House Price prediction

By Mohamed Jamyl

http://linkedin.com/in/mohamed-jamyl

https://www.kaggle.com/mohamedjamyl

https://github.com/Mohamed-Jamyl

In [2]:
```
from IPython.display import Image
Image(filename='hs.JPG')
```

Out[2]:

Project Overview

A simple yet challenging project, to predict the housing price based on certain factors like house area, bedrooms, furnished, nearness to mainroad, etc. The dataset is small yet, it's complexity arises due to the fact that it has strong multicollinearity. Can you overcome these obstacles & build a decent predictive model?

Import Libraries

In [3]:
```
from pandas import read_csv, DataFrame, concat
from matplotlib.pyplot import show, suptitle, subplots_adjust, tight_layout, subplots,scatter
from matplotlib.pyplot import figure, title, xlabel, ylabel, grid, xticks, tight_layout
from numpy import nan,log,inf
from seaborn import kdeplot, heatmap, histplot, boxplot, countplot, scatterplot,kdeplot,lmplot,lineplot,violinp
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, Ridge
from xgboost import XGBRegressor
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
from math import sqrt
from pickle import dump
```

```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

Exploratory Data Analysis (EDA)

Initial Data Understanding

- **Data loading and Inspection**
- **Data Types**
- **Missing Values**
- **Duplicates**

In [4]:
```
df_train = read_csv("train.csv")
```

In [5]:
```
df_train.head()
```

Out[5]:

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

5 rows × 81 columns

In [6]:
```
print(f'shape_train: {df_train.shape}')
```

```
shape_train: (1460, 81)
```

In [7]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     588 non-null    object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
 29  Foundation     1460 non-null   object 
 30  BsmtQual       1423 non-null   object 
 31  BsmtCond       1423 non-null   object 
 32  BsmtExposure   1422 non-null   object 
 33  BsmtFinType1   1423 non-null   object 
```

```
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

In [8]:
```
df_train.columns
```

Out[8]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
       'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType',
       'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1',
       'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating',
       'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF',
       'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

In [9]:
```
for i in df_train.columns:
    print(i," : ",df_train[i].isnull().sum())
```

```
Id  :  0
MSSubClass  :  0
MSZoning  :  0
LotFrontage  :  259
LotArea  :  0
Street  :  0
Alley  :  1369
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  :  872
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
FireplaceQu  :  690
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
PoolQC  :  1453
Fence  :  1179
MiscFeature  :  1406
MiscVal  :  0
MoSold  :  0
YrSold  :  0
SaleType  :  0
SaleCondition  :  0
SalePrice  :  0
```

In [10]:
```
df_train.duplicated().sum()
```

Out[10]: 0

---

2. **Basic Statistical Overview**

- Summary Statistical : **describe()**

In [11]:
```
df_train.describe().T
```

Out[11]:

	count	mean	std	min	25%	50%	75%	max
Id	1460.0	730.500000	421.610009	1.0	365.75	730.5	1095.25	1460.0
MSSubClass	1460.0	56.897260	42.300571	20.0	20.00	50.0	70.00	190.0
LotFrontage	1201.0	70.049958	24.284752	21.0	59.00	69.0	80.00	313.0
LotArea	1460.0	10516.828082	9981.264932	1300.0	7553.50	9478.5	11601.50	215245.0
OverallQual	1460.0	6.099315	1.382997	1.0	5.00	6.0	7.00	10.0
OverallCond	1460.0	5.575342	1.112799	1.0	5.00	5.0	6.00	9.0
YearBuilt	1460.0	1971.267808	30.202904	1872.0	1954.00	1973.0	2000.00	2010.0
YearRemodAdd	1460.0	1984.865753	20.645407	1950.0	1967.00	1994.0	2004.00	2010.0
MasVnrArea	1452.0	103.685262	181.066207	0.0	0.00	0.0	166.00	1600.0
BsmtFinSF1	1460.0	443.639726	456.098091	0.0	0.00	383.5	712.25	5644.0
BsmtFinSF2	1460.0	46.549315	161.319273	0.0	0.00	0.0	0.00	1474.0
BsmtUnfSF	1460.0	567.240411	441.866955	0.0	223.00	477.5	808.00	2336.0
TotalBsmtSF	1460.0	1057.429452	438.705324	0.0	795.75	991.5	1298.25	6110.0
1stFlrSF	1460.0	1162.626712	386.587738	334.0	882.00	1087.0	1391.25	4692.0
2ndFlrSF	1460.0	346.992466	436.528436	0.0	0.00	0.0	728.00	2065.0
LowQualFinSF	1460.0	5.844521	48.623081	0.0	0.00	0.0	0.00	572.0
GrLivArea	1460.0	1515.463699	525.480383	334.0	1129.50	1464.0	1776.75	5642.0
BsmtFullBath	1460.0	0.425342	0.518911	0.0	0.00	0.0	1.00	3.0
BsmtHalfBath	1460.0	0.057534	0.238753	0.0	0.00	0.0	0.00	2.0
FullBath	1460.0	1.565068	0.550916	0.0	1.00	2.0	2.00	3.0
HalfBath	1460.0	0.382877	0.502885	0.0	0.00	0.0	1.00	2.0
BedroomAbvGr	1460.0	2.866438	0.815778	0.0	2.00	3.0	3.00	8.0
KitchenAbvGr	1460.0	1.046575	0.220338	0.0	1.00	1.0	1.00	3.0
TotRmsAbvGrd	1460.0	6.517808	1.625393	2.0	5.00	6.0	7.00	14.0
Fireplaces	1460.0	0.613014	0.644666	0.0	0.00	1.0	1.00	3.0
GarageYrBlt	1379.0	1978.506164	24.689725	1900.0	1961.00	1980.0	2002.00	2010.0
GarageCars	1460.0	1.767123	0.747315	0.0	1.00	2.0	2.00	4.0
GarageArea	1460.0	472.980137	213.804841	0.0	334.50	480.0	576.00	1418.0
WoodDeckSF	1460.0	94.244521	125.338794	0.0	0.00	0.0	168.00	857.0
OpenPorchSF	1460.0	46.660274	66.256028	0.0	0.00	25.0	68.00	547.0
EnclosedPorch	1460.0	21.954110	61.119149	0.0	0.00	0.0	0.00	552.0
3SsnPorch	1460.0	3.409589	29.317331	0.0	0.00	0.0	0.00	508.0
ScreenPorch	1460.0	15.060959	55.757415	0.0	0.00	0.0	0.00	480.0
PoolArea	1460.0	2.758904	40.177307	0.0	0.00	0.0	0.00	738.0
MiscVal	1460.0	43.489041	496.123024	0.0	0.00	0.0	0.00	15500.0
MoSold	1460.0	6.321918	2.703626	1.0	5.00	6.0	8.00	12.0
YrSold	1460.0	2007.815753	1.328095	2006.0	2007.00	2008.0	2009.00	2010.0
SalePrice	1460.0	180921.195890	79442.502883	34900.0	129975.00	163000.0	214000.00	755000.0

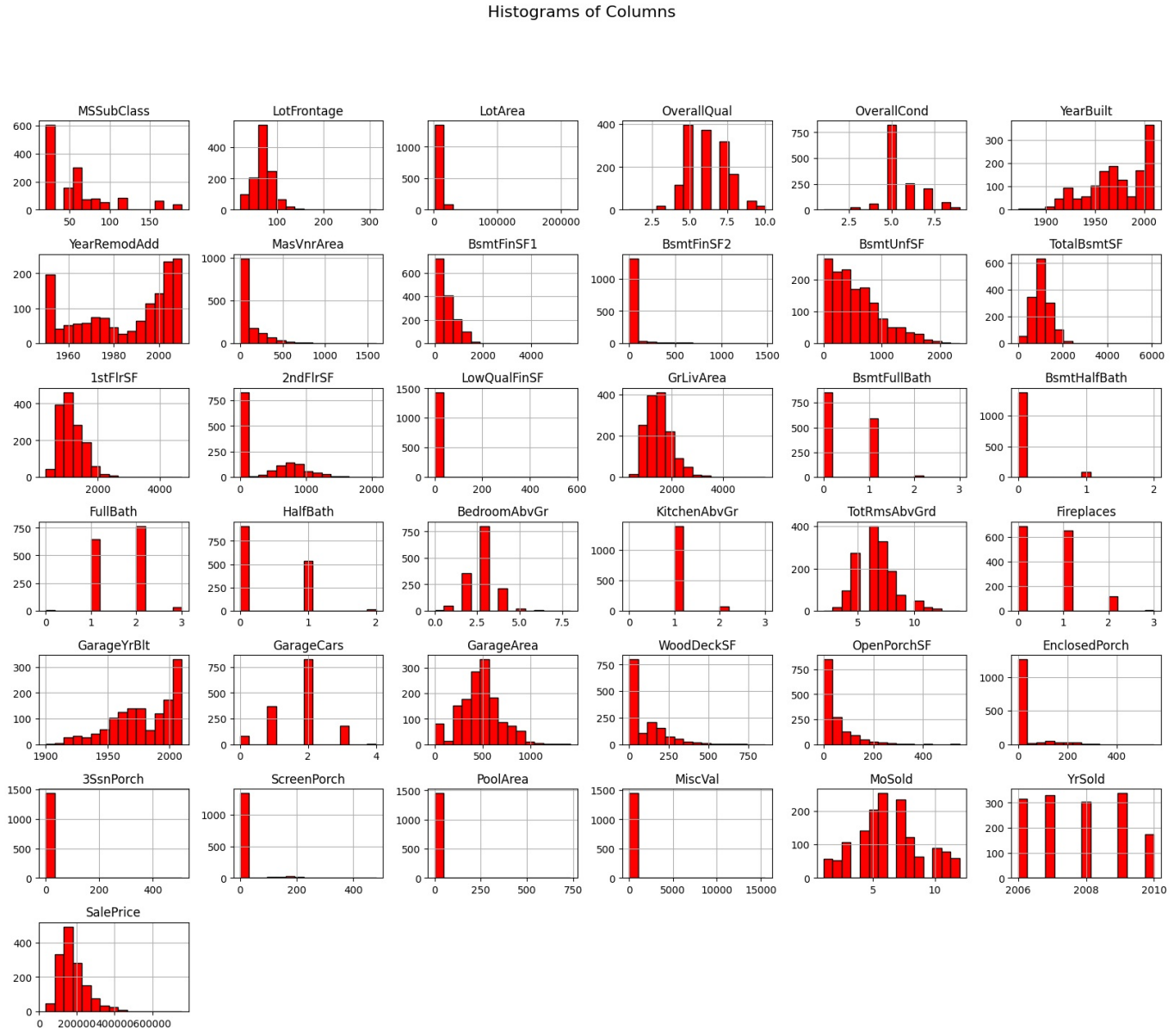
In [12]:
```
df_train.select_dtypes(include='object').describe()
```

Out[12]:

	MSZoning	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	...	GarageTy
count	1460	1460	91	1460	1460	1460	1460	1460	1460	1460	...	13
unique	5	2	2	4	4	2	5	3	25	9	...	
top	RL	Pave	Grvl	Reg	Lvl	AllPub	Inside	Gtl	NAmes	Norm	...	Att
freq	1151	1454	50	925	1311	1459	1052	1382	225	1260	...	8

4 rows × 43 columns

In [13]:
```
df_train.drop('Id',axis=1).hist(bins=15, figsize=(20, 16), color='red', edgecolor='black')
suptitle('Histograms of Columns', fontsize=16)
subplots_adjust(hspace=0.5)
show()
```



- Summary Statistical : **Value_counts()**

In [14]:
```
df_train['YearRemodAdd'].value_counts()
```

Out[14]:
```
YearRemodAdd
1950    178
2006     97
2007     76
2005     73
2004     62
        ...
2010      6
1986      5
1952      5
1983      5
1951      4
Name: count, Length: 61, dtype: int64
```

In [15]:
```
df_train['YearRemodAdd'].unique()
```

Out[15]:
```
array([2003, 1976, 2002, 1970, 2000, 1995, 2005, 1973, 1950, 1965, 2006,
       1962, 2007, 1960, 2001, 1967, 2004, 2008, 1997, 1959, 1990, 1955,
       1983, 1980, 1966, 1963, 1987, 1964, 1972, 1996, 1998, 1989, 1953,
       1956, 1968, 1981, 1992, 2009, 1982, 1961, 1993, 1999, 1985, 1979,
       1977, 1969, 1958, 1991, 1971, 1952, 1975, 2010, 1984, 1986, 1994,
       1988, 1954, 1957, 1951, 1978, 1974], dtype=int64)
```

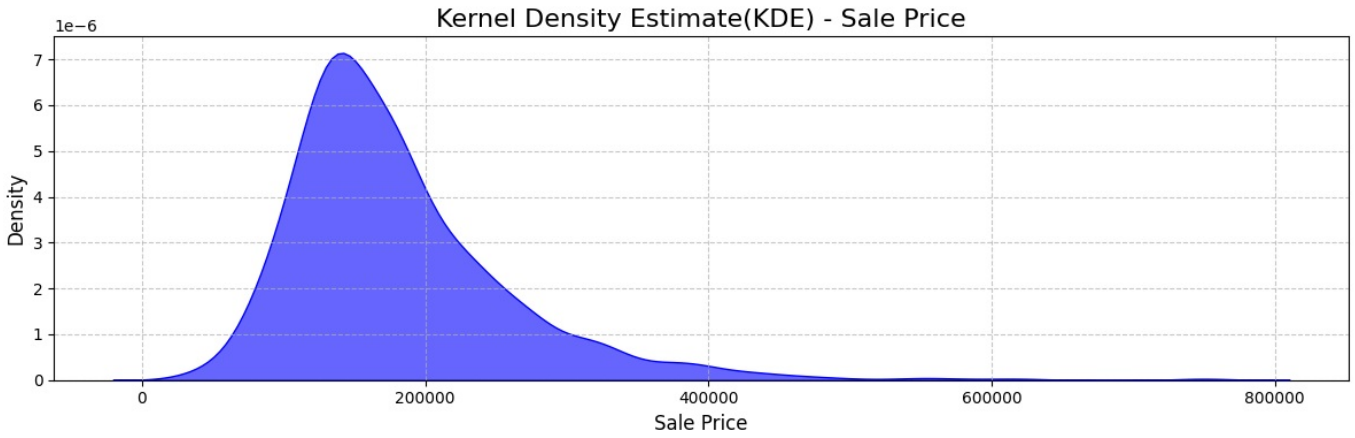
Distribution of Variables

- **Numerical Features (KDE)**

In [16]:
```
df_train['SalePrice']
```

Out[16]:
```
0       208500
1       181500
2       223500
3       140000
4       250000
         ...
1455    175000
1456    210000
1457    266500
1458    142125
1459    147500
Name: SalePrice, Length: 1460, dtype: int64
```

In [17]:
```
figure(figsize=(12,     4))
kdeplot(df_train['SalePrice'], fill=True,       color='blue', alpha=0.6)
title(f'Kernel Density Estimate(KDE) - Sale Price',     fontsize=16)
xlabel('Sale Price', fontsize=12)
ylabel('Density', fontsize=12)
grid(True, linestyle='--', alpha=0.7)
tight_layout()
show()
```



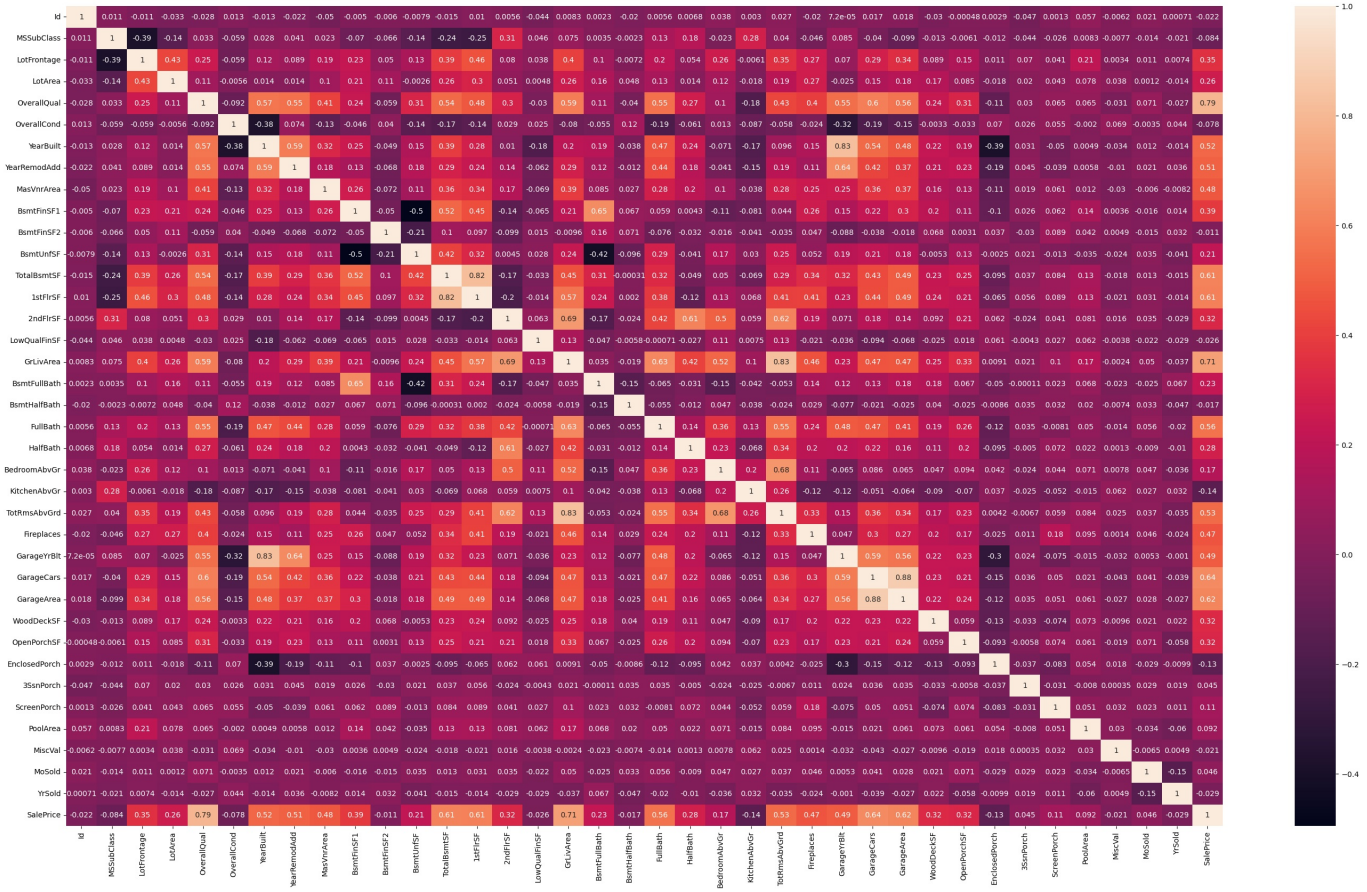
- **Peak Concentration**: The highest density of sale prices appears to be around the $150,000 to $200,000 range. This suggests that the majority of houses in dataset were sold within this price bracket.
- **Decreasing Density with Increasing Price**: As the sale price increases beyond the peak, the density of the distribution rapidly declines. This indicates that fewer and fewer houses were sold at higher price points.
- **Long Right Tail**: The presence of the long right tail, extending towards $800,000 and beyond, signifies the existence of some relatively expensive properties in dataset. These higher-priced sales are less frequent but still contribute to the overall distribution.

- **Limited Low-Priced Sales**: The density is very low for sale prices below approximately $50,000, suggesting that there are relatively few very low-priced properties in dataset.

The sale price distribution in dataset is characterized by a concentration of sales in the $150,000 to $200,000 range, with a decreasing number of sales as the price increases, and a presence of some high-value properties that create a positive skew.

Checking Correlation between the Features

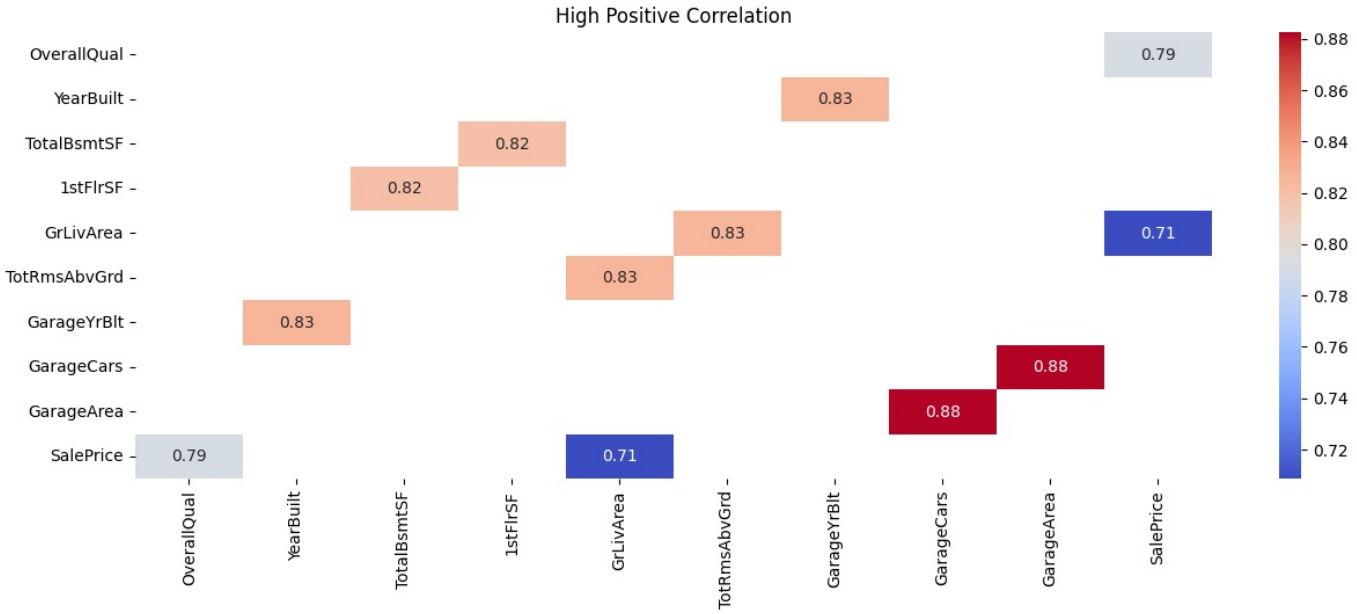
In [18]:
```
figure(figsize=(35,     20))
heatmap(df_train.select_dtypes(include='number').corr(), annot=True)
show()
```



In [19]:
```
# function to extract high positive correlated columns
def get_high_corr(df_train, threshold):
    corr = df_train.select_dtypes('number').corr()
    high_corr = corr[(corr >= threshold) & (corr != 1.000)]
    high_corr = high_corr.dropna(how='all', axis=1).dropna(how='all', axis=0)
    return high_corr

# get high positive correlated columns
high_corr = get_high_corr(df_train, 0.7)

# plot high positive correlated columns
figure(figsize=(15, 5))
plot = heatmap(high_corr, annot=True, cmap='coolwarm')
plot.set_title('High Positive Correlation')
show()
```

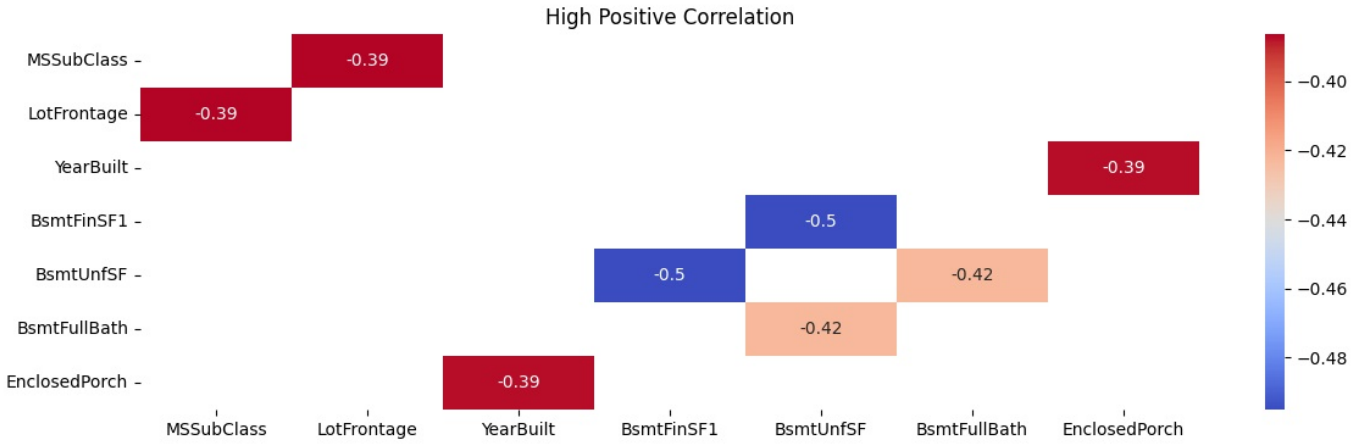


- There is a high positive correlation (0.88) between **GarageCars** and **GarageArea**
- There is a high positive correlation (0.83) between **GarageYrBlt** and **YearBuilt**
- There is a high positive correlation (0.83) between **TotRmsAbvGrd** and **GrLivArea**
- There is a high positive correlation (0.82) between **TotalBsmtSF** and **1stFlrSF**
- There is a high positive correlation (0.79) between **OverallQual** and **SalePrice**
- There is a high positive correlation (0.71) between **GrLivArea** and **SalePrice**

In [20]:
```python
# function to extract high positive correlated columns
def get_high_corr(df_train, threshold):
    corr = df_train.select_dtypes('number').corr()
    high_corr = corr[(corr <= threshold) & (corr != 1.000)]
    high_corr = high_corr.dropna(how='all', axis=1).dropna(how='all', axis=0)
    return high_corr

# get high positive correlated columns
high_corr = get_high_corr(df_train, -0.38)

# plot high positive correlated columns
figure(figsize=(14, 4))
plot = heatmap(high_corr, annot=True, cmap='coolwarm')
plot.set_title('High Positive Correlation')
show()
```



- There is a high negative correlation (-0.5) between **BsmtFinSF1r** and **BsmtUnfSF**
- There is a high negative correlation (-0.42) between **BsmtFullBath** and **BsmtUnfSF**
- There is a high negative correlation (-0.39) between **EnclosedPorch** and **YearBuilt**

Data cleaning

In [21]:
```
for i in df_train.columns:
    print(i," : ",df_train[i].isnull().sum())
```

```
Id  :  0
MSSubClass  :  0
MSZoning  :  0
LotFrontage  :  259
LotArea  :  0
Street  :  0
Alley  :  1369
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  :  872
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
FireplaceQu  :  690
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
PoolQC  :  1453
Fence  :  1179
MiscFeature  :  1406
MiscVal  :  0
MoSold  :  0
YrSold  :  0
SaleType  :  0
SaleCondition  :  0
SalePrice  :  0
```

In [22]:
```
# sum of nulls >= 30 for all data
```

```
for column in df_train.columns:
    SumOfNulls = df_train[column].isnull().sum()
    if SumOfNulls > 30:
       print(f'{column} : {SumOfNulls}')
```

```
LotFrontage : 259
Alley : 1369
MasVnrType : 872
BsmtQual : 37
BsmtCond : 37
BsmtExposure : 38
BsmtFinType1 : 37
BsmtFinType2 : 38
FireplaceQu : 690
GarageType : 81
GarageYrBlt : 81
GarageFinish : 81
GarageQual : 81
GarageCond : 81
PoolQC : 1453
Fence : 1179
MiscFeature : 1406
```

In [23]:
```
df_train = df_train.drop(['Id','EnclosedPorch','BsmtHalfBath','LowQualFinSF','MiscFeature','Fence','PoolQC','Fi
                          ,'3SsnPorch','ScreenPorch','PoolArea','MiscVal','MiscVal','BsmtFinSF2','Fireplaces'],axi
```

In [24]:
```
df_train = df_train.dropna()
```

In [25]:
```
df_train.shape
```

Out[25]:
```
(1094, 65)
```

In [26]:
```
df_train.head()
```

Out[26]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	...	GarageQual
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	TA
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl	...	TA
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl	...	TA
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl	...	TA
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl	...	TA

5 rows × 65 columns

In [27]:
```
df_train['WoodDeckSF'].value_counts()
```

Out[27]:
```
WoodDeckSF
0      559
192     35
100     30
144     27
168     23
       ...
326      1
35       1
298      1
78       1
736      1
Name: count, Length: 221, dtype: int64
```

In [28]:
```
df_train['OpenPorchSF'].value_counts()
```

Out[28]:
```
OpenPorchSF
0      470
36      24
45      16
20      16
48      14
       ...
94       1
406      1
101      1
285      1
41       1
Name: count, Length: 176, dtype: int64
```

In [29]:
```
df_train['MasVnrArea'].value_counts()
```

Out[29]:
```
MasVnrArea
0.0      638
108.0      7
16.0       7
72.0       6
80.0       6
         ...
285.0      1
921.0      1
762.0      1
594.0      1
119.0      1
Name: count, Length: 279, dtype: int64
```

In [30]:
```
# transform from flaot to int
df_train['MasVnrArea'] = df_train['MasVnrArea'].astype(int)
```

In [31]:
```
df_train['MasVnrArea'].value_counts()
```

Out[31]:
```
MasVnrArea
0      638
108      7
16       7
72       6
80       6
       ...
285      1
921      1
762      1
594      1
119      1
Name: count, Length: 279, dtype: int64
```

In [32]:
```
df_train['WoodDeckSF'].mean()
```

Out[32]:
```
94.3418647166362
```

In [33]:
```
df_train['MasVnrArea'].mean()
```

Out[33]:
```
109.85557586837294
```

In [34]:
```
# replace 0 wirh 'nan' for train data

df_train['WoodDeckSF'] = df_train['WoodDeckSF'].replace(0,nan)
df_train['OpenPorchSF'] = df_train['OpenPorchSF'].replace(0,nan)
df_train['MasVnrArea'] = df_train['MasVnrArea'].replace(0,nan)
```

In [35]:
```
# Replace 'nan' with mean

mean_WoodDeckSF = df_train['WoodDeckSF'].mean()
df_train['WoodDeckSF'].fillna(mean_WoodDeckSF,inplace=True)

mean_OpenPorchSF = df_train['OpenPorchSF'].mean()
df_train['OpenPorchSF'].fillna(mean_OpenPorchSF,inplace=True)

mean_MasVnrArea = df_train['MasVnrArea'].mean()
df_train['MasVnrArea'].fillna(mean_MasVnrArea,inplace=True)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\3504500914.py:4: FutureWarning: A value is trying to be set on a
copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on w
hich we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)'
or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df_train['WoodDeckSF'].fillna(mean_WoodDeckSF,inplace=True)
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\3504500914.py:7: FutureWarning: A value is trying to be set on a
copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on w
hich we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)'
or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df_train['OpenPorchSF'].fillna(mean_OpenPorchSF,inplace=True)
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\3504500914.py:10: FutureWarning: A value is trying to be set on
a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on w
hich we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)'
or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df_train['MasVnrArea'].fillna(mean_MasVnrArea,inplace=True)
```

In [36]:
```
df_train.head()
```

Out[36]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	...	GarageQual
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	TA
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl	...	TA
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl	...	TA
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl	...	TA
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl	...	TA

5 rows × 65 columns

In [37]:
```
df_train.duplicated().sum()
```

Out[37]:
```
0
```

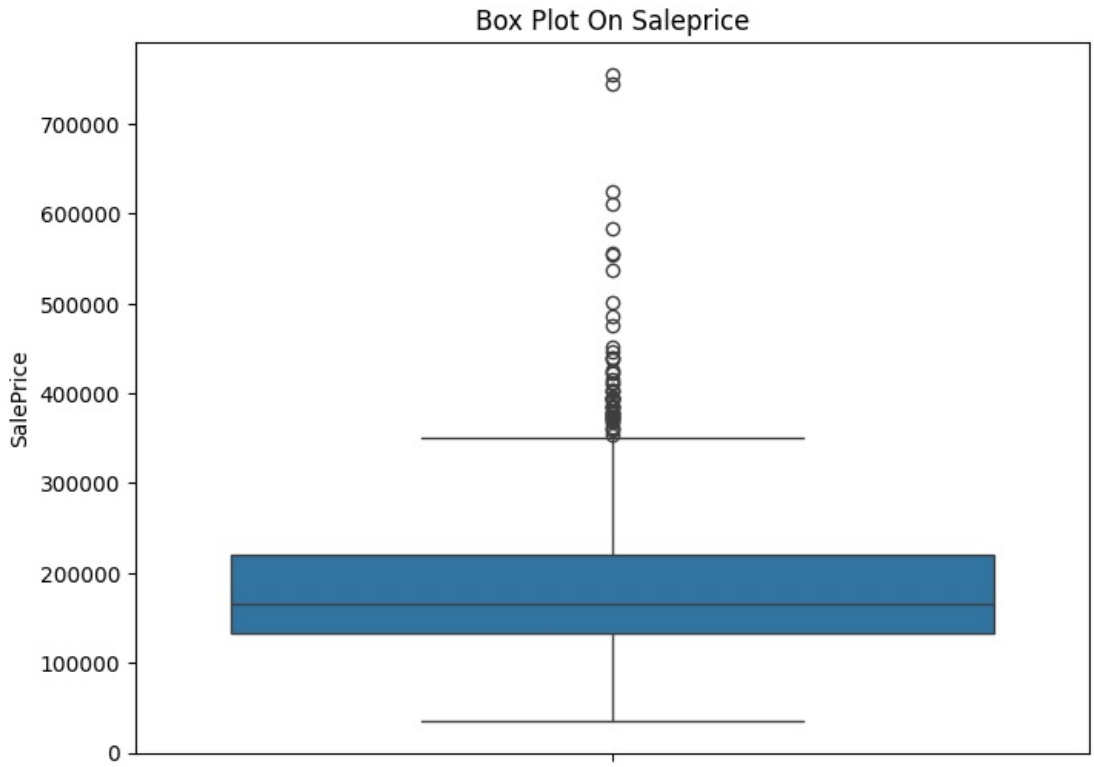
Detect outliers

In [38]:
```
df_train['SalePrice'].describe()
```

Out[38]:
```
count      1094.000000
mean     187033.263254
std       83165.332151
min       35311.000000
25%      132500.000000
50%      165750.000000
75%      221000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

In [39]:
```
fig, axes = subplots(nrows=1,ncols=1)
fig.set_size_inches(8, 6)
boxplot(data=df_train,y="SalePrice",orient="v",ax=axes)

axes.set(ylabel='SalePrice',title="Box Plot On Saleprice")
show()
```



The Box (Interquartile Range - IQR):

The blue box represents the middle 50% of the sale prices.

The bottom edge of the box indicates the first quartile (Q1), meaning 25% of the houses sold for a price below approximately $130,000.

The top edge of the box indicates the third quartile (Q3), meaning 75% of the houses sold for a price below approximately $220,000.

The line inside the box represents the median (Q2), which is the middle sale price. In this case, the median sale price is around $160,000.

The Whiskers: The lines extending from the top and bottom of the box are called whiskers. They typically extend to 1.5 times the IQR from the quartiles.

The lower whisker extends down to the lowest data point that is not considered an outlier, which is around $35,000.

The upper whisker extends up to the highest data point that is not considered an outlier, which is around $350,000.

Outliers: The circles above the upper whisker represent outliers. These are sale prices that are significantly higher than the rest of the data. There are a noticeable number of houses with sale prices ranging from approximately $350,000 to over $700,000, which are considered outliers based on the distribution of the majority of the sale prices.

The majority of houses in dataset sold for prices between approximately $130,000 and $220,000.

The median sale price is around $160,000.

There is a considerable range of sale prices, from a low of around $35,000 to a high exceeding $700,000.

There are a significant number of high-priced outliers, indicating some very expensive properties in the dataset that are not typical of the majority of sales.

The distribution of sale prices appears to be right-skewed, as the median is closer to the first quartile than the third, and there are many high-value outliers pulling the upper tail of the distribution.

Analysis

In [40]:
```
df_train
```

Out[40]:

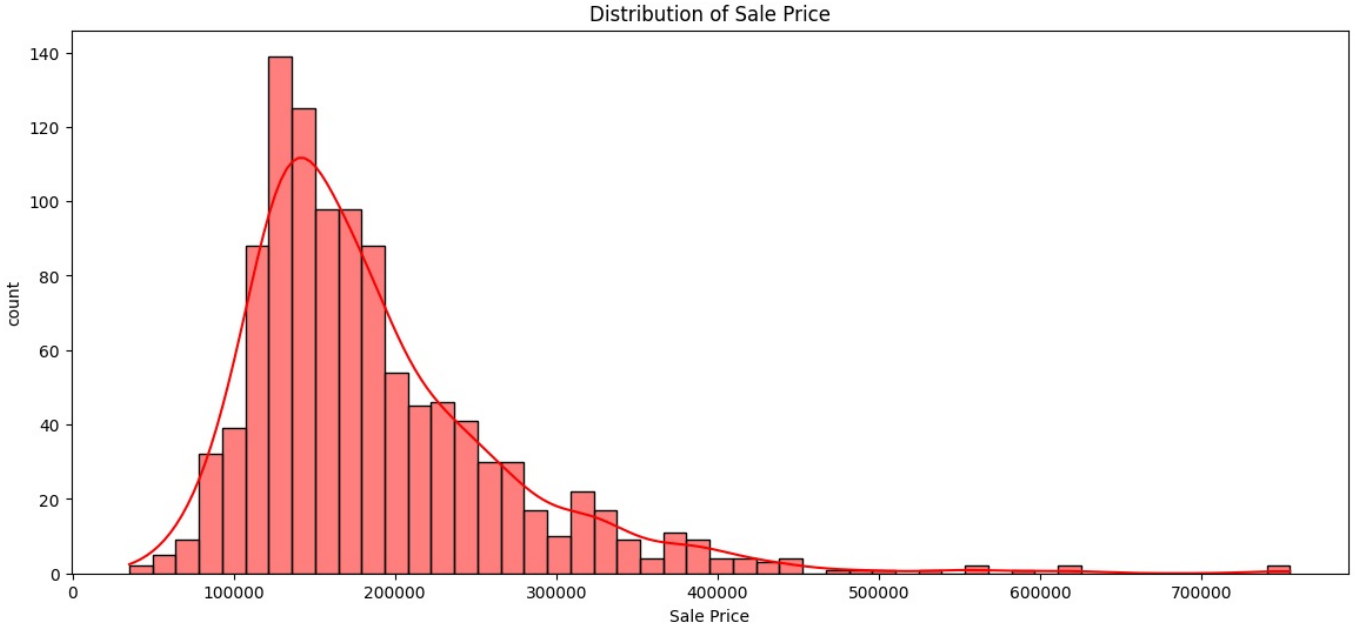
	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	...	GarageQ
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl	...	
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl	...	
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl	...	
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl	...	
...	...	...	...	...	...	...	...	...	...	...	...	
1455	60	RL	62.0	7917	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	
1456	20	RL	85.0	13175	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	
1457	70	RL	66.0	9042	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	
1458	20	RL	68.0	9717	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	
1459	20	RL	75.0	9937	Pave	Reg	Lvl	AllPub	Inside	Gtl	...	

1094 rows × 65 columns

- **Distribution of Sale Price**

In [41]:
```
figure(figsize=(14, 6))
histplot(df_train['SalePrice'], bins=50, kde=True, color='red')
title('Distribution of Sale Price')
xlabel('Sale Price')
ylabel('count')
show()

print(f"\nSkewness of Price: {df_train['SalePrice'].skew():.2f}")
print(f"Kurtosis of Price: {df_train['SalePrice'].kurt():.2f}")
```




```
Skewness of Price: 1.93
Kurtosis of Price: 6.42
```

- **Shape of the Distribution**: The distribution of 'Sale Price' is right-skewed (positively skewed). This means that the tail of the distribution extends further to the right, indicating that there are more data points with lower sale prices and fewer data points with very high sale prices.
- **Peak Concentration**: The highest frequency (count) of sales occurs in the price range of approximately $120,000 to $160,000. This is where the red KDE curve peaks and the tallest bars of the histogram are located. This suggests that the majority of sales fall within this relatively affordable range.
- **Gradual Decline**: After the peak, the frequency of sales gradually decreases as the sale price increases. The bars become shorter, and the KDE curve slopes downwards.
- **Presence of Higher-Priced Sales (Outliers/Tail)**: While the majority of sales are in the lower to mid-range, there's a long tail extending towards higher sale prices (up to around $700,000 and beyond). This indicates that there are some properties sold at much higher prices, but they are less frequent.
- **No Sales Below a Certain Price**: The distribution starts from a price greater than 0, suggesting that there are no sales recorded at extremely low or zero prices.

The 'Sale Price' distribution is characterized by a high concentration of properties sold at lower to moderate prices, with a diminishing number of sales as prices increase. The right-skewness highlights

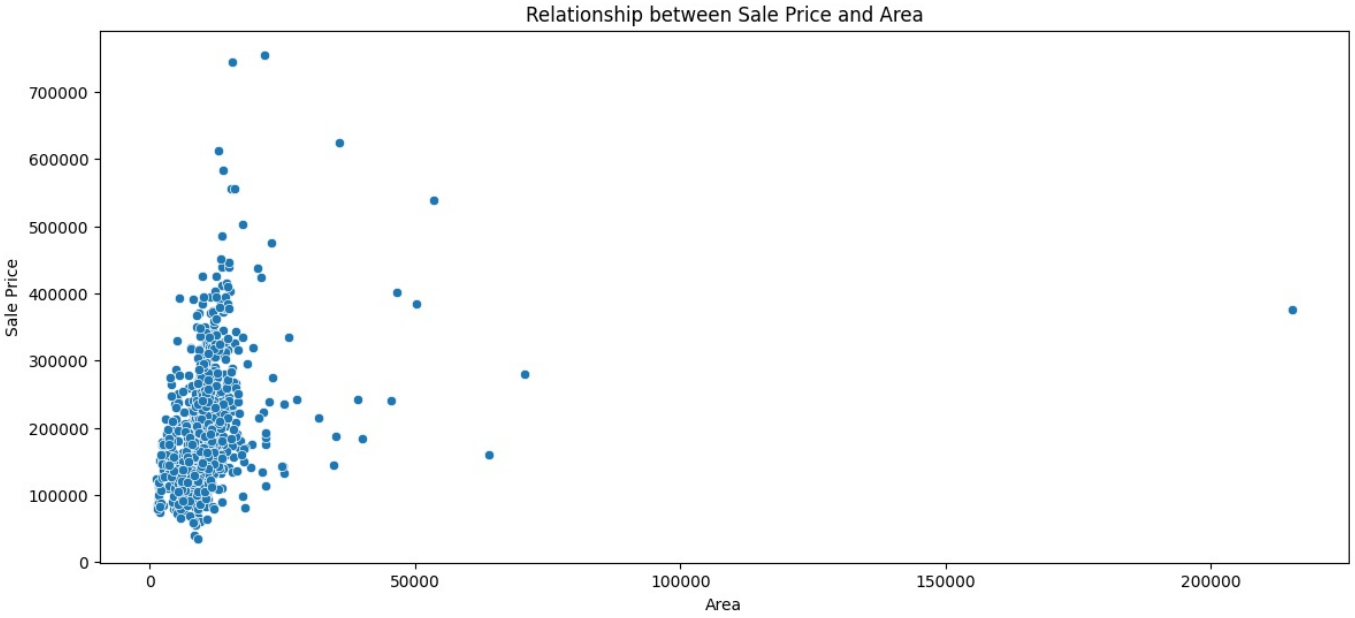
the presence of a few high-value properties that extend the tail of the distribution.

- **Relationship between Sale Price and Area**

In [42]:
```
df_train['LotArea'].describe()
```

Out[42]:
```
count      1094.000000
mean      10132.346435
std        8212.249621
min        1300.000000
25%        7606.750000
50%        9444.500000
75%       11387.250000
max      215245.000000
Name: LotArea, dtype: float64
```

In [43]:
```
figure(figsize=(14, 6))
scatterplot(x='LotArea', y='SalePrice', data=df_train)
title('Relationship between Sale Price and Area')
xlabel('Area')
ylabel('Sale Price')
show()
```

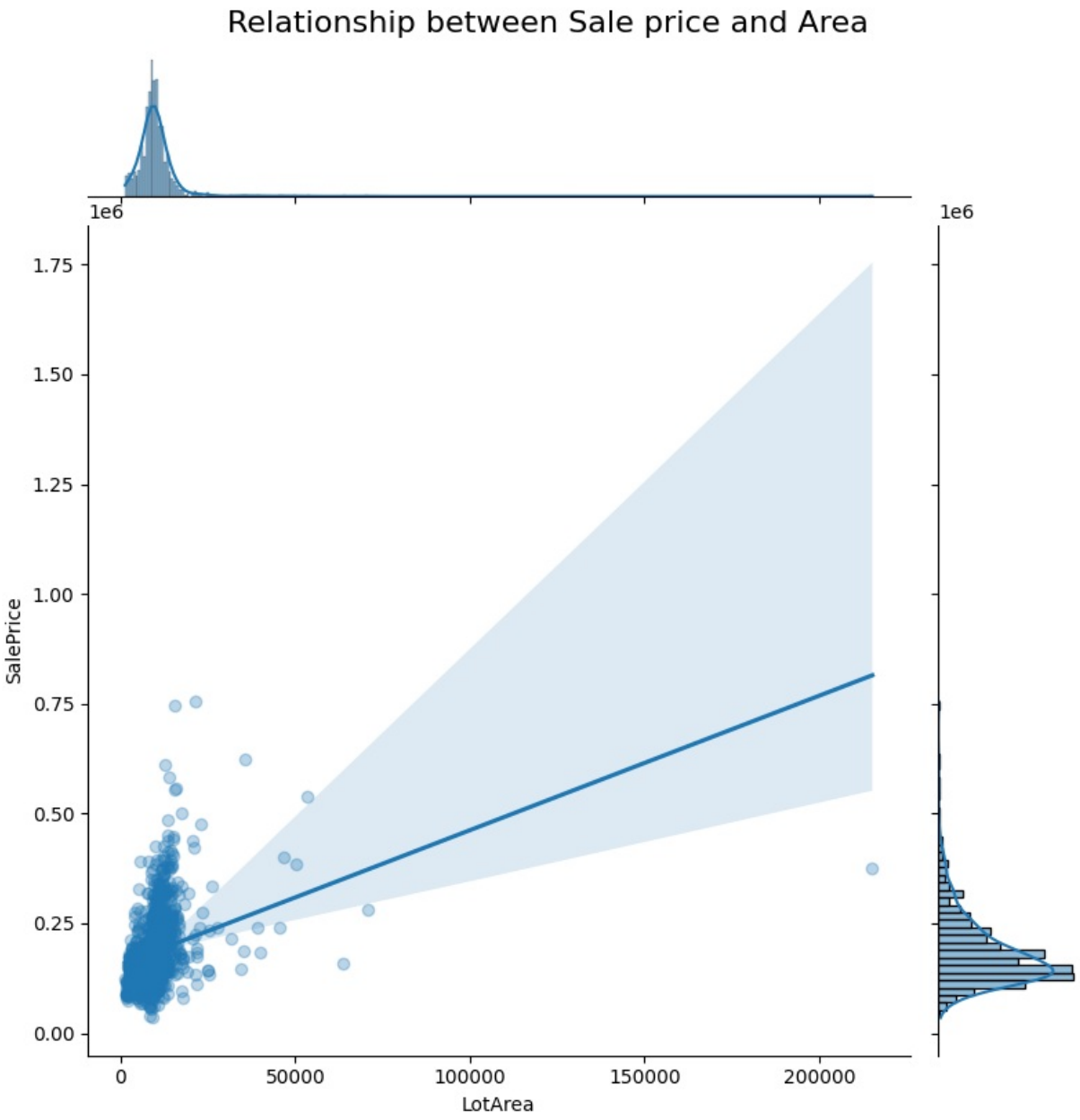


- **Positive Relationship:** There appears to be a general positive relationship between 'Area' and 'Sale Price'. As the 'Area' increases, the 'Sale Price' generally tends to increase as well.
- **Concentration of Data:** A large cluster of data points is concentrated in the lower-left portion of the plot, indicating that most properties have smaller areas and lower sale prices.
- **Increasing Spread with Area:** As the 'Area' increases, the spread of 'Sale Price' also seems to increase. This means that for larger areas, there's a wider range of possible sale prices, suggesting other factors might heavily influence the price of very large properties.
- **Outliers/High-Value Properties:** There are several data points that deviate from the main cluster, particularly at higher 'Area' and 'Sale Price' values. There's one prominent outlier with a very large 'Area' but a comparatively lower 'Sale Price' than what the trend might suggest for that size, and another with a very high 'Sale Price' for its 'Area'. These could be unusual properties or data entry errors.

This scatterplot suggests that 'Area' is a significant factor in determining 'Sale Price', with larger areas generally commanding higher prices. However, the increasing scatter at higher areas implies that for very large properties, other characteristics besides just size become increasingly influential in their pricing. The outliers indicate instances that don't fit the general trend and might warrant further investigation.

In [44]:
```
figure(figsize=(14, 4))
jointplot(x='LotArea', y='SalePrice', data=df_train, kind='reg', height=8, scatter_kws={'alpha':0.3})
suptitle('Relationship between Sale price and Area', y=1.02, fontsize=16)
show()
```

```
<Figure size 1400x400 with 0 Axes>
```



Main Scatter Plot (LotArea vs. SalePrice):

- **Positive Linear Trend**: There is a clear positive linear relationship between **LotArea** and **SalePrice**. As the **LotArea** increases, the **SalePrice** generally tends to increase as well. The blue regression line confirms this upward trend.
- **Concentration of Data**: A very large cluster of data points is concentrated in the lower-left portion of the plot, indicating that most properties have smaller lot areas and lower sale prices (e.g., **LotArea** below 50,000).
- **Increasing Variability with Area**: As the **LotArea** increases, the scatter of data points around the regression line appears to increase significantly. This means that for larger lot areas, there's a much wider range of possible sale prices. The shaded confidence interval around the regression line also widens considerably for larger **LotArea** values, reinforcing this observation.
- **Outliers/High-Value Properties**: There are several data points that lie far from the main cluster and the regression line, particularly at higher **LotArea** values. These represent properties with unusually high or low sale prices for their size.

Marginal Distribution of 'LotArea' (Top Histogram/KDE):

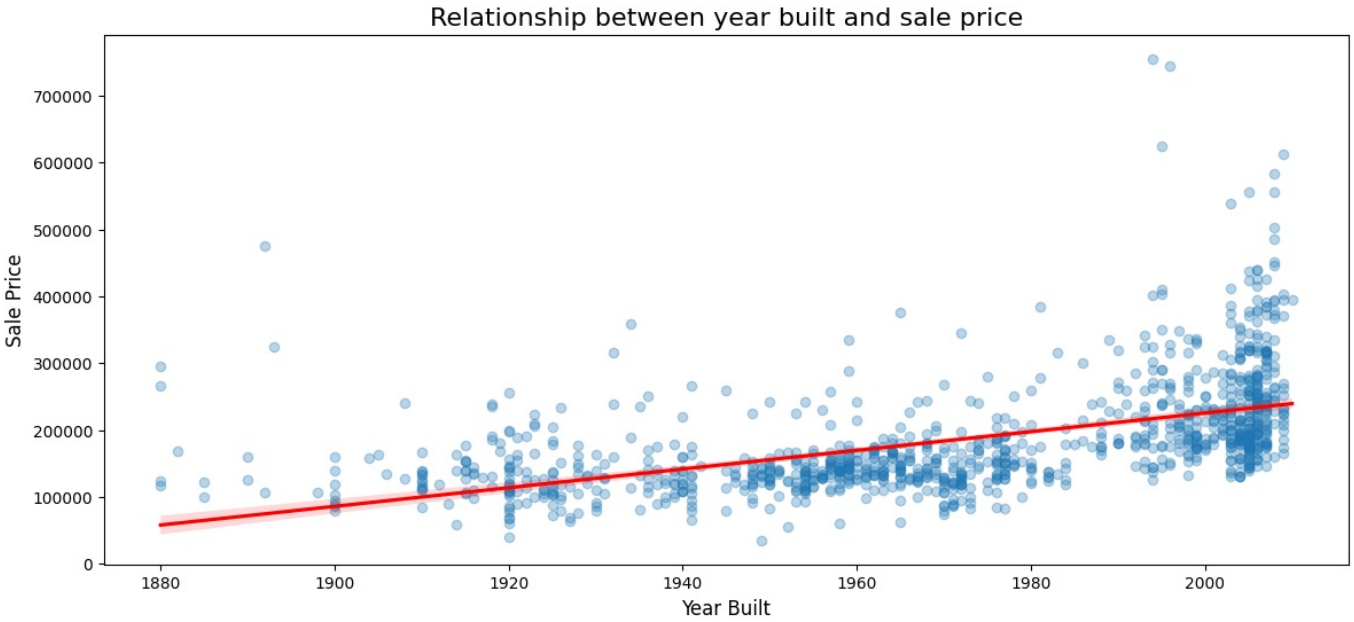
- Highly Right-Skewed: The distribution of **LotArea** is extremely right-skewed. The vast majority of properties have smaller lot areas, and there's a long tail extending to a few properties with very large lot areas. The KDE shows a sharp peak at the lower end.

Marginal Distribution of 'SalePrice' (Right Histogram/KDE):

- **Right-Skewed:** The distribution of **SalePrice** is also right-skewed, though perhaps less extremely than **LotArea**. Most properties have lower sale prices, with a tail extending to higher-priced properties. The KDE shows a peak at the lower price range.

- **Relationship between year built and sale price**

In [45]:
```
figure(figsize=(14, 6))
regplot(x='YearBuilt', y='SalePrice', data=df_train, scatter_kws={'alpha':0.3}, line_kws={'color':'red'})
title('Relationship between year built and sale price', fontsize=16)
xlabel('Year Built', fontsize=12)
ylabel('Sale Price', fontsize=12)
show()
```



- **Positive Linear Trend**: There is a clear positive linear relationship between 'Year Built' and 'Sale Price'. As the 'Year Built' increases (i.e., properties are newer), the 'Sale Price' generally tends to increase. The red regression line confirms this upward trend.
- **Increasing Variability with Time**: While the trend is positive, the scatter of data points around the regression line appears to increase as the 'Year Built' becomes more recent. This means that for older properties (e.g., before 1950), the prices are more tightly clustered around the trend line. For newer properties (e.g., after 1980), there's a much wider range of sale prices for a given year built, indicating greater variability.
- **Density of Data**: Most of the data points are concentrated in the later years (from around 1960 onwards), especially after 1980 and into the 2000s. This suggests that the dataset contains more information about newer properties.
- **Outliers/High-Value Properties**: There are several properties with very high 'Sale Price' for their 'Year Built', particularly in the more recent years. These points lie significantly above the regression line.
- **Confidence Interval**: The pink shaded area around the regression line represents the confidence interval. It shows the range within which the true regression line is likely to fall. The widening of this band in more recent years further emphasizes the increased variability in sale prices for newer properties.

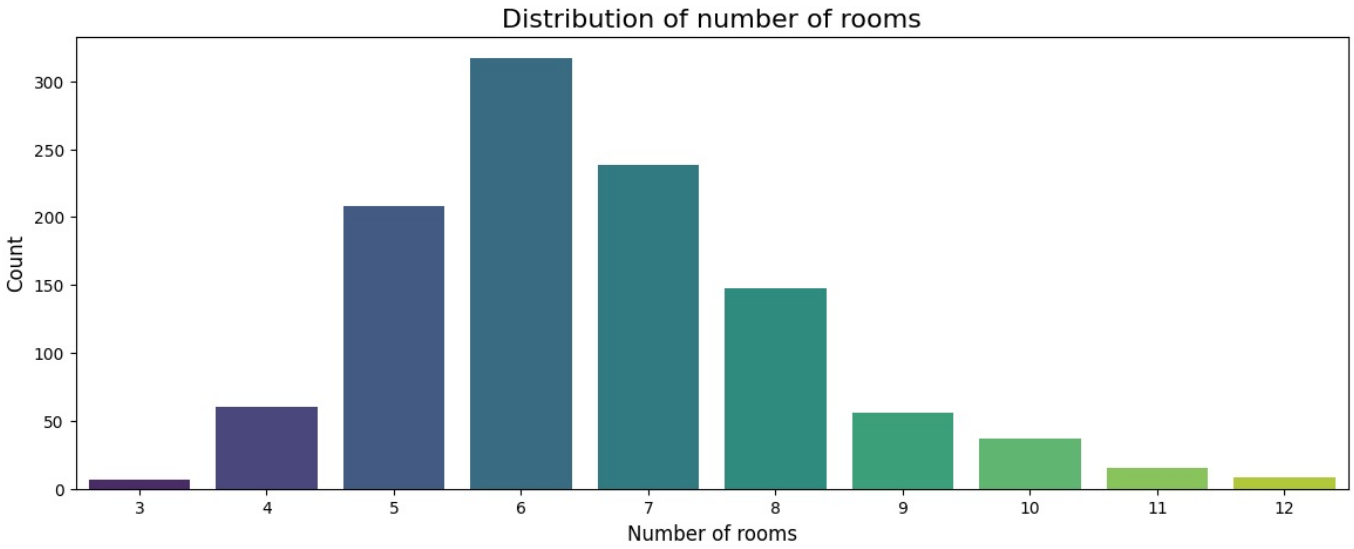
- ### Distribution of number of rooms

In [46]:
```
figure(figsize=(14, 5))
countplot(x='TotRmsAbvGrd', data=df_train, palette='viridis')
title('Distribution of number of rooms', fontsize=16)
xlabel('Number of rooms', fontsize=12)
ylabel('Count', fontsize=12)
show()
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\2908941410.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable
to `hue` and set `legend=False` for the same effect.

  countplot(x='TotRmsAbvGrd', data=df_train, palette='viridis')
```



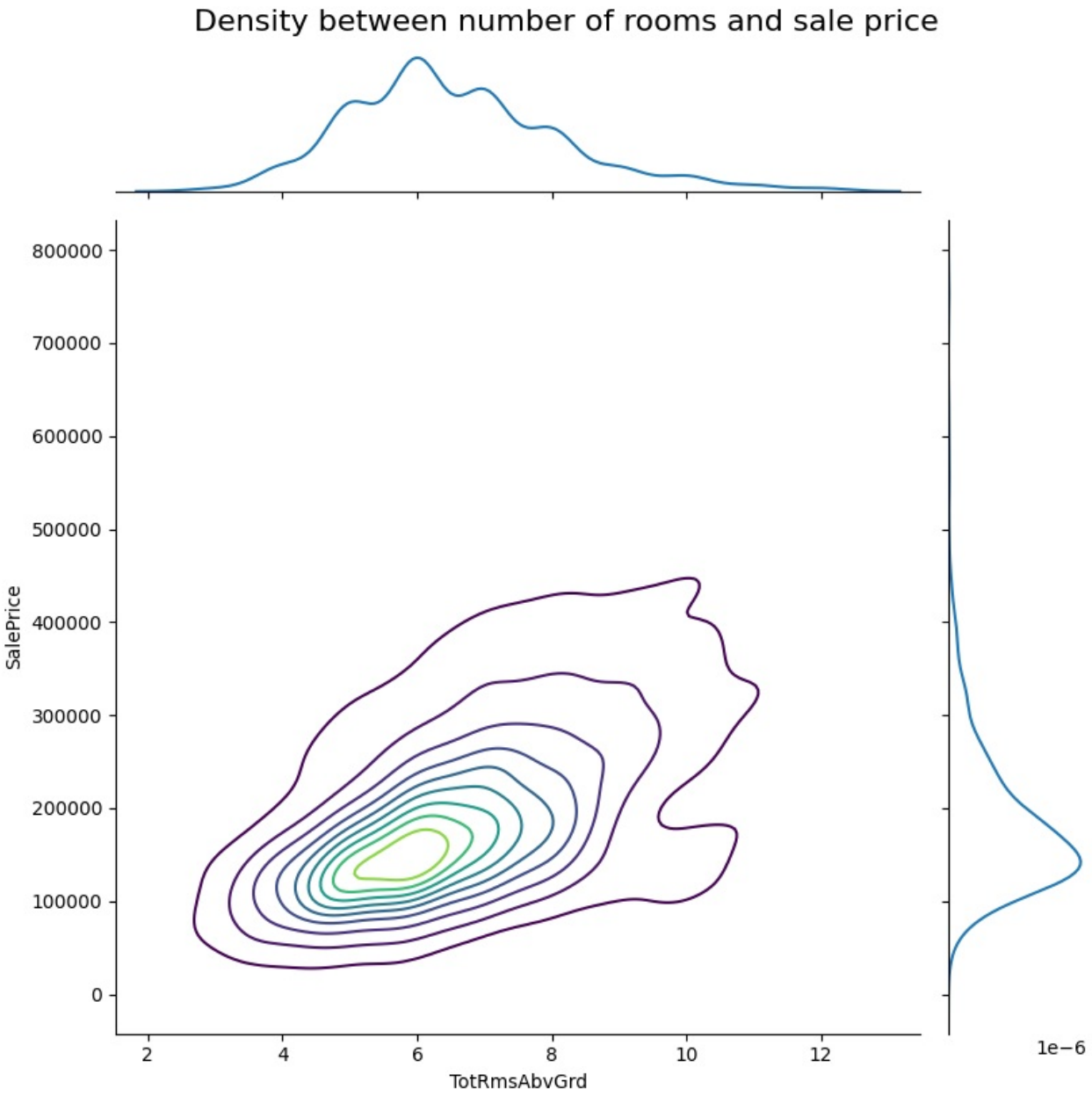
- **Most Common Room Count**: The most frequent number of rooms is 6, with a count exceeding 300 properties. This indicates that properties with 6 rooms are the most common in this dataset.
- **Bell-Shaped Tendency (with skew)**: The distribution generally shows a peak around 6 rooms and then tapers off on both sides. However, it's slightly left-skewed (or negatively skewed), meaning the tail extends more towards fewer rooms, although the drop-off is quite sharp for very low room counts.

Common Ranges:

- Properties with 5, 6, 7, and 8 rooms are quite common, with counts of over 100 each.
- Properties with 3, 4, 9, 10, 11, and 12 rooms are significantly less common.
- **Rarity of Extremes**: Very low room counts (e.g., 3 rooms) and very high room counts (e.g., 11 or 12 rooms) are rare in this dataset.

- ### Density between number of rooms and sale price

In [47]:
```
jointplot(x='TotRmsAbvGrd', y='SalePrice', data=df_train, kind='kde', height=8, cmap='viridis')
suptitle('Density between number of rooms and sale price', y=1.02, fontsize=16)
show()
```



Main Contour Plot (TotRmsAbvGrd** vs. **SalePrice**):**

- **Positive Association:** There is a general positive association between the number of rooms and sale price. As the number of rooms increases, the typical sale price also tends to increase.
- **Highest Density Area:** The densest area (indicated by the innermost, typically lighter-colored contours) is concentrated around 5-7 rooms and a '**SalePrice**' of approximately $100,000 to $200,000. This suggests that properties with this number of rooms and within this price range are the most common.

Spread and Shape:

- The contours show that for a given number of rooms, there's a range of sale prices, and for a given sale price, there's a range of room counts.
- The contours extend towards higher room counts and higher sale prices, indicating that properties with more rooms tend to have higher prices, though the density decreases significantly at the extremes.
- The shape of the contours suggests that while there's a general upward trend, the relationship isn't perfectly linear and might have some curvature or varying density.

Marginal Distribution of 'TotRmsAbvGrd**' (Top KDE Plot)**:

- **Unimodal and Skewed**: The distribution of '**TotRmsAbvGrd**' is unimodal, peaking around 6 rooms. It appears to be slightly right-skewed, with a longer tail extending towards higher room counts. This confirms that 6 rooms is the most common, and properties with many rooms are less frequent.

Marginal Distribution of 'SalePrice**' (Right KDE Plot):**

- **Right-Skewed:** The distribution of '**SalePrice**' is clearly right-skewed, with a sharp peak at lower prices and a long tail extending towards higher prices. This indicates that most properties are sold at lower prices, with fewer properties at very high prices.

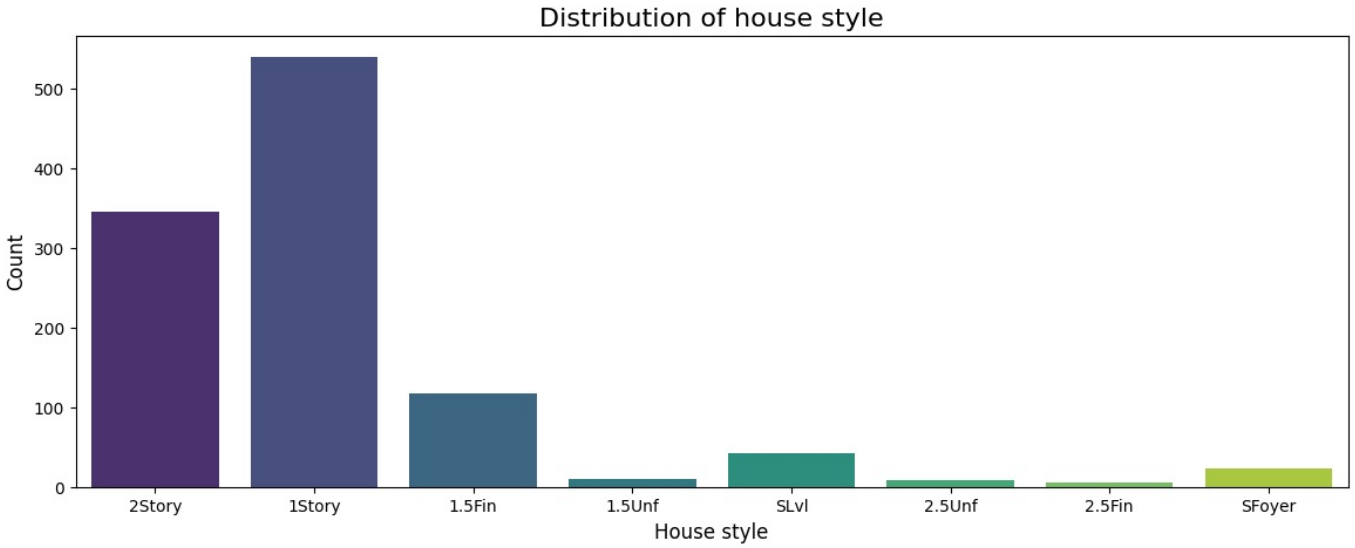
- **Distribution of house style**

In [48]:
```
figure(figsize=(14, 5))
countplot(x='HouseStyle', data=df_train, palette='viridis')
title('Distribution of house style', fontsize=16)
xlabel('House style', fontsize=12)
ylabel('Count', fontsize=12)
show()
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\4095110779.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable
to `hue` and set `legend=False` for the same effect.

  countplot(x='HouseStyle', data=df_train, palette='viridis')
```



Dominant House Styles:

- **'1Story'** is by far the most common house style, with a count exceeding 500 properties.
- **'2Story'** is the second most common, with a count around 350 properties.

Moderately Common Style:

- **'1.5Fin'** (1.5 story finished) is present in a moderate number, around 100 properties.

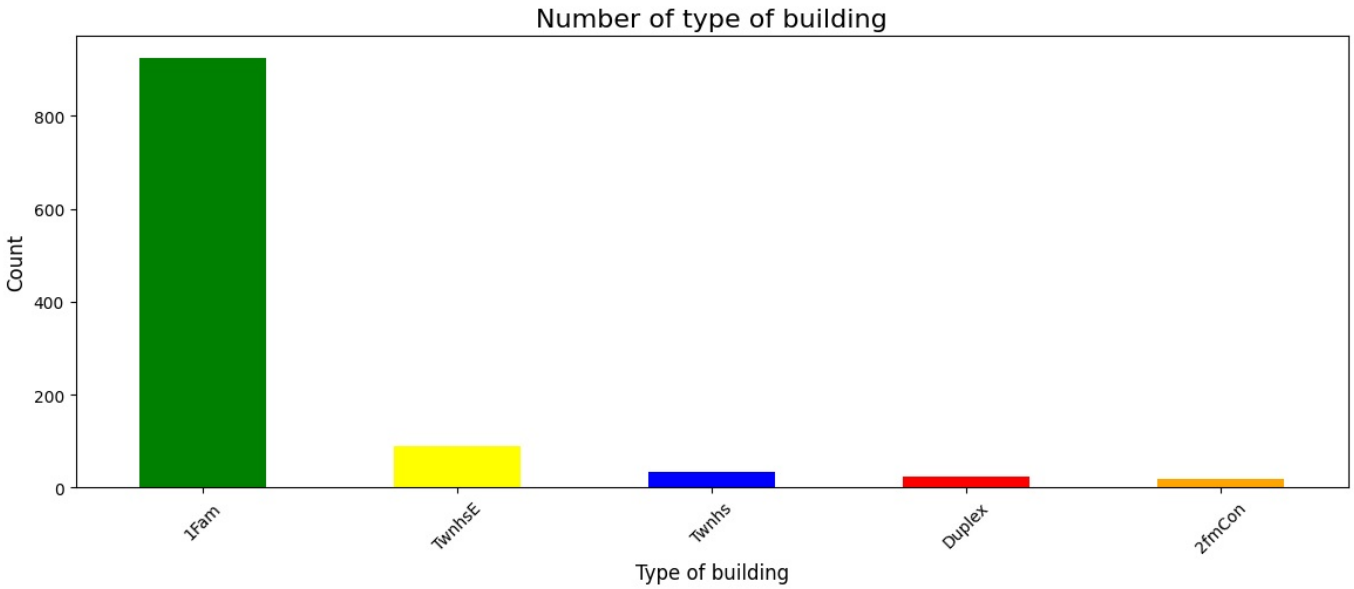
Rare Styles: All other house styles are significantly less common, with counts well below 50. These include:

- **'1.5Unf'** (1.5 story unfinished)
- **'SLvl'** (Split Level)
- **'2.5Unf'** (2.5 story unfinished)
- **'2.5Fin'** (2.5 story finished)
- **'SFoyer'** (Split Foyer)

Imbalanced Distribution: The distribution of house styles is highly imbalanced, with '1Story' and '2Story' making up the vast majority of the dataset.

- **Number of type of building**

In [49]:
```
figure(figsize=(14, 5))
df_train['BldgType'].value_counts().plot(kind='bar', color=['green','yellow','blue','red','orange'])
title('Number of type of building', fontsize=16)
xlabel('Type of building', fontsize=12)
ylabel('Count', fontsize=12)
xticks(rotation=45)
show()
```



- **Dominant Building Type**: The most common type of building is '1Fam' (likely representing single-family homes), with a count significantly exceeding 800. This type overwhelmingly dominates the dataset.

Minority Building Types: All other building types are present in much smaller numbers.

- 'TwnhsE' (Townhouse End unit) has the second-highest count, but it's still very low compared to '1Fam', around 100.
- 'Twnhs' (Townhouse Interior unit), 'Duplex', and '2fmCon' (Two-family Conversion) have very low counts, all appearing to be less than 50.
- **Imbalanced Distribution**: The distribution of building types is highly imbalanced, with '1Fam' properties representing the vast majority of the dataset.

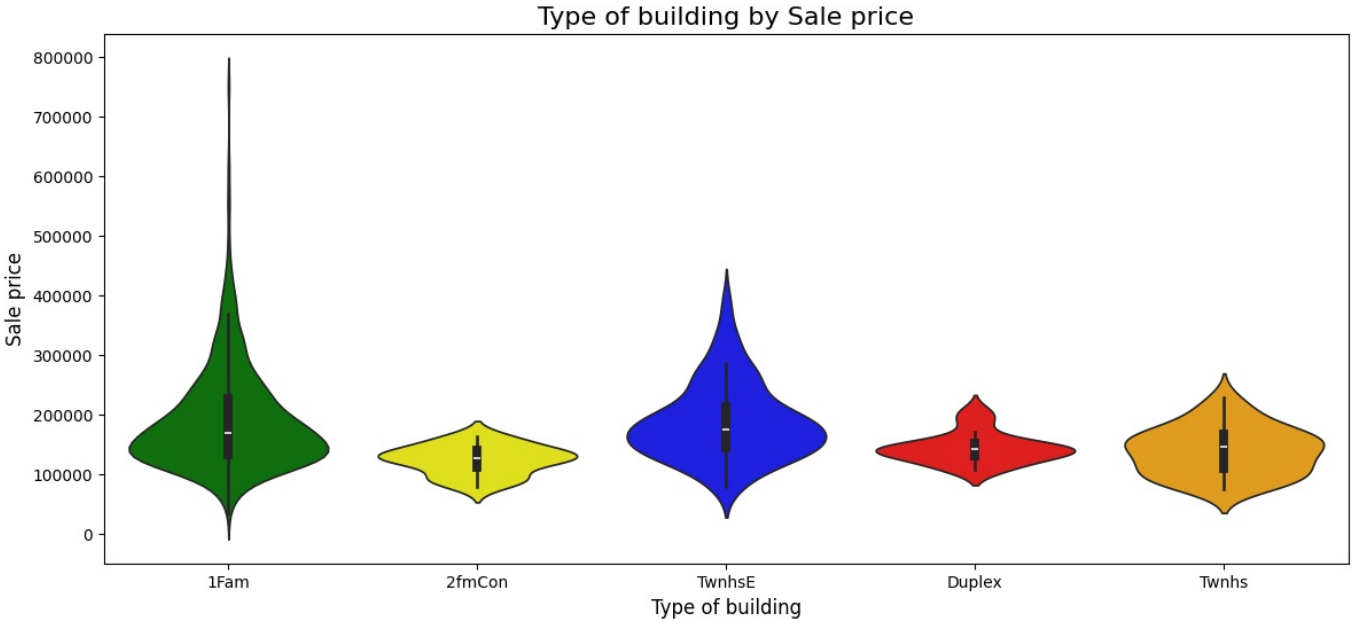
- **Type of building by Sale price**

In [50]:
```
figure(figsize=(14, 6))
violinplot(x='BldgType', y='SalePrice', data=df_train, palette=['green','yellow','blue','red','orange'])
title('Type of building by Sale price', fontsize=16)
xlabel('Type of building', fontsize=12)
ylabel('Sale price', fontsize=12)
show()
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\3996280468.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable
to `hue` and set `legend=False` for the same effect.

  violinplot(x='BldgType', y='SalePrice', data=df_train, palette=['green','yellow','blue','red','orange'])
```



'1Fam' (Single-Family Homes):

- **Widest Distribution**: This violin is the widest and tallest, indicating that '1Fam' properties are the most numerous in the dataset and have the broadest range of sale prices.
- **Median & IQR**: The median sale price for '1Fam' appears to be around $150,000 - $200,000. The box inside shows a significant interquartile range, meaning there's a wide spread in the middle 50% of prices.
- **Skewness**: The distribution is clearly right-skewed, with a longer tail extending towards higher sale prices. This means while most single-family homes are in the lower-to-mid price range, there are quite a few with much higher prices.
- **Density**: The highest density is concentrated in the lower price ranges.

'TwnhsE' (Townhouse End Unit):

- **Higher Median**: The median sale price for 'TwnhsE' appears to be higher than '1Fam', possibly around $200,000 - $250,000.
- **Moderate Spread**: The distribution is narrower than '1Fam', indicating less variability in prices.
- **Shape**: It shows a somewhat symmetrical distribution around its median, with a slight right skew.

'Twnhs' (Townhouse Interior Unit):

- **Lower Median**: The median sale price for 'Twnhs' appears to be lower than 'TwnhsE', possibly around $150,000.
- **Narrow Distribution**: This violin is quite narrow, suggesting a more concentrated range of sale prices.
- **Shape**: It appears to be relatively symmetrical.

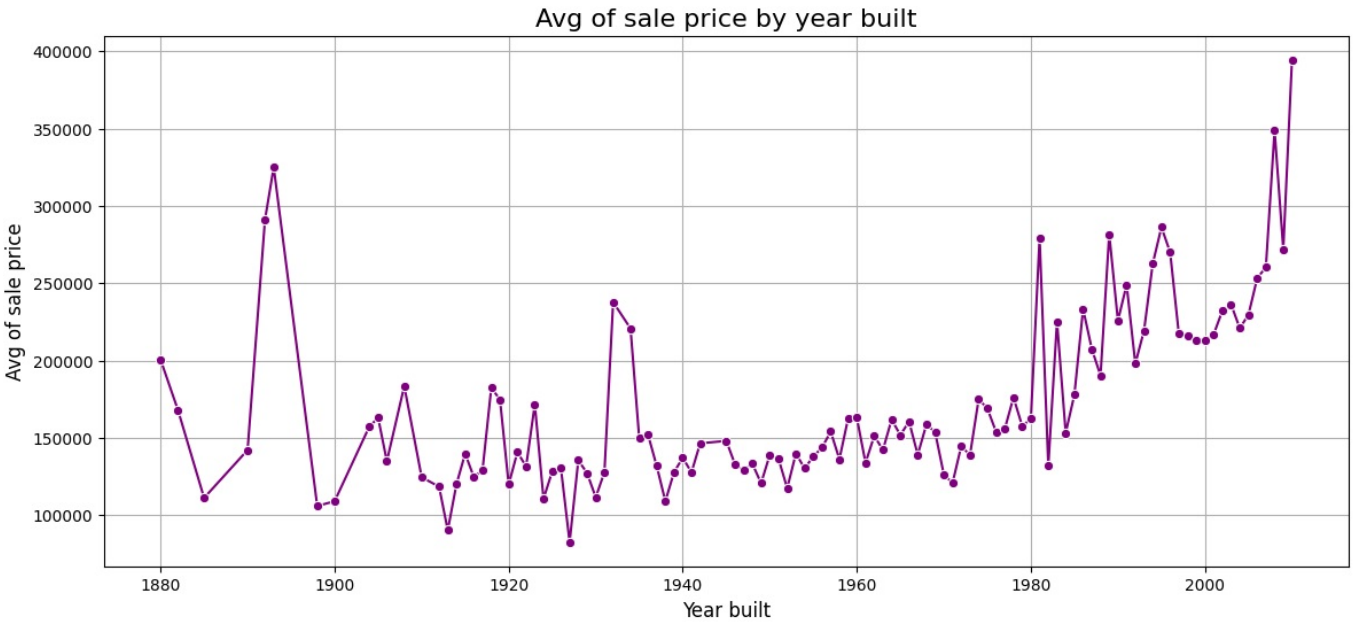
'2fmCon' (Two-Family Conversion) and 'Duplex':

- **Similar Medians**: Both '2fmCon' and 'Duplex' have similar median sale prices, which appear to be in the lower-to-mid range, possibly around $120,000 - $150,000.
- **Narrowest Distributions**: These violins are among the narrowest, indicating less variability and a more concentrated set of sale prices.
- **Density**: The density is concentrated around their respective medians.

- **Avg of sale price by year built**

In [51]:
```
avg_price_by_year = df_train.groupby('YearBuilt')['SalePrice'].mean()

figure(figsize=(14, 6))
lineplot(x=avg_price_by_year.index, y=avg_price_by_year.values, marker='o', color='purple')
title('Avg of sale price by year built', fontsize=16)
xlabel('Year built', fontsize=12)
ylabel('Avg of sale price', fontsize=12)
grid(True)
show()
```



- **General Upward Trend:** There's a general, albeit fluctuating, upward trend in the average sale price as the 'Year built' becomes more recent. Newer properties tend to have higher average sale prices.
- **Significant Fluctuations:** The plot shows considerable year-to-year fluctuations, especially in earlier periods and more recently. This suggests that while there's a long-term trend, the average price for properties built in a specific year can vary quite a bit.
- **Early Peaks and Dips (Pre-1940s):**

- There's a notable peak around 1895-1896, where the average sale price reaches over $300,000, which is quite high for that era. This is followed by a sharp dip.
- Another smaller peak occurs around the early 1930s.
- **Relatively Stable Period (1940s-1970s)**: The average sale price appears relatively more stable, albeit with minor fluctuations, in the mid-20th century.
- **Increased Volatility and Rise (Post-1980s)**:
- From the 1980s onwards, the average sale price shows a more pronounced and generally steeper increase.
- There's a significant jump in average prices in the late 1990s and especially in the 2000s, with a sharp rise towards the end of the data (around 2005-2006), where the average price approaches $400,000.
- The volatility also seems to increase in these later years.

- ### Distribution of log Sale Price

In [52]:
```
figure(figsize=(14, 6))

histplot(log(df_train['SalePrice']).replace(-inf,1e-6), bins=50, kde=True, color='green')
title('Distribution of log Sale Price')
xlabel('Log Sale Price')
ylabel('count')
show()

print(f"\nSkewness of Price: {log(df_train['SalePrice']).replace(-inf,1e-6).skew():.2f}")
```


```
Skewness of Price: 0.30
```

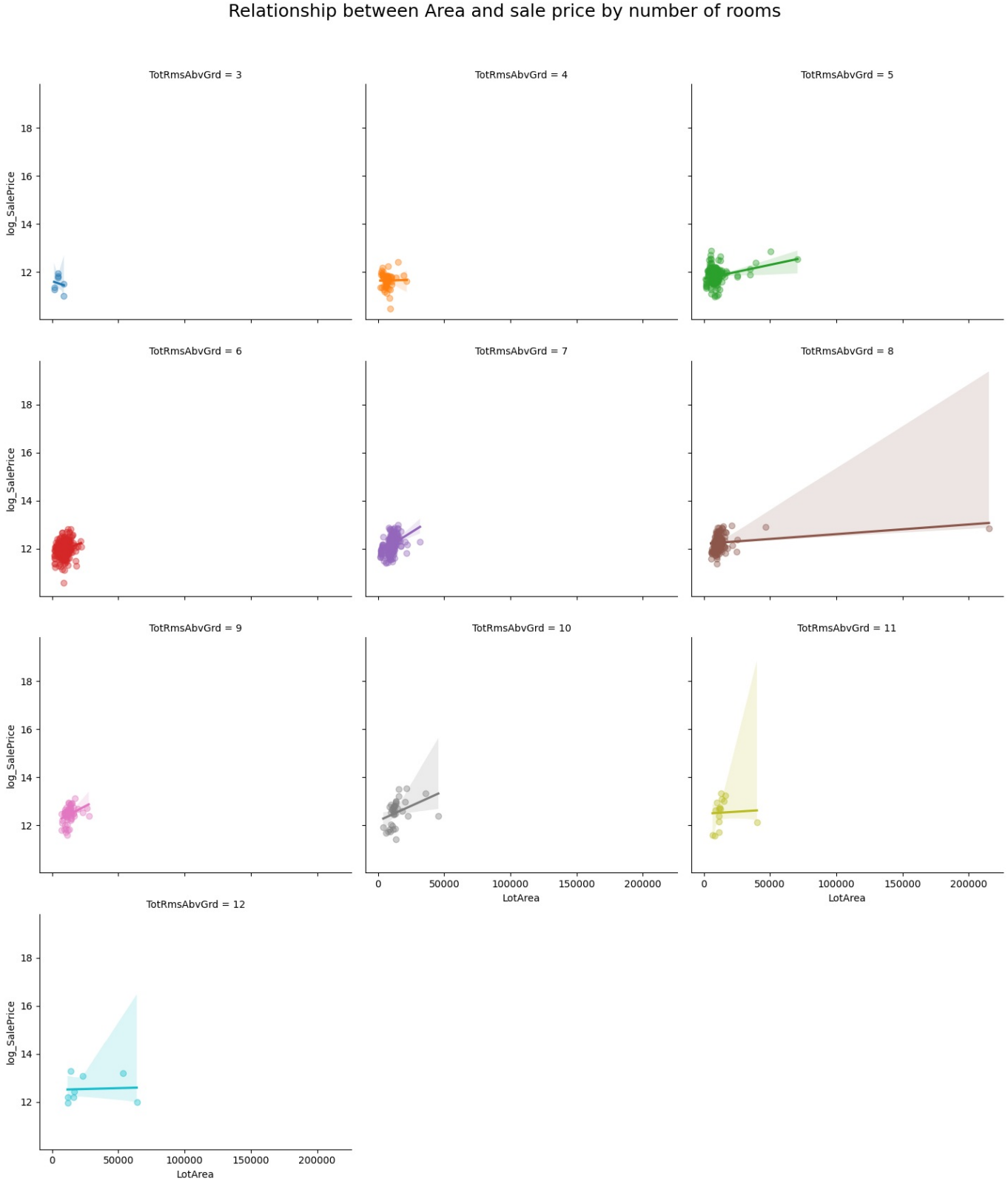
- **Shape of the Distribution:** The distribution of the log-transformed 'Sale Price' is now much more symmetrical and bell-shaped, closely resembling a normal (Gaussian) distribution.
- **Peak Concentration:** The highest frequency (count) of log-transformed sales occurs in the range of approximately 11.8 to 12.0. This is where the green KDE curve peaks and the tallest bars of the histogram are located. This suggests that after transformation, the most common 'Sale Price' (in log terms) falls within this range.
- **Spread**: The values range from approximately 10.5 to 13.5. The distribution tapers off relatively evenly on both sides of the peak.
- **Impact of Log Transformation**: Compared to the original 'Sale Price' distribution (which was highly right-skewed), this log-transformed version is much more amenable to statistical modeling techniques that assume normality or symmetry. The transformation has successfully reduced the skewness and made the data more spread out around a central tendency.

In [53]:
```
df_train['log_SalePrice'] = log(df_train['SalePrice']).replace(-inf,1e-6)
df_train['log_SalePrice']
```

Out[53]:
```
0       12.247694
1       12.109011
2       12.317167
3       11.849398
4       12.429216
          ...
1455    12.072541
1456    12.254863
1457    12.493130
1458    11.864462
1459    11.901583
Name: log_SalePrice, Length: 1094, dtype: float64
```

In [54]:
```
figure(figsize=(12, 8))
lmplot(x='LotArea', y='log_SalePrice', hue='TotRmsAbvGrd', data=df_train,
           col='TotRmsAbvGrd', col_wrap=3, height=4, aspect=1.2, scatter_kws={'alpha':0.4})
suptitle('Relationship between Area and sale price by number of rooms', y=1.05, fontsize=18)
show()
```

```
<Figure size 1200x800 with 0 Axes>
```



- **Overall Positive Trend**: For most numbers of rooms, there's a general positive linear relationship between LotArea and log_SalePrice. This means that, within each room category, larger lot areas tend to be associated with higher (log) sale prices.
- **Varying Strength of Relationship**: The strength and clarity of this relationship vary significantly across different numbers of rooms.
- **Data Density**: Many panels, especially for higher TotRmsAbvGrd values (e.g., 9, 10, 11, 12), have very few data points, making the regression lines and their confidence intervals less reliable. This reflects the distribution of TotRmsAbvGrd where 6, 7, and 8 rooms are most common.

Observations by TotRmsAbvGrd:

- ** TotRmsAbvGrd = 3 (Top Left)**:
- Shows a positive trend, but with considerable scatter.
- The confidence interval is relatively wide, indicating uncertainty due to fewer data points or higher variability.
- **TotRmsAbvGrd = 4 (Top Middle):**
- Similar to 3 rooms, a positive trend is visible, but the data points are quite spread out.
- The sample size appears small, leading to a wider confidence interval.
- **TotRmsAbvGrd = 5 (Top Right)**:
- A clearer positive trend emerges, with a denser cluster of points at lower LotArea values.
- The relationship seems more defined than for 3 or 4 rooms.

TotRmsAbvGrd = 6 (Middle Left):

- This panel has a very high density of data points, reflecting that 6 rooms is the most common.
- A strong positive linear relationship is evident, with the regression line showing a clear upward slope. The confidence interval is relatively narrow in the denser areas.
- **TotRmsAbvGrd = 7 (Middle Center)**:
- Also shows a strong positive linear relationship, similar to 6 rooms, with a good density of data points.

TotRmsAbvGrd = 8 (Middle Right):

- A positive trend is still present, but the density of points starts to decrease compared to 6 and 7 rooms.
- The confidence interval widens, especially for larger LotArea.
- **TotRmsAbvGrd = 9, 10, 11, 12 (Bottom Rows):**
- These panels have very few data points, making it difficult to confidently infer a strong relationship.
- While regression lines are drawn, their wide confidence intervals (often spanning a large vertical range) indicate high uncertainty.
- The trends, if any, are highly influenced by the few available data points. For example, TotRmsAbvGrd = 12 shows a positive trend but with only a handful of points.

In [55]:
```
df_train = df_train.drop('log_SalePrice',axis=1)
```

Transform Data

In [56]:
```
train_obj = df_train.select_dtypes(include='object')
train_non_obj = df_train.select_dtypes(exclude='object')
```

In [57]:
```
train_non_obj.shape
```

Out[57]:
```
(1094, 28)
```

In [58]:
```
train_obj.shape
```

Out[58]:
```
(1094, 37)
```

In [59]:
```
for col in train_obj.columns:
    print(f'{col} : {train_obj[col].nunique()}')
```

```
MSZoning : 5
Street : 2
LotShape : 4
LandContour : 4
Utilities : 1
LotConfig : 5
LandSlope : 3
Neighborhood : 25
Condition1 : 9
Condition2 : 6
BldgType : 5
HouseStyle : 8
RoofStyle : 5
RoofMatl : 7
Exterior1st : 14
Exterior2nd : 16
ExterQual : 4
ExterCond : 4
Foundation : 5
BsmtQual : 4
BsmtCond : 4
BsmtExposure : 4
BsmtFinType1 : 6
BsmtFinType2 : 6
Heating : 4
HeatingQC : 5
CentralAir : 2
Electrical : 5
KitchenQual : 4
Functional : 6
GarageType : 6
GarageFinish : 3
GarageQual : 5
GarageCond : 5
PavedDrive : 3
SaleType : 9
SaleCondition : 6
```

In [60]:
```
for col in train_obj.columns:
    nuniques = train_obj[col].nunique()
    if nuniques == 3  :
        print(f'{col} : {train_obj[col].nunique()}')
```

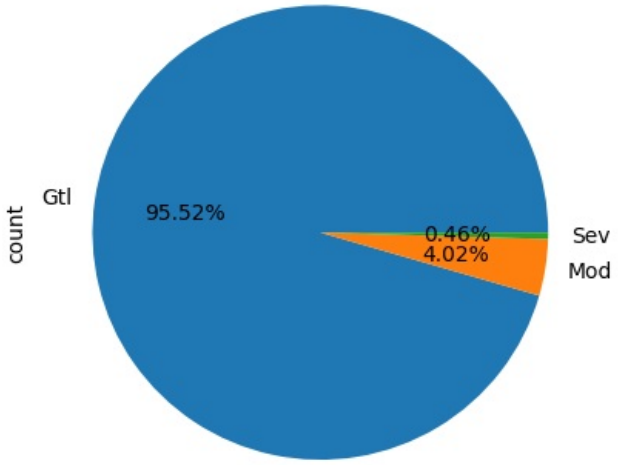
```
LandSlope : 3
GarageFinish : 3
PavedDrive : 3
```

In [61]:
```
# LandSlope: Slope of property
# Gtl (Gentle)
# Mod (Moderate)
# Sev (Severe)

train_obj['LandSlope'].value_counts() # ordinal
```

Out[61]:
```
LandSlope
Gtl    1045
Mod      44
Sev       5
Name: count, dtype: int64
```

In [62]:
```
train_obj['LandSlope'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [63]:
```
train_obj['LandSlope']= train_obj['LandSlope'].replace('Gtl',1)
train_obj['LandSlope']= train_obj['LandSlope'].replace('Mod',2)
train_obj['LandSlope']= train_obj['LandSlope'].replace('Sev',3)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\760400348.py:3: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  train_obj['LandSlope']= train_obj['LandSlope'].replace('Sev',3)
```

In [64]:
```
train_obj['LandSlope'].value_counts()
```

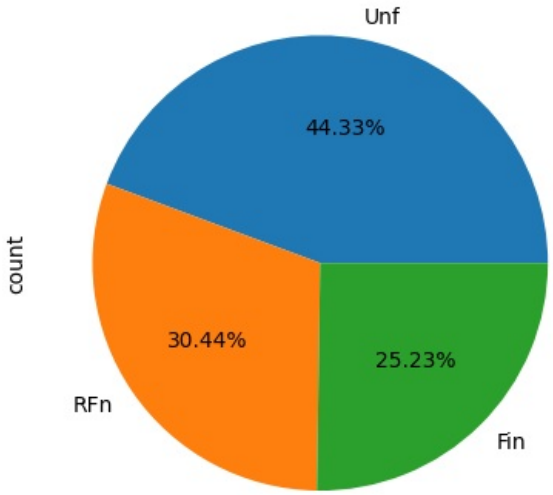
Out[64]:
```
LandSlope
1    1045
2      44
3       5
Name: count, dtype: int64
```

In [65]:
```
# GarageFinish: Interior finish of the garage
# Unf (Unfinished)
# RFn (Rough Finished)
# Fin (Finished)

train_obj['GarageFinish'].value_counts() # ordinal
```

Out[65]:
```
GarageFinish
Unf    485
RFn    333
Fin    276
Name: count, dtype: int64
```

In [66]:
```
train_obj['GarageFinish'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [67]:
```
train_obj['GarageFinish']= train_obj['GarageFinish'].replace('Unf',1)
train_obj['GarageFinish']= train_obj['GarageFinish'].replace('RFn',2)
train_obj['GarageFinish']= train_obj['GarageFinish'].replace('Fin',3)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\2205933198.py:3: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['GarageFinish']= train_obj['GarageFinish'].replace('Fin',3)
```

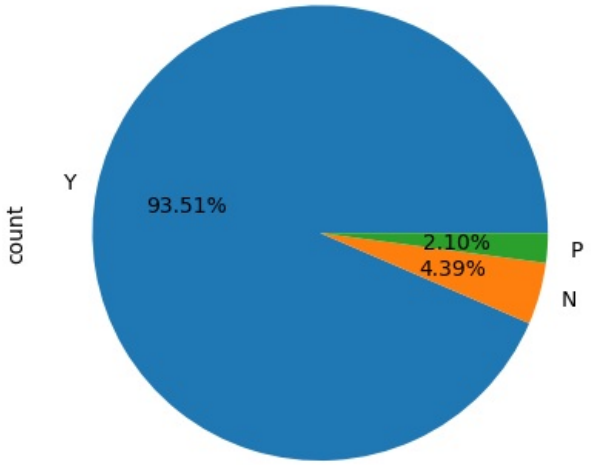
In [68]:
```
train_obj['GarageFinish'].value_counts()
```

Out[68]:
```
GarageFinish
1    485
2    333
3    276
Name: count, dtype: int64
```

In [69]:
```
# PavedDrive: Paved driveway
# Y (Yes Paved)
# P (Partially Paved)
# N (Not Paved)
train_obj['PavedDrive'].value_counts() # ordinal
```

Out[69]:
```
PavedDrive
Y    1023
N      48
P      23
Name: count, dtype: int64
```

In [70]:
```
train_obj['PavedDrive'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [71]:
```
train_obj['PavedDrive']= train_obj['PavedDrive'].replace('Y',1)
train_obj['PavedDrive']= train_obj['PavedDrive'].replace('N',2)
train_obj['PavedDrive']= train_obj['PavedDrive'].replace('P',3)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\1832947133.py:3: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['PavedDrive']= train_obj['PavedDrive'].replace('P',3)
```

In [72]:
```
train_obj['PavedDrive'].value_counts()
```

Out[72]:
```
PavedDrive
1    1023
2      48
3      23
Name: count, dtype: int64
```

In [73]:
```
for col in train_obj.columns:
    nuniques = train_obj[col].nunique()
    if nuniques == 4  :
        print(f'{col} : {train_obj[col].nunique()}')
```

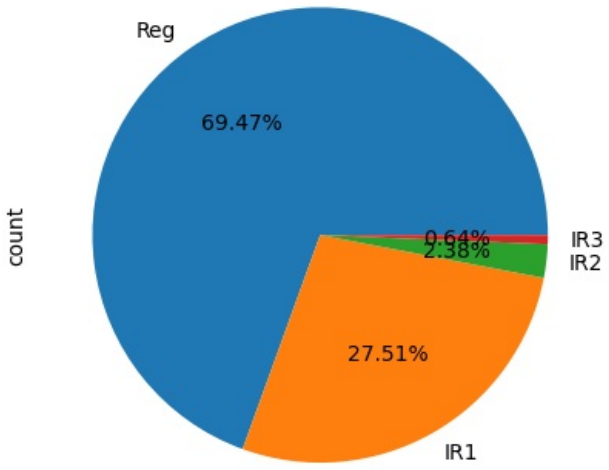
```
LotShape : 4
LandContour : 4
ExterQual : 4
ExterCond : 4
BsmtQual : 4
BsmtCond : 4
BsmtExposure : 4
Heating : 4
KitchenQual : 4
```

In [74]:
```
# LotShape : General shape of property
# Reg (Regular)
# IR1 (Slightly irregular)
# IR2 (Moderately irregular)
# IR3 (Irregular)

train_obj['LotShape'].value_counts() # ordinal
```

Out[74]:
```
LotShape
Reg    760
IR1    301
IR2     26
IR3      7
Name: count, dtype: int64
```

In [75]:
```
train_obj['LotShape'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [76]:
```
train_obj['LotShape']= train_obj['LotShape'].replace('Reg',1)
train_obj['LotShape']= train_obj['LotShape'].replace('IR1',2)
train_obj['LotShape']= train_obj['LotShape'].replace('IR2',3)
train_obj['LotShape']= train_obj['LotShape'].replace('IR3',4)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\135414595.py:4: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  train_obj['LotShape']= train_obj['LotShape'].replace('IR3',4)
```

In [77]:
```
train_obj['LotShape'].value_counts()
```

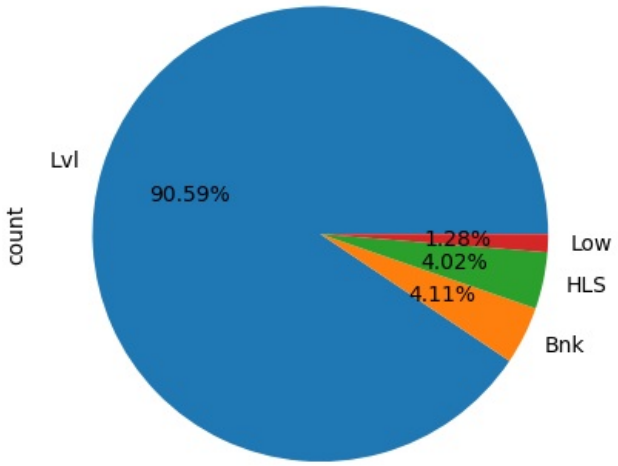
Out[77]:
```
LotShape
1    760
2    301
3     26
4      7
Name: count, dtype: int64
```

In [78]:
```
# LandContour : Flatness of the property
# Lvl (Level)
# Bnk (Banked – Slope from the street)
# HLS (Hillside – Significant slope)
# Low (Depression – Below street level)

train_obj['LandContour'].value_counts() # ordinal
```

Out[78]:
```
LandContour
Lvl    991
Bnk     45
HLS     44
Low     14
Name: count, dtype: int64
```

In [79]:
```
train_obj['LandContour'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [80]:
```
train_obj['LandContour']= train_obj['LandContour'].replace('Lvl',1)
train_obj['LandContour']= train_obj['LandContour'].replace('Bnk',2)
train_obj['LandContour']= train_obj['LandContour'].replace('HLS',3)
train_obj['LandContour']= train_obj['LandContour'].replace('Low',4)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\116715744.py:4: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  train_obj['LandContour']= train_obj['LandContour'].replace('Low',4)
```

In [81]:
```
train_obj['LandContour'].value_counts()
```

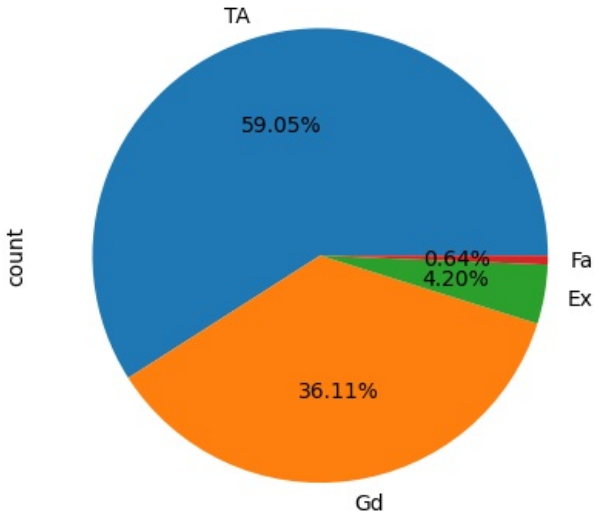
Out[81]:
```
LandContour
1    991
2     45
3     44
4     14
Name: count, dtype: int64
```

In [82]:
```
# ExterQual: Exterior material quality
# Fa (Fair)
# TA (Typical/Average)
# Gd (Good)
# Ex (Excellent)

train_obj['ExterQual'].value_counts() # ordinal
```

Out[82]:
```
ExterQual
TA    646
Gd    395
Ex     46
Fa      7
Name: count, dtype: int64
```

In [83]:
```
train_obj['ExterQual'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [84]:
```
train_obj['ExterQual']= train_obj['ExterQual'].replace('Fa',1)
train_obj['ExterQual']= train_obj['ExterQual'].replace('TA',2)
train_obj['ExterQual']= train_obj['ExterQual'].replace('Gd',3)
train_obj['ExterQual']= train_obj['ExterQual'].replace('Ex',4)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\2392043622.py:4: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['ExterQual']= train_obj['ExterQual'].replace('Ex',4)
```

In [85]:
```
train_obj['ExterQual'].value_counts()
```

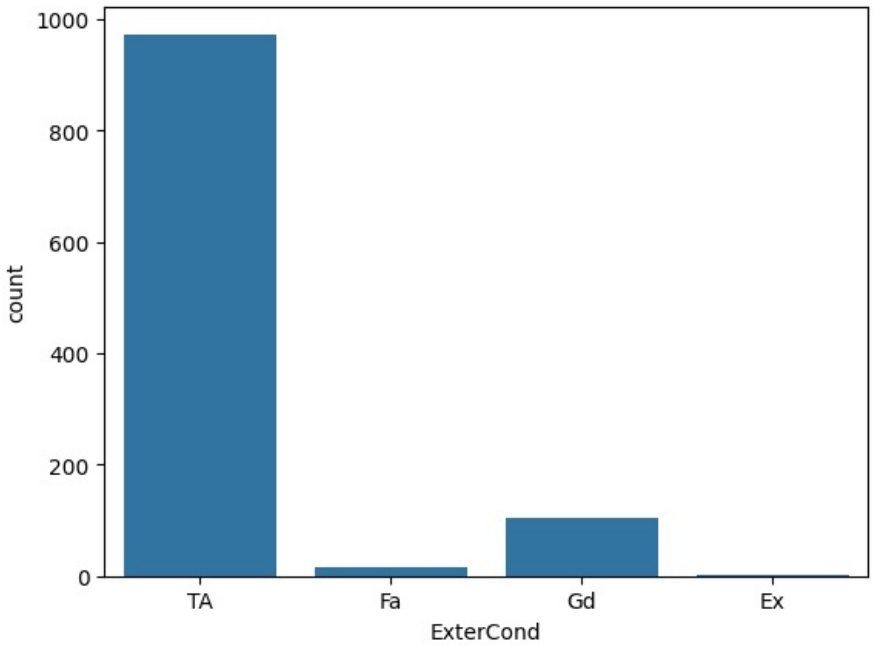
Out[85]:
```
ExterQual
2    646
3    395
4     46
1      7
Name: count, dtype: int64
```

In [86]:
```
# ExterCond: Present condition of the material on the exterior
# Fa (Fair)
# TA (Typical/Average)
# Gd (Good)
# Ex (Excellent)

train_obj['ExterCond'].value_counts() # ordinal
```

Out[86]:
```
ExterCond
TA    973
Gd    104
Fa     15
Ex      2
Name: count, dtype: int64
```

In [87]:
```
countplot(x='ExterCond', data=df_train)
show()
```



In [88]:
```
train_obj['ExterCond']= train_obj['ExterCond'].replace('Fa',1)
train_obj['ExterCond']= train_obj['ExterCond'].replace('TA',2)
train_obj['ExterCond']= train_obj['ExterCond'].replace('Gd',3)
train_obj['ExterCond']= train_obj['ExterCond'].replace('Ex',4)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\222926086.py:4: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  train_obj['ExterCond']= train_obj['ExterCond'].replace('Ex',4)
```

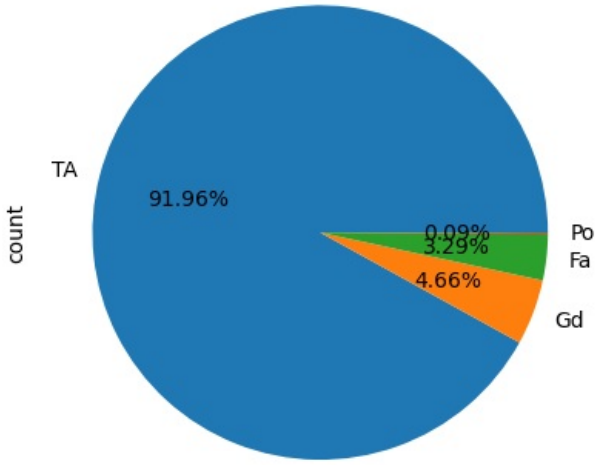
In [89]:
```
train_obj['ExterCond'].value_counts()
```

Out[89]:
```
ExterCond
2    973
3    104
1     15
4      2
Name: count, dtype: int64
```

In [90]:
```
# BsmtCond : General condition of the basement
# Gd (Good)
# TA (Typical/Average)
# Fa (Fair)
# Po (Poor)
train_obj['BsmtCond'].value_counts() # ordinal
```

Out[90]:
```
BsmtCond
TA    1006
Gd      51
Fa      36
Po       1
Name: count, dtype: int64
```

In [91]:
```
train_obj['BsmtCond'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [92]:
```
# for train data
train_obj['BsmtCond']= train_obj['BsmtCond'].replace('Gd',1)
train_obj['BsmtCond']= train_obj['BsmtCond'].replace('TA',2)
train_obj['BsmtCond']= train_obj['BsmtCond'].replace('Fa',3)
train_obj['BsmtCond']= train_obj['BsmtCond'].replace('Po',4)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\1583934741.py:5: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['BsmtCond']= train_obj['BsmtCond'].replace('Po',4)
```

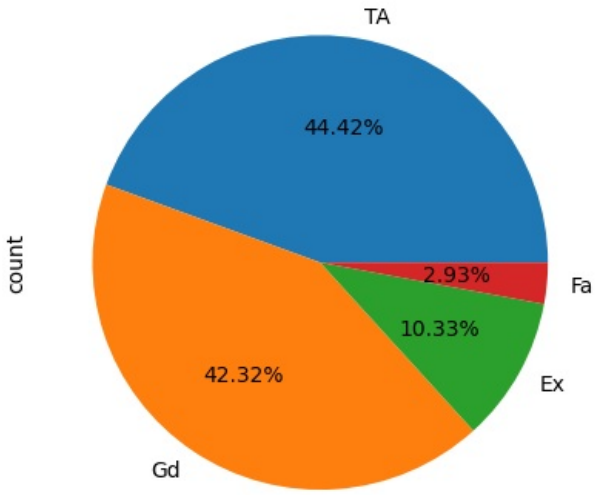
In [93]:
```
train_obj['BsmtCond'].value_counts()
```

Out[93]:
```
BsmtCond
2    1006
1      51
3      36
4       1
Name: count, dtype: int64
```

In [94]:
```
# BsmtQual: Height of the basement
# Fa (Fair)
# TA (Typical/Average)
# Gd (Good)
# Ex (Excellent)
train_obj['BsmtQual'].value_counts() # ordinal
```

Out[94]:
```
BsmtQual
TA    486
Gd    463
Ex    113
Fa     32
Name: count, dtype: int64
```

In [95]:
```
train_obj['BsmtQual'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [96]:
```
train_obj['BsmtQual']= train_obj['BsmtQual'].replace('Fa',1)
train_obj['BsmtQual']= train_obj['BsmtQual'].replace('TA',2)
train_obj['BsmtQual']= train_obj['BsmtQual'].replace('Gd',3)
train_obj['BsmtQual']= train_obj['BsmtQual'].replace('Ex',4)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\1706262065.py:4: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['BsmtQual']= train_obj['BsmtQual'].replace('Ex',4)
```

In [97]:
```
train_obj['BsmtQual'].value_counts()
```

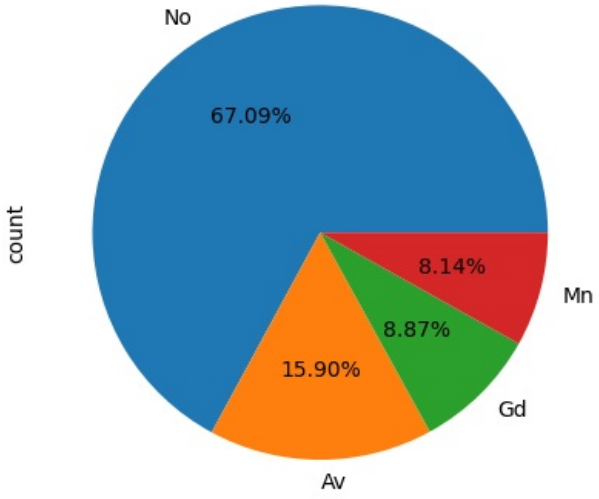
Out[97]:
```
BsmtQual
2    486
3    463
4    113
1     32
Name: count, dtype: int64
```

In [98]:
```
# BsmtExposure : Walkout or garden level basement walls
# No
# Mn (Minimum)
# Av (Average)
# Gd (Good)

train_obj['BsmtExposure'].value_counts() # ordinal
```

Out[98]:
```
BsmtExposure
No    734
Av    174
Gd     97
Mn     89
Name: count, dtype: int64
```

In [99]:
```
train_obj['BsmtExposure'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [100…
```
train_obj['BsmtExposure']= train_obj['BsmtExposure'].replace('No',1)
train_obj['BsmtExposure']= train_obj['BsmtExposure'].replace('Mn',2)
train_obj['BsmtExposure']= train_obj['BsmtExposure'].replace('Av',3)
train_obj['BsmtExposure']= train_obj['BsmtExposure'].replace('Gd',4)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\2435423177.py:4: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['BsmtExposure']= train_obj['BsmtExposure'].replace('Gd',4)
```

In [101…
```
train_obj['BsmtExposure'].value_counts()
```

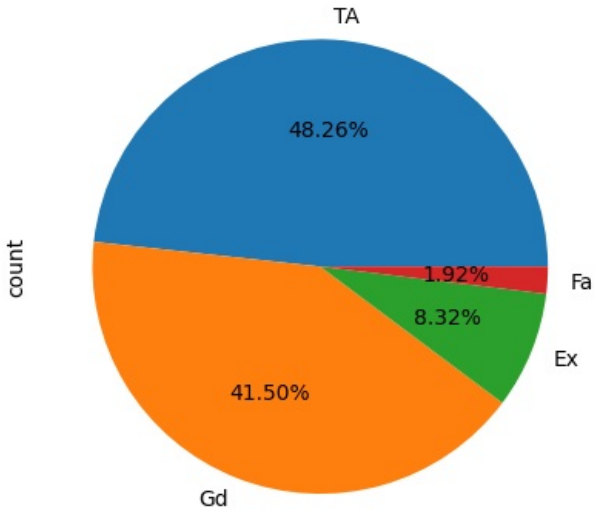
Out[101…
```
BsmtExposure
1    734
3    174
4     97
2     89
Name: count, dtype: int64
```

In [102…
```
# KitchenQual: Kitchen quality
# Fa (Fair)
# TA (Typical/Average)
# Gd (Good)
# Ex (Excellent)

train_obj['KitchenQual'].value_counts() # ordinal
```

Out[102…
```
KitchenQual
TA    528
Gd    454
Ex     91
Fa     21
Name: count, dtype: int64
```

In [103…
```
train_obj['KitchenQual'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [104…
```
train_obj['KitchenQual']= train_obj['KitchenQual'].replace('Fa',1)
train_obj['KitchenQual']= train_obj['KitchenQual'].replace('TA',2)
train_obj['KitchenQual']= train_obj['KitchenQual'].replace('Gd',3)
train_obj['KitchenQual']= train_obj['KitchenQual'].replace('Ex',4)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\3377911134.py:4: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['KitchenQual']= train_obj['KitchenQual'].replace('Ex',4)
```

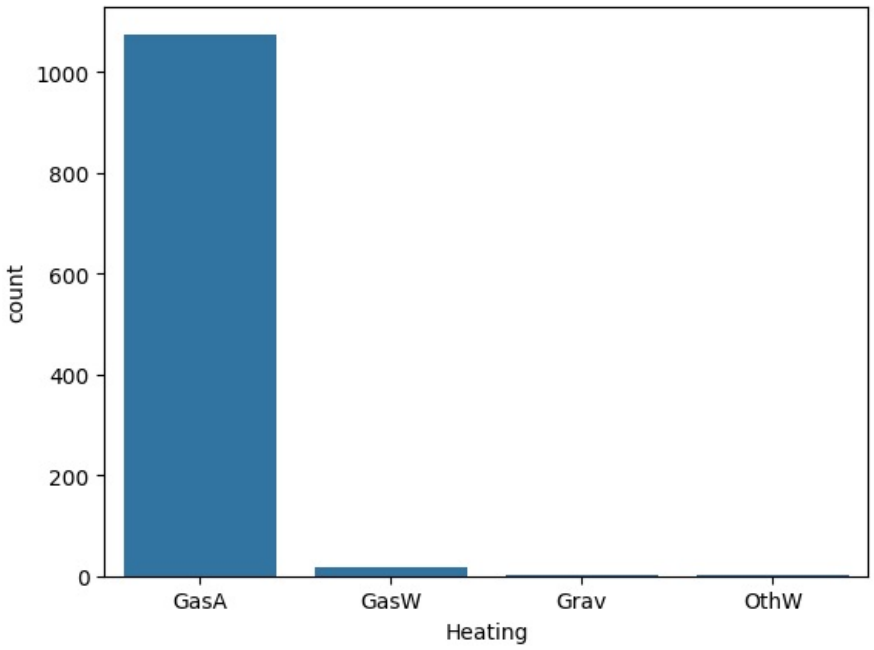
In [105…
```
train_obj['KitchenQual'].value_counts()
```

Out[105…
```
KitchenQual
2    528
3    454
4     91
1     21
Name: count, dtype: int64
```

In [106…
```
# Heating: Type of heating
train_obj['Heating'].value_counts() # nominal
```

Out[106…
```
Heating
GasA    1075
GasW      16
Grav       2
OthW       1
Name: count, dtype: int64
```

In [107…
```
countplot(x='Heating', data=df_train)
show()
```



In [108…
```
for col in train_obj.columns:
    nuniques = train_obj[col].nunique()
    if nuniques == 5  :
        print(f'{col} : {train_obj[col].nunique()}')
```

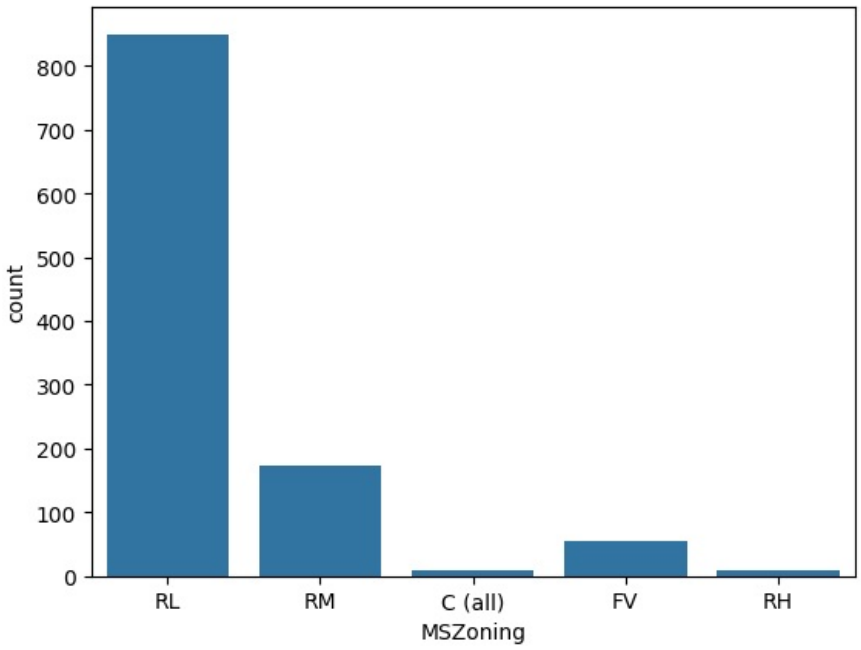
```
MSZoning : 5
LotConfig : 5
BldgType : 5
RoofStyle : 5
Foundation : 5
HeatingQC : 5
Electrical : 5
GarageQual : 5
GarageCond : 5
```

In [109…
```
# MSZoning: The general zoning classification
# RL (Residential Low Density)
# RM (Residential Medium Density)
# FV (Floating Village Residential)
# RH (Residential High Density)
# C (all) (Commercial)

train_obj['MSZoning'].value_counts() # nominal
```

Out[109…
```
MSZoning
RL         850
RM         173
FV          54
RH           9
C (all)      8
Name: count, dtype: int64
```

In [110…
```
countplot(x='MSZoning', data=df_train)
show()
```

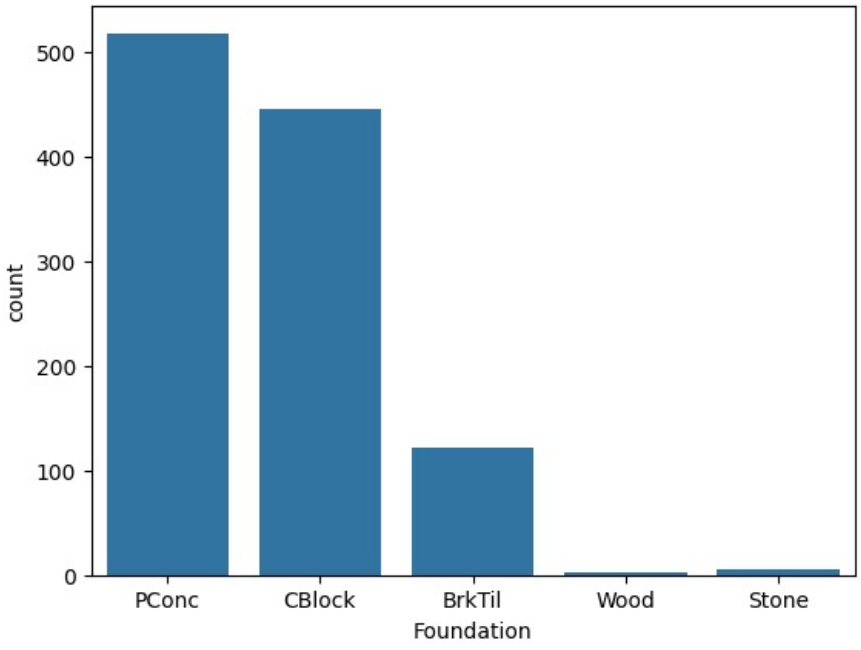


In [111…
```
# Foundation: Type of foundation
# PConc (Poured Concrete)
# CBlock (Cinder Block)
# BrkTil (Brick & Tile)
# Stone
# Wood

train_obj['Foundation'].value_counts() # nominal
```

Out[111…
```
Foundation
PConc     518
CBlock    446
BrkTil    122
Stone       6
Wood        2
Name: count, dtype: int64
```

In [112…
```
countplot(x='Foundation', data=df_train)
show()
```

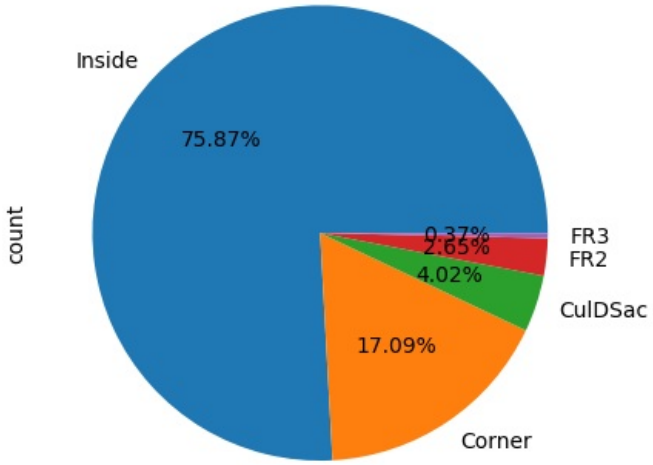


In [113…
```
# LotConfig: Lot configuration
# Inside
# Corner
# CulDSac (Cul-de-sac)
# FR2 (Frontage on 2 sides of property)
# FR3 (Frontage on 3 sides of property)
```

```
train_obj['LotConfig'].value_counts() # nominal
```

Out[113…
```
LotConfig
Inside     830
Corner     187
CulDSac     44
FR2         29
FR3          4
Name: count, dtype: int64
```

In [114…
```
train_obj['LotConfig'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



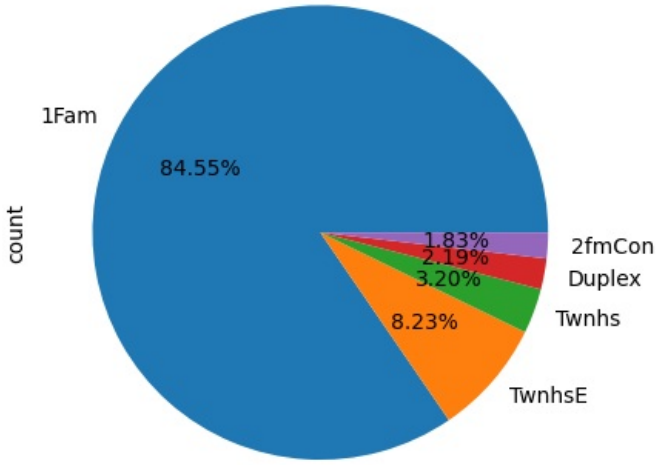
In [115…
```
train_obj['LotConfig']= train_obj['LotConfig'].replace('Inside',1)
train_obj['LotConfig']= train_obj['LotConfig'].replace('Corner',2)
train_obj['LotConfig']= train_obj['LotConfig'].replace('CulDSac',3)
train_obj['LotConfig']= train_obj['LotConfig'].replace('FR2',4)
train_obj['LotConfig']= train_obj['LotConfig'].replace('FR3',5)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\3904735806.py:5: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['LotConfig']= train_obj['LotConfig'].replace('FR3',5)
```

In [116…
```
# BldgType: Type of dwelling
train_obj['BldgType'].value_counts() # nominal
```

Out[116…
```
BldgType
1Fam      925
TwnhsE     90
Twnhs      35
Duplex     24
2fmCon     20
Name: count, dtype: int64
```

In [117…
```
train_obj['BldgType'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```

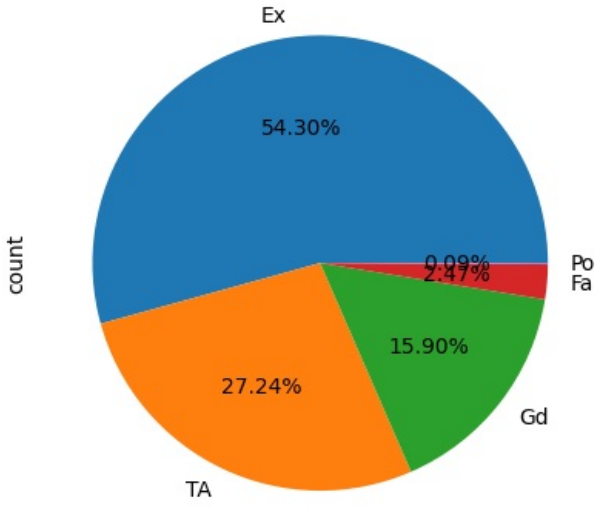


In [118…
```
# HeatingQC: Heating quality and condition
# Ex (Excellent)
# Gd (Good)
# TA (Typical/Average)
# Fa (Fair)
# Po (Poor)

train_obj['HeatingQC'].value_counts() # ordinal
```

Out[118…
```
HeatingQC
Ex    594
TA    298
Gd    174
Fa     27
Po      1
Name: count, dtype: int64
```

In [119…
```
train_obj['HeatingQC'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [120…
```
train_obj['HeatingQC']= train_obj['HeatingQC'].replace('Po',1)
train_obj['HeatingQC']= train_obj['HeatingQC'].replace('Fa',2)
train_obj['HeatingQC']= train_obj['HeatingQC'].replace('TA',3)
train_obj['HeatingQC']= train_obj['HeatingQC'].replace('Gd',4)
train_obj['HeatingQC']= train_obj['HeatingQC'].replace('Ex',5)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\824846332.py:5: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  train_obj['HeatingQC']= train_obj['HeatingQC'].replace('Ex',5)
```

In [121…
```
train_obj['HeatingQC'].value_counts()
```

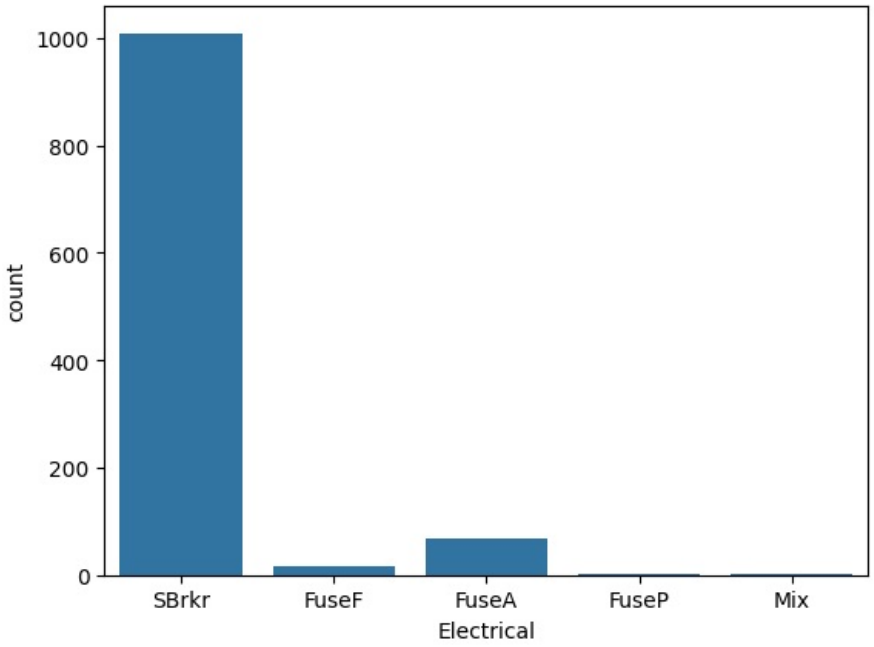
Out[121…
```
HeatingQC
5    594
3    298
4    174
2     27
1      1
Name: count, dtype: int64
```

In [122…
```
# Electrical: Electrical system
# SBrkr (Standard Circuit Breakers & Romex)
# FuseA (Fuse Box - Amp Service)
# FuseF (Fuse Box - Fair)
# FuseP (Fuse Box - Poor)
# Mix (Mixed)

train_obj['Electrical'].value_counts() # nominal
```

Out[122…
```
Electrical
SBrkr    1009
FuseA      67
FuseF      15
FuseP       2
Mix         1
Name: count, dtype: int64
```

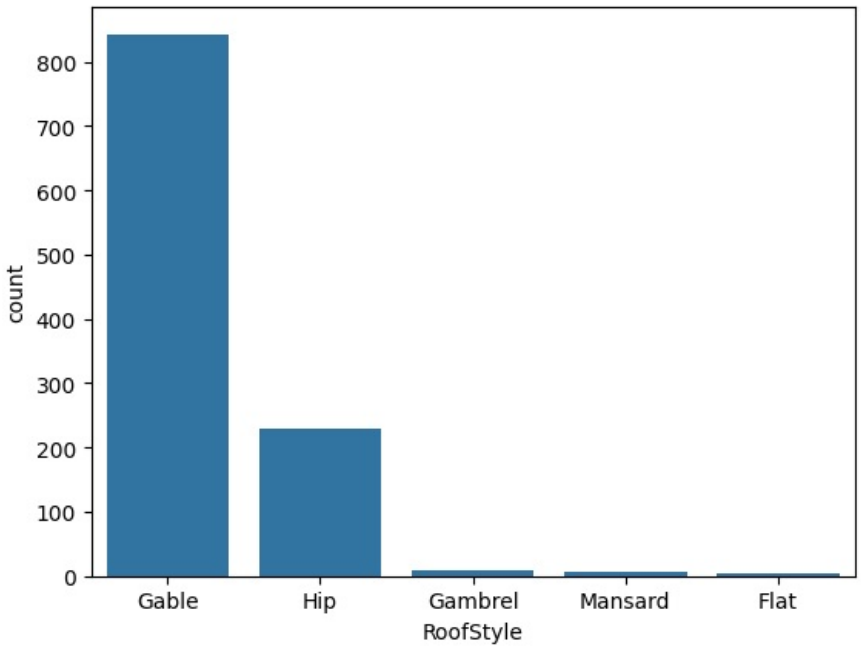
In [123…
```
countplot(x='Electrical', data=df_train)
show()
```



In [124…
```
# FireplaceQu: Fireplace quality
train_obj['RoofStyle'].value_counts() # nominal
```

Out[124…
```
RoofStyle
Gable      843
Hip        230
Gambrel     10
Mansard      6
Flat         5
Name: count, dtype: int64
```

In [125…
```
countplot(x='RoofStyle', data=df_train)
show()
```

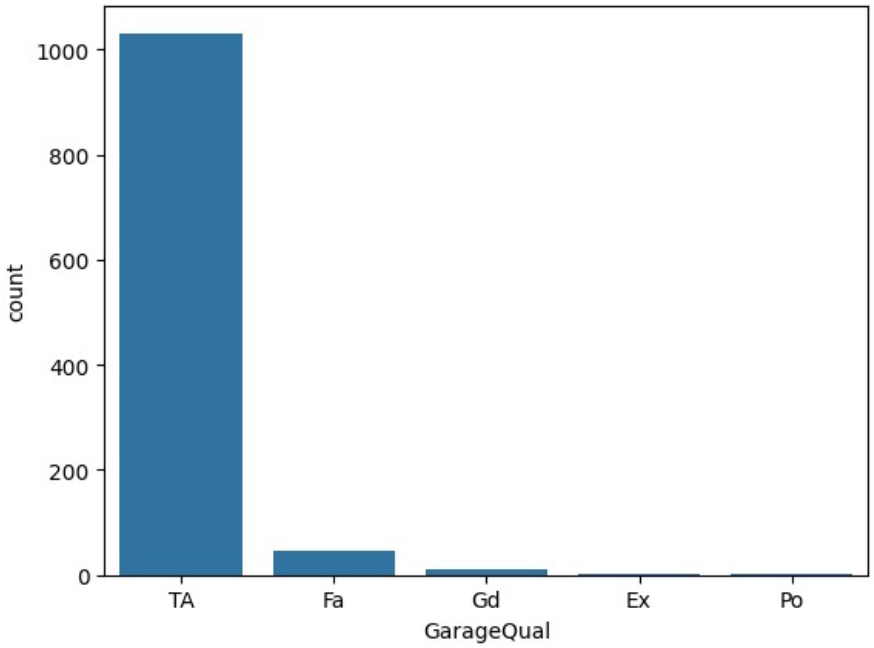


In [126…
```
# GarageQual: Garage quality
# Ex (Excellent)
# Gd (Good)
# TA (Typical/Average)
# Fa (Fair)
# Po (Poor)

train_obj['GarageQual'].value_counts() # ordinal
```

Out[126…
```
GarageQual
TA    1031
Fa      46
Gd      11
Ex       3
Po       3
Name: count, dtype: int64
```

In [127…
```
countplot(x='GarageQual', data=df_train)
show()
```



In [128…
```
train_obj['GarageQual']= train_obj['GarageQual'].replace('Po',1)
train_obj['GarageQual']= train_obj['GarageQual'].replace('Fa',2)
train_obj['GarageQual']= train_obj['GarageQual'].replace('TA',3)
train_obj['GarageQual']= train_obj['GarageQual'].replace('Gd',4)
train_obj['GarageQual']= train_obj['GarageQual'].replace('Ex',5)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\2665318924.py:5: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['GarageQual']= train_obj['GarageQual'].replace('Ex',5)
```

In [129…
```
train_obj['GarageQual'].value_counts()
```

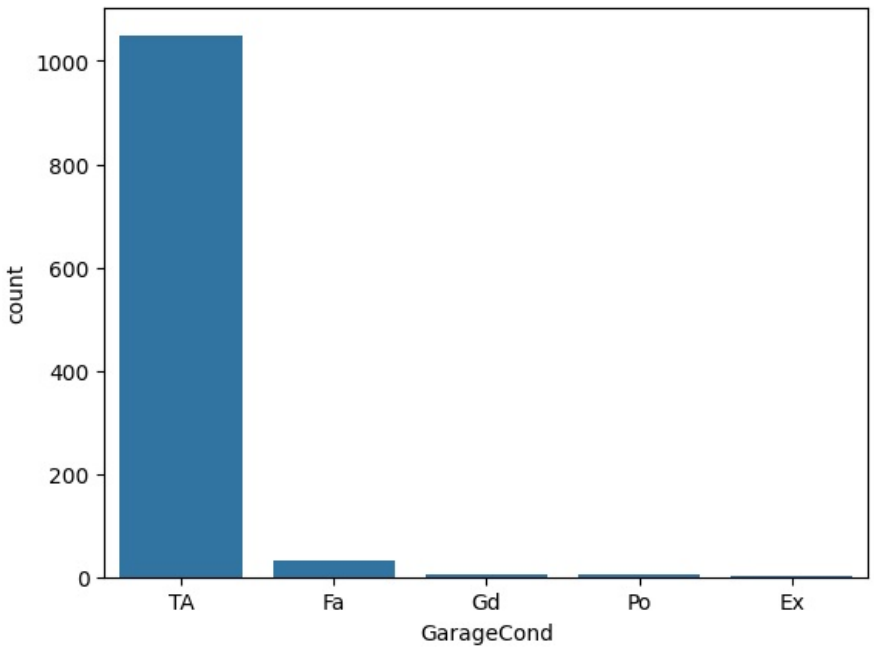
Out[129…
```
GarageQual
3    1031
2      46
4      11
5       3
1       3
Name: count, dtype: int64
```

In [130…
```
# GarageCond: Garage condition
# Ex (Excellent)
# Gd (Good)
# TA (Typical/Average)
# Fa (Fair)
# Po (Poor)

train_obj['GarageCond'].value_counts() # ordinal
```

Out[130…
```
GarageCond
TA    1050
Fa      31
Po       6
Gd       5
Ex       2
Name: count, dtype: int64
```

In [131…
```
countplot(x='GarageCond', data=df_train)
show()
```



In [132…
```
train_obj['GarageCond']= train_obj['GarageCond'].replace('Po',1)
train_obj['GarageCond']= train_obj['GarageCond'].replace('Fa',2)
train_obj['GarageCond']= train_obj['GarageCond'].replace('TA',3)
train_obj['GarageCond']= train_obj['GarageCond'].replace('Gd',4)
train_obj['GarageCond']= train_obj['GarageCond'].replace('Ex',5)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\4002507844.py:5: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['GarageCond']= train_obj['GarageCond'].replace('Ex',5)
```

In [133…
```
train_obj['GarageCond'].value_counts() # ordinal
```

Out[133…
```
GarageCond
3    1050
2      31
1       6
4       5
5       2
Name: count, dtype: int64
```

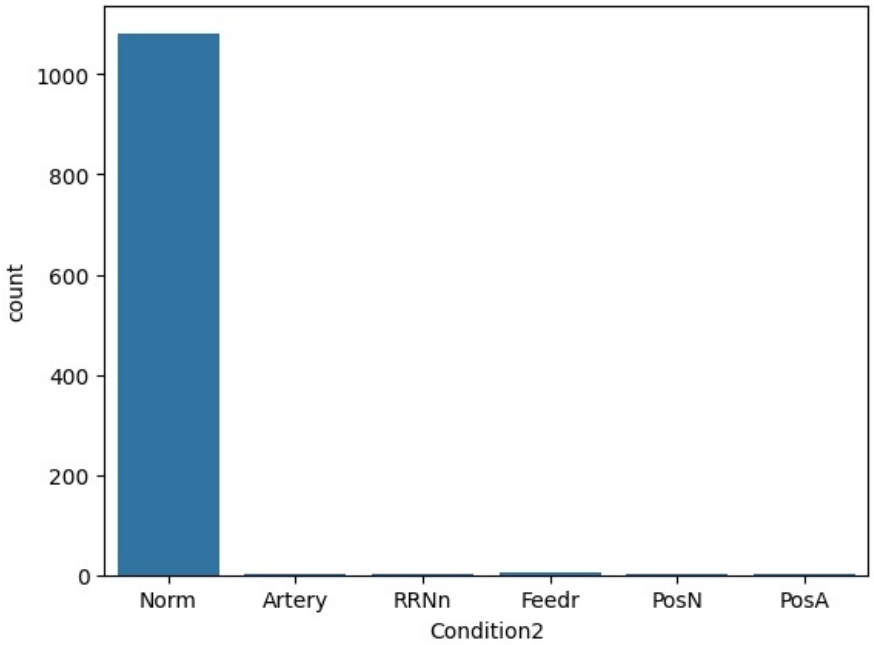
In [134…
```
for col in train_obj.columns:
    nuniques = train_obj[col].nunique()
    if nuniques == 6  :
        print(f'{col} : {train_obj[col].nunique()}')
```

```
Condition2 : 6
BsmtFinType1 : 6
BsmtFinType2 : 6
Functional : 6
GarageType : 6
SaleCondition : 6
```

In [135…
```
# Condition2: Proximity to main road or railroad (if a second is present)
train_obj['Condition2'].value_counts() # nominal
```

Out[135…
```
Condition2
Norm      1082
Feedr        5
Artery       2
RRNn         2
PosN         2
PosA         1
Name: count, dtype: int64
```

In [136…
```
countplot(x='Condition2', data=df_train)
show()
```

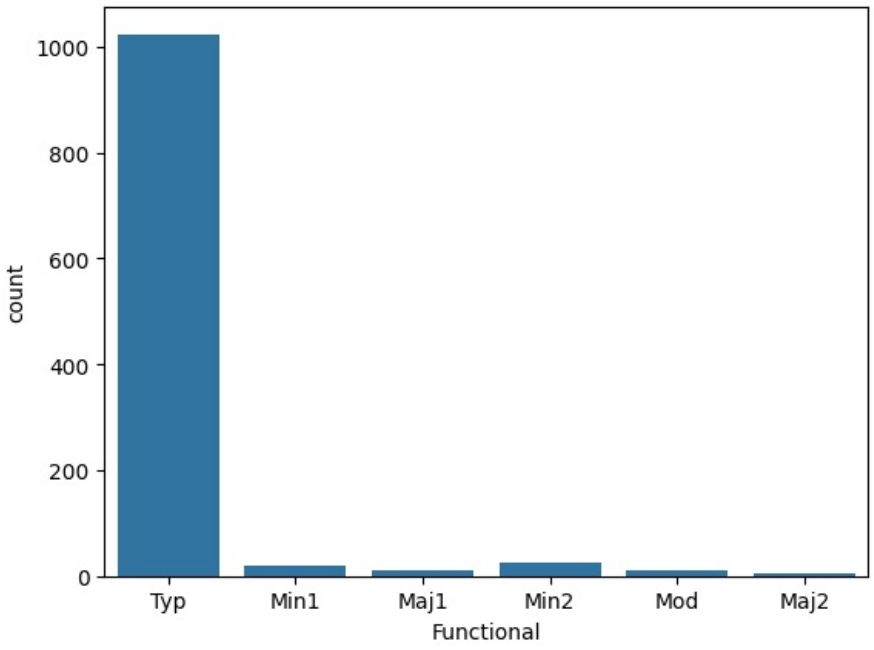


In [137…
```
# Functional: Home functionality rating
# Typ (Typical)
# Min2 (Minor Functionality Issue 2)
# Min1 (Minor Functionality Issue 1)
# Mod (Moderate Functionality Issue)
# Maj1 (Major Functionality Issue 1)
# Maj2 (Major Functionality Issue 2)

train_obj['Functional'].value_counts() # ordinal
```

Out[137…
```
Functional
Typ     1024
Min2      25
Min1      21
Maj1      10
Mod       10
Maj2       4
Name: count, dtype: int64
```

In [138…
```
countplot(x='Functional', data=df_train)
show()
```



In [139…
```
train_obj['Functional']= train_obj['Functional'].replace('Typ',1)
train_obj['Functional']= train_obj['Functional'].replace('Min2',2)
train_obj['Functional']= train_obj['Functional'].replace('Min1',3)
train_obj['Functional']= train_obj['Functional'].replace('Mod',4)
train_obj['Functional']= train_obj['Functional'].replace('Maj1',5)
train_obj['Functional']= train_obj['Functional'].replace('Maj2',6)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\4263619355.py:6: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['Functional']= train_obj['Functional'].replace('Maj2',6)
```

In [140…
```
train_obj['Functional'].value_counts()
```

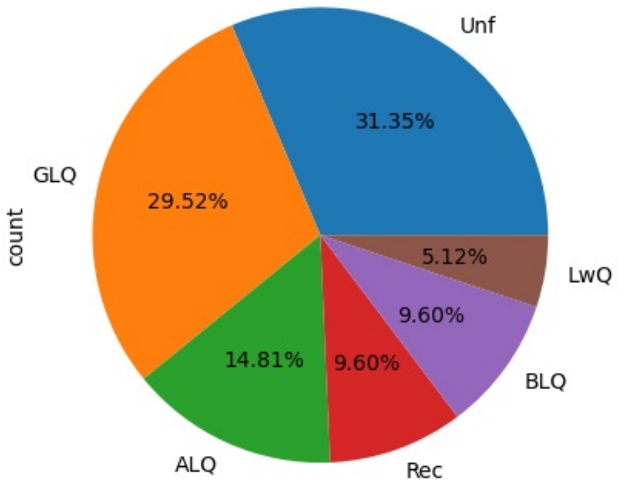
Out[140…
```
Functional
1    1024
2      25
3      21
5      10
4      10
6       4
Name: count, dtype: int64
```

In [141…
```
# BsmtFinType1: Quality of basement finished area
# Unf (Unfinished)
# GLQ (Good Living Quality)
# ALQ (Average Living Quality)
# Rec (Recreation Room)
# BLQ (Below Average Living Quality)
# LwQ (Low Quality)

train_obj['BsmtFinType1'].value_counts() # ordinal
```

Out[141…
```
BsmtFinType1
Unf    343
GLQ    323
ALQ    162
Rec    105
BLQ    105
LwQ     56
Name: count, dtype: int64
```

In [142…
```
train_obj['BsmtFinType1'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [143…
```
train_obj['BsmtFinType1']= train_obj['BsmtFinType1'].replace('Unf',1)
train_obj['BsmtFinType1']= train_obj['BsmtFinType1'].replace('GLQ',2)
train_obj['BsmtFinType1']= train_obj['BsmtFinType1'].replace('ALQ',3)
train_obj['BsmtFinType1']= train_obj['BsmtFinType1'].replace('Rec',4)
train_obj['BsmtFinType1']= train_obj['BsmtFinType1'].replace('BLQ',5)
train_obj['BsmtFinType1']= train_obj['BsmtFinType1'].replace('LwQ',6)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\3546732529.py:6: FutureWarning: Downcasting behavior in `replace
` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.inf
er_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', Tr
ue)`
  train_obj['BsmtFinType1']= train_obj['BsmtFinType1'].replace('LwQ',6)
```

In [144…
```
train_obj['BsmtFinType1'].value_counts()
```

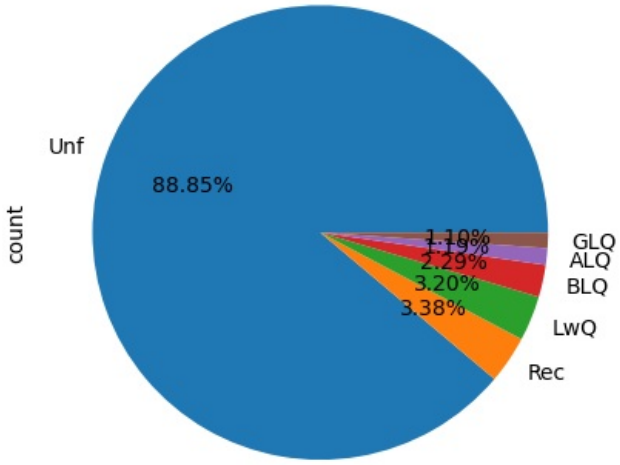
Out[144…
```
BsmtFinType1
1    343
2    323
3    162
4    105
5    105
6     56
Name: count, dtype: int64
```

In [145…
```
# BsmtFinType2: Quality of second finished area (if present)
# Unf (Unfinished)
# GLQ (Good Living Quality)
# ALQ (Average Living Quality)
# Rec (Recreation Room)
# BLQ (Below Average Living Quality)
# LwQ (Low Quality)

train_obj['BsmtFinType2'].value_counts()  # ordinal
```

Out[145…
```
BsmtFinType2
Unf    972
Rec     37
LwQ     35
BLQ     25
ALQ     13
GLQ     12
Name: count, dtype: int64
```

In [146…
```
train_obj['BsmtFinType2'].value_counts().plot.pie(autopct='%0.2f%%')
show()
```



In [147…
```
train_obj['BsmtFinType2']= train_obj['BsmtFinType2'].replace('Unf',1)
train_obj['BsmtFinType2']= train_obj['BsmtFinType2'].replace('GLQ',2)
train_obj['BsmtFinType2']= train_obj['BsmtFinType2'].replace('ALQ',3)
train_obj['BsmtFinType2']= train_obj['BsmtFinType2'].replace('Rec',4)
train_obj['BsmtFinType2']= train_obj['BsmtFinType2'].replace('BLQ',5)
train_obj['BsmtFinType2']= train_obj['BsmtFinType2'].replace('LwQ',6)
```

```
C:\Users\RPC\AppData\Local\Temp\ipykernel_14640\777848345.py:6: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  train_obj['BsmtFinType2']= train_obj['BsmtFinType2'].replace('LwQ',6)
```

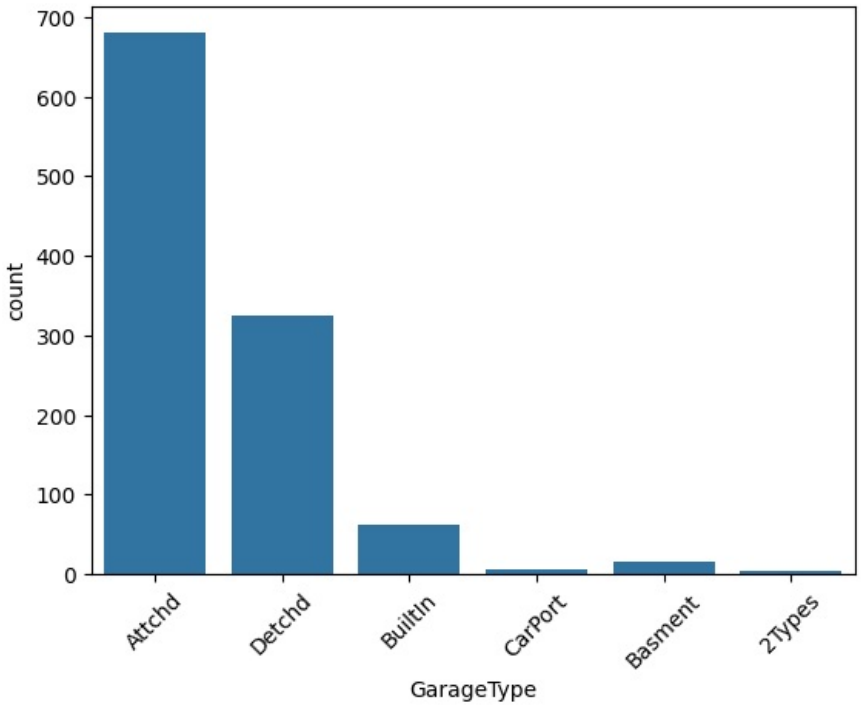
In [148…
```
train_obj['BsmtFinType2'].value_counts()
```

Out[148…
```
BsmtFinType2
1    972
4     37
6     35
5     25
3     13
2     12
Name: count, dtype: int64
```

In [149…
```
# GarageType: Garage location
train_obj['GarageType'].value_counts() # nominal   but there is number with string
```

Out[149…
```
GarageType
Attchd     680
Detchd     325
BuiltIn     63
Basment     15
CarPort      6
2Types       5
Name: count, dtype: int64
```

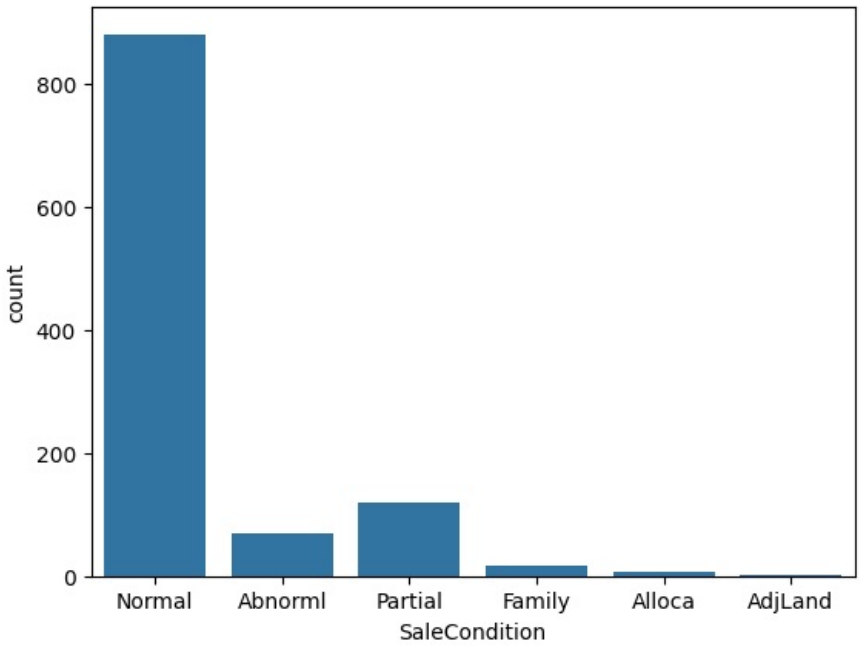
In [150…
```
countplot(x='GarageType', data=df_train)
xticks(rotation=45)
show()
```



In [151…
```
# SaleCondition: Condition of sale
train_obj['SaleCondition'].value_counts()
```

Out[151…
```
SaleCondition
Normal     880
Partial    119
Abnorml     70
Family      18
Alloca       6
AdjLand      1
Name: count, dtype: int64
```

In [152…
```
countplot(x='SaleCondition', data=df_train)
show()
```



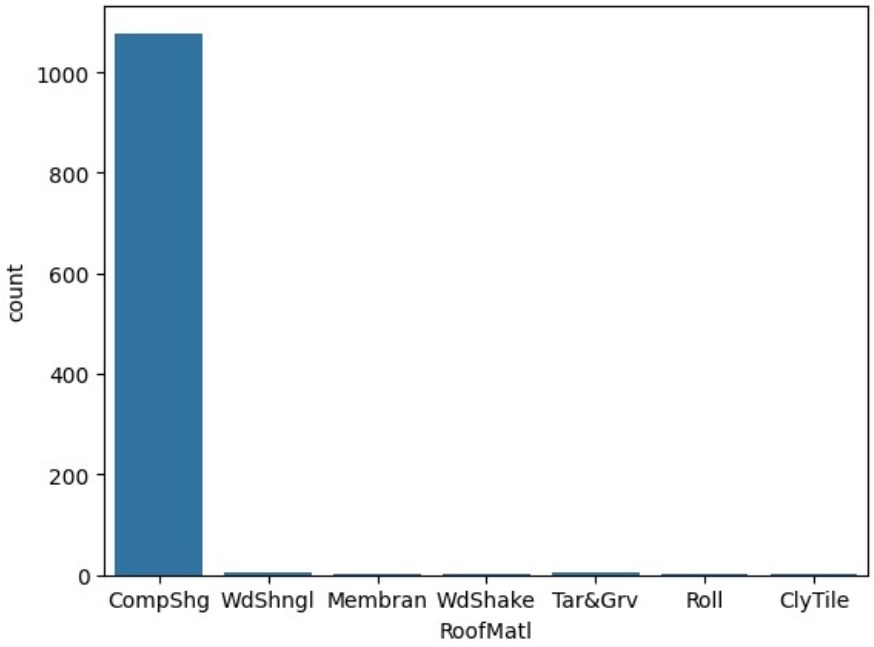
In [153…
```
for col in train_obj.columns:
    nuniques = train_obj[col].nunique()
    if nuniques == 7  :
        print(f'{col} : {train_obj[col].nunique()}')
```

```
RoofMatl : 7
```

In [154…
```
# Functional: Home functionality rating
train_obj['RoofMatl'].value_counts() # nominal
```

Out[154…
```
RoofMatl
CompShg    1078
WdShngl       6
Tar&Grv       5
WdShake       2
Membran       1
Roll          1
ClyTile       1
Name: count, dtype: int64
```

In [155…
```
countplot(x='RoofMatl', data=df_train)
show()
```



In [156…
```
for col in train_obj.columns:
    nuniques = train_obj[col].nunique()
    if nuniques >= 8  :
        print(f'{col} : {train_obj[col].nunique()}')
```

```
Neighborhood : 25
Condition1 : 9
HouseStyle : 8
Exterior1st : 14
Exterior2nd : 16
SaleType : 9
```

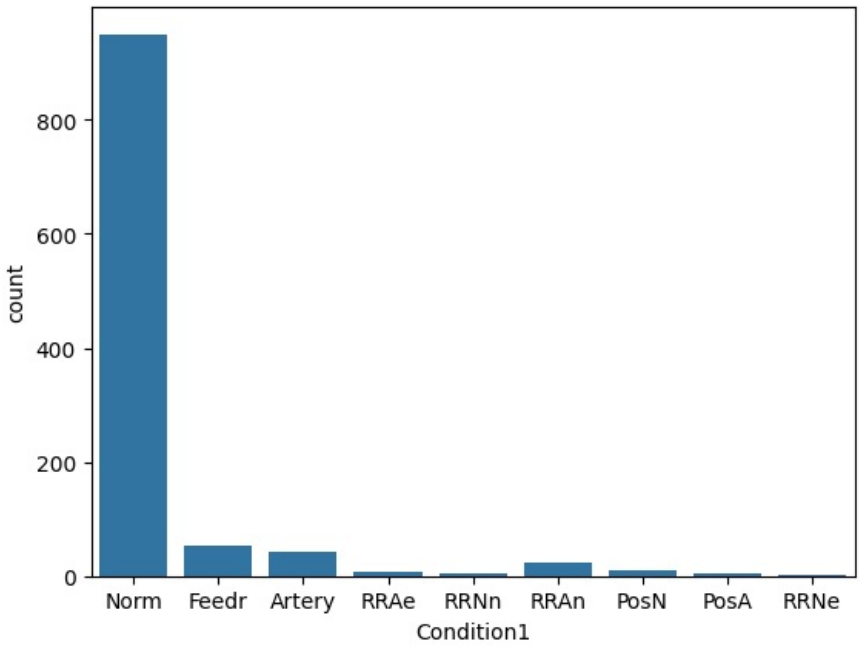
In [157…
```
# Neighborhood: Physical locations within Ames city limits
train_obj['Neighborhood'].value_counts() # nominal
```

Out[157…
```
Neighborhood
NAmes      173
CollgCr    122
OldTown     96
Somerst     75
NridgHt     74
Edwards     65
Gilbert     49
NWAmes      45
Sawyer      44
SawyerW     44
BrkSide     42
Crawfor     41
NoRidge     33
Mitchel     30
Timber      29
IDOTRR      27
StoneBr     20
SWISU       19
BrDale      15
Blmngtn     14
ClearCr     11
MeadowV     10
Veenker      7
NPkVill      7
Blueste      2
Name: count, dtype: int64
```

In [158…
```
# Condition1: Proximity to main road or railroad
train_obj['Condition1'].value_counts() # nominal
```

Out[158…
```
Condition1
Norm      950
Feedr      52
Artery     42
RRAn       24
PosN        9
RRAe        8
RRNn        4
PosA        4
RRNe        1
Name: count, dtype: int64
```

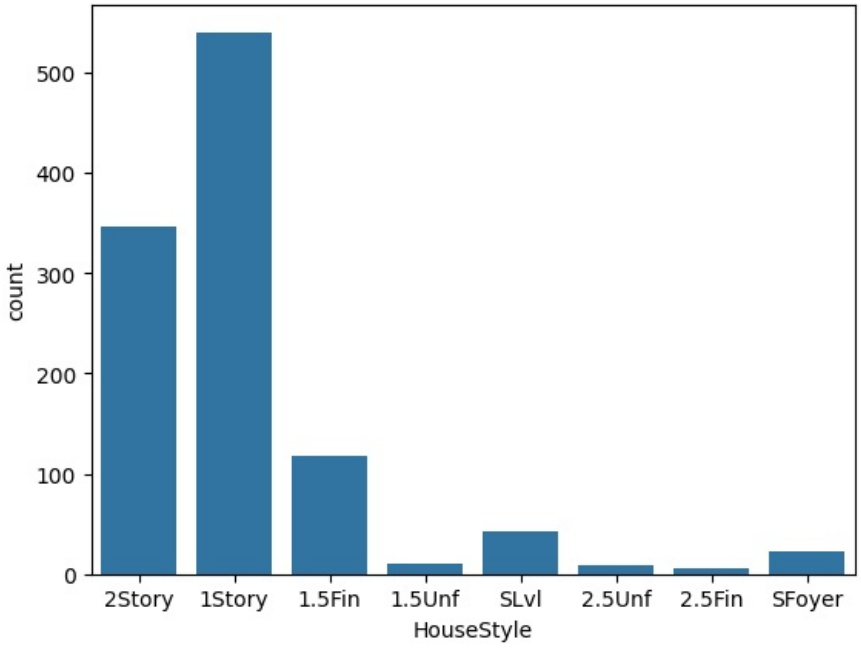
In [159…
```
countplot(x='Condition1', data=df_train)
show()
```



In [160…
```
# OverallQual: Overall material and finish quality
train_obj['HouseStyle'].value_counts() # nominal   but there is number with string
```

Out[160…
```
HouseStyle
1Story    540
2Story    346
1.5Fin    117
SLvl       43
SFoyer     23
1.5Unf     10
2.5Unf      9
2.5Fin      6
Name: count, dtype: int64
```

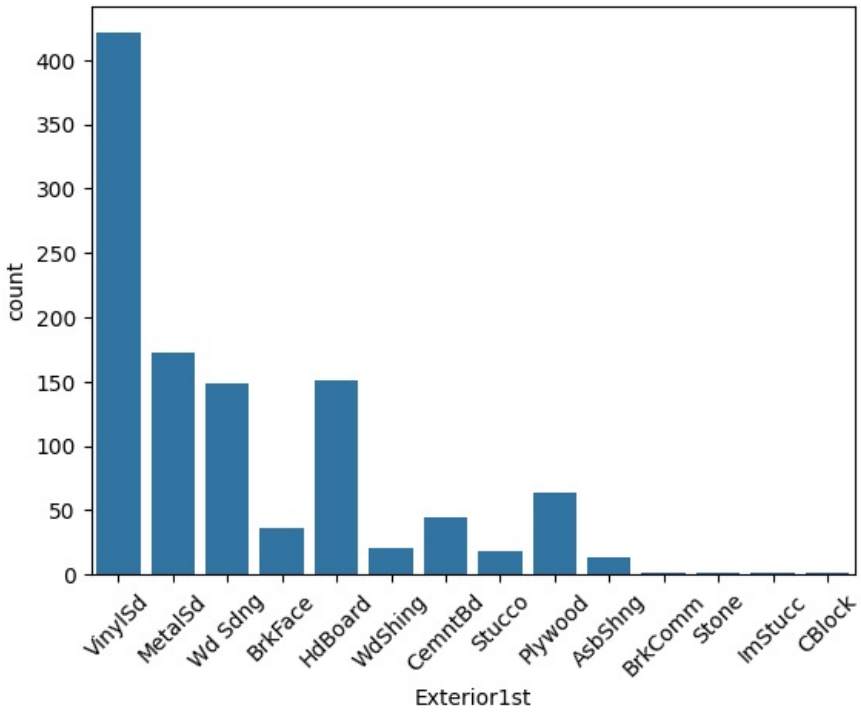
In [161…
```
countplot(x='HouseStyle', data=df_train)
show()
```



In [162…
```
# Exterior1st: Exterior covering on house
train_obj['Exterior1st'].value_counts()
```

Out[162…
```
Exterior1st
VinylSd    421
MetalSd    172
HdBoard    151
Wd Sdng    149
Plywood     64
CemntBd     45
BrkFace     36
WdShing     20
Stucco      18
AsbShng     14
BrkComm      1
Stone        1
ImStucc      1
CBlock       1
Name: count, dtype: int64
```

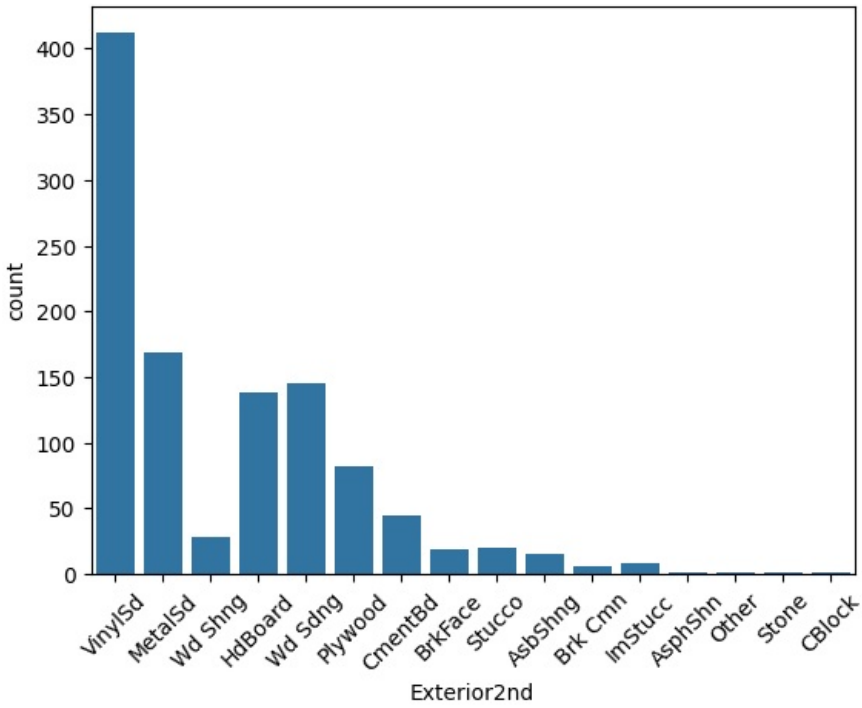
In [163…
```
countplot(x='Exterior1st', data=df_train)
xticks(rotation = 45)
show()
```



In [164…
```
# Exterior2nd: Exterior covering on house (if more than one material)
train_obj['Exterior2nd'].value_counts()  # nominal
```

Out[164…
```
Exterior2nd
VinylSd    412
MetalSd    169
Wd Sdng    145
HdBoard    138
Plywood     82
CmentBd     45
Wd Shng     28
Stucco      20
BrkFace     19
AsbShng     15
ImStucc      9
Brk Cmn      6
AsphShn      2
Stone        2
Other        1
CBlock       1
Name: count, dtype: int64
```

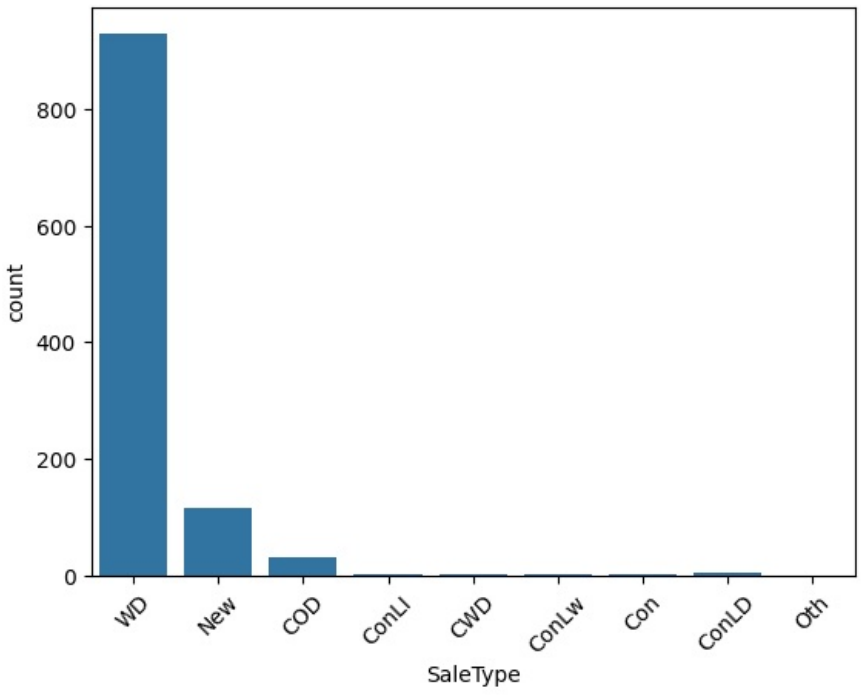
In [165…
```
countplot(x='Exterior2nd', data=df_train)
xticks(rotation=45)
show()
```



In [166…
```
# SaleType: Type of sale
train_obj['SaleType'].value_counts() # nominal
```

Out[166…
```
SaleType
WD       928
New      116
COD       31
ConLD      5
CWD        4
ConLw      4
ConLI      3
Con        2
Oth        1
Name: count, dtype: int64
```

In [167…
```
countplot(x='SaleType', data=df_train)
xticks(rotation=45)
show()
```



In [168…
```
train_obj
```

Out[168…

	MSZoning	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2	...	Electr
0	RL	Pave	1	1	AllPub	1	1	CollgCr	Norm	Norm	...	S
1	RL	Pave	1	1	AllPub	4	1	Veenker	Feedr	Norm	...	S
2	RL	Pave	2	1	AllPub	1	1	CollgCr	Norm	Norm	...	S
3	RL	Pave	2	1	AllPub	2	1	Crawfor	Norm	Norm	...	S
4	RL	Pave	2	1	AllPub	4	1	NoRidge	Norm	Norm	...	S
...	...	...	...	...	...	...	...	...	...	...	...	
1455	RL	Pave	1	1	AllPub	1	1	Gilbert	Norm	Norm	...	S
1456	RL	Pave	1	1	AllPub	1	1	NWAmes	Norm	Norm	...	S
1457	RL	Pave	1	1	AllPub	1	1	Crawfor	Norm	Norm	...	S
1458	RL	Pave	1	1	AllPub	1	1	NAmes	Norm	Norm	...	Fu
1459	RL	Pave	1	1	AllPub	1	1	Edwards	Norm	Norm	...	S

1094 rows × 37 columns

In [169…
```
train_data = concat([train_non_obj,train_obj],axis=1)
```

In [170…
```
train_data
```

Out[170…

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtUn
0	60	65.0	8450	7	5	2003	2003	196.000000	706	
1	20	80.0	9600	6	8	1976	1976	263.557018	978	
2	60	68.0	11250	7	5	2001	2002	162.000000	486	
3	70	60.0	9550	7	5	1915	1970	263.557018	216	
4	60	84.0	14260	8	5	2000	2000	350.000000	655	
...	...	...	...	...	...	...	...	...	...	
1455	60	62.0	7917	6	5	1999	2000	263.557018	0	
1456	20	85.0	13175	6	6	1978	1988	119.000000	790	
1457	70	66.0	9042	7	9	1941	2006	263.557018	275	
1458	20	68.0	9717	5	6	1950	1996	263.557018	49	
1459	20	75.0	9937	5	6	1965	1965	263.557018	830	

1094 rows × 65 columns

In [171…
```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1094 entries, 0 to 1459
Data columns (total 65 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1094 non-null   int64
 1   LotFrontage    1094 non-null   float64
 2   LotArea        1094 non-null   int64
 3   OverallQual    1094 non-null   int64
 4   OverallCond    1094 non-null   int64
 5   YearBuilt      1094 non-null   int64
 6   YearRemodAdd   1094 non-null   int64
 7   MasVnrArea     1094 non-null   float64
 8   BsmtFinSF1     1094 non-null   int64
 9   BsmtUnfSF      1094 non-null   int64
 10  TotalBsmtSF    1094 non-null   int64
 11  1stFlrSF       1094 non-null   int64
 12  2ndFlrSF       1094 non-null   int64
 13  GrLivArea      1094 non-null   int64
 14  BsmtFullBath   1094 non-null   int64
 15  FullBath       1094 non-null   int64
 16  HalfBath       1094 non-null   int64
 17  BedroomAbvGr   1094 non-null   int64
 18  KitchenAbvGr   1094 non-null   int64
 19  TotRmsAbvGrd   1094 non-null   int64
 20  GarageYrBlt    1094 non-null   float64
 21  GarageCars     1094 non-null   int64
 22  GarageArea     1094 non-null   int64
 23  WoodDeckSF     1094 non-null   float64
 24  OpenPorchSF    1094 non-null   float64
 25  MoSold         1094 non-null   int64
 26  YrSold         1094 non-null   int64
 27  SalePrice      1094 non-null   int64
 28  MSZoning       1094 non-null   object
 29  Street         1094 non-null   object
 30  LotShape       1094 non-null   int64
 31  LandContour    1094 non-null   int64
 32  Utilities      1094 non-null   object
 33  LotConfig      1094 non-null   int64
 34  LandSlope      1094 non-null   int64
 35  Neighborhood   1094 non-null   object
 36  Condition1     1094 non-null   object
 37  Condition2     1094 non-null   object
 38  BldgType       1094 non-null   object
 39  HouseStyle     1094 non-null   object
 40  RoofStyle      1094 non-null   object
 41  RoofMatl       1094 non-null   object
 42  Exterior1st    1094 non-null   object
 43  Exterior2nd    1094 non-null   object
 44  ExterQual      1094 non-null   int64
 45  ExterCond      1094 non-null   int64
 46  Foundation     1094 non-null   object
 47  BsmtQual       1094 non-null   int64
 48  BsmtCond       1094 non-null   int64
 49  BsmtExposure   1094 non-null   int64
 50  BsmtFinType1   1094 non-null   int64
 51  BsmtFinType2   1094 non-null   int64
 52  Heating        1094 non-null   object
 53  HeatingQC      1094 non-null   int64
 54  CentralAir     1094 non-null   object
 55  Electrical     1094 non-null   object
 56  KitchenQual    1094 non-null   int64
 57  Functional     1094 non-null   int64
 58  GarageType     1094 non-null   object
 59  GarageFinish   1094 non-null   int64
 60  GarageQual     1094 non-null   int64
 61  GarageCond     1094 non-null   int64
 62  PavedDrive     1094 non-null   int64
 63  SaleType       1094 non-null   object
 64  SaleCondition  1094 non-null   object
dtypes: float64(5), int64(41), object(19)
memory usage: 596.4+ KB
```

In [172…

```
train_obj2 = train_data.select_dtypes(include='object')
train_non_obj2 = train_data.select_dtypes(exclude='object')
```

In [173…

```
from sklearn.preprocessing import LabelEncoder
label = LabelEncoder()

for i in range(0,train_obj2.shape[1]):
```

```
    train_obj2.iloc[:,i]=label.fit_transform(train_obj2.iloc[:,i])

train_obj2 = train_obj2.astype(int)
```

In [174…
```
train_obj2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1094 entries, 0 to 1459
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSZoning       1094 non-null   int32
 1   Street         1094 non-null   int32
 2   Utilities      1094 non-null   int32
 3   Neighborhood   1094 non-null   int32
 4   Condition1     1094 non-null   int32
 5   Condition2     1094 non-null   int32
 6   BldgType       1094 non-null   int32
 7   HouseStyle     1094 non-null   int32
 8   RoofStyle      1094 non-null   int32
 9   RoofMatl       1094 non-null   int32
 10  Exterior1st    1094 non-null   int32
 11  Exterior2nd    1094 non-null   int32
 12  Foundation     1094 non-null   int32
 13  Heating        1094 non-null   int32
 14  CentralAir     1094 non-null   int32
 15  Electrical     1094 non-null   int32
 16  GarageType     1094 non-null   int32
 17  SaleType       1094 non-null   int32
 18  SaleCondition  1094 non-null   int32
dtypes: int32(19)
memory usage: 122.0 KB
```

In [175…
```
final_train_data = concat([train_non_obj2,train_obj2],axis=1)
```

In [176…
```
final_train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1094 entries, 0 to 1459
Data columns (total 65 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   MSSubClass     1094 non-null   int64
 1   LotFrontage    1094 non-null   float64
 2   LotArea        1094 non-null   int64
 3   OverallQual    1094 non-null   int64
 4   OverallCond    1094 non-null   int64
 5   YearBuilt      1094 non-null   int64
 6   YearRemodAdd   1094 non-null   int64
 7   MasVnrArea     1094 non-null   float64
 8   BsmtFinSF1     1094 non-null   int64
 9   BsmtUnfSF      1094 non-null   int64
 10  TotalBsmtSF    1094 non-null   int64
 11  1stFlrSF       1094 non-null   int64
 12  2ndFlrSF       1094 non-null   int64
 13  GrLivArea      1094 non-null   int64
 14  BsmtFullBath   1094 non-null   int64
 15  FullBath       1094 non-null   int64
 16  HalfBath       1094 non-null   int64
 17  BedroomAbvGr   1094 non-null   int64
 18  KitchenAbvGr   1094 non-null   int64
 19  TotRmsAbvGrd   1094 non-null   int64
 20  GarageYrBlt    1094 non-null   float64
 21  GarageCars     1094 non-null   int64
 22  GarageArea     1094 non-null   int64
 23  WoodDeckSF     1094 non-null   float64
 24  OpenPorchSF    1094 non-null   float64
 25  MoSold         1094 non-null   int64
 26  YrSold         1094 non-null   int64
 27  SalePrice      1094 non-null   int64
 28  LotShape       1094 non-null   int64
 29  LandContour    1094 non-null   int64
 30  LotConfig      1094 non-null   int64
 31  LandSlope      1094 non-null   int64
 32  ExterQual      1094 non-null   int64
 33  ExterCond      1094 non-null   int64
 34  BsmtQual       1094 non-null   int64
 35  BsmtCond       1094 non-null   int64
 36  BsmtExposure   1094 non-null   int64
 37  BsmtFinType1   1094 non-null   int64
 38  BsmtFinType2   1094 non-null   int64
 39  HeatingQC      1094 non-null   int64
 40  KitchenQual    1094 non-null   int64
 41  Functional     1094 non-null   int64
 42  GarageFinish   1094 non-null   int64
 43  GarageQual     1094 non-null   int64
 44  GarageCond     1094 non-null   int64
 45  PavedDrive     1094 non-null   int64
 46  MSZoning       1094 non-null   int32
 47  Street         1094 non-null   int32
 48  Utilities      1094 non-null   int32
 49  Neighborhood   1094 non-null   int32
 50  Condition1     1094 non-null   int32
 51  Condition2     1094 non-null   int32
 52  BldgType       1094 non-null   int32
 53  HouseStyle     1094 non-null   int32
 54  RoofStyle      1094 non-null   int32
 55  RoofMatl       1094 non-null   int32
 56  Exterior1st    1094 non-null   int32
 57  Exterior2nd    1094 non-null   int32
 58  Foundation     1094 non-null   int32
 59  Heating        1094 non-null   int32
 60  CentralAir     1094 non-null   int32
 61  Electrical     1094 non-null   int32
 62  GarageType     1094 non-null   int32
 63  SaleType       1094 non-null   int32
 64  SaleCondition  1094 non-null   int32
dtypes: float64(5), int32(19), int64(41)
memory usage: 515.2 KB
```

In [177…
```
final_train_data.shape
```

Out[177… (1094, 65)

In [178…
```
final_train_data['LotShape'].value_counts()
```

Out[178…
```
LotShape
1    760
2    301
3     26
4      7
Name: count, dtype: int64
```

In [179…
```
final_train_data['KitchenQual'].value_counts()
```

Out[179…
```
KitchenQual
2    528
3    454
4     91
1     21
Name: count, dtype: int64
```

Spliting Data to train data and test data

In [180…
```
X= final_train_data.drop(['SalePrice'],axis=1)
y= final_train_data['SalePrice']

x_train,x_test,y_train,y_test=train_test_split(X,y,train_size=0.8,random_state=1234)
```

In [181…
```
print(x_train.shape, x_test.shape)
print(y_train.shape, y_test.shape)
```

```
(875, 64) (219, 64)
(875,) (219,)
```

Creating Model

In [182…
```
r_2=[]
mse =[]
rmse=[]
mae=[]

def reg(model):
    model.fit(x_train,y_train)
    pred = model.predict(x_test)

    R2 = r2_score(y_test,pred)
    MSE = mean_squared_error(y_test,pred)
    RMSE = sqrt(mean_squared_error(y_test,pred))
    MAE = mean_absolute_error(y_test,pred)

    r_2.append(R2)
    mse.append(MSE)
    rmse.append(RMSE)
    mae.append(MAE)
```

In [183…
```
Ridge_model = Ridge()
LinearRegression_model = LinearRegression()
XGBRegressor_model = XGBRegressor()
```

In [184…
```
Algorithms = ['LinearRegression','Ridge','XGBRegressor']
```

In [185…
```
reg(LinearRegression_model)
reg(Ridge_model)
reg(XGBRegressor_model)
```

In [186…
```
result = DataFrame({'Algorithms':Algorithms,'R2':r_2,'mse':mse,'rmse':rmse,'mae':mae})
result
```

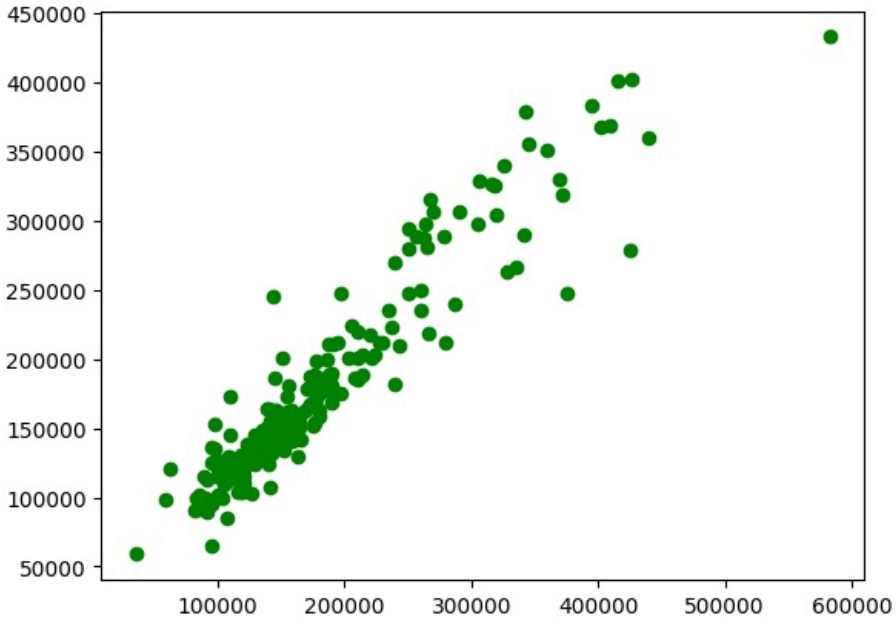
Out[186…

	Algorithms	R2	mse	rmse	mae
0	LinearRegression	0.847332	1.072496e+09	32748.978489	22774.849468
1	Ridge	0.847083	1.074246e+09	32775.698097	22739.600975
2	XGBRegressor	0.884478	8.115416e+08	28487.568657	18410.429688

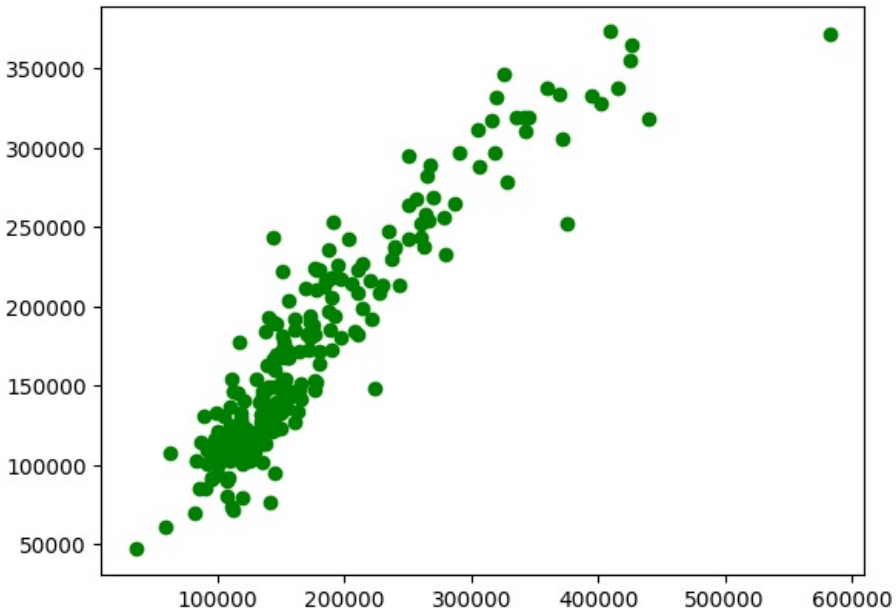
Comparison of Algorithms:

- **XGBRegressor stands out as the best-performing algorithm among the three**:
- It has the highest R2 value (0.88448), indicating that it explains a significantly larger proportion of the variance in the target variable compared to Linear Regression and Ridge.
- It has the lowest mse (811,541,568.0), rmse (28,487.57), and mae (18,410.43), which means its predictions have the smallest average errors.
- **Linear Regression and Ridge perform very similarly:**
- Their R2 values are almost identical (around 0.847).
- Their mse, rmse, and mae values are also very close, indicating similar levels of prediction error. Ridge's mae is slightly lower than Linear Regression's, but the difference is minimal.

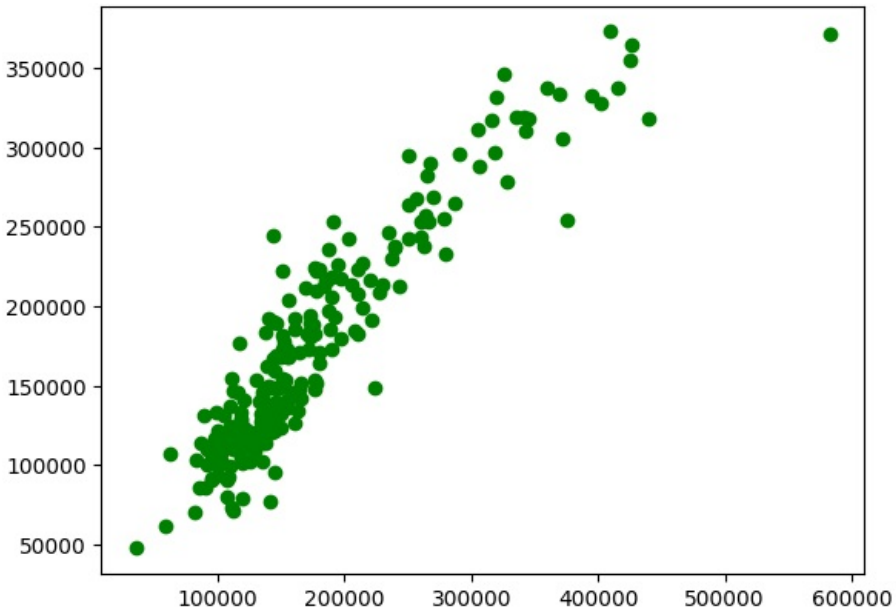
In [187…
```
XGBRegressor_model.fit(x_train,y_train)
pred = XGBRegressor_model.predict(x_test)
scatter(y_test, pred, color='g')
show()
```



In [188…
```
Ridge_model.fit(x_train,y_train)
pred = Ridge_model.predict(x_test)
scatter(y_test, pred, color='g')
show()
```



In [189…
```
LinearRegression_model.fit(x_train,y_train)
pred = LinearRegression_model.predict(x_test)
scatter(y_test, pred, color='g')
show()
```



In [190…
```
# with open('XGBRegressor_model' , 'wb') as f :
#     dump(XGBRegressor_model, f)
```

Conclusion

Based on these evaluation metrics, the XGBRegressor is the superior model for this regression task. It demonstrates significantly better predictive power by explaining more variance and achieving lower error rates compared to both Linear Regression and Ridge. This suggests that the underlying data might have non-linear relationships that XGBRegressor is better equipped to capture.

In [2]:
```
!jupyter nbconvert --to html "House Price prediction.ipynb"
```

```
[NbConvertApp] Converting notebook House Price prediction.ipynb to html
[NbConvertApp] WARNING | Alternative text is missing on 55 image(s).
[NbConvertApp] Writing 4164115 bytes to House Price prediction.html
```