# HOUSING PRICE PREDICTION

**Submitted by:**
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## ACKNOWLEDGMENT

I would like to thank Flip Robo Technologies for providing me with the opportunity to work on this project from which I have learned a lot.

Some of the reference sources are as follows:

- Internet
- Coding Ninjas
- Medium.com
- Analytics Vidhya  Stack Overflow

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## INTRODUCTION

- ### Business Problem Framing

This is a real estate problem where a US based housing company named Surprise Housing has decided to invest in Australian Market. Their agenda is to buy houses in Australia at prices below their actual value in the market and sell them at high prices to gain profit. To do this this company uses data analytics to decide in which property they must invest.
Company has collected the data of previously sold houses in Australia and with the help of this data they want to know to the value of prospective properties to decide whether it will suitable to invest in the properties or not.
To know the value of Properties Company has provided data to us to do data analysis and to extract the information of attributes which are important to predict the price of the houses. They want a machine learning model which can predict the price of houses and also the significance of each important attribute in house prediction i.e., how and to what intensity each variable impacts the price of the house.

- ### Conceptual Background of the Domain Problem

In real estate the value of property usually increases with time as seen in many countries. One of the causes for this is due to rising population.
The value of property also depends on the proximity of the property, its size its neighbourhood and audience for which the property is subjected to be sold. For example if audience is mainly concerned of commercial purpose. Then the property which is located in densely populated area will

be sold very fast and at high prices compared to the one located at remote place. Similarly if audience is concerned only on living place then property with less dense area having large area with all services will be sold at higher prices.

The company is looking at prospective properties to buy houses to enter the market. We are required to build a model using Machine Learning in order to predict the actual value of the prospective properties and decide whether to invest in them or not.

- ## Review of Literature

Houses are one of the necessary needs of each and every person around the globe and therefore housing and real estate market is one of the markets which is one of the major contributors in the world's economy. A US-based housing company named Surprise Housing has decided to enter the Australian market. The company uses data analytics to purchase houses at a price below their actual values and flip them at a higher price. We are required to build a model using Machine Learning in order to predict the actual value of the prospective properties and decide whether to invest in them or not.

With its great weather, cosmopolitan cities, diverse natural landscapes and relaxed lifestyle, it's no wonder that Australia remains a top pick for expats. Living cost in Australia for one person: $2,835 per month. Average living expenses for a couple: $4,118 per month. Average monthly living expenses for a family of 4: $5,378. Australia currently has the 16th highest cost of living in the world, with the USA and UK well behind at 21st and 33rd place respectively. Sydney and Melbourne are popular choices for expats moving to Australia. House pricing in some of the top Australian cities:-

Sydney - median house price A$1,142,212
Adelaide- median house price A$542,947
Hobbart (smaller city)- median house price A$530,570.

- ## Motivation for the Problem Undertaken

To understand real world problems where Machine Learning and Data Analysis can be applied to help organizations in various domains to make better decisions with the help of which they can gain profit or can be escaped from any loss which otherwise could be possible without the study of data .One of such domain is Real Estate.

Houses are one of the necessary need of each and every person around the globe and therefore housing and real estate market is one of the markets which is one of the major contributors in the world's economy. It is a very large market and there are various companies working in the domain. Data science comes as a very important tool to solve problems in the domain to help the companies increase their overall revenue, profits, improving their marketing strategies and focusing on changing trends in house sales and purchases. Predictive modelling, Market mix modelling, recommendation systems are some of the machine learning techniques used for achieving the business goals for housing companies. Our problem is related to one such housing company.

## Analytical Problem Framing

- **Mathematical/ Analytical Modeling of the Problem**

  In this project we have performed various mathematical and statistical analysis such as we checked description or statistical summary of the data using describe, checked correlation using corr and also visualized it using heatmap. Then we have used Z-Score to plot outliers and remove them.

In [18]:
```
# let's check the statistical summary of our dataset

housing_train.describe()
```

Out[18]:

| | Id | MSSubClass | LotFrontage | LotArea | OverallQual | OverallCond | YearBuilt | YearRemodAdd | MasVnrArea | BsmtFinSF1 | BsmtFinSF2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| count | 1168.000000 | 1168.000000 | 1168.000000 | 1168.000000 | 1168.000000 | 1168.000000 | 1168.000000 | 1168.000000 | 1168.000000 | 1168.000000 | 1168.000000 |
| mean | 724.136130 | 56.767979 | 70.807363 | 10484.749144 | 6.104452 | 5.595890 | 1970.930651 | 1984.758562 | 101.696918 | 444.726027 | 46.647260 |
| std | 416.159877 | 41.940650 | 22.440317 | 8957.442311 | 1.390153 | 1.124343 | 30.145255 | 20.785185 | 182.218483 | 462.664785 | 163.520016 |
| min | 1.000000 | 20.000000 | 21.000000 | 1300.000000 | 1.000000 | 1.000000 | 1875.000000 | 1950.000000 | 0.000000 | 0.000000 | 0.000000 |
| 25% | 360.500000 | 20.000000 | 60.000000 | 7621.500000 | 5.000000 | 5.000000 | 1954.000000 | 1966.000000 | 0.000000 | 0.000000 | 0.000000 |
| 50% | 714.500000 | 50.000000 | 70.000000 | 9522.500000 | 6.000000 | 5.000000 | 1972.000000 | 1993.000000 | 0.000000 | 385.500000 | 0.000000 |
| 75% | 1079.500000 | 70.000000 | 79.250000 | 11515.500000 | 7.000000 | 6.000000 | 2000.000000 | 2004.000000 | 160.000000 | 714.500000 | 0.000000 |
| max | 1460.000000 | 190.000000 | 313.000000 | 164660.000000 | 10.000000 | 9.000000 | 2010.000000 | 2010.000000 | 1600.000000 | 5644.000000 | 1474.000000 |

From this statistical analysis we make some of the interpretations that,

- Maximum standard deviation of 8957.44 is observed in LotArea column.
- Maximum Sale Price of a house observed is 755000 and minimum is 34900.
- In the columns Id, MS Subclass, LotArea, MasVnrArea, BsmtFinSF1, BsmtFinSF2, BsmtunfsF, TotalBsmtSF, 1stFlrSF, 2ndFlrSF, LowQualFinSF, GrLivArea, BsmtFullBath, HalfBath, TotRms Abv Grd , Wood Deck SF, OpenPorchSF, EnclosedPorch, 3SsnPorch, Screen Porch, Pool Area, Miscval, salePrice mean is considerably greater than median so the columns are positively skewed.
- In the columns FullBath, BedroomAbvGr, Fireplaces, Garagecars, GarageArea, YrSold Median is greater than mean so the columns are negatively skewed.
- In the columns Id, MSSubClass, LotFrontage, LotArea, MasVnrArea, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, 1stFlrSF, 2ndFlrSF, LowQualFinSF, GrLivArea, BsmtHalfBath, BedroomAbvGr, ToRmsAbvGrd, GarageArea, WoodDeckSF, OpenPorchSF, EnclosedPorch, 3SsnPorch, ScreenPorch, PoolArea, MiscVal, SalePrice there is considerable difference between the 75 percentile and maximum so outliers are present.

- **Data Sources and their formats**

The variable features of this problem statement are as :

MSSubClass: Identifies the type of dwelling involved in the sale

MSZoning: Identifies the general zoning classification of the sale

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access to property

Alley: Type of alley access to property

LotShape: General shape of property

LandContour: Flatness of the property

Utilities: Type of utilities available

LotConfig: Lot configuration

LandSlope: Slope of property

Neighborhood: Physical locations within Ames city limits

Condition1: Proximity to various conditions

Condition2: Proximity to various conditions (if more than one is present)

BldgType: Type of dwelling

HouseStyle: Style of dwelling

OverallQual: Rates the overall material and finish of the house

OverallCond: Rates the overall condition of the house

YearBuilt: Original construction date

YearRemodAdd: Remodel date (same as construction date if no remodeling or additions)

RoofStyle: Type of roof

RoofMatl: Roof material

Exterior1st: Exterior covering on house

Exterior2nd: Exterior covering on house (if more than one material)

MasVnrType: Masonry veneer type

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

ExterCond: Evaluates the present condition of the material on the exterior

Foundation: Type of foundation

BsmtQual: Evaluates the height of the basement

BsmtCond: Evaluates the general condition of the basement

BsmtExposure: Refers to walkout or garden level walls

BsmtFinType1: Rating of basement finished area

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Rating of basement finished area (if multiple types)

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

HeatingQC: Heating quality and condition

CentralAir: Central air conditioning

Electrical: Electrical system

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

Bedroom: Bedrooms above grade (does NOT include basement bedrooms)

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality (Assume typical unless deductions are warranted) Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

GarageType: Garage location

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

GarageCond: Garage condition

PavedDrive: Paved driveway

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

Fence: Fence quality

MiscFeature: Miscellaneous feature not covered in other categories

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

SaleCondition: Condition of sale

In [7]:
```
# Let's check the information of our dataset

housing_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1168 entries, 0 to 1167
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1168 non-null   int64
 1   MSSubClass     1168 non-null   int64
 2   MSZoning       1168 non-null   object
 3   LotFrontage    954 non-null    float64
 4   LotArea        1168 non-null   int64
 5   Street         1168 non-null   object
 6   Alley          77 non-null     object
 7   LotShape       1168 non-null   object
 8   LandContour    1168 non-null   object
 9   Utilities      1168 non-null   object
 10  LotConfig      1168 non-null   object
 11  LandSlope      1168 non-null   object
 12  Neighborhood   1168 non-null   object
 13  Condition1     1168 non-null   object
 14  Condition2     1168 non-null   object
 15  BldgType       1168 non-null   object
 16  HouseStyle     1168 non-null   object
 17  OverallQual    1168 non-null   int64
 18  OverallCond    1168 non-null   int64
 19  YearBuilt      1168 non-null   int64
 20  YearRemodAdd   1168 non-null   int64

 21  RoofStyle      1168 non-null   object
 22  RoofMatl       1168 non-null   object
 23  Exterior1st    1168 non-null   object
 24  Exterior2nd    1168 non-null   object
 25  MasVnrType     1161 non-null   object
 26  MasVnrArea     1161 non-null   float64
 27  ExterQual      1168 non-null   object
 28  ExterCond      1168 non-null   object
 29  Foundation     1168 non-null   object
 30  BsmtQual       1138 non-null   object
 31  BsmtCond       1138 non-null   object
 32  BsmtExposure   1137 non-null   object
 33  BsmtFinType1   1138 non-null   object
 34  BsmtFinSF1     1168 non-null   int64
 35  BsmtFinType2   1137 non-null   object
 36  BsmtFinSF2     1168 non-null   int64
 37  BsmtUnfSF      1168 non-null   int64
 38  TotalBsmtSF    1168 non-null   int64
 39  Heating        1168 non-null   object
 40  HeatingQC      1168 non-null   object
 41  CentralAir     1168 non-null   object
 42  Electrical     1168 non-null   object
 43  1stFlrSF       1168 non-null   int64
 44  2ndFlrSF       1168 non-null   int64
 45  LowQualFinSF   1168 non-null   int64
 46  GrLivArea      1168 non-null   int64
 47  BsmtFullBath   1168 non-null   int64
 48  BsmtHalfBath   1168 non-null   int64
 49  FullBath       1168 non-null   int64
 50  HalfBath       1168 non-null   int64
```

```
 51   BedroomAbvGr   1168 non-null   int64
 52   KitchenAbvGr   1168 non-null   int64
 53   KitchenQual    1168 non-null   object
 54   TotRmsAbvGrd   1168 non-null   int64
 55   Functional     1168 non-null   object
 56   Fireplaces     1168 non-null   int64
 57   FireplaceQu    617 non-null    object
 58   GarageType     1104 non-null   object
 59   GarageYrBlt    1104 non-null   float64
 60   GarageFinish   1104 non-null   object
 61   GarageCars     1168 non-null   int64
 62   GarageArea     1168 non-null   int64
 63   GarageQual     1104 non-null   object
 64   GarageCond     1104 non-null   object
 65   PavedDrive     1168 non-null   object
 66   WoodDeckSF     1168 non-null   int64
 67   OpenPorchSF    1168 non-null   int64
 68   EnclosedPorch  1168 non-null   int64
 69   3SsnPorch      1168 non-null   int64
 70   ScreenPorch    1168 non-null   int64
 71   PoolArea       1168 non-null   int64
 72   PoolQC         7 non-null      object
 73   Fence          237 non-null    object
 74   MiscFeature    44 non-null     object
 75   MiscVal        1168 non-null   int64
 76   MoSold         1168 non-null   int64
 77   YrSold         1168 non-null   int64
 78   SaleType       1168 non-null   object
 79   SaleCondition  1168 non-null   object
 80   SalePrice      1168 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 739.2+ KB
```

In [6]:
```
# Let's check the data types of our columns

housing_train.dtypes
```

Out[6]:
```
Id                 int64
MSSubClass         int64
MSZoning          object
LotFrontage      float64
LotArea            int64
                  ...
MoSold             int64
YrSold             int64
SaleType          object
SaleCondition     object
SalePrice          int64
Length: 81, dtype: object
```

- **Data Pre-processing Done**

  After loading all the required libraries we loaded the data into our jupyter notebook.

In [1]:
```python
# Let's import all the required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
pd.pandas.set_option('display.max_columns',None)

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from scipy import stats

from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression,Lasso,Ridge,Elastic
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor

from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV,cross_val_score
from sklearn.model_selection import GridSearchCV
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV,cross_val_score
from sklearn.model_selection import GridSearchCV

#importing warnings
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
# Let's load our dataset

housing_train=pd.read_csv("train.csv")
housing_train
```

Out[3]:

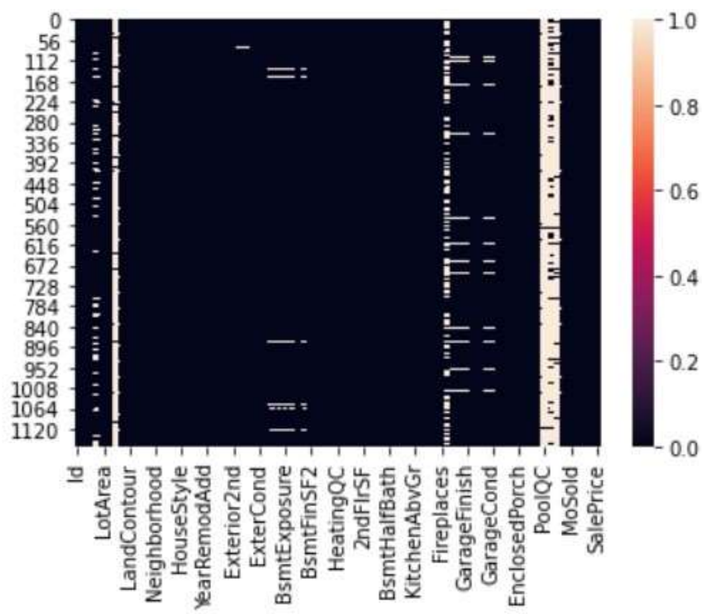
| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape |
|---|---|---|---|---|---|---|---|---|
| 0 | 127 | 120 | RL | NaN | 4928 | Pave | NaN | IR1 |
| 1 | 889 | 20 | RL | 95.0 | 15865 | Pave | NaN | IR1 |
| 2 | 793 | 60 | RL | 92.0 | 9920 | Pave | NaN | IR1 |
| 3 | 110 | 20 | RL | 105.0 | 11751 | Pave | NaN | IR1 |
| 4 | 422 | 20 | RL | NaN | 16635 | Pave | NaN | IR1 |

Feature Engineering has been used for cleaning of the data. Some unused columns have been deleted and even some columns have been bifurcated which was used in the prediction. We first done data cleaning. We first looked percentage of values missing in columns then we imputed missing values.

```
In [10]: # Let's check the missing values of top 30 columns

         housing_train.isnull().sum().sort_values(ascending = False).head(30)
```

```
Out[10]: PoolQC          1161
         MiscFeature     1124
         Alley           1091
         Fence            931
         FireplaceQu      551
         LotFrontage      214
         GarageType        64
         GarageCond        64
         GarageYrBlt       64
         GarageFinish      64
         GarageQual        64
         BsmtExposure      31
         BsmtFinType2      31
         BsmtFinType1      30
         BsmtCond          30
         BsmtQual          30
         MasVnrArea         7
         MasVnrType         7
         Exterior2nd        0
         Exterior1st        0
         OverallCond        0
         ExterQual          0
         ExterCond          0
         Foundation         0
         RoofMatl           0
```

```
In [12]: # Let's plot the heat map for our missing values

         sns.heatmap(housing_train.isnull());
```



In [13]:
```
# Let's check the percentage of missing values of each column

def missing_values_table(housing_train):
    mis_val = housing_train.isnull().sum()
    mis_val_percent = 100 * housing_train.isnull().sum() / len(housing_train)
    mis_val_table = pd.concat([mis_val, mis_val_percent], axis=1)
    mis_val_table_ren_columns = mis_val_table.rename(
    columns = {0 : 'Missing Values', 1 : '% of Total Values'})
    mis_val_table_ren_columns = mis_val_table_ren_columns[
        mis_val_table_ren_columns.iloc[:,1] != 0].sort_values(
    '% of Total Values', ascending=False).round(1)
    print ("Your selected dataframe has " + str(housing_train.shape[1]) + " columns.\n"
        "There are " + str(mis_val_table_ren_columns.shape[0]) +
            " columns that have missing values.")
    return mis_val_table_ren_columns
missing_values_table(housing_train)
```

```
Your selected dataframe has 81 columns.
There are 18 columns that have missing values.
```

Out[13]:

| | Missing Values | % of Total Values |
|---|---|---|
| PoolQC | 1161 | 99.4 |
| MiscFeature | 1124 | 96.2 |
| Alley | 1091 | 93.4 |
| Fence | 931 | 79.7 |
| FireplaceQu | 551 | 47.2 |

Out[13]:

| | Missing Values | % of Total Values |
|---|---|---|
| **PoolQC** | 1161 | 99.4 |
| **MiscFeature** | 1124 | 96.2 |
| **Alley** | 1091 | 93.4 |
| **Fence** | 931 | 79.7 |
| **FireplaceQu** | 551 | 47.2 |
| **LotFrontage** | 214 | 18.3 |
| **GarageType** | 64 | 5.5 |
| **GarageYrBlt** | 64 | 5.5 |
| **GarageFinish** | 64 | 5.5 |
| **GarageQual** | 64 | 5.5 |
| **GarageCond** | 64 | 5.5 |
| **BsmtExposure** | 31 | 2.7 |
| **BsmtFinType2** | 31 | 2.7 |
| **BsmtCond** | 30 | 2.6 |
| **BsmtFinType1** | 30 | 2.6 |
| **BsmtQual** | 30 | 2.6 |
| **MasVnrArea** | 7 | 0.6 |
| **MasVnrType** | 7 | 0.6 |

In [14]:
```
# Let's fill the missing values in categorical columns as NA

columns = ["FireplaceQu", "GarageType", "GarageFinish", "GarageQual", "GarageCond", "BsmtExposure", "BsmtFinType2", "BsmtCond", '
housing_train[columns] = housing_train[columns].fillna('NA')
```

In [15]:
```
# Let's fill the missing values in MasVnrType with None

housing_train['MasVnrType'] = housing_train['MasVnrType'].fillna('None')
```

In [16]:
```
# Let's fill the missing values in GarageYrBlt with 0

housing_train['GarageYrBlt'] = housing_train['GarageYrBlt'].fillna('0')
```

In [17]:
```
# Let's Inputing the missing values and replace it with the median

housing_train['LotFrontage'].fillna(housing_train['LotFrontage'].median(),inplace=True)
housing_train['MasVnrArea'].fillna(housing_train['MasVnrArea'].median(),inplace=True)
```

```
In [8]: # Let's explore the categorical columns

for column in housing_train.columns:
    if housing_train[column].dtypes == object:
        print(str(column) + ' : ' + str(housing_train[column].unique(
        print(housing_train[column].value_counts())
        print('\n')
```

```
MSZoning : ['RL' 'RM' 'FV' 'RH' 'C (all)']
RL         928
RM         163
FV          52
RH          16
C (all)      9
Name: MSZoning, dtype: int64


Street : ['Pave' 'Grvl']
Pave    1164
Grvl       4
Name: Street, dtype: int64


Alley : [nan 'Grvl' 'Pave']
Grvl    41
Pave    36
Name: Alley, dtype: int64
```

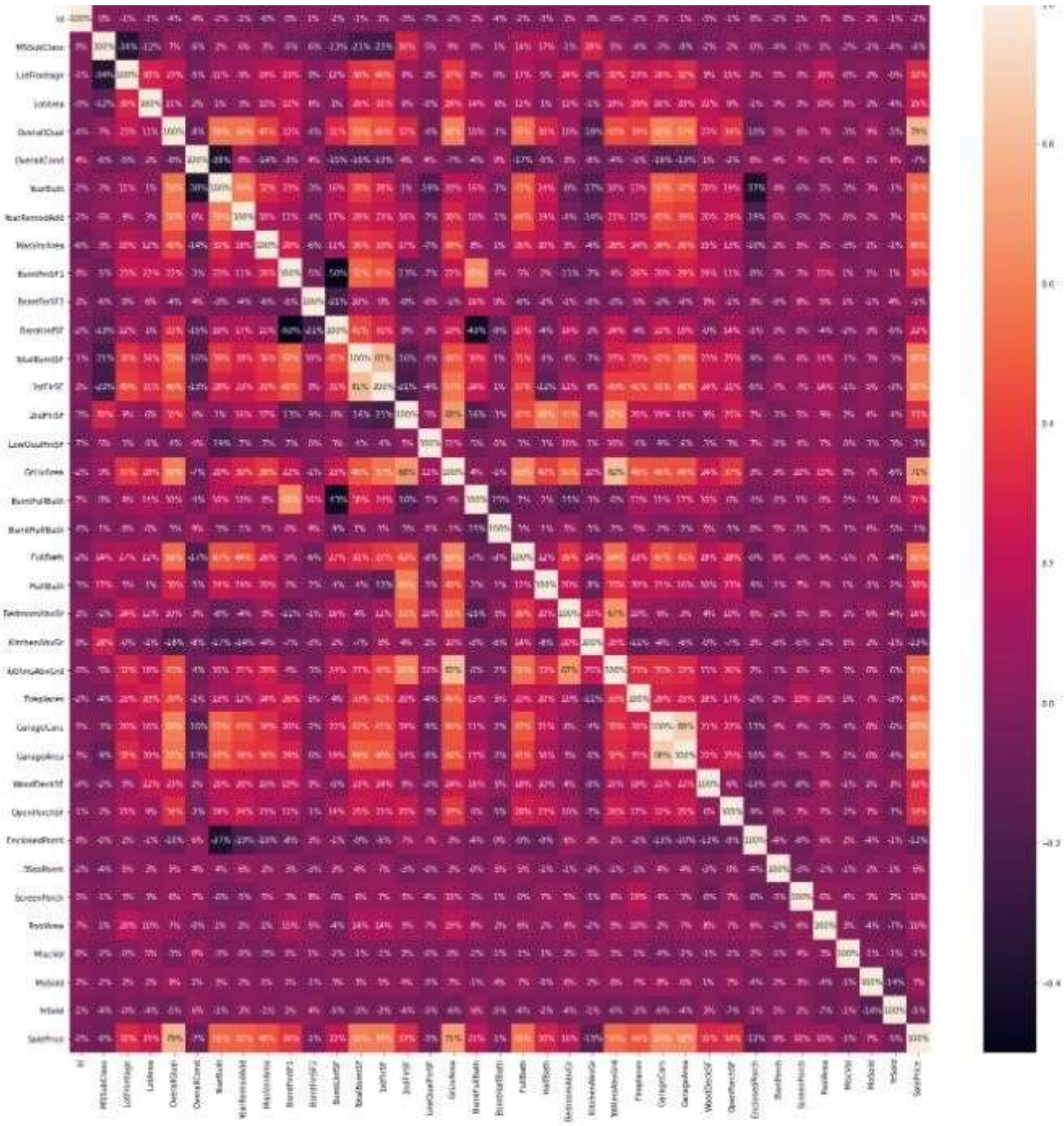
We observed that there is only one unique value present in Utilities so will be dropping this column. Then we encoded all the categorical columns into numerical columns using dummy variables.

```
In [8]: # Let's explore the categorical columns

        for column in housing_train.columns:
            if housing_train[column].dtypes == object:
                print(str(column) + ' : ' + str(housing_train[column].unique(
                print(housing_train[column].value_counts())
                print('\n')
```

```
Name: MSZoning, dtype: int64


Street : ['Pave' 'Grvl']
Pave    1164
Grvl       4
Name: Street, dtype: int64


Alley : [nan 'Grvl' 'Pave']
Grvl    41
Pave    36
Name: Alley, dtype: int64


LotShape : ['IR1' 'Reg' 'IR2' 'IR3']
Reg    740
IR1    390
IR2     32
IR3      6
```

Then we checked the correlation with the help of heatmap.

```
# Let's plot the heat map

plt.figure(figsize=(24,24))
sns.heatmap(housing_train_cor,annot=True,fmt='.0%')
plt.show()
```



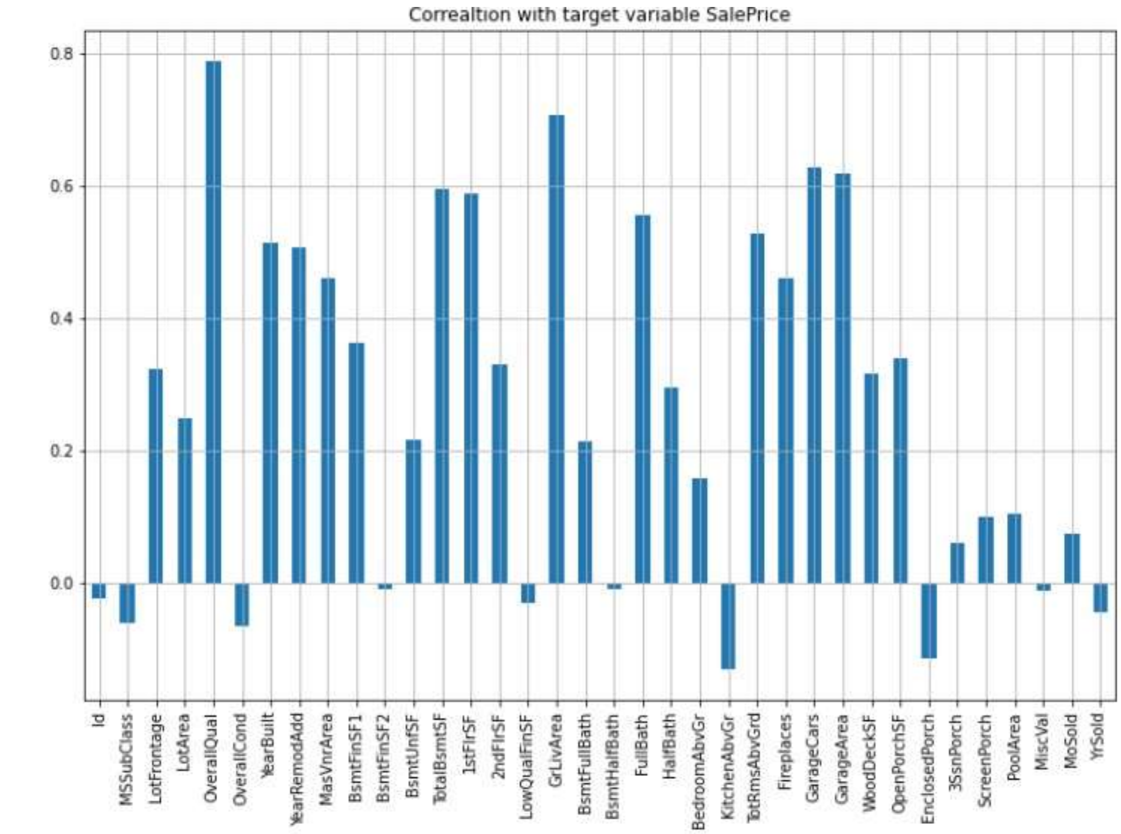
While checking the heatmap of correlation we observed that:

- SalePrice is highly positively correlated with the columns OverallQual, YearBuilt, YearRemodAdd, TotalBsmtSF, 1stFlrSF, GrLivArea, FullBath, TotRmsAbvGrd, GarageCars, GarageArea.
- SalePrice is negatively correlated with Overall Cond, KitchenAbvGr, Encloseporch, YrSold.

- We observe multicollinearity in between columns so we will be using Principal Component Analysis(PCA).
- No correlation has been observed between the column Id and other columns so we will be dropping this column.

- ## **Data Inputs- Logic- Output Relationships**

Here we check the correlation




between all our feature variables with target variable label

```
In [21]: # Let's check the correlation with target variable 'SalePrice'

         plt.figure(figsize=(12,8))
         housing_train.drop('SalePrice', axis=1).corrwith(housing_train['SalePrice']).plot(kind='bar',grid=True)
         plt.xticks(rotation='vertical')
         plt.title("Correaltion with target variable SalePrice");
```

1. The column OverallQual is most positively correlated with SalePrice.

2. The column KitchenAbvGrd is most negatively correlated with SalePrice.

Set of assumptions related to the problem under consideration

By looking into the target variable label we assumed that it was a Regression type of problem.

We observed multicollinearity in between columns so we assumed that we will be using Principal Component Analysis (PCA).

We also observed that only one single unique value was present in Utilities column so we assumed that we will be dropping these columns.

- ## Hardware and Software Requirements and Tools Used

***HARDWARE:*** HP ENVI X360AQ105X

***SOFTWARE:***

Jupyter Notebook (Anaconda 3) – Python 3.7.6

Microsoft package 2013

***LIBRARIES:***

The tools, libraries and packages we used for accomplishing this project are pandas, NumPy, matplotlib, seaborn, SciPy stats, sklearn.decomposition pca, sklearn standardscaler, GridSearchCV, joblib.

```
In [1]: # Let's import all the required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
pd.pandas.set_option('display.max_columns',None)

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from scipy import stats

from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression,Lasso,Ridge,Elastic
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor

from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV,cross_val_score
from sklearn.model_selection import GridSearchCV
```

*From sklearn. preprocessing import StandardScaler*

As these columns are different in scale, they are standardized to have common scale while building machine learning model. This is useful when you want to compare data that correspond to different units.

***from sklearn. preprocessing import Label Encoder***

Label Encoder and One Hot Encoder. These two encoders are parts of the SciKit Learn library in Python, and they are used to convert categorical data, or text data, into numbers, which our predictive models can better understand.

*from sklearn. model selection import train_test_split,cross_val_score*

Train_test_split is a function in Sklearn model selection for splitting data arrays into two subsets: for training data and for testing data. With this function, you don't need to divide the dataset manually. By default, Sklearn train_test_split will make random partitions for the two subsets.

Through pandas library we loaded our csv file 'Data file' into dataframe and performed data manipulation and analysis.

With the help of numpy we worked with arrays.
With the help of matplotlib and seaborn we did plot various graphs and figures and done data visualization.

With scipy stats we treated outliers through winsorization technique.
With sklearn.decomposition's pca package we reduced the number of feature variables from 256 to 100 by plotting scrre plot with their Eigenvalues and chose the number of columns on the basis of their nodes.

With sklearn's standardscaler package we scaled all the feature variables onto single scale.

# MODEL TRAINING

In [64]:
```
housing_train_x=housing_train_cap.drop(columns=['SalePrice'],axis=1)
y=housing_train_cap['SalePrice']
```

In [65]:
```
#Scaling input variables

sc=StandardScaler()
x=sc.fit_transform(housing_train_x)
x=pd.DataFrame(x,columns=housing_train_x.columns)
```

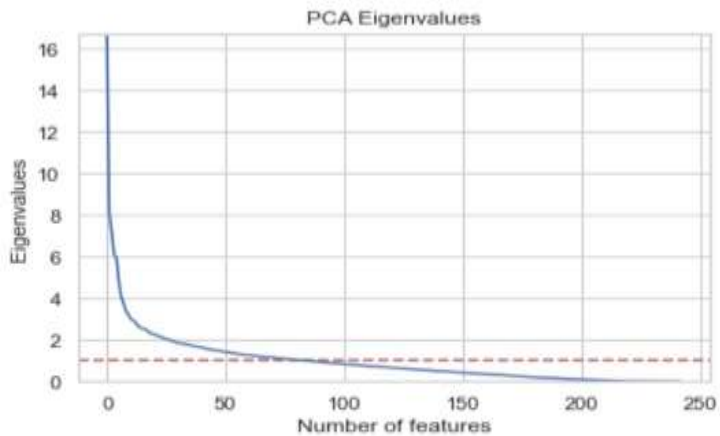
# PCA

In [66]:
```
# Let's explore the PCA

covar_matrix = PCA(n_components = len(x.columns))
covar_matrix.fit(x)
```

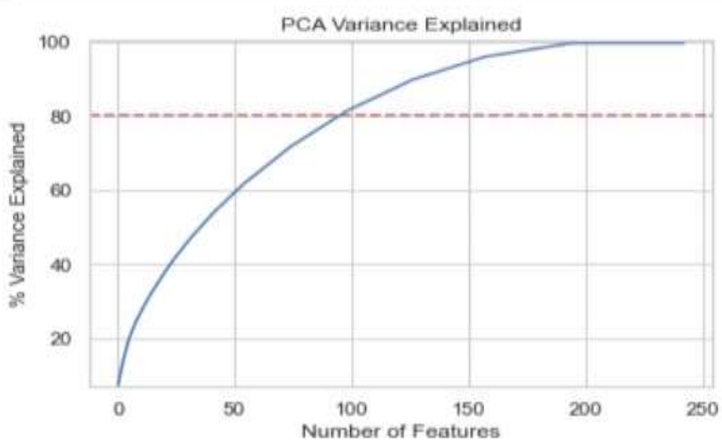
Out[66]: PCA(n_components=243)

In [67]:
```
# Let's plot the PCA componenets

plt.ylabel('Eigenvalues')
plt.xlabel('Number of features')
plt.title('PCA Eigenvalues')
plt.ylim(0,max(covar_matrix.explained_variance_))
plt.style.context('seaborn-whitegrid')
```

In [67]:
```
# Let's plot the PCA componenets

plt.ylabel('Eigenvalues')
plt.xlabel('Number of features')
plt.title('PCA Eigenvalues')
plt.ylim(0,max(covar_matrix.explained_variance_))
plt.style.context('seaborn-whitegrid')
plt.axhline(y=1, color='r', linestyle='--')
plt.plot(covar_matrix.explained_variance_)
plt.show()
```




In [68]:
```
variance = covar_matrix.explained_variance_ratio_
var=np.cumsum(np.round(covar_matrix.explained_variance_ratio_, decima

plt.ylabel('% Variance Explained')
plt.xlabel('Number of Features')
plt.title('PCA Variance Explained')
plt.ylim(min(var),100.5)
plt.style.context('seaborn-whitegrid')
plt.axhline(y=80, color='r', linestyle='--')
plt.plot(var)
plt.show()
```




In [69]:
```
pca=PCA(n_components=90)
xpca=pca.fit_transform(x)
x=xpca
```

In [70]:
```
pd.DataFrame(data=x)
```

Out[70]:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.024209 | -1.896947 | 0.132640 | 0.813270 | -2.206811 | -1.804833 | 1.036208 | 1.1 |

*from sklearn. linear_model import Logistic Regression*

The library sklearn can be used to perform logistic regression in a few lines as shown using the LogisticRegression class. It also supports multiple features. It requires the input values to be in a specific format hence they have been reshaped before training using the fit method.

*from sklearn.tree import DecisionTreeClassifier*

Decision Tree is a white box type of ML algorithm. It shares internal decision-making logic, which is not available in the black box type of algorithms such as Neural Network. Its training time is faster compared to the neural network algorithm. The time complexity of decision trees is a function of the number of records and number of attributes in the given data. The decision tree is a distribution-free or nonparametric method, which does not depend upon probability distribution assumptions. Decision trees can handle high dimensional data with good accuracy.

***from sklearn.ensemble import RandomForestClassifier***

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is controlled with the max_samples parameter if bootstrap=True (default), otherwise the whole dataset is used to build each tree.

Through GridSearchCV we were able to find the right parameters for hyperparameter tuning. Through joblib we saved our model in csv format.

# Model/s Development and Evaluation

- Identification of possible problem-solving approaches (methods)

  We first converted all our categorical variables to numeric variables with the help of dummy variables to checkout and dropped the columns which we felt were unnecessary.

  We observed skewness in data so we tried to remove the skewness through treating outliers with winsorization technique.

  The data was improper scaled so we scaled the feature variables on a single scale using sklearn's StandardScaler package.

  There were too many (256) feature variables in the data so we reduced it to 100 with the help of Principal Component Analysis(PCA) by plotting Eigenvalues and taking the number of nodes as our number of feature variables.

- Testing of Identified Approaches (Algorithms)

The algorithms we used for the training and testing are as follows:-

- Linear Regression
- Lasso
- Ridge
- Elastic Net
- SVR
- KNeighbors Regressor
- Decision Tree Regressor

- Random Forest Regressor
- Ada Boost Regressor
- Gradient Boosting Regressor

```
In [73]: model=[LinearRegression(),
                DecisionTreeRegressor(),
                KNeighborsRegressor(),
                SVR(),
                Lasso(),
                Ridge(),
                ElasticNet(),
                RandomForestRegressor(),
                AdaBoostRegressor(),
                GradientBoostingRegressor()
```

- Run and Evaluate selected models

```
In [73]: model=[LinearRegression(),
                DecisionTreeRegressor(),
                KNeighborsRegressor(),
                SVR(),
                Lasso(),
                Ridge(),
                ElasticNet(),
                RandomForestRegressor(),
                AdaBoostRegressor(),
                GradientBoostingRegressor()
               ]
         for m in model:
             m.fit(x_train,y_train)
             print('score of',m,'is:',m.score(x_train,y_train))
             predm=m.predict(x_test)
             print('Error:')
             print('Mean absolute error:',mean_absolute_error(y_test,predm))
             print('Mean squared error:',mean_squared_error(y_test,predm))
             print('Root Mean Squared Error:',np.sqrt(mean_squared_error(y_tes
             print("r2_score:",r2_score(y_test,predm))
             print('*********************************************************
             print('\n')
```

```
score of LinearRegression() is: 0.8228495368700252
Error:
Mean absolute error: 21805.768654407417
Mean squared error: 1050342129.3284745
Root Mean Squared Error: 32408.982232221897
r2_score: 0.8399373085177295
**************************************************************


score of DecisionTreeRegressor() is: 1.0
Error:
Mean absolute error: 31359.418803418805
Mean squared error: 1874550145.2564104
Root Mean Squared Error: 43296.075402470495
r2_score: 0.7143354215830102
**************************************************************


score of KNeighborsRegressor() is: 0.7907231497562741
Error:
Mean absolute error: 26583.544444444447
Mean squared error: 1539525411.2545302
Root Mean Squared Error: 39236.78645422596
r2_score: 0.7653901771146742
**************************************************************
```

```
score of SVR() is: -0.045684746681192934
Error:
Mean absolute error: 58256.37313723461
Mean squared error: 6883587037.077791
Root Mean Squared Error: 82967.38538171364
r2_score: -0.04899673872128396
**************************************************************


score of Lasso() is: 0.8228495270862598
Error:
Mean absolute error: 21802.83997938824
Mean squared error: 1050198314.0557423
Root Mean Squared Error: 32406.76339987908
r2_score: 0.8399592246715113
**************************************************************


score of Ridge() is: 0.8228494764569273
Error:
Mean absolute error: 21798.74752559169
Mean squared error: 1050034922.0479769
Root Mean Squared Error: 32404.242346457922
r2_score: 0.8399841241435969
**************************************************************
```

```
score of ElasticNet() is: 0.8157053308542571
Error:
Mean absolute error: 20530.56921156668
Mean squared error: 1042532743.7144129
Root Mean Squared Error: 32288.27563860314
```

```
score of GradientBoostingRegressor() is: 0.9723064213023661
Error:
Mean absolute error: 21353.071870540363
Mean squared error: 1004719535.3991446
Root Mean Squared Error: 31697.311169863362
r2_score: 0.8468897814052067
*************************************************************
```

- Key Metrics for success in solving problem under consideration

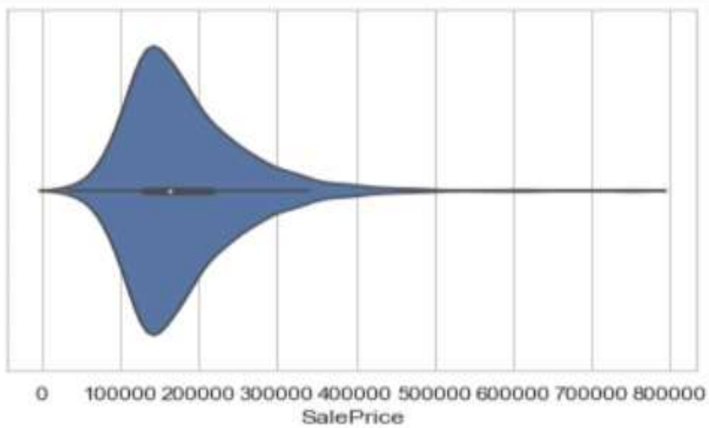
  We used the metric Root Mean Squared Error by selecting the Ridge Regressor model which was giving us best(minimum) RMSE score.

- Visualizations

# Data Visualization

## Univatriate Analysis

In [22]:
```
# Let's Check the target variable

sns.set(style='whitegrid')
sns.violinplot(housing_train['SalePrice'])
plt.show()

housing_train['SalePrice'].value_counts()
```

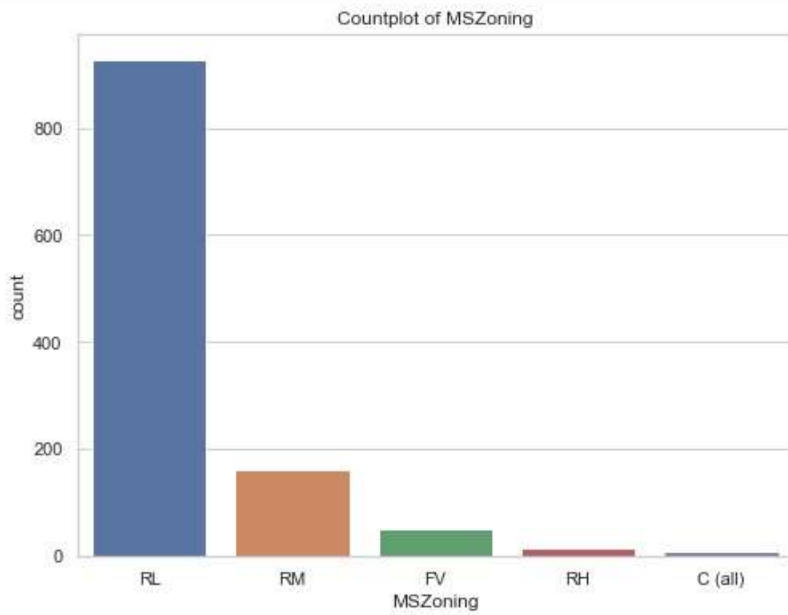



Out[22]:
```
140000    18
135000    16
155000    12
139000    11
160000    11
          ..
126175     1
204000     1
186000     1
369900     1
105500     1
Name: SalePrice, Length: 581, dtype: int64
```

### Observation:

Maximum number of SalePrice lies between 140000 and 230000.

In [23]:
```python
# Let's check the column MsZoning

plt.subplots(figsize=(8,6))
sns.countplot(x="MSZoning", data=housing_train)
plt.title("Countplot of MSZoning")
plt.xlabel('MSZoning')
plt.ylabel("count")
plt.show()

housing_train['MSZoning'].value_counts()
```

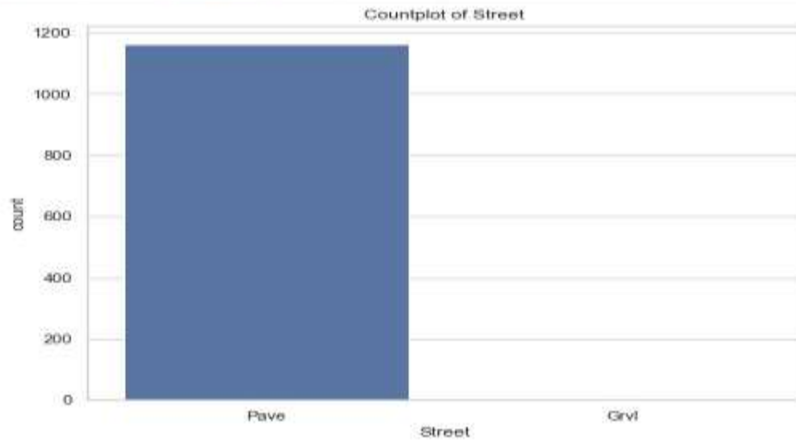



Out[23]:
```
RL         928
RM         163
FV          52
RH          16
C (all)      9
Name: MSZoning, dtype: int64
```

**Observation:**

Maximum, 928 number of MSZoning are RL.

In [24]:
```
# Let's check the column Street

plt.subplots(figsize=(8,6))
sns.countplot(x="Street", data=housing_train)
plt.title("Countplot of Street")
plt.xlabel('Street')
plt.ylabel("count")
plt.show()

housing_train['Street'].value_counts()
```

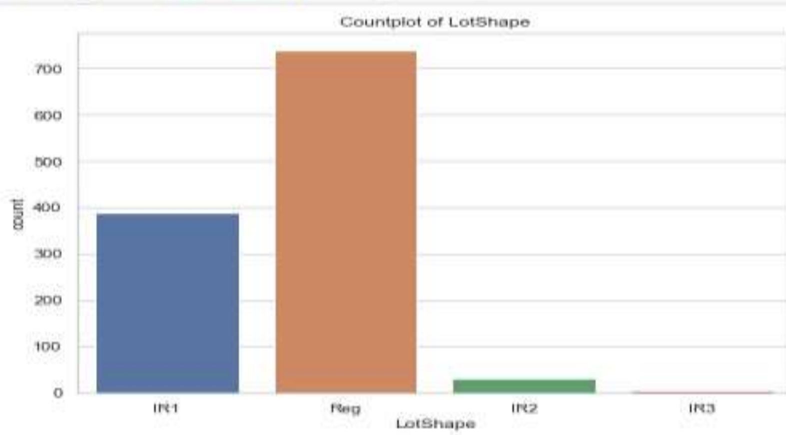



Out[24]:
```
Pave    1164
Grvl       4
Name: Street, dtype: int64
```

**Observation:**

Maximum, 1164 number of Street are Pave where as only 4 are Grvl.

In [25]:
```
# Let's check the column LotShape

plt.subplots(figsize=(8,6))
sns.countplot(x="LotShape", data=housing_train)
plt.title("Countplot of LotShape")
plt.xlabel('LotShape')
plt.ylabel("count")
plt.show()

housing_train['LotShape'].value_counts()
```

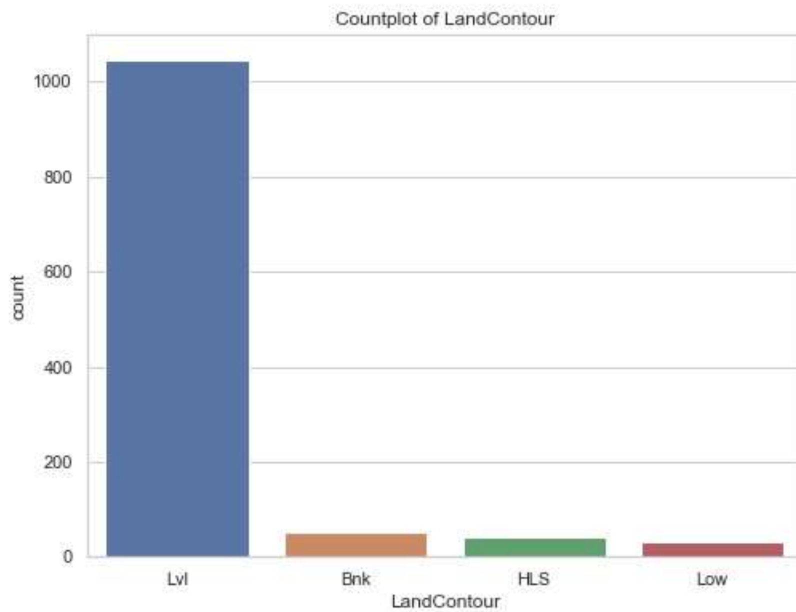



Out[25]:
```
Reg    740
IR1    390
IR2     32
IR3      6
Name: LotShape, dtype: int64
```

**Observation:**

Maximum, 740 number of LotShape are Reg.

In [26]:
```
# Let's check the column LandContour

plt.subplots(figsize=(8,6))
sns.countplot(x="LandContour", data=housing_train)
plt.title("Countplot of LandContour")
plt.xlabel('LandContour')
plt.ylabel("count")
plt.show()

housing_train['LandContour'].value_counts()
```

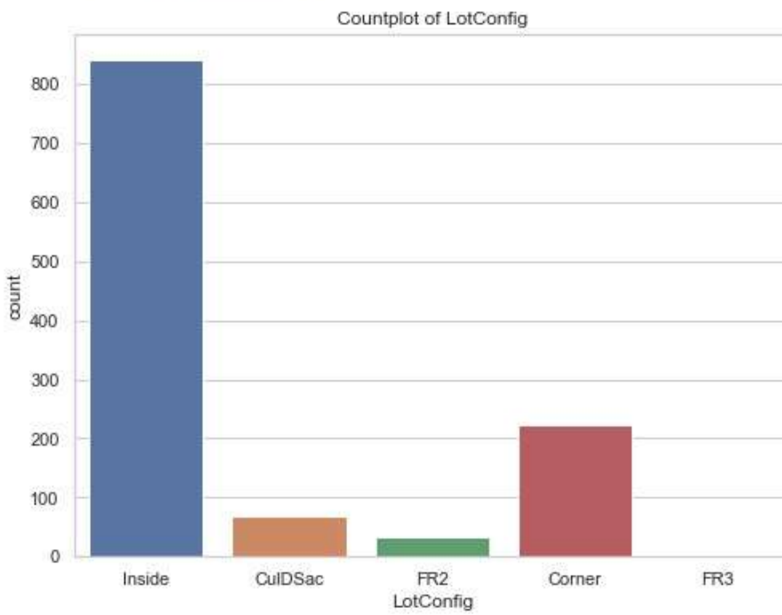



Out[26]:
```
Lvl    1046
Bnk      50
HLS      42
Low      30
Name: LandContour, dtype: int64
```

**Observation:**

Maximum, 1046 number of LandContour are Lvl.

In [27]:
```python
# Let's check the column LotConfig

plt.subplots(figsize=(8,6))
sns.countplot(x="LotConfig", data=housing_train)
plt.title("Countplot of LotConfig")
plt.xlabel('LotConfig')
plt.ylabel("count")
plt.show()

housing_train['LotConfig'].value_counts()
```

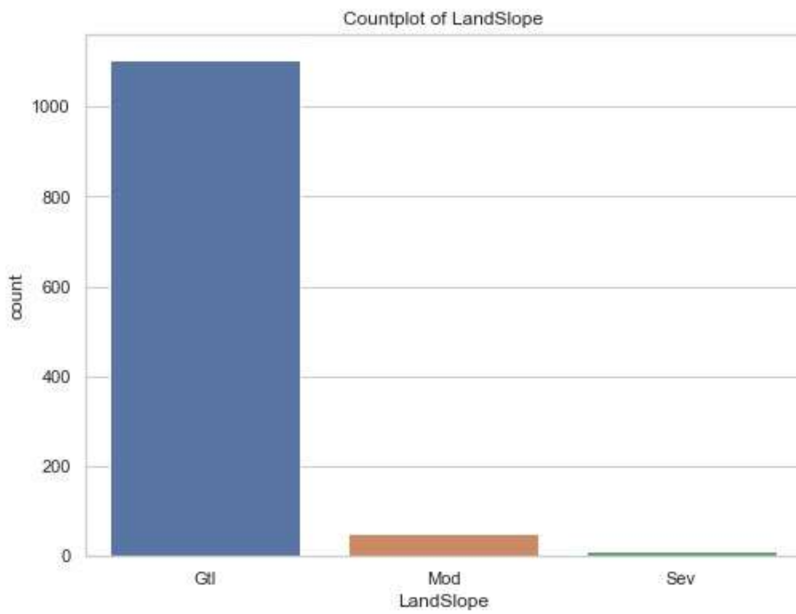



Out[27]:
```
Inside     842
Corner     222
CulDSac     69
FR2         33
FR3          2
Name: LotConfig, dtype: int64
```

**Observation:**

Maximum, 842 number of LotConfig are Inside.

In [28]:
```
# Let's check the column LandSlope

plt.subplots(figsize=(8,6))
sns.countplot(x="LandSlope", data=housing_train)
plt.title("Countplot of LandSlope")
plt.xlabel('LandSlope')
plt.ylabel("count")
plt.show()

housing_train['LandSlope'].value_counts()
```

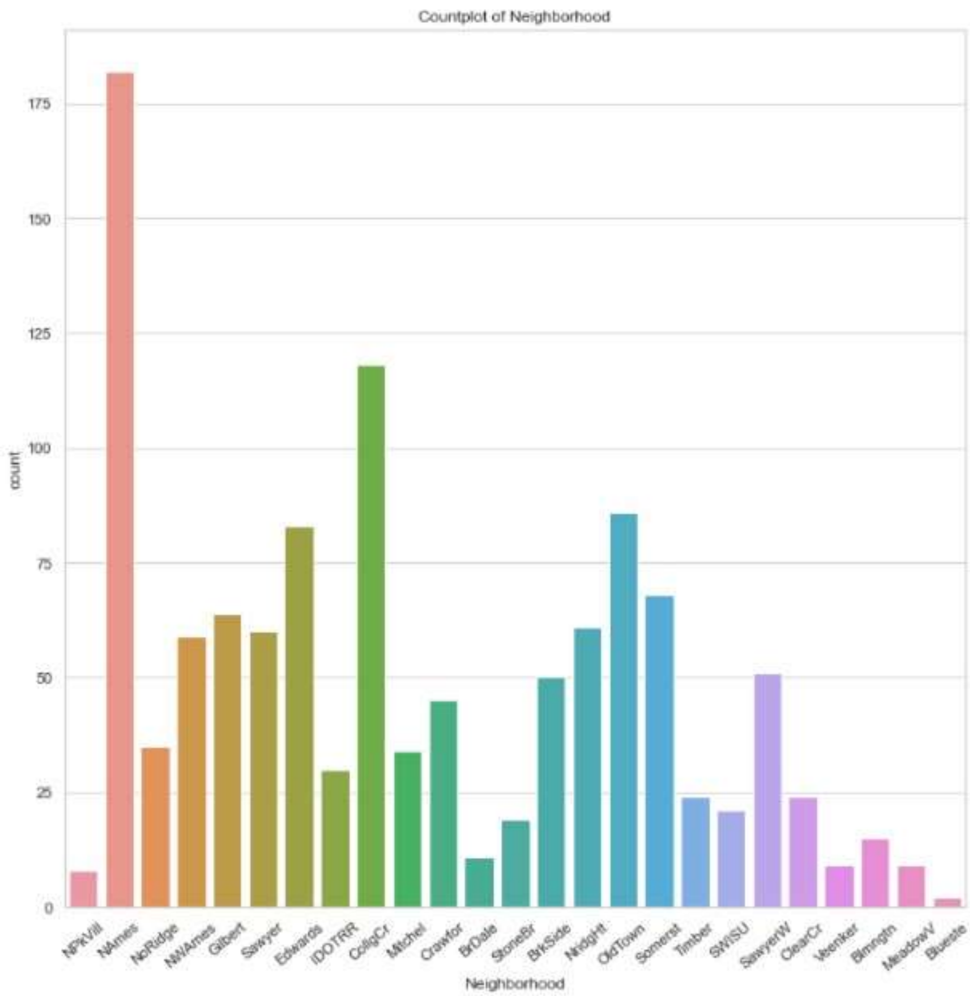



Out[28]:
```
Gtl    1105
Mod      51
Sev      12
Name: LandSlope, dtype: int64
```

**Observation:**

Maximum, 1105 number of LandSlope are Gtl.

In [29]:
```
# Let's check the column Neighborhood

plt.subplots(figsize=(12,12))
sns.countplot(x="Neighborhood", data=housing_train)
plt.title("Countplot of Neighborhood")
plt.xticks(rotation=40)
plt.xlabel('Neighborhood')
plt.ylabel("count")
plt.show()

housing_train['Neighborhood'].value_counts()
```



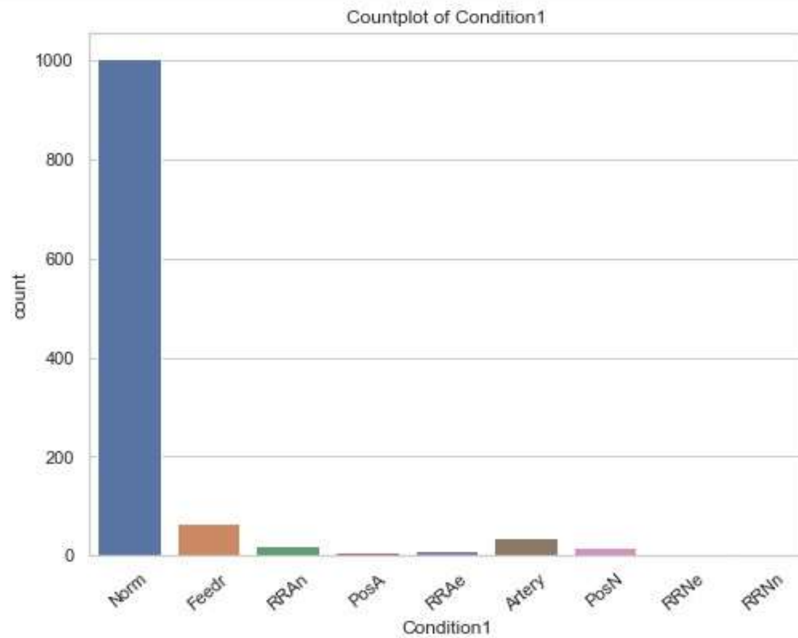

```
29]: NAmes      182
     CollgCr    118
     OldTown     86
     Edwards     83
     Somerst     68
     Gilbert     64
```

**Observation:**

Maximum, 182 number of Neighborhood are Names.

In [30]:

```
# Let's check the column Condition1

plt.subplots(figsize=(8,6))
sns.countplot(x="Condition1", data=housing_train)
plt.title("Countplot of Condition1")
plt.xticks(rotation=40)
plt.xlabel('Condition1')
plt.ylabel("count")
plt.show()

housing_train['Condition1'].value_counts()
```



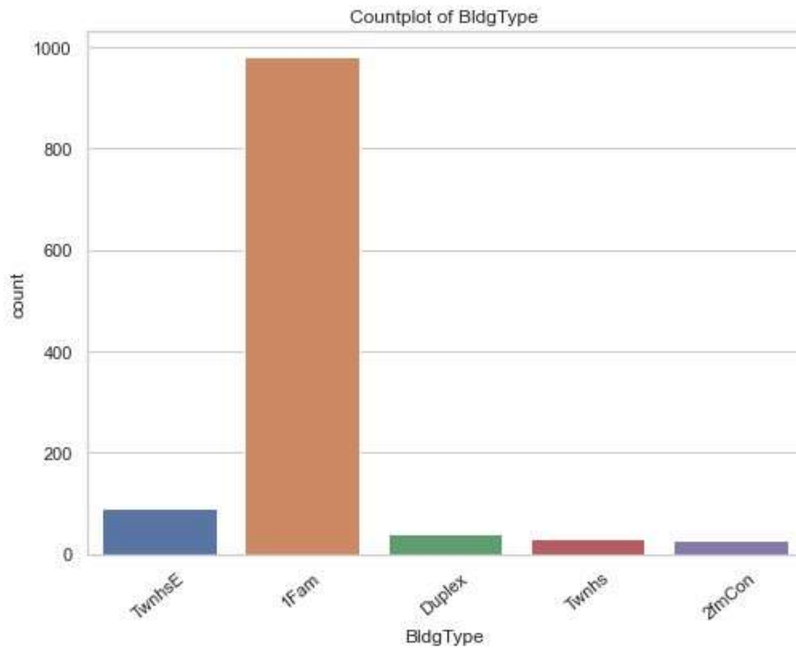

Out[30]:

```
Norm      1005
Feedr       67
Artery      38
RRAn        20
PosN        17
RRAe         9
```

**Observation:**

Maximum, 1005 number of Condition1 is Norm.

In [31]:
```
# Let's check the column BldgType

plt.subplots(figsize=(8,6))
sns.countplot(x="BldgType", data=housing_train)
plt.title("Countplot of BldgType")
plt.xticks(rotation=40)
plt.xlabel('BldgType')
plt.ylabel("count")
plt.show()

housing_train['BldgType'].value_counts()
```

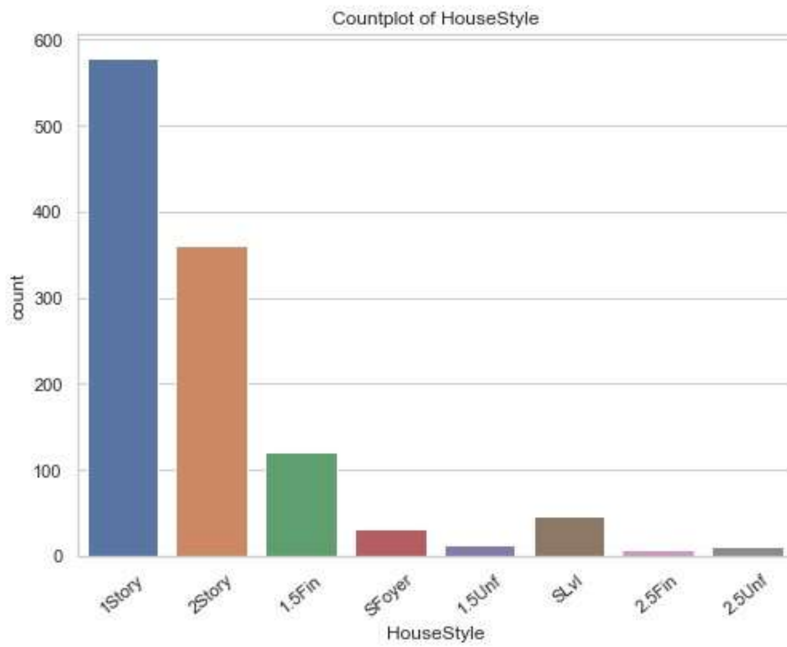



Out[31]:
```
1Fam      981
TwnhsE     90
Duplex     41
Twnhs      29
2fmCon     27
Name: BldgType, dtype: int64
```

**Observation:**

Maximum, 981 number of BldgType are 1Fam.

```
In [32]: # Let's check the column HouseStyle

plt.subplots(figsize=(8,6))
sns.countplot(x="HouseStyle", data=housing_train)
plt.title("Countplot of HouseStyle")
plt.xticks(rotation=40)
plt.xlabel('HouseStyle')
plt.ylabel("count")
plt.show()

housing_train['HouseStyle'].value_counts()
```

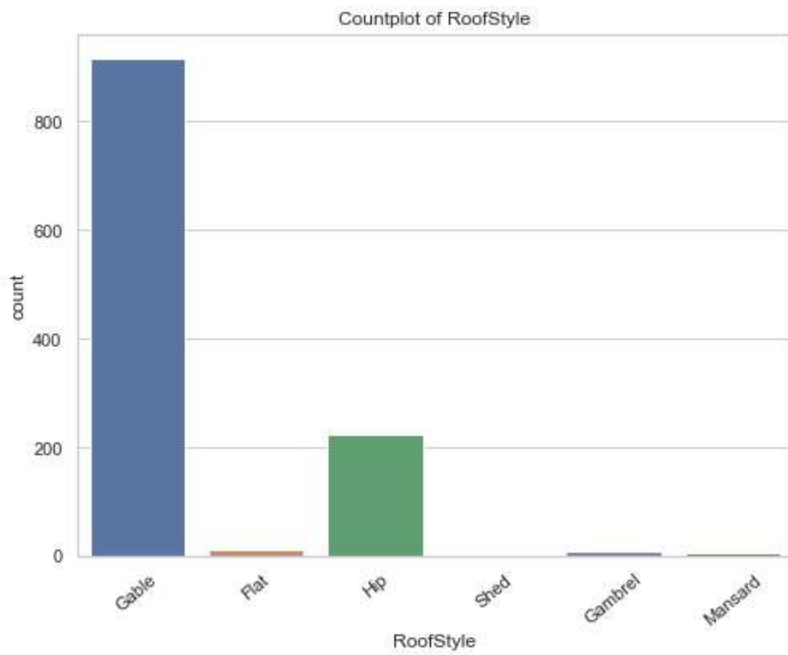



```
Out[32]: 1Story    578
2Story    361
1.5Fin    121
SLvl       47
SFoyer     32
1.5Unf     12
2.5Unf     10
2.5Fin      7
```

**Observation:**

```
1 Story has highest number of count followed by 2Story, 1.5Fin, SlvL etc
```

In [33]:
```
# Let's check the column RoofStyle

plt.subplots(figsize=(8,6))
sns.countplot(x="RoofStyle", data=housing_train)
plt.title("Countplot of RoofStyle")
plt.xticks(rotation=40)
plt.xlabel('RoofStyle')
plt.ylabel("count")
plt.show()

housing_train['RoofStyle'].value_counts()
```

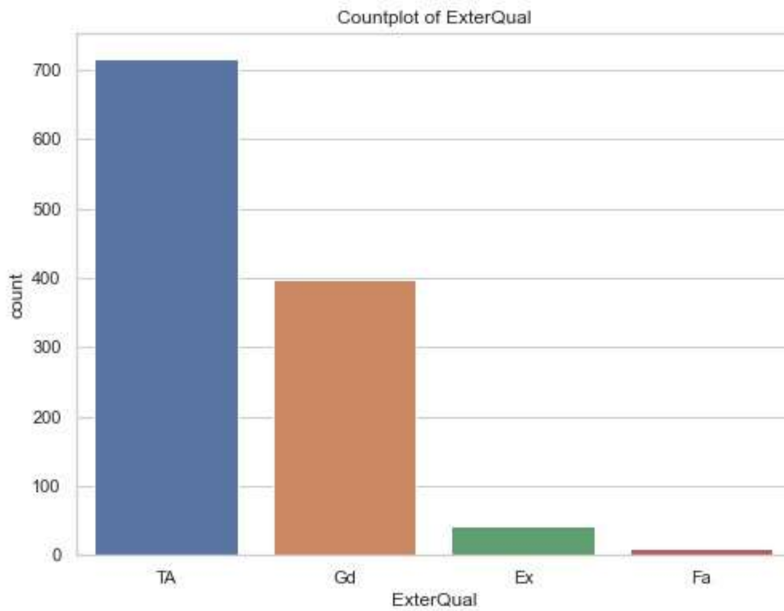



Out[33]:
```
Gable      915
Hip        225
Flat        12
Gambrel      9
Mansard      5
Shed         2
```

**Observation:**

Maximum, 915 number of RoofStyle are Gable.

In [34]:
```
# Let's check the column ExterQual

plt.subplots(figsize=(8,6))
sns.countplot(x="ExterQual", data=housing_train)
plt.title("Countplot of ExterQual")
plt.xlabel('ExterQual')
plt.ylabel("count")
plt.show()

housing_train['ExterQual'].value_counts()
```

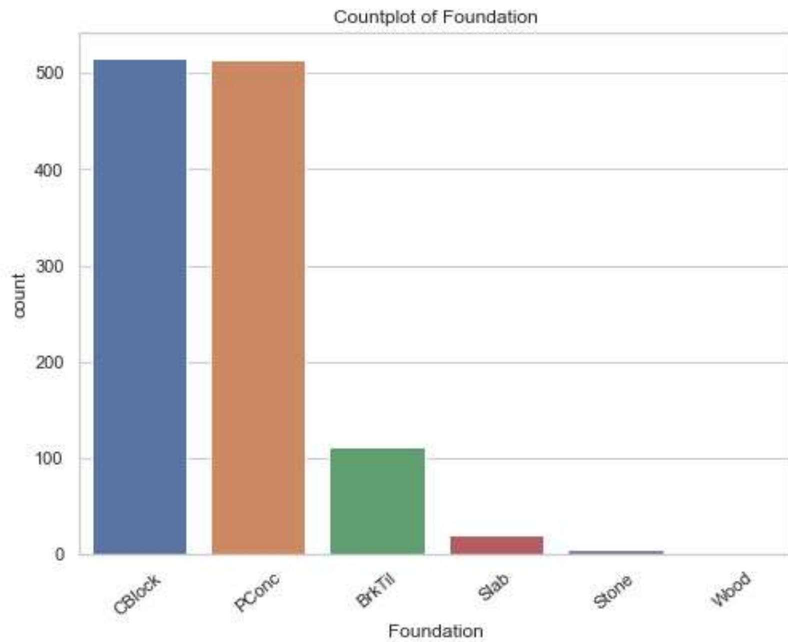



Out[34]:
```
TA    717
Gd    397
Ex     43
Fa     11
Name: ExterQual, dtype: int64
```

**Observation:** ¶

Maximum, 717 number of ExterQual is TA.

In [35]:
```
# Let's checking the column Foundation

plt.subplots(figsize=(8,6))
sns.countplot(x="Foundation", data=housing_train)
plt.title("Countplot of Foundation")
plt.xticks(rotation=40)
plt.xlabel('Foundation')
plt.ylabel("count")
plt.show()

housing_train['Foundation'].value_counts()
```

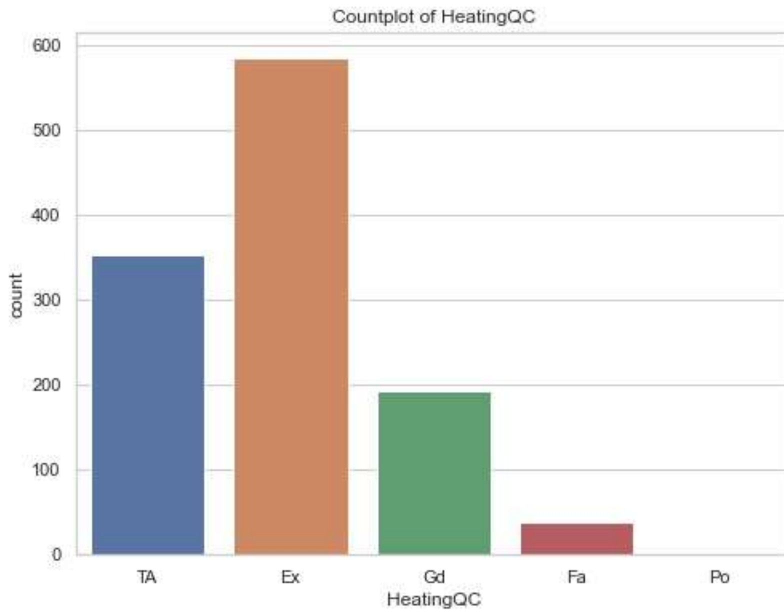



Out[35]:
```
CBlock    516
PConc     513
BrkTil    112
Slab       21
Stone       5
```

**Observation:**

Maximum, 516 number of Foundation are CBlock.

In [36]:
```
# Let's check the column HeatingQC

plt.subplots(figsize=(8,6))
sns.countplot(x="HeatingQC", data=housing_train)
plt.title("Countplot of HeatingQC")
plt.xlabel('HeatingQC')
plt.ylabel("count")
plt.show()

housing_train['HeatingQC'].value_counts()
```

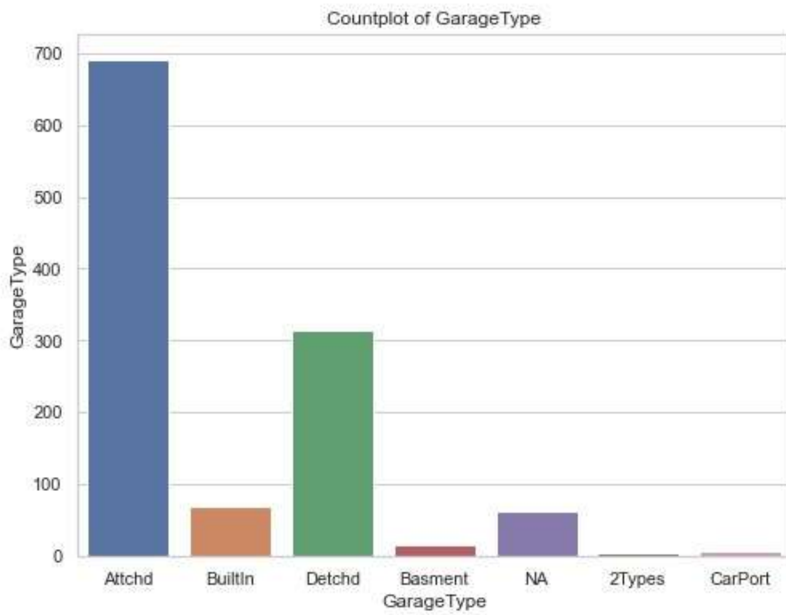



Out[36]:
```
Ex    585
TA    352
Gd    192
Fa     38
Po      1
Name: HeatingQC, dtype: int64
```

**Observation:**

Maximum, 585 number of HeatingQC is Ex.

In [37]:
```
# Let's check the column GarageType

plt.subplots(figsize=(8,6))
sns.countplot(x="GarageType", data=housing_train)
plt.title("Countplot of GarageType")
plt.xlabel('GarageType')
plt.ylabel("GarageType")
plt.show()

housing_train['GarageType'].value_counts()
```

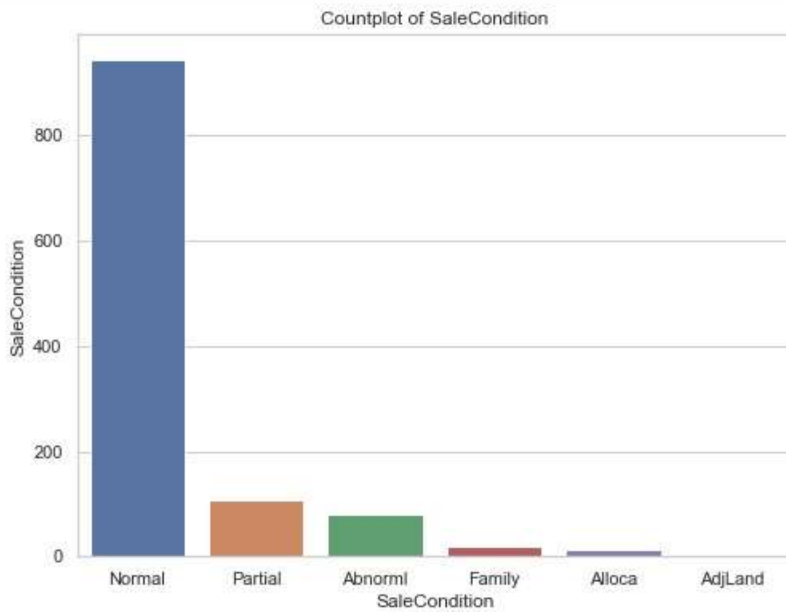



Out[37]:
```
Attchd     691
Detchd     314
BuiltIn     70
NA          64
Basment     16
CarPort      8
```

**Observation:**

Maximum, 691 number of GarageType are Attchd.

In [38]:
```
# Let's check the column SaleCondition

plt.subplots(figsize=(8,6))
sns.countplot(x="SaleCondition", data=housing_train)
plt.title("Countplot of SaleCondition")
plt.xlabel('SaleCondition')
plt.ylabel("SaleCondition")
plt.show()

housing_train['SaleCondition'].value_counts()
```

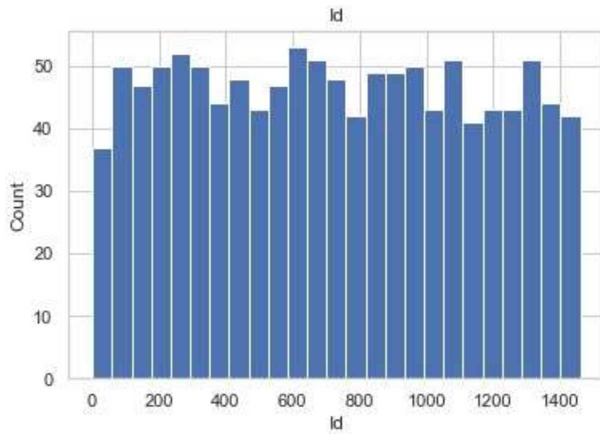


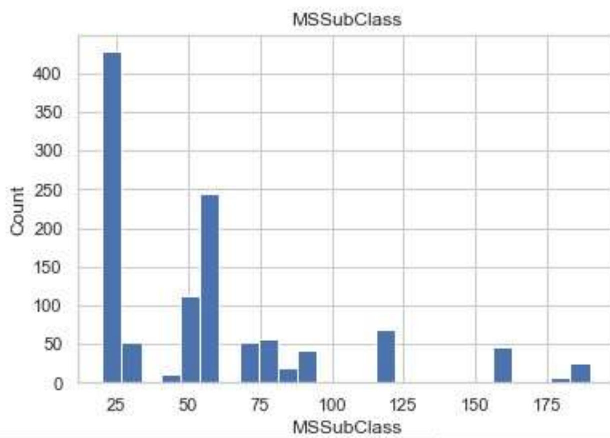

Out[38]:
```
Normal     945
Partial    108
Abnorml     81
Family      18
Alloca      12
AdjLand      4
Name: SaleCondition, dtype: int64
```

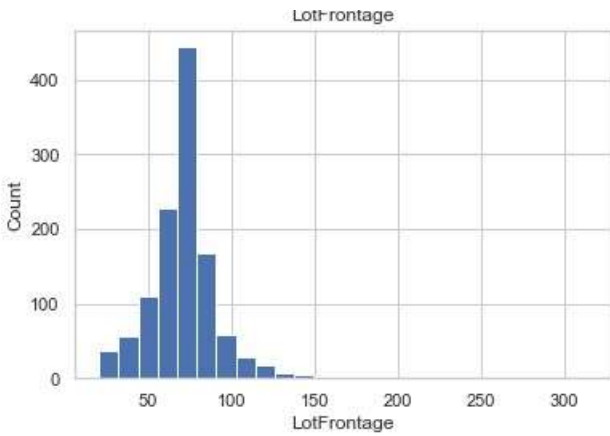
**Observation:**

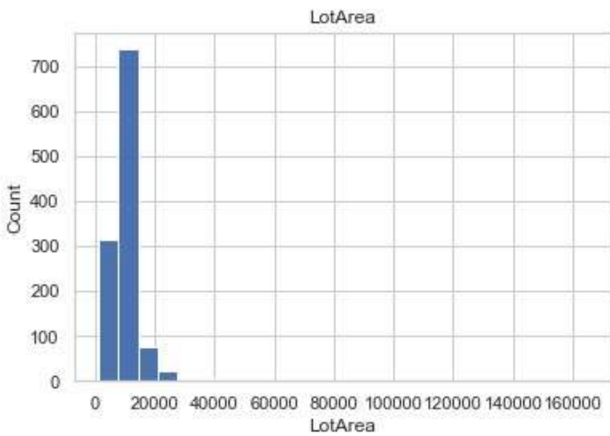
Maximum, 945 number of SaleCondition is normal.

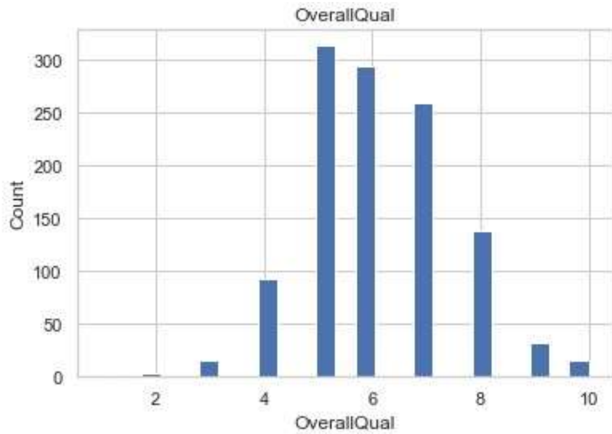
In [39]:
```python
# Let's plot the histogram of every numerical column

for col in housing_train.describe().columns:
    data=housing_train.copy()
    data[col].hist(bins=25)
    plt.xlabel(col)
    plt.ylabel("Count")
    plt.title(col)
    plt.show()
```

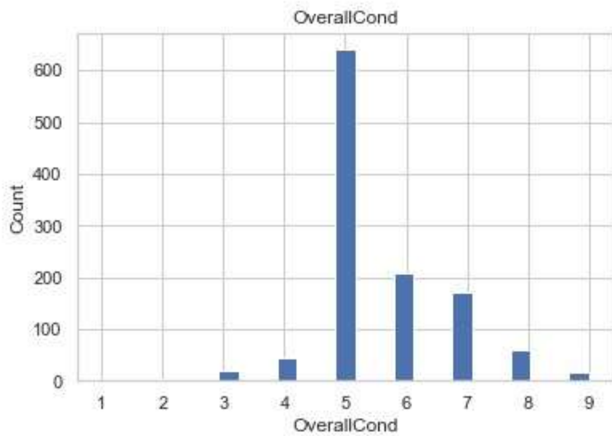


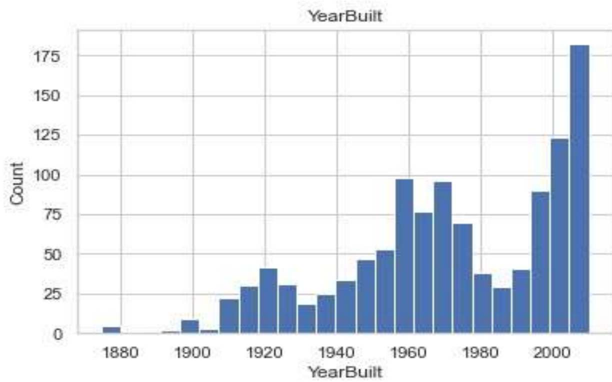




LotFrontage
Count
400
300
200
100
0
50
100
150
200
250
300
LotFrontage

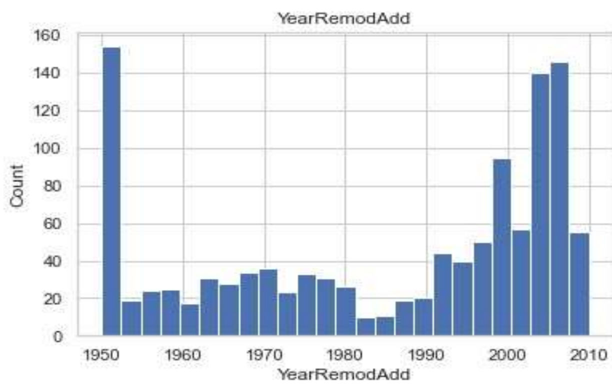

LotArea
Count
700
600
500
400
300
200
100
0
0
20000
40000
60000
80000
100000
120000
140000
160000
LotArea


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

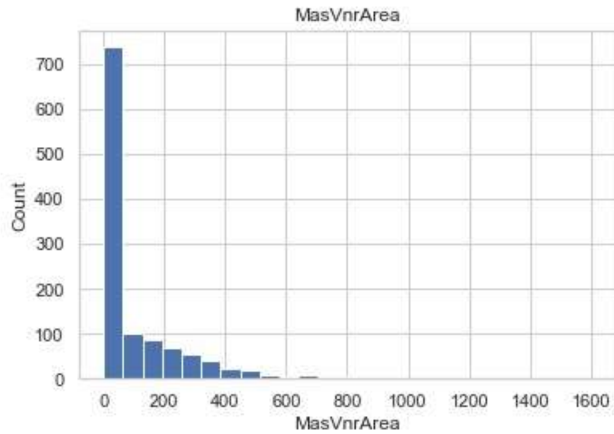

OverallCond
600
500
400
300
200
100
0
Count
1
2
3
4
5
6
7
8
9
OverallCond

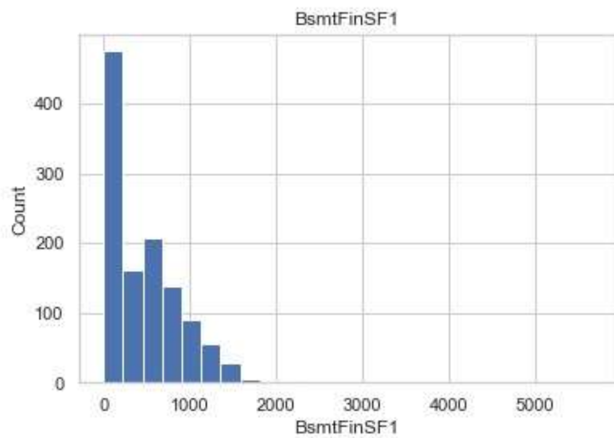


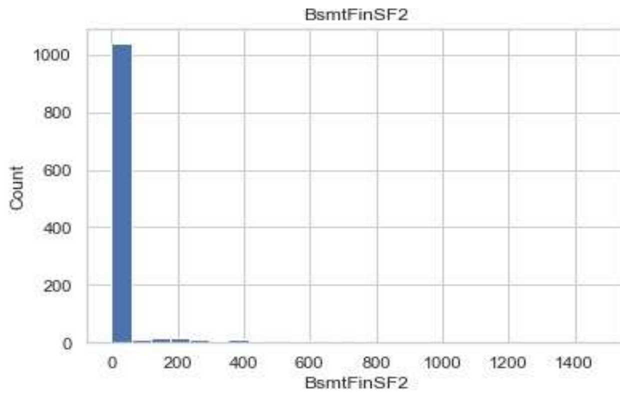
YearBuilt
175
150
125
100
75
50
25
0
Count
1880
1900
1920
1940
1960
1980
2000
YearBuilt

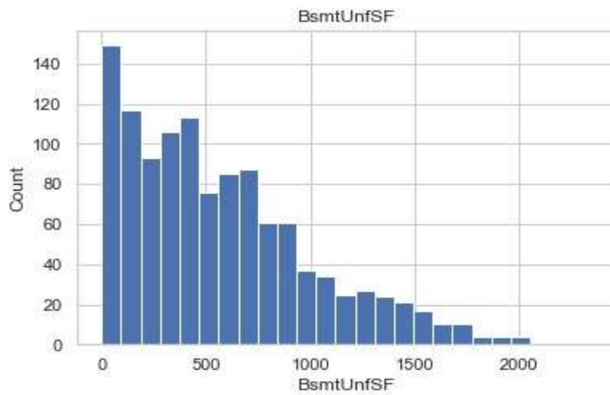



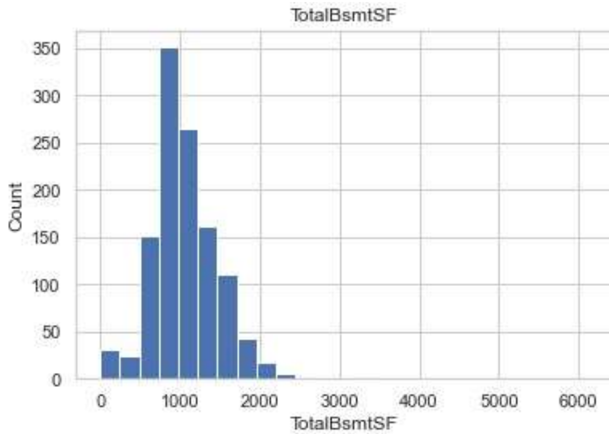
YearRemodAdd
160
140
120
100
80
60
40
20
0
Count
1950
1960
1970
1980
1990
2000
2010
YearRemodAdd


MasVnrArea
700
600
500
400
300
200
100
0
Count
0
200
400
600
800
1000
1200
1400
1600
MasVnrArea

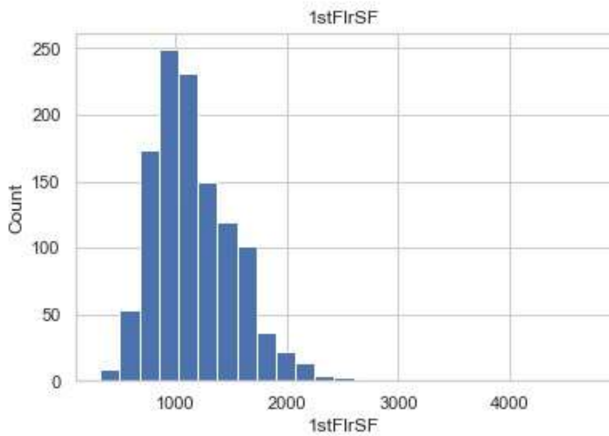

BsmtFinSF1
400
300
200
100
0
Count
0
1000
2000
3000
4000
5000
BsmtFinSF1


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

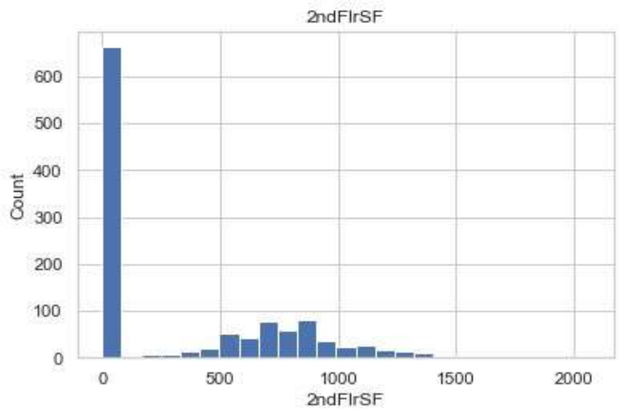

BsmtUnfSF
Count
0
20
40
60
80
100
120
140
0
500
1000
1500
2000
BsmtUnfSF

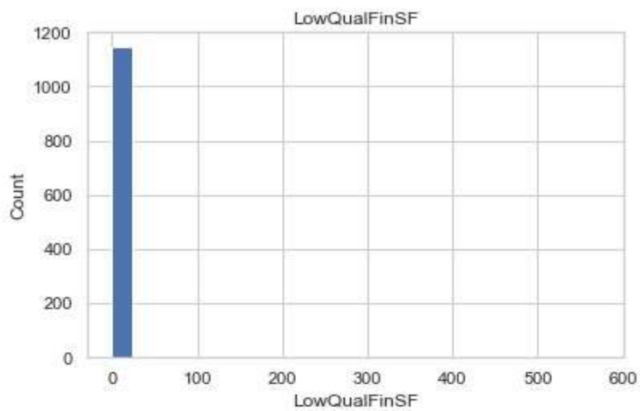


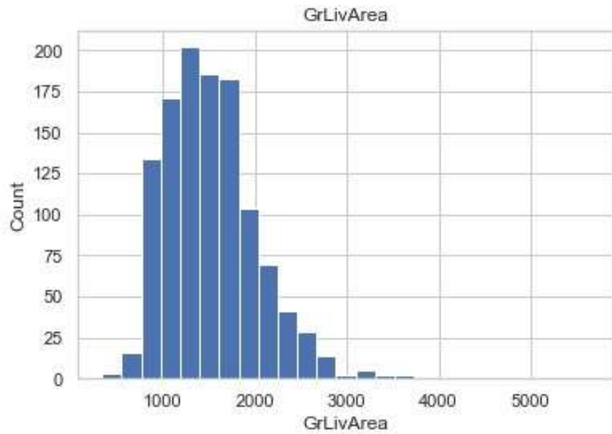
TotalBsmtSF
350
300
250
200
150
100
50
0
Count
0
1000
2000
3000
4000
5000
6000
TotalBsmtSF

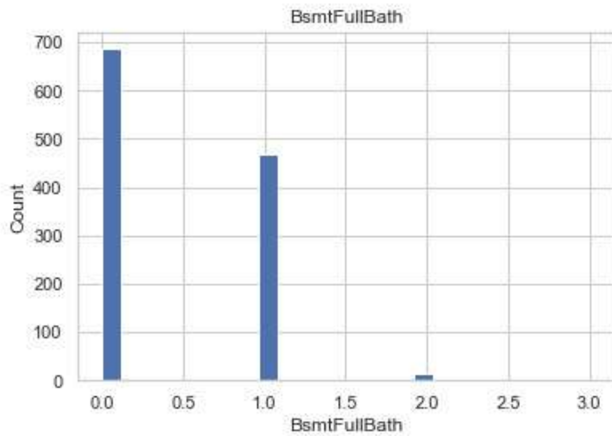



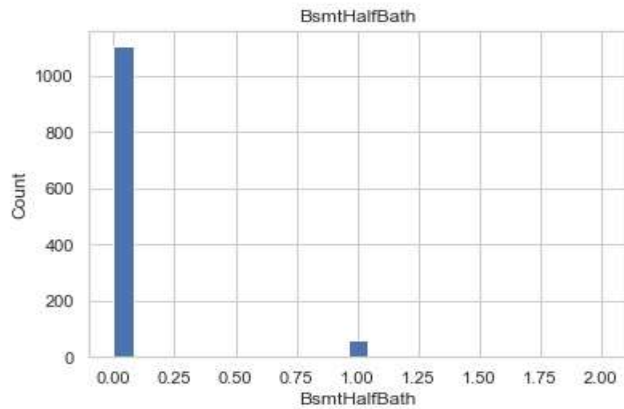
1stFlrSF
250
200
150
100
50
0
Count
1000
2000
3000
4000
1stFlrSF


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

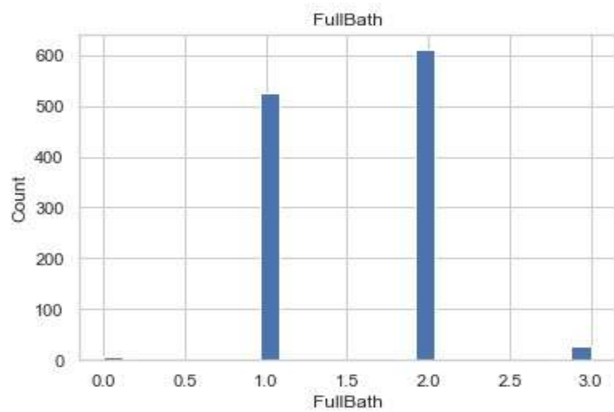

LowQualFinSF
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
600
LowQualFinSF


GrLivArea
Count
GrLivArea
200
175
150
125
100
75
50
25
0
1000
2000
3000
4000
5000

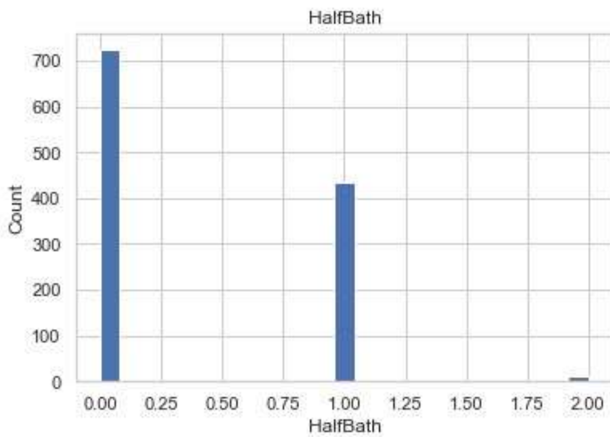

BsmtFullBath
Count
BsmtFullBath
700
600
500
400
300
200
100
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0

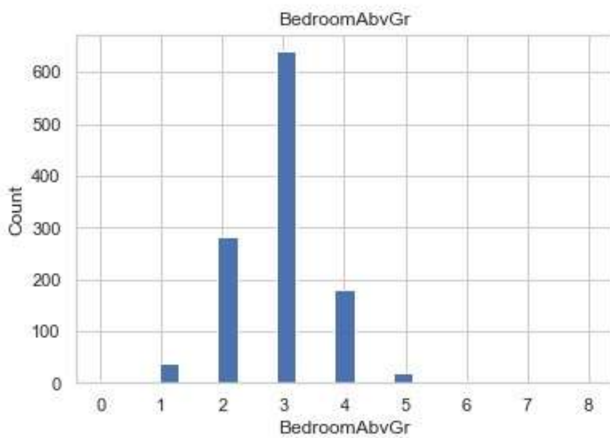


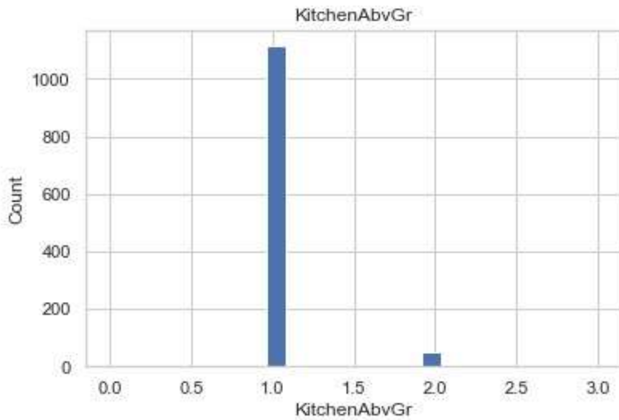
BsmtHalfBath
Count
1000
800
600
400
200
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
BsmtHalfBath

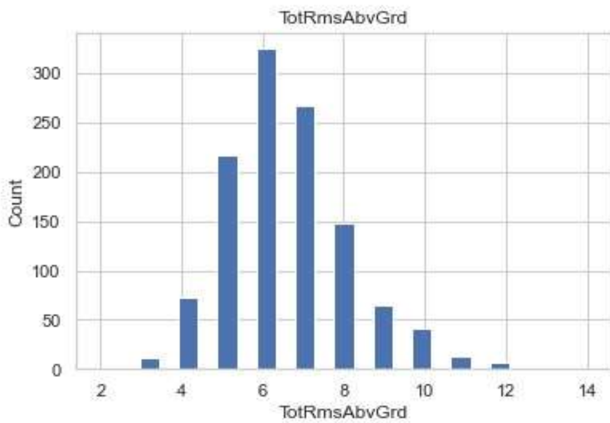
FullBath
Count
600
500
400
300
200
100
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
FullBath


HalfBath
Count
700
600
500
400
300
200
100
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
HalfBath

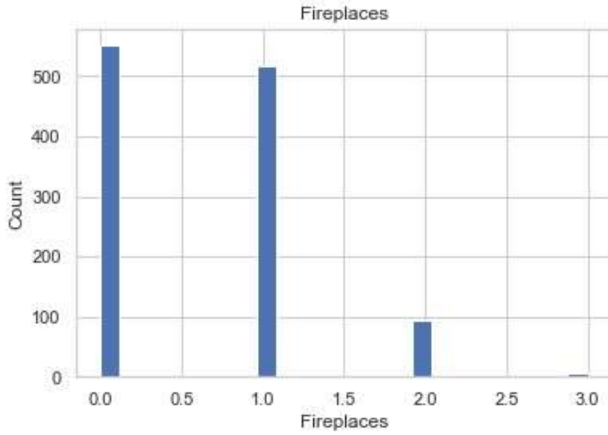

BedroomAbvGr
Count
600
500
400
300
200
100
0
0
1
2
3
4
5
6
7
8
BedroomAbvGr

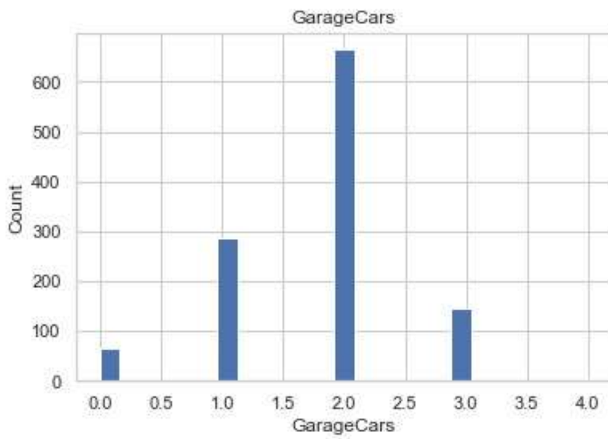


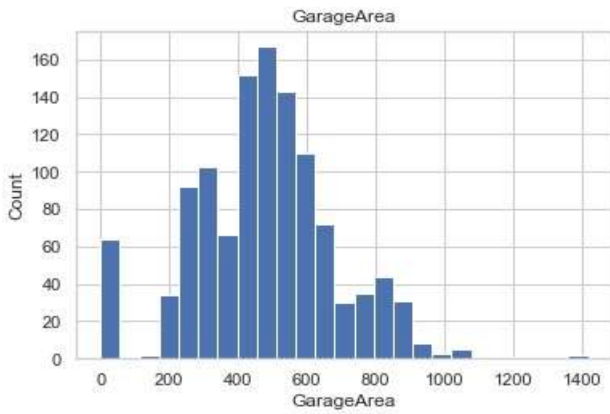
KitchenAbvGr
Count
1000
800
600
400
200
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
KitchenAbvGr

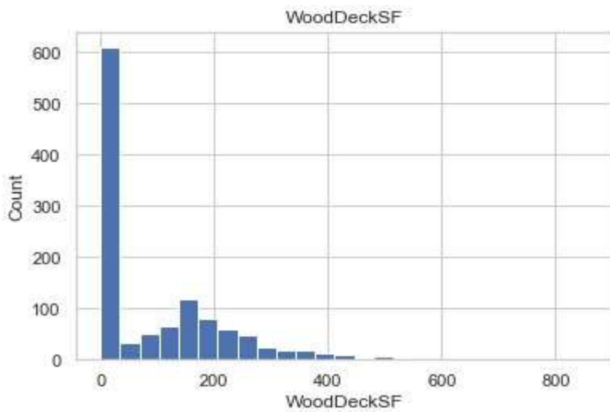



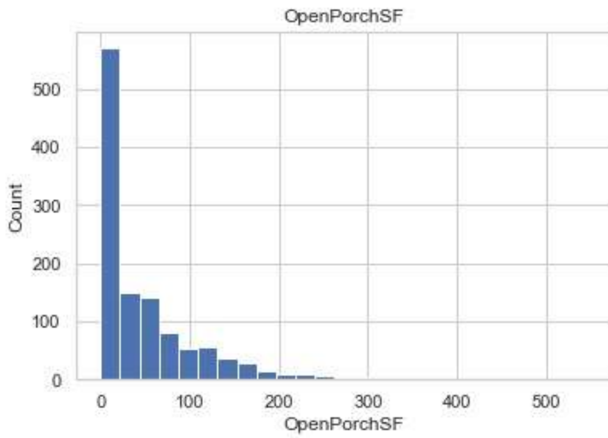
TotRmsAbvGrd
Count
300
250
200
150
100
50
0
2
4
6
8
10
12
14
TotRmsAbvGrd

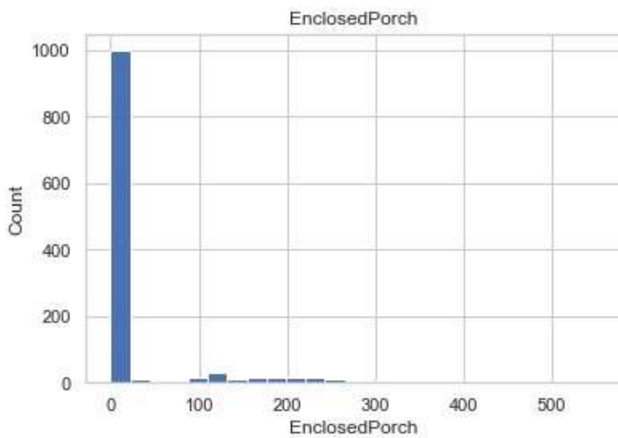

Fireplaces
500
400
300
200
100
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Fireplaces

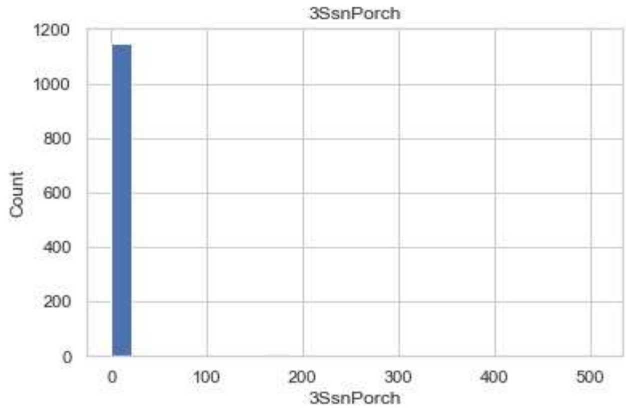

GarageCars
600
500
400
300
200
100
0
Count
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
GarageCars

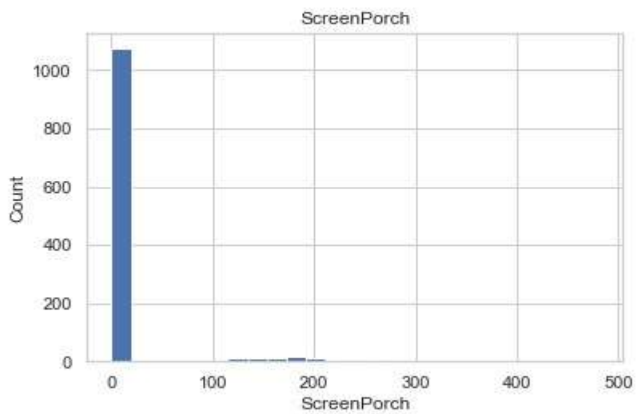

GarageArea
Count
0
20
40
60
80
100
120
140
160
0
200
400
600
800
1000
1200
1400
GarageArea

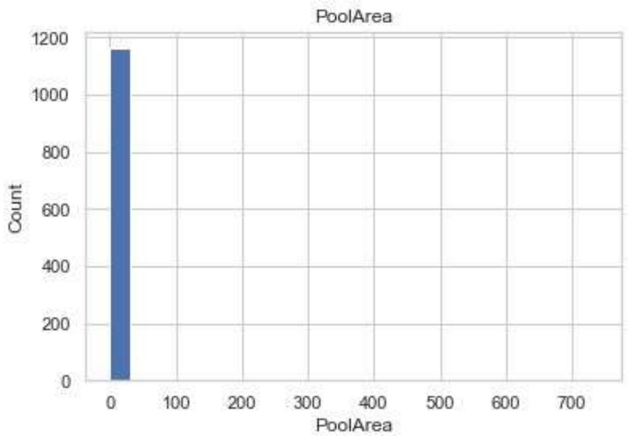

WoodDeckSF
Count
0
100
200
300
400
500
600
0
200
400
600
800
WoodDeckSF

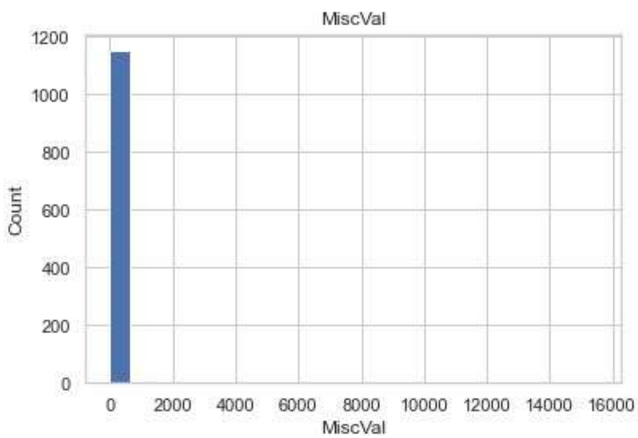

OpenPorchSF
Count
0
100
200
300
400
500
0
100
200
300
400
500
OpenPorchSF

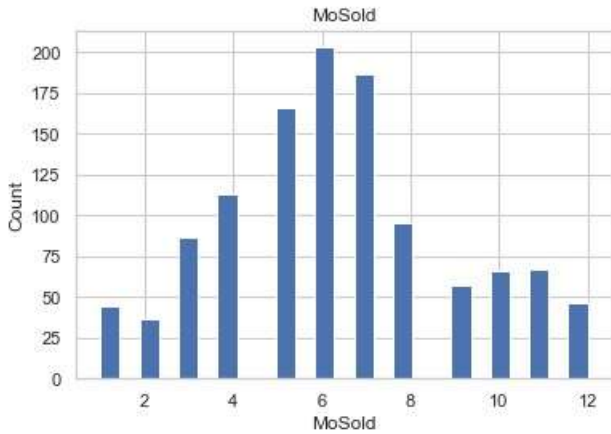

EnclosedPorch
Count
0
200
400
600
800
1000
0
100
200
300
400
500
EnclosedPorch

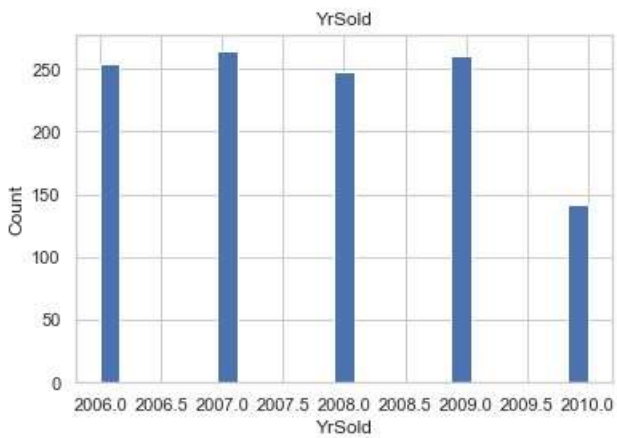

3SsnPorch
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
3SsnPorch

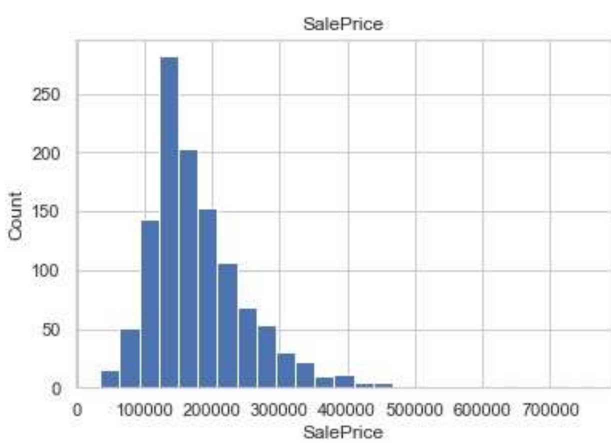

ScreenPorch
1000
800
600
400
200
0
Count
0
100
200
300
400
500
ScreenPorch


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


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

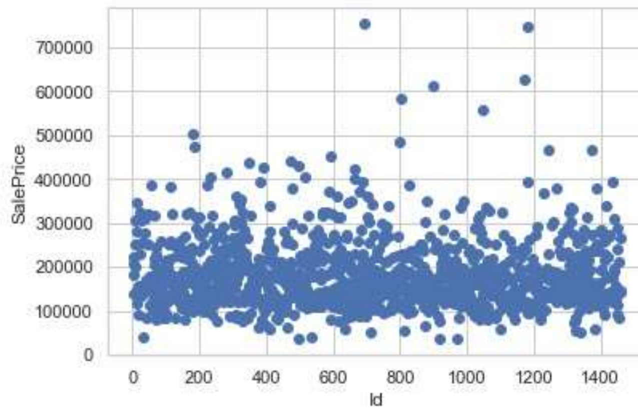

MoSold
Count
0
25
50
75
100
125
150
175
200
2
4
6
8
10
12
MoSold

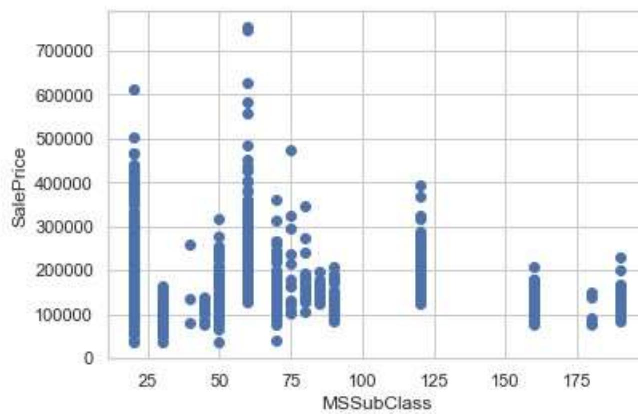

YrSold
Count
0
50
100
150
200
250
2006.0
2006.5
2007.0
2007.5
2008.0
2008.5
2009.0
2009.5
2010.0
YrSold

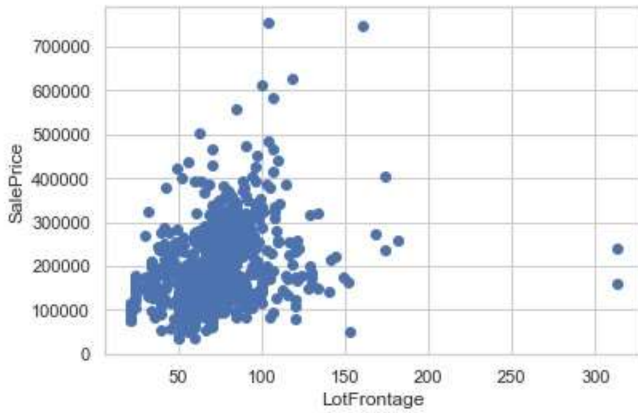

SalePrice
Count
0
50
100
150
200
250
0
100000
200000
300000
400000
500000
600000
700000
SalePrice

## Bivariate Analysis

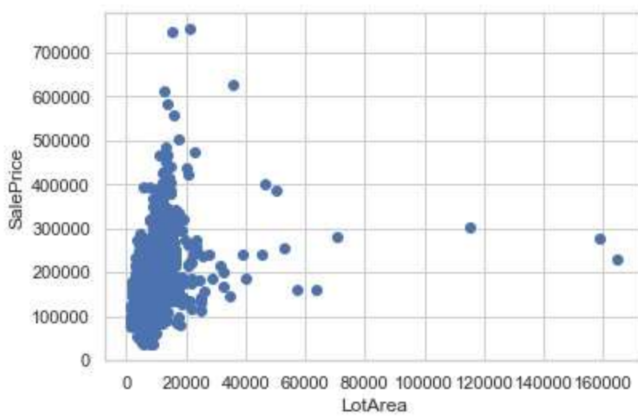
In [40]:
```
# Let's plot the Scatter plot between all feature variables and target variabl
for col in housing_train.describe().columns:
    data=housing_train.copy()
    plt.scatter(data[col],data['SalePrice'])
    plt.xlabel(col)
    plt.ylabel('SalePrice')
    plt.show()
```



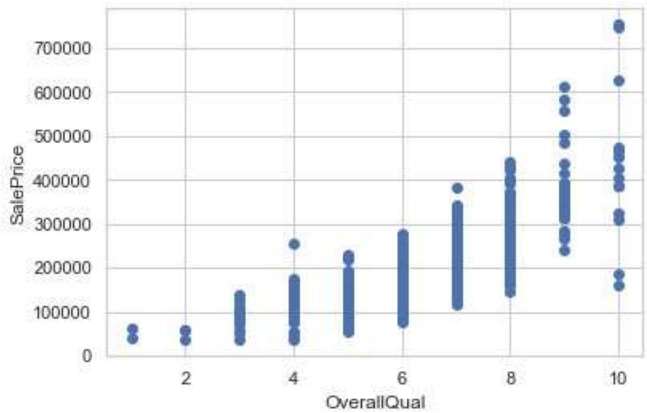





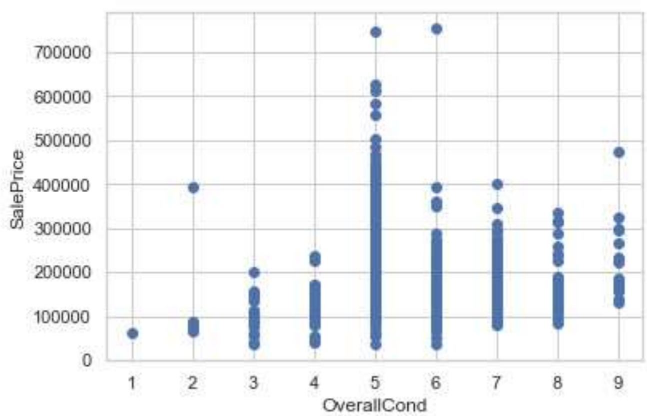
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
50
100
150
200
250
300
LotFrontage

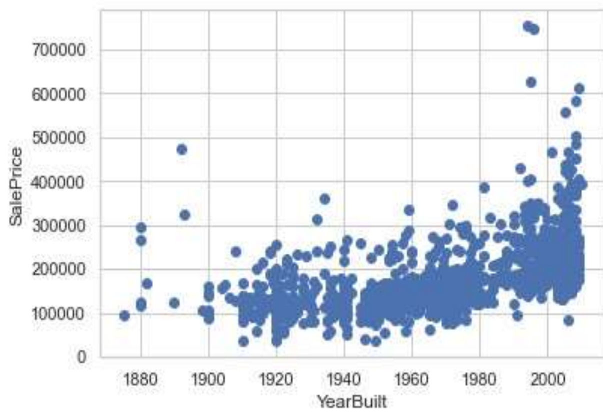
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
20000
40000
60000
80000
100000
120000
140000
160000
LotArea



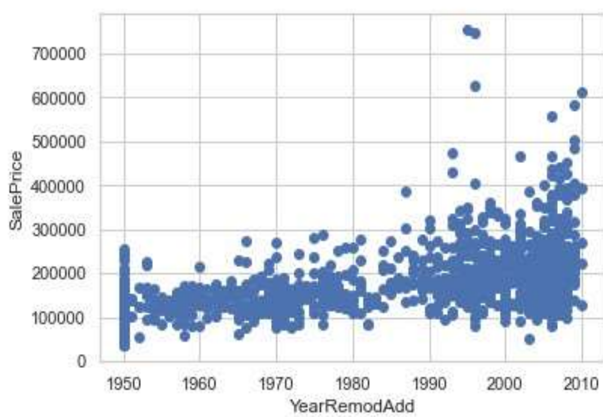
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
2
4
6
8
10
OverallQual

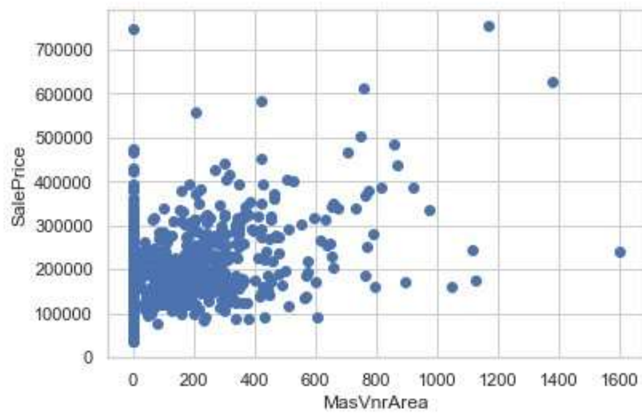
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1
2
3
4
5
6
7
8
9
OverallCond



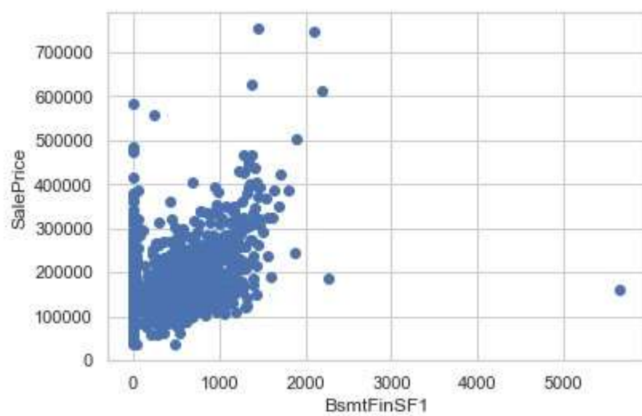
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1880
1900
1920
1940
1960
1980
2000
YearBuilt

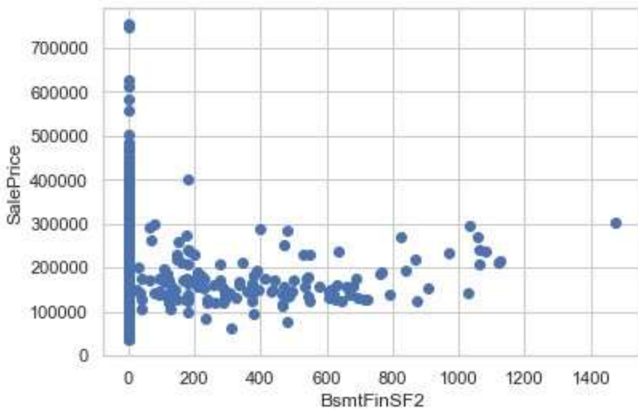
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1950
1960
1970
1980
1990
2000
2010
YearRemodAdd

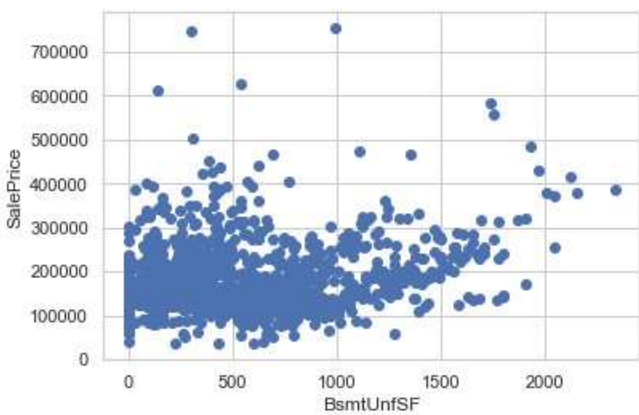


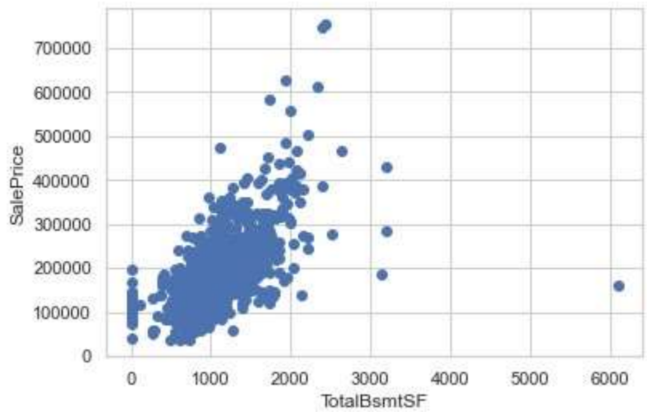
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
200
400
600
800
1000
1200
1400
1600
MasVnrArea

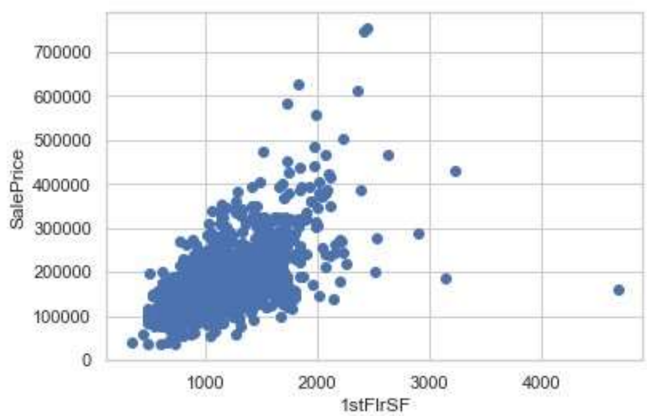
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
1000
2000
3000
4000
5000
BsmtFinSF1


700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
200
400
600
800
1000
1200
1400
BsmtFinSF2

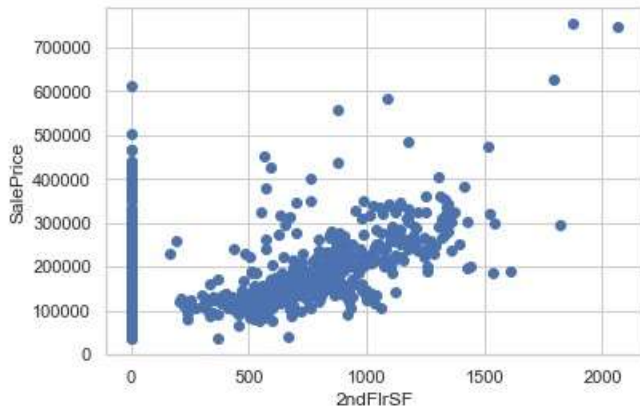

700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
500
1000
1500
2000
BsmtUnfSF



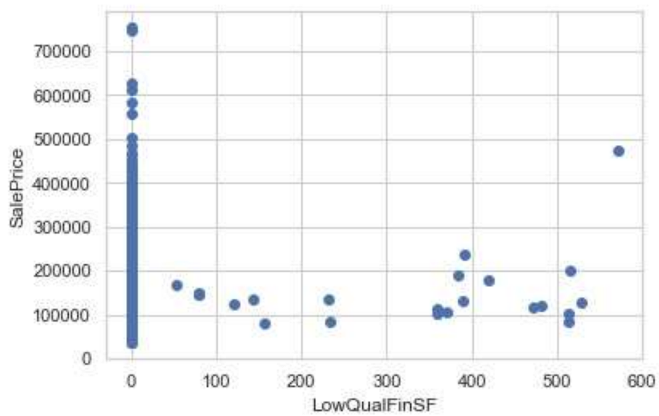
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
1000
2000
3000
4000
5000
6000
TotalBsmtSF

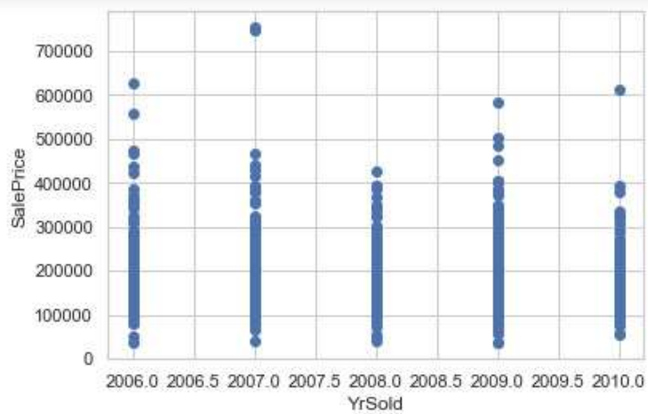
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
1000
2000
3000
4000
1stFlrSF



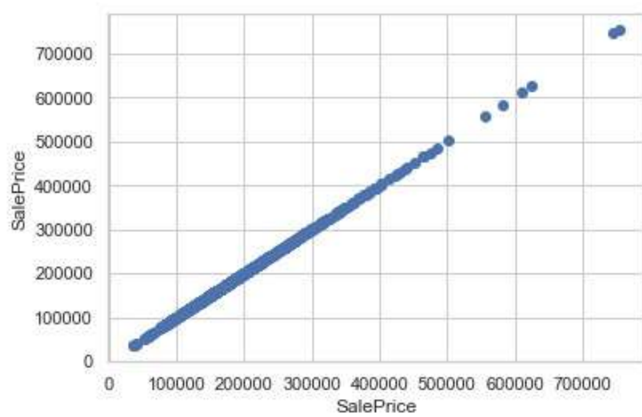
SalePrice
2ndFlrSF

SalePrice
LowQualFinSF



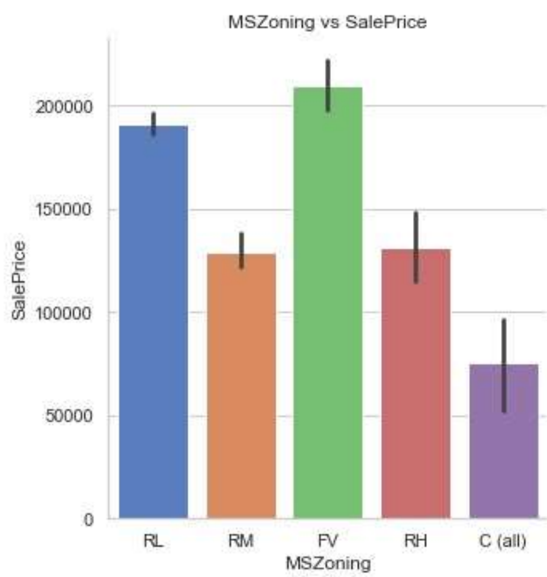
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
2006.0 2006.5 2007.0 2007.5 2008.0 2008.5 2009.0 2009.5 2010.0
YrSold

700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0 100000 200000 300000 400000 500000 600000 700000
SalePrice

In [41]:
```
# Let's plot the Factor plot of MSZoning vs SalePrice

plt.figure(figsize=(8,6))
sns.factorplot(x='MSZoning',y='SalePrice',data=housing_train,kind='bar',size=5,p
plt.title('MSZoning vs SalePrice')
plt.ylabel('SalePrice')
plt.show()
print(housing_train.groupby('SalePrice')['MSZoning'].value_counts());
```

```
<Figure size 576x432 with 0 Axes>
```



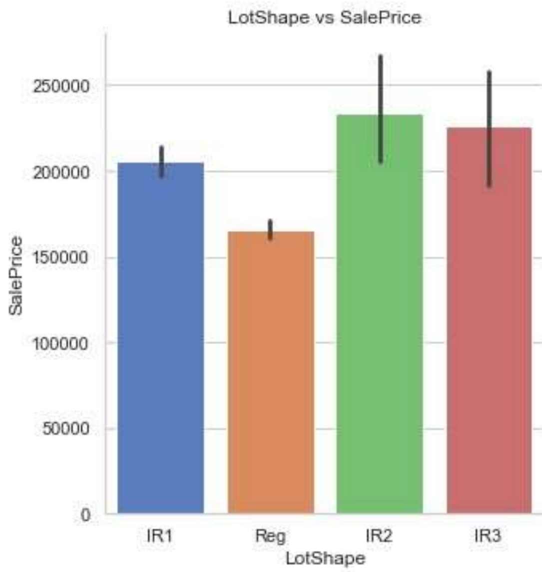

```
SalePrice  MSZoning
34900      C (all)     1
35311      C (all)     1
37900      RM          1
39300      RL          1
40000      C (all)     1
                      ..
582933     RL          1
611657     RL          1
625000     RL          1
745000     RL          1
```

**Observation:**

SalePrice is maximum with FV MSZOning.

In [42]:
```
# Let's plot the Factor plot of LotShape vs SalePrice

plt.figure(figsize=(8,6))
sns.factorplot(x='LotShape',y='SalePrice',data=housing_train,kind='bar',size=5,p
plt.title('LotShape vs SalePrice')
plt.ylabel('SalePrice')
plt.show();
print(housing_train.groupby('SalePrice')['LotShape'].value_counts());
```

```
<Figure size 576x432 with 0 Axes>
```



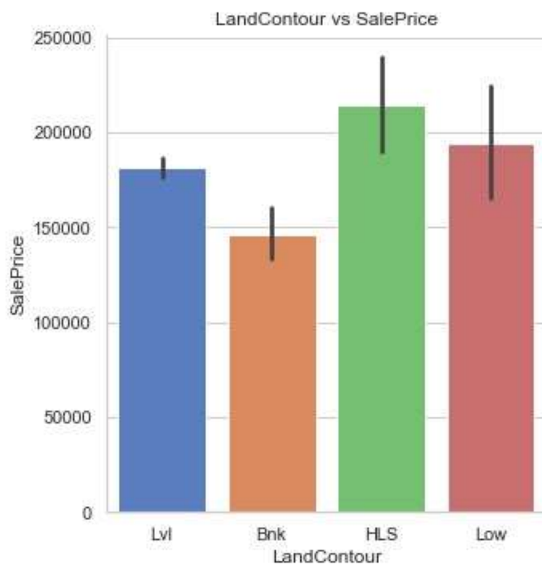

```
SalePrice  LotShape
34900      Reg         1
35311      Reg         1
37900      Reg         1
39300      Reg         1
40000      Reg         1
                      ..
582933     Reg         1
611657     IR1         1
625000     IR1         1
```

**Observation:**

SalePrice is maximum with IR2 LotShape.

In [43]:
```
# Let's plot the Factor plot of LandContour vs SalePrice

plt.figure(figsize=(8,6))
sns.factorplot(x='LandContour',y='SalePrice',data=housing_train,kind='bar',size=
plt.title('LandContour vs SalePrice')
plt.ylabel('SalePrice')
plt.show()
print(housing_train.groupby('SalePrice')['LandContour'].value_counts())
```

```
<Figure size 576x432 with 0 Axes>
```



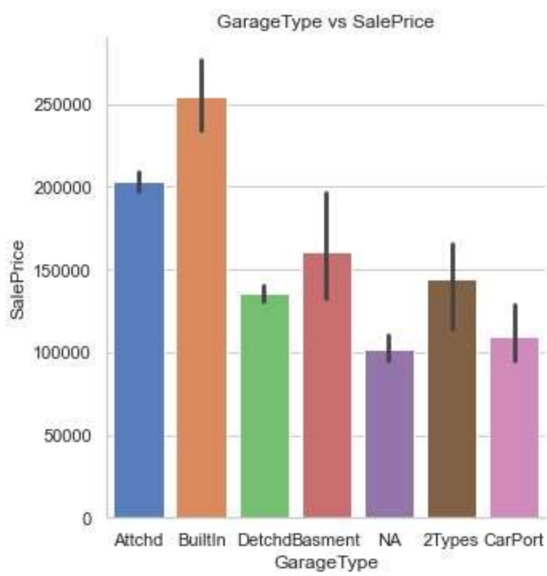

```
SalePrice  LandContour
34900      Lvl            1
35311      Lvl            1
37900      Lvl            1
39300      Low            1
40000      Lvl            1
                         ..
582933     Lvl            1
611657     Lvl            1
625000     Lvl            1
745000     Lvl            1
```

**Observation:**

SalePrice is maximum with Ex ExterQual.

```
In [48]: # Let's plot the Factor plot of GarageType vs SalePrice

plt.figure(figsize=(8,6))
sns.factorplot(x='GarageType',y='SalePrice',data=housing_train,kind='bar',size=5
plt.title('GarageType vs SalePrice')
plt.ylabel('SalePrice')
plt.show()


print(housing_train.groupby('SalePrice')['GarageType'].value_counts())
```

```
<Figure size 576x432 with 0 Axes>
```



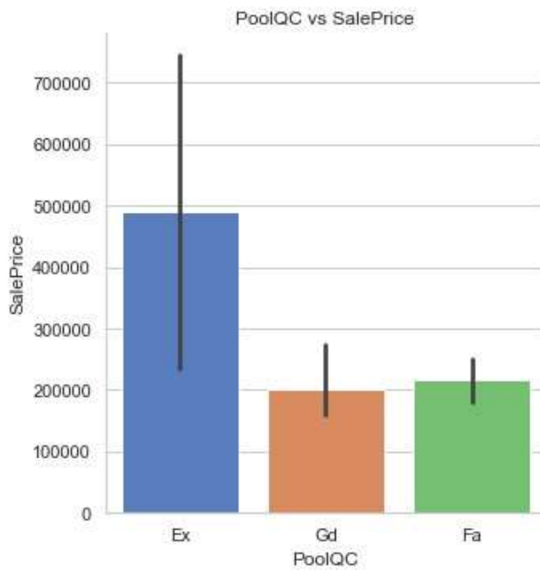

```
SalePrice  GarageType
34900      NA            1
35311      Detchd        1
37900      NA            1
39300      NA            1
40000      Detchd        1
```

**Observation:**

SalePrice is maximum with Builtin GarageType.

In [49]:
```
# Let's plot the Factor plot of PoolQC vs SalePrice

plt.figure(figsize=(8,6))
sns.factorplot(x='PoolQC',y='SalePrice',data=housing_train,kind='bar',size=5,pal
plt.title('PoolQC vs SalePrice')
plt.ylabel('SalePrice')
plt.show()

print(housing_train.groupby('SalePrice')['PoolQC'].value_counts())
```

```
<Figure size 576x432 with 0 Axes>
```

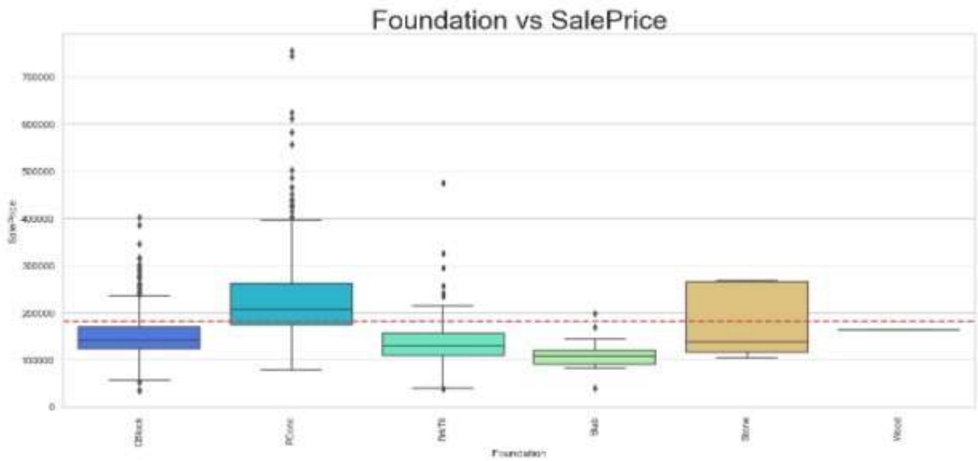



```
SalePrice  PoolQC
160000     Gd        1
171000     Gd        1
181000     Fa        1
235000     Ex        1
250000     Fa        1
274970     Gd        1
745000     Ex        1
```

**Observation:**

SalePrice is maximum with Ex PoolQC.

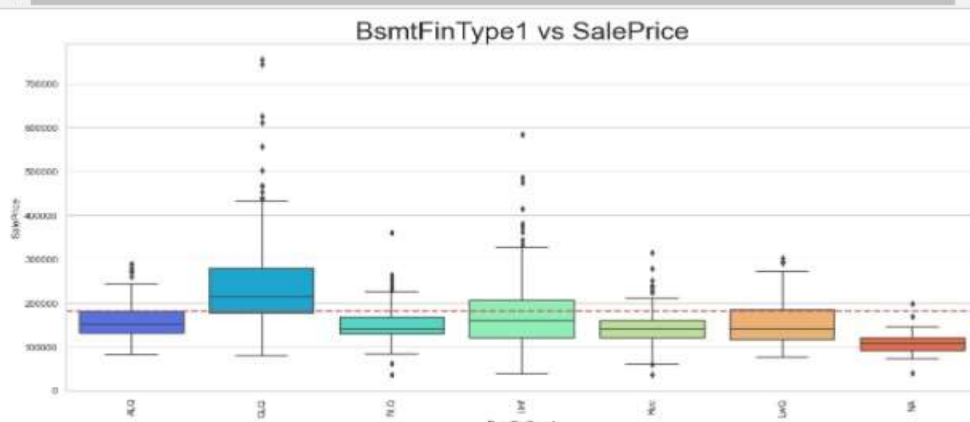
```
In [50]: # Let's plot the Foundation vs SalePrice plot

plt.figure(figsize=(18,8))
mean_price=np.mean(housing_train['SalePrice'])
sns.boxplot(y='SalePrice',x='Foundation',data=housing_train,palette="rainbow")
plt.axhline(mean_price,color='r',linestyle='dashed',linewidth=2)
plt.title("Foundation vs SalePrice",fontsize=30)
plt.xticks(rotation='vertical')
plt.show()
```




**Observation:**

SalePrice is maximum with PConc.

```
In [51]: # Let's plot the BsmtFinType1 vs SalePrice plot

plt.figure(figsize=(18,8))
mean_price=np.mean(housing_train['SalePrice'])
sns.boxplot(y='SalePrice',x='BsmtFinType1',data=housing_train,palette="rainbow")
plt.axhline(mean_price,color='r',linestyle='dashed',linewidth=2)
plt.title("BsmtFinType1 vs SalePrice",fontsize=30)
plt.xticks(rotation='vertical')
plt.show()
```



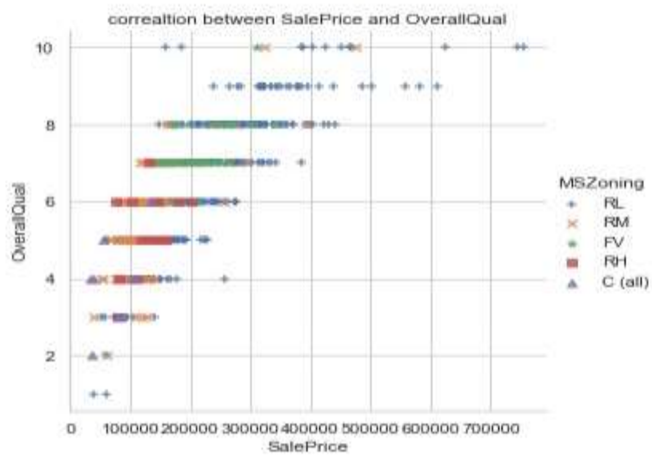

**Observation:**

SalePrice is maximum with GLQ BsmtFinType1.

## Multivariate Analysis

In [52]:
```
# Let's plot the scatter plot between SalePrice and OverallCond with respect to 
plt.figure(figsize=(14,14))
sns.lmplot(x='SalePrice',y='OverallQual',fit_reg=False,data=housing_train,hue='M
plt.xlabel('SalePrice')
plt.title('correaltion between SalePrice and OverallQual')
plt.ylabel('OverallQual')
plt.show()
```

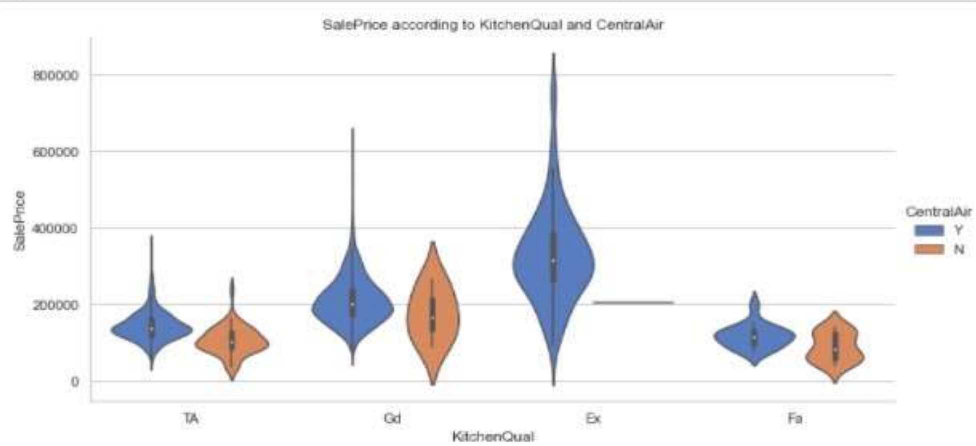
```
<Figure size 1008x1008 with 0 Axes>
```




**Observation:**

With MSZoning RL and increase in OverallQual the SalePrice of a house increases.

In [53]:
```
# Let's plot the GarageType and GarageCond with respect to SalePrice plot

sns.factorplot(x='KitchenQual',y='SalePrice',hue='CentralAir',data=housing_train
plt.title('SalePrice according to KitchenQual and CentralAir')
plt.xticks()
plt.ylabel('SalePrice')
plt.show()
```

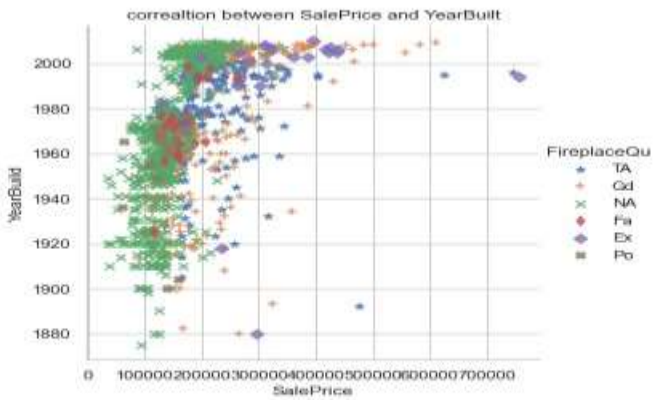



**Observation:**

SalePrice is maximum with Ex kitchenQual and CentralAir.

In [54]:
```
# Let's plot the scatter plot between SalePrice and OverallCond with respect to 
plt.figure(figsize=(14,14))
sns.lmplot(x='SalePrice',y='YearBuilt',fit_reg=False,data=housing_train,hue='Fir
plt.xlabel('SalePrice')
plt.title('correaltion between SalePrice and YearBuilt')
plt.ylabel('YearBuild')
plt.show()
```

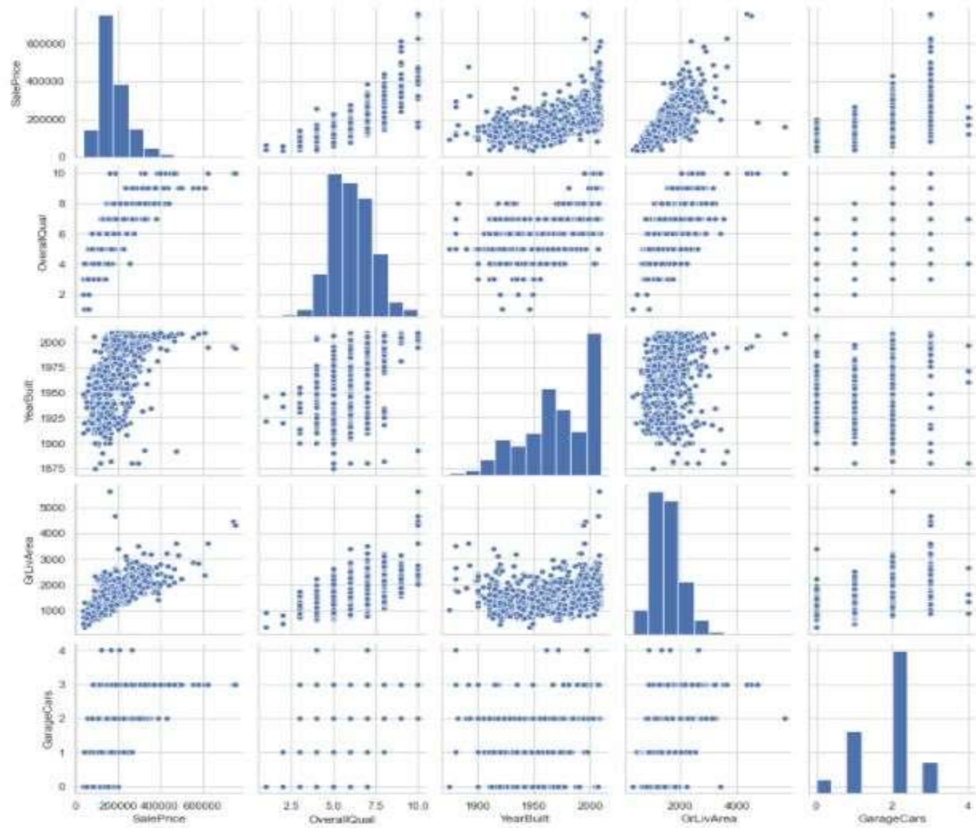
```
<Figure size 1008x1008 with 0 Axes>
```




**Observation:**

As the YearBuilt is increasing SalePrice is also increasing.

```
In [55]: # Let's plot the pairplot

         sns.pairplot(housing_train, vars=['SalePrice','OverallQual','YearBuilt','GrLivAr
```




**Observation:**

SalePrice is highly positively correlated with GrLivArea and OverallQual.

- ## Interpretation of the Results

  From the visualization we interpreted that the target variable SalePrice was highly positively correlated with the columns GrLivArea, YearBuilt, OverallQual, GarageCars, GarageArea.

  From the pre-processing we interpreted that data was improper scaled.

### Hyperparameter tuning

In [74]:
```
# Let's Use the GridSearchCV to find the best paarameters in Ridge Regressor

parameters={'alpha': [25,10,4,2,1.0,0.8,0.5,0.3,0.2,0.1,0.05,0.02,0.01]}
rg=Ridge()

reg=GridSearchCV(rg,parameters,n_jobs=-1)
reg.fit(x,y)
print(reg.best_params_)
```

```
{'alpha': 25}
```

In [75]:
```
# Let's use the Ridge Regressor with its best parameters

RG=Ridge(alpha=25)
RG.fit(x_train,y_train)
print('Score:',RG.score(x_train,y_train))
y_pred=RG.predict(x_test)
print('\n')
print('Mean absolute error:',mean_absolute_error(y_test,y_pred))
print('Mean squared error:',mean_squared_error(y_test,y_pred))
print('Root Mean Squared error:',np.sqrt(mean_squared_error(y_test,y_pred)))
print('\n')
print("r2_score:",r2_score(y_test,y_pred))
print('\n')
```

```
Score: 0.8228133117754095


Mean absolute error: 21636.271697150503
Mean squared error: 1043419637.663922
Root Mean Squared error: 32302.006712647468


r2_score: 0.8409922339716864
```

From the modeling we interpreted that after hyperparameter tuning Ridge Regressor works best with respect to our model with minimum RMSE of 32302

# CONCLUSION

- ## Key Findings and Conclusions of the Study

  In this project we have tried to show how the house prices vary and what are the factors related to the changing of house prices. The best(minimum) RMSE score was achieved using the best parameters of Ridge Regressor through GridSearchCV though Lasso Regressor model performed well too.

- ## Learning Outcomes of the Study in respect of Data Science

This project has demonstrated the importance of sampling effectively, modelling and predicting data.

Through different powerful tools of visualization, we were able to analyse and interpret different hidden insights about the data.

Through data cleaning we were able to remove unnecessary columns and outliers from our dataset due to which our model would have suffered from overfitting or underfitting.

The few challenges while working on this project where: -

- Improper scaling
- Too many features
- Missing values
- Skewed data due to outliers

The data was improper scaled so we scaled it to a single scale using sklearns's package StandardScaler.

There were too many (256) features present in the data so we applied Principal Component Analysis (PCA) and found out the Eigenvalues and on the basis of number of nodes we were able able to reduce our features upto 90 columns.

There were lot of missing values present in different columns which we imputed on the basis of our understanding.

The columns were skewed due to presence of outliers which we handled through winsorization technique.

- ## Limitations of this work and Scope for Future Work

  While we couldn't reach out goal of minimum RMSE in house price prediction without letting the model to overfit, we did end up creating a system that can with enough time and data get very close to that goal. As with any project there is room for improvement here. The very nature of this project allows for multiple algorithms to be integrated together as modules and their results can be combined to increase the accuracy of the final result. This model can further be improved with the addition of more algorithms into it. However, the output of these algorithms needs to be in the same format as the others. Once that condition is satisfied, the modules are easy to add as done in the code. This provides a great degree of modularity and versatility to the project.