HouseRegressions_Team_6

July 18, 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 Support Vector Regression, Ridge Regression 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 (RMSE) 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 (RMSE) and model selection

- Following are the scores (RMSE) from Support Vector Regression, Ridge and XG Boost Regressor
  - best Support Vector regression score (RMSE) is: -100085.7038582825
  - best Ridge regression score (RMSE) is: -49146.2619536027
  - best XGBoost score (RMSE) is: -44868.30845180691
- Based on the above Scores, we selected XG Boost Regressor as our desired model.

0.1.2 Baseline Prediction

- Below are the baseline prediction metrics using mean()
- MAE=63001.37238631565
- MSE=7761052223.808897
- RMSE=88096.83435747788

0.1.3 RMSE for XG Boost Regressor

- Train RMSE of XG Boost Regressor is 44868.30845180691
- Test RMSE of our best estimator, which is XGBoost Regressor, is 35280.55625966848.
- In this case, **RMSE in test dataset was observed lower than in train dataset**
- Our model is better than the baseline model (RMSE=88096.83435747788 for baseline vs RMSE=35280.55625966848 for XG Boost)

Test Data RMSE

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

City	r_square	mean_absolute_error	mean_square_error	sqrt_mean_square_error	mean_SalesPrice
Newark-DE	-0.306535	118402.943024	1.814122e+10	134689.355951	308017.207071
Bear-DE	0.070029	108738.838409	1.547942e+10	124416.327675	338265.816327
Wilmington-DE	-0.069775	159559.169559	5.428372e+10	232988.673812	328693.668342
Ames-IA	-0.298120	112514.734786	1.908495e+10	138148.291188	286503.689474

0.1.4 Conclusion

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

0.1.5 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.

0.1.6 Inflation Adjustment

- Installed and imported the cpi package (https://www.bls.gov/)

- Used Year sold and the current Price to get the Adjusted SalesPrice.

0.1.7 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

0.1.8 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.

0.1.9 Imputers

- SimpleImputer was used to handle the incoming null values.

0.1.10 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.

0.1.11 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

0.1.12 Model Training, Tuning & Evaluation

- Support Vector Regressor, Ridge regressor and XGBoost Regressor were trained with different parameters and below are the best parameter selection for each.
- Support Vector regression:
  - {'clf_svr___kernel': 'linear'}

- 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.

0.1.13 Final Selection of Model

- Following are the scores from Support Vector Regression, Ridge and XG Boost Regressor
  - best Support Vector regression score (RMSE) is: -100085.7038582825
  - best Ridge regression score (RMSE) is: -49146.2619536027
  - best XGBoost score (RMSE) is: -44868.30845180691
- Based on the above Scores, we selected XG Boost Regressor as our desired model.

0.1.14 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	mean_SalesPrice
Newark-DE	-0.306535	118402.943024	1.814122e+10	134689.355951	308017.207071
Bear-DE	0.070029	108738.838409	1.547942e+10	124416.327675	338265.816327
Wilmington-DE	-0.069775	159559.169559	5.428372e+10	232988.673812	328693.668342
Ames-IA	-0.298120	112514.734786	1.908495e+10	138148.291188	286503.689474

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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

import cpi
cpi.update()
```

0.1.15 Data Set

[2]:
```
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]:
```
housingData.shape
```

[3]: (1460, 81)

[4]:
```
# 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
```

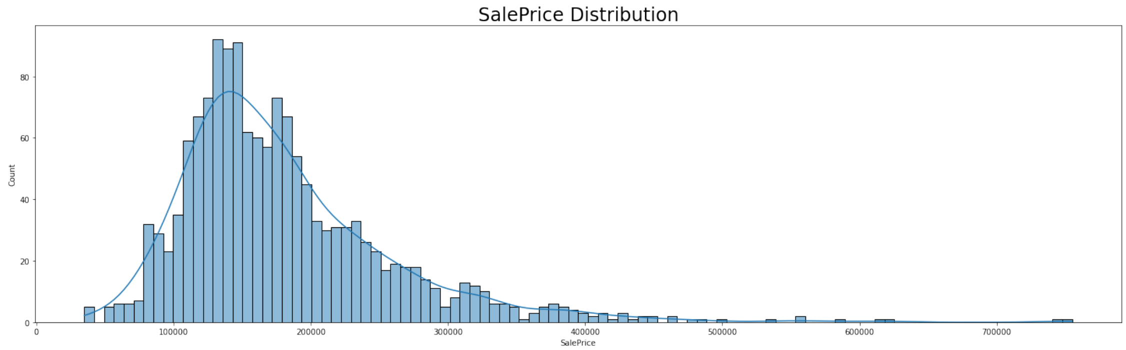
0.2.2 Continuous Columns Information

[8]:
```python
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]:
```python
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]:
```python
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]:
```python
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)
#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

- Oldest house was built in the year 1872 while the newest house in 2010.

[14]:
```
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

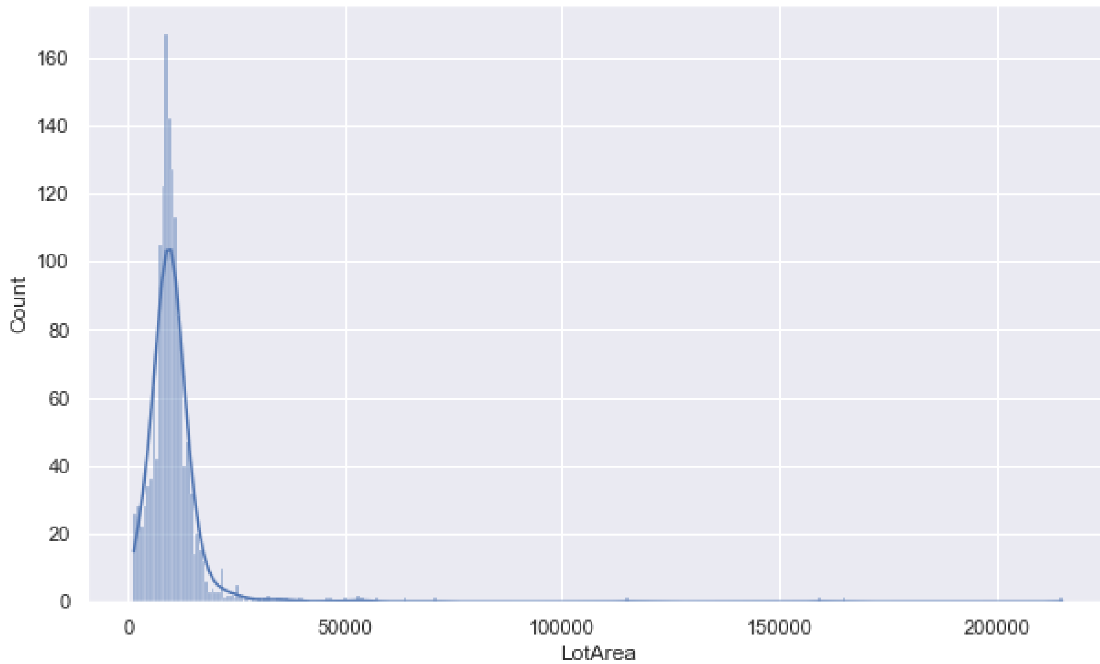
	25%	50%	75%	max
Id	365.750000	730.500000	1095.25000	1460.000000
MSSubClass	20.000000	50.000000	70.00000	190.000000
LotFrontage	59.000000	69.000000	80.00000	313.000000
LotArea	7553.500000	9478.500000	11601.50000	215245.000000
OverallQual	5.000000	6.000000	7.00000	10.000000
OverallCond	5.000000	5.000000	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
```

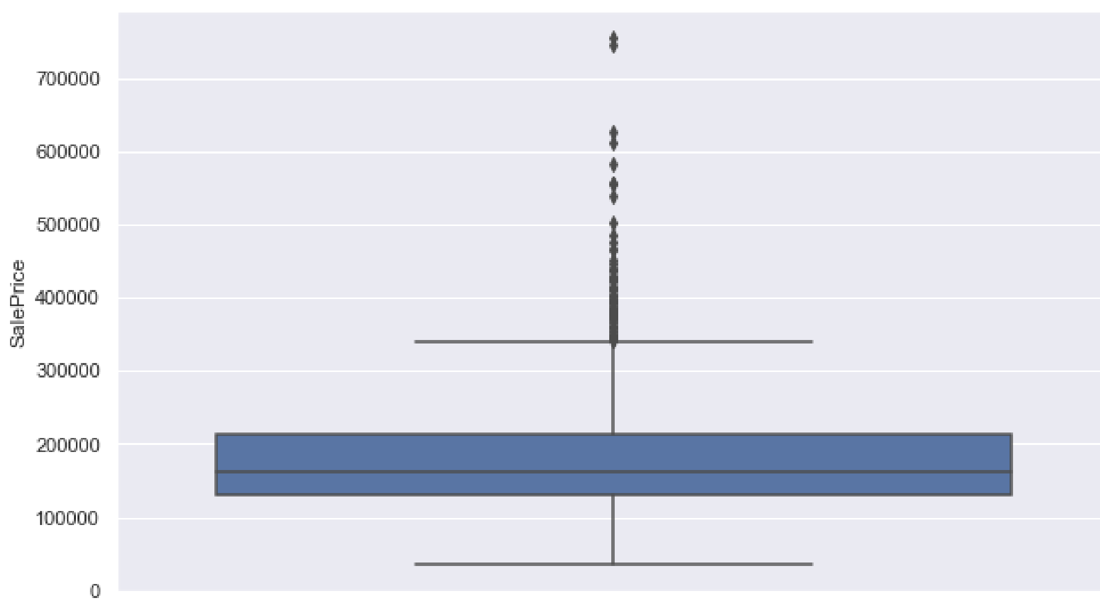
Following were the observations for LotArea and checking for Distribution and Box plot for outliers:

- 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()
```



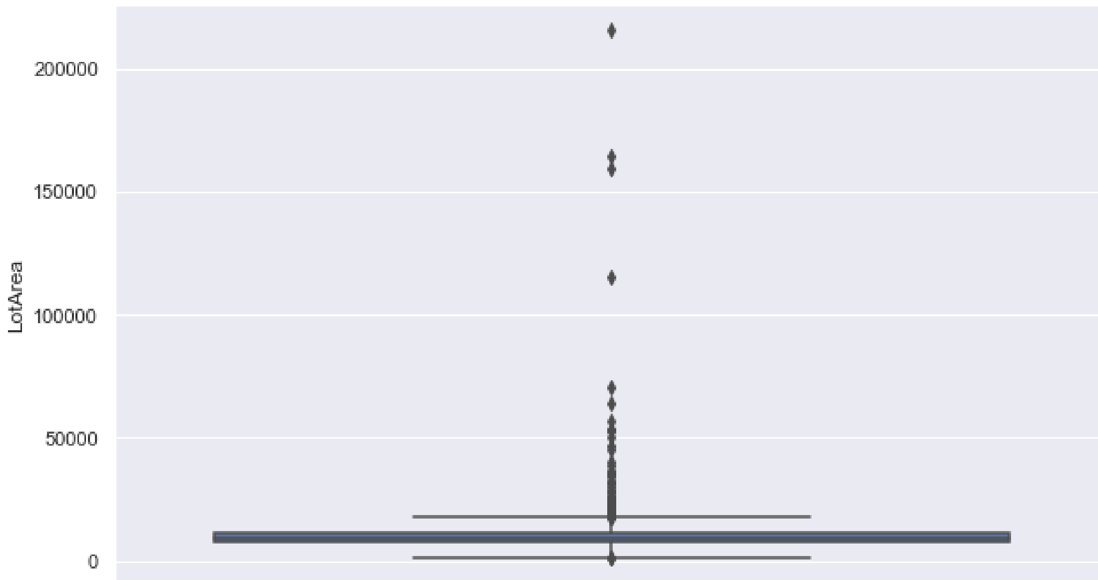
[16]:
```
plt.figure(figsize=(10,6))
sns.boxplot(y='SalePrice',data=housingData)
plt.show()
```



0.2.6 Removing Outlier

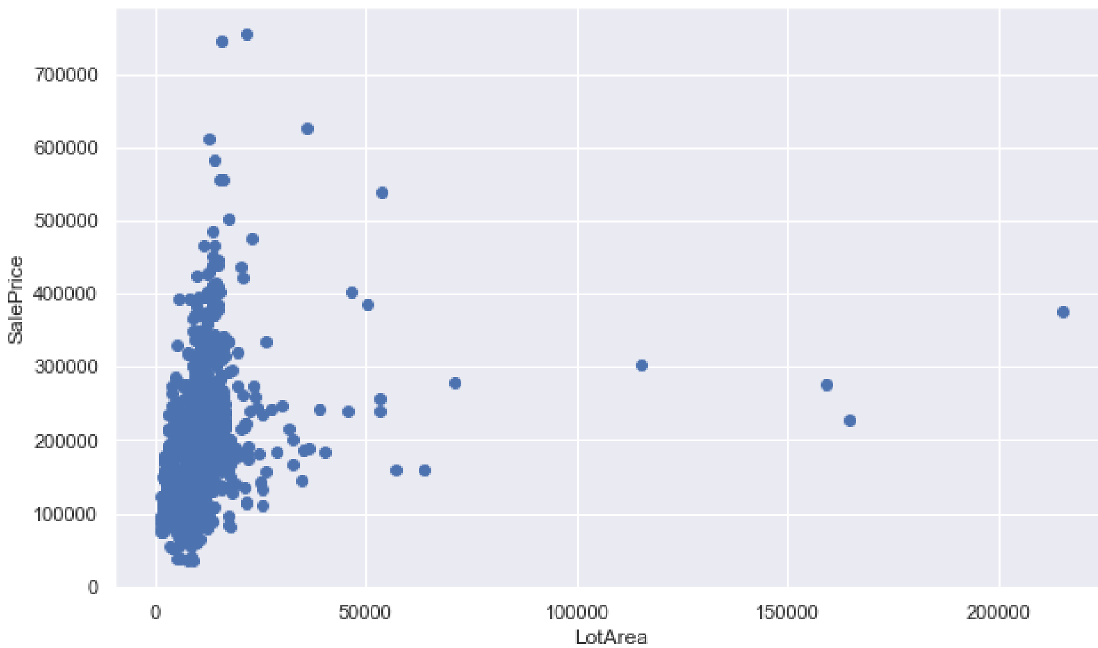
In order to avoid outliers, LotArea greater than 50,000 sq.ft. were eliminated

[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')

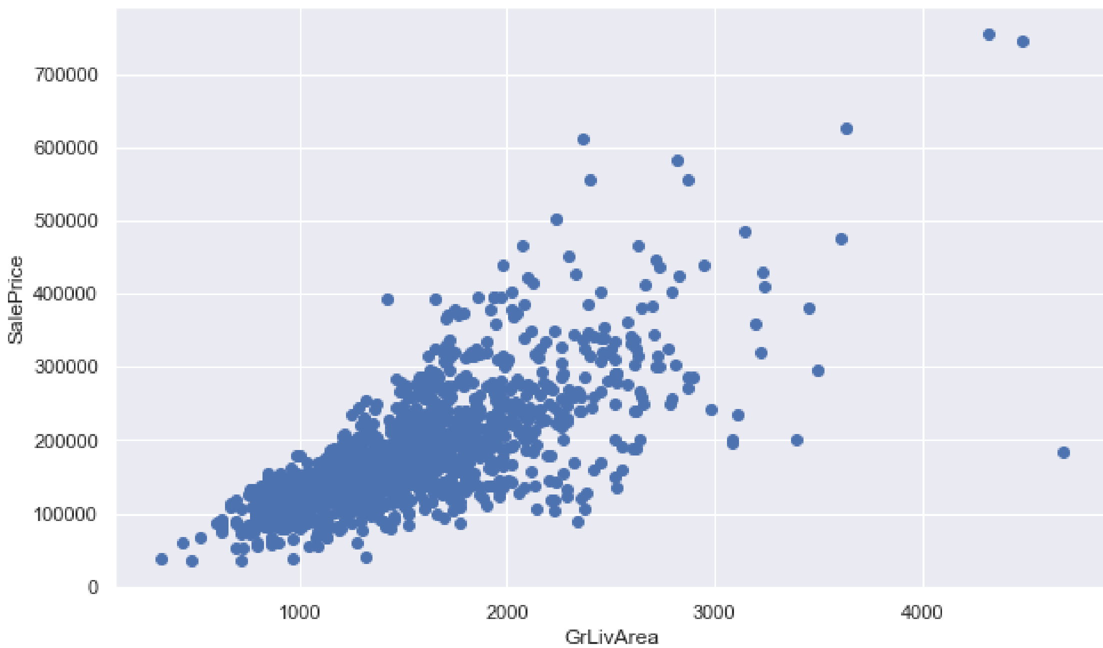


[19]:
```
# Dropping lotArea greater than 50000 to remove outlier
housingData = housingData[housingData.LotArea <= 50000].copy()
housingData.shape
```

[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')
```

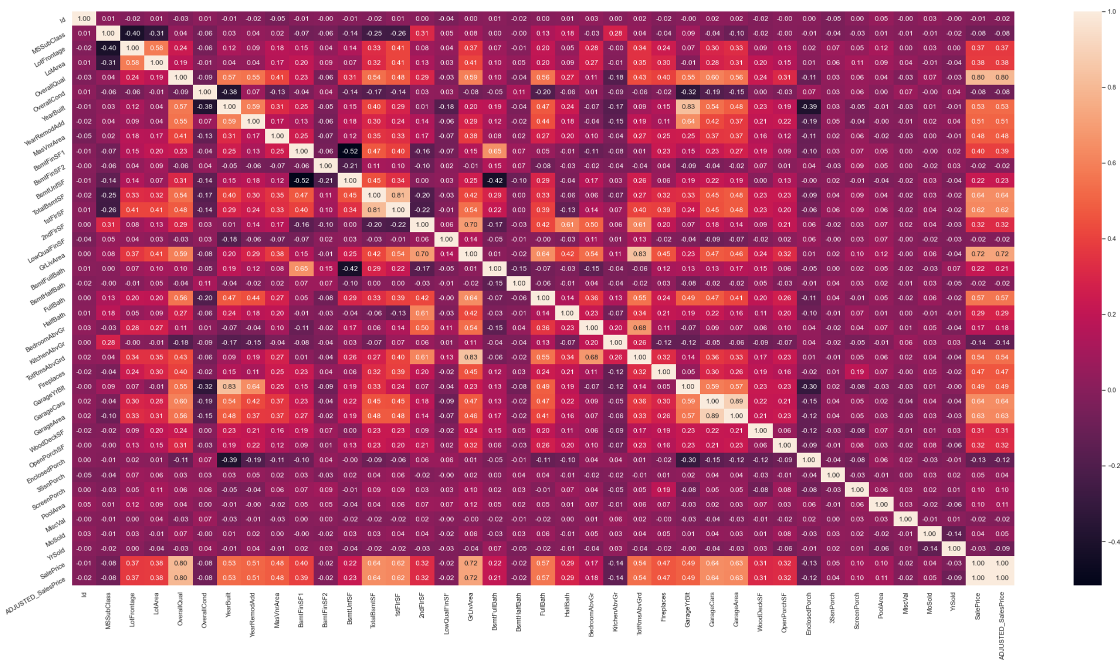
[20]: Text(0, 0.5, 'SalePrice')



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]:
```python
# 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
```

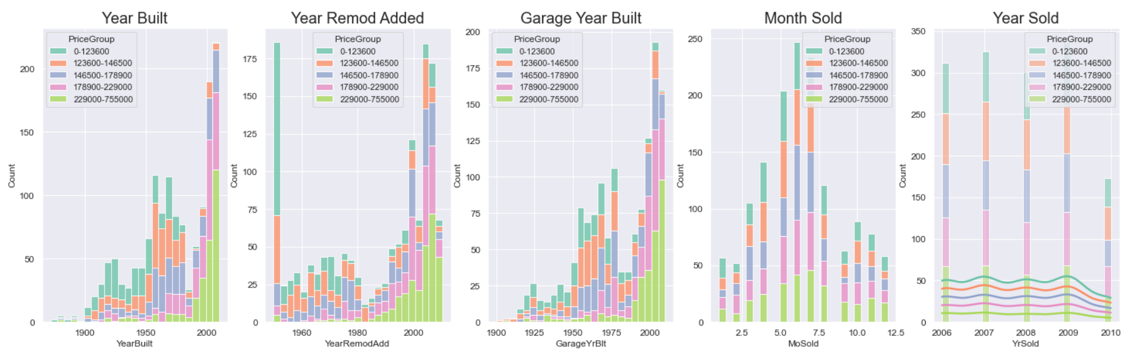
- For visualization, it will be good to group the prices onto manageable levels.
- The above groups look good

[24]:
```python
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]:
```python
# build figure
fig = plt.figure(figsize=(25,7))

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

```
# 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

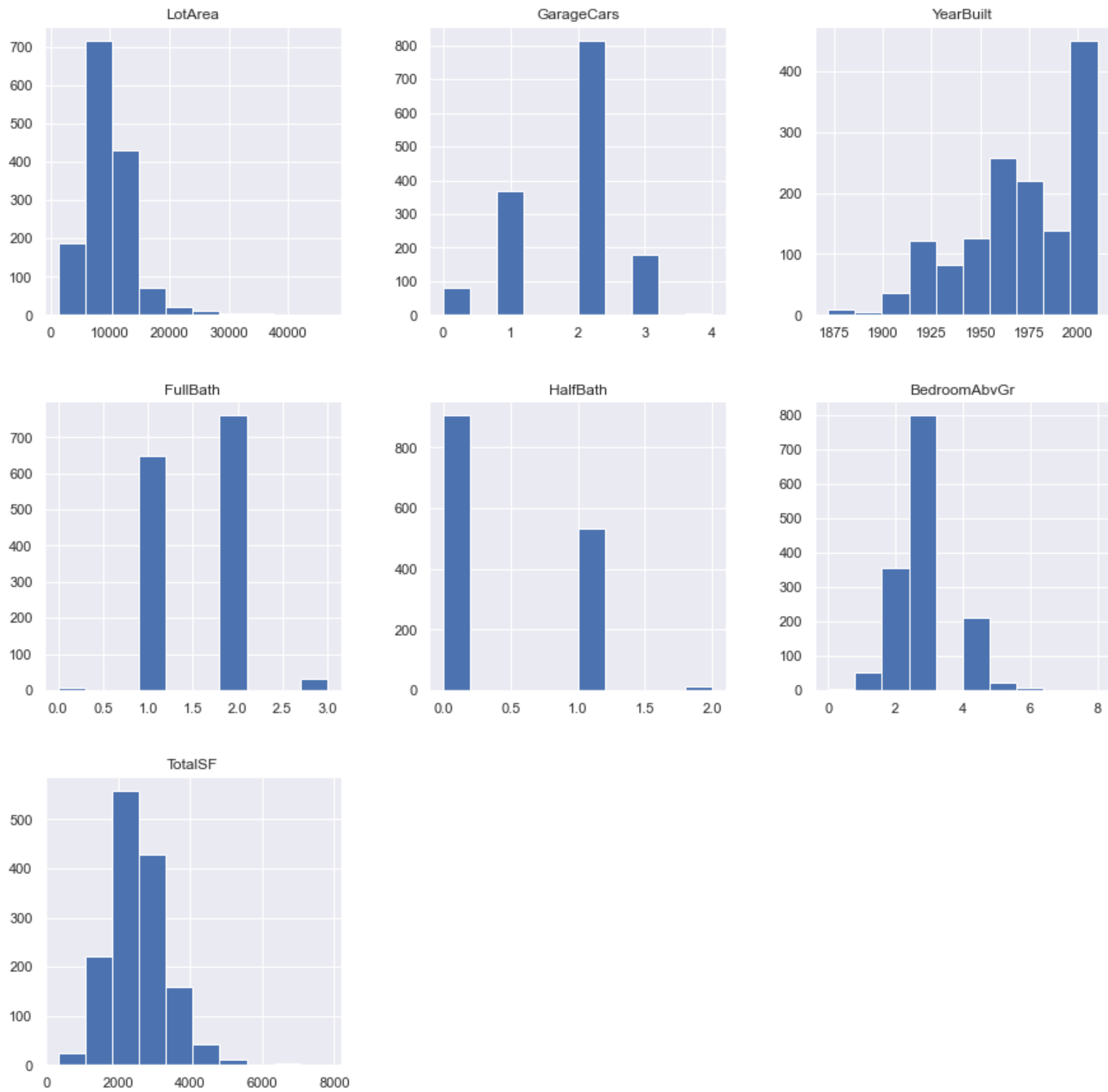
[27]:
```
# Adding one extra feature -> total sqfootage feature
housingData['TotalSF'] = housingData['TotalBsmtSF'] + housingData['1stFlrSF'] +␣
↪housingData['2ndFlrSF']
```

[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
```

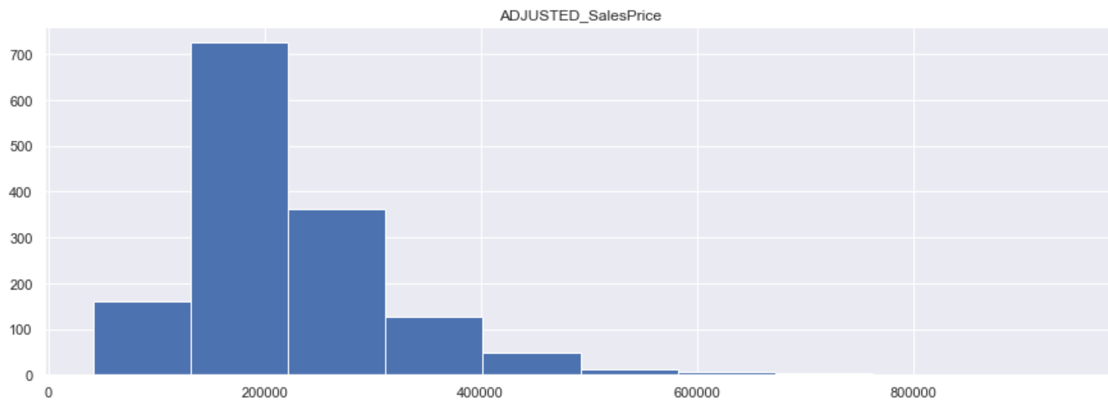
[29]:
```
X.hist(figsize=(15,15))
```

[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)
```



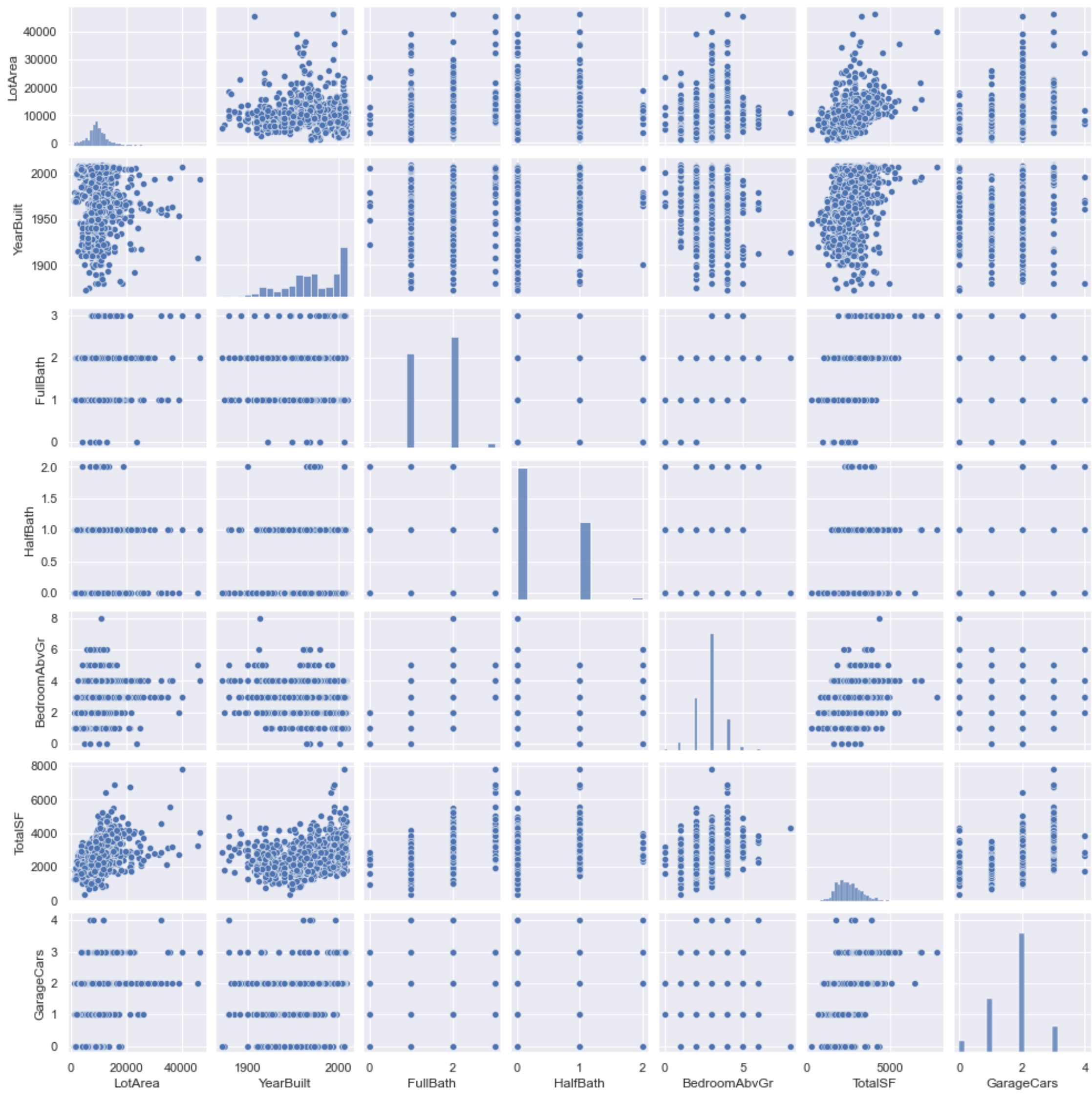

```
[30]: Y.hist(figsize=(15,5))
```

```
[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 0x20c8312fd30>



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
```

[35]:
```
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 (SVR, Ridge, XGBoost) to the same pre-processing pipeline and tune the some parameters using GridSearch with cross validation. Then, we compare their RMSE and choose the best model to proceed.

0.4.1 Using Support Vector Regression Model

[131]:
```
# we show how to use GridSearch with K-fold cross validation (K=5) to fine tune␣
↪the model
# we use the neg_root_mean_squared_error as the scoring metric

from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVR


pipeline_svr = Pipeline(steps=[
```

```
    ('preprocessor', preprocessor),
    ('clf_svr', SVR()),
])

parameters_svr=[
    {
        'clf_svr__kernel': ['linear','rbf','poly','sigmoid']#,'precomputed'

    }
]

grid_search_svr = GridSearchCV(pipeline_svr,parameters_svr,␣
 ↪cv=5,scoring='neg_root_mean_squared_error')
```

[142]:
```
grid_search_svr.fit(X_train, y_train.values.ravel())
```

[142]:
```
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_svr', SVR())]),
             param_grid=[{'clf_svr__kernel': ['linear', 'rbf', 'poly',
                                               'sigmoid']}],
             scoring='neg_root_mean_squared_error')
```

[143]:
```
# check the best performing parameter combination
grid_search_svr.best_params_
```

[143]:
```
{'clf_svr__kernel': 'linear'}
```

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

[128]:

```
['mean_fit_time',
 'mean_score_time',
 'mean_test_score',
 'param_clf_svr__kernel',
 'params',
 'rank_test_score',
 'split0_test_score',
 'split1_test_score',
 'split2_test_score',
 'split3_test_score',
 'split4_test_score',
 'std_fit_time',
 'std_score_time',
 'std_test_score']
```

[144]:

```
# best linear regression model test score
grid_search_svr.best_score_
```

[144]:

```
-100085.7038582825
```

- Best Score (RMSE) using Support Vector regression is -100085.7038582825

0.4.2 Using Ridge Regression Model

[132]:

```
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,␣
 ↪scoring='neg_root_mean_squared_error')
```

[133]:

```
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
```

[133]:

```
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]}],
             scoring='neg_root_mean_squared_error')
```

[134]:

```
# best linear ridge regressor model test score
grid_search_rg.best_score_
```

[134]:

```
-49146.2619536027
```

- Best Score (RMSE) using Ridge regression model is -49146.2619536027

0.4.3 Using XGBoost Regressor Model

[135]:
```
# 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,scoring='neg_root_mean_squared_error')
```

[136]:
```
grid_search_xg.fit(X_train, y_train)
```

[136]:
```
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…
                                                       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]}],
                 scoring='neg_root_mean_squared_error')
```

[137]:
```
grid_search_xg.best_score_
```

[137]:
```
-44868.30845180691
```

- Best Score (RMSE) using XGBoost Regression model is -44868.30845180691

0.4.4 Comparing Best Score (RMSE) among Support Vector Regression , Ridge Regression and XGBoost Regressor

[151]:
```
# best test score
print('best Support Vector regression score (RMSE) is: ', grid_search_svr.
 ↪best_score_)
print('best Ridge regression score (RMSE) is: ', grid_search_rg.best_score_)
print('best XGBoost score (RMSE) is: ', grid_search_xg.best_score_)
```

```
best Support Vector regression score (RMSE) is:  -100085.7038582825
best Ridge regression score (RMSE) is:  -49146.2619536027
best XGBoost score (RMSE) is:  -44868.30845180691
```

- Among Support Vector Regression, Ridge REgression and XGBoost Regressor models, XGBoost Regressor has the least RMSE error. Hence, XGBoost Regressor is selected.

[150]:
```
# best parameters for all three are:
print('best parameter for Support Vector regression are: ', grid_search_svr.
 ↪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 Support Vector regression are:  {'clf_svr__kernel': 'linear'}
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 (RMSE).

0.4.5 Baseline Prediction

[190]:
```
y_baseline_value=y_test['ADJUSTED_SalesPrice'].mean()
y_baseline_pred=[y_baseline_value]*len(y_test)
```

[191]:
```
#===========   RMSE and other metrics ===================
r_square_baseline= metrics.r2_score(y_test, y_baseline_pred)
mae_y_baseline = metrics.mean_absolute_error(y_test, y_baseline_pred)
mse_y_baseline = metrics.mean_squared_error(y_test, y_baseline_pred)
rmse_y_baseline = np.sqrt(metrics.mean_squared_error(y_test, y_baseline_pred))

print("Baseline Prediction \nr_square={0}␣
↪\nmean_absolute_error={1}\nmean_square_error={2}\nsqrt_mean_square_error={3}".
↪format(r_square_baseline,mae_y_baseline,mse_y_baseline,rmse_y_baseline))
```

```
Baseline Prediction
r_square=0.0
mean_absolute_error=63001.37238631565
mean_square_error=7761052223.808897
sqrt_mean_square_error=88096.83435747788
```

0.4.6 Select the Best Model, which is XGBoost Regressor in this case, and run compute the RMSE

[49]:
```
# select the best model
# the best parameters are shown, note SimpleImputer() implies that mean␣
↪strategry is used
clf_best = grid_search_xg.best_estimator_
```

[51]:
```
# 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)
```

[192]:
```
#===========   RMSE 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␣
↪Prediction\nr_square={0}\nmean_absolute_error={1}\nmean_square_error={2}\nsqrt_mean_square_
↪format(r_square,mae_y,mse_y,rmse_y))
```

```
XGBoost Prediction
r_square=0.8396199878447974
mean_absolute_error=22590.187043391896
mean_square_error=1244717649.991633
sqrt_mean_square_error=35280.55625966848
```

0.4.7 Observation

- Our model is better than the baseline model (RMSE=88096.83435747788 for baseline vs RMSE=35280.55625966848 for XG Boost)
- Train RMSE of XG Boost Regressor is 44868.30845180691
- Test RMSE of our best estimator, which is XGBoost Regressor, is 35280.55625966848.
- In this case, RMSE in **test dataset was observed lower 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 XG Boost Regressor and create a plot.

[53]:
```
clf_best.named_steps
```

[53]:
```
{'preprocessor': ColumnTransformer(transformers=[('num_pipeline',
                                   Pipeline(steps=[('num_imputer',
                                                    SimpleImputer()),
                                                   ('scaler',
StandardScaler())]),
                                   ['LotArea', 'YearBuilt', 'FullBath',
                                    'HalfBath', 'BedroomAbvGr', 'TotalSF',
                                    'GarageCars']),
                                  ('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)}
```

[54]:
```
clf_best.named_steps['preprocessor']
```

[54]:
```
ColumnTransformer(transformers=[('num_pipeline',
                                 Pipeline(steps=[('num_imputer',
                                                  SimpleImputer()),
                                                 ('scaler', StandardScaler())]),
                                 ['LotArea', 'YearBuilt', 'FullBath',
                                  'HalfBath', 'BedroomAbvGr', 'TotalSF',
                                  'GarageCars']),
                                ('cat_pipeline',
                                 Pipeline(steps=[('onehot',
```

```
OneHotEncoder(handle_unknown='ignore'))]),
                                  ['BldgType'])])
```

[55]:
```
i = clf_best.named_steps['clf_XG'].feature_importances_
i
```

[55]:
```
array([0.01635961, 0.07381907, 0.02667094, 0.02828762, 0.01716838,
       0.4238823 , 0.25741047, 0.03396913, 0.00581329, 0.08678783,
       0.00667852, 0.0231528 ], dtype=float32)
```

[56]:
```
clf_best['preprocessor'].transformers_
```

[56]:
```
[('num_pipeline',
  Pipeline(steps=[('num_imputer', SimpleImputer()), ('scaler',
StandardScaler())]),
  ['LotArea',
   'YearBuilt',
   'FullBath',
   'HalfBath',
   'BedroomAbvGr',
   'TotalSF',
   'GarageCars']),
 ('cat_pipeline',
  Pipeline(steps=[('onehot', OneHotEncoder(handle_unknown='ignore'))]),
  ['BldgType'])]
```

[57]:
```
# get columnTransformer
clf_best[0]
```

[57]:
```
ColumnTransformer(transformers=[('num_pipeline',
                                 Pipeline(steps=[('num_imputer',
                                                  SimpleImputer()),
                                                 ('scaler', StandardScaler())]),
                                 ['LotArea', 'YearBuilt', 'FullBath',
                                  'HalfBath', 'BedroomAbvGr', 'TotalSF',
                                  'GarageCars']),
                                ('cat_pipeline',
                                 Pipeline(steps=[('onehot',
OneHotEncoder(handle_unknown='ignore'))]),
                                 ['BldgType'])])
```

[58]:
```
clf_best[0].transformers_
```

[58]:
```
[('num_pipeline',
  Pipeline(steps=[('num_imputer', SimpleImputer()), ('scaler',
StandardScaler())]),
  ['LotArea',
```

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

[59]:
```
num_original_feature_names = clf_best[0].transformers_[0][2]
num_original_feature_names
```

[59]:
```
['LotArea',
 'YearBuilt',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'TotalSF',
 'GarageCars']
```

[60]:
```
cat_original_feature_names = clf_best[0].transformers_[1][2]
cat_original_feature_names
```

[60]:
```
['BldgType']
```

[61]:
```
cat_new_feature_names = list(clf_best[0].transformers_[1][1]['onehot'].
 ↪get_feature_names(cat_original_feature_names))
cat_new_feature_names
```

[61]:
```
['BldgType_1Fam',
 'BldgType_2fmCon',
 'BldgType_Duplex',
 'BldgType_Twnhs',
 'BldgType_TwnhsE']
```

[62]:
```
feature_names = num_original_feature_names + cat_new_feature_names
feature_names
```

[62]:
```
['LotArea',
 'YearBuilt',
 'FullBath',
 'HalfBath',
 'BedroomAbvGr',
 'TotalSF',
 'GarageCars',
 'BldgType_1Fam',
```

```
 'BldgType_2fmCon',
 'BldgType_Duplex',
 'BldgType_Twnhs',
 'BldgType_TwnhsE']
```

[63]:
```
r = pd.DataFrame(i, index=feature_names, columns=['importance'])
r
```

[63]:

	importance
LotArea	0.016360
YearBuilt	0.073819
FullBath	0.026671
HalfBath	0.028288
BedroomAbvGr	0.017168
TotalSF	0.423882
GarageCars	0.257410
BldgType_1Fam	0.033969
BldgType_2fmCon	0.005813
BldgType_Duplex	0.086788
BldgType_Twnhs	0.006679
BldgType_TwnhsE	0.023153

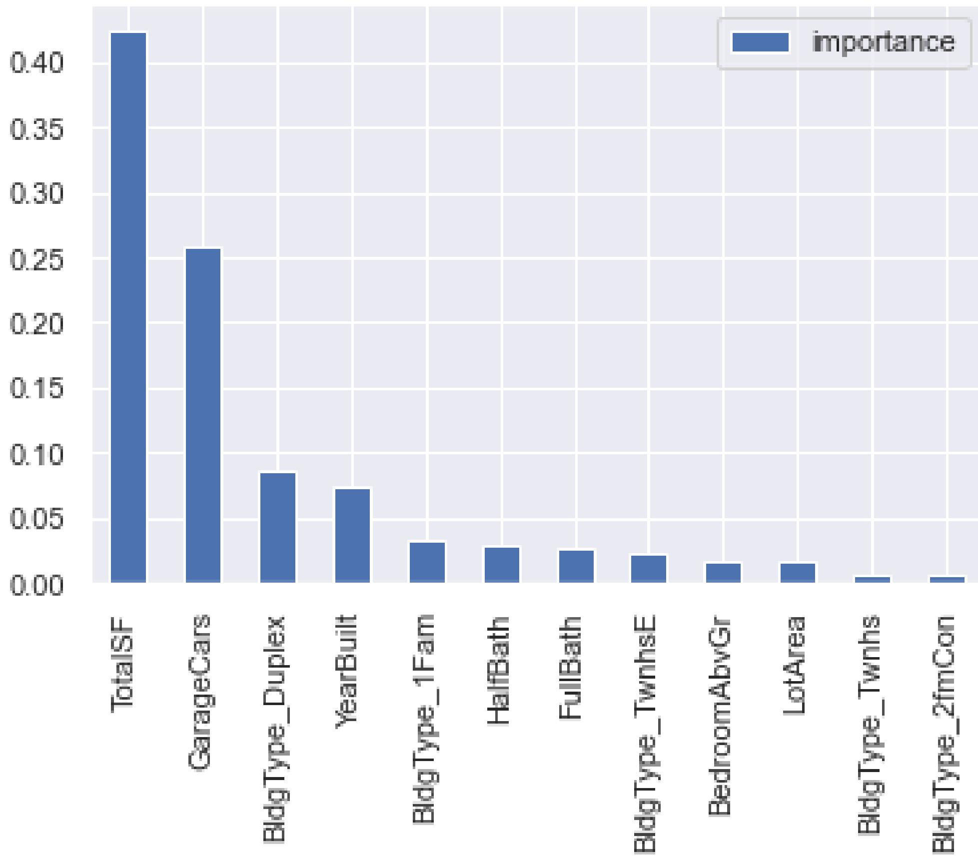
[64]:
```
r.sort_values('importance', ascending=False)
```

[64]:

	importance
TotalSF	0.423882
GarageCars	0.257410
BldgType_Duplex	0.086788
YearBuilt	0.073819
BldgType_1Fam	0.033969
HalfBath	0.028288
FullBath	0.026671
BldgType_TwnhsE	0.023153
BedroomAbvGr	0.017168
LotArea	0.016360
BldgType_Twnhs	0.006679
BldgType_2fmCon	0.005813

[65]:
```
r.sort_values('importance', ascending=False).plot.bar()
```

[65]: <AxesSubplot:>



0.6 Remove unimportant Features

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

[153]:
```
# 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,scoring='neg_root_mean_squared_error')

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

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

```
best XG Boost score is:  -44868.30845180691
best XG Boost score after feature selection is:  -44868.30845180691
```

0.7 Persists the model

[67]:
```
# Save the model as a pickle file
import joblib
joblib.dump(clf_best, "Housing.pickle")
```

[67]:
```
['Housing.pickle']
```

[68]:
```
# Load the model from a pickle file
saved_xg_clf = joblib.load("Housing.pickle")
saved_xg_clf
```

[68]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num_pipeline',
Pipeline(steps=[('num_imputer',
SimpleImputer()),
                                                                   ('scaler',
StandardScaler())]),
                                                  ['LotArea', 'YearBuilt',
                                                   'FullBath', 'HalfBath',
                                                   'BedroomAbvGr', 'TotalSF',
```

```
                                                     'GarageCars']),
                                                    ('cat_pipeline',
                                                     Pipeline(steps=[('onehot',
OneHotEncoder(handle_unknown='ignore'))]),
                                                     ['BldgType'])])),
                ('clf_…
                              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	mean_SalesPrice
Newark-DE	-0.306535	118402.943024	1.814122e+10	134689.355951	308017.207071
Bear-DE	0.070029	108738.838409	1.547942e+10	124416.327675	338265.816327
Wilmington-DE	-0.069775	159559.169559	5.428372e+10	232988.673812	328693.668342
Ames-IA	-0.298120	112514.734786	1.908495e+10	138148.291188	286503.689474

0.8.1 Newark, DE

[69]:
```
X_test.head()
```

[69]:
```
       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
```

[70]:
```
#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" })
```

[71]:
```
# 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"}
```

[72]:
```
# Map the building type using replace function

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

[73]:
```
newark_test_df.BldgType.value_counts()
```

[73]:
```
1Fam      132
Twnhs      63
Duplex      3
land        2
Name: BldgType, dtype: int64
```

[74]:
```
# land not part of training, so we removed it.

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

[75]:
```
# 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()
```

[75]:
```
  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
```

[76]:
```
# 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

[77]:
```
#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" })
```

[78]:
```
# Map the building type using replace function
bear_test_df['BldgType'].replace(BldgTypedi, inplace=True)

bear_test_df.head()
```

[78]:
```
   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
```

[79]:
```
bear_test_df.BldgType.value_counts()
```

[79]:
```
1Fam      125
Twnhs      66
Duplex      5
mobile      3
land        1
Name: BldgType, dtype: int64
```

[80]:
```
# 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']]
```

[81]:
```
# 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

[82]:
```python
#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" })
```

[83]:
```python
# Map the building type using replace function

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

wilmigton_test_df.head()
```

[83]:
```
   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
```

[84]:
```python
wilmigton_test_df.BldgType.value_counts()
```

[84]:
```
1Fam      124
Twnhs      68
2fmCon      7
```

```
mobile       1
Name: BldgType, dtype: int64
```

[85]:
```
# 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']]
```

[86]:
```
# 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

[87]:
```
#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" })
```

[88]:
```
# Map the building type using replace function

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

ames_test_df.head()
```

[88]:

	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
```

[89]:
```
ames_test_df.BldgType.value_counts()
```

[89]:
```
1Fam      157
Twnhs      26
2fmCon      7
land        7
farm        3
Name: BldgType, dtype: int64
```

[90]:
```
# 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']]
```

[91]:
```
# 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

[113]:
```
# 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)

#------------------------------
#calculate the mean SalesPrice value as the base value
newark_mean_SalesPrice=newark_test_df['SalePrice'].mean(skipna=False)
bear_mean_SalesPrice=bear_test_df['SalePrice'].mean(skipna=False)
ames_mean_SalesPrice=ames_test_df['SalePrice'].mean(skipna=True)
wilmington_mean_SalesPrice=wilmigton_test_df['SalePrice'].mean(skipna=True)
```

[93]:
```
# 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()
```

[94]:
```
# 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)
```

[117]:
```
#===========   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, newark_mean_SalesPrice])
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,␣
 ↪bear_mean_SalesPrice])

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,wilmington_mean_SalesPrice])

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,ames_mean_SalesPrice ])

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=-0.30653533595856053::mean_absolute_error=118402.9430239899::m
ean_square_error=18141222606.58218::sqrt_mean_square_error=134689.35595132297::

-------------------------Bear------------------------------
XGBoost::r_square=0.07002930419408915::mean_absolute_error=108738.83840880102::m
ean_square_error=15479422592.212631::sqrt_mean_square_error=124416.32767532014::

-------------------------Wilmington------------------------------
XGBoost::r_square=-0.06977474732716038::mean_absolute_error=159559.16955873117::
mean_square_error=54283722124.90736::sqrt_mean_square_error=232988.67381249965::

-------------------------Ames------------------------------
XGBoost::r_square=-0.29812010850684456::mean_absolute_error=112514.73478618421::
mean_square_error=19084950358.05947::sqrt_mean_square_error=138148.29118762008::
```

[118]:
```
## 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','mean_SalesPrice'])

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

```
perfdata_df
```

[118]:

```
            City  r_square  mean_absolute_error  mean_square_error  \
0      Newark-DE -0.306535        118402.943024       1.814122e+10
1        Bear-DE  0.070029        108738.838409       1.547942e+10
2  Wilmington-DE -0.069775        159559.169559       5.428372e+10
3        Ames-IA -0.298120        112514.734786       1.908495e+10

   sqrt_mean_square_error  mean_SalesPrice
0           134689.355951    308017.207071
1           124416.327675    338265.816327
2           232988.673812    328693.668342
3           138148.291188    286503.689474
```