FLIP ROBO

HOUSE PRICE PREDICITION

Submitted by:

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ACKNOWLEDGMENT

Following are the references used in this House price prediction project:

- https://www.cse.ust.hk/~rossiter/independent_studies_projects/real_estate_prediction/real_estate_report.pdf
- https://towardsdatascience.com/create-a-model-to-predict-house-prices-using-python-d34fe8fad88f
- https://yalantis.com/blog/predictive-algorithm-for-house-price/

INTRODUCTION

- Business Problem Framing:

We are required to model the price of houses with the available independent variables. This model will 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:

A US-based housing company named Surprise Housing has comes up with a decision to enter the Australian market in the Real Estate Industry. 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.

> The company is looking at prospective properties to buy houses to enter the market. I need 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.

- Review of Literature:

Houses are one of the necessary need of each and every person around the globe 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 large 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. As per the requirement the company is looking at prospective properties to buy houses to enter the market. I need 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?

- Motivation for the Problem Undertaken:

  This project helps me understand the House price prediction for a foreign country (Australia) and the real estate industry and its customer behaviour. With the right set of datasets in hand I have built a model that helps the enterprise take the right decision that is whether to enter into the market and invest in housing property or nor and the selling price of the property. This also motivate learn about real estate industry in details and how it helps build the economic development in the particular country.

Analytical Problem Framing

- Mathematical/ Analytical Modelling of the Problem:

In this particular project I need to understand whether to invest in the Australian market and in real estate industry and what are the important factors to predict the price of the house. I have used a Gradient Boosting Regressor model to predict the housing pricing and could help the client in further investment in this particular Australians market and into property segment and improvement in choice of consumers.

- Data Sources and their formats:
- Data sources are provided internally by the enterprise.

  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
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

MasVnrType: Masonry veneer type

BrkCmn	Brick Common
BrkFace	Brick Face
CBlock	Cinder Block
None	None
Stone	Stone

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

Ex	Excellent
Gd	Good
TA	Average/Typical
Fa	Fair
Po	Poor

ExterCond: Evaluates the present condition of the material on the exterior

Ex	Excellent
Gd	Good
TA	Average/Typical
Fa	Fair
Po	Poor

Foundation: Type of foundation

BrkTil	Brick & Tile
CBlock	Cinder Block
PConc	Poured Contrete
Slab	Slab
Stone	Stone
Wood	Wood

BsmtQual: Evaluates the height of the basement

Ex	Excellent (100+ inches)
Gd	Good (90-99 inches)
TA	Typical (80-89 inches)
Fa	Fair (70-79 inches)
Po	Poor (<70 inches
NA	No Basement

BsmtCond: Evaluates the general condition of the basement

Ex	Excellent
Gd	Good
TA	Typical - slight dampness allowed
Fa	Fair - dampness or some cracking or settling
Po	Poor - Severe cracking, settling, or wetness
NA	No Basement

BsmtExposure: Refers to walkout or garden level walls

Gd	Good Exposure
Av	Average Exposure (split levels or foyers typically score average or above)
Mn	Mimimum Exposure
No	No Exposure
NA	No Basement

BsmtFinType1: Rating of basement finished area

GLQ	Good Living Quarters

ALQ	Average Living Quarters
BLQ	Below Average Living Quarters
Rec	Average Rec Room
LwQ	Low Quality
Unf	Unfinshed
NA	No Basement

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Rating of basement finished area (if multiple types)

GLQ	Good Living Quarters
ALQ	Average Living Quarters
BLQ	Below Average Living Quarters
Rec	Average Rec Room
LwQ	Low Quality
Unf	Unfinshed
NA	No Basement

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of basement area

TotalBsmtSF: Total square feet of basement area

Heating: Type of heating

Floor	Floor Furnace
GasA	Gas forced warm air furnace
GasW	Gas hot water or steam heat
Grav	Gravity furnace
OthW	Hot water or steam heat other than gas
Wall	Wall furnace

HeatingQC: Heating quality and condition

Ex	Excellent
Gd	Good
TA	Average/Typical
Fa	Fair

Po Poor

CentralAir: Central air conditioning

N No
Y Yes

Electrical: Electrical system

SBrkr	Standard Circuit Breakers & Romex
FuseA	Fuse Box over 60 AMP and all Romex wiring (Average)
FuseF	60 AMP Fuse Box and mostly Romex wiring (Fair)
FuseP	60 AMP Fuse Box and mostly knob & tube wiring (poor)
Mix	Mixed

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

Bedroom: Bedrooms above grade (does NOT include basement bedrooms)

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

Ex Excellent
Gd Good

TA Typical/Average
Fa Fair
Po Poor

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality (Assume typical unless deductions are warranted)

Typ Typical Functionality
Min1 Minor Deductions 1
Min2 Minor Deductions 2
Mod Moderate Deductions
Maj1 Major Deductions 1
Maj2 Major Deductions 2
Sev Severely Damaged
Sal Salvage only

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

Ex Excellent - Exceptional Masonry Fireplace
Gd Good - Masonry Fireplace in main level
TA Average - Prefabricated Fireplace in main living area or Masonry Fireplace in basement
Fa Fair - Prefabricated Fireplace in basement
Po Poor - Ben Franklin Stove
NA No Fireplace

GarageType: Garage location

2Types More than one type of garage
Attchd Attached to home
Basement Basement Garage
BuiltIn Built-In (Garage part of house - typically has room above garage)
CarPort Car Port
Detchd Detached from home
NA No Garage

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

Fin	Finished
RFn	Rough Finished
Unf	Unfinished
NA	No Garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

Ex	Excellent
Gd	Good
TA	Typical/Average
Fa	Fair
Po	Poor
NA	No Garage

GarageCond: Garage condition

Ex	Excellent
Gd	Good
TA	Typical/Average
Fa	Fair
Po	Poor
NA	No Garage

PavedDrive: Paved driveway

Y	Paved
P	Partial Pavement
N	Dirt/Gravel

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

Ex	Excellent
Gd	Good
TA	Average/Typical
Fa	Fair
NA	No Pool

Fence: Fence quality

GdPrv	Good Privacy
MnPrv	Minimum Privacy
GdWo	Good Wood
MnWw	Minimum Wood/Wire
NA	No Fence

MiscFeature: Miscellaneous feature not covered in other categories

Elev	Elevator
Gar2	2nd Garage (if not described in garage section)
Othr	Other
Shed	Shed (over 100 SF)
TenC	Tennis Court
NA	None

MiscVal: $Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

WD Warranty Deed - Conventional
CWD Warranty Deed - Cash
VWD Warranty Deed - VA Loan
New Home just constructed and sold
COD Court Officer Deed/Estate
Con Contract 15% Down payment regular terms
ConLw Contract Low Down payment and low interest
ConLI Contract Low Interest
ConLD Contract Low Down
Oth Other

SaleCondition: Condition of sale

Normal Normal Sale
Abnorml Abnormal Sale - trade, foreclosure, short sale
AdjLand Adjoining Land Purchase
Alloca Allocation - two linked properties with separate deeds, typically condo with a garage unit
Family Sale between family members
Partial Home was not completed when last assessed (associated with New Homes)

- Data Pre-processing:

In the data pre-processing stage, I have found out if there is any missing data in dataset, for a particular column if there are any outliers present and how to handle the outliers. I have also dropped a few columns that are not require for model building process. I have also found the total shape of the data set. I have also found out the dataset description using describe method. So, in this pre-processing process I have mainly cleansed the data and prepared the right set of data for further processing & for predicting the model.

- Data Inputs- Logic- Output Relationships:

  To find out the relationship between all the input variable I have used correlation function and find out whether there is a positive/negative relationship between a pair of variables. From this describe function that also known as Five-point summary analysis if there are any outliers are present for a particular column. Also five point summary analysis was done for the target variable to explore & understand the data in a better way.

- State the set of assumptions (if any) related to the problem under consideration:

  Since all the dataset provided and defined properly so in this dataset, I assume Sale Price/LogofPrice as the target variable for this project. Rest of the parameters are used as input variables.

- Hardware and Software Requirements and Tools Used:

  For this particular dataset the Hardware is used Windows as operating system, and the software used are mainly Jupyter notebook for model building and various internal packages that are defined in the anaconda/jupyter notebook.

Model/s Development and Evaluation

- Identification of possible problem-solving approaches (methods):

  For this particular project I have used different Regression models to predict the outcome of this dataset. After the model implementation GradientBoostinRegressor method predicted the best outcome out of all the process in terms of accuracy score and also I have used cross validation to flag the problem related overfitting or selection bias for the dataset and hence we can use this model for further evaluation.

- Testing of Identified Approaches (Algorithms):

I have used mainly different Regression methods to get the outcome of the house price prediction and 75% data used for training purpose and rest 25% are used for testing the prediction of the accuracy score for this machine learning model building process.

- Run and Evaluate selected models:

  To predict the result of this dataset below are machine learning models used for evaluations.

ML Algorithm Used	Predicted Score
Random Forest Regressor	87.54%
Decision Tree Regressor	77.86%
Gradient Boosting Regressor	90.18%
Ada Boosting Regressor	83.43%
Extra Tree Regressor	87.50%
Linear Regression	88.39%

Out of all the machine learning models used I have selected Gradient Boosting Regressor model for further evaluation of this project.

- Key Metrics for success in solving problem under consideration

  The key metrics that were mainly taken into consideration were the followings:

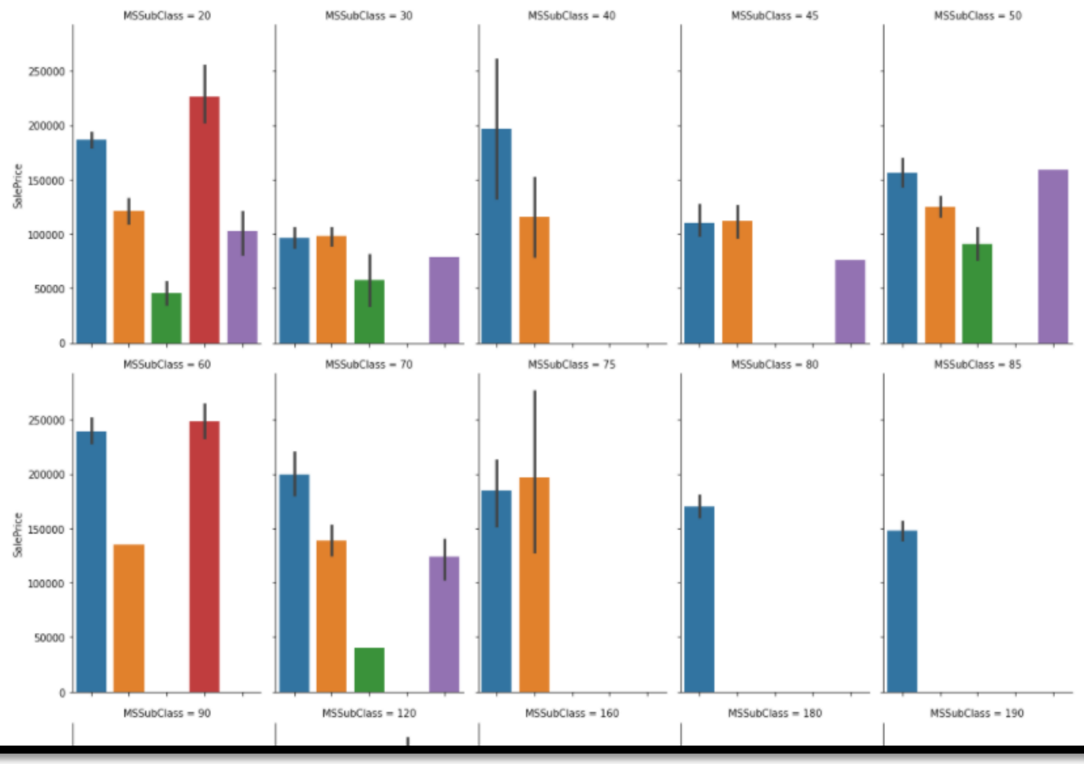
  - Saleprice
  - Neighborhood
  - MSSubClass

- MSZoning
- SaleType
- Condition1
- Condition2
- SaleCondition

These are the prime metrics under consideration, but there are factors too can be considered for solving the house price prediction.

- Visualizations

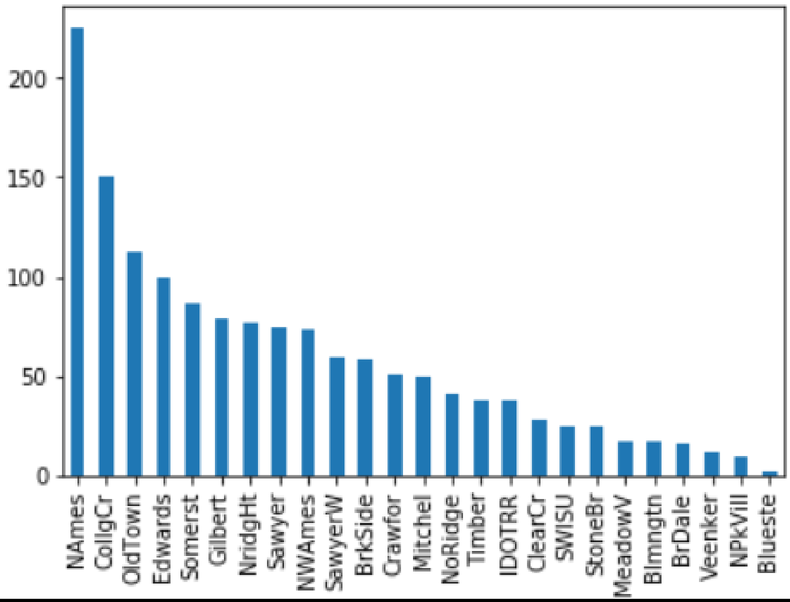
```
In [25]: sns.factorplot(x='MSZoning', y='SalePrice', col='MSSubClass', data=df, kind='bar', col_wrap=5, aspect=0.6)

C:\Users\sodainmind\anaconda3\lib\site-packages\seaborn\categorical.py:3669: UserWarning: The `factorplot` function has been re
named to `catplot`. The original name will be removed in a future release. Please update your code. Note that the default `kind
` in `factorplot` (`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)

Out[25]: <seaborn.axisgrid.FacetGrid at 0x18d52b8a4c8>
```



From the above factorplot I have understand the general zoning classification of the sale and sale price for the particular zone and also find out the type of dwelling involved in the sale of the house.

```
df['Neighborhood'].value_counts().plot(kind='bar')
```

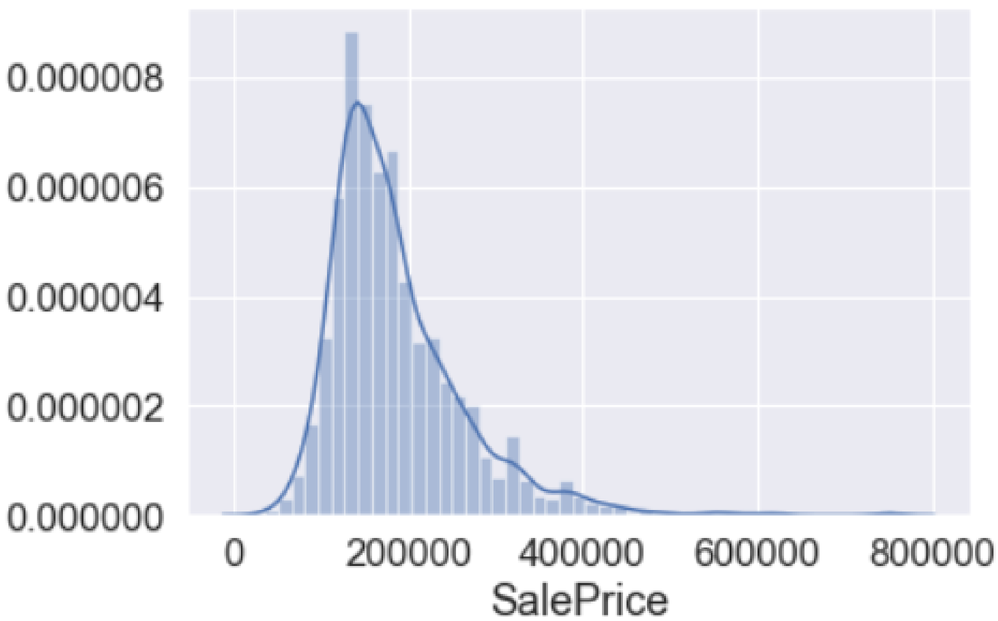
```
<matplotlib.axes._subplots.AxesSubplot at 0x18d58d01748>
```



From the above bar plot I have understand the Physical locations within city limits.

```
sns.distplot(df.SalePrice)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x18d5a787988>
```



From the above distribution plot I got to know how the house sales price are distributed using the univariate analysis.

- Interpretation of the Results

  - Gradient Boosting Regressor algorithm predict best result for this dataset.
  - I have also find out the RMSE score that is 0.015 for the predicted value of gradient boosting regressor algorithm technique.
  - I have also find out the Ridge (reduce the model complexity by keeping all the parameters) & Lasso (minimize the error also find out the shrinkage) method using cross validation technique to optimized the model for prediction and regularize (**some bias over high variance**) it.

CONCLUSION

- Key Findings and Conclusions of the Study:
  - I used various regressor methods and out of all machine learning algorithm used, Gradient boosting Regressor yields the best results.
  - This house price prediction can be used market development as well as for economic development of the country.
- Learning Outcomes of the Study in respect of Data Science:

  As per as learning outcomes is concerned, I have learnt the following things:

  - Algorithm need to be used by understanding the dataset.

- From describe method we can get some knowledge related to outliers present in the particular columns (large difference between 75th percentile and maximum percentile)
- I also understand the visualization of related features and importance related to dataset.

Challenges:

- It was difficult to load the dataset in notebook as it took some time.
- Running each line code was a bit slow in notebook, possibly due to high volume of data.
- Since the sale price is depends on too many factors so understanding dynamic pricing was a bit challenging but further research can be done on this to understand it in a better way.

- Limitations of this work and Scope for Future Work:
  - Since I have only used a sample dataset, hence sometimes it is difficult to understand the overall impact of this house price prediction process.

  - I have not used the Elastic Net regressor method for predicting the outcome, otherwise I would have find out the ridge regression coefficient and then done step by step lasso sort shrinkage coefficient then the predicted outcome may have been be better.