In [450]:
```
%config IPCompleter.greedy=True
```

In [465]:
```
%%javascript
require("notebook/js/notebook").Notebook.prototype.scroll_to_bottom = function () {}
```

Import Library

In [452]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.utils import resample
from imblearn.over_sampling import SMOTENC,RandomOverSampler,KMeansSMOTE
from sklearn.impute import KNNImputer
from sklearn.preprocessing import LabelEncoder
import io
import requests
import numpy as np;
import sklearn
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model  import Ridge,Lasso,RidgeCV, LassoCV, ElasticNet, ElasticNetCV, LinearRegression
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.linear_model import Lasso
from sklearn.feature_selection import SelectFromModel
np.random.seed(0)
sns.set()
pd.set_option("display.max_rows", None, "display.max_columns", None)
%matplotlib inline

# machine learning
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
```

Step1: Acquire data

In [453]:
```
train_df = pd.read_csv('bh_train.csv')
test_df = pd.read_csv('bh_test.csv')
combine = [train_df, test_df]
```

Step2: Analyze the dataset

In [459]:
```
train_df.shape,test_df.shape
```

Out[459]:
```
((1460, 81), (1459, 80))
```

In [460]:
```
train_df.columns.values
```

Out[460]:
```
array(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'RoofStyle', 'RoofMatl',
       'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
       'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
       'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC',
       'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu',
       'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageCars',
       'GarageArea', 'GarageQual', 'GarageCond', 'PavedDrive',
       'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
       'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature',
       'MiscVal', 'MoSold', 'YrSold', 'SaleType', 'SaleCondition',
       'SalePrice'], dtype=object)
```

In [461]:
```
train_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 
```

In [466]:
```
train_df.describe()
```

Out[466]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000	1460.000000	1460.000000
mean	730.500000	56.897260	70.049958	10516.828082	6.099315	5.575342	1971.267808
std	421.610009	42.300571	24.284752	9981.264932	1.382997	1.112799	30.202904
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000000	1872.000000
25%	365.750000	20.000000	59.000000	7553.500000	5.000000	5.000000	1954.000000
50%	730.500000	50.000000	69.000000	9478.500000	6.000000	5.000000	1973.000000
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000	6.000000	2000.000000
max	1460.000000	190.000000	313.000000	215245.000000	10.000000	9.000000	2010.000000

EXPLORATORY DATA ANALYSIS -- START

Step3: Distribution of Missing Value feature

In [467]:
```
train_df.isnull().sum()
```

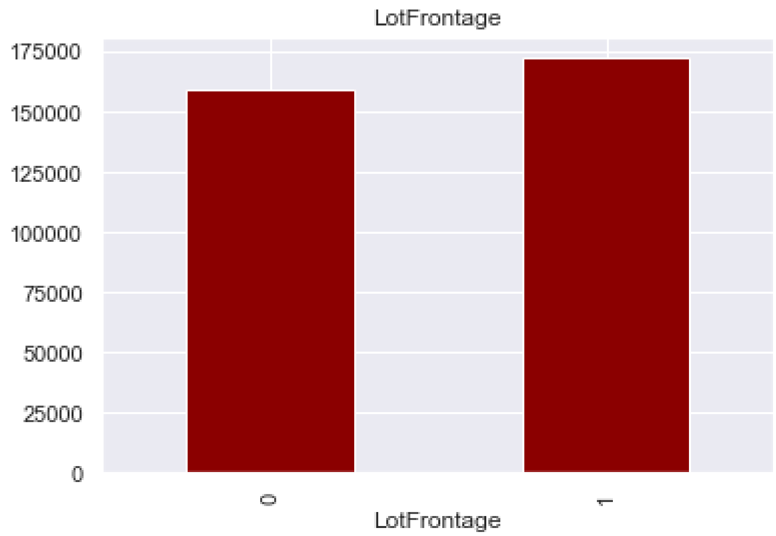
```
BsmtUnfSF        0
TotalBsmtSF      0
Heating          0
HeatingQC        0
CentralAir       0
Electrical       1
1stFlrSF         0
2ndFlrSF         0
LowQualFinSF     0
GrLivArea        0
BsmtFullBath     0
BsmtHalfBath     0
FullBath         0
HalfBath         0
BedroomAbvGr     0
KitchenAbvGr     0
KitchenQual      0
TotRmsAbvGrd     0
Functional       0
```

In [468]:
```
missing_feature = [items for items in train_df.columns if train_df[items].isna().sum()>0]

for item in missing_feature:
    print(item, np.round(train_df[item].isnull().mean(), 3),  ' % missing values')
```

```
LotFrontage 0.177  % missing values
Alley 0.938  % missing values
MasVnrType 0.005  % missing values
MasVnrArea 0.005  % missing values
BsmtQual 0.025  % missing values
BsmtCond 0.025  % missing values
BsmtExposure 0.026  % missing values
BsmtFinType1 0.025  % missing values
BsmtFinType2 0.026  % missing values
Electrical 0.001  % missing values
FireplaceQu 0.473  % missing values
GarageType 0.055  % missing values
GarageYrBlt 0.055  % missing values
GarageFinish 0.055  % missing values
GarageQual 0.055  % missing values
GarageCond 0.055  % missing values
PoolQC 0.995  % missing values
Fence 0.808  % missing values
MiscFeature 0.963  % missing values
```

Observation: There are lots of missing values and we need to find the relationship with target variable (EDA OBS ID : EDA_OBS_1)

In [469]:
```
temp_train_df = train_df.copy()
%matplotlib inline

for item in missing_feature:
    # let's make a variable that indicates 1 if the observation was missing or zero otherwise
    temp_train_df[item] = np.where(temp_train_df[item].isnull(), 1, 0)
    temp_train_df.groupby(item)['SalePrice'].median().plot.bar( color='darkred')
    plt.title(item)
    plt.show()
```



Observation: There exists a relationship between missing value and Target Variable i.e., Sales Price. In Feature Engineering Phase we willl be imputing all missing values using suitable imputers available in sklearn library (OBS ID : EDA_OBS_2)

Step4: Count of Id column

In [470]:
```
print("Houses ID {}".format(len(train_df.Id)))
```

Houses ID 1460

Observation: Since ID column dows not contribute in calculation, therefore we will be dropping in Feature Engineering(OBS ID : EDA_OBS_3)

Step5: Distribution of Numerical feature

In [471]:
```
numerical_features = [item for item in train_df.columns if train_df[item].dtypes != 'O']
print('Number of numerical variables: ', len(numerical_features))
train_df[numerical_features].head()
```

Number of numerical variables: 38

Out[471]:

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

Observation: There are 38 columns having numerical values and imputation will be done if Nan is found(OBS ID : EDA_OBS_4)

Step6: Distribution of Temporal feature feature

In [474]:
```
year_feature = [item for item in numerical_features if 'Yr' in item or 'Year' in item]
year_feature
```

Out[474]:
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

In [476]:
```
for item in year_feature:
    print(item, train_df[item].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]
```

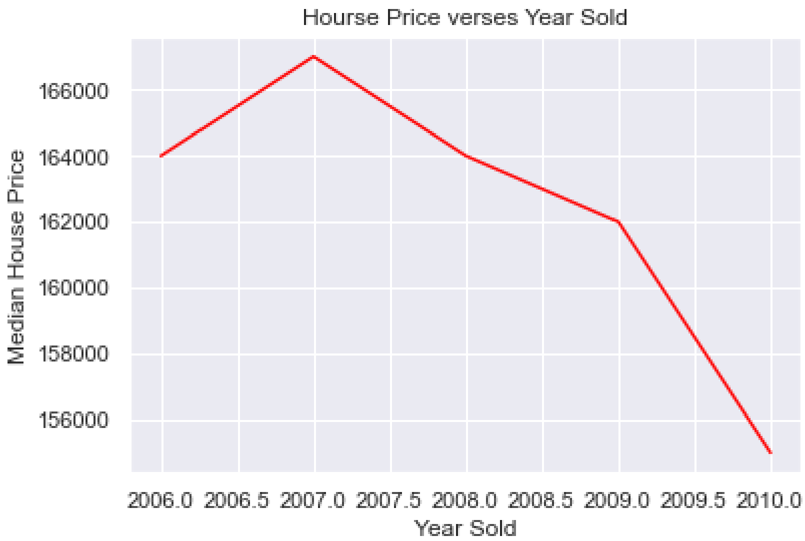
Observation: There are 4 columns having date values and removing multiple columns in date (OBS ID : EDA_OBS_5)

Step7: Multivariate Analysis

Multivariate Analysis: Analysis between Sales Price(Target variable) with Sold Year with additional ammenities

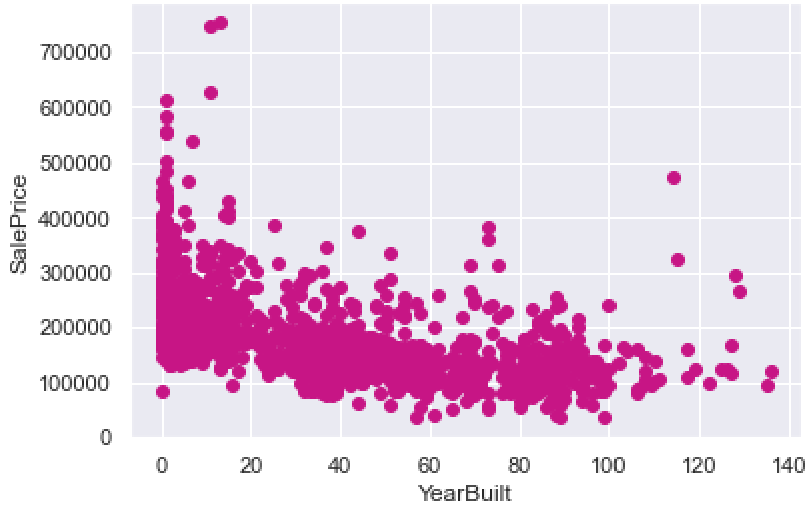
In [477]:
```
temp_train_df = train_df.copy()
temp_train_df .groupby('YrSold')['SalePrice'].median().plot( color='red')
plt.xlabel('Year Sold')
plt.ylabel('Median House Price')
plt.title('Hourse Price verses Year Sold')
```

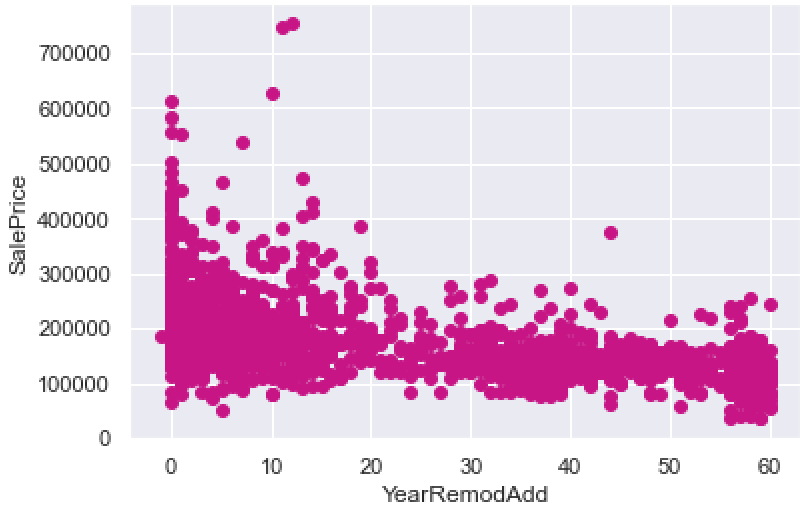
Out[477]: Text(0.5, 1.0, 'Hourse Price verses Year Sold')

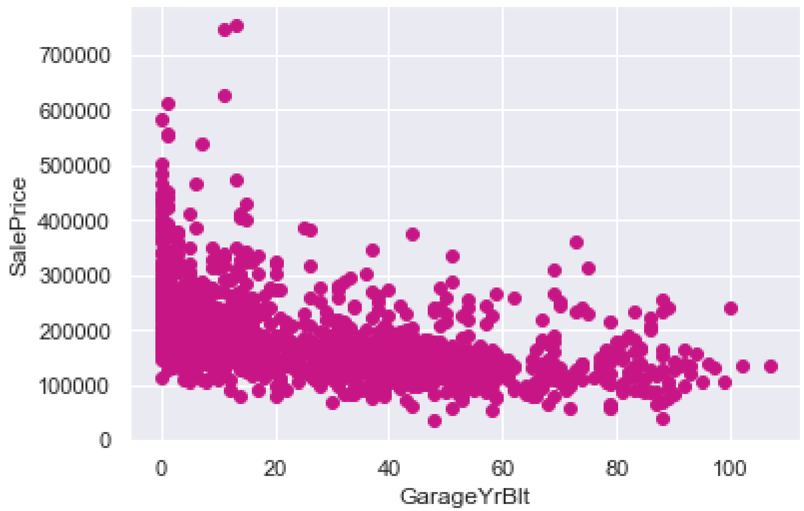


Observation: Initially Selling Price increased with Year but there is fall in price as the year progress. This can not be true and we need to investigate more in depth. Rather the comparing with Year sold we will compare with other variable related to year like year in which remodelling was done and year in which house was built. (OBS ID : EDA_OBS_6)

In [478]:
```
temp_train_df = train_df.copy()

for item in year_feature:
    if item != 'YrSold':
        temp_train_df[item]=temp_train_df['YrSold'] - temp_train_df[item]  #after how many years of house built or  modelled, t
        plt.scatter(temp_train_df[item],temp_train_df['SalePrice'], color='mediumvioletred')
        plt.xlabel(item)
        plt.ylabel('SalePrice')
        plt.show()
```







Observation: From the above three scatter plot we can clearly see that the house which were built

recently or house which were remodelled were sold at higher price.(OBS ID : EDA_OBS_7)

Step8: Multivariate Analysis

Multivariate Analysis: Analysis between Sales Price(Target variable) with numerical features.

Numerical variables are usually of 2 type Continous variable and Discrete Variables

Below is analysis with discreate variable

In [479]:
```
temp_train_df = train_df.copy()

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

```
Discrete Variables Count: 17
```

In [480]:
```
discrete_feature
```

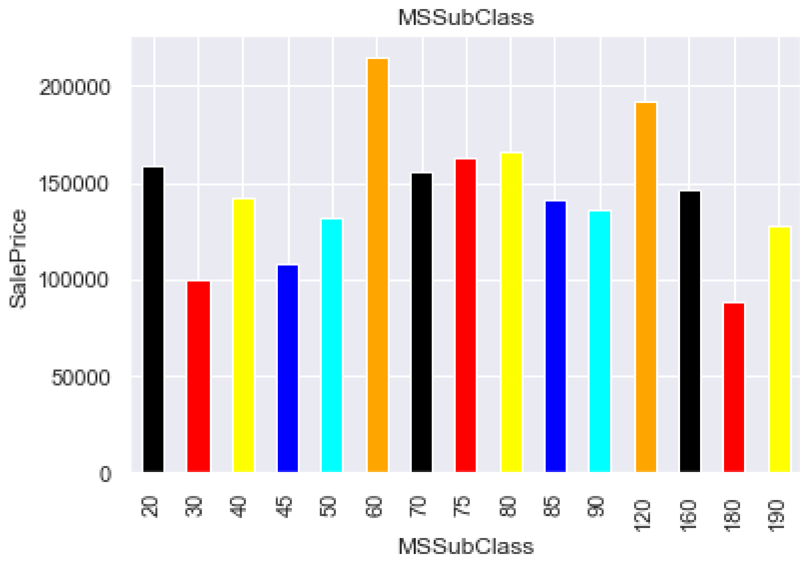
Out[480]:
```
['MSSubClass',
 'OverallQual',
 'OverallCond',
 'LowQualFinSF',
 'BsmtFullBath',
 'BsmtHalfBath',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'KitchenAbvGr',
 'TotRmsAbvGrd',
 'Fireplaces',
 'GarageCars',
 '3SsnPorch',
 'PoolArea',
 'MiscVal',
 'MoSold']
```

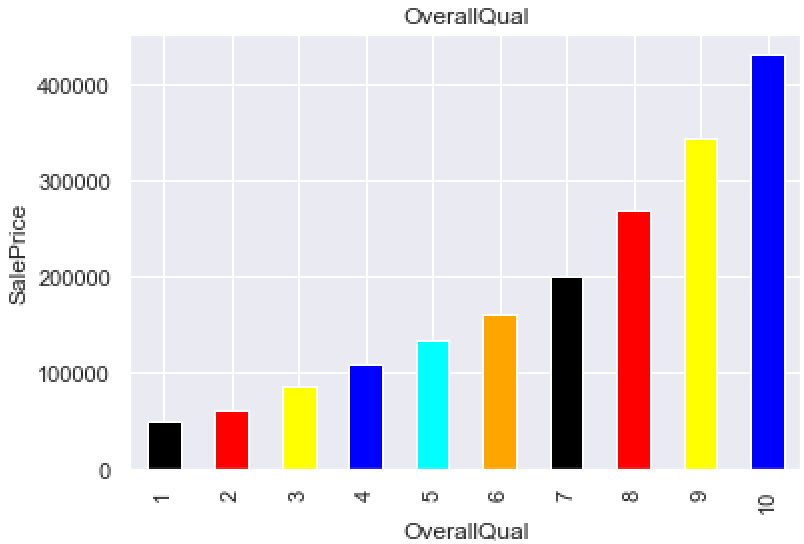
In [481]:
```
temp_train_df[discrete_feature].head()
```

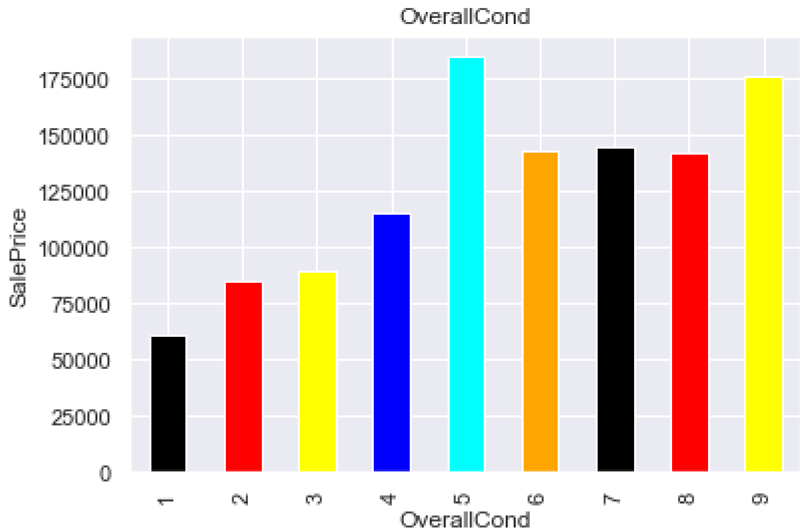
Out[481]:

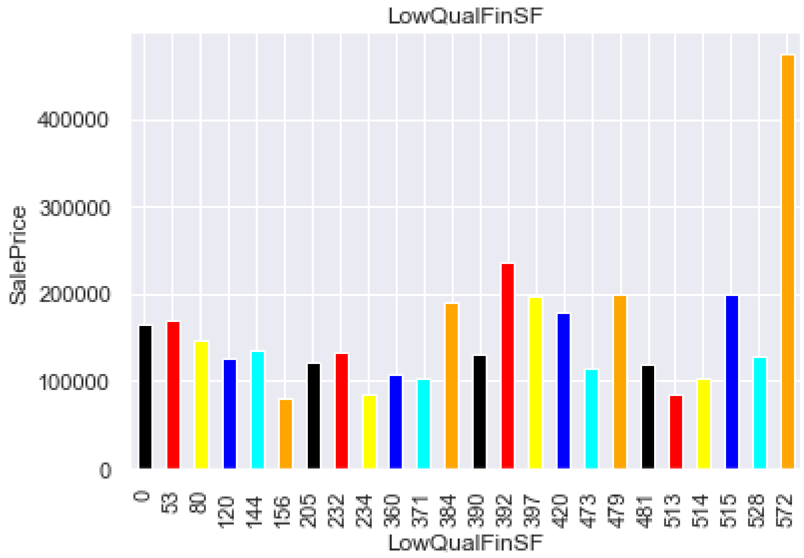
	MSSubClass	OverallQual	OverallCond	LowQualFinSF	BsmtFullBath	BsmtHalfBath	FullBath	Half
0	60	7	5	0	1	0	2	
1	20	6	8	0	0	1	2	
2	60	7	5	0	1	0	2	
3	70	7	5	0	1	0	1	
4	60	8	5	0	1	0	2	

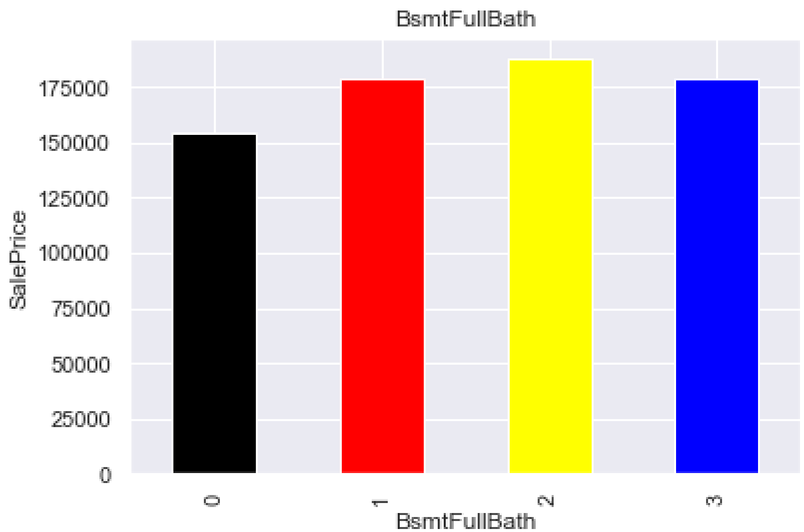
In [482]:
```
## Analysis between Sales Price(Target variable) with discreate features.
temp_train_df=train_df.copy()

for item in discrete_feature:
    temp_train_df.groupby(item)['SalePrice'].median().plot.bar(color=['black', 'red', 'yellow', 'blue', 'cyan','orange'])
    plt.xlabel(item)
    plt.ylabel('SalePrice')
    plt.title(item)
    plt.show()
```

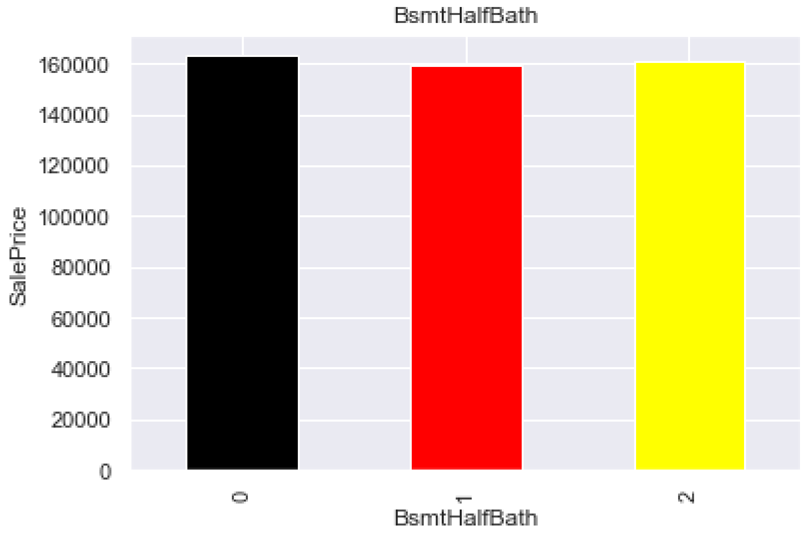


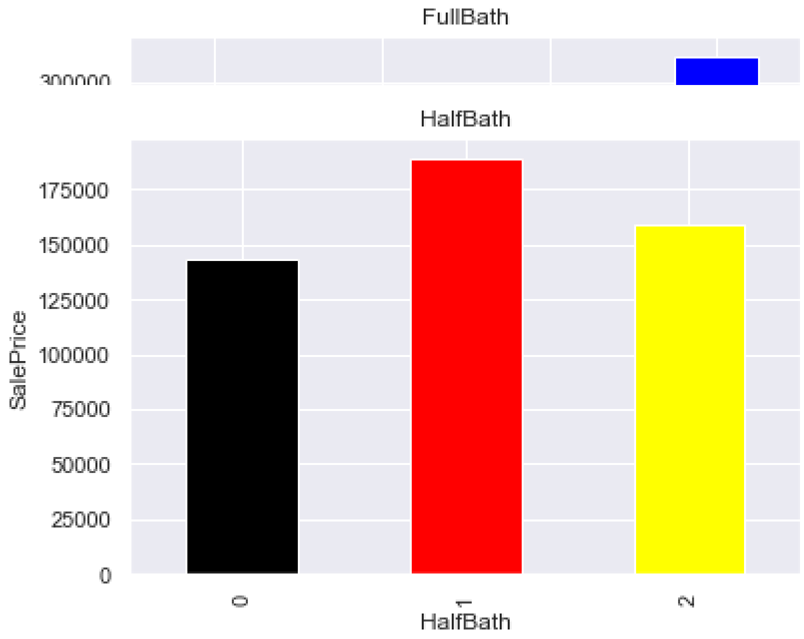

OverallQual
400000
300000
200000
100000
0
SalePrice
1
2
3
4
5
6
7
8
9
10
OverallQual

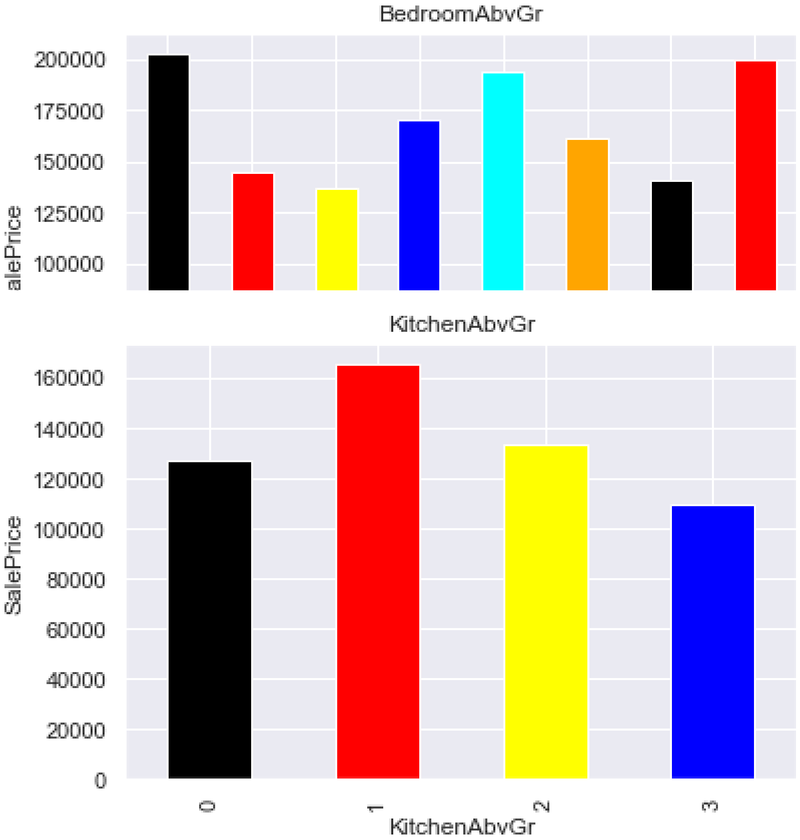

OverallCond
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
1
2
3
4
5
6
7
8
9
OverallCond

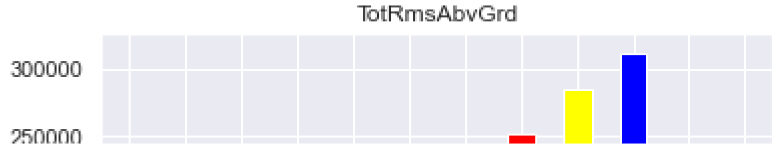

LowQualFinSF
SalePrice
400000
300000
200000
100000
0
0
53
80
120
144
156
205
232
234
360
371
384
390
392
397
420
473
479
481
513
514
515
528
572
LowQualFinSF

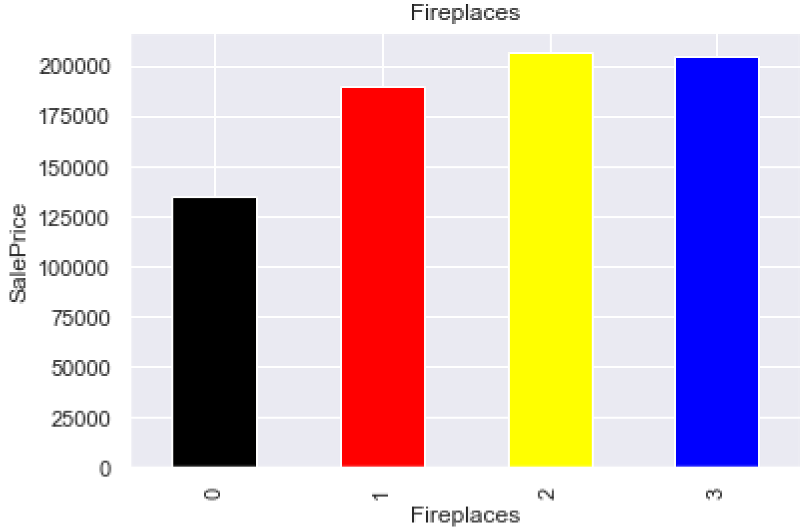

BsmtFullBath
SalePrice
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
BsmtFullBath

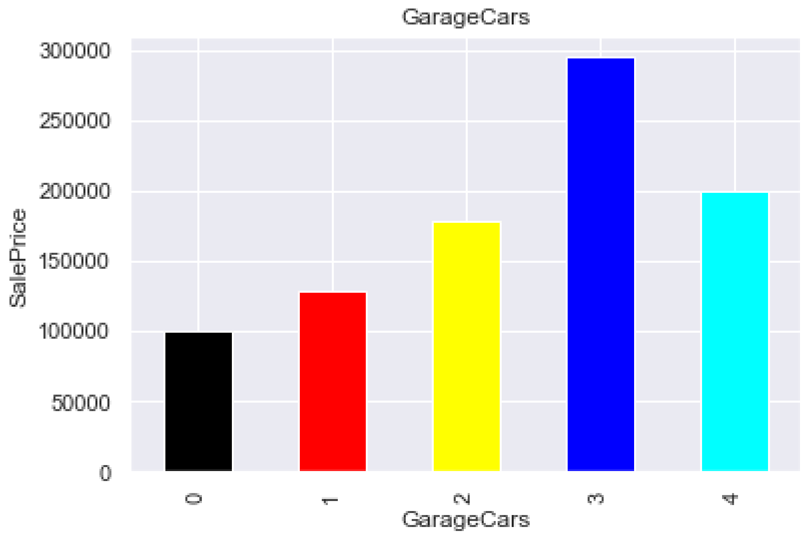

BsmtHalfBath
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
0
1
2
BsmtHalfBath

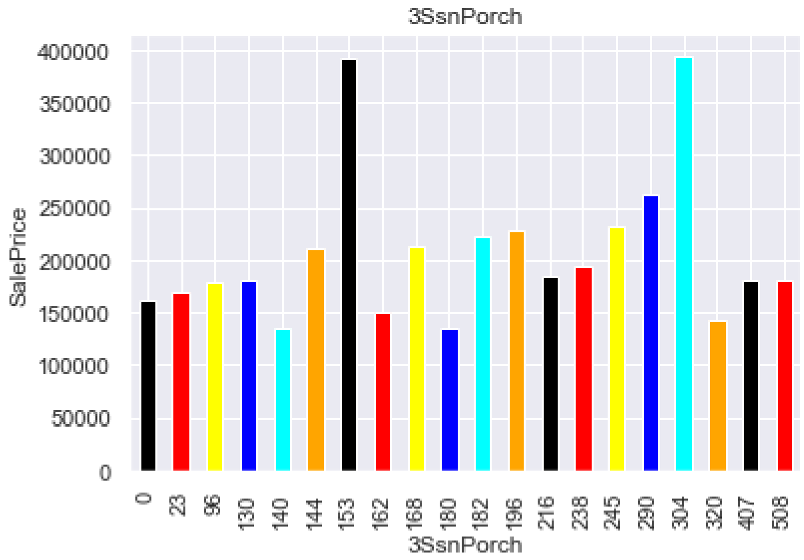

FullBath
300000
HalfBath
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
0
1
2
HalfBath

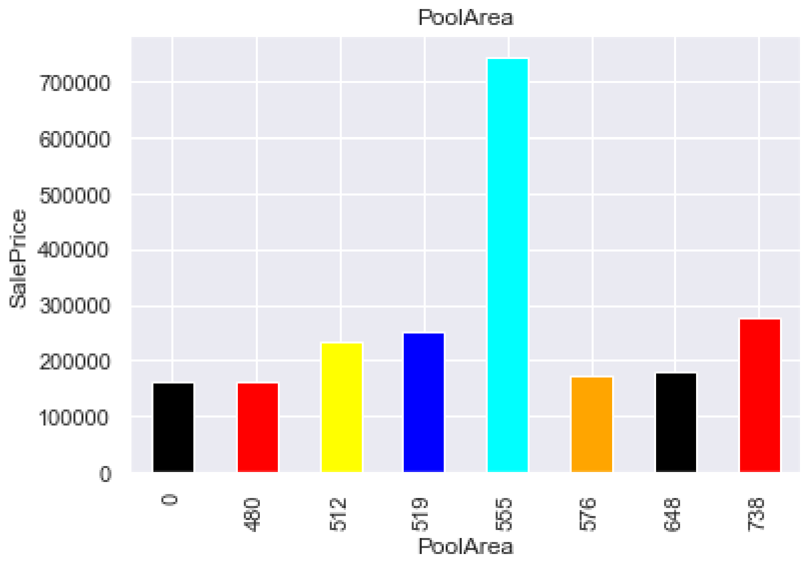

BedroomAbvGr
200000
175000
150000
125000
100000
alePrice
KitchenAbvGr
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
0
1
2
3
KitchenAbvGr

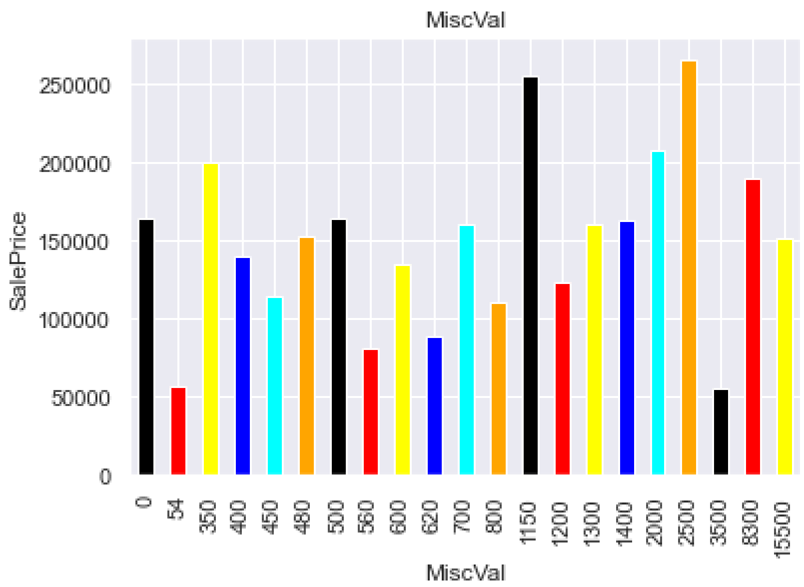

TotRmsAbvGrd
300000
250000

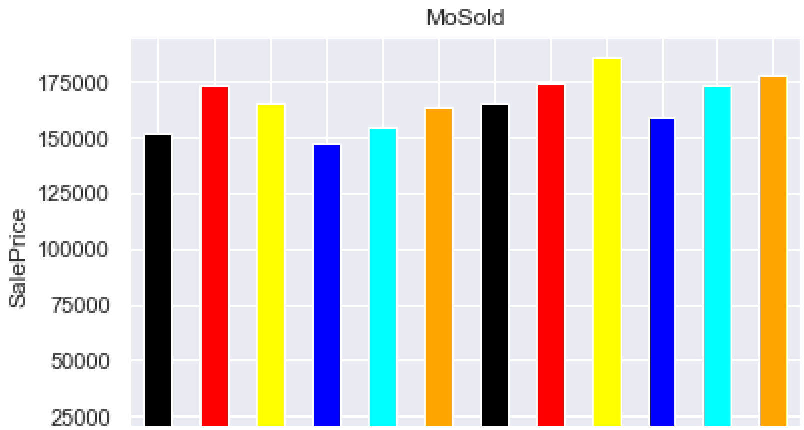

Fireplaces
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
Fireplaces


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



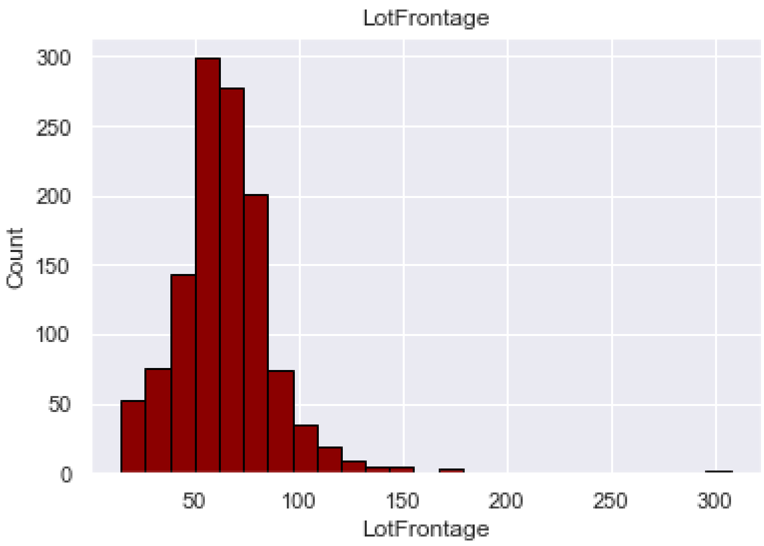
Observation: From the above histogram we found in some of the cases there is exponential relationship, in some cases it is normal or in some cases it is partially exponential. There are non linear relationship also. Therefore we can conclude that whese variables have some or large relationship with target variable Sale Price. We will explore more during feature selection phase.(OBS ID : EDA_OBS_7)

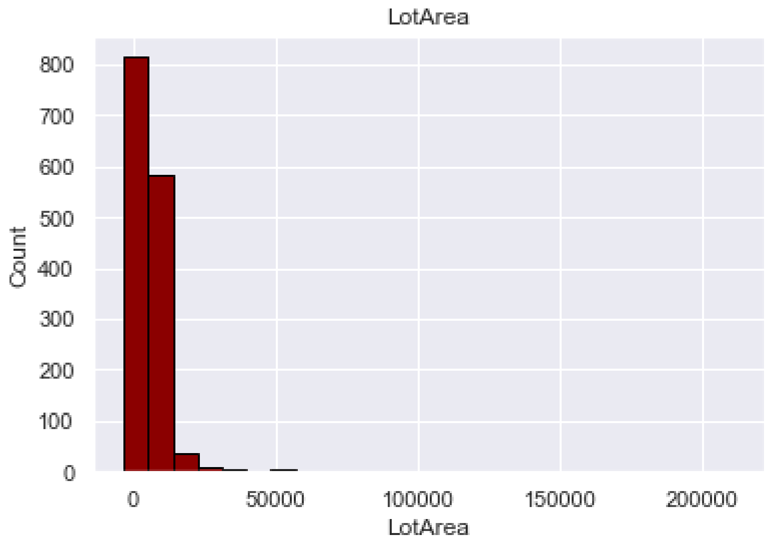
Below is analysis with numerical variable:

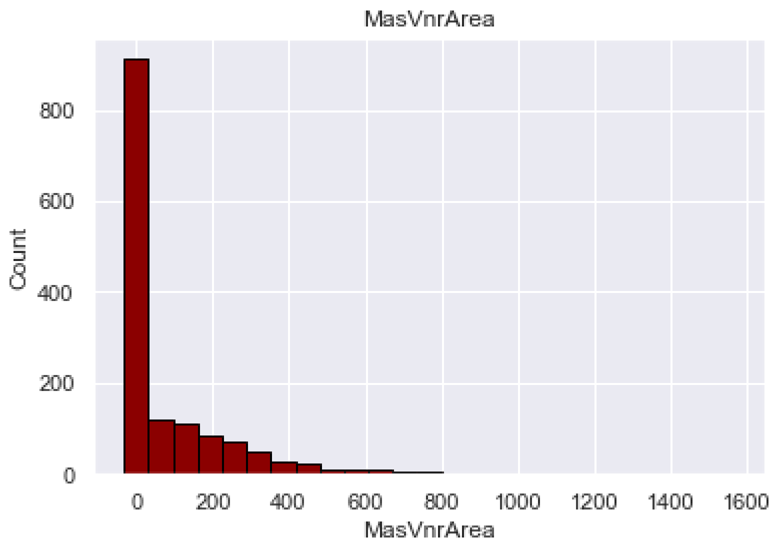
In [483]:
```
#This which are not discreate are numerical
continuous_feature=[item for item in numerical_features if item not in discrete_feature+year_feature+['Id']]
print("Continuous feature Count {}".format(len(continuous_feature)))
```

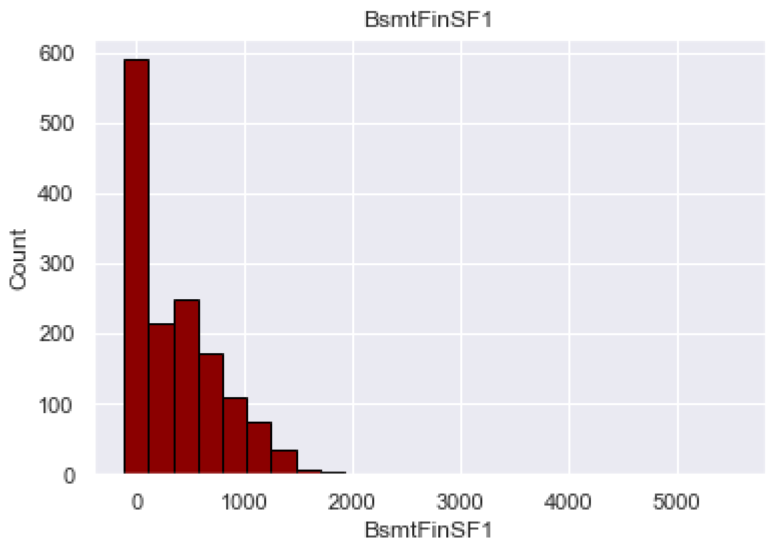
```
Continuous feature Count 16
```

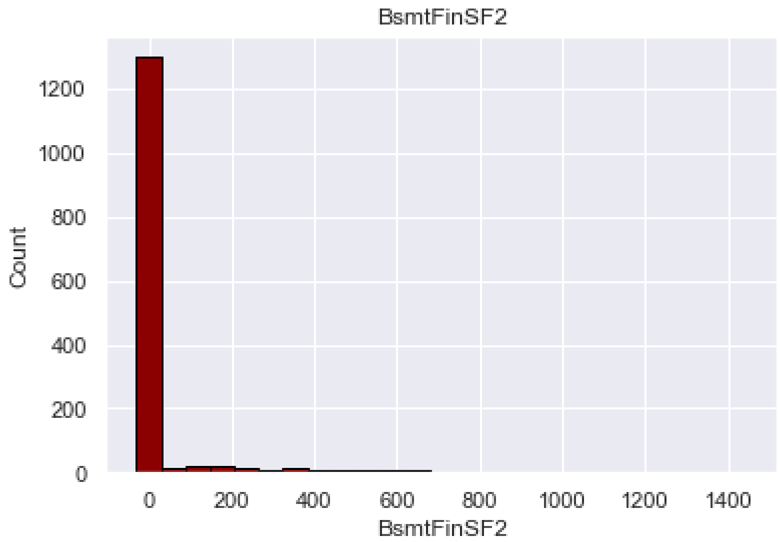
In [485]:
```
temp_train_df=train_df.copy()
%matplotlib inline
for item in continuous_feature:
    temp_train_df[item].hist(bins=25,align='left', color='darkred', edgecolor='black',  linewidth=1)
    plt.xlabel(item)
    plt.ylabel("Count")
    plt.title(item)
    plt.show()
```

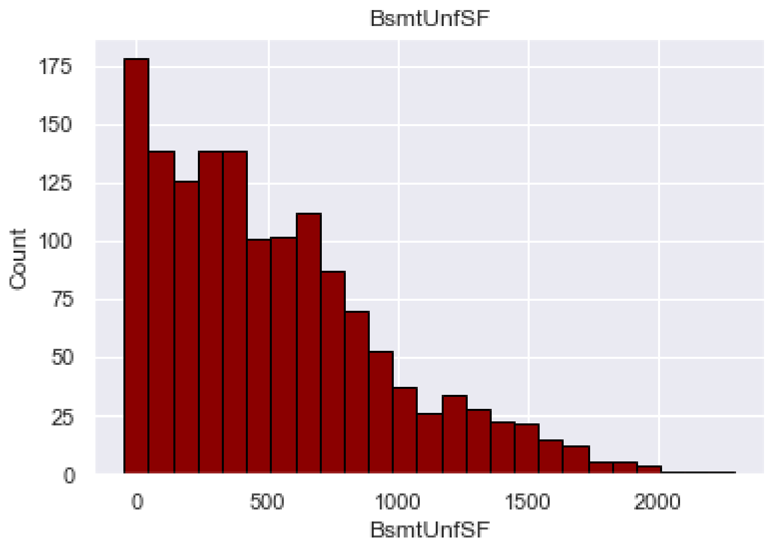


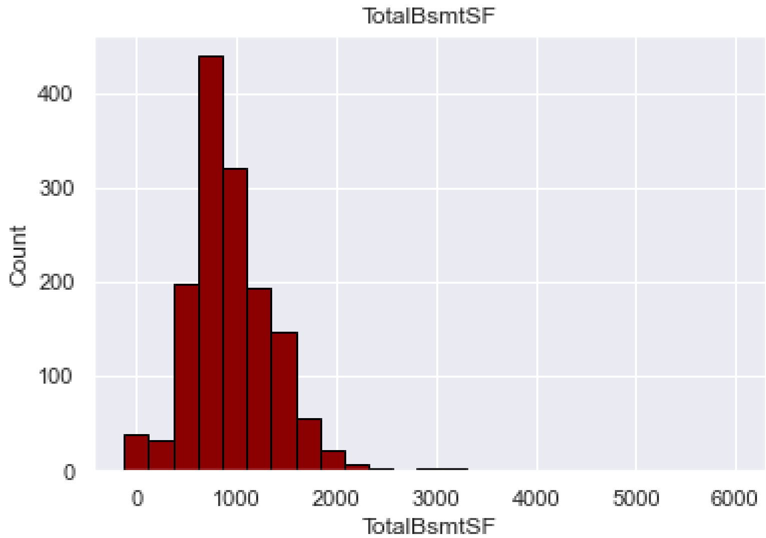

LotArea
800
700
600
500
400
300
200
100
0
Count
0
50000
100000
150000
200000
LotArea

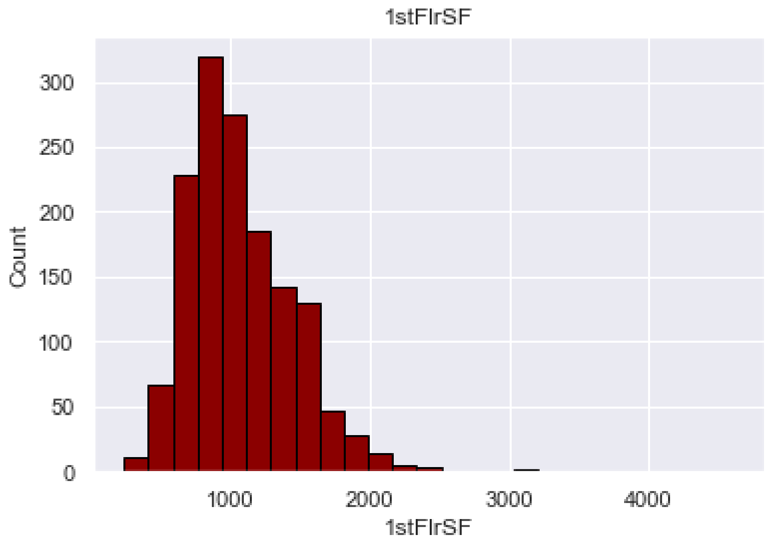

MasVnrArea
800
600
400
200
0
Count
0
200
400
600
800
1000
1200
1400
1600
MasVnrArea

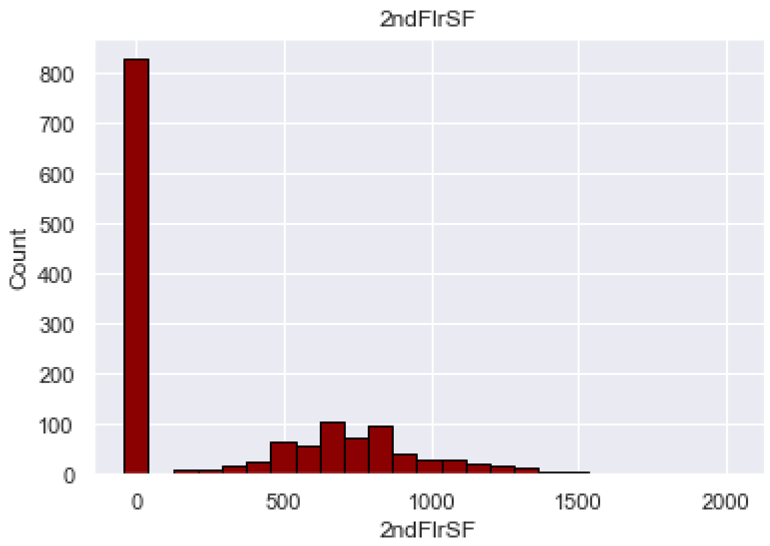

BsmtFinSF1
600
500
400
300
200
100
0
Count
0
1000
2000
3000
4000
5000
BsmtFinSF1

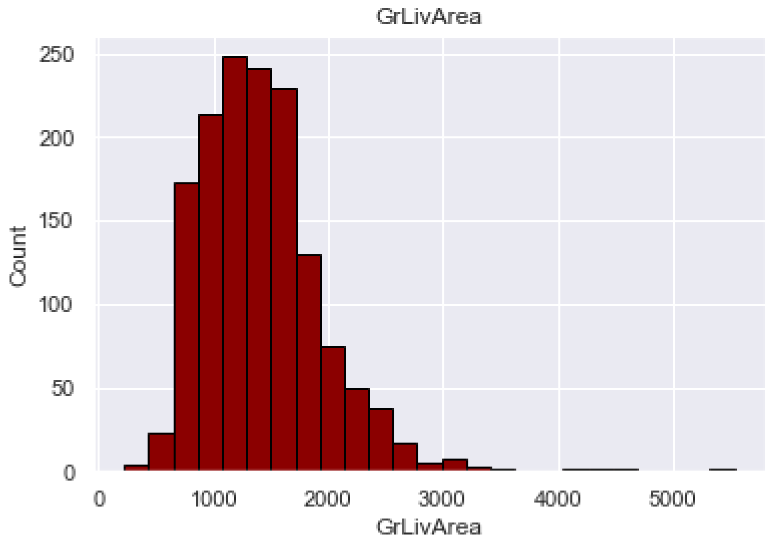

BsmtFinSF2
Count
0
200
400
600
800
1000
1200
0
200
400
600
800
1000
1200
1400
BsmtFinSF2

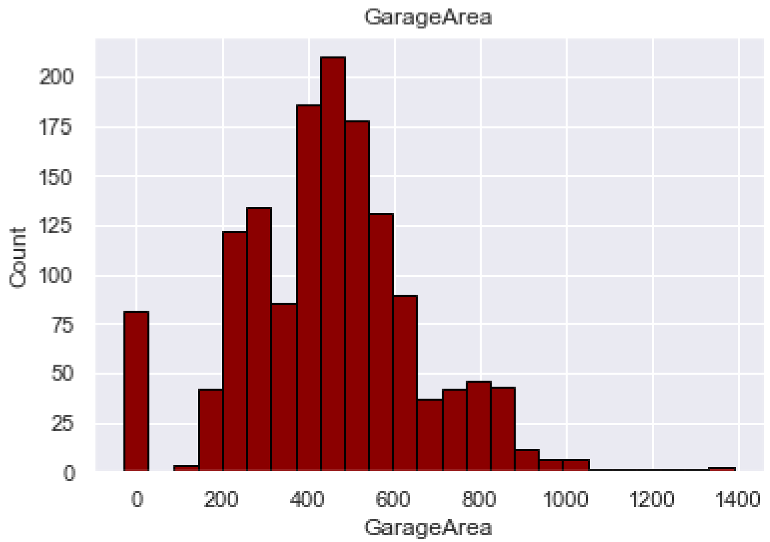

BsmtUnfSF
Count
0
25
50
75
100
125
150
175
0
500
1000
1500
2000
BsmtUnfSF

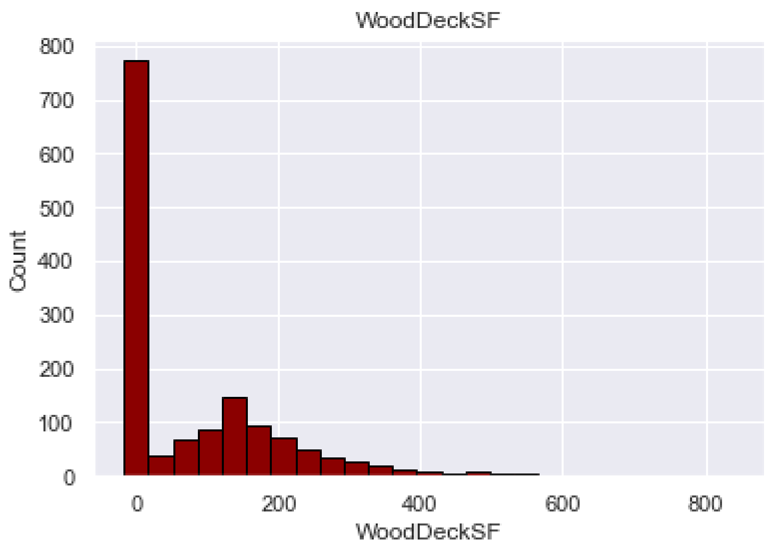

TotalBsmtSF
Count
0
100
200
300
400
0
1000
2000
3000
4000
5000
6000
TotalBsmtSF

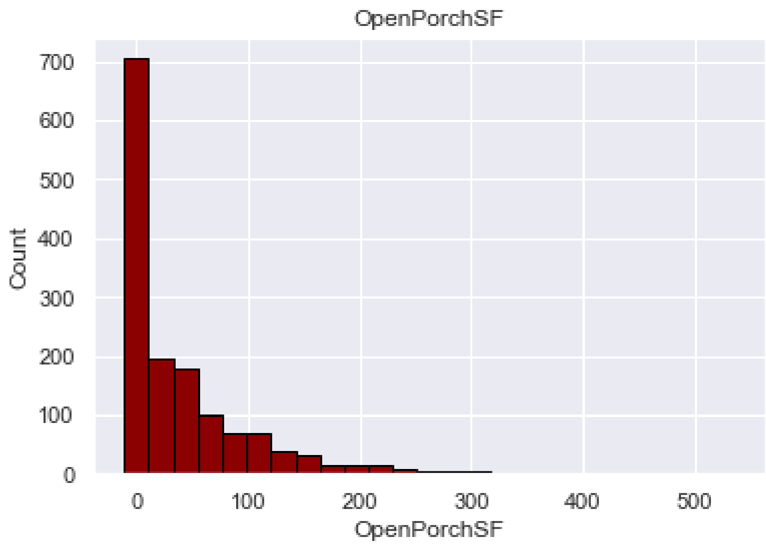

1stFlrSF
Count
0
50
100
150
200
250
300
1000
2000
3000
4000
1stFlrSF

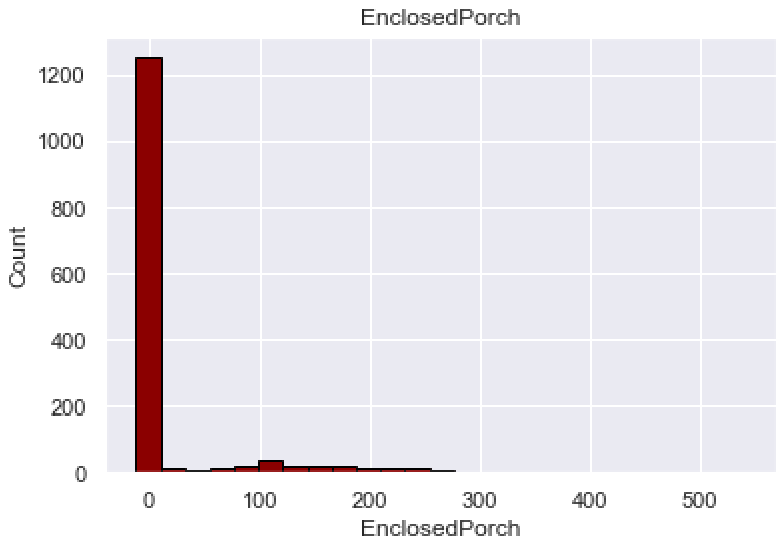

2ndFlrSF
Count
0
100
200
300
400
500
600
700
800
0
500
1000
1500
2000
2ndFlrSF

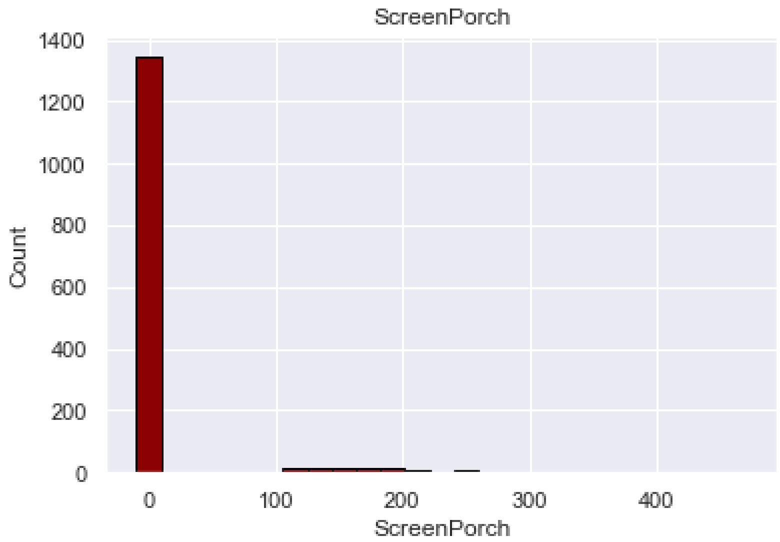

GrLivArea
250
200
150
100
50
0
Count
0
1000
2000
3000
4000
5000
GrLivArea


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


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


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

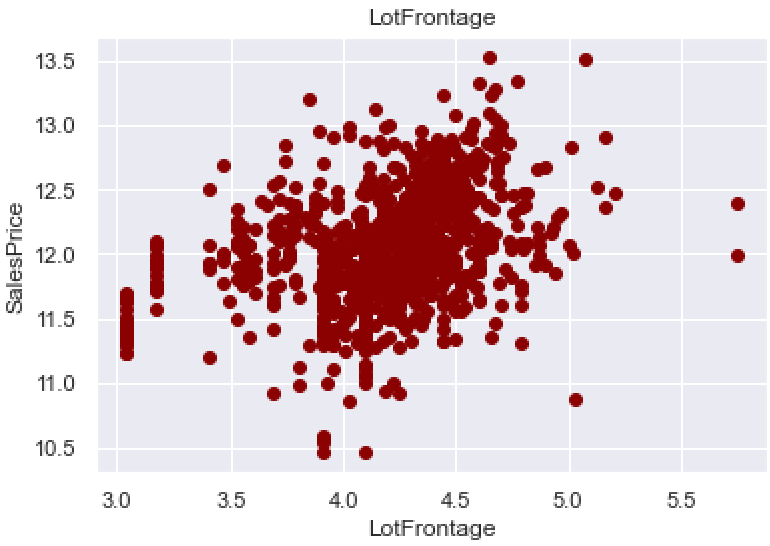

EnclosedPorch
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
EnclosedPorch

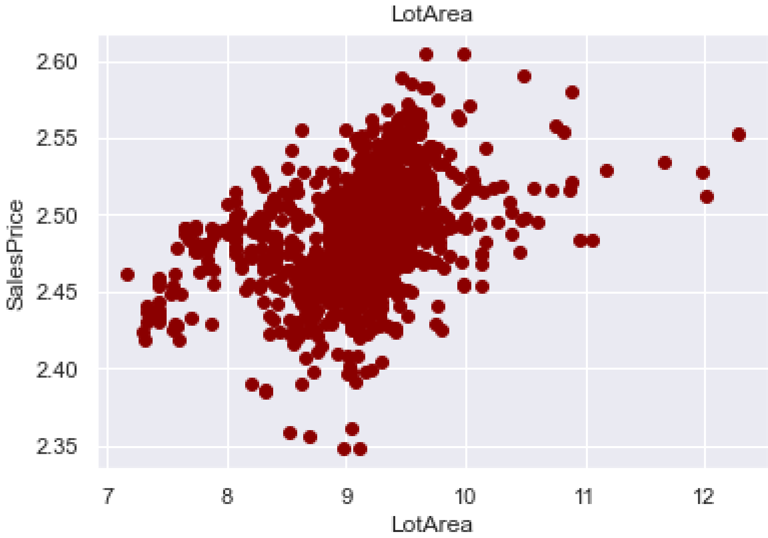

ScreenPorch
Count
1400
1200
1000
800
600
400
200
0
0
100
200
300
400
ScreenPorch

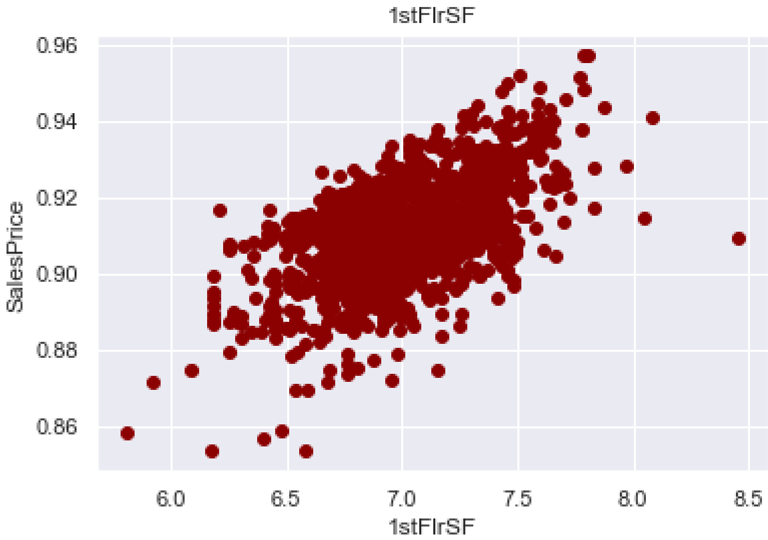

SalePrice
Count
350
300
250
200
150
100
50
0
0
100000
200000
300000
400000
500000
600000
700000
SalePrice

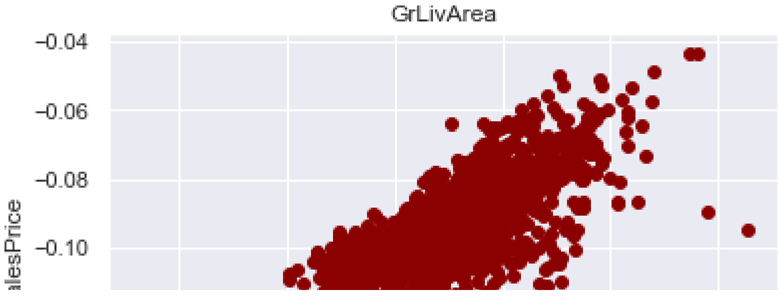
Observation: From the above histogram we found that there is some skewness in some of the features. Therefore we will apply log normal(OBS ID : EDA_OBS_8)

In [486]:
```
data=train_df.copy()
for item in continuous_feature:
    if 0 in data[item].unique():
        pass #bypassing the cases
    else:
        if(item != 'SalePrice'):
            data[item]=np.log(data[item])
            data['SalePrice']=np.log(data['SalePrice'])
            plt.scatter(data[item],data['SalePrice'],color='darkred')
            plt.xlabel(item)
            plt.ylabel('SalesPrice')
            plt.title(item)
            plt.show()
```




LotArea
SalesPrice
2.60
2.55
2.50
2.45
2.40
2.35
7
8
9
10
11
12
LotArea

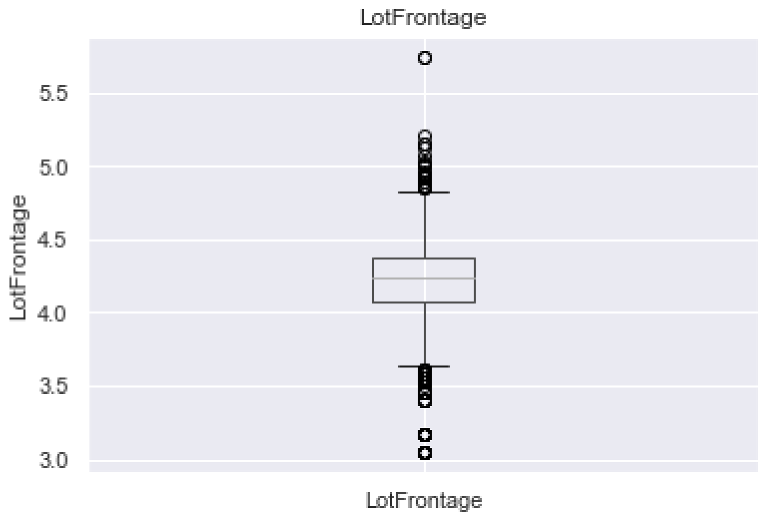

1stFlrSF
SalesPrice
0.96
0.94
0.92
0.90
0.88
0.86
6.0
6.5
7.0
7.5
8.0
8.5
1stFlrSF

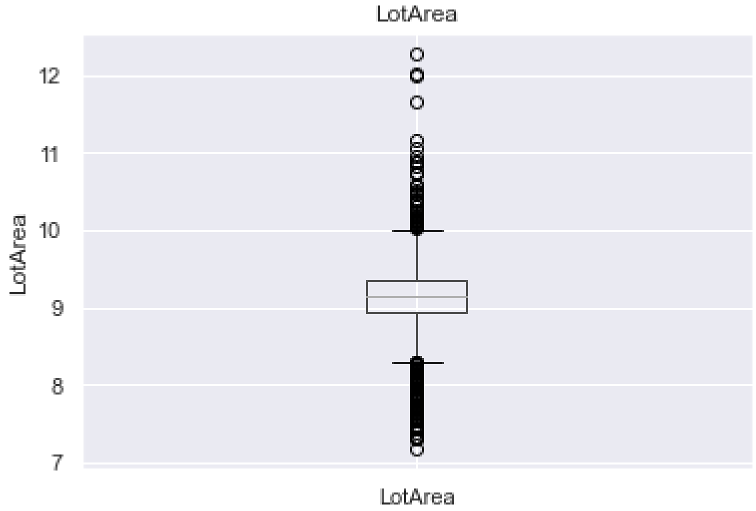


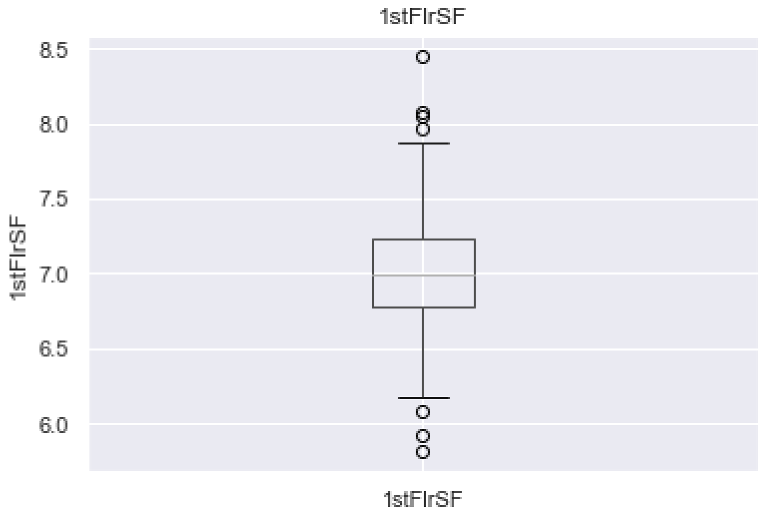
Observation: After applying log normal transformation, we found that skewness got reduced and nearly normal distribution.(OBS ID : EDA_OBS_9)

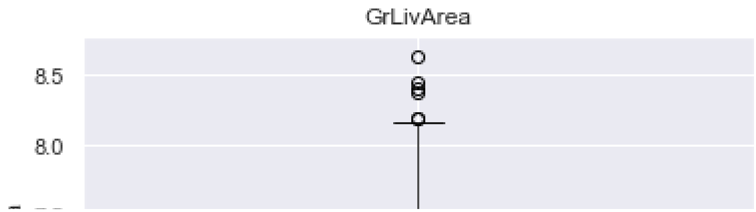
Step8: Outlier Analysis

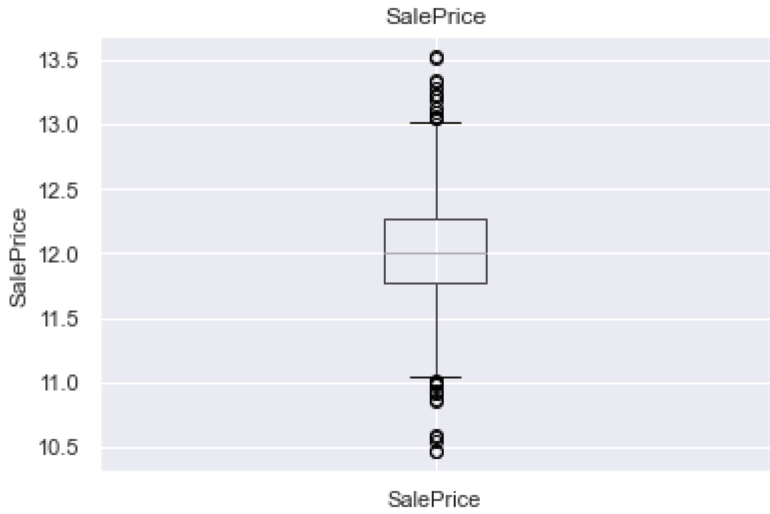
In [488]:
```
data=train_df.copy()

%matplotlib inline

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




LotArea
12
11
10
9
8
7
LotArea
LotArea


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





Observation: After applying boxplot, we found the outliers in continous variables and we will remove in feature engineering.(OBS ID : EDA_OBS_10)

Step9: Categorical Features

In [492]:
```
data=train_df.copy()
categorical_features=[feature for feature in data.columns if data[feature].dtypes=='O']
categorical_features
```

Out[492]:
```
['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 [493]:
```
data[categorical_features].head()
```

Out[493]:

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

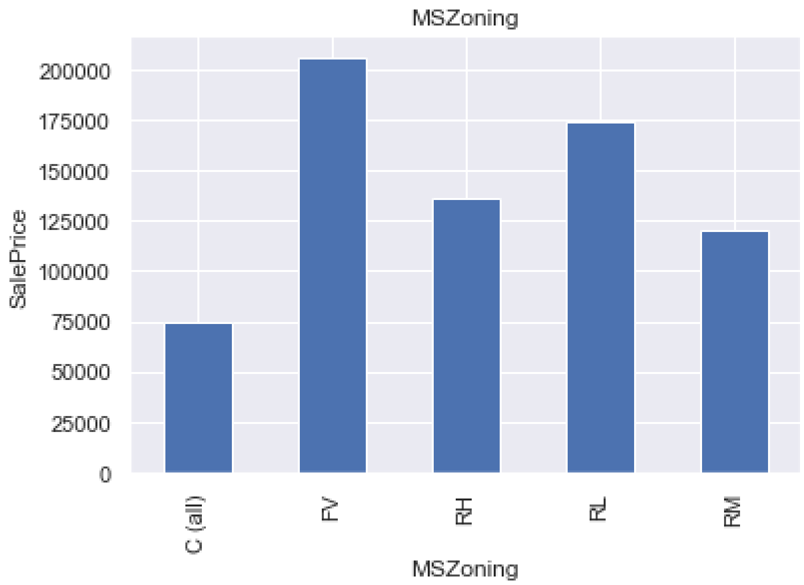
Finding number of category

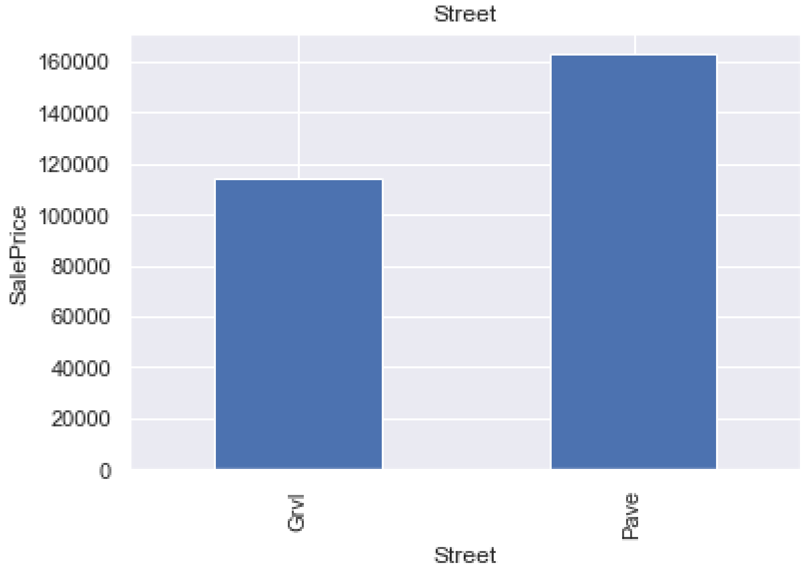
In [494]:
```
for feature in categorical_features:
    print('The feature is {} and number of categories are {}'.format(feature,len(data[feature].unique())))
```

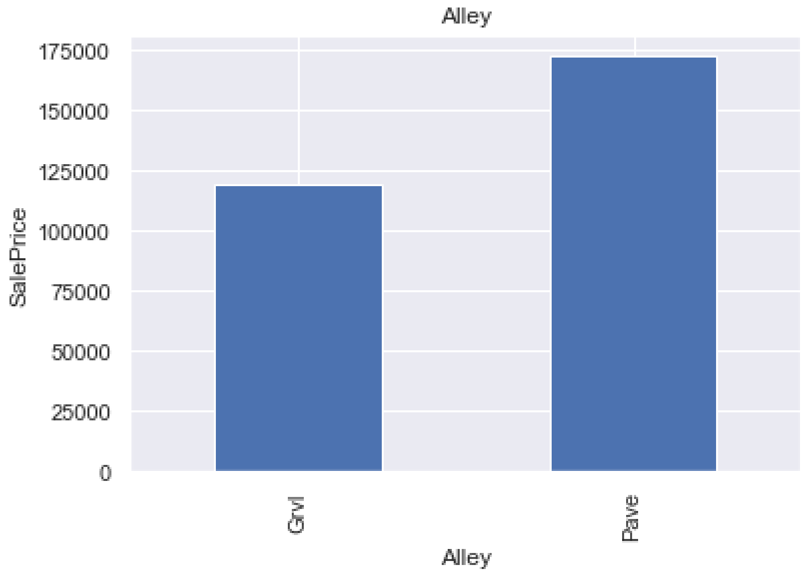
```
The feature is MSZoning and number of categories are 5
The feature is Street and number of categories are 2
The feature is Alley and number of categories are 3
The feature is LotShape and number of categories are 4
The feature is LandContour and number of categories are 4
The feature is Utilities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

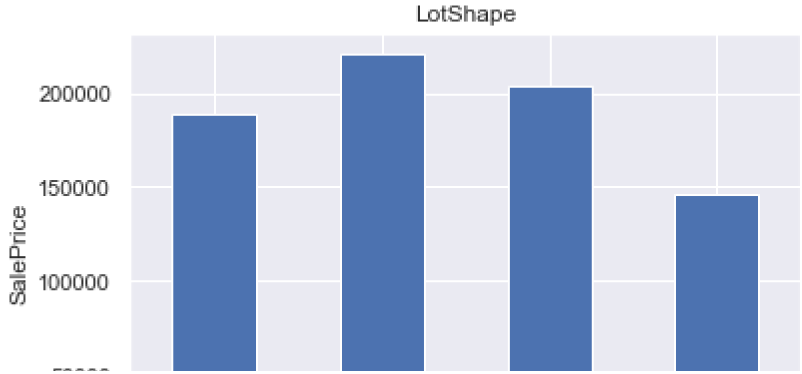
```
The feature is PoolQC and number of categories are 4
The feature is Fence and number of categories are 5
The feature is MiscFeature and number of categories are 5
The feature is SaleType and number of categories are 9
The feature is SaleCondition and number of categories are 6
```

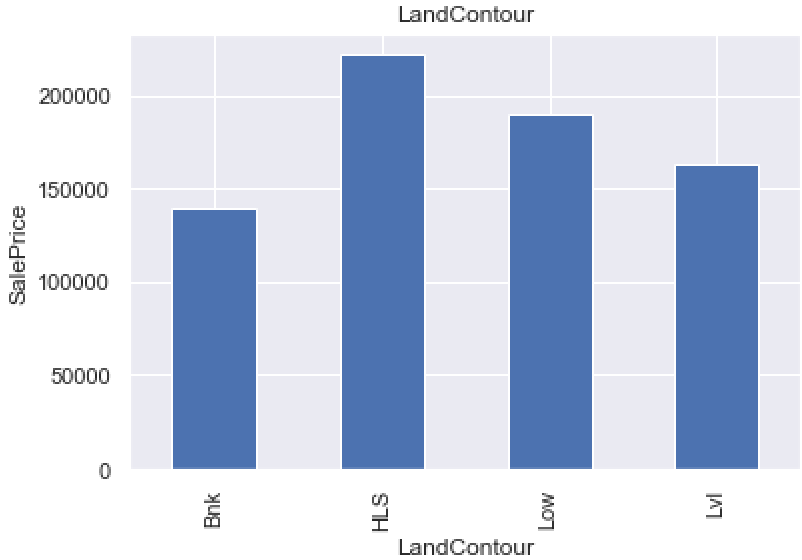
In [495]:
```
#data=dataset.copy()
%matplotlib inline
for item in categorical_features:
    data.groupby(item)['SalePrice'].median().plot.bar()
    plt.xlabel(item)
    plt.ylabel('SalePrice')
    plt.title(item)
    plt.show()
```

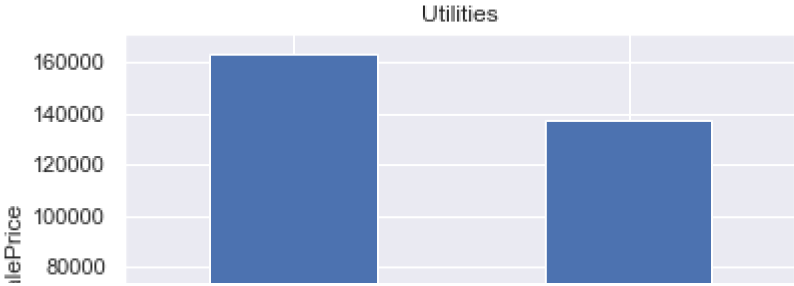


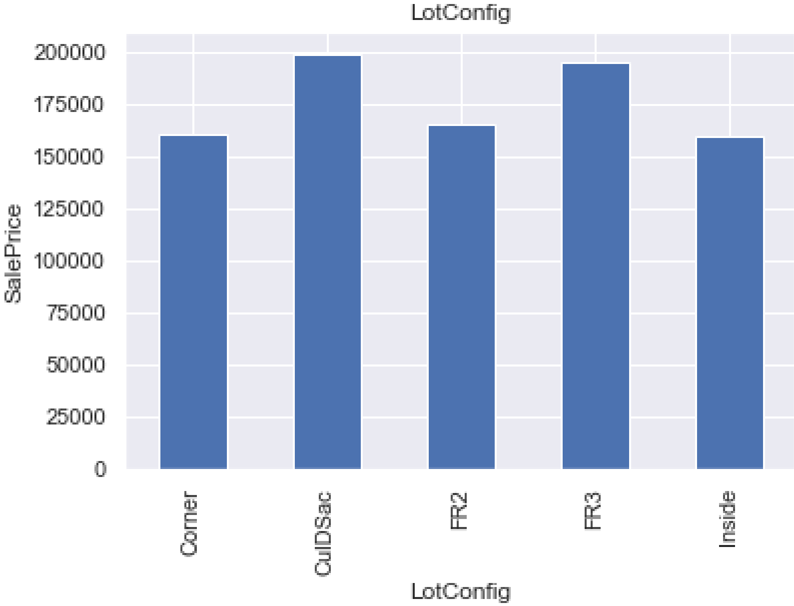

Street
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
Grvl
Pave
Street

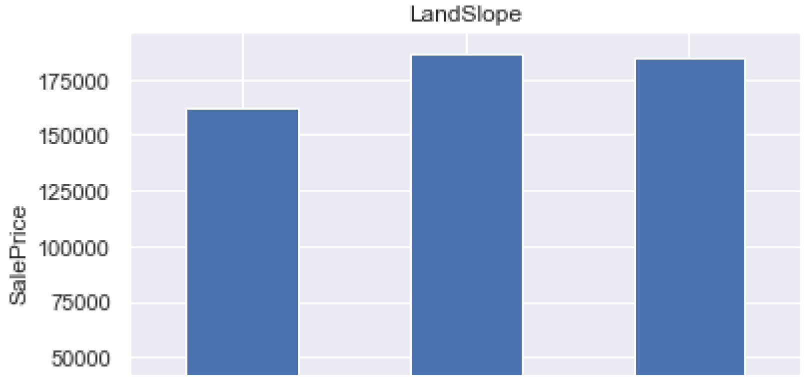

Alley
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
Grvl
Pave
Alley

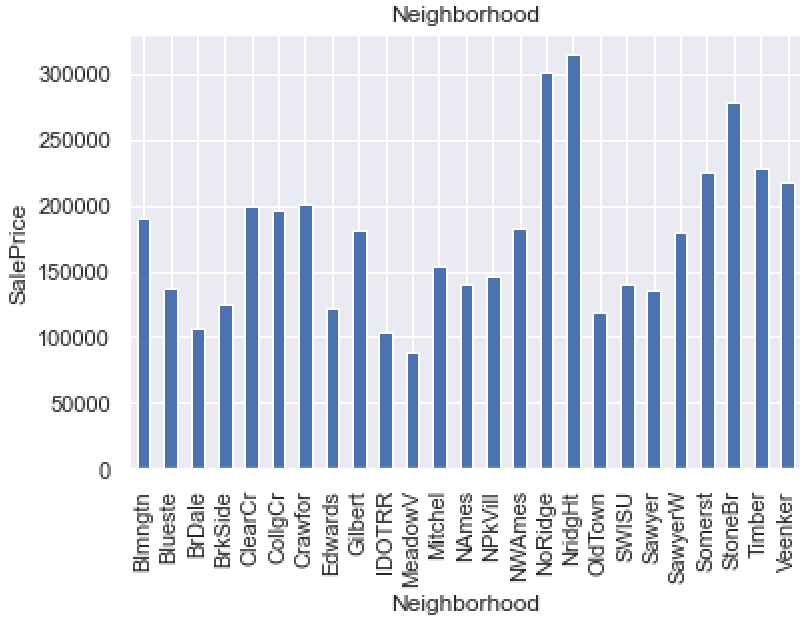

LotShape
SalePrice
200000
150000
100000

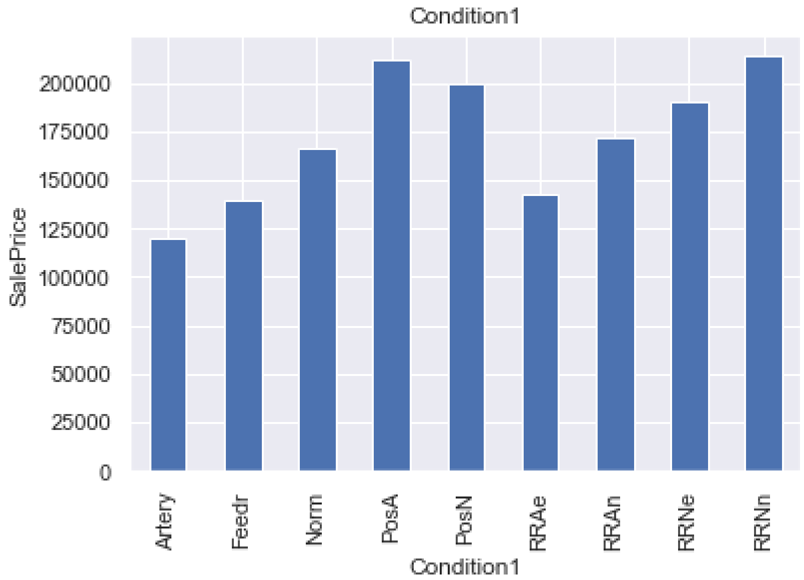

LandContour
SalePrice
200000
150000
100000
50000
0
Bnk
HLS
Low
Lvl
LandContour

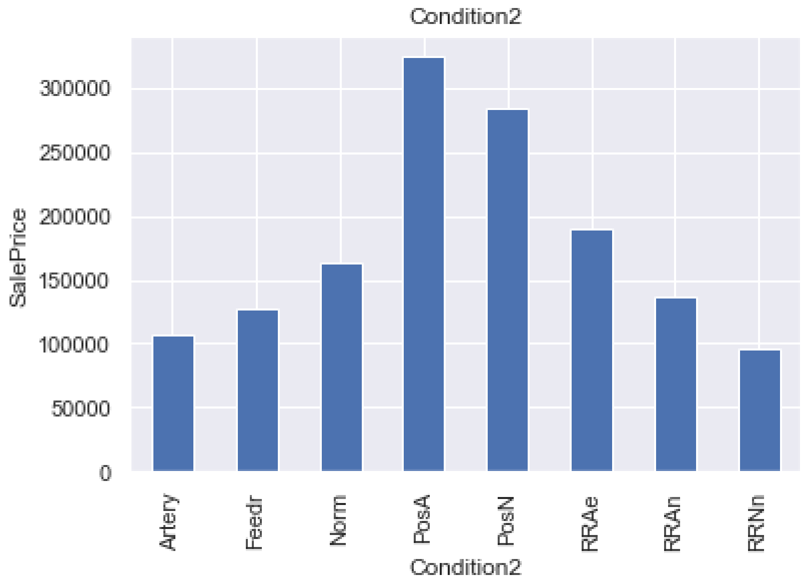

Utilities
160000
140000
120000
100000
80000
lePrice

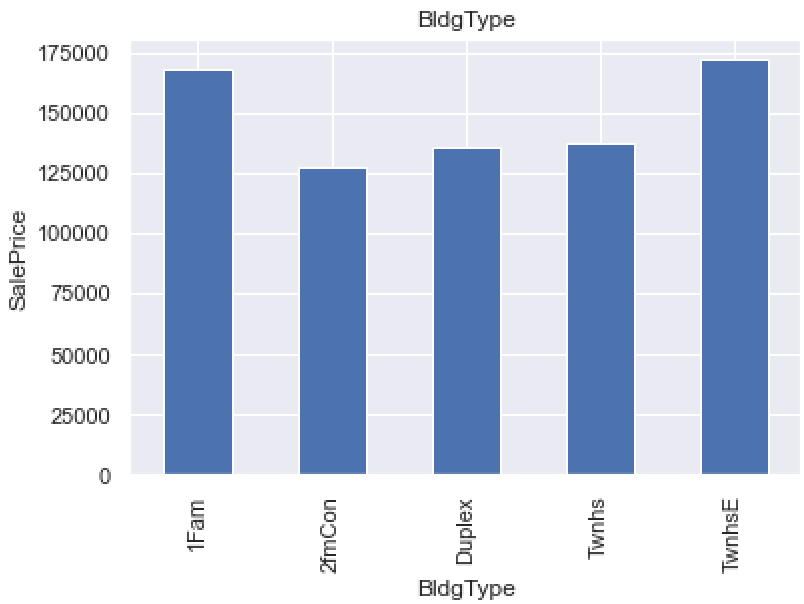

LotConfig
200000
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
Corner
CulDSac
FR2
FR3
Inside
LotConfig

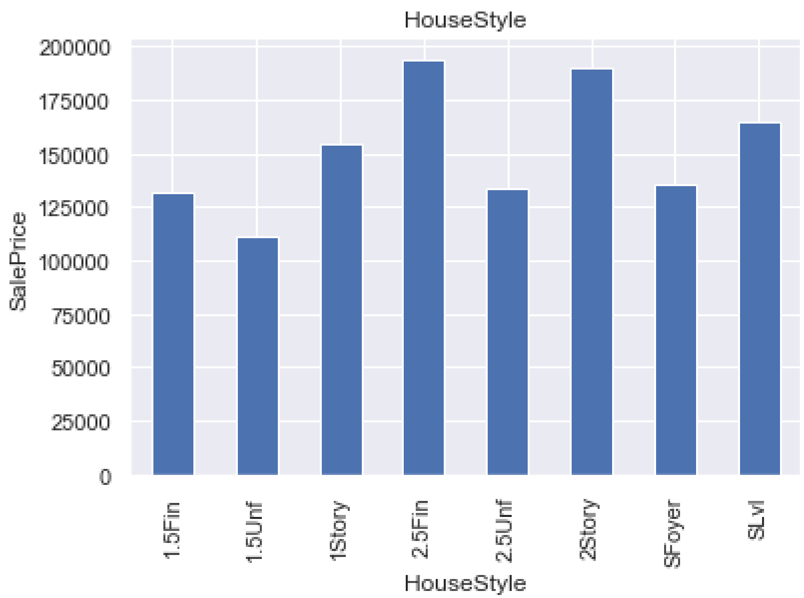

LandSlope
SalePrice
175000
150000
125000
100000
75000
50000

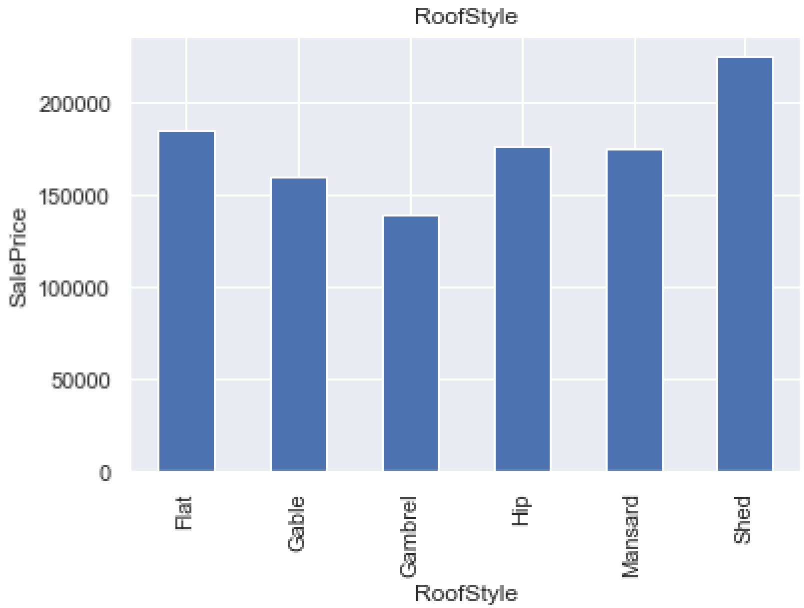

Neighborhood
SalePrice
300000
250000
200000
150000
100000
50000
0
Blmngtn
Blueste
BrDale
BrkSide
ClearCr
CollgCr
Crawfor
Edwards
Gilbert
IDOTRR
MeadowV
Mitchel
NAmes
NPkVill
NWAmes
NoRidge
NridgHt
OldTown
SWISU
Sawyer
SawyerW
Somerst
StoneBr
Timber
Veenker
Neighborhood

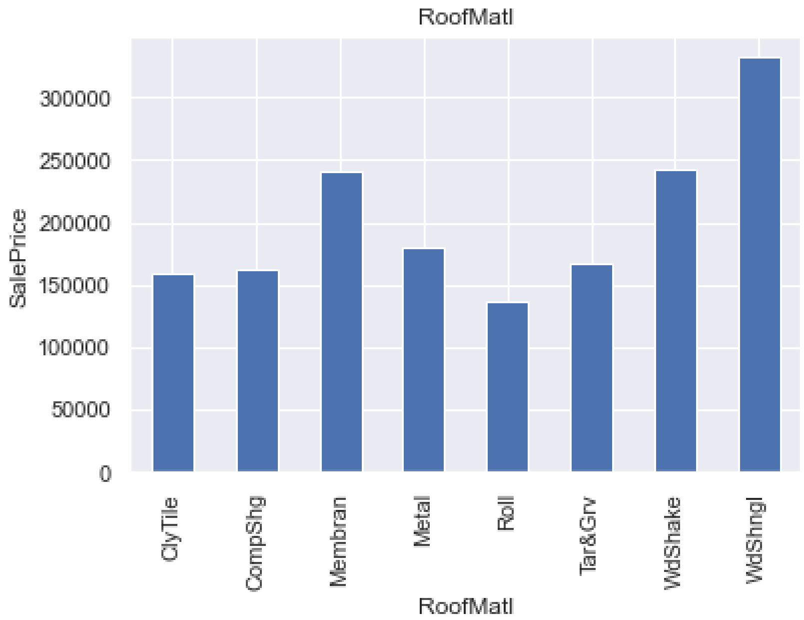

Condition1
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNe
RRNn
Condition1

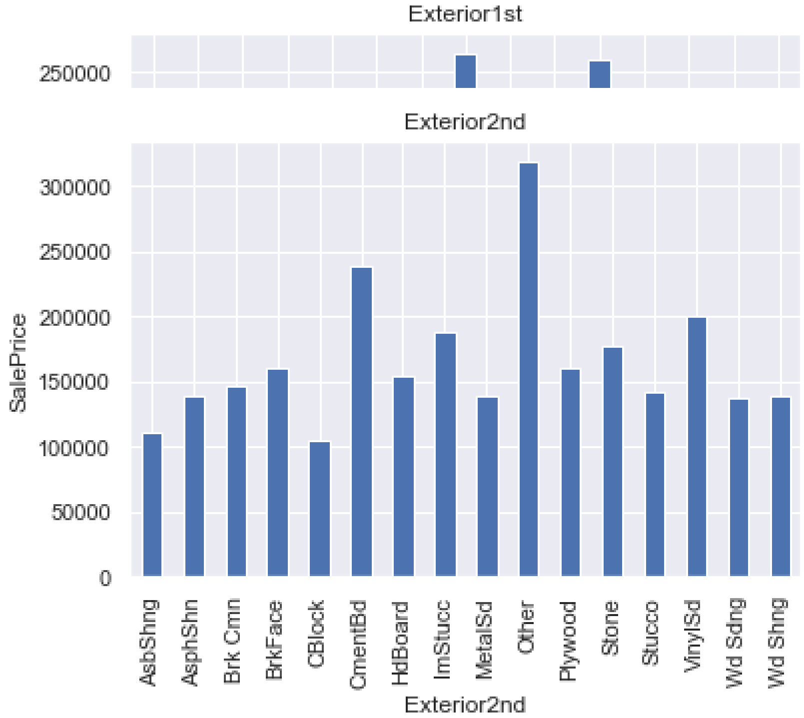

Condition2
SalePrice
300000
250000
200000
150000
100000
50000
0
Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNn
Condition2

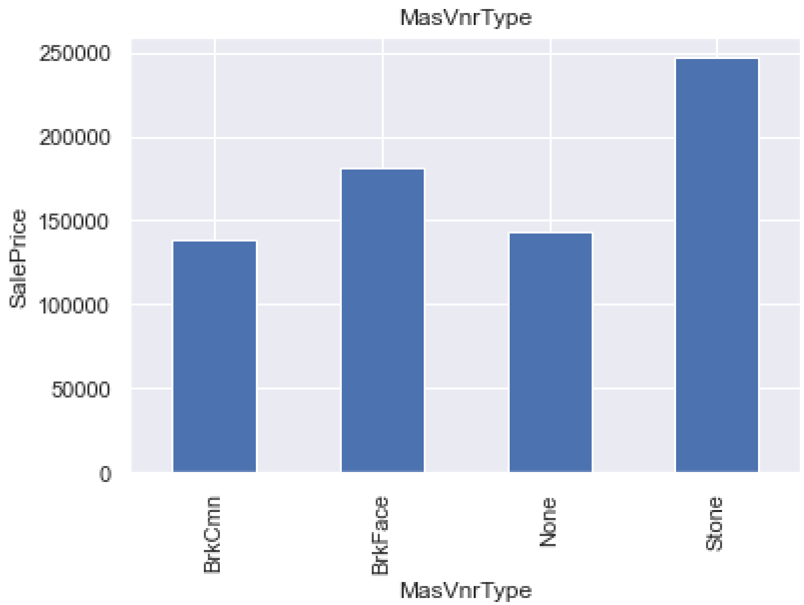

BldgType
SalePrice
175000
150000
125000
100000
75000
50000
25000
0
1Fam
2fmCon
Duplex
Twnhs
TwnhsE
BldgType

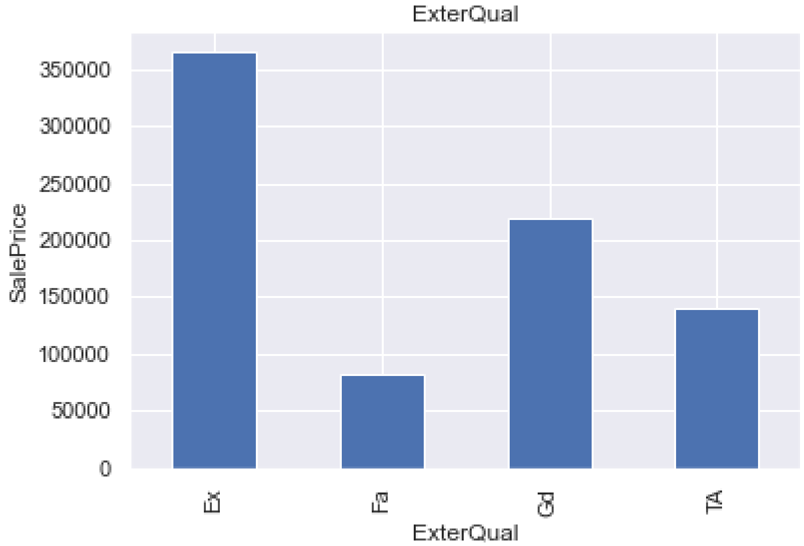

HouseStyle
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
1.5Fin
1.5Unf
1Story
2.5Fin
2.5Unf
2Story
SFoyer
SLvl
HouseStyle

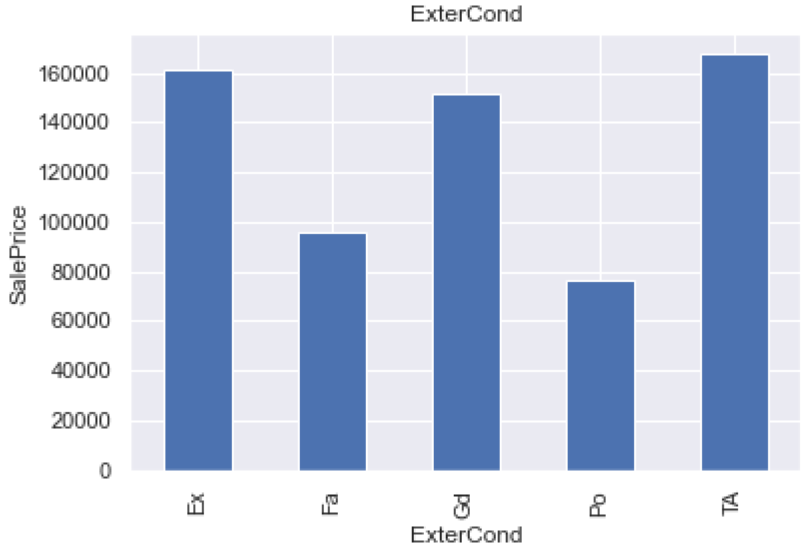

RoofStyle
SalePrice
200000
150000
100000
50000
0
Flat
Gable
Gambrel
Hip
Mansard
Shed
RoofStyle

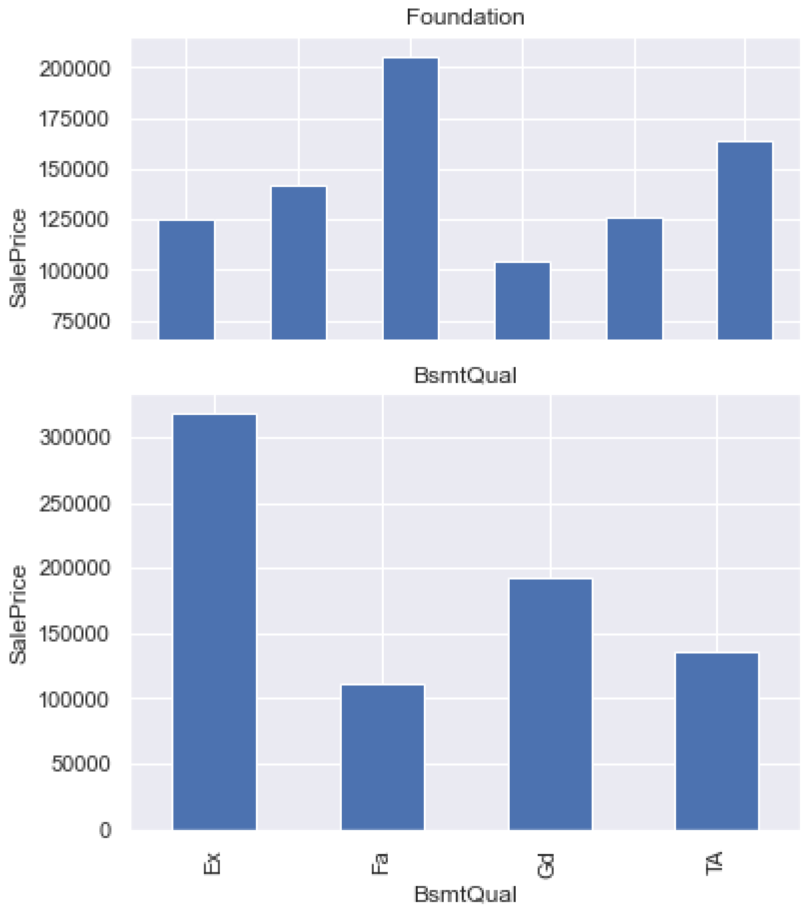

RoofMatl
SalePrice
300000
250000
200000
150000
100000
50000
0
ClyTile
CompShg
Membran
Metal
Roll
Tar&Grv
WdShake
WdShngl
RoofMatl

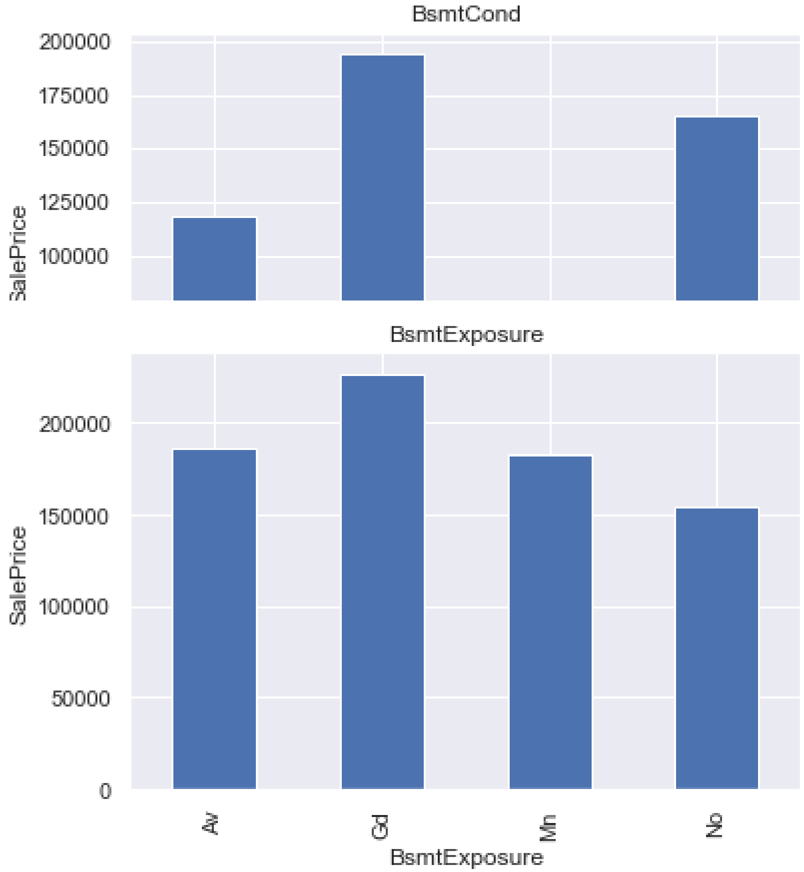

Exterior1st
250000
Exterior2nd
300000
250000
200000
150000
100000
50000
0
SalePrice
AsbShng
AsphShn
Brk Cmn
BrkFace
CBlock
CmentBd
HdBoard
ImStucc
MetalSd
Other
Plywood
Stone
Stucco
VinylSd
Wd Sdng
Wd Shng
Exterior2nd

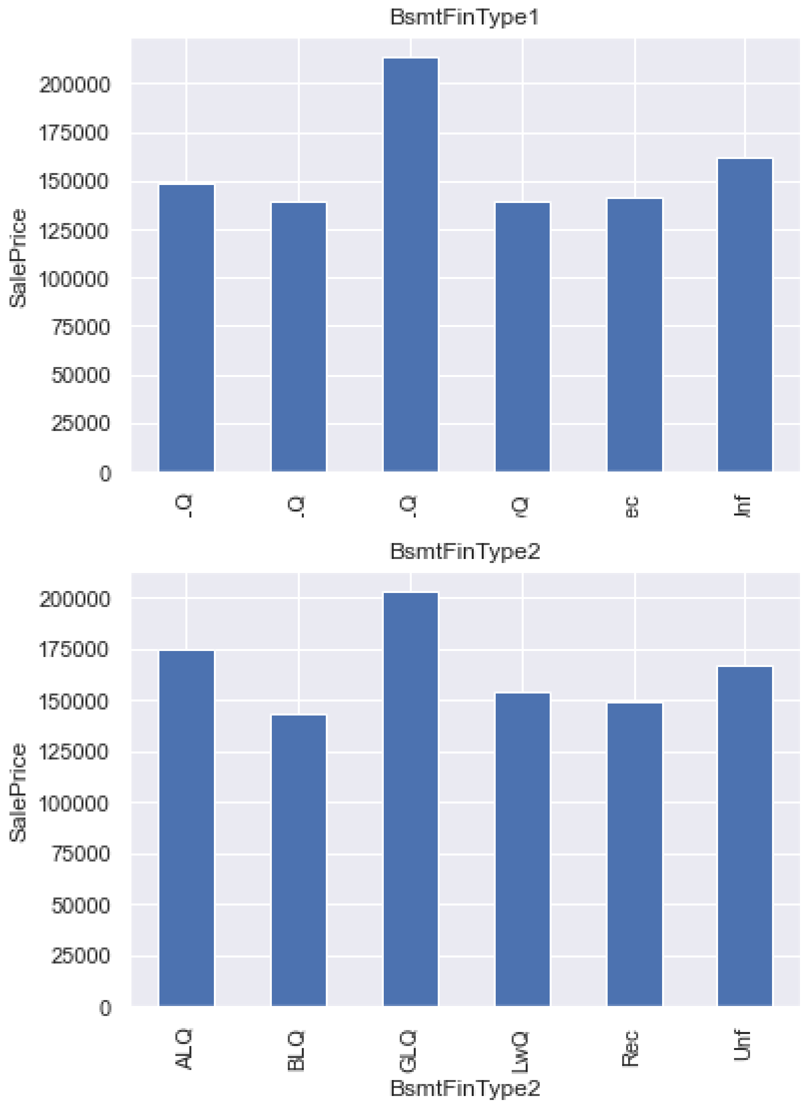

MasVnrType
250000
200000
150000
100000
50000
0
SalePrice
BrkCmn
BrkFace
None
Stone
MasVnrType

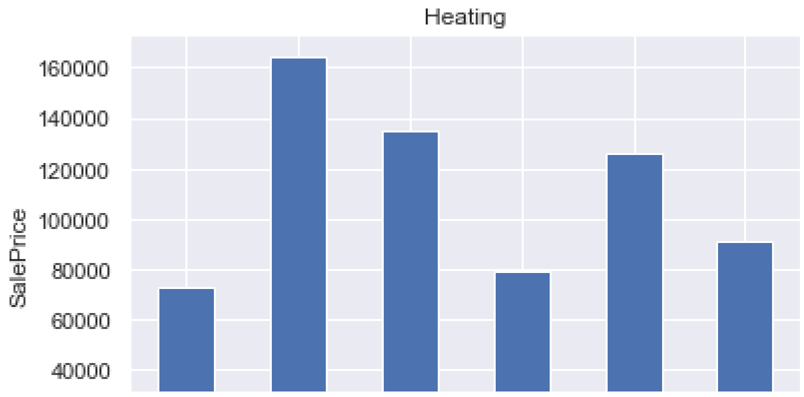

ExterQual
SalePrice
350000
300000
250000
200000
150000
100000
50000
0
Ex
Fa
Gd
TA
ExterQual

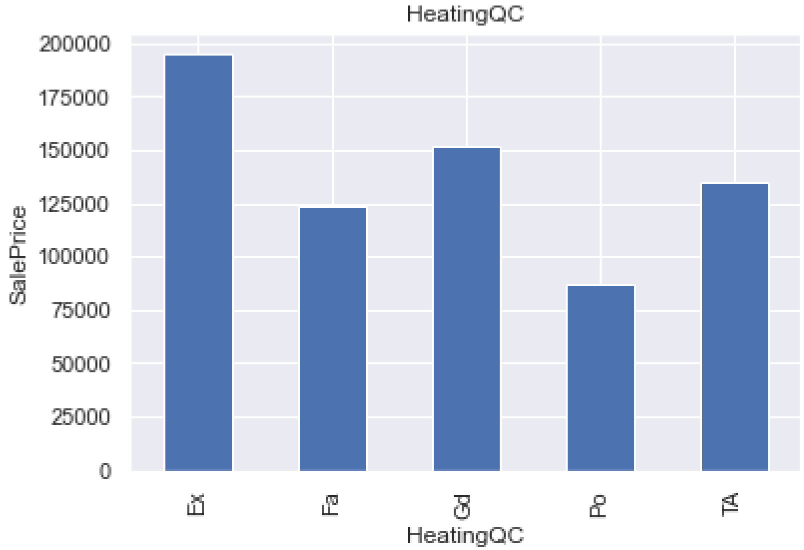

ExterCond
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
Ex
Fa
Gd
Po
TA
ExterCond

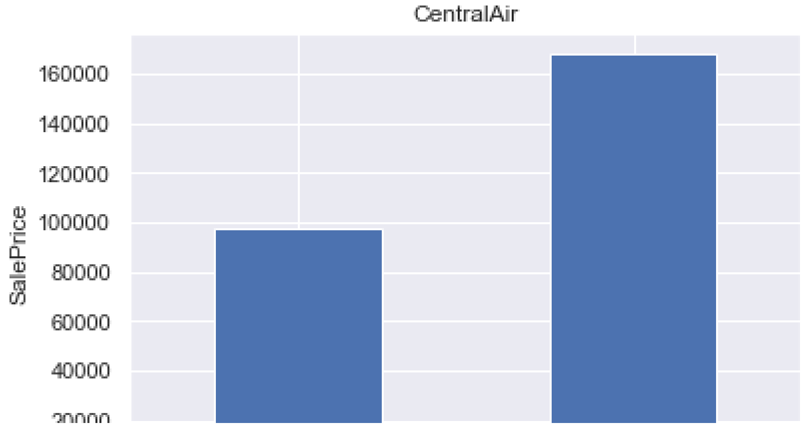

Foundation
200000
175000
150000
125000
100000
75000
SalePrice
BsmtQual
300000
250000
200000
150000
100000
50000
0
SalePrice
Ex
Fa
Gd
TA
BsmtQual

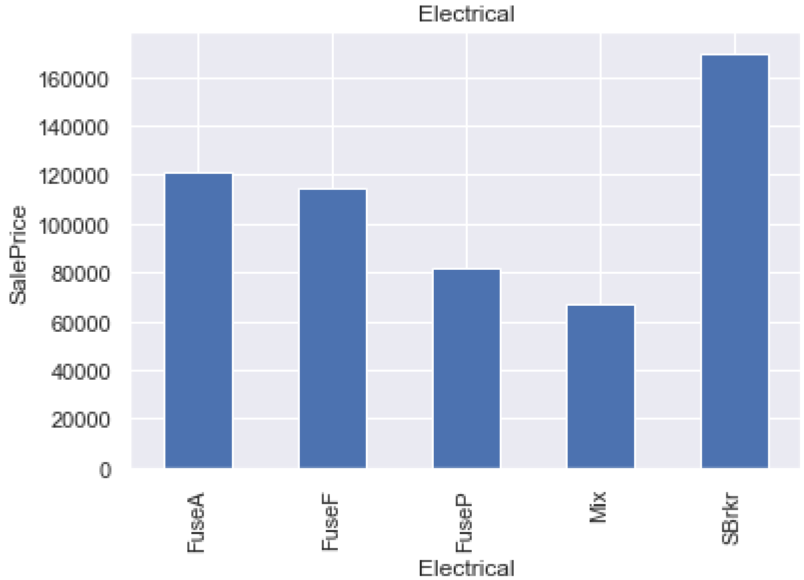

BsmtCond
200000
175000
150000
125000
100000
SalePrice
BsmtExposure
200000
150000
100000
50000
0
SalePrice
Av
Gd
Mn
No
BsmtExposure

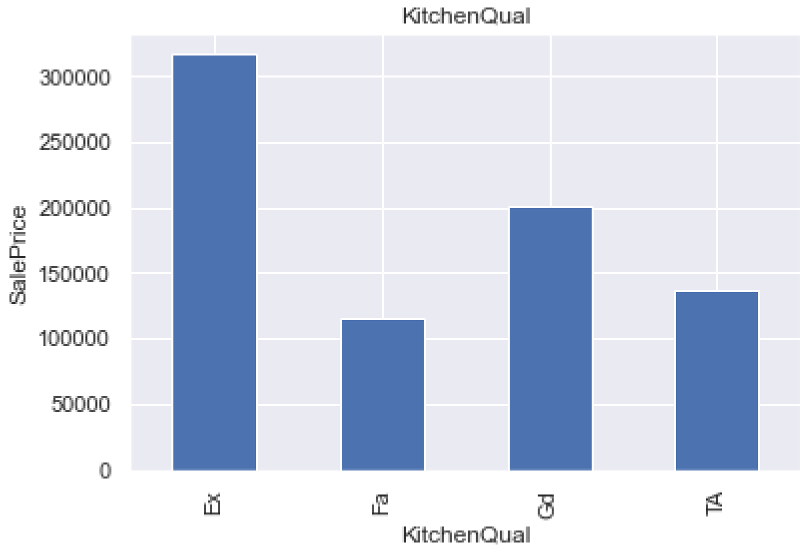

BsmtFinType1
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
.Q
.Q
.Q
rQ
ec
Jnf
BsmtFinType2
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
ALQ
BLQ
GLQ
LwQ
Rec
Unf
BsmtFinType2

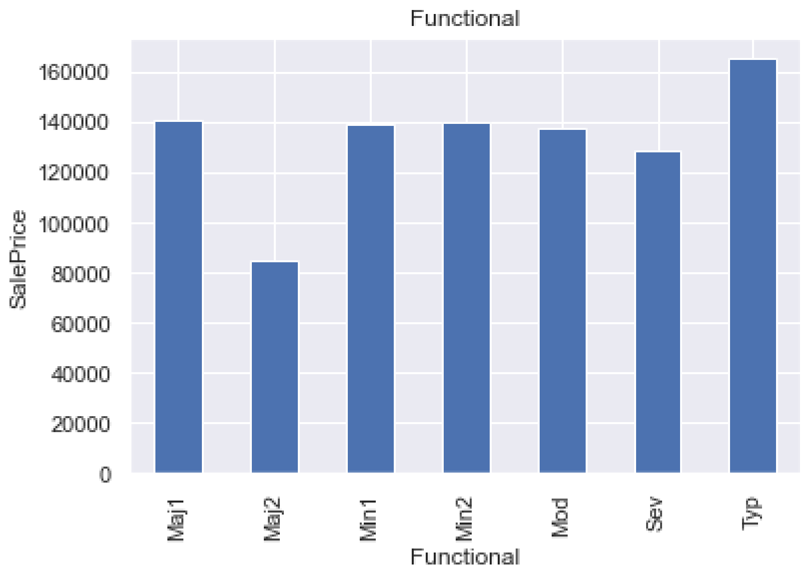

Heating
160000
140000
120000
100000
80000
60000
40000
SalePrice

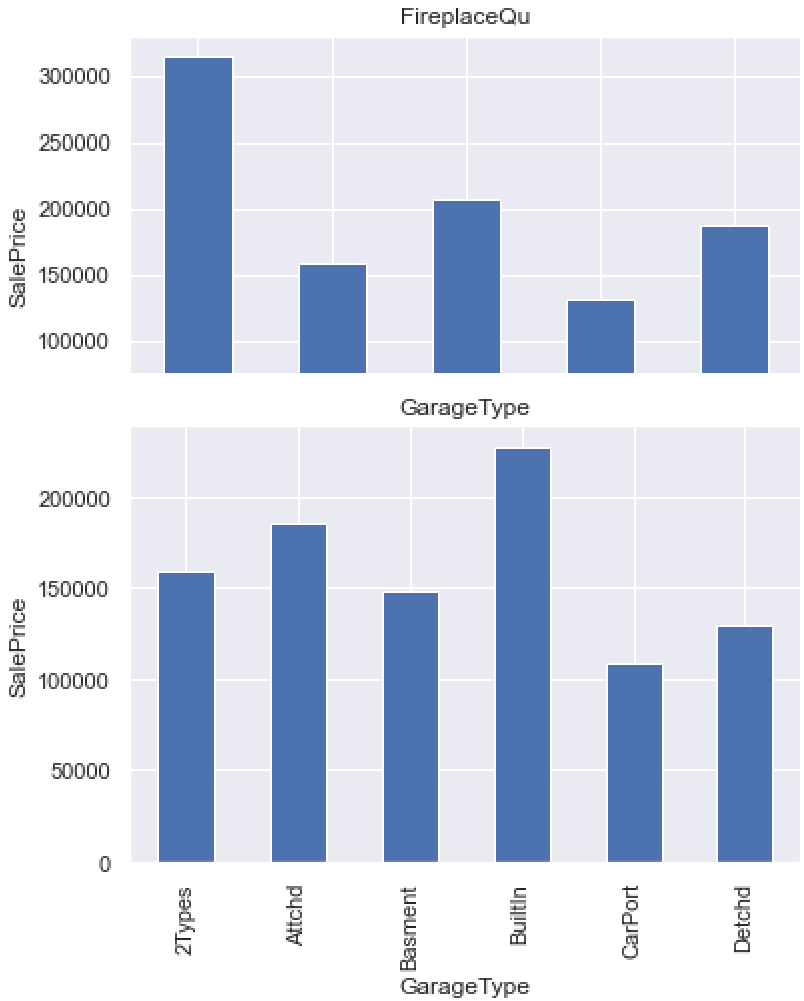

HeatingQC
200000
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
Ex
Fa
Gd
Po
TA
HeatingQC

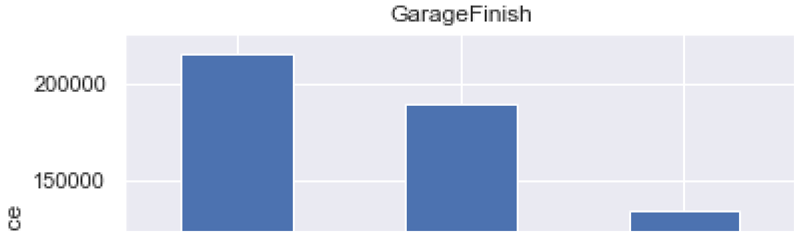

CentralAir
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000

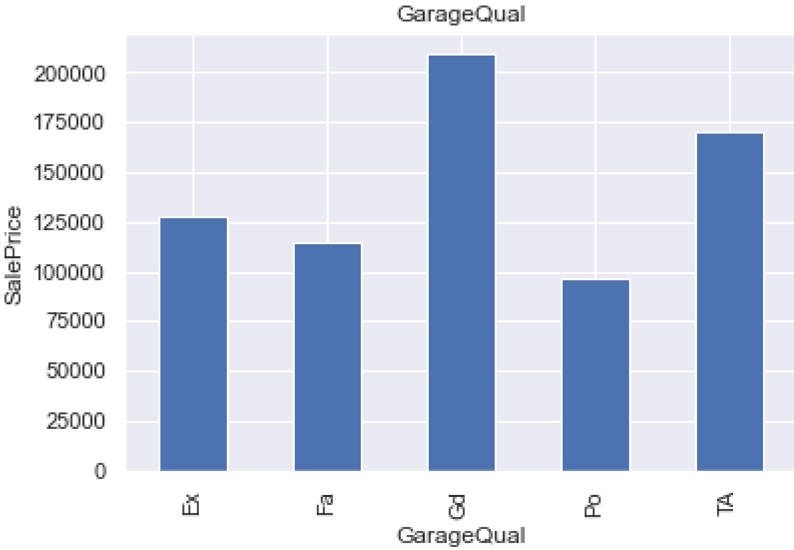

Electrical
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
FuseA
FuseF
FuseP
Mix
SBrkr
Electrical

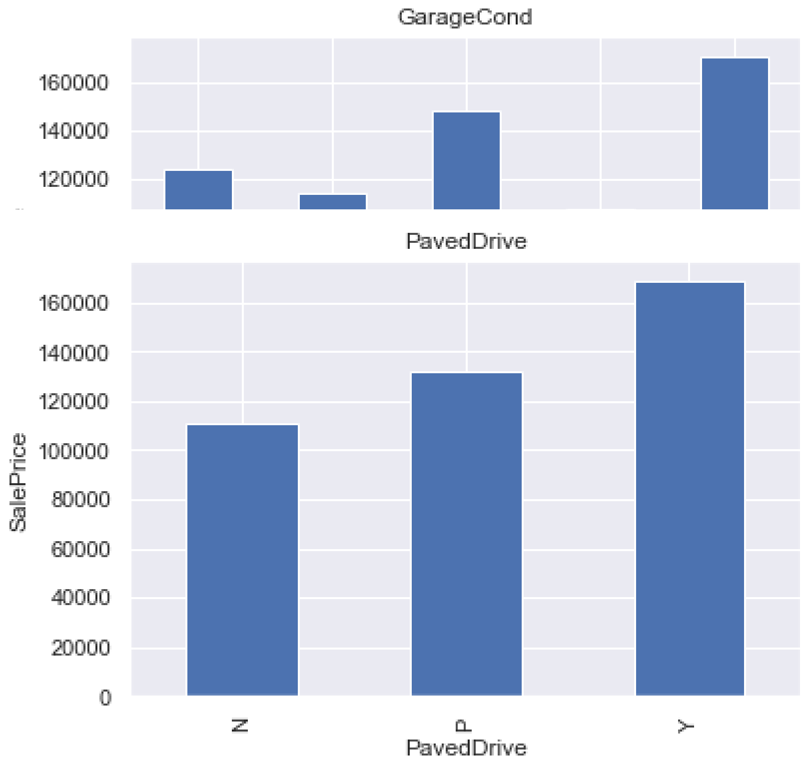

KitchenQual
SalePrice
300000
250000
200000
150000
100000
50000
0
Ex
Fa
Gd
TA
KitchenQual

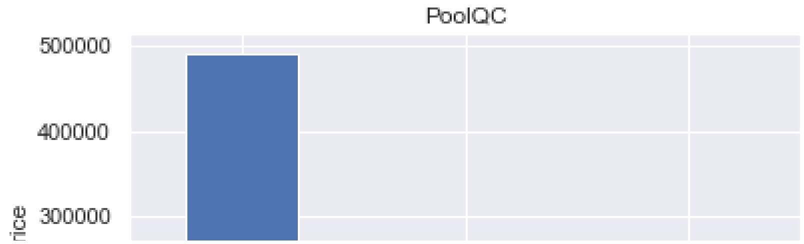

Functional
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
Maj1
Maj2
Min1
Min2
Mod
Sev
Typ
Functional

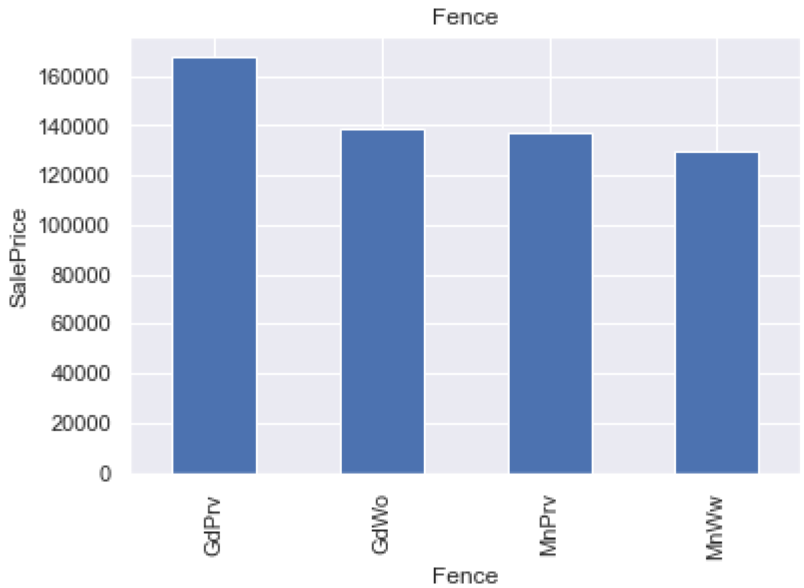

FireplaceQu
SalePrice
300000
250000
200000
150000
100000
GarageType
SalePrice
200000
150000
100000
50000
0
2Types
Attchd
Basment
BuiltIn
CarPort
Detchd
GarageType

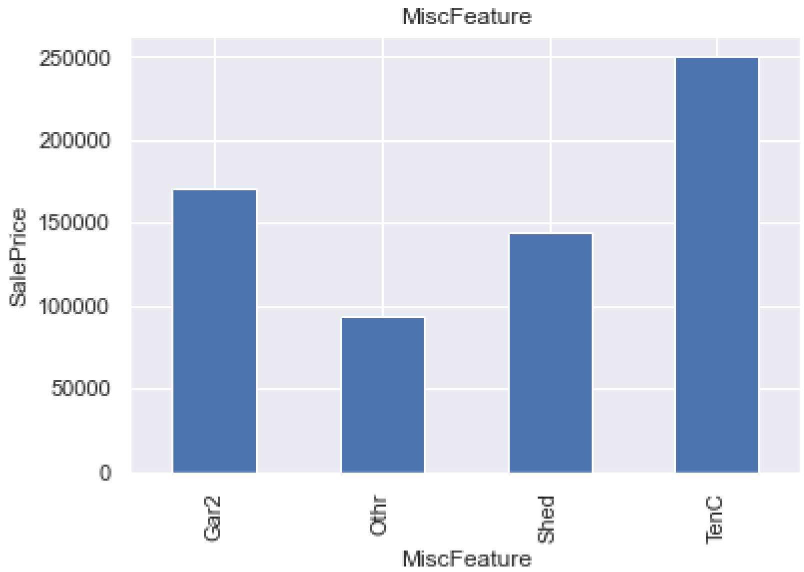

GarageFinish
200000
150000
ce

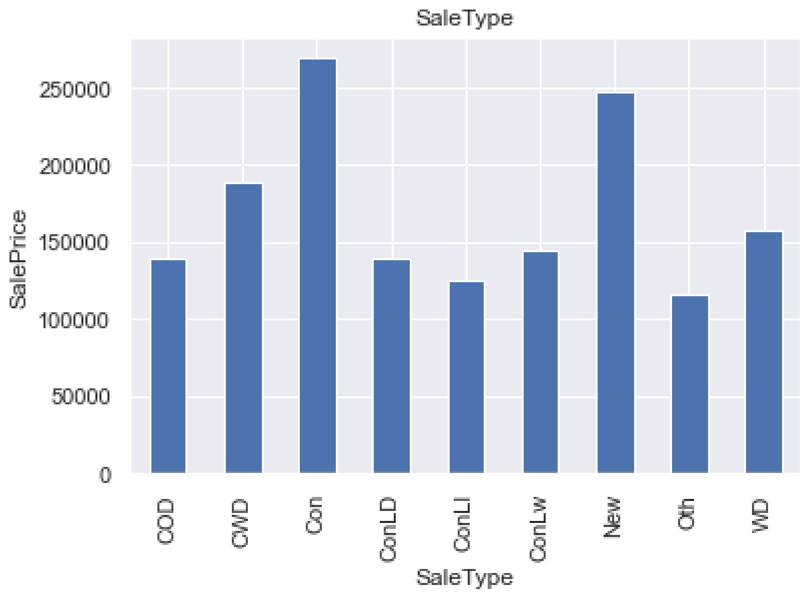

GarageQual
200000
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
Ex
Fa
Gd
Po
TA
GarageQual

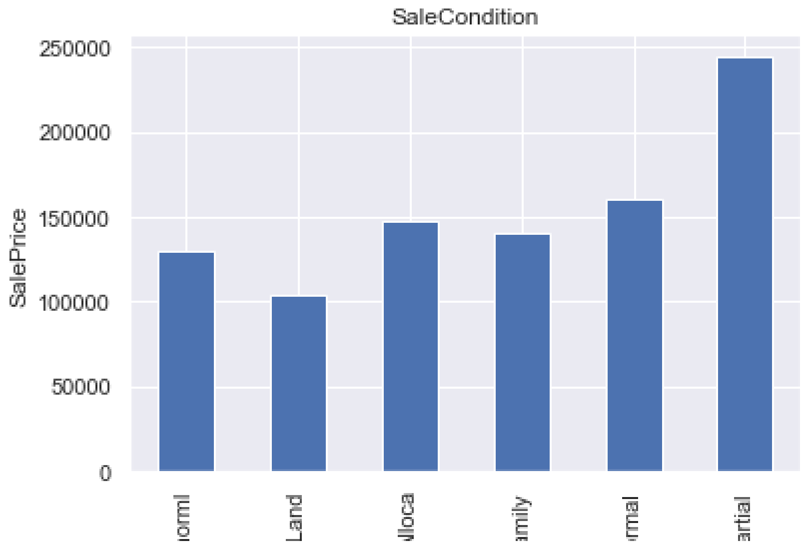

GarageCond
160000
140000
120000
PavedDrive
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
N
P
Y
PavedDrive


PoolQC
500000
400000
300000
rice


Fence
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
GdPrv
GdWo
MnPrv
MnWw
Fence


MiscFeature
SalePrice
250000
200000
150000
100000
50000
0
Gar2
Othr
Shed
TenC
MiscFeature


SaleType
SalePrice
250000
200000
150000
100000
50000
0
COD
CWD
Con
ConLD
ConLI
ConLw
New
Oth
WD
SaleType



Observation: From the above histogram we found in some of the cases there is exponential relationship, in some cases it is normal or in some cases it is partially exponential. There are non linear relationship also. Therefore we can conclude that whese variables have some or large relationship with target variable Sale Price. We will explore more during feature selection phase.(OBS ID : EDA_OBS_11)

EXPLORATORY DATA ANALYSIS -- END

FEATURE ENGINEERING -- START

Step:9 Missing Value Imputation

Imputation Step: Categorical Imputation followed by Numerical Imputation

In [542]:
```
train_df = pd.read_csv('bh_train.csv')
test_df = pd.read_csv('bh_test.csv')
combine = [train_df, test_df]
```

Categorical Imputation

In [543]:
```
print('Test Data')
features_nan_test=[item for item in test_df.columns if test_df[item].isnull().sum()>1 and test_df[item].dtypes=='O']

for item in features_nan_test:
    print("{}: {}% missing values".format(item,np.round(test_df[item].isnull().mean(),4)))
```

```
Test Data
MSZoning: 0.0027% missing values
Alley: 0.9267% missing values
Utilities: 0.0014% 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
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
```

In [544]:
```
## Replace missing value with a new label
def replace_cat_feature(dataset,features_nan_test):
    data=dataset.copy()
    data[features_nan_test]=data[features_nan_test].fillna('Missing')
    return data

test_df=replace_cat_feature(test_df,features_nan_test)
test_df[features_nan_test].isnull().sum()
```

Out[544]:
```
MSZoning        0
Alley           0
Utilities       0
MasVnrType      0
BsmtQual        0
BsmtCond        0
BsmtExposure    0
BsmtFinType1    0
BsmtFinType2    0
Functional      0
FireplaceQu     0
GarageType      0
GarageFinish    0
GarageQual      0
GarageCond      0
PoolQC          0
Fence           0
MiscFeature     0
dtype: int64
```

In [545]:
```
print('Train Data')
features_nan=[item for item in train_df.columns if train_df[item].isnull().sum()>1 and train_df[item].dtypes=='O']

for item in features_nan:
    print("{}: {}% missing values".format(item,np.round(train_df[item].isnull().mean(),4)))
```

```
Train Data
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
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 [546]:
```
## Replace missing value with a new label
def replace_cat_feature(dataset,features_nan_test):
    data=dataset.copy()
    data[features_nan_test]=data[features_nan_test].fillna('Missing')
    return data

train_df=replace_cat_feature(train_df,features_nan)
train_df[features_nan].isnull().sum()
```

Out[546]:
```
Alley           0
MasVnrType      0
BsmtQual        0
BsmtCond        0
BsmtExposure    0
BsmtFinType1    0
BsmtFinType2    0
FireplaceQu     0
GarageType      0
GarageFinish    0
GarageQual      0
GarageCond      0
PoolQC          0
Fence           0
MiscFeature     0
dtype: int64
```

Decision: The conventional categorical imputing method is used All the blank field in categorical values are imputed with missing.

Related EDA ID: EDA_OBS_1, EDA_OBS_2,

Step:2 Categorical Variables: Handling Categorical variable using Custom Encoding through enumerating with dynamic variable or it can be one hot encoding

In [552]:
```
categorical_features=[feature for feature in train_df.columns if train_df[feature].dtype=='O']

for item in categorical_features:
   labels_ordered=train_df.groupby([item])['SalePrice'].mean().sort_values().index
   labels_ordered={k:i for i,k in enumerate(labels_ordered,0)}
   train_df[item]=train_df[item].map(labels_ordered)

train_df.head()
```

Out[552]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	L
0	1	60	3	65.0	8450	1	2	0	1	1	
1	2	20	3	80.0	9600	1	2	0	1	1	
2	3	60	3	68.0	11250	1	2	1	1	1	
3	4	70	3	60.0	9550	1	2	1	1	1	
4	5	60	3	84.0	14260	1	2	1	1	1	

In [553]:
```
categorical_features=[feature for feature in test_df.columns if test_df[feature].dtype=='O']

for item in categorical_features:
   labels_ordered=test_df.groupby([item])['Id'].mean().sort_values().index
   labels_ordered={k:i for i,k in enumerate(labels_ordered,0)}
   test_df[item]=test_df[item].map(labels_ordered)

test_df.head()
```

Out[553]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
0	1461	20	0	80.0	11622	1	1	2	0	1
1	1462	20	2	81.0	14267	1	1	1	0	1
2	1463	60	2	74.0	13830	1	1	1	0	1
3	1464	60	2	78.0	9978	1	1	1	0	1
4	1465	120	2	43.0	5005	1	1	1	2	1

Decision: Post Missing Value Imputation, we found that cateogical values in data which we converted to numerical before we feed the data to algorithm.

Related EDA ID: EDA_OBS_1, EDA_OBS_2

Numerical Imputation

In [554]:

```
imputer=KNNImputer(n_neighbors=3, weights='uniform',missing_values=np.nan)
new_array=imputer.fit_transform(train_df) # impute the missing values
#convert the nd-array returned in the step above to a Dataframe
train_df=pd.DataFrame(data=np.round(new_array), columns=train_df.columns)
train_df.head()
```

Out[554]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
0	1.0	60.0	3.0	65.0	8450.0	1.0	2.0	0.0	1.0	1.0
1	2.0	20.0	3.0	80.0	9600.0	1.0	2.0	0.0	1.0	1.0
2	3.0	60.0	3.0	68.0	11250.0	1.0	2.0	1.0	1.0	1.0
3	4.0	70.0	3.0	60.0	9550.0	1.0	2.0	1.0	1.0	1.0
4	5.0	60.0	3.0	84.0	14260.0	1.0	2.0	1.0	1.0	1.0

In [555]:

```
imputer=KNNImputer(n_neighbors=3, weights='uniform',missing_values=np.nan)
new_array=imputer.fit_transform(test_df) # impute the missing values
#convert the nd-array returned in the step above to a Dataframe
test_df=pd.DataFrame(data=np.round(new_array), columns=test_df.columns)
test_df.head(20)
```

Out[555]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Uti
0	1461.0	20.0	0.0	80.0	11622.0	1.0	1.0	2.0	0.0	
1	1462.0	20.0	2.0	81.0	14267.0	1.0	1.0	1.0	0.0	
2	1463.0	60.0	2.0	74.0	13830.0	1.0	1.0	1.0	0.0	
3	1464.0	60.0	2.0	78.0	9978.0	1.0	1.0	1.0	0.0	
4	1465.0	120.0	2.0	43.0	5005.0	1.0	1.0	1.0	2.0	
5	1466.0	60.0	2.0	75.0	10000.0	1.0	1.0	1.0	0.0	
6	1467.0	20.0	2.0	69.0	7980.0	1.0	1.0	1.0	0.0	
7	1468.0	60.0	2.0	63.0	8402.0	1.0	1.0	1.0	0.0	

Decision: The numerical imputation is done using KNNImputer.

Related EDA ID: EDA_OBS_4,EDA_OBS_6,EDA_OBS_7

Step:10 Temporal Variables: Converting ['YearBuilt','YearRemodAdd','GarageYrBlt'] to numeric for standatization

In [556]:

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

for item in ['YearBuilt','YearRemodAdd','GarageYrBlt']:
    train_df[item]=train_df['YrSold']-train_df[item]

## Temporal Variables (Date Time Variables) ---

for item in ['YearBuilt','YearRemodAdd','GarageYrBlt']:
    test_df[item]=test_df['YrSold']-test_df[item]
```

In [557]:

```
train_df.head()
```

Out[557]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
0	1.0	60.0	3.0	65.0	8450.0	1.0	2.0	0.0	1.0	1.0
1	2.0	20.0	3.0	80.0	9600.0	1.0	2.0	0.0	1.0	1.0
2	3.0	60.0	3.0	68.0	11250.0	1.0	2.0	1.0	1.0	1.0
3	4.0	70.0	3.0	60.0	9550.0	1.0	2.0	1.0	1.0	1.0
4	5.0	60.0	3.0	84.0	14260.0	1.0	2.0	1.0	1.0	1.0

In [558]:
```
test_df.head()
```

Out[558]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utiliti
0	1461.0	20.0	0.0	80.0	11622.0	1.0	1.0	2.0	0.0	1
1	1462.0	20.0	2.0	81.0	14267.0	1.0	1.0	1.0	0.0	1
2	1463.0	60.0	2.0	74.0	13830.0	1.0	1.0	1.0	0.0	1
3	1464.0	60.0	2.0	78.0	9978.0	1.0	1.0	1.0	0.0	1
4	1465.0	120.0	2.0	43.0	5005.0	1.0	1.0	1.0	2.0	1

Decision: Only Date variable YearSold is kept and other date year variable are made with respect to YearSold.

Related EDA ID: EDA_OBS_5,

Step:11 Numerical Variable Log Normalization

In [559]:
```
import numpy as np
num_features=['LotFrontage', 'LotArea', '1stFlrSF', 'GrLivArea']

for item in num_features:
    train_df[item]=np.log(train_df[item])
```

In [560]:
```
import numpy as np
num_features=['LotFrontage', 'LotArea', '1stFlrSF', 'GrLivArea']

for item in num_features:
    test_df[item]=np.log(test_df[item])
```

In [561]:
```
train_df.head()
```

Out[561]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
0	1.0	60.0	3.0	4.174387	9.041922	1.0	2.0	0.0	1.0	1.0
1	2.0	20.0	3.0	4.382027	9.169518	1.0	2.0	0.0	1.0	1.0
2	3.0	60.0	3.0	4.219508	9.328123	1.0	2.0	1.0	1.0	1.0
3	4.0	70.0	3.0	4.094345	9.164296	1.0	2.0	1.0	1.0	1.0
4	5.0	60.0	3.0	4.430817	9.565214	1.0	2.0	1.0	1.0	1.0

In [562]:
```
test_df.head()
```

Out[562]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utiliti
0	1461.0	20.0	0.0	4.382027	9.360655	1.0	1.0	2.0	0.0	
1	1462.0	20.0	2.0	4.394449	9.565704	1.0	1.0	1.0	0.0	
2	1463.0	60.0	2.0	4.304065	9.534595	1.0	1.0	1.0	0.0	
3	1464.0	60.0	2.0	4.356709	9.208138	1.0	1.0	1.0	0.0	
4	1465.0	120.0	2.0	3.761200	8.518193	1.0	1.0	1.0	2.0	

Decision: Normalization of data using log.normal for selected numerical columns

Related EDA ID: EDA_OBS_6,EDA_OBS_7,EDA_OBS_8,EDA_OBS_9,EDA_OBS_11

Step:11: Categorical Variables: Handling Categorical Variable with less than 1% contribution, although this can be also achieve in PCA

In [516]:
```
categorical_features=[feature for feature in train_df.columns if train_df[feature].dtype=='O']
```

In [517]:
```
for item  in categorical_features:
    temp=train_df.groupby(item)['SalePrice'].count()/len(train_df)
    temp_df=temp[temp>0.01].index
    train_df[item]=np.where(train_df[item].isin(temp_df),train_df[item],'Rare_var')
```

In [518]:
```
train_df['SalePrice'].head()
```

Out[518]:
```
0    208500.0
1    181500.0
2    223500.0
3    140000.0
4    250000.0
Name: SalePrice, dtype: float64
```

In [519]:
```
train_df.head()
```

Out[519]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities
0	1.0	60.0	3.0	4.174387	9.041922	1.0	2.0	0.0	1.0	1.0
1	2.0	20.0	3.0	4.382027	9.169518	1.0	2.0	0.0	1.0	1.0
2	3.0	60.0	3.0	4.219508	9.328123	1.0	2.0	1.0	1.0	1.0
3	4.0	70.0	3.0	4.094345	9.164296	1.0	2.0	1.0	1.0	1.0
4	5.0	60.0	3.0	4.430817	9.565214	1.0	2.0	1.0	1.0	1.0

In [520]:
```
for item  in categorical_features:
    temp=test_df.groupby(item)['Id'].count()/len(test_df)
    temp_df=temp[temp>0.01].index
    test_df[item]=np.where(test_df[item].isin(temp_df),test_df[item],'Rare_var')
```

In [515]:
```
test_df.head()
```

Out[515]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilitie
0	1461	20	0	4.382027	9.360655	1	1	2	0	
1	1462	20	2	4.394449	9.565704	1	1	1	0	
2	1463	60	2	4.304065	9.534595	1	1	1	0	
3	1464	60	2	4.356709	9.208138	1	1	1	0	
4	1465	120	2	3.761200	8.518193	1	1	1	2	

Decision: Removed all the variables which are less important less than 1%

In [521]:
```
train_df.shape,test_df.shape
```

Out[521]: ((1460, 81), (1459, 80))

Step:11 : Outlier Removal

In [563]:
```
data=train_df.copy()
q = data['LotFrontage'].quantile(0.95)
data  = data[data['LotFrontage']<q]

q = data['LotArea'].quantile(0.99)
data  = data[data['LotArea']<q]

q = data['1stFlrSF'].quantile(0.99)
data  = data[data['1stFlrSF']<q]

q = data['GrLivArea'].quantile(0.99)
data  = data[data['GrLivArea']<q]

q = data['SalePrice'].quantile(0.99)
data  = data[data['SalePrice']<q]
train_df=data
```

In [564]:
```
data=test_df.copy()
q = data['LotFrontage'].quantile(0.95)
data  = data[data['LotFrontage']<q]

q = data['LotArea'].quantile(0.99)
data  = data[data['LotArea']<q]

q = data['1stFlrSF'].quantile(0.99)
data  = data[data['1stFlrSF']<q]

q = data['GrLivArea'].quantile(0.99)
data  = data[data['GrLivArea']<q]
test_df=data
```

Decision: Removed all the outliers by discarding 1% extreme values by looking at the bloxplot and checking the removal by hit and trial.

EDA_OBS_10

Step:12 : Feature Scaling

In [565]:
```
feature_scale=[item for item in train_df.columns if item not in ['Id','SalePrice']]

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

Out[565]:
```
MinMaxScaler()
```

In [566]:
```
scaler.transform(train_df[feature_scale])
```

Out[566]:
```
array([[0.23529412, 0.75      , 0.69791414, ..., 0.5       , 0.5       ,
        0.8       ],
       [0.        , 0.75      , 0.82617236, ..., 0.25      , 0.5       ,
        0.8       ],
       [0.23529412, 0.75      , 0.7257849 , ..., 0.5       , 0.5       ,
        0.8       ],
       ...,
       [0.29411765, 0.75      , 0.70734482, ..., 1.        , 0.5       ,
        0.8       ],
       [0.        , 0.75      , 0.7257849 , ..., 1.        , 0.5       ,
        0.8       ],
       [0.        , 0.75      , 0.78630711, ..., 0.5       , 0.5       ,
        0.8       ]])
```

In [567]:
```
train_df = pd.concat([train_df[['Id' ,'SalePrice']].reset_index(drop=True),
                    pd.DataFrame(scaler.transform(train_df[feature_scale]), columns=feature_scale)],
                    axis=1)
```

In [568]:
```
train_df.head()
```

Out[568]:

	Id	SalePrice	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContou
0	1.0	208500.0	0.235294	0.75	0.697914	0.623403	1.0	1.0	0.000000	0.33333
1	2.0	181500.0	0.000000	0.75	0.826172	0.665899	1.0	1.0	0.000000	0.33333
2	3.0	223500.0	0.235294	0.75	0.725785	0.718722	1.0	1.0	0.333333	0.33333
3	4.0	140000.0	0.294118	0.75	0.648472	0.664160	1.0	1.0	0.333333	0.33333
4	5.0	250000.0	0.235294	0.75	0.856310	0.797685	1.0	1.0	0.333333	0.33333

In [569]:
```
feature_scale=[item for item in test_df.columns if item not in ['Id']]

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

scaler.transform(train_df[feature_scale])

test_df = pd.concat([test_df[['Id']].reset_index(drop=True),
                    pd.DataFrame(scaler.transform(test_df[feature_scale]), columns=feature_scale)],
                    axis=1)
test_df.head()
```

Out[569]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utiliti
0	1461.0	0.000000	0.0	0.826172	0.767005	1.0	0.5	0.666667	0.000000	
1	1462.0	0.000000	0.4	0.833846	0.843069	1.0	0.5	0.333333	0.000000	
2	1463.0	0.235294	0.4	0.778016	0.831529	1.0	0.5	0.333333	0.000000	
3	1464.0	0.235294	0.4	0.810534	0.710427	1.0	0.5	0.333333	0.000000	
4	1465.0	0.588235	0.4	0.442690	0.454487	1.0	0.5	0.333333	0.666667	

Decision: Feature Scaling is done as part of data standarization by keeping the data in some range(0 to 1)¶

FEATURE ENGINEERING -- END

MODEL Training and Hyperparameter Tunning:

Linear Regression

KNN or k-Nearest Neighbors

Naive Bayes classifier

Decision Tree

Random Forrest

In [570]:
```
x_sampled = train_df.drop(['Id','SalePrice'],axis=1).iloc[:,:80]
y_sampled = train_df['SalePrice']
X_test  = test_df.drop('Id',axis=1).iloc[:,:]
x_sampled.shape, y_sampled.shape,X_test.shape
```

Out[570]: ((1324, 79), (1324,), (1340, 79))

In [572]:
```
decision_tree = DecisionTreeClassifier()
#decision_tree.fit(X_train, Y_train)
decision_tree.fit(x_sampled,y_sampled)
Y_pred = decision_tree.predict(X_test)
acc_decision_tree = round(decision_tree.score(x_sampled,y_sampled) * 100, 2)
acc_decision_tree
```

Out[572]: 100.0

In [573]:
```
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(x_sampled,y_sampled)
Y_pred = knn.predict(X_test)
acc_knn = round(knn.score(x_sampled,y_sampled) * 100, 2)
acc_knn
```

Out[573]: 29.98

In [574]:
```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(x_sampled,y_sampled)
Y_pred = random_forest.predict(X_test)
random_forest.score(x_sampled,y_sampled)
acc_random_forest = round(random_forest.score(x_sampled,y_sampled) * 100, 2)
acc_random_forest
```

Out[574]: 100.0

In [575]:
```
gaussian = GaussianNB()
gaussian.fit(x_sampled,y_sampled)
Y_pred = gaussian.predict(X_test)
acc_gaussian = round(gaussian.score(x_sampled,y_sampled) * 100, 2)
acc_gaussian
```

Out[575]: 72.05

In [576]:
```
def adj_r2(x,y):
    r2 = regression.score(x,y)
    n = x.shape[0]
    p = x.shape[1]
    adjusted_r2 = 1-(1-r2)*(n-1)/(n-p-1)
    return adjusted_r2

regression = LinearRegression()
regression.fit(X_train,y_train)
reg_score = round(regression.score(X_train,y_train)*100,2)
adj_r2 = round(adj_r2(X_train,y_train)*100,2)
reg_score,adj_r2
```

Out[576]: (90.3, 89.68)

In [582]:
```
# Lasso Regularization
# LassoCV will return best alpha and coefficients after performing 10 cross validations
lasscv = LassoCV(alphas = None,cv =10, max_iter = 100000, normalize = True)
lasscv.fit(X_train, y_train)

# best alpha parameter
alpha = lasscv.alpha_
alpha

#now that we have best parameter, let's use Lasso regression and see how well our data has fitted before

lasso_reg = Lasso(alpha)
lasso_reg.fit(X_train, y_train)
```

In [587]:
```
lasso=lasso_reg.score(X_train, y_train)*100
lasso
```

Out[587]: 90.31929514005681

In [588]:
```
# Using Ridge regression model
# RidgeCV will return best alpha and coefficients after performing 10 cross validations.
# We will pass an array of random numbers for ridgeCV to select best alpha from them

alphas = np.random.uniform(low=0, high=10, size=(50,))
ridgecv = RidgeCV(alphas = alphas,cv=10,normalize = True)
ridgecv.fit(X_train, y_train)

ridgecv.alpha_

ridge_model = Ridge(alpha=ridgecv.alpha_)
ridge_model.fit(X_train, y_train)

ridge=ridge_model.score(X_train, y_train)*100
ridge
```

Out[588]: 90.36113152808686

In [590]:
```
models = pd.DataFrame({
    'Model': ['Linear Regression', 'Lasso','Ridge',
              'KNN', 'Random Forest', 'Naive Bayes','Decision Tree'],
    'Score': [adj_r2, lasso,ridge,
              acc_knn, acc_random_forest, acc_gaussian, acc_decision_tree]})
models.sort_values(by='Score', ascending=False)
```

Out[590]:

	Model	Score
4	Random Forest	100.000000
6	Decision Tree	100.000000
2	Ridge	90.361132
1	Lasso	90.319295
0	Linear Regression	89.680000
5	Naive Bayes	72.050000
3	KNN	29.980000

MODEL Training and Hyperparameter Tunning -- end

In [437]:
```
%%javascript
require("notebook/js/notebook").Notebook.prototype.scroll_to_bottom = function () {}
```

In [ ]:
```
```