In [2]:

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

In [3]:

```
df=pd.read_csv('train1.csv')
```

In [4]:

```
df.head()
```

Out[4]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighbor |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 60 | RL | 65.0 | 8450 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | Co |
| **1** | 2 | 20 | RL | 80.0 | 9600 | Pave | NaN | Reg | Lvl | AllPub | FR2 | Gtl | Ve |
| **2** | 3 | 60 | RL | 68.0 | 11250 | Pave | NaN | IR1 | Lvl | AllPub | Inside | Gtl | Co |
| **3** | 4 | 70 | RL | 60.0 | 9550 | Pave | NaN | IR1 | Lvl | AllPub | Corner | Gtl | Cr |
| **4** | 5 | 60 | RL | 84.0 | 14260 | Pave | NaN | IR1 | Lvl | AllPub | FR2 | Gtl | NoR |

In [5]:

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

Out[5]:

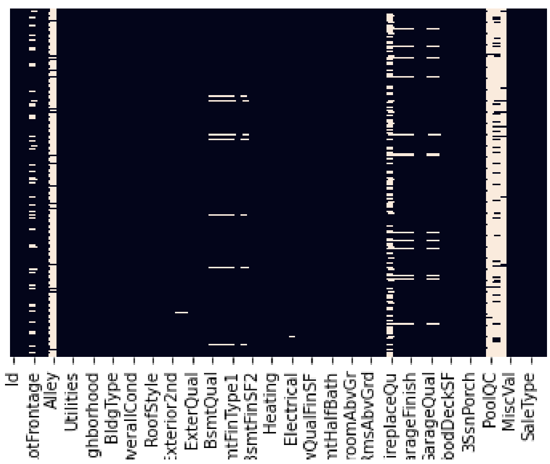
```
RL         1151
RM          218
FV           65
RH           16
C (all)      10
Name: MSZoning, dtype: int64
```

In [6]:

```
#Heatr map for null values
sns.heatmap(df.isnull(),yticklabels=False,cbar=False)
```

Out[6]:

<AxesSubplot:>



In [7]:

```
df.shape
```

Out[7]:

```
(1460, 81)
```

In [5]:

```
#Checking percentage of nan values present
#Make the list of features with missing values
features_with_na= [feat for feat in df.columns if df[feat].isnull().sum()>=1]

#Print feature name and percentage of missung values
for feature in features_with_na:
    print(feature, np.round(df[feature].isnull().mean(), 4),  ' % missing values')
```

```
LotFrontage 0.1774  % missing values
Alley 0.9377  % missing values
MasVnrType 0.0055  % missing values
MasVnrArea 0.0055  % missing values
BsmtQual 0.0253  % missing values
BsmtCond 0.0253  % missing values
BsmtExposure 0.026  % missing values
BsmtFinType1 0.0253  % missing values
BsmtFinType2 0.026  % missing values
Electrical 0.0007  % missing values
FireplaceQu 0.4726  % missing values
GarageType 0.0555  % missing values
GarageYrBlt 0.0555  % missing values
GarageFinish 0.0555  % missing values
GarageQual 0.0555  % missing values
GarageCond 0.0555  % missing values
PoolQC 0.9952  % missing values
Fence 0.8075  % missing values
MiscFeature 0.963  % missing values
```

In [6]:

```
features_with_na
```

Out[6]:

```
['LotFrontage',
 'Alley',
 'MasVnrType',
 'MasVnrArea',
 'BsmtQual',
 'BsmtCond',
 'BsmtExposure',
 'BsmtFinType1',
 'BsmtFinType2',
 'Electrical',
 'FireplaceQu',
 'GarageType',
 'GarageYrBlt',
 'GarageFinish',
 'GarageQual',
 'GarageCond',
 'PoolQC',
 'Fence',
 'MiscFeature']
```

In [562]:

```
df.isnull().sum()
```

Out[562]:

```
Id                 0
MSSubClass         0
MSZoning           0
LotFrontage      259
LotArea            0
                ...
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
Length: 81, dtype: int64
```

In [563]:

```
df.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     1452 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
```

# Analyzing using Sweetviz Library

In [16]:

```python
import sweetviz
my_report = sweetviz.analyze([df,'Train'],target_feat='SalePrice')
```

```
:FEATURES DONE:                    |█████████████████████| [100%]   01:02  -> (00:00 left)
:PAIRWISE DONE:                    |█████████████████████| [100%]   00:09  -> (00:00 left)
```

```
Creating Associations graph... DONE!
```

In [18]:

```python
my_report.show_html('Report.html')
```

```
Report Report.html was generated! NOTEBOOK/COLAB USERS: no browser will pop up, the report is save
d in your notebook/colab files.
```

In [19]:

```python
##Comparing Train and Test dataframes
df2= pd.read_csv('test1.csv')
my_report1 = sweetviz.compare([df,'Train'],[df2,'test'],"SalePrice")
```

```
:FEATURES DONE:                    |█████████████████████| [100%]   01:13  -> (00:00 left)
:PAIRWISE DONE:                    |█████████████████████| [100%]   00:21  -> (00:00 left)
```

```
Creating Associations graph... DONE!
```

In [21]:

```python
my_report1.show_html('Report.html')
```

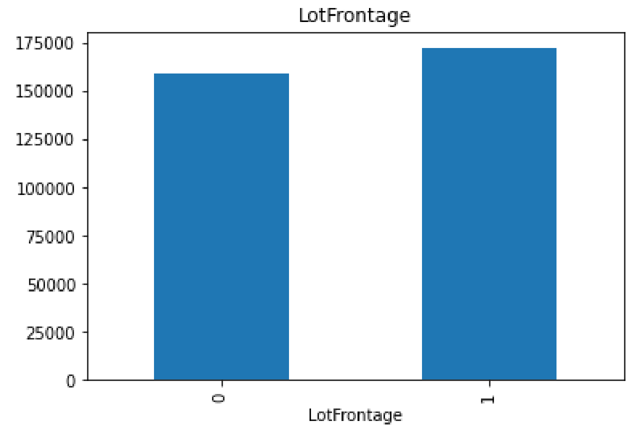
```
Report Report.html was generated! NOTEBOOK/COLAB USERS: no browser will pop up, the report is save
d in your notebook/colab files.
```

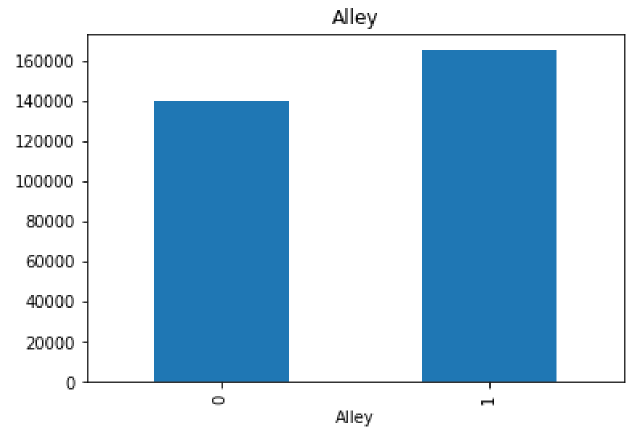
**Since there are many missing values, we need to find a relationship b/w missing values and Sales Price**

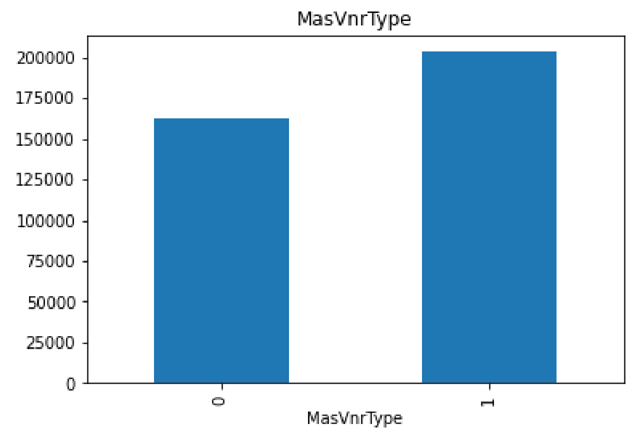
Let's plot some diagram for this relationship

In [7]:

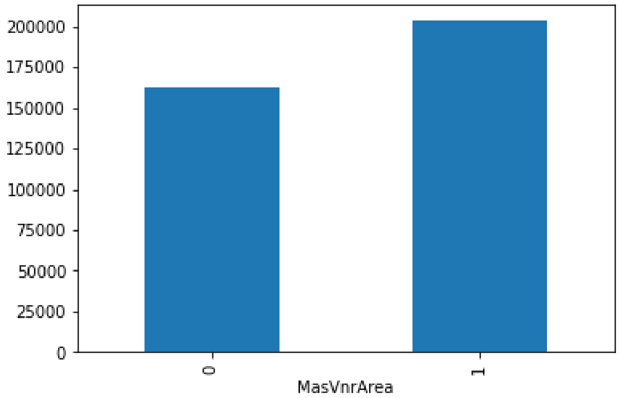
```
for features in features_with_na:
    data = df.copy()

    #Let's make a variable that indicates 1 if the observation was missing or 0 otherwise
    data[features] = np.where(data[features].isnull(),1,0)

    #Let's calculate the median SalePrice where the information was missing or present
    data.groupby(features)['SalePrice'].median().plot.bar()
    plt.title(features)
    plt.show()
```

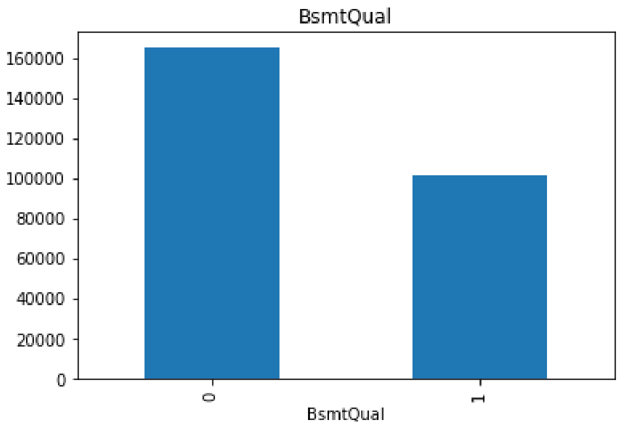


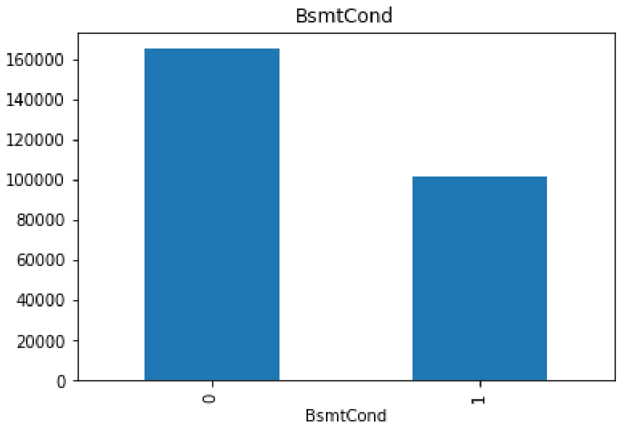



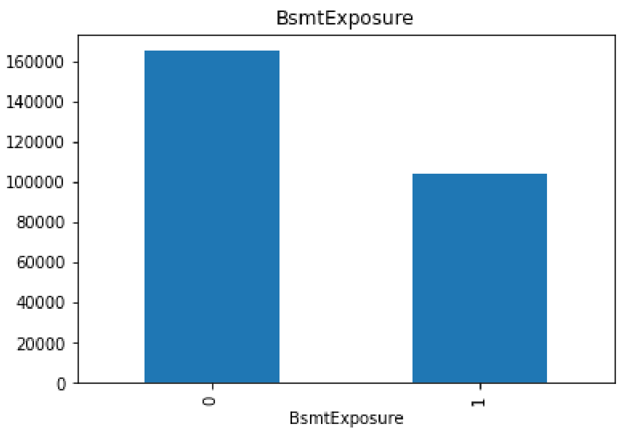



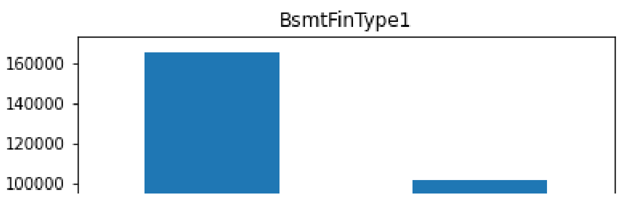

MasVnrArea

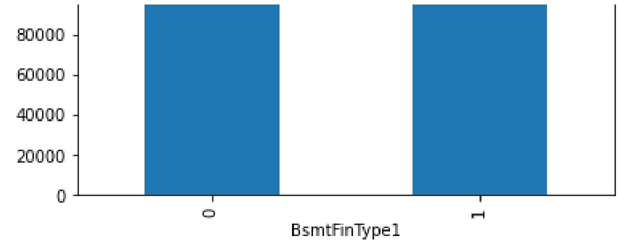

200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
MasVnrArea

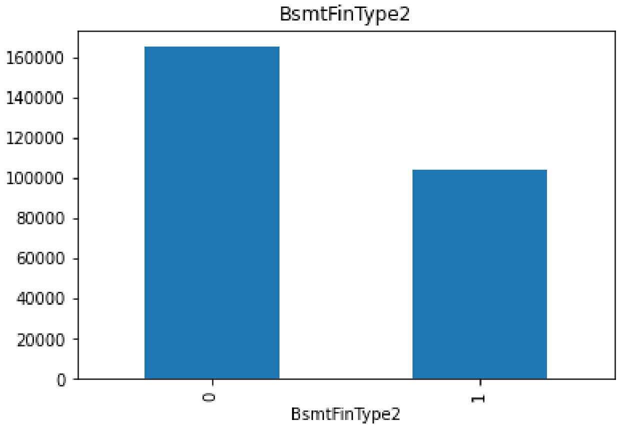

BsmtQual
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtQual

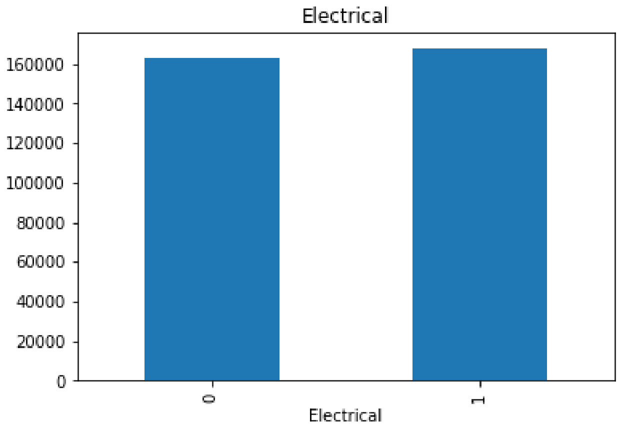

BsmtCond
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtCond

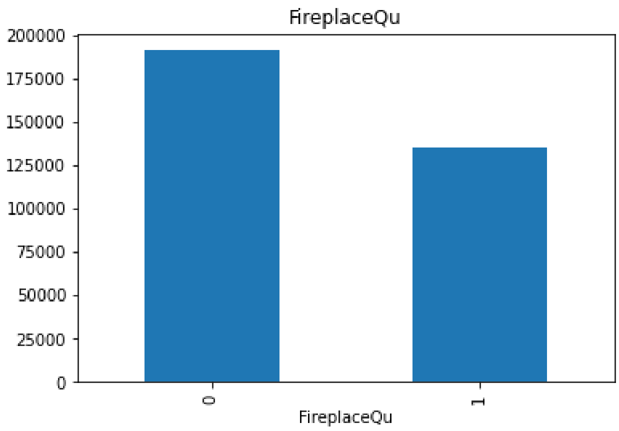

BsmtExposure
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtExposure

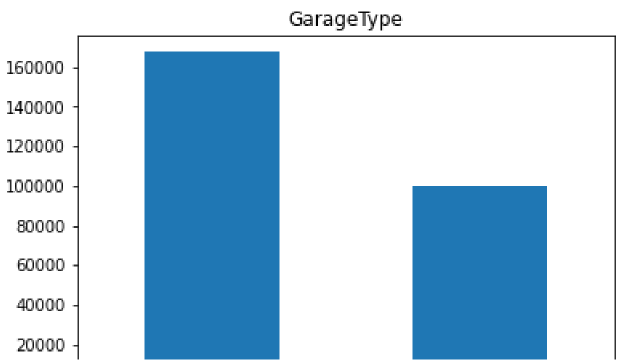

BsmtFinType1
160000
140000
120000
100000


80000
60000
40000
20000
0
0
1
BsmtFinType1

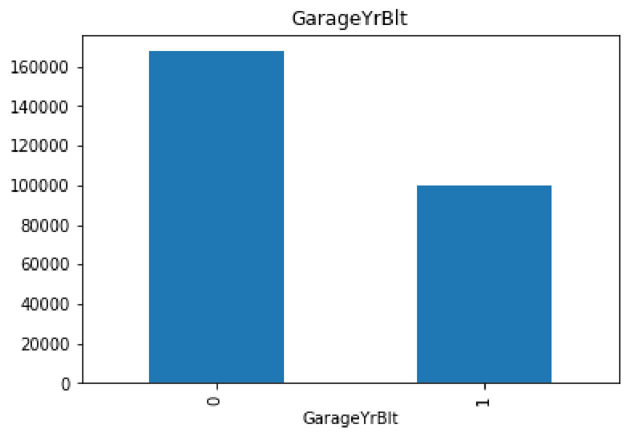

BsmtFinType2
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtFinType2

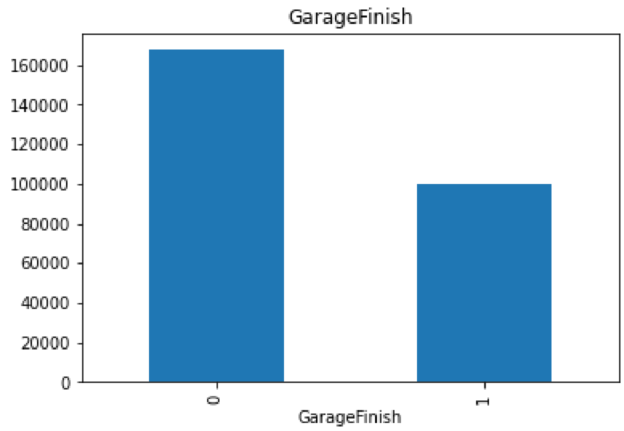

Electrical
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
Electrical

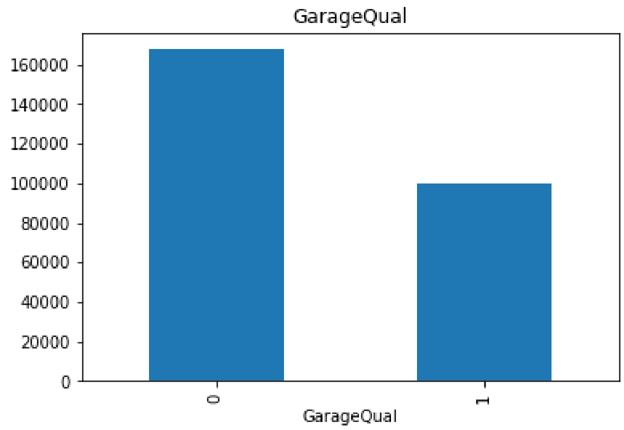

FireplaceQu
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
FireplaceQu

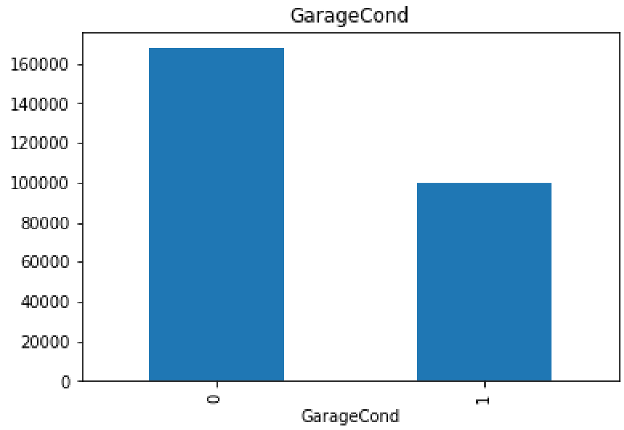

GarageType
160000
140000
120000
100000
80000
60000
40000
20000

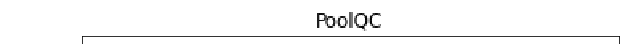

0
0
1
GarageType

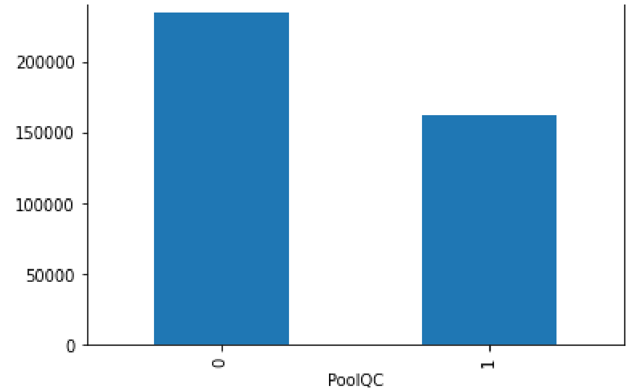

GarageYrBlt
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
GarageYrBlt

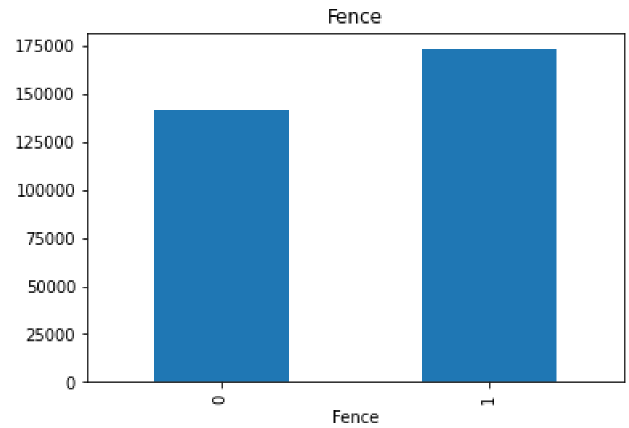

GarageFinish
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
GarageFinish

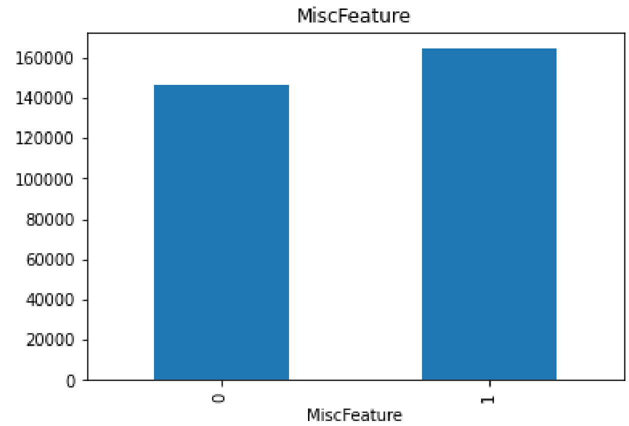

GarageQual
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
GarageQual


GarageCond
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
GarageCond


PoolQC




Here With the relation between the missing values and the dependent variable is clearly visible.So We need to replace these nan values with something meaningful which we will do in the Feature Engineering section

From the above dataset some of the features like Id is not required

In [8]:

```
print("Id of houses {}".format(len(df.Id)))
```

```
Id of houses 1460
```

### Numerical Variables

In [9]:

```
numerical_features = [feature for feature in df.columns if df[feature].dtypes!= 'O' ]
print("no. of numerical features {}".format(len(numerical_features)))

#Visualize the numerical features
df[numerical_features].head()
```

```
no. of numerical features 38
```

Out[9]:

| | Id | MSSubClass | LotFrontage | LotArea | OverallQual | OverallCond | YearBuilt | YearRemodAdd | MasVnrArea | BsmtFinSF1 | BsmtFinSF2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 60 | 65.0 | 8450 | 7 | 5 | 2003 | 2003 | 196.0 | 706 | 0 |
| **1** | 2 | 20 | 80.0 | 9600 | 6 | 8 | 1976 | 1976 | 0.0 | 978 | 0 |
| **2** | 3 | 60 | 68.0 | 11250 | 7 | 5 | 2001 | 2002 | 162.0 | 486 | 0 |
| **3** | 4 | 70 | 60.0 | 9550 | 7 | 5 | 1915 | 1970 | 0.0 | 216 | 0 |
| **4** | 5 | 60 | 84.0 | 14260 | 8 | 5 | 2000 | 2000 | 350.0 | 655 | 0 |

## Temporal Variables(e.g. Datetime variables)

From the Dataset we have 4 year variables. We have to extract information from the datetime variables like no. of years or no. of days. One example in this specific scenario can be difference in years between the year the house was built and the year the house was sold.

In [10]:

```
year_feature = [feature for feature in numerical_features if 'Yr' in feature or 'Year' in feature]
year_feature
```

Out[10]:

```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

In [11]:

```
# Let's explore the content of these year variables
for feature in year_feature:
    print(feature,df[feature].unique())
```

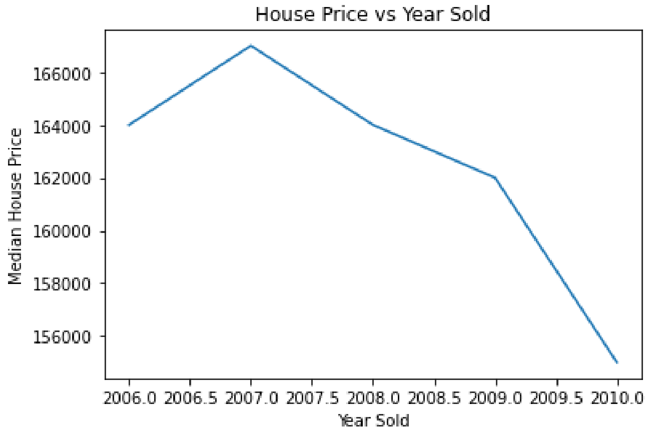
```
YearBuilt [2003 1976 2001 1915 2000 1993 2004 1973 1931 1939 1965 2005 1962 2006
 1960 1929 1970 1967 1958 1930 2002 1968 2007 1951 1957 1927 1920 1966
 1959 1994 1954 1953 1955 1983 1975 1997 1934 1963 1981 1964 1999 1972
 1921 1945 1982 1998 1956 1948 1910 1995 1991 2009 1950 1961 1977 1985
 1979 1885 1919 1990 1969 1935 1988 1971 1952 1936 1923 1924 1984 1926
 1940 1941 1987 1986 2008 1908 1892 1916 1932 1918 1912 1947 1925 1900
 1980 1989 1992 1949 1880 1928 1978 1922 1996 2010 1946 1913 1937 1942
 1938 1974 1893 1914 1906 1890 1898 1904 1882 1875 1911 1917 1872 1905]
YearRemodAdd [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]
GarageYrBlt [2003. 1976. 2001. 1998. 2000. 1993. 2004. 1973. 1931. 1939. 1965. 2005.
 1962. 2006. 1960. 1991. 1970. 1967. 1958. 1930. 2002. 1968. 2007. 2008.
 1957. 1920. 1966. 1959. 1995. 1954. 1953.   nan 1983. 1977. 1997. 1985.
 1963. 1981. 1964. 1999. 1935. 1990. 1945. 1987. 1989. 1915. 1956. 1948.
 1974. 2009. 1950. 1961. 1921. 1900. 1979. 1951. 1969. 1936. 1975. 1971.
 1923. 1984. 1926. 1955. 1986. 1988. 1916. 1932. 1972. 1918. 1980. 1924.
 1996. 1940. 1949. 1994. 1910. 1978. 1982. 1992. 1925. 1941. 2010. 1927.
 1947. 1937. 1942. 1938. 1952. 1928. 1922. 1934. 1906. 1914. 1946. 1908.
 1929. 1933.]
YrSold [2008 2007 2006 2009 2010]
```

In [12]:

```
# Let's analyze the Temporal Datetime variable
##We will check if there is a relation b/w year the house is sold and the SalePrice

df.groupby('YrSold')['SalePrice'].median().plot()
plt.xlabel('Year Sold')
plt.ylabel('Median House Price')
plt.title('House Price vs Year Sold')
```

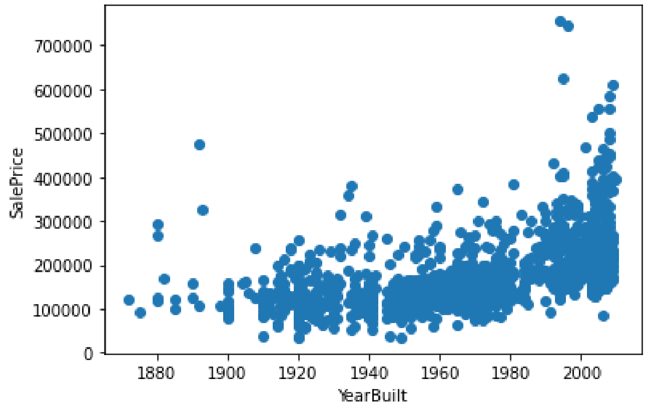
Out[12]:

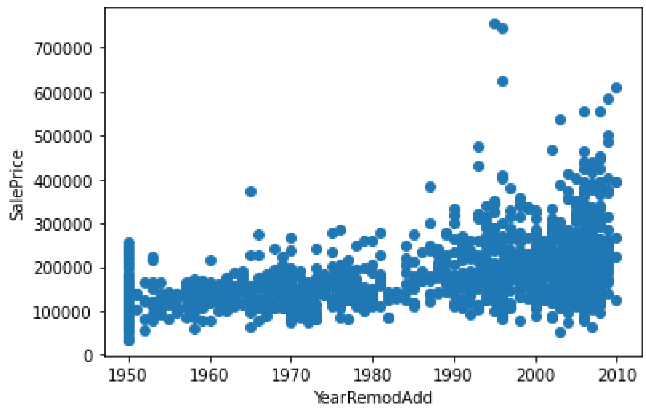
```
Text(0.5, 1.0, 'House Price vs Year Sold')
```

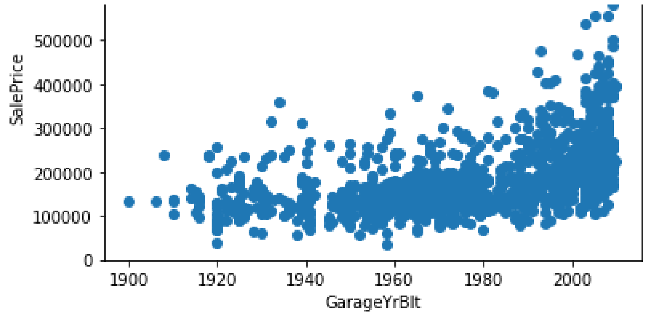



In [13]:

```python
# Here we will compare the difference b/w all year features with SalePrice
for feature in year_feature:
    if feature!= 'YrSold':
        data=df.copy()
        #df[feature]=df['YrSold']-df[feature]

        plt.scatter(df[feature],df['SalePrice'])
        plt.xlabel(feature)
        plt.ylabel('SalePrice')
        plt.show()
```




In [14]:

```
## Numerical variables are usually of 2 type
## 1. Continous variable 2. Discrete Variables

discrete_feature=[feature for feature in numerical_features if len(df[feature].unique())<25 and fea
ture not in year_feature]
print("Discrete Variables Count: {}".format(len(discrete_feature)))
```

```
Discrete Variables Count: 17
```

In [15]:

```
discrete_feature
```

Out[15]:

```
['MSSubClass',
 'OverallQual',
 'OverallCond',
 'LowQualFinSF',
 'BsmtFullBath',
 'BsmtHalfBath',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'KitchenAbvGr',
 'TotRmsAbvGrd',
 'Fireplaces',
 'GarageCars',
 '3SsnPorch',
 'PoolArea',
 'MiscVal',
 'MoSold']
```

In [16]:

```
df[discrete_feature].head()
```

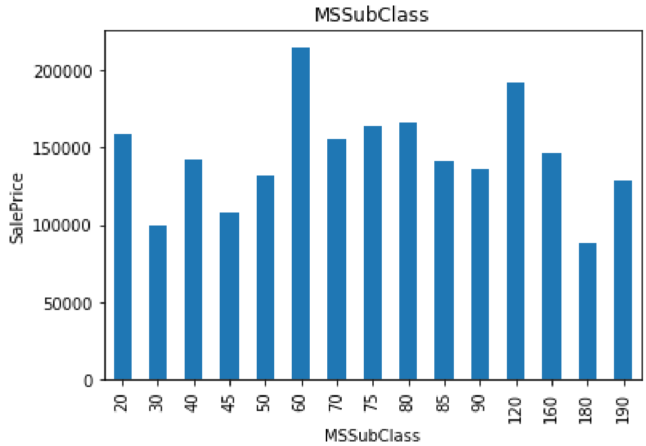
Out[16]:

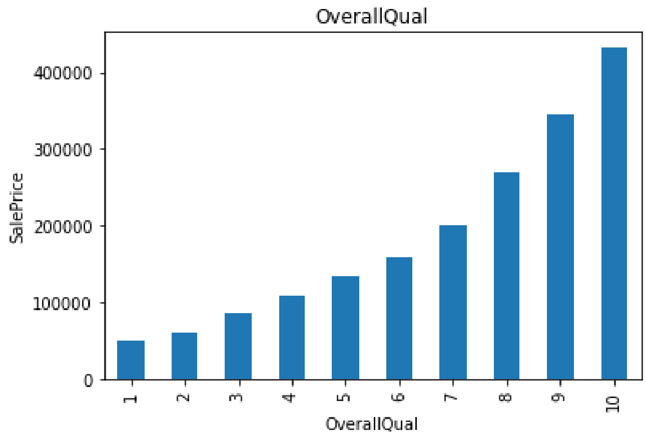
| | MSSubClass | OverallQual | OverallCond | LowQualFinSF | BsmtFullBath | BsmtHalfBath | FullBath | HalfBath | BedroomAbvGr | KitchenAb |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 60 | 7 | 5 | 0 | 1 | 0 | 2 | 1 | 3 | |
| **1** | 20 | 6 | 8 | 0 | 0 | 1 | 2 | 0 | 3 | |
| **2** | 60 | 7 | 5 | 0 | 1 | 0 | 2 | 1 | 3 | |
| **3** | 70 | 7 | 5 | 0 | 1 | 0 | 1 | 0 | 3 | |
| **4** | 60 | 8 | 5 | 0 | 1 | 0 | 2 | 1 | 4 | |

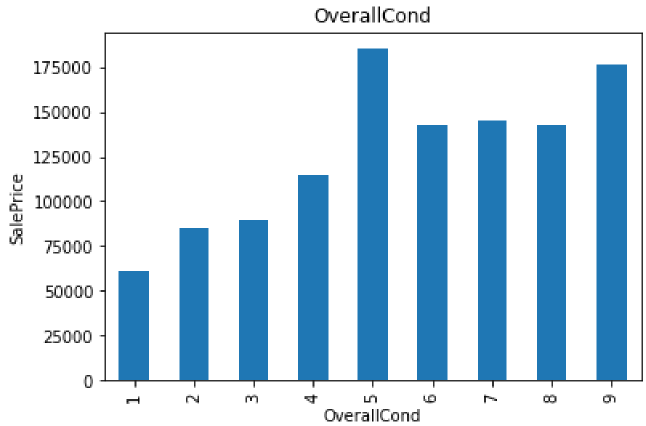
In [17]:

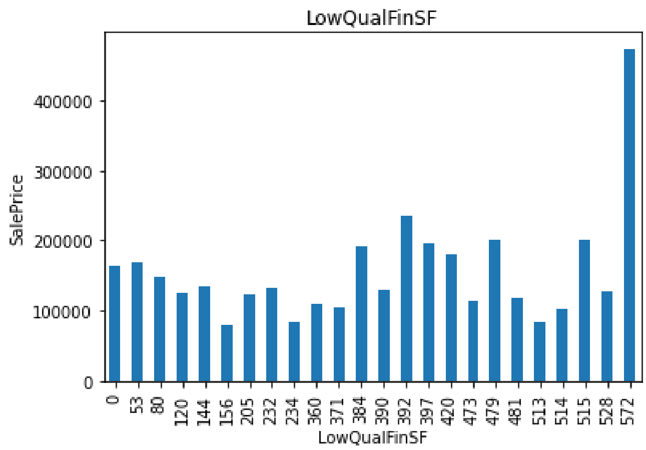
```
## Lets Find the realtionship between them and Sale PRice

for feature in discrete_feature:
    data=df.copy()
    data.groupby(feature)['SalePrice'].median().plot.bar()
    plt.xlabel(feature)
```

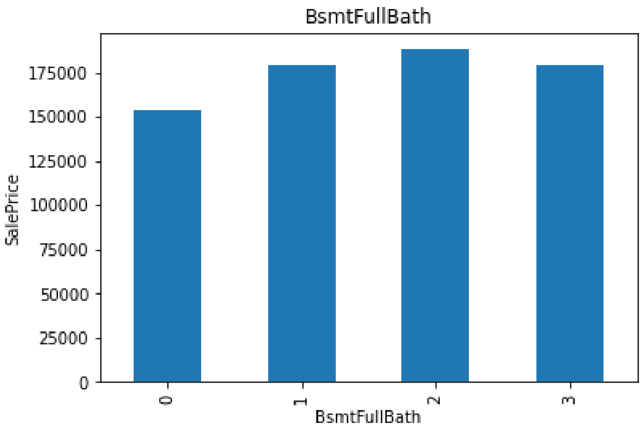
```
    plt.xlabel(feature)
    plt.ylabel('SalePrice')
    plt.title(feature)
    plt.show()
```

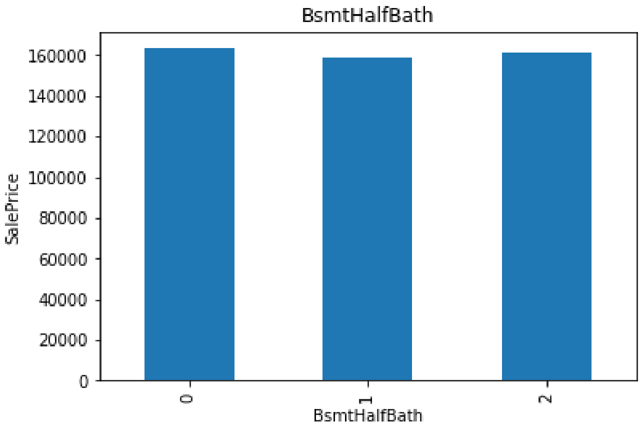


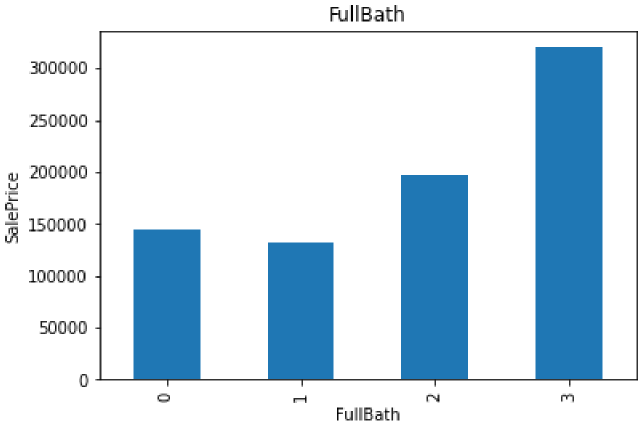



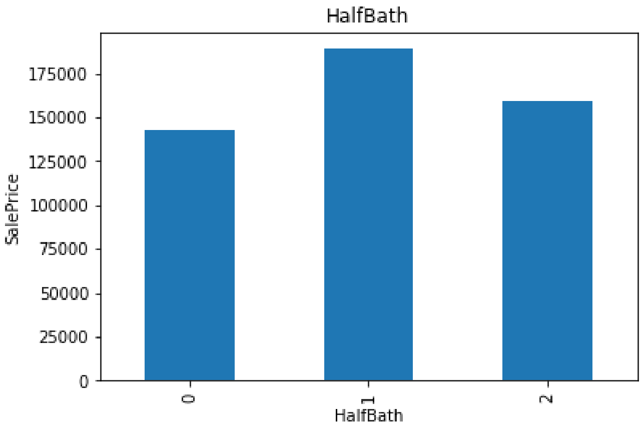



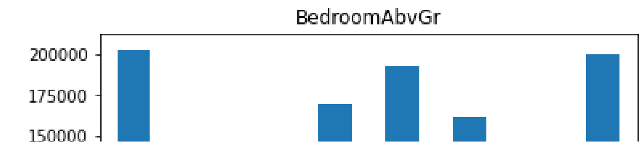



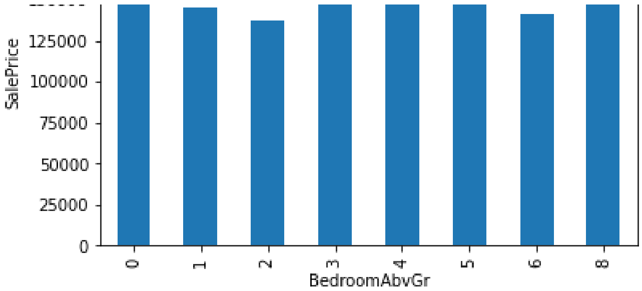

BsmtFullBath
SalePrice
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
BsmtFullBath

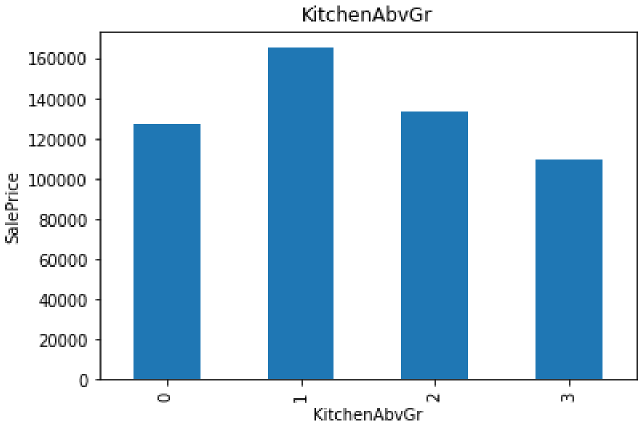

BsmtHalfBath
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
2
BsmtHalfBath

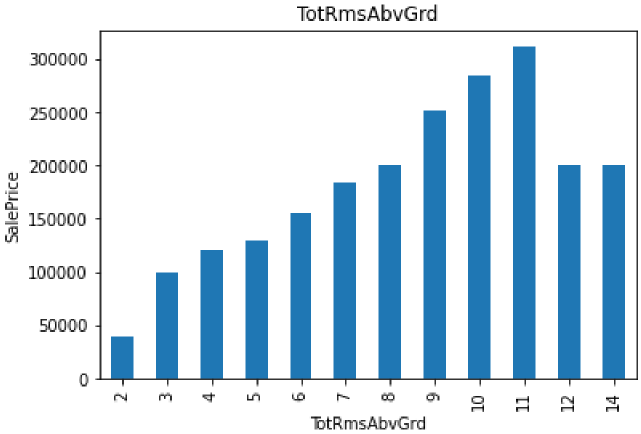

FullBath
SalePrice
300000
250000
200000
150000
100000
50000
0
0
1
2
3
FullBath

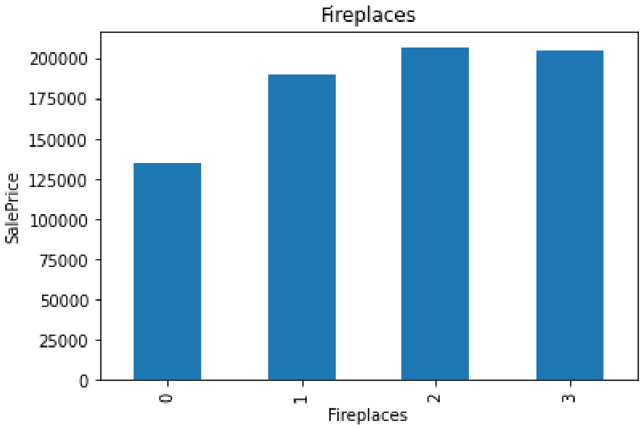

HalfBath
SalePrice
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
HalfBath

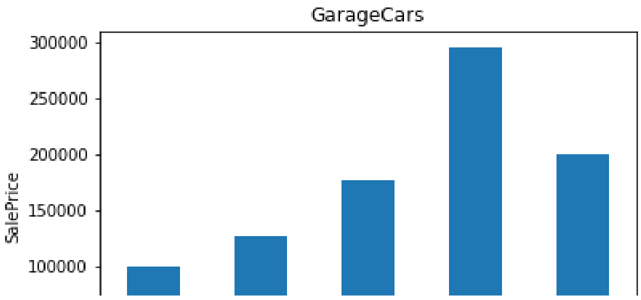

BedroomAbvGr
200000
175000
150000

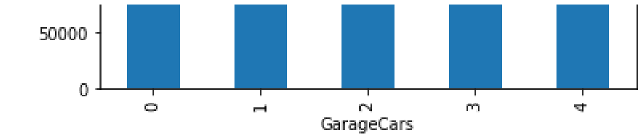

SalePrice
125000
100000
75000
50000
25000
0
0
1
2
3
4
5
6
8
BedroomAbvGr

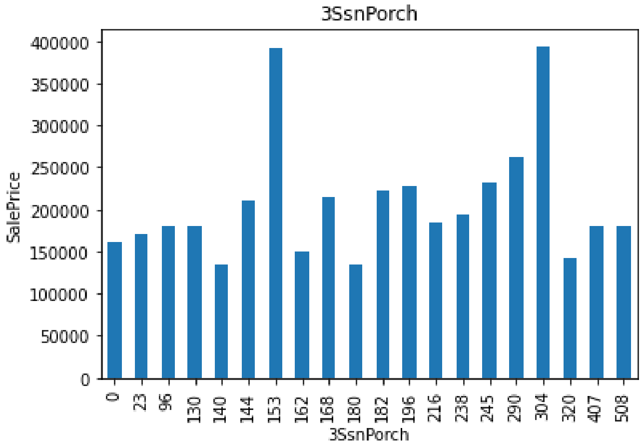

KitchenAbvGr
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
2
3
KitchenAbvGr

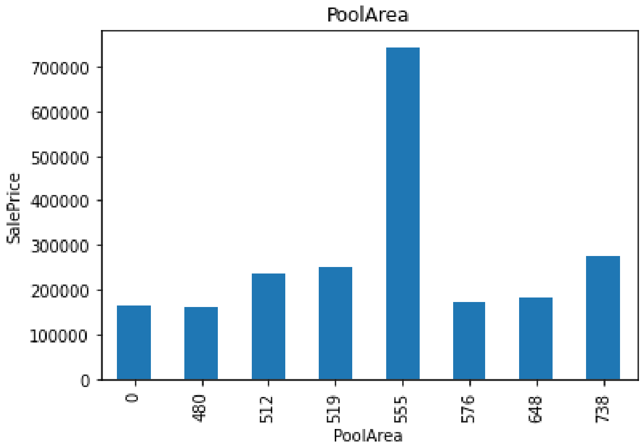

TotRmsAbvGrd
SalePrice
300000
250000
200000
150000
100000
50000
0
2
3
4
5
6
7
8
9
10
11
12
14
TotRmsAbvGrd

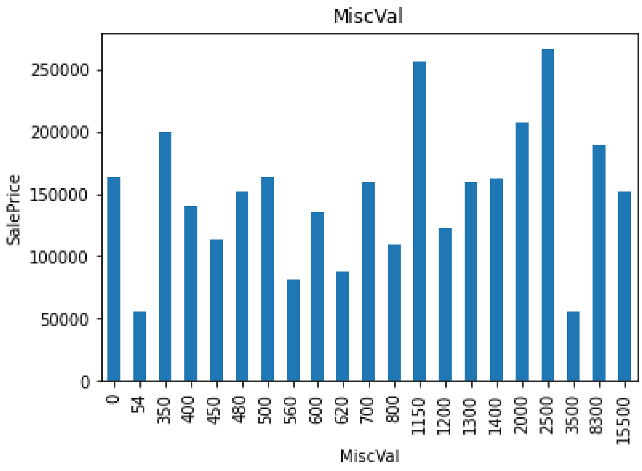

Fireplaces
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
Fireplaces

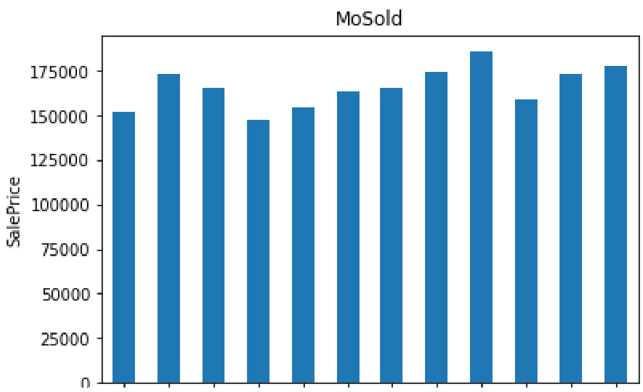

GarageCars
SalePrice
300000
250000
200000
150000
100000


50000
0
0
1
2
3
4
GarageCars


3SsnPorch
400000
350000
300000
250000
200000
150000
100000
50000
0
SalePrice
0
23
96
130
140
144
153
162
168
180
182
196
216
238
245
290
304
320
407
508
3SsnPorch


PoolArea
700000
600000
500000
400000
300000
200000
100000
0
SalePrice
0
480
512
519
555
576
648
738
PoolArea


MiscVal
250000
200000
150000
100000
50000
0
SalePrice
0
54
350
400
450
480
500
560
600
620
700
800
1150
1200
1300
1400
2000
2500
3500
8300
15500
MiscVal


MoSold
175000
150000
125000
100000
75000
50000
25000
0
SalePrice


## Continuous Variable

In [18]:

```
continuous_feature= [feature for feature in numerical_features if feature not in discrete_feature+y
ear_feature+['Id']]
print("Continuous feature Count {}".format(len(continuous_feature)))
```

```
Continuous feature Count 16
```

In [19]:

```
continuous_feature
```

Out[19]:

```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch',
 'SalePrice']
```

In [20]:

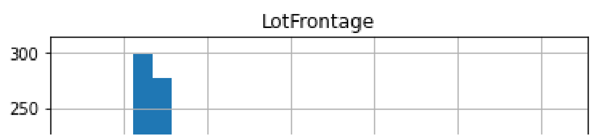
```
df[continuous_feature].head()
```

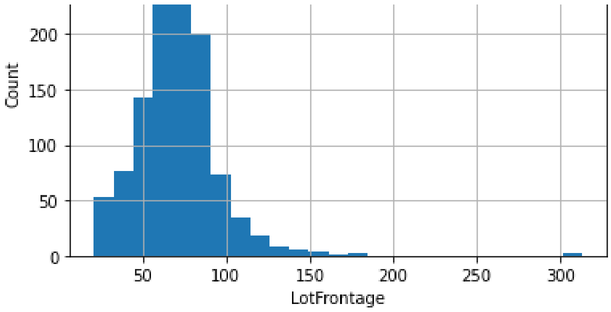
Out[20]:

| | LotFrontage | LotArea | MasVnrArea | BsmtFinSF1 | BsmtFinSF2 | BsmtUnfSF | TotalBsmtSF | 1stFlrSF | 2ndFlrSF | GrLivArea | GarageArea |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 65.0 | 8450 | 196.0 | 706 | 0 | 150 | 856 | 856 | 854 | 1710 | 548 |
| **1** | 80.0 | 9600 | 0.0 | 978 | 0 | 284 | 1262 | 1262 | 0 | 1262 | 460 |
| **2** | 68.0 | 11250 | 162.0 | 486 | 0 | 434 | 920 | 920 | 866 | 1786 | 608 |
| **3** | 60.0 | 9550 | 0.0 | 216 | 0 | 540 | 756 | 961 | 756 | 1717 | 642 |
| **4** | 84.0 | 14260 | 350.0 | 655 | 0 | 490 | 1145 | 1145 | 1053 | 2198 | 836 |

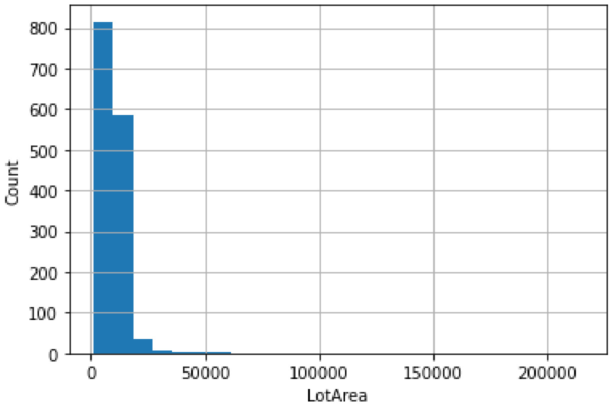
In [21]:

```
for feature in continuous_feature:
    data=df.copy()
    data[feature].hist(bins=25)
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.title(feature)
    plt.show()
```

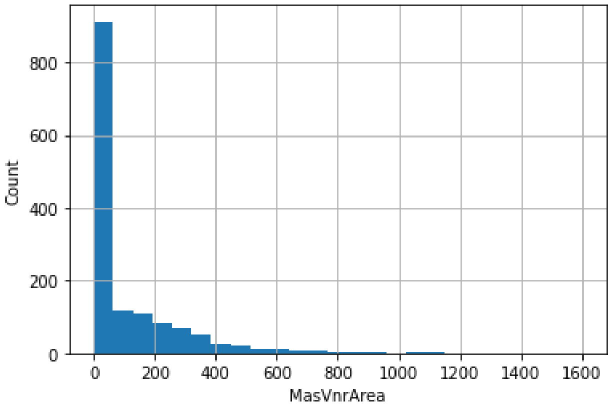




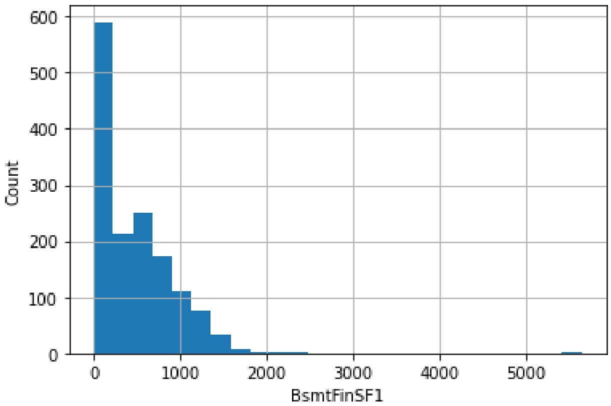

LotArea



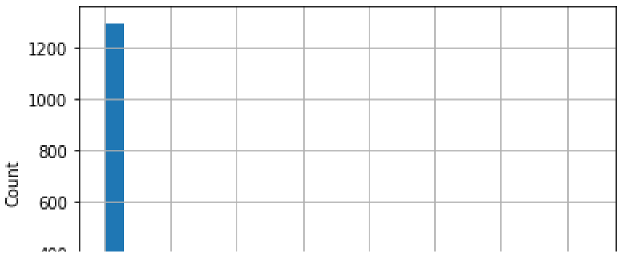

MasVnrArea

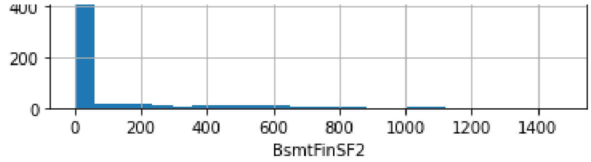


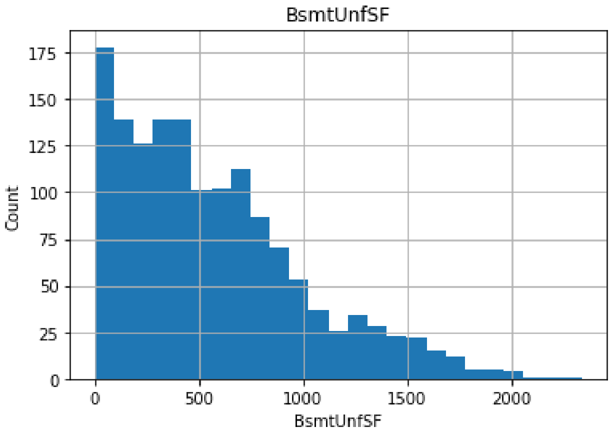

BsmtFinSF1

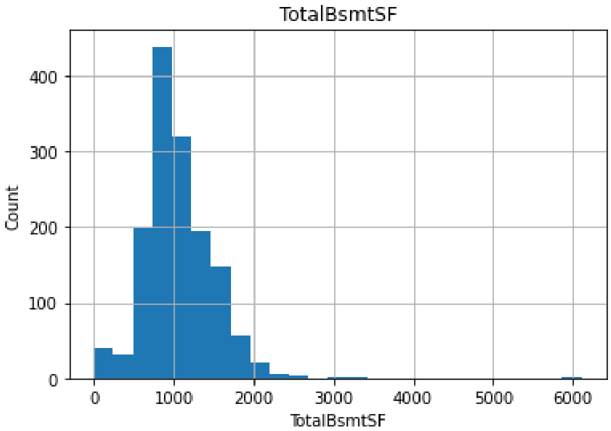


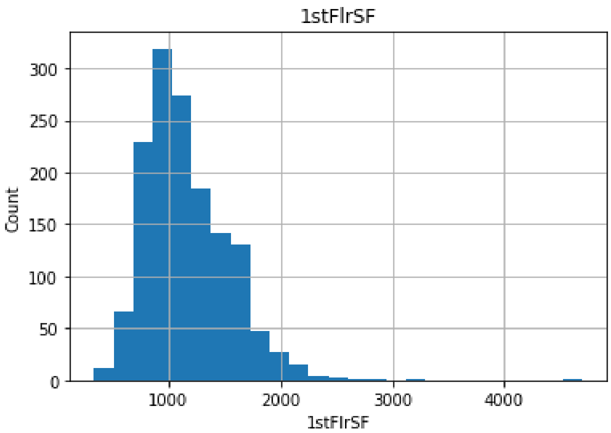

BsmtFinSF2

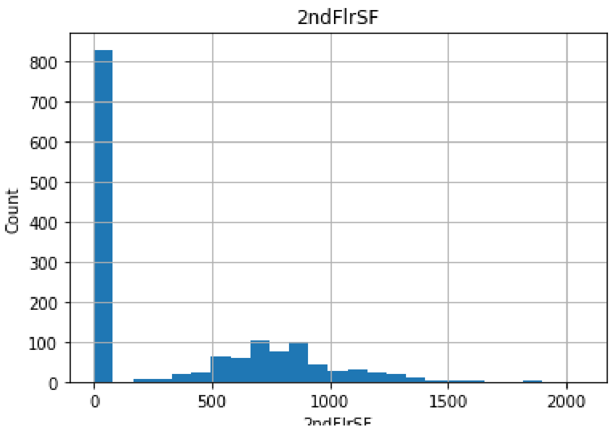


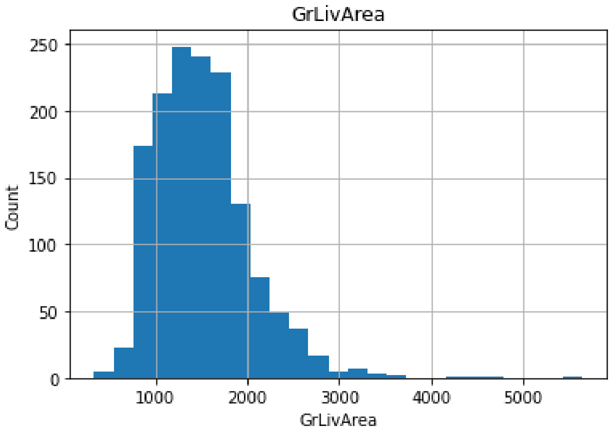

0
200
400
0
200
400
600
800
1000
1200
1400
BsmtFinSF2

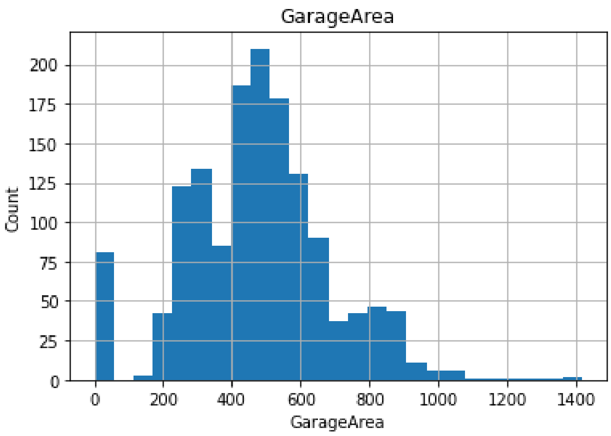

BsmtUnfSF
Count
BsmtUnfSF

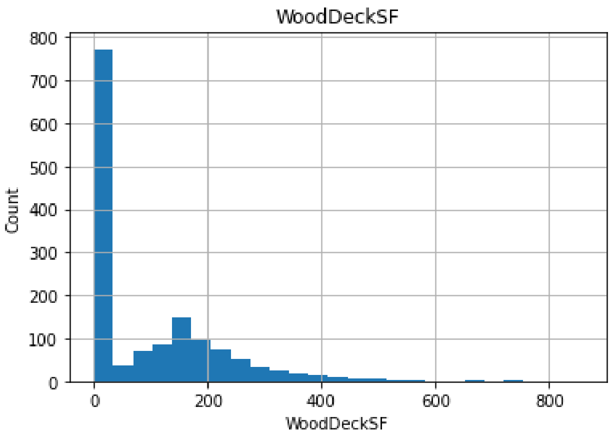

TotalBsmtSF
Count
TotalBsmtSF

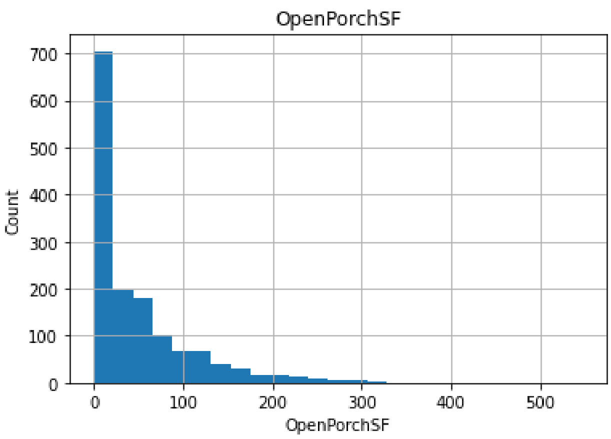

1stFlrSF
Count
1stFlrSF

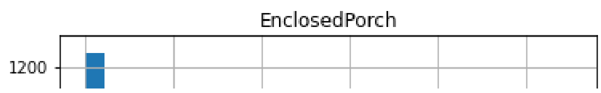

2ndFlrSF
Count

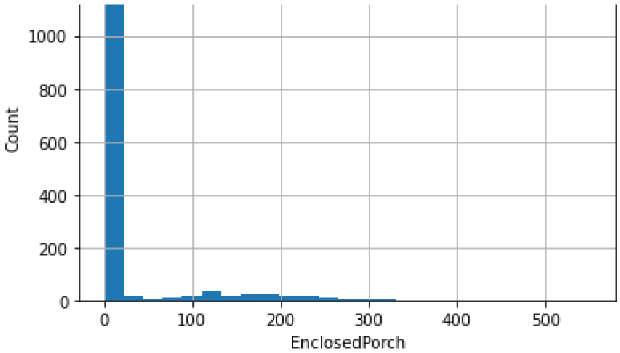

GrLivArea
Count
250
200
150
100
50
0
1000
2000
3000
4000
5000
GrLivArea

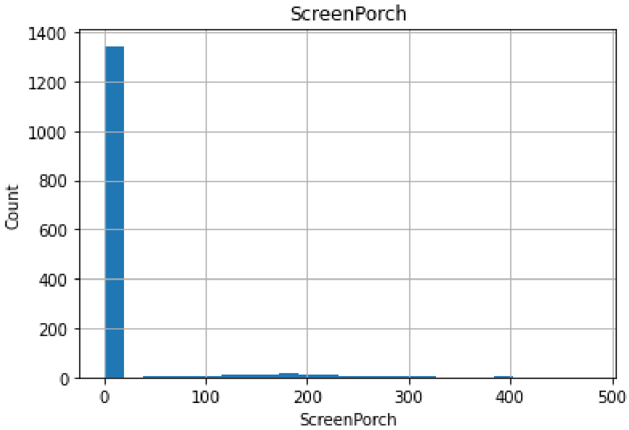

GarageArea
Count
200
175
150
125
100
75
50
25
0
0
200
400
600
800
1000
1200
1400
GarageArea

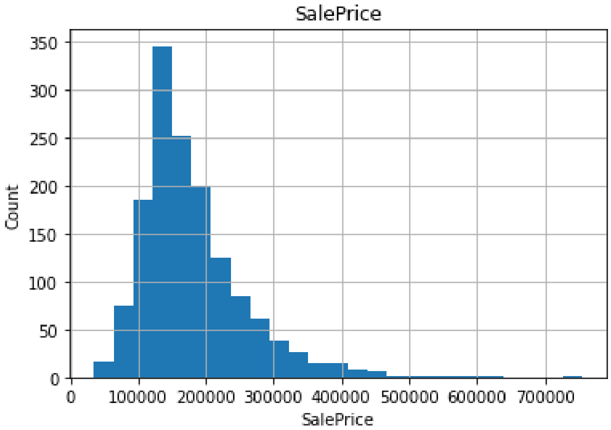

WoodDeckSF
Count
800
700
600
500
400
300
200
100
0
0
200
400
600
800
WoodDeckSF


OpenPorchSF
Count
700
600
500
400
300
200
100
0
0
100
200
300
400
500
OpenPorchSF


EnclosedPorch
1200



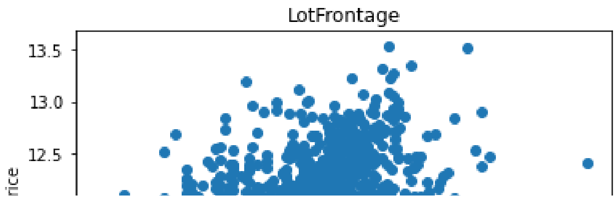



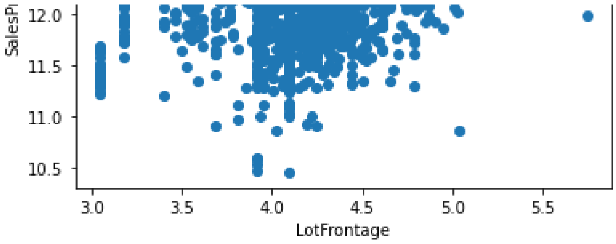



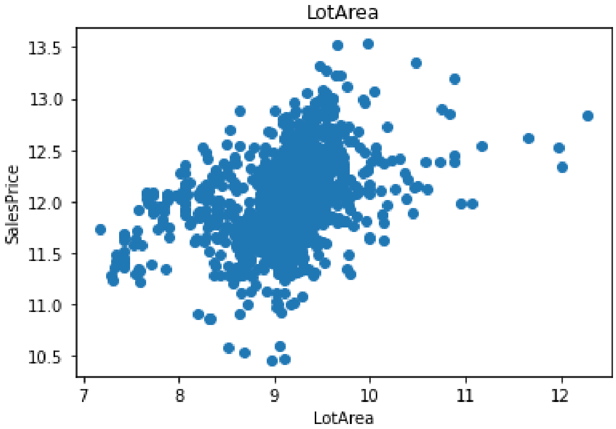

**We will be using Logarithmic Transformation**

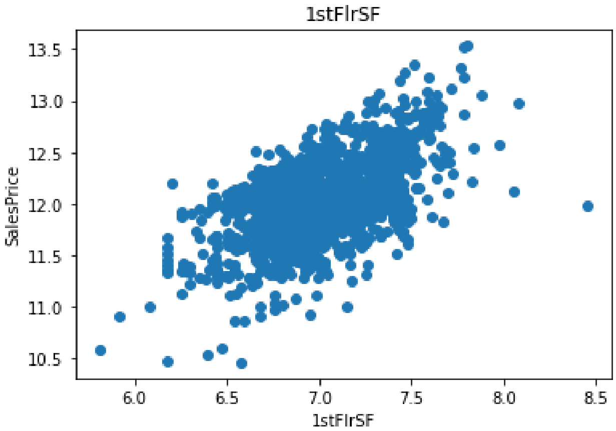
In [166]:

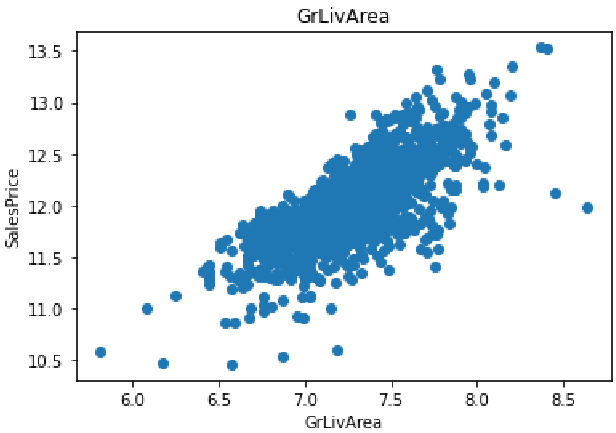
```
for feature in continuous_feature:
    data=df.copy()
    if 0 in data[feature].unique():
        pass
    else:
        data[feature]=np.log(data[feature])
        data['SalePrice']=np.log(data['SalePrice'])
        plt.scatter(x=data[feature],y=data['SalePrice'])
        plt.xlabel(feature)
        plt.ylabel('SalesPrice')
        plt.title(feature)
        plt.show()
```

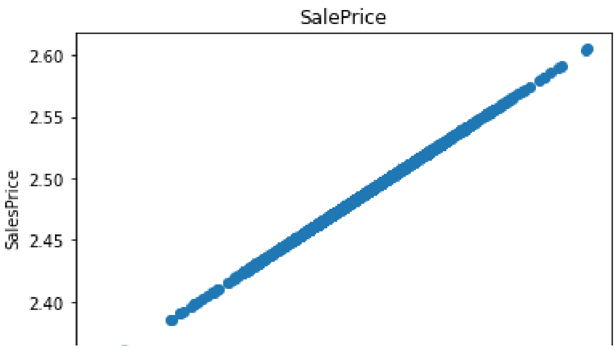


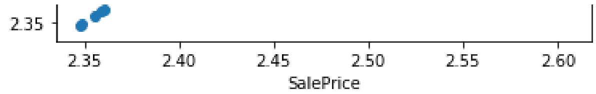

SalesPr
12.0
11.5
11.0
10.5
3.0
3.5
4.0
4.5
5.0
5.5
LotFrontage


LotArea
SalesPrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
7
8
9
10
11
12
LotArea


1stFlrSF
SalesPrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
6.0
6.5
7.0
7.5
8.0
8.5
1stFlrSF


GrLivArea
SalesPrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
6.0
6.5
7.0
7.5
8.0
8.5
GrLivArea


SalePrice
SalesPrice
2.60
2.55
2.50
2.45
2.40




In [22]:

```
df_copy = df.copy()
```

In [23]:

```
df_copy.head()
```

Out[23]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighbor |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 60 | RL | 65.0 | 8450 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | Cc |
| **1** | 2 | 20 | RL | 80.0 | 9600 | Pave | NaN | Reg | Lvl | AllPub | FR2 | Gtl | Ve |
| **2** | 3 | 60 | RL | 68.0 | 11250 | Pave | NaN | IR1 | Lvl | AllPub | Inside | Gtl | Cc |
| **3** | 4 | 70 | RL | 60.0 | 9550 | Pave | NaN | IR1 | Lvl | AllPub | Corner | Gtl | Cr |
| **4** | 5 | 60 | RL | 84.0 | 14260 | Pave | NaN | IR1 | Lvl | AllPub | FR2 | Gtl | Nol |

In [24]:

```
df = df_copy
```

We can observe monotonic relationships b/w the continuous variables and the dependent variable

In [25]:

```
df.head()
```

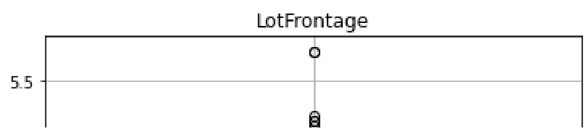
Out[25]:

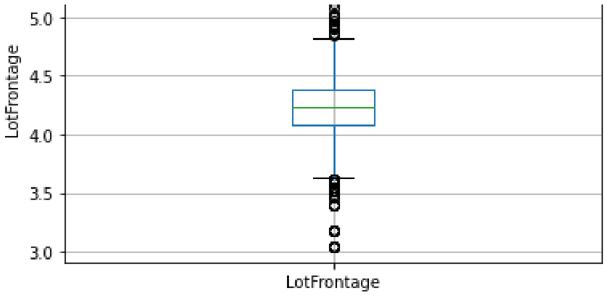
| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighbor |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 60 | RL | 65.0 | 8450 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | Cc |
| **1** | 2 | 20 | RL | 80.0 | 9600 | Pave | NaN | Reg | Lvl | AllPub | FR2 | Gtl | Ve |
| **2** | 3 | 60 | RL | 68.0 | 11250 | Pave | NaN | IR1 | Lvl | AllPub | Inside | Gtl | Cc |
| **3** | 4 | 70 | RL | 60.0 | 9550 | Pave | NaN | IR1 | Lvl | AllPub | Corner | Gtl | Cr |
| **4** | 5 | 60 | RL | 84.0 | 14260 | Pave | NaN | IR1 | Lvl | AllPub | FR2 | Gtl | Nol |

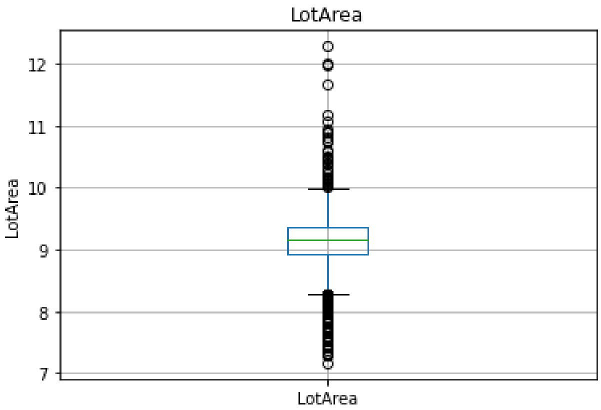
## Outliers

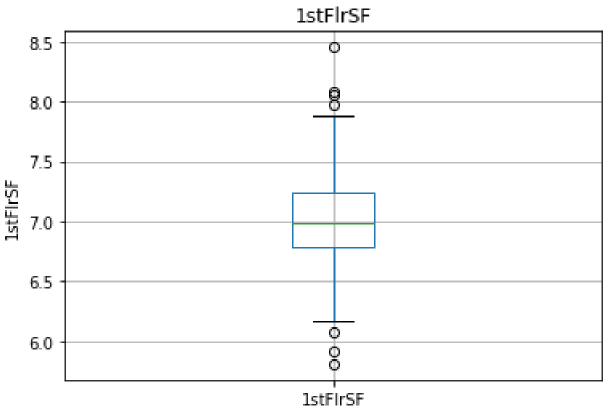
In [26]:

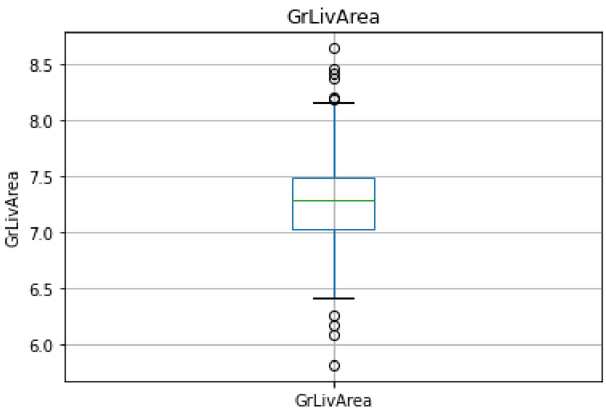
```
for feature in continuous_feature:
    data=df.copy()

    if 0 in data[feature].unique():
        pass
    else:
        data[feature]=np.log(data[feature])
        data.boxplot(column=feature)
        plt.ylabel(feature)
        plt.title(feature)
        plt.show()
```

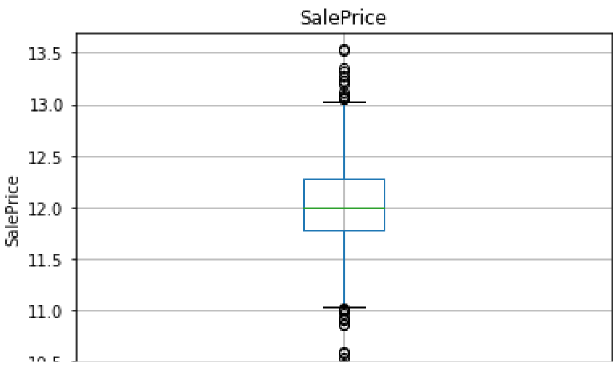



LotFrontage
LotFrontage
5.0
4.5
4.0
3.5
3.0


LotArea
LotArea
LotArea
12
11
10
9
8
7


1stFlrSF
1stFlrSF
1stFlrSF
8.5
8.0
7.5
7.0
6.5
6.0


GrLivArea
GrLivArea
GrLivArea
8.5
8.0
7.5
7.0
6.5
6.0


SalePrice
SalePrice
13.5
13.0
12.5
12.0
11.5
11.0


In [27]:

```
data.head()
```

Out[27]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighbor |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 60 | RL | 65.0 | 8450 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | Co |
| **1** | 2 | 20 | RL | 80.0 | 9600 | Pave | NaN | Reg | Lvl | AllPub | FR2 | Gtl | Ve |
| **2** | 3 | 60 | RL | 68.0 | 11250 | Pave | NaN | IR1 | Lvl | AllPub | Inside | Gtl | Co |
| **3** | 4 | 70 | RL | 60.0 | 9550 | Pave | NaN | IR1 | Lvl | AllPub | Corner | Gtl | Cr |
| **4** | 5 | 60 | RL | 84.0 | 14260 | Pave | NaN | IR1 | Lvl | AllPub | FR2 | Gtl | No |

In [28]:

```
data=df.copy()
```

In [29]:

```
continuous_feature
```

Out[29]:

```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch',
 'SalePrice']
```

In [30]:

```
for feature in continuous_feature:
        IQR = np.percentile(df[feature],75) - np.percentile(df[feature],25)
        lb = np.percentile(df[feature],25)-IQR*1.5
        ub = np.percentile(df[feature],75)+IQR*1.5

        df[feature] = np.where(df[feature]>ub,ub,df[feature])
        df[feature] = np.where(df[feature]<lb,lb,df[feature])
        df[feature] = np.log1p(df[feature])
```

In [ ]:

```

```

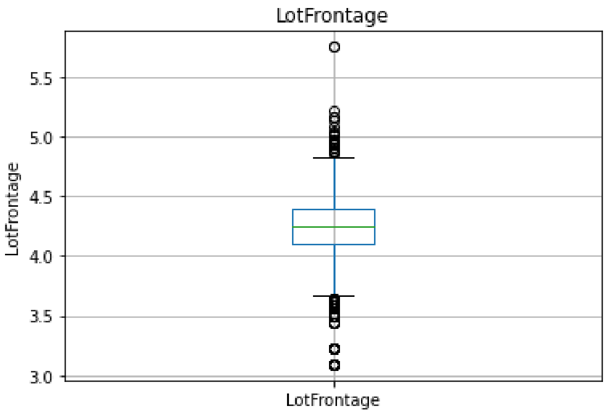
In [588]:

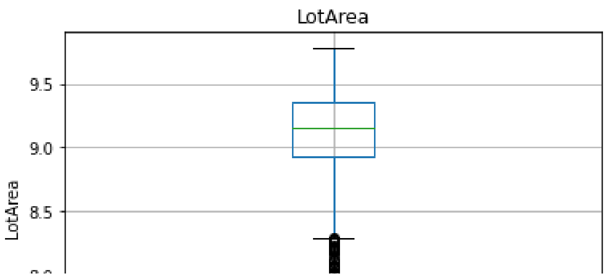
```
#import scipy
#for feature in continuous_feature:
  #   df[feature] = scipy.stats.boxcox(df[feature].values)
```

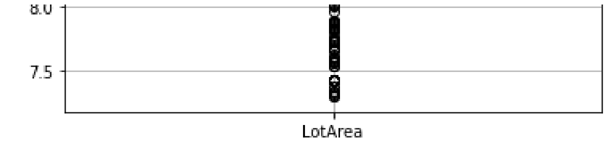
```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-588-b6fa7f7530c5> in <module>
      1 import scipy
      2 for feature in continuous_feature:
----> 3     df[feature] = scipy.stats.boxcox(df[feature].values)

~\Anaconda3\lib\site-packages\pandas\core\frame.py in __setitem__(self, key, value)
   3035         else:
   3036             # set column
-> 3037             self._set_item(key, value)
   3038 
   3039     def _setitem_slice(self, key: slice, value):

~\Anaconda3\lib\site-packages\pandas\core\frame.py in _set_item(self, key, value)
   3111         """
   3112         self._ensure_valid_index(value)
-> 3113         value = self._sanitize_column(key, value)
   3114         NDFrame._set_item(self, key, value)
   3115 

~\Anaconda3\lib\site-packages\pandas\core\frame.py in _sanitize_column(self, key, value, 
broadcast)
   3756 
   3757             # turn me into an ndarray
-> 3758             value = sanitize_index(value, self.index)
   3759             if not isinstance(value, (np.ndarray, Index)):
   3760                 if isinstance(value, list) and len(value) > 0:

~\Anaconda3\lib\site-packages\pandas\core\internals\construction.py in sanitize_index(data, index)
    746     if len(data) != len(index):
    747         raise ValueError(
--> 748             "Length of values "
    749             f"({len(data)}) "
    750             "does not match length of index "

ValueError: Length of values (2) does not match length of index (1460)
```

In [31]:

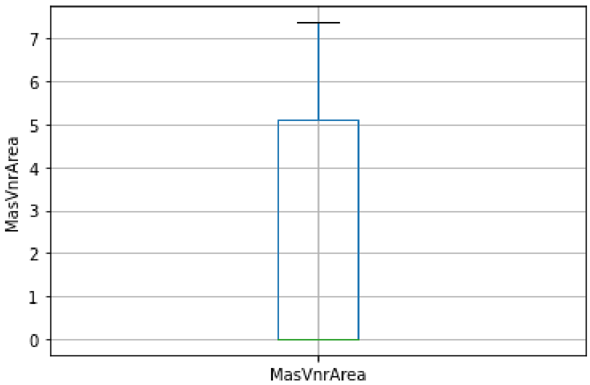
```
for feature in continuous_feature:
        df.boxplot(column=feature)
        plt.ylabel(feature)
        plt.title(feature)
        plt.show()
```



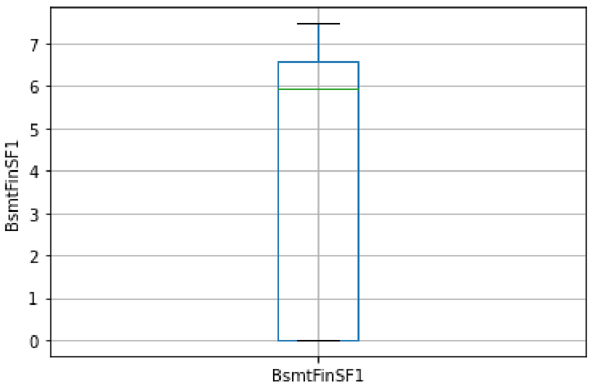





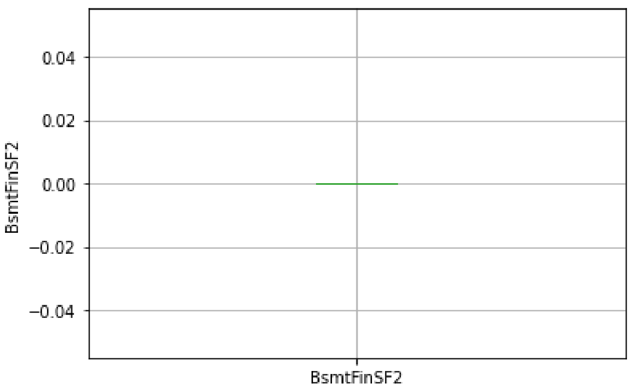

MasVnrArea



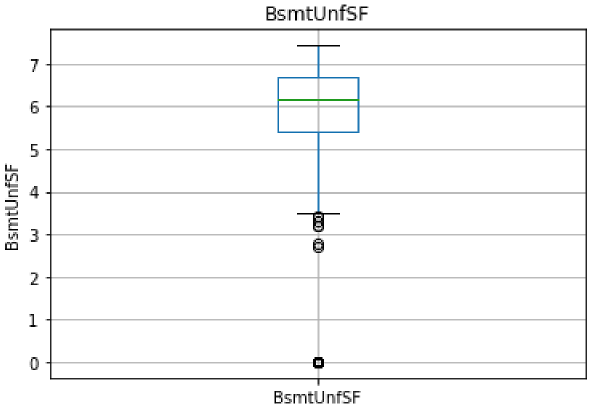

BsmtFinSF1



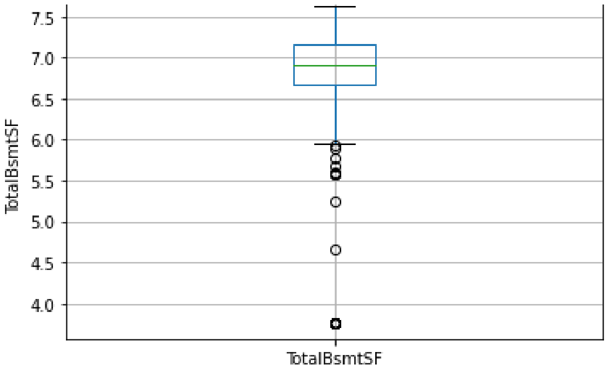

BsmtFinSF2

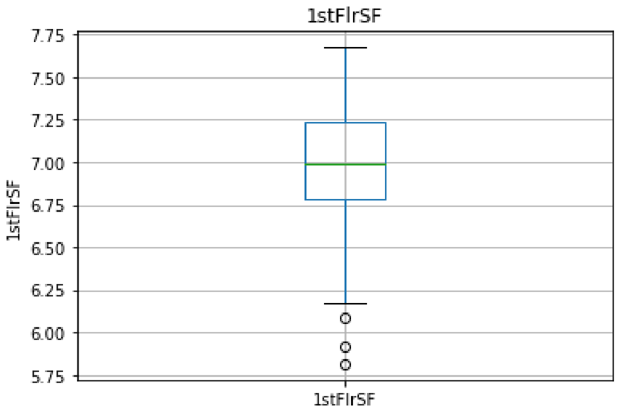


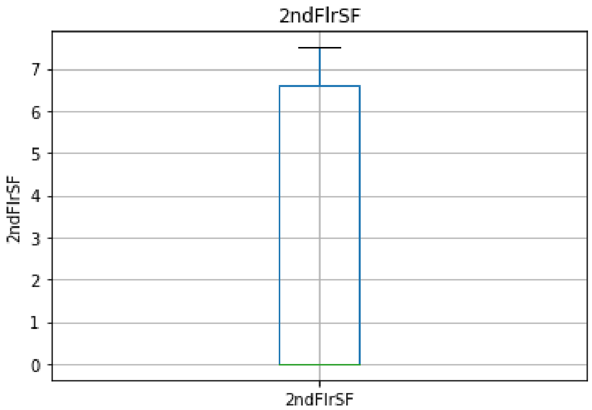

BsmtUnfSF

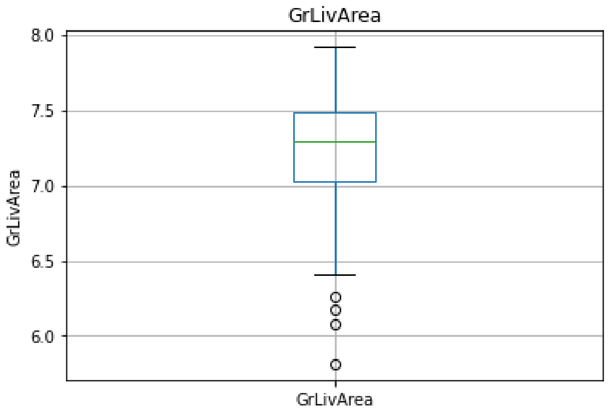


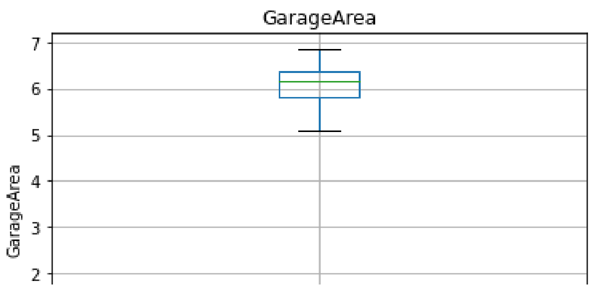

TotalBsmtSF

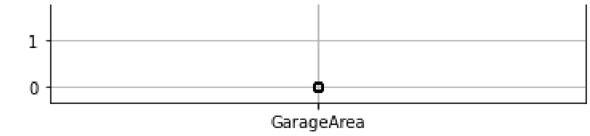

TotalBsmtSF
TotalBsmtSF
7.5
7.0
6.5
6.0
5.5
5.0
4.5
4.0

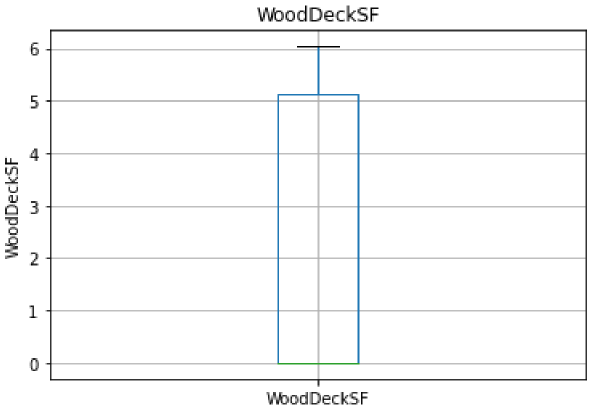

1stFlrSF
1stFlrSF
1stFlrSF
7.75
7.50
7.25
7.00
6.75
6.50
6.25
6.00
5.75

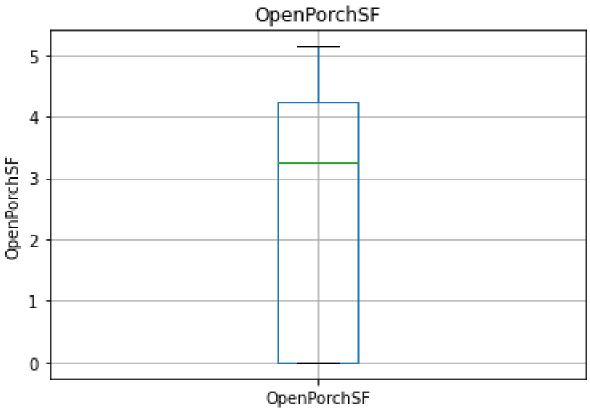

2ndFlrSF
2ndFlrSF
2ndFlrSF
7
6
5
4
3
2
1
0

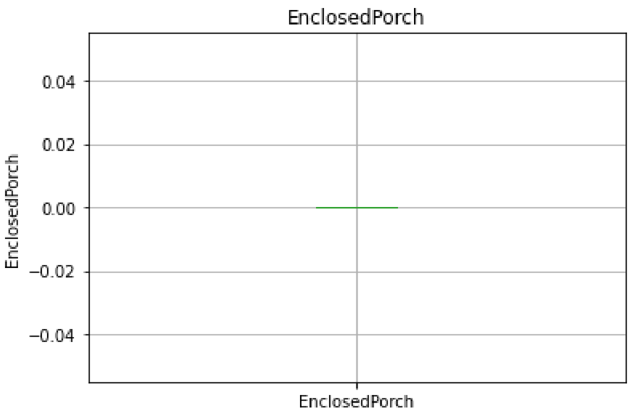

GrLivArea
GrLivArea
GrLivArea
8.0
7.5
7.0
6.5
6.0

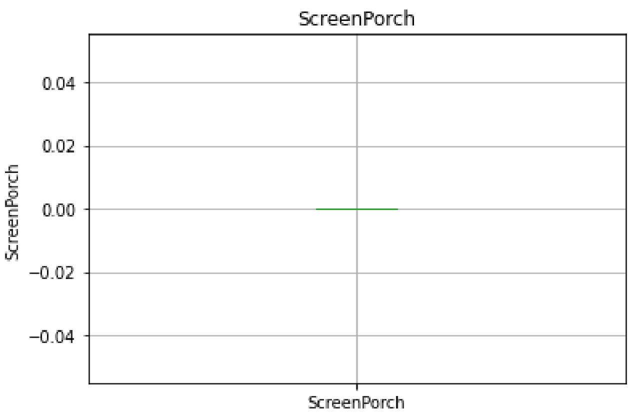

GarageArea
GarageArea
7
6
5
4
3
2


1
0
GarageArea

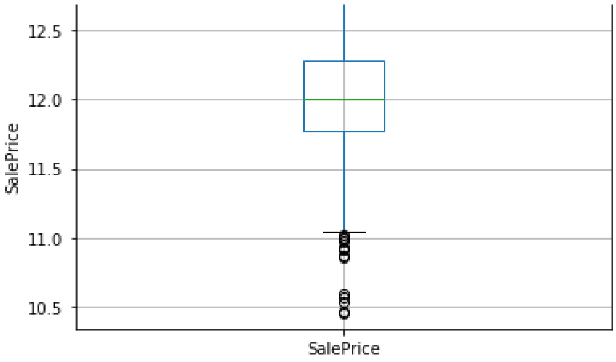

WoodDeckSF
6
5
4
3
2
1
0
WoodDeckSF
WoodDeckSF


OpenPorchSF
5
4
3
2
1
0
OpenPorchSF
OpenPorchSF


EnclosedPorch
0.04
0.02
0.00
−0.02
−0.04
EnclosedPorch
EnclosedPorch


ScreenPorch
0.04
0.02
0.00
−0.02
−0.04
ScreenPorch
ScreenPorch


SalePrice

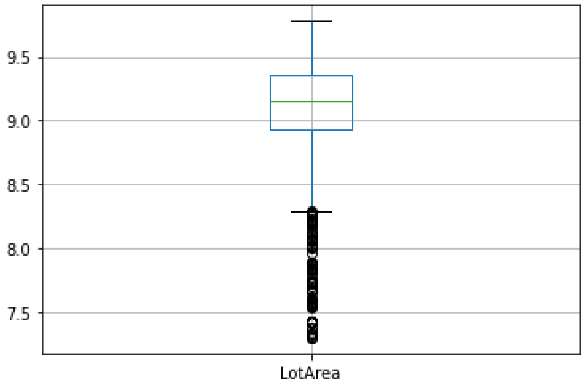



In [437]:

```
data.boxplot(column='LotArea')
#sns.boxplot(df['LotArea'])
```

Out[437]:

```
<AxesSubplot:>
```




In [32]:

```
continuous_feature
```

Out[32]:

```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch',
 'SalePrice']
```

## Categorical Variables

In [33]:

```
categorical_features= [feature for feature in df.columns if df[feature].dtypes=='O']
categorical_features
```

Out[33]:

```
['MSZoning',
```

```
['MSZoning',
 'Street',
 'Alley',
 'LotShape',
 'LandContour',
 'Utilities',
 'LotConfig',
 'LandSlope',
 'Neighborhood',
 'Condition1',
 'Condition2',
 'BldgType',
 'HouseStyle',
 'RoofStyle',
 'RoofMatl',
 'Exterior1st',
 'Exterior2nd',
 'MasVnrType',
 'ExterQual',
 'ExterCond',
 'Foundation',
 'BsmtQual',
 'BsmtCond',
 'BsmtExposure',
 'BsmtFinType1',
 'BsmtFinType2',
 'Heating',
 'HeatingQC',
 'CentralAir',
 'Electrical',
 'KitchenQual',
 'Functional',
 'FireplaceQu',
 'GarageType',
 'GarageFinish',
 'GarageQual',
 'GarageCond',
 'PavedDrive',
 'PoolQC',
 'Fence',
 'MiscFeature',
 'SaleType',
 'SaleCondition']
```

In [34]:

```
df[categorical_features].head()
```

Out[34]:

| | MSZoning | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighborhood | Condition1 | Condition2 | BldgType |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | RL | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | CollgCr | Norm | Norm | 1Fam |
| 1 | RL | Pave | NaN | Reg | Lvl | AllPub | FR2 | Gtl | Veenker | Feedr | Norm | 1Fam |
| 2 | RL | Pave | NaN | IR1 | Lvl | AllPub | Inside | Gtl | CollgCr | Norm | Norm | 1Fam |
| 3 | RL | Pave | NaN | IR1 | Lvl | AllPub | Corner | Gtl | Crawfor | Norm | Norm | 1Fam |
| 4 | RL | Pave | NaN | IR1 | Lvl | AllPub | FR2 | Gtl | NoRidge | Norm | Norm | 1Fam |

In [35]:

```
for feature in categorical_features:
    print('The feature is {} and number of categories are {}'.format(feature,len(df[feature].unique
()))) 
```

```
The feature is MSZoning and number of categories are 5
The feature is Street and number of categories are 2
The feature is Alley and number of categories are 3
The feature is LotShape and number of categories are 4
The feature is LandContour and number of categories are 4
The feature is Utilities and number of categories are 2
The feature is LotConfig and number of categories are 5
The feature is LandSlope and number of categories are 3
```

```
The feature is Neighborhood and number of categories are 25
The feature is Condition1 and number of categories are 9
The feature is Condition2 and number of categories are 8
The feature is BldgType and number of categories are 5
The feature is HouseStyle and number of categories are 8
The feature is RoofStyle and number of categories are 6
The feature is RoofMatl and number of categories are 8
The feature is Exterior1st and number of categories are 15
The feature is Exterior2nd and number of categories are 16
The feature is MasVnrType and number of categories are 5
The feature is ExterQual and number of categories are 4
The feature is ExterCond and number of categories are 5
The feature is Foundation and number of categories are 6
The feature is BsmtQual and number of categories are 5
The feature is BsmtCond and number of categories are 5
The feature is BsmtExposure and number of categories are 5
The feature is BsmtFinType1 and number of categories are 7
The feature is BsmtFinType2 and number of categories are 7
The feature is Heating and number of categories are 6
The feature is HeatingQC and number of categories are 5
The feature is CentralAir and number of categories are 2
The feature is Electrical and number of categories are 6
The feature is KitchenQual and number of categories are 4
The feature is Functional and number of categories are 7
The feature is FireplaceQu and number of categories are 6
The feature is GarageType and number of categories are 7
The feature is GarageFinish and number of categories are 4
The feature is GarageQual and number of categories are 6
The feature is GarageCond and number of categories are 6
The feature is PavedDrive and number of categories are 3
The feature is PoolQC and number of categories are 4
The feature is Fence and number of categories are 5
The feature is MiscFeature and number of categories are 5
The feature is SaleType and number of categories are 9
The feature is SaleCondition and number of categories are 6
```

In [108]:

```
l1 = list()
for f in df['Neighborhood'].unique():

    l1.append(df.Neighborhood[df['Neighborhood']==f].value_counts()[0])
    print(df.groupby(f).count())
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-108-33e1a564f248> in <module>
      3 
      4     l1.append(df.Neighborhood[df['Neighborhood']==f].value_counts()[0])
----> 5     print(df.groupby(f).count())

~\Anaconda3\lib\site-packages\pandas\core\frame.py in groupby(self, by, axis, level, as_index, sort, group_keys, squeeze, observed, dropna)
   6512             squeeze=squeeze,
   6513             observed=observed,
-> 6514             dropna=dropna,
   6515         )
   6516 

~\Anaconda3\lib\site-packages\pandas\core\groupby\groupby.py in __init__(self, obj, keys, axis, level, grouper, exclusions, selection, as_index, sort, group_keys, squeeze, observed, mutated, dropna)
    531                 observed=observed,
    532                 mutated=self.mutated,
--> 533                 dropna=self.dropna,
    534             )
    535 

~\Anaconda3\lib\site-packages\pandas\core\groupby\grouper.py in get_grouper(obj, key, axis, level, sort, observed, mutated, validate, dropna)
    775                 in_axis, name, level, gpr = False, None, gpr, None
    776             else:
--> 777                 raise KeyError(gpr)
    778         elif isinstance(gpr, Grouper) and gpr.key is not None:
    779             # Add key to exclusions
```

```
KeyError: 'CollgCr'
```

In [131]:

```
l1 = dict()
l2=list()
for f in df['Neighborhood'].unique():
    #print(df.groupby(f)['SalePrice'].count())
    l1[df.Neighborhood[df['Neighborhood']==f].value_counts().index[0]] = df.Neighborhood[df['Neighb
orhood']==f].value_counts()[0]
```

In [129]:

```
df.Neighborhood[df['Neighborhood']==f].value_counts()[0]
```

Out[129]:

```
150
```

In [132]:

```
l1
```

Out[132]:

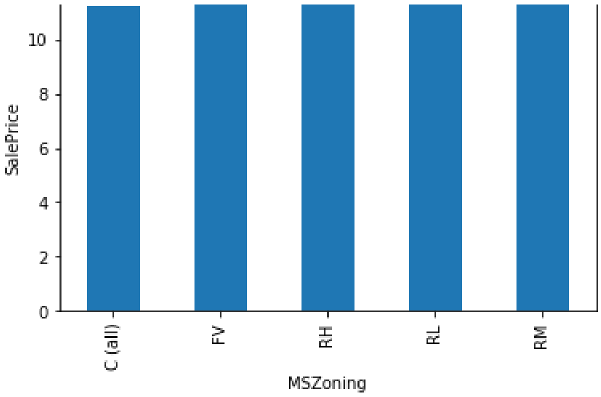
```
{'CollgCr': 150,
 'Veenker': 11,
 'Crawfor': 51,
 'NoRidge': 41,
 'Mitchel': 49,
 'Somerst': 86,
 'NWAmes': 73,
 'OldTown': 113,
 'BrkSide': 58,
 'Sawyer': 74,
 'NridgHt': 77,
 'NAmes': 225,
 'SawyerW': 59,
 'IDOTRR': 37,
 'MeadowV': 17,
 'Edwards': 100,
 'Timber': 38,
 'Gilbert': 79,
 'StoneBr':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

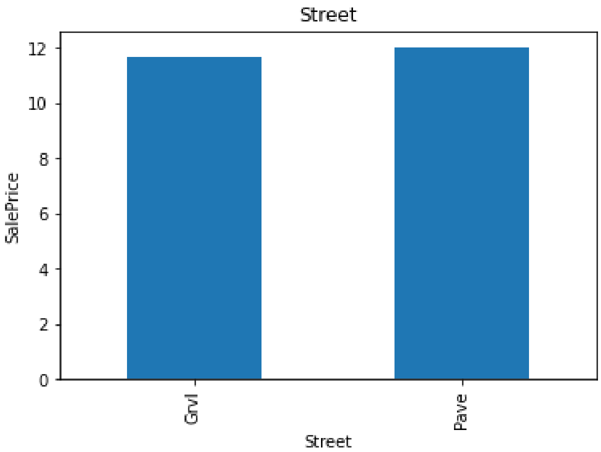
In [595]:

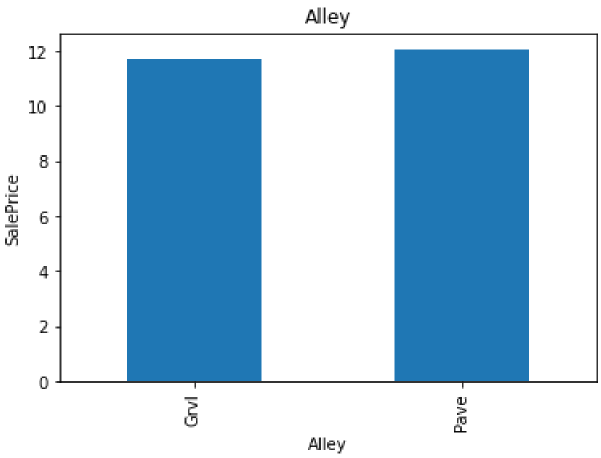
```
## Finding the relationship b/w Categorical features and the SalePrice
```

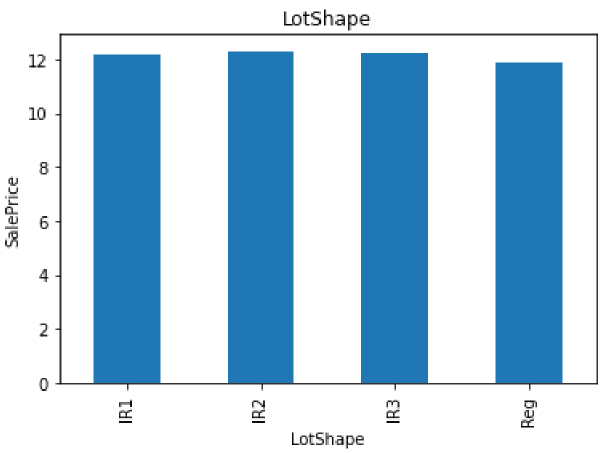
In [36]:

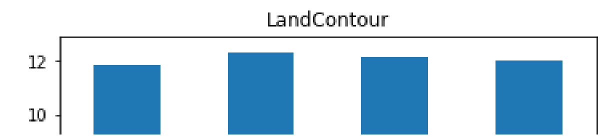
```
for feature in categorical_features:
    data=df.copy()
    data.groupby(feature)['SalePrice'].median().plot.bar()
    plt.xlabel(feature)
    plt.ylabel('SalePrice')
    plt.title(feature)
    plt.show()
```

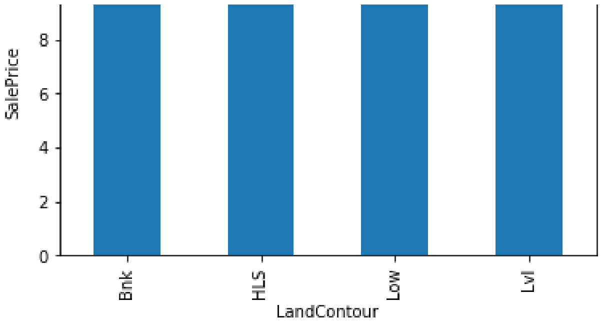

SalePrice
MSZoning
C (all)
FV
RH
RL
RM

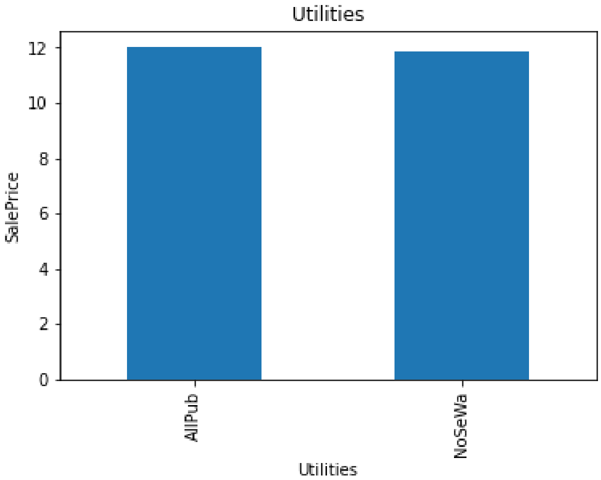

Street
SalePrice
Grvl
Pave
Street

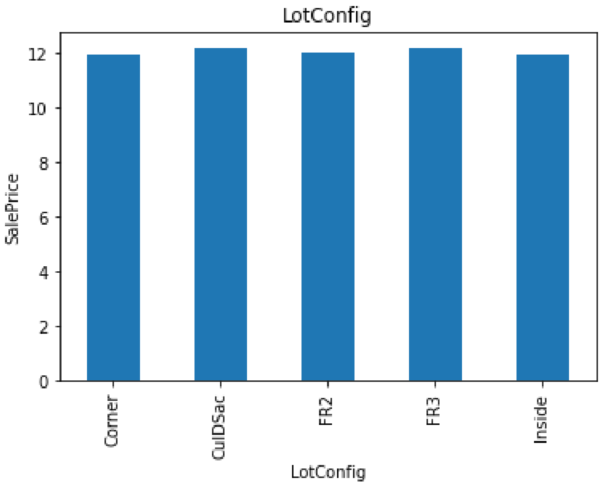

Alley
SalePrice
Grvl
Pave
Alley

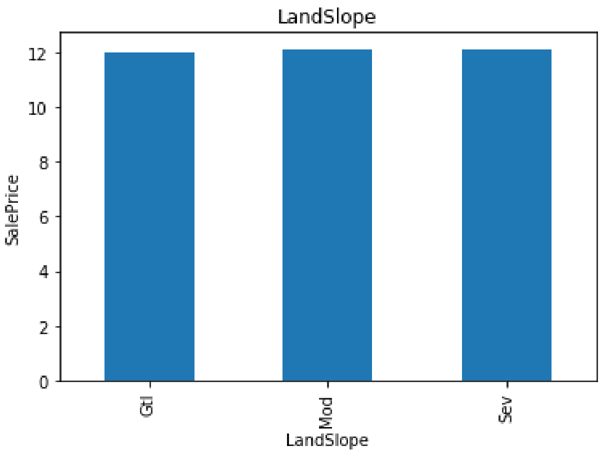

LotShape
SalePrice
IR1
IR2
IR3
Reg
LotShape

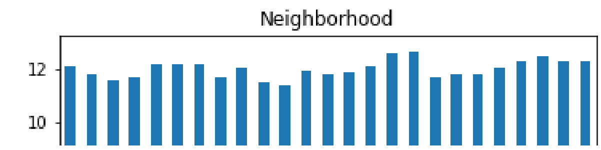

LandContour

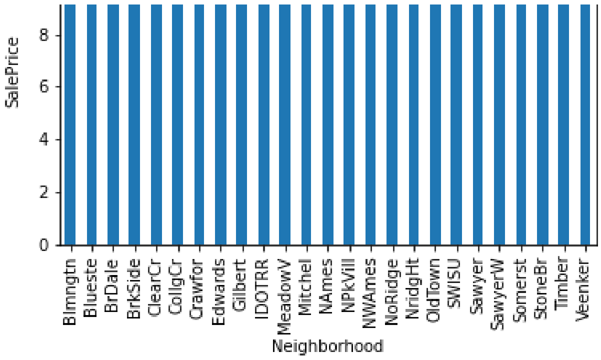

SalePrice
0
2
4
6
8
Bnk
HLS
Low
Lvl
LandContour

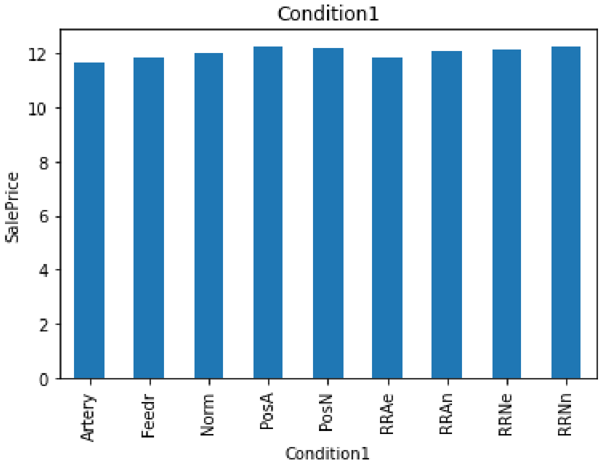

Utilities
SalePrice
0
2
4
6
8
10
12
AllPub
NoSeWa
Utilities

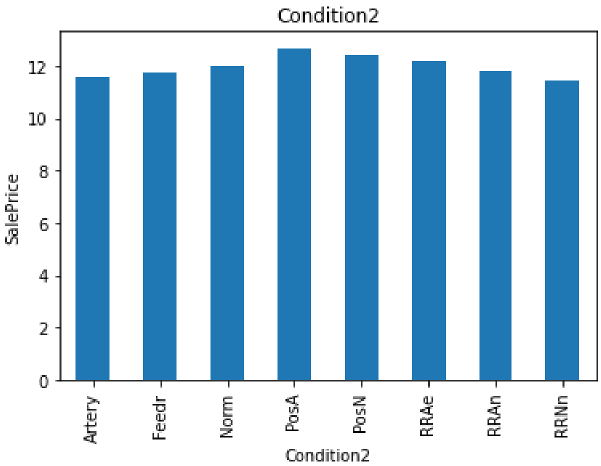

LotConfig
SalePrice
0
2
4
6
8
10
12
Corner
CulDSac
FR2
FR3
Inside
LotConfig

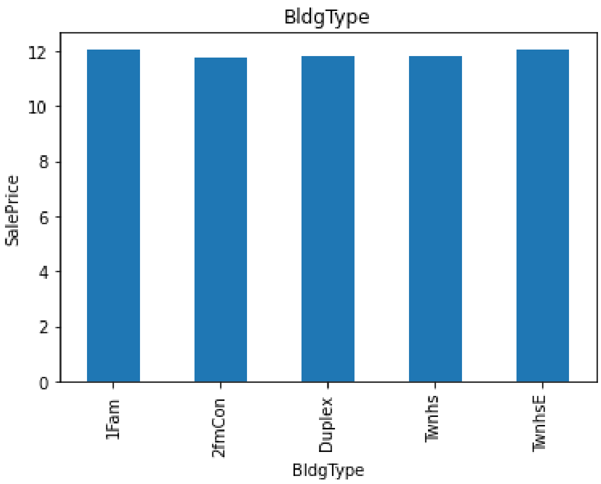

LandSlope
SalePrice
0
2
4
6
8
10
12
Gtl
Mod
Sev
LandSlope

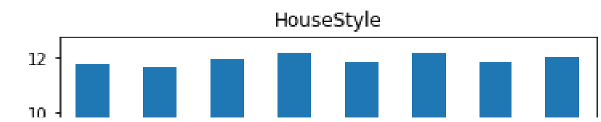

Neighborhood
10
12

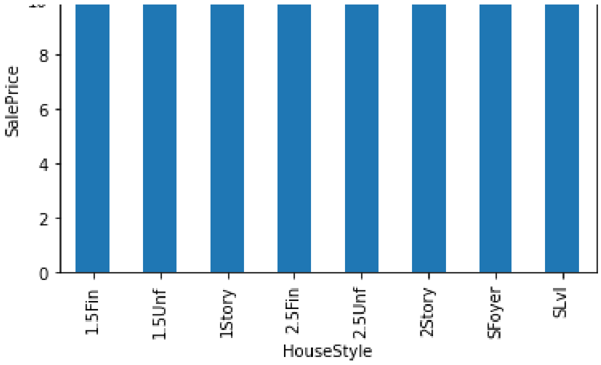

SalePrice
0
2
4
6
8
Blmngtn
Blueste
BrDale
BrkSide
ClearCr
CollgCr
Crawfor
Edwards
Gilbert
IDOTRR
MeadowV
Mitchel
NAmes
NPkVill
NWAmes
NoRidge
NridgHt
OldTown
SWISU
Sawyer
SawyerW
Somerst
StoneBr
Timber
Veenker
Neighborhood


Condition1
SalePrice
0
2
4
6
8
10
12
Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNe
RRNn
Condition1

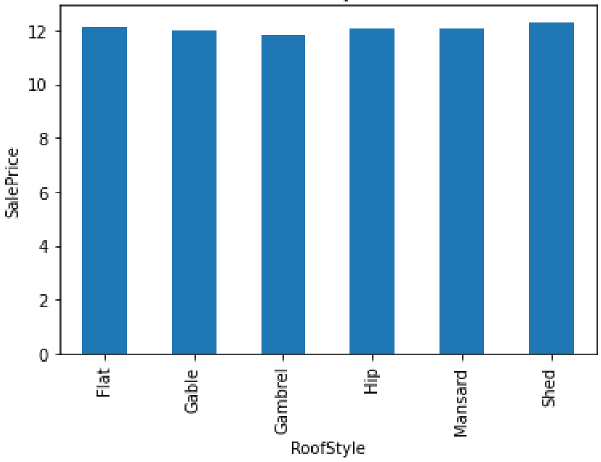

Condition2
SalePrice
0
2
4
6
8
10
12
Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNn
Condition2


BldgType
SalePrice
0
2
4
6
8
10
12
1Fam
2fmCon
Duplex
Twnhs
TwnhsE
BldgType

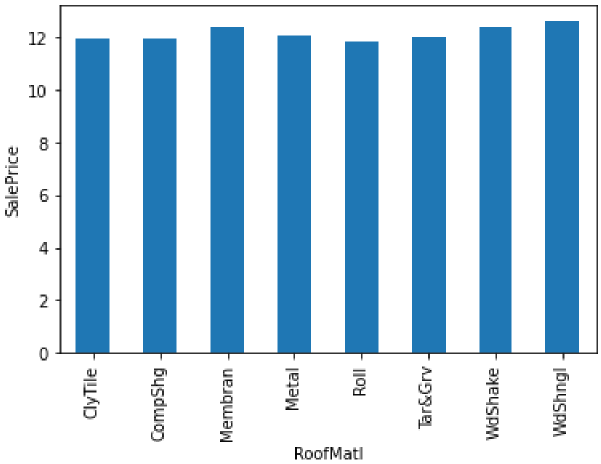

HouseStyle
12
10



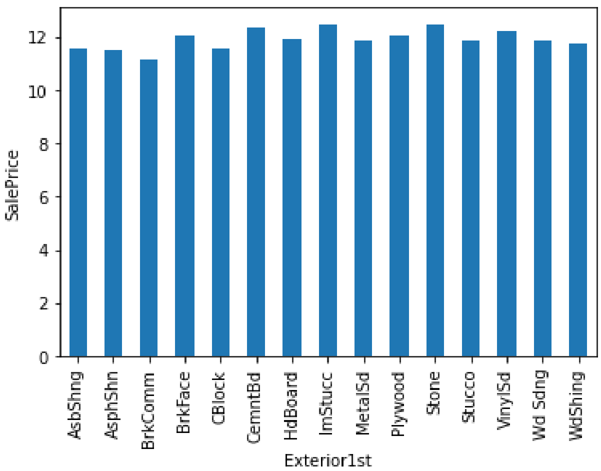

RoofStyle



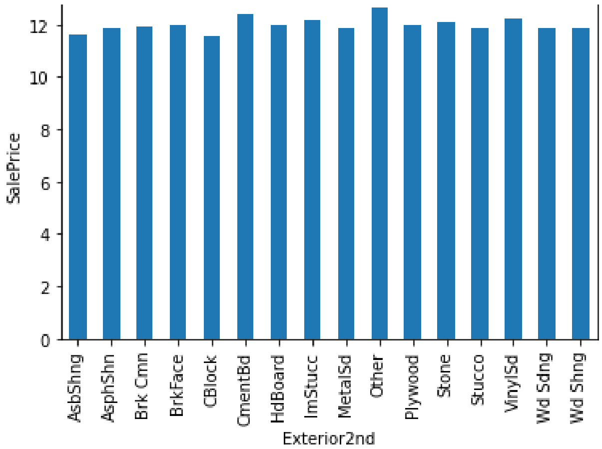

RoofMatl

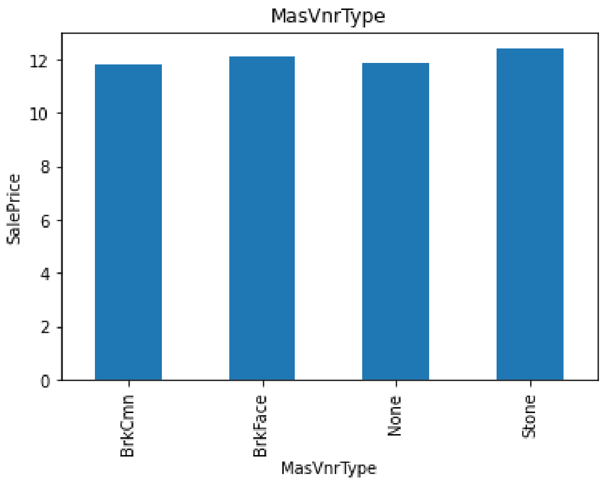


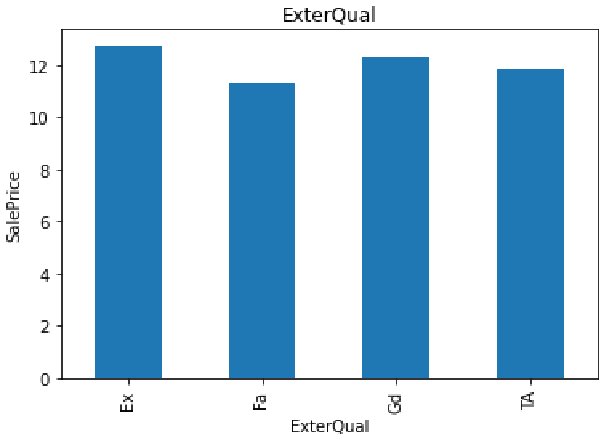

Exterior1st

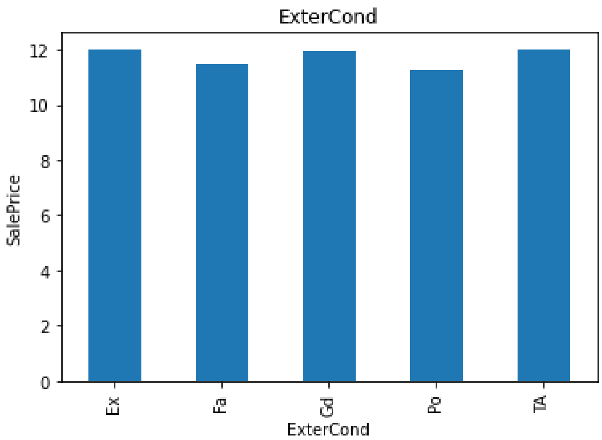



Exterior2nd

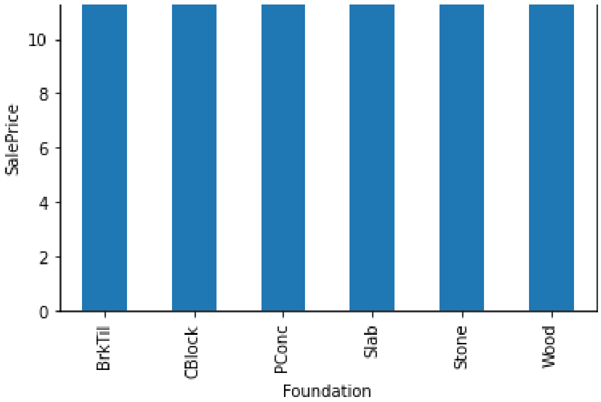

SalePrice
0
2
4
6
8
10
12
AsbShng
AsphShn
Brk Cmn
BrkFace
CBlock
CmentBd
HdBoard
ImStucc
MetalSd
Other
Plywood
Stone
Stucco
VinylSd
Wd Sdng
Wd Shng
Exterior2nd

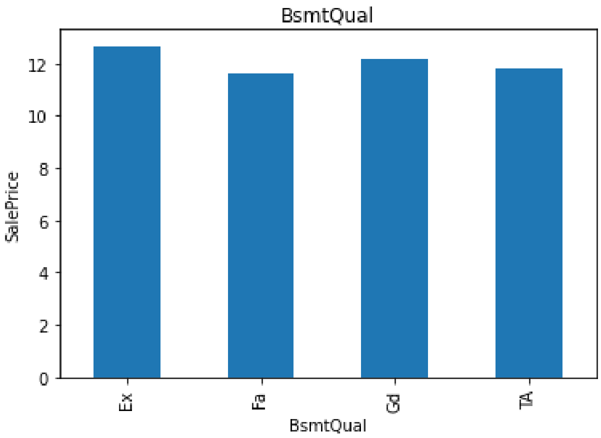

MasVnrType
SalePrice
0
2
4
6
8
10
12
BrkCmn
BrkFace
None
Stone
MasVnrType

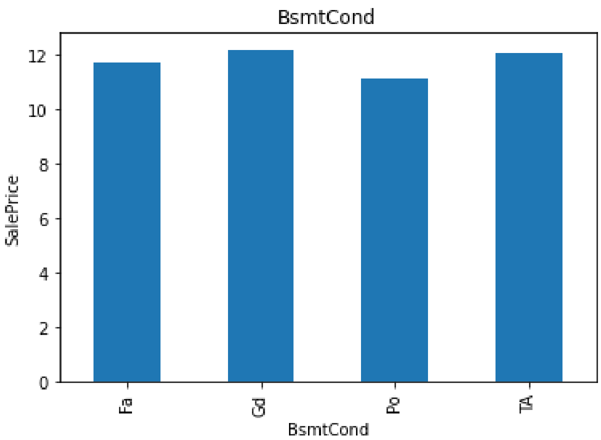

ExterQual
SalePrice
0
2
4
6
8
10
12
Ex
Fa
Gd
TA
ExterQual

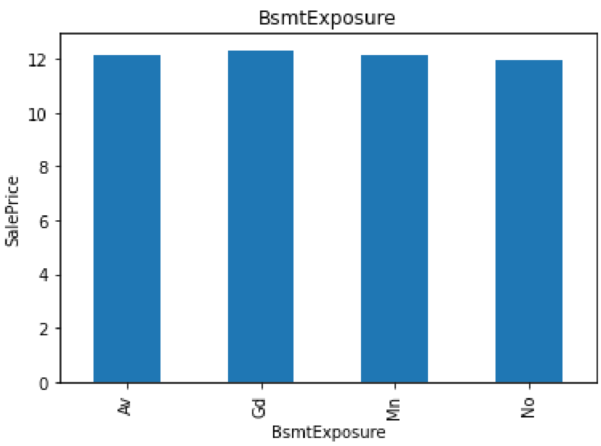

ExterCond
SalePrice
0
2
4
6
8
10
12
Ex
Fa
Gd
Po
TA
ExterCond

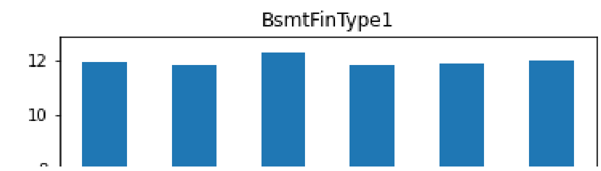

Foundation
12

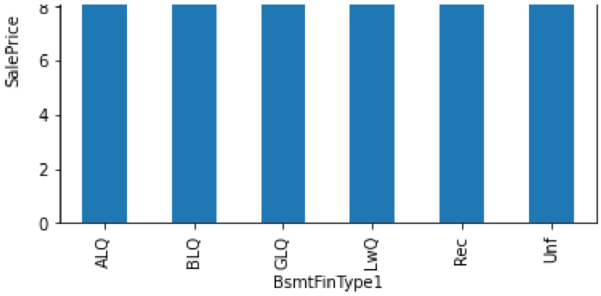

SalePrice
Foundation
BrkTil
CBlock
PConc
Slab
Stone
Wood

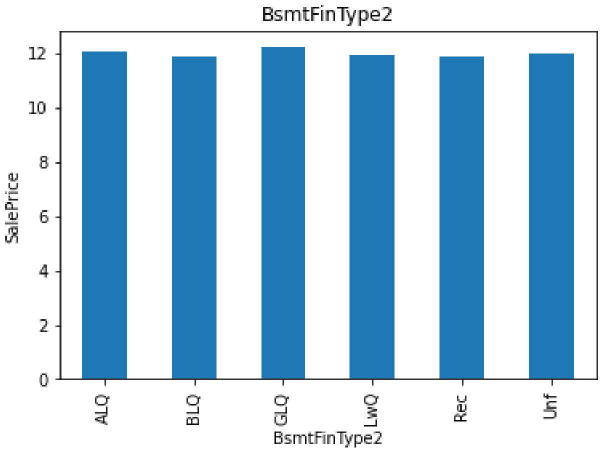

BsmtQual
SalePrice
Ex
Fa
Gd
TA
BsmtQual

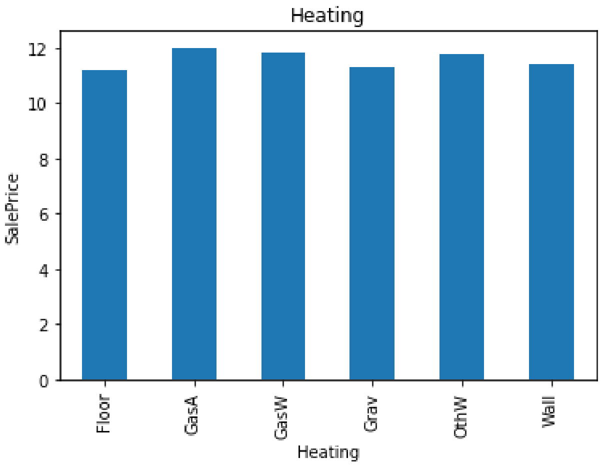

BsmtCond
SalePrice
Fa
Gd
Po
TA
BsmtCond

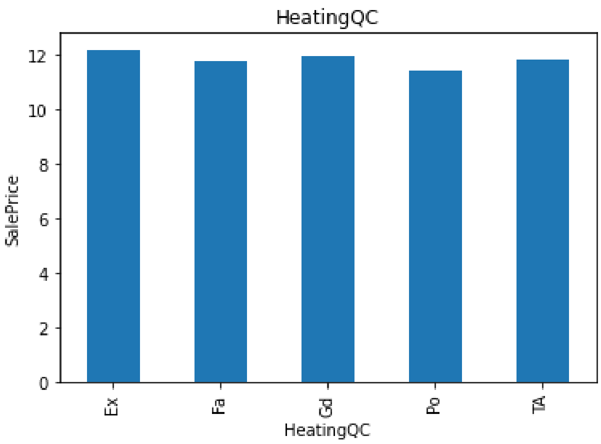

BsmtExposure
SalePrice
Av
Gd
Mn
No
BsmtExposure

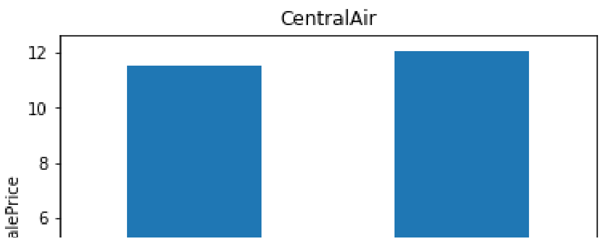

BsmtFinType1

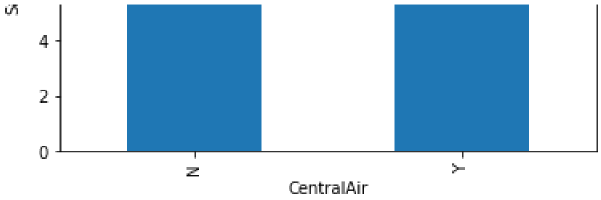

SalePrice
0
2
4
6
8
ALQ
BLQ
GLQ
LwQ
Rec
Unf
BsmtFinType1

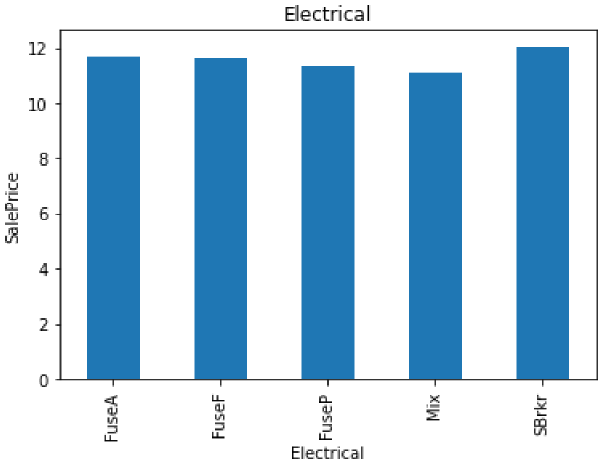

BsmtFinType2
SalePrice
0
2
4
6
8
10
12
ALQ
BLQ
GLQ
LwQ
Rec
Unf
BsmtFinType2

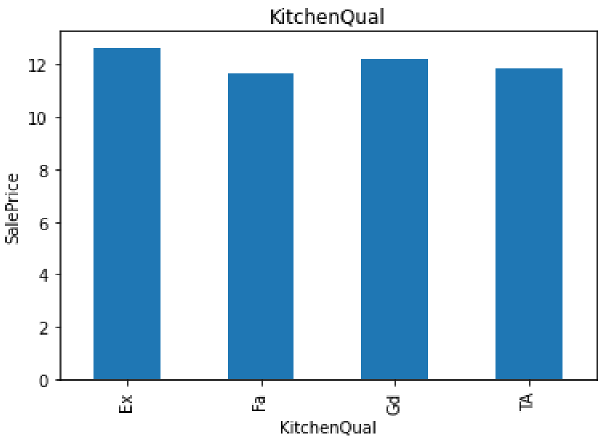

Heating
SalePrice
0
2
4
6
8
10
12
Floor
GasA
GasW
Grav
OthW
Wall
Heating

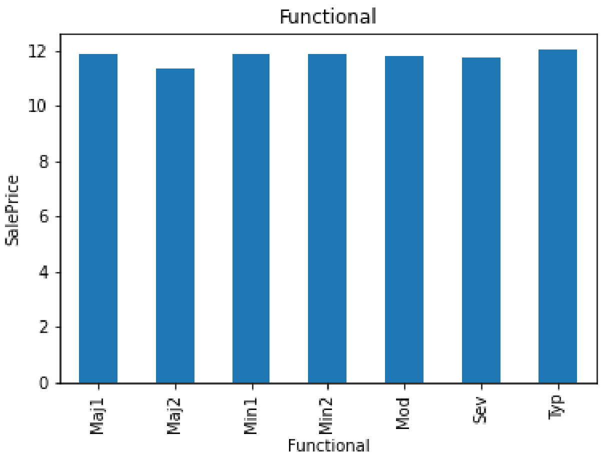

HeatingQC
SalePrice
0
2
4
6
8
10
12
Ex
Fa
Gd
Po
TA
HeatingQC

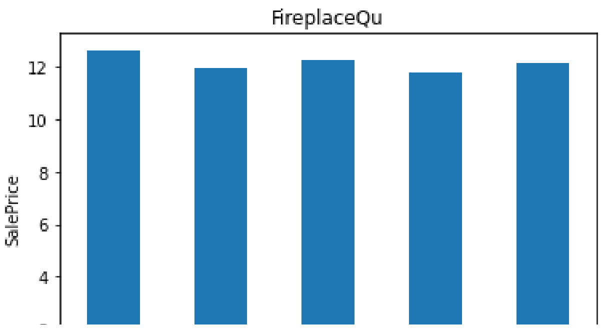

CentralAir
alePrice
6
8
10
12

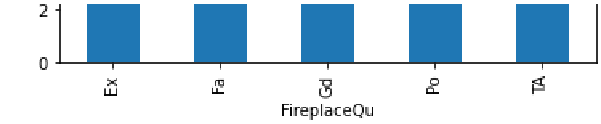

4
2
0
N
Y
CentralAir

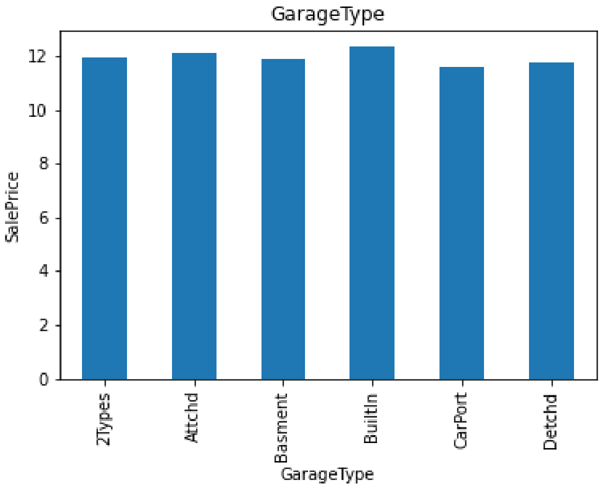

Electrical
12
10
8
6
4
2
0
SalePrice
FuseA
FuseF
FuseP
Mix
SBrkr
Electrical

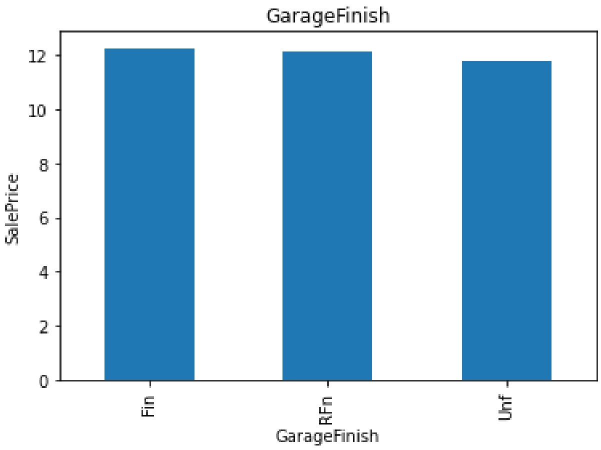

KitchenQual
12
10
8
6
4
2
0
SalePrice
Ex
Fa
Gd
TA
KitchenQual

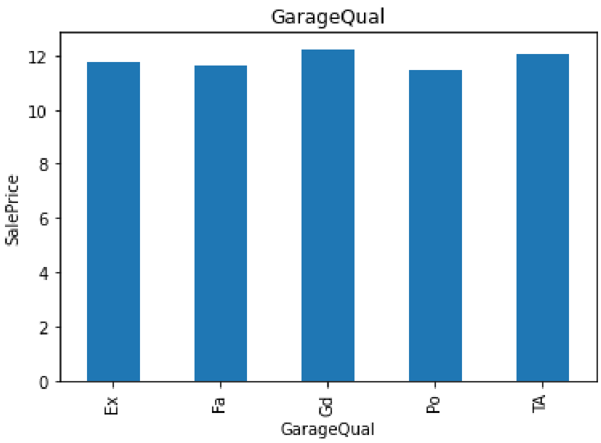

Functional
12
10
8
6
4
2
0
SalePrice
Maj1
Maj2
Min1
Min2
Mod
Sev
Typ
Functional

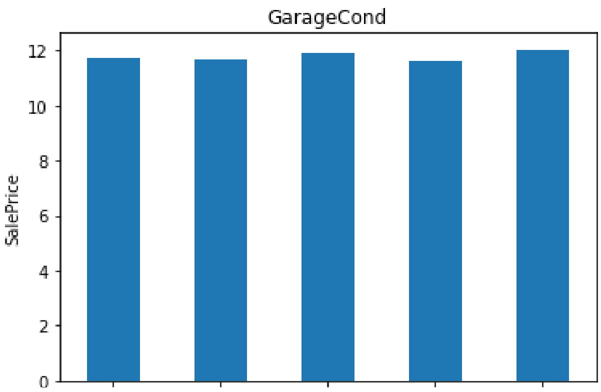

FireplaceQu
12
10
8
6
4
SalePrice


2
0
Ex
Fa
Gd
Po
TA
FireplaceQu

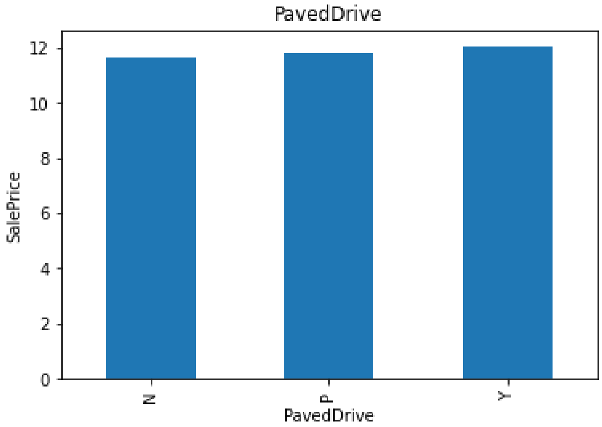

GarageType
SalePrice
12
10
8
6
4
2
0
2Types
Attchd
Basment
BuiltIn
CarPort
Detchd
GarageType

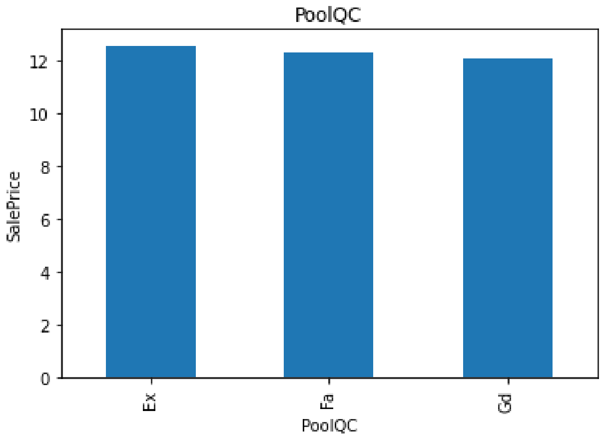

GarageFinish
SalePrice
12
10
8
6
4
2
0
Fin
RFn
Unf
GarageFinish

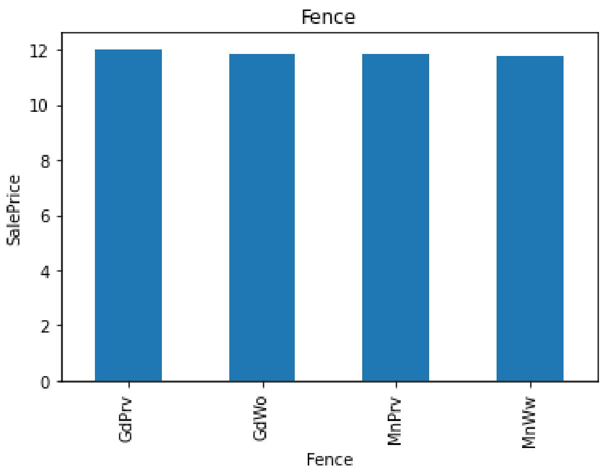

GarageQual
SalePrice
12
10
8
6
4
2
0
Ex
Fa
Gd
Po
TA
GarageQual

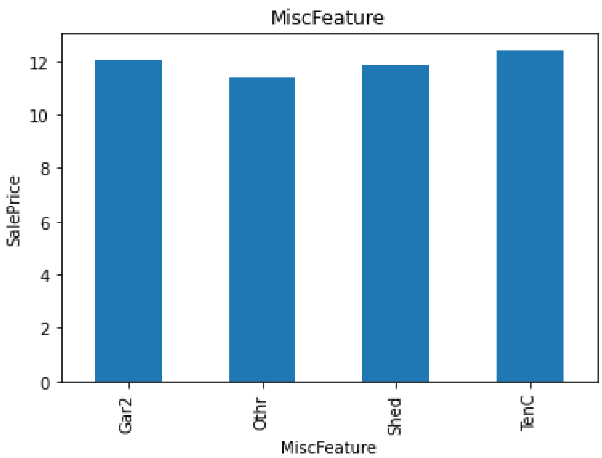

GarageCond
SalePrice
12
10
8
6
4
2
0

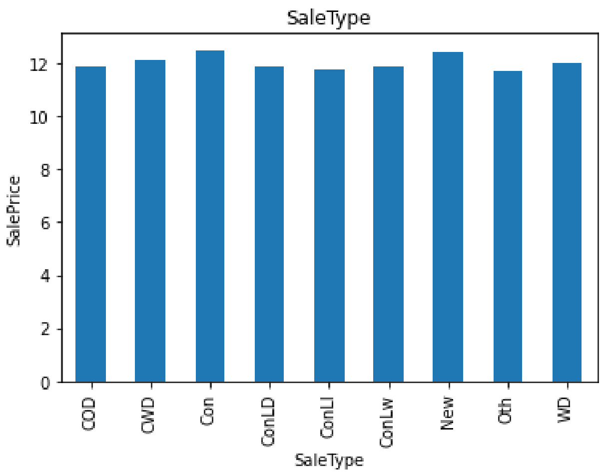

Ex
Fa
Gd
Po
TA
GarageCond

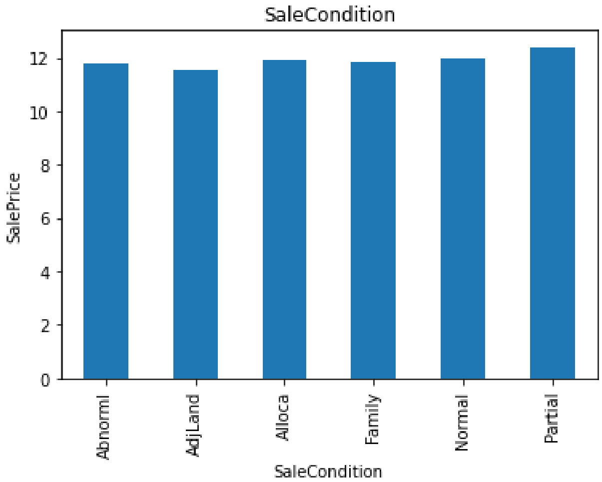

PavedDrive
SalePrice
0
2
4
6
8
10
12
N
P
Y
PavedDrive


PoolQC
SalePrice
0
2
4
6
8
10
12
Ex
Fa
Gd
PoolQC


Fence
SalePrice
0
2
4
6
8
10
12
GdPrv
GdWo
MnPrv
MnWw
Fence


MiscFeature
SalePrice
0
2
4
6
8
10
12
Gar2
Othr
Shed
TenC
MiscFeature




# Feature Engineering

We will be performing all the below steps in Feature Engineering: 1.Handling missing values 2.Handling Temporal variables 3.Handling Categorical variables: remove rare labels 4.Standardize the values of the variables to the same range

## Missing Values

In [37]:

```
## Let us capture all the nan values
## First lets handle Categorical features which are missing

features_nan= [feature for feature in df.columns if df[feature].dtypes=='O' and df[feature].isnull(
).sum()>=1]

for feature in features_nan:
    print('{}: {} missing values'.format(feature,np.round(df[feature].isnull().mean(),4)))
```

```
Alley: 0.9377 missing values
MasVnrType: 0.0055 missing values
BsmtQual: 0.0253 missing values
BsmtCond: 0.0253 missing values
BsmtExposure: 0.026 missing values
BsmtFinType1: 0.0253 missing values
BsmtFinType2: 0.026 missing values
Electrical: 0.0007 missing values
FireplaceQu: 0.4726 missing values
GarageType: 0.0555 missing values
GarageFinish: 0.0555 missing values
GarageQual: 0.0555 missing values
GarageCond: 0.0555 missing values
PoolQC: 0.9952 missing values
```

```
Fence: 0.8075 missing values
MiscFeature: 0.963 missing values
```

In [38]:

```python
## Replace missing value with a new label
def replace_cat_feature(df,features_nan):
    data=df.copy()

    data[features_nan] = np.where(data[features_nan].isnull(),'Missing',data[features_nan])
    #data[features_nan]=data[features_nan].fillna('Missing')
    return data
df=replace_cat_feature(df,features_nan)
```

In [39]:

```python
df[features_nan].isnull().sum()
```

Out[39]:

```
Alley           0
MasVnrType      0
BsmtQual        0
BsmtCond        0
BsmtExposure    0
BsmtFinType1    0
BsmtFinType2    0
Electrical      0
FireplaceQu     0
GarageType      0
GarageFinish    0
GarageQual      0
GarageCond      0
PoolQC          0
Fence           0
MiscFeature     0
dtype: int64
```

In [40]:

```python
df.head(20)
```

Out[40]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neigl |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 60 | RL | 4.189655 | 9.042040 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **1** | 2 | 20 | RL | 4.394449 | 9.169623 | Pave | Missing | Reg | Lvl | AllPub | FR2 | Gtl | |
| **2** | 3 | 60 | RL | 4.234107 | 9.328212 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **3** | 4 | 70 | RL | 4.110874 | 9.164401 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| **4** | 5 | 60 | RL | 4.442651 | 9.565284 | Pave | Missing | IR1 | Lvl | AllPub | FR2 | Gtl | |
| **5** | 6 | 50 | RL | 4.454347 | 9.555064 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **6** | 7 | 20 | RL | 4.330733 | 9.218804 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **7** | 8 | 60 | RL | NaN | 9.247925 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| **8** | 9 | 50 | RM | 3.951244 | 8.719481 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **9** | 10 | 190 | RL | 3.931826 | 8.912069 | Pave | Missing | Reg | Lvl | AllPub | Corner | Gtl | |
| **10** | 11 | 20 | RL | 4.262680 | 9.323758 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **11** | 12 | 60 | RL | 4.454347 | 9.386392 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **12** | 13 | 20 | RL | NaN | 9.470317 | Pave | Missing | IR2 | Lvl | AllPub | Inside | Gtl | |
| **13** | 14 | 20 | RL | 4.521789 | 9.273597 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **14** | 15 | 20 | RL | NaN | 9.298443 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| **15** | 16 | 45 | RM | 3.951244 | 8.719481 | Pave | Missing | Reg | Lvl | AllPub | Corner | Gtl | |
| **16** | 17 | 20 | RL | NaN | 9.327412 | Pave | Missing | IR1 | Lvl | AllPub | CulDSac | Gtl | |
| **17** | 18 | 90 | RL | 4.290459 | 9.286560 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neigl |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **18** | 19 | 20 | RL | [illegible] | [illegible] | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **19** | 20 | 20 | RL | 4.262680 | 8.930759 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |

In [41]:

```
## Now lets check for numerical variables that contains missing values

numerical_with_nan=[feature for feature in df.columns if df[feature].isnull().sum()>=1 and df[featu
re].dtypes!='O']

## We will print the numerical nan variables and percentage of missing values

for feature in numerical_with_nan:
    print("{}: {}% missing value".format(feature,np.round(df[feature].isnull().mean()*100,4)))
```

```
LotFrontage: 17.7397% missing value
MasVnrArea: 0.5479% missing value
GarageYrBlt: 5.5479% missing value
```

In [42]:

```
#Replacing the numerical missing values
for feature in numerical_with_nan:
    ## We will replace by using median since there are outliers

    ## create a new feature to capture nan values
    df[feature+'nan'] = np.where(df[feature].isnull(),1,0)

    ## ## We will replace by using median since there are outliers
    df[feature].fillna(df[feature].median(),inplace=True)

df[numerical_with_nan].isnull().sum()
```

Out[42]:

```
LotFrontage     0
MasVnrArea      0
GarageYrBlt     0
dtype: int64
```

In [43]:

```
df.head(10)
```

Out[43]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neigh |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 60 | RL | 4.189655 | 9.042040 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **1** | 2 | 20 | RL | 4.394449 | 9.169623 | Pave | Missing | Reg | Lvl | AllPub | FR2 | Gtl | |
| **2** | 3 | 60 | RL | 4.234107 | 9.328212 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **3** | 4 | 70 | RL | 4.110874 | 9.164401 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| **4** | 5 | 60 | RL | 4.442651 | 9.565284 | Pave | Missing | IR1 | Lvl | AllPub | FR2 | Gtl | |
| **5** | 6 | 50 | RL | 4.454347 | 9.555064 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **6** | 7 | 20 | RL | 4.330733 | 9.218804 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **7** | 8 | 60 | RL | 4.248495 | 9.247925 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | I |
| **8** | 9 | 50 | RM | 3.951244 | 8.719481 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **9** | 10 | 190 | RL | 3.931826 | 8.912069 | Pave | Missing | Reg | Lvl | AllPub | Corner | Gtl | |

In [44]:

```
## Temporal Variables (Date Time Variables)

for feature in ['YearBuilt','YearRemodAdd','GarageYrBlt']:
```

```
    df[feature]=df['YrSold']-df[feature]
```

In [45]:

```
df.head()
```

Out[45]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighl |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 60 | RL | 4.189655 | 9.042040 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| 1 | 2 | 20 | RL | 4.394449 | 9.169623 | Pave | Missing | Reg | Lvl | AllPub | FR2 | Gtl | |
| 2 | 3 | 60 | RL | 4.234107 | 9.328212 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| 3 | 4 | 70 | RL | 4.110874 | 9.164401 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| 4 | 5 | 60 | RL | 4.442651 | 9.565284 | Pave | Missing | IR1 | Lvl | AllPub | FR2 | Gtl | |

In [46]:

```
df[['YearBuilt','YearRemodAdd','GarageYrBlt']].head()
```

Out[46]:

| | YearBuilt | YearRemodAdd | GarageYrBlt |
|---|---|---|---|
| 0 | 5 | 5 | 5.0 |
| 1 | 31 | 31 | 31.0 |
| 2 | 7 | 6 | 7.0 |
| 3 | 91 | 36 | 8.0 |
| 4 | 8 | 8 | 8.0 |

## Numerical Variables

Since the numerical variables are skewed, we will perform log normal distribution

In [47]:

```
df.head()
```

Out[47]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighl |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 60 | RL | 4.189655 | 9.042040 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| 1 | 2 | 20 | RL | 4.394449 | 9.169623 | Pave | Missing | Reg | Lvl | AllPub | FR2 | Gtl | |
| 2 | 3 | 60 | RL | 4.234107 | 9.328212 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| 3 | 4 | 70 | RL | 4.110874 | 9.164401 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| 4 | 5 | 60 | RL | 4.442651 | 9.565284 | Pave | Missing | IR1 | Lvl | AllPub | FR2 | Gtl | |

In [48]:

```
#Considering only non zero value features, as we're taking log
num_features=['LotFrontage', 'LotArea', '1stFlrSF', 'GrLivArea', 'SalePrice']

#for feature in num_features:
#    df[feature]=np.log(df[feature])
```

## Categorical Features

In [49]:

```python
categorical_features=[feature for feature in df.columns if df[feature].dtype=='O']
```

In [50]:

```python
df.head()
```

Out[50]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighl |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 60 | RL | 4.189655 | 9.042040 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| 1 | 2 | 20 | RL | 4.394449 | 9.169623 | Pave | Missing | Reg | Lvl | AllPub | FR2 | Gtl | |
| 2 | 3 | 60 | RL | 4.234107 | 9.328212 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| 3 | 4 | 70 | RL | 4.110874 | 9.164401 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| 4 | 5 | 60 | RL | 4.442651 | 9.565284 | Pave | Missing | IR1 | Lvl | AllPub | FR2 | Gtl | |

In [51]:

```python
df[categorical_features]
```

Out[51]:

| | MSZoning | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighborhood | Condition1 | Condition2 | Bldg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | RL | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | CollgCr | Norm | Norm | |
| 1 | RL | Pave | Missing | Reg | Lvl | AllPub | FR2 | Gtl | Veenker | Feedr | Norm | |
| 2 | RL | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | CollgCr | Norm | Norm | |
| 3 | RL | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | Crawfor | Norm | Norm | |
| 4 | RL | Pave | Missing | IR1 | Lvl | AllPub | FR2 | Gtl | NoRidge | Norm | Norm | |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 1455 | RL | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | Gilbert | Norm | Norm | |
| 1456 | RL | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | NWAmes | Norm | Norm | |
| 1457 | RL | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | Crawfor | Norm | Norm | |
| 1458 | RL | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | NAmes | Norm | Norm | |
| 1459 | RL | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | Edwards | Norm | Norm | |

1460 rows × 43 columns

In [52]:

```python
for feature in categorical_features:
    labels_ordered=df.groupby([feature])['SalePrice'].mean().sort_values().index
    labels_ordered={k:i for i,k in enumerate(labels_ordered,0)}
    df[feature]=df[feature].map(labels_ordered)
    #df2[feature]=df2[feature].map(labels_ordered)   # For test data as SalePrice column is not pre
sent
```

In [53]:

```python
df.head()
```

Out[53]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighbo |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 60 | 3 | 4.189655 | 9.042040 | 1 | 2 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 2 | 20 | 3 | 4.394449 | 9.169623 | 1 | 2 | 0 | 1 | 1 | 2 | 0 | |
| 2 | 3 | 60 | 3 | 4.234107 | 9.328212 | 1 | 2 | 1 | 1 | 1 | 0 | 0 | |

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighbo |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 4 | 70 | 3 | 4.110874 | 9.164401 | 1 | 2 | 1 | 1 | 1 | 1 | 0 | |
| 4 | 5 | 60 | 3 | 4.442651 | 9.565284 | 1 | 2 | 1 | 1 | 1 | 2 | 0 | |

In [54]:

```
len(df.columns)
```

Out[54]:

```
84
```

## Feature Scaling

In [55]:

```
feature_scale=[feature for feature in df.columns if feature not in ['SalePrice','Id']]
len(feature_scale)
```

Out[55]:

```
82
```

In [56]:

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
scaler.fit(df[feature_scale])
```

Out[56]:

```
MinMaxScaler(copy=True, feature_range=(0, 1))
```

In [57]:

```
scaler.transform(df[feature_scale])
```

Out[57]:

```
array([[0.23529412, 0.75      , 0.41326841, ..., 0.        , 0.        ,
         0.        ],
       [0.        , 0.75      , 0.49030656, ..., 0.        , 0.        ,
         0.        ],
       [0.23529412, 0.75      , 0.42998996, ..., 0.        , 0.        ,
         0.        ],
       ...,
       [0.29411765, 0.75      , 0.41892525, ..., 0.        , 0.        ,
         0.        ],
       [0.        , 0.75      , 0.42998996, ..., 0.        , 0.        ,
         0.        ],
       [0.        , 0.75      , 0.46633838, ..., 0.        , 0.        ,
         0.        ]])
```

In [58]:

```
df.head()
```

Out[58]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighbo |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 60 | 3 | 4.189655 | 9.042040 | 1 | 2 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 2 | 20 | 3 | 4.394449 | 9.169623 | 1 | 2 | 0 | 1 | 1 | 2 | 0 | |
| 2 | 3 | 60 | 3 | 4.234107 | 9.328212 | 1 | 2 | 1 | 1 | 1 | 0 | 0 | |
| 3 | 4 | 70 | 3 | 4.110874 | 9.164401 | 1 | 2 | 1 | 1 | 1 | 1 | 0 | |
| 4 | 5 | 60 | 3 | 4.442651 | 9.565284 | 1 | 2 | 1 | 1 | 1 | 2 | 0 | |

In [59]:

```
#Transform the train and test set, and add on the Id and SalePrice variables
data = pd.concat([df[['Id','SalePrice']].reset_index(drop=True),
                  pd.DataFrame(scaler.transform(df[feature_scale]),
                               columns=feature_scale)],axis=1)
```

In [60]:

```
data.head(20)
```

Out[60]:

| | Id | SalePrice | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlc |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 12.247699 | 0.235294 | 0.75 | 0.413268 | 0.702292 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.00 | |
| **1** | 2 | 12.109016 | 0.000000 | 0.75 | 0.490307 | 0.753770 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.50 | |
| **2** | 3 | 12.317171 | 0.235294 | 0.75 | 0.429990 | 0.817759 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.00 | |
| **3** | 4 | 11.849405 | 0.294118 | 0.75 | 0.383633 | 0.751663 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.25 | |
| **4** | 5 | 12.429220 | 0.235294 | 0.75 | 0.508439 | 0.913414 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.50 | |
| **5** | 6 | 11.870607 | 0.176471 | 0.75 | 0.512839 | 0.909290 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.00 | |
| **6** | 7 | 12.634606 | 0.000000 | 0.75 | 0.466338 | 0.773614 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.00 | |
| **7** | 8 | 12.206078 | 0.235294 | 0.75 | 0.435403 | 0.785364 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.25 | |
| **8** | 9 | 11.774528 | 0.176471 | 0.25 | 0.323585 | 0.572143 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.00 | |
| **9** | 10 | 11.678448 | 1.000000 | 0.75 | 0.316280 | 0.649850 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.25 | |
| **10** | 11 | 11.771444 | 0.000000 | 0.75 | 0.440738 | 0.815961 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.00 | |
| **11** | 12 | 12.736814 | 0.235294 | 0.75 | 0.512839 | 0.841233 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.00 | |
| **12** | 13 | 11.877576 | 0.000000 | 0.75 | 0.435403 | 0.875096 | 1.0 | 1.0 | 1.000000 | 0.333333 | 1.0 | 0.00 | |
| **13** | 14 | 12.540761 | 0.000000 | 0.75 | 0.538208 | 0.795722 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.00 | |
| **14** | 15 | 11.964007 | 0.000000 | 0.75 | 0.435403 | 0.805747 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.25 | |
| **15** | 16 | 11.790565 | 0.147059 | 0.25 | 0.323585 | 0.572143 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.25 | |
| **16** | 17 | 11.911708 | 0.000000 | 0.75 | 0.435403 | 0.817436 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 1.00 | |
| **17** | 18 | 11.407576 | 0.411765 | 0.75 | 0.451188 | 0.800953 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.00 | |
| **18** | 19 | 11.976666 | 0.000000 | 0.75 | 0.418925 | 0.897103 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.00 | |
| **19** | 20 | 11.842236 | 0.000000 | 0.75 | 0.440738 | 0.657391 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.00 | |

In [61]:

```
data.to_csv('X_train_outlier_removed_3.csv',index=False)
```

# Feature Selection

In [62]:

```
dataset=pd.read_csv('X_train_outlier_removed_3.csv')
```

In [63]:

```
dataset.head()
```

Out[63]:

| | Id | SalePrice | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlop |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 12.247699 | 0.235294 | 0.75 | 0.413268 | 0.702292 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.00 | 0. |
| **1** | 2 | 12.109016 | 0.000000 | 0.75 | 0.490307 | 0.753770 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.50 | 0. |
| **2** | 3 | 12.317171 | 0.235294 | 0.75 | 0.429990 | 0.817759 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.00 | 0. |

| | Id | SalePrice | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlop |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **3** | 4 | 11.849405 | 0.294118 | 0.75 | 0.383633 | 0.751663 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.25 | 0. |
| **4** | 5 | 12.429220 | 0.235294 | 0.75 | 0.508439 | 0.913414 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.50 | 0. |

In [64]:

```
len(dataset.columns)
```

Out[64]:

```
84
```

In [65]:

```
##Capture the dependent feature
y_train=dataset[['SalePrice']]
```

In [66]:

```
y_train
```

Out[66]:

| | SalePrice |
|---|---|
| **0** | 12.247699 |
| **1** | 12.109016 |
| **2** | 12.317171 |
| **3** | 11.849405 |
| **4** | 12.429220 |
| **...** | ... |
| **1455** | 12.072547 |
| **1456** | 12.254868 |
| **1457** | 12.493133 |
| **1458** | 11.864469 |
| **1459** | 11.901590 |

1460 rows × 1 columns

In [67]:

```
##Drop dependent feature from dataset
X_train=dataset.drop(['Id','SalePrice'],axis=1)
```

In [68]:

```
from sklearn.linear_model import Lasso
from sklearn.feature_selection import SelectFromModel

pd.pandas.set_option('display.max_columns',None)
```

In [69]:

```
### Apply Feature Selection
# first, I specify the Lasso Regression model, and I
# select a suitable alpha (equivalent of penalty).
# The bigger the alpha the less features that will be selected.

# Then I use the selectFromModel object from sklearn, which
# will select the features which coefficients are non-zero

feature_sel_model = SelectFromModel(Lasso(alpha=0.005,random_state=0))
```

In [70]:

In [70]:

```
feature_sel_model.fit(X_train,y_train)
```

Out[70]:

```
SelectFromModel(estimator=Lasso(alpha=0.005, copy_X=True, fit_intercept=True,
                                max_iter=1000, normalize=False, positive=False,
                                precompute=False, random_state=0,
                                selection='cyclic', tol=0.0001,
                                warm_start=False),
                max_features=None, norm_order=1, prefit=False, threshold=None)
```

In [71]:

```
feature_sel_model.get_support()
```

Out[71]:

```
array([False, False, False,  True, False, False, False, False, False,
       False, False,  True, False, False, False, False,  True, False,
       False,  True, False, False, False, False, False, False, False,
       False,  True,  True, False,  True, False,  True, False, False,
       False,  True, False,  True,  True, False,  True, False, False,
        True, False, False, False, False, False, False,  True, False,
       False, False,  True,  True, False,  True,  True, False, False,
        True, False,  True,  True, False, False, False, False, False,
       False, False, False, False, False, False,  True, False, False,
       False])
```

In [72]:

```
# let's print the number of total and selected features

selected_feat = X_train.columns[(feature_sel_model.get_support())]

#Let's print some stats
print('total features: {}'.format((X_train.shape[1])))
print('selected features: {}'.format(len(selected_feat)))
print('features with coefficients shrank to zero: {}'.format(X_train.shape[1]-len(selected_feat)))
```

```
total features: 82
selected features: 22
features with coefficients shrank to zero: 60
```

In [73]:

```
selected_feat
```

Out[73]:

```
Index(['LotArea', 'Neighborhood', 'OverallQual', 'YearRemodAdd', 'Foundation',
       'BsmtQual', 'BsmtExposure', 'BsmtFinSF1', 'TotalBsmtSF', 'HeatingQC',
       'CentralAir', '1stFlrSF', 'GrLivArea', 'KitchenQual', 'FireplaceQu',
       'GarageType', 'GarageFinish', 'GarageCars', 'GarageCond', 'WoodDeckSF',
       'OpenPorchSF', 'SaleCondition'],
      dtype='object')
```

In [74]:

```
X_train=X_train[selected_feat]
```

In [75]:

```
X_train.head()
```

Out[75]:

| | LotArea | Neighborhood | OverallQual | YearRemodAdd | Foundation | BsmtQual | BsmtExposure | BsmtFinSF1 | TotalBsmtSF | HeatingQC |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.702292 | 0.625000 | 0.666667 | 0.098361 | 1.0 | 0.75 | 0.25 | 0.876524 | 0.774017 | 1.00 |

| | LotArea | Neighborhood | OverallQual | YearRemodAdd | Foundation | BsmtQual | BsmtExposure | BsmtFinSF1 | TotalBsmtSF | HeatingQC |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.753770 | 0.833333 | 0.555556 | 0.524590 | 0.4 | 0.75 | 1.00 | 0.920010 | 0.874333 | 1.00 |
| **2** | 0.817759 | 0.625000 | 0.666667 | 0.114754 | 1.0 | 0.75 | 0.50 | 0.826724 | 0.792647 | 1.00 |
| **3** | 0.751663 | 0.708333 | 0.666667 | 0.606557 | 0.2 | 0.50 | 0.25 | 0.718730 | 0.741922 | 0.75 |
| **4** | 0.913414 | 1.000000 | 0.777778 | 0.147541 | 1.0 | 0.75 | 0.75 | 0.866522 | 0.849186 | 1.00 |

In [76]:

```
X_train.to_csv("X_train_.csv")
```

# Test Data

In [77]:

```
df2=pd.read_csv('test1.csv')
```

In [78]:

```
df2
```

Out[78]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Nei |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 20 | RH | 80.0 | 11622 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | |
| **1** | 1462 | 20 | RL | 81.0 | 14267 | Pave | NaN | IR1 | Lvl | AllPub | Corner | Gtl | |
| **2** | 1463 | 60 | RL | 74.0 | 13830 | Pave | NaN | IR1 | Lvl | AllPub | Inside | Gtl | |
| **3** | 1464 | 60 | RL | 78.0 | 9978 | Pave | NaN | IR1 | Lvl | AllPub | Inside | Gtl | |
| **4** | 1465 | 120 | RL | 43.0 | 5005 | Pave | NaN | IR1 | HLS | AllPub | Inside | Gtl | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1454** | 2915 | 160 | RM | 21.0 | 1936 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | |
| **1455** | 2916 | 160 | RM | 21.0 | 1894 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | |
| **1456** | 2917 | 20 | RL | 160.0 | 20000 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | |
| **1457** | 2918 | 85 | RL | 62.0 | 10441 | Pave | NaN | Reg | Lvl | AllPub | Inside | Gtl | |
| **1458** | 2919 | 60 | RL | 74.0 | 9627 | Pave | NaN | Reg | Lvl | AllPub | Inside | Mod | |

1459 rows × 80 columns

In [79]:

```
#Checking percentage of nan values present
#Make the list of features with missing values
features_with_na= [feat for feat in df2.columns if df2[feat].isnull().sum()>=1]

#Print feature name and percentage of missung values
for feature in features_with_na:
    print(feature, np.round(df2[feature].isnull().mean(), 4),  ' % missing values')
```

```
MSZoning 0.0027  % missing values
LotFrontage 0.1556  % missing values
Alley 0.9267  % missing values
Utilities 0.0014  % missing values
Exterior1st 0.0007  % missing values
Exterior2nd 0.0007  % missing values
MasVnrType 0.011  % missing values
MasVnrArea 0.0103  % missing values
BsmtQual 0.0302  % missing values
BsmtCond 0.0308  % missing values
BsmtExposure 0.0302  % missing values
BsmtFinType1 0.0288  % missing values
BsmtFinSF1 0.0007  % missing values
BsmtFinType2 0.0288  % missing values
BsmtFinSF2 0.0007  % missing values
```

```
BsmtUnfSF 0.0007  % missing values
TotalBsmtSF 0.0007  % missing values
BsmtFullBath 0.0014  % missing values
BsmtHalfBath 0.0014  % missing values
KitchenQual 0.0007  % missing values
Functional 0.0014  % missing values
FireplaceQu 0.5003  % missing values
GarageType 0.0521  % missing values
GarageYrBlt 0.0535  % missing values
GarageFinish 0.0535  % missing values
GarageCars 0.0007  % missing values
GarageArea 0.0007  % missing values
GarageQual 0.0535  % missing values
GarageCond 0.0535  % missing values
PoolQC 0.9979  % missing values
Fence 0.8012  % missing values
MiscFeature 0.965  % missing values
SaleType 0.0007  % missing values
```

### Feature Engineering

In [80]:

```
## Let us capture all the nan values
## First lets handle Categorical features which are missing

features_nan= [feature for feature in df2.columns if df2[feature].dtypes=='O' and df2[feature].isnu
ll().sum()>=1]

for feature in features_nan:
    print('{}: {} missing values'.format(feature,np.round(df2[feature].isnull().mean(),4)))
```

```
MSZoning: 0.0027 missing values
Alley: 0.9267 missing values
Utilities: 0.0014 missing values
Exterior1st: 0.0007 missing values
Exterior2nd: 0.0007 missing values
MasVnrType: 0.011 missing values
BsmtQual: 0.0302 missing values
BsmtCond: 0.0308 missing values
BsmtExposure: 0.0302 missing values
BsmtFinType1: 0.0288 missing values
BsmtFinType2: 0.0288 missing values
KitchenQual: 0.0007 missing values
Functional: 0.0014 missing values
FireplaceQu: 0.5003 missing values
GarageType: 0.0521 missing values
GarageFinish: 0.0535 missing values
GarageQual: 0.0535 missing values
GarageCond: 0.0535 missing values
PoolQC: 0.9979 missing values
Fence: 0.8012 missing values
MiscFeature: 0.965 missing values
SaleType: 0.0007 missing values
```

In [81]:

```
features_nan2= [feature for feature in df2.columns if
df2[feature].dtypes==('float64'or'int64'or'int32'or'O') and df2[feature].isnull().sum()>=1]
```

In [82]:

```
features_nan2
```

Out[82]:

```
['LotFrontage',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
```

```
 'TotalBsmtSF',
 'BsmtFullBath',
 'BsmtHalfBath',
 'GarageYrBlt',
 'GarageCars',
 'GarageArea']
```

In [83]:

```
## Replace missing value with a new label
def replace_cat_feature(df2,features_nan):
    data=df2.copy()

    data[features_nan] = np.where(data[features_nan].isnull(),'Missing',data[features_nan])
    #data[features_nan]=data[features_nan].fillna('Missing')
    return data
df2=replace_cat_feature(df2,features_nan)
```

In [84]:

```
df2[features_nan].isnull().sum()
```

Out[84]:

```
MSZoning        0
Alley           0
Utilities       0
Exterior1st     0
Exterior2nd     0
MasVnrType      0
BsmtQual        0
BsmtCond        0
BsmtExposure    0
BsmtFinType1    0
BsmtFinType2    0
KitchenQual     0
Functional      0
FireplaceQu     0
GarageType      0
GarageFinish    0
GarageQual      0
GarageCond      0
PoolQC          0
Fence           0
MiscFeature     0
SaleType        0
dtype: int64
```

In [85]:

```
df2.head()
```

Out[85]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neig |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 20 | RH | 80.0 | 11622 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **1** | 1462 | 20 | RL | 81.0 | 14267 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| **2** | 1463 | 60 | RL | 74.0 | 13830 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **3** | 1464 | 60 | RL | 78.0 | 9978 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **4** | 1465 | 120 | RL | 43.0 | 5005 | Pave | Missing | IR1 | HLS | AllPub | Inside | Gtl | |

In [86]:

```
## Now lets check for numerical variables that contains missing values

numerical_with_nan=[feature for feature in df2.columns if df2[feature].isnull().sum()>=1 and df2[fe
ature].dtypes!='O']

## We will print the numerical nan variables and percentage of missing values
```

```
for feature in numerical_with_nan:
    print("{}: {}% missing value".format(feature,np.round(df2[feature].isnull().mean()*100,4)))
```

```
LotFrontage: 15.5586% missing value
MasVnrArea: 1.0281% missing value
BsmtFinSF1: 0.0685% missing value
BsmtFinSF2: 0.0685% missing value
BsmtUnfSF: 0.0685% missing value
TotalBsmtSF: 0.0685% missing value
BsmtFullBath: 0.1371% missing value
BsmtHalfBath: 0.1371% missing value
GarageYrBlt: 5.3461% missing value
GarageCars: 0.0685% missing value
GarageArea: 0.0685% missing value
```

In [87]:

```
#Replacing the numerical missing values
for feature in numerical_with_nan:
    ## We will replace by using median since there are outliers

    ## create a new feature to capture nan values
    df2[feature+'nan'] = np.where(df2[feature].isnull(),1,0)

    ## ## We will replace by using median since there are outliers
    df2[feature].fillna(df2[feature].median(),inplace=True)

df2[numerical_with_nan].isnull().sum()
```

Out[87]:

```
LotFrontage     0
MasVnrArea      0
BsmtFinSF1      0
BsmtFinSF2      0
BsmtUnfSF       0
TotalBsmtSF     0
BsmtFullBath    0
BsmtHalfBath    0
GarageYrBlt     0
GarageCars      0
GarageArea      0
dtype: int64
```

In [88]:

```
#For temporal_feature
temporal_feat= [feature for feature in df2.columns if 'Year' in feature or 'Yr'in feature]
temporal_feat
```

Out[88]:

```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold', 'GarageYrBltnan']
```

In [89]:

```
## Temporal Variables (Date Time Variables)

for feature in ['YearBuilt','YearRemodAdd','GarageYrBlt']:

    df2[feature]=df2['YrSold']-df2[feature]
```

In [90]:

```
df2.head()
```

Out[90]:

| Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neig |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neig |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 20 | RH | 80.0 | 11622 | Pave | Missing | Reg | Lvl | AllPub | Inside | Gtl | |
| **1** | 1462 | 20 | RL | 81.0 | 14267 | Pave | Missing | IR1 | Lvl | AllPub | Corner | Gtl | |
| **2** | 1463 | 60 | RL | 74.0 | 13830 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **3** | 1464 | 60 | RL | 78.0 | 9978 | Pave | Missing | IR1 | Lvl | AllPub | Inside | Gtl | |
| **4** | 1465 | 120 | RL | 43.0 | 5005 | Pave | Missing | IR1 | HLS | AllPub | Inside | Gtl | |

In [91]:

```
df2[['YearBuilt','YearRemodAdd','GarageYrBlt']].head()
```

Out[91]:

| | YearBuilt | YearRemodAdd | GarageYrBlt |
|---|---|---|---|
| **0** | 49 | 49 | 49.0 |
| **1** | 52 | 52 | 52.0 |
| **2** | 13 | 12 | 13.0 |
| **3** | 12 | 12 | 12.0 |
| **4** | 18 | 18 | 18.0 |

In [92]:

```
for feature in categorical_features:
    df3=pd.read_csv('train1.csv')
    df3[feature]=np.where(df3[feature].isnull(),'Missing',df3[feature])
    labels_ordered=df3.groupby([feature])['SalePrice'].mean().sort_values().index
    labels_ordered={k:i for i,k in enumerate(labels_ordered,0)}
    df2[feature]=df2[feature].map(labels_ordered)  # For test data as SalePrice column is not prese
nt
```

In [93]:

```
df2
```

Out[93]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Nei |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 20 | 2.0 | 80.0 | 11622 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1** | 1462 | 20 | 3.0 | 81.0 | 14267 | 1 | 2 | 1 | 1 | 1.0 | 2 | 0 | |
| **2** | 1463 | 60 | 3.0 | 74.0 | 13830 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **3** | 1464 | 60 | 3.0 | 78.0 | 9978 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **4** | 1465 | 120 | 3.0 | 43.0 | 5005 | 1 | 2 | 1 | 3 | 1.0 | 0 | 0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1454** | 2915 | 160 | 1.0 | 21.0 | 1936 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1455** | 2916 | 160 | 1.0 | 21.0 | 1894 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1456** | 2917 | 20 | 3.0 | 160.0 | 20000 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1457** | 2918 | 85 | 3.0 | 62.0 | 10441 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1458** | 2919 | 60 | 3.0 | 74.0 | 9627 | 1 | 2 | 0 | 1 | 1.0 | 0 | 1 | |

1459 rows × 91 columns

## Missing Values

In [94]:

```
## Let us capture all the nan values
## First lets handle Categorical features which are missing
```

```
features_nan= [feature for feature in df2.columns if df2[feature].dtypes=='O' and df2[feature].isnu
ll().sum()>=1]
```

In [95]:

```
continuous_feature
```

Out[95]:

```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch',
 'SalePrice']
```

In [96]:

```
continuous_feature.append('SalePrice')
```

In [97]:

```
continuous_feature
```

Out[97]:

```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch',
 'SalePrice',
 'SalePrice']
```

In [103]:

```
continuous_feature.remove('SalePrice')
```

In [104]:

```
continuous_feature
```

Out[104]:

```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
```

```
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch']
```

In [105]:

```python
continuous_feature_test = continuous_feature
```

In [266]:

```python
continuous_feature_test
```

Out[266]:

```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch']
```

In [269]:

```python
df3
```

Out[269]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Ne |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 20 | 2.0 | 1.685370 | 2.338024 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1** | 1462 | 20 | 3.0 | 1.687642 | 2.357620 | 1 | 2 | 1 | 1 | 1.0 | 2 | 0 | |
| **2** | 1463 | 60 | 3.0 | 1.671001 | 2.354672 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **3** | 1464 | 60 | 3.0 | 1.680725 | 2.323195 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **4** | 1465 | 120 | 3.0 | 1.565317 | 2.253226 | 1 | 2 | 1 | 3 | 1.0 | 0 | 0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1454** | 2915 | 160 | 1.0 | 1.552447 | 2.223847 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1455** | 2916 | 160 | 1.0 | 1.552447 | 2.223847 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1456** | 2917 | 20 | 3.0 | 1.734031 | 2.377858 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1457** | 2918 | 85 | 3.0 | 1.637663 | 2.327628 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1458** | 2919 | 60 | 3.0 | 1.671001 | 2.319681 | 1 | 2 | 0 | 1 | 1.0 | 0 | 1 | |

1459 rows × 91 columns

In [107]:

```python
for feature in continuous_feature_test:
    IQR = np.percentile(df2[feature],75) - np.percentile(df2[feature],25)
    lb = np.percentile(df2[feature],25)-IQR*1.5
    ub = np.percentile(df2[feature],75)+IQR*1.5

    df2[feature] = np.where(df2[feature]>ub,ub,df2[feature])
    df2[feature] = np.where(df2[feature]<lb,lb,df2[feature])
    df2[feature] = np.log1p(df2[feature])
```

In [270]:

```
outlier_dict = dict()
for feature in continuous_feature_test:
    IQR = np.percentile(df4[feature],75) - np.percentile(df4[feature],25)
    lb = np.percentile(df4[feature],25)-IQR*1.5
    ub = np.percentile(df4[feature],75)+IQR*1.5

    df4[feature] = np.where(df4[feature]>ub,ub,df4[feature])
    df4[feature] = np.where(df4[feature]<lb,lb,df4[feature])
    df4[feature] = np.log1p(df4[feature])

    dict_feature = dict()

    dict_feature['IQR'] = IQR
    dict_feature['Lower_bound'] = lb
    dict_feature['Upper_bound'] = ub

    outlier_dict[feature] = dict_feature
```

In [276]:

```
outlier_dict_percentile = dict()
for feature in continuous_feature_test:
    percentile_99th = np.percentile(df4[feature],99)
    percentile_1st = np.percentile(df4[feature],1)
    median_value = df[feature].median()

    #df4[feature] = np.where(df4[feature]>ub,ub,df4[feature])
    #df4[feature] = np.where(df4[feature]<lb,lb,df4[feature])
    #df4[feature] = np.log1p(df4[feature])

    dict_feature_percentile = dict()

    dict_feature_percentile['1st'] = percentile_1st
    dict_feature_percentile['99th'] = percentile_99th
    dict_feature_percentile['Median'] = median_value

    outlier_dict_percentile[feature] = dict_feature_percentile
```

In [313]:

```
outlier_dict
```

Out[313]:

```
{'LotFrontage': {'IQR': 0.04935468226831574,
  'Lower_bound': 1.5573383767939242,
  'Upper_bound': 1.7547571058671871},
 'LotArea': {'IQR': 0.04379367920570498,
  'Lower_bound': 2.2276674956502895,
  'Upper_bound': 2.4028422124731095},
 'MasVnrArea': {'IQR': 1.807263688716924,
  'Lower_bound': -2.710895533075386,
  'Upper_bound': 4.51815922179231},
 'BsmtFinSF1': {'IQR': 2.0313085443910763,
  'Lower_bound': -3.0469628165866145,
  'Upper_bound': 5.078271360977691},
 'BsmtFinSF2': {'IQR': 0.0, 'Lower_bound': 0.0, 'Upper_bound': 0.0},
 'BsmtUnfSF': {'IQR': 0.18331923565035124,
  'Lower_bound': 1.5806774813803603,
  'Upper_bound': 2.313954423981765},
 'TotalBsmtSF': {'IQR': 0.06419941643668414,
  'Lower_bound': 1.9404545836622826,
  'Upper_bound': 2.1972522494090194},
 '1stFlrSF': {'IQR': 0.057334072754528176,
  'Lower_bound': 1.9647389718441362,
  'Upper_bound': 2.194075262862249},
 '2ndFlrSF': {'IQR': 2.0172564188484525,
  'Lower_bound': -3.025884628272679,
  'Upper_bound': 5.043141047121131},
 'GrLivArea': {'IQR': 0.05240691570189382,
```

```
  'Lower_bound': 2.00329608628795,
  'Upper_bound': 2.212923749095525},
 'GarageArea': {'IQR': 0.0839762094741221,
  'Lower_bound': 1.7858261957612633,
  'Upper_bound': 2.1217310336577517},
 'WoodDeckSF': {'IQR': 1.813178226960568,
  'Lower_bound': -2.719767340440852,
  'Upper_bound': 4.53294556740142},
 'OpenPorchSF': {'IQR': 1.6659050929776016,
  'Lower_bound': -2.4988576394664026,
  'Upper_bound': 4.164762732444004},
 'EnclosedPorch': {'IQR': 0.0, 'Lower_bound': 0.0, 'Upper_bound': 0.0},
 'ScreenPorch': {'IQR': 0.0, 'Lower_bound': 0.0, 'Upper_bound': 0.0}}
```

In [277]:

```python
outlier_dict_percentile
```

Out[277]:

```
{'LotFrontage': {'1st': 0.9389670210672053,
  '99th': 1.005777194524828,
  'Median': 4.248495242049359},
 'LotArea': {'1st': 1.1717597387980652,
  '99th': 1.2172418461444838,
  'Median': 9.156886838722746},
 'MasVnrArea': {'1st': 0.0, '99th': 1.080725717331393, 'Median': 0.0},
 'BsmtFinSF1': {'1st': 0.0,
  '99th': 1.1415626429333063,
  'Median': 5.951942943437755},
 'BsmtFinSF2': {'1st': 0.0, '99th': 0.0, 'Median': 0.0},
 'BsmtUnfSF': {'1st': 0.9480519541451999,
  '99th': 1.1411474047821348,
  'Median': 6.170651297395139},
 'TotalBsmtSF': {'1st': 1.0785641896913982,
  '99th': 1.1495254945144728,
  'Median': 6.900226885665022},
 '1stFlrSF': {'1st': 1.0916336887769167,
  '99th': 1.1505971766270453,
  'Median': 6.992096005027085},
 '2ndFlrSF': {'1st': 0.0, '99th': 1.1339307567244956, 'Median': 0.0},
 'GrLivArea': {'1st': 1.1040865573224683,
  '99th': 1.1578527534077312,
  'Median': 7.289610521451167},
 'GarageArea': {'1st': 1.0245444885448576,
  '99th': 1.1194590497357892,
  'Median': 6.175867270105761},
 'WoodDeckSF': {'1st': 0.0, '99th': 1.0824768370427216, 'Median': 0.0},
 'OpenPorchSF': {'1st': 0.0,
  '99th': 1.0382629710766498,
  'Median': 3.258096538021482},
 'EnclosedPorch': {'1st': 0.0, '99th': 0.0, 'Median': 0.0},
 'ScreenPorch': {'1st': 0.0, '99th': 0.0, 'Median': 0.0}}
```

In [272]:

```python
np.save('outlier_dict.npy', outlier_dict)
```

In [273]:

```python
outlier_dict = np.load('outlier_dict.npy',allow_pickle='TRUE').item()
```

In [274]:

```python
outlier_dict
```

Out[274]:

```
{'LotFrontage': {'IQR': 0.04935468226831574,
  'Lower_bound': 1.5573383767939242,
  'Upper_bound': 1.7547571058671871},
 'LotArea': {'IQR': 0.04379367920570498,
```

```
  'Lower_bound': 2.2276674956502895,
  'Upper_bound': 2.4028422124731095},
 'MasVnrArea': {'IQR': 1.807263688716924,
  'Lower_bound': -2.710895533075386,
  'Upper_bound': 4.51815922179231},
 'BsmtFinSF1': {'IQR': 2.0313085443910763,
  'Lower_bound': -3.0469628165866145,
  'Upper_bound': 5.078271360977691},
 'BsmtFinSF2': {'IQR': 0.0, 'Lower_bound': 0.0, 'Upper_bound': 0.0},
 'BsmtUnfSF': {'IQR': 0.18331923565035124,
  'Lower_bound': 1.5806774813803603,
  'Upper_bound': 2.313954423981765},
 'TotalBsmtSF': {'IQR': 0.06419941643668414,
  'Lower_bound': 1.9404545836622826,
  'Upper_bound': 2.1972522494090194},
 '1stFlrSF': {'IQR': 0.057334072754528176,
  'Lower_bound': 1.9647389718441362,
  'Upper_bound': 2.194075262862249},
 '2ndFlrSF': {'IQR': 2.0172564188484525,
  'Lower_bound': -3.025884628272679,
  'Upper_bound': 5.043141047121131},
 'GrLivArea': {'IQR': 0.05240691570189382,
  'Lower_bound': 2.00329608628795,
  'Upper_bound': 2.212923749095525},
 'GarageArea': {'IQR': 0.0839762094741221,
  'Lower_bound': 1.7858261957612633,
  'Upper_bound': 2.1217310336577517},
 'WoodDeckSF': {'IQR': 1.813178226960568,
  'Lower_bound': -2.719767340440852,
  'Upper_bound': 4.53294556740142},
 'OpenPorchSF': {'IQR': 1.6659050929776016,
  'Lower_bound': -2.4988576394664026,
  'Upper_bound': 4.164762732444004},
 'EnclosedPorch': {'IQR': 0.0, 'Lower_bound': 0.0, 'Upper_bound': 0.0},
 'ScreenPorch': {'IQR': 0.0, 'Lower_bound': 0.0, 'Upper_bound': 0.0}}
```

In [311]:

```
df5 = scaler.transform(entry.values)
```

In [312]:

```
df5
```

Out[312]:

```
array([[ 0.23529412,  0.75      , -0.79284434, -2.46147135,  1.        ,
         1.        ,  0.33333333,  0.33333333,  1.        ,  0.5       ,
         0.        ,  0.58333333,  0.5       ,  0.57142857,  1.        ,
         0.85714286,  0.55555556,  0.5       ,  0.125     ,  0.27868852,
         0.2       ,  0.28571429,  0.57142857,  0.6       ,  0.25      ,
         0.        ,  0.33333333,  0.75      ,  1.        ,  0.75      ,
         0.75      ,  0.25      ,  0.83333333,  0.        ,  0.83333333,
         0.        ,  0.14933515, -0.68589666,  1.        ,  0.75      ,
         1.        ,  1.        , -2.52667414,  0.14869381,  0.        ,
        -2.22033716,  0.        ,  0.        ,  0.66666667,  0.5       ,
         0.375     ,  0.33333333,  0.33333333,  0.41666667,  1.        ,
         0.33333333,  0.6       ,  0.83333333,  0.1588785 ,  1.        ,
         0.5       ,  0.15846407,  0.6       ,  1.        ,  1.        ,
         0.17051883,  0.19276367,  0.        ,  0.        ,  0.        ,
         0.        ,  0.        ,  1.        ,  0.75      ,  0.        ,
         0.27272727,  1.        ,  0.5       ,  0.8       ,  0.        ,
         0.        ,  0.        ],
       [ 0.        ,  0.75      , -0.79582296, -2.46419335,  1.        ,
         1.        ,  0.33333333,  0.33333333,  1.        ,  0.        ,
         0.        ,  0.58333333,  0.5       ,  0.57142857,  1.        ,
         0.71428571,  0.55555556,  0.75      ,  0.13235294,  0.06557377,
         0.2       ,  0.28571429,  0.57142857,  0.6       ,  0.25      ,
         0.        ,  0.33333333,  0.5       ,  1.        ,  0.75      ,
         0.75      ,  0.25      ,  0.66666667,  0.14939098,  0.83333333,
         0.        ,  0.14165235, -0.68131628,  1.        ,  1.        ,
         1.        ,  1.        , -2.51681676,  0.        ,  0.        ,
        -2.2264923 ,  0.33333333,  0.        ,  0.66666667,  0.        ,
         0.375     ,  0.33333333,  0.33333333,  0.33333333,  1.        ,
         0.        ,  0.2       ,  0.83333333,  0.1682243 ,  1.        ,
```

```
        0.5       ,  0.15813936,  0.6       ,  1.        ,  1.        ,
        0.17913993,  0.17098136,  0.        ,  0.        ,  0.        ,
        0.        ,  0.        ,  0.75      ,  0.25      ,  0.03225806,
        0.18181818,  1.        ,  0.5       ,  0.8       ,  1.        ,
        0.        ,  0.        ],
      [ 0.23529412,  0.75      , -0.79748355, -2.46356472,  1.        ,
        1.        ,  0.33333333,  0.33333333,  1.        ,  0.        ,
        0.        ,  0.58333333,  0.5       ,  0.57142857,  1.        ,
        0.85714286,  0.55555556,  0.5       ,  0.08823529,  0.21311475,
        0.2       ,  0.28571429,  0.78571429,  0.8       ,  0.25      ,
        0.        ,  0.33333333,  0.75      ,  1.        ,  0.75      ,
        0.75      ,  0.25      ,  0.83333333,  0.        ,  0.83333333,
        0.        ,  0.14952897, -0.68552412,  1.        ,  0.75      ,
        1.        ,  1.        , -2.52590066,  0.14710633,  0.        ,
       -2.22255773,  0.        ,  0.        ,  0.66666667,  0.5       ,
        0.375     ,  0.33333333,  0.33333333,  0.41666667,  1.        ,
        0.33333333,  0.8       ,  0.83333333,  0.11214953,  1.        ,
        0.5       ,  0.15767064,  0.6       ,  1.        ,  1.        ,
        0.        ,  0.191258  ,  0.        ,  0.        ,  0.        ,
        0.        ,  0.        ,  1.        ,  0.75      ,  0.        ,
        0.36363636,  1.        ,  0.5       ,  0.8       ,  0.        ,
        0.        ,  0.        ],
      [ 0.        ,  0.75      , -0.78963255, -2.46126415,  1.        ,
        1.        ,  0.        ,  0.33333333,  1.        ,  0.        ,
        0.        ,  0.58333333,  0.5       ,  0.57142857,  1.        ,
        0.71428571,  0.66666667,  0.5       ,  0.14705882,  0.3442623 ,
        0.2       ,  0.28571429,  0.57142857,  0.6       ,  0.25      ,
        0.        ,  0.33333333,  0.75      ,  1.        ,  0.75      ,
        0.75      ,  1.        ,  1.        ,  0.14718463,  0.83333333,
        0.        ,  0.14851019, -0.68021437,  1.        ,  0.75      ,
        1.        ,  1.        , -2.51422013,  0.        ,  0.        ,
       -2.2241952 ,  0.33333333,  0.        ,  0.33333333,  0.5       ,
        0.25      ,  0.33333333,  0.66666667,  0.25      ,  1.        ,
        0.33333333,  0.        ,  0.83333333,  0.18691589,  0.33333333,
        0.5       ,  0.15942294,  0.6       ,  1.        ,  1.        ,
        0.17242555,  0.        ,  0.        ,  0.        ,  0.        ,
        0.        ,  0.        ,  1.        ,  0.75      ,  0.        ,
        0.09090909,  1.        ,  0.5       ,  0.8       ,  0.        ,
        0.        ,  0.        ],
      [ 0.        ,  0.75      , -0.79465653, -2.46356761,  1.        ,
        1.        ,  0.        ,  0.33333333,  1.        ,  0.5       ,
        0.        ,  0.41666667,  0.5       ,  0.57142857,  1.        ,
        0.71428571,  0.33333333,  0.5       ,  0.29411765,  0.67213115,
        0.2       ,  0.28571429,  0.64285714,  0.66666667,  0.25      ,
        0.        ,  0.33333333,  0.75      ,  0.4       ,  0.5       ,
        0.75      ,  0.25      ,  0.66666667,  0.14854051,  0.5       ,
        0.        ,  0.12759079, -0.68430057,  1.        ,  0.5       ,
        1.        ,  1.        , -2.52336026,  0.        ,  0.        ,
       -2.23228098,  0.33333333,  0.        ,  0.33333333,  0.        ,
        0.25      ,  0.33333333,  0.33333333,  0.16666667,  1.        ,
        0.        ,  0.2       ,  0.83333333,  0.37383178,  1.        ,
        0.5       ,  0.15967177,  0.6       ,  1.        ,  1.        ,
        0.17444781,  0.        ,  0.        ,  0.        ,  0.        ,
        0.        ,  0.        ,  0.5       ,  0.75      ,  0.        ,
        0.27272727,  1.        ,  0.5       ,  0.8       ,  0.        ,
        0.        ,  0.        ]])
```

In [310]:

```
entry = entry[feature_scale]
```

In [ ]:

```

```

In [308]:

```
len(entry[feature_scale].columns)
```

Out[308]:

```
82
```

In [304]:

```
entry = pd.DataFrame(df4.iloc[5:10],columns = df4.columns)
```

In [307]:

```
X_train
```

Out[307]:

| | LotArea | Neighborhood | OverallQual | YearRemodAdd | Foundation | BsmtQual | BsmtExposure | BsmtFinSF1 | TotalBsmtSF | Heating |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.702292 | 0.625000 | 0.666667 | 0.098361 | 1.0 | 0.75 | 0.25 | 0.876524 | 0.774017 | |
| **1** | 0.753770 | 0.833333 | 0.555556 | 0.524590 | 0.4 | 0.75 | 1.00 | 0.920010 | 0.874333 | |
| **2** | 0.817759 | 0.625000 | 0.666667 | 0.114754 | 1.0 | 0.75 | 0.50 | 0.826724 | 0.792647 | |
| **3** | 0.751663 | 0.708333 | 0.666667 | 0.606557 | 0.2 | 0.50 | 0.25 | 0.718730 | 0.741922 | |
| **4** | 0.913414 | 1.000000 | 0.777778 | 0.147541 | 1.0 | 0.75 | 0.75 | 0.866522 | 0.849186 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1455** | 0.676006 | 0.583333 | 0.555556 | 0.131148 | 1.0 | 0.75 | 0.25 | 0.000000 | 0.801753 | |
| **1456** | 0.881485 | 0.541667 | 0.555556 | 0.377049 | 0.4 | 0.75 | 0.25 | 0.891523 | 0.926129 | |
| **1457** | 0.729610 | 0.708333 | 0.666667 | 0.081967 | 0.6 | 0.50 | 0.25 | 0.750860 | 0.850761 | |
| **1458** | 0.758657 | 0.416667 | 0.444444 | 0.245902 | 0.4 | 0.50 | 0.50 | 0.522629 | 0.833603 | |
| **1459** | 0.767689 | 0.208333 | 0.444444 | 0.721311 | 0.4 | 0.50 | 0.25 | 0.898113 | 0.873101 | |

1460 rows × 22 columns

In [262]:

```
df4 = df3
```

In [ ]:

In [263]:

```
df2
```

Out[263]:

| | LotArea | Neighborhood | OverallQual | YearRemodAdd | Foundation | BsmtQual | BsmtExposure | BsmtFinSF1 | TotalBsmtSF | Heating |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2.338024 | 10 | 5 | 49 | 2 | 2 | 1 | 1.967197 | 2.051984 | |
| **1** | 2.357620 | 10 | 6 | 52 | 2 | 2 | 1 | 2.057798 | 2.103272 | |
| **2** | 2.354672 | 14 | 5 | 12 | 5 | 3 | 1 | 2.037911 | 2.058487 | |
| **3** | 2.323195 | 14 | 6 | 12 | 5 | 2 | 1 | 2.001739 | 2.058212 | |
| **4** | 2.253226 | 22 | 8 | 18 | 5 | 3 | 1 | 1.883419 | 2.098680 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1454** | 2.223847 | 0 | 4 | 36 | 2 | 2 | 1 | 0.000000 | 1.988484 | |
| **1455** | 2.223847 | 0 | 4 | 36 | 2 | 2 | 1 | 1.876926 | 1.988484 | |
| **1456** | 2.377858 | 11 | 5 | 10 | 2 | 2 | 1 | 2.093184 | 2.093184 | |
| **1457** | 2.327628 | 11 | 5 | 14 | 5 | 3 | 3 | 1.920306 | 2.056267 | |
| **1458** | 2.319681 | 11 | 7 | 12 | 5 | 3 | 3 | 2.032350 | 2.067464 | |

1459 rows × 22 columns

In [259]:

```
outlier_dict = dict()
```

```
outlier_dict = {a:1,2,3}
```

```
  File "<ipython-input-259-ed9478547cb2>", line 2
    outlier_dict = {a:1,2,3}
                       ^
SyntaxError: invalid syntax
```

In [164]:

```
#Numerical Variables
#Since the numerical variables are skewed, we will perform log normal distribution
```

In [191]:

```
num_features=['LotFrontage', 'LotArea', '1stFlrSF', 'GrLivArea']
#for feature in num_features:
    #df2[feature]=np.log(df2[feature])
```

In [108]:

```
df2.shape
```

Out[108]:

```
(1459, 91)
```

In [109]:

```
## Replace missing value with a new label
def replace_cat_feature(df,features_nan):
    data=df.copy()

    data[features_nan] = np.where(data[features_nan].isnull(),'Missing',data[features_nan])
    #data[features_nan]=data[features_nan].fillna('Missing')
    return data
df2=replace_cat_feature(df2,features_nan)
```

In [110]:

```
## Let us capture all the nan values
## First lets handle Categorical features which are missing

features_nan= [feature for feature in df2.columns if df2[feature].dtypes=='O' and df2[feature].isnu
ll().sum()>=1]

for feature in features_nan:
    print('{}: {} missing values'.format(feature,np.round(df2[feature].isnull().mean(),4)))
```

In [111]:

```
df2.head()
```

Out[111]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neigh |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 20 | 2.0 | 1.685370 | 2.338024 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1** | 1462 | 20 | 3.0 | 1.687642 | 2.357620 | 1 | 2 | 1 | 1 | 1.0 | 2 | 0 | |
| **2** | 1463 | 60 | 3.0 | 1.671001 | 2.354672 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **3** | 1464 | 60 | 3.0 | 1.680725 | 2.323195 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **4** | 1465 | 120 | 3.0 | 1.565317 | 2.253226 | 1 | 2 | 1 | 3 | 1.0 | 0 | 0 | |

In [112]:

```
df2.to_csv('test_outlier_removed',index=False)
```

## Prediciton and selecting the Algorithm

In [113]:

```
import xgboost
regressor=xgboost.XGBRegressor()
```

```
C:\Users\Hp\Anaconda3\lib\site-packages\dask\dataframe\utils.py:14: FutureWarning:
pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

In [114]:

```
booster=['gbtree','gblinear']
base_score=[0.25,0.5,0.75,1]
```

In [115]:

```
## Hyper Parameter Optimization


n_estimators = [100, 500, 900, 1100, 1500]
max_depth = [2, 3, 5, 10, 15]
booster=['gbtree','gblinear']
learning_rate=[0.05,0.1,0.15,0.20]
min_child_weight=[1,2,3,4]

# Define the grid of hyperparameters to search
hyperparameter_grid = {
    'n_estimators': n_estimators,
    'max_depth':max_depth,
    'learning_rate':learning_rate,
    'min_child_weight':min_child_weight,
    'booster':booster,
    'base_score':base_score
    }
```

In [116]:

```
# Set up the random search with 4-fold cross validation
from sklearn.model_selection import RandomizedSearchCV
#from sklearn.base import clone
# Set up the random search with 4-fold cross validation
random_cv = RandomizedSearchCV(estimator=regressor,
            param_distributions=hyperparameter_grid,
            cv=5, n_iter=50,
            scoring = 'neg_mean_absolute_error',n_jobs = 4,
            verbose = 5,
            return_train_score = True,
            random_state=42)
```

In [117]:

```
random_cv.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
```

```
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  10 tasks      | elapsed:   13.3s
[Parallel(n_jobs=4)]: Done  64 tasks      | elapsed:   56.0s
[Parallel(n_jobs=4)]: Done 154 tasks      | elapsed:  1.4min
[Parallel(n_jobs=4)]: Done 250 out of 250 | elapsed:  1.9min finished
```

Out[117]:

```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=XGBRegressor(base_score=None, booster=None,
                                          colsample_bylevel=None,
```

```
                                        colsample_bynode=None,
                                        colsample_bytree=None, gamma=None,
                                        gpu_id=None, importance_type='gain',
                                        interaction_constraints=None,
                                        learning_rate=None,
                                        max_delta_step=None, max_depth=None,
                                        min_child_weight=None, missing=nan,
                                        monotone_constraints=None,
                                        n_...
                   iid='deprecated', n_iter=50, n_jobs=4,
                   param_distributions={'base_score': [0.25, 0.5, 0.75, 1],
                                        'booster': ['gbtree', 'gblinear'],
                                        'learning_rate': [0.05, 0.1, 0.15, 0.2],
                                        'max_depth': [2, 3, 5, 10, 15],
                                        'min_child_weight': [1, 2, 3, 4],
                                        'n_estimators': [100, 500, 900, 1100,
                                                         1500]},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=True, scoring='neg_mean_absolute_error',
                   verbose=5)
```

In [185]:

```
random_cv.best_estimator_
```

Out[185]:

```
XGBRegressor(base_score=0.25, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.05, max_delta_step=0, max_depth=2,
             min_child_weight=4, missing=nan, monotone_constraints='()',
             n_estimators=900, n_jobs=0, num_parallel_tree=1,
             objective='reg:squarederror', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

In [119]:

```
random_cv.best_params_
```

Out[119]:

```
{'n_estimators': 900,
 'min_child_weight': 4,
 'max_depth': 2,
 'learning_rate': 0.05,
 'booster': 'gbtree',
 'base_score': 0.25}
```

In [120]:

```
regressor=xgboost.XGBRegressor(base_score=0.25, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.05, max_delta_step=0, max_depth=2,
             min_child_weight=4, missing=None, monotone_constraints='()',
             n_estimators=900, n_jobs=0, num_parallel_tree=1,
             objective='reg:squarederror', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1)
```

In [121]:

```
regressor.fit(X_train,y_train)
```

Out[121]:

```
XGBRegressor(base_score=0.25, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.05, max_delta_step=0, max_depth=2,
             min_child_weight=4, missing=None, monotone_constraints='()',
```

```
             n_estimators=900, n_jobs=0, num_parallel_tree=1,
             objective='reg:squarederror', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

In [152]:

```
df2 = pd.read_csv('test_outlier_removed')
```

In [153]:

```
df3=df2.copy()
```

In [167]:

```
df3
```

Out[167]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Ne |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 20 | 2.0 | 1.685370 | 2.338024 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1** | 1462 | 20 | 3.0 | 1.687642 | 2.357620 | 1 | 2 | 1 | 1 | 1.0 | 2 | 0 | |
| **2** | 1463 | 60 | 3.0 | 1.671001 | 2.354672 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **3** | 1464 | 60 | 3.0 | 1.680725 | 2.323195 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **4** | 1465 | 120 | 3.0 | 1.565317 | 2.253226 | 1 | 2 | 1 | 3 | 1.0 | 0 | 0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1454** | 2915 | 160 | 1.0 | 1.552447 | 2.223847 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1455** | 2916 | 160 | 1.0 | 1.552447 | 2.223847 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1456** | 2917 | 20 | 3.0 | 1.734031 | 2.377858 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1457** | 2918 | 85 | 3.0 | 1.637663 | 2.327628 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1458** | 2919 | 60 | 3.0 | 1.671001 | 2.319681 | 1 | 2 | 0 | 1 | 1.0 | 0 | 1 | |

1459 rows × 91 columns

In [168]:

```
df2=df3[feature_scale]
```

In [160]:

```
NaN_values
```

Out[160]:

```
['MSZoning', 'Utilities', 'Functional']
```

In [171]:

```
NaN_values = [f for f in df2.columns if df2[f].isnull().sum()>1]
for f in NaN_values:
    df2[f] = np.where(df2[f].isnull()==True,df2[f].median(),df2[f])
```

```
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports until
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports until
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports until
```

In [172]:

```
NaN_values = [f for f in df2.columns if df2[f].isnull().sum()>1]
```

In [174]:

```
df2.head()
```

Out[174]:

| | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Neighborhoo |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 20 | 2.0 | 1.685370 | 2.338024 | 1 | 2 | 0 | 1 | 1.0 | 0 | 0 | |
| **1** | 20 | 3.0 | 1.687642 | 2.357620 | 1 | 2 | 1 | 1 | 1.0 | 2 | 0 | |
| **2** | 60 | 3.0 | 1.671001 | 2.354672 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **3** | 60 | 3.0 | 1.680725 | 2.323195 | 1 | 2 | 1 | 1 | 1.0 | 0 | 0 | |
| **4** | 120 | 3.0 | 1.565317 | 2.253226 | 1 | 2 | 1 | 3 | 1.0 | 0 | 0 | |

In [175]:

```
df_Test = scaler.transform(df2)
```

In [176]:

```
df_Test
```

Out[176]:

```
array([[ 0.        ,  0.5       , -0.528776  , ...,  0.        ,
         0.        ,  0.        ],
       [ 0.        ,  0.75      , -0.52792134, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.23529412,  0.75      , -0.5341814 , ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [ 0.        ,  0.75      , -0.5104711 , ...,  0.        ,
         0.        ,  0.        ],
       [ 0.38235294,  0.75      , -0.54672237, ...,  0.        ,
         0.        ,  1.        ],
       [ 0.23529412,  0.75      , -0.5341814 , ...,  0.        ,
         0.        ,  0.        ]])
```

In [177]:

```
#Converting transformed Test data into dataframe, and adding on the Id variables
data2 = pd.concat([df3[['Id']].reset_index(drop=True),
                  pd.DataFrame(df_Test,columns=feature_scale)],axis=1)
```

In [181]:

```
data2
```

Out[181]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Ne |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Ne |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 0.000000 | 0.50 | -0.528776 | 2.002693 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1** | 1462 | 0.000000 | 0.75 | -0.527921 | -1.994787 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.5 | 0.0 | |
| **2** | 1463 | 0.235294 | 0.75 | -0.534181 | -1.995976 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **3** | 1464 | 0.235294 | 0.75 | -0.530523 | -2.008677 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **4** | 1465 | 0.588235 | 0.75 | -0.573937 | -2.036908 | 1.0 | 1.0 | 0.333333 | 1.000000 | 1.0 | 0.0 | 0.0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1454** | 2915 | 0.823529 | 0.25 | -0.578778 | -2.048762 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1455** | 2916 | 0.823529 | 0.25 | -0.578778 | -2.048762 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1456** | 2917 | 0.000000 | 0.75 | -0.510471 | -1.986621 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1457** | 2918 | 0.382353 | 0.75 | -0.546722 | -2.006888 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1458** | 2919 | 0.235294 | 0.75 | -0.534181 | -2.010094 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.5 | |

1459 rows × 83 columns

In [182]:

```
data_transformed = data2
```

In [183]:

```
y_pred=regressor.predict(data2[selected_feat])
```

In [184]:

```
import pickle
filename='finalized_model.pkl'
pickle.dump(classifier,open(filename, 'wb'))
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-184-5aa639eacc20> in <module>
      1 import pickle
      2 filename='finalized_model.pkl'
----> 3 pickle.dump(classifier,open(filename, 'wb'))

NameError: name 'classifier' is not defined
```

In [186]:

```
y_pred
```

Out[186]:

```
array([11.300088, 11.361431, 11.551709, ..., 11.304848, 11.272297,
       11.654555], dtype=float32)
```

In [187]:

```
pred = np.exp(y_pred)
```

In [188]:

```
pred
```

Out[188]:

```
array([ 80828.74,  85942.27, 103954.56, ...,  81214.39,  78613.36,
       115215.01], dtype=float32)
```

In [683]:

```
##Create Sample Submission file and Submit
pred=pd.DataFrame(pred)
sub_df=pd.read_csv('sample_submission.csv')
datasets=pd.concat([sub_df['Id'],pred],axis=1)
datasets.columns=['Id','SalePrice']
datasets.to_csv('sample_submission_outlier_removed_4.csv',index=False)
```

# Random Forest

In [191]:

```
from sklearn.model_selection import RandomizedSearchCV
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt','log2']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 1000,10)]
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10,14]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4,6,8]
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
              'criterion':['mse']}
print(random_grid)
```

```
{'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000], 'max_features':
['auto', 'sqrt', 'log2'], 'max_depth': [10, 120, 230, 340, 450, 560, 670, 780, 890, 1000],
'min_samples_split': [2, 5, 10, 14], 'min_samples_leaf': [1, 2, 4, 6, 8], 'criterion': ['mse']}
```

In [192]:

```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor()
rf_randomcv = RandomizedSearchCV(estimator=rf,param_distributions=random_grid,n_iter=100,verbose=2,
random_state=100,n_jobs=-1)

rf_randomcv.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  4.7min
[Parallel(n_jobs=-1)]: Done 357 tasks      | elapsed: 11.8min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed: 16.4min finished
C:\Users\Hp\Anaconda3\lib\site-packages\sklearn\model_selection\_search.py:739:
DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change th
e shape of y to (n_samples,), for example using ravel().
  self.best_estimator_.fit(X, y, **fit_params)
```

Out[192]:

```
RandomizedSearchCV(cv=None, error_score=nan,
                   estimator=RandomForestRegressor(bootstrap=True,
                                                   ccp_alpha=0.0,
                                                   criterion='mse',
                                                   max_depth=None,
                                                   max_features='auto',
                                                   max_leaf_nodes=None,
```

```
                                                  max_samples=None,
                                                  min_impurity_decrease=0.0,
                                                  min_impurity_split=None,
                                                  min_samples_leaf=1,
                                                  min_samples_split=2,
                                                  min_weight_fraction_leaf=0.0,
                                                  n_estimators=100,
                                                  n_jobs=None, oob_score=F...
                   param_distributions={'criterion': ['mse'],
                                        'max_depth': [10, 120, 230, 340, 450,
                                                      560, 670, 780, 890,
                                                      1000],
                                        'max_features': ['auto', 'sqrt',
                                                         'log2'],
                                        'min_samples_leaf': [1, 2, 4, 6, 8],
                                        'min_samples_split': [2, 5, 10, 14],
                                        'n_estimators': [200, 400, 600, 800,
                                                         1000, 1200, 1400, 1600,
                                                         1800, 2000]},
                   pre_dispatch='2*n_jobs', random_state=100, refit=True,
                   return_train_score=False, scoring=None, verbose=2)
```

In [193]:

```
rf_randomcv.best_params_
```

Out[193]:

```
{'n_estimators': 1400,
 'min_samples_split': 2,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 780,
 'criterion': 'mse'}
```

In [194]:

```
rf_randomcv.best_estimator_
```

Out[194]:

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=780, max_features='sqrt', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=1400, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

In [197]:

```
rf_model = RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=1000, max_features='sqrt', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=1400, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
```

In [198]:

```
rf_model.fit(X_train,y_train)
```

```
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: DataConversionWarning: A column-v
ector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for
example using ravel().
  """Entry point for launching an IPython kernel.
```

Out[198]:

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
```

```
                   max_depth=1000, max_features='sqrt', max_leaf_nodes=None,
                   max_samples=None, min_impurity_decrease=0.0,
                   min_impurity_split=None, min_samples_leaf=1,
                   min_samples_split=2, min_weight_fraction_leaf=0.0,
                   n_estimators=1400, n_jobs=None, oob_score=False,
                   random_state=None, verbose=0, warm_start=False)
```

In [212]:

```
df2_copy = df2
```

In [239]:

```
data_copy = data2
```

In [242]:

```
data2 = data2[selected_feat]
```

In [244]:

```
len(data2.columns)
```

Out[244]:

```
22
```

In [246]:

```
data2['KitchenQual'] = np.where(data2['KitchenQual'].isnull(),data2['KitchenQual'].mode()[0],data2[
'KitchenQual'])
```

```
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [247]:

```
data2.isnull().sum()
```

Out[247]:

```
LotArea          0
Neighborhood     0
OverallQual      0
YearRemodAdd     0
Foundation       0
BsmtQual         0
BsmtExposure     0
BsmtFinSF1       0
TotalBsmtSF      0
HeatingQC        0
CentralAir       0
1stFlrSF         0
GrLivArea        0
KitchenQual      0
FireplaceQu      0
GarageType       0
GarageFinish     0
GarageCars       0
GarageCond       0
WoodDeckSF       0
OpenPorchSF      0
SaleCondition    0
dtype: int64
```

In [248]:

```
y_pred_rf = rf_model.predict(data2)
```

In [249]:

```
y_pred_rf
```

Out[249]:

```
array([11.43936272, 11.48522739, 11.7722309 , ..., 11.59621426,
       11.42732151, 11.86304742])
```

In [251]:

```
pred_rf = np.exp(y_pred_rf)
```

In [252]:

```
pred_rf
```

Out[252]:

```
array([ 92907.78462916,  97268.19970787, 129602.96013692, ...,
       108685.56442052,  91795.77136121, 141924.06222125])
```

In [253]:

```
##Create Sample Submission file and Submit
pred=pd.DataFrame(pred_rf)
sub_df=pd.read_csv('sample_submission.csv')
datasets_rf=pd.concat([sub_df['Id'],pred],axis=1)
datasets_rf.columns=['Id','SalePrice']
datasets_rf.to_csv('sample_submission_random_forest.csv',index=False)
```

## Artificial Neuron Network Implementation

In [167]:

```
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LeakyReLU,PReLU,ELU
from keras.layers import Dropout
```

In [235]:

```
# Initialising the ANN
classifier = Sequential()

# Adding the input layer and the first hidden layer
classifier.add(Dense(output_dim = 50, init = 'he_uniform',activation='relu',input_dim =18))

# Adding the second hidden layer
classifier.add(Dense(output_dim = 50, init = 'he_uniform',activation='relu'))

# Adding the third hidden layer
classifier.add(Dense(output_dim = 50, init = 'he_uniform',activation='relu'))
# Adding the output layer
classifier.add(Dense(output_dim = 1, init = 'he_uniform'))

# Compiling the ANN
classifier.compile(loss=root_mean_squared_error, optimizer='Adamax')

# Fitting the ANN to the Training set
model=classifier.fit(X_train2[selected_feat].values, y_train.values,validation_split=0.20, batch_si
ze = 10, nb_epoch = 100)
```

```
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:5: UserWarning: Update your `Dense`
call to the Keras 2 API: `Dense(activation="relu", input_dim=18, units=50,
kernel_initializer="he_uniform")`
  """
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:8: UserWarning: Update your `Dense`
call to the Keras 2 API: `Dense(activation="relu", units=50, kernel_initializer="he_uniform")`

C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: UserWarning: Update your `Dense`
call to the Keras 2 API: `Dense(activation="relu", units=50, kernel_initializer="he_uniform")`
  # This is added back by InteractiveShellApp.init_path()
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:13: UserWarning: Update your `Dense`
call to the Keras 2 API: `Dense(units=1, kernel_initializer="he_uniform")`
  del sys.path[0]
C:\Users\Hp\Anaconda3\lib\site-packages\ipykernel_launcher.py:19: UserWarning: The `nb_epoch`
argument in `fit` has been renamed `epochs`.
```

```
Train on 1168 samples, validate on 292 samples
Epoch 1/100
1168/1168 [==============================] - 0s 376us/step - loss: 2.0856 - val_loss: 0.9168
Epoch 2/100
1168/1168 [==============================] - 0s 212us/step - loss: 0.8518 - val_loss: 0.7471
Epoch 3/100
1168/1168 [==============================] - 0s 236us/step - loss: 0.6976 - val_loss: 0.6179
Epoch 4/100
1168/1168 [==============================] - 0s 181us/step - loss: 0.5818 - val_loss: 0.5579
Epoch 5/100
1168/1168 [==============================] - 0s 190us/step - loss: 0.5083 - val_loss: 0.4413
Epoch 6/100
1168/1168 [==============================] - 0s 225us/step - loss: 0.4466 - val_loss: 0.4219
Epoch 7/100
1168/1168 [==============================] - 0s 234us/step - loss: 0.3956 - val_loss: 0.3692
Epoch 8/100
1168/1168 [==============================] - 0s 242us/step - loss: 0.3478 - val_loss: 0.3261
Epoch 9/100
1168/1168 [==============================] - 0s 189us/step - loss: 0.3150 - val_loss: 0.3011
Epoch 10/100
1168/1168 [==============================] - 0s 226us/step - loss: 0.2880 - val_loss: 0.2719
Epoch 11/100
1168/1168 [==============================] - 0s 190us/step - loss: 0.2797 - val_loss: 0.2710
Epoch 12/100
1168/1168 [==============================] - 0s 224us/step - loss: 0.2385 - val_loss: 0.2455
Epoch 13/100
1168/1168 [==============================] - 0s 198us/step - loss: 0.2570 - val_loss: 0.2356
Epoch 14/100
1168/1168 [==============================] - 0s 199us/step - loss: 0.2227 - val_loss: 0.2326
Epoch 15/100
1168/1168 [==============================] - 0s 250us/step - loss: 0.2075 - val_loss: 0.2185
Epoch 16/100
1168/1168 [==============================] - 0s 237us/step - loss: 0.2049 - val_loss: 0.2178
Epoch 17/100
1168/1168 [==============================] - 0s 229us/step - loss: 0.1993 - val_loss: 0.2756
Epoch 18/100
1168/1168 [==============================] - 0s 226us/step - loss: 0.1786 - val_loss: 0.1976
Epoch 19/100
1168/1168 [==============================] - 0s 232us/step - loss: 0.1821 - val_loss: 0.1895
Epoch 20/100
1168/1168 [==============================] - 0s 183us/step - loss: 0.1773 - val_loss: 0.2176
Epoch 21/100
1168/1168 [==============================] - 0s 231us/step - loss: 0.1806 - val_loss: 0.2028
Epoch 22/100
1168/1168 [==============================] - 0s 191us/step - loss: 0.1870 - val_loss: 0.2719
Epoch 23/100
1168/1168 [==============================] - 0s 223us/step - loss: 0.1779 - val_loss: 0.1856
Epoch 24/100
1168/1168 [==============================] - 0s 197us/step - loss: 0.1581 - val_loss: 0.2005
Epoch 25/100
1168/1168 [==============================] - 0s 237us/step - loss: 0.1674 - val_loss: 0.1793
Epoch 26/100
1168/1168 [==============================] - 0s 187us/step - loss: 0.1638 - val_loss: 0.2133
Epoch 27/100
1168/1168 [==============================] - 0s 230us/step - loss: 0.1644 - val_loss: 0.1894
Epoch 28/100
1168/1168 [==============================] - 0s 242us/step - loss: 0.1474 - val_loss: 0.1724
Epoch 29/100
1168/1168 [==============================] - 0s 199us/step - loss: 0.1586 - val_loss: 0.2318
Epoch 30/100
```

```
Epoch 30/100
1168/1168 [==============================] - 0s 228us/step - loss: 0.1747 - val_loss: 0.1772
Epoch 31/100
1168/1168 [==============================] - 0s 184us/step - loss: 0.1468 - val_loss: 0.1912
Epoch 32/100
1168/1168 [==============================] - 0s 285us/step - loss: 0.1574 - val_loss: 0.2353
Epoch 33/100
1168/1168 [==============================] - 0s 294us/step - loss: 0.1490 - val_loss: 0.2075
Epoch 34/100
1168/1168 [==============================] - 0s 284us/step - loss: 0.1418 - val_loss: 0.1767
Epoch 35/100
1168/1168 [==============================] - 0s 310us/step - loss: 0.1675 - val_loss: 0.2312
Epoch 36/100
1168/1168 [==============================] - 0s 293us/step - loss: 0.1496 - val_loss: 0.1742
Epoch 37/100
1168/1168 [==============================] - 0s 298us/step - loss: 0.1391 - val_loss: 0.1826
Epoch 38/100
1168/1168 [==============================] - 0s 314us/step - loss: 0.1509 - val_loss: 0.1857
Epoch 39/100
1168/1168 [==============================] - 0s 310us/step - loss: 0.1476 - val_loss: 0.2243
Epoch 40/100
1168/1168 [==============================] - 0s 303us/step - loss: 0.1454 - val_loss: 0.1811
Epoch 41/100
1168/1168 [==============================] - 0s 284us/step - loss: 0.1391 - val_loss: 0.2497
Epoch 42/100
1168/1168 [==============================] - 0s 293us/step - loss: 0.1498 - val_loss: 0.1785
Epoch 43/100
1168/1168 [==============================] - 0s 246us/step - loss: 0.1379 - val_loss: 0.1679
Epoch 44/100
1168/1168 [==============================] - 0s 213us/step - loss: 0.1435 - val_loss: 0.2048
Epoch 45/100
1168/1168 [==============================] - 0s 226us/step - loss: 0.1490 - val_loss: 0.1810
Epoch 46/100
1168/1168 [==============================] - 0s 237us/step - loss: 0.1545 - val_loss: 0.1651
Epoch 47/100
1168/1168 [==============================] - 0s 197us/step - loss: 0.1389 - val_loss: 0.1740
Epoch 48/100
1168/1168 [==============================] - 0s 231us/step - loss: 0.1496 - val_loss: 0.1910
Epoch 49/100
1168/1168 [==============================] - 0s 177us/step - loss: 0.1321 - val_loss: 0.2061
Epoch 50/100
1168/1168 [==============================] - 0s 194us/step - loss: 0.1467 - val_loss: 0.1683
Epoch 51/100
1168/1168 [==============================] - 0s 254us/step - loss: 0.1499 - val_loss: 0.1742
Epoch 52/100
1168/1168 [==============================] - 0s 275us/step - loss: 0.1361 - val_loss: 0.1697
Epoch 53/100
1168/1168 [==============================] - 0s 187us/step - loss: 0.1337 - val_loss: 0.1735
Epoch 54/100
1168/1168 [==============================] - 0s 279us/step - loss: 0.1450 - val_loss: 0.1683
Epoch 55/100
1168/1168 [==============================] - 0s 246us/step - loss: 0.1320 - val_loss: 0.1990
Epoch 56/100
1168/1168 [==============================] - 0s 242us/step - loss: 0.1279 - val_loss: 0.1675
Epoch 57/100
1168/1168 [==============================] - 0s 180us/step - loss: 0.1314 - val_loss: 0.1813
Epoch 58/100
1168/1168 [==============================] - 0s 191us/step - loss: 0.1441 - val_loss: 0.1750
Epoch 59/100
1168/1168 [==============================] - 0s 199us/step - loss: 0.1289 - val_loss: 0.2319
Epoch 60/100
1168/1168 [==============================] - 0s 238us/step - loss: 0.1337 - val_loss: 0.1788
Epoch 61/100
1168/1168 [==============================] - 0s 217us/step - loss: 0.1345 - val_loss: 0.2189
Epoch 62/100
1168/1168 [==============================] - 0s 240us/step - loss: 0.1250 - val_loss: 0.1623
Epoch 63/100
1168/1168 [==============================] - 0s 246us/step - loss: 0.1299 - val_loss: 0.1690
Epoch 64/100
1168/1168 [==============================] - 0s 234us/step - loss: 0.1255 - val_loss: 0.1658
Epoch 65/100
1168/1168 [==============================] - 0s 246us/step - loss: 0.1255 - val_loss: 0.2062
Epoch 66/100
1168/1168 [==============================] - 0s 204us/step - loss: 0.1397 - val_loss: 0.2213
Epoch 67/100
1168/1168 [==============================] - 0s 267us/step - loss: 0.1450 - val_loss: 0.1736
Epoch 68/100
1168/1168 [==============================] - 0s 182us/step - loss: 0.1353 - val_loss: 0.1964
```

```
1168/1168 [==============================] - 0s 182us/step - loss: 0.1555 - val_loss: 0.1904
Epoch 69/100
1168/1168 [==============================] - 0s 268us/step - loss: 0.1261 - val_loss: 0.1772
Epoch 70/100
1168/1168 [==============================] - 0s 217us/step - loss: 0.1280 - val_loss: 0.1909
Epoch 71/100
1168/1168 [==============================] - 0s 246us/step - loss: 0.1295 - val_loss: 0.1912
Epoch 72/100
1168/1168 [==============================] - 0s 197us/step - loss: 0.1325 - val_loss: 0.1709
Epoch 73/100
1168/1168 [==============================] - 0s 257us/step - loss: 0.1474 - val_loss: 0.2074
Epoch 74/100
1168/1168 [==============================] - 0s 234us/step - loss: 0.1331 - val_loss: 0.1660
Epoch 75/100
1168/1168 [==============================] - 0s 252us/step - loss: 0.1326 - val_loss: 0.1885
Epoch 76/100
1168/1168 [==============================] - 0s 209us/step - loss: 0.1267 - val_loss: 0.1654
Epoch 77/100
1168/1168 [==============================] - 0s 237us/step - loss: 0.1341 - val_loss: 0.2183
Epoch 78/100
1168/1168 [==============================] - 0s 187us/step - loss: 0.1257 - val_loss: 0.1774
Epoch 79/100
1168/1168 [==============================] - 0s 186us/step - loss: 0.1234 - val_loss: 0.1714
Epoch 80/100
1168/1168 [==============================] - 0s 188us/step - loss: 0.1225 - val_loss: 0.1939
Epoch 81/100
1168/1168 [==============================] - 0s 175us/step - loss: 0.1275 - val_loss: 0.1700
Epoch 82/100
1168/1168 [==============================] - 0s 216us/step - loss: 0.1207 - val_loss: 0.1588
Epoch 83/100
1168/1168 [==============================] - 0s 208us/step - loss: 0.1273 - val_loss: 0.1668
Epoch 84/100
1168/1168 [==============================] - 0s 236us/step - loss: 0.1201 - val_loss: 0.1577
Epoch 85/100
1168/1168 [==============================] - 0s 180us/step - loss: 0.1178 - val_loss: 0.1766
Epoch 86/100
1168/1168 [==============================] - 0s 199us/step - loss: 0.1237 - val_loss: 0.1676
Epoch 87/100
1168/1168 [==============================] - 0s 223us/step - loss: 0.1362 - val_loss: 0.1808
Epoch 88/100
1168/1168 [==============================] - 0s 220us/step - loss: 0.1147 - val_loss: 0.1658
Epoch 89/100
1168/1168 [==============================] - 0s 274us/step - loss: 0.1253 - val_loss: 0.2225
Epoch 90/100
1168/1168 [==============================] - 0s 298us/step - loss: 0.1217 - val_loss: 0.1904
Epoch 91/100
1168/1168 [==============================] - 0s 297us/step - loss: 0.1214 - val_loss: 0.1718
Epoch 92/100
1168/1168 [==============================] - 0s 296us/step - loss: 0.1244 - val_loss: 0.1548
Epoch 93/100
1168/1168 [==============================] - 0s 299us/step - loss: 0.1221 - val_loss: 0.1591
Epoch 94/100
1168/1168 [==============================] - 0s 323us/step - loss: 0.1156 - val_loss: 0.1645
Epoch 95/100
1168/1168 [==============================] - 0s 295us/step - loss: 0.1190 - val_loss: 0.1709
Epoch 96/100
1168/1168 [==============================] - 0s 287us/step - loss: 0.1318 - val_loss: 0.1668
Epoch 97/100
1168/1168 [==============================] - 0s 327us/step - loss: 0.1253 - val_loss: 0.1876
Epoch 98/100
1168/1168 [==============================] - 0s 305us/step - loss: 0.1219 - val_loss: 0.1695
Epoch 99/100
1168/1168 [==============================] - 0s 293us/step - loss: 0.1282 - val_loss: 0.1962
Epoch 100/100
1168/1168 [==============================] - 0s 257us/step - loss: 0.1266 - val_loss: 0.1569
```

In [171]:

```python
from keras import backend as K
def root_mean_squared_error(y_true, y_pred):
        return K.sqrt(K.mean(K.square(y_pred - y_true)))
```

In [178]:

```python
X_train2.shape
```

Out[178]:

```
(1460, 82)
```

In [175]:

```
y_train.shape
```

Out[175]:

```
(1460, 1)
```

In [233]:

```
data2[selected_feat].shape
```

Out[233]:

```
(1459, 18)
```

In [177]:

```
X_train2=dataset.drop(['Id','SalePrice'],axis=1)
```

In [236]:

```
ann_pred=classifier.predict(data2[selected_feat])#.iloc[:,1:].values)
```

In [217]:

```
data2.isnull()==True
```

Out[217]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Ne |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **1** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **2** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **3** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **4** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1454** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **1455** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **1456** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **1457** | False | False | False | False | False | False | False | False | False | False | False | False | |
| **1458** | False | False | False | False | False | False | False | False | False | False | False | False | |

1459 rows × 83 columns

In [212]:

```
data2
```

Out[212]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Ne |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1461 | 0.000000 | 0.50 | 0.495064 | 0.428726 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1** | 1462 | 0.000000 | 0.75 | 0.499662 | 0.468857 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.5 | 0.0 | |
| **2** | 1463 | 0.235294 | 0.75 | 0.466207 | 0.462769 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.0 | 0.0 | |

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Ne |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **3** | 1464 | 0.235294 | 0.75 | 0.485693 | 0.398875 | 1.0 | 1.0 | 0.333333 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **4** | 1465 | 0.588235 | 0.75 | 0.265271 | 0.263841 | 1.0 | 1.0 | 0.333333 | 1.000000 | 1.0 | 0.0 | 0.0 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **1454** | 2915 | 0.823529 | 0.25 | 0.000000 | 0.077946 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1455** | 2916 | 0.823529 | 0.25 | 0.000000 | 0.073654 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1456** | 2917 | 0.000000 | 0.75 | 0.751625 | 0.534967 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1457** | 2918 | 0.382353 | 0.75 | 0.400718 | 0.407753 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |
| **1458** | 2919 | 0.235294 | 0.75 | 0.466207 | 0.391866 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.5 | |

1459 rows × 83 columns

In [231]:

```
data2[data2['MSZoning'].isnull()==True]
```

Out[231]:

| | Id | MSSubClass | MSZoning | LotFrontage | LotArea | Street | Alley | LotShape | LandContour | Utilities | LotConfig | LandSlope | Ne |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **455** | 1916 | 0.058824 | NaN | 0.609556 | 0.551654 | 0.0 | 1.0 | 0.000000 | 0.333333 | NaN | 0.0 | 0.0 | |
| **756** | 2217 | 0.000000 | NaN | 0.495064 | 0.473158 | 1.0 | 1.0 | 0.000000 | 0.666667 | 1.0 | 0.0 | 0.5 | |
| **790** | 2251 | 0.294118 | NaN | 0.429425 | 0.738567 | 1.0 | 1.0 | 0.333333 | 0.666667 | 1.0 | 0.0 | 0.0 | |
| **1444** | 2905 | 0.000000 | NaN | 0.660252 | 0.622313 | 1.0 | 1.0 | 0.000000 | 0.333333 | 1.0 | 0.0 | 0.0 | |

In [237]:

```
ann_pred
```

Out[237]:

```
array([[11.637968 ],
       [11.928009 ],
       [12.033077 ],
       ...,
       [11.865556 ],
       [11.660313 ],
       [12.2346115]], dtype=float32)
```

In [238]:

```
np.exp(ann_pred)
```

Out[238]:

```
array([[113319.67],
       [151449.73],
       [168228.3 ],
       ...,
       [142280.5 ],
       [115880.26],
       [205790.  ]], dtype=float32)
```

In [240]:

```
##Create Sample Submission file and Submit using ANN
pred_ann=pd.DataFrame(np.exp(ann_pred))
sub_df=pd.read_csv('sample_submission.csv')
datasets=pd.concat([sub_df['Id'],pred_ann],axis=1)
datasets.columns=['Id','SalePrice']
datasets.to_csv('sample_submission_ann2.csv',index=False)
```

In [197]:

```
pred_ann.isnull().sum()
```

Out[197]:

```
0    9
dtype: int64
```

In [193]:

```
pred
```

Out[193]:

| | 0 |
|---|---|
| 0 | 119480.039062 |
| 1 | 137401.000000 |
| 2 | 169420.203125 |
| 3 | 178905.687500 |
| 4 | 179471.828125 |
| ... | ... |
| 1454 | 79608.859375 |
| 1455 | 71195.601562 |
| 1456 | 139554.359375 |
| 1457 | 109234.429688 |
| 1458 | 208175.281250 |

1459 rows × 1 columns

In [ ]:

```
##Create Sample Submission file and Submit
pred=pd.DataFrame(pred)
sub_df=pd.read_csv('sample_submission.csv')
datasets=pd.concat([sub_df['Id'],pred],axis=1)
datasets.columns=['Id','SalePrice']
datasets.to_csv('sample_submission_3.csv',index=False)
```