Project presentation on
:-

PFA HOUSING PROJECT

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INTRODUCTION

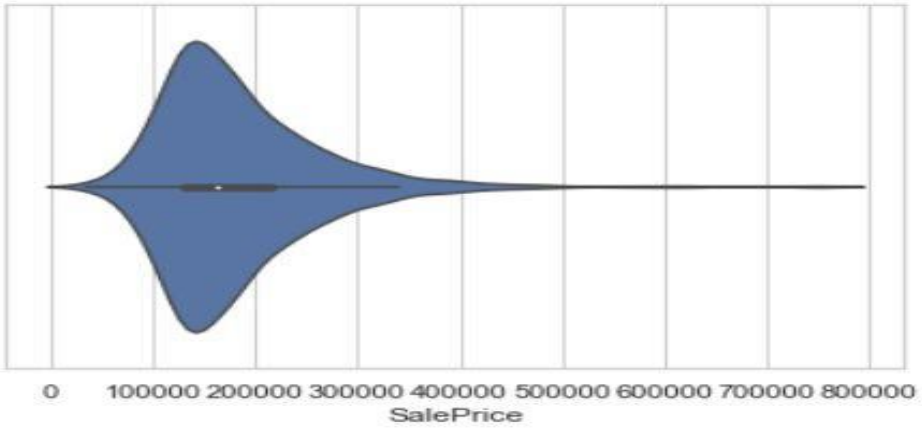
Problem statement and understanding

- 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.

- We 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.

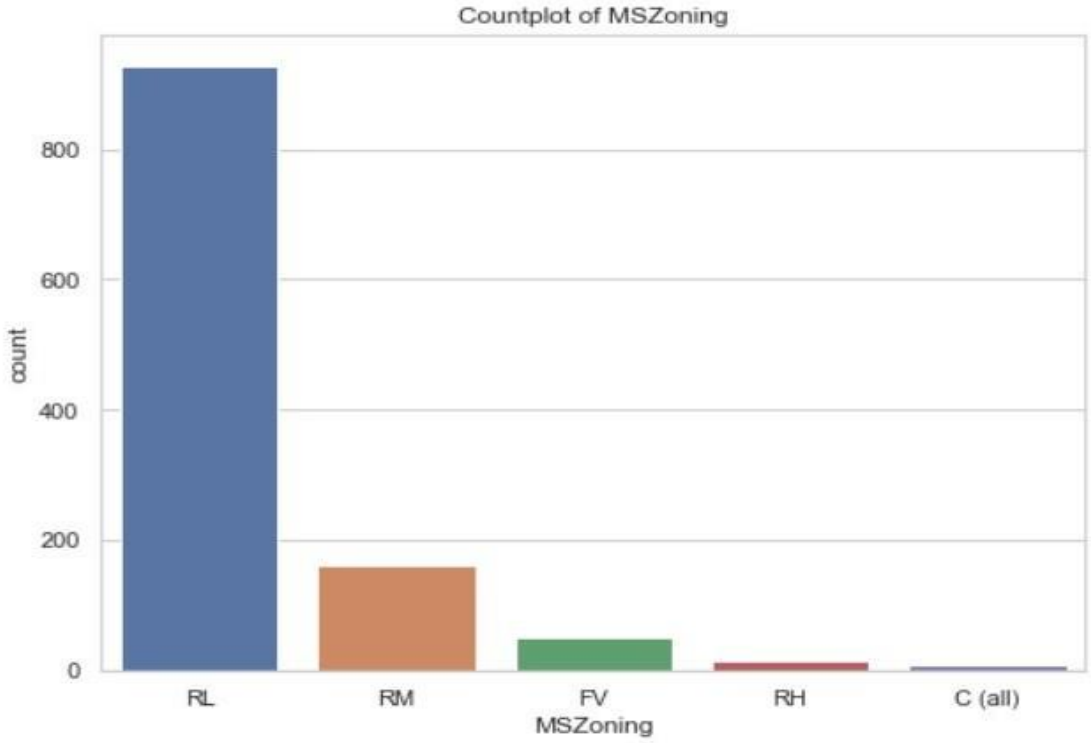
EDA steps and Visualization




```
140000     18
135000     16
155000     12
139000     11
160000     11
           ..
126175      1
204000      1
186000      1
369900      1
105500      1
Name: SalePrice, Length: 581, dtype: int64
```

Observation:

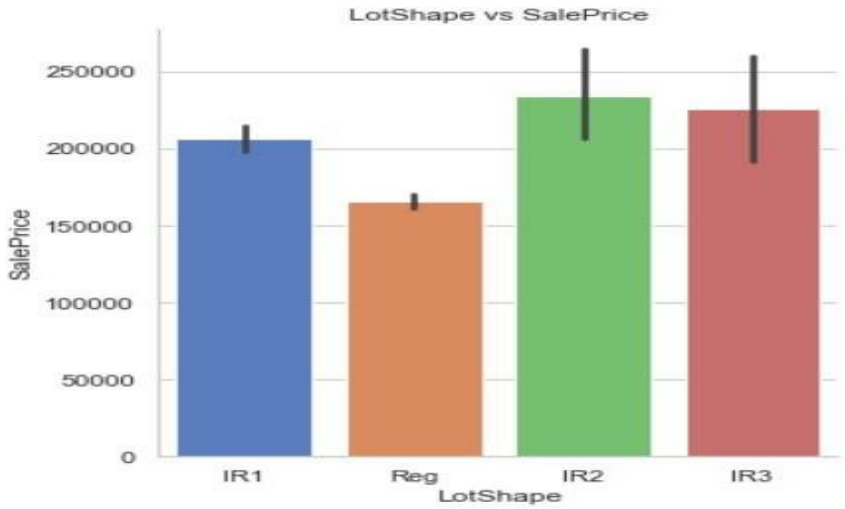
Maximum number of SalePrice lies between 140000 and 230000.




```
RL         928
RM         163
FV          52
RH          16
C (all)      9
Name: MSZoning, dtype: int64
```

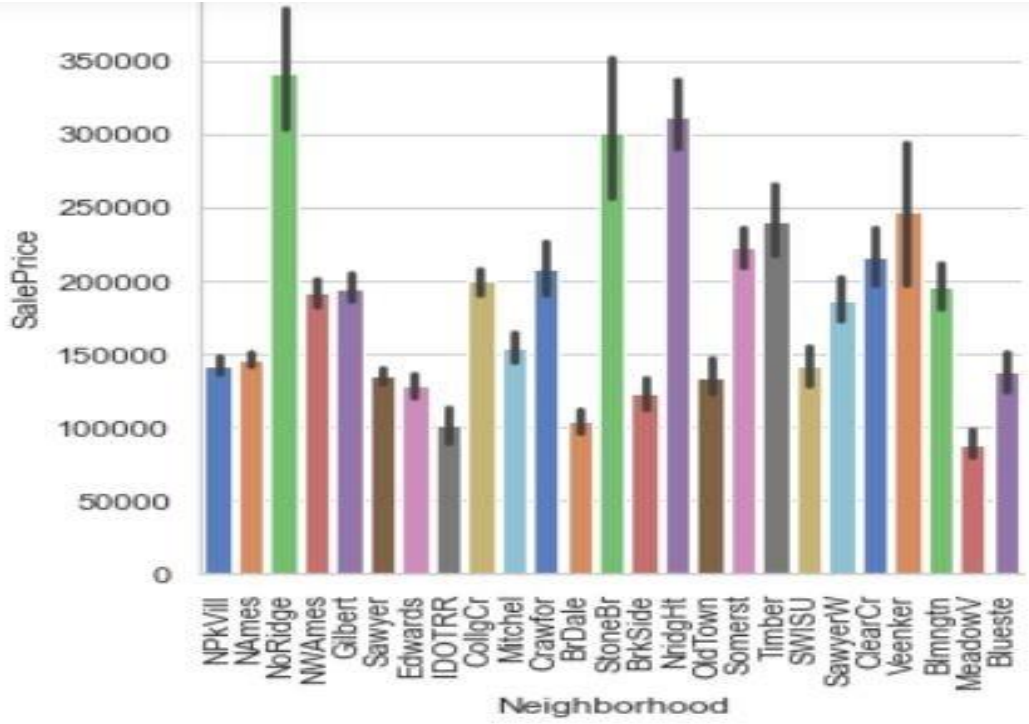
Observation:

Maximum, 928 number of MSZoning are RL.




```
SalePrice  LotShape
34900      Reg          1
35311      Reg          1
37900      Reg          1
39300      Reg          1
40000      Reg          1
                       ..
582933     Reg          1
611657     IR1          1
625000     IR1          1
745000     IR1          1
755000     IR1          1
Name: LotShape, Length: 733, dtype: int64
```

Observation:
SalePrice is maximum with IR2 LotShape.

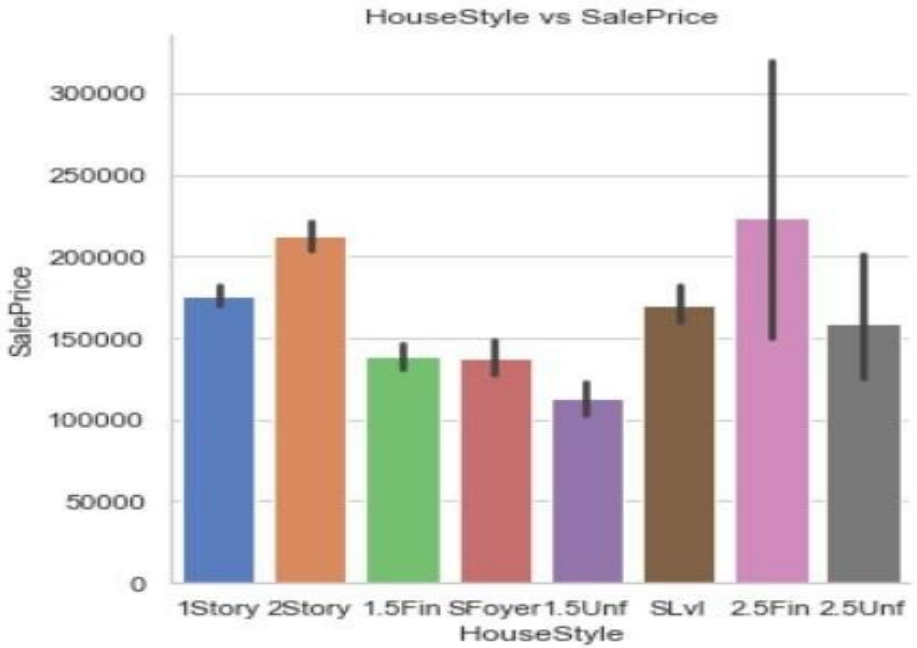


SalePrice	Neighborhood	
34900	IDOTRR	1
35311	IDOTRR	1
37900	OldTown	1
39300	BrkSide	1
40000	IDOTRR	1
		..
582933	NridgHt	1
611657	NridgHt	1
625000	NoRidge	1
745000	NoRidge	1
755000	NoRidge	1

Name: Neighborhood, Length: 1013, dtype: int64

Observation:

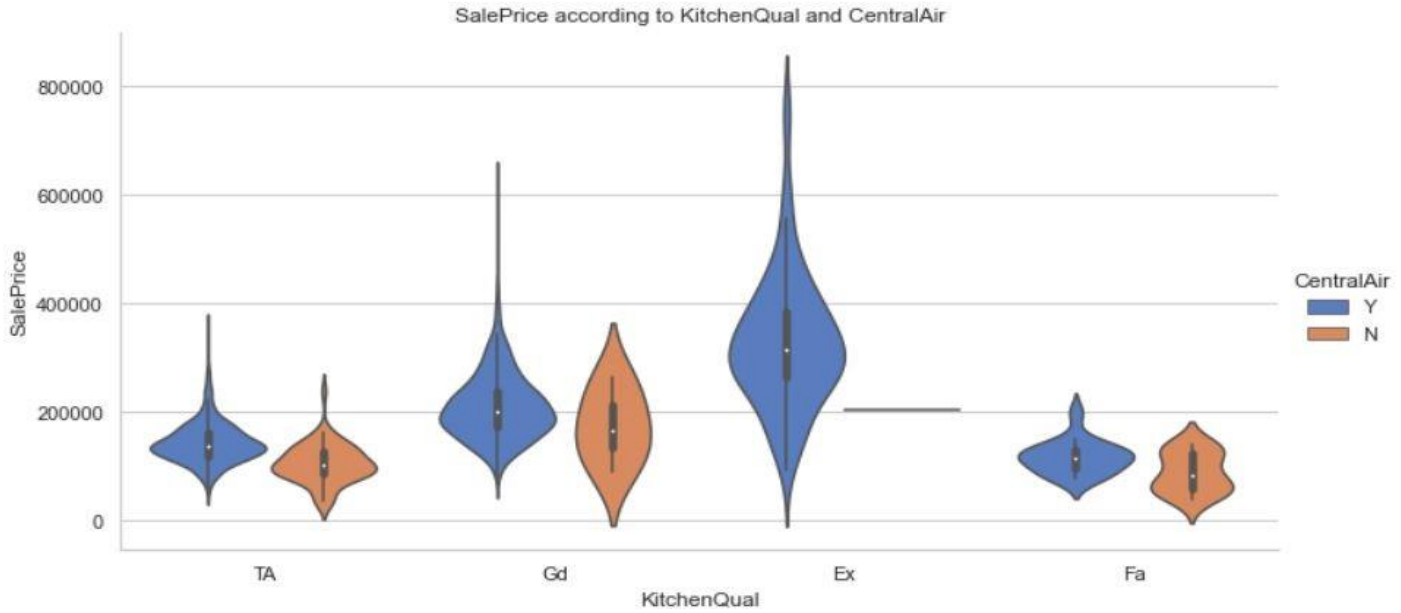
SalePrice is maximum with NoRidge Neighborhood.




```
SalePrice  HouseStyle
34900      1Story         1
35311      1Story         1
37900      1.5Fin         1
39300      1Story         1
40000      2Story         1
                         ..
582933     2Story         1
611657     1Story         1
625000     2Story         1
745000     2Story         1
755000     2Story         1
Name: HouseStyle, Length: 840, dtype: int64
```

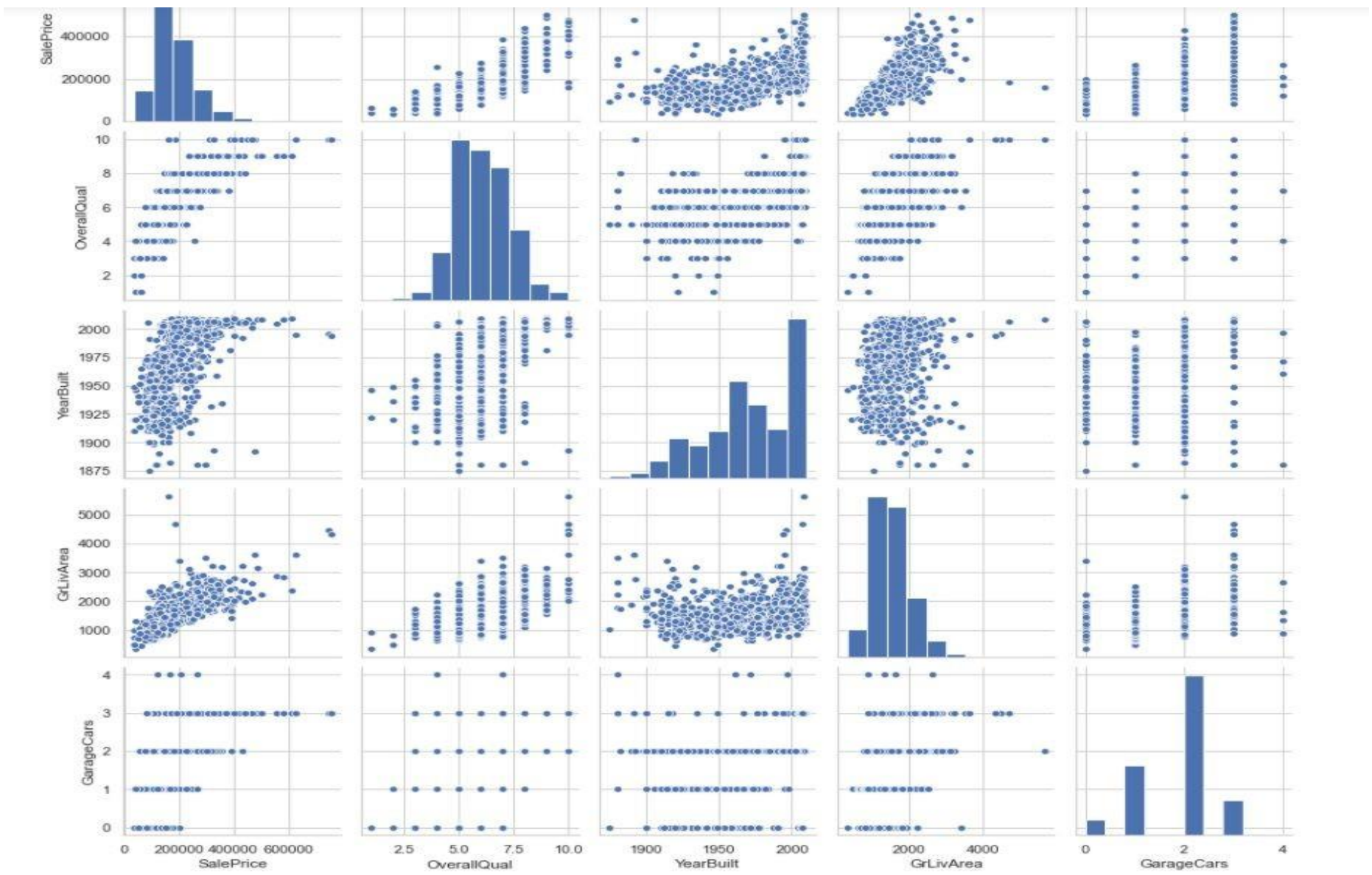
Observation:
SalePrice is maximum with 2.5Fin HouseStyle.

```
#checking GarageType and GarageCond with respect to SalePrice
sns.factorplot(x='KitchenQual',y='SalePrice',hue='CentralAir',data=df,kind='violin',size=5,palette='muted',aspect=2)
plt.title('SalePrice according to KitchenQual and CentralAir')
plt.xticks()
plt.ylabel('SalePrice')
plt.show()
```



Observation:

SalePrice is maximum with Ex kitchenQual and CentralAir.



Observation:

SalePrice is highly positively correlated with GrLivArea and

OverallQual.

Steps and assumptions used to complete the project

Data Preprocessing Done

- We first done data cleaning. We first looked percentage of values missing in columns then we imputed missing values

.

	Missing Values	% of Total Values
PoolQC	1161	99.4
MiscFeature	1124	96.2
Alley	1091	93.4
Fence	931	79.7
FireplaceQu	551	47.2
LotFrontage	214	18.3
GarageType	64	5.5
GarageYrBlt	64	5.5
GarageFinish	64	5.5
GarageQual	64	5.5
GarageCond	64	5.5
BsmtExposure	31	2.7
BsmtFinType2	31	2.7
BsmtCond	30	2.6
BsmtFinType1	30	2.6
BsmtQual	30	2.6

- We then explored categorical variables

Exploring categorical columns

```
#exploring categorical columns
for column in df.columns:
    if df[column].dtypes == object:
        print(str(column) + ' : ' + str(df[column].unique()))
        print(df[column].value_counts())
        print('**********************************************************************************************************')
        print('\n')
```

```
MSZoning : ['RL' 'RM' 'FV' 'RH' 'C (all)']
RL         928
RM         163
FV          52
RH          16
C (all)      9
Name: MSZoning, dtype: int64
**********************************************************************************************************


Street : ['Pave' 'Grvl']
Pave    1164
Grvl       4
Name: Street, dtype: int64
**********************************************************************************************************


Alley : [nan 'Grvl' 'Pave']
Grvl    41
Pave    36
```

- We observed that there is only one unique value present in Utilities so will be dropping this column.

- Then we encoded all the categorical columns into numerical colums using dummy variables.

Encoding categorical columns

```
categorical_cols = ['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'LotConfig', 'LandSlope', 'Neighborhood', 'Conditic

df = pd.get_dummies(df, columns = categorical_cols, drop_first=True)
```

```
df
```

	Id	MSSubClass	LotFrontage	LotArea	Utilities	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnf
0	127	120	70.0	4928	AllPub	6	5	1976	1976	0.0	120	0	9
1	889	20	95.0	15865	AllPub	8	6	1970	1970	0.0	351	823	10
2	793	60	92.0	9920	AllPub	7	5	1996	1997	0.0	862	0	2
3	110	20	105.0	11751	AllPub	6	6	1977	1977	480.0	705	0	11
4	422	20	70.0	16635	AllPub	6	7	1977	2000	126.0	1246	0	3
...	...	...	...	...	...	...	...	...	...	...	...	...	
1163	289	20	70.0	9819	AllPub	5	5	1967	1967	31.0	450	0	4
1164	554	20	67.0	8777	AllPub	4	5	1949	2003	0.0	0	0	
1165	196	160	24.0	2280	AllPub	6	6	1976	1976	0.0	566	0	2
1166	31	70	50.0	8500	AllPub	4	4	1920	1950	0.0	0	0	6
1167	617	60	70.0	7861	AllPub	6	5	2002	2003	0.0	457	0	3

1168 rows × 259 columns

- While checking the heatmap of correlation we observed that,

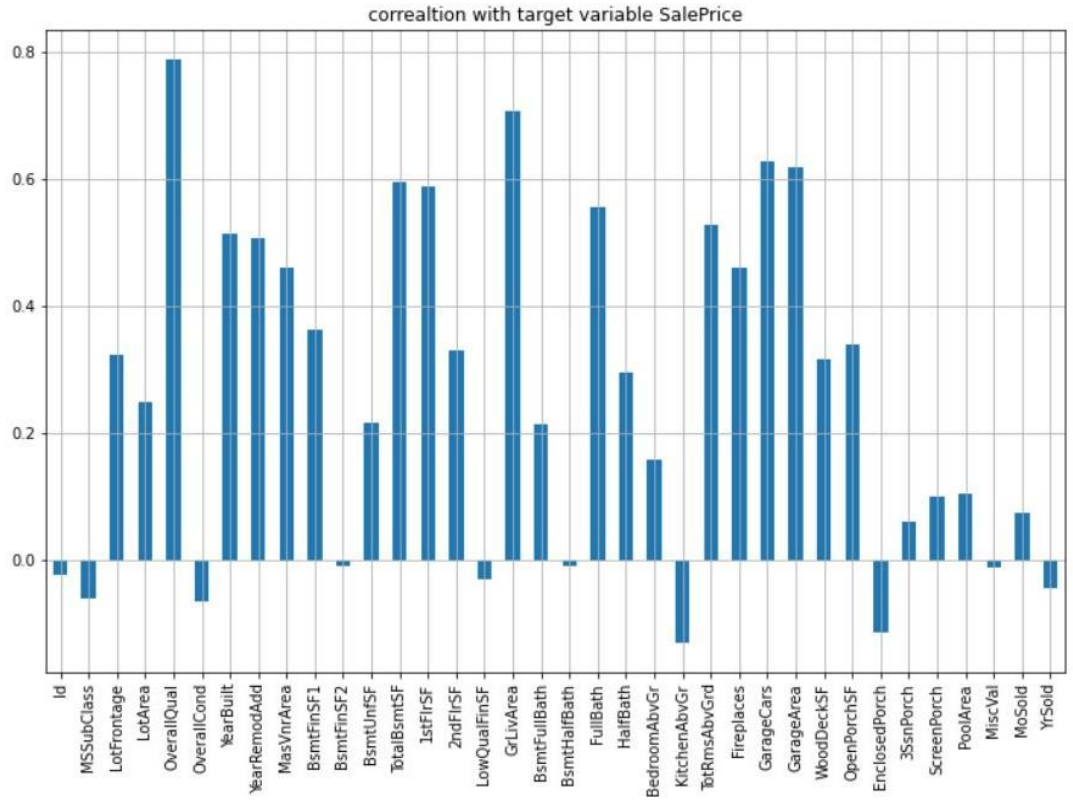
- 1. SalePrice is highly positively correlated with the columns OverallQual, YearBuilt, YearRemodAdd, TotalBsmtSF, 1stFlrSF, GrLivArea, FullBath, TotRmsAbvGrd, GarageCars, GarageArea.

- 2. SalePrice is negatively correlated with OverallCond, KitchenAbvGr, Encloseporch, YrSold.

- 3. We observe multicollinearity in between columns so we will be using Principal Component Analysis(PCA).

- 4. No correlation has been observed between the column Id and other columns so we will be dropping this column.

- Here we check the correlation between all our feature variables with target variable label.



1. The column OverallQual is most positively correlated with SalePrice.

2. The column KitchenAbvGrd is most negatively correlated with

SalePrice.

problem-solving approaches

- We first converted all our categorical variables to numeric variables with the help of dummy variables to checkout and dropped the columns which we felt were unnecessary.

- We observed skewness in data so we tried to remove the skewness through treating outliers with winsorization technique.

- The data was improper scaled so we scaled the feature variables on a single scale using sklearn’s StandardScaler package.

- There were too many (256) feature variables in the data so we reduced it to 100 with the help of Principal Component

Analysis(PCA) by plotting Eigenvalues and taking the number of nodes as our number of feature variables.

Set of assumptions related to the problem under consideration

- By looking into the target vaariable label we assumed that it was a Regression type of problem.
- We observed multicollinearity in between columns so we assumed that we will be using Principal Component Analysis (PCA).
- We also observed that only one single unique value was present in

Utilities column so we assumed that we will be dropping this columns.

Model Dashboard

```
#Importing all model library
from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor

#Importing Boosting models
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor

#importing error metrics
from sklearn.model_selection import GridSearchCV,cross_val_score
```

score of LinearRegression() is: 0.8224023067822429
Error:
Nean absoluz e error: 21983. 03594681287
Nean squared error : 1016181146.2848227
Root Mean Squared E Pror: 31877. 59630657278
r2 score : 0. 8451431350165133

score of DecisionTreeRegressor() is: 1.0
Error:
Mean absolute error: 33349.05128205128
Mean squared error: 2904893311.905583
Root Mean Squared Error: 53897.062182515874
r2 score: 0.5573203920994878
****

score of KNeighborsRegressor() is: 0.7910630500200235
Error:
Mean absoluz e error: 26847. 8367521367 US
Nean squared error : 16718B2262. 554359
Root Mean Squared E Pror: 40888. 65689349992
rd score : 0.7452261836776653
****

score of sVR() is: -0.04563664106634713
Error:
Mean absolute error: 58255.16893502842
Mean squared error: 6883309069.209987
Root Mean Squared Error: 82965.71020132345
r2 score: -0.04895437891886911
****

```
Model: Lasso()
Score: [0.85207898 0.74649293 0.78624285 0.69359244 0.81790264 0.69908843
 0.79772316 0.69620109 0.60174926 0.83774268]
Mean score: 0.75288144698B4274
Standard deviation: 0.07b429695lb426799
```

```
Model: Ridge()
Score: [0.8520Bl4Z 0.74653129 0.7B6382l5 0.69365996 0.8179455  0.699l3Z48
 0.7978861  0.69675913 0.60263B2  0.83781317j
Mean score: 0.75308Z9395860547
Standard deviation: 0.075Z2890383BZZ077
```

```
Model: ElasticNet()
Score: [0.84352472 0.74457611 0.81461183 0.71347987 0.82780B9s B.og l44zs
```
6. 842653B8 6. 78494133 6. 79472646 0. 83876943]
Nean *score : 8.* 79141280542952B6
Standard dev1at1on : 0.05524013251954638

model : RandoniForestRegres son( )
```
Score: [0.78642659 0.708A1927 0.80088874 0.7741654A 0.78435B31 0.5748967
 0.79620818 0.80767199 0.B5233B38 0.80521004]
Mean score: 0.7690583639721766
```
Standard devlat1on : 0.B7368999923937654

model : Ada Boost Regres sor ( )
Sao*re:* [0. 67687313 0. G3623881 0. 67 S 34235 6. 68152378 0. 61651457 0.54811785
0. 6737292 0. 72426054 6. 67222986 0. 69365946]
Mean score: 0.6597891543469266
Standard deviation: 0.046385992712606065

model : G rad1ent Boost 1ngRegres *sor* ( )
Score: [0.79A35779 0.7301687 0.81540851 0.75602916 0.78039711 0.67290297
0.80468041 0.78554125 0.8A626604 0.77022326]
Mean score: 0.7755975195869904
Standard deviation: 0.045738804971296516

Finalized Model

```
RG=Ridge(alpha=25)
RG.fit(x_train,y_train)
print('Score:',RG.score(x_train,y_train))
y_pred=RG.predict(x_test)
print('\n')
print('Mean absolute error:',mean_absolute_error(y_test,y_pred))
print('Mean squared error:',mean_squared_error(y_test,y_pred))
print('Root Mean Squared error:',np.sqrt(mean_squared_error(y_test,y_pred)))
print('\n')
print("r2_score:",r2_score(y_test,y_pred))
print('\n')
```

```
Score: 0.8223601918721507


Mean absolute error: 21831.129709253644
Mean squared error: 1011636781.6056582
Root Mean Squared error: 31806.238092639283


r2_score: 0.8458356553118661
```

Conclusion

In this project we have tried to show how the house prices vary and what are the factors related to the changing of house prices.
The best(minimum) RMSE score was achieved using the best parameters of Ridge Regressor through GridSearchCV though Lasso Regressor model performed well too. While we couldn’t reach out goal of minimum RMSE in house price prediction without letting the model to overfit, we did end up creating a system that can with enough time and data get very close to that goal.

Acknowledgement

I would like to express my special thanks of grattitude to the sources Medium, TowardsDataScience, StackOverflow, KrishNaik’s youtube channel which helped me to accomplish this project.