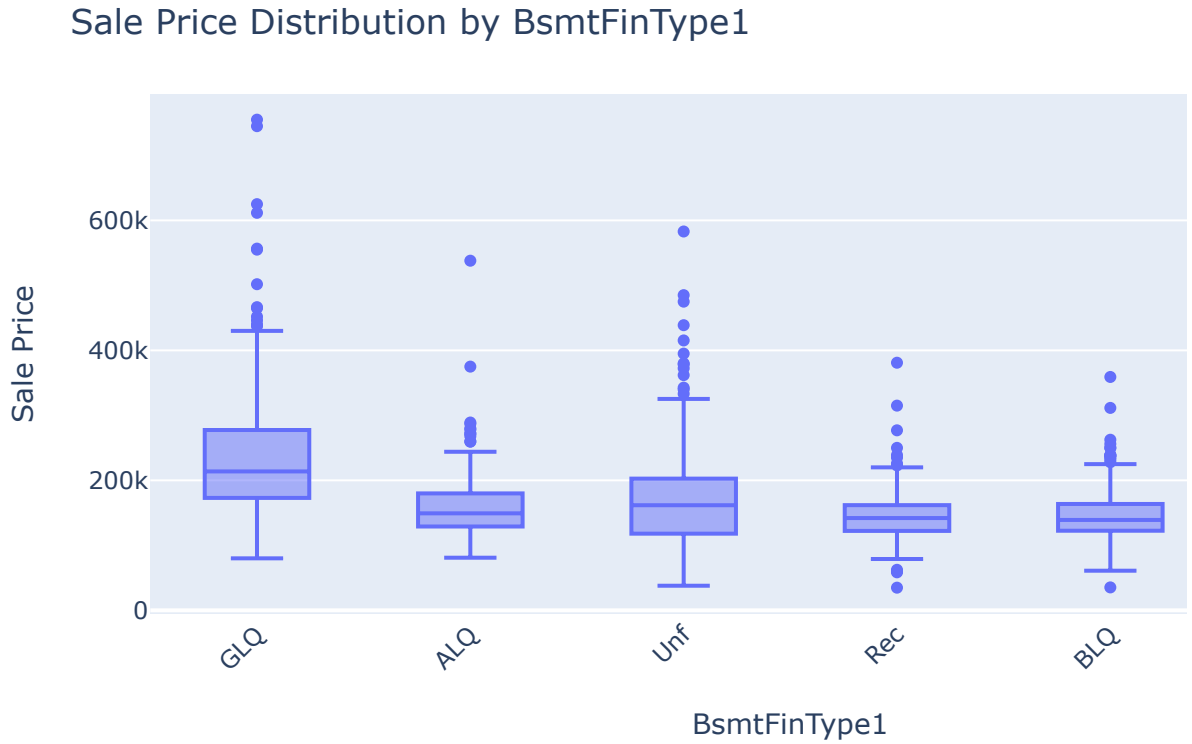

Sale Price Distribution by MasVnrType
Sale Price
600k
400k
200k
0
BrkFace
None
Stone
MasVnrType

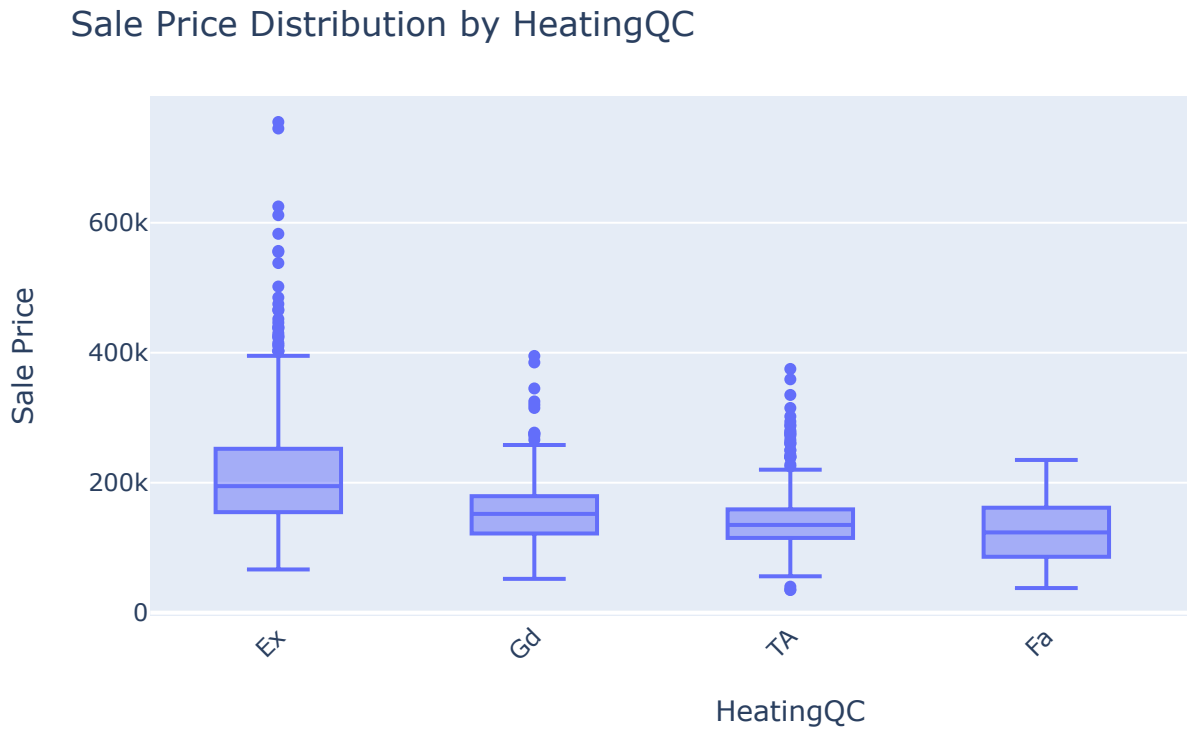

Sale Price Distribution by ExterQual
Sale Price
600k
400k
200k
0
Gd
TA
Ex
ExterQual

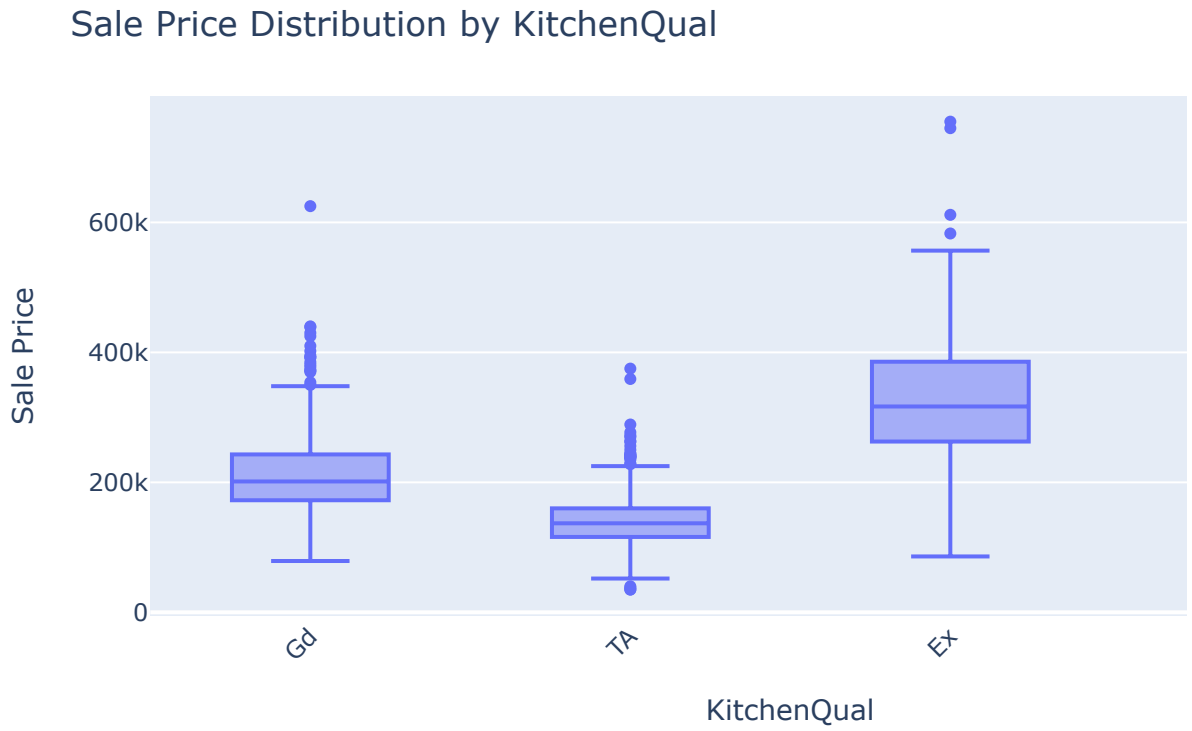

Sale Price Distribution by Foundation
Sale Price
600k
400k
200k
0
PConc
CBlock
BrkTil
Wood
Slab
Foundation

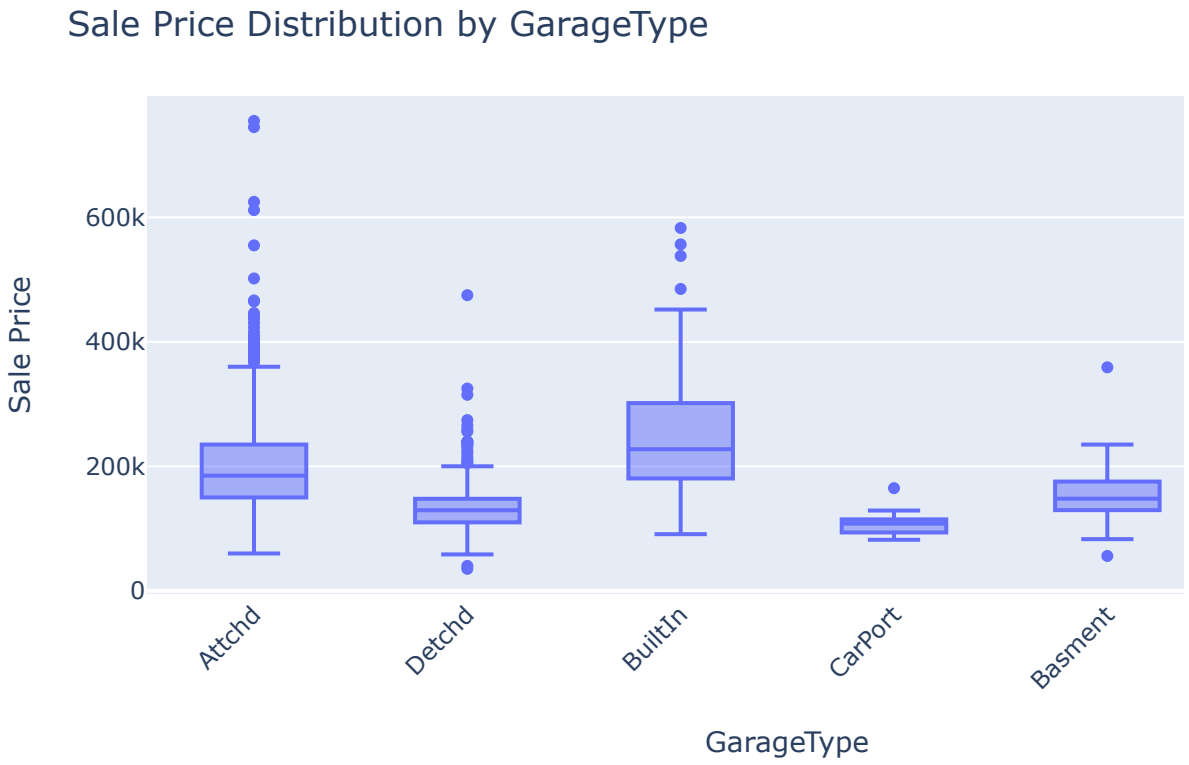

Sale Price Distribution by BsmtQual
Sale Price
600k
400k
200k
0
Gd
TA
Ex
BsmtQual

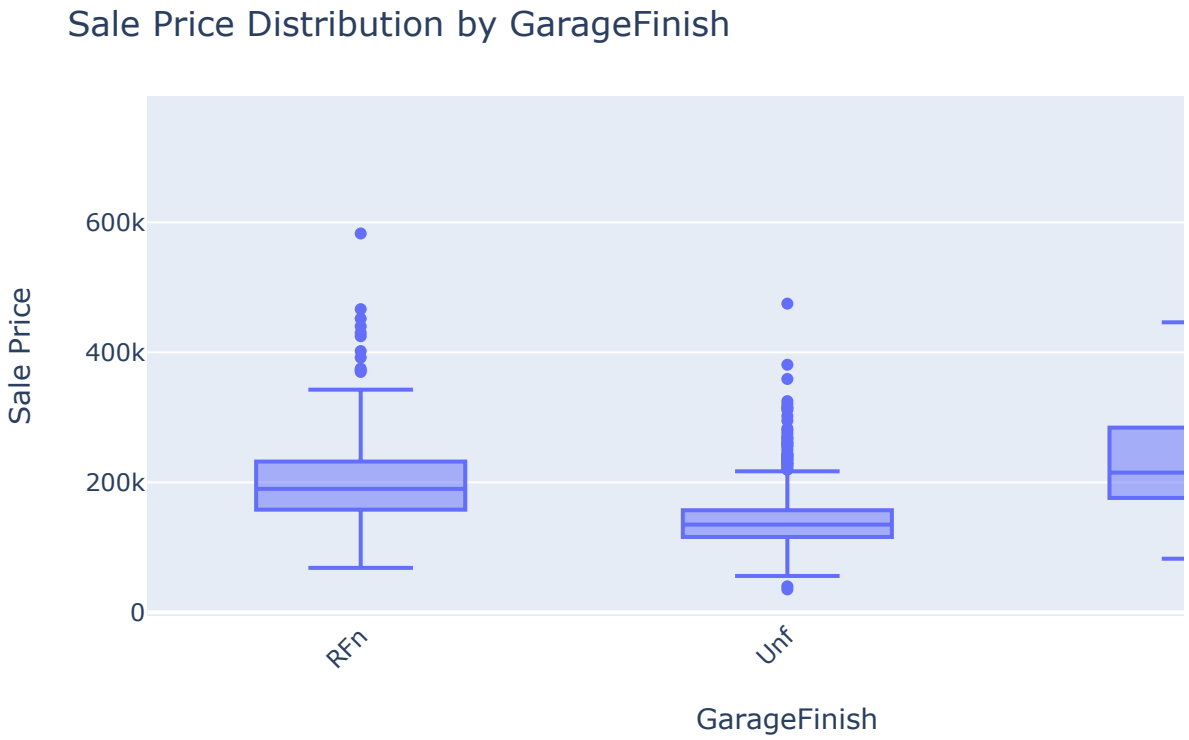

Sale Price Distribution by BsmtExposure
Sale Price
600k
400k
200k
0
No
Gd
Mn
BsmtExposure

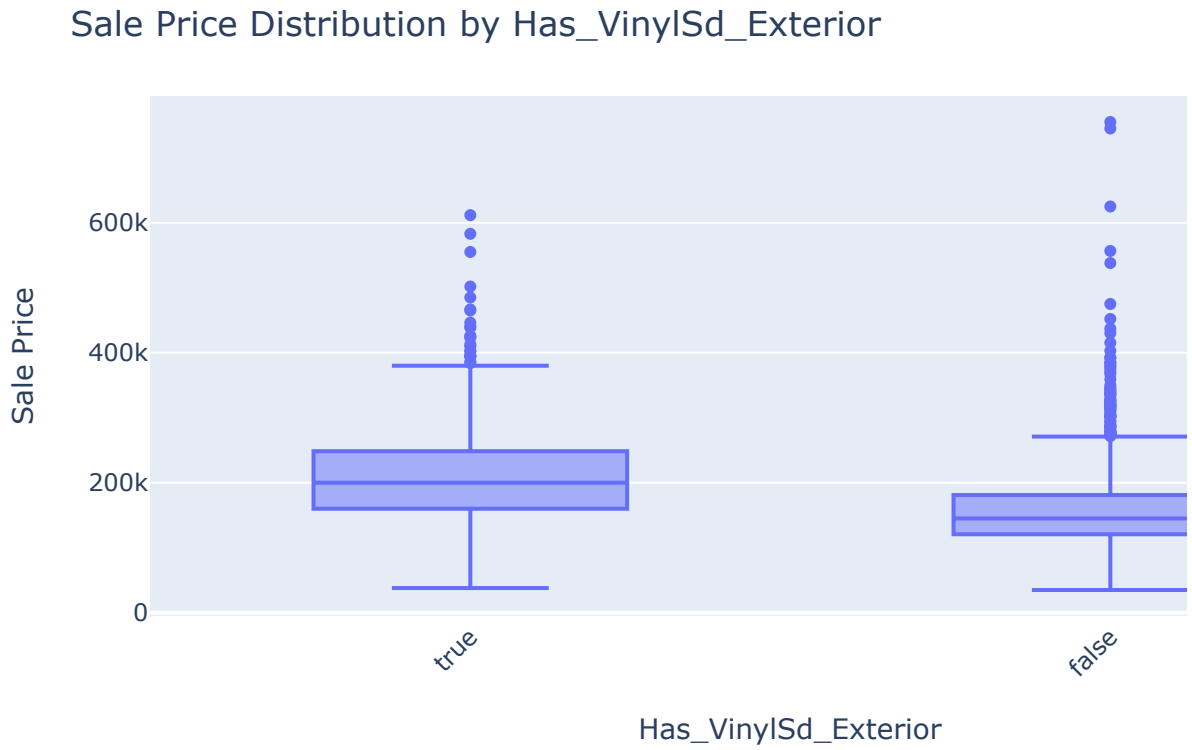

Sale Price Distribution by BsmtFinType1
Sale Price
600k
400k
200k
0
GLQ
ALQ
Unf
Rec
BLQ
BsmtFinType1

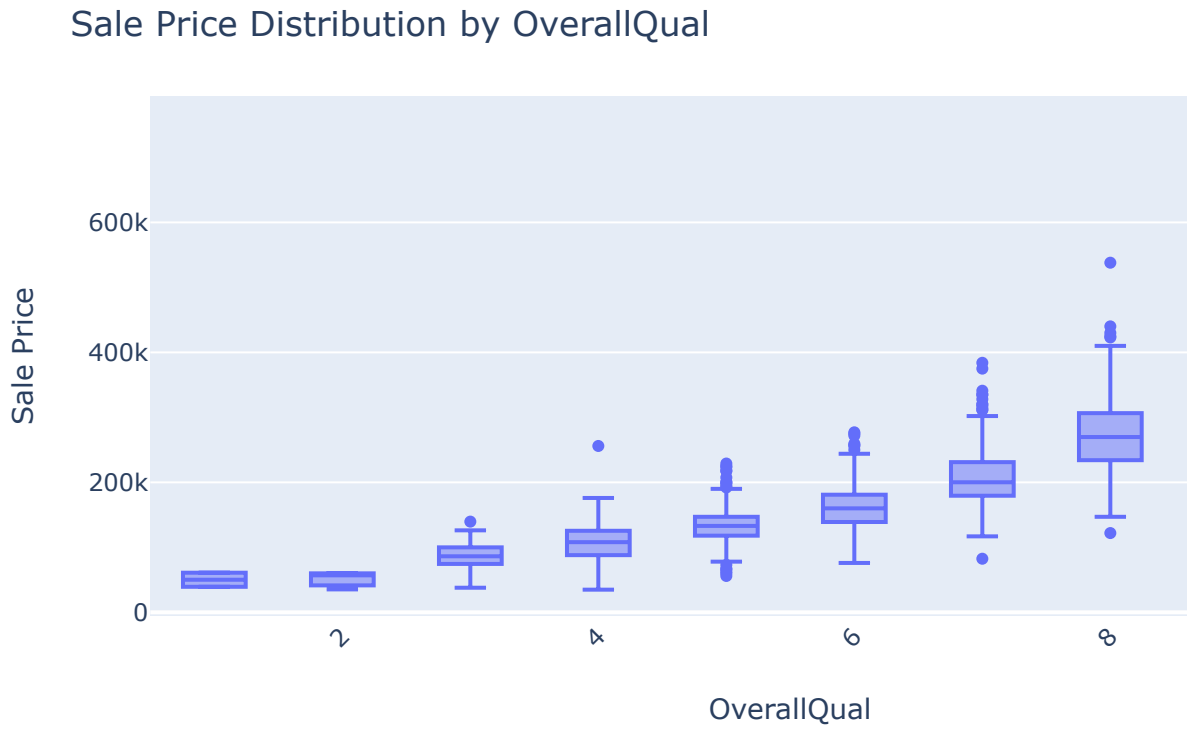

Sale Price Distribution by HeatingQC
Sale Price
600k
400k
200k
0
Ex
Gd
TA
Fa
HeatingQC


Sale Price Distribution by KitchenQual
Sale Price
600k
400k
200k
0
Gd
TA
Ex
KitchenQual


Sale Price Distribution by GarageType
Sale Price
600k
400k
200k
0
Attchd
Detchd
BuiltIn
CarPort
Basment
GarageType


Sale Price Distribution by GarageFinish
Sale Price
600k
400k
200k
0
RFn
Unf
GarageFinish

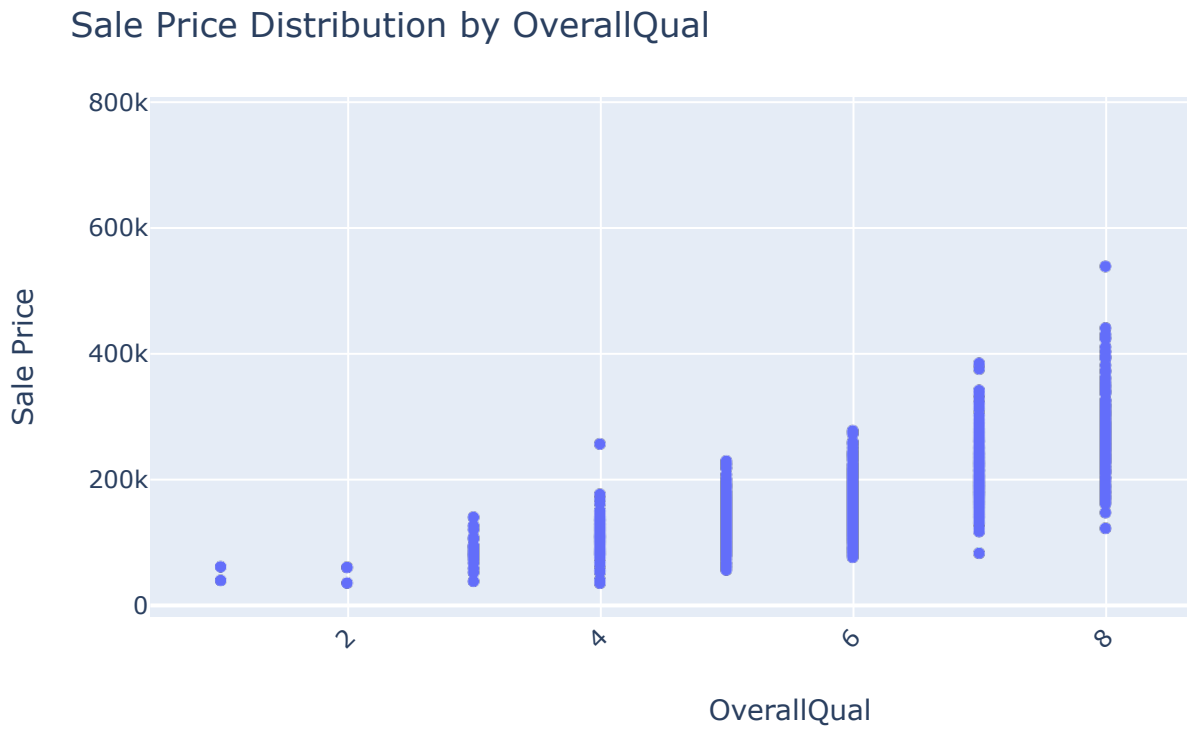


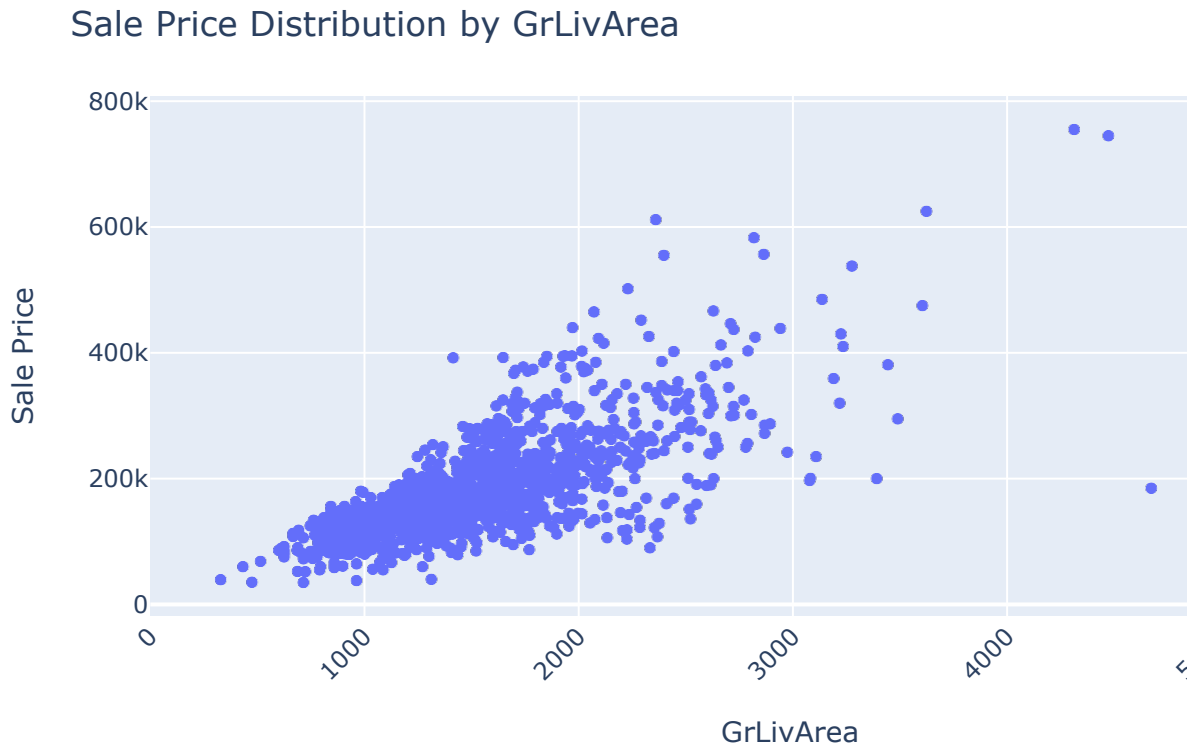


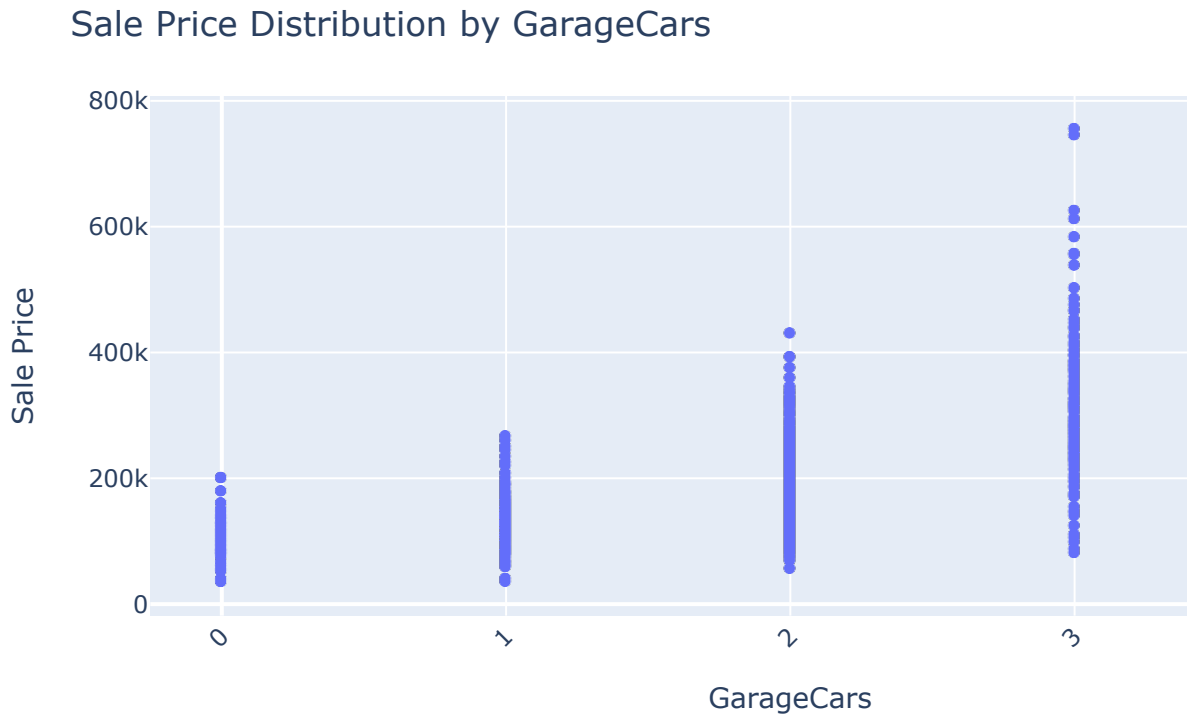

```
<Figure size 640x480 with 0 Axes>
```

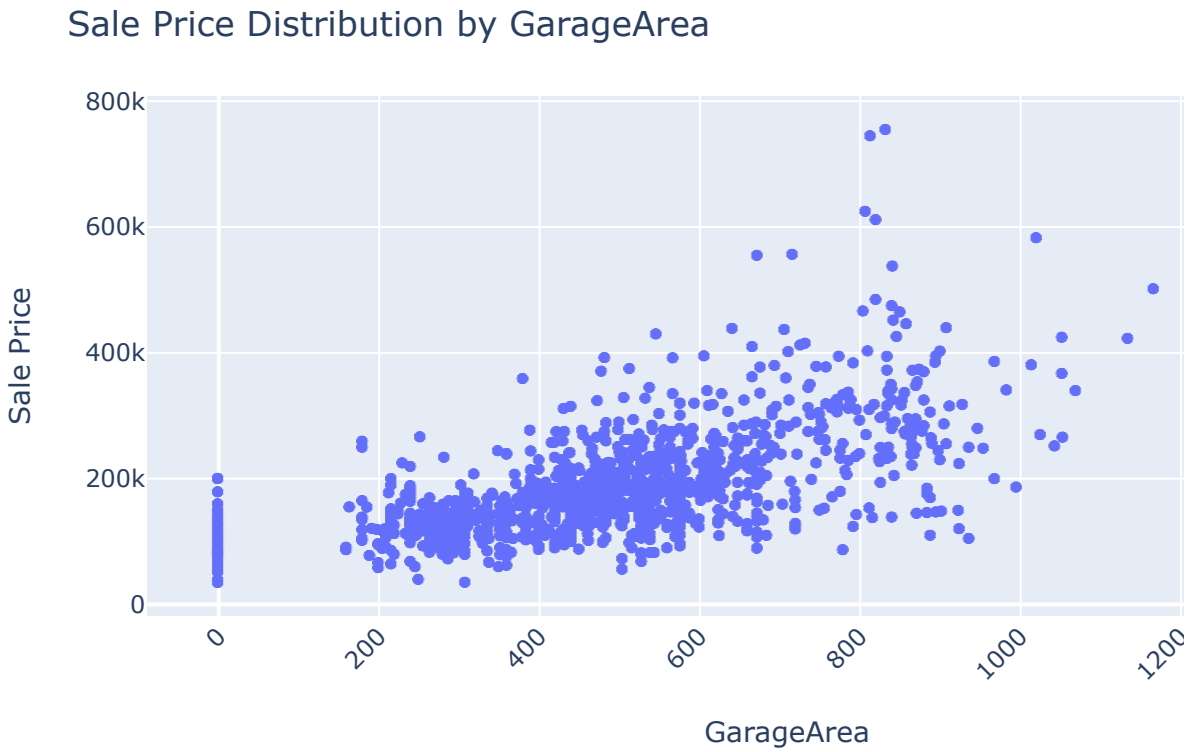
In [ ]:

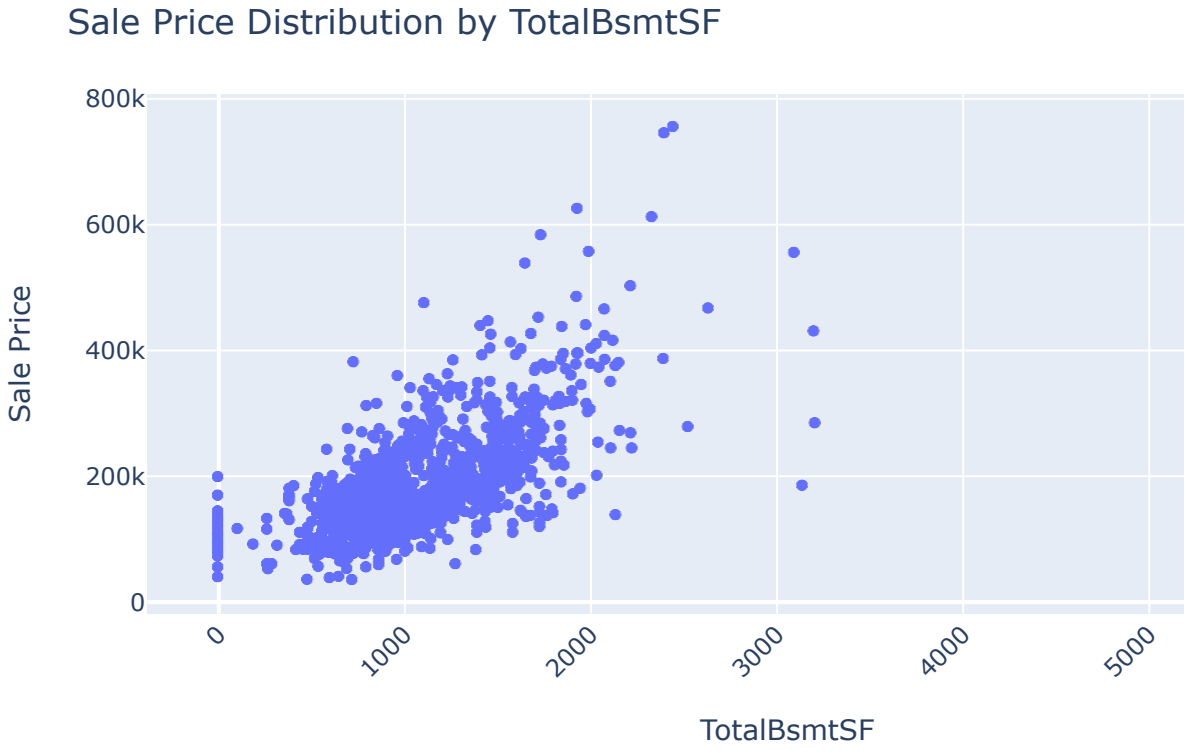
In [70]:
```
Num_col = ['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF', '

for column in df1.columns:
    if column in Num_col:
        fig = px.scatter(df1, x=df1[column], y='SalePrice')
        fig.update_layout(
            title=f'Sale Price Distribution by {column}',
            xaxis=dict(title=column),
            yaxis=dict(title='Sale Price'),
            xaxis_tickangle=-45,
            width=800,
            height=400,
        )
        fig.show()

plt.tight_layout()
plt.show()
```

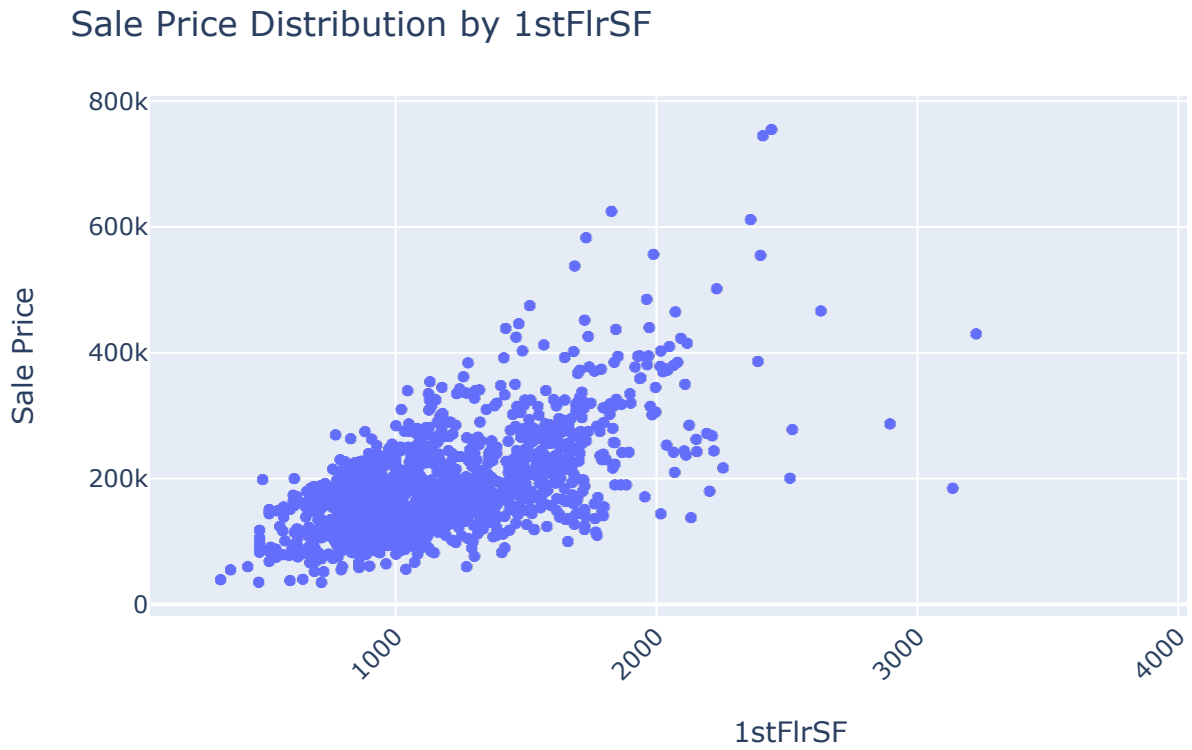


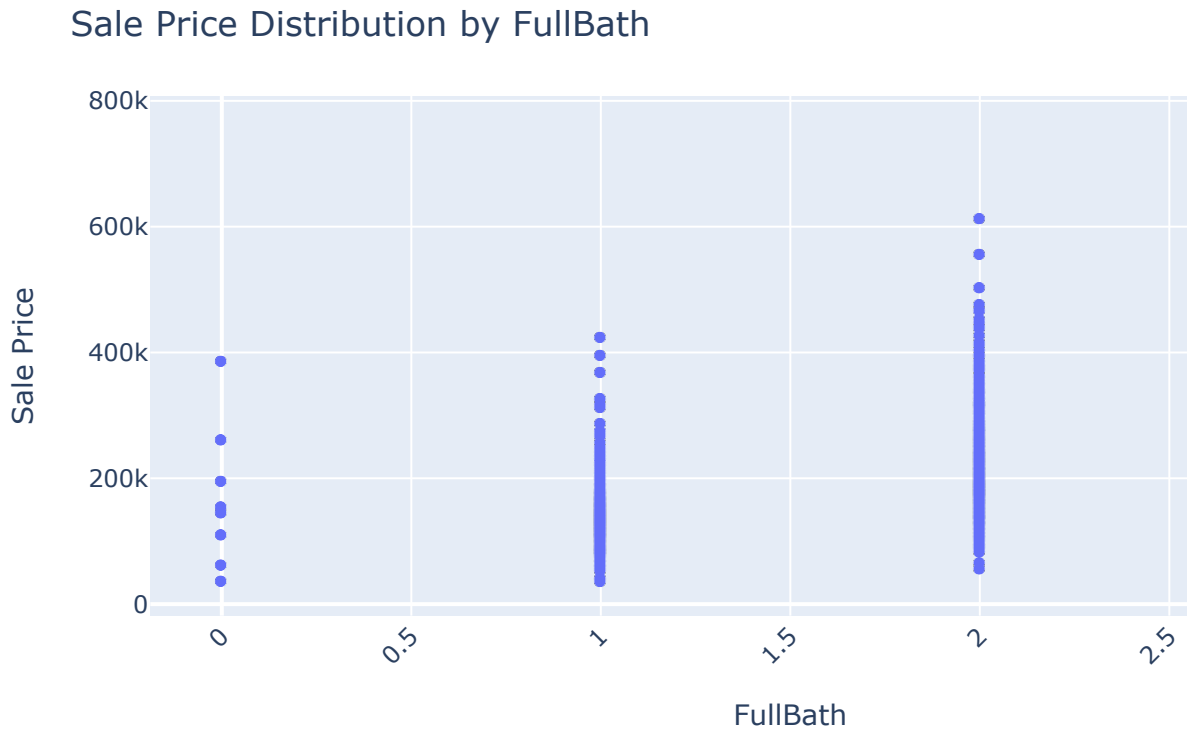

Sale Price Distribution by GrLivArea
800k
600k
400k
200k
0
Sale Price
0
1000
2000
3000
4000
GrLivArea

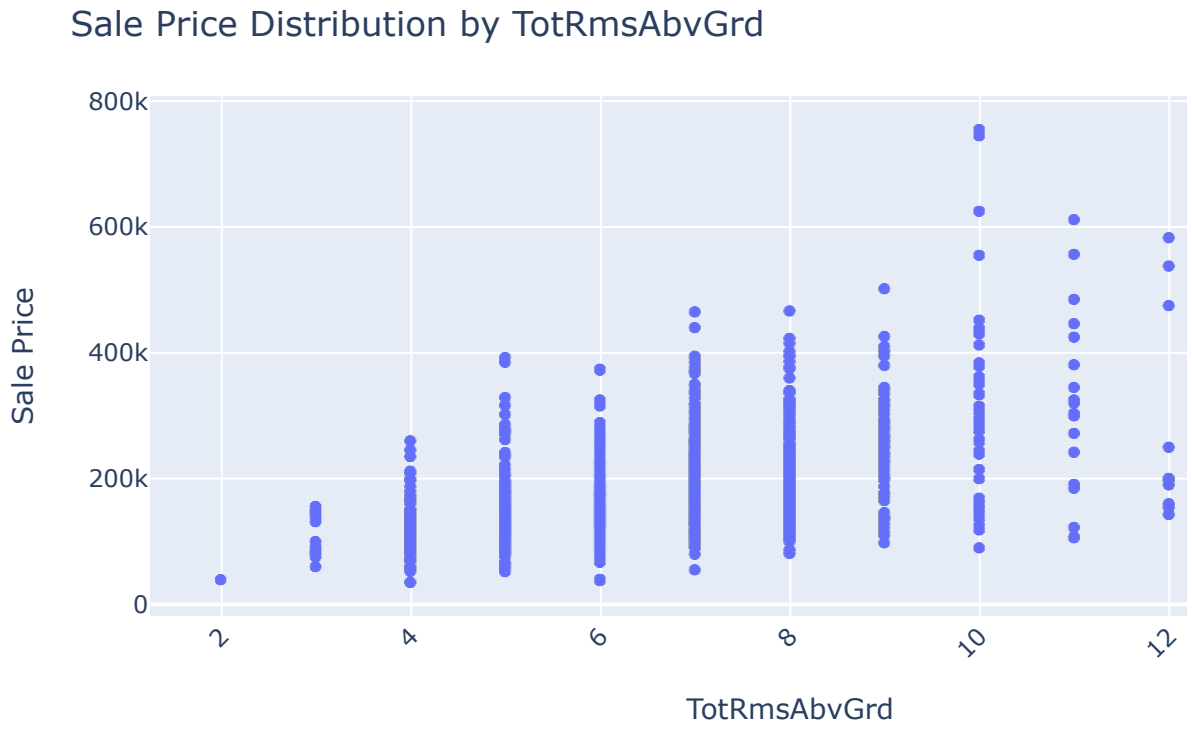

Sale Price Distribution by GarageCars
800k
600k
400k
200k
0
Sale Price
0
1
2
3
GarageCars

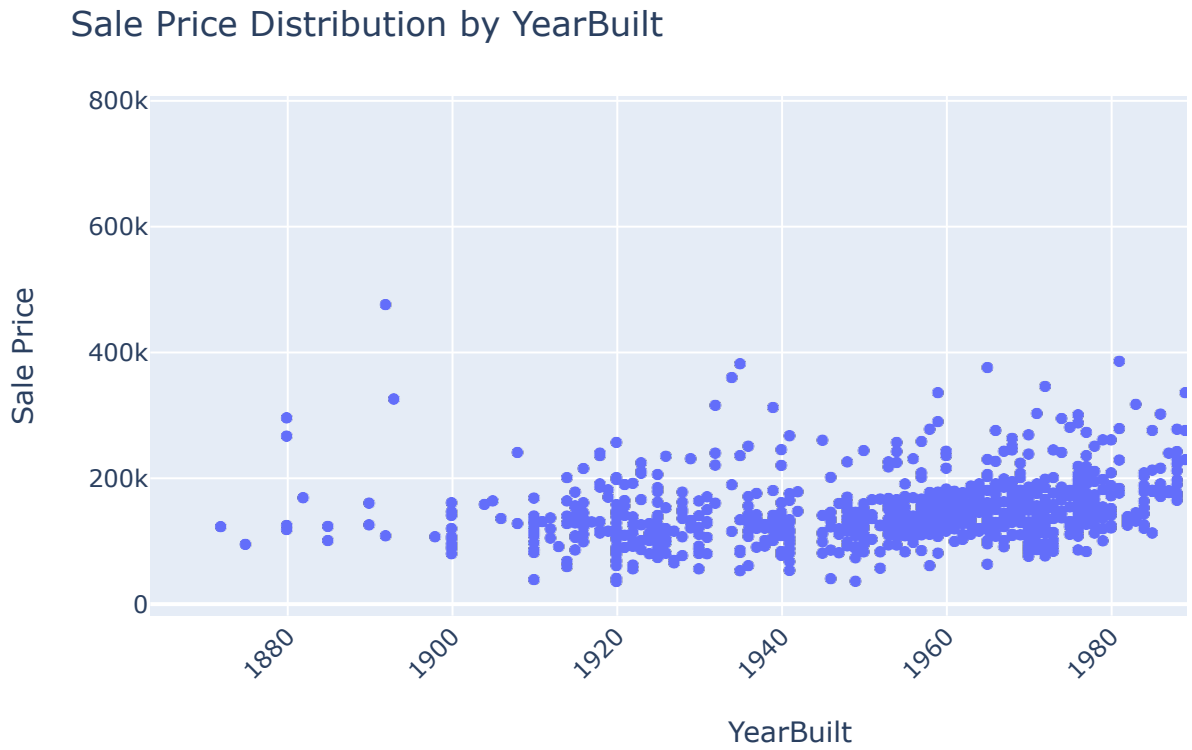

Sale Price Distribution by GarageArea
800k
600k
400k
200k
0
Sale Price
0
200
400
600
800
1000
1200
GarageArea

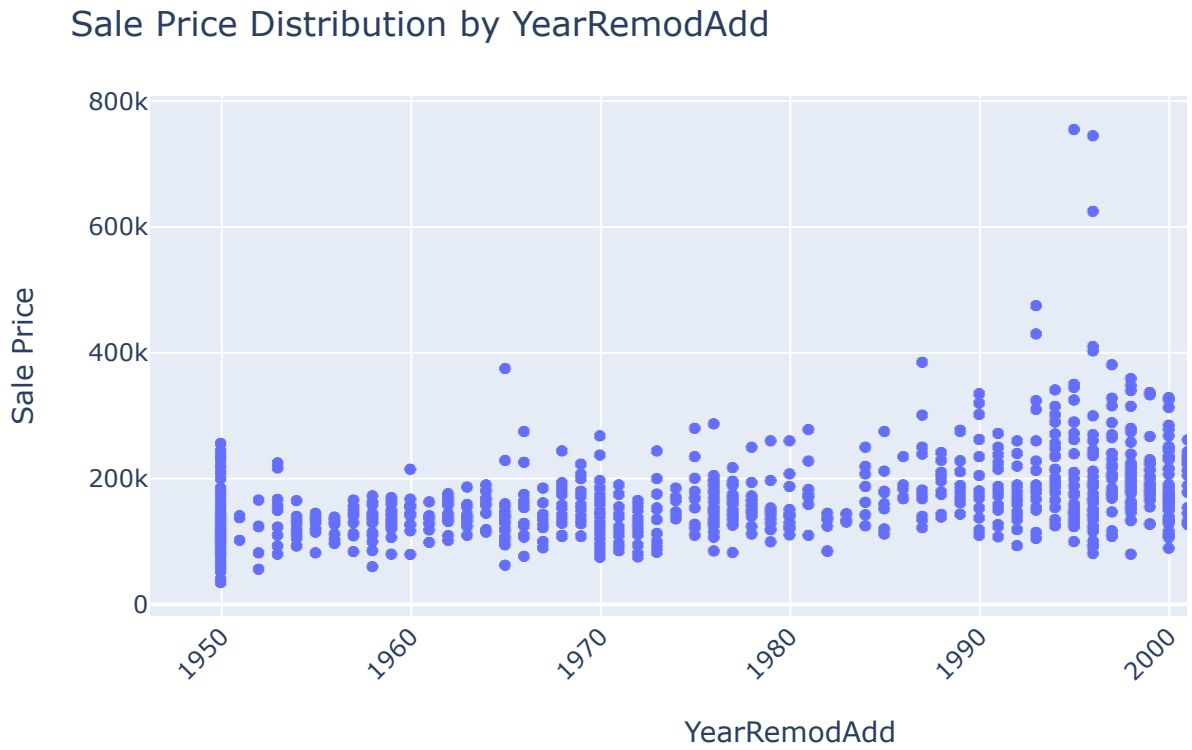

Sale Price Distribution by TotalBsmtSF
800k
600k
400k
200k
0
Sale Price
0
1000
2000
3000
4000
5000
TotalBsmtSF

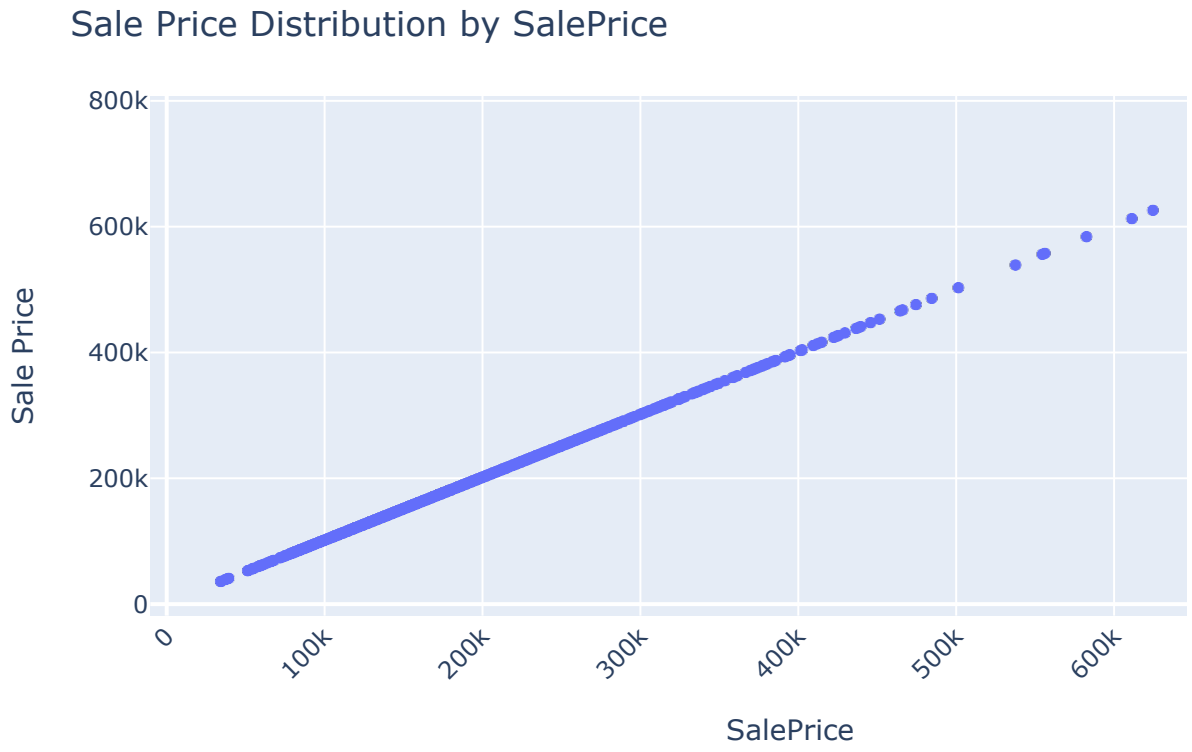

Sale Price Distribution by 1stFlrSF
800k
600k
400k
200k
0
Sale Price
1000
2000
3000
4000
1stFlrSF


Sale Price Distribution by FullBath
800k
600k
400k
200k
0
Sale Price
0
0.5
1
1.5
2
2.5
FullBath


Sale Price Distribution by TotRmsAbvGrd
800k
600k
400k
200k
0
Sale Price
2
4
6
8
10
12
TotRmsAbvGrd


Sale Price Distribution by YearBuilt
800k
600k
400k
200k
0
Sale Price
1880
1900
1920
1940
1960
1980
YearBuilt






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

In [71]:
```
for col in df1:
    print(col)
    print(df1[col].value_counts())
```

```
LotShape
Reg    925
IR1    484
IR2     41
IR3     10
Name: LotShape, dtype: int64
HouseStyle
1Story    726
2Story    445
1.5Fin    154
SLvl       65
SFoyer     37
1.5Unf     14
2.5Unf     11
2.5Fin      8
Name: HouseStyle, dtype: int64
MasVnrType
None       864
BrkFace    445
Stone      128
BrkCmn      15
Name: MasVnrType, dtype: int64
ExterQual
TA    906
Gd    488
Ex     52
Fa     14
Name: ExterQual, dtype: int64
Foundation
PConc     647
CBlock    634
BrkTil    146
Slab       24
Stone       6
Wood        3
Name: Foundation, dtype: int64
BsmtQual
TA    649
Gd    618
Ex    121
Fa     35
Name: BsmtQual, dtype: int64
BsmtExposure
No    953
Av    221
Gd    134
Mn    114
Name: BsmtExposure, dtype: int64
BsmtFinType1
Unf    430
GLQ    418
ALQ    220
BLQ    148
Rec    133
LwQ     74
Name: BsmtFinType1, dtype: int64
HeatingQC
Ex    741
TA    428
```

```
Gd    241
Fa     49
Po      1
Name: HeatingQC, dtype: int64
KitchenQual
TA    735
Gd    586
Ex    100
Fa     39
Name: KitchenQual, dtype: int64
GarageType
Attchd     870
Detchd     387
BuiltIn     88
Basment     19
CarPort      9
2Types       6
Name: GarageType, dtype: int64
GarageFinish
Unf    605
RFn    422
Fin    352
Name: GarageFinish, dtype: int64
Has_VinylSd_Exterior
False    943
True     517
Name: Has_VinylSd_Exterior, dtype: int64
OverallQual
5     397
6     374
7     319
8     168
4     116
9      43
3      20
10     18
2       3
1       2
Name: OverallQual, dtype: int64
GrLivArea
864     22
1040    14
894     11
1456    10
848     10
        ..
2296     1
1123     1
1199     1
1473     1
1256     1
Name: GrLivArea, Length: 861, dtype: int64
GarageCars
2    824
1    369
3    181
0     81
4      5
Name: GarageCars, dtype: int64
```

```
GarageArea
0      81
440    49
576    47
240    38
484    34
       ..
320     1
594     1
831     1
878     1
192     1
Name: GarageArea, Length: 441, dtype: int64
TotalBsmtSF
0       37
864     35
672     17
912     15
1040    14
        ..
1838     1
1581     1
707      1
611      1
1542     1
Name: TotalBsmtSF, Length: 721, dtype: int64
1stFlrSF
864     25
1040    16
912     14
894     12
848     12
        ..
1509     1
2515     1
605      1
3138     1
1256     1
Name: 1stFlrSF, Length: 753, dtype: int64
FullBath
2    768
1    650
3     33
0      9
Name: FullBath, dtype: int64
TotRmsAbvGrd
6     402
7     329
5     275
8     187
4      97
9      75
10     47
11     18
3      17
12     11
2       1
14      1
Name: TotRmsAbvGrd, dtype: int64
```

YearBuilt	
2006	67
2005	64
2004	54
2007	49
2003	45
1976	33
1977	32
1920	30
1959	26
1998	25
1999	25
1965	24
2000	24
1970	24
1954	24
1958	24
2008	23
2002	23
1972	23
1971	22
1968	22
1950	20
1957	20
2001	20
1994	19
1962	19
1940	18
1966	18
2009	18
1995	18
1910	17
1993	17
1960	17
1963	16
1978	16
1925	16
1955	16
1967	16
1996	15
1941	15
1964	15
1961	14
1948	14
1956	14
1969	14
1997	14
1992	13
1953	12
1990	12
1949	12
1973	11
1988	11
1900	10
1974	10
1915	10
1980	10
1984	9
1926	9

```
1936     9
1979     9
1930     9
1922     8
1975     8
1939     8
1916     8
1928     7
1914     7
1923     7
1924     7
1918     7
1946     7
1935     6
1951     6
1921     6
1945     6
1982     6
1931     6
1986     5
1937     5
1981     5
1991     5
1947     5
1952     5
1985     5
1929     4
1938     4
1983     4
1932     4
1880     4
1919     3
1989     3
1912     3
1927     3
1987     3
1934     3
1942     2
1890     2
1885     2
1908     2
1892     2
1913     1
1893     1
1906     1
2010     1
1898     1
1904     1
1882     1
1875     1
1911     1
1917     1
1872     1
1905     1
Name: YearBuilt, dtype: int64
YearRemodAdd
1950    178
2006     97
2007     76
```

```
2005     73
2004     62
2000     55
2003     51
2002     48
2008     40
1996     36
1998     36
1995     31
1976     30
1999     30
1970     26
1977     25
1997     25
2009     23
1994     22
2001     21
1972     20
1965     19
1993     19
1959     18
1971     18
1992     17
1968     17
1978     16
1966     15
1958     15
1990     15
1969     14
1954     14
1991     14
1962     14
1963     13
1960     12
1980     12
1967     12
1973     11
1989     11
1964     11
1953     10
1979     10
1987     10
1956     10
1975     10
1955      9
1957      9
1985      9
1988      9
1981      8
1961      8
1984      7
1982      7
1974      7
2010      6
1986      5
1952      5
1983      5
1951      4
Name: YearRemodAdd, dtype: int64
```

```
SalePrice
140000    20
135000    17
155000    14
145000    14
190000    13
          ..
202665     1
164900     1
208300     1
181500     1
147500     1
Name: SalePrice, Length: 663, dtype: int64
```

In [72]:
```
check = ['None', 'BrkFace']
df1['MasVnrType'] = df1['MasVnrType'].apply(lambda x: x if x in check else 'others'
```

In [73]:
```
check = ['None', 'BrkFace']
df1['MasVnrType'] = df1['MasVnrType'].apply(lambda x: x if x in check else 'others'
```

In [74]:
```
check = ['Reg', 'IR1']
df1['LotShape'] = df1['LotShape'].apply(lambda x: x if x in check else 'others')
```

In [75]:
```
check = ['1Story', '2Story','1.5Fin']
df1['HouseStyle'] = df1['HouseStyle'].apply(lambda x: x if x in check else 'others'
```

In [76]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 0 to 1459
Data columns (total 24 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   LotShape              1460 non-null   object
 1   HouseStyle            1460 non-null   object
 2   MasVnrType            1460 non-null   object
 3   ExterQual             1460 non-null   object
 4   Foundation            1460 non-null   object
 5   BsmtQual              1423 non-null   object
 6   BsmtExposure          1422 non-null   object
 7   BsmtFinType1          1423 non-null   object
 8   HeatingQC             1460 non-null   object
 9   KitchenQual           1460 non-null   object
 10  GarageType            1379 non-null   object
 11  GarageFinish          1379 non-null   object
 12  Has_VinylSd_Exterior  1460 non-null   bool
 13  OverallQual           1460 non-null   int64
 14  GrLivArea             1460 non-null   int64
 15  GarageCars            1460 non-null   int64
 16  GarageArea            1460 non-null   int64
 17  TotalBsmtSF           1460 non-null   int64
 18  1stFlrSF              1460 non-null   int64
 19  FullBath              1460 non-null   int64
 20  TotRmsAbvGrd          1460 non-null   int64
 21  YearBuilt             1460 non-null   int64
 22  YearRemodAdd          1460 non-null   int64
 23  SalePrice             1460 non-null   int64
dtypes: bool(1), int64(11), object(12)
memory usage: 307.5+ KB
```

Ordinal

In [77]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OrdinalEncoder
```

In [78]:
```
df1 = df1.fillna(df1.mode().iloc[0])
```

In [79]:
```
order_qual = ["Fa", "TA", "Gd", "Ex"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["ExterQual"]])

df1["ExterQual"]=pd.DataFrame(qual_label.transform(df1[["ExterQual"]]))
```

In [80]:
```
order_qual = ["Fa", "TA", "Gd", "Ex"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["BsmtQual"]])

df1["BsmtQual"]=pd.DataFrame(qual_label.transform(df1[["BsmtQual"]]))
```

In [81]:
```
order_qual = ["Reg", "IR1", "others"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["LotShape"]])

df1["LotShape"]=pd.DataFrame(qual_label.transform(df1[["LotShape"]]))
```

In [82]:
```
order_qual = ["1Story", "2Story", "1.5Fin","others"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["HouseStyle"]])

df1["HouseStyle"]=pd.DataFrame(qual_label.transform(df1[["HouseStyle"]]))
```

In [83]:
```
order_qual = ["None", "BrkFace","others"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["MasVnrType"]])

df1["MasVnrType"]=pd.DataFrame(qual_label.transform(df1[["MasVnrType"]]))
```

In [84]:
```
order_qual = ["PConc", "CBlock","BrkTil", "Slab", "Stone","Wood"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["Foundation"]])

df1["Foundation"]=pd.DataFrame(qual_label.transform(df1[["Foundation"]]))
```

In [85]:
```
order_qual = ["No", "Av","Gd", "Mn"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["BsmtExposure"]])

df1["BsmtExposure"]=pd.DataFrame(qual_label.transform(df1[["BsmtExposure"]]))
```

In [86]:
```
order_qual = ["Unf", "GLQ","ALQ", "BLQ","Rec","LwQ"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["BsmtFinType1"]])

df1["BsmtFinType1"]=pd.DataFrame(qual_label.transform(df1[["BsmtFinType1"]]))
```

In [87]:
```
order_qual = ["Fa", "TA", "Gd", "Ex", "Po"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["HeatingQC"]])

df1["HeatingQC"]=pd.DataFrame(qual_label.transform(df1[["HeatingQC"]]))
df1["HeatingQC"].value_counts()
```

Out[87]:
```
3.0    741
1.0    428
2.0    241
0.0     49
4.0      1
Name: HeatingQC, dtype: int64
```

In [88]:
```
order_qual = ["Fa", "TA", "Gd", "Ex"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["KitchenQual"]])

df1["KitchenQual"]=pd.DataFrame(qual_label.transform(df1[["KitchenQual"]]))
```

In [89]:
```
order_qual = ["Attchd", "Detchd","BuiltIn", "Basment","CarPort","2Types"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["GarageType"]])

df1["GarageType"]=pd.DataFrame(qual_label.transform(df1[["GarageType"]]))
```

In [90]:
```
order_qual = ["Unf", "RFn","Fin"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(df1[["GarageFinish"]])

df1["GarageFinish"]=pd.DataFrame(qual_label.transform(df1[["GarageFinish"]]))
```

In [91]:
```
df1.head()
```

Out[91]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFin1
0	0.0	1.0	1.0	2.0	0.0	2.0	0.0	
1	0.0	0.0	0.0	1.0	1.0	2.0	2.0	
2	1.0	1.0	1.0	2.0	0.0	2.0	3.0	
3	1.0	1.0	0.0	1.0	2.0	1.0	0.0	
4	1.0	1.0	1.0	2.0	0.0	2.0	1.0	

Label Encoder

In [92]:
```
label_encoder = LabelEncoder()


df1['Has_VinylSd_Exterior'] = label_encoder.fit_transform(df1['Has_VinylSd_Exterior
```

In [93]:
```
df1.head()
```

Out[93]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFin1
0	0.0	1.0	1.0	2.0	0.0	2.0	0.0	
1	0.0	0.0	0.0	1.0	1.0	2.0	2.0	
2	1.0	1.0	1.0	2.0	0.0	2.0	3.0	
3	1.0	1.0	0.0	1.0	2.0	1.0	0.0	
4	1.0	1.0	1.0	2.0	0.0	2.0	1.0	

In [94]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1460 entries, 0 to 1459
Data columns (total 24 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   LotShape              1460 non-null   float64
 1   HouseStyle            1460 non-null   float64
 2   MasVnrType            1460 non-null   float64
 3   ExterQual             1460 non-null   float64
 4   Foundation            1460 non-null   float64
 5   BsmtQual              1460 non-null   float64
 6   BsmtExposure          1460 non-null   float64
 7   BsmtFinType1          1460 non-null   float64
 8   HeatingQC             1460 non-null   float64
 9   KitchenQual           1460 non-null   float64
 10  GarageType            1460 non-null   float64
 11  GarageFinish          1460 non-null   float64
 12  Has_VinylSd_Exterior  1460 non-null   int64  
 13  OverallQual           1460 non-null   int64  
 14  GrLivArea             1460 non-null   int64  
 15  GarageCars            1460 non-null   int64  
 16  GarageArea            1460 non-null   int64  
 17  TotalBsmtSF           1460 non-null   int64  
 18  1stFlrSF              1460 non-null   int64  
 19  FullBath              1460 non-null   int64  
 20  TotRmsAbvGrd          1460 non-null   int64  
 21  YearBuilt             1460 non-null   int64  
 22  YearRemodAdd          1460 non-null   int64  
 23  SalePrice             1460 non-null   int64  
dtypes: float64(12), int64(12)
memory usage: 317.4 KB
```

Normalization

In [95]:
```
from sklearn.preprocessing import StandardScaler
```

In [96]:
```
numeric_col=df_best_num_feature.columns[:-1]
numeric_col
```

Out[96]:
```
Index(['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF',
       '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd'],
      dtype='object')
```

In [97]:
```
scaler = StandardScaler()
```

In [98]:
```
df1[numeric_col] = scaler.fit_transform(df1[numeric_col])
```

In [99]:
```
df1.head()
```

Out[99]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	0.0	1.0	1.0	2.0	0.0	2.0	0.0	
1	0.0	0.0	0.0	1.0	1.0	2.0	2.0	
2	1.0	1.0	1.0	2.0	0.0	2.0	3.0	
3	1.0	1.0	0.0	1.0	2.0	1.0	0.0	
4	1.0	1.0	1.0	2.0	0.0	2.0	1.0	

In [221…
```
df1.drop(columns=['Has_VinylSd_Exterior'], inplace=True)
```

Model Building

The heart of this project lies in building a predictive model. We will explore various regression algorithms, tune hyperparameters, and train models to predict house prices accurately.

test train split

In [222…
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error
```

In [223…
```
y=df1['SalePrice']
```

In [224…
```
x=df1.drop(columns=['SalePrice'], axis=1)
```

In [225…
```
print(f"Y shape{y.shape}")
print(f"X shape{x.shape}")
```

```
Y shape(1460,)
X shape(1460, 22)
```

In [226…
```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_s
```

In [227…
```
model= LinearRegression()
```

In [228…
```
model.fit(X_train, y_train)
print(f"X_train shape{X_train.shape}")
print(f"y_train shape{y_train.shape}")
```

```
X_train shape(1168, 22)
y_train shape(1168,)
```

Linear Model

- Model Predict

In [229…
```
y_pred = model.predict(X_test)
print(f"X_test shape{X_test.shape}")
```

```
X_test shape(292, 22)
```

In [230…
```
mse=mean_squared_error(y_test, y_pred)
print(f"Mean Square Error {mse}")
```

```
Mean Square Error 2259584718.0229216
```

In [231…
```
r2score=r2_score(y_test, y_pred)
print("R2 Score :\t{:.3F} %".format(r2score*100))
```

```
R2 Score :      67.280 %
```

In [232…
```
r2score=r2_score(y_test,y_pred)
print("R2 Score :\t{:.3F} %".format(r2score*100))
```

```
R2 Score :      67.280 %
```

In [305…
```
mae=mean_absolute_error(y_test, y_pred)
print(f"Mean Absolute Error{mae}")
```

```
Mean Absolute Error24664.75520090369
```

Test Data

In [150…
```
test.head()
```

Out[150]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
0	1461	20	RH	80.0	11622	Pave	NaN	Reg	Lvl	A
1	1462	20	RL	81.0	14267	Pave	NaN	IR1	Lvl	A
2	1463	60	RL	74.0	13830	Pave	NaN	IR1	Lvl	A
3	1464	60	RL	78.0	9978	Pave	NaN	IR1	Lvl	A
4	1465	120	RL	43.0	5005	Pave	NaN	IR1	HLS	A

In [151…
```
Id=test['Id']
```

In [152…
```
test.columns
```

Out[152]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition'],
      dtype='object')
```

In [153…
```
num_col=df_best_num_feature.columns[:-1]
```

In [154…
```
num_col
```

Out[154]:
```
Index(['OverallQual', 'GrLivArea', 'GarageCars', 'GarageArea', 'TotalBsmtSF',
       '1stFlrSF', 'FullBath', 'TotRmsAbvGrd', 'YearBuilt', 'YearRemodAdd'],
      dtype='object')
```

In [155…
```
test_col=test.columns
```

In [156…
```
test_col
```

Out[156]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition'],
      dtype='object')
```

In [157…
```
common_num_col=test_col.intersection(num_col)
```

In [160…
```
test_num_df=test[common_num_col].copy()
```

In [161…
```
test_num_df.isnull().sum()
```

Out[161]:
```
OverallQual     0
YearBuilt       0
YearRemodAdd    0
TotalBsmtSF     1
1stFlrSF        0
GrLivArea       0
FullBath        0
TotRmsAbvGrd    0
GarageCars      1
GarageArea      1
dtype: int64
```

In [162…
```
test_num_df = test_num_df.fillna(test_num_df.mode().iloc[0])
```

In [163…
```
test_num_df.isnull().sum()
```

Out[163]:
```
OverallQual     0
YearBuilt       0
YearRemodAdd    0
TotalBsmtSF     0
1stFlrSF        0
GrLivArea       0
FullBath        0
TotRmsAbvGrd    0
GarageCars      0
GarageArea      0
dtype: int64
```

Working on Test Category Columns

In [234…
```
relevant_columns.head()
```

Out[234]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	Reg	2Story	BrkFace	Gd	PConc	Gd	No	
1	Reg	1Story	None	TA	CBlock	Gd	Gd	
2	IR1	2Story	BrkFace	Gd	PConc	Gd	Mn	
3	IR1	2Story	None	TA	BrkTil	TA	No	
4	IR1	2Story	BrkFace	Gd	PConc	Gd	Av	

- Intersections of cat columns

In [235…
```
cat_col=relevant_columns.columns
```

In [168…
```
common_cat_col=test_col.intersection(cat_col)
common_cat_col
```

Out[168]:
```
Index(['LotShape', 'HouseStyle', 'MasVnrType', 'ExterQual', 'Foundation',
       'BsmtQual', 'BsmtExposure', 'BsmtFinType1', 'HeatingQC', 'KitchenQual',
       'GarageType', 'GarageFinish'],
      dtype='object')
```

In [236…
```
test_cat_df=test[common_cat_col].copy()
```

In [237…
```
test_cat_df.head()
```

Out[237]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	Reg	1Story	None	TA	CBlock	TA	No	
1	IR1	1Story	BrkFace	TA	CBlock	TA	No	
2	IR1	2Story	None	TA	PConc	Gd	No	
3	IR1	2Story	BrkFace	TA	PConc	TA	No	
4	IR1	1Story	None	Gd	PConc	Gd	No	

In [238…
```
test_cat_df.isnull().sum()
```

Out[238]:
```
LotShape         0
HouseStyle       0
MasVnrType      16
ExterQual        0
Foundation       0
BsmtQual        44
BsmtExposure    44
BsmtFinType1    42
HeatingQC        0
KitchenQual      1
GarageType      76
GarageFinish    78
dtype: int64
```

In [239…
```
test_cat_df = test_cat_df.fillna(test_cat_df.mode().iloc[0])
```

In [240…
```
test_cat_df.isnull().sum()
```

Out[240]:
```
LotShape        0
HouseStyle      0
MasVnrType      0
ExterQual       0
Foundation      0
BsmtQual        0
BsmtExposure    0
BsmtFinType1    0
HeatingQC       0
KitchenQual     0
GarageType      0
GarageFinish    0
dtype: int64
```

In [241…
```
df1.head(1)
```

Out[241]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	0.0	1.0	1.0	2.0	0.0	2.0	0.0	

In [242…
```
test_cat_df.head(1)
```

Out[242]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	Reg	1Story	None	TA	CBlock	TA	No	

In [243…
```
test_num_df.head(1)
```

Out[243]:

	OverallQual	YearBuilt	YearRemodAdd	TotalBsmtSF	1stFlrSF	GrLivArea	FullBath	TotRmsAb
0	-0.751101	-0.340945	-1.072885	-0.368484	-0.654561	-1.215588	-1.02872	-0.91

In [277…
```
# for i in test_cat_df:
#     print(i)
#     print(test_cat_df[i].value_counts())
```

In [303…
```
# for i in df1:
#     print(i)
#     print(df1[i].value_counts())
```

Feature Missmatch in test dataset so we will concat the Numeric and categorical dataset in new dataframe and will match the feature with Df1

In [244…
```
test_df1=pd.concat([test_cat_df, test_num_df],axis=1)
```

In [245…
```
test_df1.head(1)
```

Out[245]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	Reg	1Story	None	TA	CBlock	TA	No	

In [189…
```
test_df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 22 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   LotShape      1459 non-null   object 
 1   HouseStyle    1459 non-null   object 
 2   MasVnrType    1459 non-null   object 
 3   ExterQual     1459 non-null   float64
 4   Foundation    1459 non-null   object 
 5   BsmtQual      1459 non-null   float64
 6   BsmtExposure  1459 non-null   object 
 7   BsmtFinType1  1459 non-null   object 
 8   HeatingQC     1459 non-null   object 
 9   KitchenQual   1459 non-null   object 
 10  GarageType    1459 non-null   object 
 11  GarageFinish  1459 non-null   object 
 12  OverallQual   1459 non-null   int64  
 13  YearBuilt     1459 non-null   int64  
 14  YearRemodAdd  1459 non-null   int64  
 15  TotalBsmtSF   1459 non-null   float64
 16  1stFlrSF      1459 non-null   int64  
 17  GrLivArea     1459 non-null   int64  
 18  FullBath      1459 non-null   int64  
 19  TotRmsAbvGrd  1459 non-null   int64  
 20  GarageCars    1459 non-null   float64
 21  GarageArea    1459 non-null   float64
dtypes: float64(5), int64(7), object(10)
memory usage: 250.9+ KB
```

In [246…

```
def transform_dataframe(df):
    check = ['None', 'BrkFace']
    df['MasVnrType'] = df['MasVnrType'].apply(lambda x: x if x in check else 'other

    check = ['Reg', 'IR1']
    df['LotShape'] = df['LotShape'].apply(lambda x: x if x in check else 'others')

    check = ['1Story', '2Story', '1.5Fin']
    df['HouseStyle'] = df['HouseStyle'].apply(lambda x: x if x in check else 'other



    order_qual = ["PConc", "CBlock","BrkTil", "Slab", "Stone","Wood"]
    qual_label=OrdinalEncoder(categories=[order_qual])
    qual_label.fit(df[["Foundation"]])

    df["Foundation"]=pd.DataFrame(qual_label.transform(df[["Foundation"]]))

    order_qual = ["No", "Av","Gd", "Mn"]
    qual_label=OrdinalEncoder(categories=[order_qual])
    qual_label.fit(df[["BsmtExposure"]])

    df["BsmtExposure"]=pd.DataFrame(qual_label.transform(df[["BsmtExposure"]]))

    order_qual = ["Unf", "GLQ","ALQ", "BLQ","Rec","LwQ"]
    qual_label=OrdinalEncoder(categories=[order_qual])
    qual_label.fit(df[["BsmtFinType1"]])

    df["BsmtFinType1"]=pd.DataFrame(qual_label.transform(df[["BsmtFinType1"]]))


    order_qual = ["Fa", "TA", "Gd", "Ex", "Po"]
    qual_label=OrdinalEncoder(categories=[order_qual])
    qual_label.fit(df[["HeatingQC"]])

    df["HeatingQC"]=pd.DataFrame(qual_label.transform(df[["HeatingQC"]]))


    order_qual = ["Fa", "TA", "Gd", "Ex"]
    qual_label=OrdinalEncoder(categories=[order_qual])
    qual_label.fit(df[["KitchenQual"]])

    df["KitchenQual"]=pd.DataFrame(qual_label.transform(df[["KitchenQual"]]))

    order_qual = ["Attchd", "Detchd","BuiltIn", "Basment","CarPort","2Types"]
    qual_label=OrdinalEncoder(categories=[order_qual])
    qual_label.fit(df[["GarageType"]])

    df["GarageType"]=pd.DataFrame(qual_label.transform(df[["GarageType"]]))

    order_qual = ["Unf", "RFn","Fin"]
    qual_label=OrdinalEncoder(categories=[order_qual])
    qual_label.fit(df[["GarageFinish"]])

    df["GarageFinish"]=pd.DataFrame(qual_label.transform(df[["GarageFinish"]]))



    return df
```

```
    return df


test_df1 = transform_dataframe(test_df1)
```

In [247…
```
test_df1.head()
```

Out[247]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	Reg	1Story	None	TA	1.0	TA	0.0	
1	IR1	1Story	BrkFace	TA	1.0	TA	0.0	
2	IR1	2Story	None	TA	0.0	Gd	0.0	
3	IR1	2Story	BrkFace	TA	0.0	TA	0.0	
4	IR1	1Story	None	Gd	0.0	Gd	0.0	

In [248…
```
order_qual = ["Reg", "IR1", "others"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(test_df1[["LotShape"]])

test_df1["LotShape"]=pd.DataFrame(qual_label.transform(test_df1[["LotShape"]]))

order_qual = ["1Story", "2Story", "1.5Fin","others"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(test_df1[["HouseStyle"]])

test_df1["HouseStyle"]=pd.DataFrame(qual_label.transform(test_df1[["HouseStyle"]]))

order_qual = ["None", "BrkFace","others"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(test_df1[["MasVnrType"]])

test_df1["MasVnrType"]=pd.DataFrame(qual_label.transform(test_df1[["MasVnrType"]]))
```

In [249…
```
test_df1.head()
```

Out[249]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	0.0	0.0	0.0	TA	1.0	TA	0.0	
1	1.0	0.0	1.0	TA	1.0	TA	0.0	
2	1.0	1.0	0.0	TA	0.0	Gd	0.0	
3	1.0	1.0	1.0	TA	0.0	TA	0.0	
4	1.0	0.0	0.0	Gd	0.0	Gd	0.0	

In [250…
```
df_best_num_feature.head()
```

Out[250]:

	OverallQual	GrLivArea	GarageCars	GarageArea	TotalBsmtSF	1stFlrSF	FullBath	TotRmsAbvGr
0	7	1710	2	548	856	856	2	
1	6	1262	2	460	1262	1262	2	
2	7	1786	2	608	920	920	2	
3	7	1717	3	642	756	961	1	
4	8	2198	3	836	1145	1145	2	

In [251…
```
backup=test_df1.copy()
```

In [252…
```
def standard_scalar_fun(df):
    # Assuming df contains the numeric columns you want to standardize
    numeric_col = df.columns[:-1]  # Use df.columns[:-1] to exclude the last column

    scaler = StandardScaler()
    df[numeric_col] = scaler.fit_transform(df[numeric_col])
    return df
```

In [253…
```
test_num_df = standard_scalar_fun(test_num_df)
```

In [254…
```
test_num_df
```

Out[254]:

	OverallQual	YearBuilt	YearRemodAdd	TotalBsmtSF	1stFlrSF	GrLivArea	FullBath	TotRn
0	-0.751101	-0.340945	-1.072885	-0.368484	-0.654561	-1.215588	-1.028720	
1	-0.054877	-0.439695	-1.214908	0.639542	0.433298	-0.323539	-1.028720	
2	-0.751101	0.844059	0.678742	-0.264750	-0.574165	0.294508	0.773083	
3	-0.054877	0.876976	0.678742	-0.269260	-0.579190	0.243004	0.773083	
4	1.337571	0.679475	0.394694	0.529042	0.310192	-0.424487	0.773083	
...	...	...	...	...	...	...	...	
1454	-1.447325	-0.044694	-0.646813	-1.126195	-1.533893	-0.811797	-1.028720	
1455	-1.447325	-0.044694	-0.646813	-1.126195	-1.533893	-0.811797	-1.028720	
1456	-0.751101	-0.373861	0.584059	0.402757	0.169499	-0.539856	-1.028720	
1457	-0.751101	0.679475	0.394694	-0.300831	-0.468645	-1.063136	-1.028720	
1458	0.641347	0.712392	0.489377	-0.111404	-0.403324	1.058827	0.773083	

1459 rows × 10 columns

In [255…
```
test_df2 =pd.concat([test_df1.iloc[:, :12],test_num_df],axis=1 )
```

In [256…
```
test_df2.head(2)
```

Out[256]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFin1
0	0.0	0.0	0.0	TA	1.0	TA	0.0	
1	1.0	0.0	1.0	TA	1.0	TA	0.0	

In [257…
```
test_df1.iloc[:, :12]
```

Out[257]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	Bsmt
0	0.0	0.0	0.0	TA	1.0	TA	0.0	
1	1.0	0.0	1.0	TA	1.0	TA	0.0	
2	1.0	1.0	0.0	TA	0.0	Gd	0.0	
3	1.0	1.0	1.0	TA	0.0	TA	0.0	
4	1.0	0.0	0.0	Gd	0.0	Gd	0.0	
...	...	...	...	...	...	...	...	...
1454	0.0	1.0	0.0	TA	1.0	TA	0.0	
1455	0.0	1.0	0.0	TA	1.0	TA	0.0	
1456	0.0	0.0	0.0	TA	1.0	TA	0.0	
1457	0.0	3.0	0.0	TA	0.0	Gd	1.0	
1458	0.0	1.0	1.0	TA	0.0	Gd	1.0	

1459 rows × 12 columns

In [272…
```
train_col=df1.columns[:-1]
```

In [273…
```
train_col
```

Out[273]:
```
Index(['LotShape', 'HouseStyle', 'MasVnrType', 'ExterQual', 'Foundation',
       'BsmtQual', 'BsmtExposure', 'BsmtFinType1', 'HeatingQC', 'KitchenQual',
       'GarageType', 'GarageFinish', 'OverallQual', 'GrLivArea', 'GarageCars',
       'GarageArea', 'TotalBsmtSF', '1stFlrSF', 'FullBath', 'TotRmsAbvGrd',
       'YearBuilt', 'YearRemodAdd'],
      dtype='object')
```

In [275…
```
test_df3.columns
```

Out[275]:
```
Index(['LotShape', 'HouseStyle', 'MasVnrType', 'ExterQual', 'Foundation',
       'BsmtQual', 'BsmtExposure', 'BsmtFinType1', 'HeatingQC', 'KitchenQual',
       'GarageType', 'GarageFinish', 'OverallQual', 'GrLivArea', 'GarageCars',
       'GarageArea', 'TotalBsmtSF', '1stFlrSF', 'FullBath', 'TotRmsAbvGrd',
       'YearBuilt', 'YearRemodAdd'],
      dtype='object')
```

In [266…
```
common_columns = set(df1.columns.tolist()).intersection(test_df2.columns.tolist())
print(len(common_columns))
print(len(df1.columns.tolist()))
```

```
22
23
```

In [274…
```
test_df3=test_df2[train_col]
```

In [284…
```
test_df3['BsmtQual'].value_counts()
```

Out[284]:
```
TA    678
Gd    591
Ex    137
Fa     53
Name: BsmtQual, dtype: int64
```

In [286…
```
test_df3.head(2)
```

Out[286]:

	LotShape	HouseStyle	MasVnrType	ExterQual	Foundation	BsmtQual	BsmtExposure	BsmtFinT
0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
1	1.0	0.0	1.0	0.0	1.0	0.0	0.0	

In [285…
```
order_qual = ["TA", "Gd","Ex","Fa"]
qual_label=OrdinalEncoder(categories=[order_qual])
qual_label.fit(test_df3[["BsmtQual"]])

test_df3["BsmtQual"]=pd.DataFrame(qual_label.transform(test_df3[["BsmtQual"]]))
```

In [287…
```
# order_qual = ["TA", "Gd","Ex","Fa"]
# qual_label=OrdinalEncoder(categories=[order_qual])
# qual_label.fit(test_df3[["ExterQual"]])

# test_df3["ExterQual"]=pd.DataFrame(qual_label.transform(test_df3[["ExterQual"]]))
```

Test Model fit in to algorithm to predict test data

In [306…
```
x_test=test_df3.copy()
```

In [307…
```
test_data_predict=model.predict(x_test)
# results_df = pd.DataFrame({'Id': id, 'SalePrice': test_data_predict})
# results_df.to_csv('house_prices_LinearRegression.csv', index=False)
```

In [308…
```
test_data_predict=test_data_predict.round(3)
```

In [309…
```
results_df = pd.DataFrame({'Id': Id, 'SalePrice': test_data_predict})
```

In [310…
```
results_df
```

Out[310]:

	Id	SalePrice
0	1461	6764220.764
1	1462	3009809.795
2	1463	4554987.177
3	1464	4458130.080
4	1465	4823571.943
...	...	...
1454	2915	68675.243
1455	2916	2683463.277
1456	2917	5384924.426
1457	2918	100951.441
1458	2919	6146383.799

1459 rows × 2 columns

In [302…

```
results_df.to_csv('house_prices_Advanced_linear_regression.csv', index=False)
```

Conclusion

In the final section, we will summarize our findings, discuss the model's strengths and weaknesses, and offer insights into potential areas for improvement.

- Our Linear Regression model, with an R2 score of 67.280%, demonstrates promise in explaining housing price variations.
- However, improvements are needed to reduce the Mean Square Error (MSE) of approximately 2,259,584,718.02 and the
- Mean Absolute Error (MAE) of $24,664.76.

Further refinement is recommended to enhance predictive accuracy.