HOUSE PRICE

PREDICTION

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(internship-28)

ACKNOWLEDGMENT I would like to thank my mentors at Data Trained, who taught me the concepts of Data Analysis, building a machine learning model, and tuning the parameters for best outcomes.

I would also like to thank my mentor in Fliprobo, Khushboo Garg , for providing me with the dataset and problem statement for performing this wonderful task.

INTRODUCTION:

Business Problem Framing The objective was to model the price of houses with the available independent variables. This model can then be used by the management to understand how exactly the prices vary with the variables. They can accordingly manipulate the strategy of the firm and concentrate on areas that will yield high returns. Further, the model will be a good way for the management to understand the pricing dynamics of a new market.

Conceptual Background of the Domain Problem:

Houses are one of the necessary need of each and every person around the world and therefore housing and real estate market is one of the markets which is one of the major contributors in the world's economy. It is a very larges market and there are various companies working in the domain. Data science comes as a very important tool to solve problems in the domain to help the companies increase their overall revenue, profits, improving their marketing strategies and focusing on changing trends in house sales and purchases. Predictive modelling, Market mix modelling, recommendation systems are some of the machine learning techniques used for achieving the business goals for housing companies. Our problem is related to one such housing company. A US-based housing company named Surprise Housing has decided to enter the Australian market. The company uses data analytics to purchase houses at a price below their actual values and flip them at a higher price. For the same purpose, the company has collected a data set from the sale of houses in Australia. The data is provided in the CSV file below. The company is looking at prospective properties to buy houses to enter the market. I was required to build a model using Machine Learning in order to predict the actual value of the prospective properties and decide whether to invest in them or not.

For this company wants to know :

- Which variables are important to predict the price of variable?
- How do these variables describe the price of the house?

Technical Requirements:

- Data contains 1460 entries each having 81 variables.
- Data contains Null values. You need to treat them using the domain knowledge and your own understanding.
- Extensive EDA has to be performed to gain relationships of important variable and price.
- Data contains numerical as well as categorical variable. You need to handle them accordingly.
- Need to build Machine Learning models, apply regularization and determine the optimal values of Hyper Parameters.
- Need to find important features which affect the price positively or negatively.

Analytical Problem Framing

• Mathematical/ Analytical Modelling of the Problem:

This is a Regression problem, where our end goal is to predict the Prices of House based on given data. I will be dividing my data into Training and Testing parts. A Regression Model will be built and trained using the Training data and the Test data will be used to predict the outcomes. This will be compared with available test results to find how well the model has performed. The 'r2' score will be used to determine the best model among,

- Linear Regression with Lasso,Ridge
- Random ForestRegression
- XGBoost
- The best results were obtained using Lasso Regression. So, let's understand a little about it.

In a simple regression problem (a single x and a single y), the form of the model would be:

y = B0 + B1*x, where B0

—intercept
B1 —coefficient x —independent
variable y —output or
the dependent variable .

I   n higher dimensions when we have more than one input (x), The General equation for a Multiple linear regression with p — independent variables:

Y=B0 + B1 * X1 + B2 * X2 + ………… + Bp * Xp + E(Random Error or Noise)

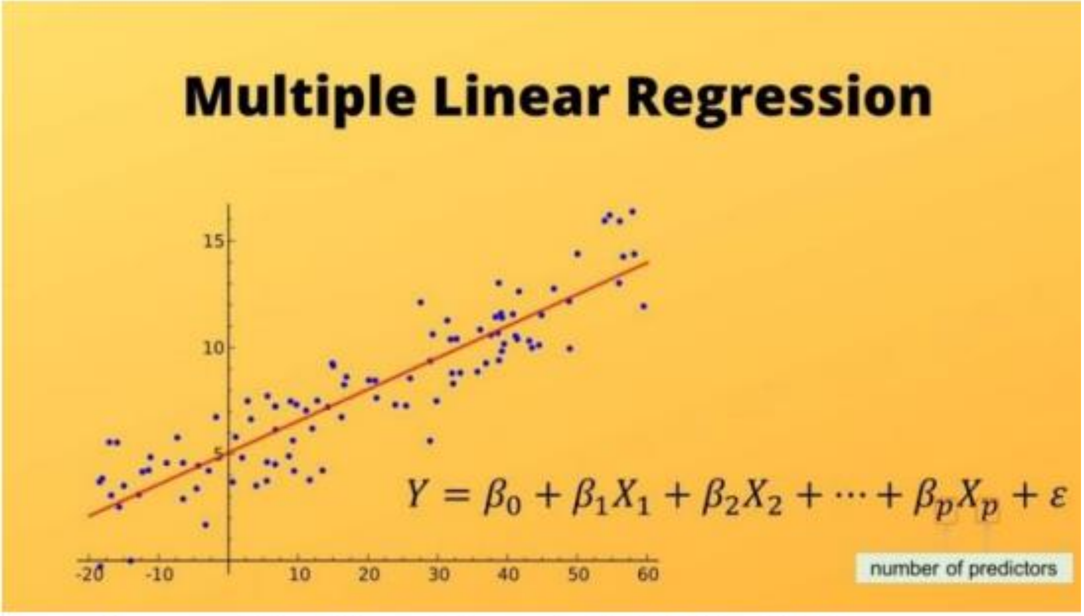


Image Source: https://morioh.com/p/0d9b2bedf683

Let's consider a regression scenario where 'y' is the predicted vector and 'x' is the feature matrix. Basically, in any regression problem, we try to minimize the squared error. Let 'β' be the vector of parameters (weights of importance of features) and 'p' be the number of features Now, let's discuss the case of lasso regression, which is also called L1 regression since it uses the L1 norm for regularization. In lasso regression, we try to solve the below minimization problem:

$$Min_\beta \, L_1 = (y - x\beta)^2 + \lambda \sum_{i=1}^{p} |\beta_i|$$

For simplicity, let p=1 and βi = β. Now

$$\begin{aligned} L_1 &= (y - x\beta)^2 + \lambda|\beta| \\ &= \mathrm{y}^2 - 2\mathrm{xy}\beta + x^2\beta^2 + \lambda|\beta| \end{aligned}$$

Example: Suppose we are building a linear model out of two features, we'll have two coefficients (β1 and β2). For better understanding let β1 = 10 and β2 = 1000. In lasso regression, the L1 penalty would look like,

$L1p = |\beta 1| + |\beta 2|$ Shrinking $\beta 1$ to 8 and $\beta 2$ to 100 would minimize the penalty to 108 from 1010, which means in this case the change is not so significant just by shrinking the larger quantity. So, in the case of the L1 penalty, both the coefficients have to be shrunk to extremely. small values, in order to achieve regularization. And in this whole process, some coefficients may shrink to zero. 1 [Ref: URL for the above explanation in the foot note]

Assumptions:

There are four assumptions associated with a linear regression model:

1. Linearity: The relationship between X and the mean of Y is linear.
2. Homoscedasticity: The variance of residual is the same for any value of X
3. Independence: Observations are independent of each other.
4. Normality: For any fixed value of X, Y is normally distributed.

Data Sources and their formats

A US-based housing company named Surprise Housing has decided to enter the Australian market. The company uses data analytics to purchase houses at a price below their actual values and flip them at a higher price. For the same purpose, the company has collected a data set from the sale of houses in Australia. The data is provided in the CSV file Here's how the top 10 rows of the data looks like:

```
# Rows, Columns
df.shape
```

```
(1460, 81)
```

Out[7]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	S
0	127	120	RL	NaN	4928	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2007	
1	889	20	RL	95.0	15865	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	10	2007	
2	793	60	RL	92.0	9920	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	6	2007	
3	110	20	RL	105.0	11751	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0	1	2010	
4	422	20	RL	NaN	16635	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	6	2009	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1163	289	20	RL	NaN	9819	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0	2	2010	
1164	554	20	RL	67.0	8777	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0	5	2009	
1165	196	160	RL	24.0	2280	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	7	2009	
1166	31	70	C (all)	50.0	8500	Pave	Pave	Reg	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0	7	2008	
1167	617	60	RL	NaN	7861	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	6	2006	

1168 rows × 81 columns

Heating	HeatingQC	CentralAir	Electrical	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvG
GasA	Ex	Y	SBrkr	856	854	0	1710	1	0	2	1	
GasA	Ex	Y	SBrkr	1262	0	0	1262	0	1	2	0	
GasA	Ex	Y	SBrkr	920	866	0	1786	1	0	2	1	
GasA	Gd	Y	SBrkr	961	756	0	1717	1	0	1	0	
GasA	Ex	Y	SBrkr	1145	1053	0	2198	1	0	2	1	
GasA	Ex	Y	SBrkr	796	566	0	1362	1	0	1	1	
GasA	Ex	Y	SBrkr	1694	0	0	1694	1	0	2	0	
GasA	Ex	Y	SBrkr	1107	983	0	2090	1	0	2	1	
GasA	Gd	Y	FuseF	1022	752	0	1774	0	0	2	0	
GasA	Ex	Y	SBrkr	1077	0	0	1077	1	0	1	0	

KitchenAbvGr	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	FireplaceQu	GarageType	GarageYrBlt	GarageFinish	GarageCars	GarageArea	GarageQual
1	Gd	8	Typ	0	NaN	Attchd	2003.0	RFn	2	548	TA
1	TA	6	Typ	1	TA	Attchd	1976.0	RFn	2	460	TA
1	Gd	6	Typ	1	TA	Attchd	2001.0	RFn	2	608	TA
1	Gd	7	Typ	1	Gd	Detchd	1998.0	Unf	3	642	TA
1	Gd	9	Typ	1	TA	Attchd	2000.0	RFn	3	836	TA
1	TA	5	Typ	0	NaN	Attchd	1993.0	Unf	2	480	TA
1	Gd	7	Typ	1	Gd	Attchd	2004.0	RFn	2	636	TA
1	TA	7	Typ	2	TA	Attchd	1973.0	RFn	2	484	TA
2	TA	8	Min1	2	TA	Detchd	1931.0	Unf	2	468	Fa
2	TA	5	Typ	2	TA	Attchd	1939.0	RFn	1	205	Gd

GarageCond	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold
TA	Y	0	61	0	0	0	0	NaN	NaN	NaN	0	2
TA	Y	298	0	0	0	0	0	NaN	NaN	NaN	0	5
TA	Y	0	42	0	0	0	0	NaN	NaN	NaN	0	9
TA	Y	0	35	272	0	0	0	NaN	NaN	NaN	0	2
TA	Y	192	84	0	0	0	0	NaN	NaN	NaN	0	12
TA	Y	40	30	0	320	0	0	NaN	MnPrv	Shed	700	10
TA	Y	255	57	0	0	0	0	NaN	NaN	NaN	0	8
TA	Y	235	204	228	0	0	0	NaN	NaN	Shed	350	11
TA	Y	90	0	205	0	0	0	NaN	NaN	NaN	0	4

YrSold	SaleType	SaleCondition	SalePrice
2008	WD	Normal	208500
2007	WD	Normal	181500
2008	WD	Normal	223500
2006	WD	Abnorml	140000
2008	WD	Normal	250000
2009	WD	Normal	143000
2007	WD	Normal	307000
2009	WD	Normal	200000
2008	WD	Abnorml	129900
2008	WD	Normal	118000

The last Feature: SalePrice is the target variable. The above Snapshots show all the features and the top 10 rows. As mentioned earlier, there are 1460 rows and 81 columns

Data Describtion:

MSSubClass: Identifies the type of dwelling involved in the sale.

20 1-STORY 1946 & NEWER ALL STYLES

30 1-STORY 1945 & OLDER

40 1-STORY W/FINISHED ATTIC ALL AGES

45 1-1/2 STORY - UNFINISHED ALL AGES

50 1-1/2 STORY FINISHED ALL AGES

60 2-STORY 1946 & NEWER

70 2-STORY 1945 & OLDER

75 2-1/2 STORY ALL AGES

80 SPLIT OR MULTI-LEVEL

85 SPLIT FOYER

90 DUPLEX - ALL STYLES AND AGES

120 1-STORY PUD (Planned Unit Development) - 1946 & NEWER

150 1-1/2 STORY PUD - ALL AGES

160 2-STORY PUD - 1946 & NEWER

180 PUD - MULTILEVEL - INCL SPLIT LEV/FOYER

190 2 FAMILY CONVERSION - ALL STYLES AND AGES

MSZoning: Identifies the general zoning classification of the sale.

A Agriculture

C Commercial

FV Floating Village Residential

I Industrial

RH Residential High Density

RL Residential Low Density

RP Residential Low Density Park

RM Residential Medium Density

LotFrontage: Linear feet of street connected to property

LotArea: Lot size in square feet

Street: Type of road access to property

Grvl Gravel

Pave Paved

Alley: Type of alley access to property

Grvl Gravel Pave Paved

NA No alley access

LotShape: General shape of property

Reg Regular

IR1 Slightly irregular

IR2 Moderately Irregular

IR3 Irregular

LandContour: Flatness of the property

Lvl	Near Flat/Level

Bnk	Banked - Quick and significant rise from street grade to building

HLS	Hillside - Significant slope from side to side

Low	Depression

Utilities: Type of utilities available

AllPub	All public Utilities (E,G,W,& S)

NoSewr	Electricity, Gas, and Water (Septic Tank)

NoSeWa	Electricity and Gas Only

ELO	Electricity only

LotConfig: Lot configuration

Inside	Inside lot

Corner	Corner lot

CulDSac	Cul-de-sac

FR2	Frontage on 2 sides of property

FR3	Frontage on 3 sides of property

LandSlope: Slope of property

Gtl	Gentle slope
Mod	Moderate Slope
Sev	Severe Slope

Neighborhood: Physical locations within Ames city limits

Blmngtn	Bloomington Heights	
Blueste	Bluestem	
BrDale	Briardale	
BrkSide	Brookside	
ClearCr	Clear Creek	
CollgCr	College Creek	
Crawfor	Crawford	
Edwards	Edwards	
Gilbert	Gilbert	
IDOTRR	Iowa DOT and Rail Road	
MeadowV	Meadow Village	
Mitchel	Mitchell Names	North Ames
NoRidge	Northridge	

NPkVill	Northpark Villa
NridgHt	Northridge Heights
NWAmes	Northwest Ames
OldTown	Old Town
SWISU	South & West of Iowa State University
Sawyer	Sawyer
SawyerW	Sawyer West
Somerst	Somerset
StoneBr	Stone Brook
Timber	Timberland
Veenker	Veenker

Condition1: Proximity to various conditions

Artery	Adjacent to arterial street
Feedr	Adjacent to feeder street
Norm	Normal
RRNn	Within 200' of North-South Railroad
RRAn	Adjacent to North-South Railroad
PosN	Near positive off-site feature--park, greenbelt, etc.
PosA	Adjacent to postive off-site feature
RRNe	Within 200' of East-West Railroad

RRAe Adjacent to East-West Railroad Condition2: Proximity to various conditions (if more than one is present)

Artery Adjacent to arterial street

Feedr Adjacent to feeder street

Norm Normal

RRNn Within 200' of North-South Railroad

RRAn Adjacent to North-South Railroad

PosN Near positive off-site feature--park, greenbelt, etc.

PosA Adjacent to postive off-site feature

RRNe Within 200' of East-West Railroad

RRAe Adjacent to East-West Railroad

BldgType: Type of dwelling

1Fam Single-family Detached

2FmCon Two-family Conversion; originally built as one-family dwelling

Duplx Duplex

TwnhsE Townhouse End Unit

TwnhsI Townhouse Inside Unit

HouseStyle: Style of dwelling

1Story One story

1.5Fin One and one-half story: 2nd level finished

1.5Unf One and one-half story: 2nd level unfinished

2Story Two story 2.5Fin Two and one-half story: 2nd level finished

2.5Unf Two and one-half story: 2nd level unfinished

SFoyer Split Foyer

SLvl Split Level

OverallQual: Rates the overall material and finish of the house

10 Very Excellent

9 Excellent

8 Very Good

7 Good

6 Above Average

5 Average

4 Below Average

3 Fair

2 Poor

1 Very Poor

OverallCond: Rates the overall condition of the house

10 Very Excellent

9 Excellent

8 Very Good

7 Good

6 Above Average

5 Average 4 Below Average

3 Fair

2 Poor

1 Very Poor

YearBuilt: Original construction date

YearRemodAdd: Remodel date (same as construction date if no remodeling or additions)

RoofStyle: Type of roof

Flat Flat

Gable Gable

Gambrel Gabrel (Barn)

Hip Hip

Mansard Mansard

Shed Shed

RoofMatl: Roof material

ClyTile Clay or Tile

CompShg Standard (Composite) Shingle

Membran Membrane

Metal Metal

Roll Roll

Tar&Grv Gravel & Tar

WdShake Wood Shakes

WdShngl Wood Shingles

Exterior1st: Exterior covering on house

AsbShng Asbestos Shingles

AsphShn Asphalt Shingles

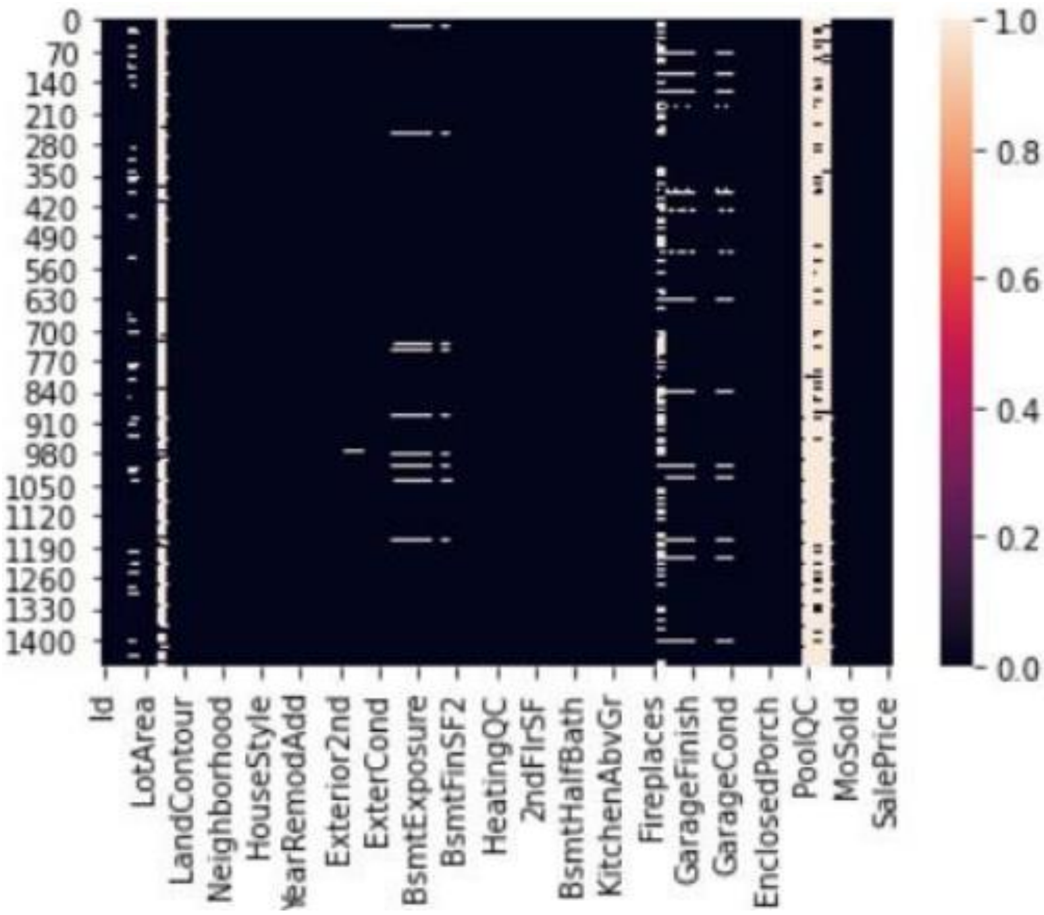
BrkComm	Brick Common
BrkFace	Brick Face
CBlock	Cinder Block
CemntBd	Cement Board
HdBoard	Hard Board
ImStucc	Imitation Stucco
MetalSd	Metal Siding
Other	Other
Plywood	Plywood
PreCast	PreCast
Stone	Stone
Stucco	Stucco
VinylSd	Vinyl Siding
Wd Sdng	Wood Siding
WdShing	Wood Shingles

Exterior2nd: Exterior covering on house (if more than one material)

AsbShng	Asbestos Shingles
AsphShn	Asphalt Shingles
BrkComm	Brick Common

BrkFace	Brick Face
CBlock	Cinder Block
CemntBd	Cement Board

Data Pre-processing:



The above heatmap shows there are many Null Values, which can't be processed. One Observation here is that a lot of variables have been labelled at NaN, but they are actually not null values and have certain meaning. For Example, • NA in feature 'Alley' means No_Alley • in case of PoolQC, NA means 'No Pool' (* Refer Data Description at the end of the notebook) I've replaced them with actual variables before going further. First let us handle Categorical features which are missing; based on domain knowledge and given explanation. The percentage of Null values in Categorical features: Alley: 0.9377% missing values MasVnrType: 0.0055% missing values BsmtQual: 0.0253% missing values BsmtCond: 0.0253% missing values BsmtExposure: 0.026% missing values BsmtFinType1: 0.0253% missing values BsmtFinType2: 0.026% missing values FireplaceQu: 0.4726% missing values GarageType: 0.0555% missing values GarageFinish: 0.0555% missing values GarageQual: 0.0555% missing values GarageCond: 0.0555% missing values PoolQC: 0.9952% missing values Fence: 0.8075% missing values MiscFeature: 0.963% missing values

Then I replaced all other categorical missing values with a new label 'Missing'. The numerical missing values will be imputed during feature engineering

Numerical variables

```
# list of numerical variables
numerical_features = [feature for feature in df.columns if df[feature].dtypes != 'O']

print('Number of numerical variables: ', len(numerical_features))

# visualise the numerical variables
df[numerical_features].head()
```

```
Number of numerical variables:  37
```

Identified all features that were numerical

Year Features

```
# (identified features with Year using key words 'year' or 'yr' in column headers)
year_feature = [feature for feature in numerical_features if 'Yr' in feature or 'Year' in feature]

year_feature
```

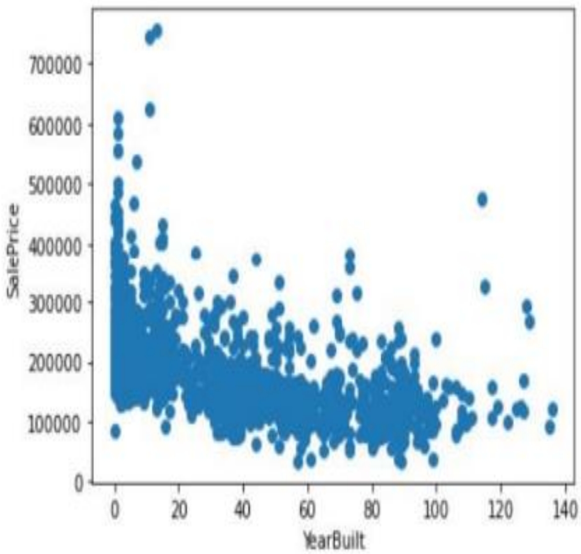
```
['YearBuilt', 'YearRemodAdd', 'GarageYrBlt', 'YrSold']
```

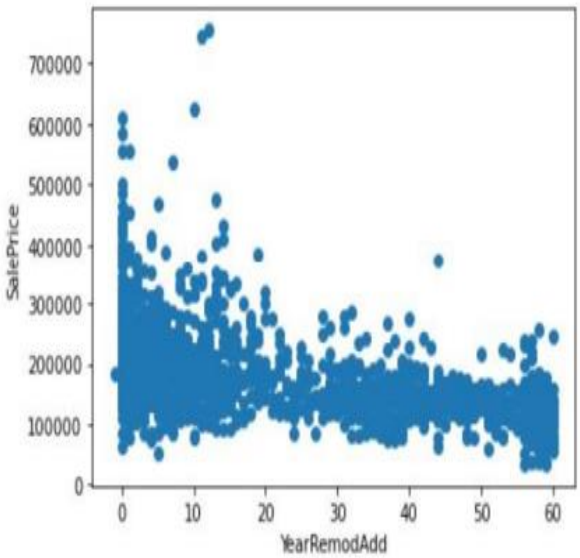
```
# Analyzing Prices of House vs Year Built
df.groupby('YrSold')['SalePrice'].mean().plot()
plt.title("Mean House Price vs YearSold")
```

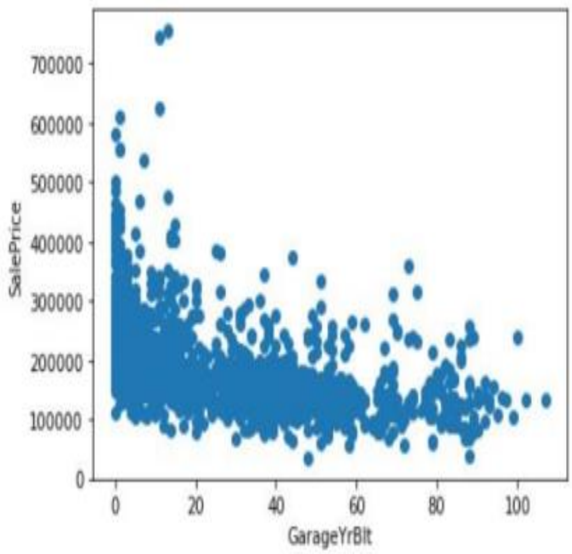
```
Text(0.5, 1.0, 'Mean House Price vs YearSold')
```

There seems to be a peak in House Prices, but a sharp drop in between 2007 to 2008. This can be due to Economic Crash. "Economies worldwide slowed during this period since credit tightened and international trade declined. Housing markets suffered and unemployment soared, resulting in evictions and foreclosures."

Let's see the scatterplot between All years features with SalePrice







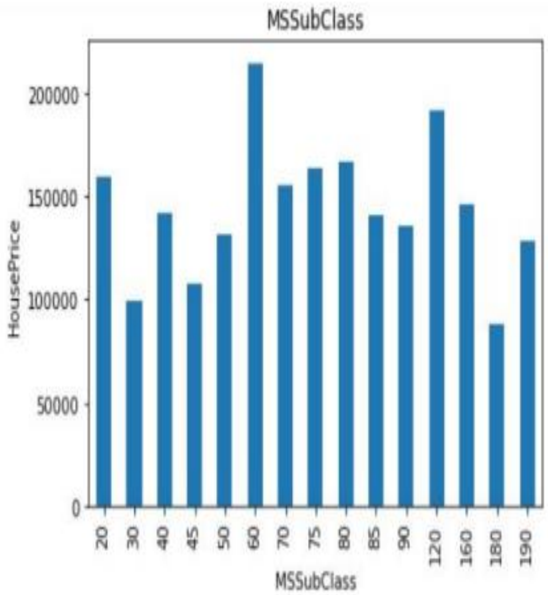
- Obs 1: The Houses built recently have Higher Sales Price.
- Obs 2: The Houses remodelled recently have Higher Sales Price.
- Obs 3: The Houses whose Garages were built recently have Higher Sales Price.

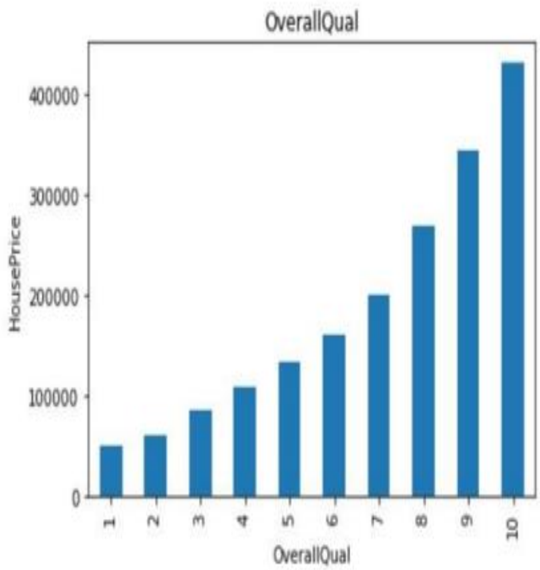
Identifying Discrete Variables

The following 17 features were identified as discrete variables:

['MSSubClass', 'OverallQual', 'OverallCond', 'LowQualFinSF', 'BsmtFullB ath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenA bvGr', 'TotRmsAbvGrd', 'Fireplaces', 'GarageCars', '3SsnPorch', 'PoolAr ea', 'MiscVal', 'MoSold']

Plotted Bar Plots like these to understand relations with Sale Price:-





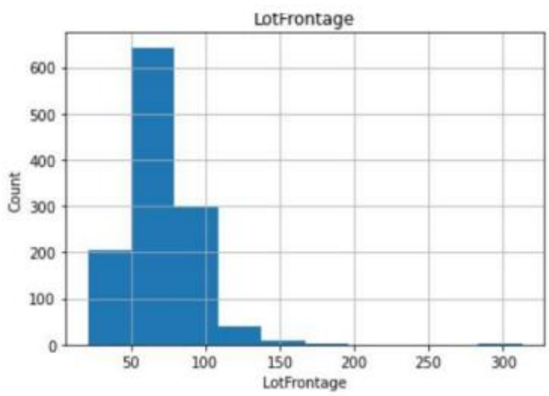
Similarly, plotted for all discrete values, and observed features.

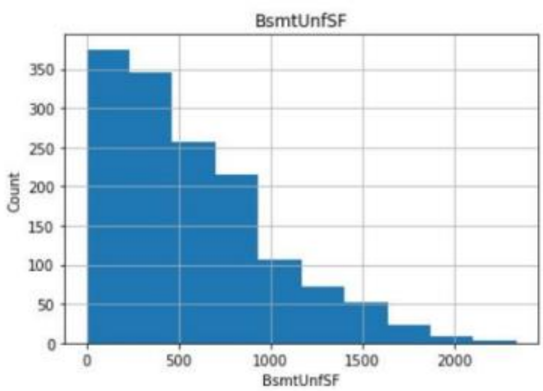
Identifying Continuous Features:-

```
continuous_feature=[feature for feature in numerical_features if feature not in discrete_feature+year_feature+['Id']]
print("Continuous feature Count",len(continuous_feature))
```

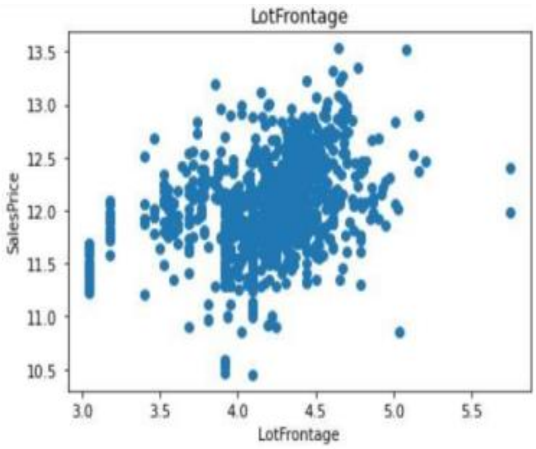
```
Continuous feature Count 16
```

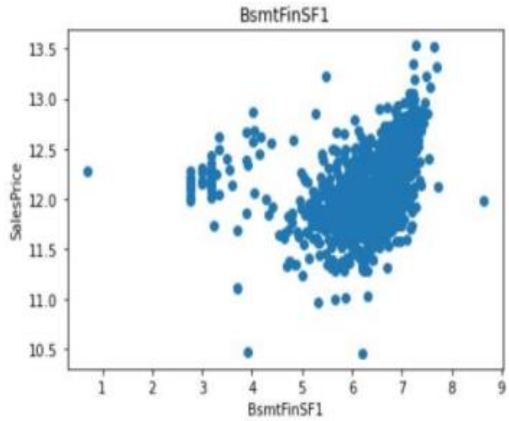
I’ve plotted Histograms for all 16 features like the following:





As clear from above a lot of features were not normally distributed. Let's I did log transformation, plotted the scatterplots to see the trends.





Categorical Features

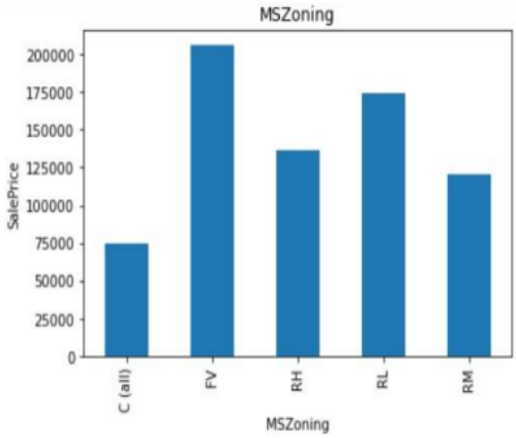
```
categorical_features=[feature for feature in df.columns if df[feature].dtypes=='O']
```

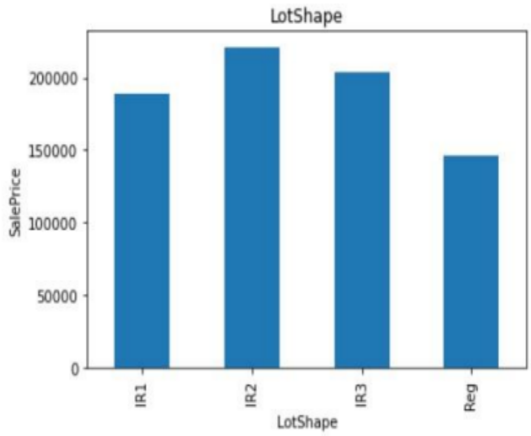
Identified total unique categories in each feature:

MSZoning has 5 categories
Street has 2 categories
Alley has 3 categories
LotShape has 4 categories
LandContour has 4 categories
Utilities has 2 categories
LotConfig has 5 categories
LandSlope has 3 categories
Neighborhood has 25 categories
Condition1 has 9 categories
Condition2 has 8 categories
BldgType has 5 categories
HouseStyle has 8 categories
RoofStyle has 6 categories
RoofMatl has 8 categories
Exterior1st has 15 categories

Exterior2nd has 16 categories
MasVnrType has 5 categories
ExterQual has 4 categories
ExterCond has 5 categories
Foundation has 6 categories
BsmtQual has 5 categories
BsmtCond has 5 categories
BsmtExposure has 5 categories
BsmtFinType1 has 7 categories
BsmtFinType2 has 7 categories
Heating has 6 categories
HeatingQC has 5 categories
CentralAir has 2 categories
Electrical has 6 categories
KitchenQual has 4 categories
Functional has 7 categories
FireplaceQu has 6 categories
GarageType has 7 categories
GarageFinish has 4 categories
GarageQual has 6 categories
GarageCond has 6 categories
PavedDrive has 3 categories
PoolQC has 4 categories
Fence has 5 categories
MiscFeature has 5 categories
SaleType has 9 categories
SaleCondition has 6 categories

Plotted all Categorical variables vs SalesPrice as shown below





Feature Engineering

I had already treated all Null Values in categorical Features, Now I will check for numerical variables. Imputed the numerical null values with medians.

Now, as there were some features(Temporal) which contained year values. Differences

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

:

Handling Rare Categorical Feature

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

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

Label Encoding the Categorical Features For Machine to understand

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in categorical_features:
    df[i]=le.fit_transform(df[i])
```

Skewness in some Continuous Variables

There are a lot of skewed variables. I have treated them with log1 transformation.

Before treating Skewness ,spliting in train and test :-

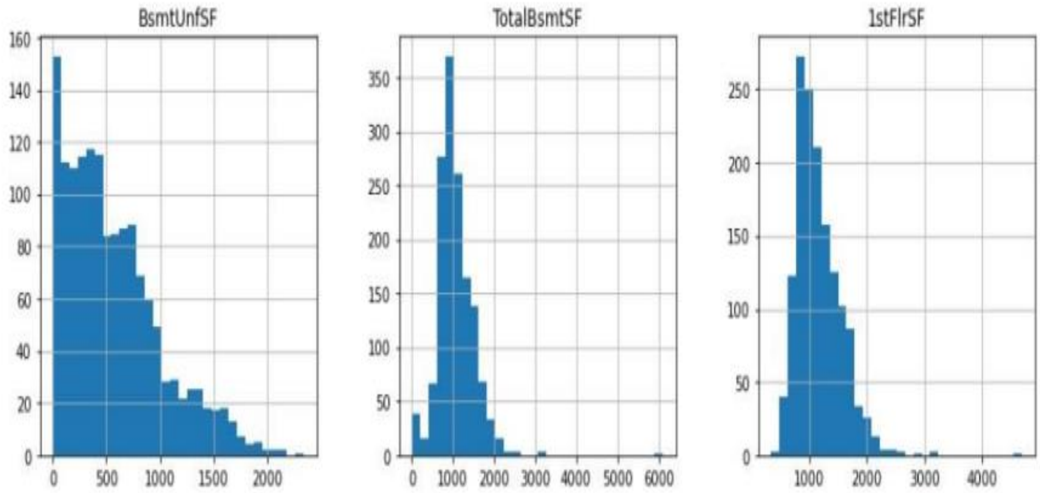
```
from sklearn.model_selection import train_test_split
df_train,df_test = train_test_split(df,train_size=0.8,test_size=0.2,random_state=42)
```

80% data will be used for training and 20% for Testing.

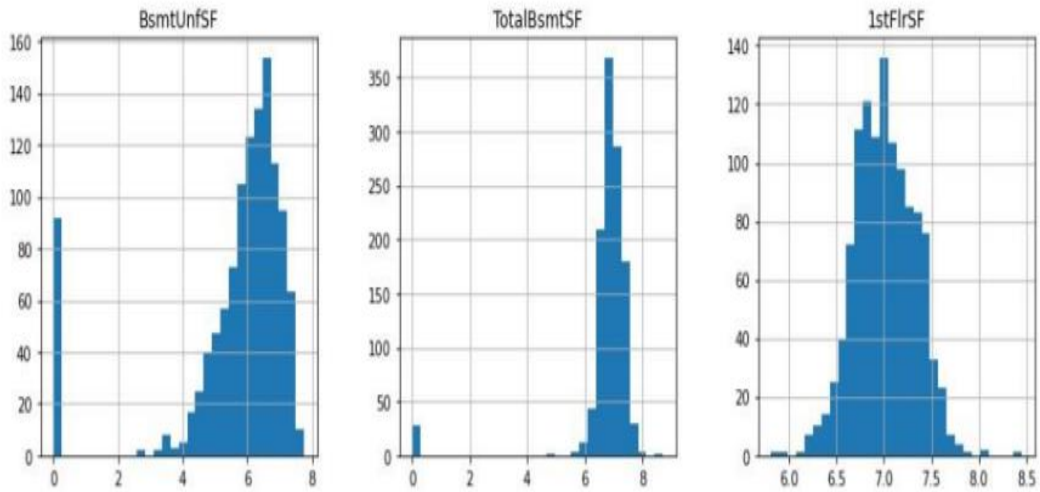
Reducing Skewness

```
for col in df_train[continuous_feature].columns:
    if df_train.skew().loc[col]>0.55 and col!='SalePrice':
        df_train[col]=np.log1p(df_train[col])
```

As seen in the below examples, I've treated all the features.



Before Treating for Skewness



After Treating for Skewness

Scaling the dataset

Splitting Dependent and Independent Features

```
y_train = df_train.pop('SalePrice')
X_train = df_train
```

```
y_test = df_test.pop('SalePrice')
X_test = df_test
```

```
#Lets scale the parameters
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_train=pd.DataFrame(X_train,columns=df_train.columns)
X_train.head()
```

```
#Lets scale the test parameters
X_test=sc.fit_transform(X_test)
X_test=pd.DataFrame(X_test,columns=df_test.columns)
X_test.head()
```

I've used Standard Scalar to make all the data comparable.

Modelling

1. Random Forest Regressor with PCA

```
# Selecting 70 features, as it explains 99% of data
```

```
pca = PCA(n_components=70)
x=pca.fit_transform(x)
x_t=X_test.copy()
x_t=pca.fit_transform(x_t)
```

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import RandomizedSearchCV
parameters={'bootstrap': [True, False],
 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, None],
 'max_features': ['auto', 'sqrt'],
 'min_samples_leaf': [1, 2, 4],
 'min_samples_split': [2, 5, 10],
 'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000]}
rfr=RandomForestRegressor()
rand = RandomizedSearchCV(estimator = rfr, param_distributions = parameters,
                          n_iter = 100, cv = 3, verbose=2, random_state=42, n_jobs = -1,scoring='r2')
rand.fit(x,y_train)
rand.best_params_
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:   54.6s
[Parallel(n_jobs=-1)]: Done 146 tasks      | elapsed:  6.9min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 18.9min finished
```

```
rfr=RandomForestRegressor(n_estimators =1800,
                          min_samples_split= 5,
                          min_samples_leaf= 4,
                          max_features= 'auto',
                          max_depth= 80,
                          bootstrap= True)
```

```
rfr.fit(x,y_train)
y_pred = rfr.predict(x_t)
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
print("RMSE is: ",np.sqrt(mean_squared_error(y_test,y_pred)))
print("r2_score is: ",r2_score(y_test,y_pred))
```

Results: Top 10 Features and R2 Score:-

	Features	Gini-Importance
0	MSSubClass	0.801095
1	LotFrontage	0.058321
2	LotShape	0.005449
3	Alley	0.005347
4	LotArea	0.005258
5	Utilities	0.002516
6	MSZoning	0.002034
7	Street	0.001795
8	LandContour	0.001484
9	LotConfig	0.001342

```
RMSE is:  41621.690289391634
r2_score is:  0.7741471411055758
```

2. XGBoost Regressor with PCA:-

```
params = {
        'min_child_weight': [1, 5, 10],
        'gamma': [0.5, 1, 1.5, 2, 5],
        'subsample': [0.6, 0.8, 1.0],
        'colsample_bytree': [0.6, 0.8, 1.0],
        'max_depth': [3, 4, 5]
        }
```

```
xg = XGBRegressor(learning_rate=0.02, n_estimators=600,
                    silent=True, nthread=1)
```

```
skf = StratifiedKFold(n_splits=5, shuffle = True, random_state = 1001)

random_search = RandomizedSearchCV(xg, param_distributions=params, n_iter=5, scoring='r2',
                                   n_jobs=4, cv=skf.split(x,y_train), verbose=3, random_state=1001 )
```

```
random_search.fit(x,y_train)
random_search.best_params_
```

```
Fitting 5 folds for each of 5 candidates, totalling 25 fits
```

```
[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  25 out of  25 | elapsed:   45.1s finished
```

```
xg = XGBRegressor(learning_rate=0.02, n_estimators=600,
                    silent=True, nthread=1,subsample = 0.8,
                    min_child_weight= 1, max_depth = 4, gamma = 1,
                    colsample_bytree = 1.0)
```

```
xg.fit(x,y_train)
y_pred = xg.predict(x_t)
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
print("RMSE is: ",np.sqrt(mean_squared_error(y_test,y_pred)))
print("r2_score is: ",r2_score(y_test,y_pred))
```

Result:-

```
RMSE is:  43960.40768938855
r2_score is:  0.7480527695932312
```

The score was way less than Random Forest, so I've rejected this model. Then I checked with the following models.

3. Linear Regression with RFE

a. Lasso b. Ridge

Preparing the Data by reducing features using RFE

```python
# Eliminate features at a step 0.05*n_featurees
from sklearn.feature_selection import RFECV
from sklearn.model_selection import KFold
def feature_RFE(model,train_data,y_data):
    support = []
    n_features = []
    scores = []
    rfecv = RFECV(estimator=model, step=0.05, cv=KFold(5,random_state=0,shuffle=True))
    rfecv.fit(train_data, y_train)
    return rfecv
```

```python
# Now we run RFE for linear regression
from sklearn.linear_model import LinearRegression
lm  = LinearRegression()
rfecv = feature_RFE(lm,X_train,y_train)
```

```python
print("Optimal RFE number of features : %d" % rfecv.n_features_)
print("Feature Ranking: ")
print(rfecv.ranking_)
```

```
Optimal RFE number of features : 49
Feature Ranking:
[ 1  8  1  1  1  1  2  1  1  4  1  1  7  1  1  1  1  1  1 10  1  1  1  1
  2 11  1 11  1  1  1  1  1  1  6  3  4  5  5 11  9 10  1  1 10  1  1  9
  1  1  1  1  1  1  1  1  3  1  6  1  1  1  6  1  2  1  8  7  3  1  1  1
  8  5  7  4  9  1  1]
```

```python
from sklearn.feature_selection import RFE
lm.fit(X_train,y_train)
rfe = RFE(lm,49)
rfe.fit(X_train,y_train)
```

```
RFE(estimator=LinearRegression(), n_features_to_select=49)
```

```
rfe_scores = pd.DataFrame(list(zip(X_train.columns,rfe.support_,rfe.ranking_)))
rfe_scores.columns = ['Column_Names','Status','Rank']
rfe_sel_columns = list(rfe_scores[rfe_scores.Status==True].Column_Names)
```

Lets filter the train and test set for the RFE selected columns

```
X_train_lm = X_train[rfe_sel_columns]
X_test_lm = X_test[rfe_sel_columns]
```

```
X_train_lm.shape
```

```
(1168, 49)
```

3 a) Lasso regression model with Grid search CV

```
GridSearchCV(cv=KFold(n_splits=10, random_state=42, shuffle=True),
             estimator=Lasso(),
             param_grid={'alpha': [0.001, 0.01, 0.1, 1.0, 5.0, 10.0, 20.0]},
             return_train_score=True, scoring='r2', verbose=1)
```

```
lasso = Lasso(alpha=20)
lasso.fit(X_train_lm,y_train)

y_train_pred = lasso.predict(X_train_lm)
y_test_pred = lasso.predict(X_test_lm)

print(r2_score(y_true=y_train,y_pred=y_train_pred))
print(r2_score(y_true=y_test,y_pred=y_test_pred))
```

R2 Scores for Train and Test Data

```
0.8413407167403752
0.8115457630494485
```

3 b) Now lets use the ridge regression

```
GridSearchCV(cv=KFold(n_splits=10, random_state=42, shuffle=True),
             estimator=Ridge(),
             param_grid={'alpha': [0.001, 0.01, 0.1, 0.2, 0.5, 0.9, 1.0, 5.0,
                                   10.0, 20.0]},
             return_train_score=True, scoring='r2', verbose=1)
```

```
# Checking the best parameter(Alpha value)
model_cv.best_params_
```

```
{'alpha': 20.0}
```

```
ridge = Ridge(alpha=20)
ridge.fit(X_train_lm,y_train)

y_train_pred = ridge.predict(X_train_lm)
print(r2_score(y_train,y_train_pred))
y_test_pred = ridge.predict(X_test_lm)
print(r2_score(y_test,y_test_pred))
```

R2 Scores for Train and Test Data

```
0.8399787386121278
0.8112957990384801
```

Finally, after all the model testing, I’ve found Lasso Ridge to be the best performing model. Building final Model.

Final Model

```
lasso = Lasso(alpha=20)
lasso.fit(X_train_lm,y_train)

y_train_pred = lasso.predict(X_train_lm)
y_test_pred = lasso.predict(X_test_lm)

print(r2_score(y_true=y_train,y_pred=y_train_pred))
print(r2_score(y_true=y_test,y_pred=y_test_pred))
```

```
0.8413407167403752
0.8115457630494485
```

The R2 score is almost equal for both training and test data.

```
print("RMSE is: ",np.sqrt(mean_squared_error(y_test,y_pred)))
```

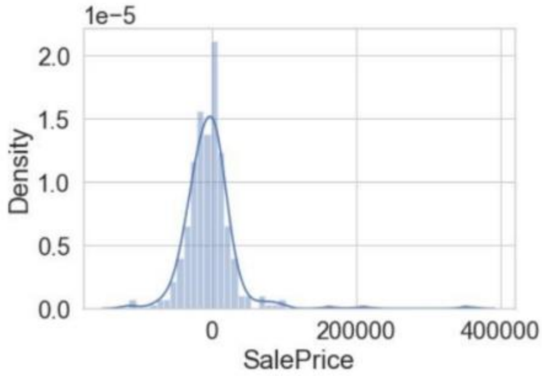
```
RMSE is:  43960.40768938855
```

```
sns.distplot(y_test-y_test_pred)
```

```
<AxesSubplot:xlabel='SalePrice', ylabel='Density'>
```

```
sns.distplot(y_test-y_test_pred)
```

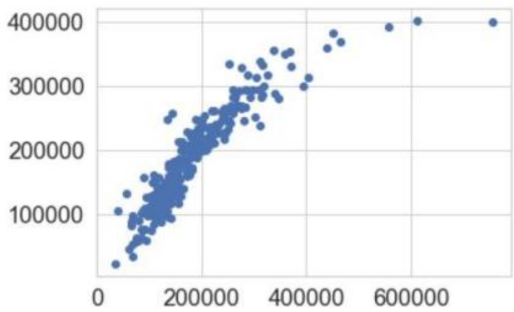
<AxesSubplot:xlabel='SalePrice', ylabel='Density'>




```
# We are getting an almost normal distribution in our predicted values
```

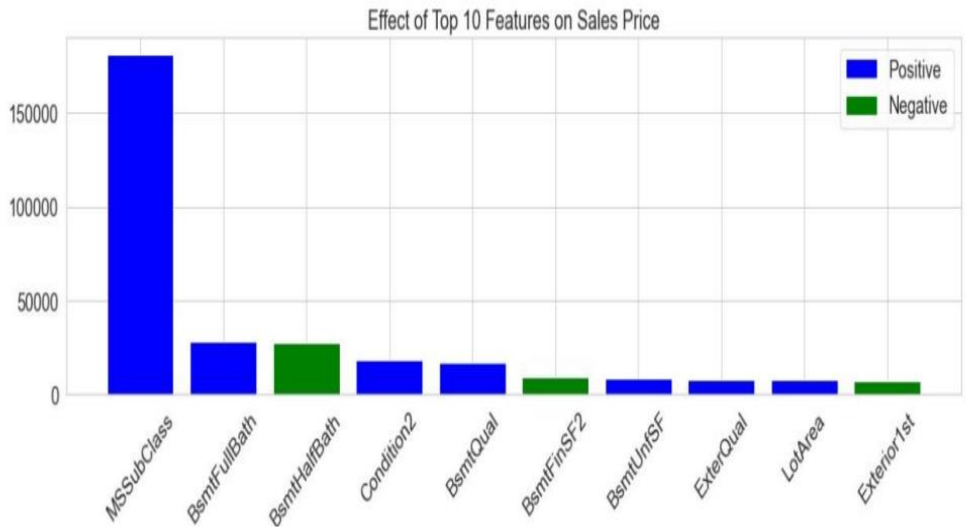
```
plt.scatter(y_test,y_test_pred)
```

<matplotlib.collections.PathCollection at 0x1a95d102130>



Top 10 Features Based on effect on Sales Price of House

	Feature	Coef	Coef_Absolute
0	MSSubClass	181441.541952	181441.541952
46	BsmtFullBath	28383.907099	28383.907099
47	BsmtHalfBath	-27781.415681	27781.415681
13	Condition2	18222.129811	18222.129811
29	BsmtQual	16988.777175	16988.777175
35	BsmtFinSF2	-9269.760718	9269.760718
36	BsmtUnfSF	8861.579874	8861.579874
26	ExterQual	8201.874033	8201.874033
3	LotArea	8057.779549	8057.779549
22	Exterior1st	-7578.851452	7578.851452



CONCLUSION

• Key Findings and Conclusions of the Study:

• MS Sub Class seems to have the biggest impact on House Prices, followed by Basement Full Bath and Basement Half Bath
• Other than the Basement related features, Condition 2, Exterior Quality and Lot Area are some of the other important features.
• Learning Outcomes of the Study in respect of Data Science
• Got to understand about the concept of Data Leakage. All transformation must be done after splitting the data to test and train, otherwise the parameters are affected.
• Used RFE for the first time. It is a great technique for Feature Selection.
• Learned about the usage of Lasso and Ridge Regression.

• Limitations of this work and Scope for Future Work
The `biggest limitation I observed was that not all categories of a particular feature were available in the training data. So, if there is a new category in the test data/new data, the model would not be able to identify the new categories.

Example: All 8 categories in MSZoning are:

MSZoning: Identifies the general zoning classification of the sale.

A	Agriculture
C	Commercial
FV	Floating Village Residential
I	Industrial
RH	Residential High Density
RL	Residential Low Density
RP	Residential Low Density Park
RM	Residential Medium Density

Thankyou for watching