FLIP ROBO

House Price Prediction

Submitted by:

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ACKNOWLEDGMENT

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INTRODUCTION

- ## Business Problem Statement
  - 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 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?
- ## Conceptual Background of the Domain Problem

  - Houses are one of the necessary needs 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.

Review
  - 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.

- ## Motivation for the Problem Undertaken
  - Having lived in India for so many years if there is one thing that I had been taking for granted, it's those housing and rental prices continue to rise. Housing prices have recovered remarkably well, especially in major housing markets.

- So, to maintain the transparency among customers and also the comparison can be made easy through this model. If customer finds the price of house at some given website higher than the price predicted by the model, so he can reject that house.
- So we have to predict the pricing as per customers requirement and needs.

Analytical Problem Framing

- ## Dataset Representation:

```
data_train=pd.read_csv("D:\\fliprobo\\project\\P4\\Project-Housing--2-\\Project-Housing_splitted\\train.csv")
data_test=pd.read_csv("D:\\fliprobo\\project\\P4\\Project-Housing--2-\\Project-Housing_splitted\\test.csv")
```

```
data_train.head(5)
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	Mo
0	127	120	RL	NaN	4928	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	
1	889	20	RL	95.0	15865	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	
2	793	60	RL	92.0	9920	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	
3	110	20	RL	105.0	11751	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0	
4	422	20	RL	NaN	16635	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	

5 rows × 81 columns

Observation:

1. Seeing the data, we have to build a model which can be used to predict the SalePrice.
2. The data seems to be a combination of both numerical and categorical features.

So clearly it is a regression problem.

- ## Data Sources and their formats & inferences

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

Neighbourhood: 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
NAmes	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 positive 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 positive 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 remodelling or additions)

RoofStyle: Type of roof

Flat	Flat
Gable	Gable
Gambrel	Gabrel (Barn)
HipHip	
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)
MnMimimum 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
SevSeverely 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
Basment 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)

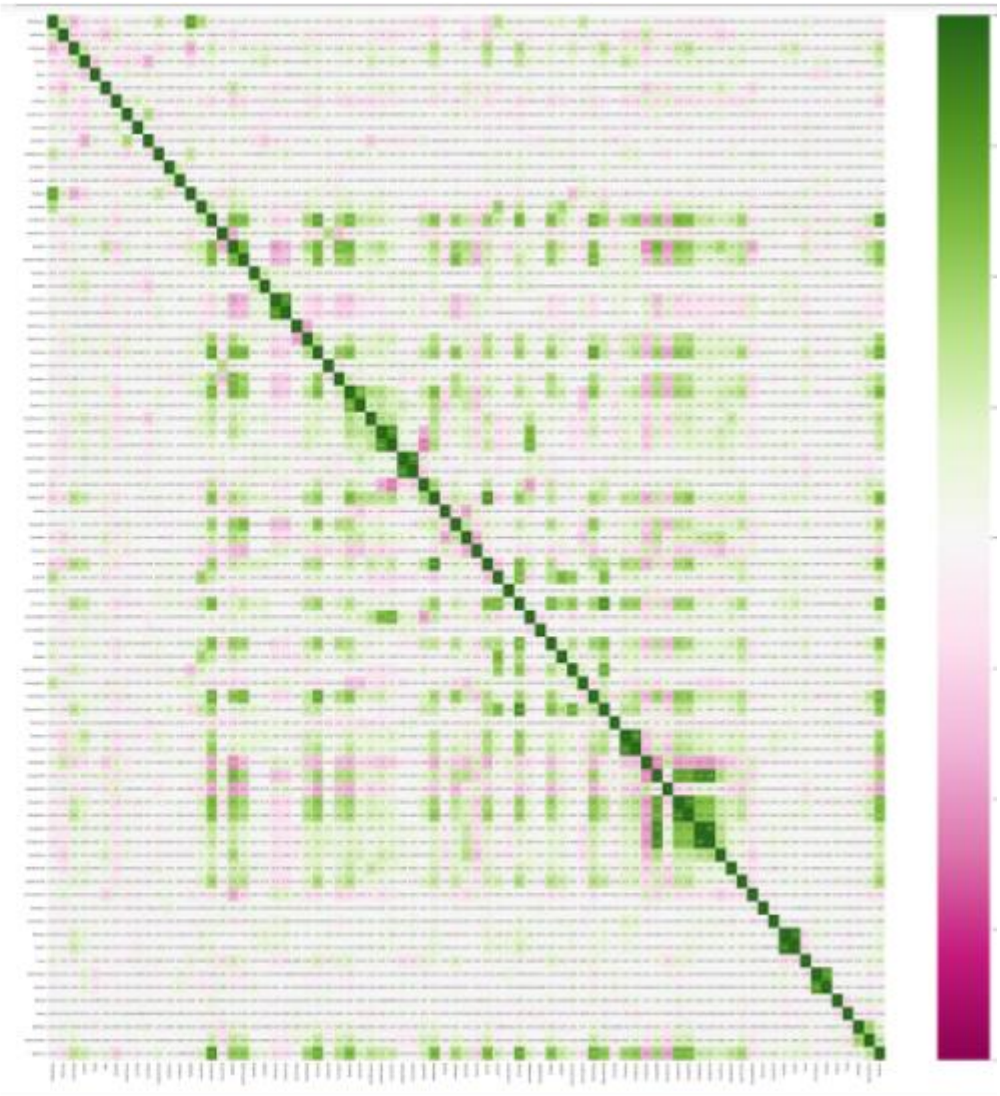
SaleType: Type of sale

    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**
  a. Removed Null- values from the dataset by replacing null values with not available.
  b. Dropped Utilities and Id features as Id Consist for houses is unique and the utilities for each house were same.
  c. GarageBuilt this type feature has null values so we replaced it by 1800 because such null values are because of no garage in the houses and replaced by 1800 so that no- high variance will occur in the dataset.
  d. LotFrontage: This feature is of object as there were some methods in it because of which it transformed to object type so we replaced it by its mean.
  e. We transformed Categorical values into Integer type by replacing for some features because there some features whose values was not in the test dataset while it was in train dataset. And for some features that were telling about condition and quality so I replace it by their respective no. in ordered way like Excellent we give 10 while for poor 0. Otherwise for all categorical feature I used Label Encoder technique.
- **Data Inputs- Logic- Output Relationships**
- **Multi-Colinearity :**



Observations:

- Exterior1st & Exterior2nd ---> 80% collinear to each other.
- GrLivArea & TotRmsAbvGrd are 82% collinear to each other.
- TotalBsmtSF&1stFlrSF--->81% collinear with each other.
- BsmtFinSF2&BsmtFinType2 ----> -81% collinear.
- BsmtFinSF1&BsmtFinType1 ----> -73% collinear.
- GarageCars & GarageArea ----> 88% collinear to each other.
- FirePlace&FireQual are 72% collinear to each other.
- MiscFeature & MiscVal are 78% collinear to each other.
- PoolArea & PoolQC are collinear about -93%.

- Assumption for the problem:

So clearly it is a Regression problem.

- Hardware and Software Requirements and Tools Used

  Software Used:

    - Jupyter Notebook
    - Ms-Paint
    - MS-PowerPoint
    - MS-Word

  Hardware used:

    - Laptop
    - Good internet connectivity

Model/s Development and Evaluation

- Identification of possible problem-solving approaches (methods)

    - ✓ Used PCA i.e., Principal Component Analysis for feature Selection.
    - ✓ Reduced Skewness from the dataset.
    - ✓ Reduced Outliers using Z-Score technique
    - ✓ Dropped columns on the basis multi-Collinearity
    - ✓ Used Square root for some feature to reduce the variance.

- **Testing of Identified Approaches (Algorithms)**

➢ Used 8 models that are:

- ✓ Linear Regression
- ✓ Decision Tree
- ✓ Random Forest
- ✓ Gradient Boosting
- ✓ AdaBoost
- ✓ Bagging
- ✓ Support Vector Machine

✓ Xtreme Gradient Boost

- Run and Evaluate selected models

Code:

```
Linear=LinearRegression()
DecisionTree=DecisionTreeRegressor()
RandomForest=RandomForestRegressor()
AdaBoost=AdaBoostRegressor()
Bagging=BaggingRegressor()
knn=KNeighborsRegressor()
GB=GradientBoostingRegressor()
xgb_=xgb.XGBRegressor()
SVM=SVR()
algo=[Linear,DecisionTree,Bagging,RandomForest,AdaBoost,SVM,xgb_,GB]
```

```
model_acc_rs={}
maximum_acc=[]
for model in algo:
    max_accuracy=0
    for i in range(100,300,3):
        X_train,X_test,Y_train,Y_test=train_test_split(X_,Y,test_size=0.2,random_state=i)
        model.fit(X_train,Y_train)
        Y_pred=model.predict(X_test)
        accuracy=r2_score(Y_test,Y_pred)*100
        if accuracy>max_accuracy:
            max_accuracy=accuracy
            rs=i
            mae=mean_absolute_error(Y_test,Y_pred)
            mse=mean_squared_error(Y_test,Y_pred)
            rmse=np.sqrt(mean_squared_error(Y_test,Y_pred))
    maximum_acc.append(max_accuracy)
    model_acc_rs[model]=[max_accuracy,rs]
    print(f"\n\n{model}:\n-------------------------\n-------------------------\n")
    print(f"The highest accuracy is {max_accuracy} of model {model} at random state {rs}")


    print("\nMEAN ABSOLUTE ERROR:",mae)

    print(f"\nMEAN SQUARED ERROR for the model:",mse)

    print(f"\nROOT MEAN SQUARED ERROR for the model:",rmse)
```

Output:

```
LinearRegression():
---------------------------
---------------------------

The highest accuracy is 83.74382264988157 of model LinearRegression() at random state 265

MEAN ABSOLUTE ERROR: 0.21047610641617584

MEAN SQUARED ERROR for the model: 0.07252010324974262

ROOT MEAN SQUARED ERROR for the model: 0.2692955685668493


DecisionTreeRegressor():
---------------------------
---------------------------

The highest accuracy is 76.81395032699955 of model DecisionTreeRegressor() at random state 121

MEAN ABSOLUTE ERROR: 0.27608817757009346

MEAN SQUARED ERROR for the model: 0.16016224349485983

ROOT MEAN SQUARED ERROR for the model: 0.4002027529826098


BaggingRegressor():
---------------------------
---------------------------

The highest accuracy is 85.81038319493597 of model BaggingRegressor() at random state 265

MEAN ABSOLUTE ERROR: 0.18003154672897198

MEAN SQUARED ERROR for the model: 0.06330101189318223

ROOT MEAN SQUARED ERROR for the model: 0.25159692345730744
```

```
RandomForestRegressor():
---------------------------
---------------------------

The highest accuracy is 86.95452962214638 of model RandomForestRegressor() at random state 232

MEAN ABSOLUTE ERROR: 0.1810994172897196

MEAN SQUARED ERROR for the model: 0.07526532731106444

ROOT MEAN SQUARED ERROR for the model: 0.27434527025459077


AdaBoostRegressor():
---------------------------
---------------------------

The highest accuracy is 78.54854539910119 of model AdaBoostRegressor() at random state 241

MEAN ABSOLUTE ERROR: 0.2532571475529633

MEAN SQUARED ERROR for the model: 0.12241932774262242

ROOT MEAN SQUARED ERROR for the model: 0.3498847349379827


SVR():
---------------------------
---------------------------

The highest accuracy is 87.46977883412816 of model SVR() at random state 265

MEAN ABSOLUTE ERROR: 0.17519935799998998

MEAN SQUARED ERROR for the model: 0.05589831564457652

ROOT MEAN SQUARED ERROR for the model: 0.23642824629171644
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=4,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None):
---------------------------
---------------------------

The highest accuracy is 86.53285946032526 of model XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=4,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None) at random state 265

MEAN ABSOLUTE ERROR: 0.18244316520690917

MEAN SQUARED ERROR for the model: 0.060077987670877124

ROOT MEAN SQUARED ERROR for the model: 0.2451081142493596


GradientBoostingRegressor():
---------------------------
---------------------------

The highest accuracy is 89.22902650943777 of model GradientBoostingRegressor() at random state 265

MEAN ABSOLUTE ERROR: 0.16065382498527178

MEAN SQUARED ERROR for the model: 0.04805017150173519

ROOT MEAN SQUARED ERROR for the model: 0.21920349336115788
```

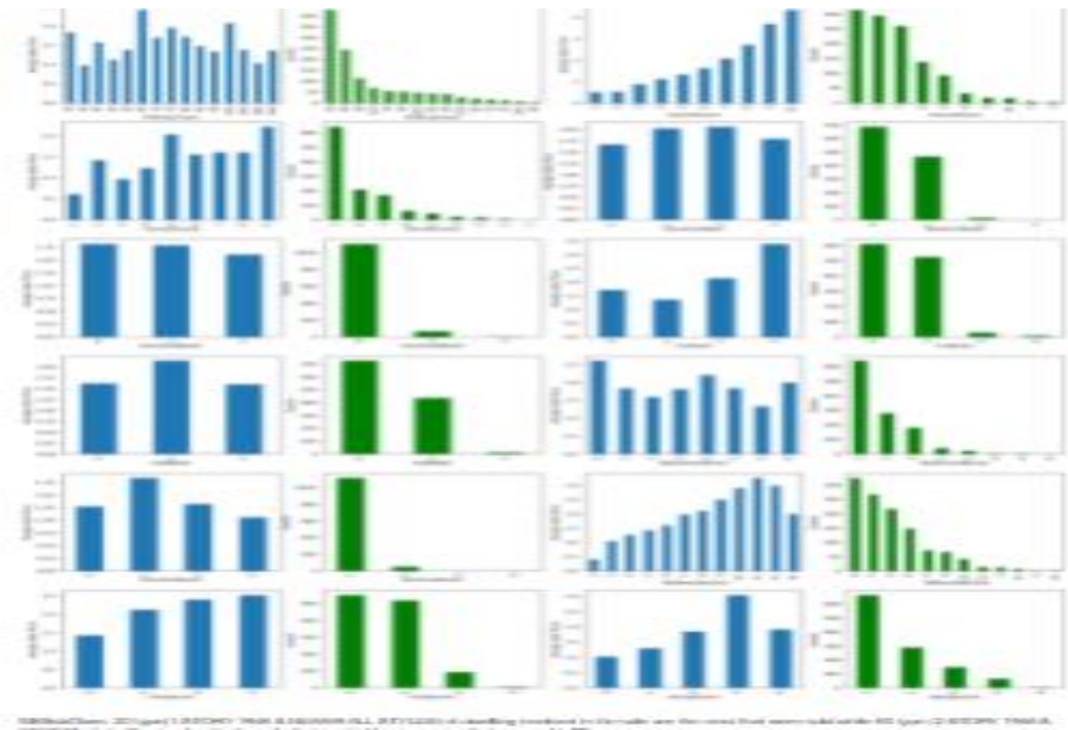
- Key Metrics for success in solving problem under consideration

- As we get the r2 score for each model but we didn't know the finalized model.
- So, we find CV Score for each model with k-fold CV between the 3 to 9.
- Best cv score for each model with the best cv we gathered.
- After gathering cv score for each model we get difference between Cv Score and r2 score for each model
- The least difference for the model Random Forest we get 3.64.

```
The least difference between the accuracy and CV score of each model is::

LinearRegression()::4.17
DecisionTreeRegressor()::8.93
BaggingRegressor()::3.97
RandomForestRegressor()::3.64
AdaBoostRegressor()::6.06
SVR()::4.98
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
             gamma=0, gpu_id=-1, importance_type=None,
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=100, n_jobs=4,
             num_parallel_tree=1, predictor='auto', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)::4.92
GradientBoostingRegressor()::5.48
```

- Visualizations



Observations:

- MSZoning: Floating Village Residential (FV) has highest average Sale Price of the houses and RL (Residential Low Density) types of Zoning has highest types of houses and very low amount of houses for commercial(C) types of Zoning.

- Street: Paved Type of road access to property has highest average Sale Prices for the houses and Low amount of houses are there that are Gravel Type of road access to property.

- Alley: No alley access types of such houses are very common and their prices for Sale is highest.

- Lot Shape : Not much info we gathered from Lo Shape but Moderate type of irregularities has highest averge sale Price while Irregular type of records are not much available in our dataset.

- LandContour: HLS(Hillside - Significant slope from side to side) has highest Sales Price while Flat type buildings has higher o. of records in the dataset.

- LotConfig: Cul-de-sac & Frontage on 3 sides of property (CullDSac & Fr3) having highest Sale Prices for the houses while such type of houses is rarely available.

- LandSlope: No such impact n the SalePrice for the houses while Gentle Slope (Gtl) has highest no. of records among them.

- Neighbourhood: North Ames (NAmes) such type houses are mostly available.

- Condition1: It shows the Proximity to various conditions in which we found that RRNn & PosA (Within 200' of North-South Railroad and Adjacent to positive off-site feature) such type has highest average Sale Prices for the houses. While Norm (NOrmal0 type of houses are easily available for Sale.

- Condition2: It is Proximity to various conditions in which PosA (Adjacent to positive off-site feature) types has highest SalePrice while Norm i.e., Normal proximity to various condition such type are easily available in Sale.

- Bldg Type: it is type of dwelling in the house in which Single-family Detached & Townhouse End Unit (1Farm & TwnhsE) has highest SalePrice and 2FmCon type are rarely found to Sale.

- HouseStyle: Two and one-half story: 2nd level finished (2.5 Fin) such houses are rarely available to sale and has highest prices for Sale.

- RoofStyle: Shed type of roof in the houses are very rarely available for sale and are expensive.

- RoofMatl: Wood Shingles type of material used for roofs in the houses are rarely available and such houses are expensive.

- Exterior1st: Exterior covering on house in that Imitation Stucco of exterior used in the houses are rarely available and such houses are costly.

- Exterior2nd: Other type Exterior covering on house are rarely available in the sale are costly such houses.

- MasVnrType: Stone type Masonry veneer type of houses are expensive and Brick Common type of masonry veneer type of houses are rarely available in the Sales.

- ExterQual: Evaluates the quality of the material on the exterior in which Excellent quality of houses are raely available and are expensive ones in the Sale.

- ExterCond: Evaluates the present condition of the material on the exterior in which Excellent quality of houses are rarely available and are expensive ones in the Sale.

- Foundation: Poured Contrete Type of foundation are costly in Sale of houses while wood type are rarely available in Sale of Houses.

- BsmtQual: Excellent Quality of basement in the houses are expensive while fair type of basement quality are rarely available in the sale of houses.

- BsmtCond: The basement condition is good then such houses are exensive while Poor type of basement Condition are rare.

- Basement Exposure: The exposure of the basement is better their prices for sale is better while No basement in houses are very easy eaily vailable in the sale.

- BsmtFinType1: Better the Living Quarters better the sale Prices for the houses and there bery less houses that doen't have basement in it.

- BsmtFinType2: Better the Living Quarters better the sale Prices for the houses and mostly houses have unfinished basement in it.

- Heating: GasA(Gas forced warm air furnace) type of heating in the houses are mostly in the houses and such type of heating container has high sale Price.

- HeatingQC: Better the heating Quality and its conditions better the Sale Price for the houses.

- CentralAir : Mostly houses has Central Air in it and are Costly.

- Electrical: Mostly houses has Electical system of SBrkr(Standard Circuit Breakers & Romex) in it and are Costly.

- KitchenQual: Better the quality of kitchen of the houses better their Sale Price.

- Functional: Home functionality Typ(typical) type are in most of houses and such houses have high salePrice.

- FirePlaceQual: Better the quality for fire place having higher Sale Prices for such houses.

- GarageType: Builtin Garage types of houses are expensive in Sale Price and 2Types are rarely available for sale.

- Garage finish: better the finishing of garagee better the Sale Price and vary rare houses that has not Garage in it.

- Garage Qual: Better the quality of garage in the houses higher the prices of houses. And mostly houses their garage quality is typical/Average.

- GarageCond: Good and Typical/Average type of garage condition in the houses has hhigher SalePrice of the houses.

- Paved drive: Paved(Y) driveway has highest average Sale Price of the houses and mostly founded during Sale of houses.

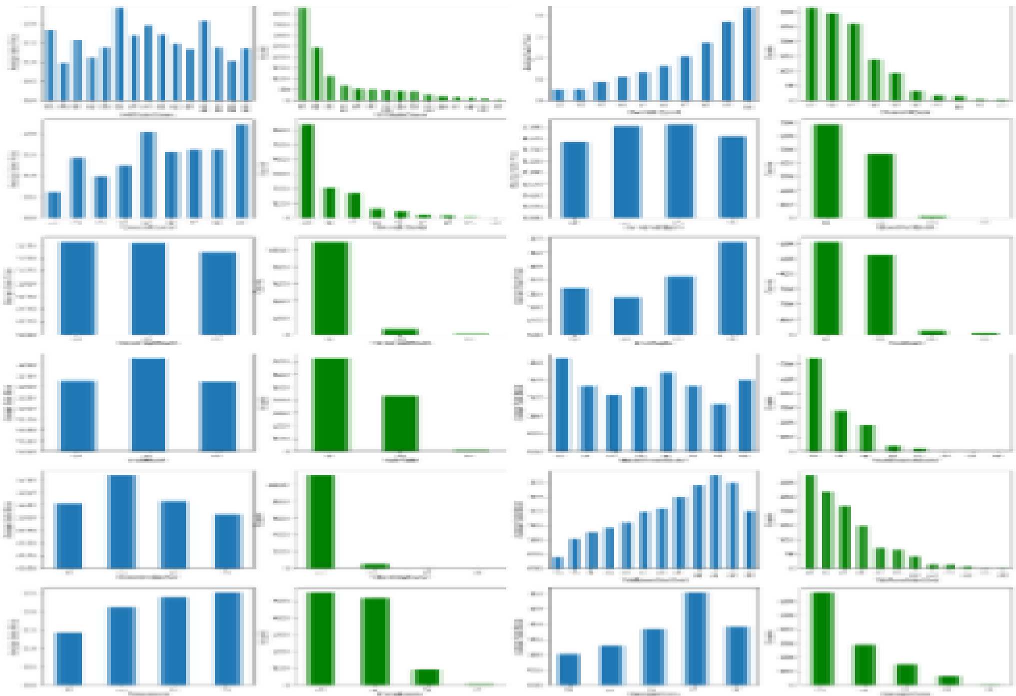
- PoolQC: Better the qaulity and conditions for the pool of the houses better the Sale Price of the houses. Most of houses hasn't have pool in it.

- Fence: Fence is not impacting much to Sle Price for the houses but mostly houses doen't have fencing in it.

- MiscFeature: Miscellaneous feature not covered in other categories in which houses Tennis Court is available such houss has higher Sale Pice. Mostly houses hases has no ther miscellaneaous features in it.

- SaleType: con(Contract 15% Down payment regular terms) and New(Home just constructed and sold) such types of sales has highest SalePrices. mostly houses are those whose Sale type WD (Warranty Deed - Conventional).

- Sale COndition: Partial [Home was not completed when last assessed (associated with New Homes)] such condition of Sales are having High Sale prices for the houses. While most of houses has normal Sale Condition.



Observations:

MSSubClass: 20 type(1-STORY 1946 & NEWER ALL STYLES) of dwelling involved in the sale are the most that were sold while 60 type (2-STORY 1946 & NEWER) of dwelling involved in the sale that are highly expensive that were sold.

OverallQual: As in data description there we set a no. from 1 to 10 that specifies the quality so in accordance with that higher the quality higher the price for sale. And there are very less no. for records for quality of houses 1 7 2 that are very poor/ poor

OverallCond: Here I analyse that the average overall condition of houses i.e. 5 were more in sale from both graph as beteer the conditions of houses their prices for sale in increasing.

BsmFullBath: there are zero no. of full basement bathrrom records are high from both for these grapd i aalysed that more the no. of basement Full bathrooms more the seles price for the house.

BsmtHalfBath: from both graphs there is ionly analyse that there are more no. of houss that has no half bathroom in basement.

FullBath: Increased in the no. of full bathrooms will result in the increase in sale price for the houses and there are very less records for the the O & 3 no. of bathrooms.

HalfBath: there are very no. of houses that has 2 no. of Half bathrooms but the average sale price for having only 1 halfbathroom is maximum.

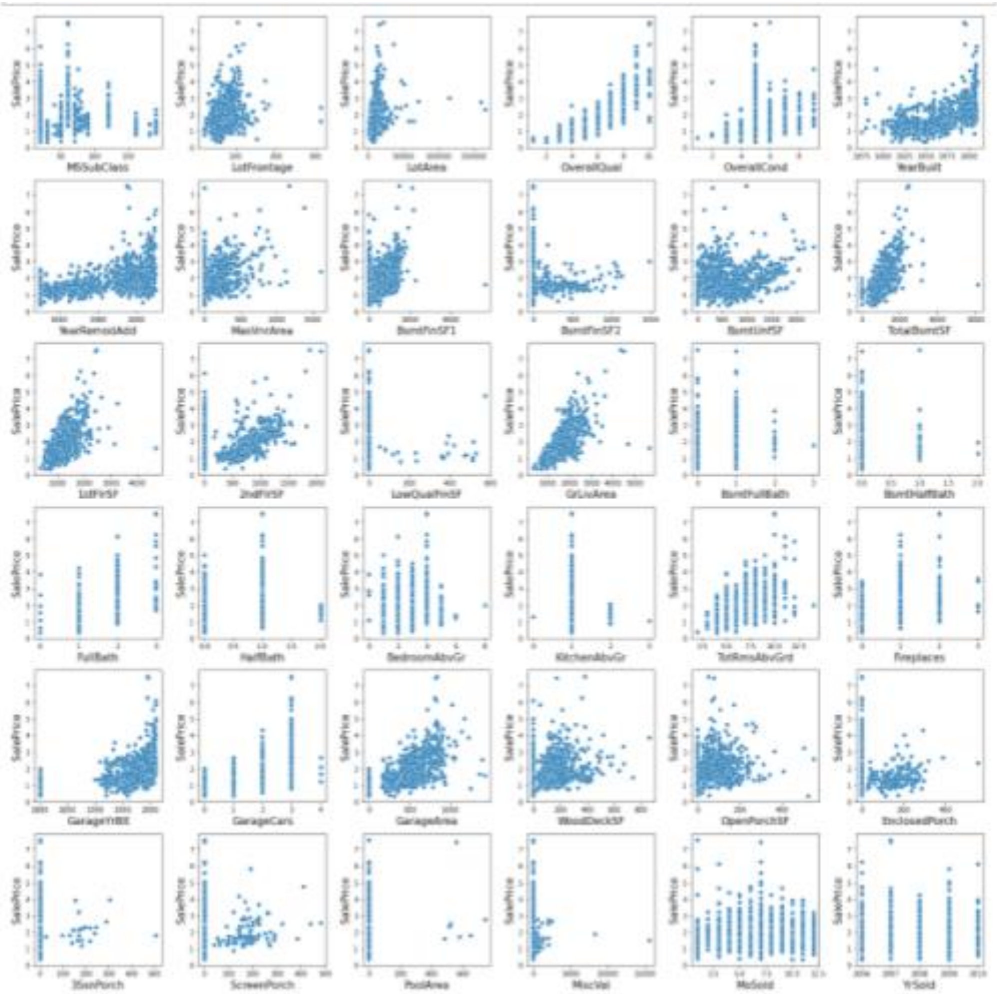
BedroooomAbvGr: there no such impacts for the no. of bedroooms to the salePrice but there very less no of records for 6,0,8 no. of bedroooms that lead model to underfiited.

KitchenAbvGr: very less records for the houses having 3 or no kitchen above gorund and the sale price are high for having only 1 kitchen in the house.

TotRmsAbvGrd: here we analyse that the salePrice is increasing w.r.t. increase in the no. of rooms above ground while there are very less records for having 2 & 14 no. of rooms in the house.

Fireplaces: Increased no. of fireplaces is impacting the increase in the SalePrice of the houses.

GarageCars: More No. of cars capacity in the house more its sale Price.



Observations:

LotFrontage: Linear feet of street connected to property is somehow seems that there is some linear relation between them.

LotArea: Not so specific but the lot area somehow seems like to be very slight increase in the area leads to extra amount of change in increasing manner of SalesPrice.

MasVnArea: Masonry veneer area except zero area there is linear reltions that tells that increase in the masonary ares lead to increase the sales Price of the houses.

BsmtFinSF1: Basement finished Type 1 rather than zero square feet there is some min amount of increase in the area there is good amount of increase in SalePrice of House.

BsmtFinSF2: Not much impacts it showing to the target variable.

BsmtUnfSf: Not much impacts it showing to the target variable.

TotalBsmtSF: Shows that there is increase in the total areas for the basement in the house leads to increase in the SalePrice.

1stFlrSF: In this more area in on the 1st Floor of houses will impact to increase in the sale price of the houses.

2ndFlrSF: In this more area in on the 2nd Floor of houses will impact to increase in the sale price of the houses.

LowQualFinSF: Not much impacts it showing to the target variable.

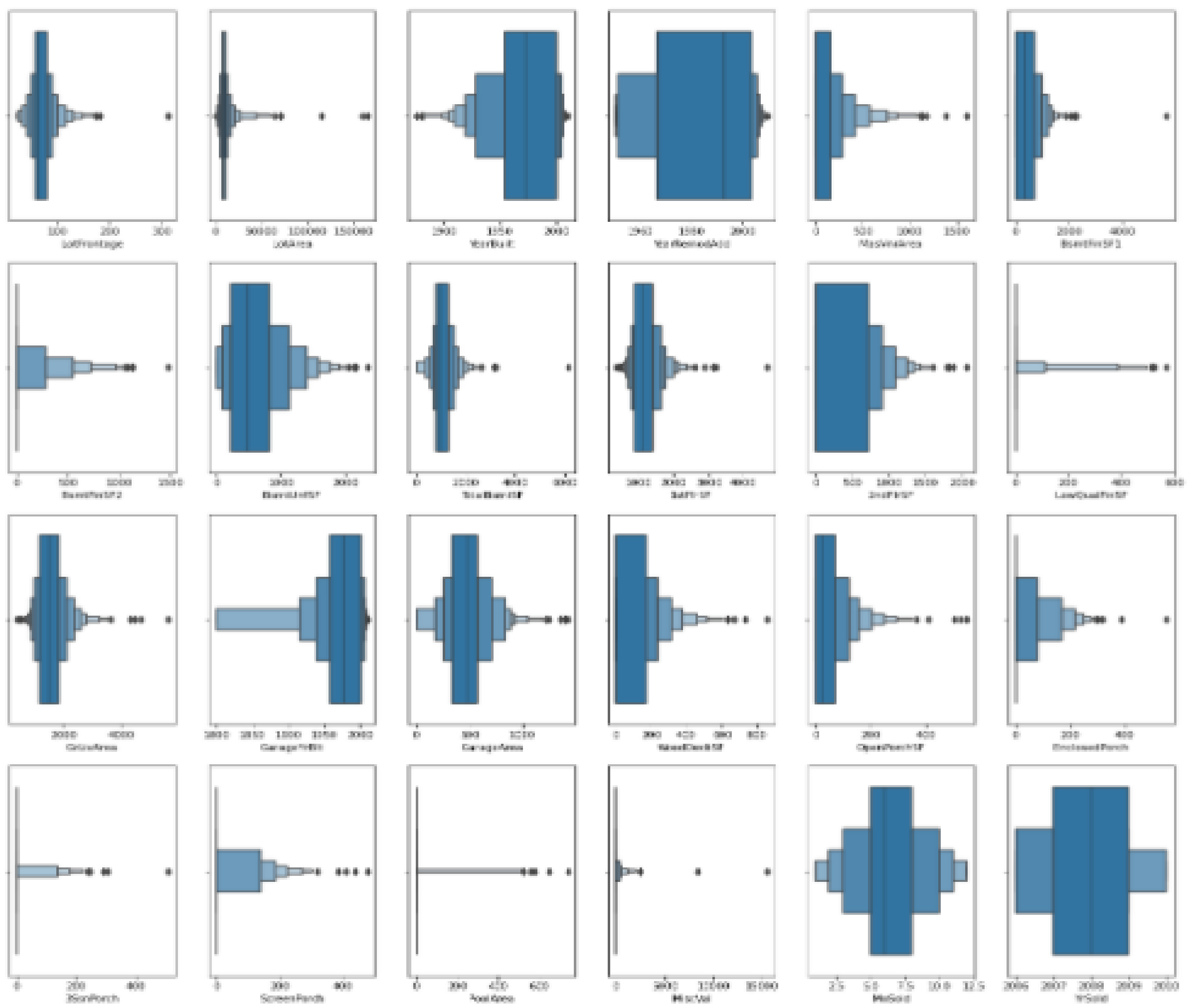
GrLivArea: In this more increase in above grade (ground) living area will impact to increase in the sale price of the houses.

GarageArea: Except with the 0 area there is some linear relation that stats that increase in the Garage area increase the Sale price of the House.

WoodDeckSF: Except with the 0 area sq. ft. there is some linear relation that stats that increase in the Wood Deck area increase the Sale price of the House. And seems to be outliers in it.

OpenPorchSF:Except with the 0 area sq. ft. there is some linear relation that stats that increase in the open Porch area increase the Sale price of the House. And seems to be outliers in it.

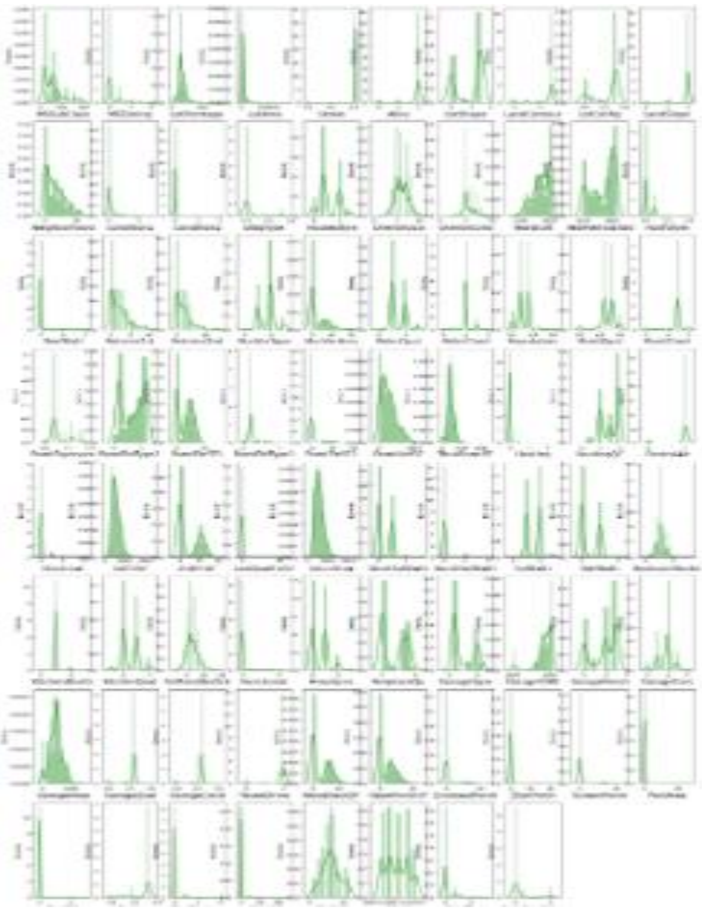
Enclosed Porch, 3SnPorch,ScreenPorch, PoolArea,MiscVal these area very less founded in the houses due to which not much info we gathered from graph.

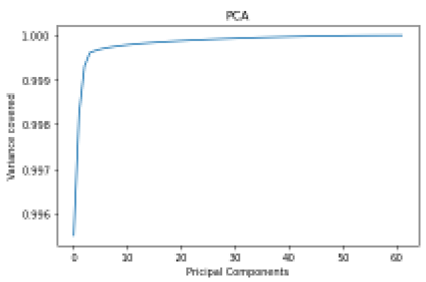


Observations:

LotArea, BsmtFinSF1, BsmtFinSF2, TotalBsmtSF, 1stFlrSF, GrLivArea, EnclosedPorch, 3SsnPorch, MiscVal.

These features consisting outliers in it.





Observations:
From above figure we analyze that after selecting 20 feature there is should be very minute variance that lead to predict the label.

- Interpretation of the Results
  - ✓ Firstly, we removed null values by their respective values with their respective features.
  - ✓ We know that the over all quality and Condition, the area for different type like for basement, floors, features in the houses and their conditions, Sale type and its Conditions, Garages

areas, No. Of cars parking in that houses, remodelling of the houses, etc such types of features are impacting more to predict the sale price for the houses.

- ✓ We get to know about the problem existence like outliers, skewness, high- variance, Corelation of each feature with the target variable.
- ✓ Transformed Columns with their respective values or by the Label Encoder techniques.
- ✓ Used PCA for feature selection
- ✓ Find the best r2 score with their respective random state.
- ✓ Selected Random Forest as the finalized model.
- ✓ Performed Hyper tunning for the best model.
- ✓ Predicted values for the test dataset by Random Forest default parameterized model.
- ✓ Save The Model.

CONCLUSION

- Learning Outcomes of the Study in respect of Data Science

- Our customers requirements are our highest priority so the project was built to satisfy their needs so the project works well and there is no customer churn

- We should maintain the transparency among customers and also the comparison can be made easy through this model. If customer finds the price of house at some given website higher than the price predicted by the model, so he can reject that house.
- So we have to predict the pricing as per customers requirement and needs.

- Limitations of this work and Scope for Future Work

- 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.
- But still customers are always comparing the prices hence we should keep on updating our project to meet their necessity.

Thank You!!