HOUSING: PRICE PREDICTION

Submitted by:

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Sample Documentation and Data Description without which working in this project would have been very challenging .

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INTRODUCTION

Problem Statement:

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.

- Conceptual Background of the Domain Problem

  Observation Based on the above data, we can drop the following columns - LotFrontage - Alley - FireplaceQu - PoolQC - Fence - MiscFeature - Id (dropping this not because of count, irrelevant) - MoSold (dropping this not because of count, irrelevant) - Street (dropping this not because of count, irrelevant) - Utilities (dropping this not because of count, irrelevant)

- Review of Literature

The company is looking at prospective properties to buy houses to enter the market. You are 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?

- ## Motivation for the Problem Undertaken

It is 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.

Analytical Problem Framing

- ## Mathematical/ Analytical Modeling of the Problem

Data contains 1460 entries each having 81 variables.
Data contains Null values. We need to treat them using the domain knowledge and our own understanding.
Extensive EDA has to be performed to gain relationships of important variable and price.
Data contains numerical as well as categorical variable. We need to handle them accordingly.
We have to build Machine Learning models, apply regularization and determine the optimal values of Hyper Parameters.
We need to find important features which affect the price positively or negatively.
Two datasets are being provided to you (test.csv, train.csv). We will train on train.csv dataset and predict on test.csv file.

```
In [4]:
print(test.shape)
print(train.shape)

(292, 80)
(1168, 81)
```

- ## 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 .

: 1 train

```
train
```

:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Co
0	127	120	RL	NaN	4928	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	NPkVill	Norm	
1	889	20	RL	95.0	15865	Pave	NaN	IR1	Lvl	AllPub	Inside	Mod	NAmes	Norm	
2	793	60	RL	92.0	9920	Pave	NaN	IR1	Lvl	AllPub	CulDSac	Gtl	NoRidge	Norm	
3	110	20	RL	105.0	11751	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	NWAmes	Norm	
4	422	20	RL	NaN	16635	Pave	NaN	IR1	Lvl	AllPub	FR2	Gtl	NWAmes	Norm	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1163	289	20	RL	NaN	9819	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	Sawyer	Norm	
1164	554	20	RL	67.0	8777	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	Edwards	Feedr	
1165	196	160	RL	24.0	2280	Pave	NaN	Reg	Lvl	AllPub	FR2	Gtl	NPkVill	Norm	
1166	31	70	C (all)	50.0	8500	Pave	Pave	Reg	Lvl	AllPub	Inside	Gtl	IDOTRR	Feedr	
1167	617	60	RL	NaN	7861	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	Gilbert	Norm	

1168 rows × 81 columns

n [5]: 1 test

ut[5]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Co
0	337	20	RL	86.0	14157	Pave	NaN	IR1	HLS	AllPub	Corner	Gtl	StoneBr	Norm	
1	1018	120	RL	NaN	5814	Pave	NaN	IR1	Lvl	AllPub	CulDSac	Gtl	StoneBr	Norm	
2	929	20	RL	NaN	11838	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	
3	1148	70	RL	75.0	12000	Pave	NaN	Reg	Bnk	AllPub	Inside	Gtl	Crawfor	Norm	
4	1227	60	RL	86.0	14598	Pave	NaN	IR1	Lvl	AllPub	CulDSac	Gtl	Somerst	Feedr	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
287	83	20	RL	78.0	10206	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	Somerst	Norm	
288	1048	20	RL	57.0	9245	Pave	NaN	IR2	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	
289	17	20	RL	NaN	11241	Pave	NaN	IR1	Lvl	AllPub	CulDSac	Gtl	NAmes	Norm	
290	523	50	RM	50.0	5000	Pave	NaN	Reg	Lvl	AllPub	Corner	Gtl	BrkSide	Feedr	
291	1379	160	RM	21.0	1953	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	BrDale	Norm	

292 rows × 80 columns

- Data Pre-Processing

Storing null values in train , then printing columns with more than 0 null values

Impute missing values

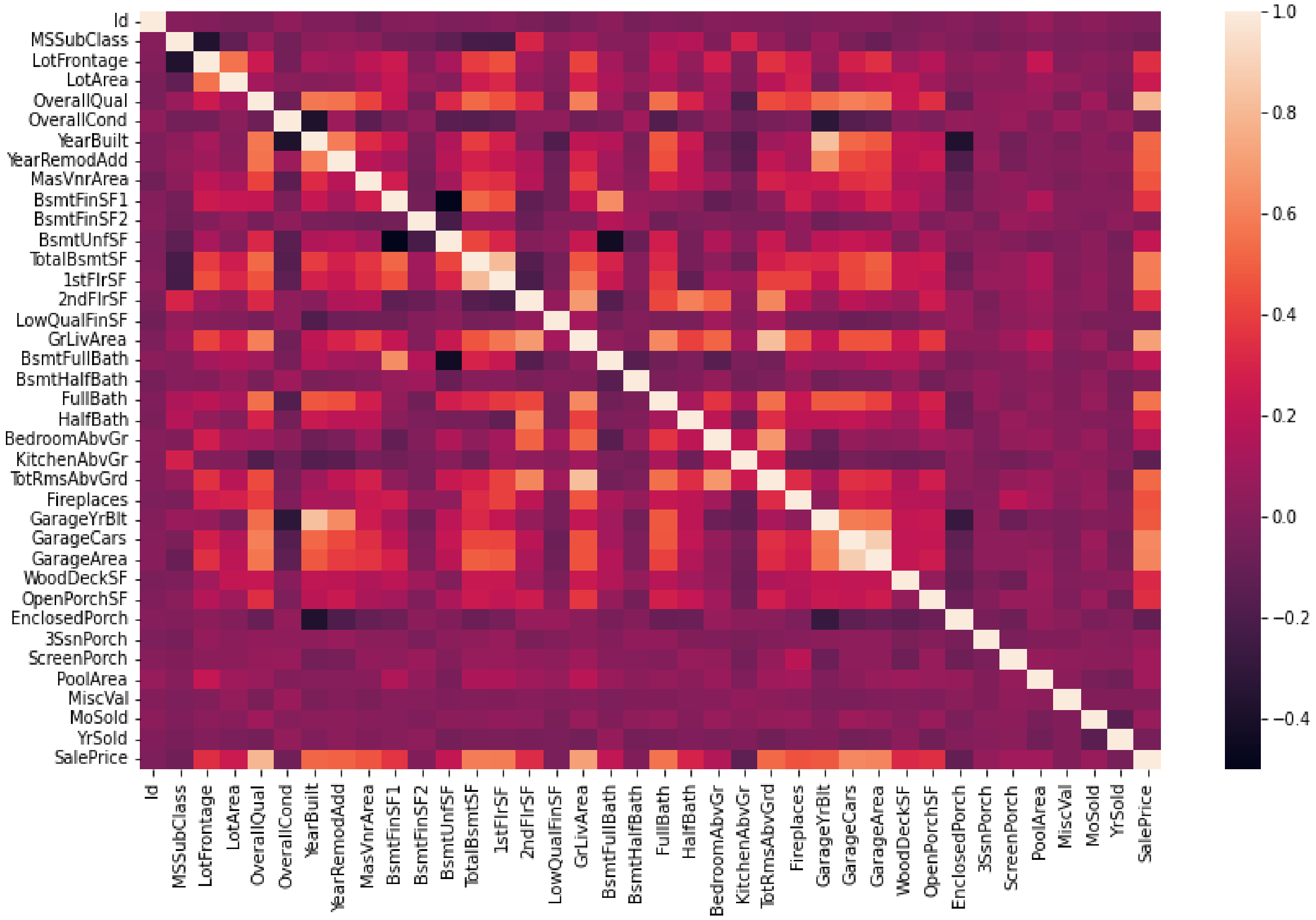
Dropping columns which has around 50 percent missing values

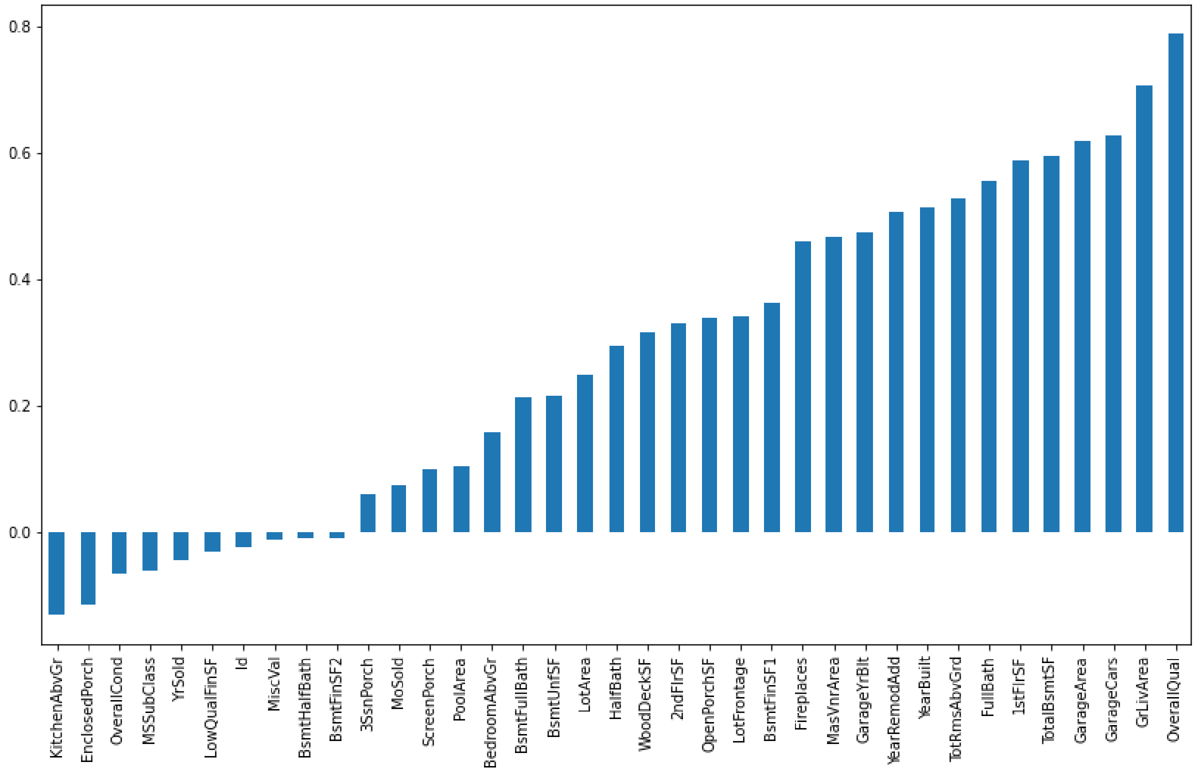
Selecting categorical features and level encoding

Label encoding of input features

Scaling input and test data using StandardScaler module.

- Data Inputs- Logic- Output Relationships





- Hardware and Software Requirements and Tools Used

The General Hardware used for this project is :-

8 GB RAM

512GB SSD

Intel i5 processor

The Software and tools used for this project is :-

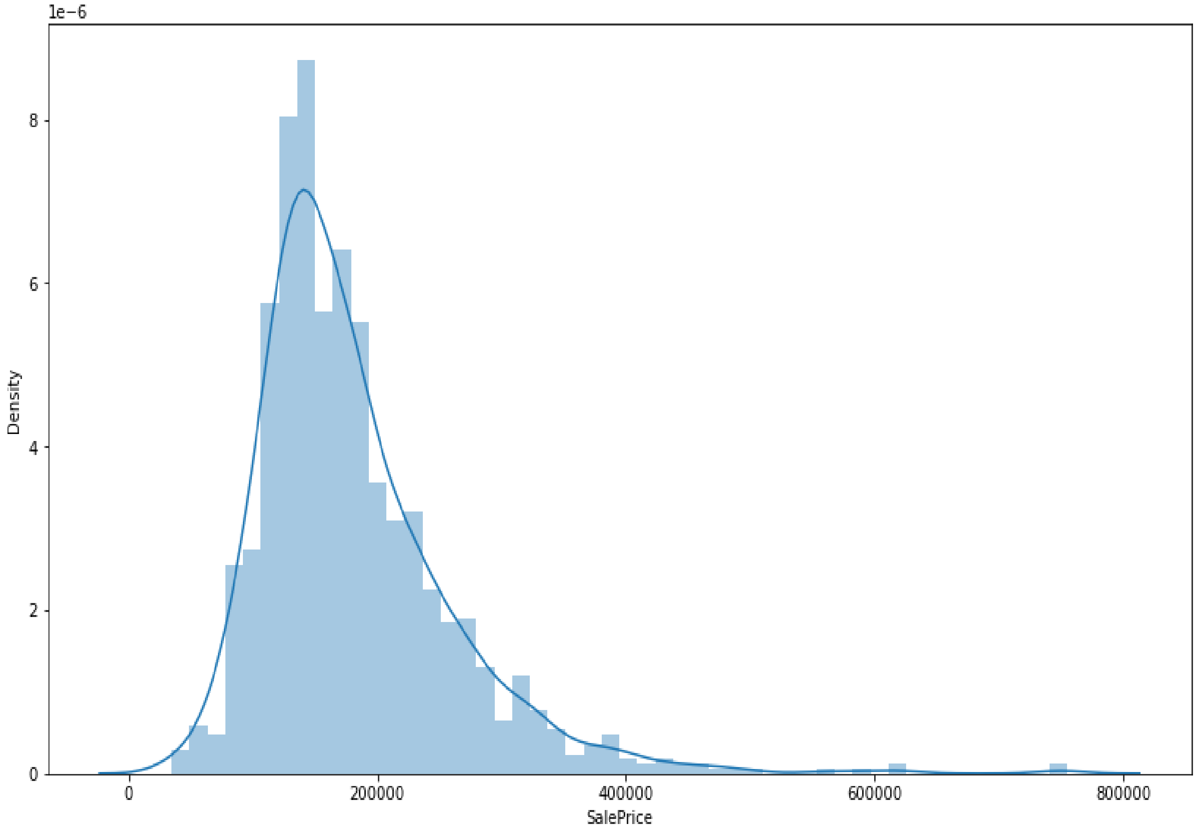
Python (Jupyter Notebook)

Scikit Learn

Various tools :- Pandas , Matplotlib , NumPy , Seaborn etc

Model/s Development and Evaluation

Following is the distribution plot of MarketValue which is our Target.



The Different Models which are used are :-

1. Linear Regression
2. Ridge Regression
3. XGB Regressor
4. Random forest model
5. Decision Tree Regressor
6. Ada AdaBoost Regressor

CONCLUSION

We used various different types of models and used RSME score to determine which model is best.

Root mean squared error (RMSE) is the square root of the mean of the square of all of the error.

1) Linear Regression

In [143]:
```
# Linear Regression
lr = LinearRegression()
lr.fit(x,y)
predictions = lr.predict(test)
predict = np.exp(predictions)
lr.score(x, y)
```

Out[143]: 0.8356490151289271

In [136]:
```
# RMSE score of Linear Regression
ypred_lr=lr.predict(test)
print('RMSE of Linear Regression: ',mse(y,ypred_lr)**1/2)
```

```
RMSE of Linear Regression:  513778348.6236443
```

2) Ridge Regression

In [144]:
```
# Ridge Regression
from sklearn.linear_model import Ridge
ri = Ridge(alpha=20)
ri.fit(x,y)
predictions = ri.predict(test)
predict = np.exp(predictions)
ri.score(x,y)
```

Out[144]: 0.8355653574947441

In [138]:
```
# RMSE score of Ridge
ypred_ri=ri.predict(test)
print('RMSE of Ridge: ',mse(y,ypred_ri)**1/2)
```

```
RMSE of Ridge:  514050338.7360278
```

3) XGB Regressor

In [145]:
```
# XGB Regressor
from xgboost import XGBRegressor
xgb = XGBRegressor()
xgb.fit(x,y)
predictions = xgb.predict(test)
predict = np.exp(predictions)
xgb.score(x,y)
```

Out[145]: 0.9998657151440404

In [139]:
```
# RMSE score of XGB Regressor
ypred_xgb=xgb.predict(test)
print('RMSE of XGBRegressor: ',mse(y,ypred_xgb)**1/2)
```

```
RMSE of XGBRegressor:  419797.0369346566
```

4) Random forest model

In [132]:
```
# Random forest model
model_rf=RandomForestRegressor(n_estimators=500)
model_rf.fit(x,y)
model_rf.score(x,y)
```

Out[132]: 0.9797036141489379

In [140]:
```
# RMSE score of Random Forest
ypred_rf=model_rf.predict(test)
print('RMSE of Random Forest: ',mse(y,ypred_rf)**1/2)
```

```
RMSE of Random Forest:  63449914.5854991
```

5) Decision Tree Regressor

In [133]:
```
# Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor
model_dt=DecisionTreeRegressor(criterion='mse')
model_dt.fit(x,y)
model_dt.score(x,y)
```
Out[133]: 1.0

In [141]:
```
# RMSE score of Decision Tree
ypred_dt=model_dt.predict(test)
print('RMSE value of Decision Tree: ',mse(y,ypred_dt)**1/2)
```
```
RMSE value of Decision Tree:  0.0
```

6) Ada AdaBoost Regressor

In [134]:
```
# AdaAdaBoostRegressor
from sklearn.ensemble import AdaBoostRegressor
model_adb=AdaBoostRegressor(n_estimators=300)
model_adb.fit(x,y)
model_adb.score(x,y)
```
Out[134]: 0.8542028130266888

In [142]:
```
# RMSE score of AdaBoost Forest
ypred_adb=model_adb.predict(test)
print('RMSE of AdaBoost: ',mse(y,ypred_adb)**1/2)
```
```
RMSE of AdaBoost:  455786519.2427143
```

We can see that the Decision tree is the best model, with best RSME score .