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1. Problem Setting

Housing sale is an ever-changing market, and its dynamics keep fluctuating with various factors like economic status, interest rates, etc. A housing sale forecast will benefit a large population such as potential buyers, sellers, investors, insurance agencies, bankers, real estate marketers etc., and allow them to understand the marketing conditions to expect in the coming time. This will also allow them to gain a perspective of how to sustain in this competitive market.

2. Problem Definition

This analysis will facilitate in predicting the housing sale prices taking into account housing attributes such as floor plan and area, number of bedrooms/ bathrooms, types of utilities offered, neighbourhood etc. The aim is to project the sale prices with highest accuracy by identifying the best model using data mining techniques.

3. Data Source

This dataset has been taken from a *Kaggle – a Data Science and Machine Learning Community.* It provides a platform to explore and publish the open source datasets on 1K^{+} datasets on projects in various domain, and collaborate with Data Professionals.

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

4. Data Description

This data contains housing sale prices with 79 explanatory variables describing almost every aspect of residential homes in Ames, Iowa. Through this project, we will be predicting the sale price (target variable) of the house based on various predictors including the categorical and numerical independent variables playing roles in pricing at various scale in market.

The dataset contains the following attributes

S.No	Variable Name	Description
1	SalePrice	Property’s sale price (USD) - Output variable (Target)
2	MSSubClass	Identifies the type of dwelling involved in the sale
3	MSZoning	Identifies the general zoning classification - Agricultural, Commercial, Residential etc
4	LotFrontage	Linear feet of street connected to property
5	LotArea	Area of the lot (square feet)
6	Street	Type of road access - Gravel, Paved
7	Alley	Type of alley access - Gravel, Paved, No alley
8	LotShape	General shape of property - Regular, Irregular
9	LandContour	Flatness of the property - Level, Banked, Hillside, Depression
10	Utilities	Type of utilities available - Electricity, Gas, Water, All
11	LotConfig	Lot configuration - Inside, Corner, Frontage
12	LandSlope	Slope of property - Gentle, Moderate, Severe
13	Neighborhood	Physical locations within the city limits
14	Condition1	Proximity to main road or railroad
15	Condition2	Proximity to main road or railroad (if a second is present)
16	BldgType	Type of dwelling - Single family, Duplex, Townhouse
17	HouseStyle	Style of dwelling - One story, Two strory, Split foyer
18	OverallQual	Overall material and finish quality - Poor, Fair, Good, Excellent
19	OverallCond	Overall condition rating - Poor, Fair, Good, Excellent
20	YearBuilt	Original construction date
21	YearRemodAdd	Remodel date
22	RoofStyle	Type of roof - Flat, Gable, Hip, Shed
23	RoofMatl	Roof material - Membrane, Metal, Wood
24	Exterior1st	Exterior covering on house -Brick, Cinder, Cement etc.
25	Exterior2nd	Exterior covering on house (if more than one material)
26	MasVnrType	Masonry veneer type - Brick, Cinder, Stone
27	MasVnrArea	Masonry veneer area in square feet
28	ExterQual	Exterior material quality - Poor, Fair, Good, Excellent
29	ExterCond	Present condition of the material on the exterior
30	Foundation	Type of foundation - Brick, Cinder, Stone, Wood
31	BsmtQual	Height of the basement - No Basement, Poor, Good, Fair, Excellent
32	BsmtCond	General condition of the basement - No Basement, Poor, Good, Fair, Excellent
33	BsmtExposure	Walkout or garden level basement walls - No Basement, Poor, Good, Fair, Excellent

34	BsmtFinType1	Quality of basement finished area
35	BsmtFinSF1	Type 1 finished square feet
36	BsmtFinType2	Quality of second finished area (if present)
37	BsmtFinSF2	Type 2 finished square feet
38	BsmtUnfSF	Unfinished square feet of basement area
39	TotalBsmtSF	Total square feet of basement area
40	Heating	Type of heating - Floor, Gas, Hot water, Wall furnace
41	HeatingQC	Heating quality and condition - Poor, Good, Fair, Excellent
42	CentralAir	Central air conditioning - Yes, No
43	Electrical	Electrical system - Standard, Fuse Box, Mixed
44	1stFlrSF	First Floor square feet
45	2ndFlrSF	Second floor square feet
46	LowQualFinSF	Low quality finished square feet (all floors)
47	GrLivArea	Above grade (ground) living area square feet
48	BsmtFullBath	Basement full bathrooms
49	BsmtHalfBath	Basement half bathrooms
50	FullBath	Full bathrooms above grade
51	HalfBath	Half baths above grade
52	Bedroom	Number of bedrooms above basement level
53	Kitchen	Number of kitchens
54	KitchenQual	Kitchen quality - Poor, Fair, Good, Excellent
55	TotRmsAbvGrd	Total rooms above grade
56	Functional	Home functionality rating - Typical, Minor, Moderate, Major, Severe damage
57	Fireplaces	Number of fireplaces
58	FireplaceQu	Fireplace quality - Average, Good, Excellent
59	GarageType	Garage location - No garage, Detached, Built-in, Basement, More than 1
60	GarageYrBlt	Year garage was built
61	GarageFinish	Interior finish of the garage - No garage, Unfinished, Rough finished, Finished
62	GarageCars	Size of garage in car capacity
63	GarageArea	Size of garage in square feet
64	GarageQual	Garage quality - No garage, Poor, Fair, Good, Excellent
65	GarageCond	Garage condition
66	PavedDrive	Paved driveway - Paved, Partial paved, Gravel
67	WoodDeckSF	Wood deck area in square feet
68	OpenPorchSF	Open porch area in square feet
69	EnclosedPorch	Enclosed porch area in square feet
70	3SsnPorch	Three season porch area in square feet
71	ScreenPorch	Screen porch area in square feet
72	PoolArea	Pool area in square feet
73	PoolQC	Pool quality - No pool, Poor, Fair, Good, Excellent

74	Fence	Fence quality - No fence, Poor, Fair, Good, Excellent
75	MiscFeature	Miscellaneous feature not covered in other categories - Elevator, 2nd garage, Tennis court, None
76	MiscVal	Price Value of miscellaneous feature (USD)
77	MoSold	Month Sold
78	YrSold	Year Sold
79	SaleType	Type of sale - Warranty deed, Court office deed, Contract, Other
80	SaleCondition	Condition of sale - Normal, Abnormal, Partial, Allocation

The existing dataset has already been partitioned into training and test datasets into a 50-50 proportion. The training data has 80 columns (79 attributes, 1 target variable) and 1460 rows. The test data has 79 columns (79 attributes and no target variable) and 1459 rows. The test data is unlabeled that is, we do not have the actual sale price values. We will partition the train data for training the model and choosing the best model validation and further use the test data to validate the chosen model.

5. Data Processing

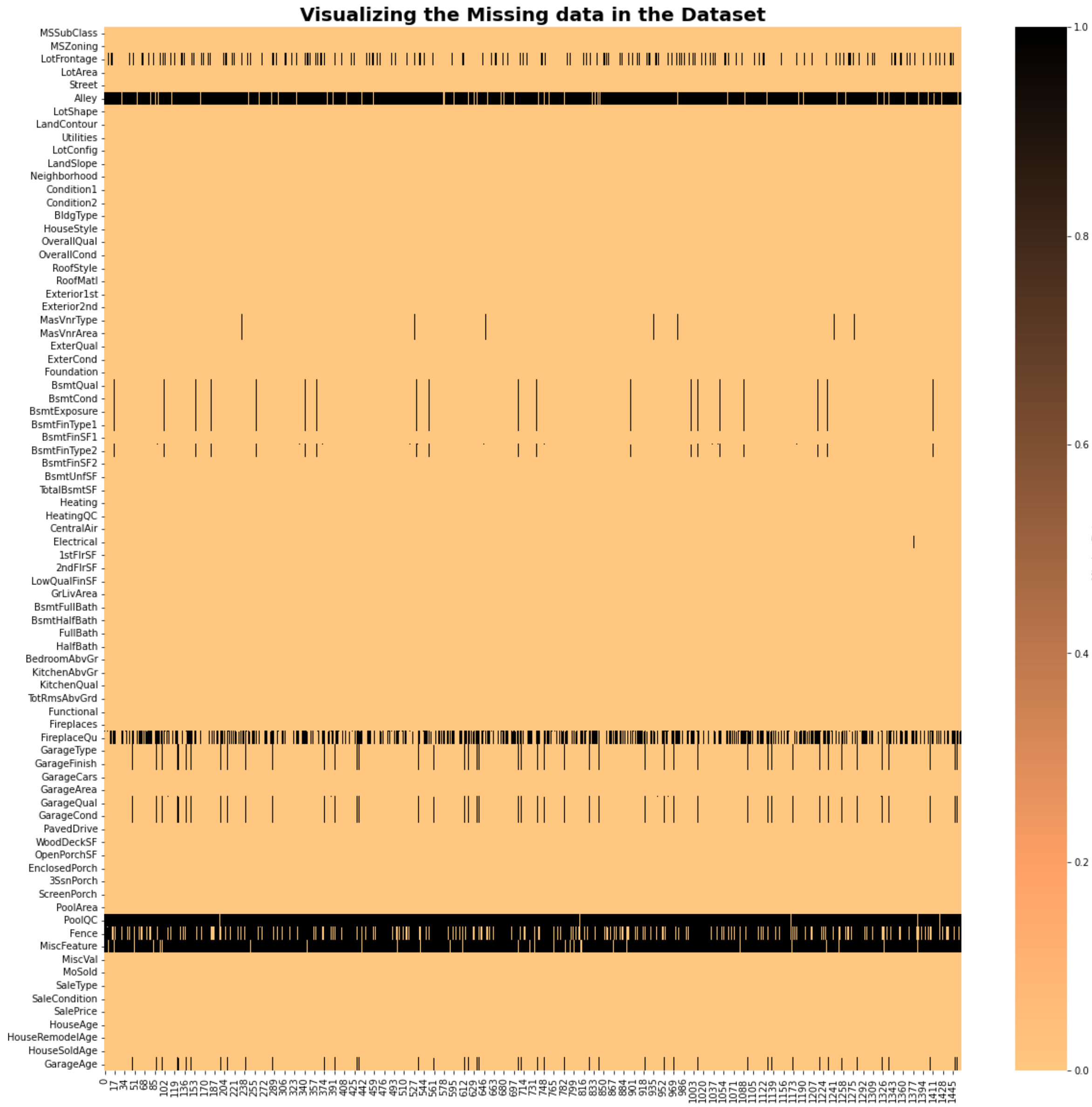
5.1. Dealing with Date columns – Age Calculations

We have 4 columns denoting the year the house was built, remodelled, sold and the year the garage was built. It makes more sense to calculate the respective ages of these Year columns as the year alone is not insightful. Hence, we have manipulated the data by calculating their ages up to today's year.

- **YearBuilt**
- **YearRemodAdd**
- **YrSold**
- **GarageYrBlt**

5.2. Dealing with missing values

We have ample of missing values in our dataset which has been visualized in the below heatmap and need to be imputed with relevant statistical measures for Machine Learning model fitting. We try to explore these missing values for numerical and categorical columns individually as the process of imputations are to be used for both data types.



5.2.1. Numerical columns

We have 3 numerical columns with missing values. We have used the threshold as 17% for the missing values i.e., all the columns having missing values more than this threshold will be dropped. Thus, we are dropping 1 column (**LotFrontage**). Another column containing missing values is **MasVnrArea** where these missing values signify that such houses don't have masonry veneer. Thus, it makes sense to impute these NaNs with 0. As for the 3rd column **GarageAge**, missing value means that there is no garage present in the house. Thus, similarly, we have imputed these values with 0.

Dropped Numerical Columns:

- **LotFrontage**
- **MasVnrArea**
- **GarageAge**

5.2.2. Categorical columns

As for the categorical columns, they have NAs which do not actually represent missing values. For example, in the column **Alley**, the actual data contains NA which is abbreviated for No Alley Access, hence we cannot consider such values as missing values. Hence, in order to deal with such values, we have replaced all NA values with 'None'.

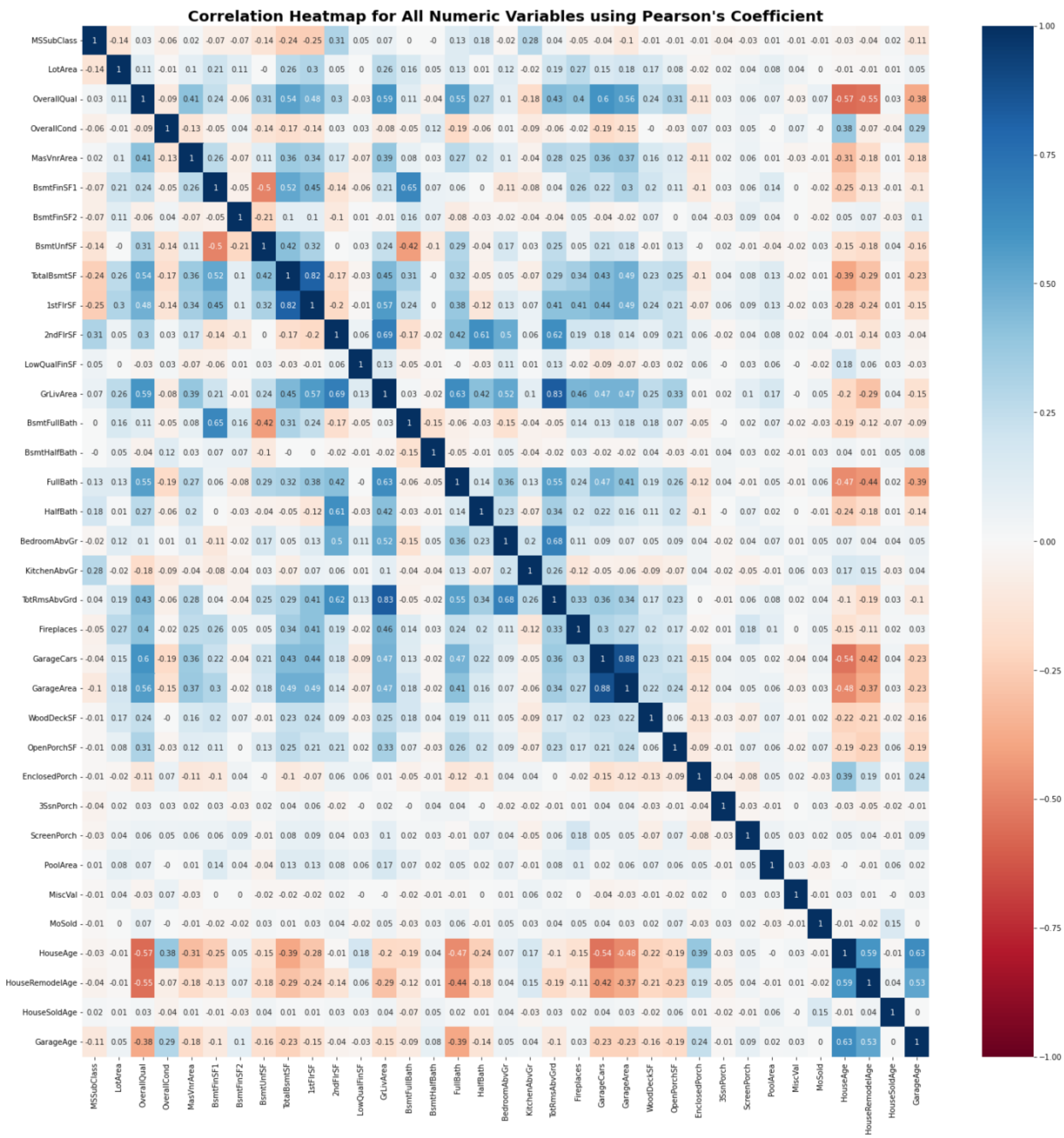
6. Dimensionality Reduction

6.1. Correlation Matrix for Numeric Variables (Pearson's Coefficient)

As part of dimension reduction, we have calculated the correlation between every 2 numerical columns using Pearson's coefficient. Pearson's correlation coefficient is a bivariate correlation that measures the linear correlation between two sets of data, whose value ranges from -1 to 1. Essentially, it is a normalized measurement of their covariances. If a pair of variables are highly correlated (here we have considered 0.8 as the cutoff for highly correlated variables), then we drop one of the column-pair.

- This method gives us a correlation matrix which has been represented using the below heatmap.
- Based on the obtained correlation matrix, the below 3 pairs of variables are highly correlated.

Predictor1	**Predictor2**	**Correlation Coefficient**
TotalBsmtSF	1stFlrSF	0.81953
TotRmsAbvGrd	GrLivArea	0.825489
GarageCars	GarageArea	0.882475



Due to the higher correlation between the pair of predictors we have dropped one of them to avoid the presence of unwanted bias in the predictions as mentioned below -

- **TotalBsmtSF**
- **TotRmsAbvGrd**
- **GarageCars**

6.2. Correlation Matrix for Categorical Variables (Crammer's Rule)

Definition

This rule is used to calculate the correlation between two categorical variables for selecting one category among the pairs in case of a higher correlation between them. The coefficient's value varies from 0 to 1.

We have defined a function for calculating the correlation matrix between categorical columns of the dataset using the Crammer's Rule. This user-defined function has been obtained from Kaggle: https://www.kaggle.com/chrisbss1/cramer-s-v-correlation-matrix

The function's output returns a confusion matrix including all the categorical columns and their respective correlation values. Based on this, we have identified the following pairs of highly correlated columns (with correlation values greater than 0.6):

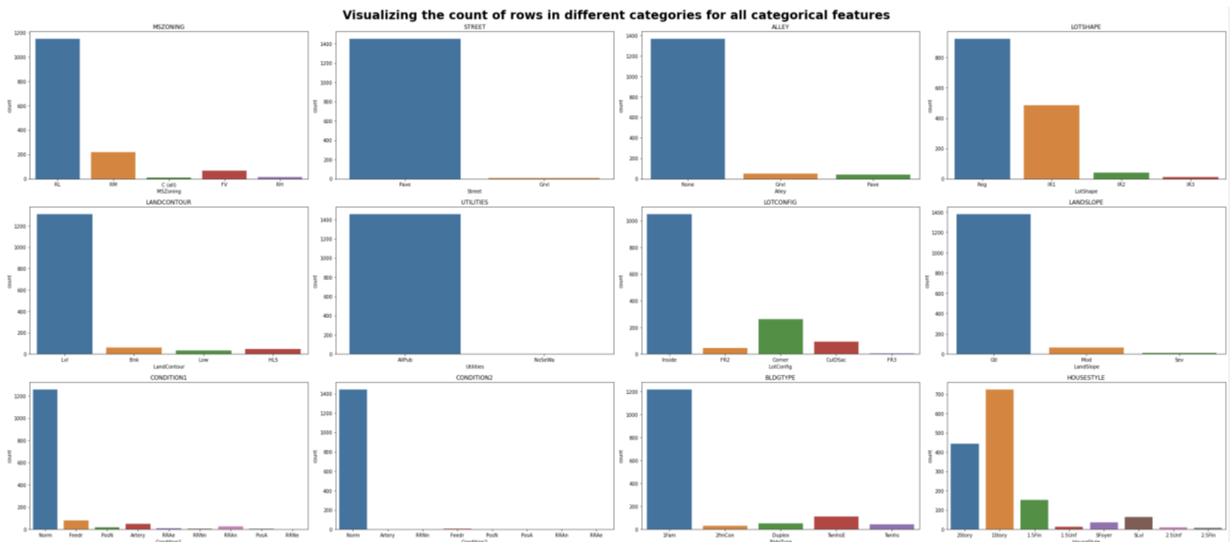
Predictor1	**Predictor2**	**Correlation Coefficient**
BsmtQual	BsmtFinType	0.607478
GarageFinish	GarageQual	0.610604
GarageCond	GarageFinish	0.613192
MSZoning	Neighborhood	0.644037
GarageType	GarageFinish	0.743423
GarageCond	GarageQual	0.799799
Exterior2nd	Exterior1st	0.851769

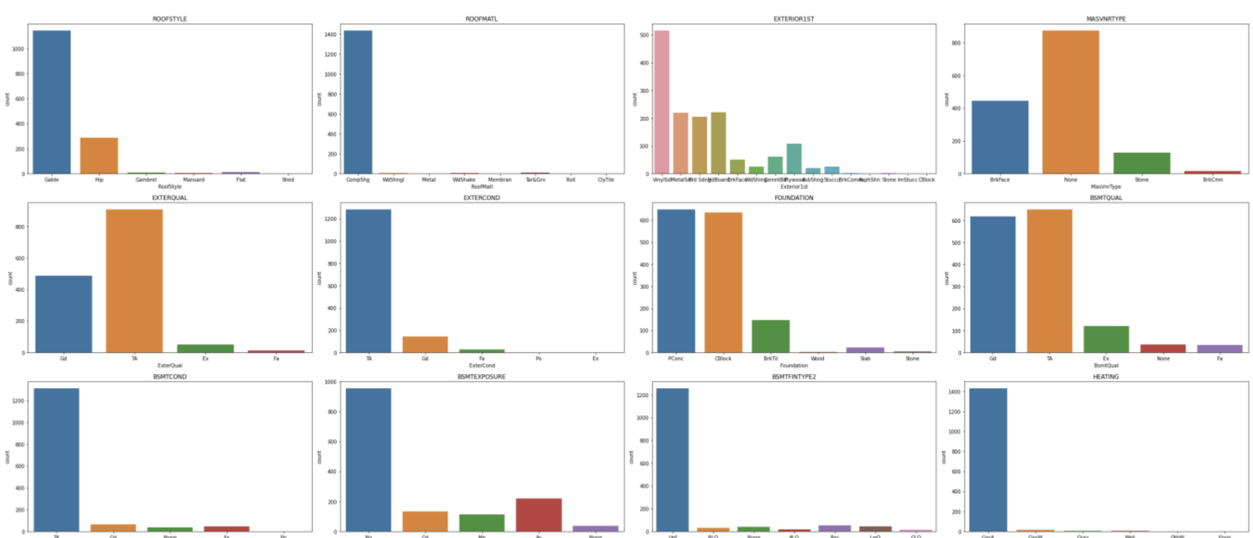
In order to identify the categorical columns that can be dropped, we used this matrix of highly correlated columns and checked the number of categories for each of the pair of columns. The category having more number of categorical values is chosen to be dropped so that while encoding the categorical columns into numerical, a lesser number of newer columns are created.

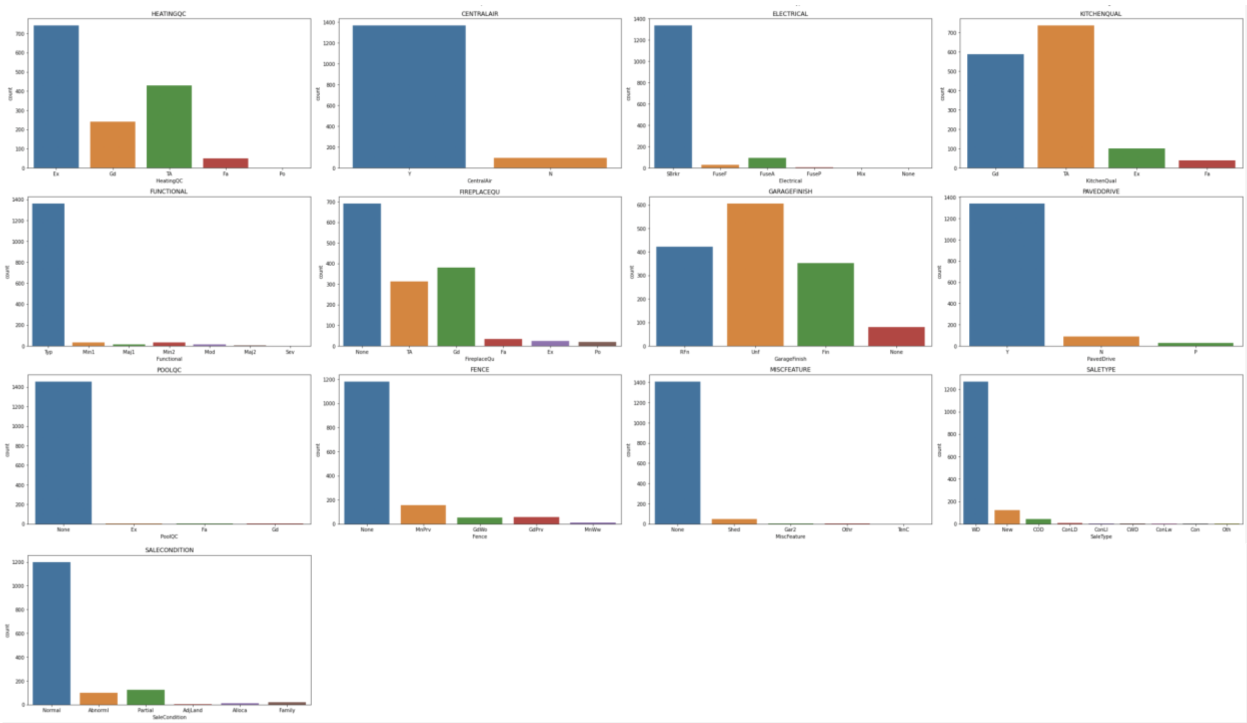
7. Data Exploration

7.1. Combining Categories – by plotting histogram of different categories

We have a lot of categorical columns containing rare categories that can be combined together under a single category. This is done so that during encoding these categorical columns into numerical values, lesser number of new columns are created. In order to visualize which categories can be combined together, we created the following bar chart. Further, we have fixed a threshold of 20% of the most dominant category, that is, if any category has records 20% less than the most dominant category, then we combine such categories under "Other" category. This is done for all the 37 categorical columns.







By combining the small number categories, we have decreased 104 categories (cumulative sum of all categorical columns combined).

7.2. Assessing Correlation between Predictors and Target variable:

As we know that the presence of uncorrelated predictors with the target variable increases the variance in the predicted output, we are eliminating the weakly correlated variables.

7.2.1. Numerical Predictor and Target Variable

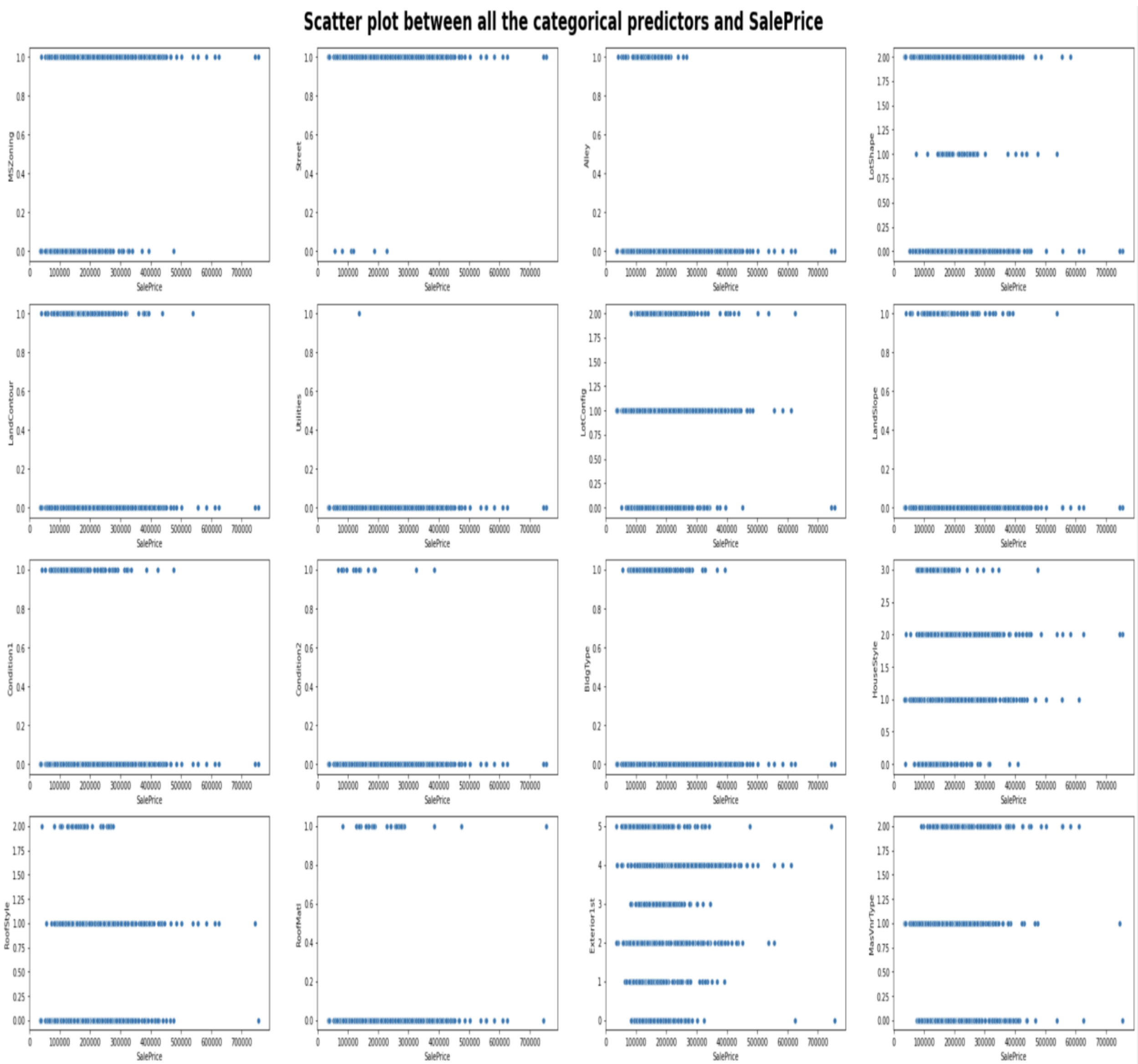
We have performed a correlation coefficient analysis between all the numerical predictors and the target variable. This has been visualized with the help of the scatter plots.

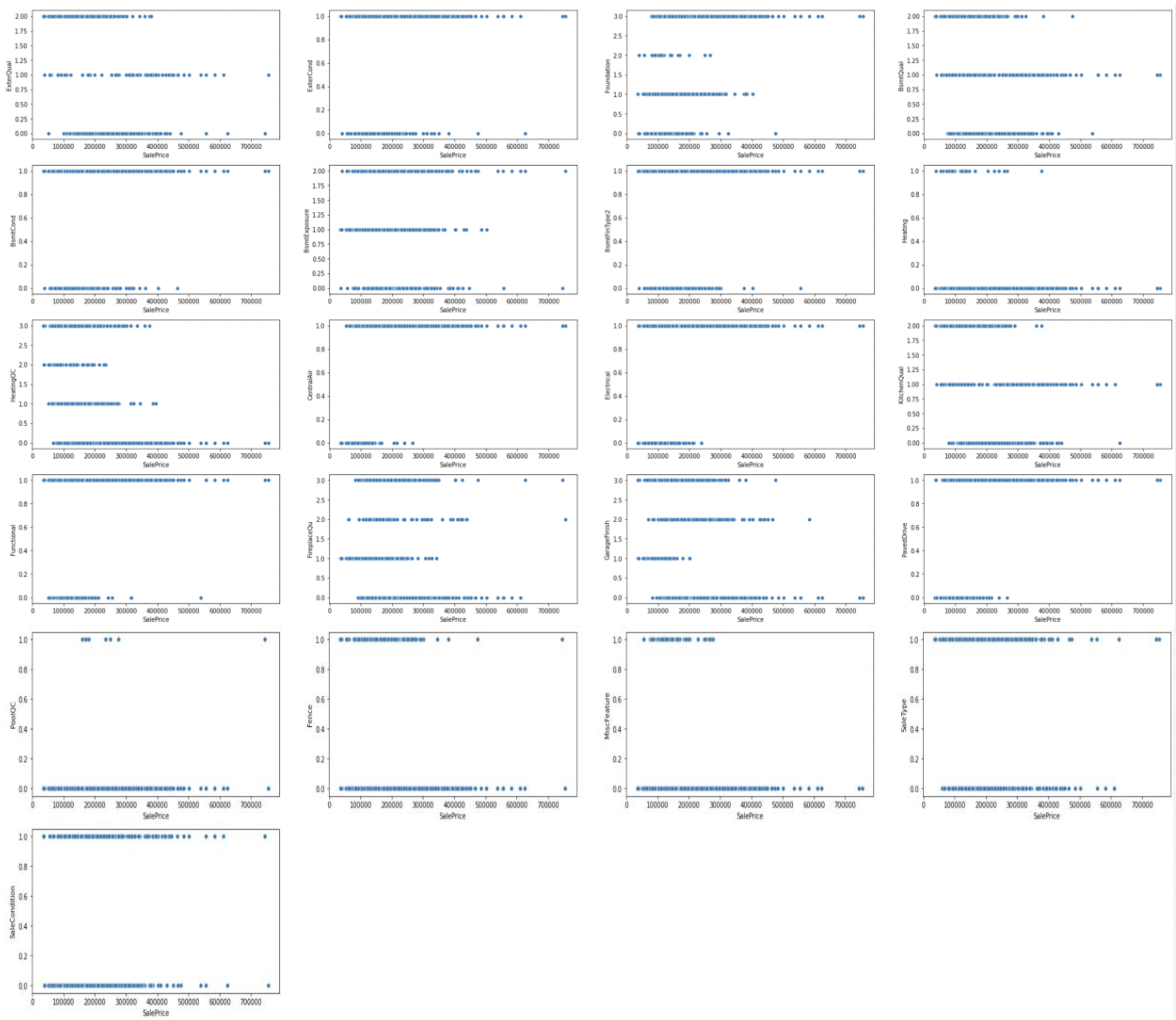
Using this correlation analysis, we can identify that, columns such as **'MSSubClass'**, '**OverallQual'**, **'OverallCond'** etc. are weakly correlated with target. We have used the threshold as 0.2 (Pearson Correlation coefficient) which means all the predictors having correlation coefficient values with target of 0.2 or lesser will be dropped. Using this, we successfully dropped 14 numerical columns.

Scatter plot between all the numerical predictors and target variable SalePrice

7.2.2. Categorical Predictor and Target Variable

- We have used the ***Label Encoder*** from the "pre-processing" library to perform the encoding of categorical variables in order to calculate the correlation between all the categorical predictors and Target – **SalePrice** and plotted the scatter plot.
- Calculated the Pearson correlation coefficient between all the predictors and Target and dropped the variables having coefficients less than 0.2.
- Using the above criterion, we were able to remove 25 categorical columns which would help us acquire lesser variance in the predicted output.





7.3. Data Encoding

Performed the **"Target Encoding"** as part of data encoding, a technique that results in only 1 dummy variable for a categorical column based on the mean value of the **Target** variable. "Target Encoder" function has been used from the "category_encoders" library which is replacing categorical values with the respective mean of Target Variable.

We have chosen **Target Encoding** over **One- Hot Encoding** due to its benefit of not adding to the dimensionality of the dataset. Although "One-Hot Encoding" is an extremely easy technique to understand, it significantly increases the dimensionality of a dataset depending on the number of categories present in all the categorical columns.

8. Data Preparation/Modelling

The final data that we have obtained contains 30 features and 1460 records.

8.1. Standardization

Our data contains values ranging from 1,300 to 215,245 square feet for the column 'LotArea'. On the other hand, it also contains single-digit values for 'OverallQual' denoting the overall quality of the house. Based on the fact that our data has a very large-scale difference, we have standardized the data to bring the values on the same scale.

8.2. Data Partitioning

Further, before model exploration, we perform a split in the dataset to create partitioning into training and validation data. We have used the 75-25% ratio for data partition. All the 30 features are collectively stored in variable X and the target variable is stored in y. After performing data partitioning, we have obtained X_train, X_test, y_train, y_test.

X_train = contains data of independent variables used for training model.
y_train = contains data of dependent variable used for training model.
X_test = contains data of independent variables used for testing model.
y_test = contains data of dependent variable used for testing model.

Post performing split, our data looks like this:

Training

X_train	1095	30
y_train	1095	1

Validation

X_test	365	30
y_test	365	1

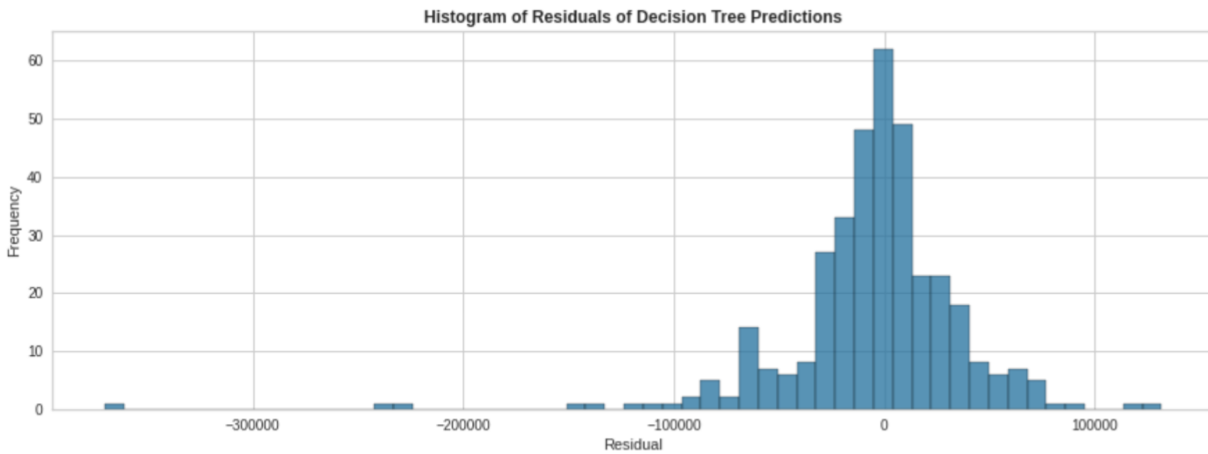
9. Model Exploration

9.1. Decision Trees

Using decision trees, we have tried to predict the value of the target variable (Sales Price). Decision tree is an algorithm that tries to strategically split a node into 2 or more sub-nodes in order to increase homogeneity of the resulting sub-nodes. Each node in the decision tree acts as a test case for some feature and based on the decision made at every node, the data is split into 2 or more sub-nodes. Decision trees end with leaf nodes that attempt to achieve maximum homogeneity without overfitting the data.

In our case, firstly, we tried to obtain the tree depth (number of edges from leaf node to the tree's root node). This has been done by calculating the mean squared error obtained by predicting the target values with varying tree depths. Ultimately, we obtained 5 as the optimal tree depth.

Using this, we predicted the Sales Price and corresponding residual values (y actual – y predicted). This has been demonstrated using the histogram plot.



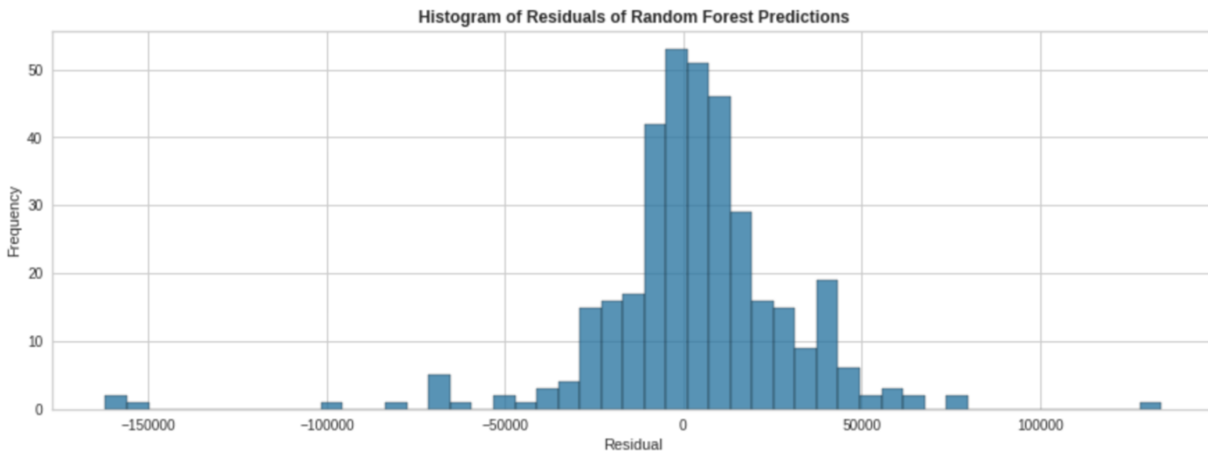
Finally, we evaluated the performance of the model using various prediction measures as below:

R^2 score	0.724329
Mean Squared Error	1.931161e+09
Root Mean Squared Error	43944.978499
Mean Absolute Error	27152.969863

9.2. Random Forest

Random Forest is an ensemble of decision trees created using the bagging method (which states that a combination of learning models improves the overall method). Random forest adds randomness to the model while growing the trees, that is, while splitting a node, it searches for the best feature among a random subset of features. Therefore, in random forest, only a random subset of features are taken into consideration while fitting the model. This allows us to obtain better models as compared to decision trees.

We have applied the Random Forest regressor for our dataset, obtaining predictions on the target variable. The residuals obtained are plotted in the below histogram:



Moreover, the performance of the predictions is measured using the following parameters:

R^2 score	0.884731
Mean Squared Error	8.177464e+08
Root Mean Squared Error	28596.264753
Mean Absolute Error	18628.220648

9.3. Linear Regression

Linear Regression is the machine learning model which fits the data assuming the linear relationship between predictors and target variable. Our will the multiple linear regression as it has more than one input variable. We have used "LinearRegression" which uses "ordinary least squares" procedure to estimate the coefficients by minimizing the sum of squared errors between the predicted output and the actual output.

The performance evaluation of the model has been calculated as below-

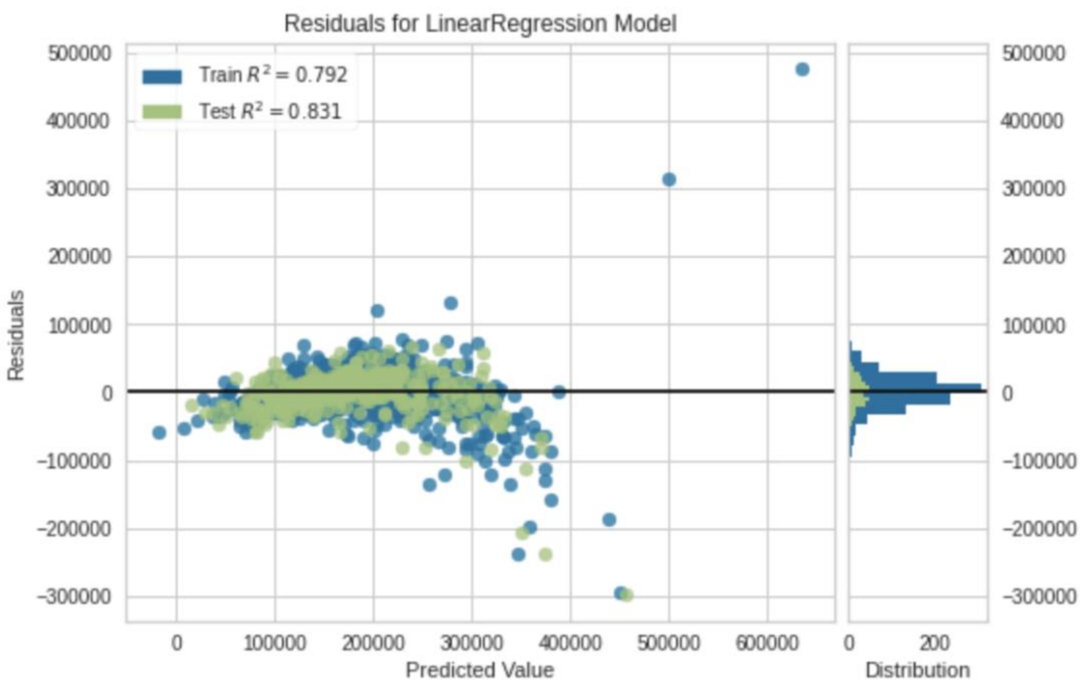
S.No	Scores	Values
0	Coefficient of determination (R^2)	0.814358
1	Intercept	181712.286758
2	Slope	[4668.985483135239, 18210.965719479453, 3308.3...

The model parameters have been estimated as below –

index	Predictor	coefficient
0	LotArea	4668.98548
1	OverallQual	18210.9657
2	MasVnrArea	3308.32644
3	BsmtFinSF1	1568.29054
4	BsmtUnfSF	-1531.1486
5	1stFlrSF	6537.63204
6	2ndFlrSF	3121.07288
7	GrLivArea	15804.2844
8	BsmtFullBath	4387.43285
9	FullBath	872.330225
10	HalfBath	956.291662
11	Fireplaces	4649.30997
12	GarageArea	6473.29485
13	WoodDeckSF	2697.36698
14	OpenPorchSF	-1304.1872
15	HouseAge	1769.66914
16	HouseRemodelAge	-834.52123
17	GarageAge	49.2898028
18	MSZoning	4537.36059
19	LotShape	2717.62801
20	ExterQual	4904.8676
21	Foundation	376.66594
22	BsmtQual	11860.4973
23	HeatingQC	1824.50046

24	CentralAir	1382.21958
25	Electrical	-553.91849
26	KitchenQual	8780.04397
27	GarageFinish	57.8447931
28	PavedDrive	246.13389
29	SaleType	4403.54471

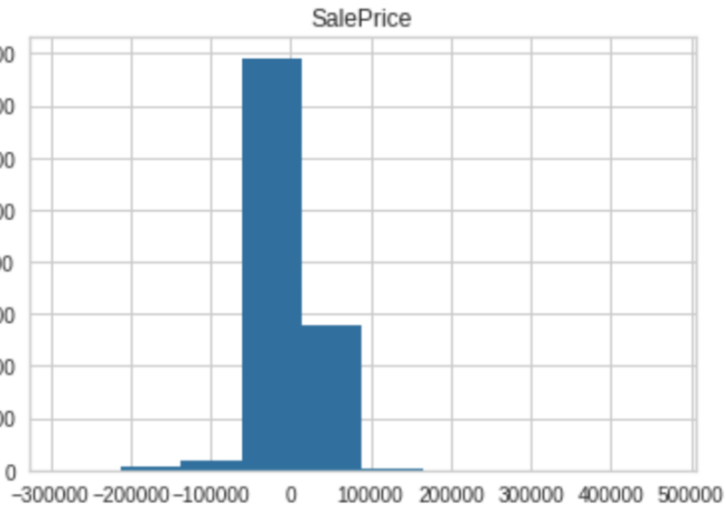
We have used “ResidualsPlot” from “YellowBrick.regressor” library to visualize the scores of the fitted model on the validation and training dataset.



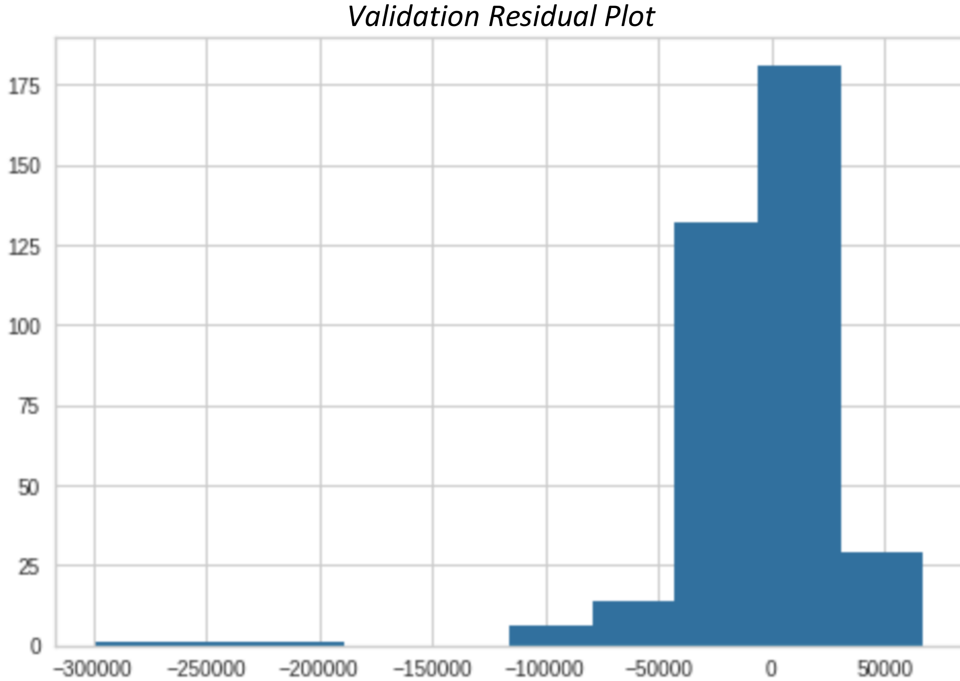
The various errors are calculated using “RegressionSummary” function –

```
Regression statistics

Mean Error (ME) : 3629.0352
Root Mean Squared Error (RMSE) : 34390.7353
Mean Absolute Error (MAE) : 21610.8772
Mean Percentage Error (MPE) : 0.5491
Mean Absolute Percentage Error (MAPE) : 12.715
```

Training Residual Plot



Validation Residual Plot

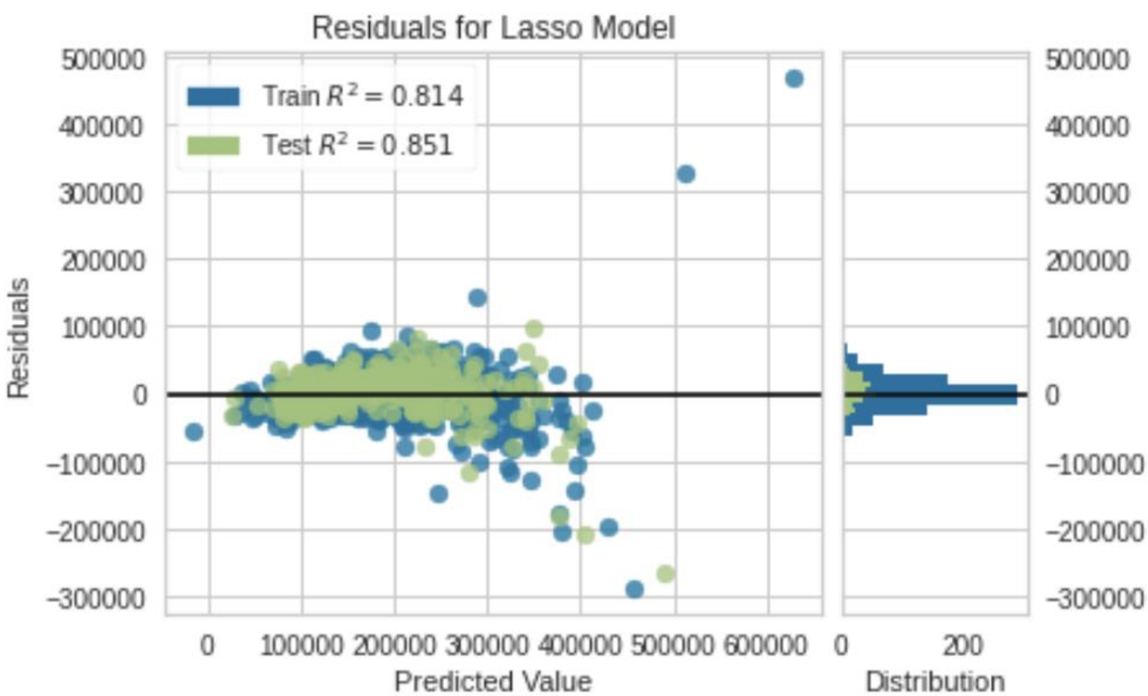


9.4. Regularized Linear Regression Model – Lasso

Lasso is a type of linear regression model which uses "shrinkage" wherein data points are shrunk towards any statistical measure. It uses **L1** regularization and applies penalties based on the sum of absolute values of coefficients.

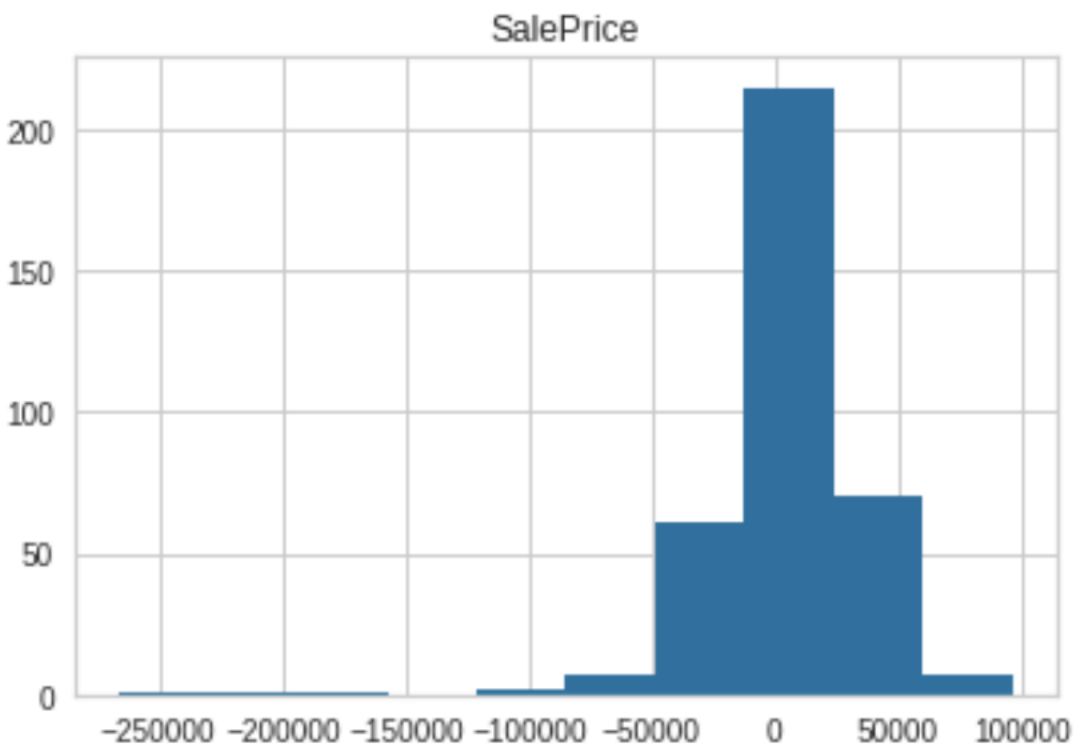
The performance evaluation of the model has been calculated as below-

S.No	Scores	Values
0	Coefficient of determination (R^2)	0.851572
1	Intercept	-28930.649996
2	Slope	[0.46126203383172, 19843.38400698893, 18.99501...



We can see that the R^2 is not improved using Lasso Model which uses alpha = 1 as default.

Validation Residual Plot



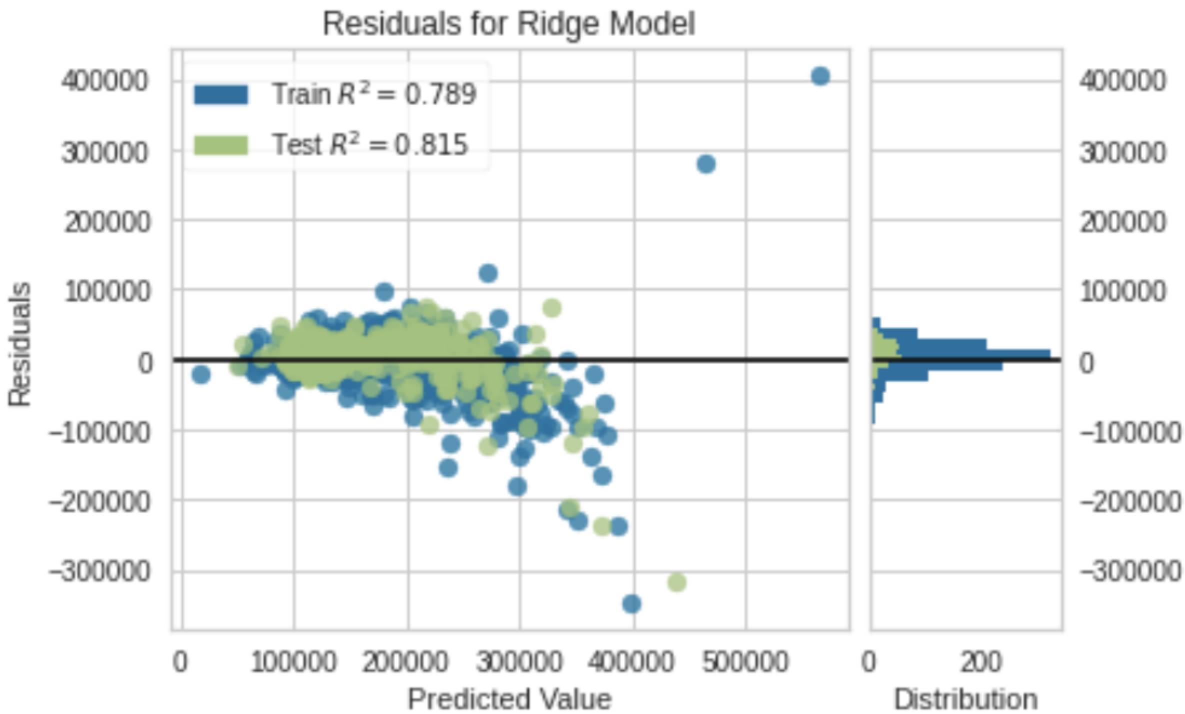

```
Regression statistics

                      Mean Error (ME) : 3631.2808
       Root Mean Squared Error (RMSE) : 34407.5348
            Mean Absolute Error (MAE) : 21603.3905
          Mean Percentage Error (MPE) : 0.5390
Mean Absolute Percentage Error (MAPE) : 12.7077
```

9.5. Regularized Linear Regression Model – Ridge

Lasso is a type of linear regression model which uses "shrinkage" wherein data points are shrunk towards any statistical measure. It uses **L2** regularization and applies a penalty based on the sum of squared coefficients.

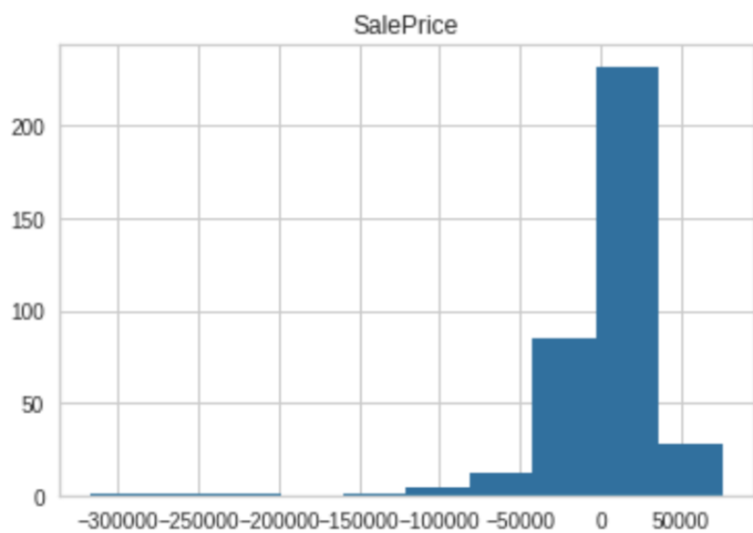
The performance evaluation of the model has been calculated as below-

S.No	Scores	Values
0	Coefficient of determination (R^2)	0.815312
1	Intercept	43234.690169
2	Slope	[0.3315319382310712, 8459.551315963707, 28.038...



We can see that the R^2 score of Test dataset is reduced

Validation Residual Plot



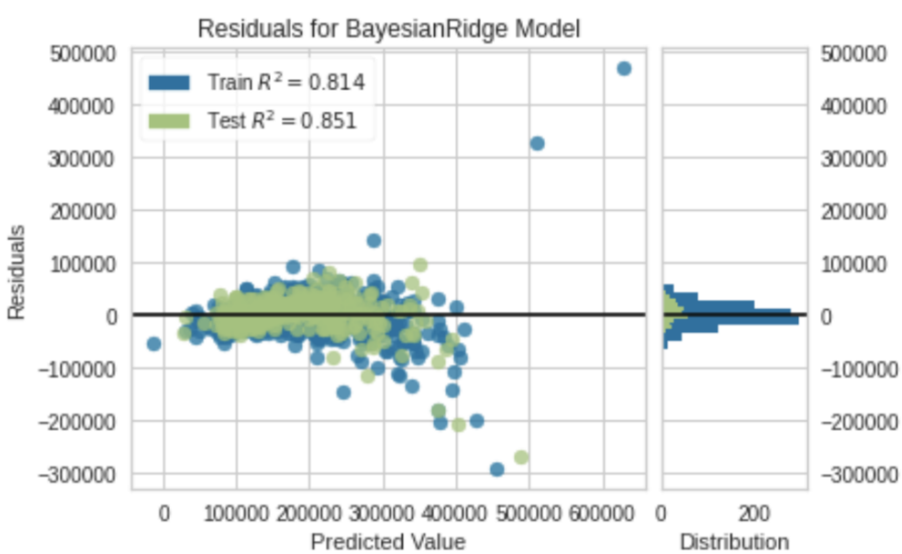
```
Regression statistics

                        Mean Error (ME) : 1934.4418
       Root Mean Squared Error (RMSE) : 38836.1704
            Mean Absolute Error (MAE) : 22705.8181
          Mean Percentage Error (MPE) : -3.1038
Mean Absolute Percentage Error (MAPE) : 12.3542
```

9.6. Regularized Linear Regression Model – Bayesian

It uses Gaussian distribution to make the predictions instead of point estimates. We use probability distribution to estimate the target variable and the regression model is sampled from Normal distribution.

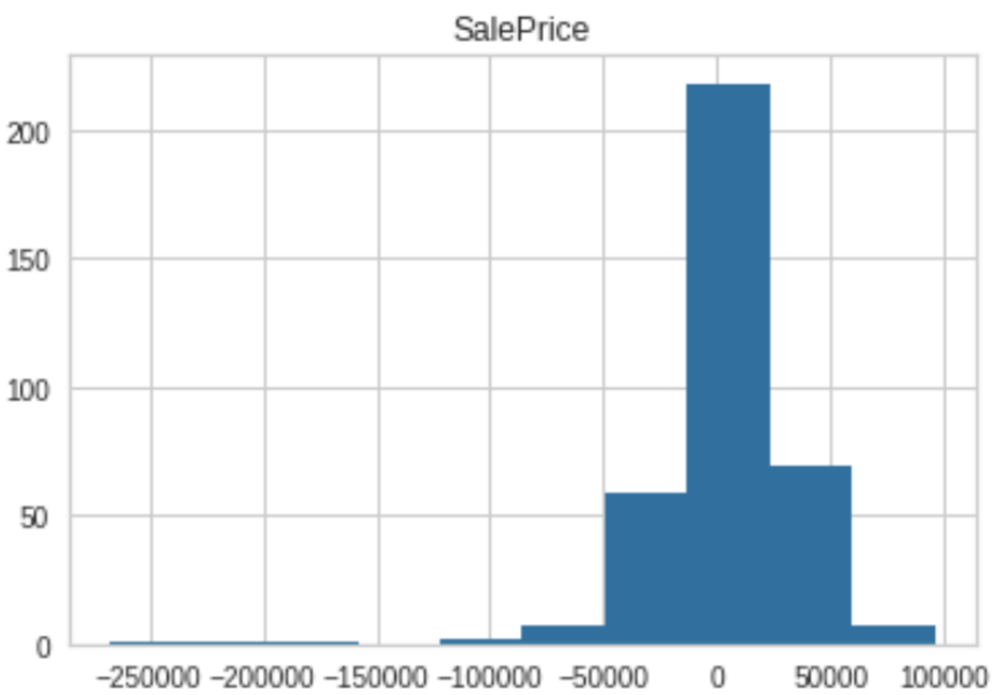
The output variable is generated using Normal distribution metrics – means and variances

S.No	Scores	Values
0	Coefficient of determination (R^2)	0.851394
1	Intercept	-23290.7
2	Slope	[0.45192006229283005, 18676.54858595858, 20.30...



```
Regression statistics

                      Mean Error (ME) : 3499.7098
       Root Mean Squared Error (RMSE) : 34416.9572
            Mean Absolute Error (MAE) : 21512.8742
          Mean Percentage Error (MPE) : 0.3556
Mean Absolute Percentage Error (MAPE) : 12.5695
```

Validation Residual Plot



The below table summarizes the performance of various machine learning models on validation dataset.

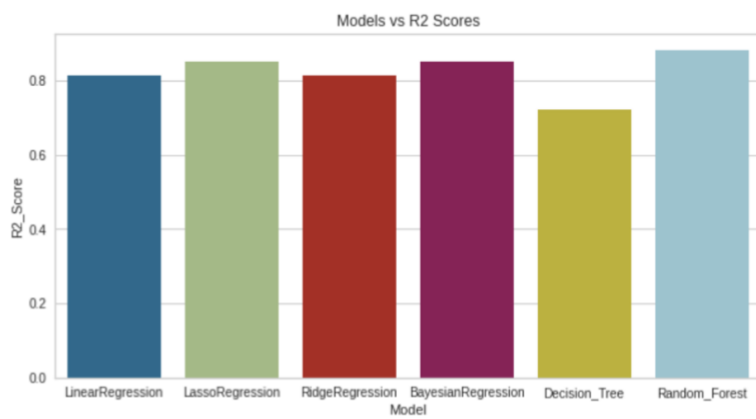
10. Performance Evaluation and Comparison

Model Name	MSE	RMSE	MAE	R^2
Linear Regression	1.182723e+09	34390.735	21610.877	0.791584
Lasso Regression	1.183878e+09	34407.535	21603.39	0.831003
Ridge Regression	1.508248e+09	38836.17	22705.818	0.784699
Bayesian Regression	1.184527e+09	34416.957	21512.874	0.83091
Decision Tree	1949306000	44150.94421	27318.75069	0.721739
Random Forest	***807492500***	***28416.41284***	***18047.65975***	***0.884731***

We have plotted the different measures of performance – R2 Score, RMSE, MSE, MAE for every model and selected the Random Forest as the best performing model.

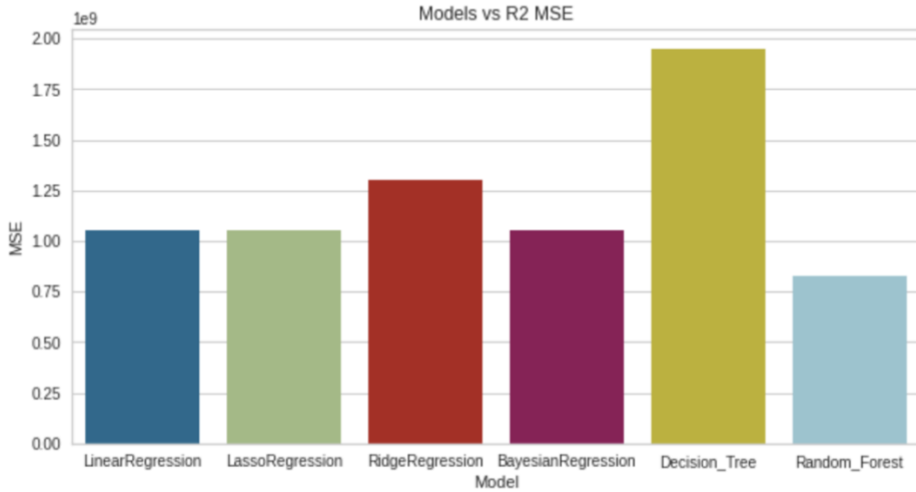
10.1. Coefficient of Determination (R-Squared)

Using the Barplot to visualize the different metrics



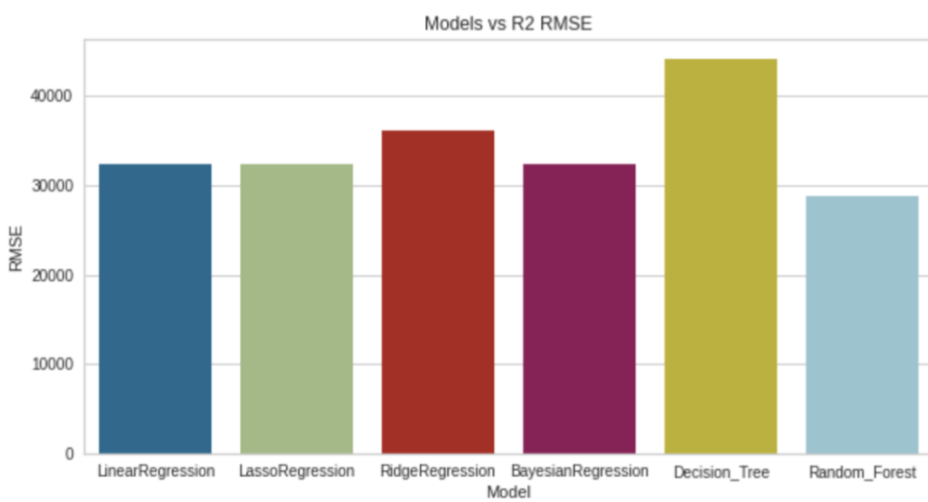
- ***As per the above figure, Random Forest has the highest R2- score.***

10.2. Mean Squared Error



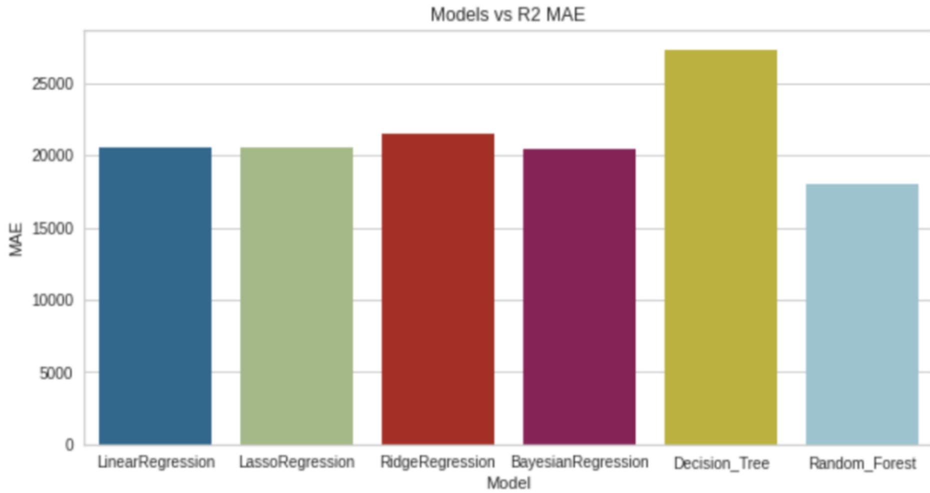
- ***As per the above figure, Random Forest has the lowest MSE***

10.3. Root Mean Squared Error



- ***In the above barplot Random Forest can be seen with the lowest RMSE***

10.4. Mean Absolute Error



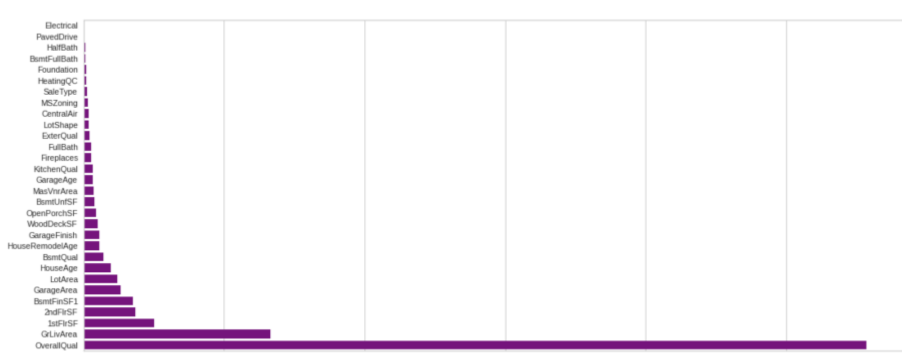
- ***Even MAE is the lowest for Random Forest***

By assessing all the measures, we observed that the **Random Forest** has been performing in the best way by reducing all kinds of errors.

After comparing all the models we came to the conclusion that the ***Random Forest*** is the best possible machine learning model to make the prediction of House sale Price with minimal error measurements among all other models.

Furth more, we calculated the importance of features and identified the most significant predictors among all the features.

The below graph shows the importance of all the features.



	Feature Names	Feature Importance
1	OverallQual	0.55735
7	GrLivArea	0.1327
5	1stFlrSF	0.050113
6	2ndFlrSF	0.036664
3	BsmtFinSF1	0.035239
12	GarageArea	0.026169
0	LotArea	0.024062
15	HouseAge	0.019498
22	BsmtQual	0.014204
16	HouseRemodelAge	0.011253
27	GarageFinish	0.011217
13	WoodDeckSF	0.010149
14	OpenPorchSF	0.008763
4	BsmtUnfSF	0.00756
2	MasVnrArea	0.00711
17	GarageAge	0.006746
26	KitchenQual	0.006708
11	Fireplaces	0.005573