HouseRegressions_Team_6_12Jul

July 12, 2021

0.1 Overview of the Project

- The dataset contains 1460 rows and 81 columns and has data of houses sold during the period 2006-2010 in the city of Ames, IA.
- The dataset has 43 categorical and 38 numerical fields which we can use.
- 19 columns were identified as having NULL values, out of which 4 columns have more than 70 percent were NULL, which were dropped
- Executed a Heat Map to check for Variable Co-relation . We have minimal co-relation which is good
- Checked for outliers and acted on that data as appropriate. Removed LotArea greater than 50,000 sq. ft
- Created New Features for Total Square Feet.
- Adjusted the SalesPrice for Inflation using CPI package
- Created a data pipeline for Numerical and Categorical Features which did the following:
  - Simple Imputer to handle null values
  - Scalers to scale the data to better fit the model
  - Ran One Hot Encoding on categorical data
- Finally executed Linear Regression, Ridge and XG Boost Regressor to train the Model using GridSearchCV to test multiple parameters.
- Identified XG Boost Regressor as the best performing model by comparing the results and persisted it to apply on test data.
- Downloaded the latest housing data sets for Newark-DE, Wilmington-DE, Bear-DE and Ames-IA using US Real Estate api from RapidApi (https://rapidapi.com/datascraper/api/us-real-estate/) and used the saved model to predict the house prices.
- A web app was developed using Streamlit and deployed to Heroku which can be accessed using:
  - https://housing-demo-team6.herokuapp.com/

0.1.1 Summary of the best scores and model selection

- Following are the scores from Linear Regression, Ridge and XG Boost Regressor
  - linear regression score is: 0.7494241357121679
  - Ridge regression score is: 0.7459059322291025
  - XGBoost Regressor score is: 0.7852363569881567
- Based on the above Scores, we selected XG Boost Regressor as our desired model.

0.1.2 Accuracy metrics for XG Boost Regressor

- Train accuracy of XG Boost Regressor is 0.7852363569881567

- Test accuracy of our best estimator, which is XGBoost Regressor, is 0.8396.
- In this case, accuracy in test dataset was observed higher than in train dataset

Test Data Accuracy

- Below table lists down the performance metrics for each of the cities

City	r_square	mean_absolute_error	mean_square_error	sqrt_mean_square_error
Newark-DE	-0.184925	109995.238084	1.645267e+10	128267.963373
Bear-DE	0.113418	106598.324378	1.475721e+10	121479.258206
Wilmington-DE	-0.081391	161541.067093	5.487316e+10	234250.206711
Ames-IA	-0.452275	119947.499630	2.135133e+10	146120.934070

0.1.3 Conclusion

- We have higher accuracy on housingData (train/test split).
- The model accuracy on the 4 selected cities (Wilmington-DE, Bear-DE, Newark-DE, Ames-IA), was very low.
- Hence, we can conclude that training data cannot be directly used to predict house prices of different geographical locations.
- To be added

0.1.4 Initial Data Analysis

- The dataset contains 1460 rows and 81 columns and has data of houses sold during the period 2006-2010 in the city of Ames, IA.
- The dataset has 43 categorical and 38 numerical fields which we can use.
- Executed Describe, info() to find the type of data and 19 columns were identified as having NULL values
- Out of 19, 4 columns have more than 70 percent NULLs
- Garage car size, Year Built and Total Square Feet have high correlation with Sales Price.
- In the train data, the oldest house was built in 1872 and newest house in 2010.

0.1.5 Inflation Adjustment

- Installed and imported the cpi package (https://www.bls.gov/)
- Used Year sold and the current Price to get the Adjusted SalesPrice.

0.1.6 Data Cleansing

- Out of 19 which had nulls, 4 columns having more than 70 percent NULLs were dropped
- Ran box plot for finding outliers and LotArea greater than 50,000 sq.ft. were eliminated

0.1.7 Data Correlation

- Plotted histogram for the columns: LotArea,BldgType,YearBuilt,FullBath,HalfBath,BedroomAbvGr,Garage
- Relationships of columns with SalesPrice
  - Smaller increase in LotArea increased SalesPrice by a higher margin
  - Living Area was linearly related to the SalesPrice.
  - Total of Basement, 1st and 2nd floor square footage was highly correlated to SalesPrice.

0.1.8 Imputers

- SimpleImputer was used to handle the incoming null values.

0.1.9 Feature Engineering

- Added Total Square Feet as a new feature, which is total of Basement, 1st and 2nd floor square feet.
- Final Features used were
  - LotArea
  - BldgType
  - YearBuilt
  - FullBath
  - HalfBath
  - BedroomAbvGr
  - GarageCars
  - Total Square Feet
- These features were common among the datasets from different cities and were also highly correlated to the SalesPrice.

0.1.10 Data Pre-processing pipeline

- Following steps were added in the data pipeline
  - Missing data: used SimpleImputer()
  - Feature scaling : used StandardScaler()
  - Categorical feature encoding: used Onehot Encoder
  - Transformation: used ColumnTransformer() to transform the numerical and categorical features

0.1.11 Model Training, Tuning & Evaluation

- Linear regressor, Ridge regressor and XGBoost Regressor were trained with different parameters and below are the best parameter selection for each.
- Linear regression:
  - {'classifier__copy_X': True, 'classifier__fit_intercept': False, 'classifier__normalize': True}
- Ridge regressor:
  - {'clf_RG__alpha': 0.2, 'clf_RG__copy_X': True, 'clf_RG__fit_intercept': False}
- XGBoost regressor:
  - {'clf_XG__learning_rate': 0.1, 'clf_XG__max_depth': 5, 'clf_XG__n_estimators': 100}

- Checked the important features during tuning and removed the least important feature 'HouseStyle' from the dataset which increased our score.

0.1.12 Final Selection of Model

- Following are the scores from Linear Regression, Ridge and XG Boost Regressor
  - linear regression score is: 0.7494241357121679
  - Ridge regression score is: 0.7459059322291025
  - XGBoost Regressor score is: 0.7852363569881567
- Based on the above Scores, we selected XG Boost Regressor as our desired model.

0.1.13 Prediction using the test datasets

- Read the datasets into the data frame and pulled only the common features.
- Renamed the columns to match the column names in X, Y dataframes.
- Transformed the "None" values to 0 in Newark Dataset.
- Created a dictionary to map the values in Building Type to match with our training dataset and removed 'Farm', 'mobile' and 'Land' types.
- Changed the order of the columns to match with X dataframe as it is important for scikit learn library.
- Used clf_best.predict to predict the values of houses for each city and compared it to the actual data.

Observations

- Below table lists down the performance metrics for each of the cities

City	r_square	mean_absolute_error	mean_square_error	sqrt_mean_square_error
Newark-DE	-0.184925	109995.238084	1.645267e+10	128267.963373
Bear-DE	0.113418	106598.324378	1.475721e+10	121479.258206
Wilmington-DE	-0.081391	161541.067093	5.487316e+10	234250.206711
Ames-IA	-0.452275	119947.499630	2.135133e+10	146120.934070

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[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
from scipy.stats import norm, skew
from IPython.display import display, HTML

import seaborn as sns
from sklearn import metrics

import xgboost as xgb
```

```python
import cpi
cpi.update()
```

0.1.14 Data Set

[2]:
```python
housingData=pd.read_csv('Data/housing.csv')
housingData.head()
```

[2]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg
2   3          60       RL         68.0    11250   Pave   NaN      IR1
3   4          70       RL         60.0     9550   Pave   NaN      IR1
4   5          60       RL         84.0    14260   Pave   NaN      IR1

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

0.2 Basic EDA

- The dataset has shape of 1460x81 and has 43 numerical and 38 categorical columns
- Few of the numerical columns can be interpreted as categorical features such as OverallQual, OverallCond, # of Baths, Kitchens, years.
- Few of the fields have more than 80% as single value in the data and should be careful while using these as it will skew the results.
  - MSZoning, LandContour, LandSlope, BldgType etc.

[3]:
```python
housingData.shape
```

[3]:
```
(1460, 81)
```

[4]:
```python
# divide data into categorical and numerical features
cat, num = [], []
```

```
for i in housingData.columns:
    d = housingData.dtypes[i]
    if d == 'object':
        cat.append(i)
    else:
        num.append(i)

print("Categorical: {}".format(cat))
print("\n")
print("-------------------------------------------------------------------------------------")
print("\n")
print("Numerical: {}".format(num))
```

```
Categorical: ['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']


--------------------------------------------------------------------------------
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Numerical: ['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']
```

[5]:
```
# Checking length of categorical and numerical
print("Length of categorical: {}".format(len(cat)))
print("Length of numerical: {}".format(len(num)))
```

```
Length of categorical: 43
Length of numerical: 38
```

[6]:
```
# Referred from kaggle (https://www.kaggle.com/stefanschulmeister87/
↪visual-data-inspection-and-xgboost)

column_informations = {}
```

```
num_values = len(housingData)
for col in housingData.columns:
    num_unique = housingData[col].nunique()
    num_nulls = round(housingData[col].isna().sum()/num_values,2)
    d_type = housingData.dtypes[col]

    if (num_unique < 30):
        # discrete column
        info_str = "["
        value_counts = housingData[col].value_counts()
        single_value_weight = round(value_counts.iloc[0] / num_values, 2)
        for index, value in value_counts.items():
            info_str += f"{value} X {index}, "
        column_informations[col] = {"d_type":d_type, "discret": True,␣
 ↪"percentage_of_missing_values": num_nulls, "single_value_weight":␣
 ↪single_value_weight,
                                    "min": 0.0, "max": 0.0, "mean": 0.0,␣
 ↪"median": 0.0, "info_str": info_str[:-2] + "]"}
    else:
        # continuous column
        if d_type == "int64" or d_type == "float64":
            column_informations[col] = {"d_type":d_type, "discret": False,␣
 ↪"percentage_of_missing_values": num_nulls, "single_value_weight": 0.0,
                                        "min": housingData[col].min(), "max":␣
 ↪housingData[col].max(), "mean": round(housingData[col].mean(), 2),
                                        "median": round(housingData[col].
 ↪median(), 2), "info_str": ""}
        else:
            column_informations[col] = {"d_type":d_type, "discret": False,␣
 ↪"percentage_of_missing_values": num_nulls, "min": "-", "max": "-",
                                        "mean": "-", "median": "-", "info_str":␣
 ↪""}

# build DataFrame from dictionary
info_df = pd.DataFrame.from_dict(column_informations, orient='index')
```

0.2.1 Discrete Columns Information

[7]:
```
display(HTML(info_df[info_df["discret"]==True][["d_type",␣
 ↪"percentage_of_missing_values", "single_value_weight", "info_str"]].
 ↪to_html()))
print(len(info_df[info_df["discret"]==True]))
```

```
<IPython.core.display.HTML object>
```

```
61
```

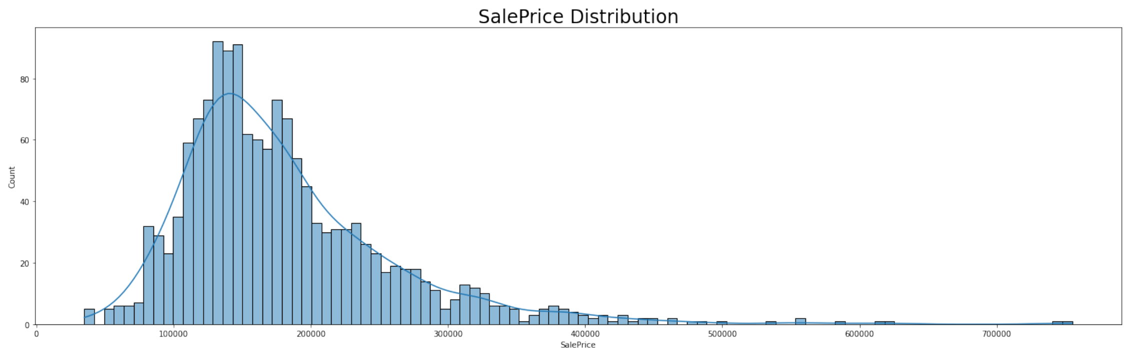
0.2.2 Continuous Columns Information

[8]:
```
display(HTML(info_df[info_df["discret"]==False][["d_type",␣
↪"percentage_of_missing_values", "min", "max", "mean", "median"]].to_html()))
print(len(info_df[info_df["discret"]==False]))
```

```
<IPython.core.display.HTML object>
```

```
20
```

[9]:
```
fig = plt.figure(figsize=(25,7))
sns.histplot(data = housingData,x="SalePrice", kde=True, bins=100,␣
↪palette="Set2", multiple="stack").set_title('SalePrice Distribution',␣
↪fontdict= {'fontsize': 24});
```



0.2.3 Adjust for inflation using CPI

- Use YrSold and SalePrice to adjust the dollar to current date.

[10]:
```
housingData['ADJUSTED_SalesPrice'] = housingData.apply(lambda x: cpi.inflate(x.
↪SalePrice, x.YrSold), axis=1)
```

0.2.4 Find missing Data

- 19 columns have missing data
- Alley, PoolQC, Fence and MiscFeature have more than 70% missing values so we decided to drop these fields.

[11]:
```
def find_missing_percent(data):
    """
    Returns dataframe containing the total missing values and percentage of␣
↪total
    missing values of a column.
    """
```

```
    miss_df = pd.DataFrame({'ColumnName':[],'TotalMissingVals':
↪[],'PercentMissing':[]})
    for col in data.columns:
        sum_miss_val = data[col].isnull().sum()
        percent_miss_val = round((sum_miss_val/data.shape[0])*100,2)
        miss_df = miss_df.append(dict(zip(miss_df.
↪columns,[col,sum_miss_val,percent_miss_val])),ignore_index=True)
    return miss_df
```

[12]:
```
miss_df = find_missing_percent(housingData)
'''Displays columns with missing values'''
display(miss_df[miss_df['PercentMissing']>0.0])
print("\n")

print("Number of columns with missing values:
↪"+(str(miss_df[miss_df['PercentMissing']>0.0].shape[0])))
```

	ColumnName	TotalMissingVals	PercentMissing
3	LotFrontage	259.0	17.74
6	Alley	1369.0	93.77
25	MasVnrType	8.0	0.55
26	MasVnrArea	8.0	0.55
30	BsmtQual	37.0	2.53
31	BsmtCond	37.0	2.53
32	BsmtExposure	38.0	2.60
33	BsmtFinType1	37.0	2.53
35	BsmtFinType2	38.0	2.60
42	Electrical	1.0	0.07
57	FireplaceQu	690.0	47.26
58	GarageType	81.0	5.55
59	GarageYrBlt	81.0	5.55
60	GarageFinish	81.0	5.55
63	GarageQual	81.0	5.55
64	GarageCond	81.0	5.55
72	PoolQC	1453.0	99.52
73	Fence	1179.0	80.75
74	MiscFeature	1406.0	96.30

```
Number of columns with missing values:19
```

[13]:
```
drop_cols = miss_df[miss_df['PercentMissing'] >70.0].ColumnName.tolist()

print("Number of columns with more than 70%:"+ str(len(drop_cols)))
housingData = housingData.drop(drop_cols,axis=1)
```

```python
#test = test.drop(drop_cols,axis =1)

miss_df = miss_df[miss_df['ColumnName'].isin(housingData.columns)]
'''Columns to Impute'''
impute_cols = miss_df[miss_df['TotalMissingVals']>0.0].ColumnName.tolist()
miss_df[miss_df['TotalMissingVals']>0.0]
```

```
Number of columns with more than 70%:4
```

[13]:

	ColumnName	TotalMissingVals	PercentMissing
3	LotFrontage	259.0	17.74
25	MasVnrType	8.0	0.55
26	MasVnrArea	8.0	0.55
30	BsmtQual	37.0	2.53
31	BsmtCond	37.0	2.53
32	BsmtExposure	38.0	2.60
33	BsmtFinType1	37.0	2.53
35	BsmtFinType2	38.0	2.60
42	Electrical	1.0	0.07
57	FireplaceQu	690.0	47.26
58	GarageType	81.0	5.55
59	GarageYrBlt	81.0	5.55
60	GarageFinish	81.0	5.55
63	GarageQual	81.0	5.55
64	GarageCond	81.0	5.55

0.2.5 Basic Stats

- Few Observations
- The

[14]:
```python
housingData.describe().transpose()
```

[14]:

	count	mean	std	min \
Id	1460.0	730.500000	421.610009	1.000000
MSSubClass	1460.0	56.897260	42.300571	20.000000
LotFrontage	1201.0	70.049958	24.284752	21.000000
LotArea	1460.0	10516.828082	9981.264932	1300.000000
OverallQual	1460.0	6.099315	1.382997	1.000000
OverallCond	1460.0	5.575342	1.112799	1.000000
YearBuilt	1460.0	1971.267808	30.202904	1872.000000
YearRemodAdd	1460.0	1984.865753	20.645407	1950.000000
MasVnrArea	1452.0	103.685262	181.066207	0.000000
BsmtFinSF1	1460.0	443.639726	456.098091	0.000000
BsmtFinSF2	1460.0	46.549315	161.319273	0.000000
BsmtUnfSF	1460.0	567.240411	441.866955	0.000000
TotalBsmtSF	1460.0	1057.429452	438.705324	0.000000
1stFlrSF	1460.0	1162.626712	386.587738	334.000000

2ndFlrSF	1460.0	346.992466	436.528436	0.000000
LowQualFinSF	1460.0	5.844521	48.623081	0.000000
GrLivArea	1460.0	1515.463699	525.480383	334.000000
BsmtFullBath	1460.0	0.425342	0.518911	0.000000
BsmtHalfBath	1460.0	0.057534	0.238753	0.000000
FullBath	1460.0	1.565068	0.550916	0.000000
HalfBath	1460.0	0.382877	0.502885	0.000000
BedroomAbvGr	1460.0	2.866438	0.815778	0.000000
KitchenAbvGr	1460.0	1.046575	0.220338	0.000000
TotRmsAbvGrd	1460.0	6.517808	1.625393	2.000000
Fireplaces	1460.0	0.613014	0.644666	0.000000
GarageYrBlt	1379.0	1978.506164	24.689725	1900.000000
GarageCars	1460.0	1.767123	0.747315	0.000000
GarageArea	1460.0	472.980137	213.804841	0.000000
WoodDeckSF	1460.0	94.244521	125.338794	0.000000
OpenPorchSF	1460.0	46.660274	66.256028	0.000000
EnclosedPorch	1460.0	21.954110	61.119149	0.000000
3SsnPorch	1460.0	3.409589	29.317331	0.000000
ScreenPorch	1460.0	15.060959	55.757415	0.000000
PoolArea	1460.0	2.758904	40.177307	0.000000
MiscVal	1460.0	43.489041	496.123024	0.000000
MoSold	1460.0	6.321918	2.703626	1.000000
YrSold	1460.0	2007.815753	1.328095	2006.000000
SalePrice	1460.0	180921.195890	79442.502883	34900.000000
ADJUSTED_SalesPrice	1460.0	222479.997443	98225.097351	42102.312888

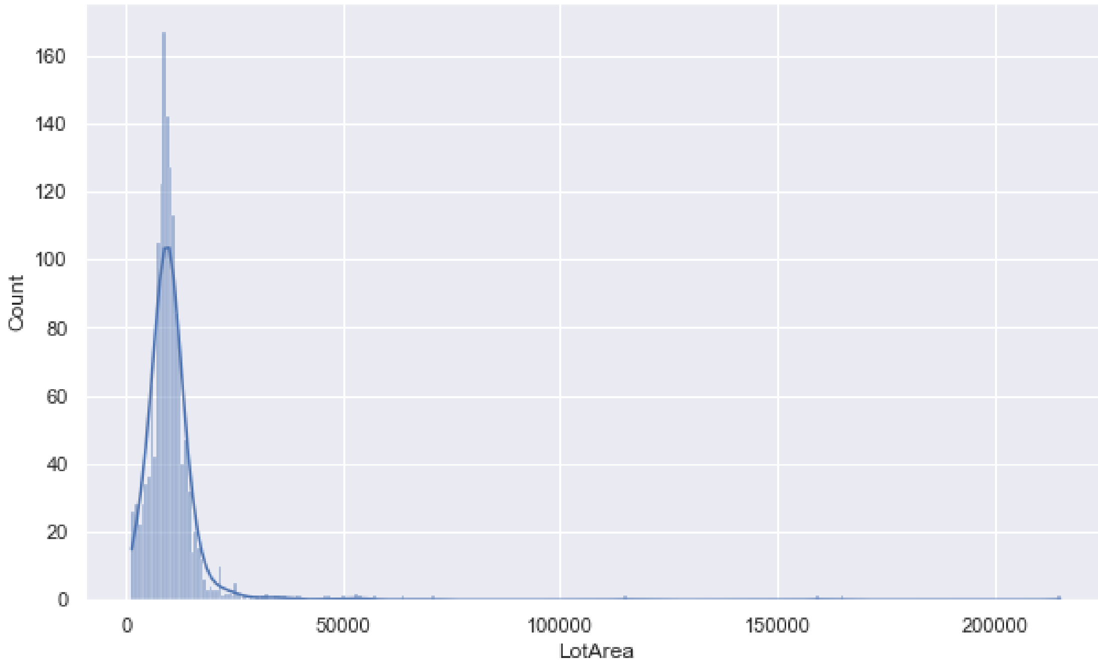
	25%	50%	75%	max
Id	365.750000	730.500000	1095.25000	1460.000000
MSSubClass	20.000000	50.000000	70.00000	190.000000
LotFrontage	59.000000	69.000000	80.00000	313.000000
LotArea	7553.500000	9478.500000	11601.50000	215245.000000
OverallQual	5.000000	6.000000	7.00000	10.000000
OverallCond	5.000000	5.000000	6.00000	9.000000
YearBuilt	1954.000000	1973.000000	2000.00000	2010.000000
YearRemodAdd	1967.000000	1994.000000	2004.00000	2010.000000
MasVnrArea	0.000000	0.000000	166.00000	1600.000000
BsmtFinSF1	0.000000	383.500000	712.25000	5644.000000
BsmtFinSF2	0.000000	0.000000	0.00000	1474.000000
BsmtUnfSF	223.000000	477.500000	808.00000	2336.000000
TotalBsmtSF	795.750000	991.500000	1298.25000	6110.000000
1stFlrSF	882.000000	1087.000000	1391.25000	4692.000000
2ndFlrSF	0.000000	0.000000	728.00000	2065.000000
LowQualFinSF	0.000000	0.000000	0.00000	572.000000
GrLivArea	1129.500000	1464.000000	1776.75000	5642.000000
BsmtFullBath	0.000000	0.000000	1.00000	3.000000
BsmtHalfBath	0.000000	0.000000	0.00000	2.000000
FullBath	1.000000	2.000000	2.00000	3.000000

```
HalfBath                   0.000000       0.000000       1.00000       2.000000
BedroomAbvGr               2.000000       3.000000       3.00000       8.000000
KitchenAbvGr               1.000000       1.000000       1.00000       3.000000
TotRmsAbvGrd               5.000000       6.000000       7.00000      14.000000
Fireplaces                 0.000000       1.000000       1.00000       3.000000
GarageYrBlt             1961.000000    1980.000000    2002.00000    2010.000000
GarageCars                 1.000000       2.000000       2.00000       4.000000
GarageArea               334.500000     480.000000     576.00000    1418.000000
WoodDeckSF                 0.000000       0.000000     168.00000     857.000000
OpenPorchSF                0.000000      25.000000      68.00000     547.000000
EnclosedPorch              0.000000       0.000000       0.00000     552.000000
3SsnPorch                  0.000000       0.000000       0.00000     508.000000
ScreenPorch                0.000000       0.000000       0.00000     480.000000
PoolArea                   0.000000       0.000000       0.00000     738.000000
MiscVal                    0.000000       0.000000       0.00000   15500.000000
MoSold                     5.000000       6.000000       8.00000      12.000000
YrSold                  2007.000000    2008.000000    2009.00000    2010.000000
SalePrice             129975.000000  163000.000000  214000.00000  755000.000000
ADJUSTED_SalesPrice   160434.872676  200206.227431  260846.39369  942415.453695
```

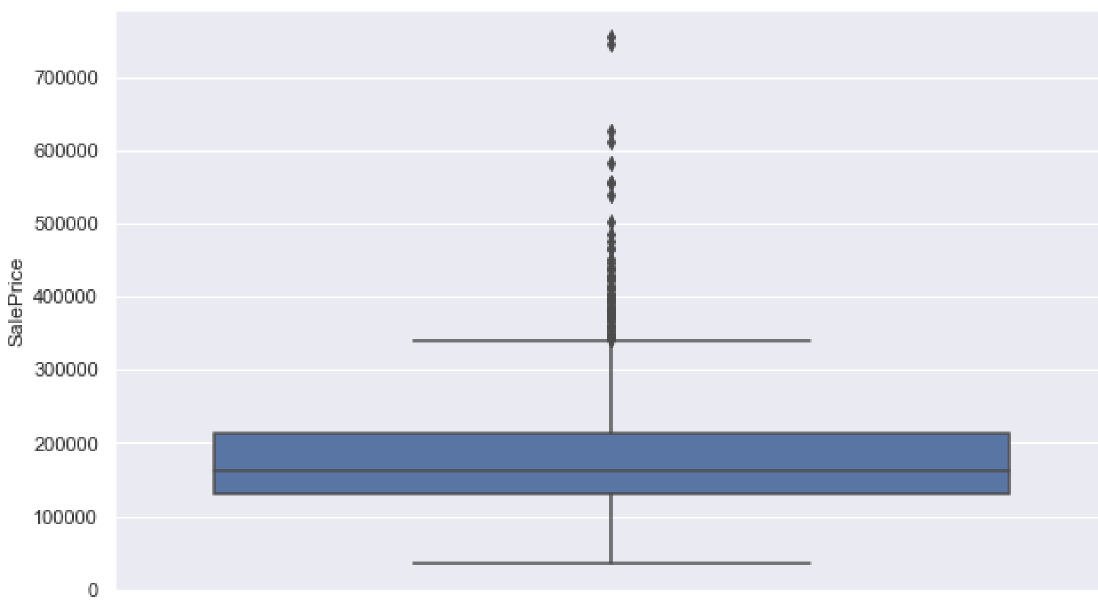
Following were the observations for LotArea and checking for Distribution and Box plot for outliers:

- Run a HISTOGRAM on LotArea as that is typically the most import for a price! Run for where value is not null
- Histogram to see the frequency ranges and it shows 500 sq as most common
- Run a Distribution plot to validate the same
- Run a BOX PLOT which is very important to check for OUTLIERS

[15]:
```
sns.set()
plt.figure(figsize=(10,6))
sns.histplot(housingData['LotArea'], kde=True)
plt.show()
```



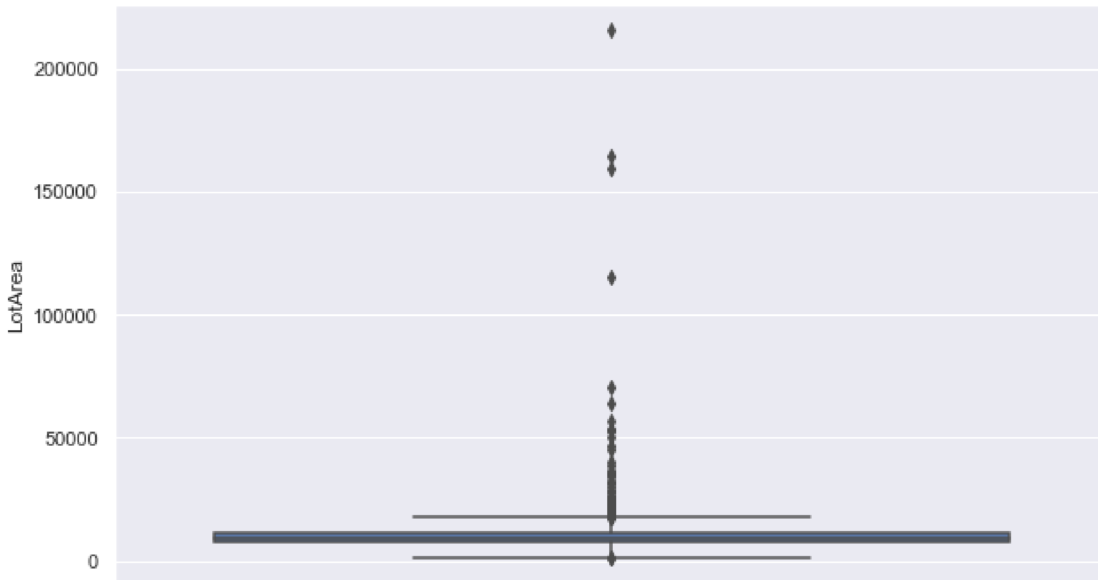
[16]:
```
plt.figure(figsize=(10,6))
sns.boxplot(y='SalePrice',data=housingData)
plt.show()
```



0.2.6 Removing Outlier

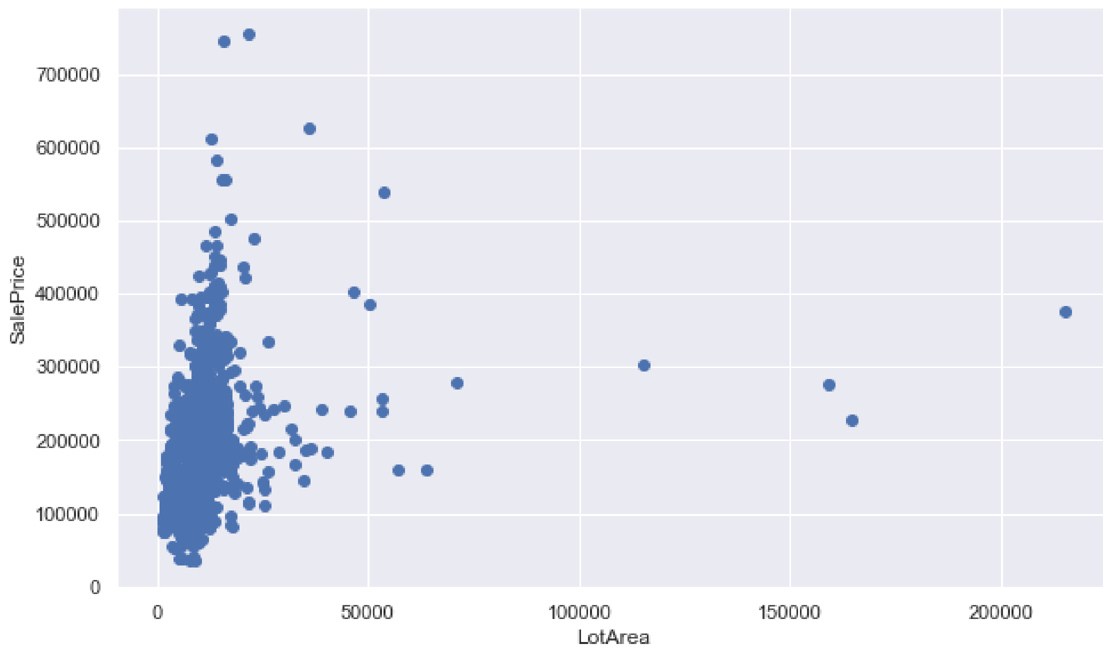
In order to avoid outliers, LotArea greater than 50,000 sq.ft. were eliminated

[17]:
```
plt.figure(figsize=(10,6))
sns.boxplot(y='LotArea',data=housingData)
plt.show()
```



[18]:
```
# Analysing the LotArea Feature against SalePrice
plt.figure(figsize=(10,6))
plt.scatter(housingData.LotArea, housingData.SalePrice)
plt.xlabel('LotArea')
plt.ylabel('SalePrice')
# it shows outliers in it
```

[18]:
```
Text(0, 0.5, 'SalePrice')
```

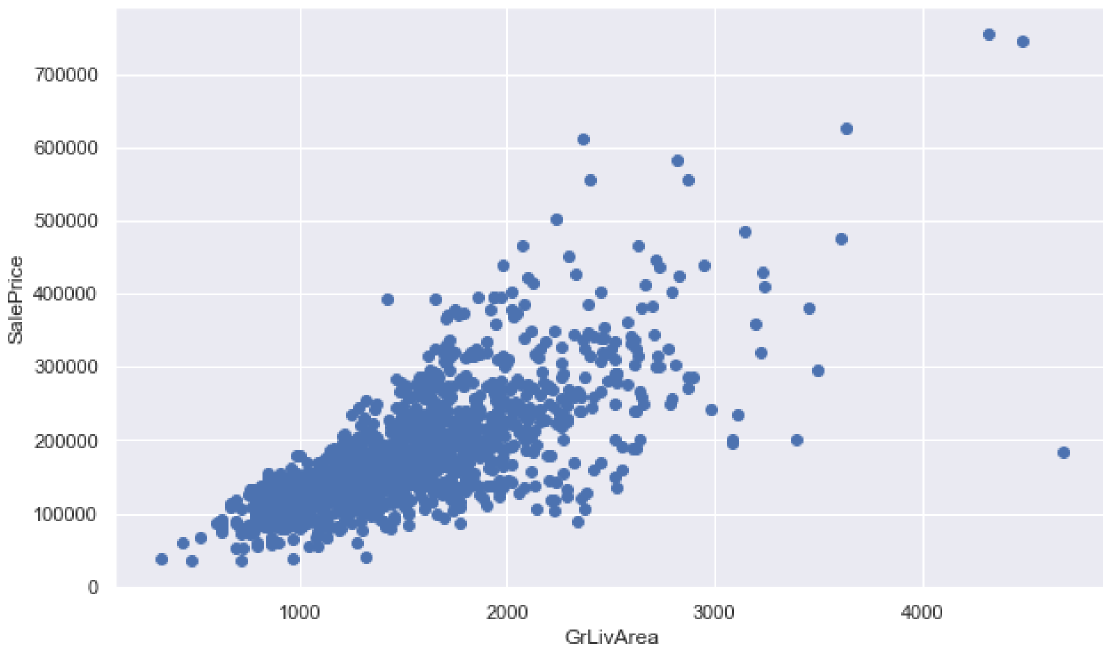


[19]:
```
# Dropping lotArea greater than 50000 to remove outlier
housingData = housingData[housingData.LotArea <= 50000].copy()
housingData.shape
```

[19]: (1449, 78)

[20]:
```
# Observing the Column output GrLivArea against Output SalePrice
# To check for outliers
plt.figure(figsize=(10,6))
plt.scatter(housingData.GrLivArea, housingData.SalePrice)
plt.xlabel('GrLivArea')
plt.ylabel('SalePrice')
```

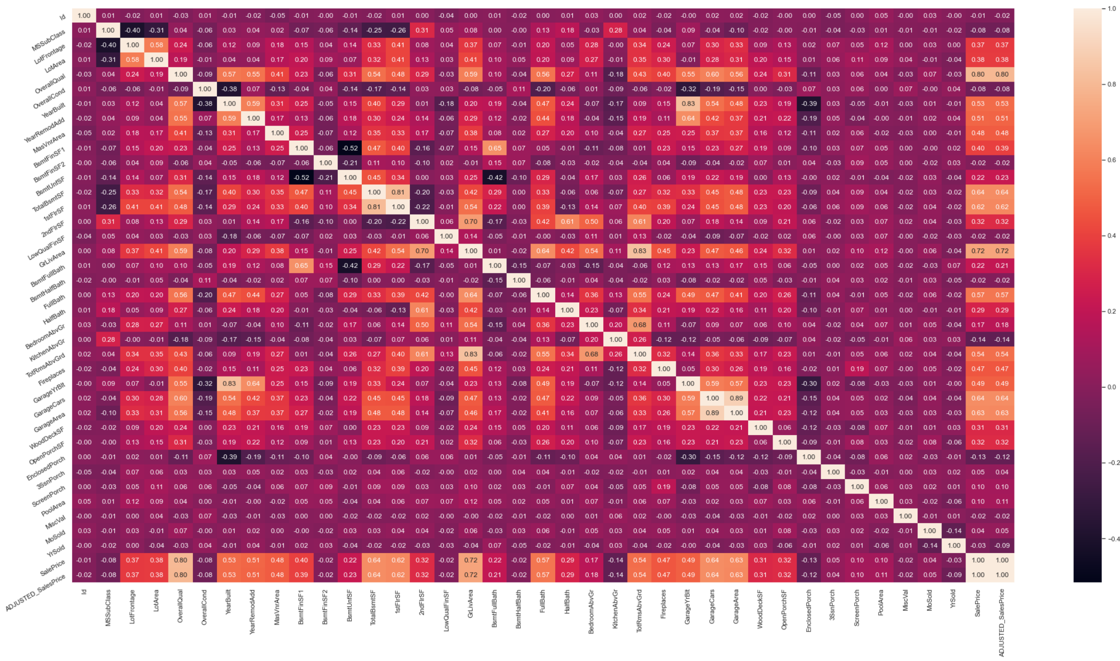
[20]: Text(0, 0.5, 'SalePrice')



0.2.7 Attribute Correlation Metrics

-

[21]:
```
corr = housingData.corr()
sns.set_context("notebook", font_scale=1.0, rc={"lines.linewidth": 2.5})
plt.figure(figsize=(36,18))
a = sns.heatmap(corr, annot=True, fmt='.2f')
rotx = a.set_xticklabels(a.get_xticklabels(), rotation=90)
roty = a.set_yticklabels(a.get_yticklabels(), rotation=30)
```



[22]:

```
number_of_price_groups = 5
number_of_values_per_group = len(housingData)/number_of_price_groups

visual_df = housingData.copy()
visual_df.sort_values(by=['SalePrice'], inplace=True, ignore_index=True)

# get group ranges (we want the same amount of members in each group)
last_boundary = 0
bounder_dict={}
for i in range(number_of_price_groups):
    boundary = visual_df.iloc[int((i+1)*number_of_values_per_group) -␣
 ↪1]["SalePrice"]
    bounder_dict[f"{last_boundary}-{boundary}"] = [last_boundary, boundary]
    last_boundary = boundary

def get_price_group(price, bounder_dict):
    group_lable = "-"
    for group in bounder_dict.keys():
        if bounder_dict[group][0] < price <= bounder_dict[group][1]:
            group_lable=group
    return group_lable

visual_df["PriceGroup"]=visual_df["SalePrice"].map(lambda x: get_price_group(x,␣
 ↪bounder_dict));
```

[23]:
```
# let's check:
indexs =[]
for group in visual_df["PriceGroup"].unique():
    indexs.append(visual_df[["SalePrice",␣
 ↪"PriceGroup"]][visual_df["PriceGroup"]==group].head(1).index[0])
visual_df.loc[indexs][["SalePrice", "PriceGroup"]]
```

[23]:

	SalePrice	PriceGroup
0	34900	0-123600
289	124000	123600-146500
579	146800	146500-178900
869	179000	178900-229000
1159	229456	229000-755000

- For visualization, it will be good to group the prices onto manageable levels.
- The above groups look good

[24]:
```
date_features = ["YearBuilt", "YearRemodAdd", "GarageYrBlt", "MoSold", "YrSold"]
info_df.loc[date_features]
```

[24]:

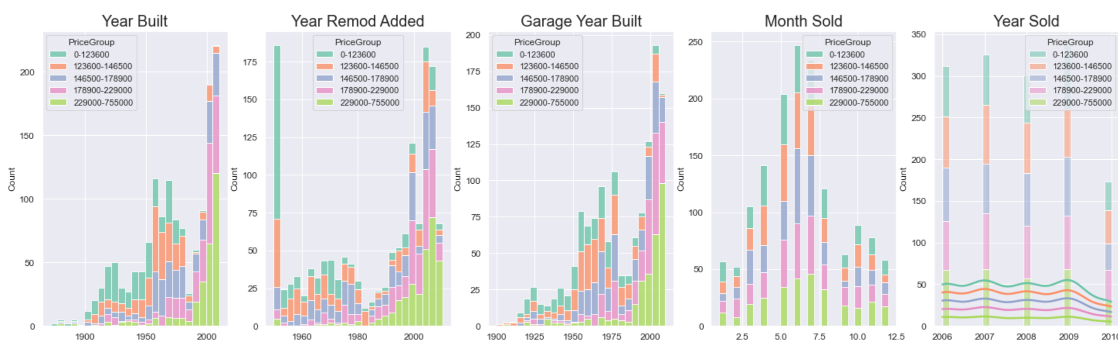
	d_type	discret	percentage_of_missing_values	\
YearBuilt	int64	False	0.00	
YearRemodAdd	int64	False	0.00	
GarageYrBlt	float64	False	0.06	
MoSold	int64	True	0.00	
YrSold	int64	True	0.00	

	single_value_weight	min	max	mean	median	\
YearBuilt	0.00	1872.0	2010.0	1971.27	1973.0	
YearRemodAdd	0.00	1950.0	2010.0	1984.87	1994.0	
GarageYrBlt	0.00	1900.0	2010.0	1978.51	1980.0	
MoSold	0.17	0.0	0.0	0.00	0.0	
YrSold	0.23	0.0	0.0	0.00	0.0	

	info_str
YearBuilt	
YearRemodAdd	
GarageYrBlt	
MoSold	[253 X 6, 234 X 7, 204 X 5, 141 X 4, 122 X 8, …
YrSold	[338 X 2009, 329 X 2007, 314 X 2006, 304 X 200…

[25]:
```
# build figure
fig = plt.figure(figsize=(25,7))

# add grid to figure
gs = fig.add_gridspec(1,5)
```

```python
# fill grid with subplots
ax00 = fig.add_subplot(gs[0,0])
ax01 = fig.add_subplot(gs[0,1])
ax02 = fig.add_subplot(gs[0,2])
ax03 = fig.add_subplot(gs[0,3])
ax04 = fig.add_subplot(gs[0,4])


# adjust subheadline fontsize
ax00.set_title('Year Built', fontsize=20)
ax01.set_title('Year Remod Added', fontsize=20)
ax02.set_title('Garage Year Built', fontsize=20)
ax03.set_title('Month Sold', fontsize=20)
ax04.set_title('Year Sold', fontsize=20)

# adjust lable fontsize
ax00.tick_params(labelsize=12)
ax01.tick_params(labelsize=12)
ax02.tick_params(labelsize=12)
ax03.tick_params(labelsize=12)
ax04.tick_params(labelsize=12)

# plot (ax=axxx is important)
sns.histplot(data = visual_df,x="YearBuilt", kde=False, ax=ax00, bins=25, palette="Set2", multiple="stack", hue="PriceGroup")
sns.histplot(data = visual_df,x="YearRemodAdd", kde=False, ax=ax01, bins=25, palette="Set2", multiple="stack", hue="PriceGroup")
sns.histplot(data = visual_df,x="GarageYrBlt", kde=False, ax=ax02, bins=25, palette="Set2", multiple="stack", hue="PriceGroup")
sns.histplot(data = visual_df,x="MoSold", kde=False, ax=ax03, bins=25, palette="Set2", multiple="stack", hue="PriceGroup")
sns.histplot(data = visual_df,x="YrSold", kde=True, ax=ax04, bins=25, palette="Set2", multiple="stack", hue="PriceGroup");
```



0.2.8 Skewness Levels on numerical Features

- Applying skewness, we find that the below fields are highly skewed.

[26]:
```
# Checking skewness level on numerical features to remove
skewed_feats = housingData[num].apply(lambda x: skew(x.dropna())).\
sort_values(ascending=False)
skewness = pd.DataFrame({"Skewness ": skewed_feats})
skewness
```

[26]:

	Skewness
MiscVal	24.427220
PoolArea	15.882700
3SsnPorch	10.253854
LowQualFinSF	8.966866
KitchenAbvGr	4.464409
BsmtFinSF2	4.284977
ScreenPorch	4.129883
BsmtHalfBath	4.113098
EnclosedPorch	3.073602
MasVnrArea	2.693526
OpenPorchSF	2.378517
LotArea	2.260330
SalePrice	1.892673
LotFrontage	1.530859
WoodDeckSF	1.430546
MSSubClass	1.399019
GrLivArea	1.121198
1stFlrSF	0.970776
BsmtUnfSF	0.915698
2ndFlrSF	0.807616
BsmtFinSF1	0.797493
OverallCond	0.687559
HalfBath	0.675846
TotRmsAbvGrd	0.652749
Fireplaces	0.634565
TotalBsmtSF	0.583005
BsmtFullBath	0.573989
BedroomAbvGr	0.237672
MoSold	0.211470
OverallQual	0.209281
GarageArea	0.135726
YrSold	0.094324
FullBath	0.046703
Id	-0.006476
GarageCars	-0.336880
YearRemodAdd	-0.502515
YearBuilt	-0.612570

```
GarageYrBlt    -0.652760
```

- We will not remove outliers from every feature as it may affect the model since test set will have outliers too and our model needs to be robust against them

0.2.9 Adding new feature

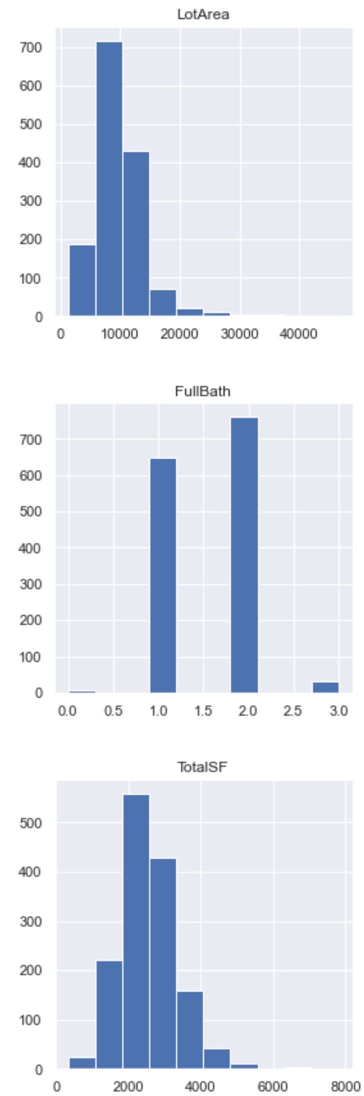
[27]:
```
# Adding one extra feature -> total sqfootage feature
housingData['TotalSF'] = housingData['TotalBsmtSF'] + housingData['1stFlrSF'] +
↪housingData['2ndFlrSF']
```

[28]:
```
X=housingData[['LotArea','BldgType','GarageCars','YearBuilt','FullBath','HalfBath','BedroomAbv
↪copy()
Y=housingData[['ADJUSTED_SalesPrice']]
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1449 entries, 0 to 1459
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   LotArea      1449 non-null   int64
 1   BldgType     1449 non-null   object
 2   GarageCars   1449 non-null   int64
 3   YearBuilt    1449 non-null   int64
 4   FullBath     1449 non-null   int64
 5   HalfBath     1449 non-null   int64
 6   BedroomAbvGr 1449 non-null   int64
 7   TotalSF      1449 non-null   int64
dtypes: int64(7), object(1)
memory usage: 101.9+ KB
```

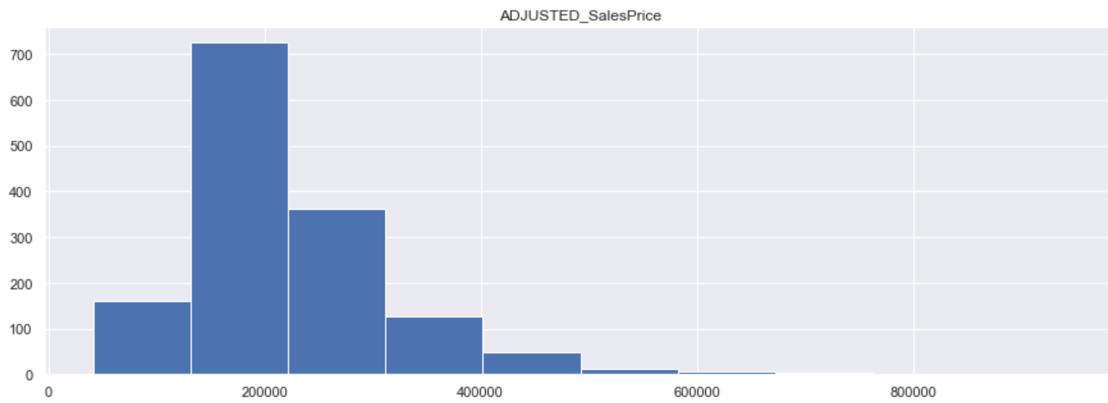
[29]:
```
X.hist(figsize=(15,15))
```

[29]:
```
array([[<AxesSubplot:title={'center':'LotArea'}>,
        <AxesSubplot:title={'center':'GarageCars'}>,
        <AxesSubplot:title={'center':'YearBuilt'}>],
       [<AxesSubplot:title={'center':'FullBath'}>,
        <AxesSubplot:title={'center':'HalfBath'}>,
        <AxesSubplot:title={'center':'BedroomAbvGr'}>],
       [<AxesSubplot:title={'center':'TotalSF'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```



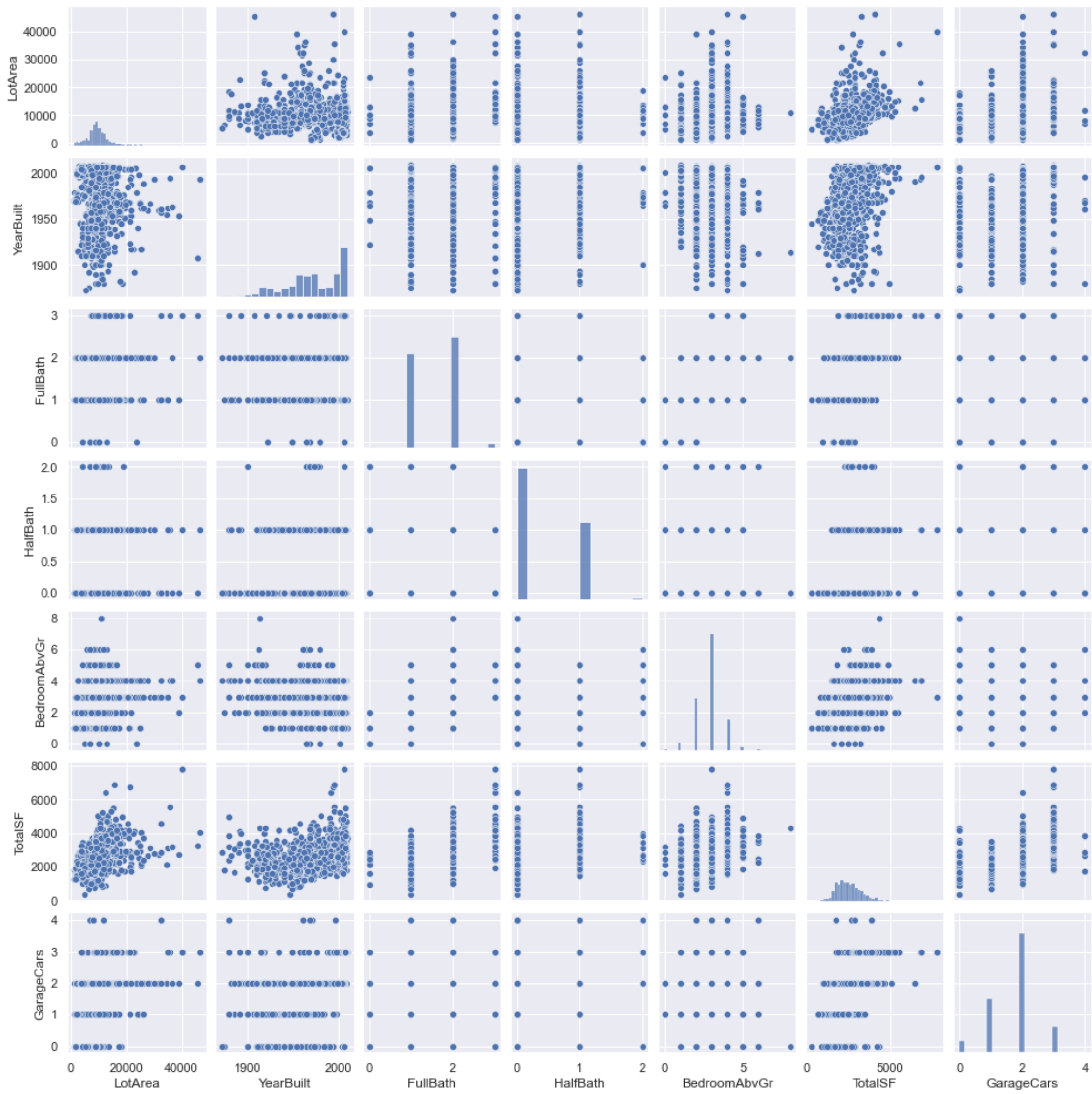

```
[30]: Y.hist(figsize=(15,5))
```

```
[30]: array([[<AxesSubplot:title={'center':'ADJUSTED_SalesPrice'}>]],
            dtype=object)
```




```
[31]: sns.pairplot(X[['LotArea', 'YearBuilt', 'FullBath',␣
       ↪'HalfBath','BedroomAbvGr','TotalSF','GarageCars']], height=2)
```

```
[31]: <seaborn.axisgrid.PairGrid at 0x24cce5f3fd0>
```



0.2.10 Split the data into train and test

[32]:
```
# Split the data into a training set and a test set.
# Any number for the random_state is fine, see 42: https://en.wikipedia.org/
↪wiki/42_(number)
# We choose to use 20% (test_size=0.2) of the data set as the test set.

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,␣
↪random_state=42)

print(X_train.shape)
```

```
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1159, 8)
(290, 8)
(1159, 1)
(290, 1)
```

[33]:
```
num_features =['LotArea', 'YearBuilt', 'FullBath',␣
↪'HalfBath','BedroomAbvGr','TotalSF','GarageCars']
cat_features = ['BldgType']
```

0.3 Data pre-processing

We will build a pipeline to do some of the following tasks:

- Missing data
- Feature scaling (important for certain model such as Gradient Descent based models)
- Categorical feature encoding
- Outlier removal
- Transformation
- Custom processing

[34]:
```
# any missing values?
X_train.isnull().sum()
```

[34]:
```
LotArea         0
BldgType        0
GarageCars      0
YearBuilt       0
FullBath        0
HalfBath        0
BedroomAbvGr    0
TotalSF         0
dtype: int64
```

[124]:
```
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.preprocessing import PolynomialFeatures

# Create the preprocessing pipeline for numerical features
# Pipeline(steps=[(name1, transform1), (name2, transform2), ...])
# NOTE the step names can be arbitrary

# Step 1 is feature scaling via standardization - making features look like␣
↪normal-distributed
```

```
# see sandardization: https://scikit-learn.org/stable/modules/generated/sklearn.
↪preprocessing.StandardScaler.html)
num_pipeline = Pipeline(
    steps=[
        ('num_imputer', SimpleImputer()),
        ('scaler', StandardScaler())
        ]
)

# Create the preprocessing pipelines for the categorical features
# There are two steps in this pipeline:
# Step 1: one hot encoding

cat_pipeline = Pipeline(
    steps=[
                ('onehot', OneHotEncoder(handle_unknown = 'ignore'))
    ]
)

# Assign features to the pipelines and Combine two pipelines to form the␣
↪preprocessor
from sklearn.compose import ColumnTransformer

preprocessor = ColumnTransformer(
    transformers=[
        ('num_pipeline', num_pipeline, num_features),
        ('cat_pipeline', cat_pipeline, cat_features),
    ]
)
```

0.4 Model traning, tuning, evaluation and selection

- Next, we attach three different models (Linear, Ridge, XGBoost) to the same pre-processing pipeline and tune the some parameters using GridSearch with cross validation. Then, we compare their performance and choose the best model to proceed.

0.4.1 Using Linear Regression Model

[125]:
```
# we show how to use GridSearch with K-fold cross validation (K=2) to fine tune␣
↪the model
# we use the accuracy as the scoring metric with training score␣
↪return_train_score=True
from sklearn.model_selection import GridSearchCV

# try Linear Regression
from sklearn.linear_model import LinearRegression
```

```python
# rf pipeline
pipeline_lr = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LinearRegression()),
])

parameters_lr=[
    {
        'classifier__fit_intercept': [True,False],
        'classifier__copy_X': [True, False],
        'classifier__normalize': [True, False]
    }
]

grid_search_lr = GridSearchCV(pipeline_lr,parameters_lr, cv=2)
```

[126]:
```python
grid_search_lr.fit(X_train, y_train)
```

[126]:
```
GridSearchCV(cv=2,
             estimator=Pipeline(steps=[('preprocessor',
ColumnTransformer(transformers=[('num_pipeline',
Pipeline(steps=[('num_imputer',
          SimpleImputer()),
         ('scaler',
          StandardScaler())]),
['LotArea',
'YearBuilt',
'FullBath',
'HalfBath',
'BedroomAbvGr',
'TotalSF']),
('cat_pipeline',
Pipeline(steps=[('onehot',
          OneHotEncoder(handle_unknown='ignore'))]),
['BldgType'])])),
                                       ('classifier', LinearRegression())]),
             param_grid=[{'classifier__copy_X': [True, False],
                          'classifier__fit_intercept': [True, False],
                          'classifier__normalize': [True, False]}])
```

[127]:
```python
# check the best performing parameter combination
grid_search_lr.best_params_
```

[127]:
```
{'classifier__copy_X': True,
 'classifier__fit_intercept': False,
 'classifier__normalize': True}
```

[128]:
```
# build-in CV results keys
sorted(grid_search_lr.cv_results_.keys())
```

[128]:
```
['mean_fit_time',
 'mean_score_time',
 'mean_test_score',
 'param_classifier__copy_X',
 'param_classifier__fit_intercept',
 'param_classifier__normalize',
 'params',
 'rank_test_score',
 'split0_test_score',
 'split1_test_score',
 'std_fit_time',
 'std_score_time',
 'std_test_score']
```

[129]:
```
# best linear regression model test score
grid_search_lr.best_score_
```

[129]:
```
0.7494241357121679
```

- Best Score using linear regression is 0.757

0.4.2 Using Ridge Regression Model

[130]:
```
from sklearn.linear_model import Ridge

# rf pipeline
pipeline_rg = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('clf_RG', Ridge()),
])

parameters_rg=[
    {
        'clf_RG__alpha': [0,0.2,0.01,1.0],
        'clf_RG__copy_X': [True, False],
        'clf_RG__fit_intercept': [True, False]
    }
]

grid_search_rg = GridSearchCV(pipeline_rg,parameters_rg, cv=5)
```

[131]:
```
grid_search_rg.fit(X_train, y_train)
```

```
D:\Softwares\anaconda3\envs\MISY631\lib\site-
packages\sklearn\linear_model\_ridge.py:148: LinAlgWarning: Ill-conditioned
```

```
matrix (rcond=3.99231e-18): result may not be accurate.
  overwrite_a=True).T
D:\Softwares\anaconda3\envs\MISY631\lib\site-
packages\sklearn\linear_model\_ridge.py:148: LinAlgWarning: Ill-conditioned
matrix (rcond=3.37772e-17): result may not be accurate.
  overwrite_a=True).T
D:\Softwares\anaconda3\envs\MISY631\lib\site-
packages\sklearn\linear_model\_ridge.py:148: LinAlgWarning: Ill-conditioned
matrix (rcond=3.99231e-18): result may not be accurate.
  overwrite_a=True).T
D:\Softwares\anaconda3\envs\MISY631\lib\site-
packages\sklearn\linear_model\_ridge.py:148: LinAlgWarning: Ill-conditioned
matrix (rcond=3.37772e-17): result may not be accurate.
  overwrite_a=True).T
```

[131]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preprocessor',
ColumnTransformer(transformers=[('num_pipeline',
Pipeline(steps=[('num_imputer',
          SimpleImputer()),
         ('scaler',
          StandardScaler())]),
['LotArea',
'YearBuilt',
'FullBath',
'HalfBath',
'BedroomAbvGr',
'TotalSF']),
('cat_pipeline',
Pipeline(steps=[('onehot',
          OneHotEncoder(handle_unknown='ignore'))]),
['BldgType'])])),
                                       ('clf_RG', Ridge())]),
             param_grid=[{'clf_RG__alpha': [0, 0.2, 0.01, 1.0],
                          'clf_RG__copy_X': [True, False],
                          'clf_RG__fit_intercept': [True, False]}])
```

[132]:
```
# best linear ridge regressor model test score
grid_search_rg.best_score_
```

[132]:
```
0.7459059322291025
```

- Best Score using Ridge regression model is 0.756

0.4.3 Using XGBoost Regressor Model

[133]:
```
# XGBoost pipeline
pipeline_xg = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('clf_XG', xgb.XGBRegressor()),
])

parameters_xg=[
    {
        'clf_XG__max_depth': [5,10,15,20,25,30],
        'clf_XG__learning_rate': [0.001,0.01,0.1,0.5],
        'clf_XG__n_estimators': [100,150,200,250,300]

    }
]

grid_search_xg = GridSearchCV(pipeline_xg,parameters_xg, cv=5)
```

[134]:
```
grid_search_xg.fit(X_train, y_train)
```

[134]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preprocessor',
ColumnTransformer(transformers=[('num_pipeline',
Pipeline(steps=[('num_imputer',
          SimpleImputer()),
         ('scaler',
          StandardScaler())]),
['LotArea',
'YearBuilt',
'FullBath',
'HalfBath',
'BedroomAbvGr',
'TotalSF']),
('cat_pipeline',
Pipeline(steps=[('onehot',
          OneHotEncoder(handle_unknown='ignore'))]),
['BldgTy…
                                                     monotone_constraints=None,
                                                     n_estimators=100,
                                                     n_jobs=None,
                                                     num_parallel_tree=None,
                                                     random_state=None,
                                                     reg_alpha=None,
                                                     reg_lambda=None,
                                                     scale_pos_weight=None,
                                                     subsample=None,
```

```
                                                     tree_method=None,
                                                     validate_parameters=None,
                                                     verbosity=None))]),
             param_grid=[{'clf_XG__learning_rate': [0.001, 0.01, 0.1, 0.5],
                          'clf_XG__max_depth': [5, 10, 15, 20, 25, 30],
                          'clf_XG__n_estimators': [100, 150, 200, 250, 300]}])
```

[135]:
```python
grid_search_xg.best_score_
```

[135]:
```
0.7852363569881567
```

- Best Score using XGBoost Regression model is 0.793

0.4.4 Comparing Best Score among Linear Regression , Ridge Regression and XGBoost Regressor

[136]:
```python
# best test score
print('best linear regression score is: ', grid_search_lr.best_score_)
print('best Ridge regression score is: ', grid_search_rg.best_score_)
print('best XGBoost  score is: ', grid_search_xg.best_score_)
```

```
best linear regression score is:  0.7494241357121679
best Ridge regression score is:  0.7459059322291025
best XGBoost  score is:  0.7852363569881567
```

- Among Linear Regression, Ridge REgression and XGBoost Regressor models, XGBoost Regressor has the highest score. Hence, XGBoost Regressor is selected.

[137]:
```python
# best parameters for all three are:
print('best parameter for linear regression are: ', grid_search_lr.best_params_)
print('best Ridge regression regression are: ', grid_search_rg.best_params_)
print('best XGBoost regression are: ', grid_search_xg.best_params_)
```

```
best parameter for linear regression are:  {'classifier__copy_X': True,
'classifier__fit_intercept': False, 'classifier__normalize': True}
best Ridge regression regression are:  {'clf_RG__alpha': 0.2, 'clf_RG__copy_X':
True, 'clf_RG__fit_intercept': False}
best XGBoost regression are:  {'clf_XG__learning_rate': 0.1,
'clf_XG__max_depth': 5, 'clf_XG__n_estimators': 100}
```

- XGBoost Regresson with learning rate= 0.1, Maximum depth of 5 and 100 estimators will yeild best score.

0.4.5 Select the Best Model, which is XGBoost Regressor in this case, and run compute the accuracy

[138]:
```
# select the best model
# the best parameters are shown, note SimpleImputer() implies that mean␣
↪strategry is used
clf_best = grid_search_xg.best_estimator_
```

[139]:
```
from sklearn.metrics import accuracy_score
```

[140]:
```
# final test on the testing set
# To predict on new data: simply calling the predict method
# the full pipeline steps will be applied to the testing set followed by the␣
↪prediction
y_pred = clf_best.predict(X_test)

# calculate accuracy, Note: y_test is the ground truth for the tesing set
# we have similiar score for the testing set as the cross validation score -␣
↪good

#print('Accuracy Score :' (accuracy_score(y_test, y_pred)))
```

[141]:
```
#===========   R-square and other metrics ===================
r_square= metrics.r2_score(y_test, y_pred)
mae_y = metrics.mean_absolute_error(y_test, y_pred)
mse_y = metrics.mean_squared_error(y_test, y_pred)
rmse_y = np.sqrt(metrics.mean_squared_error(y_test, y_pred))

print("XGBoost::r_square={0}::mean_absolute_error={1}::mean_square_error={2}::
↪sqrt_mean_square_error={3}::".format(r_square,mae_y,mse_y,rmse_y))
```

```
XGBoost::r_square=0.8362369337842224::mean_absolute_error=22898.551479500307::me
an_square_error=1270973709.2317245::sqrt_mean_square_error=35650.718214809145::
```

0.4.6 Observation

- Train accuracy of XG Boost Regressor is 0.7852363569881567
- Test accuracy of our best estimator, which is XGBoost Regressor, is 0.8396.
- In this case, accuracy in test dataset was observed higher than in train dataset

0.5 Feature Importance

Given that we are using pipeline and one-hot encoding, the feature importance scores are not very straightforward to get. The following code shows how to get the feature importance scores from the Linear regression and create a plot.

[142]:
```
clf_best.named_steps
```

[142]:
```
{'preprocessor': ColumnTransformer(transformers=[('num_pipeline',
                                  Pipeline(steps=[('num_imputer',
                                                   SimpleImputer()),
                                                  ('scaler',
StandardScaler())]),
                                  ['LotArea', 'YearBuilt', 'FullBath',
                                   'HalfBath', 'BedroomAbvGr', 'TotalSF']),
                                 ('cat_pipeline',
                                  Pipeline(steps=[('onehot',
OneHotEncoder(handle_unknown='ignore'))]),
                                  ['BldgType'])]),
 'clf_XG': XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.1, max_delta_step=0, max_depth=5,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=12, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)}
```

[143]:
```
clf_best.named_steps['preprocessor']
```

[143]:
```
ColumnTransformer(transformers=[('num_pipeline',
                                 Pipeline(steps=[('num_imputer',
                                                  SimpleImputer()),
                                                 ('scaler', StandardScaler())]),
                                 ['LotArea', 'YearBuilt', 'FullBath',
                                  'HalfBath', 'BedroomAbvGr', 'TotalSF']),
                                ('cat_pipeline',
                                 Pipeline(steps=[('onehot',
OneHotEncoder(handle_unknown='ignore'))]),
                                 ['BldgType'])])
```

[144]:
```
i = clf_best.named_steps['clf_XG'].feature_importances_
i
```

[144]:
```
array([0.02239089, 0.1246154 , 0.03957238, 0.03812768, 0.0167276 ,
       0.57821256, 0.06250247, 0.02828226, 0.04206564, 0.01857724,
       0.02892581], dtype=float32)
```

[145]:
```
clf_best['preprocessor'].transformers_
```

[145]:
```
[('num_pipeline',
  Pipeline(steps=[('num_imputer', SimpleImputer()), ('scaler',
StandardScaler())]),
  ['LotArea', 'YearBuilt', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'TotalSF']),
 ('cat_pipeline',
```

```
 Pipeline(steps=[('onehot', OneHotEncoder(handle_unknown='ignore'))]),
 ['BldgType']),
('remainder', 'drop', [2])]
```

[146]:
```
# get columnTransformer
clf_best[0]
```

[146]:
```
ColumnTransformer(transformers=[('num_pipeline',
                                 Pipeline(steps=[('num_imputer',
                                                  SimpleImputer()),
                                                 ('scaler', StandardScaler())]),
                                 ['LotArea', 'YearBuilt', 'FullBath',
                                  'HalfBath', 'BedroomAbvGr', 'TotalSF']),
                                ('cat_pipeline',
                                 Pipeline(steps=[('onehot',
OneHotEncoder(handle_unknown='ignore'))]),
                                 ['BldgType'])])
```

[147]:
```
clf_best[0].transformers_
```

[147]:
```
[('num_pipeline',
  Pipeline(steps=[('num_imputer', SimpleImputer()), ('scaler',
StandardScaler())]),
  ['LotArea', 'YearBuilt', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'TotalSF']),
 ('cat_pipeline',
  Pipeline(steps=[('onehot', OneHotEncoder(handle_unknown='ignore'))]),
  ['BldgType']),
 ('remainder', 'drop', [2])]
```

[148]:
```
num_original_feature_names = clf_best[0].transformers_[0][2]
num_original_feature_names
```

[148]:
```
['LotArea', 'YearBuilt', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'TotalSF']
```

[149]:
```
cat_original_feature_names = clf_best[0].transformers_[1][2]
cat_original_feature_names
```

[149]:
```
['BldgType']
```

[150]:
```
cat_new_feature_names = list(clf_best[0].transformers_[1][1]['onehot'].
 ↪get_feature_names(cat_original_feature_names))
cat_new_feature_names
```

[150]:
```
['BldgType_1Fam',
 'BldgType_2fmCon',
 'BldgType_Duplex',
 'BldgType_Twnhs',
```

```
 'BldgType_TwnhsE']
```

[151]:
```
feature_names = num_original_feature_names + cat_new_feature_names
feature_names
```

[151]:
```
['LotArea',
 'YearBuilt',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'TotalSF',
 'BldgType_1Fam',
 'BldgType_2fmCon',
 'BldgType_Duplex',
 'BldgType_Twnhs',
 'BldgType_TwnhsE']
```

[152]:
```
r = pd.DataFrame(i, index=feature_names, columns=['importance'])
r
```

[152]:

	importance
LotArea	0.022391
YearBuilt	0.124615
FullBath	0.039572
HalfBath	0.038128
BedroomAbvGr	0.016728
TotalSF	0.578213
BldgType_1Fam	0.062502
BldgType_2fmCon	0.028282
BldgType_Duplex	0.042066
BldgType_Twnhs	0.018577
BldgType_TwnhsE	0.028926

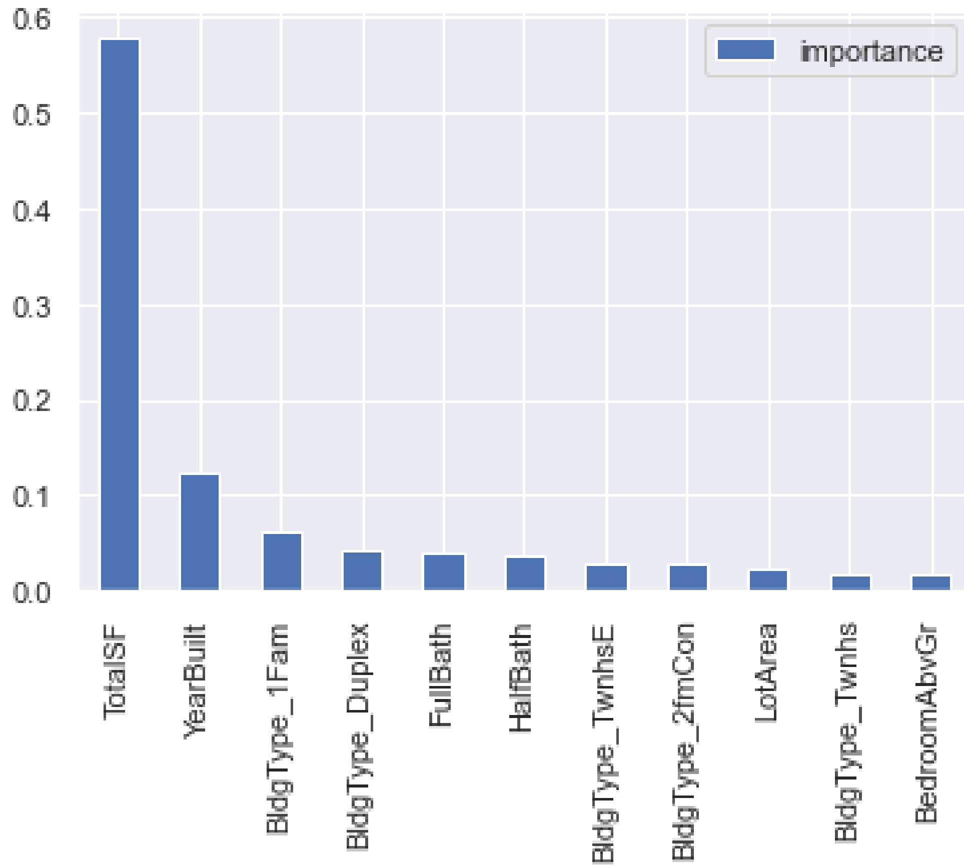
[153]:
```
r.sort_values('importance', ascending=False)
```

[153]:

	importance
TotalSF	0.578213
YearBuilt	0.124615
BldgType_1Fam	0.062502
BldgType_Duplex	0.042066
FullBath	0.039572
HalfBath	0.038128
BldgType_TwnhsE	0.028926
BldgType_2fmCon	0.028282
LotArea	0.022391
BldgType_Twnhs	0.018577
BedroomAbvGr	0.016728

[154]:
```
r.sort_values('importance', ascending=False).plot.bar()
```

[154]: <AxesSubplot:>



0.6 Remove unimportant Features

- HouseStyle was removed from the list of features as it had very less importance.

[155]:
```
# we remove unimportant features: House Style and see the model is affected
# result: no difference with less features!!

num_features =['LotArea', 'YearBuilt', 'FullBath',␣
↪'HalfBath','BedroomAbvGr','TotalSF']
cat_features = ['BldgType']

# you must update preprocess and pipeline after changing the feature list
preprocessor = ColumnTransformer(
    transformers=[
        ('num_pipeline', num_pipeline, num_features),
        ('cat_pipeline', cat_pipeline, cat_features),
```

```
    ]
)

pipeline_xg_updated = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('clf_XG', xgb.XGBRegressor()),
])

parameters_xg=[
    {
        'clf_XG__max_depth': [5,10,15,20,25,30],
        'clf_XG__learning_rate': [0.001,0.01,0.1,0.5],
        'clf_XG__n_estimators': [100,150,200,250,300]

    }
]

grid_search_xg_updated = GridSearchCV(pipeline_xg_updated,parameters_xg, cv=5)

# train the model using the updated full pipeline
grid_search_xg_updated.fit(X_train, y_train)

print('best dt score is: ', grid_search_xg.best_score_)
print('best dt score after feature selection is: ', grid_search_xg_updated.
 ↪best_score_)
```

```
best dt score is:  0.7852363569881567
best dt score after feature selection is:  0.7852363569881567
```

0.7 Persists the model

[156]:
```
# Save the model as a pickle file
import joblib
joblib.dump(clf_best, "Housing.pickle")
```

[156]:
```
['Housing.pickle']
```

[157]:
```
# Load the model from a pickle file
saved_xg_clf = joblib.load("Housing.pickle")
saved_xg_clf
```

[157]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num_pipeline',
Pipeline(steps=[('num_imputer',
SimpleImputer()),
                                                                  ('scaler',
StandardScaler())]),
```

```
                                            ['LotArea', 'YearBuilt',
                                             'FullBath', 'HalfBath',
                                             'BedroomAbvGr', 'TotalSF']),
                                           ('cat_pipeline',
                                            Pipeline(steps=[('onehot',
OneHotEncoder(handle_unknown='ignore'))]),

                                            ['BldgType'])])),
                ('clf_XG',
                 XGBRegres…
                              colsample_bytree=1, gamma=0, gpu_id=-1,
                              importance_type='gain',
                              interaction_constraints='', learning_rate=0.1,
                              max_delta_step=0, max_depth=5, min_child_weight=1,
                              missing=nan, monotone_constraints='()',
                              n_estimators=100, n_jobs=12, num_parallel_tree=1,
                              random_state=0, reg_alpha=0, reg_lambda=1,
                              scale_pos_weight=1, subsample=1,
                              tree_method='exact', validate_parameters=1,
                              verbosity=None))])
```

0.8 Using Test Datasets for prediction

- Read the datasets into the data frame and pulled only the common features.
- Renamed the columns to match the column names in X, Y frame.
- Transformed the "None" values to 0 in Newark Dataset.
- Created a dictionary to map the values in Building Type to match with our training dataset and removed 'Farm', 'mobile' and 'Land' types.
- Changed the order of the columns to match with X frame as its important for scikit learn
- Used clf_best.predict to predict the values of houses for each city and compared it to the actual data.

Observations

- Below table lists down the performance metrics for each of the cities

City	r_square	mean_absolute_error	mean_square_error	sqrt_mean_square_error
Newark-DE	-0.184925	109995.238084	1.645267e+10	128267.963373
Bear-DE	0.113418	106598.324378	1.475721e+10	121479.258206
Wilmington-DE	-0.081391	161541.067093	5.487316e+10	234250.206711
Ames-IA	-0.452275	119947.499630	2.135133e+10	146120.934070

0.8.1 Newark, DE

[182]:
```
X_test.head()
```

[182]:
```
      LotArea BldgType  GarageCars  YearBuilt  FullBath  HalfBath  \
545     13837     1Fam           3       1988         2         1
762      8640     1Fam           2       2009         2         1
49       7742     1Fam           1       1966         1         0
1390     9100     1Fam           2       2000         2         0
142      8520     1Fam           2       1952         2         0

      BedroomAbvGr  TotalSF
545              4     3387
762              3     2303
49               3     1910
1390             3     3050
142              4     2295
```

[190]:
```
#Read Newark Dataset and fetch the columns which were identified as features

newark_df=pd.read_csv('Data/Delaware - Newark.csv')
newark_test_df=newark_df[['description/year_built','description/
 ↪lot_sqft','description/sqft','description/baths_full',
                          'description/baths_half','description/
 ↪type','description/beds','description/garage','description/
 ↪sold_price','description/sold_date']].copy()

newark_test_df=newark_test_df.rename(columns={"description/year_built":␣
 ↪"YearBuilt", "description/lot_sqft": "LotArea", "description/sqft":"TotalSF"␣
 ↪,
                                              "description/baths_full":␣
 ↪"FullBath", "description/baths_half": "HalfBath", "description/type":␣
 ↪"BldgType", "description/beds":"BedroomAbvGr",
                               "description/garage": "GarageCars", "description/
 ↪sold_price": "SalePrice", "description/sold_date":"YrSold" })
```

[159]:
```
# Create a dictionary of Building Type to map the test dataset to training data␣
 ↪set

BldgTypedi = {"single_family": "1Fam", "townhomes": "Twnhs", "duplex_triplex":␣
 ↪"Duplex", "condos":"Twnhs", "multi_family":"2fmCon"}
```

[191]:
```
# Map the building type using replace function

newark_test_df['BldgType'].replace(BldgTypedi, inplace=True)
```

[194]:
```
newark_test_df.BldgType.value_counts()
```

[194]:
```
1Fam      132
Twnhs      63
Duplex      3
Name: BldgType, dtype: int64
```

[193]:
```
# land not part of training, so we removed it.

newark_test_df=newark_test_df[newark_test_df.BldgType!='land']
```

[195]:
```
# Change the order of the test data frame to match with X data
newark_test_df =␣
↪newark_test_df[['LotArea','BldgType','GarageCars','YearBuilt','FullBath','HalfBath','Bedroo
↪'YrSold']]
newark_test_df.head()
```

[195]:
```
  LotArea BldgType GarageCars YearBuilt FullBath HalfBath BedroomAbvGr  \
0    7841     1Fam          1      1965        1        1            3
1    1742    Twnhs       None      1993        1        1            2
2    6534     1Fam       None      1988        2     None            3
3    None    Twnhs       None      1969        1     None            2
4   15246     1Fam          2      1992        2        2            3

  TotalSF  SalePrice      YrSold
0    3001     310000  2021-06-25
1    2176     195900  2021-06-25
2    1300     260000  2021-06-25
3    1070     132000  2021-06-25
4    3467     467500  2021-06-25
```

[196]:
```
# Update all the values of 'None' to 0

newark_test_df.loc[newark_test_df['GarageCars'] == 'None', 'GarageCars'] = 0
newark_test_df.loc[newark_test_df['HalfBath'] == 'None', 'HalfBath'] = 0
newark_test_df.loc[newark_test_df['LotArea'] == 'None', 'LotArea'] = 0
newark_test_df.loc[newark_test_df['TotalSF'] == 'None', 'TotalSF'] = 0
newark_test_df.loc[newark_test_df['FullBath'] == 'None', 'FullBath'] = 0
```

0.8.2 Bear, DE

[165]:
```
#Read Bear Dataset and fetch the columns which were identified as features

bear_df=pd.read_csv('Data/Delaware - Bear.csv')
bear_test_df=bear_df[['description/year_built','description/
↪lot_sqft','description/sqft','description/baths_full','description/
↪baths_half',
                        'description/type','description/beds','description/
↪garage','description/sold_price','description/sold_date']].copy()
```

```
#rename the columns to match the X, Y data

bear_test_df=bear_test_df.rename(columns={"description/year_built":␣
↪"YearBuilt", "description/lot_sqft": "LotArea", "description/sqft":"TotalSF"␣
↪, "description/baths_full": "FullBath",
                                "description/baths_half": "HalfBath",␣
↪"description/type": "BldgType", "description/beds":"BedroomAbvGr",
                                "description/garage": "GarageCars", "description/
↪sold_price": "SalePrice", "description/sold_date":"YrSold" })
```

[166]:
```
# Map the building type using replace function
bear_test_df['BldgType'].replace(BldgTypedi, inplace=True)

bear_test_df.head()
```

[166]:
```
   YearBuilt  LotArea  TotalSF  FullBath  HalfBath BldgType  BedroomAbvGr  \
0     2001.0   9583.0   4050.0       3.0       1.0     1Fam           4.0
1     1988.0   8276.0   2025.0       2.0       1.0     1Fam           4.0
2     2018.0   3049.0   2950.0       3.0       1.0    Twnhs           4.0
3     1973.0  27878.0   1975.0       2.0       1.0     1Fam           4.0
4     2002.0   3485.0   1850.0       2.0       2.0    Twnhs           3.0

   GarageCars  SalePrice      YrSold
0         2.0     510000  2021-06-25
1         1.0     365000  2021-06-23
2         2.0     385000  2021-06-21
3         1.0     335000  2021-06-21
4         1.0     350000  2021-06-21
```

[167]:
```
bear_test_df.BldgType.value_counts()
```

[167]:
```
1Fam      125
Twnhs      66
Duplex      5
mobile      3
land        1
Name: BldgType, dtype: int64
```

[203]:
```
# Change the order of the test data frame to match with X data
bear_test_df =␣
↪bear_test_df[['LotArea','BldgType','GarageCars','YearBuilt','FullBath','HalfBath','BedroomA
↪'YrSold']]
```

[204]:
```
# land and mobile not part of training, so we removed it.

bear_test_df=bear_test_df[bear_test_df.BldgType!='land']
```

```
bear_test_df=bear_test_df[bear_test_df.BldgType!='mobile']
```

0.8.3 Wilmington, DE

[169]:
```
#Read Wilmington Dataset and fetch the columns which were identified as features

wilmigton_df=pd.read_csv('Data/Delaware - Wilmington.csv')

wilmigton_test_df=wilmigton_df[['description/year_built','description/
↪lot_sqft','description/sqft','description/baths_full','description/
↪baths_half',
                                 'description/type','description/
↪beds','description/garage','description/sold_price','description/
↪sold_date']].copy()

#rename the columns to match the X, Y data
wilmigton_test_df=wilmigton_test_df.rename(columns={"description/year_built":␣
↪"YearBuilt", "description/lot_sqft": "LotArea", "description/sqft":"TotalSF"␣
↪, "description/baths_full": "FullBath",
                                "description/baths_half": "HalfBath",␣
↪"description/type": "BldgType", "description/beds":"BedroomAbvGr",
                                "description/garage": "GarageCars", "description/
↪sold_price": "SalePrice", "description/sold_date":"YrSold" })
```

[170]:
```
# Map the building type using replace function

wilmigton_test_df['BldgType'].replace(BldgTypedi, inplace=True)

wilmigton_test_df.head()
```

[170]:
```
   YearBuilt  LotArea  TotalSF  FullBath  HalfBath BldgType  BedroomAbvGr  \
0     1935.0   9583.0   2025.0       2.0       NaN     1Fam             4
1     1968.0      NaN      NaN       2.0       NaN    Twnhs             2
2     1920.0   3920.0   2725.0       NaN       NaN   2fmCon             0
3     1959.0  10890.0   2186.0       2.0       NaN     1Fam             3
4     1958.0   8712.0   2553.0       2.0       1.0     1Fam             4

   GarageCars  SalePrice      YrSold
0         NaN     275000  2021-06-25
1         NaN     155000  2021-06-25
2         NaN     451000  2021-06-25
3         1.0     341000  2021-06-25
4         1.0     385000  2021-06-25
```

[171]:
```
wilmigton_test_df.BldgType.value_counts()
```

[171]:
```
1Fam      124
Twnhs      68
2fmCon      7
mobile      1
Name: BldgType, dtype: int64
```

[205]:
```
# Change the order of the test data frame to match with X data
wilmigton_test_df =␣
↪wilmigton_test_df[['LotArea','BldgType','GarageCars','YearBuilt','FullBath','HalfBath','Bed
↪'YrSold']]
```

[206]:
```
# Mobile not part of training, so we removed it.

wilmigton_test_df=wilmigton_test_df[wilmigton_test_df.BldgType!='mobile']
```

0.8.4 Ames, IA

[173]:
```
#Read Ames Dataset and fetch the columns which were identified as features

ames_df=pd.read_csv('Data/IA - Ames.csv')


ames_test_df=ames_df[['description/year_built','description/
↪lot_sqft','description/sqft','description/baths_full','description/
↪baths_half',
                      'description/type','description/beds','description/
↪garage','description/sold_price','description/sold_date']].copy()

#rename the columns to match the X, Y data
ames_test_df=ames_test_df.rename(columns={"description/year_built":␣
↪"YearBuilt", "description/lot_sqft": "LotArea", "description/sqft":"TotalSF"␣
↪, "description/baths_full": "FullBath",
                              "description/baths_half": "HalfBath",␣
↪"description/type": "BldgType", "description/beds":"BedroomAbvGr",
                              "description/garage": "GarageCars", "description/
↪sold_price": "SalePrice", "description/sold_date":"YrSold" })
```

[174]:
```
# Map the building type using replace function

ames_test_df['BldgType'].replace(BldgTypedi, inplace=True)

ames_test_df.head()
```

[174]:
```
   YearBuilt  LotArea  TotalSF  FullBath  HalfBath BldgType  BedroomAbvGr  \
0     1914.0   6098.0   1747.0       1.0       NaN     1Fam           3.0
1     1998.0   9600.0   1539.0       2.0       1.0     1Fam           4.0
```

```
2     1994.0   8276.0    990.0       2.0       NaN     1Fam            3.0
3     2007.0  10411.0   1646.0       2.0       1.0     1Fam            4.0
4     2006.0   6240.0   1325.0       3.0       NaN    Twnhs            3.0

   GarageCars  SalePrice      YrSold
0         NaN     211000  2021-06-25
1         2.0     269900  2021-06-23
2         2.0     206500  2021-06-23
3         2.0     345000  2021-06-21
4         2.0     329900  2021-06-21
```

[175]:
```
ames_test_df.BldgType.value_counts()
```

[175]:
```
1Fam      157
Twnhs      26
2fmCon      7
land        7
farm        3
Name: BldgType, dtype: int64
```

[207]:
```
# Change the order of the test data frame to match with X data
ames_test_df =␣
↪ames_test_df[['LotArea','BldgType','GarageCars','YearBuilt','FullBath','HalfBath','BedroomA
↪'YrSold']]
```

[208]:
```
# Mobile, Land, Farm not part of training, so we removed it.

ames_test_df=ames_test_df[ames_test_df.BldgType!='mobile']
ames_test_df=ames_test_df[ames_test_df.BldgType!='land']
ames_test_df=ames_test_df[ames_test_df.BldgType!='farm']
```

0.8.5 Model prediction using the test dataset

[209]:
```
# Preparing the final dataset  by dropping the SalesPrice and Year Sold

newark_test_final=newark_test_df.drop(['SalePrice', 'YrSold'], axis=1)
bear_test_final=bear_test_df.drop(['SalePrice', 'YrSold'], axis=1)
ames_test_final=ames_test_df.drop(['SalePrice', 'YrSold'], axis=1)
wilmington_test_final=wilmigton_test_df.drop(['SalePrice', 'YrSold'], axis=1)
```

[210]:
```
# Creating y_test data frames to compare the predicted values and finding␣
↪accuracy

y_newark_test=newark_test_df['SalePrice'].copy()
y_bear_test=bear_test_df['SalePrice'].copy()
y_ames_test=ames_test_df['SalePrice'].copy()
y_wilmington_test=wilmigton_test_df['SalePrice'].copy()
```

[211]:
```python
# Executing the model with the test data sets

y_newark_pred = clf_best.predict(newark_test_final)
y_bear_pred = clf_best.predict(bear_test_final)
y_ames_pred = clf_best.predict(ames_test_final)
y_wilmington_pred = clf_best.predict(wilmington_test_final)
```

[220]:
```python
#===========   R-square and other metrics ===================
r_square_newark= metrics.r2_score(y_newark_test, y_newark_pred)
mae_y_newark = metrics.mean_absolute_error(y_newark_test, y_newark_pred)
mse_y_newark = metrics.mean_squared_error(y_newark_test, y_newark_pred)
rmse_y_newark = np.sqrt(metrics.mean_squared_error(y_newark_test,␣
 ↪y_newark_pred))

perfdata = []
perfdata.append(['Newark-DE', r_square_newark, mae_y_newark,␣
 ↪mse_y_newark,rmse_y_newark])
print('-------------------------Newark------------------------------')
print("XGBoost::r_square={0}::mean_absolute_error={1}::mean_square_error={2}::
 ↪sqrt_mean_square_error={3}::".
 ↪format(r_square_newark,mae_y_newark,mse_y_newark,rmse_y_newark))

#===========   R-square and other metrics ===================
r_square_bear= metrics.r2_score(y_bear_test, y_bear_pred)
mae_y_bear = metrics.mean_absolute_error(y_bear_test, y_bear_pred)
mse_y_bear = metrics.mean_squared_error(y_bear_test, y_bear_pred)
rmse_y_bear = np.sqrt(metrics.mean_squared_error(y_bear_test, y_bear_pred))

perfdata.append(['Bear-DE', r_square_bear, mae_y_bear, mse_y_bear,rmse_y_bear])

print('\n-------------------------Bear------------------------------')
print("XGBoost::r_square={0}::mean_absolute_error={1}::mean_square_error={2}::
 ↪sqrt_mean_square_error={3}::".
 ↪format(r_square_bear,mae_y_bear,mse_y_bear,rmse_y_bear))

#===========   R-square and other metrics ===================
r_square_wilmington= metrics.r2_score(y_wilmington_test, y_wilmington_pred)
mae_y_wilmington = metrics.mean_absolute_error(y_wilmington_test,␣
 ↪y_wilmington_pred)
mse_y_wilmington = metrics.mean_squared_error(y_wilmington_test,␣
 ↪y_wilmington_pred)
rmse_y_wilmington = np.sqrt(metrics.mean_squared_error(y_wilmington_test,␣
 ↪y_wilmington_pred))
perfdata.append(['Wilmington-DE', r_square_wilmington, mae_y_wilmington,␣
 ↪mse_y_wilmington,rmse_y_wilmington])
```

```
print('\n-------------------------Wilmington------------------------------')
print("XGBoost::r_square={0}::mean_absolute_error={1}::mean_square_error={2}::
↪sqrt_mean_square_error={3}::".
↪format(r_square_wilmington,mae_y_wilmington,mse_y_wilmington,rmse_y_wilmington))

#===========   R-square and other metrics ===================
r_square_ames= metrics.r2_score(y_ames_test, y_ames_pred)
mae_y_ames = metrics.mean_absolute_error(y_ames_test, y_ames_pred)
mse_y_ames = metrics.mean_squared_error(y_ames_test, y_ames_pred)
rmse_y_ames = np.sqrt(metrics.mean_squared_error(y_ames_test, y_ames_pred))
perfdata.append(['Ames-IA', r_square_ames, mae_y_ames, mse_y_ames,rmse_y_ames])

print('\n-------------------------Ames------------------------------')
print("XGBoost::r_square={0}::mean_absolute_error={1}::mean_square_error={2}::
↪sqrt_mean_square_error={3}::".
↪format(r_square_ames,mae_y_ames,mse_y_ames,rmse_y_ames))
```

```
-------------------------Newark------------------------------
XGBoost::r_square=-0.18492539069381864::mean_absolute_error=109995.23808396465::
mean_square_error=16452670427.774572::sqrt_mean_square_error=128267.96337267764:
:

-------------------------Bear------------------------------
XGBoost::r_square=0.11341828597980574::mean_absolute_error=106598.32437818877::m
ean_square_error=14757210174.191347::sqrt_mean_square_error=121479.25820563504::

-------------------------Wilmington------------------------------
XGBoost::r_square=-0.0813908456232999::mean_absolute_error=161541.0670932789::me
an_square_error=54873159343.9656::sqrt_mean_square_error=234250.20671061444::

-------------------------Ames------------------------------
XGBoost::r_square=-0.45227453500939774::mean_absolute_error=119947.49962993422::
mean_square_error=21351327373.55799::sqrt_mean_square_error=146120.9340702351::
```

[225]:
```
## Storing Performance Data to use in the streamlit app

perfdata_df = pd.DataFrame(perfdata, columns=['City', 'r_square',␣
↪'mean_absolute_error','mean_square_error','sqrt_mean_square_error'])

perfdata_df.to_csv(r'Data/perfData.csv',index = False, header=True)
perfdata_df
```

[225]:

	City	r_square	mean_absolute_error	mean_square_error \
0	Newark-DE	-0.184925	109995.238084	1.645267e+10
1	Bear-DE	0.113418	106598.324378	1.475721e+10
2	Wilmington-DE	-0.081391	161541.067093	5.487316e+10
3	Ames-IA	-0.452275	119947.499630	2.135133e+10

	sqrt_mean_square_error
0	128267.963373
1	121479.258206
2	234250.206711
3	146120.934070