House Price Prediction

Life Cycle of a Machine Learning Project

1. Understanding the Problem Statement
2. Data Collection
3. EDA (Exploratory Data Analysis)
4. Data Cleaning
5. Data Pre-Processing
6. Model Training
7. Choose Best Model

Problem Statement

1. This dataset contains data for houeses to be sold and various features of those houses.
2. Aim is to predict the price of the house based on the features.
3. Before creating a model we need to do EDA.

Data Description

Description of the data is present in 'data_description.txt' file

A) Importing Data and Required Packages

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

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

```
C:\Users\Sachin Dev\AppData\Roaming\Python\Python38\site-packages\pandas\core\c
omputation\expressions.py:20: UserWarning: Pandas requires version '2.7.3' or n
ewer of 'numexpr' (version '2.7.1' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
```

In [2]:
```
pd.pandas.set_option('display.max_columns',None)
```

Import csv as Pandas Dataframe

In [3]:
```
df = pd.read_csv('HousingData.csv')
```

Show Top 5 Rows

In [4]:
```
df.head()
```

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

Show Bottom 5 Rows

In [5]:
```
df.tail()
```

Out[5]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	Lvl
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	Lvl
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	Lvl
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	Lvl
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	Lvl

Shape of the data

In [6]:
```
df.shape
```

Out[6]:
```
(1460, 81)
```

There are 81 columns in the datset. So, we will need to do feature selection at one point.

Check Null Values and Data Types

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     1452 non-null   object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
 29  Foundation     1460 non-null   object 
 30  BsmtQual       1423 non-null   object 
 31  BsmtCond       1423 non-null   object 
 32  BsmtExposure   1422 non-null   object 
 33  BsmtFinType1   1423 non-null   object 
 34  BsmtFinSF1     1460 non-null   int64  
 35  BsmtFinType2   1422 non-null   object 
 36  BsmtFinSF2     1460 non-null   int64  
 37  BsmtUnfSF      1460 non-null   int64  
 38  TotalBsmtSF    1460 non-null   int64  
 39  Heating        1460 non-null   object 
 40  HeatingQC      1460 non-null   object 
 41  CentralAir     1460 non-null   object 
 42  Electrical     1459 non-null   object 
 43  1stFlrSF       1460 non-null   int64  
 44  2ndFlrSF       1460 non-null   int64  
 45  LowQualFinSF   1460 non-null   int64  
 46  GrLivArea      1460 non-null   int64  
 47  BsmtFullBath   1460 non-null   int64  
 48  BsmtHalfBath   1460 non-null   int64  
```

```
 49  FullBath       1460 non-null   int64  
 50  HalfBath       1460 non-null   int64  
 51  BedroomAbvGr   1460 non-null   int64  
 52  KitchenAbvGr   1460 non-null   int64  
 53  KitchenQual    1460 non-null   object 
 54  TotRmsAbvGrd   1460 non-null   int64  
 55  Functional     1460 non-null   object 
 56  Fireplaces     1460 non-null   int64  
 57  FireplaceQu    770 non-null    object 
 58  GarageType     1379 non-null   object 
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object 
 61  GarageCars     1460 non-null   int64  
 62  GarageArea     1460 non-null   int64  
 63  GarageQual     1379 non-null   object 
 64  GarageCond     1379 non-null   object 
 65  PavedDrive     1460 non-null   object 
 66  WoodDeckSF     1460 non-null   int64  
 67  OpenPorchSF    1460 non-null   int64  
 68  EnclosedPorch  1460 non-null   int64  
 69  3SsnPorch      1460 non-null   int64  
 70  ScreenPorch    1460 non-null   int64  
 71  PoolArea       1460 non-null   int64  
 72  PoolQC         7 non-null      object 
 73  Fence          281 non-null    object 
 74  MiscFeature    54 non-null     object 
 75  MiscVal        1460 non-null   int64  
 76  MoSold         1460 non-null   int64  
 77  YrSold         1460 non-null   int64  
 78  SaleType       1460 non-null   object 
 79  SaleCondition  1460 non-null   object 
 80  SalePrice      1460 non-null   int64  
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

Some features have a lot of Null Values

Exploring Data

Check Missing Values

In [8]:
```
###1: create a list of features which has missing values
features_with_na = [feature for feature in df.columns if df[feature].isnull(

###2: printing the names of features and % of missing values
for feature in features_with_na:
    print(feature, np.round(df[feature].isnull().mean()*100 , 4), '%missing
```

```
LotFrontage 17.7397 %missing values
Alley 93.7671 %missing values
MasVnrType 0.5479 %missing values
MasVnrArea 0.5479 %missing values
BsmtQual 2.5342 %missing values
BsmtCond 2.5342 %missing values
BsmtExposure 2.6027 %missing values
BsmtFinType1 2.5342 %missing values
BsmtFinType2 2.6027 %missing values
FireplaceQu 47.2603 %missing values
GarageType 5.5479 %missing values
GarageYrBlt 5.5479 %missing values
GarageFinish 5.5479 %missing values
GarageQual 5.5479 %missing values
GarageCond 5.5479 %missing values
PoolQC 99.5205 %missing values
Fence 80.7534 %missing values
MiscFeature 96.3014 %missing values
```

In [9]:
```
len(features_with_na)
```

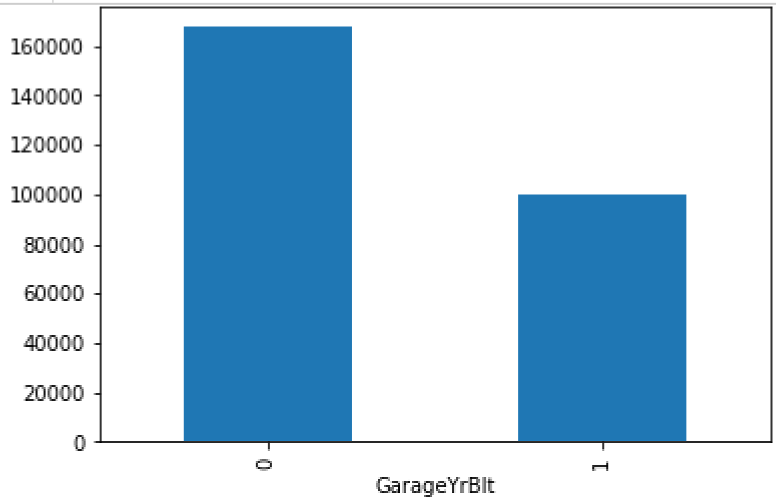
Out[9]: 18

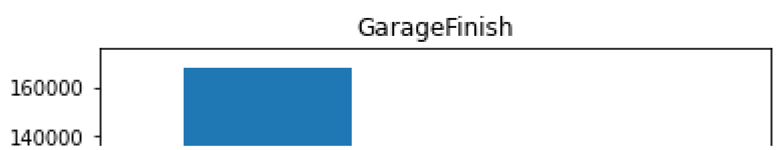
There are 18 features which have missing values and out of these 18 features 4features have more than 80% Null values

Since there are many missing values, we need to find the relationship between missing values and SalesPrice(Target Column)

In [10]:

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

    ### making a variable that indicates 1 if observation is missing and 0 o
    data[feature] = np.where(data[feature].isnull(), 1, 0) ### this will cre


    ### calculate mean of SalesPrice where information is missing or present
    data.groupby(feature)['SalePrice'].median().plot.bar()
    plt.title(feature)
    plt.show()
```





Here the relation of dependent features is clearly visible with the missing values. So, we will need to replace these Nan values with something meaningful during feature engineering process.

Also, some features like Id etc are not required so we can drop these features

In [ ]:

```

```

Numerical Features

In [11]:

```
numerical_features = [feature for feature in df.columns if df[feature].dtype
print("Number of numerical features: ",len(numerical_features))

```

```
Number of numerical features:  38
```

In [12]:

```
### Top 5 rows of numerical features
df[numerical_features].head()
```

Out[12]:

	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 [13]:
```
for feature in numerical_features:
    print(feature)
```

```
Id
MSSubClass
LotFrontage
LotArea
OverallQual
OverallCond
YearBuilt
YearRemodAdd
MasVnrArea
BsmtFinSF1
BsmtFinSF2
BsmtUnfSF
TotalBsmtSF
1stFlrSF
2ndFlrSF
LowQualFinSF
GrLivArea
BsmtFullBath
BsmtHalfBath
FullBath
HalfBath
BedroomAbvGr
KitchenAbvGr
TotRmsAbvGrd
Fireplaces
GarageYrBlt
GarageCars
GarageArea
WoodDeckSF
OpenPorchSF
EnclosedPorch
3SsnPorch
ScreenPorch
PoolArea
MiscVal
MoSold
YrSold
SalePrice
```

Datetime Features (Temporal Variables)

In the dataset, we have few Year features. We can extract information from these features. Eg: THe difference b/w the year house built and the year house sold.

In [14]:
```
year_feature = [feature for feature in numerical_features if 'Yr' in feature
year_feature
```

Out[14]:
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

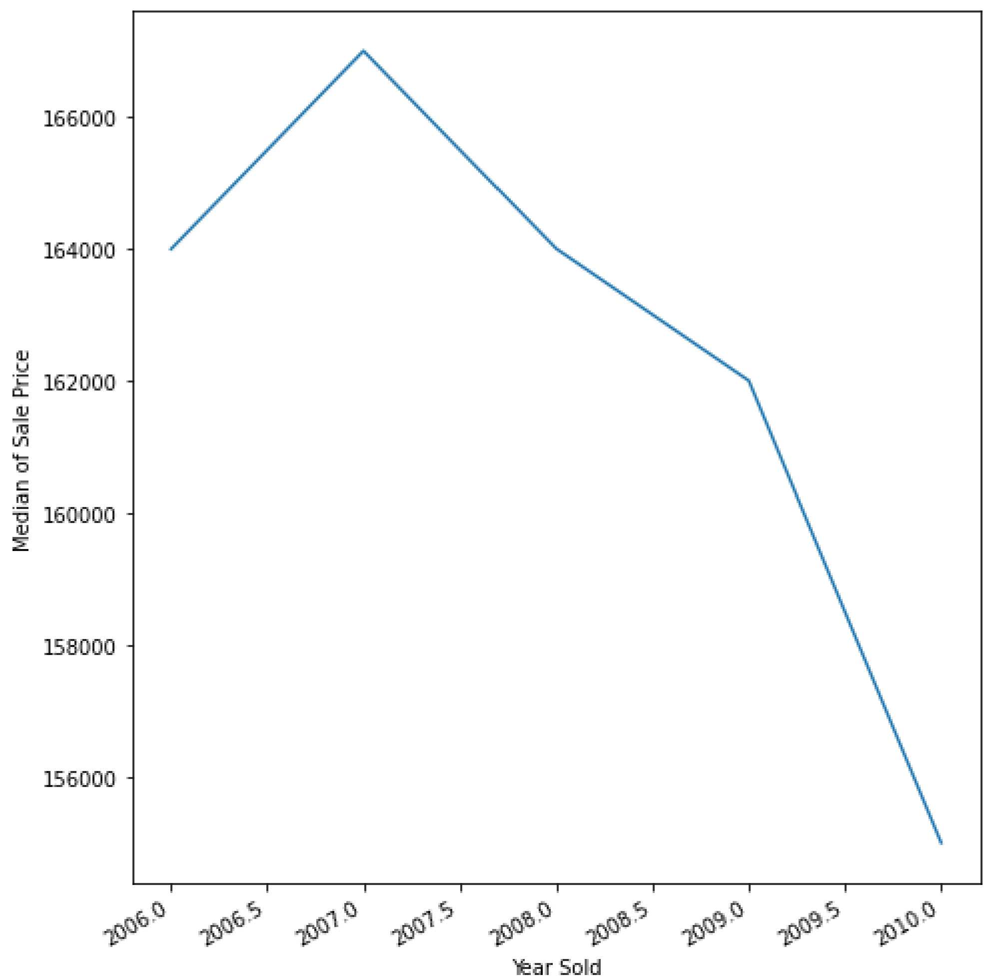
Exploring year_feature

In [15]:
```
for feature in year_feature:
    print(feature, df[feature].unique())
    print('---------------------------------'*3)
```

```
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]
-------------------------------------------------------------------------------
-------------------
```

Relation between Year sold and SalePrice

In [16]:
```
plt.figure(figsize=(7,7))

df.groupby('YrSold')['SalePrice'].median().plot()

plt.gcf().autofmt_xdate()
plt.xlabel("Year Sold Vs Sale Price")
plt.xlabel('Year Sold')
plt.ylabel('Median of Sale Price')
plt.tight_layout()
plt.show()
```



Clearly we can see that from 2007 onwards Price of Houses decreases with the increase in Year

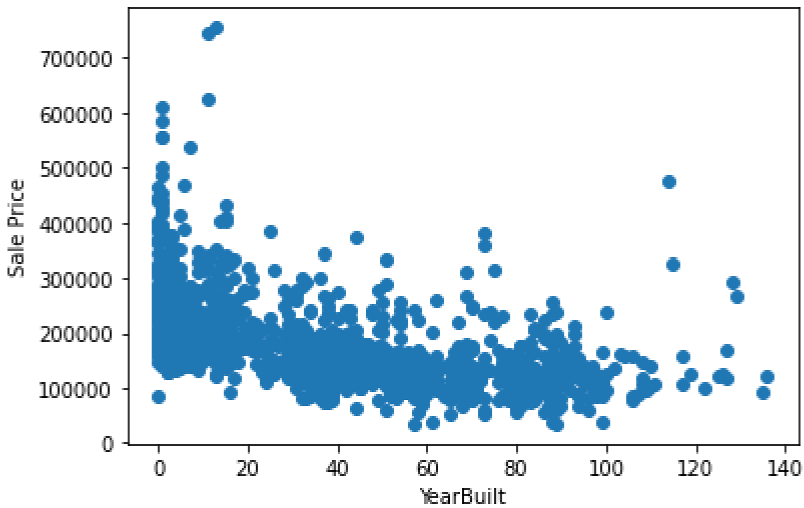
Compare the difference b/w all year features with sale price

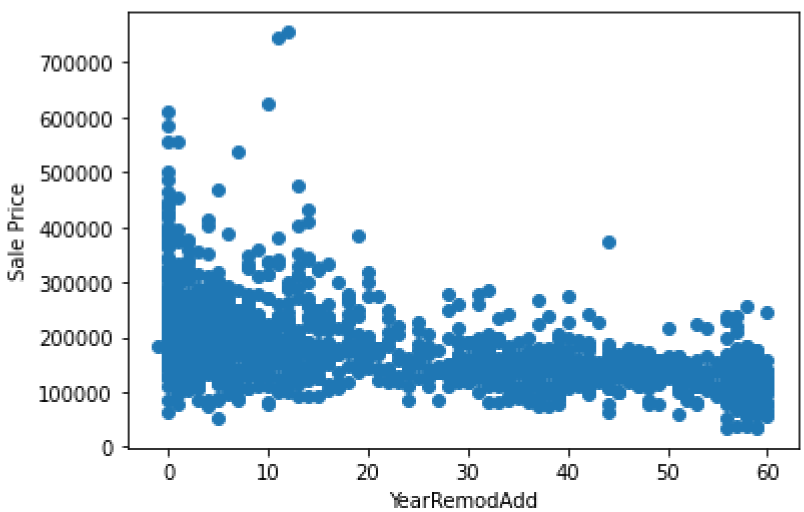
In [17]:
```
year_feature
```

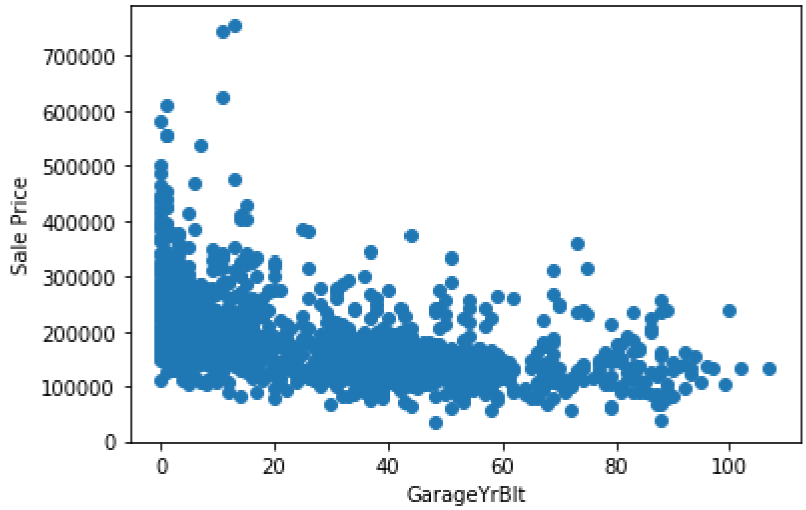
Out[17]:
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

In [18]:

```
for feature in year_feature:
    if feature != 'YrSold':
        data = df.copy()

        ### eg feature is YearBuilt = 1960 and Yr Sold = 2000
        ### so, data[feature] = 2000 - 1960 = 40yrs

        data[feature] = data['YrSold'] - data[feature]

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







AS expected the newer the house or renovated early or new garage, higher the price.

Discrete Features

In [19]:
```
### variables with less than 25 unique values
### and variables should not be preset in year features
### exlude Id cloumn also

discrete_feature = [feature for feature in numerical_features if len(df[feat
print("Number of Discrete Features: {}".format(len(discrete_feature)))
```

```
Number of Discrete Features: 17
```

In [20]:
```
discrete_feature
```

Out[20]:
```
['MSSubClass',
 'OverallQual',
 'OverallCond',
 'LowQualFinSF',
 'BsmtFullBath',
 'BsmtHalfBath',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'KitchenAbvGr',
 'TotRmsAbvGrd',
 'Fireplaces',
 'GarageCars',
 '3SsnPorch',
 'PoolArea',
 'MiscVal',
 'MoSold']
```

Visualize Discrete features

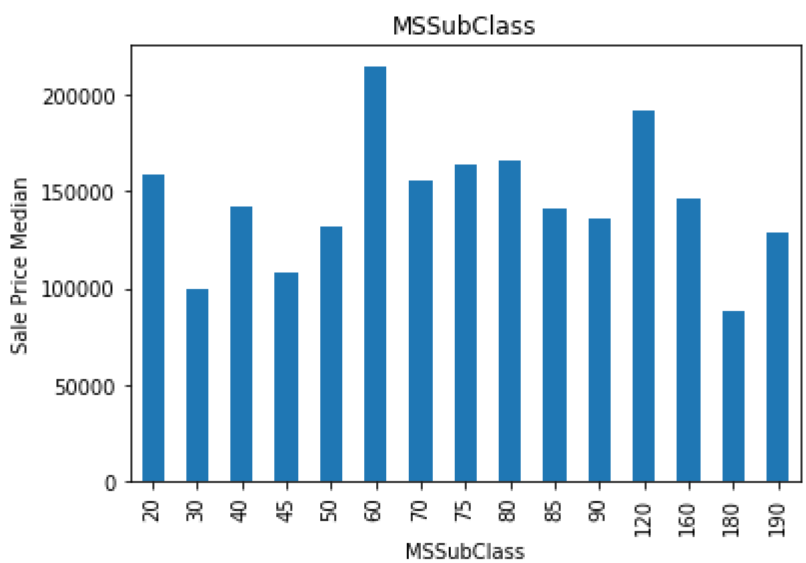
In [21]:
```
df[discrete_feature].head()
```

Out[21]:

	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	

Relationship of Discrete features with Price Column

In [22]:
```

for feature in discrete_feature:
    data = df.copy()

    data.groupby(feature)['SalePrice'].median().plot.bar()
    plt.xlabel(feature)
    plt.ylabel('Sale Price Median')
    plt.title(feature)
    plt.show()
```



Observations

1. Over all Quality have Positive Correlation with Sale Price
2. Full Bath have positive correlation with Sale Price.
3. Sale Price increase with the increase in TotRmsAbvGrd from 2 to 11 then sale price decreases.
4. Even single Fireplace can impact or increase the price of the House.
5. Houses with 3 GarageCars have the highest price.

Continuous Features

In [23]:
```
### variables that are not present in discrete feature and year feature list
### Also exclude Id column

continuous_feature = [feature for feature in numerical_features if feature n
print(f'Number of Continuous Features: {len(continuous_feature)}')
```

```
Number of Continuous Features: 16
```

In [24]:
```
continuous_feature
```

Out[24]:
```
['LotFrontage',
 'LotArea',
 'MasVnrArea',
 'BsmtFinSF1',
 'BsmtFinSF2',
 'BsmtUnfSF',
 'TotalBsmtSF',
 '1stFlrSF',
 '2ndFlrSF',
 'GrLivArea',
 'GarageArea',
 'WoodDeckSF',
 'OpenPorchSF',
 'EnclosedPorch',
 'ScreenPorch',
 'SalePrice']
```

Visualize continuous_features

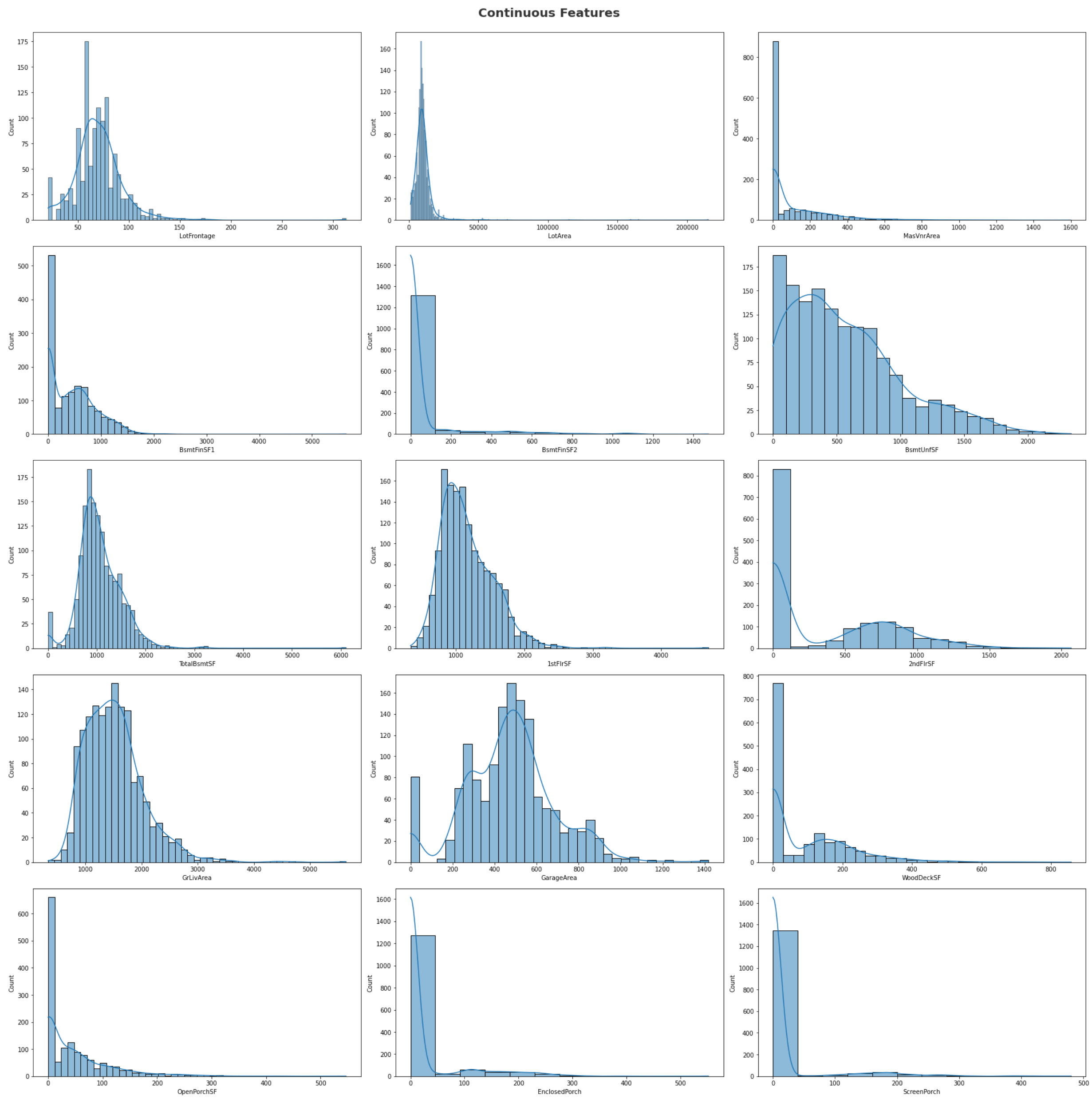
In [25]:
```
df[continuous_feature].head()
```

Out[25]:

	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stFlrS
0	65.0	8450	196.0	706	0	150	856	85
1	80.0	9600	0.0	978	0	284	1262	126
2	68.0	11250	162.0	486	0	434	920	92
3	60.0	9550	0.0	216	0	540	756	96
4	84.0	14260	350.0	655	0	490	1145	114

Analyze continuous features with the help of Histograms

In [26]:
```python
plt.figure(figsize=(25,25))
plt.suptitle("Continuous Features",fontsize=20,fontweight='bold',alpha=0.8,y

for i in range(len(continuous_feature)):
    if continuous_feature[i] != 'SalePrice':
        plt.subplot(5,3,i+1)
        sns.histplot(data=df,x=df[continuous_feature[i]],kde=True)
        plt.xlabel(continuous_feature[i])
        plt.ylabel("Count")
        plt.tight_layout()
```

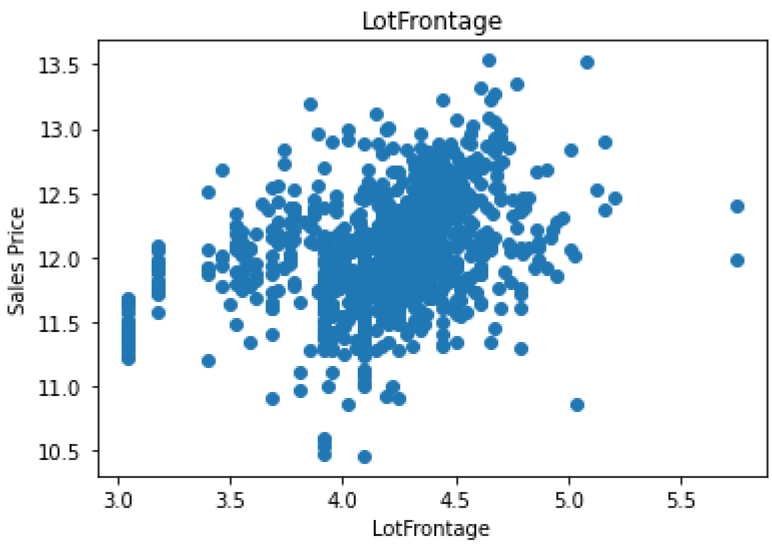


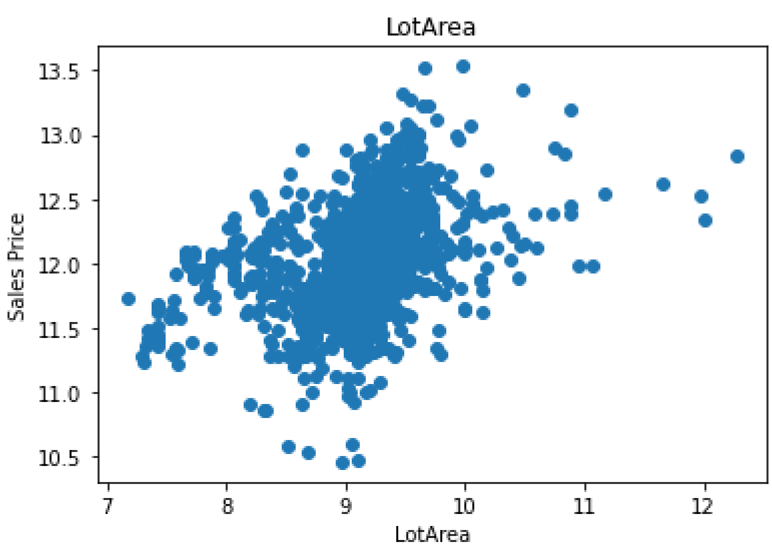
There are a lot of columns which are skewed.

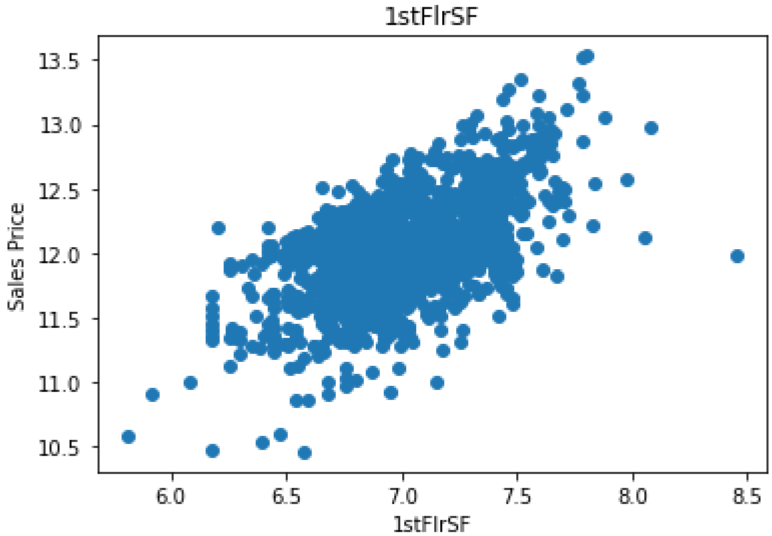
log Transformation to convert skewed data to normal distribution

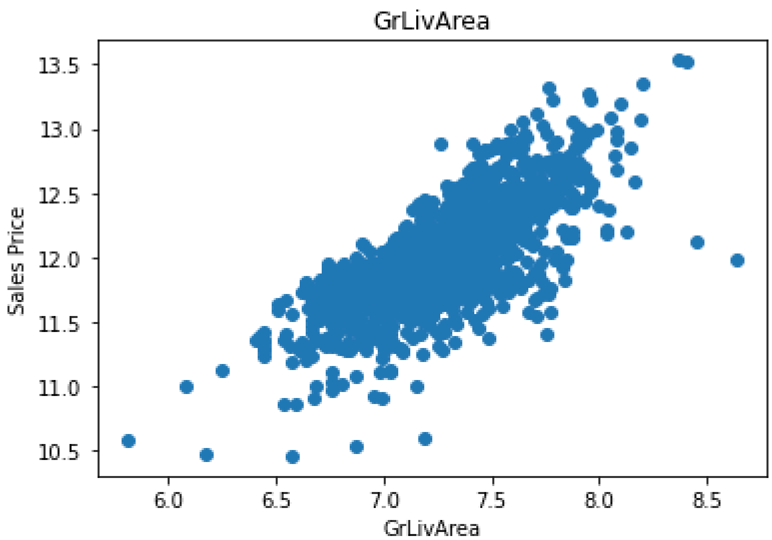
In [27]:

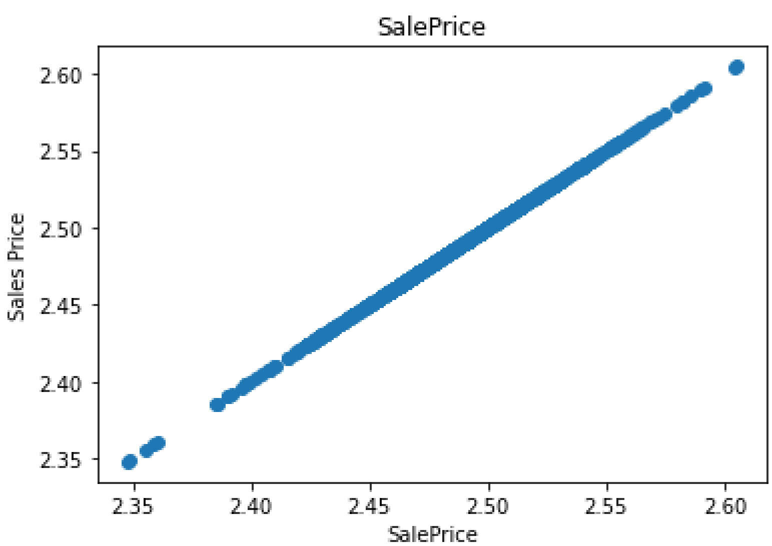
```python
for feature in continuous_feature:
    data = df.copy()

    ##skip 0 because log(0) --> infinte
    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.title(feature)
        plt.ylabel('Sales Price')
        plt.show()
```







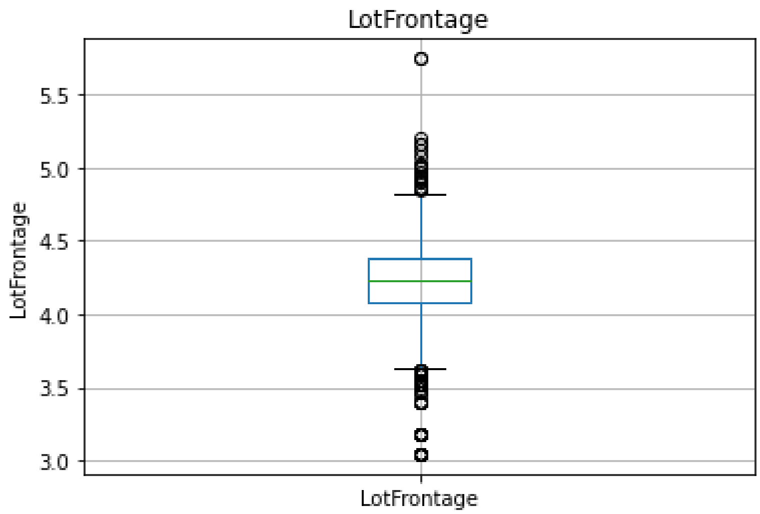


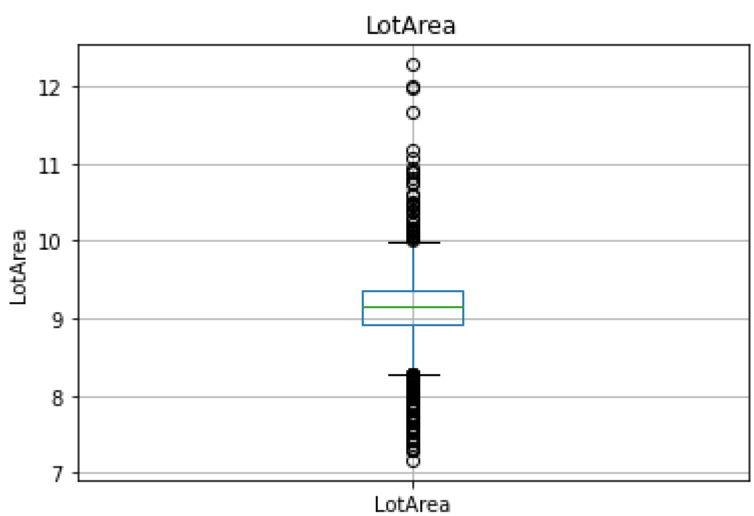


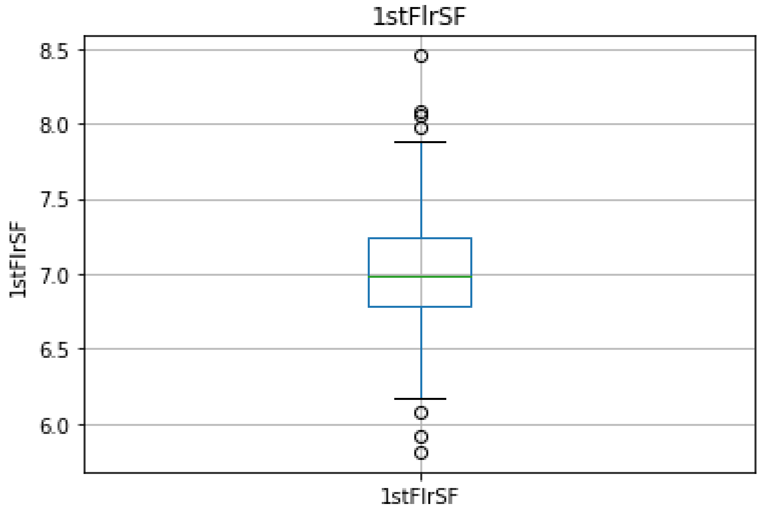
Check Outliers

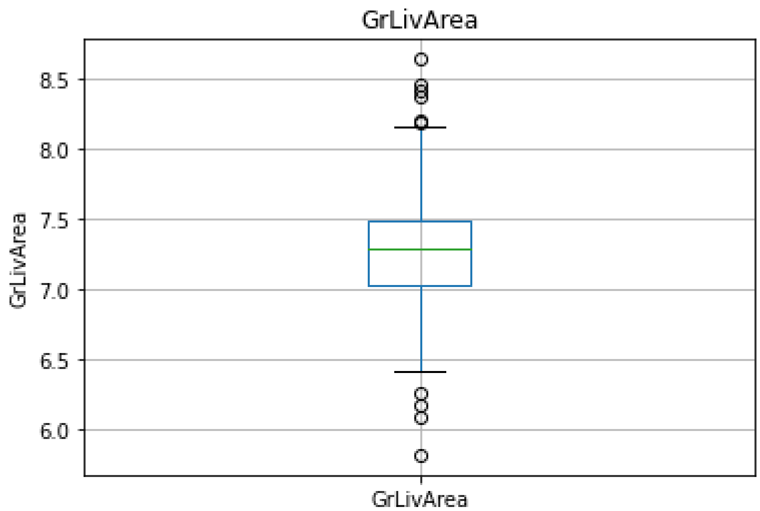
In [28]:

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









There are lot of outliers in the dataset

Categorical Variables

In [29]:
```
categorical_feature = [feature for feature in df.columns if df[feature].dtyp
print(f"Number of Categorical Feature: {len(categorical_feature)}")
```

```
Number of Categorical Feature: 43
```

In [30]:
```
categorical_feature
```

Out[30]:
```
['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 [31]:
```
df[categorical_feature].head()
```

Out[31]:

	MSZoning	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood
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

Cardinal Values -- categories inside categorical values

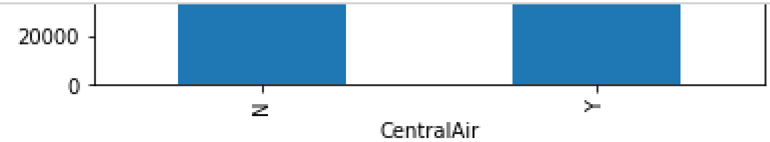
In [32]:
```
for feature in categorical_feature:
    print('feature is {} and num of categories are {}'.format(feature,len(df
```

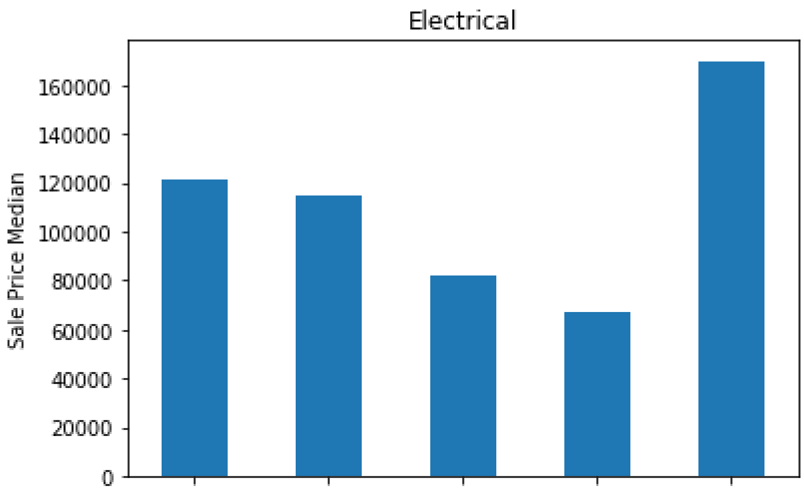
```
feature is MSZoning and num of categories are 5
feature is Street and num of categories are 2
feature is Alley and num of categories are 3
feature is LotShape and num of categories are 4
feature is LandContour and num of categories are 4
feature is Utilities and num of categories are 2
feature is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

Relationship Between Categorical feature and Sale Price

In [33]:

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





Feature Engineering

Missing Values for Categorical Features

In [34]:

```python
features_nan = [feature for feature in df.columns if df[feature].isnull().su

for feature in features_nan:
    print('{}: {}% missing values'.format(feature, np.round(df[feature].isnu
```

```
Alley: 93.7671% missing values
MasVnrType: 0.5479% missing values
BsmtQual: 2.5342% missing values
BsmtCond: 2.5342% missing values
BsmtExposure: 2.6027% missing values
BsmtFinType1: 2.5342% missing values
BsmtFinType2: 2.6027% missing values
FireplaceQu: 47.2603% missing values
GarageType: 5.5479% missing values
GarageFinish: 5.5479% missing values
GarageQual: 5.5479% missing values
GarageCond: 5.5479% missing values
PoolQC: 99.5205% missing values
Fence: 80.7534% missing values
MiscFeature: 96.3014% missing values
```

Replacing missing values for Categorical Features with a new label

In [35]:
```
def replace_cat_features(df,features_nan):
    data = df.copy()
    data[features_nan] = data[features_nan].fillna('Missing')
    return data

df = replace_cat_features(df,features_nan)
df[features_nan].isnull().sum()
```

Out[35]:
```
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
```

In [36]:
```
df.head()
```

Out[36]:

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

In [ ]:
```

```

Missing Values for Numerical Variables

In [37]:
```
numerical_with_nan = [feature for feature in df.columns if df[feature].isnul

for feature in numerical_with_nan:
    print('{}: {}%missing values'.format(feature,np.round(df[feature].isnull
```

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

Replacing Numeric Missing Values

In [38]:
```
for feature in numerical_with_nan:
    median_value = df[feature].median()

    ### creating a new feature if feature has Nan then replace it with 1 els
    df[feature+'nan'] = np.where(df[feature].isnull(),1,0)
    df[feature].fillna(median_value,inplace=True)

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

Out[38]:
```
LotFrontage    0
MasVnrArea     0
GarageYrBlt    0
dtype: int64
```

In [39]:
```
df.head(20)
```

Out[39]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Ut
0	1	60	RL	65.0	8450	Pave	Missing	Reg	Lvl	/
1	2	20	RL	80.0	9600	Pave	Missing	Reg	Lvl	/
2	3	60	RL	68.0	11250	Pave	Missing	IR1	Lvl	/
3	4	70	RL	60.0	9550	Pave	Missing	IR1	Lvl	/
4	5	60	RL	84.0	14260	Pave	Missing	IR1	Lvl	/
5	6	50	RL	85.0	14115	Pave	Missing	IR1	Lvl	/
6	7	20	RL	75.0	10084	Pave	Missing	Reg	Lvl	/
7	8	60	RL	69.0	10382	Pave	Missing	IR1	Lvl	/
8	9	50	RM	51.0	6120	Pave	Missing	Reg	Lvl	/
9	10	190	RL	50.0	7420	Pave	Missing	Reg	Lvl	/
10	11	20	RL	70.0	11200	Pave	Missing	Reg	Lvl	/
11	12	60	RL	85.0	11924	Pave	Missing	IR1	Lvl	/
12	13	20	RL	69.0	12968	Pave	Missing	IR2	Lvl	/
13	14	20	RL	91.0	10652	Pave	Missing	IR1	Lvl	/
14	15	20	RL	69.0	10920	Pave	Missing	IR1	Lvl	/
15	16	45	RM	51.0	6120	Pave	Missing	Reg	Lvl	/
16	17	20	RL	69.0	11241	Pave	Missing	IR1	Lvl	/
17	18	90	RL	72.0	10791	Pave	Missing	Reg	Lvl	/
18	19	20	RL	66.0	13695	Pave	Missing	Reg	Lvl	/
19	20	20	RL	70.0	7560	Pave	Missing	Reg	Lvl	/

Datetime Variables

In [40]:
```
for feature in ['YearBuilt', 'YearRemodAdd', 'GarageYrBlt']:
    df[feature] = df['YrSold'] - df[feature]
```

In [41]:
```python
df.head()
```

Out[41]:

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

In [42]:
```python
df[['YearBuilt', 'YearRemodAdd', 'GarageYrBlt']].head()
```

Out[42]:

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

Transform skewed feature with the help of log normal distribution

In [43]:
```python
df.head()
```

Out[43]:

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

In [44]:
```python
num_features = ['LotFrontage','LotArea','1stFlrSF','GrLivArea','SalePrice']

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

In [45]:
```
df.head()
```

Out[45]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Uti
0	1	60	RL	4.174387	9.041922	Pave	Missing	Reg	Lvl	A
1	2	20	RL	4.382027	9.169518	Pave	Missing	Reg	Lvl	A
2	3	60	RL	4.219508	9.328123	Pave	Missing	IR1	Lvl	A
3	4	70	RL	4.094345	9.164296	Pave	Missing	IR1	Lvl	A
4	5	60	RL	4.430817	9.565214	Pave	Missing	IR1	Lvl	A

Handling Rare Categorical Features

We will remove categorical features that are present less than 1% of the observations

In [46]:

```
categorical_features = [feature for feature in df.columns if df[feature].dty
categorical_features
```

Out[46]:

```
['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 [47]:

```
for feature in categorical_features:
    temp = df.groupby(feature)['SalePrice'].count()
    print(temp)
```

```
BrDale      16
BrkSide     58
ClearCr     28
CollgCr    150
Crawfor     51

Edwards    100
Gilbert     79
IDOTRR      37
MeadowV     17
Mitchel     49
NAmes      225
NPkVill      9
NWAmes      73
NoRidge     41
NridgHt     77
OldTown    113
SWISU       25
Sawyer      74
```

In [48]:

```
for feature in categorical_features:
    temp = df.groupby(feature)['SalePrice'].count()/len(df)
    temp_df = temp[temp > 0.01].index
    df[feature] = np.where(df[feature].isin(temp_df),df[feature],'Rare_Var')
```

In [49]:

```
df.head()
```

Out[49]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Uti
0	1	60	RL	4.174387	9.041922	Pave	Missing	Reg	Lvl	A
1	2	20	RL	4.382027	9.169518	Pave	Missing	Reg	Lvl	A
2	3	60	RL	4.219508	9.328123	Pave	Missing	IR1	Lvl	A
3	4	70	RL	4.094345	9.164296	Pave	Missing	IR1	Lvl	A
4	5	60	RL	4.430817	9.565214	Pave	Missing	IR1	Lvl	A

In [ ]: