In [1]:
```
## Data Analysis Phase
## MAin aim is to understand more about the data

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
## Display all the columns of the dataframe

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

In [5]:
```
dataset=pd.read_csv(r'C:\Users\jerusha josine\Downloads\houseprices\train.csv')

## print shape of dataset with rows and columns
print(dataset.shape)
```

```
(1460, 81)
```

In [6]:
```
## print the top5 records
dataset.head()
```

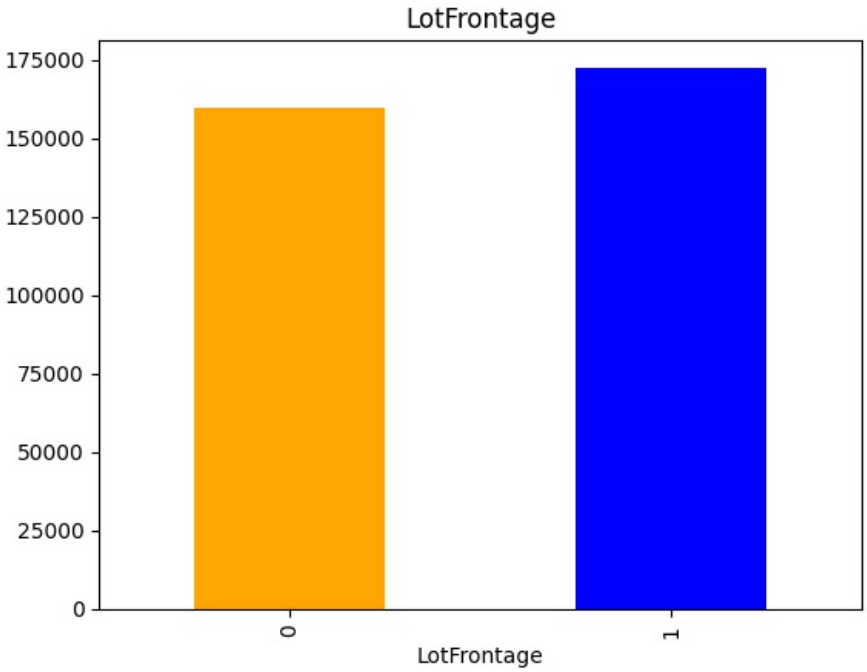
Out[6]:

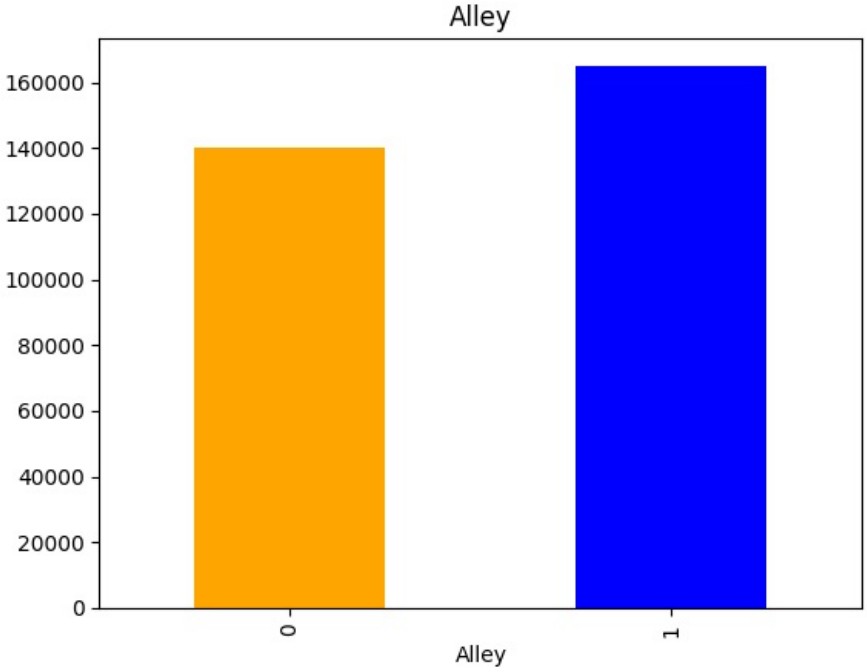
	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	C
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	FR2	Gtl	Veenker	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	CollgCr	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	Corner	Gtl	Crawfor	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	FR2	Gtl	NoRidge	

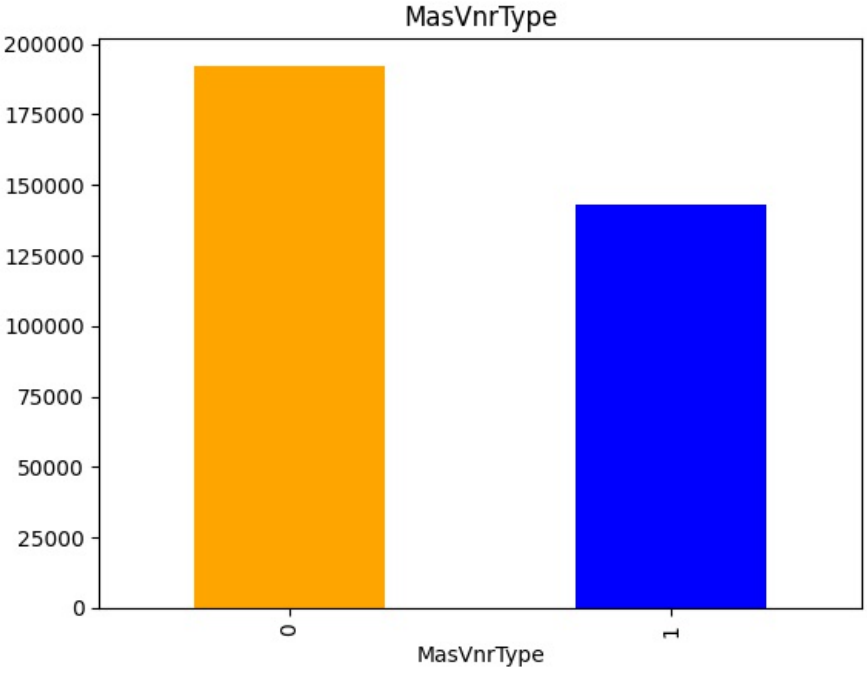
In [7]:
```
## Here we will check the percentage of nan values present in each feature
## 1 -step make the list of features which has missing values
features_with_na=[features for features in dataset.columns if dataset[features].isnull().sum()>1]
## 2- step print the feature name and the percentage of missing values

for feature in features_with_na:
    print(feature, np.round(dataset[feature].isnull().mean(), 4),  ' % missing values')
```

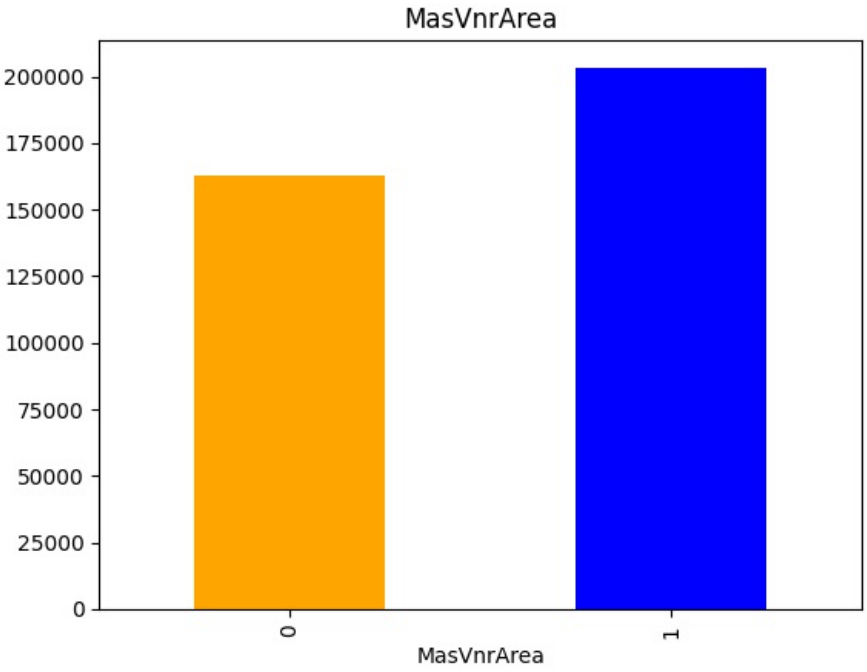
```
LotFrontage 0.1774  % missing values
Alley 0.9377  % missing values
MasVnrType 0.5973  % missing values
MasVnrArea 0.0055  % missing values
BsmtQual 0.0253  % missing values
BsmtCond 0.0253  % missing values
BsmtExposure 0.026  % missing values
BsmtFinType1 0.0253  % missing values
BsmtFinType2 0.026  % missing values
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
```

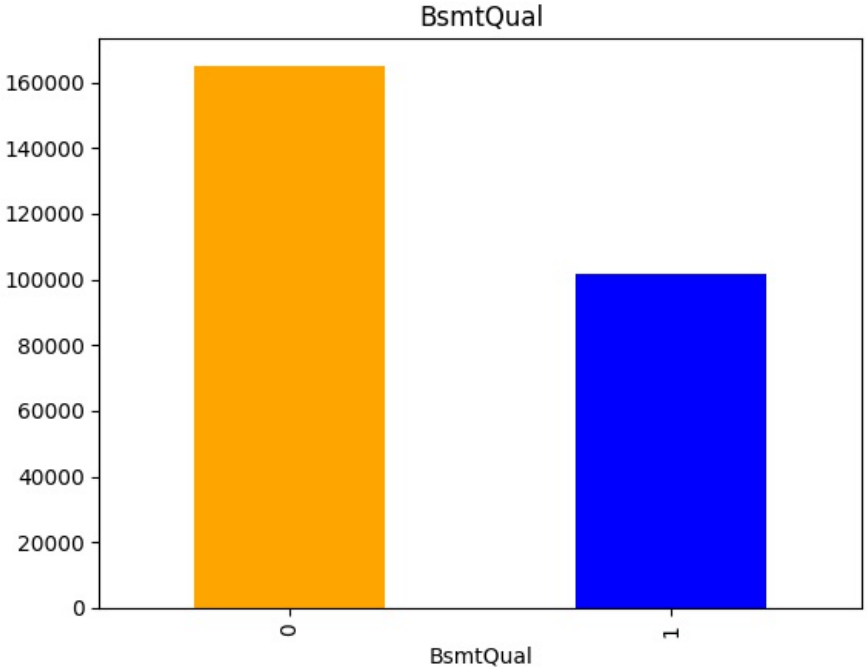
In [9]:
```
for feature in features_with_na:
    data = dataset.copy()

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

    # let's calculate the mean SalePrice where the information is missing or present
    data.groupby(feature)['SalePrice'].median().plot.bar(color=['orange','blue'])
    plt.title(feature)
    plt.show()
```

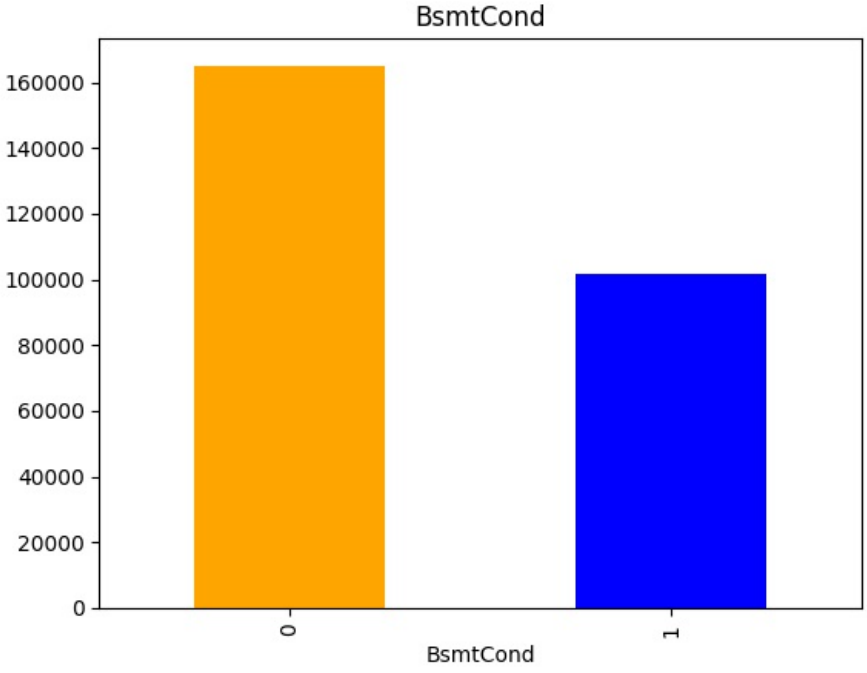

LotFrontage
175000
150000
125000
100000
75000
50000
25000
0
0
1
LotFrontage

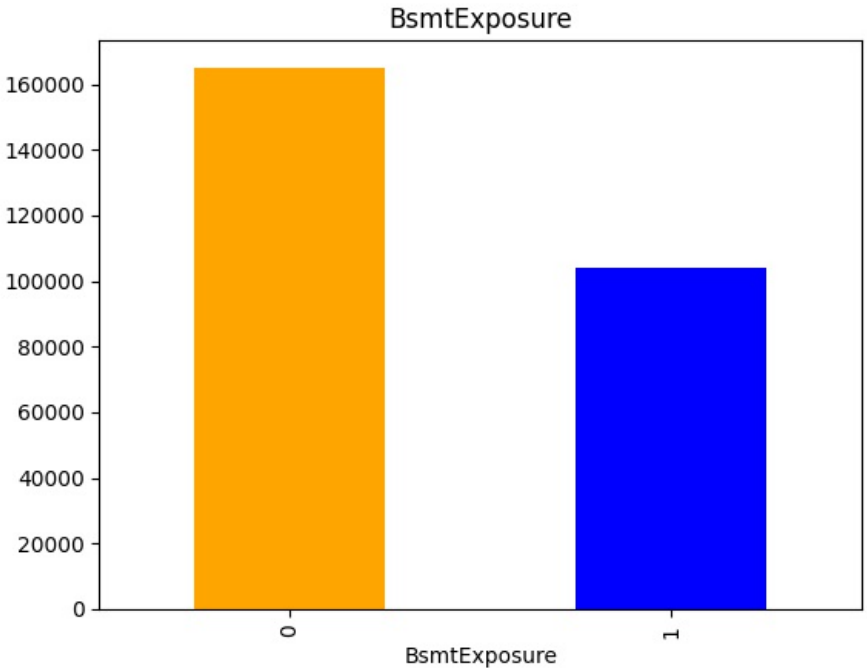

Alley
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
Alley

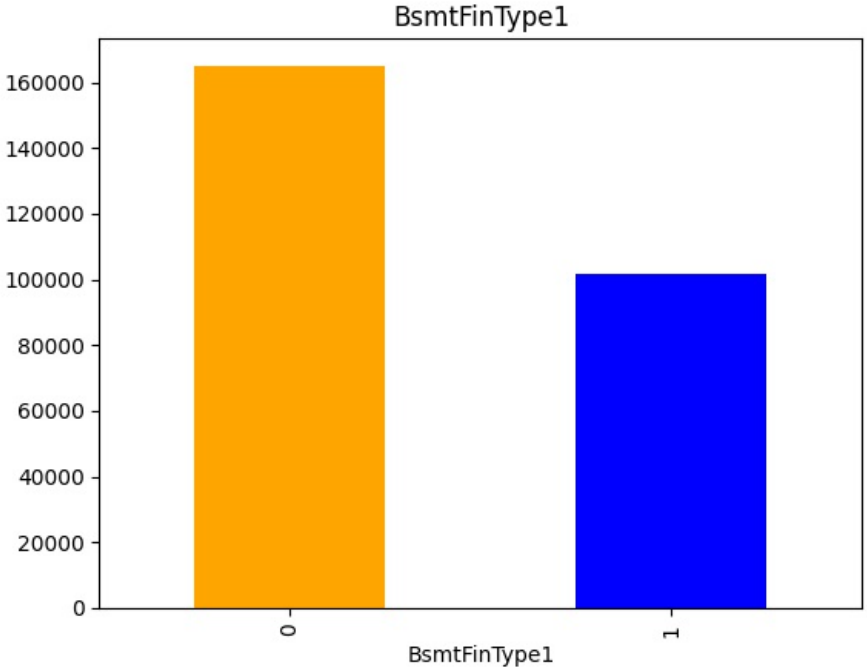

MasVnrType
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
MasVnrType

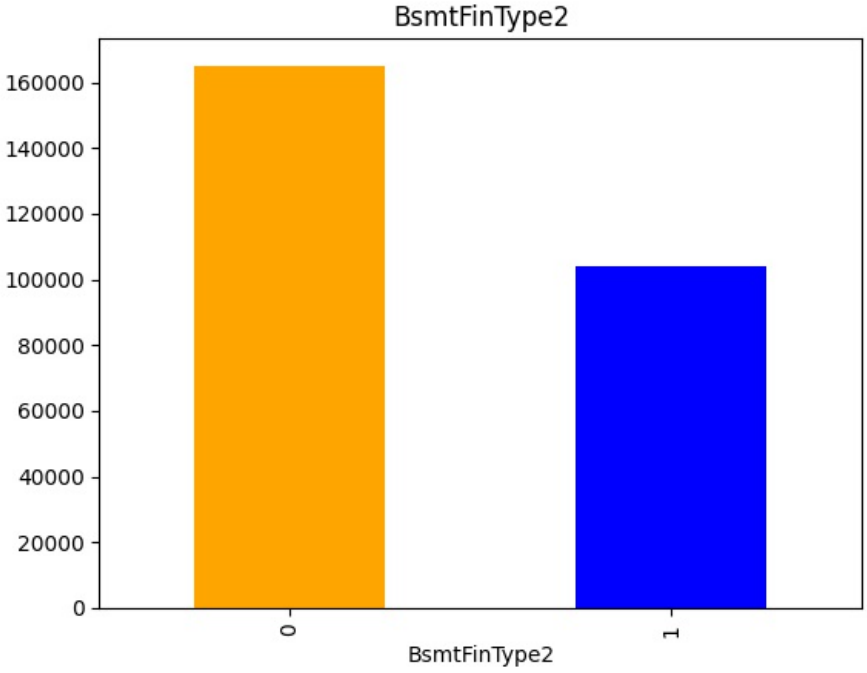

MasVnrArea
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
MasVnrArea

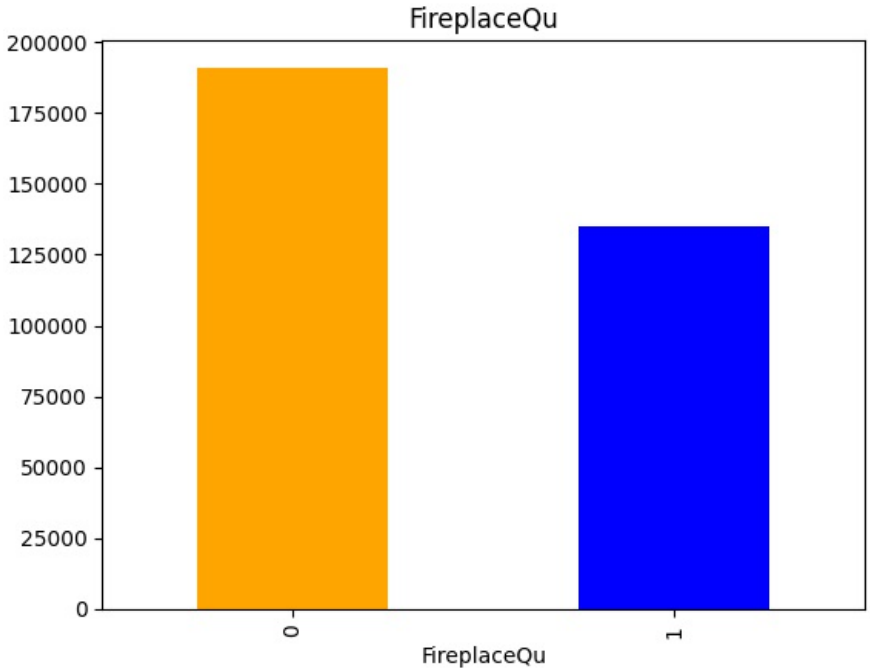

BsmtQual
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtQual

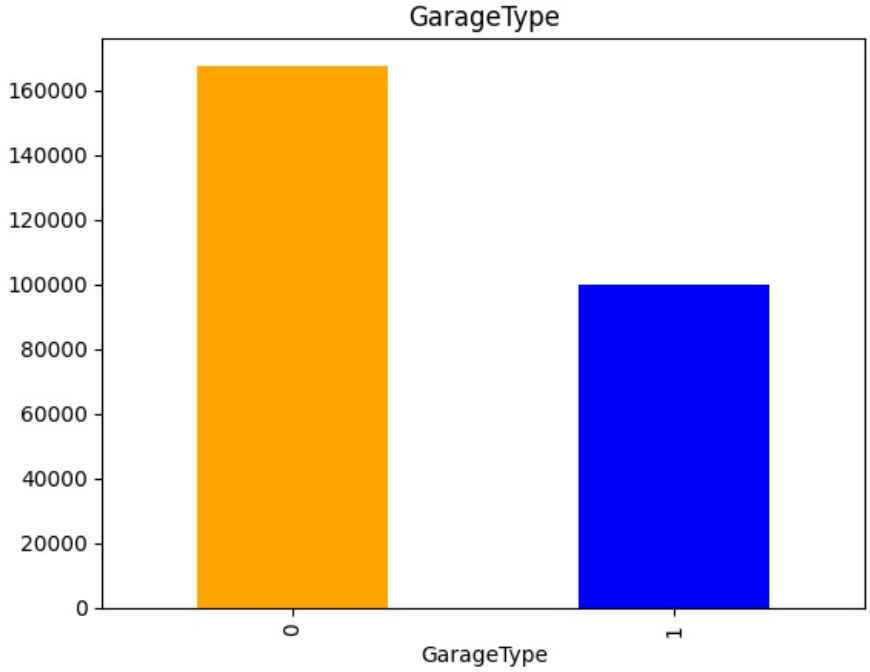

BsmtCond
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtCond

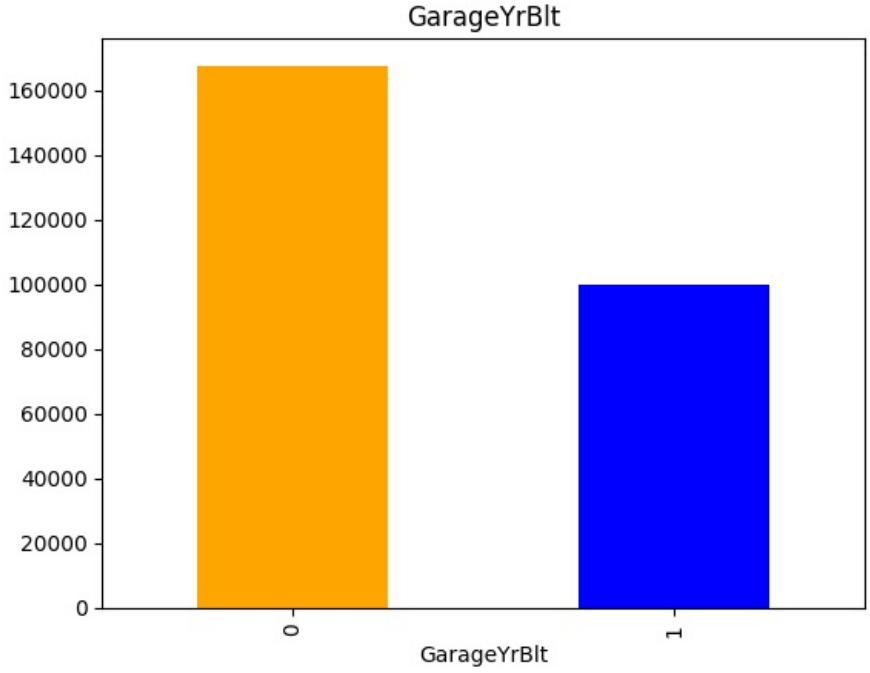

BsmtExposure
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtExposure

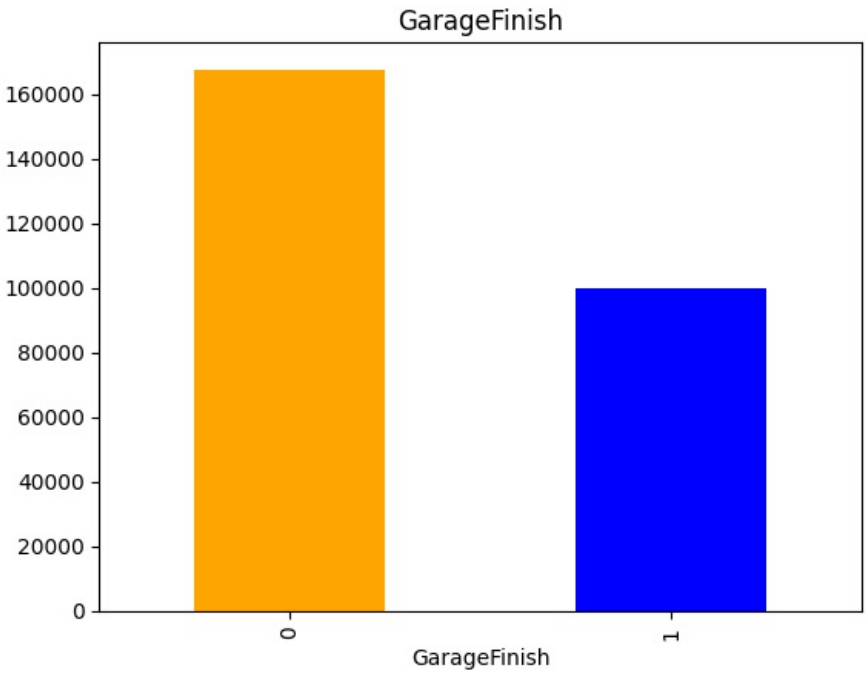

BsmtFinType1
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtFinType1

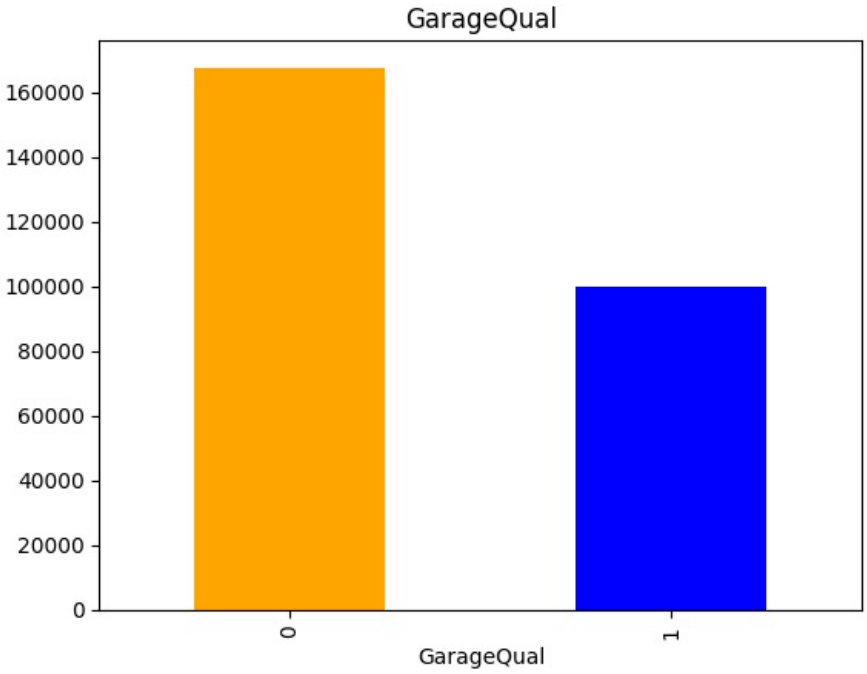

BsmtFinType2
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
BsmtFinType2

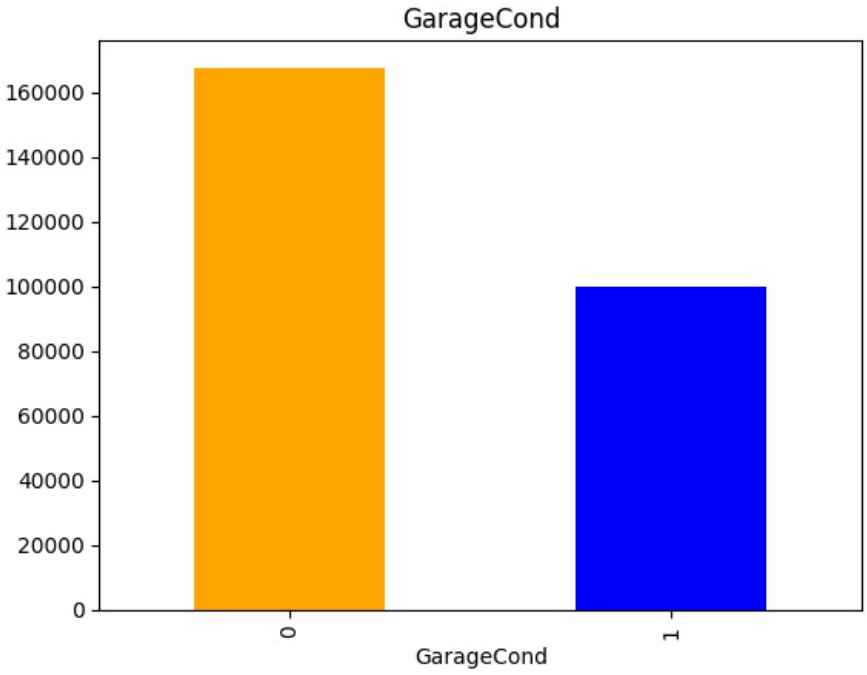

FireplaceQu
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
FireplaceQu

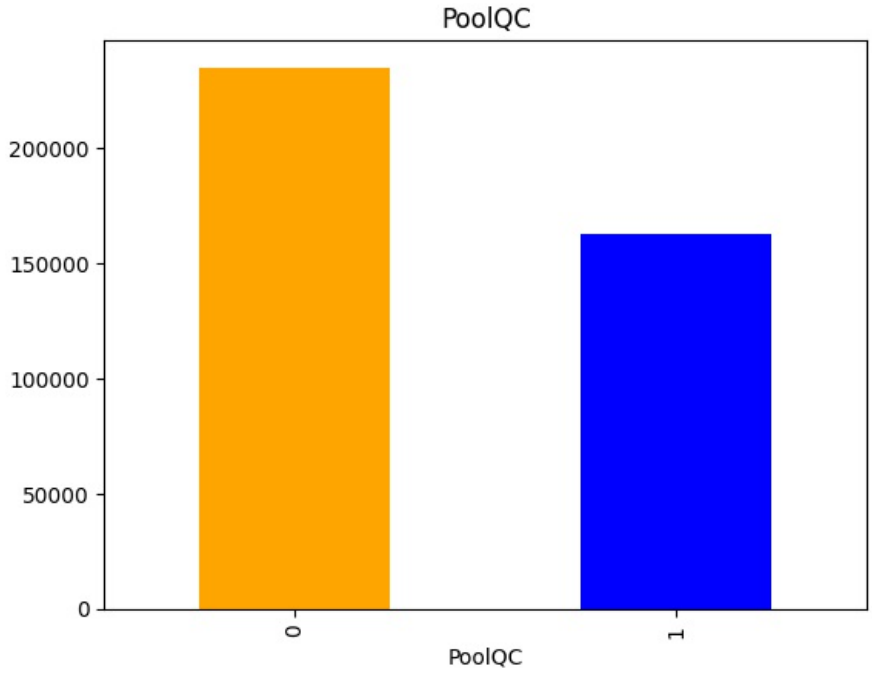

GarageType
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
GarageType

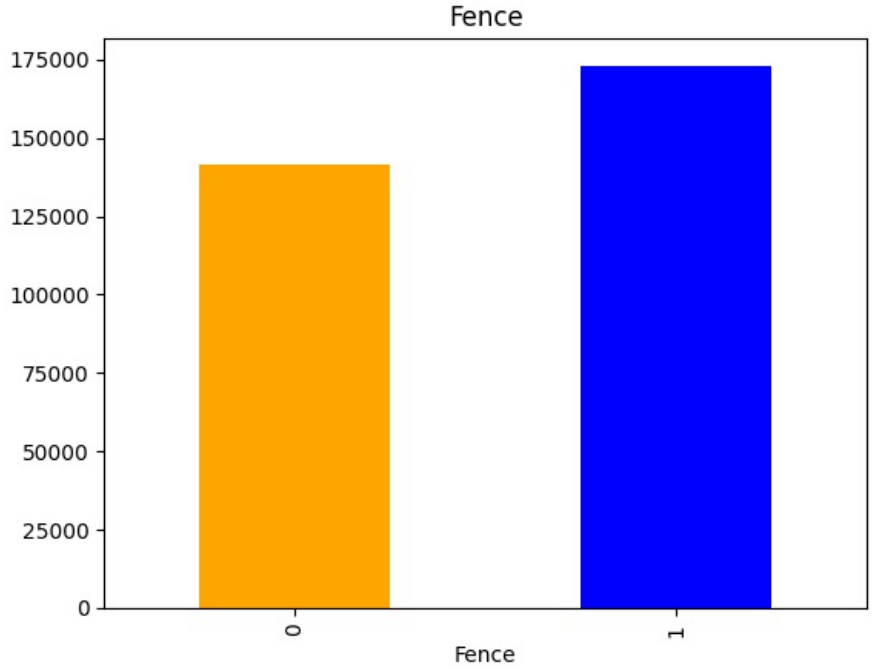

GarageYrBlt
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
GarageYrBlt

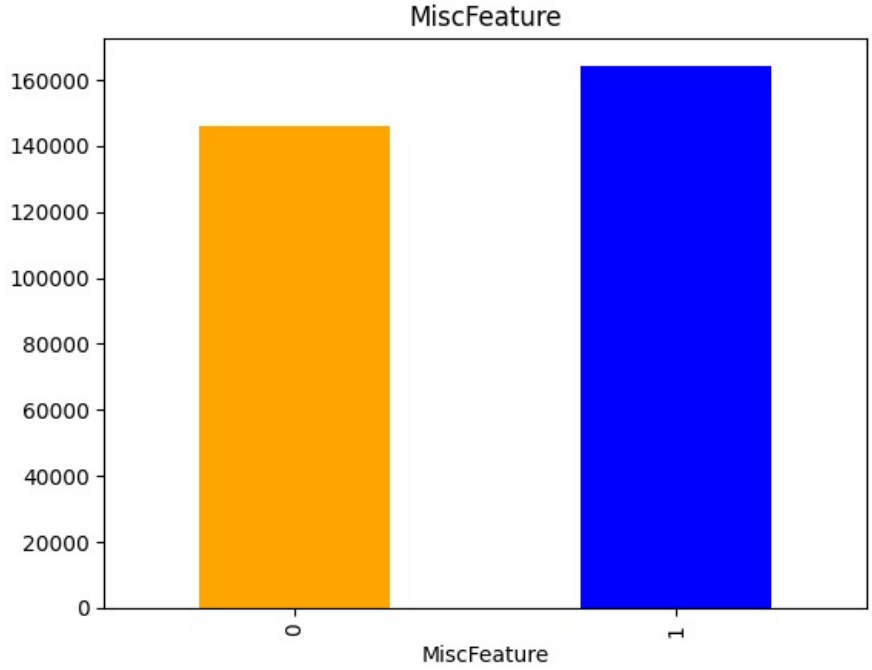

GarageFinish
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
GarageFinish


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







In [10]:
```
print("Id of Houses {}".format(len(dataset.Id)))
```

```
Id of Houses 1460
```

In [11]:
```
# list of numerical variables
numerical_features = [feature for feature in dataset.columns if dataset[feature].dtypes != 'O']

print('Number of numerical variables: ', len(numerical_features))

# visualise the numerical variables
dataset[numerical_features].head()
```

```
Number of numerical variables:  38
```

Out[11]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	Bsmt
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	

In [12]:
```
# list of variables that contain year information
year_feature = [feature for feature in numerical_features if 'Yr' in feature or 'Year' in feature]

year_feature
```

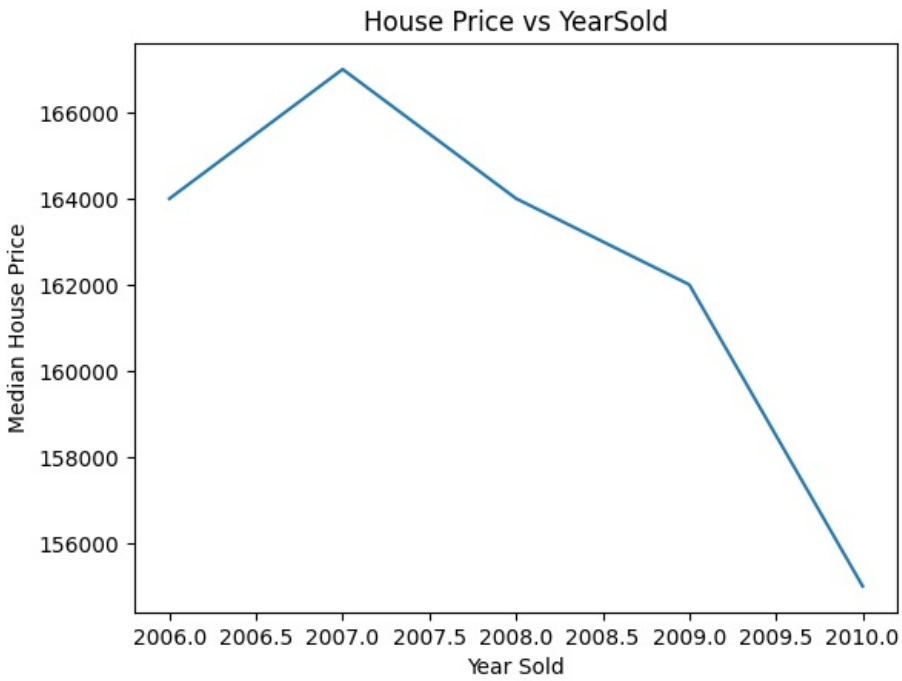
Out[12]:
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

In [13]:
```
# let's explore the content of these year variables
for feature in year_feature:
    print(feature, dataset[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 [14]:
```
## Lets analyze the Temporal Datetime Variables
## We will check whether there is a relation between year the house is sold and the sales price

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

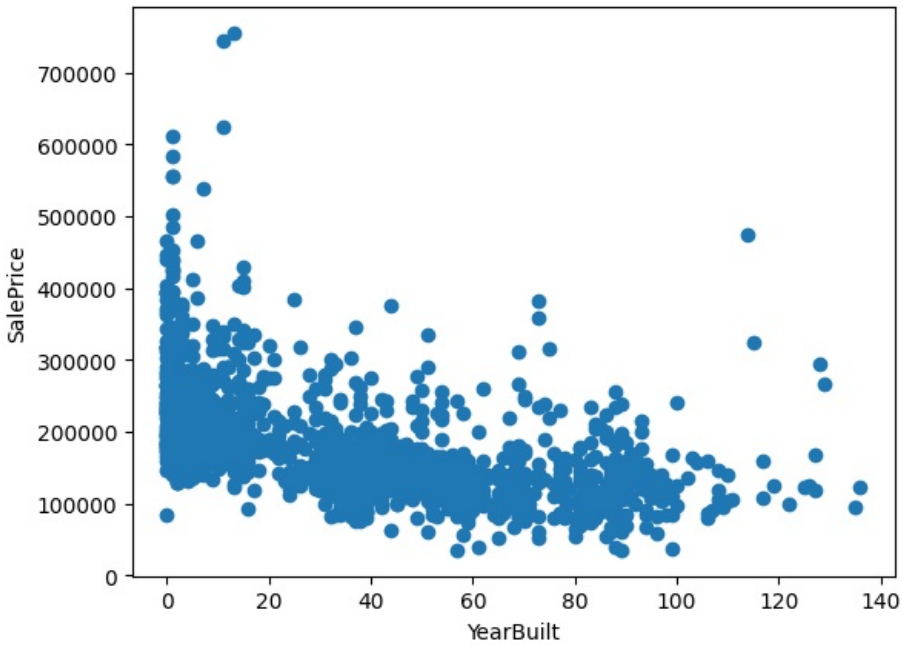
Out[14]:
```
Text(0.5, 1.0, 'House Price vs YearSold')
```

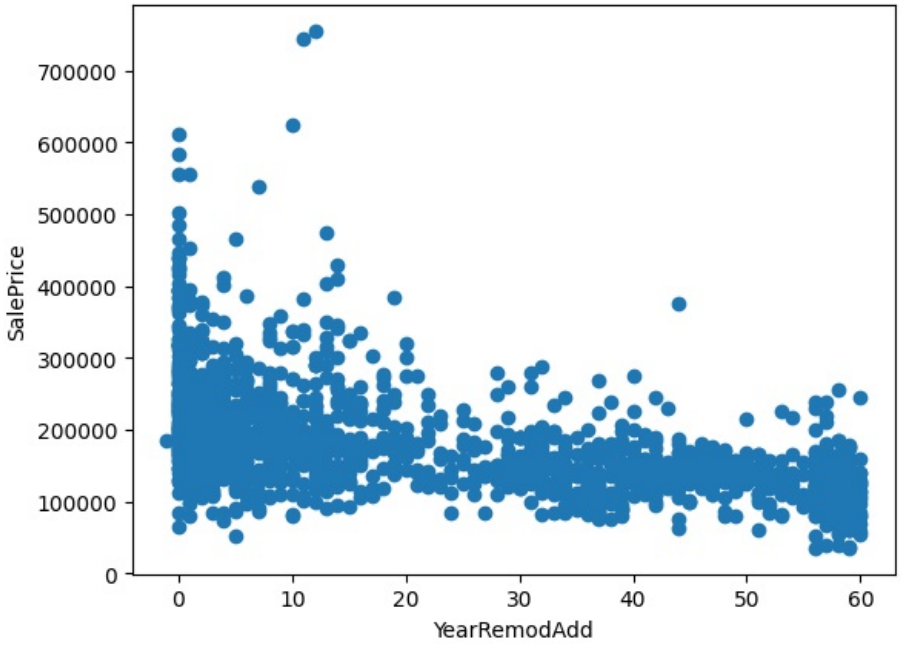


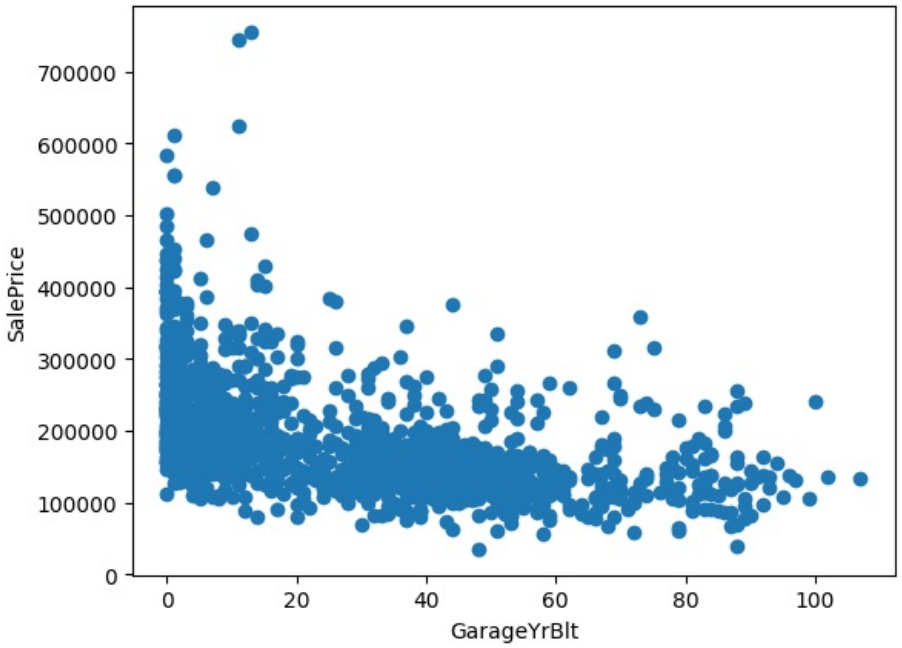
In [15]:
```
year_feature
```

Out[15]:
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

In [16]:
```
## Here we will compare the difference between All years feature with SalePrice

for feature in year_feature:
    if feature!='YrSold':
        data=dataset.copy()
        ## We will capture the difference between year variable and year the house was sold for
        data[feature]=data['YrSold']-data[feature]

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







In [17]:
```
## Numerical variables are usually of 2 type
## 1. Continous variable and Discrete Variables

discrete_feature=[feature for feature in numerical_features if len(dataset[feature].unique())<25 and feature no
print("Discrete Variables Count: {}".format(len(discrete_feature)))
```

```
Discrete Variables Count: 17
```

In [18]:
```
discrete_feature
```

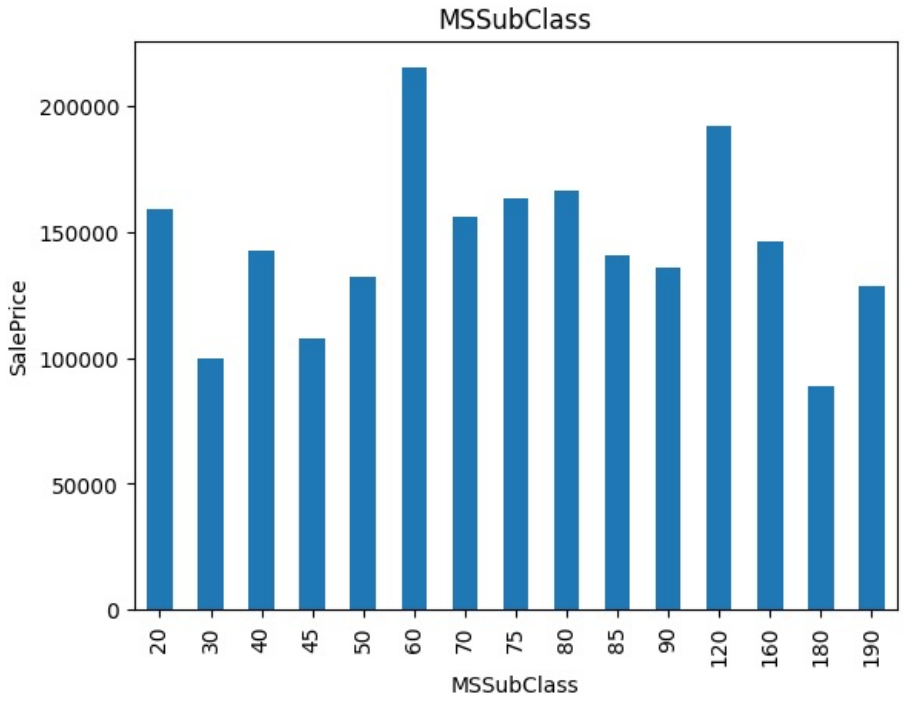
Out[18]:
```
['MSSubClass',
 'OverallQual',
 'OverallCond',
 'LowQualFinSF',
 'BsmtFullBath',
 'BsmtHalfBath',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'KitchenAbvGr',
 'TotRmsAbvGrd',
 'Fireplaces',
 'GarageCars',
 '3SsnPorch',
 'PoolArea',
 'MiscVal',
 'MoSold']
```

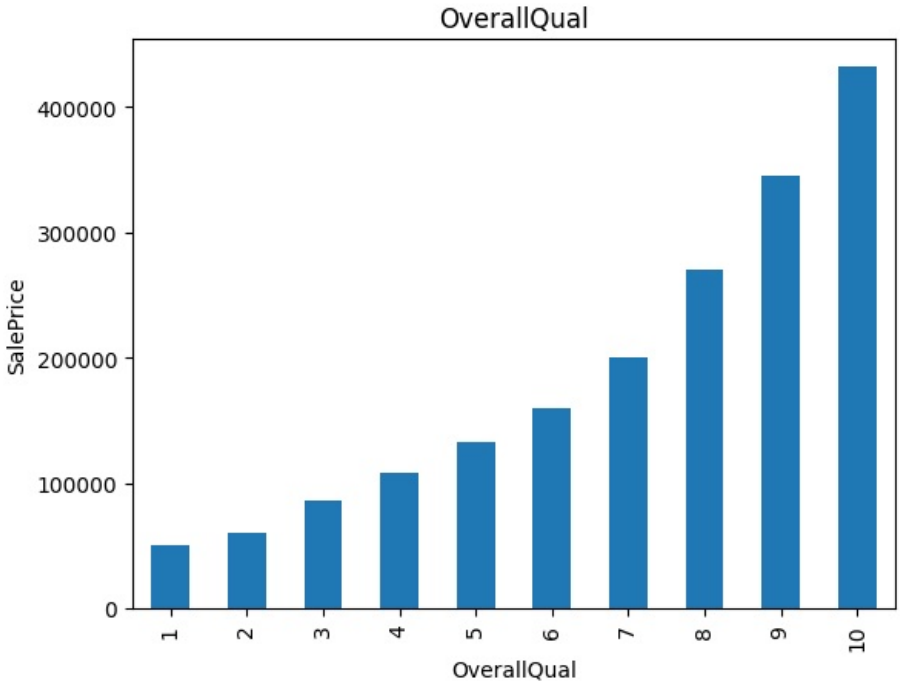
In [19]:
```
dataset[discrete_feature].head()
```

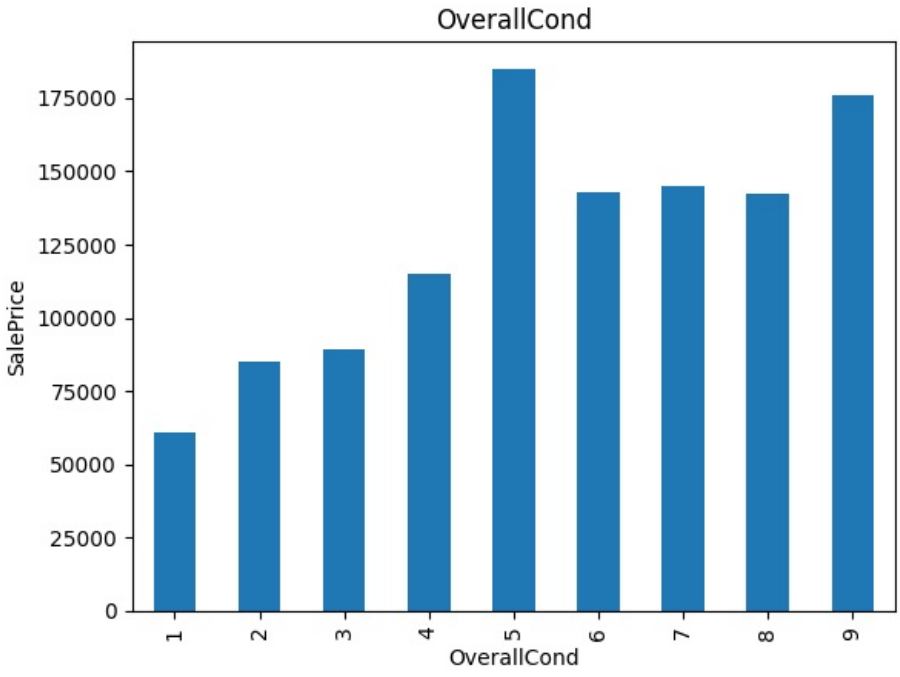
Out[19]:

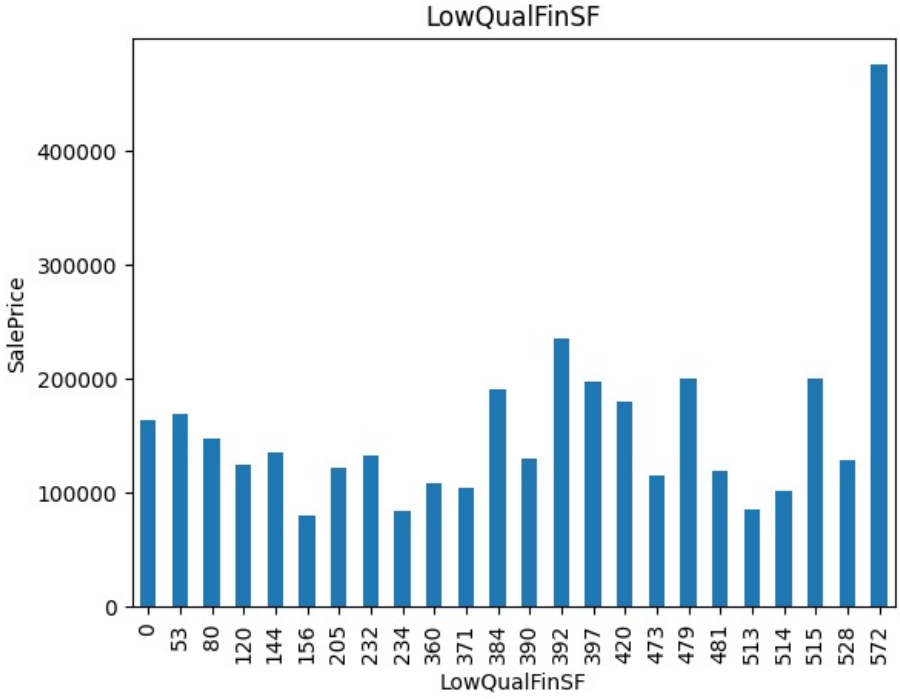
	MSSubClass	OverallQual	OverallCond	LowQualFinSF	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	To
0	60	7	5	0	1	0	2	1	3	1	
1	20	6	8	0	0	1	2	0	3	1	
2	60	7	5	0	1	0	2	1	3	1	
3	70	7	5	0	1	0	1	0	3	1	
4	60	8	5	0	1	0	2	1	4	1	

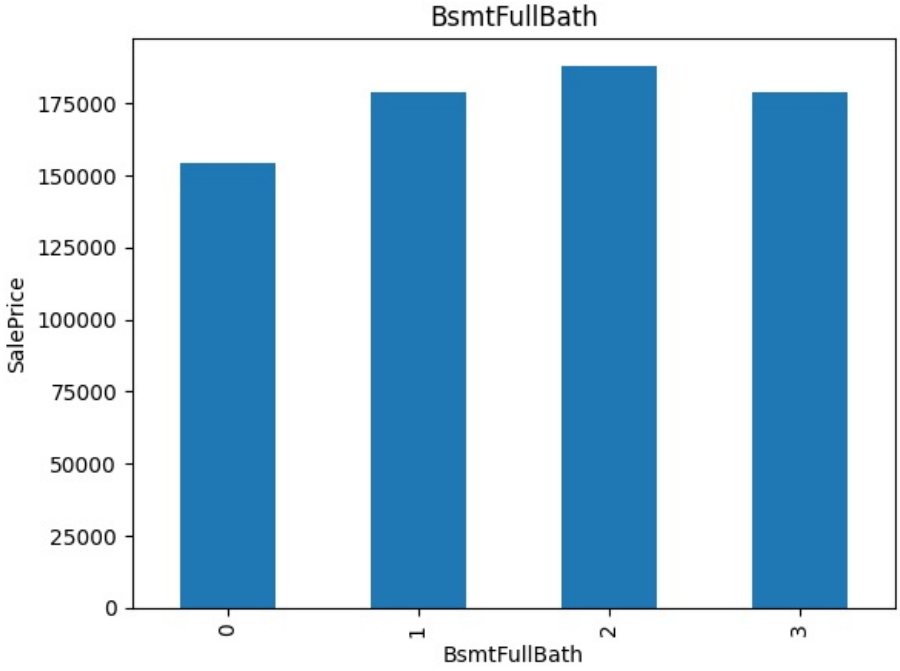
In [22]:
```
## Lets Find the realtionship between them and Sale PRice

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

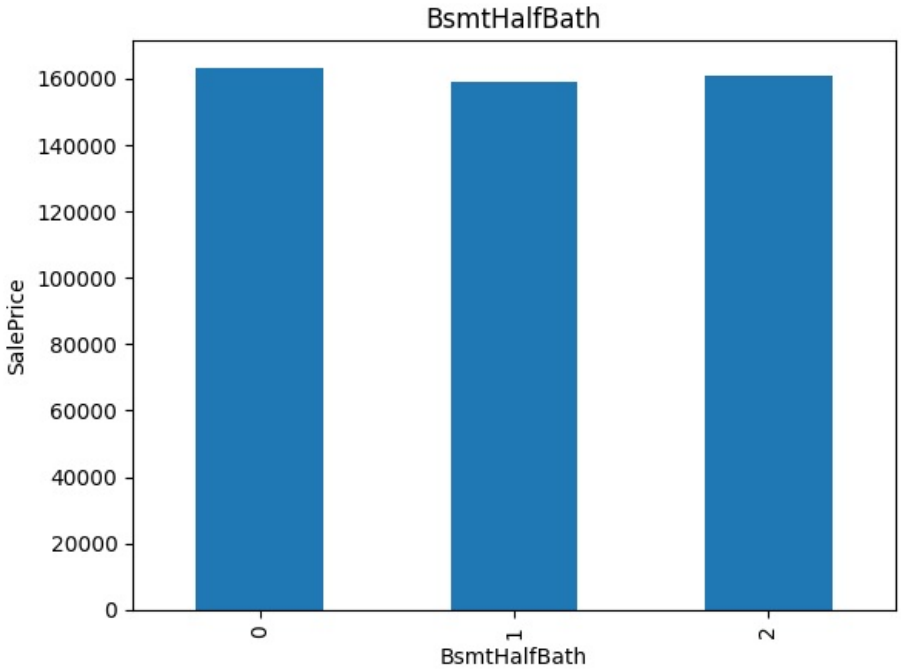


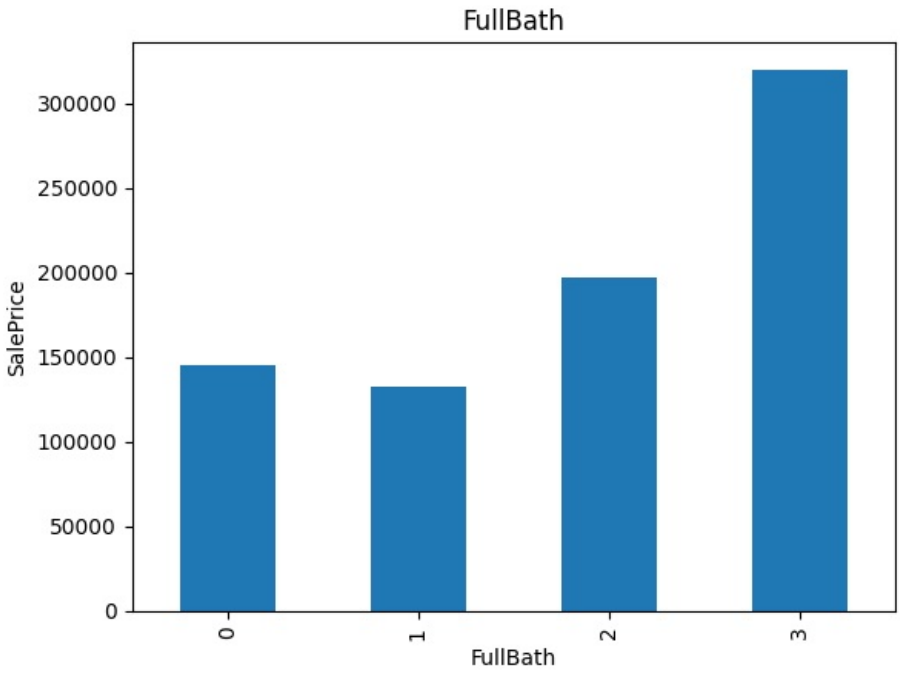

OverallQual
400000
300000
200000
100000
0
SalePrice
1
2
3
4
5
6
7
8
9
10
OverallQual

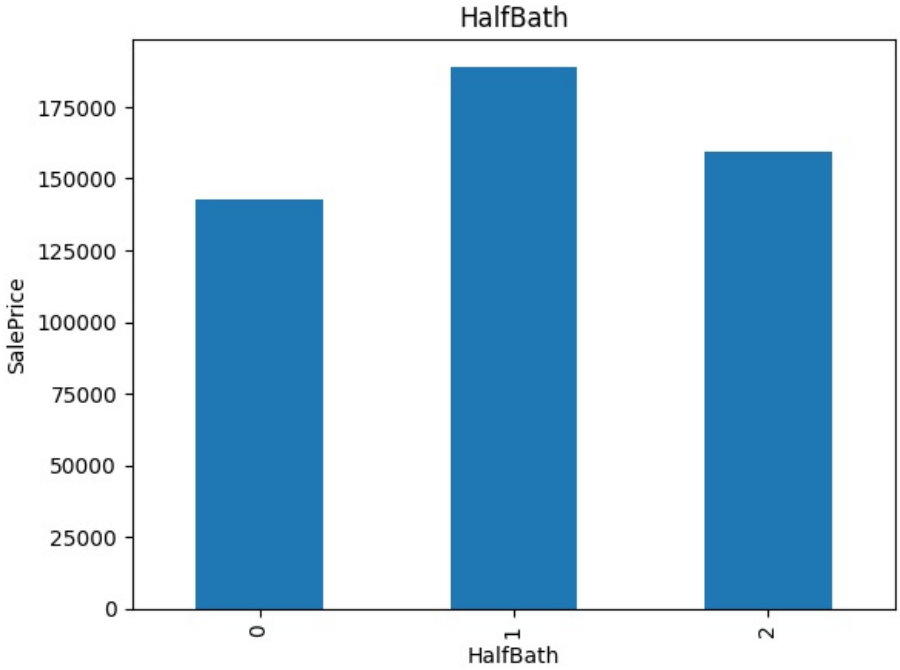

OverallCond
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
1
2
3
4
5
6
7
8
9
OverallCond

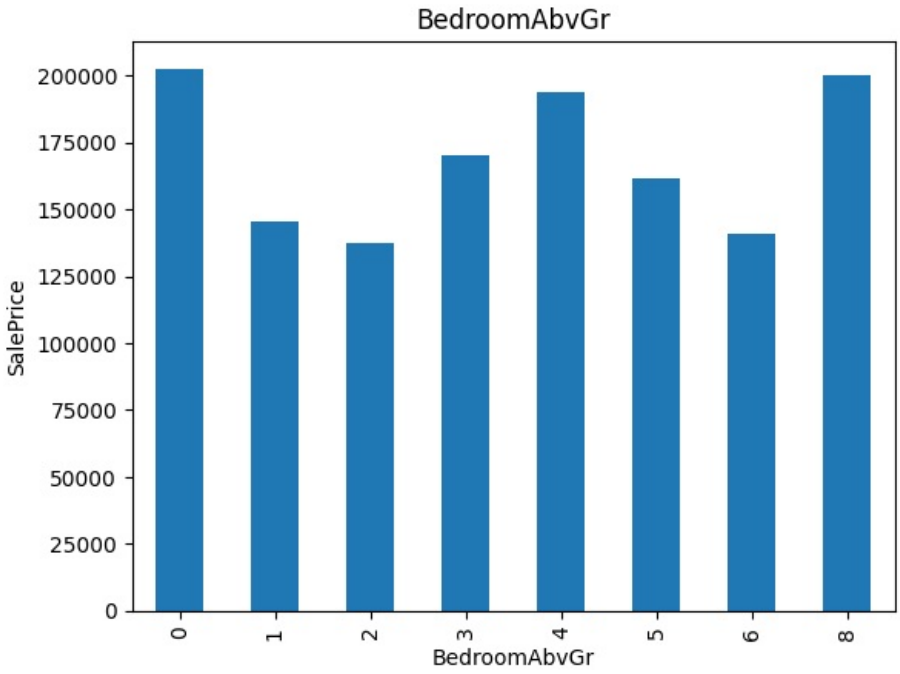

LowQualFinSF
SalePrice
400000
300000
200000
100000
0
0
53
80
120
144
156
205
232
234
360
371
384
390
392
397
420
473
479
481
513
514
515
528
572
LowQualFinSF

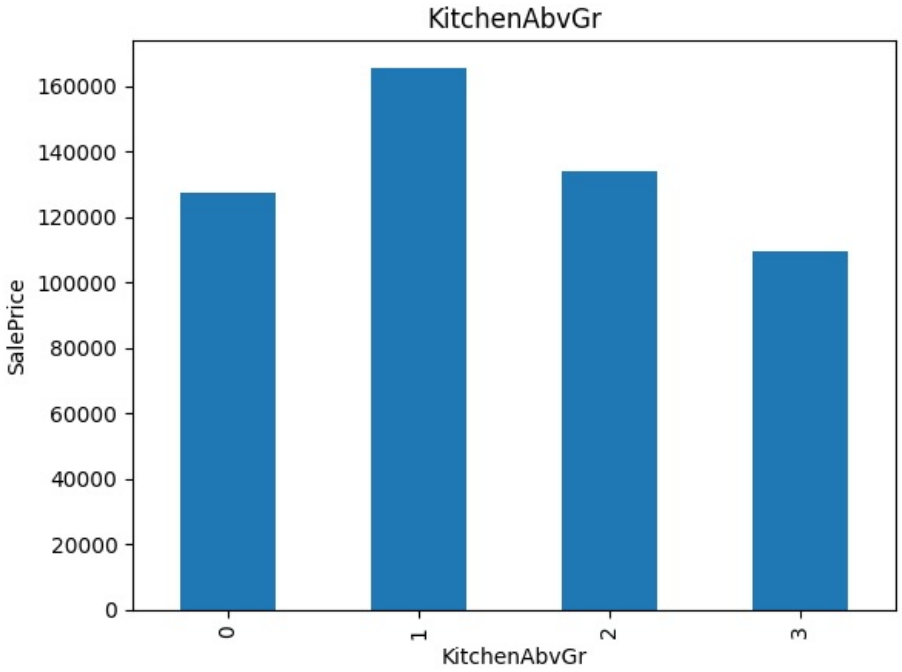

BsmtFullBath
SalePrice
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
BsmtFullBath

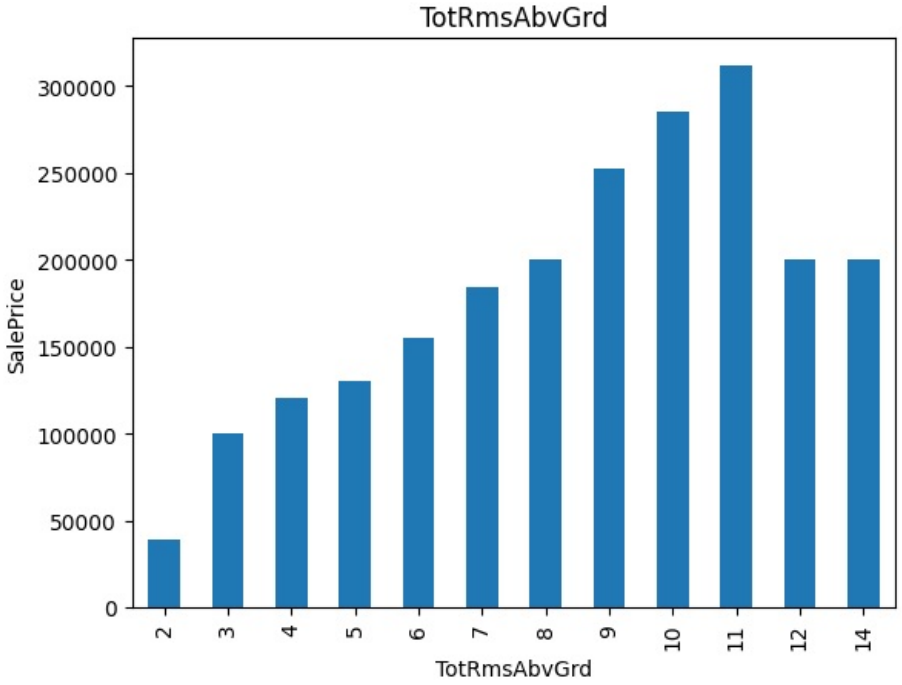

BsmtHalfBath
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
0
1
2
BsmtHalfBath

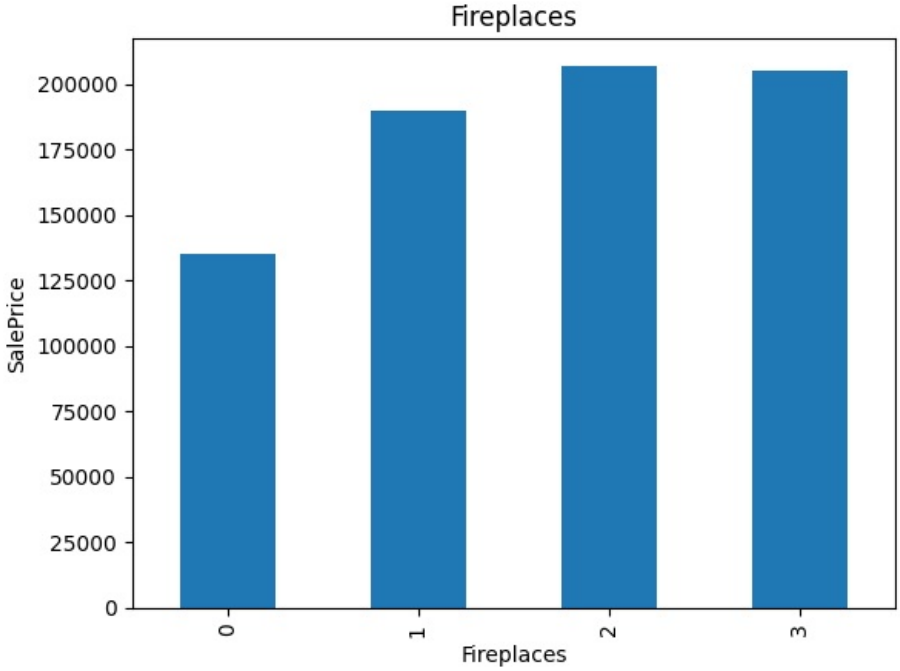

FullBath
300000
250000
200000
150000
100000
50000
0
SalePrice
0
1
2
3
FullBath

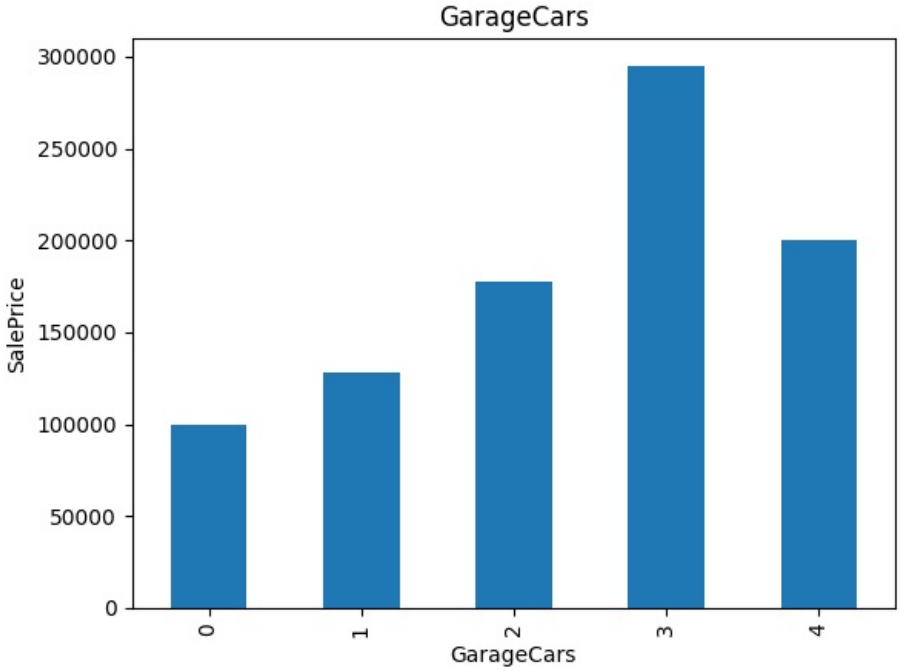

HalfBath
SalePrice
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
HalfBath

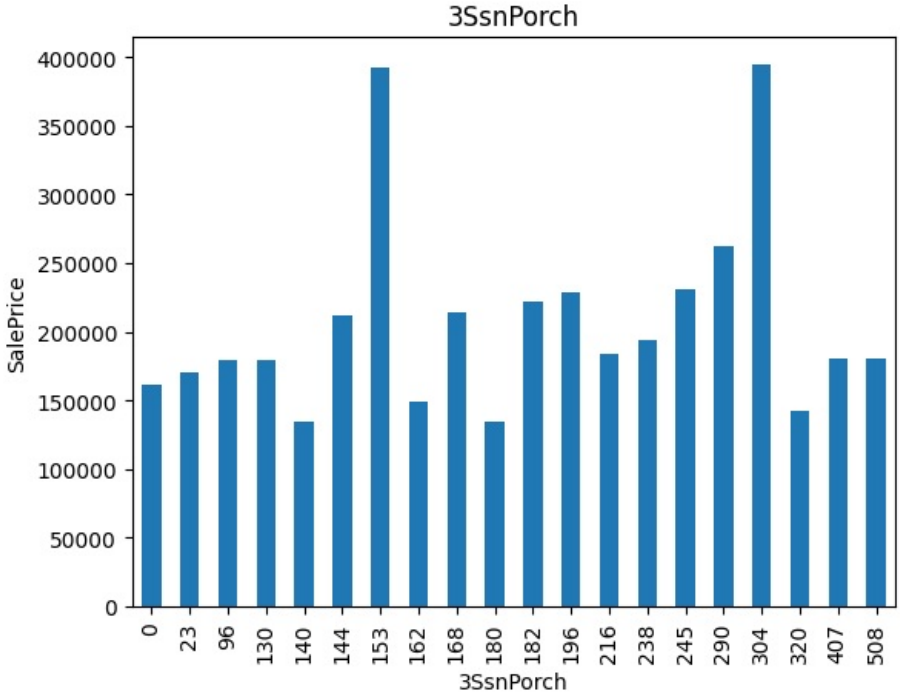

BedroomAbvGr
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
4
5
6
8
BedroomAbvGr

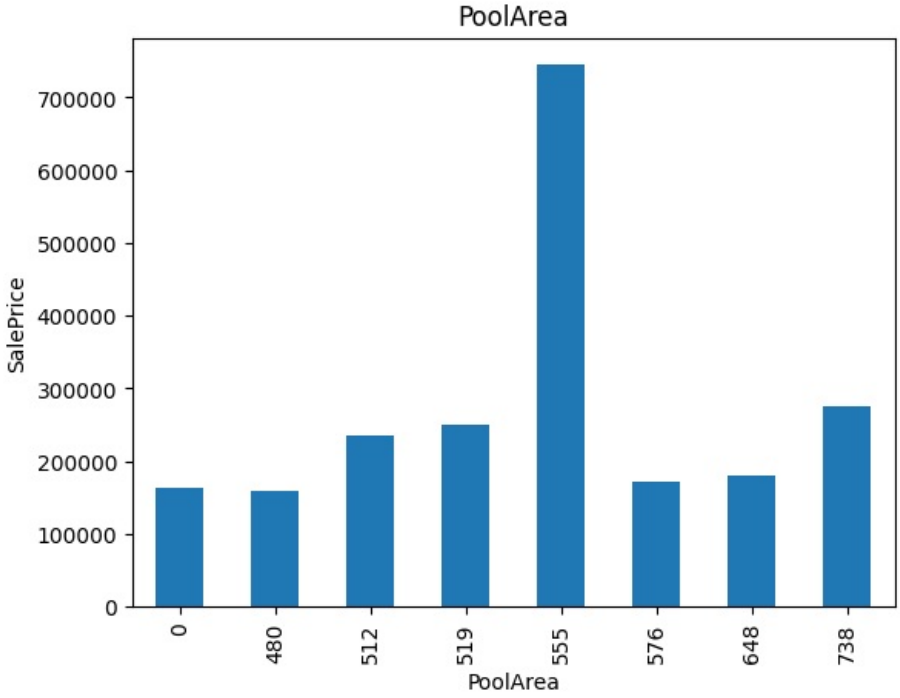

KitchenAbvGr
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
2
3
KitchenAbvGr

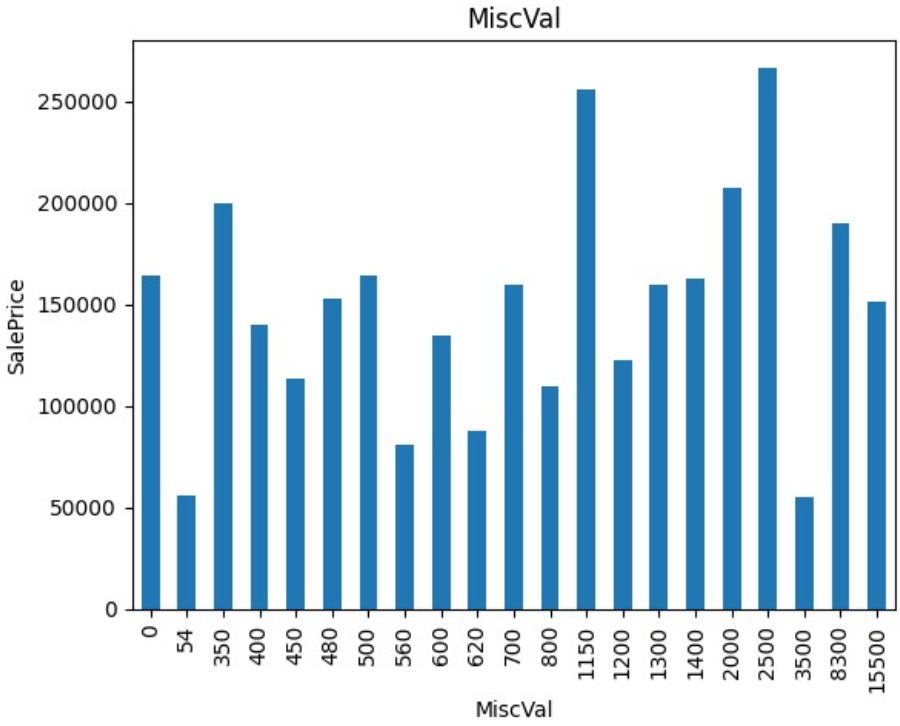

TotRmsAbvGrd
SalePrice
300000
250000
200000
150000
100000
50000
0
2
3
4
5
6
7
8
9
10
11
12
14
TotRmsAbvGrd

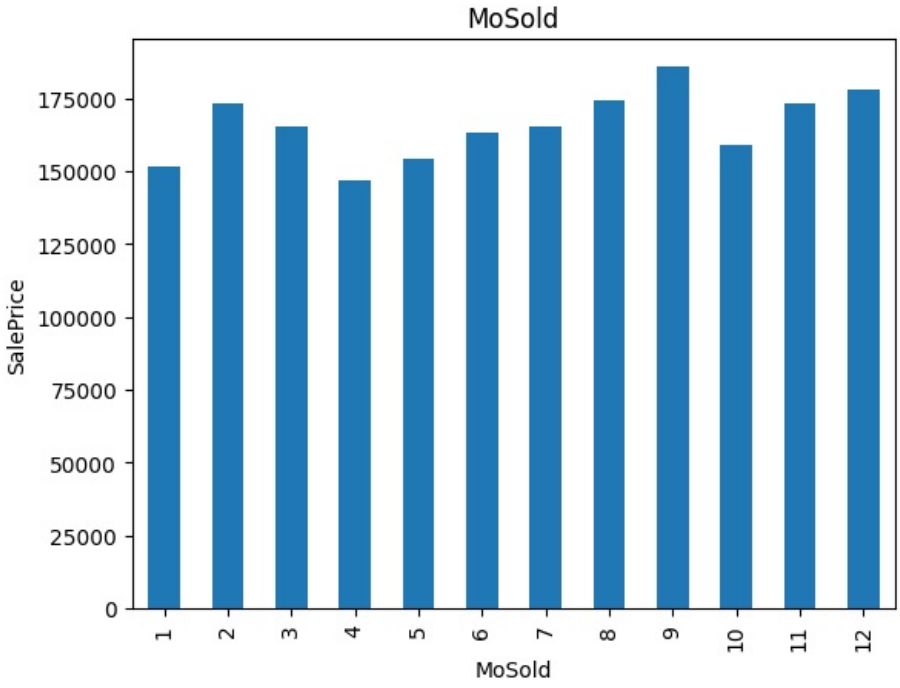

Fireplaces
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
Fireplaces


GarageCars
SalePrice
300000
250000
200000
150000
100000
50000
0
0
1
2
3
4
GarageCars


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


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





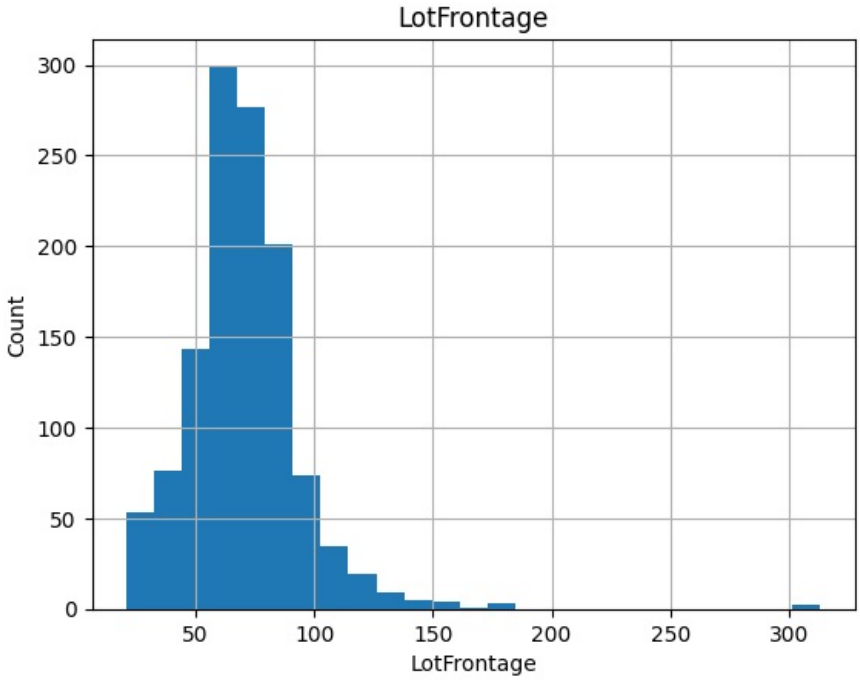
In [23]:
```
## There is a relationship between variable number and SalePrice
```

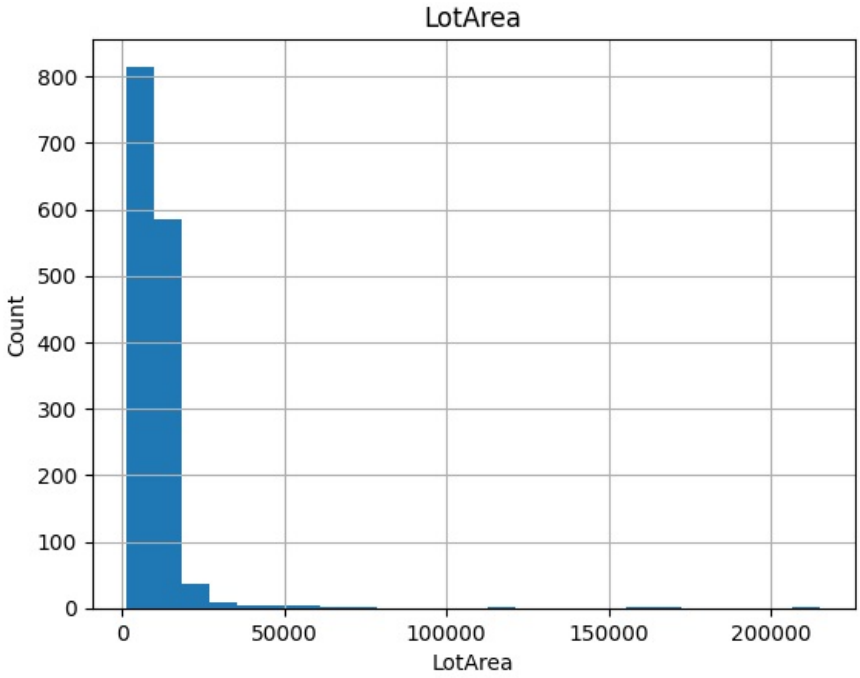
In [24]:
```
continuous_feature=[feature for feature in numerical_features if feature not in discrete_feature+year_feature+[
print("Continuous feature Count {}".format(len(continuous_feature)))
```

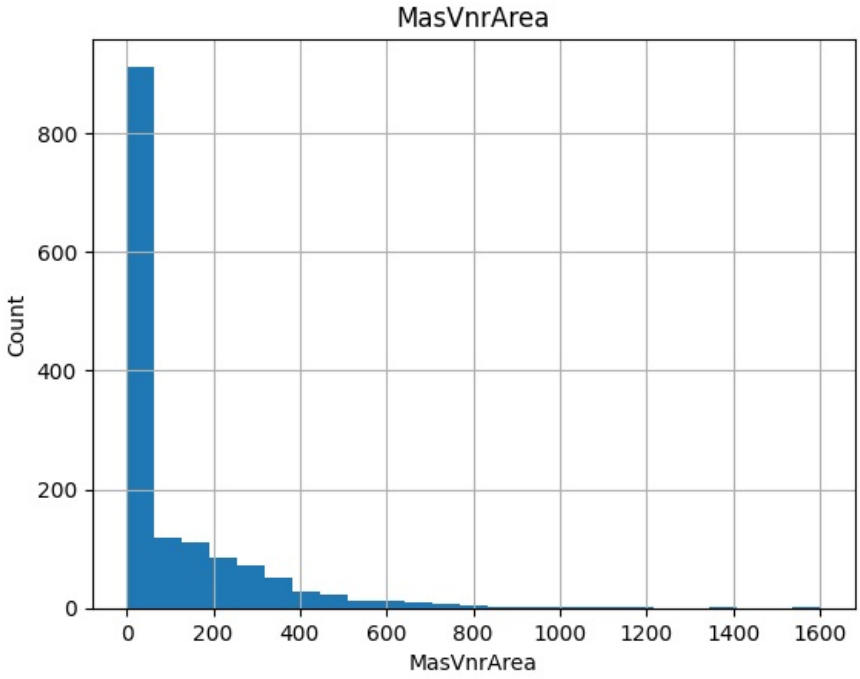
```
Continuous feature Count 16
```

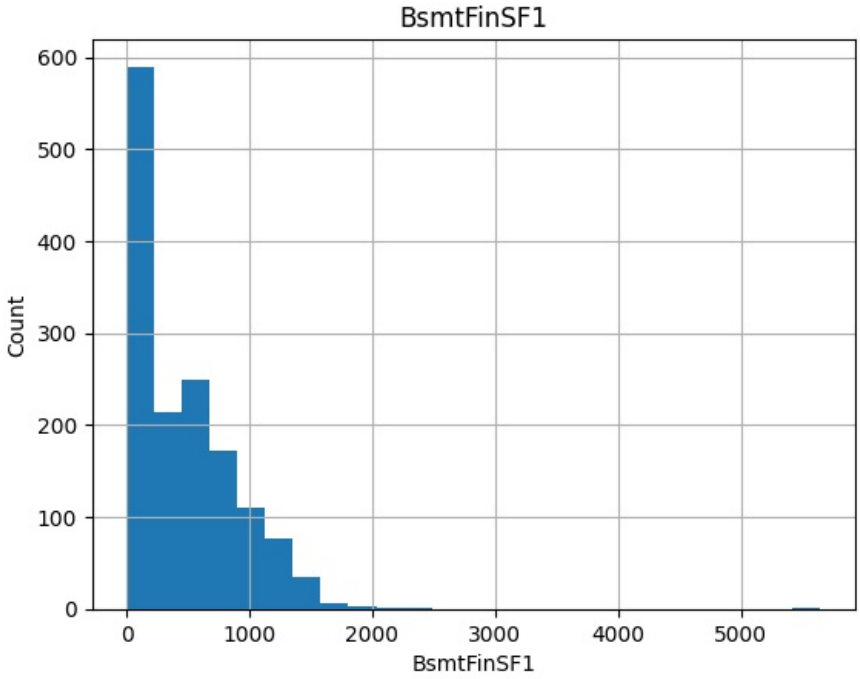
In [25]:
```
## Lets analyse the continuous values by creating histograms to understand the distribution
```

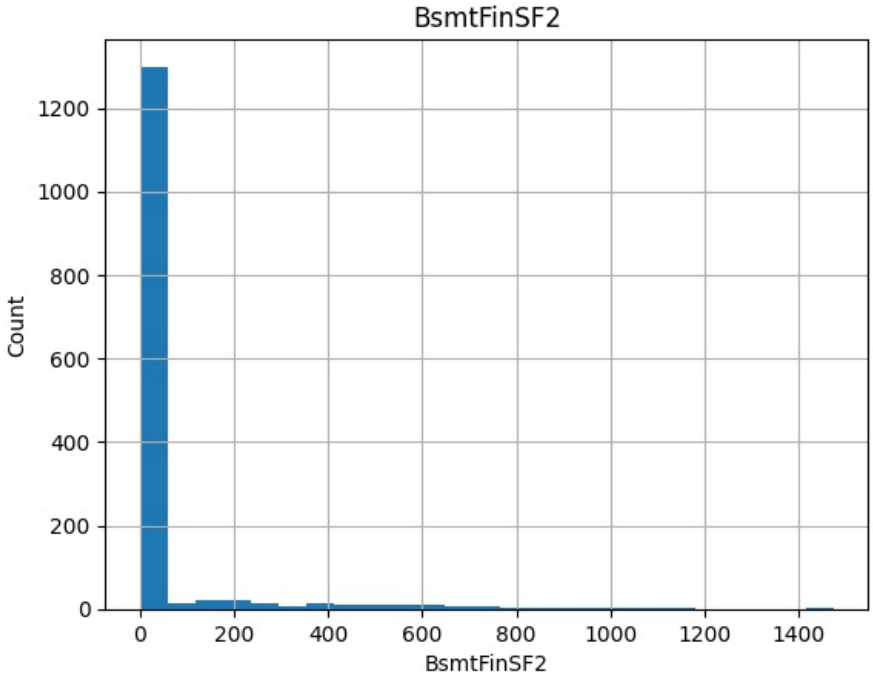
```
for feature in continuous_feature:
    data=dataset.copy()
    data[feature].hist(bins=25)
    plt.xlabel(feature)
    plt.ylabel("Count")
    plt.title(feature)
    plt.show()
```

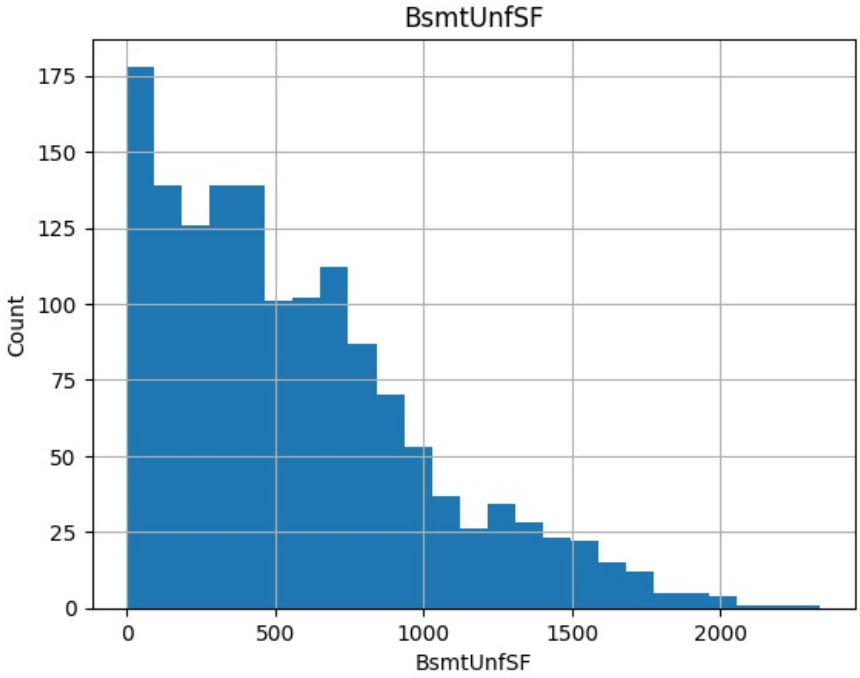


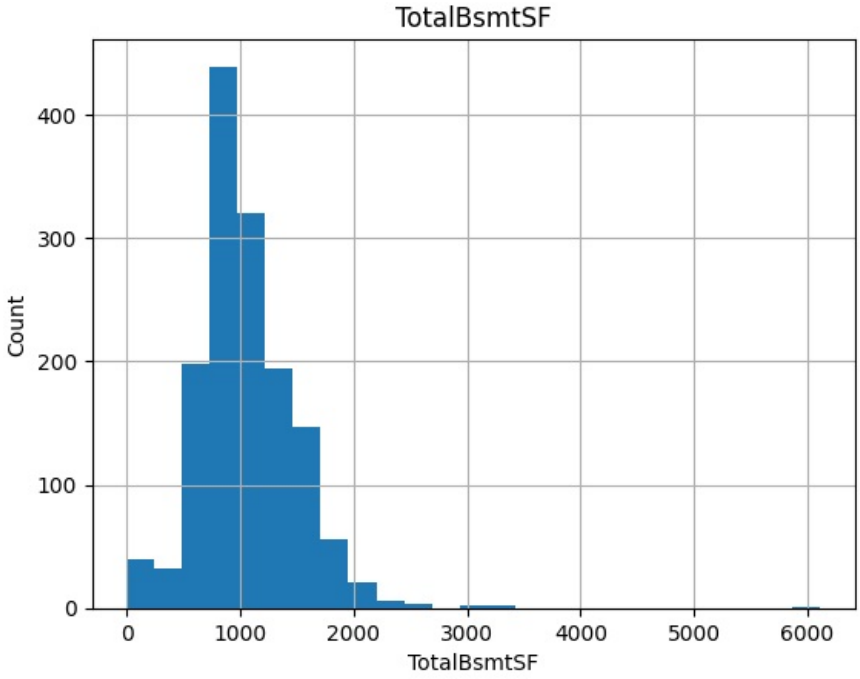


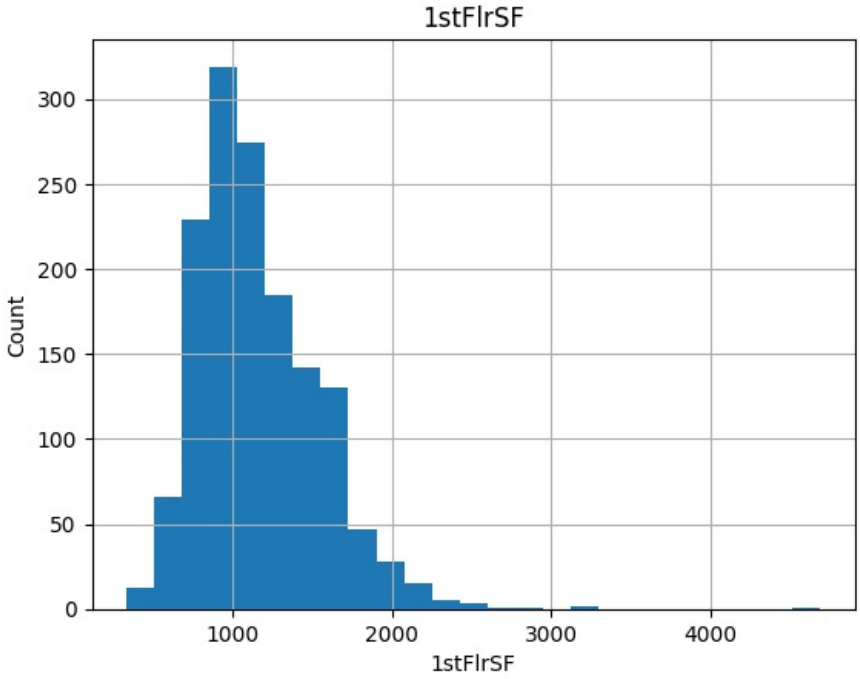

MasVnrArea
Count
0
200
400
600
800
0
200
400
600
800
1000
1200
1400
1600
MasVnrArea

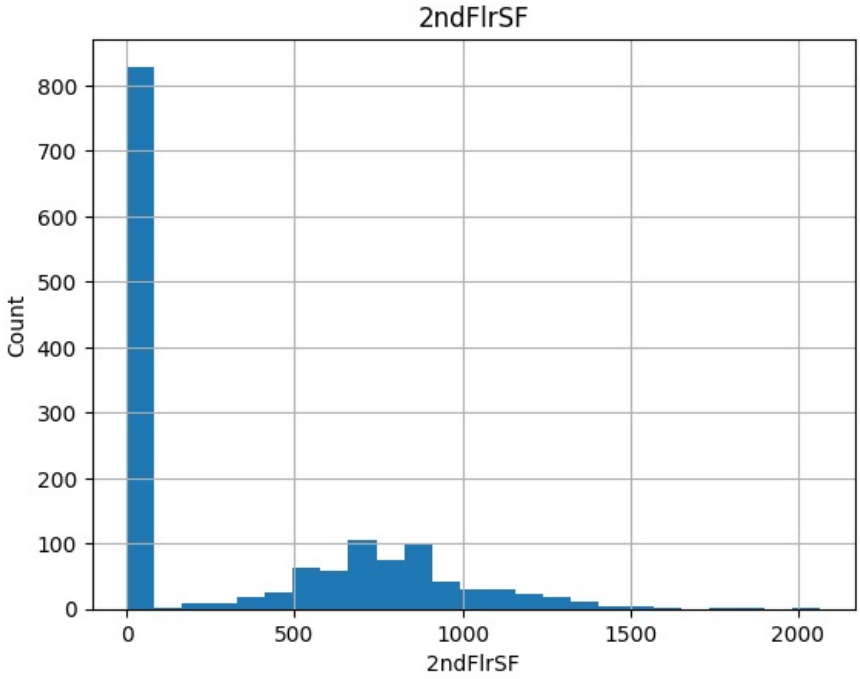

BsmtFinSF1
Count
0
100
200
300
400
500
600
0
1000
2000
3000
4000
5000
BsmtFinSF1

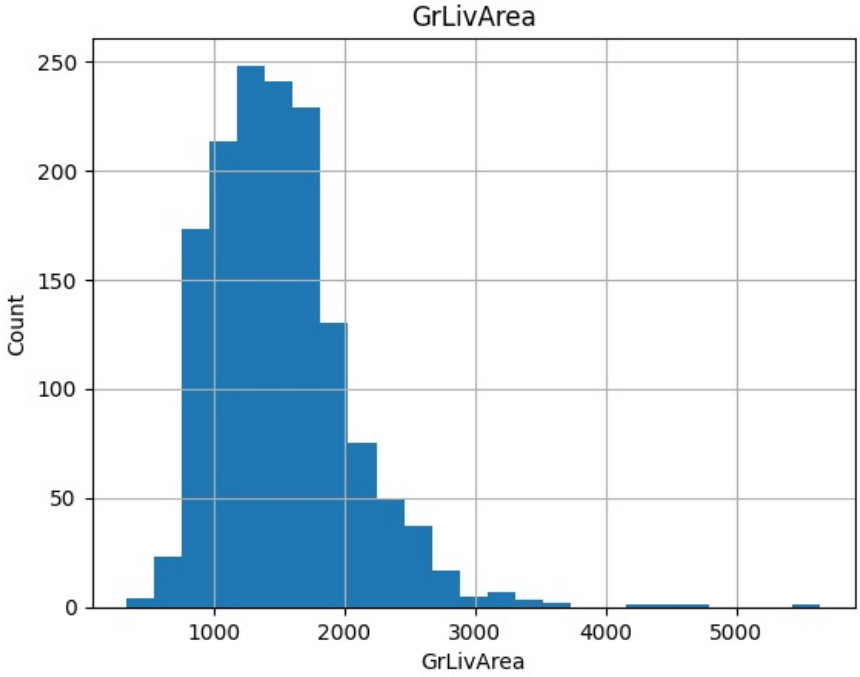

BsmtFinSF2
Count
BsmtFinSF2
0
200
400
600
800
1000
1200
1400

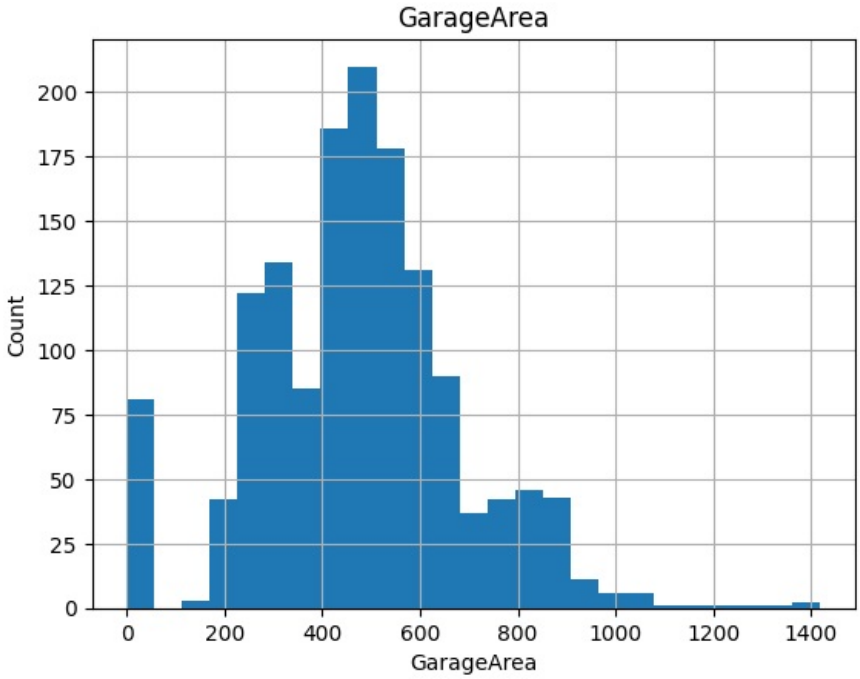

BsmtUnfSF
Count
BsmtUnfSF
0
25
50
75
100
125
150
175
0
500
1000
1500
2000

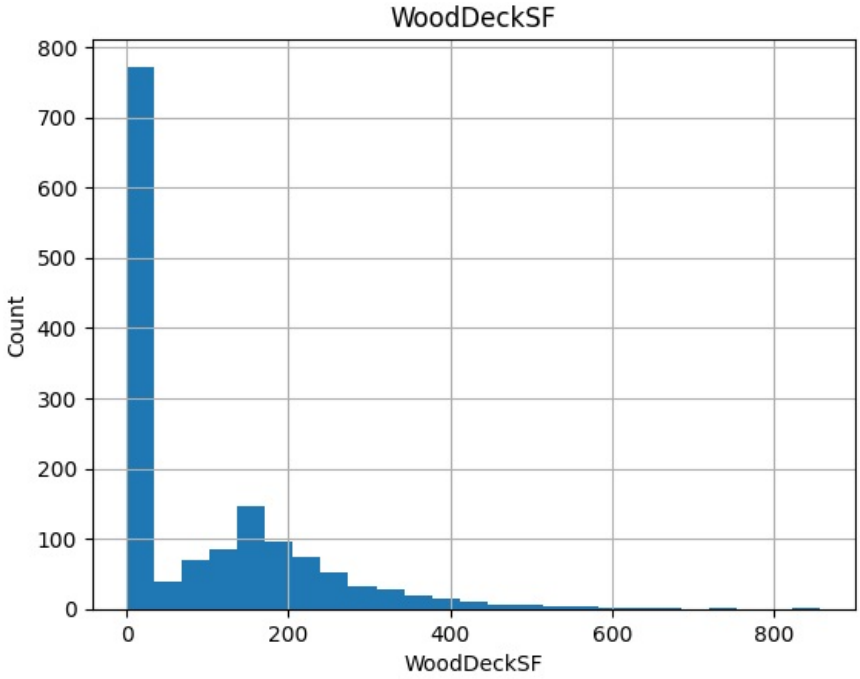

TotalBsmtSF
Count
TotalBsmtSF
0
100
200
300
400
0
1000
2000
3000
4000
5000
6000

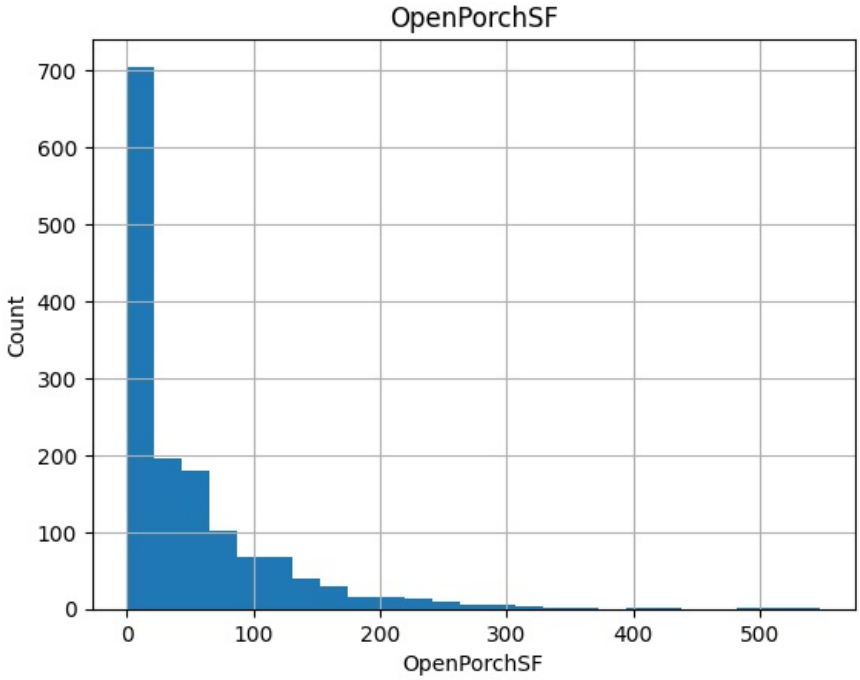

1stFlrSF
Count
1stFlrSF
0
50
100
150
200
250
300
1000
2000
3000
4000

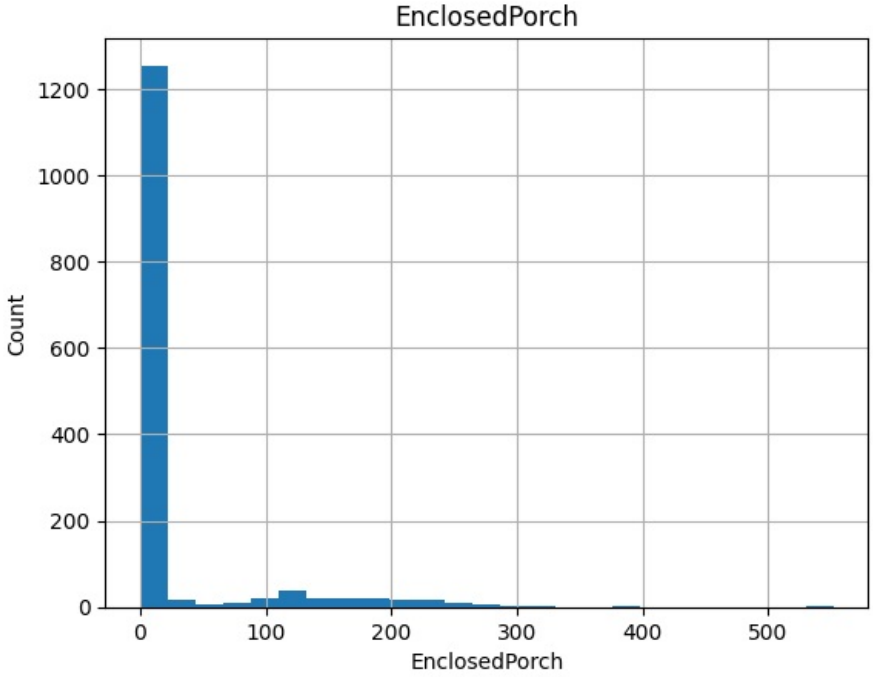

2ndFlrSF
Count
2ndFlrSF
0
100
200
300
400
500
600
700
800
0
500
1000
1500
2000

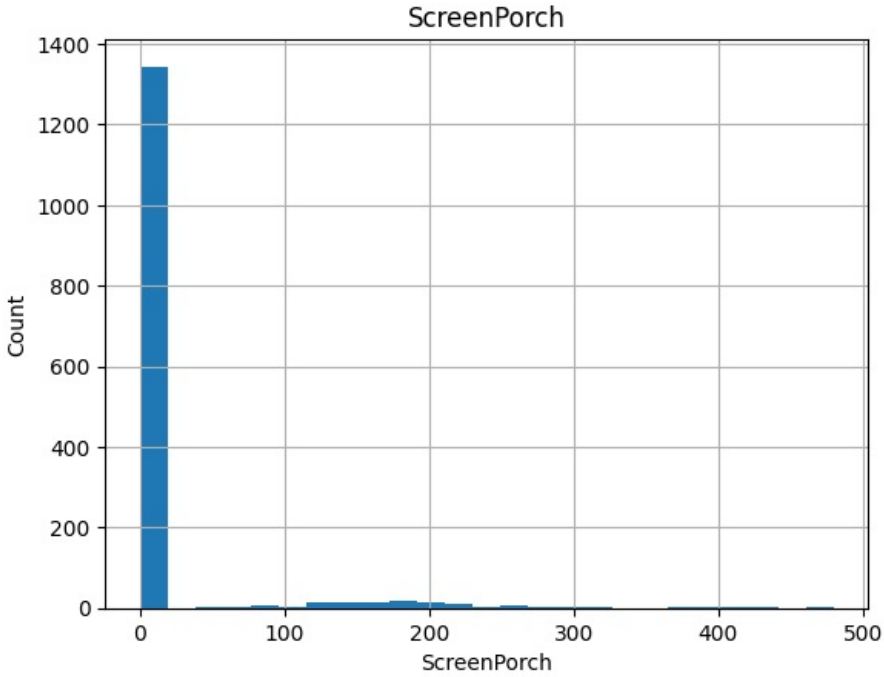

GrLivArea
Count
GrLivArea
0
50
100
150
200
250
1000
2000
3000
4000
5000

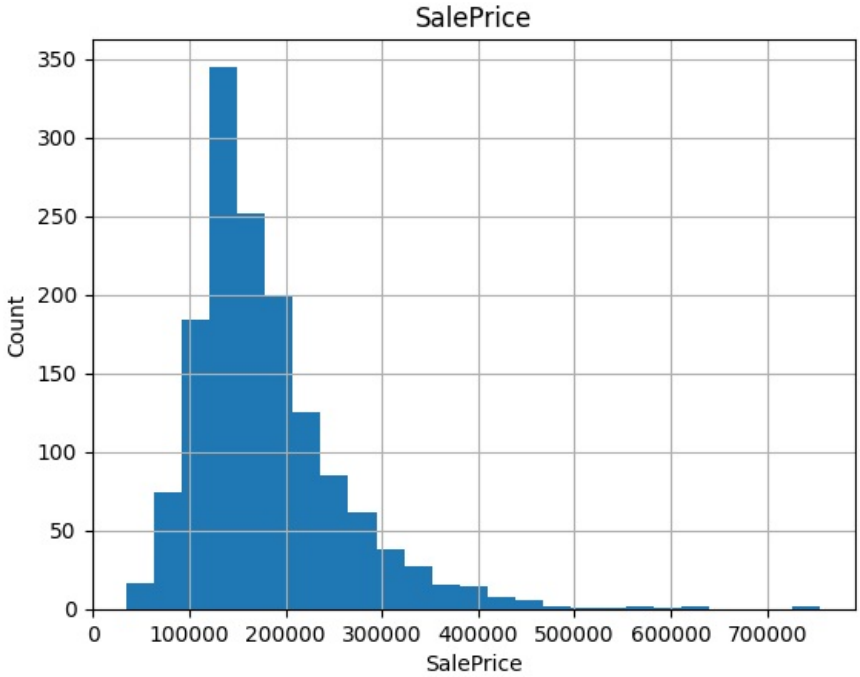

GarageArea
Count
GarageArea
0
25
50
75
100
125
150
175
200
0
200
400
600
800
1000
1200
1400


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


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

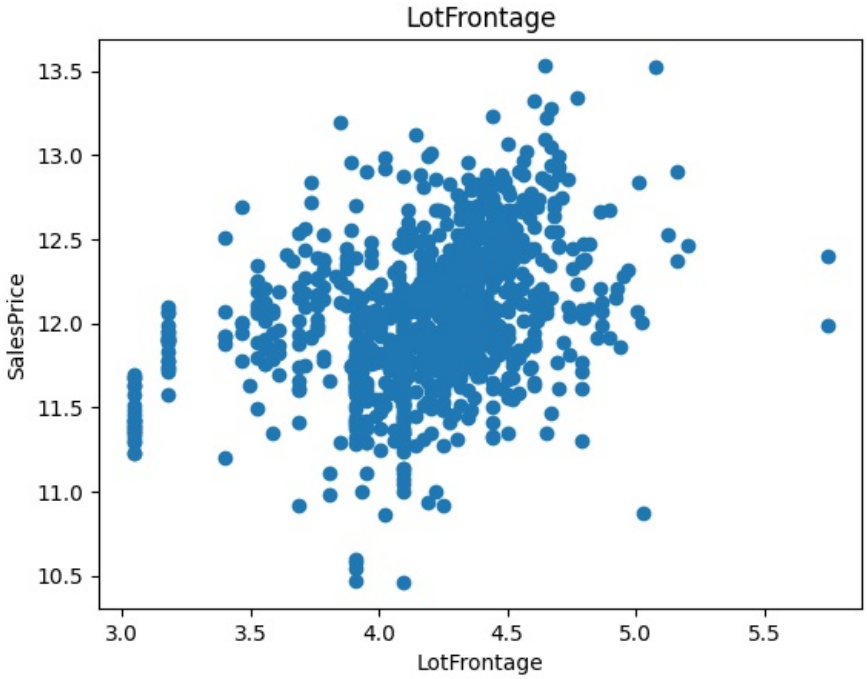

EnclosedPorch
Count
EnclosedPorch
0
100
200
300
400
500
0
200
400
600
800
1000
1200

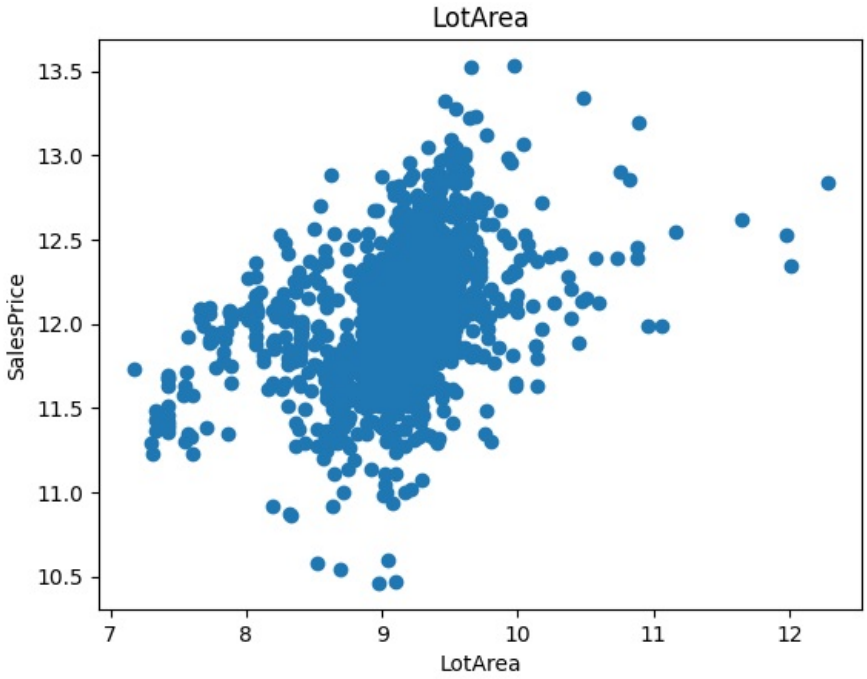


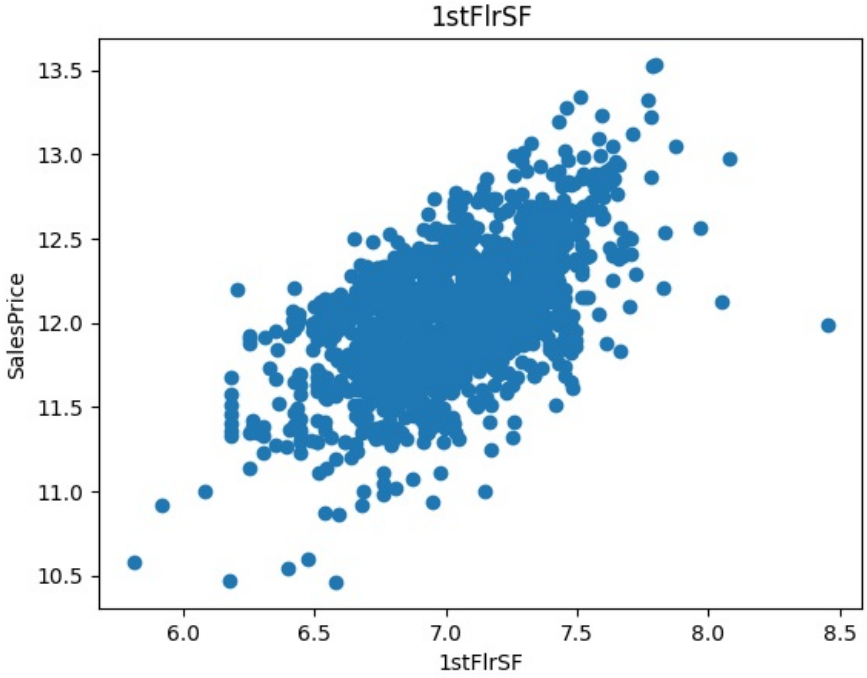


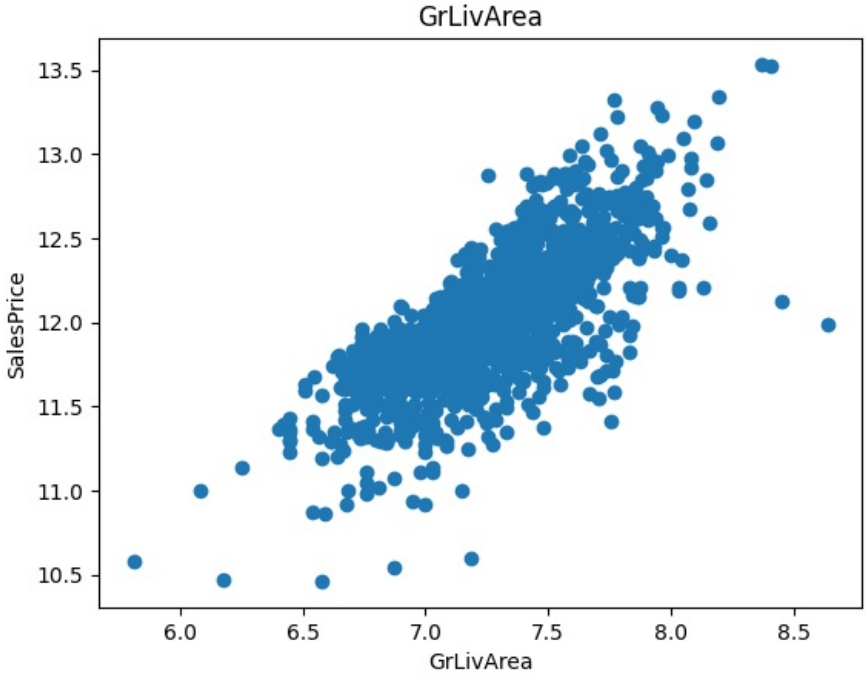
In [26]:
```
## We will be using logarithmic transformation


for feature in continuous_feature:
    data=dataset.copy()
    if 0 in data[feature].unique():
```

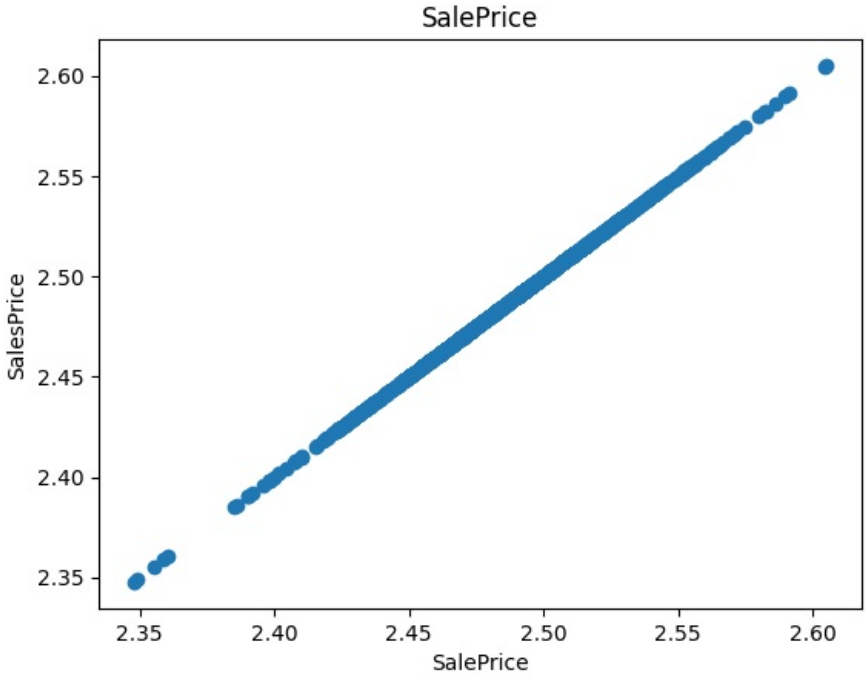
```
        pass
    else:
        data[feature]=np.log(data[feature])
        data['SalePrice']=np.log(data['SalePrice'])
        plt.scatter(data[feature],data['SalePrice'])
        plt.xlabel(feature)
        plt.ylabel('SalesPrice')
        plt.title(feature)
        plt.show()
```



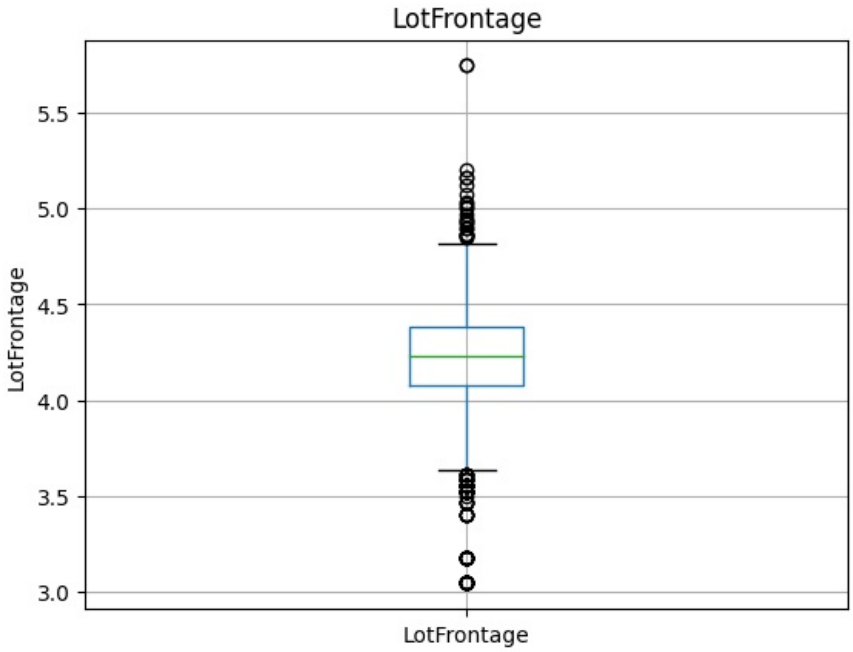


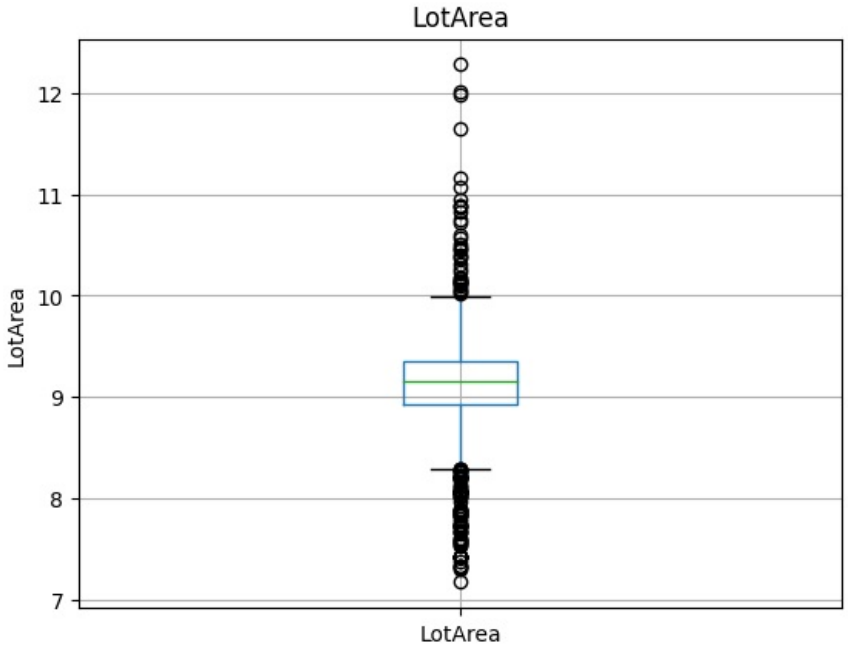

1stFlrSF
SalesPrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
6.0
6.5
7.0
7.5
8.0
8.5
1stFlrSF

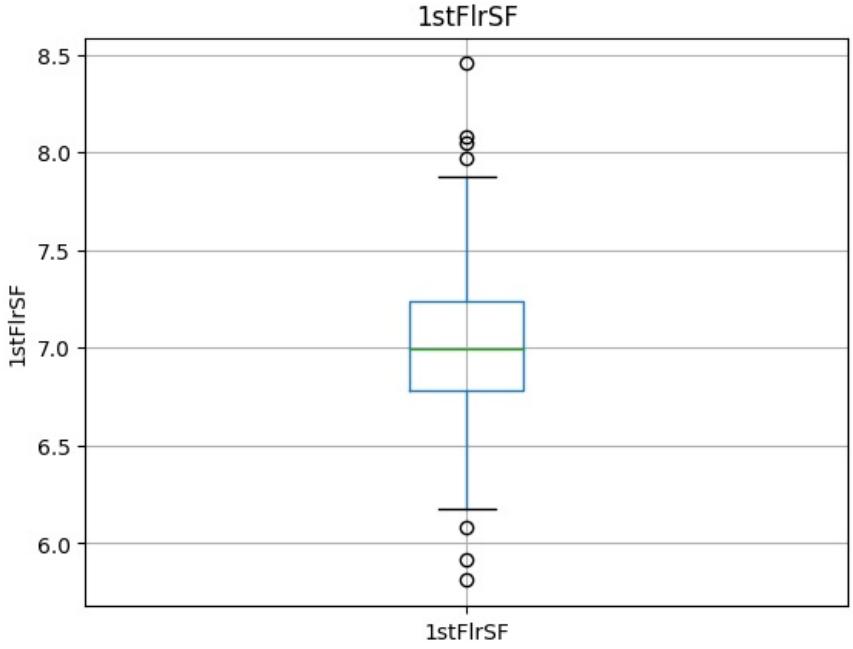

GrLivArea
SalesPrice
13.5
13.0
12.5
12.0
11.5
11.0
10.5
6.0
6.5
7.0
7.5
8.0
8.5
GrLivArea



In [27]:
```
for feature in continuous_feature:
    data=dataset.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()
```




LotArea
12
11
10
9
8
7
LotArea
LotArea


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

In [28]:
```
categorical_features=[feature for feature in dataset.columns if data[feature].dtypes=='O']
categorical_features
```

Out[28]:
```
['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 [29]:
```
dataset[categorical_features].head()
```

Out[29]:

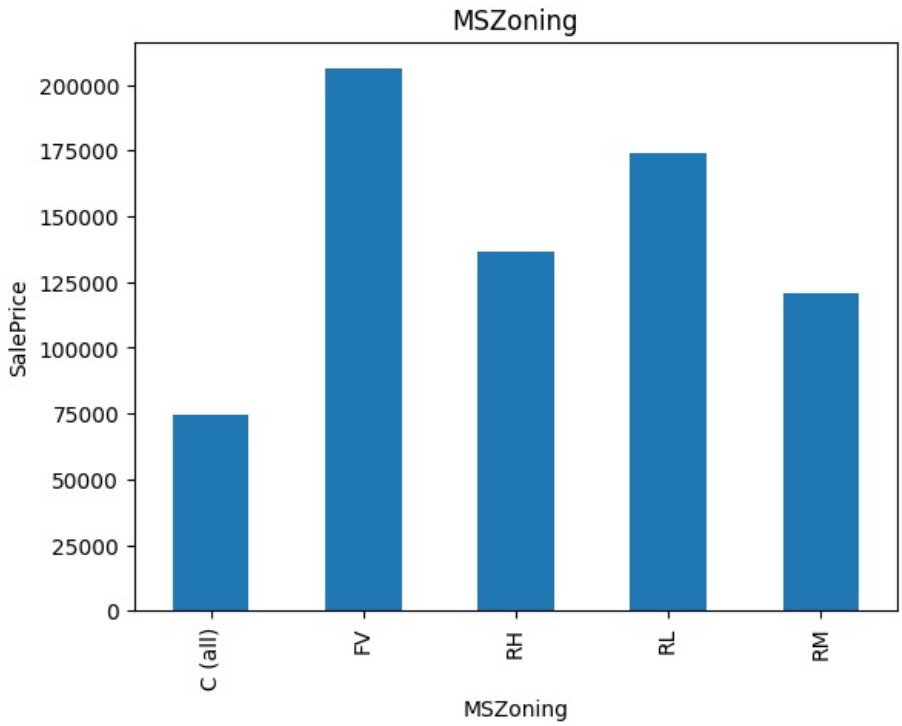
	MSZoning	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2	BldgType	House
0	RL	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	1Fam	2
1	RL	Pave	NaN	Reg	Lvl	AllPub	FR2	Gtl	Veenker	Feedr	Norm	1Fam	1
2	RL	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	CollgCr	Norm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

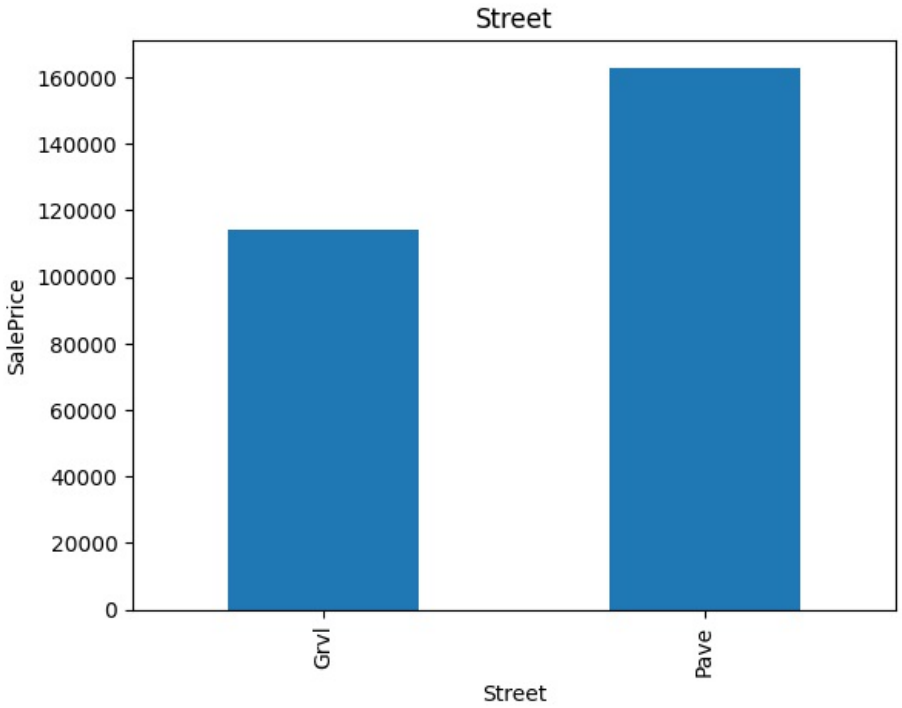
In [34]:
```
for feature in categorical_features:
    print('The feature is {} and number of categories are {}'.format(feature,len(dataset[feature])))
```

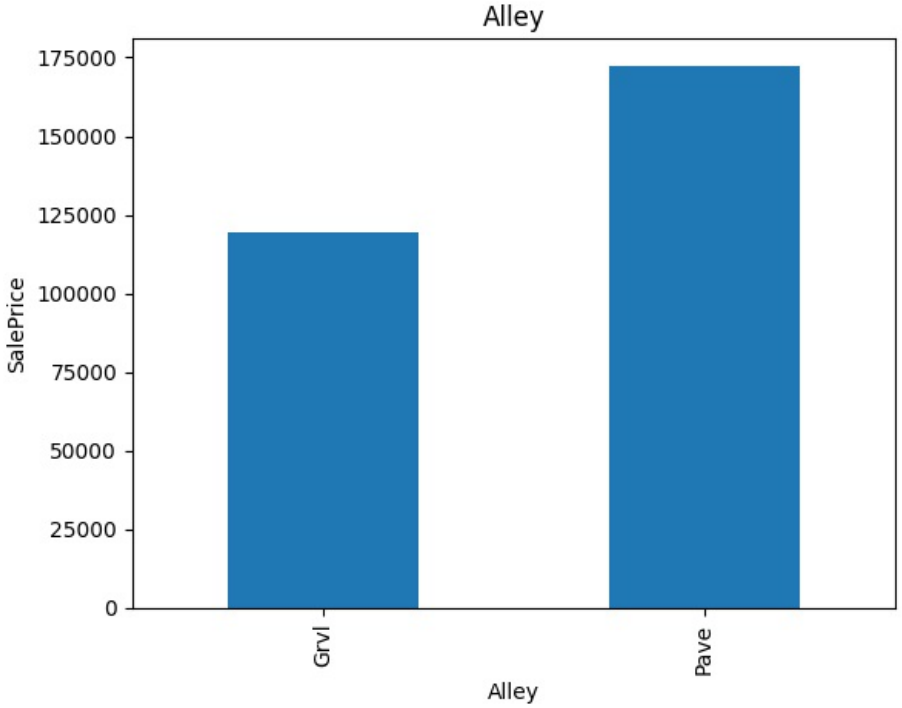
```
The feature is MSZoning and number of categories are 1460
The feature is Street and number of categories are 1460
The feature is Alley and number of categories are 1460
The feature is LotShape and number of categories are 1460
The feature is LandContour and number of categories are 1460
The feature is Utilities and number of categories are 1460
The feature is LotConfig and number of categories are 1460
The feature is LandSlope and number of categories are 1460
The feature is Neighborhood and number of categories are 1460
The feature is Condition1 and number of categories are 1460
The feature is Condition2 and number of categories are 1460
The feature is BldgType and number of categories are 1460
The feature is HouseStyle and number of categories are 1460
The feature is RoofStyle and number of categories are 1460
The feature is RoofMatl and number of categories are 1460
The feature is Exterior1st and number of categories are 1460
The feature is Exterior2nd and number of categories are 1460
The feature is MasVnrType and number of categories are 1460
The feature is ExterQual and number of categories are 1460
The feature is ExterCond and number of categories are 1460
The feature is Foundation and number of categories are 1460
The feature is BsmtQual and number of categories are 1460
The feature is BsmtCond and number of categories are 1460
The feature is BsmtExposure and number of categories are 1460
The feature is BsmtFinType1 and number of categories are 1460
The feature is BsmtFinType2 and number of categories are 1460
The feature is Heating and number of categories are 1460
The feature is HeatingQC and number of categories are 1460
The feature is CentralAir and number of categories are 1460
The feature is Electrical and number of categories are 1460
The feature is KitchenQual and number of categories are 1460
The feature is Functional and number of categories are 1460
The feature is FireplaceQu and number of categories are 1460
The feature is GarageType and number of categories are 1460
The feature is GarageFinish and number of categories are 1460
The feature is GarageQual and number of categories are 1460
The feature is GarageCond and number of categories are 1460
The feature is PavedDrive and number of categories are 1460
The feature is PoolQC and number of categories are 1460
The feature is Fence and number of categories are 1460
The feature is MiscFeature and number of categories are 1460
The feature is SaleType and number of categories are 1460
The feature is SaleCondition and number of categories are 1460
```

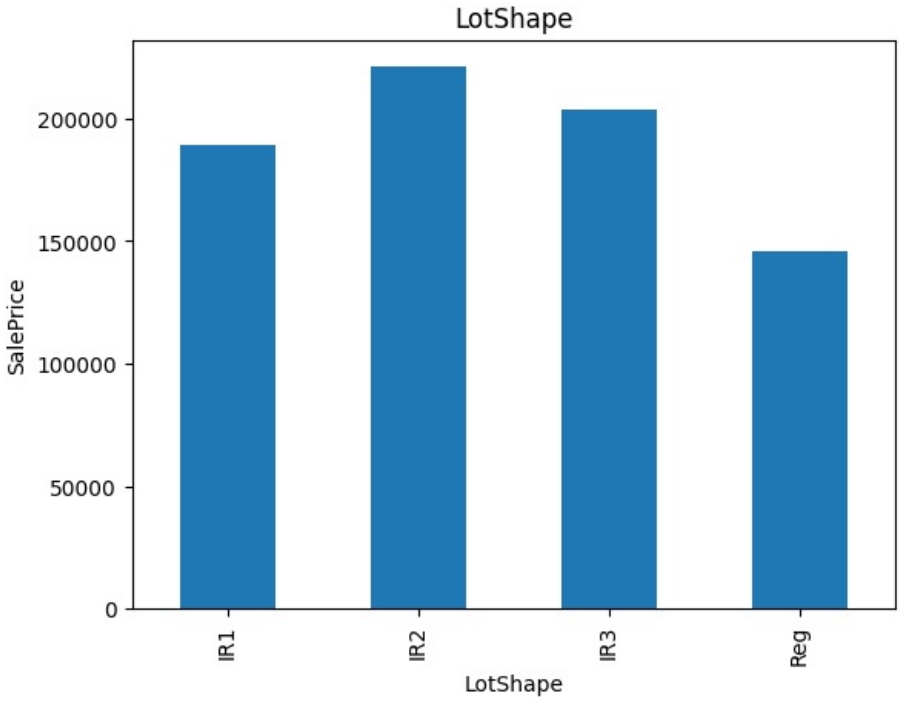
In [ ]:
```
## Find out the relationship between categorical variable and dependent feature SalesPrices
```

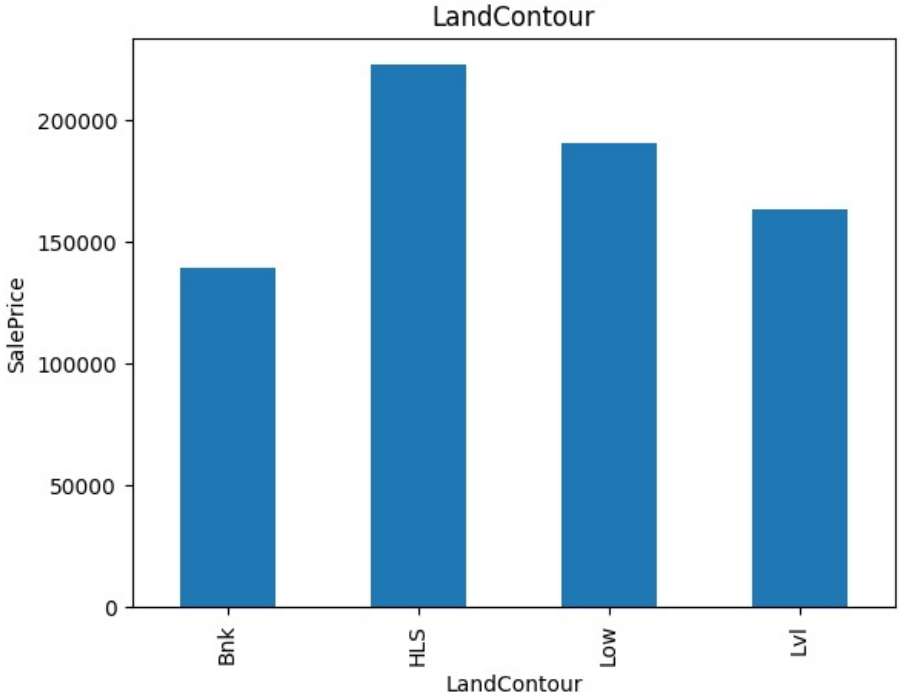
In [35]:
```
for feature in categorical_features:
    data=dataset.copy()
    data.groupby(feature)['SalePrice'].median().plot.bar()
    plt.xlabel(feature)
    plt.ylabel('SalePrice')
    plt.title(feature)
    plt.show()
```

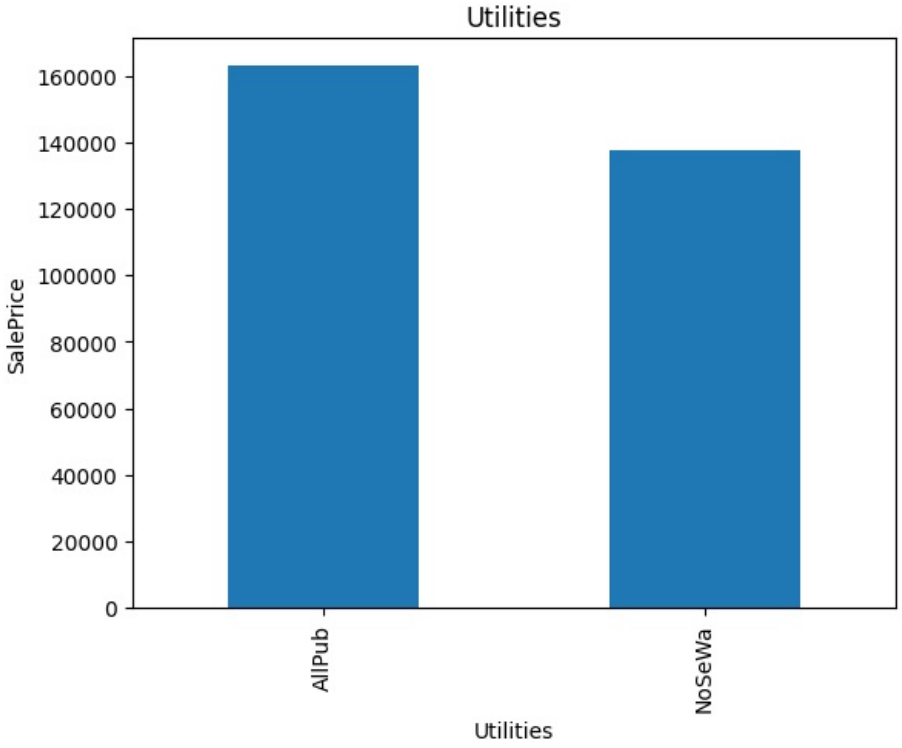


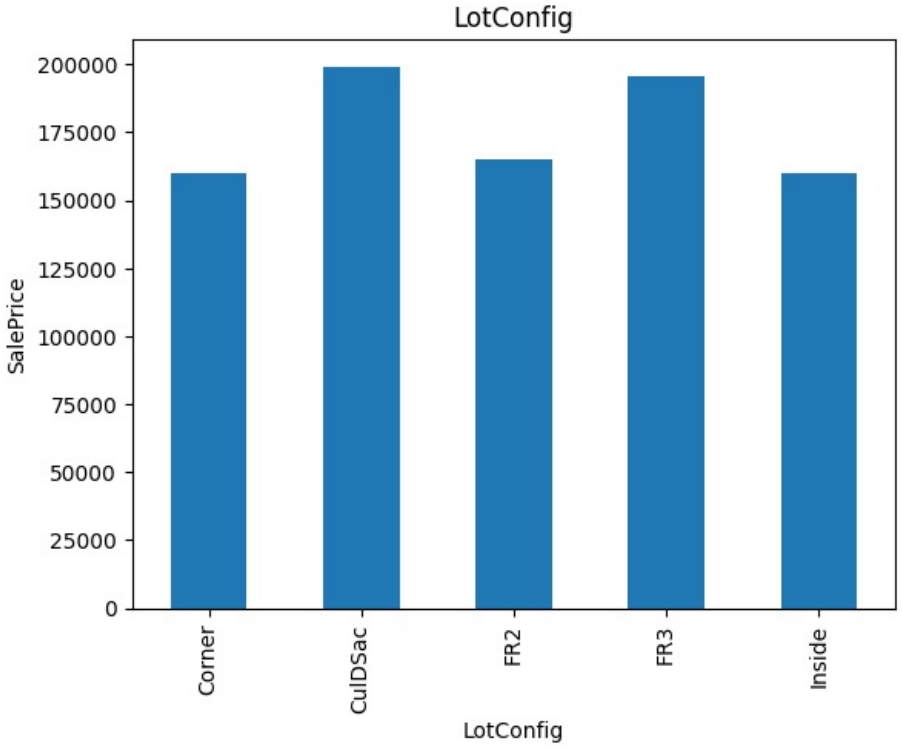

Street
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
Grvl
Pave
Street

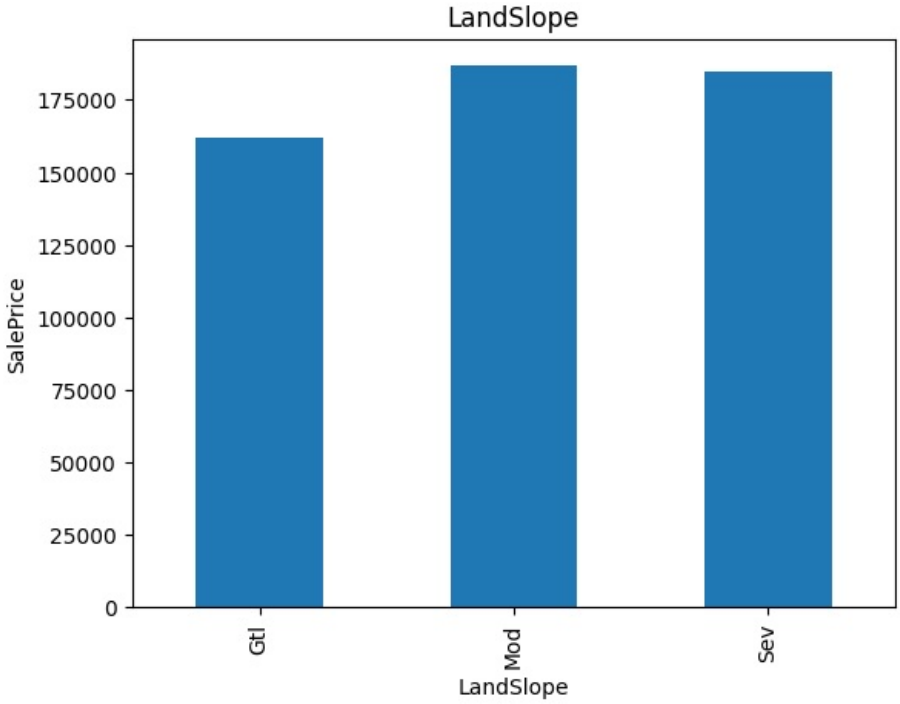

Alley
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
Grvl
Pave
Alley

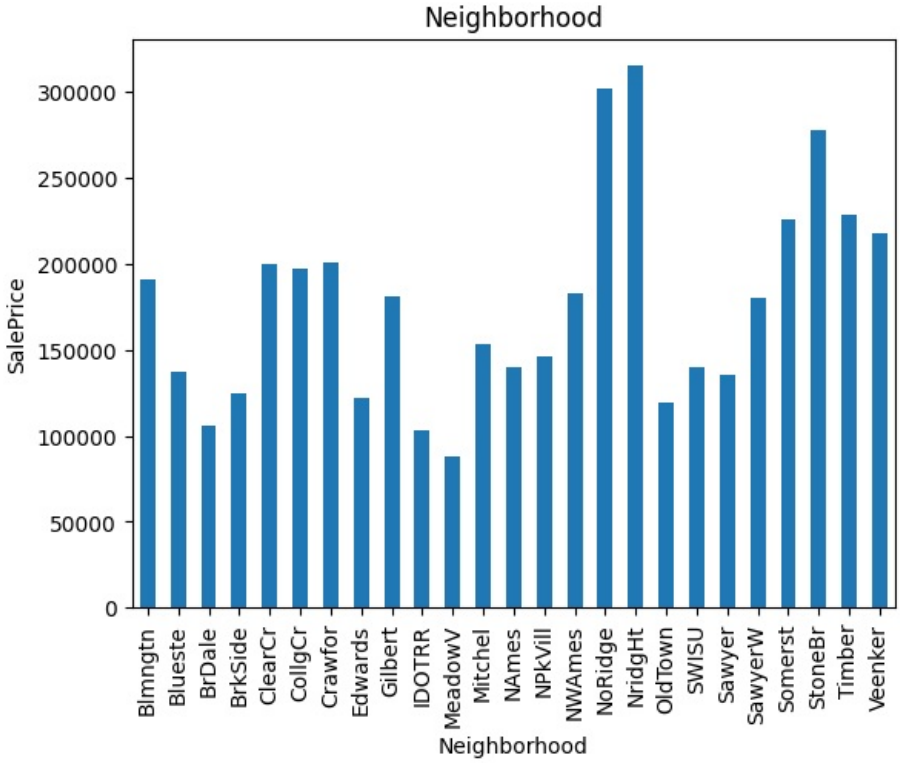

LotShape
SalePrice
200000
150000
100000
50000
0
IR1
IR2
IR3
Reg
LotShape

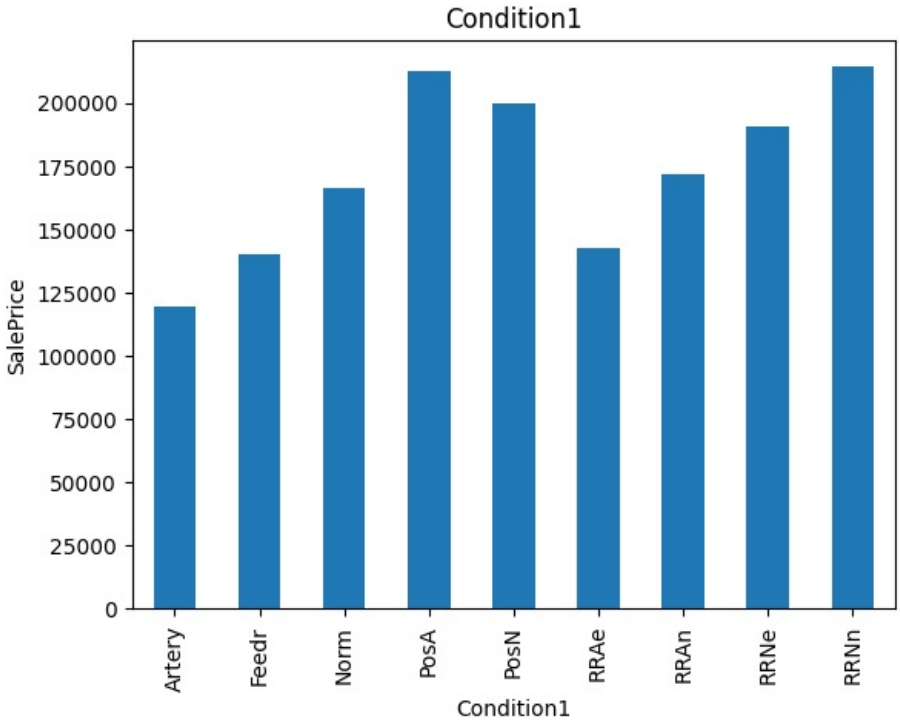

LandContour
SalePrice
200000
150000
100000
50000
0
Bnk
HLS
Low
Lvl
LandContour

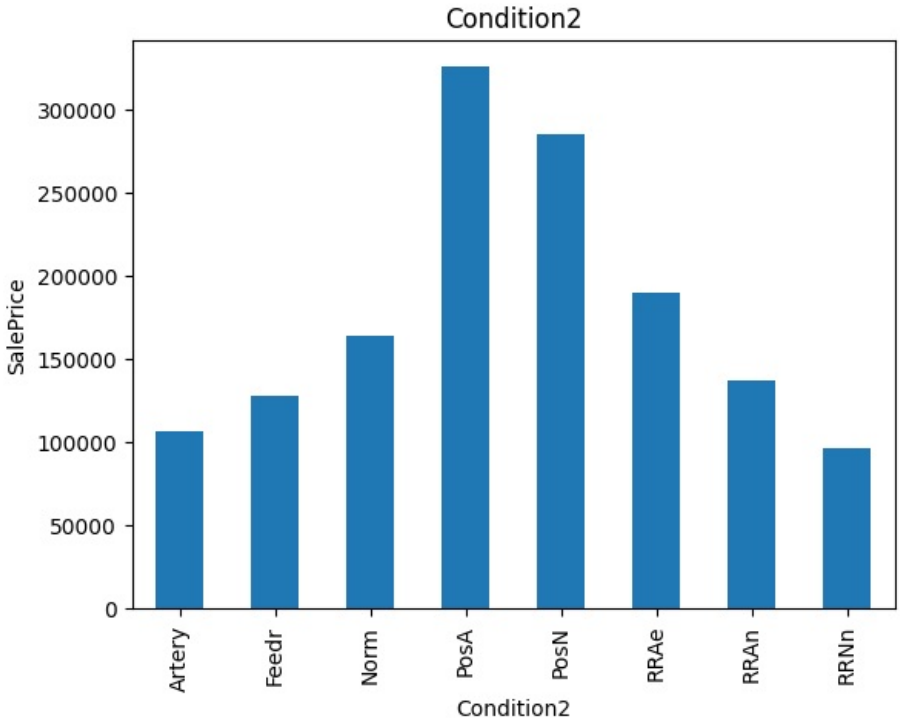

Utilities
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
AllPub
NoSeWa
Utilities

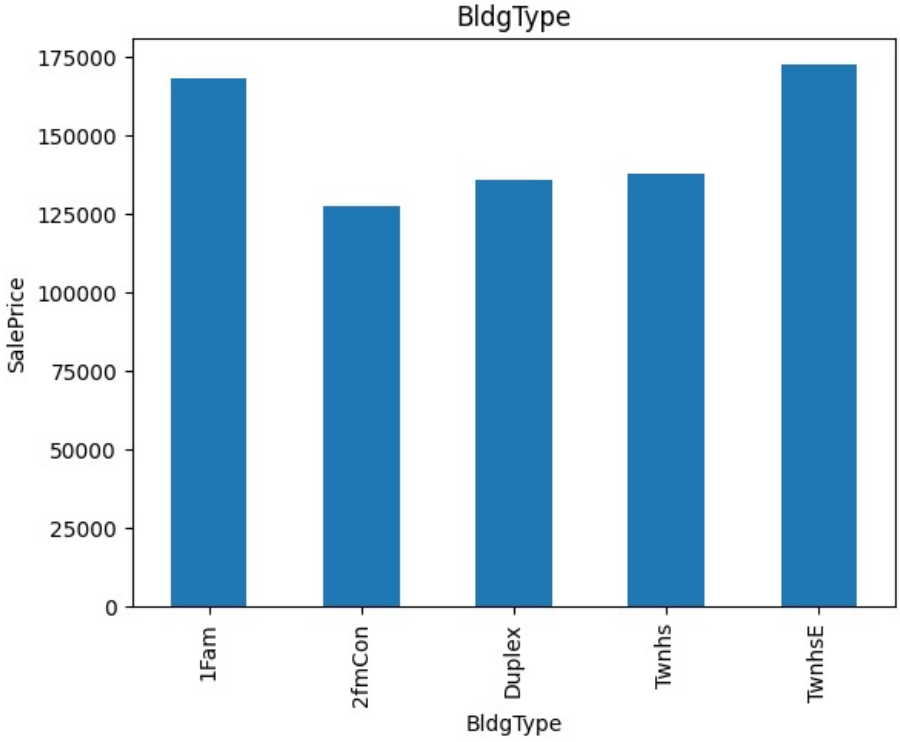

LotConfig
200000
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
Corner
CulDSac
FR2
FR3
Inside
LotConfig

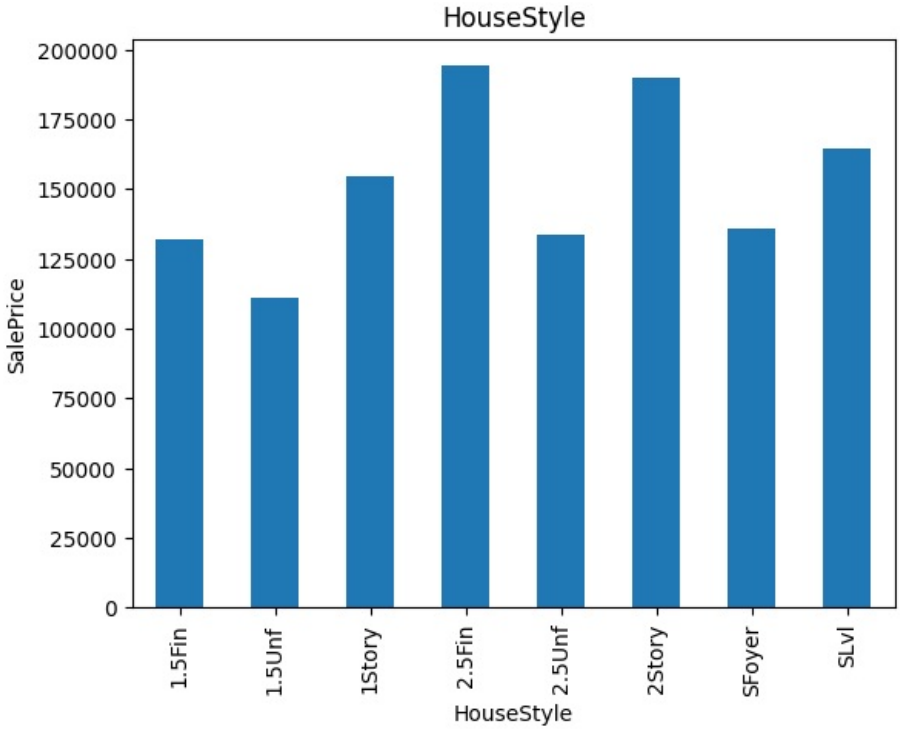

LandSlope
SalePrice
175000
150000
125000
100000
75000
50000
25000
0
Gtl
Mod
Sev
LandSlope

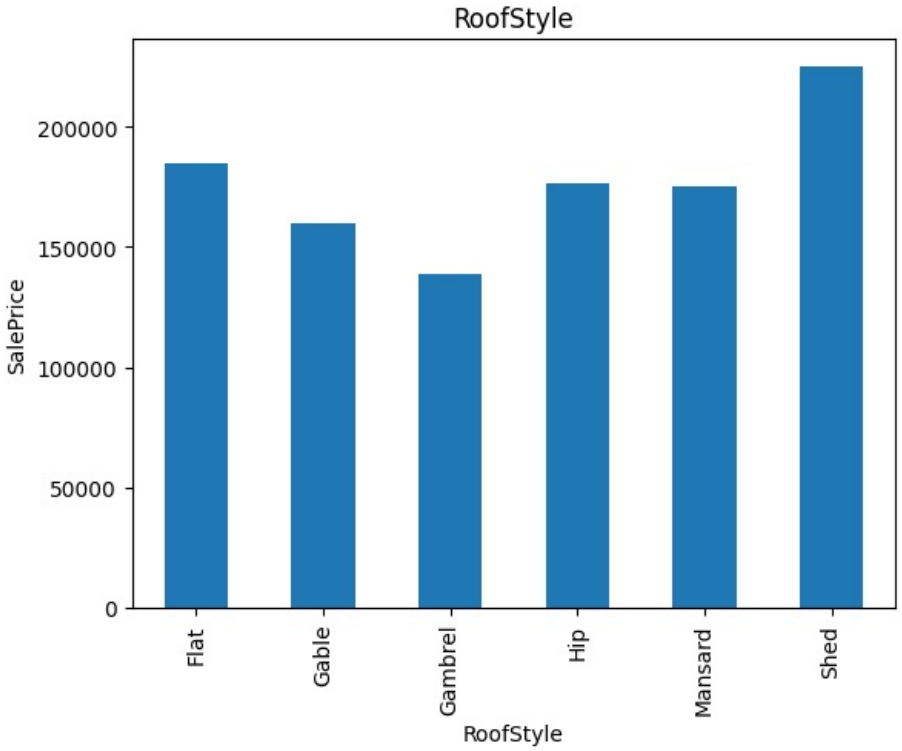

Neighborhood
SalePrice
300000
250000
200000
150000
100000
50000
0
Blmngtn
Blueste
BrDale
BrkSide
ClearCr
CollgCr
Crawfor
Edwards
Gilbert
IDOTRR
MeadowV
Mitchel
NAmes
NPkVill
NWAmes
NoRidge
NridgHt
OldTown
SWISU
Sawyer
SawyerW
Somerst
StoneBr
Timber
Veenker
Neighborhood

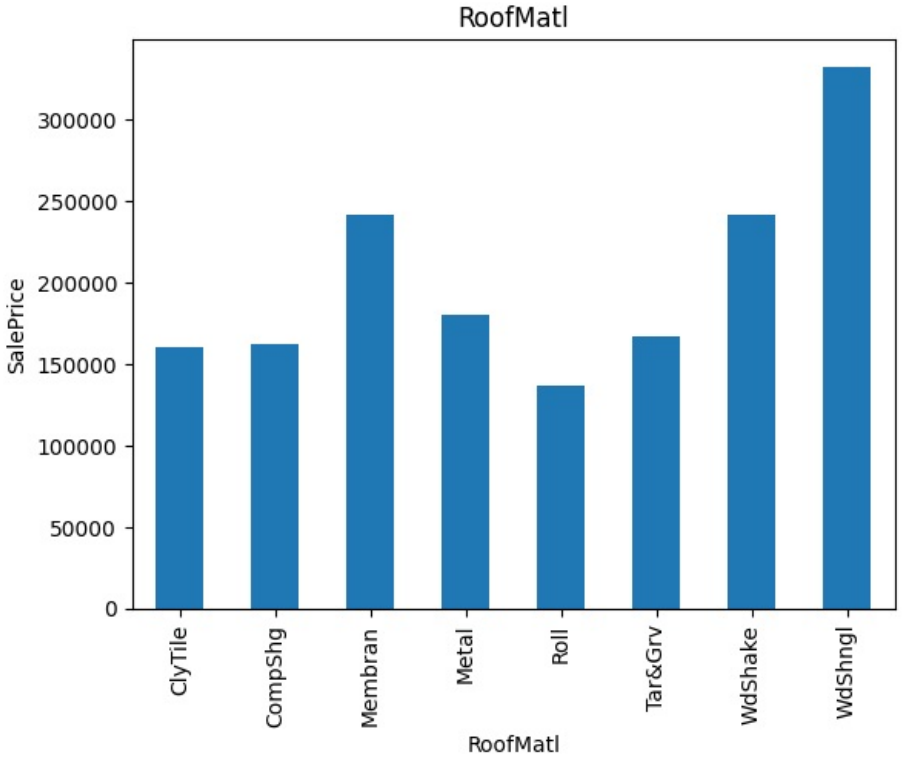

Condition1
SalePrice
0
25000
50000
75000
100000
125000
150000
175000
200000
Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNe
RRNn
Condition1

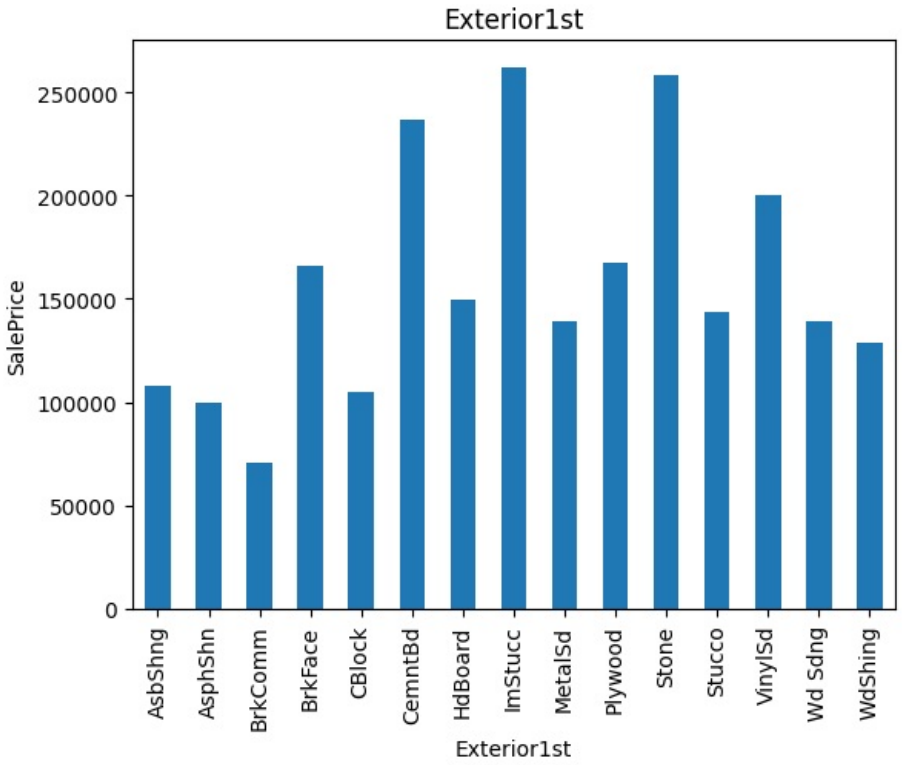

Condition2
SalePrice
0
50000
100000
150000
200000
250000
300000
Artery
Feedr
Norm
PosA
PosN
RRAe
RRAn
RRNn
Condition2

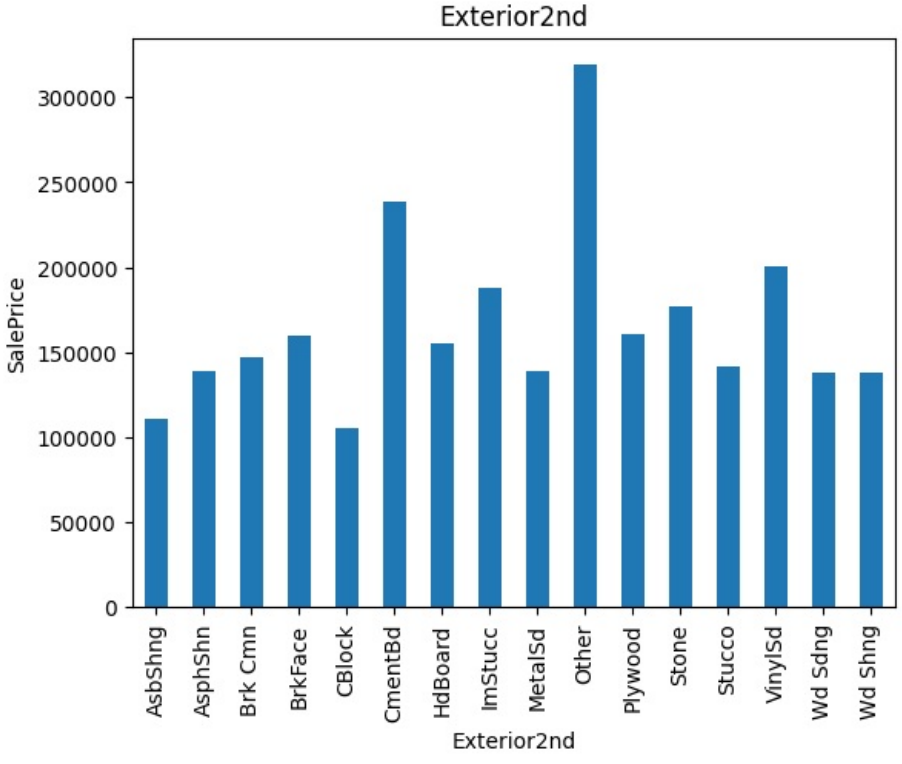

BldgType
SalePrice
175000
150000
125000
100000
75000
50000
25000
0
1Fam
2fmCon
Duplex
Twnhs
TwnhsE
BldgType

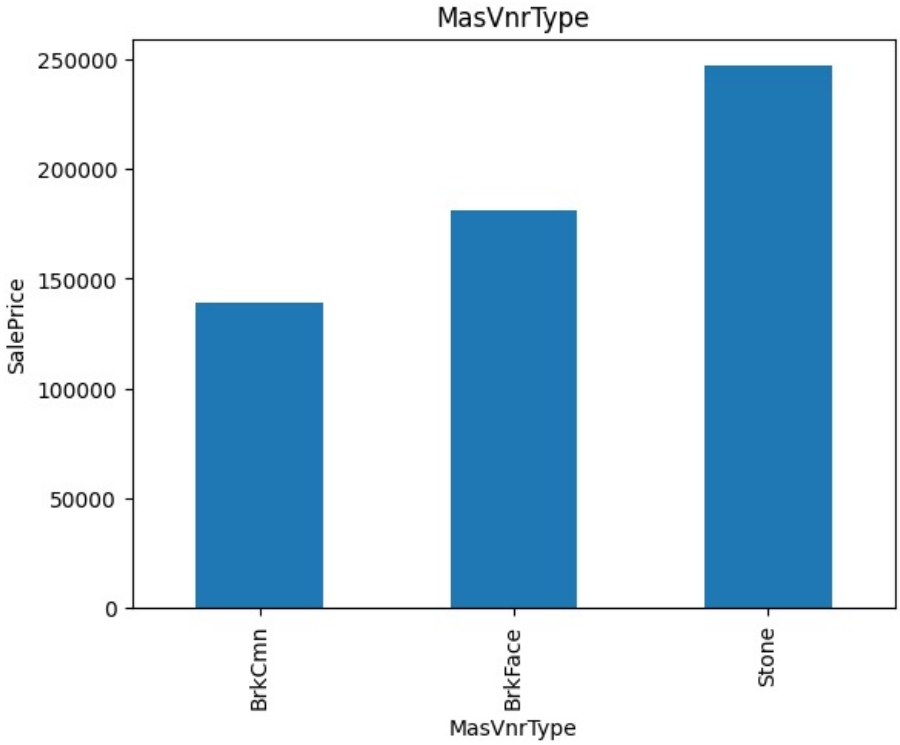

HouseStyle
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
1.5Fin
1.5Unf
1Story
2.5Fin
2.5Unf
2Story
SFoyer
SLvl
HouseStyle

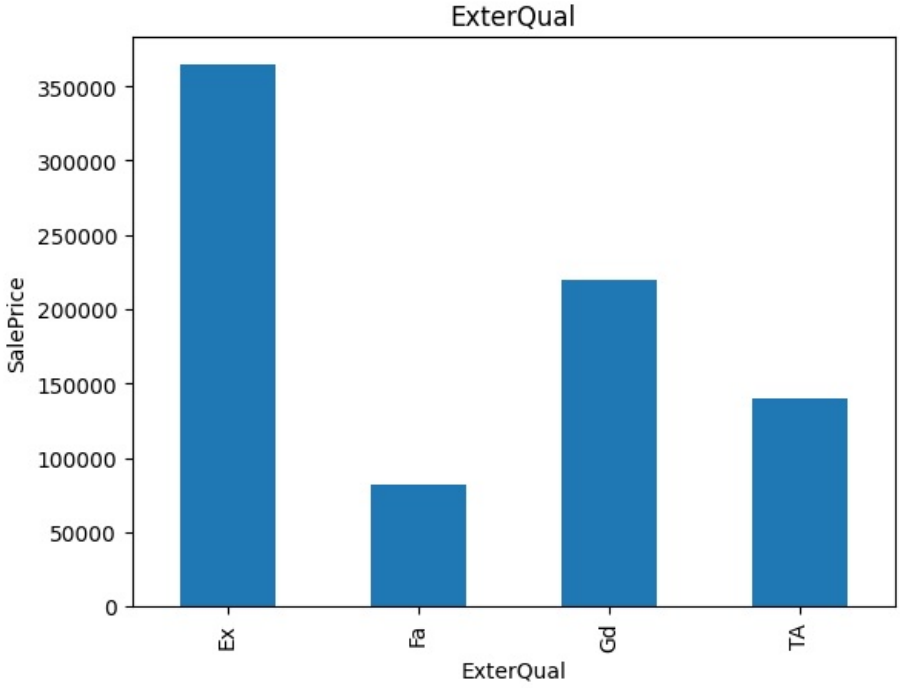

RoofStyle
SalePrice
200000
150000
100000
50000
0
Flat
Gable
Gambrel
Hip
Mansard
Shed
RoofStyle

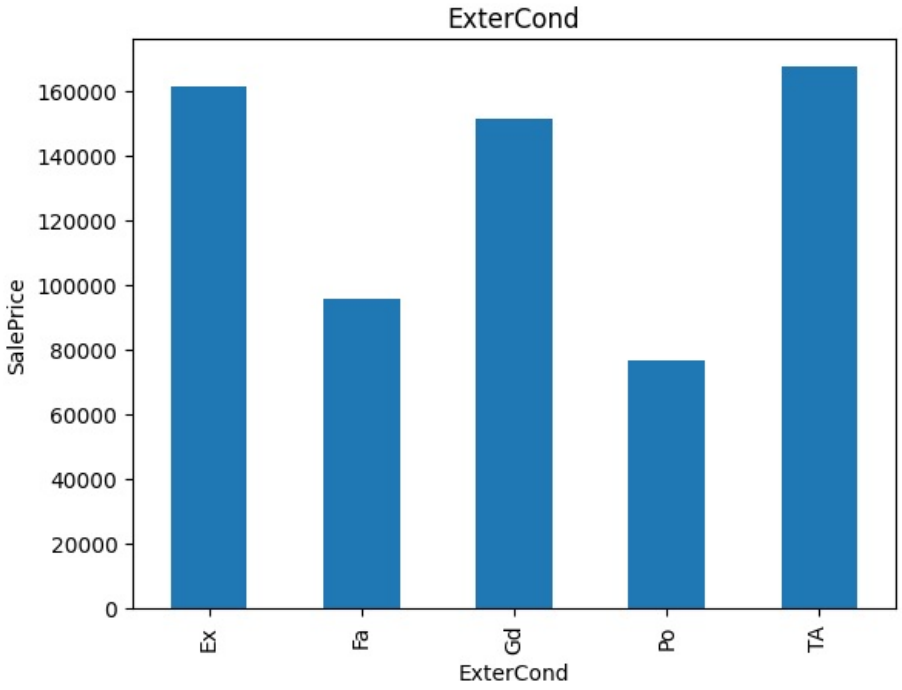

RoofMatl
SalePrice
300000
250000
200000
150000
100000
50000
0
ClyTile
CompShg
Membran
Metal
Roll
Tar&Grv
WdShake
WdShngl
RoofMatl

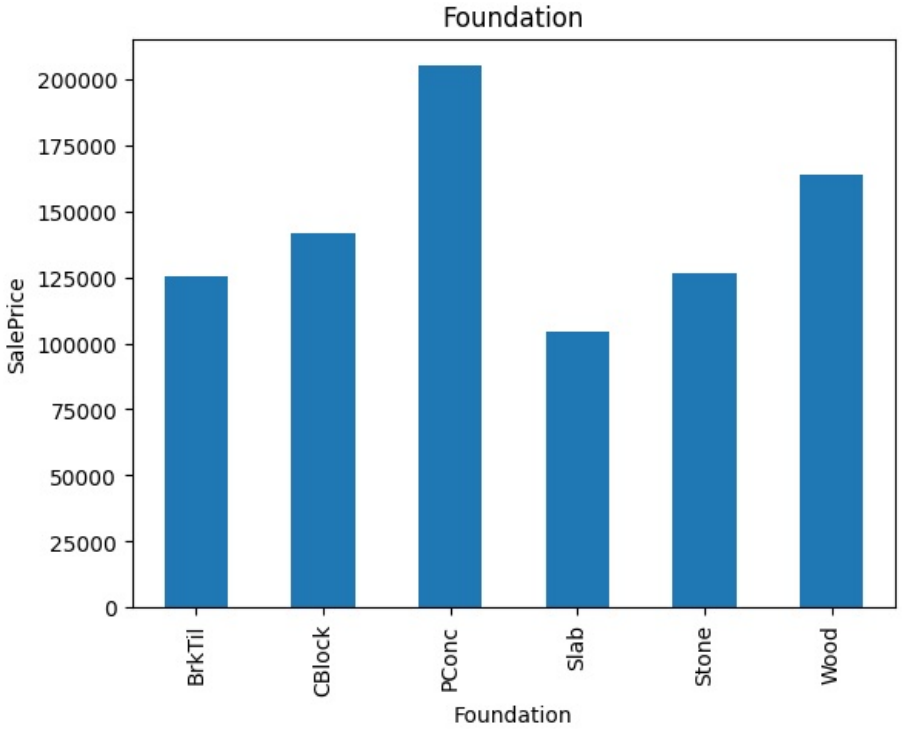

Exterior1st
SalePrice
0
50000
100000
150000
200000
250000
AsbShng
AsphShn
BrkComm
BrkFace
CBlock
CemntBd
HdBoard
ImStucc
MetalSd
Plywood
Stone
Stucco
VinylSd
Wd Sdng
WdShing
Exterior1st

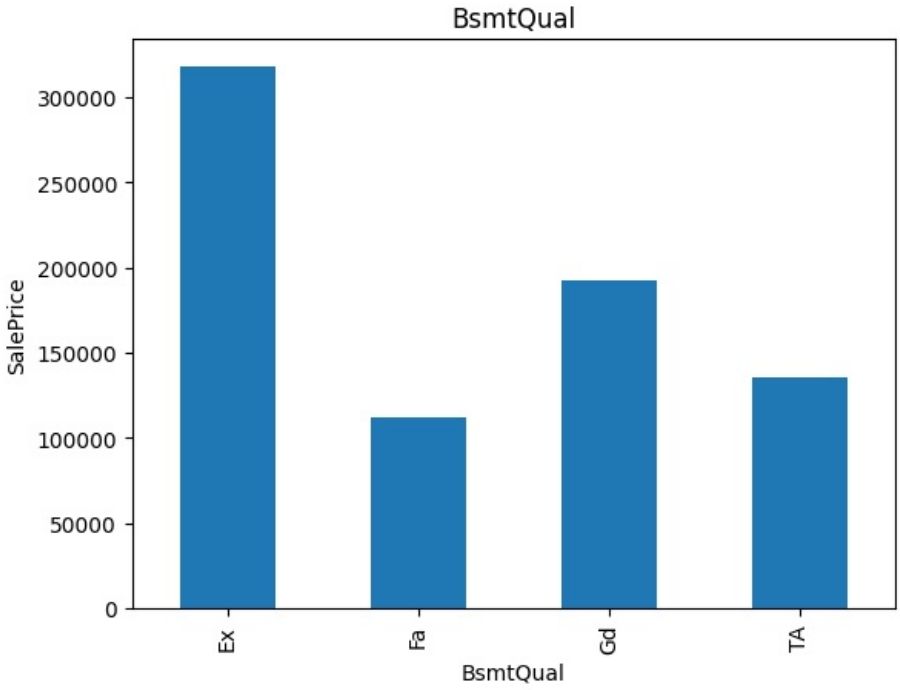

Exterior2nd
SalePrice
0
50000
100000
150000
200000
250000
300000
AsbShng
AsphShn
Brk Cmn
BrkFace
CBlock
CmentBd
HdBoard
ImStucc
MetalSd
Other
Plywood
Stone
Stucco
VinylSd
Wd Sdng
Wd Shng
Exterior2nd

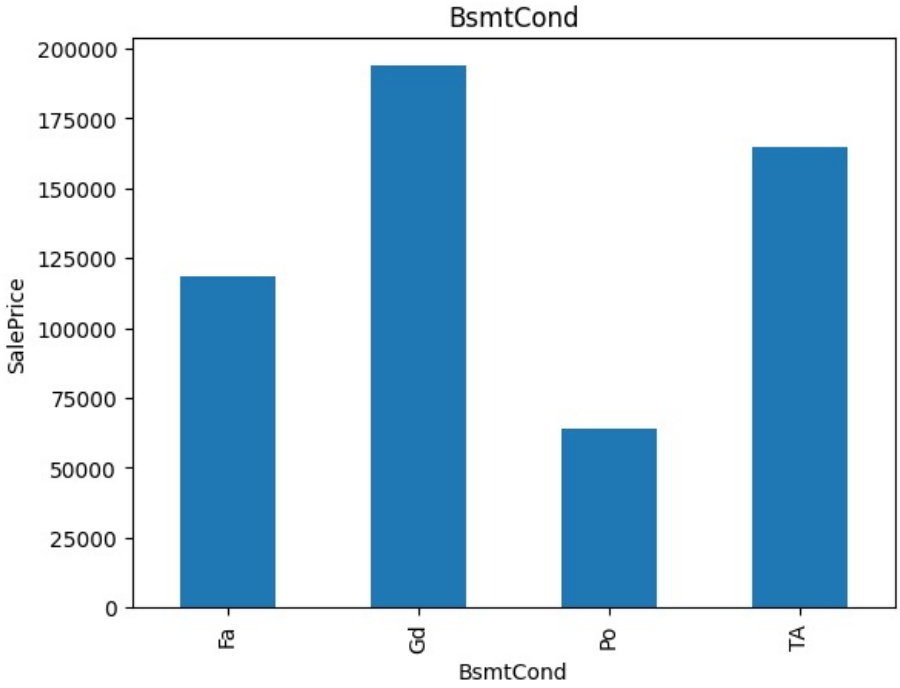

MasVnrType
250000
200000
150000
100000
50000
0
SalePrice
BrkCmn
BrkFace
Stone
MasVnrType

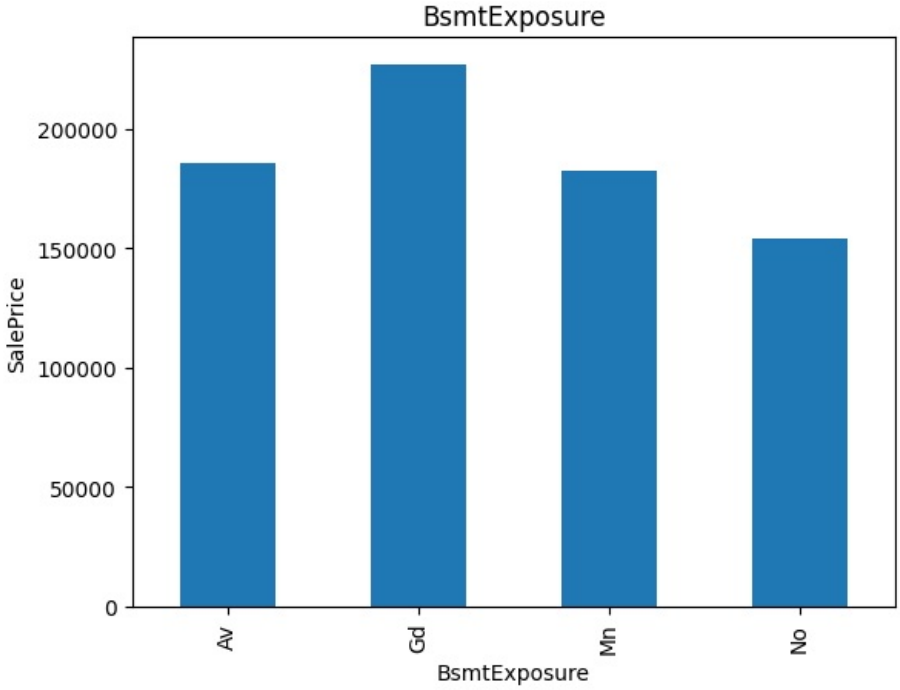

ExterQual
350000
300000
250000
200000
150000
100000
50000
0
SalePrice
Ex
Fa
Gd
TA
ExterQual

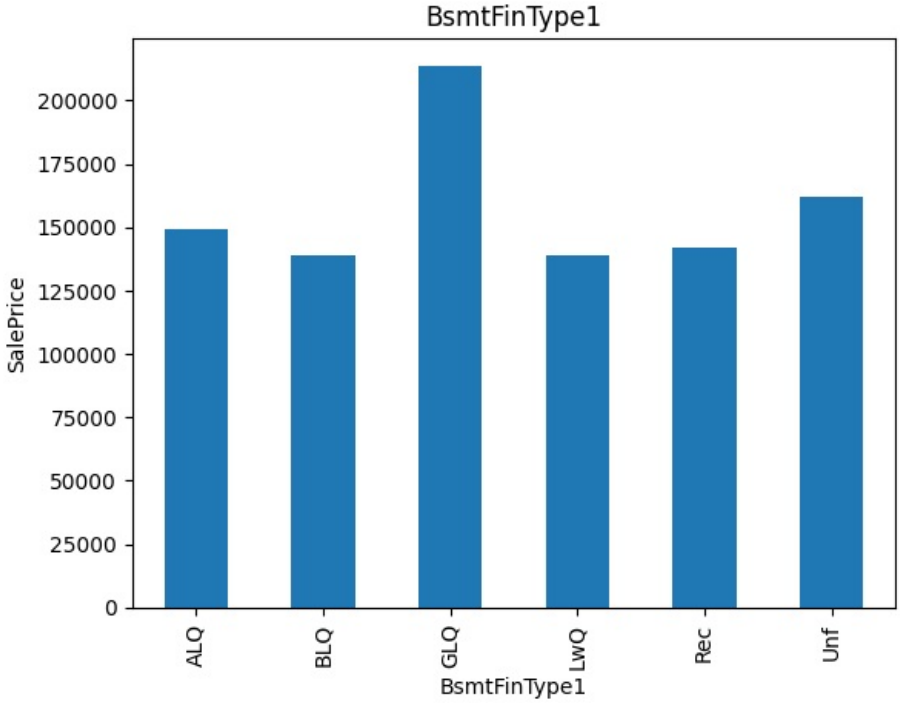

ExterCond
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
Ex
Fa
Gd
Po
TA
ExterCond

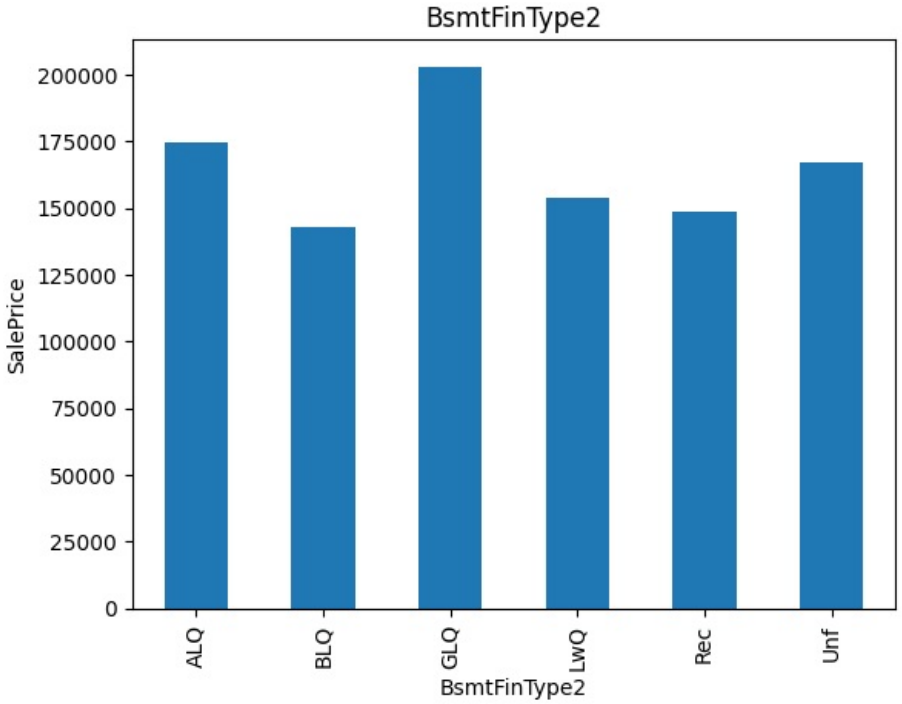

Foundation
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
BrkTil
CBlock
PConc
Slab
Stone
Wood
Foundation

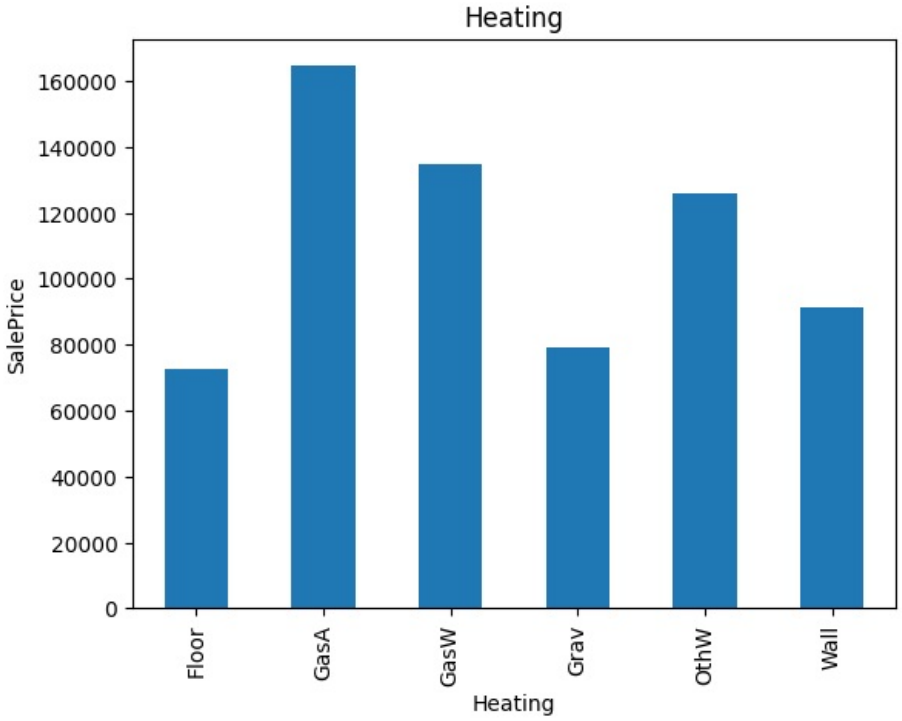

BsmtQual
300000
250000
200000
150000
100000
50000
0
SalePrice
Ex
Fa
Gd
TA
BsmtQual

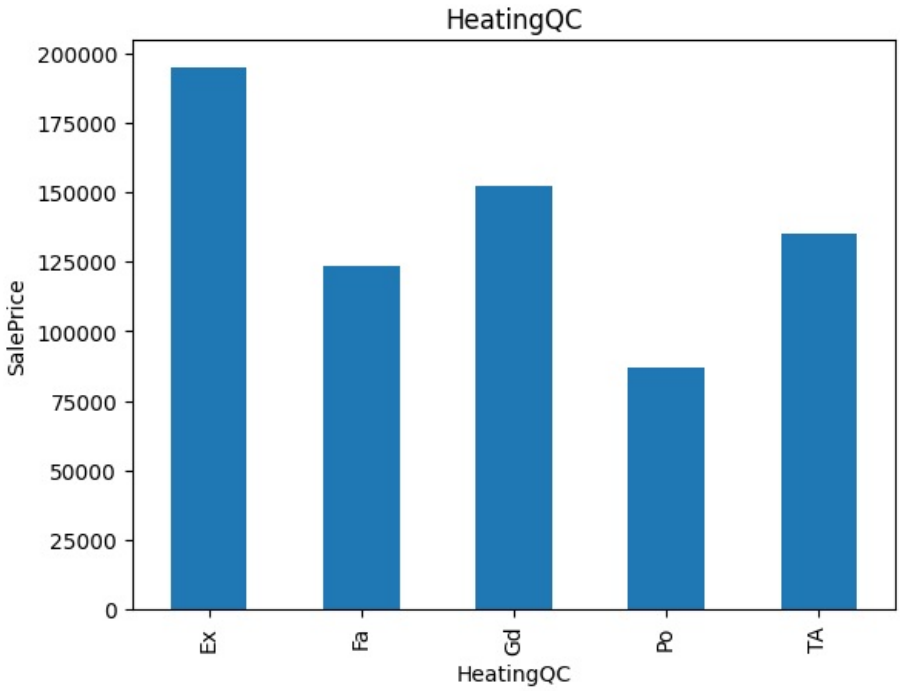

BsmtCond
200000
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
Fa
Gd
Po
TA
BsmtCond

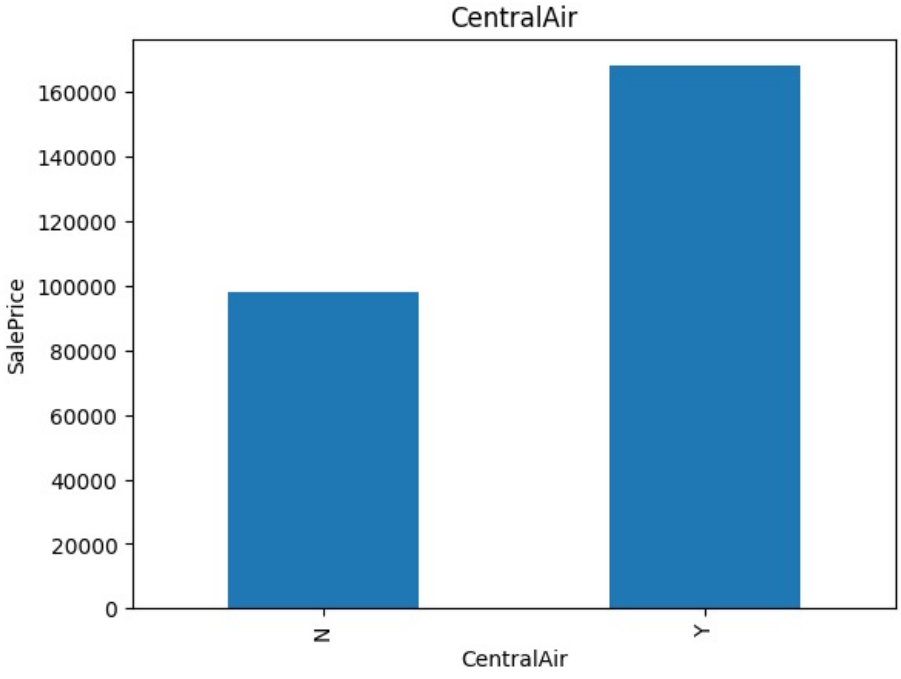

BsmtExposure
SalePrice
200000
150000
100000
50000
0
Av
Gd
Mn
No
BsmtExposure

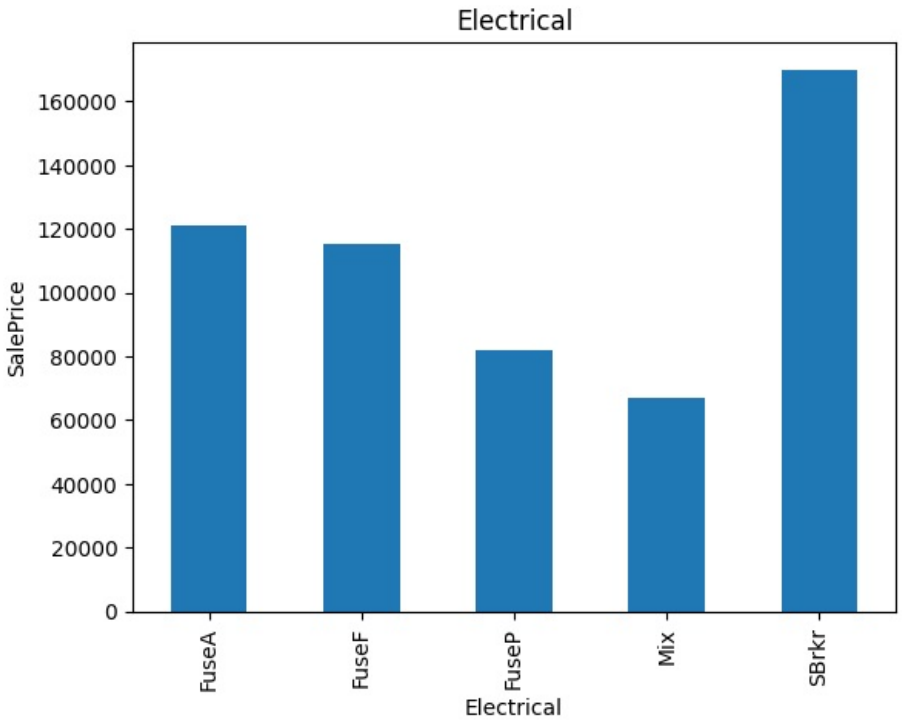

BsmtFinType1
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
ALQ
BLQ
GLQ
LwQ
Rec
Unf
BsmtFinType1

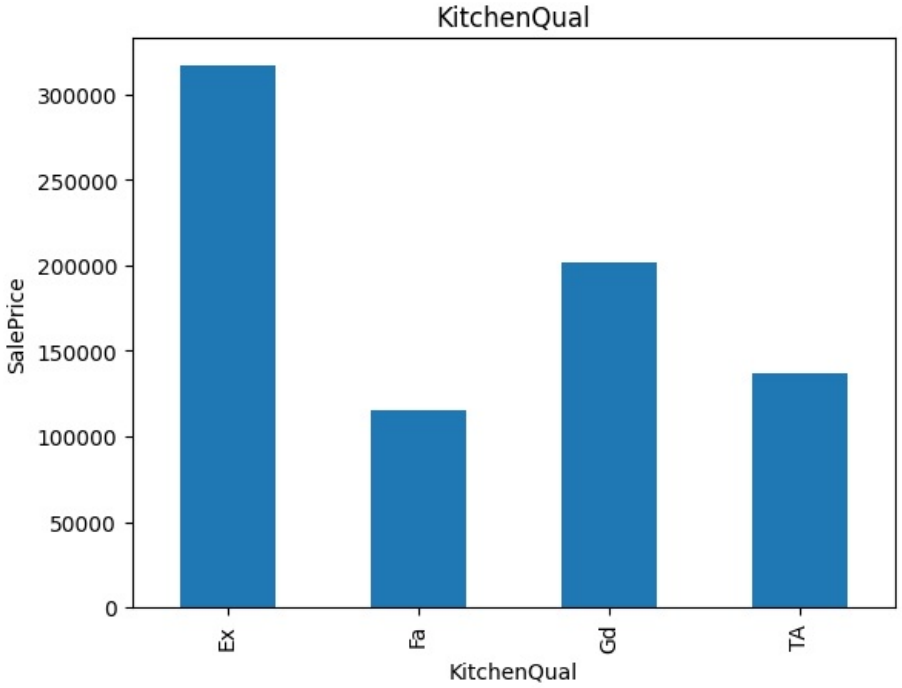

BsmtFinType2
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
ALQ
BLQ
GLQ
LwQ
Rec
Unf
BsmtFinType2

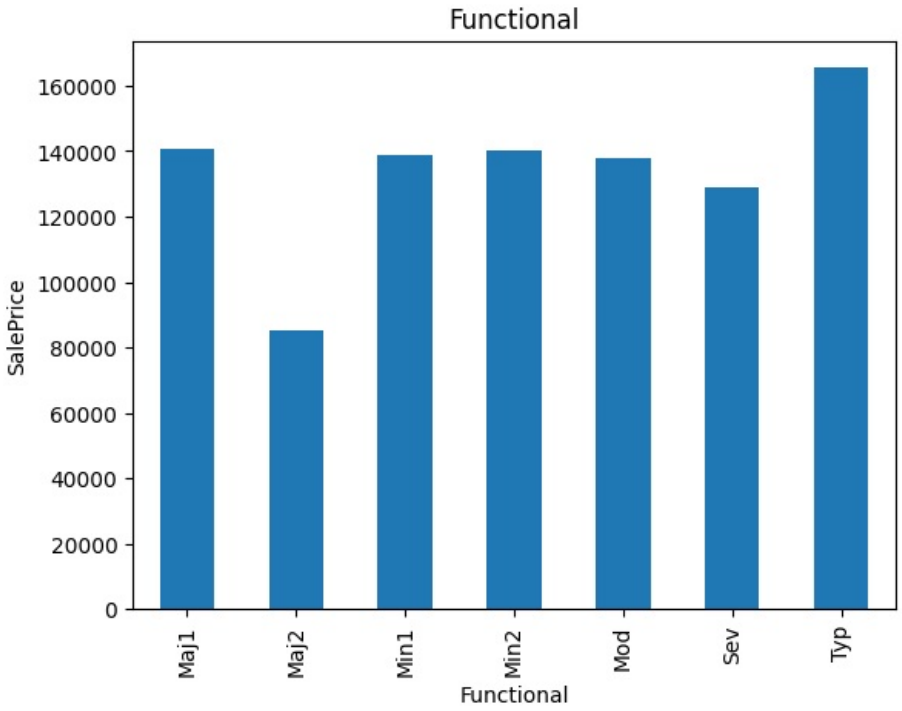

Heating
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
Floor
GasA
GasW
Grav
OthW
Wall
Heating

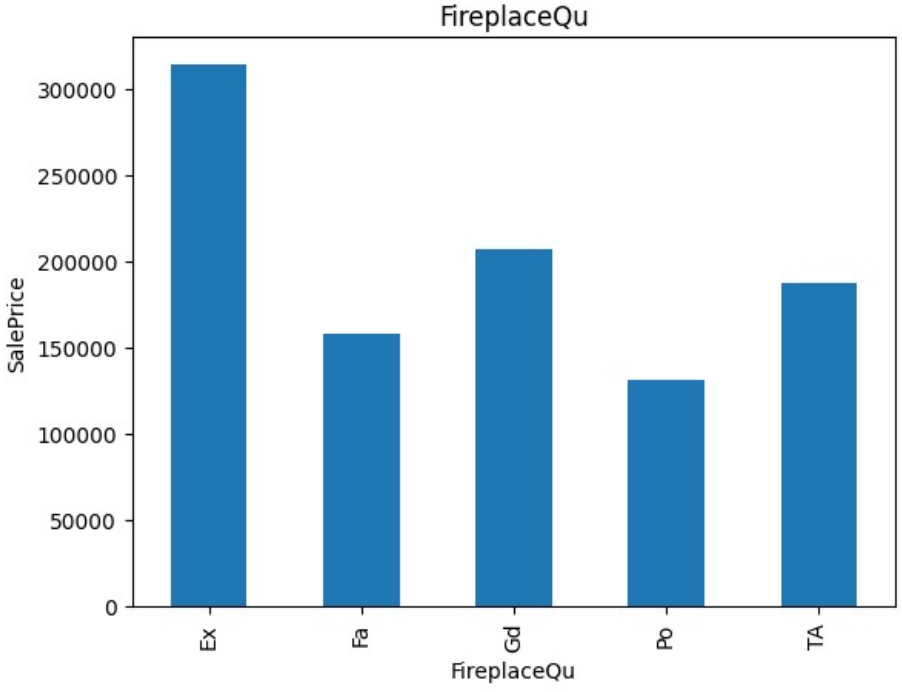

HeatingQC
200000
175000
150000
125000
100000
75000
50000
25000
0
SalePrice
Ex
Fa
Gd
Po
TA
HeatingQC

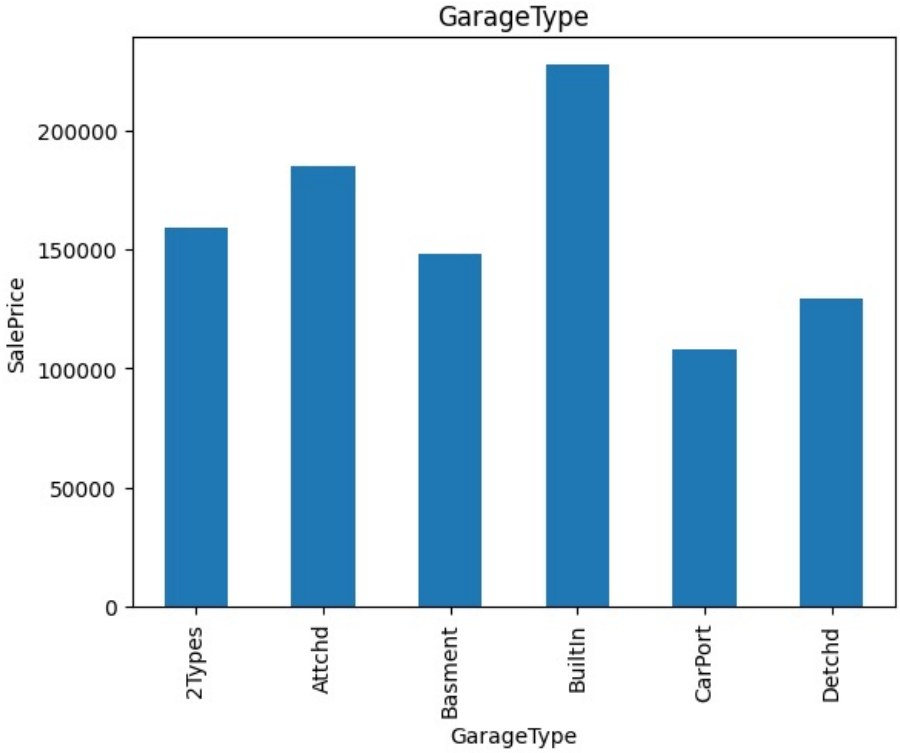

CentralAir
160000
140000
120000
100000
80000
60000
40000
20000
0
SalePrice
N
Y
CentralAir

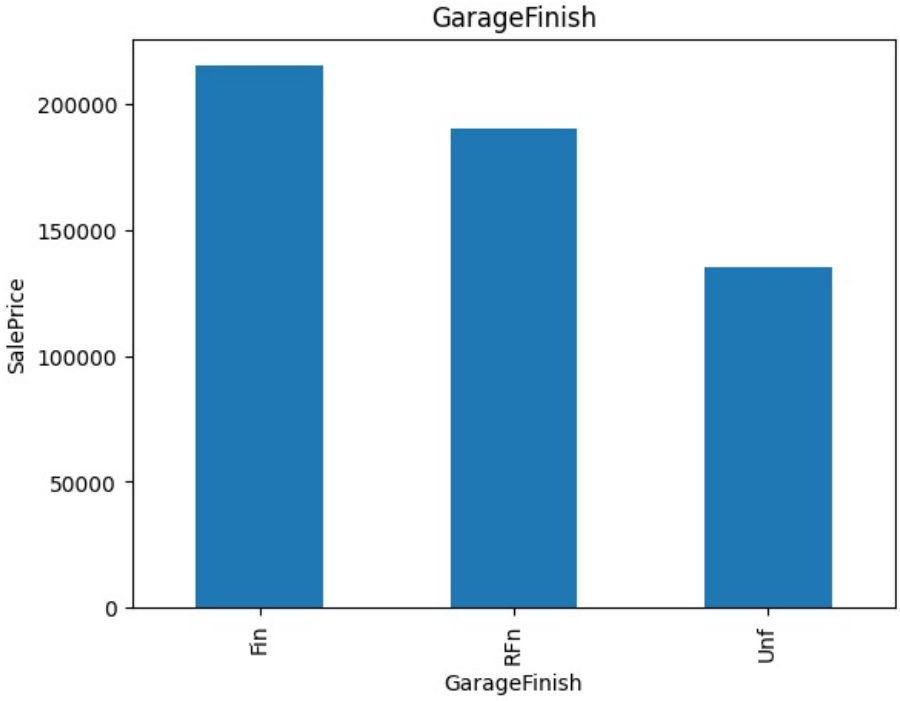

Electrical
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
FuseA
FuseF
FuseP
Mix
SBrkr
Electrical

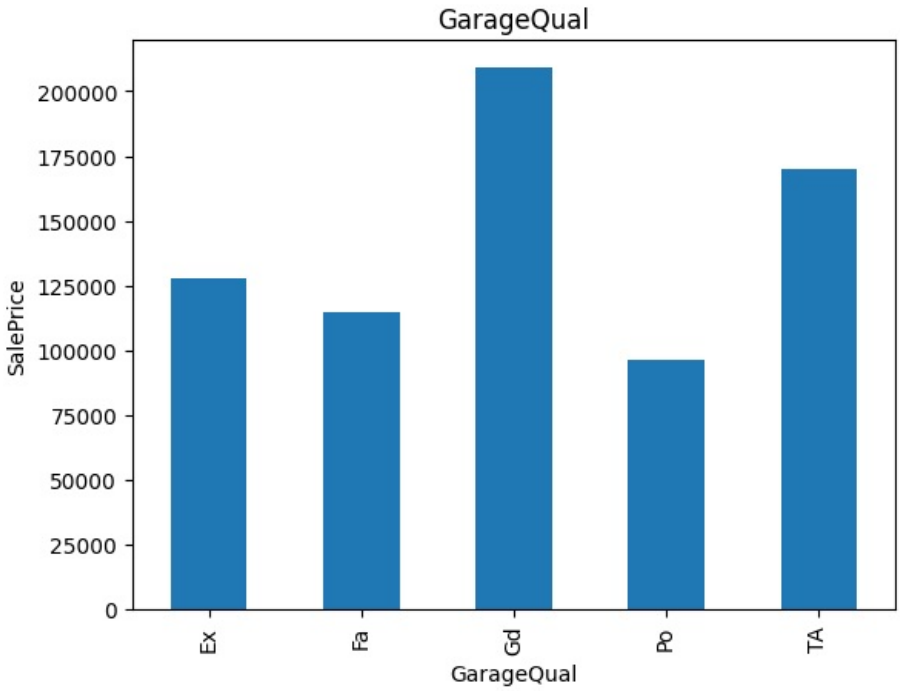

KitchenQual
SalePrice
300000
250000
200000
150000
100000
50000
0
Ex
Fa
Gd
TA
KitchenQual

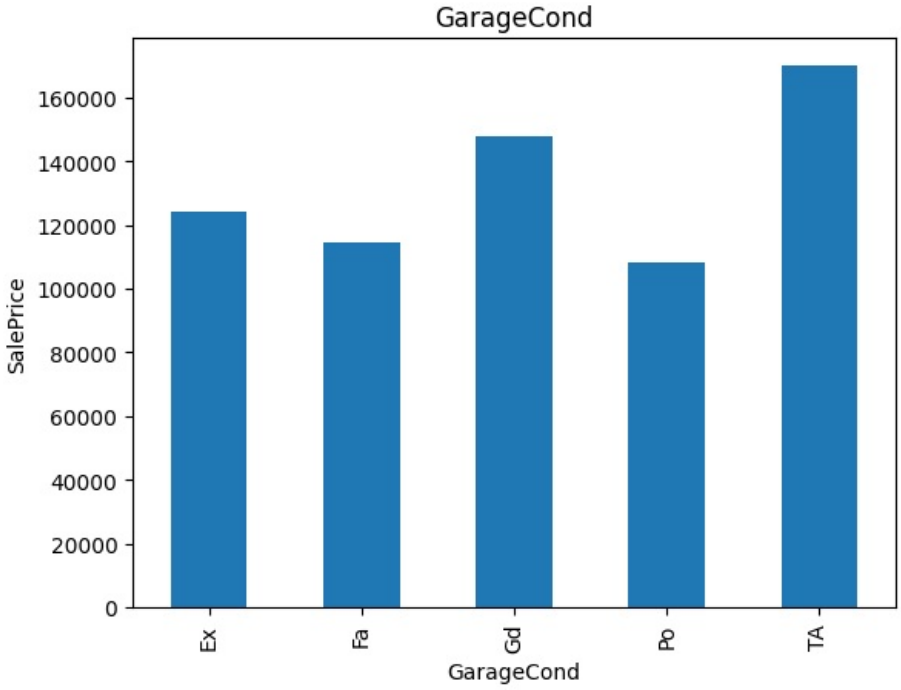

Functional
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
Maj1
Maj2
Min1
Min2
Mod
Sev
Typ
Functional

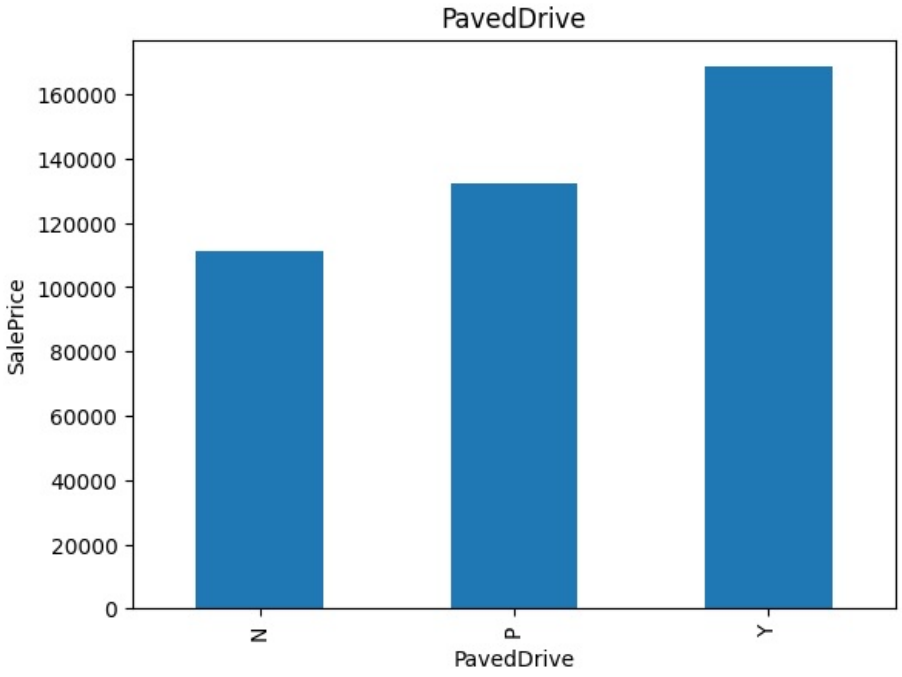

FireplaceQu
SalePrice
300000
250000
200000
150000
100000
50000
0
Ex
Fa
Gd
Po
TA
FireplaceQu

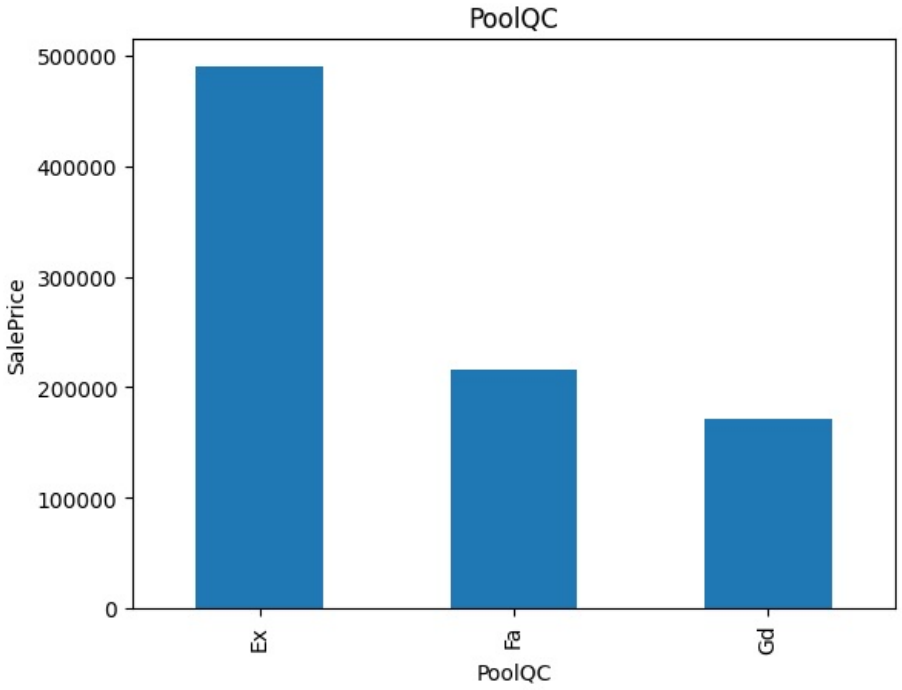

GarageType
SalePrice
200000
150000
100000
50000
0
2Types
Attchd
Basment
BuiltIn
CarPort
Detchd
GarageType

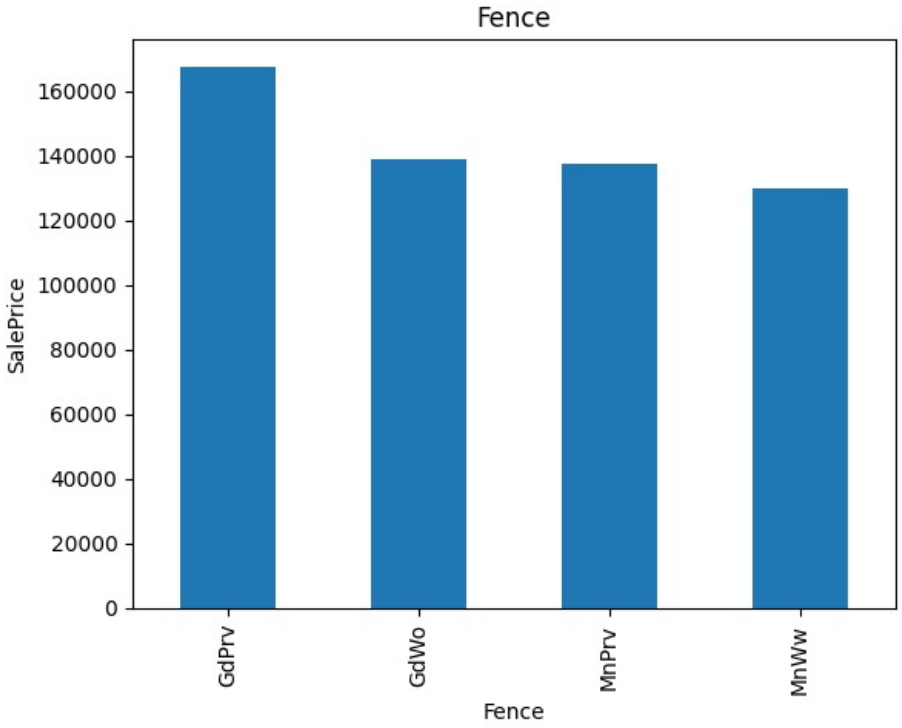

GarageFinish
SalePrice
200000
150000
100000
50000
0
Fin
RFn
Unf
GarageFinish

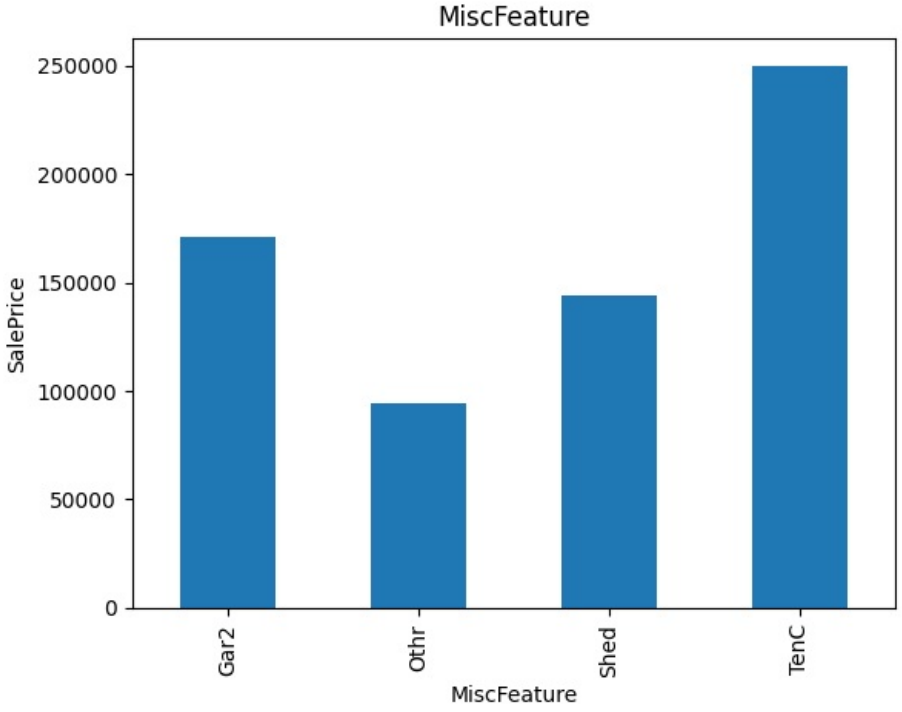

GarageQual
SalePrice
200000
175000
150000
125000
100000
75000
50000
25000
0
Ex
Fa
Gd
Po
TA
GarageQual

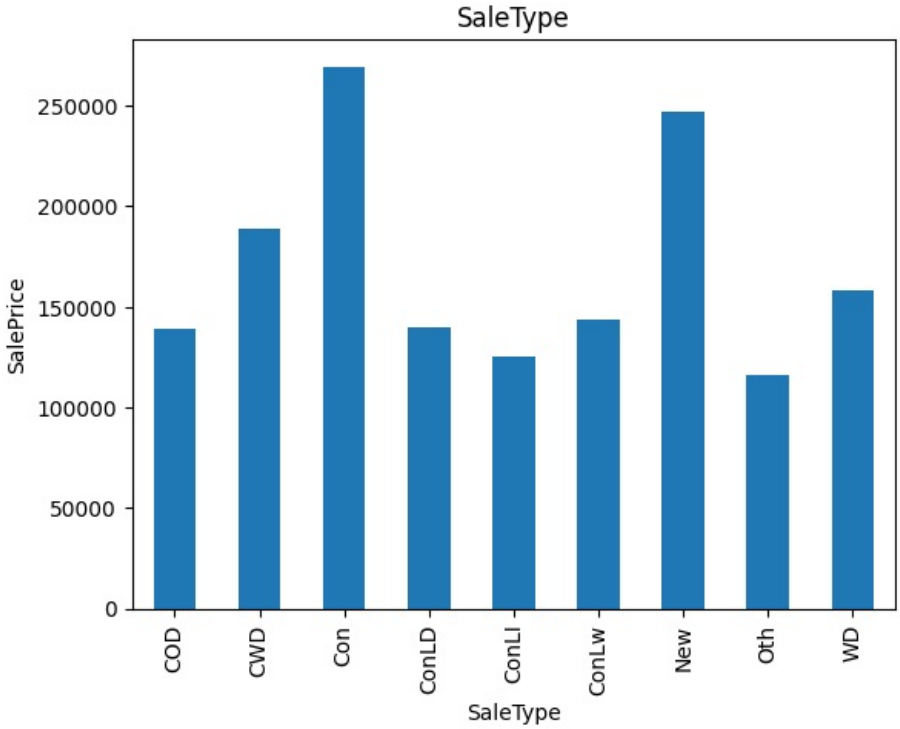

GarageCond
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
Ex
Fa
Gd
Po
TA
GarageCond

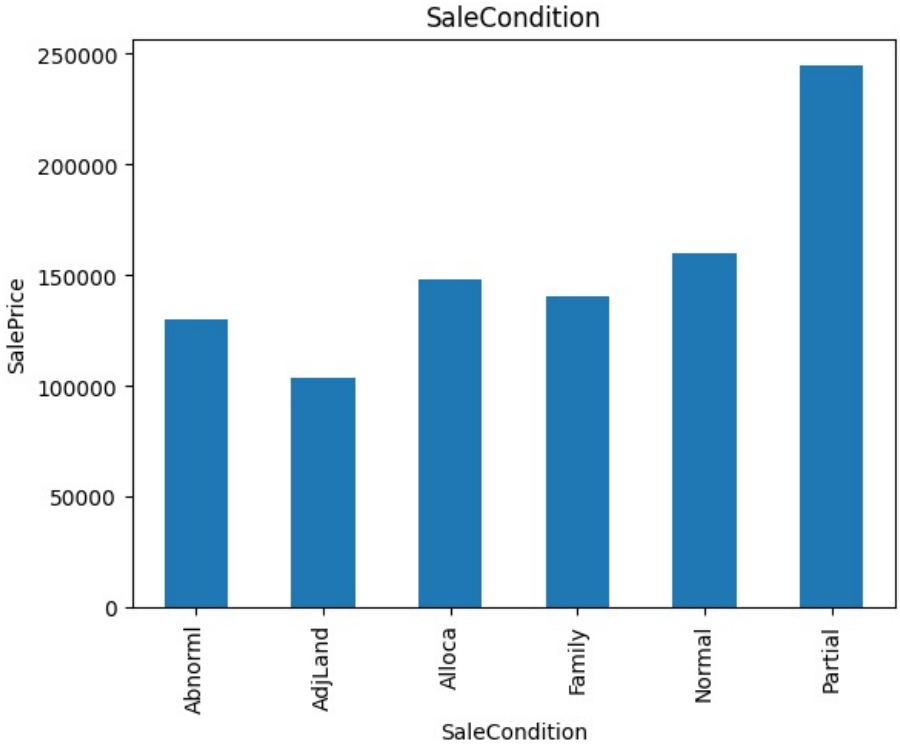

PavedDrive
SalePrice
160000
140000
120000
100000
80000
60000
40000
20000
0
N
P
Y
PavedDrive


PoolQC
SalePrice
500000
400000
300000
200000
100000
0
Ex
Fa
Gd
PoolQC


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


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





In [ ]: