ExploratoryData Analysis Phase

Project Name: House Prices: Advanced Regression Techniques

The main aim of this project is to perform exploratory data analysis to see if there is any correlation between the variables and also to analyse the distribution of the dataset.

Dataset to downloaded from the below link

https://www.kaggle.com/c/house-prices-advanced-regression-techniques/data (https://www.kaggle.com/c/house-prices-advanced-regression-techniques/data)

Importing useful modules

In [2]:
```
## 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 [3]:
```
dataset=pd.read_csv('train.csv')

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

```
(1460, 81)
```

In [4]:
```
## print the top5 records
dataset.head(5)
```

Out[4]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilitie
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPu
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPu
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPu
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPu
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPu

In Data Analysis We will Analyze To Find out the below stuff

1. Missing Values
2. All The Numerical Variables
3. Distribution of the Numerical Variables
4. Categorical Variables
5. Cardinality of Categorical Variables
6. Outliers
7. Relationship between independent and dependent feature(SalePrice)

Missing Values

Here we will check the percentage of nan values present in each feature

1 -step make the list of features which has missing values

2- step print the feature name and the percentage of missing values

In [5]:
```
features_with_na=[features for features in dataset.columns if dataset[features].i

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

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

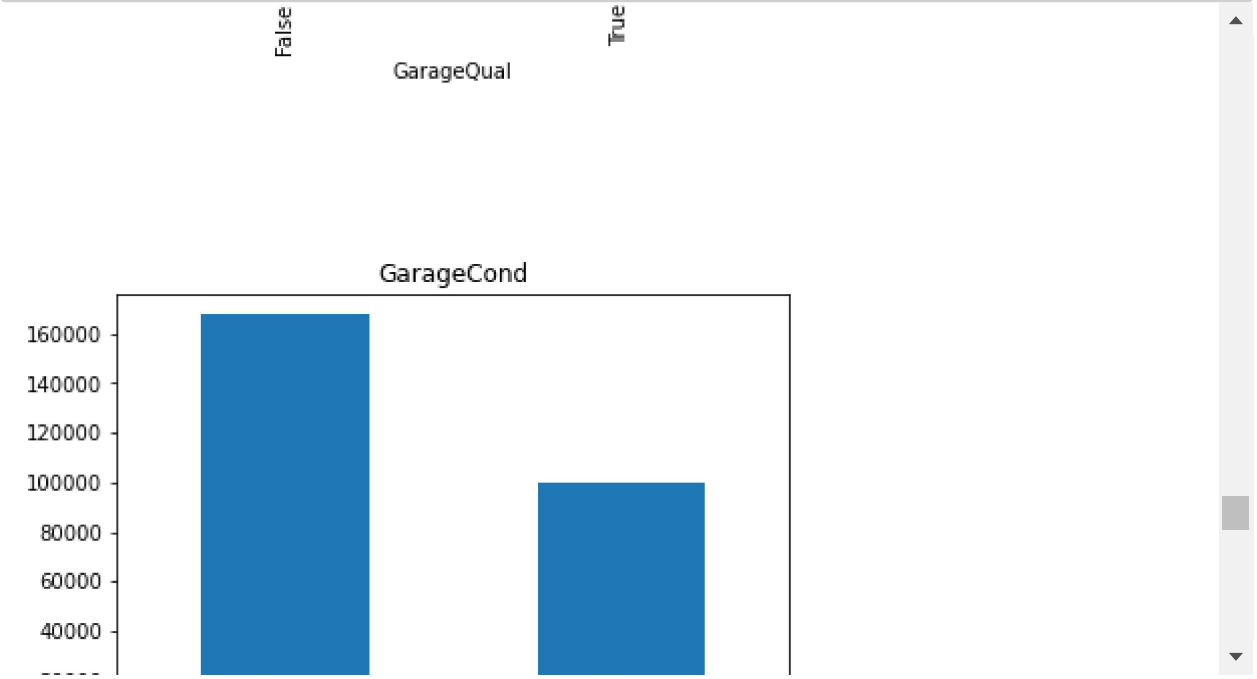
Since they are many missing values, we need to find the relationship between missing values and Sales Price

Let's plot some diagram for this relationship

In [13]:
```
for feature in features_with_na:
    data = dataset.copy()

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

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



Here With the relation between the missing values and the dependent variable is clearly visible.So We need to replace these nan values with something meaningful

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

In [15]:
```
print("Id of Houses {}".format(len(dataset.Id)))
```

```
Id of Houses 1460
```

Numerical Variables

In [16]:
```
# list of numerical variables. O means object
numerical_features = [feature for feature in dataset.columns if dataset[feature].

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

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

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

Out[16]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	Ma
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	

In [20]:
```
(dataset[numerical_features]..shape
```

Out[20]:
```
(1460, 38)
```

Temporal Variables(Eg: Datetime Variables)

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

In [21]:
```
# list of variables that contain year information
year_feature = [feature for feature in numerical_features if 'Yr' in feature or '

year_feature
```

Out[21]:
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

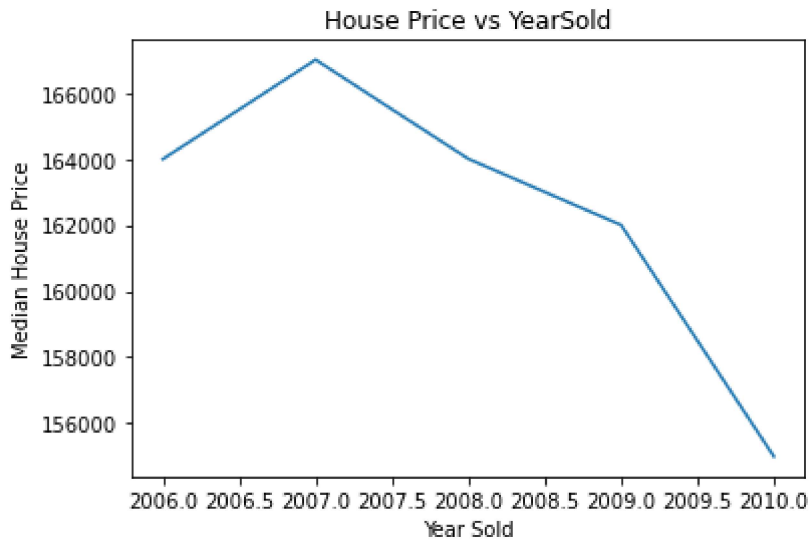
In [22]:
```
# let's explore the content of these year variables
for feature in year_feature:
    print(feature, dataset[feature].unique())
```

```
YearBuilt [2003 1976 2001 1915 2000 1993 2004 1973 1931 1939 1965 2005 1962 200
6
 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 [23]:
```
## Lets analyze the Temporal Datetime Variables
## We will check whether there is a relation between year the house is sold and t

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

Out[23]: Text(0.5, 1.0, 'House Price vs YearSold')



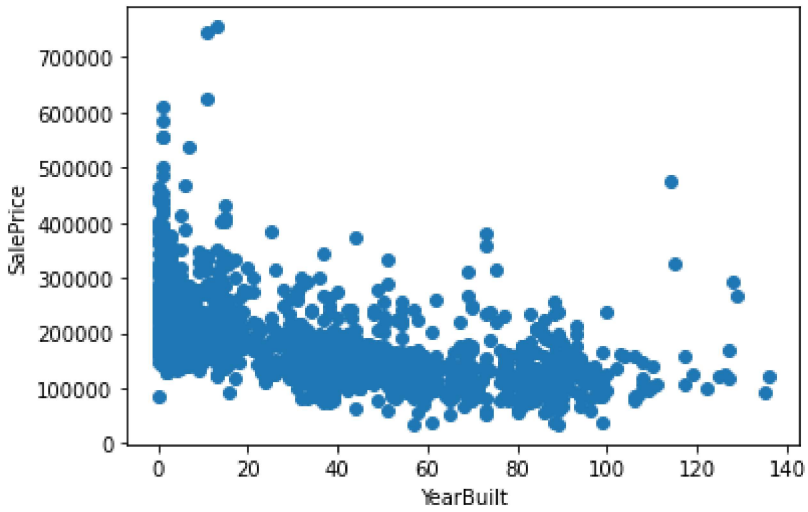
In [25]:
```
year_feature
```

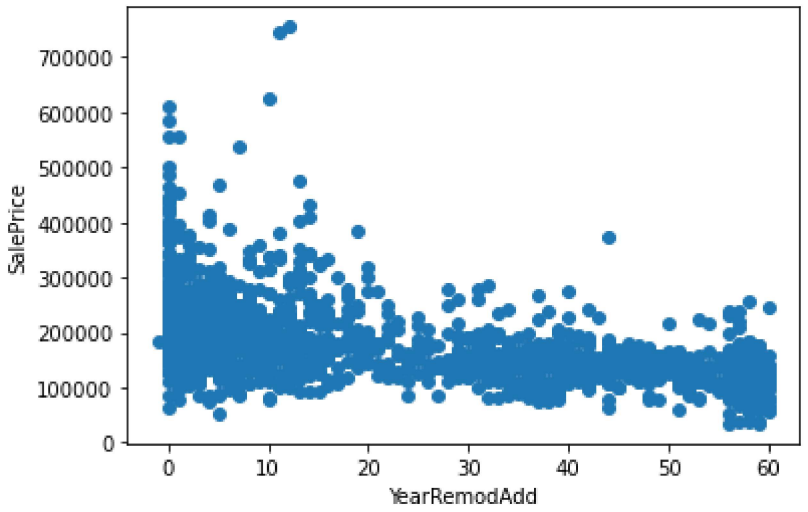
Out[25]: ['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']

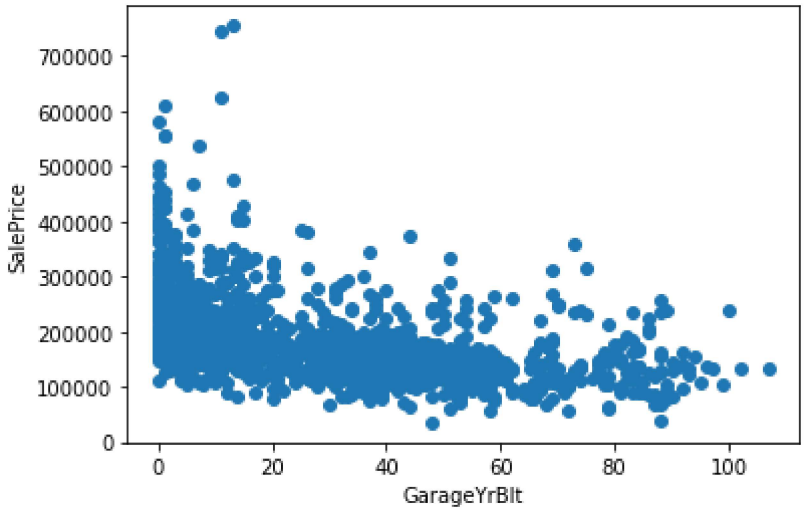
In [26]:
```
## Here we will compare the difference between All years feature with SalePrice

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

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







In [28]:
```
## Numerical variables are usually of 2 type
## 1. Continous variable and Discrete Variables

discrete_feature=[feature for feature in numerical_features if len(dataset[featur
print("Discrete Variables Count: {}".format(len(discrete_feature)))
```

```
Discrete Variables Count: 17
```

In [29]:
```
discrete_feature
```

Out[29]:
```
['MSSubClass',
 'OverallQual',
 'OverallCond',
 'LowQualFinSF',
 'BsmtFullBath',
 'BsmtHalfBath',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'KitchenAbvGr',
 'TotRmsAbvGrd',
 'Fireplaces',
 'GarageCars',
 '3SsnPorch',
 'PoolArea',
 'MiscVal',
 'MoSold']
```

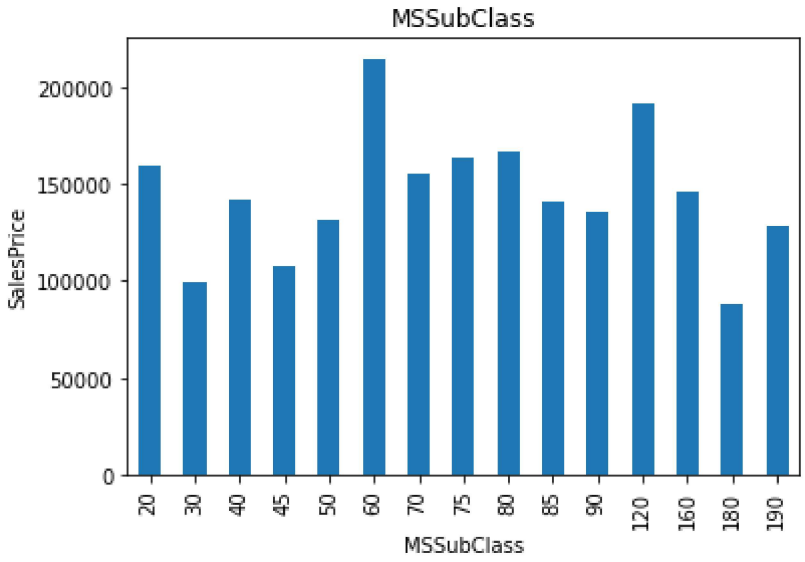
In [31]:
```
dataset[discrete_feature].head()
```

Out[31]:

	MSSubClass	OverallQual	OverallCond	LowQualFinSF	BsmtFullBath	BsmtHalfBath	FullBath	H
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 [33]:
```
## lets fine the relationship between them and sales price

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



This shows that there is a relationship between the variables.