FLIP ROBO

Housing Price Prediction

Submitted by:

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ACKNOWLEDGMENT

I would like to thanks to Flip Robo Technologies to give me a wonderful opportunity. This project is given by my SME Ms Sapna Verma. I have referred below resources that helped and guided me in completion of this project as below:-

- https://www.kaggle.com/erick5/predicting-house-prices-with-machine-learning
- https://studygyaan.com/data-science-ml/linear-regression-machine-learning-project-forhouse-price-prediction
- https://loddonhouse.co.uk/?gclid=CjwKCAjw-ZCKBhBkEiwAM4qfF_ZWhedS9VWDcP3TZ5_SVB7xuurHYsU5s4MaQzoRhiVB5fnbA1l1DxoC3G0QAvD_BwE

INTRODUCTION

Business Problem Framing

- 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.

- 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. 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

Predicting sale prices for houses, even stranger ones. Use a test-driven approach to build a Linear Regression model using Python from scratch. We will use our trained model to predict house sale prices and extend it to a multivariate Linear Regression.

Review of Literature

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

Technical Requirements:

- Data contains 1460 entries each having 81 variables.
- Data contains Null values. We 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. 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 us (test.csv, train.csv). We will train on train.csv dataset and predict on test.csv file.

The “Data file.csv” and “Data description.txt” are enclosed with this file.

Motivation for the Problem Undertaken

- House is one of the important elements in basic human needs. People need a house to stay away from danger, hot weather, rainy day and as well as a place to stay calm. As long as people can fill the comfort of living under a roof then it is called a house. However, the things that matter is that the affordability of a person to purchase a house. Some people can afford a house that is really comfortable to stay in and some not. People who are called the rich and famous can afford a house that is almost called a heaven and some can only lives in an ordinary but comfortable house. But it doesnââ‚¬â„¢t matter how our house may look like because the price of house is what that matter. We can see that the housing price is increasing as the time goes by. This may be an important area to look upon because more or less it could affect the economic level of a country. Therefore, a housing price can be defined as the rate of payment that one has to pay in order to purchase a house and for sure there are several factors that lead to housing price determination.
- In my own point of view, I believe that the increment of a housing price is due to the price increment in the raw material. Many may have similar idea but after looking into 10 journals as references for my propose topic, I have found out several more important variables that leads to the factors of housing price determination. There are few number of knowledgeable individual turned up and able to find the contributing factors in determination of housing price. One who has studied using an empirical analysis has shown that income (demography trends) and nominal interest rates are the key explanatory factors in housing price. On the other hand, the equity returns may also have been an influential factor in the determination of housing price.

Analytical Problem Framing

Mathematical/ Analytical Modeling of the Problem

- This problem is a Linear Regression problem. The dataset is in CSV format and It contains 1460 training data points and 81 features that might help us predict the selling price of a house.
- Build a model of housing prices to predict median house values in California using the provided dataset.
- Train the model to learn from the data to predict the median housing price in any district, given all the other metrics.
- Predict housing prices based on median_income and plot the regression chart for it.

Data Sources and their formats

This Dataset is provided by Flip Robo Technologies CSV format. In this dataset, there are 1460 rows and 81 columns.

Load Data

```
In [92]: #uploading test dataset
test=pd.read_csv("Housing_test.csv")
train=pd.read_csv("Housing_train.csv")
```

```
In [93]: test
Out[93]:
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Cc
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

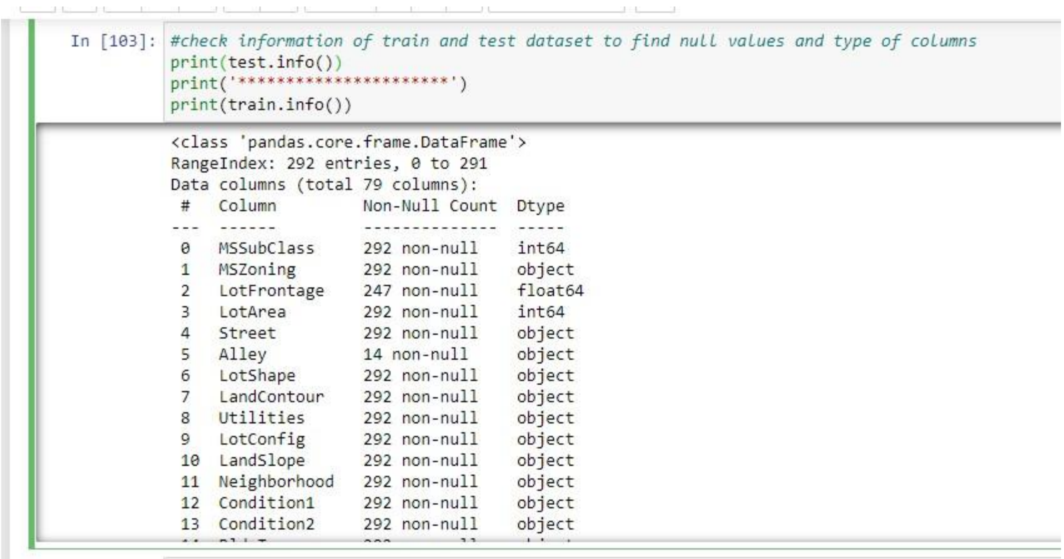
```
In [94]: train
Out[94]:
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Cc
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	

```
In [102]: #Letscheck columns name of both dataset
print(train.columns)
print("**********")
print(test.columns)
```

```
Index(['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'Alley',
       'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
       'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
       'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
       'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
       'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
       'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC',
       'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
       'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
       'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
       'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
       'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'MiscVal',
       'MoSold', 'YrSold', 'SaleType', 'SaleCondition', 'SalePrice'],
      dtype='object')
**********
Index(['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'Alley',
       'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
       'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
       'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
       'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
       'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
       'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC',
       'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
       'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
       'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
       'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
       'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'MiscVal',
       'MoSold', 'YrSold', 'SaleType', 'SaleCondition'],
      dtype='object')
```

#check information of train and test dataset to find null values and type of columns print(test.info()) print('**********************') print(train.info())



```
In [103]: #check information of train and test dataset to find null values and type of columns
          print(test.info())
          print('**********************')
          print(train.info())

          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 292 entries, 0 to 291
          Data columns (total 79 columns):
           #   Column        Non-Null Count  Dtype
          ---  ------        --------------  -----
           0   MSSubClass    292 non-null    int64
           1   MSZoning      292 non-null    object
           2   LotFrontage   247 non-null    float64
           3   LotArea       292 non-null    int64
           4   Street        292 non-null    object
           5   Alley         14 non-null     object
           6   LotShape      292 non-null    object
           7   LandContour   292 non-null    object
           8   Utilities     292 non-null    object
           9   LotConfig     292 non-null    object
           10  LandSlope     292 non-null    object
           11  Neighborhood  292 non-null    object
           12  Condition1    292 non-null    object
           13  Condition2    292 non-null    object
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 292 entries, 0 to 291 Data columns (total 79 columns):

```
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
0    MSSubClass    292 non-null    int64
1    MSZoning      292 non-null    object
2    LotFrontage   247 non-null    float64
3    LotArea       292 non-null    int64
4    Street        292 non-null    object
5    Alley         14 non-null     object
6    LotShape      292 non-null    object
7    LandContour   292 non-null    object
8    Utilities     292 non-null    object
9    LotConfig     292 non-null    object
10   LandSlope     292 non-null    object
11   Neighborhood  292 non-null    object
12   Condition1    292 non-null    object
13   Condition2    292 non-null    object   14  BldgType      292 non-null    object
15   HouseStyle    292 non-null    object
16   OverallQual   292 non-null    int64
17   OverallCond   292 non-null    int64
18   YearBuilt     292 non-null    int64
19   YearRemodAdd  292 non-null    int64
20   RoofStyle     292 non-null    object   21  RoofMatl      292 non-null    object
 22  Exterior1st   292 non-null    object
```

23 Exterior2nd 292 non-null object
24 MasVnrType 291 non-null object
25 MasVnrArea 291 non-null float64
26 ExterQual 292 non-null object
27 ExterCond 292 non-null object
28 Foundation 292 non-null object
29 BsmtQual 285 non-null
object
30 BsmtCond 285 non-null object
31 BsmtExposure 285 non-null object
32 BsmtFinType1 285 non-null
object
33 BsmtFinSF1 292 non-null int64
34 BsmtFinType2 285 non-null object
35 BsmtFinSF2 292 non-null int64
36 BsmtUnfSF 292 non-null
int64 37 TotalBsmtSF 292 non-
null int64 38 Heating 292
non-null object
39 HeatingQC 292 non-null object
40 CentralAir 292 non-null object
41 Electrical 291 non-null object 42
1stFlrSF 292 non-null int64
43 2ndFlrSF 292 non-null int64
44 LowQualFinSF 292 non-null int64
45 GrLivArea 292 non-null int64
46 BsmtFullBath 292 non-null int64
47 BsmtHalfBath 292 non-null int64
48 FullBath 292 non-null int64
49 HalfBath 292 non-null int64
50 BedroomAbvGr 292 non-null int64
51 KitchenAbvGr 292 non-null int64
52 KitchenQual 292 non-null object
53 TotRmsAbvGrd 292 non-null int64
54 Functional 292 non-null object
55 Fireplaces 292 non-null int64
56 FireplaceQu 153 non-null object
57 GarageType 275 non-null object
58 GarageYrBlt 275 non-null float64
59 GarageFinish 275 non-null object

60 GarageCars 292 non-null int64
61 GarageArea 292 non-null int64
62 GarageQual 275 non-null object
63 GarageCond 275 non-null object
64 PavedDrive 292 non-null object
65 WoodDeckSF 292 non-null int64
66 OpenPorchSF 292 non-null int64
67 EnclosedPorch 292 non-null int64
68 3SsnPorch 292 non-null int64
69 ScreenPorch 292 non null int64
70 PoolArea 292 non-null int64
71 PoolQC 0 non-null float64 72 Fence 44 non-null object
73 MiscFeature 10 non-null object
74 MiscVal 292 non-null int64
75 MoSold 292 non-null int64
76 YrSold 292 non-null int64
77 SaleType 292 non-null object 78 SaleCondition 292 non-null object dtypes: float64(4), int64(33), object(42) memory usage: 180.3+ KB
None
****

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1168 entries, 0 to 1167 Data columns (total 80 columns):

```
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
0    MSSubClass    1168 non-null   int64
1    MSZoning      1168 non-null   object
2    LotFrontage   954 non-null    float64
3    LotArea       1168 non-null   int64
4    Street        1168 non-null   object
5    Alley         77 non-null     object
6    LotShape      1168 non-null   object
7    LandContour   1168 non-null   object
8    Utilities     1168 non-null   object
9    LotConfig     1168 non-null   object
10   LandSlope     1168 non-null   object
```

11 Neighborhood 1168 non-null object
12 Condition1 1168 non-null object
13 Condition2 1168 non-null object
14 BldgType 1168 non-null object
15 HouseStyle 1168 non-null object
16 OverallQual 1168 non-null int64
17 OverallCond 1168 non-null int64
18 YearBuilt 1168 non-null int64
19 YearRemodAdd 1168 non-null int64
20 RoofStyle 1168 non-null object
21 RoofMatl 1168 non-null object
22 Exterior1st 1168 non-null object
23 Exterior2nd 1168 non-null object
24 MasVnrType 1161 non-null object
25 MasVnrArea 1161 non-null float64
26 ExterQual 1168 non-null object
27 ExterCond 1168 non-null object
28 Foundation 1168 non null object
29 BsmtQual 1138 non-null object
30 BsmtCond 1138 non-null object
31 BsmtExposure 1137 non-null object
32 BsmtFinType1 1138 non-null object
33 BsmtFinSF1 1168 non-null int64
34 BsmtFinType2 1137 non-null object
35 BsmtFinSF2 1168 non-null int64
36 BsmtUnfSF 1168 non-null int64
37 TotalBsmtSF 1168 non-null int64
38 Heating 1168 non-null object
39 HeatingQC 1168 non-null object
40 CentralAir 1168 non-null object
41 Electrical 1168 non-null object
42 1stFlrSF 1168 non-null int64
43 2ndFlrSF 1168 non-null int64

44 LowQualFinSF 1168 non-null
int64
45 GrLivArea 1168 non-null
int64
46 BsmtFullBath 1168 non-null
int64
47 BsmtHalfBath 1168 non-null
int64
48 FullBath 1168 non-null int64
49 HalfBath 1168 non-null int64
50 BedroomAbvGr 1168 non-null
int64
51 KitchenAbvGr 1168 non-null
int64
52 KitchenQual 1168 non-null
object
53 TotRmsAbvGrd 1168 non-null
int64
54 Functional 1168 non-null
object
55 Fireplaces 1168 non-null int64
56 FireplaceQu 617 non-null
object
57 GarageType 1104 non-null
object
58 GarageYrBlt 1104 non-null
float64
59 GarageFinish 1104 non-null
object
60 GarageCars 1168 non-null
int64
61 GarageArea 1168 non-null
int64
62 GarageQual 1104 non-null
object
63 GarageCond 1104 non-null
object
64 PavedDrive 1168 non-null
object
65 WoodDeckSF 1168 non-null
int64

66 OpenPorchSF 1168 non-null
int64
67 EnclosedPorch 1168 non-null
int64
68 3SsnPorch 1168 non-null
int64
69 ScreenPorch 1168 non-null
int64
70 PoolArea 1168 non-null int64
71 PoolQC 7 non-null object
72 Fence 237 non-null object
73 MiscFeature 44 non-null
object
74 MiscVal 1168 non-null int64
75 MoSold 1168 non null int64

76 YrSold 1168 non-null int64
77 SaleType 1168 non-null object
78 SaleCondition 1168 non-null object
79 SalePrice 1168 non-null int64 dtypes: float64(3), int64(34), object(43) memory usage: 730.1+ KB
None

Check the Data type

```
print(test.dtypes)
print('**************')
print(train.dtypes)
```

```
MSSubClass        int64
MSZoning         object
LotFrontage     float64
LotArea           int64
Street           object
...
MiscVal           int64
MoSold            int64
YrSold            int64
SaleType         object
SaleCondition    object
Length: 79, dtype: object
**************
MSSubClass        int64
MSZoning         object
LotFrontage     float64
LotArea           int64
Street           object
...
MoSold            int64
YrSold            int64
SaleType         object
SaleCondition    object
SalePrice         int64
Length: 80, dtype: object
```


```
In [104]: print(test.dtypes)
          print('**************')
          print(train.dtypes)

MSSubClass        int64
MSZoning         object
LotFrontage     float64
LotArea           int64
Street           object
                  ...
MiscVal           int64
MoSold            int64
YrSold            int64
SaleType         object
SaleCondition    object
Length: 79, dtype: object
**************
MSSubClass        int64
MSZoning         object
LotFrontage     float64
LotArea           int64
Street           object
                  ...
MoSold            int64
YrSold            int64
SaleType         object
SaleCondition    object
SalePrice         int64
Length: 80, dtype: object
```


Observation: There are two types of data present in the dataset categorical and numerical.

Data Preprocessing Done

- I checked the information, data types, null values, correlation of the independent and dependent features and f**rom the correlation table.**
- Some columns can't have any negative value, so those columns were treated accordingly.
- Treated Null vales accordingly columns type.
- Skewness,Outliers are treated manually for the features giving some important information, and then the threshold values were set to make the data free from outliers.
- Applied StandardScaler.
- Applied various machine learning model and compared it.

Handling Missing Values

```
# Let's check the missing values of top 30 columns

print(train.isnull().values.any()) print("*******************")

print(train.isnull().sum().sort_values(ascending =

False).head(30))

print("*****************************************")

print(test.isnull().sum().sort_values(ascending = False).head(30))
```

```
True
*******************
PoolQC          1161
MiscFeature     1124
Alley           1091
Fence            931
FireplaceQu      551
LotFrontage      214
GarageType        64
GarageFinish      64
GarageQual        64
GarageCond        64
GarageYrBlt       64
BsmtExposure      31
BsmtFinType2      31
BsmtCond          30
BsmtFinType1      30
BsmtQual          30
MasVnrArea         7
MasVnrType         7
RoofStyle          0
RoofMatl           0
ExterQual          0
Exterior1st        0
Exterior2nd        0
YearBuilt          0
ExterCond          0
Foundation         0
```

```
    YearRemodAdd       0
    SalePrice          0
    OverallCond        0
    OverallQual        0
    dtype: int64
****************************************
PoolQC          292
MiscFeature     282
Alley           278
Fence           248
FireplaceQu     139
LotFrontage      45
GarageCond       17
GarageType       17
GarageYrBlt      17
GarageFinish     17
GarageQual       17
BsmtFinType1      7
BsmtExposure      7
BsmtCond          7
BsmtQual          7
BsmtFinType2      7
Electrical        1
MasVnrArea        1
MasVnrType        1
LandSlope         0
RoofMatl          0
MSZoning          0
LotArea           0
Street            0
LotShape          0
Foundation        0
ExterCond         0
ExterQual         0
Exterior2nd       0 Exterior1st
0
dtype: int64
```

Observation:

In train dataset There are 18 columns that have missing values. Major missing values columns are PoolQC, 1124-in MiscFeature, 11091-in Alley, 931-in Fence, 551-in FireplaceQu

There are 1161-missing values in the column PoolQC, 1124-in MiscFeature, 11091-in Alley, 931-in Fence, 551-in FireplaceQu,214- in LotFrontage, 64-each in GarageType, GarageCond, GarageYrBlt, GarageFinish, GarageQual, 31-in BsmtExposure and BsmtFinType2, 30-in BsmtCond and BsmtQual, 7in MasVnrArea and MasVnrType present in our dataset.

IN test Dataset There are 19 columns that have missing values. Major missing values columns are PoolQC 292 MiscFeature 282 Alley 278 Fence 248 FireplaceQu 139

Total Missing Value Percantage for Train dataset

```
Your selected dataframe has 80 columns.
There are 18 columns that have missing values.
```

Out[107]:

	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
MasVnrArea	7	0.6
MasVnrType	7	0.6

Total Missing Value Percantage for Test Dataset

t[108]:

	Missing Values	% of Total Values
PoolQC	292	100.0
MiscFeature	282	96.6
Alley	278	95.2
Fence	248	84.9
FireplaceQu	139	47.6
LotFrontage	45	15.4
GarageType	17	5.8
GarageYrBlt	17	5.8
GarageFinish	17	5.8
GarageQual	17	5.8
GarageCond	17	5.8
BsmtExposure	7	2.4
BsmtFinType1	7	2.4
BsmtFinType2	7	2.4
BsmtCond	7	2.4
BsmtQual	7	2.4
MasVnrArea	1	0.3
MasVnrType	1	0.3
Electrical	1	0.3

In [105]:

```
# Let's explore the categorical columns

for column in train.columns:
    if train[column].dtypes == object:
        print(str(column) + ' : ' + str(train[column].unique()))
        print(train[column].value_counts())
        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
Name: Alley, dtype: int64

LotShape : ['IR1' 'Reg' 'IR2' 'IR3']
Reg 740
IR1 390
IR2 32
IR3 6
Name: LotShape, dtype: int64

LandContour : ['Lvl' 'Bnk' 'HLS' 'Low']
Lvl 1046 Bnk
50
HLS 42
Low 30
Name: LandContour, dtype: int64

Utilities : ['AllPub']
AllPub 1168
Name: Utilities, dtype: int64

LotConfig : ['Inside' 'CulDSac' 'FR2' 'Corner' 'FR3']
Inside 842
Corner 222
CulDSac 69
FR2 33
FR3 2
Name: LotConfig, dtype: int64

LandSlope : ['Gtl' 'Mod' 'Sev']
Gtl 1105
Mod 51
Sev 12
Name: LandSlope, dtype: int64

Neighborhood : ['NPkVill' 'NAmes' 'NoRidge' 'NWAmes' 'Gilbert' 'Sawyer' 'Edwards'
 'IDOTRR' 'CollgCr' 'Mitchel' 'Crawfor' 'BrDale' 'StoneBr' 'BrkSide'
 'NridgHt' 'OldTown' 'Somerst' 'Timber' 'SWISU' 'SawyerW' 'ClearCr'
 'Veenker' 'Blmngtn' 'MeadowV' 'Blueste']
NAmes 182 CollgCr
118
OldTown 86
Edwards 83
Somerst 68
Gilbert 64
NridgHt 61
Sawyer 60
NWAmes 59
SawyerW 51
BrkSide 50
Crawfor 45
NoRidge 35
Mitchel 34
IDOTRR 30
Timber 24
ClearCr 24
SWISU 21
StoneBr 19
Blmngtn 15
BrDale 11
MeadowV 9
Veenker 9
NPkVill 8
Blueste 2
Name: Neighborhood, dtype: int64

Condition1 : ['Norm' 'Feedr' 'RRAn' 'PosA' 'RRAe' 'Artery' 'PosN' 'RRNe' 'RRNn']
Norm 1005
Feedr 67
Artery 38
RRAn 20
PosN 17
RRAe 9
PosA 6
RRNn 4
RRNe 2
Name: Condition1, dtype: int64

Condition2 : ['Norm' 'RRAe' 'Feedr' 'PosN' 'Artery' 'RRNn' 'PosA' 'RRAn']
Norm 1154
Feedr 6
Artery 2
PosN 2
RRAe 1
RRNn 1

RRAn 1
PosA 1
Name: Condition2, dtype: int64

BldgType : ['TwnhsE' '1Fam' 'Duplex' 'Twnhs' '2fmCon']
1Fam 981
TwnhsE 90
Duplex 41
Twnhs 29
2fmCon 27
Name: BldgType, dtype: int64

HouseStyle : ['1Story' '2Story' '1.5Fin' 'SFoyer' '1.5Unf' 'SLvl' '2.5Fin' '2.5Unf']
1Story 578
2Story 361
1.5Fin 121 SLvl
47
SFoyer 32
1.5Unf 12
2.5Unf 10
2.5Fin 7
Name: HouseStyle, dtype: int64

RoofStyle : ['Gable' 'Flat' 'Hip' 'Shed' 'Gambrel' 'Mansard']
Gable 915
Hip 225
Flat 12
Gambrel 9
Mansard 5
Shed 2
Name: RoofStyle, dtype: int64

RoofMatl : ['CompShg' 'Tar&Grv' 'WdShngl' 'WdShake' 'Roll' 'ClyTile' 'Metal'
'Membran']
CompShg 1144
Tar&Grv 10
WdShngl 6
WdShake 4
Membran 1
Metal 1
ClyTile 1
Roll 1
Name: RoofMatl, dtype: int64

Exterior1st : ['Plywood' 'Wd Sdng' 'MetalSd' 'CemntBd' 'VinylSd' 'HdBoard' 'Stucco'
'WdShing' 'BrkFace' 'Stone' 'AsbShng' 'AsphShn' 'ImStucc' 'BrkComm']
VinylSd 396
HdBoard 179
MetalSd 178

```
Wd Sdng    174
Plywood     93
CemntBd     42
BrkFace     41
Stucco      22
WdShing     19
AsbShng     19
Stone        2
AsphShn      1
BrkComm      1
ImStucc      1
Name: Exterior1st, dtype: int64


Exterior2nd : ['Plywood' 'Wd Sdng' 'MetalSd' 'CmentBd' 'VinylSd' 'HdBoard' 'Wd Shng'
 'Stucco' 'ImStucc' 'Stone' 'BrkFace' 'AsbShng' 'Brk Cmn' 'AsphShn'
 'Other']
VinylSd    387
MetalSd    173
HdBoard    170
Wd Sdng    165
Plywood    118
CmentBd     42
Wd Shng     31
Stucco      23
BrkFace     20
AsbShng     18
ImStucc      8
Brk Cmn      5
Stone        4
AsphShn      3
Other        1
Name: Exterior2nd, dtype: int64


MasVnrType : ['None' 'BrkFace' 'Stone' 'BrkCmn' nan]
None       696
BrkFace    354
Stone       98
BrkCmn      13
Name: MasVnrType, dtype: int64


ExterQual : ['TA' 'Gd' 'Ex' 'Fa']
TA    717
Gd    397
Ex     43
Fa     11
Name: ExterQual, dtype: int64


ExterCond : ['TA' 'Gd' 'Fa' 'Po' 'Ex']
TA    1022
Gd     117
```

```
Fa      26
Ex       2
Po       1
Name: ExterCond, dtype: int64


Foundation : ['CBlock' 'PConc' 'BrkTil' 'Slab' 'Stone' 'Wood']
CBlock    516
PConc     513
BrkTil    112
Slab       21
Stone       5
Wood        1
Name: Foundation, dtype: int64


BsmtQual : ['Gd' 'TA' 'Ex' nan 'Fa']
TA    517
Gd    498
Ex     94 Fa
29
Name: BsmtQual, dtype: int64


BsmtCond : ['TA' 'Gd' 'Fa' nan 'Po']
TA    1041
Gd      56
Fa      39
Po       2
Name: BsmtCond, dtype: int64


BsmtExposure : ['No' 'Gd' 'Av' 'Mn' nan]
No    756
Av    180
Gd    108
Mn     93
Name: BsmtExposure, dtype: int64


BsmtFinType1 : ['ALQ' 'GLQ' 'BLQ' 'Unf' 'Rec' 'LwQ' nan]
Unf    345
GLQ    330
ALQ    174 BLQ
121
Rec    109
LwQ     59
Name: BsmtFinType1, dtype: int64


BsmtFinType2 : ['Unf' 'Rec' 'BLQ' 'GLQ' nan 'ALQ' 'LwQ']
Unf    1002
Rec      43
LwQ      40
```

BLQ 24 ALQ
16
GLQ 12
Name: BsmtFinType2, dtype: int64

Heating : ['GasA' 'GasW' 'Floor' 'OthW' 'Wall' 'Grav']
GasA 1143
GasW 14
Grav 5
Wall 4
Floor 1
OthW 1
Name: Heating, dtype: int64

HeatingQC : ['TA' 'Ex' 'Gd' 'Fa' 'Po']
Ex 585
TA 352
Gd 192
Fa 38
Po 1
Name: HeatingQC, dtype: int64

CentralAir : ['Y' 'N']
Y 1090
N 78
Name: CentralAir, dtype: int64

Electrical : ['SBrkr' 'FuseA' 'FuseF' 'FuseP' 'Mix']
SBrkr 1070
FuseA 74
FuseF 21
FuseP 2
Mix 1
Name: Electrical, dtype: int64

KitchenQual : ['TA' 'Gd' 'Ex' 'Fa']
TA 578
Gd 478
Ex 82
Fa 30
Name: KitchenQual, dtype: int64

Functional : ['Typ' 'Mod' 'Maj1' 'Min1' 'Min2' 'Sev' 'Maj2']
Typ 1085
Min2 30
Min1 25
Mod 12
Maj1 11

```
Maj2       4
Sev        1
Name: Functional, dtype: int64


FireplaceQu : ['TA' 'Gd' nan 'Fa' 'Ex' 'Po']
Gd    301
TA    252
Fa     25
Ex     21
Po     18
Name: FireplaceQu, dtype: int64


GarageType : ['Attchd' 'BuiltIn' 'Detchd' 'Basment' nan '2Types' 'CarPort']
Attchd     691
Detchd     314
BuiltIn     70
Basment     16
CarPort      8
2Types       5
Name: GarageType, dtype: int64


GarageFinish : ['RFn' 'Unf' 'Fin' nan]
Unf    487
RFn    339
Fin    278
Name: GarageFinish, dtype: int64


GarageQual : ['TA' 'Fa' nan 'Gd' 'Ex' 'Po']
TA    1050
Fa      39
Gd      11
Po       2
Ex       2
Name: GarageQual, dtype: int64


GarageCond : ['TA' 'Fa' 'Gd' nan 'Po' 'Ex']
TA    1061
Fa      28
Gd       8
Po       6
Ex       1
Name: GarageCond, dtype: int64


PavedDrive : ['Y' 'N' 'P']
Y    1071
N      74
P      23
Name: PavedDrive, dtype: int64
```

PoolQC : [nan 'Ex' 'Gd' 'Fa']
Gd   3
Fa   2 Ex
2
Name: PoolQC, dtype: int64

Fence : [nan 'MnPrv' 'GdPrv' 'GdWo' 'MnWw']
MnPrv   129
GdPrv   51
GdWo   47
MnWw   10
Name: Fence, dtype: int64

MiscFeature : [nan 'Shed' 'Gar2' 'TenC' 'Othr']
Shed   40
Gar2   2
TenC   1
Othr   1
Name: MiscFeature, dtype: int64

SaleType : ['WD' 'COD' 'New' 'ConLI' 'ConLw' 'Con' 'ConLD' 'Oth' 'CWD']
WD   999
New   106
COD   38
ConLD   8
ConLI   5
ConLw   4
Oth   3
CWD   3
Con   2
Name: SaleType, dtype: int64

SaleCondition : ['Normal' 'Partial' 'Abnorml' 'Family' 'Alloca' 'AdjLand']
Normal   945 Partial
108
Abnorml   81
Family   18
Alloca   12
AdjLand   4
Name: SaleCondition, dtype: int64

Observation:
There is only one unique value present in utilities column so we will be dropping this column.

2. In categorical columns there are missing values present in coumns Alley, MasVnrType, BsmtQual, BsmtCond, BsmtExposure, BsmtFinType1, BsmtFinType2, FireplaceQu,

GarageType, GarageFinish, GarageQual, GarageCond, PoolQC, Fence, MiscFeature **Fill Missing Values**

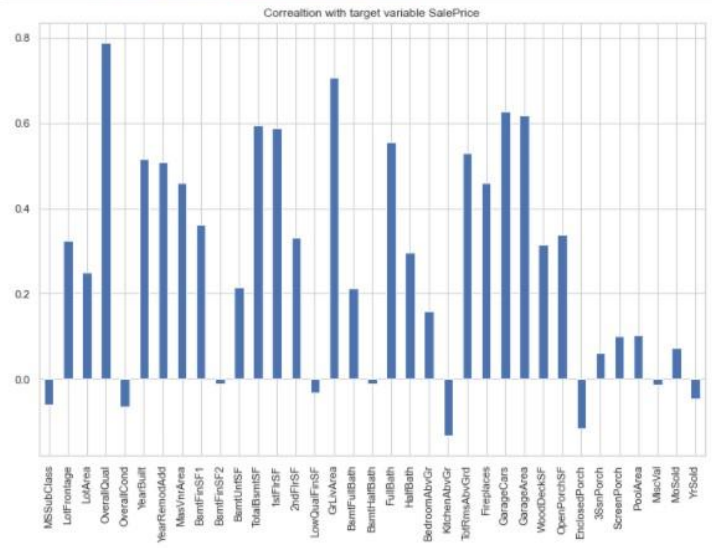
```
In [111]: # Let's fill the missing values in categorical columns as NA in train dataset

columns = ["FireplaceQu", "GarageType", "GarageFinish", "GarageQual", "GarageCond", "BsmtExposure", "BsmtFinType2", "BsmtCond", '
train[columns] = train[columns].fillna('NA')

# Let's fill the missing values in MasVnrType with None
train['MasVnrType'] = train['MasVnrType'].fillna('None')

# Let's fill the missing values in GarageYrBlt with 0
train['GarageYrBlt'] = train['GarageYrBlt'].fillna('0')

# Let's Imputing the missing values and replace it with the median
train['LotFrontage'].fillna(train['LotFrontage'].median(),inplace=True)
train['MasVnrArea'].fillna(train['MasVnrArea'].median(),inplace=True)
```

```
In [112]: # Let's fill the missing values in categorical columns as NA in test dataset

columns = ["FireplaceQu", "GarageType", "GarageFinish", "GarageQual", "GarageCond", "BsmtExposure", "BsmtFinType2", "BsmtCond", '
test[columns] = test[columns].fillna('NA')

# Let's fill the missing values in MasVnrType with None
test['MasVnrType'] = test['MasVnrType'].fillna('None')

# Let's fill the missing values in GarageYrBlt with 0
test['GarageYrBlt'] = test['GarageYrBlt'].fillna('0')

# Let's Imputing the missing values and replace it with the median
test['LotFrontage'].fillna(test['LotFrontage'].median(),inplace=True)
test['MasVnrArea'].fillna(test['MasVnrArea'].median(),inplace=True)
```

Data Inputs- Logic- Output Relationships

Lets check the correlation with target variable "Salesprice".

```
In [118]: # Let's check the correlation with target variable 'SalePrice'

plt.figure(figsize=(12,8))
train.drop('SalePrice', axis=1).corrwith(train['SalePrice']).plot(kind='bar',grid=True)
plt.xticks(rotation='vertical')
plt.title("Correaltion with target variable SalePrice");
```



Observation:

Observation:

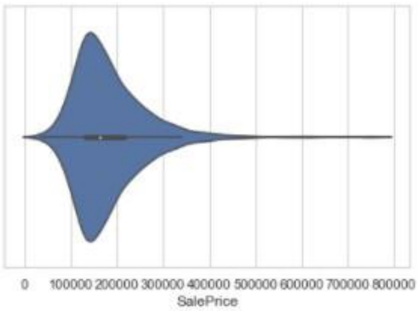
1. The column OverallQual is most positively correlated with SalePrice.

2.The column KitchenAbvGrd and EnclosedPorch is most negatively correlated with SalePrice.

Maximum number of SalePrice lies between 140000 and 230000.

Univatriate Analysis

In [119]:
```
# Let's Check the target variable

sns.set(style='whitegrid')
sns.violinplot(train['SalePrice'])
plt.show()

train['SalePrice'].value_counts()
```



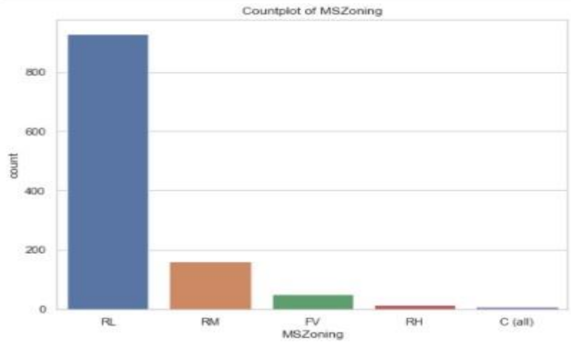
Out[119]:
```
140000    18
135000    16
155000    12
139000    11
160000    11
          ..
126175     1
204000     1
186000     1
369900     1
105500     1
Name: SalePrice, Length: 581, dtype: int64
```

Maximum number of SalePrice lies between 140000 and 230000.

Maximum, 928 number of MSZoning are RL

Maximum number of SalePrice lies between 140000 and 230000.

In [120]:
```
# Let's check the column MSZoning

plt.subplots(figsize=(8,6))
sns.countplot(x="MSZoning", data=train)
plt.title("Countplot of MSZoning")
plt.xlabel('MSZoning')
plt.ylabel("count")
plt.show()

train['MSZoning'].value_counts()
```



Out[120]:
```
RL         928
RM         163
FV          52
RH          16
C (all)      9
Name: MSZoning, dtype: int64
```

Bivariate Analysis

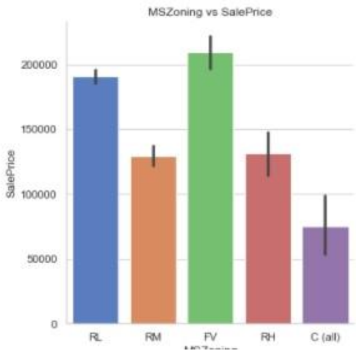
Let's plot the Scatter plot between all feature variables and target variable for col in train.describe().columns:

```
data=train.copy()
plt.scatter(data[col],data['SalePrice'])
plt.xlabel(col)    plt.ylabel('SalePrice')
plt.show()
```

1. **SalePrice is maximum with FV MSZOning.**

```
In [129]: # Let's plot the Factor plot of MSZoning vs SalePrice

          plt.figure(figsize=(8,6))
          sns.factorplot(x='MSZoning',y='SalePrice',data=train,kind='bar',size=5,palette='muted',aspect=1)
          plt.title('MSZoning vs SalePrice')
          plt.ylabel('SalePrice')
          plt.show()
          print(train.groupby('SalePrice')['MSZoning'].value_counts());
```

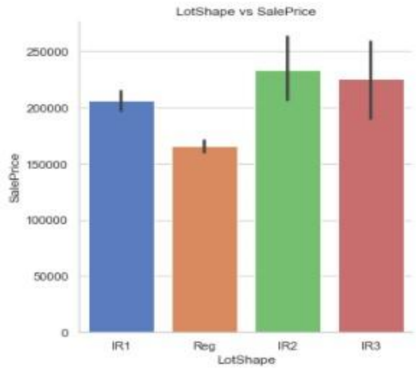
<Figure size 576x432 with 0 Axes>



2. **SalePrice is maximum with IR2 LotShape.**

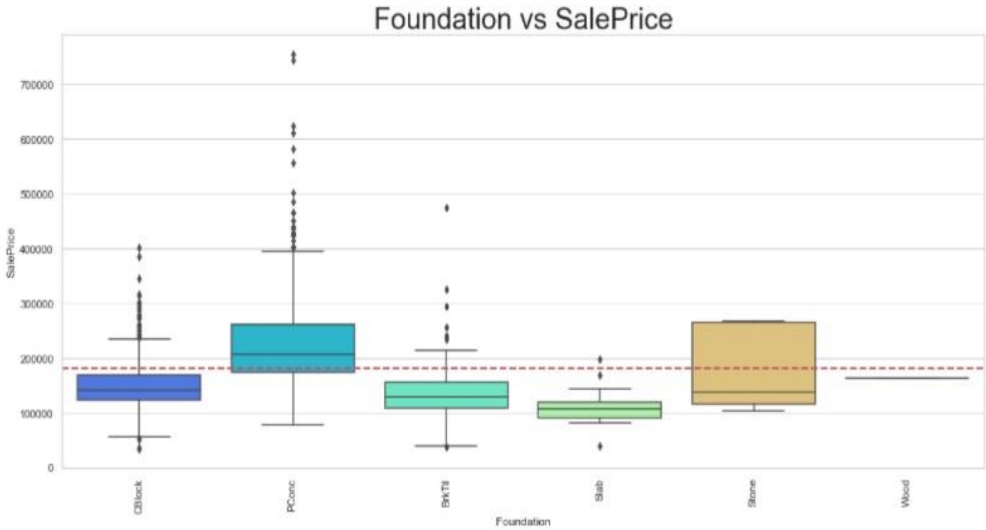
```
In [130]: # Let's plot the Factor plot of LotShape vs SalePrice

          plt.figure(figsize=(8,6))
          sns.factorplot(x='LotShape',y='SalePrice',data=train,kind='bar',size=5,palette='muted',aspect=1)
          plt.title('LotShape vs SalePrice')
          plt.ylabel('SalePrice')
          plt.show();
          print(train.groupby('SalePrice')['LotShape'].value_counts());
```

```
<Figure size 576x432 with 0 Axes>
```



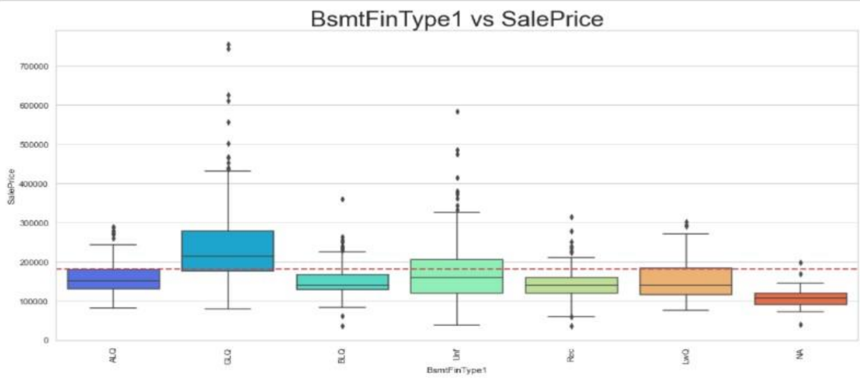
3. SalePrice is maximum with PConc

In [133]:
```
# Let's plot the Foundation vs SalePrice plot

plt.figure(figsize=(18,8))
mean_price=np.mean(train['SalePrice'])
sns.boxplot(y='SalePrice',x='Foundation',data=train,palette="rainbow")
plt.axhline(mean_price,color='r',linestyle='dashed',linewidth=2)
plt.title("Foundation vs SalePrice",fontsize=30)
plt.xticks(rotation='vertical')
plt.show()
```



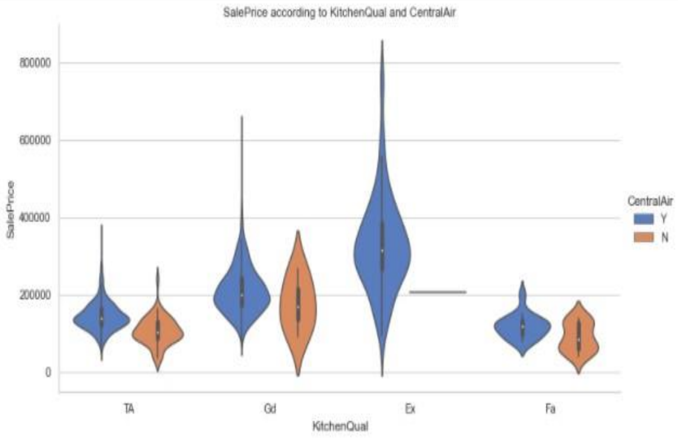
4. SalePrice is maximum with GLQ BsmtFinType1.

In [134]:
```
# Let's plot the BsmtFinType1 vs SalePrice plot

plt.figure(figsize=(18,8))
mean_price=np.mean(train['SalePrice'])
sns.boxplot(y='SalePrice',x='BsmtFinType1',data=train,palette="rainbow")
plt.axhline(mean_price,color='r',linestyle='dashed',linewidth=2)
plt.title("BsmtFinType1 vs SalePrice",fontsize=30)
plt.xticks(rotation='vertical')
plt.show()
```



Multivariate Analysis

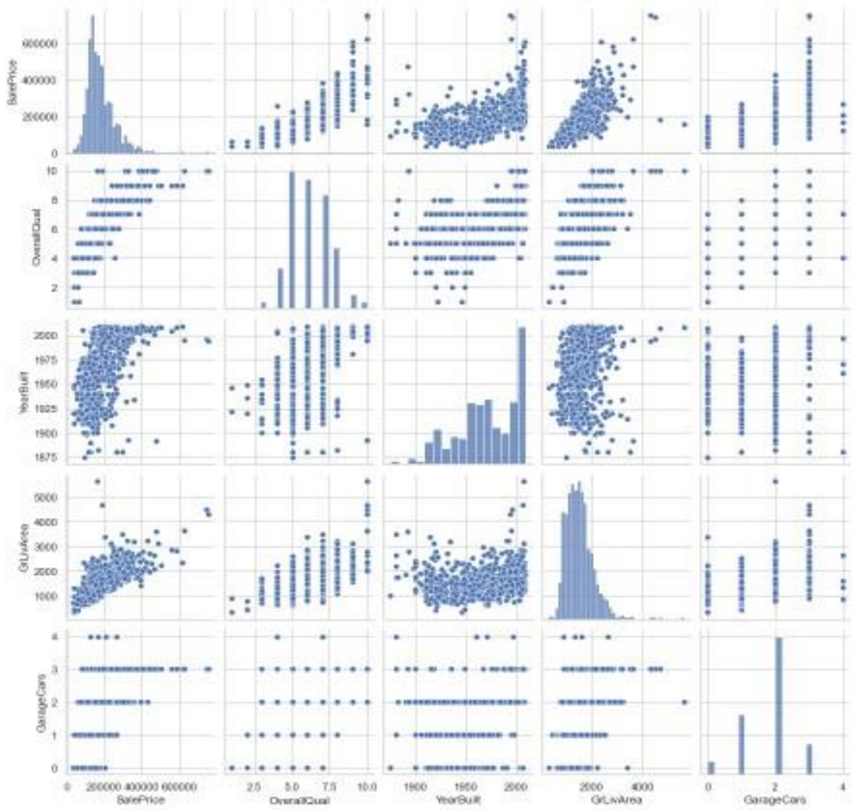
```
In [135]: # Let's plot the GarageType and GarageCond with respect to SalePrice plot

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



 # Let's plot the pairplot

sns.pairplot(train, vars=['SalePrice','OverallQual','YearBuilt','GrLivArea','GarageCars']);

```
In [136]: # Let's plot the pairplot
          sns.pairplot(train, vars=['SalePrice','OverallQual','YearBuilt','GrLivArea','GarageCars']);
```



- State the set of assumptions (if any) related to the problem under consideration
  I have not consider any pre-assumption , project performance from beginning to end is based on data facts only.

- **Hardware and Software Requirements and Tools Used** Windows Edition-Windows 8.1 Pro
  Processor-Intel(R) Core(TM) i3-5005U CPU @ 2.00GHz 2.00GHz
  Installed memory RAM- 4 GB
  System Type-64 bit OS, x64 based processor

  Software Requirement- Anaconda 4.9.2 , Python 3.8.5, Jupiter Notebook.

  Libraries used:-

```
In [ ]: # Let's import all the required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
pd.pandas.set_option('display.max_columns',None)

from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from scipy import stats

from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor

from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV,cross_val_score
from sklearn.model_selection import GridSearchCV

#importing warnings
import warnings
warnings.filterwarnings('ignore')
```

Model/s Development and Evaluation

- Identification of possible problem-solving approaches (methods)
- **Analytical Approach –**Based on type of data by performing EDA I have decided which model to be used for this data.
- **Statistical Approach –** Data should be in scaled manner, it should not be distorted, for that all values using mean method due to continuous data numbers.

Statistical Approach for train Dataset

In [113]:
```
# Let's check the statistical summary of our dataset
train.describe()
```

Out[113]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF
count	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000	1168.000000
mean	56.767979	70.807363	10484.749144	6.104452	5.595890	1970.930651	1984.758562	101.696918	444.726027	46.647260	569.721747
std	41.940650	22.440317	8957.442311	1.390153	1.124343	30.145255	20.785185	182.218483	462.664785	163.520016	449.375525
min	20.000000	21.000000	1300.000000	1.000000	1.000000	1875.000000	1950.000000	0.000000	0.000000	0.000000	0.000000
25%	20.000000	60.000000	7621.500000	5.000000	5.000000	1954.000000	1966.000000	0.000000	0.000000	0.000000	216.000000
50%	50.000000	70.000000	9522.500000	6.000000	5.000000	1972.000000	1993.000000	0.000000	385.500000	0.000000	474.000000
75%	70.000000	79.250000	11515.500000	7.000000	6.000000	2000.000000	2004.000000	160.000000	714.500000	0.000000	816.000000
max	190.000000	313.000000	164660.000000	10.000000	9.000000	2010.000000	2010.000000	1600.000000	5644.000000	1474.000000	2336.000000

1. Maximum standard deviation of 8957.44 is observed in LotArea column.

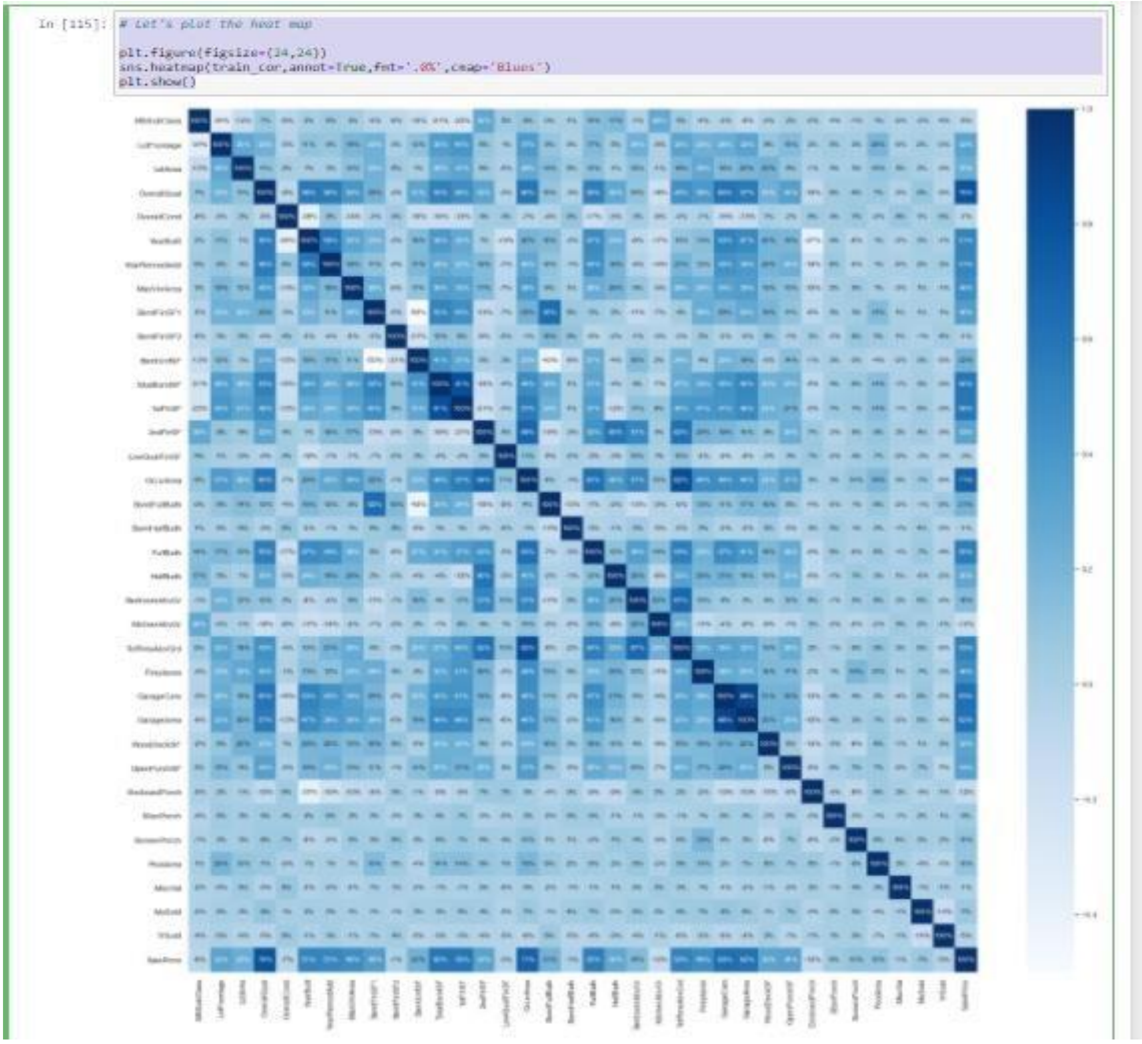
2.Maximum SalePrice of a house observed is 755000 and minimum is 34900.

3. In the columns Id, MSSubclass, LotArea, MasVnrArea, BsmtFinSF1, BsmtFinSF2, BsmtUnfsF, TotalBsmtSF, 1stFlrSF, 2ndFlrSF, LowQualFinSF, GrLivArea, BsmtFullBath, HalfBath, TotRmsAbvGrd, WoodDeckSF, OpenPorchSF, EnclosedPorch, 3SsnPorch, ScreenPorch, PoolArea, Miscval, salePrice mean is considerably greater than median so the columns are positively skewed.
4. In the columns FullBath, BedroomAbvGr, Fireplaces, Garagecars, GarageArea, YrSold Median is greater than mean so the columns are negatively skewed.
5. In the columns Id, MSSubClass, LotFrontage, LotArea, MasVnrArea, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, 1stFlrSF, 2ndFlrSF, LowQualFinSF, GrLivArea, BsmtHalfBath, BedroomAbvGr, ToRmsAbvGrd, GarageArea, WoodDeckSF, OpenPorchSF, EnclosedPorch, 3SsnPorch, ScreenPorch, PoolArea, MiscVal, SalePrice there is considerable difference between the 75 percentile and maximum so outliers are present.

Checking Correlation with Heatmap

Let's plot the heat map

plt.figure(figsize=(24,24))
sns.heatmap(train_cor,annot=True,fmt='.0%',cmap='Blues') plt.show()



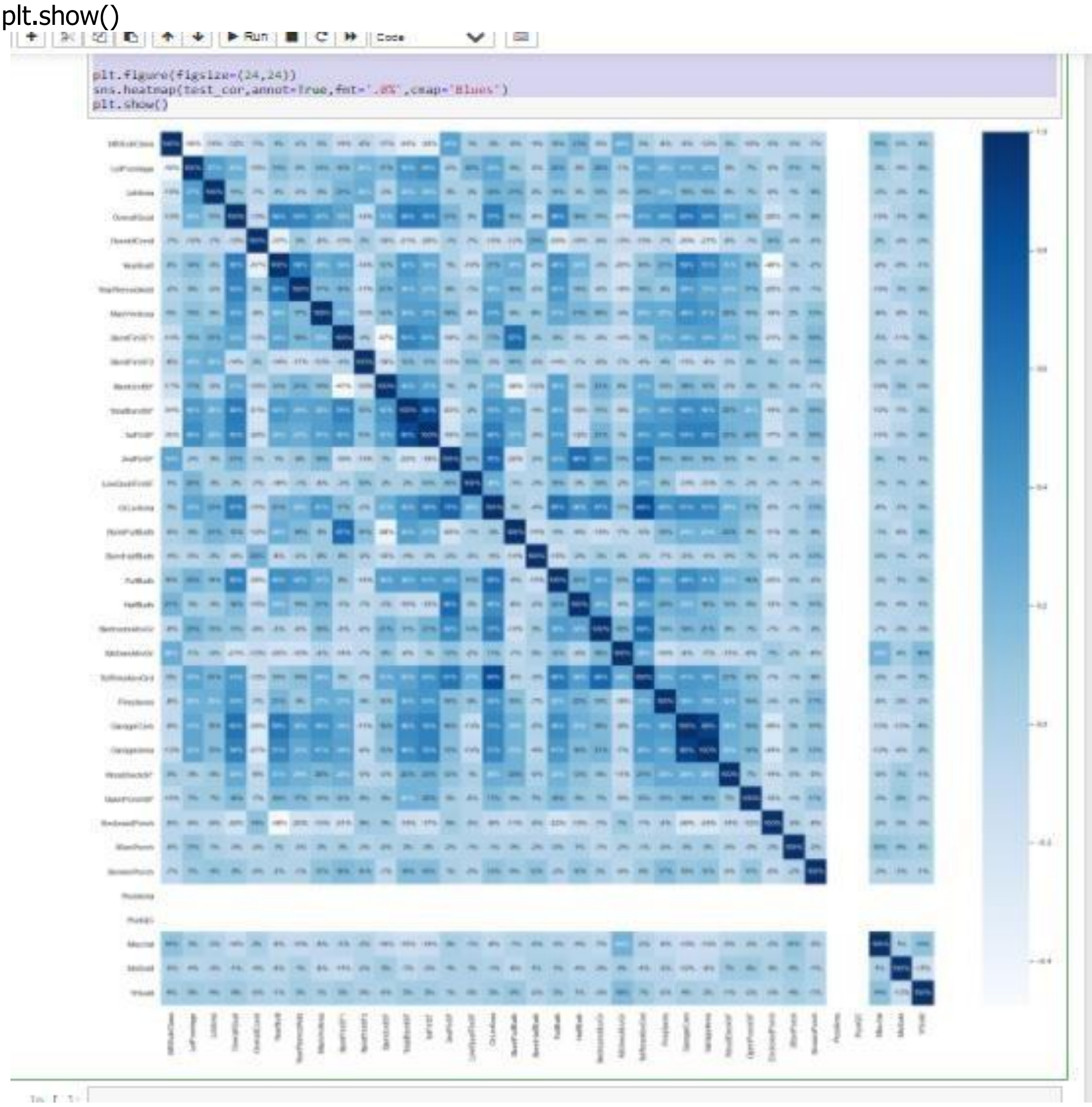
1.SalePrice is highly positively correlated with the columns OverallQual, YearBuilt, YearRemodAdd, TotalBsmtSF, 1stFlrSF, GrLivArea, FullBath, TotRmsAbvGrd, GarageCars, GarageArea.

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).

Let's plot the heat map for test dataset

```
plt.figure(figsize=(24,24))
sns.heatmap(test_cor,annot=True,fmt='.0%',cmap='Blues')
plt.show()
```



Handling Outliers and skewness

Handling outliers and skewness

In [142]:
```
# Let's make a copy of our dataset

train_cap = train.copy()
```

In [143]:
```
def percentile_capping(train, cols, from_low_end, from_high_end):
    for col in cols:
        stats.mstats.winsorize(a=train[col], limits=(from_low_end, from_high_end), inplace=True)
```

In [144]:
```
features=['MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea','BsmtFi
```

In [145]:
```
percentile_capping(train, features, 0.01, 0.10)
# Let's check the shape

train_cap.shape
```

Out[145]: (1168, 244)

In [146]:
```
for col in features:
    plt.figure(figsize=(16,4))

    plt.subplot(141)
    sns.distplot(train[col], label="skew: " + str(np.round(train[col].skew(),2)))
    plt.title('Before')
    plt.legend()

    plt.subplot(142)
    sns.distplot(train_cap[col], label="skew: " + str(np.round(train_cap[col].skew(),2)))
    plt.title('After')
    plt.legend()

    plt.subplot(143)
    sns.boxplot(train[col])
    plt.title('Before')

    plt.subplot(144)
    sns.boxplot(train_cap[col])
    plt.title('After')
    plt.tight_layout()
    plt.show();
```

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

All Algorithms list

from sklearn.metrics import
mean_absolute_error from sklearn.metrics
import mean_squared_error from sklearn.metrics
import r2_score from sklearn import
linear_model
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor

from sklearn.ensemble import RandomForestRegressor from
sklearn.ensemble import AdaBoostRegressor from
sklearn.ensemble import GradientBoostingRegressor from
sklearn.model_selection import GridSearchCV,cross_val_score
from sklearn.model_selection import GridSearchCV

```
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
from sklearn.svm import SVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor

from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV,cross_val_score
from sklearn.model_selection import GridSearchCV
```

Below are Linear Regression algorithms used for the training and testing this dataset.

```
model=[LinearRegression(),
DecisionTreeRegressor(),
      KNeighborsRegressor(),
      SVR(),
      Lasso(),
      Ridge(),
      ElasticNet(),
      RandomForestRegressor(),
      AdaBoostRegressor(),
```

```
In [167]: model=[LinearRegression(),
                 DecisionTreeRegressor(),
                 KNeighborsRegressor(),
                 SVR(),
                 Lasso(),
                 Ridge(),
                 ElasticNet(),
                 RandomForestRegressor(),
                 AdaBoostRegressor(),
```

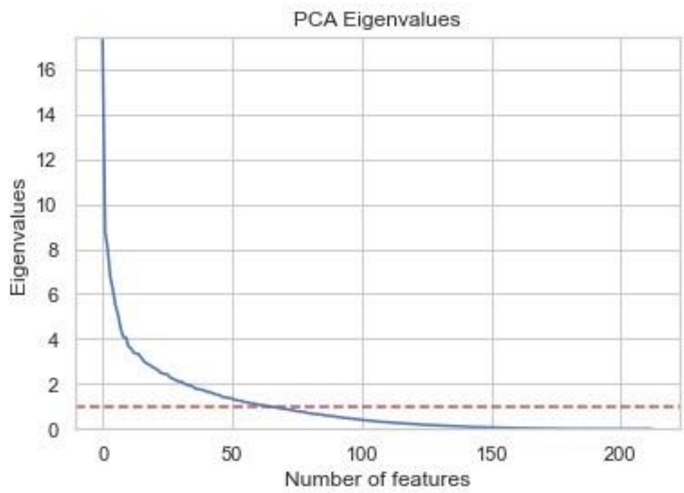
a. Run and Evaluate selected models

PCA

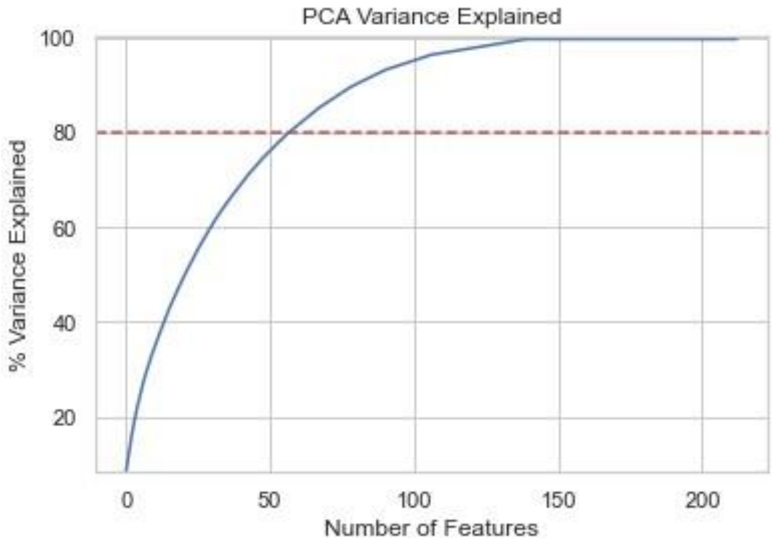
```
In [154]: # Let's explore the PCA train dataset

          covar_matrix = PCA(n_components = len(x.columns))
          covar_matrix.fit(x)

Out[154]: PCA(n_components=243)

In [155]: # Let's check the PCA test dataset

          covar_matrix = PCA(n_components = len(x1.columns))
          covar_matrix.fit(x1)

Out[155]: PCA(n_components=213)
```

```
In [156]: # Let's plot the PCA componenets

          plt.ylabel('Eigenvalues')
          plt.xlabel('Number of features')
          plt.title('PCA Eigenvalues')
          plt.ylim(0,max(covar_matrix.explained_variance_))
          plt.style.context('seaborn-whitegrid')
          plt.axhline(y=1, color='r', linestyle='--')
          plt.plot(covar_matrix.explained_variance_)
          plt.show()
```

plt.show()



In [157]:
```
variance = covar_matrix.explained_variance_ratio_
var=np.cumsum(np.round(covar_matrix.explained_variance_ratio_, decimals=3)*100)

plt.ylabel('% Variance Explained')
plt.xlabel('Number of Features')
plt.title('PCA Variance Explained')
plt.ylim(min(var),100.5)
plt.style.context('seaborn-whitegrid')
plt.axhline(y=80, color='r', linestyle='--')
plt.plot(var)
plt.show()
```



Lets find the best Random forest score

In [162]:
```
# Let's find the best random state

max_r_score=0
for r_state in range(1,100):
    x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=r_state,test_size=0.20)
    regr=linear_model.LinearRegression()
    regr.fit(x_train,y_train)
    y_pred=regr.predict(x_test)
    r2_scr=r2_score(y_test,y_pred)
    if r2_scr>max_r_score:
        max_r_score=r2_scr
        final_r_state=r_state
print("max r2 score corresponding to",final_r_state,"is",max_r_score)
```

```
max r2 score corresponding to 48 is 0.8496659416265843
```

max r2 score corresponding to 48 is 0.8496659416265843

```
In [163]: # Let's split the dataset into test and train

          x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=54)
```

```
In [167]: model=[LinearRegression(),
                 DecisionTreeRegressor(),
                 KNeighborsRegressor(),
                 SVR(),
                 Lasso(),
                 Ridge(),
                 ElasticNet(),
                 RandomForestRegressor(),
                 AdaBoostRegressor(),

                ]
          for m in model:
              m.fit(x_train,y_train)
              print('score of',m,'is:',m.score(x_train,y_train))
              predm=m.predict(x_test)
              print('Error:')
              print('Mean absolute error:',mean_absolute_error(y_test,predm))
              print('Mean squared error:',mean_squared_error(y_test,predm))
              print('Root Mean Squared Error:',np.sqrt(mean_squared_error(y_test,predm)))
              print("r2_score:",r2_score(y_test,predm))
              print('**************************************************************')
              print('\n')
```

score of LinearRegression() is: 0.82477807880984 Error:
Mean absolute error: 21214.668674560457
Mean squared error: 988711234.5151851 Root
Mean Squared Error: 31443.778947753482
r2_score: 0.8493293024469674
****

score of DecisionTreeRegressor() is: 1.0 Error:
Mean absolute error: 32526.239316239316
Mean squared error: 2655740464.3076925 Root
Mean Squared Error: 51533.87686083488
r2_score: 0.5952890446589649
****

score of KNeighborsRegressor() is: 0.8005580881741488 Error:
Mean absolute error: 26287.979487179484
Mean squared error: 1638191388.2099144 Root
Mean Squared Error: 40474.57706029693
r2_score: 0.7503543698398546
****

score of SVR() is: -0.04568255380776742 Error:
Mean absolute error: 58256.27581850125
Mean squared error: 6883564961.965359 Root
Mean Squared Error: 82967.2523467263
r2_score: -0.04899337467274023
****

score of Lasso() is: 0.8247780692387235 Error:
Mean absolute error: 21212.494199237746
Mean squared error: 988627101.9067537
Root Mean Squared Error: 31442.441093317702 r2_score:
0.8493421234996235
****

score of Ridge() is: 0.8247780154162465 Error:
Mean absolute error: 21207.71025561312
Mean squared error: 988429671.2769494 Root
Mean Squared Error: 31439.301380230278
r2_score: 0.8493722101514916
****

score of ElasticNet() is: 0.8174701175087531 Error:
Mean absolute error: 19910.440060332676
Mean squared error: 1002174977.3116897 Root
Mean Squared Error: 31657.147333764766
r2_score: 0.8472775491665279
****

score of RandomForestRegressor() is: 0.96680098429731 Error:
Mean absolute error: 21953.085384615388
Mean squared error: 1164063400.6093924 Root
Mean Squared Error: 34118.37335819796
r2_score: 0.8226072098272706
****

score of AdaBoostRegressor() is: 0.8380210963982864 Error:
Mean absolute error: 30931.247989936797
Mean squared error: 1749721542.0135958 Root
Mean Squared Error: 41829.67298477954
r2_score: 0.7333581777413218
****

Ridge is giving us minimum Rmse score so we choose it as our final model.

- **Key Metrics for success in solving problem under consideration**

 Key Metrics used were the Lasso, ridge, Elasticnet to find r2 Score and GridsearcCV score as this was Linear Regression problem and we focus more on R2score metrics to observe Mean absolute error, Mean squared error and Root Mean Squared Error.

- **Visualizations**

Hyperperameter tunning

```
In [79]: # Let's Use the GridSearchCV to find the best paarameters in Ridge Regressor

parameters={'alpha': [25,10,4,2,1.0,0.8,0.5,0.3,0.2,0.1,0.05,0.02,0.01]}
rg=Ridge()

reg=GridSearchCV(rg,parameters,n_jobs=-1)
reg.fit(x,y)
print(reg.best_params_)

{'alpha': 25}
```

```
In [80]: # Let's use the Ridge Regressor with its best parameters

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: 0.8325270027518725
```

Score: 0.8325270027518725

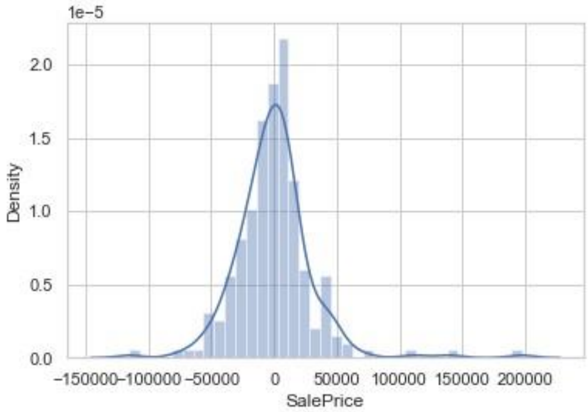
Mean absolute error: 20277.903007353238
Mean squared error: 921483021.3925847
Root Mean Squared error: 30355.938815865746

r2_score: 0.8595742773322715

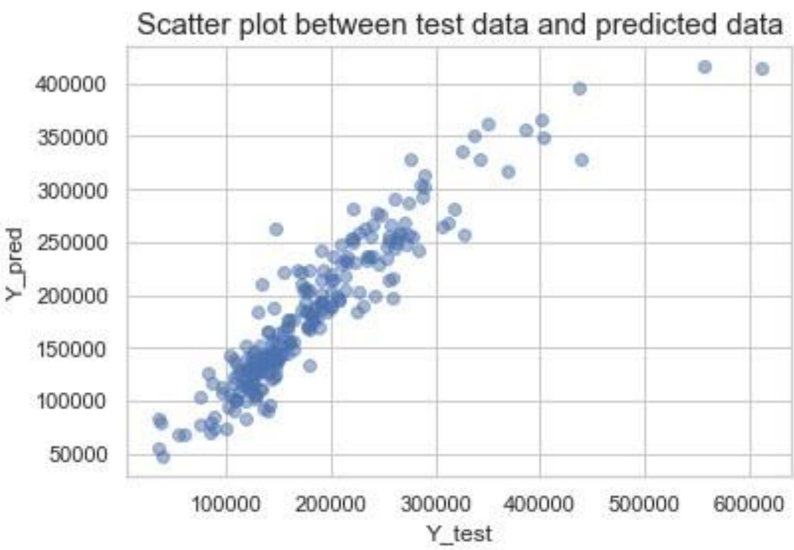
```
In [81]: # Let's Cross validate the Ridge model

score=cross_val_score(RG,x,y,cv=10,scoring='r2')
print("Score:",score)
print('Mean Score:',score.mean())
print("Standard deviation:",score.std())

Score: [0.87093015 0.79113836 0.83668642 0.68392408 0.82132711 0.40663273
 0.78924226 0.76344277 0.66557158 0.87778786]
Mean Score: 0.7506683331134026
Standard deviation: 0.13280051158633877
```

```
# Let's plot the distribution plot and the Gaussian plot

sns.distplot(y_test-y_pred)
plt.show()
```

```
In [82]:  # Let's plot the distribution plot and the Gaussian plot

          sns.distplot(y_test-y_pred)
          plt.show()
```




```
In [83]:  # Let' plot the Scatter plot between test data and predicted data

          plt.scatter(y_test,y_pred, alpha=0.5)
          plt.xlabel("Y_test")
          plt.ylabel("Y_pred")
          plt.title("Scatter plot between test data and predicted data",fontsize=15)
          plt.show()
```



- **Interpretation of the Results**

  Data Pre-processing done by performing EDA (Exploratory Data Analysis), checking for best r2 score.

We will save our Model by Ridge Regression as it is giving us minimum Rmse score as it's having 303 69.236527153855 and r2_score: 0.8594512207052254.

Model Saving

```
In [84]: #Ridge Regressor is giving us minimum Rmse score so we choose it as our final model.
         # Let's save our best model

         import joblib
         joblib.dump(RG,'Housing_Price_Project.pkl')

Out[84]: ['Housing_Price_Project.pkl']

In [85]: # Let;s load our save model

         model=joblib.load('Housing_Price_Project.pkl')

In [86]: # Let's Test our save model

         import sys
         nums= model.predict(x1)
         np.set_printoptions(threshold=sys.maxsize)
         print(nums)
```

CONCLUSION

- **Key Findings and Conclusions of the Study**

  Linear regression models assume that the relationship between a dependent continuous variable Y and one or more explanatory (independent) variables X is linear (that is, a straight line). It's used to predict values within a continuous range, (e.g. sales, price) rather than trying to classify them into categories (e.g. cat, dog).

- **Learning Outcomes of the Study in respect of Data Science**

- This dataset is Linear Regression in nature, we can verify data by using read method & get stats related information for each column using describe method.
- Visualizations, Pre-processing and Data Cleaning part was very crucial as without all these all method we were not able to judge the data effectively and won't be able to remove the outliers, handling null values and adding into the errors.
- Data contains numerical as well as categorical variable. So we handled them accordingly
- Check the r2 score using Mean absolute error, Mean squared error & get root mean squared error score.
- Train data using Linear Regression models to get the best score & finalise best score giver model for this dataset.
- Get the test score for same model.
- Save file using joblib library.

- **Limitations of this work and Scope for Future Work**

  Visualizations helped a lot in finding out those outliers values and helped in finding out the features having direct relation between the feature and the label.

Its always good to to have complete data while performing model but 7-8 % of data can be excluded based on performance impact.

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