In [1]:
```
# importing libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# display all the columns in the dataset
pd.pandas.set_option('display.max_columns',None)
```

In [3]:
```
# reading train and test data

train = pd.read_csv('train.csv')

```

In [4]:
```
# 1st 5 rows of train data
train.head()
```

Out[4]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2	BldgType	Ho
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	1Fam	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	FR2	Gtl	Veenker	Feedr	Norm	1Fam	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	1Fam	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	Corner	Gtl	Crawfor	Norm	Norm	1Fam	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	FR2	Gtl	NoRidge	Norm	Norm	1Fam	

In [5]:
```
# shape
train.shape
```

Out[5]:
```
(1460, 81)
```

In [6]:
```
# basic information about train
train.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
```

In [7]:
```
# statistical information
train.describe()
```

Out[7]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalB
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000	1452.000000	1460.000000	1460.000000	1460.000000	1460.
mean	730.500000	56.897260	70.049958	10516.828082	6.099315	5.575342	1971.267808	1984.865753	103.685262	443.639726	46.549315	567.240411	1057.
std	421.610009	42.300571	24.284752	9981.264932	1.382997	1.112799	30.202904	20.645407	181.066207	456.098091	161.319273	441.866955	438.
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000000	1872.000000	1950.000000	0.000000	0.000000	0.000000	0.000000	0.
25%	365.750000	20.000000	59.000000	7553.500000	5.000000	5.000000	1954.000000	1967.000000	0.000000	0.000000	0.000000	223.000000	795.
50%	730.500000	50.000000	69.000000	9478.500000	6.000000	5.000000	1973.000000	1994.000000	0.000000	383.500000	0.000000	477.500000	991.
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000	6.000000	2000.000000	2004.000000	166.000000	712.250000	0.000000	808.000000	1298.
max	1460.000000	190.000000	313.000000	215245.000000	10.000000	9.000000	2010.000000	2010.000000	1600.000000	5644.000000	1474.000000	2336.000000	6110.

In [8]:
```
# null values
nan_values_train = [feature for feature in train.columns if train[feature].isnull().any() == True]
print(nan_values_train)
len(nan_values_train)
```

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

Out[8]: 19

19 columns with missing values

In [9]:
```
# percentage of null values
for feature in nan_values_train:
    print(feature,':', round(train[feature].isnull().sum()/len(train)*100,2))
```

```
LotFrontage : 17.74
Alley : 93.77
MasVnrType : 0.55
MasVnrArea : 0.55
BsmtQual : 2.53
BsmtCond : 2.53
BsmtExposure : 2.6
BsmtFinType1 : 2.53
BsmtFinType2 : 2.6
Electrical : 0.07
FireplaceQu : 47.26
GarageType : 5.55
GarageYrBlt : 5.55
GarageFinish : 5.55
GarageQual : 5.55
GarageCond : 5.55
PoolQC : 99.52
Fence : 80.75
MiscFeature : 96.3
```

In [10]:
```
# reading test file
test = pd.read_csv('test.csv')
```

In [11]:
```
# 1st 5 rows of test data
test.head()
```

Out[11]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2	BldgType
0	1461	20	RH	80.0	11622	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	NAmes	Feedr	Norm	1Fam
1	1462	20	RL	81.0	14267	Pave	NaN	IR1	Lvl	AllPub	Corner	Gtl	NAmes	Norm	Norm	1Fam
2	1463	60	RL	74.0	13830	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	Gilbert	Norm	Norm	1Fam
3	1464	60	RL	78.0	9978	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	Gilbert	Norm	Norm	1Fam
4	1465	120	RL	43.0	5005	Pave	NaN	IR1	HLS	AllPub	Inside	Gtl	StoneBr	Norm	Norm	TwnhsE

In [12]:
```
# shape
test.shape
```

Out[12]: (1459, 80)

In [13]:
```
# basic information
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1459 non-null   int64  
 1   MSSubClass     1459 non-null   int64  
 2   MSZoning       1455 non-null   object 
 3   LotFrontage    1232 non-null   float64
 4   LotArea        1459 non-null   int64  
 5   Street         1459 non-null   object 
 6   Alley          107 non-null    object 
 7   LotShape       1459 non-null   object 
 8   LandContour    1459 non-null   object 
 9   Utilities      1457 non-null   object 
 10  LotConfig      1459 non-null   object 
 11  LandSlope      1459 non-null   object 
 12  Neighborhood   1459 non-null   object 
 13  Condition1     1459 non-null   object 
```

In [14]:
```
# nan values
nan_values_test = [feature for feature in test.columns if test[feature].isnull().any() == True]
print(nan_values_test)
len(nan_values_test)
```

```
['MSZoning', 'LotFrontage', 'Alley', 'Utilities', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'BsmtQual', 'BsmtCond', 'BsmtExpos
ure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalfBath', 'KitchenQual',
'Functional', 'FireplaceQu', 'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond', 'PoolQC', 'F
ence', 'MiscFeature', 'SaleType']
```

Out[14]: 33

in test data we have 33 columns with missing values

In [15]:
```
# percentage of null values
for feature in nan_values_test:
    print(feature,':', round(train[feature].isnull().sum()/len(train)*100,2))
```

```
MSZoning : 0.0
LotFrontage : 17.74
Alley : 93.77
Utilities : 0.0
Exterior1st : 0.0
Exterior2nd : 0.0
MasVnrType : 0.55
MasVnrArea : 0.55
BsmtQual : 2.53
BsmtCond : 2.53
BsmtExposure : 2.6
BsmtFinType1 : 2.53
BsmtFinSF1 : 0.0
BsmtFinType2 : 2.6
BsmtFinSF2 : 0.0
BsmtUnfSF : 0.0
TotalBsmtSF : 0.0
BsmtFullBath : 0.0
BsmtHalfBath : 0.0
KitchenQual : 0.0
Functional : 0.0
FireplaceQu : 47.26
GarageType : 5.55
GarageYrBlt : 5.55
GarageFinish : 5.55
GarageCars : 0.0
GarageArea : 0.0
GarageQual : 5.55
GarageCond : 5.55
PoolQC : 99.52
Fence : 80.75
MiscFeature : 96.3
SaleType : 0.0
```

In [16]:
```
# print('Features and there repestive categories/classes for training data and testing data:')
# for feature in cat_col:
#     for j in cat_col_test:
#         print('{} : {},{}'.format(feature,len(df[feature].unique()),len(df_test[feature].unique())))
#         break
```

combining training and testing data for better EDA and Preprocessing

In [17]:
```
df = train.append(test)
```

In [18]:
```
df.shape
```

Out[18]: (2919, 81)

Null/ nan/ missing values

In [19]:
```
nan_values = [feature for feature in df.columns if (df[feature].isnull().any() == True and feature !='SalePrice')]
print(nan_values)
len(nan_values)
```

```
['MSZoning', 'LotFrontage', 'Alley', 'Utilities', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'BsmtQual', 'BsmtCond', 'BsmtExpos
ure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Electrical', 'BsmtFullBath', 'BsmtHalfBath', 'K
itchenQual', 'Functional', 'FireplaceQu', 'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
'PoolQC', 'Fence', 'MiscFeature', 'SaleType']
```

Out[19]: 34

In [20]:
```
# percentage of missing values
for feature in nan_values:
    print(f'{feature} : {round(df[feature].isnull().sum()*100/len(df),4)}')
```

```
MSZoning : 0.137
LotFrontage : 16.6495
Alley : 93.2169
Utilities : 0.0685
Exterior1st : 0.0343
Exterior2nd : 0.0343
MasVnrType : 0.8222
MasVnrArea : 0.7879
BsmtQual : 2.7749
BsmtCond : 2.8092
BsmtExposure : 2.8092
BsmtFinType1 : 2.7064
BsmtFinSF1 : 0.0343
BsmtFinType2 : 2.7407
BsmtFinSF2 : 0.0343
BsmtUnfSF : 0.0343
TotalBsmtSF : 0.0343
Electrical : 0.0343
BsmtFullBath : 0.0685
BsmtHalfBath : 0.0685
KitchenQual : 0.0343
Functional : 0.0685
FireplaceQu : 48.6468
GarageType : 5.3786
GarageYrBlt : 5.4471
GarageFinish : 5.4471
GarageCars : 0.0343
GarageArea : 0.0343
GarageQual : 5.4471
GarageCond : 5.4471
PoolQC : 99.6574
Fence : 80.4385
MiscFeature : 96.4029
SaleType : 0.0343
```

Observation:

here we will fill columns having less than 40% missing values with appropiate approach
and dropping columns with more than 40% missing values as if we fill it will mostly inappropiate data.

Also we wont be dropping SalePrice as ofcourse there wont be any saleprice column in test data

In [21]:
```
# dropping those features whose null values are greater than 40%
for i in range(3):
    for feature in nan_values:
        if feature != 'SalePrice':
            if round(df[feature].isnull().sum()*100/len(df),4)>40:
                nan_values.remove(feature)
                df.drop(feature,axis=1, inplace=True)
```

In [22]:
```
print(nan_values)
len(nan_values)
```

```
['MSZoning', 'LotFrontage', 'Utilities', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'Bs
mtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Electrical', 'BsmtFullBath', 'BsmtHalfBath', 'KitchenQua
l', 'Functional', 'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond', 'SaleType']
```

Out[22]: 29

In [23]:
```
    # seperating categorical and numerical columns
    cat_col = df.select_dtypes(include='O').columns
    print(cat_col)
    print(len(cat_col))

    num_col = df.select_dtypes(exclude='O').columns
    print(num_col)
    print(len(num_col))
```

```
Index(['MSZoning', 'Street', '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', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond',
       'PavedDrive', 'SaleType', 'SaleCondition'],
      dtype='object')
38
Index(['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'],
      dtype='object')
38
```

In [24]:
```
    len(df.columns) == len(num_col) + len(cat_col)
```

Out[24]: True

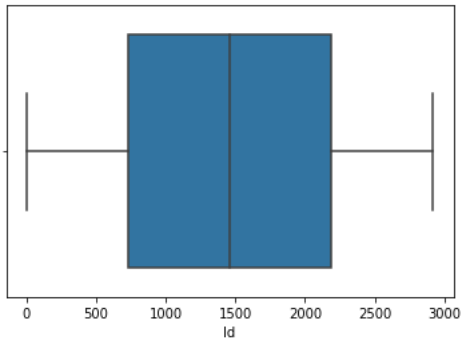
In [25]:
```
    # filling categorical nan values with mode
    for i in range(3):
        for feature in nan_values:
            if feature in cat_col:
                df[feature] = df[feature].fillna(df[feature].mode()[0])
                nan_values.remove(feature)
```

In [26]:
```
    print(nan_values)
    len(nan_values)
```

```
['LotFrontage', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalfBath', 'GarageYrBlt', 'GarageCa
rs', 'GarageArea']
```

Out[26]: 11

In [27]:
```
    # checking outliers in numerical columns

    for feature in num_col:
        # highlighting columns with nan values with red color
        if feature in nan_values:
            sns.boxplot(df[feature], color='RED')
            plt.show()
        # keeping default color for columns without nan values
        else:
            sns.boxplot(df[feature])
            plt.show()
```



Observations:

For both features with missing values and features without misssing values have outliers present in it
From point of view of feautures with missing values we need to fill with median as mean will be shift towards the outliers.

In [28]:
```
# filling numerical nan values with median
for i in range(4):
    for feature in nan_values:
        if feature in num_col:
            df[feature] = df[feature].fillna(df[feature].median())
            nan_values.remove(feature)
```

In [29]:
```
print(nan_values)
len(nan_values)
```

```
[]
```

Out[29]:
```
0
```

In [30]:
```
df.isnull().sum().sum()
```

Out[30]:
```
1459
```

1459 are null values from Saleprice of test.csv

In [31]:
```
df.head()
```

Out[31]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2	BldgType	HouseSty
0	1	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	1Fam	2Sto
1	2	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl	Veenker	Feedr	Norm	1Fam	1Sto
2	3	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	1Fam	2Sto
3	4	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl	Crawfor	Norm	Norm	1Fam	2Sto
4	5	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl	NoRidge	Norm	Norm	1Fam	2Sto

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

In [32]:
```
year_feature = [feature for feature in num_col if 'Yr' in feature or 'Year' in feature]
year_feature
```

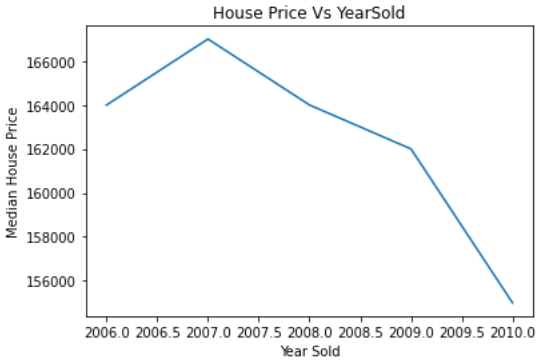
Out[32]:
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

In [33]:
```
# lets explore th content of these year variables
for feature in year_feature:
    print(feature, df[feature].unique())
```

```
YearBuilt [2003 1976 2001 1915 2000 1993 2004 1973 1931 1939 1965 2005 1962 2006
 1960 1929 1970 1967 1958 1930 2002 1968 2007 1951 1957 1927 1920 1966
 1959 1994 1954 1953 1955 1983 1975 1997 1934 1963 1981 1964 1999 1972
 1921 1945 1982 1998 1956 1948 1910 1995 1991 2009 1950 1961 1977 1985
 1979 1885 1919 1990 1969 1935 1988 1971 1952 1936 1923 1924 1984 1926
 1940 1941 1987 1986 2008 1908 1892 1916 1932 1918 1912 1947 1925 1900
 1980 1989 1992 1949 1880 1928 1978 1922 1996 2010 1946 1913 1937 1942
 1938 1974 1893 1914 1906 1890 1898 1904 1882 1875 1911 1917 1872 1905
 1907 1896 1902 1895 1879 1901]
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. 1979. 1983. 1977. 1997. 1985.
 1963. 1981. 1964. 1999. 1935. 1990. 1945. 1987. 1989. 1915. 1956. 1948.
 1974. 2009. 1950. 1961. 1921. 1900. 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. 1917. 1896. 1895. 2207. 1943. 1919.]
YrSold [2008 2007 2006 2009 2010]
```

In [34]:
```
# we will check whether there is a relation between year the house is sold and SalePrice

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

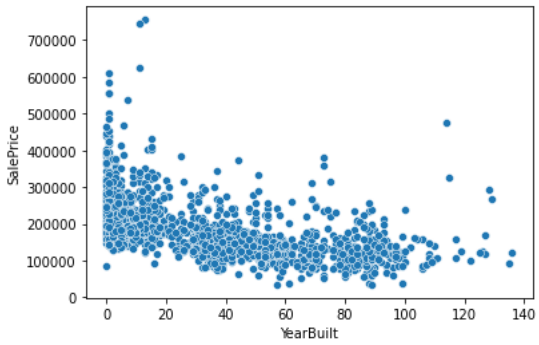
Out[34]: Text(0.5, 1.0, 'House Price Vs YearSold')

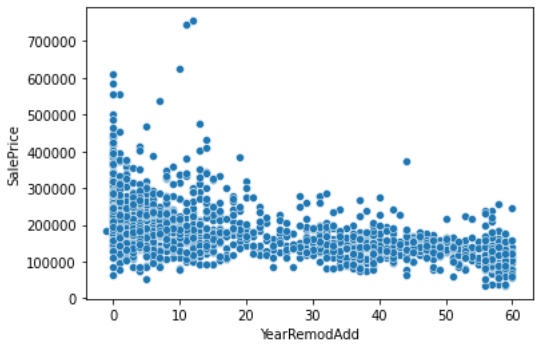


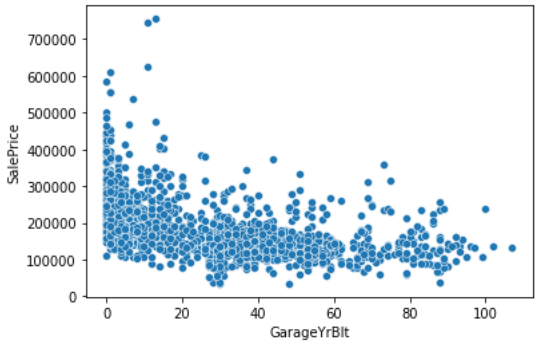
Observation:

As the number of year increases house prices are decreasing
But in reality it is completly opposite

In [35]:
```
    ## Here we will compare the difference between All year features with SalePrice

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

        ## We will capture the difference between year variable and year the house was sold for
        data[feature]=data['YrSold']-data[feature]
        sns.scatterplot(data[feature], data['SalePrice'])
#         plt.scatter(data[feature],data['SalePrice'])
#         plt.xlabel(feature)
#         plt.ylabel('SalePrice')
        plt.show()
```







Observations:

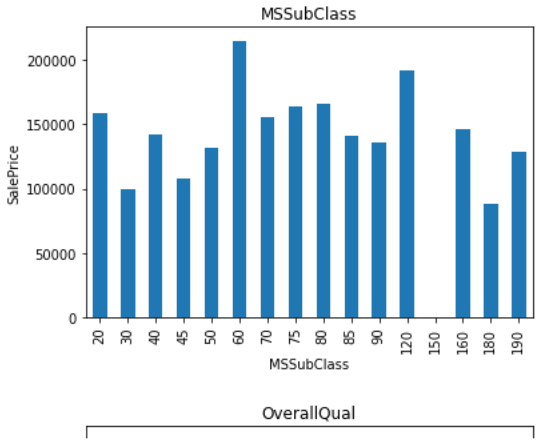
For all the 3 graphs, The initial year's sale price is more than the later on price
The price gradually decreases as it gets old

In [36]:
```
## Numerical variables are usually of 2 type
## 1. Continous variable and Discrete Variables

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

discrete_feature
```

```
Discrete Variables Count: 14
```

Out[36]:
```
['MSSubClass',
 'OverallQual',
 'OverallCond',
 'BsmtFullBath',
 'BsmtHalfBath',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'KitchenAbvGr',
 'TotRmsAbvGrd',
 'Fireplaces',
 'GarageCars',
 'PoolArea',
 'MoSold']
```

In [37]:
```
# relationship between descrete variable and saleprice

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



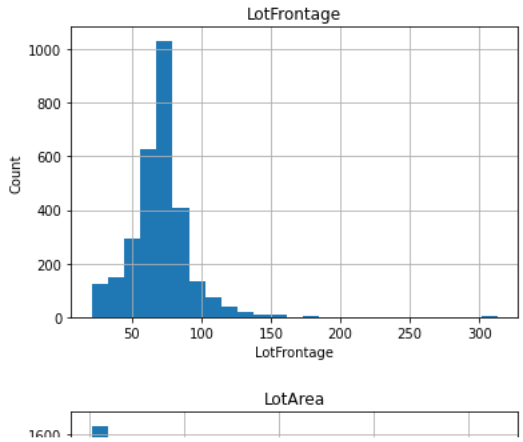
Observations:

There are all descrete features like OverallQual, GarageCars which are clearly affecting the saleprice
except BsmtHalfBath which has no impact on saleprice

In [38]:
```
continuous_feature=[feature for feature in num_col if feature not in discrete_feature+year_feature+['Id']]
print("Continuous feature Count {}".format(len(continuous_feature)))
```

```
Continuous feature Count 19
```

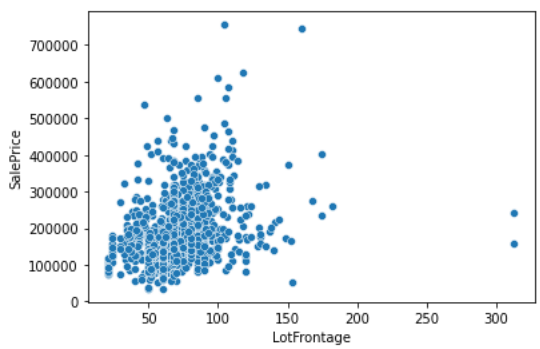
In [39]:
```
## Lets analyse the continuous values by creating histograms to understand the distribution

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



Observations:

all the histograms are right skewed. which means most of the values are concentrated at the left side of the graph and very less values are spreaded towards right side.

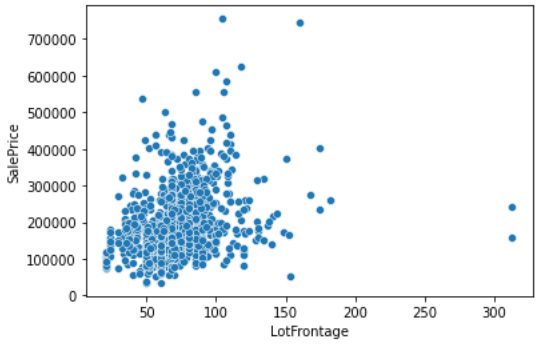
In [40]:
```
# relationship between continuous variables and SalePrice
for feature in continuous_feature:
    data = df.copy()
    if feature!='SalePrice':
        sns.scatterplot(data[feature], data['SalePrice'])
        plt.show()
```

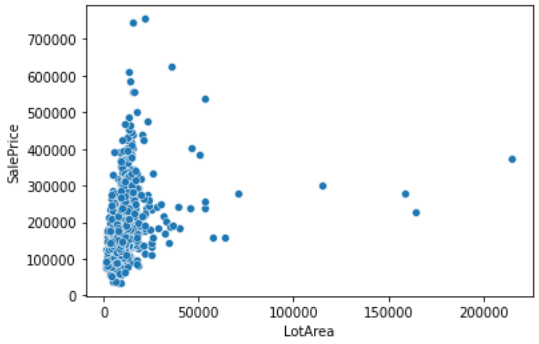


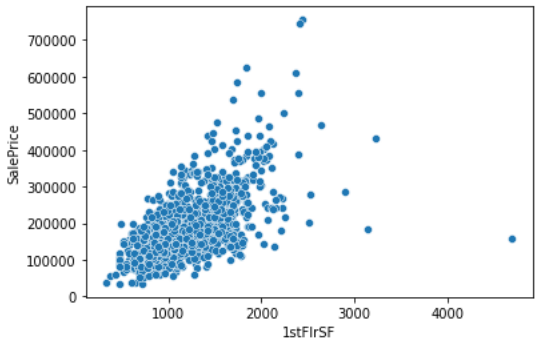
Observations:

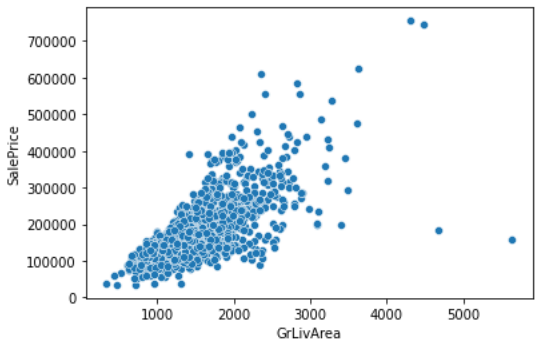
there is relationship between continuous variable and SalePrice we can see that everygraph is positively related to the SalePrice For each feature, as its value increases SalePrice is also increasing

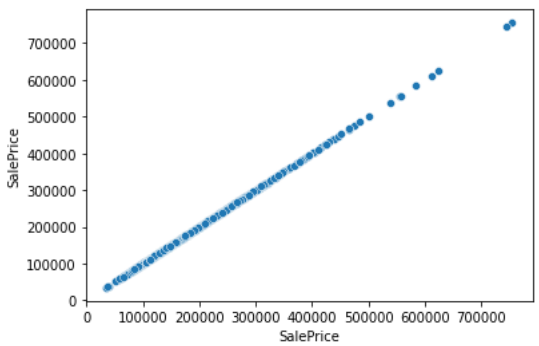
In [41]:
```
# features without having 0 value
for feature in continuous_feature:
    data = df.copy()
    if 0 in data[feature].unique():
        pass
    else:
        sns.scatterplot(data[feature], data['SalePrice'])
        plt.show()
```







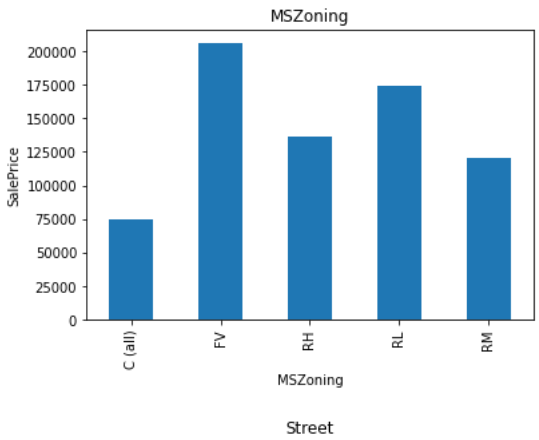




Observations:

All the features are clearly positively related to salePrice which dont have 0 value in it.

In [42]:
```
for feature in cat_col:
    data=df.copy()
    data.groupby(feature)['SalePrice'].median().plot.bar()
    plt.xlabel(feature)
    plt.ylabel('SalePrice')
    plt.title(feature)
    plt.show()
```



Street

Observations:

Every categorical feature affecting SalePrice
For different classes we have different saleprice

In [43]:
```
# feature engineering
for feature in ['YearBuilt','YearRemodAdd','GarageYrBlt']:
    df[feature]=df['YrSold']-df[feature]
```

In [44]:
```
df[['YearBuilt','YearRemodAdd','GarageYrBlt']].head(2)
```

Out[44]:

	YearBuilt	YearRemodAdd	GarageYrBlt
0	5	5	5.0
1	31	31	31.0

In [45]:
```
df.drop('Id', axis=1,inplace=True)
```

Encoding

In [46]:
```
cat_col
```

Out[46]:
```
Index(['MSZoning', 'Street', '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', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond',
       'PavedDrive', 'SaleType', 'SaleCondition'],
      dtype='object')
```

In [47]:
```
df_encoded = (pd.get_dummies(df[cat_col],drop_first = True))
```

In [48]:
```
df = df.drop(columns=list(cat_col))
```

In [49]:
```
final_df = pd.concat([df_encoded,df],axis=1)
```

In [50]:
```
final_df.shape
```

Out[50]:
```
(2919, 233)
```

In [51]:
```
final_df
```

Out[51]:

	MSZoning_FV	MSZoning_RH	MSZoning_RL	MSZoning_RM	Street_Pave	LotShape_IR2	LotShape_IR3	LotShape_Reg	LandContour_HLS	LandContour_Low	LandContour_L
0	0	0	1	0	1	0	0	1	0	0	
1	0	0	1	0	1	0	0	1	0	0	
2	0	0	1	0	1	0	0	0	0	0	
3	0	0	1	0	1	0	0	0	0	0	
4	0	0	1	0	1	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	
1454	0	0	0	1	1	0	0	1	0	0	
1455	0	0	0	1	1	0	0	1	0	0	
1456	0	0	1	0	1	0	0	1	0	0	
1457	0	0	1	0	1	0	0	1	0	0	
1458	0	0	1	0	1	0	0	1	0	0	

2919 rows × 233 columns

In [52]:
```
# Seperating data into training  dataset
df_ = final_df.iloc[:1460,:]
```

In [53]:
```
# accessing X_training data
# final_df.iloc[:1460,:-1]

# accessing X_testing data
# final_df.iloc[1460:,:-1]

# accessing Y_training
# final_df.iloc[:1460,-1]
```

In [54]:
```
# Seperating data into training and testing dataset

X_train = final_df.iloc[:1460,:-1]
X_test = final_df.iloc[1460:,:-1]

y_train = final_df.iloc[:1460,-1]
```

Scaling

In [55]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler
```

In [56]:
```
minmax = MinMaxScaler()
std_scaler = StandardScaler()
```

In [57]:
```
X_train_minmax = minmax.fit_transform(X_train)
X_test_minmax  = minmax.transform(X_test)

X_train_std_scaler = std_scaler.fit_transform(X_train)
X_test_std_scaler  = std_scaler.transform(X_test)
```

Model Building

In [58]:
```
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.svm import SVR
```

In [59]:
```
def model(model, X_train, y_train, X_test):

    # initializing model
    reg = model()

    # fitting model
    reg.fit(X_train, y_train)

    # making prediction
    y_train_pred = reg.predict(X_train)
    global y_test_pred
    y_test_pred = reg.predict(X_test)

   # evaluation matrics
    print('Training data')
    print('R2_score:', round(r2_score(y_train, y_train_pred),2), " | RMSE",np.sqrt(round(mean_squared_error(y_train, y_train_pred),2)) )
    print()

#     print('Testing data')
#     print('R2_score:', round(r2_score(y_test, y_test_pred),2), " | RMSE",np.sqrt(round(mean_squared_error(y_test, y_test_pred),2)))
#     print()
    return model
```

Linear Regression

In [60]:
```
model(LinearRegression, X_train, y_train, X_test)
```

```
Training data
R2_score: 0.93  | RMSE 20940.141965612365
```

Out[60]: sklearn.linear_model._base.LinearRegression

In [61]:
```
# linear regression on standard scaler
model(LinearRegression, X_train_std_scaler, y_train, X_test_std_scaler)
```

```
Training data
R2_score: 0.93  | RMSE 20940.13535940014
```

Out[61]: sklearn.linear_model._base.LinearRegression

In [62]:
```
# linear regression on minmax scaler
model(LinearRegression, X_train_minmax, y_train, X_test_minmax)
```

```
Training data
R2_score: 0.93  | RMSE 21038.077407881166
```

Out[62]: sklearn.linear_model._base.LinearRegression

Ridge Regression

In [63]:
```
model(Ridge, X_train, y_train, X_test)
```

```
Training data
R2_score: 0.91  | RMSE 24122.259284528056
```

Out[63]: sklearn.linear_model._ridge.Ridge

In [64]:
```
# ridge regression on standard scaler
model(Ridge, X_train_minmax, y_train, X_test_minmax)
```

```
Training data
R2_score: 0.91  | RMSE 24249.785686475665
```

Out[64]: sklearn.linear_model._ridge.Ridge

In [65]:
```
# ridge regression on minmax scaler
model(Ridge, X_train_minmax, y_train, X_test_minmax)
```

```
Training data
R2_score: 0.91  | RMSE 24249.785686475665
```

Out[65]: sklearn.linear_model._ridge.Ridge

Lasso Regressor

In [66]:
```
model(Lasso, X_train, y_train, X_test)
```

```
Training data
R2_score: 0.93  | RMSE 20957.66802318426
```

Out[66]: sklearn.linear_model._coordinate_descent.Lasso

In [67]:
```
# Lasso regression on minmax scaler
model(Lasso, X_train_minmax, y_train, X_test_minmax)
```

```
Training data
R2_score: 0.93  | RMSE 20958.41526952837
```

Out[67]: sklearn.linear_model._coordinate_descent.Lasso

In [68]:
```
# Lasso regression on minmax scaler
model(Lasso, X_train_minmax, y_train, X_test_minmax)
```

```
Training data
R2_score: 0.93  | RMSE 20958.41526952837
```

Out[68]: sklearn.linear_model._coordinate_descent.Lasso

RandomForestRegressor

In [69]:
```
model(RandomForestRegressor, X_train, y_train, X_test )
```

```
Training data
R2_score: 0.98  | RMSE 11063.006542527217
```

Out[69]: sklearn.ensemble._forest.RandomForestRegressor

In [70]:
```
# RandomForestRegressor on minmax scaler
model(RandomForestRegressor, X_train_minmax, y_train, X_test_minmax)
```

```
Training data
R2_score: 0.98  | RMSE 11031.7689719283
```

Out[70]: sklearn.ensemble._forest.RandomForestRegressor

In [71]:
```
# RandomForestRegressor on standard scaler scaler
model(RandomForestRegressor, X_train_std_scaler, y_train, X_test_std_scaler)
```

```
Training data
R2_score: 0.98  | RMSE 10980.470459411108
```

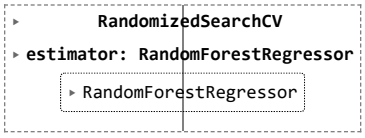
Out[71]: sklearn.ensemble._forest.RandomForestRegressor

In [73]:
```
from sklearn.model_selection import RandomizedSearchCV
```

In [74]:
```
# hyper parameter tunig for random forest
params =  {
 'max_depth': [2,3,4,5,6,7,10],
 'min_samples_leaf': [4, 6, 8],
 'min_samples_split': [5, 7,10],
 'n_estimators': [100,300, 500]}

reg = RandomForestRegressor()

model_reg = RandomizedSearchCV(estimator = reg, param_distributions = params, n_iter = 10,
                               cv = 5, verbose= 1, random_state= 101, n_jobs = -1)
model_reg.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

Out[74]:



In [75]:
```
model_reg.best_params_
```

Out[75]:
```
{'n_estimators': 100,
 'min_samples_split': 5,
 'min_samples_leaf': 4,
 'max_depth': 7}
```

In [76]:
```
model_reg.best_score_
```

Out[76]: 0.8441776129696752

In [78]:
```
y_test_pred = model_reg.predict(X_test)
```

In [80]:
```
# create sample submission file and submit
pred = pd.DataFrame(y_test_pred)
sub_df=pd.read_csv('sample_submission.csv')
datasets=pd.concat([sub_df['Id'],pred],axis=1)
datasets.columns=['Id','SalePrice']
datasets.to_csv('sample_submission_rf.csv',index=False)
```

XGBRegressor

In [81]:
```
model(xgb.XGBRegressor, X_train, y_train, X_test )
```

```
Training data
R2_score: 1.0  | RMSE 1720.6611287525502
```

Out[81]: xgboost.sklearn.XGBRegressor

In [82]:
```
# XGBregressor on minmax scaler
model(xgb.XGBRegressor, X_train_minmax, y_train, X_test_minmax)
```

```
Training data
R2_score: 1.0  | RMSE 1720.6611287525502
```

Out[82]: xgboost.sklearn.XGBRegressor

In [83]:
```
# XGBregressor on standard scaler scaler
model(xgb.XGBRegressor, X_train_std_scaler, y_train, X_test_std_scaler)
```

```
Training data
R2_score: 1.0  | RMSE 1720.6611287525502
```

Out[83]: xgboost.sklearn.XGBRegressor

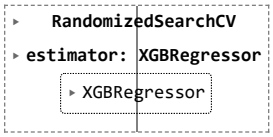
In [84]:
```
## Hyper Parameter Optimization


params = {
    'n_estimators' : [100,300,500],
    "learning_rate" : [0.05, 0.10, 0.15, 0.20, 0.25, 0.30 ] ,
    'max_depth' : [2, 3, 5, 10, 15],
    "gamma" : [ 0.0, 0.1, 0.2 , 0.3, 0.4 ],
    'min_child_weight' : [1,2,3,4]
}
```

In [85]:
```
# Set up the random search with cross validation

from sklearn.model_selection import RandomizedSearchCV

random_cv = RandomizedSearchCV(xgb.XGBRegressor(),
            param_distributions=params,
            cv=5, n_iter=50,
            scoring = 'neg_mean_absolute_error',n_jobs = 4,
            verbose = 5,
            return_train_score = True,
            random_state=42)
```

In [86]:
```
random_cv.fit(X_train,y_train)
```

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

Out[86]:



In [87]:
```
random_cv.best_estimator_
```

Out[87]:
```
                                XGBRegressor

XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
             colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
             early_stopping_rounds=None, enable_categorical=False,
             eval_metric=None, feature_types=None, gamma=0.0, gpu_id=-1,
             grow_policy='depthwise', importance_type=None,
             interaction_constraints='', learning_rate=0.1, max_bin=256,
             max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
             max_depth=2, max_leaves=0, min_child_weight=2, missing=nan,
             monotone_constraints='()', n_estimators=500, n_jobs=0,
             num_parallel_tree=1, predictor='auto', random_state=0, ...)
```

In [88]:
```
random_cv.best_score_
```

Out[88]:
```
-15709.462465218321
```

In [89]:
```
y_test_pred = random_cv.predict(X_test)
```

Submission file

In [90]:
```
import pickle
filename='finalized_model.pkl'
pickle.dump(random_cv, open(filename, 'wb'))
```

In [91]:
```
y_test_pred
```

Out[91]:
```
array([117140.73, 163495.6 , 185914.48, ..., 173005.19, 126411.88,
       241123.75], dtype=float32)
```

In [92]:
```
# create sample submission file and submit
pred = pd.DataFrame(y_test_pred)
sub_df=pd.read_csv('sample_submission.csv')
datasets=pd.concat([sub_df['Id'],pred],axis=1)
datasets.columns=['Id','SalePrice']
datasets.to_csv('sample_submission.csv',index=False)
```

In [ ]:

In [ ]: