Advanced Data Analysis- 101

- This is the 1st Notebook
- Author: **Rahul Sawhney**

Welcome to the advanced Data Analysis 101.

Note From the Author -

- *Every Data is different, Thus different data problems requires different data techniques. Don't set these functions/Class as the benchmark for all the Data Analysis tasks.*
- *Learning Data Analysis, without having a Strong grip in Statistics is like inventing an optimization algorithm from the scratch without knowing how to code.*
- *Improving the codes given in this notebook would be highly appreciable*

Control Flow -

- Data Characteristics
- Missing values plot
- Some Statistical Tests
- Target Transformation
- Correation-Coefficient class
- Date-time Plots
- Categorical Feature Analysis
- Numeric Feature Analysis
- anomaly detection*

Data Analysis -

Data analysis is a process of inspecting, cleansing, transforming and modeling data with the goal of discovering useful information, informing conclusions and supporting decision-making. Data analysis has multiple facets and approaches, encompassing diverse techniques under a variety of names, and is used in different business, science, and social science domains. In today's business world, data analysis plays a role in making decisions more scientific and helping businesses operate more effectively

In [2]:

```
# importing the libraries
import numpy as np
import pandas as pd
pd.set_option("display.max_columns", 100)
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
import warnings
warnings.filterwarnings("ignore")
```

Why Data Characteristics ?

- For Analysis of Data, It is very important to undertand the characteristics of the data.
- In Industry, It DOES NOT MATTERS what tools you use for analysing data but what really matters is what INSIGHTS you can drawn for that data.

In [10]:
```python
# importing the dataset
train = pd.read_csv("train.csv", sep =",", squeeze = True)
test = pd.read_csv("test.csv",  sep =",", squeeze = True)
a_train = train.copy()

# concatenating train and test
dataset = pd.concat((train, test))

# Setting the target Variable
SalePrice = train["SalePrice"]
dataset.drop(columns = ["SalePrice"], axis = 1, inplace = True)


# ---------------- FUNCTION 1: DATA CHARACTERISTICS  -----------------------#
# Data Characteristics
def data_characteristics(dataset):
    # shape of the dataset
    print("Shape of the Dataset : {}".format(dataset.shape))
    print("Number of Columns in the Dataset : {}".format(dataset.shape[1]))
    print("Number of Rows in the Dataset : {}".format(dataset.shape[0]))
    print("-"*40)

    # Understanding the Number of Numeric and Categorical features in dataset
    numeric_features = dataset.select_dtypes(include = [np.number])
    categoric_features = dataset.select_dtypes(exclude = [np.number])
    print("Number of Numerical Features : {}".format(numeric_features.shape[1]))
    print("Number of Categorical Features : {}".format(categoric_features.shape[1]))
    print("-"*40)

    # Unique values
    print("No of unique values : {}".format(dataset.nunique()))
    print("-"*40)

    # Number of NOT NULL Values
    print("No of NON-NANS : {}".format(dataset.count()))
    print("-"*40)

    # Understanding the dataset
    print("Information of the Dataset : {}".format(dataset.info(verbose = False, memory_usage = "deep")))
    print("-"*40)

#-----------------------------------------------------------------------------#

# dataset Characteristics
print(data_characteristics(dataset))

# Statistical Summary of the dataset
print("Statistical Summary of the Dataset : ")
dataset.describe(include = "all", percentiles = [.15, .25, .50, .75, .85]).transpose()
```

```python
# Statistical Summary of the dataset
print("Statistical Summary of the Dataset : ")
dataset.describe(include = "all", percentiles = [.15, .25, .50, .75, .85]).transpose()
```

```
Shape of the Dataset : (2919, 80)
Number of Columns in the Dataset : 80
Number of Rows in the Dataset : 2919
----------------------------------------
Number of Numerical Features : 37
Number of Categorical Features : 43
----------------------------------------
No of unique values : Id              2919
MSSubClass         16
MSZoning            5
LotFrontage       128
LotArea          1951
                 ...
MiscVal            38
MoSold             12
YrSold              5
SaleType            9
SaleCondition       6
Length: 80, dtype: int64
----------------------------------------
No of NON-NANS : Id              2919
MSSubClass       2919
MSZoning         2915
LotFrontage      2433
LotArea          2919
                 ...
MiscVal          2919
MoSold           2919
YrSold           2919
SaleType         2918
SaleCondition    2919
Length: 80, dtype: int64
----------------------------------------
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2919 entries, 0 to 1458
Columns: 80 entries, Id to SaleCondition
dtypes: float64(11), int64(26), object(43)
memory usage: 7.8 MB
Information of the Dataset : None
----------------------------------------
None
Statistical Summary of the Dataset :
```

Out[10]:

	count	unique	top	freq	mean	std	min	15%	25%	50%	75%	85%	max
Id	2919	NaN	NaN	NaN	1460	842.787	1	438.7	730.5	1460	2189.5	2481.3	2919
MSSubClass	2919	NaN	NaN	NaN	57.1377	42.5176	20	20	20	50	70	90	190
MSZoning	2915	5	RL	2265	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
LotFrontage	2433	NaN	NaN	NaN	69.3058	23.3449	21	50	59	68	80	88	313
LotArea	2919	NaN	NaN	NaN	10168.1	7887	1300	6120	7478	9453	11570	13072	215245
...	...	...	...	...	...	...	...	...	...	...	...	...	...
MiscVal	2919	NaN	NaN	NaN	50.826	567.402	0	0	0	0	0	0	17000
MoSold	2919	NaN	NaN	NaN	6.21309	2.71476	1	3	4	6	8	9	12
YrSold	2919	NaN	NaN	NaN	2007.79	1.31496	2006	2006	2007	2008	2009	2009	2010
SaleType	2918	9	WD	2525	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
SaleCondition	2919	6	Normal	2402	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

80 rows × 13 columns

In [11]:

```python
# Looking at the datset
dataset.head()
```

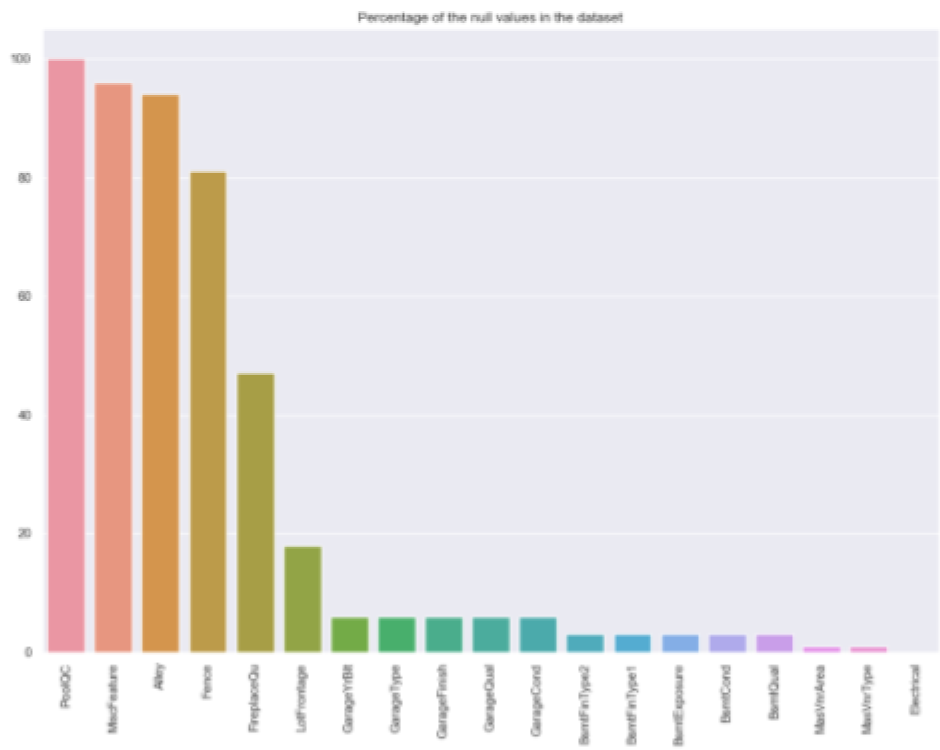
Out[11]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Cond
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	FR2	Gtl	Veenker	Feedr	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	Corner	Gtl	Crawfor	Norm	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	FR2	Gtl	NoRidge	Norm	

Why Missing Values Plot ?

The concept of missing values is important to understand in order to successfully manage data. If the missing values are not handled properly by the researcher, then he/she may end up drawing an inaccurate inference about the data. Due to improper handling, the result obtained by the researcher will differ from ones where the missing values are present.

In [12]:
```python
# ---------------- FUNCTION 1: MISSING VALUES PLOT -----------------------#
# Percentage of Null Vlues
def check_null(dataset):
    null_per = (dataset.isnull().sum() / len(dataset)) * 100

    try:
        # droping columns having null percentage to 0
        null_per = round(null_per.drop(null_per[null_per == 0].index)).sort_values(ascending = False)

        # plotting the bar plot of NULL %
        plt.figure(figsize = (14,10))
        null_plot = sns.barplot(x = null_per.index , y = null_per)
        plt.xticks(rotation = "90")
        plt.title("Percentage of the null values in the dataset")
        plt.show()

    except:
        print("There is NO null values in the dataset")
        print("Returning the dataset....")
        return dataset

    return null_plot

#-----------------------------------------------------------------------------#

check_null(a_train)
```



Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x202a4223c20>

In [19]:
```python
# droping High-Null columns

dataset.drop(columns = ["Id","PoolQC", "MiscFeature","Alley",
                        "Fence", "FireplaceQu"], axis = 1, inplace = True)
dataset.head()
```

Out[19]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	Condition2	Bld
0	60	RL	65.0	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	
1	20	RL	80.0	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl	Veenker	Feedr	Norm	
2	60	RL	68.0	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl	CollgCr	Norm	Norm	
3	70	RL	60.0	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl	Crawfor	Norm	Norm	
4	60	RL	84.0	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl	NoRidge	Norm	Norm	

Importance of Statistical Tests

Anova -

Analysis of variance (ANOVA) is a collection of statistical models and their associated estimation procedures (such as the "variation" among and between groups) used to analyze the differences among group means in a sample. ANOVA was developed by the statistician Ronald Fisher. The ANOVA is based on the law of total variance, where the observed variance in a particular variable is partitioned into components attributable to different sources of variation. In its simplest form, ANOVA provides a statistical test of whether two or more population means are equal, and therefore generalizes the t-test beyond two means.

F-test score: ANOVA assumes the means of all groups are the same, calculates how much the actual means deviate from the assumption, and reports it as the F-test score. A larger score means there is a larger difference between the means.

P-value: P-value tells how statistically significant is our calculated score value.

Mutual Information -

Mutual information is calculated between two variables and measures the reduction in uncertainty for one variable given a known value of the other variable. The mutual information between two random variables X and Y can be stated formally as follows:

I(X ; Y) = H(X) – H(X | Y) Where I(X ; Y) is the mutual information for X and Y, H(X) is the entropy for X and H(X | Y) is the conditional entropy for X given Y. The result has the units of bits.

Mutual information is a measure of dependence or "mutual dependence" between two random variables. As such, the measure is symmetrical, meaning that I(X ; Y) = I(Y ; X).

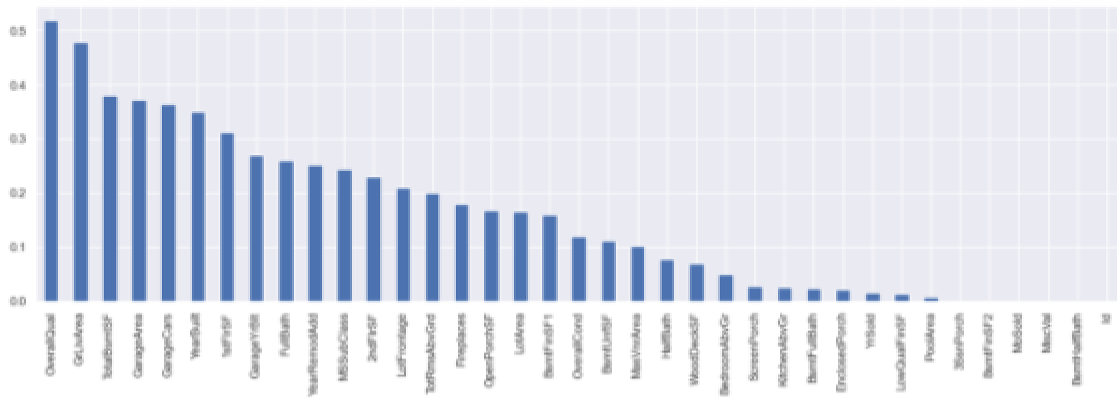
In [17]:
```
# Applying Some Statistical Test
class Statistical_tests:
    def __init__(self, train):
        self.train = train

    # --------------------------- FUNCTION 1: ANOVA --------------------------------#
    def Anova(self):
        from scipy import stats
        categoric_features = self.train.select_dtypes(exclude = [np.number]).columns
        train[categoric_features] = train[categoric_features].fillna("missing")

        # Making the ANOVA
        anova = {"feature":[], "f":[], "p":[]}
        for cat in train[categoric_features]:
            group_prices = []

            for group in train[cat].unique():
                group_prices.append(train[train[cat] == group]["SalePrice"].values)

            f, p = stats.f_oneway(*group_prices)
            anova['feature'].append(cat)
            anova['f'].append(f)
            anova['p'].append(p)

        anova = pd.DataFrame(anova)
        anova = anova[["feature","f","p"]]
        anova.sort_values("p", inplace = True)


        return anova
```

```python
    # -------------------------- FUNCTION 2: MUTUAL-INFORMATION ----------------------------#
    def mutual_information(self):

        # Choosing the numeric features
        numerics = ["int16", "int32", "int64", "float16", "float32", "float64"]
        numeric_vars = list(self.train.select_dtypes(include = numerics).columns)
        train = self.train[numeric_vars]



        # Splitting the numerical dataset into train and test set
        from sklearn.model_selection import train_test_split
        x_train, x_test, y_train, y_test = train_test_split(train.iloc[:,:-1],
                                                            train.iloc[:,-1],
                                                            test_size = 0.3,
                                                            random_state = 0)

        from sklearn.feature_selection import mutual_info_regression
        from sklearn.feature_selection import SelectPercentile


        mi = mutual_info_regression(x_train.fillna(0), y_train)
        mi = pd.Series(mi)
        mi.index = x_train.columns
        mi = mi.sort_values(ascending = False)

        # Plotting the Bar-plot of the dataset
        mi.sort_values(ascending = False).plot.bar(figsize = (18,5))

        # Selecting the best Numeric-Features
        features = SelectPercentile(mutual_info_regression,
                                    percentile = 10).fit(x_train.fillna(0), y_train)

        # Returning the Support of the columns of the x_train
        return x_train.columns[features.get_support()]

    #-------------------------------------------------------------------------------------#

# Accessing the Class + method
sts = Statistical_tests(train)
sts.mutual_information()
sts.Anova()
```

Out[17]:

	feature	f	p
8	Neighborhood	71.784865	1.558600e-225
18	ExterQual	443.334831	1.439551e-204
21	BsmtQual	316.148635	8.158548e-196
30	KitchenQual	407.806352	3.032213e-192
34	GarageFinish	213.867028	6.228747e-115
32	FireplaceQu	121.075121	2.971217e-107
20	Foundation	100.253851	5.791895e-91
33	GarageType	80.379992	6.117026e-87
24	BsmtFinType1	64.688200	2.386358e-71
27	HeatingQC	88.394462	2.667062e-67
17	MasVnrType	84.672201	1.054025e-64
23	BsmtExposure	63.939761	7.557758e-50
42	SaleCondition	45.578428	7.988268e-44
15	Exterior1st	18.611743	2.586089e-43
16	Exterior2nd	17.500840	4.842186e-43
41	SaleType	28.863054	5.039767e-42
0	MSZoning	43.840282	8.817634e-35
12	HouseStyle	19.595001	3.376777e-25
35	GarageQual	25.776093	5.388762e-25
36	GarageCond	25.750153	5.711746e-25
3	LotShape	40.132852	6.447524e-25
28	CentralAir	98.305344	1.809506e-22
37	PavedDrive	42.024179	1.803569e-18
29	Electrical	18.460192	8.226925e-18
13	RoofStyle	17.805497	3.653523e-17
22	BsmtCond	19.708139	8.195794e-16
39	Fence	13.433276	9.379977e-11
11	BldgType	13.011077	2.056736e-10
4	LandContour	12.850188	2.742217e-08
25	BsmtFinType2	7.565378	5.225649e-08
14	RoofMatl	6.727305	7.231445e-08
9	Condition1	6.118017	8.904549e-08
2	Alley	15.176614	2.996380e-07
19	ExterCond	8.798714	5.106681e-07
38	PoolQC	10.509853	7.700989e-07

24	BsmtFinType1	64.688200	2.386358e-71
27	HeatingQC	88.394462	2.667062e-67
17	MasVnrType	84.672201	1.054025e-64
23	BsmtExposure	63.939761	7.557758e-50
42	SaleCondition	45.578428	7.988268e-44
15	Exterior1st	18.611743	2.586089e-43
16	Exterior2nd	17.500840	4.842186e-43
41	SaleType	28.863054	5.039767e-42
0	MSZoning	43.840282	8.817634e-35
12	HouseStyle	19.595001	3.376777e-25
35	GarageQual	25.776093	5.388762e-25
36	GarageCond	25.750153	5.711746e-25
3	LotShape	40.132852	6.447524e-25
28	CentralAir	98.305344	1.809506e-22
37	PavedDrive	42.024179	1.803569e-18
29	Electrical	18.460192	8.226925e-18
13	RoofStyle	17.805497	3.653523e-17
22	BsmtCond	19.708139	8.195794e-16
39	Fence	13.433276	9.379977e-11
11	BldgType	13.011077	2.056736e-10
4	LandContour	12.850188	2.742217e-08
25	BsmtFinType2	7.565378	5.225649e-08
14	RoofMatl	6.727305	7.231445e-08
9	Condition1	6.118017	8.904549e-08
2	Alley	15.176614	2.996380e-07
19	ExterCond	8.798714	5.106681e-07
38	PoolQC	10.509853	7.700989e-07
8	LotConfig	7.809954	3.163167e-06
31	Functional	4.057875	4.841697e-04
26	Heating	4.259819	7.534721e-04
40	MiscFeature	2.593622	3.500367e-02
10	Condition2	2.073899	4.342566e-02
1	Street	2.459290	1.170486e-01
7	LandSlope	1.958817	1.413964e-01
5	Utilities	0.298804	5.847168e-01



- From the Anova: I can Conclude that the Features having P-Value >= 0.05 is NOT Relevent in predicting the Target when they are used in Model Building. Hence, We will remove those irrelevent features
- Therefore Street, landSlope and Utilities are NOT important in Predicting the Target SalePrice
- I will Deal with the Feature Selection from Mutual-Information in Feature Selection module

In [23]:

```
# Dropping the Irrelevent columns
dataset.drop(columns=["Street", "Utilities", "LandSlope"],
             axis= 1, inplace = True)
dataset.head()
```

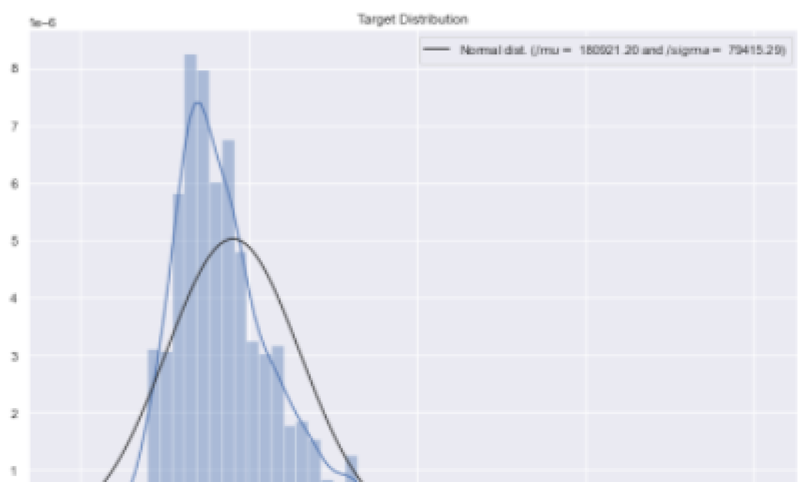
Out[23]:

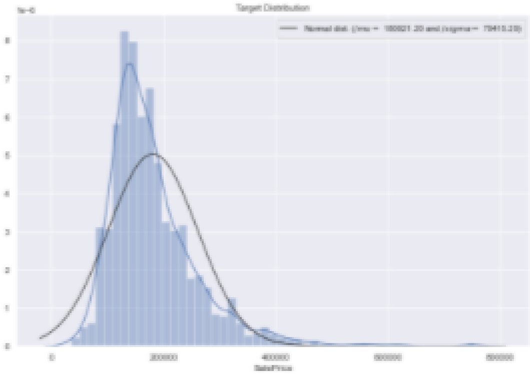
	MSSubClass	MSZoning	LotFrontage	LotArea	LotShape	LandContour	LotConfig	Neighborhood	Condition1	Condition2	BldgType	HouseStyle	OverallQ
0	60	RL	65.0	8450	Reg	Lvl	Inside	CollgCr	Norm	Norm	1Fam	2Story	
1	20	RL	80.0	9600	Reg	Lvl	FR2	Veenker	Feedr	Norm	1Fam	1Story	
2	60	RL	68.0	11250	IR1	Lvl	Inside	CollgCr	Norm	Norm	1Fam	2Story	
3	70	RL	60.0	9550	IR1	Lvl	Corner	Crawfor	Norm	Norm	1Fam	2Story	
4	60	RL	84.0	14260	IR1	Lvl	FR2	NoRidge	Norm	Norm	1Fam	2Story	

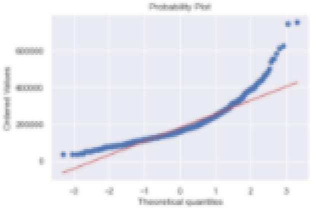
Target Transformation

- The distribution of a variable is a description of the relative numbers of times each possible outcome will occur in a number of trials. The function describing the probability that a given value will occur is called the probability density function (abbreviated PDF), and the function describing the cumulative probability that a given value or any value smaller than it will occur is called the distribution function (or cumulative distribution function, abbreviated CDF).
- If our Target is not Normally distributed, then it will impact the performance of linear Models

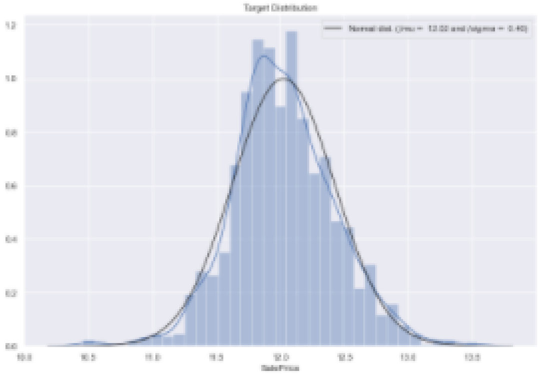
In [24]:
```python
class Transform_target_distribution:
    def __init__(self, target):
        self.target = target

    # -------------------- FUNCTION 1: INITIAL DISTRIBUTION -----------------------------#
    # Initial distribution of the Target
    def check_target_distribution(self):
        from scipy import stats
        plt.figure(figsize = (12,8))
        plot1 = sns.distplot(self.target , fit = stats.norm)
        plt.title("Target Distribution")

        # getting the params
        (mu, sigma) = stats.norm.fit(self.target)
        # Legend of the distribution
        plt.legend(["Normal dist. ($/mu=$ {:.2f} and $/sigma=$ {:.2f})".format(mu, sigma)], loc="best")

        # making the QQ plot / Probability plot
        fig = plt.figure()
        plot2 = stats.probplot(self.target, plot = plt)
        plt.show()

        # printing the plots
        print(plot1)
        print(plot2)
        print("-"*50)

    # -------------------- FUNCTION 2: TRANSFORMED DISTRIBUTION -------------------------#
    # Transforming the distribution of the Target
    def log_distribution(self):
        from scipy import stats
        target2 = np.log(self.target)
        plt.figure(figsize = (12,8))
        plot3 = sns.distplot(target2 , fit = stats.norm)
        plt.title("Target Distribution")

        # getting the params
        (mu, sigma) = stats.norm.fit(target2)
        # Legend of the distribution
        plt.legend(["Normal dist. ($/mu=$ {:.2f} and $/sigma=$ {:.2f})".format(mu, sigma)], loc="best")

        # making the QQ plot / Probability plot
        fig = plt.figure()
        plot4 = stats.probplot(target2, plot = plt)
        plt.show()

        print(plot3)
        print(plot4)
        print("-"*50)

    #------------------------------------------------------------------------------------------


# Accessing the Class
object = Transform_target_distribution(train["SalePrice"])
object.check_target_distribution()
object.log_distribution()

# Changing Saleprice to Log(SalePrice)
train["SalePrice"] = np.log(train["SalePrice"])
```

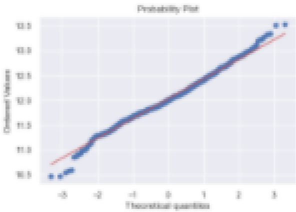







```
AxesSubplot(0.125,0.125;0.775x0.755)
((array([-3.30513952, -3.07794228, -2.90038705, ...,  2.90038705,
        3.07794228,  3.30513952]), array([ 34900,  35311,  37900, ..., 625000, 745000, 755000], dtype=int64)), (74160.16474519415, 180921.19589041095, 0.9319665641512986))
--------------------------------------------------
```






```
AxesSubplot(0.125,0.125;0.775x0.755)
((array([-3.30513952, -3.07794228, -2.90038705, ...,  2.90038705,
        3.07794228,  3.30513952]), array([10.46024211, 10.47194981, 10.54270639, ..., 13.34550693,
       13.5211395 , 13.53447303])), (0.39826223688161938, 12.024050901109181, 0.9953761475636614))
--------------------------------------------------
```

Corration Coefficient -

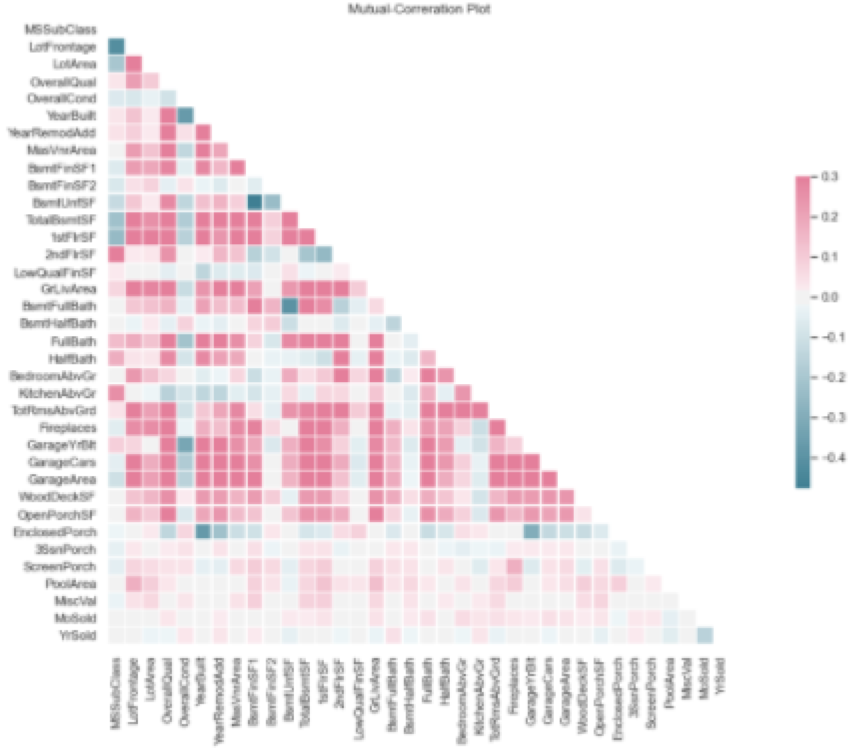
The correlation coefficient is a statistical measure of the strength of the relationship between the relative movements of two variables. The values range between -1.0 and 1.0. A calculated number greater than 1.0 or less than -1.0 means that there was an error in the correlation measurement. A correlation of -1.0 shows a perfect negative correlation, while a correlation of 1.0 shows a perfect positive correlation. A correlation of 0.0 shows no linear relationship between the movement of the two variables.

Correration Coefficient -

The correlation coefficient is a statistical measure of the strength of the relationship between the relative movements of two variables. The values range between -1.0 and 1.0. A calculated number greater than 1.0 or less than -1.0 means that there was an error in the correlation measurement. A correlation of -1.0 shows a perfect negative correlation, while a correlation of 1.0 shows a perfect positive correlation. A correlation of 0.0 shows no linear relationship between the movement of the two variables.

In [25]:

```python
# Correration-Coefficient class
class Correration:
    def __init__(self, dataset):
        self.dataset = dataset


    # ------------------------ FUNCTION 1: CORRERATION-COEFFICIENT ------------------------#
    # Making a Correration-coefficient plot
    def correration_coefficient(self):
        # taking only numeric columns + corr_matrix
        numeric_features = self.dataset.select_dtypes(include = [np.number])
        corr_matrix = numeric_features.corr()

        # Setting style + mask + axes + custom_cmap
        sns.set(style = "white")
        mask = np.triu(np.ones_like(corr_matrix, dtype = np.bool))
        f, ax = plt.subplots(figsize = (20, 10))
        cmap = sns.diverging_palette(220, 1, as_cmap=True)

        # Setting the Heatmap
        sns.heatmap(data = corr_matrix,
                    mask=mask,
                    cmap=cmap,
                    vmax=.3,
                    center=0,
                    square=True,
                    linewidths=.5,
                    cbar_kws={"shrink": .5})

        plt.title("Mutual-Correration Plot")
        plt.show()

    # ---------------------- FUNCTION 2: CORRERATED-FEATURES --------------------------#
    # Getting the list of Correrated features
    def select_correration(self):
        # making a set
        corr_set = set()

        # making a corr matrix
        corr_matrix = self.dataset.corr()

        # select value under some threshold
        for i in range(len(corr_matrix.columns)):
            for j in range(i):
                if abs(corr_matrix.iloc[i,j]) > 0.8:
                    matrix = corr_matrix.columns[i]

                    # adding the values in set
                    corr_set.add(matrix)

        print("-"*40)
        print("Number of Correrated features: {}".format(len(corr_set)))
        print("List of Correrated Features: {}".format(list(corr_set)))
        print("-"*40)


    # --------------------- FUNCTION 3: FEATURES-CORRERATION --------------------------#
    def feature_correration(self):
        corr_matrix = self.dataset.corr()
        corr_matrix = corr_matrix.abs().unstack()
        corr_matrix = corr_matrix.sort_values(ascending = False)

        #select values of corr_matrix above the threshold set
        corr_matrix = corr_matrix[(corr_matrix >= 0.8) & (corr_matrix < 1)]

        corr_matrix = pd.DataFrame(corr_matrix).reset_index()
        corr_matrix.columns = ["feature_1","feature_2", "correration"]

        print(corr_matrix)

    #-----------------------------------------------------------------------------------#

# Accessing the Correration Class + methods
corr_class = Correration(dataset)
corr_class.correration_coefficient()
corr_class.select_correration()
corr_class.feature_correration()
```




```
----------------------------------------
Number of Correrated features: 4
List of Correrated Features: ['TotRmsAbvGrd', '1stFlrSF', 'GarageYrBlt', 'GarageArea']
----------------------------------------
     feature_1    feature_2  correration
0   GarageArea   GarageCars     0.889700
1   GarageCars   GarageArea     0.889700
2    YearBuilt  GarageYrBlt     0.834812
3  GarageYrBlt    YearBuilt     0.834812
4    GrLivArea TotRmsAbvGrd     0.808354
5 TotRmsAbvGrd    GrLivArea     0.808354
6  TotalBsmtSF     1stFlrSF     0.801670
7     1stFlrSF  TotalBsmtSF     0.801670
```

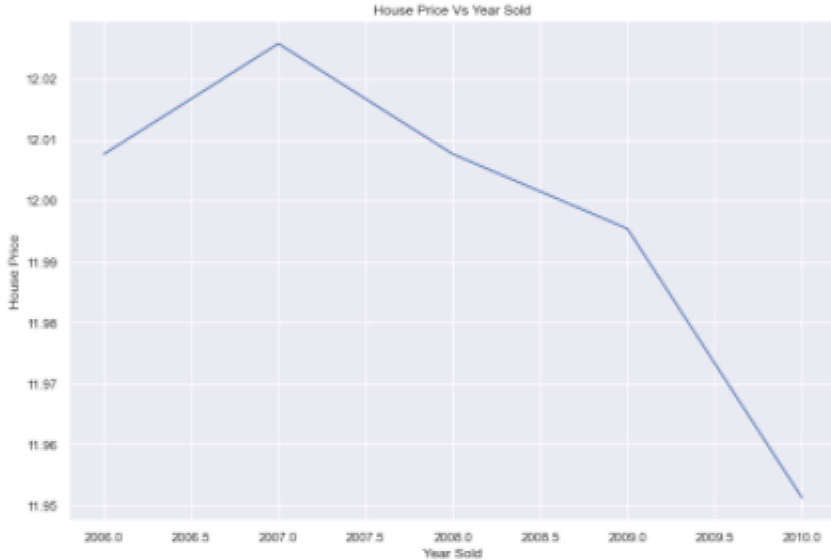
- From the above plot, I can conclude that there are total of 4 variables correrated with each other, which adds redundent information in our dataset.
- Multicoliniear causes affect the accuracy of linear models like SVM, Multiple Regression etc..

Date-Time plot

In [27]:
```
# Understanding the Date-time variable
def date_time_plot(dataset):
    sns.set()
    c_data = dataset.copy()

    # grouping YrSold with SalePrice
    dataset.groupby("YrSold")["SalePrice"].median().plot(figsize = (12, 8))
    plt.xlabel("Year Sold")
    plt.ylabel("House Price")
    plt.title("House Price Vs Year Sold")
    plt.show()

date_time_plot(train)
```

House Price Vs Year Sold

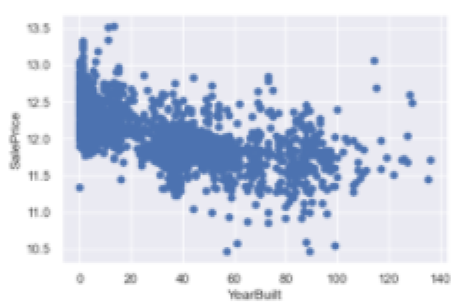
```
date_time_plot(train)
```



- From this plot, I can conclude that the Price of the House decreases with the increase in year

In [28]:
```
def date_time_compare_plots(dataset):
    # Goal: Compare the difference of all features with Target Variable

    # Selecting the Date-time features
    year_features = dataset[["YearBuilt", "YearRemodAdd", "GarageYrBlt", "YrSold"]]

    # Looking through each features
    for feature in year_features:
        print("-"*40)
        if feature!= "YrSold":
            c_data = dataset.copy()
            c_data[feature] = c_data["YrSold"]- c_data[feature]

            # Makinf the Scatter plot
            plt.scatter(c_data[feature], c_data["SalePrice"])
            plt.xlabel(feature)
            plt.ylabel("SalePrice")
            plt.show()


date_time_compare_plots(train)
```

```
----------------------------------------
```

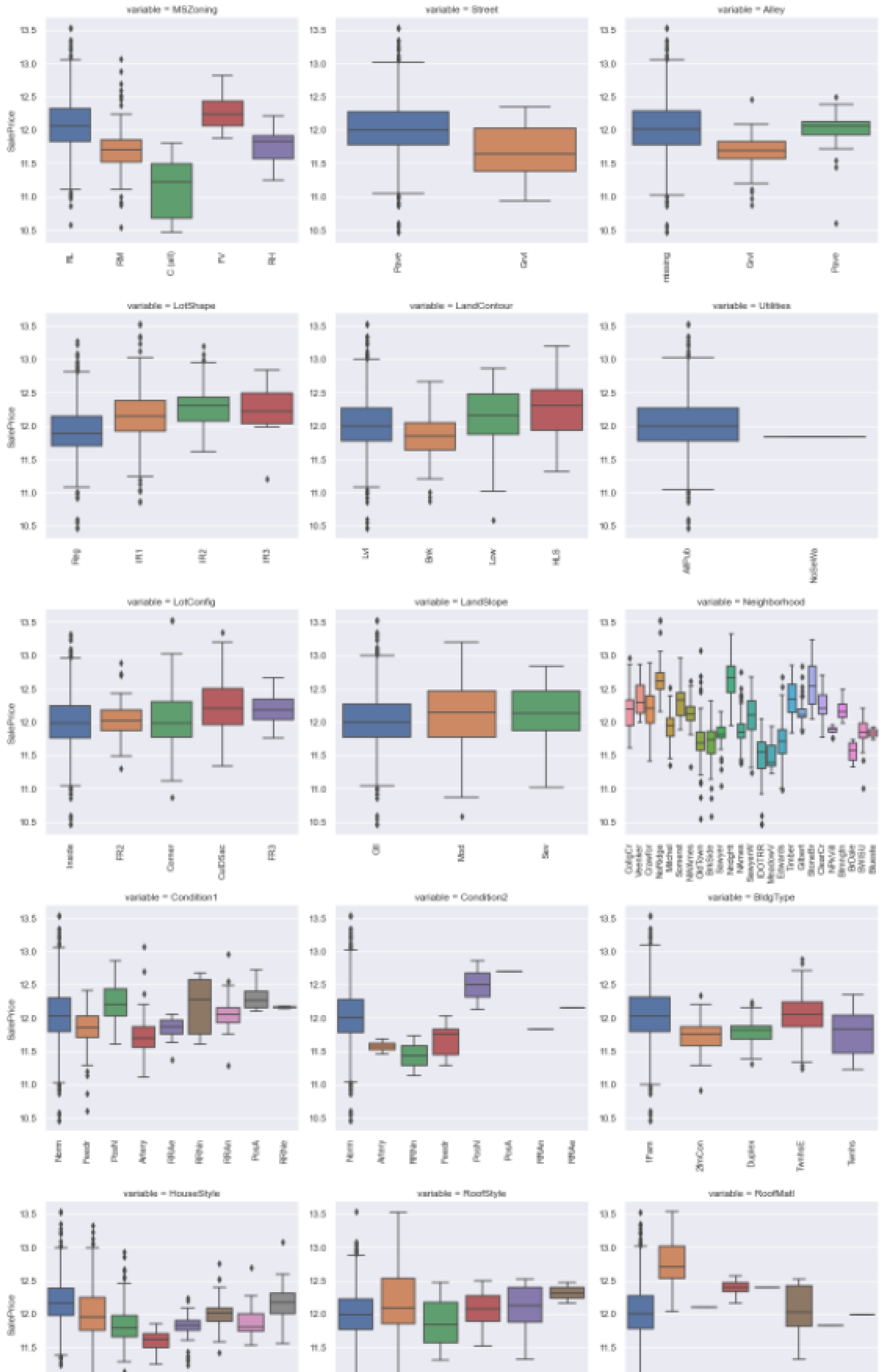



```
----------------------------------------
```

Categorical Features Analysis

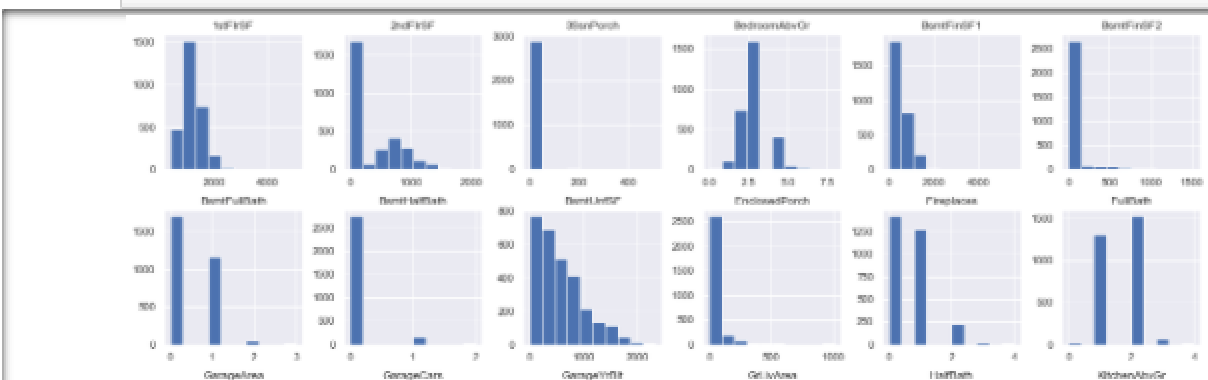
In [53]:
```
# Categorical Feature Analysis Class
class Categorical_feature_analysis:
    def __init__(self, dataset, train):
        self.dataset = dataset
        self.train = train

    # ------------------------------ FUNCTION 1: CARDINALITY ---------------------------------------------#
    # Function to Check Cardinality of the categorical features
    def Cardinality(self):
        for feature in self.dataset.columns:
            # Selecting only the categorical variables
            if self.dataset[feature].dtypes == 'object':
                # Filling the missing values with mode
                self.dataset[feature] = self.dataset[feature].fillna(self.dataset[feature].mode().iloc[0])
                # Selecting the len(unique values) of each categorical
                unique_category = len(self.dataset[feature].unique())
                print("Features in dataset '{column_name}' has '{unique_category}' unique categories".
                      format(column_name = feature, unique_category=unique_category))


    # ------------------------- FUNCTION 2: CARDINALITY PLOTS (Count plot) -----------------------------#
    def Cardinality_plot(self):
        # Selecting the Categorical features
        categoric_features = self.dataset.select_dtypes(exclude = [np.number])
        # Looping through all the categorical features
        for feature in categoric_features:
            c_data = self.dataset.copy()
            sns.countplot(categoric_features[feature])
            plt.xlabel(feature)
            plt.ylabel("Cardinality")
            plt.title(feature)
            plt.show()

    # ------------------------------------ FUNCTION 3: Outliers Analysis --------------------------------#
    def Outliers_Analysis(self):
        # Selecting the categorical features
        categorical_features = self.train.select_dtypes(exclude = [np.number])
        # Looping through all the categorical features
        for feature in categorical_features:
            self.train[feature] = self.train[feature].astype("category")
            if self.train[feature].isnull().any():
                self.train[feature] = self.train[feature].cat.add_categories(["MISSING"])
                self.train[feature] = self.train[feature].fillna(["MISSING"])

        # Function: BOX Plot
        def box_plot(x, y, **kwargs):
            sns.boxplot(x = x, y = y)
            # x->rotation
            x = plt.xticks(rotation = 90)

        # Defining the Facedgrid and mapping box_plot
        f = pd.melt(self.train, id_vars = ["SalePrice"], value_vars = categorical_features)
        g = sns.FacetGrid(f, col = "variable", col_wrap = 3, sharex = False, sharey = False, size = 5)
        g = g.map(box_plot, "value", "SalePrice")

    #-----------------------------------------------------------------------------------------------------#


# Accessing the Categorical Analysis Class + methods
cfa = Categorical_feature_analysis(dataset, train)
cfa.Outliers_Analysis()
```

```
eda.outliers_analysis()
```



Numerical Feature Analysis

In [69]:
```python
# Numerical Feature Analysis
class Numerical_feature_analysis:
    def __init__(self, dataset, train):
        self.dataset = dataset
        self.train = train

    # ------------------------------- FUNCTION 1: DISTRIBUTIONS --------------------------------------------#
    def distribution_plot(self):
        # Selecting the numeric features
        numeric_feature = self.dataset.select_dtypes(include = [np.number])
        # making  a copy + histplot
        c_data = numeric_feature.copy()
        c_data.hist(figsize = (20,20))
        plt.show()

    # ------------------------------- FUNCTION 2: Outliers Analysis --------------------------------#
    # This code is Not Working, Check if you can rectify the Error or come up with a new function.
    # Function Goal: Give the box plot of all the Numeric features in the dataset having 3 Columns.

    """
    def Numeric_Outliers_Analysis(self):
        # Selecting the categorical features
        numeric_features = self.train.select_dtypes(include = [np.number])
        # Looping through all the categorical features
        for feature in numeric_features:
            self.train[feature] = self.train[feature].astype("integer")
            if self.train[feature].isnull().any():
                self.train[feature] = self.train[feature].cat.add_categories(["MISSING"])
                self.train[feature] = self.train[feature].fillna(["MISSING"])

        # Function: BOX Plot
        def box_plot(x, y, **kwargs):
            sns.boxplot(x = x, y = y)
            # x->rotation
            x = plt.xticks(rotation = 90)

        # Defining the Facedgrid and mapping box_plot
        f = pd.melt(self.train, id_vars = ["SalePrice"], value_vars = numeric_features)
        g = sns.FacetGrid(f, col = "variable", col_wrap = 3, sharex = False, sharey = False, size = 5)
        g = g.map(box_plot, "value", "SalePrice")

    """
    # -------------------------------------------------------------------------------------------------#

nfa = Numerical_feature_analysis(dataset, train)
#nfa.Numeric_Outliers_Analysis()
nfa.distribution_plot()
```



Note from the Author -

- I will be keep updating this Data Analysis Notebook as I gain more analytics skills.
- All These Functions and Classes are working.

NEXT -

- Feature Engineering Notebook