Importing Necessary Libraries and Load train and test dataset:

```
#Import some libraries to perform some calculations, visualization, plotting, remove warnings and other usage of functions

import pandas as pd
import matplotlib.pyplot as plt
import seaborn  as sns
from scipy import stats
import numpy as np
import warnings
warnings.filterwarnings("ignore")
```

```
#Load the train dataset of Housing price and stored in variable called hou:

hou = pd.read_csv("/content/train.csv")
hou
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...	PoolArea	PoolQC	Fence	MiscFeature	MiscVal	MoSold	YrSold	Sal
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2008	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	5	2007	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	9	2008	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	2	2006	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...	0	NaN	NaN	NaN	0	12	2008	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	8	2007	
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	MnPrv	NaN	0	2	2010	
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	GdPrv	Shed	2500	5	2010	
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	4	2010	
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	Lvl	AllPub	...	0	NaN	NaN	NaN	0	6	2008	

1460 rows × 81 columns

Histogram

Distribution of Target Variable:

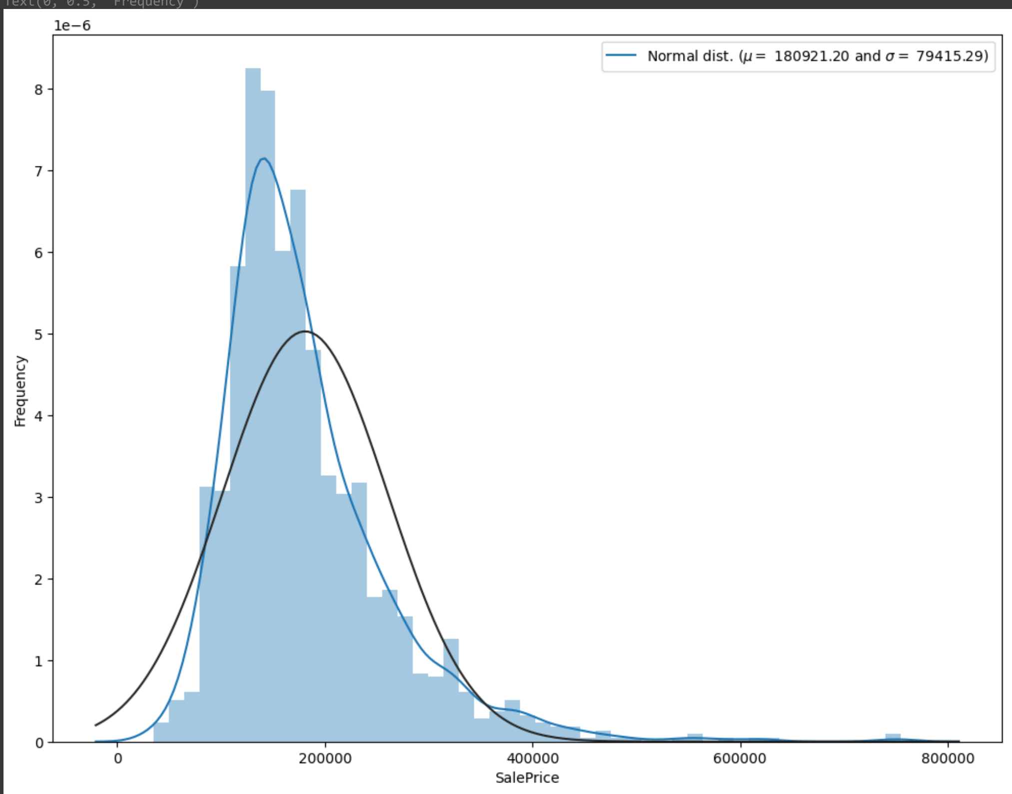
A "dist plot" typically refers to a distribution plot, which is a graphical representation of the distribution of a dataset. It helps you understand the underlying probability distribution of the data, providing insights into the central tendency, spread, and shape of the data.

```
plt.subplots(figsize=(12,9))
sns.distplot(hou['SalePrice'], fit=stats.norm)

(mu, sigma) = stats.norm.fit(hou['SalePrice'])

# plot with the distribution
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f})'.format(mu, sigma)], loc = 'best')
plt.ylabel('Frequency')
```

```
Text(0, 0.5, 'Frequency')
```



This target varibale is right skewed. Now, we need to tranform this variable and make it normal distribution.

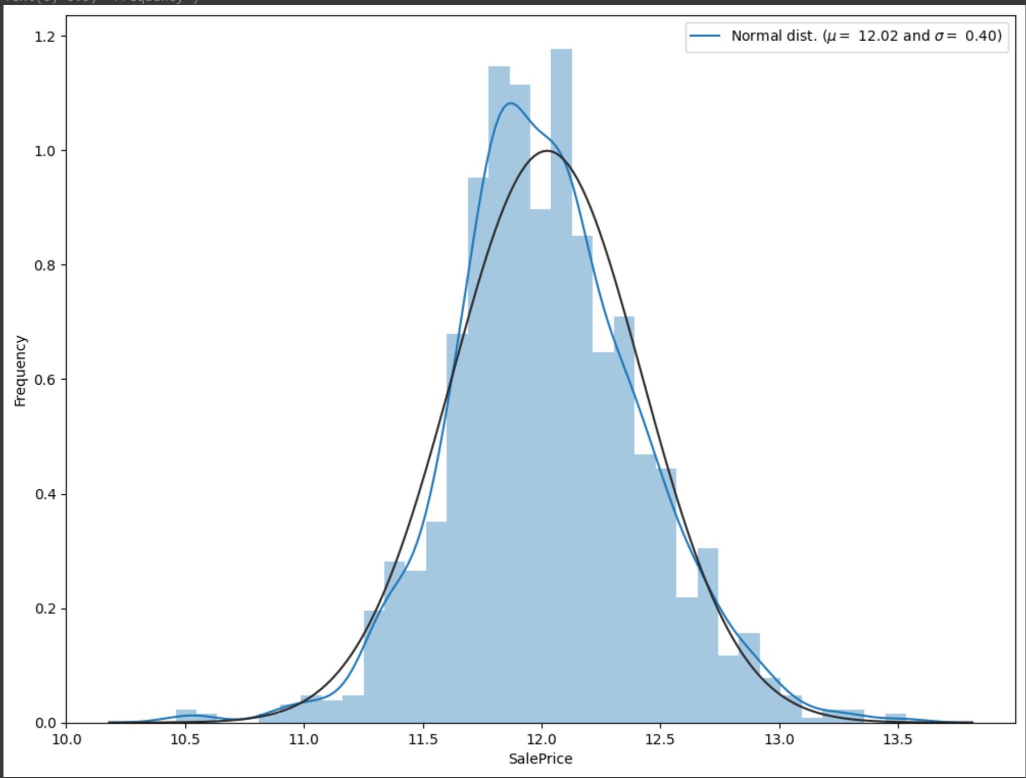
```
#we use log function which is in numpy
hou['SalePrice'] = np.log1p(hou['SalePrice'])

#Check again for more normal distribution
plt.subplots(figsize=(12,9))
sns.distplot(hou['SalePrice'], fit=stats.norm)

# Get the fitted parameters used by the function
(mu, sigma) = stats.norm.fit(hou['SalePrice'])

# plot with the distribution
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f})'.format(mu, sigma)], loc = 'best')
plt.ylabel('Frequency')
```

```
Text(0, 0.5, 'Frequency')
```



Quantity of Missing Values

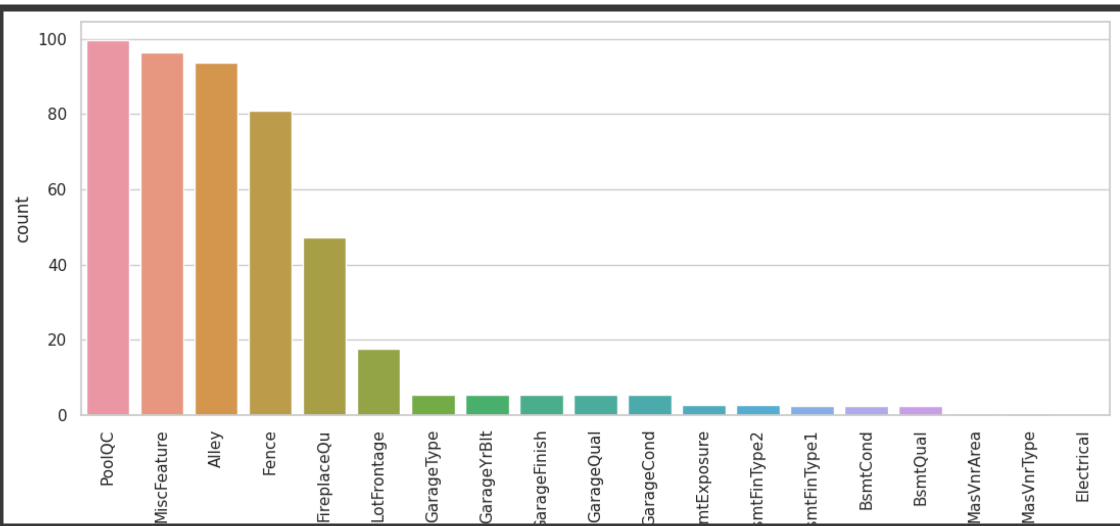
```
Isnull =  hou.isnull().sum() / len(hou)*100
Isnull = Isnull[Isnull>0]
Isnull.sort_values(inplace = True, ascending = False)
Isnull
```

```
PoolQC          99.520548
MiscFeature     96.301370
Alley           93.767123
Fence           80.753425
FireplaceQu     47.260274
LotFrontage     17.739726
GarageType       5.547945
GarageYrBlt      5.547945
GarageFinish     5.547945
GarageQual       5.547945
GarageCond       5.547945
BsmtExposure     2.602740
BsmtFinType2     2.602740
BsmtFinType1     2.534247
BsmtCond         2.534247
BsmtQual         2.534247
MasVnrArea       0.547945
MasVnrType       0.547945
Electrical       0.068493
dtype: float64
```

```
#Convert into dataframe
Isnull = Isnull.to_frame()
Isnull.columns = ['count']
Isnull.index.names = ['Name']

# print(Isnull)
Isnull['Name'] = Isnull.index

#plot Missing values
plt.figure(figsize=(13, 5))
sns.set(style='whitegrid')
sns.barplot(x='Name', y='count', data=Isnull)
plt.xticks(rotation = 90)
plt.show()
```



Finding Top Features in coorelation

```
#Separate variable into new dataframe from original dataframe which has only numerical values
#there is 38 numerical attribute from 81 attributes

train_corr = hou.select_dtypes(include = [np.number])
```

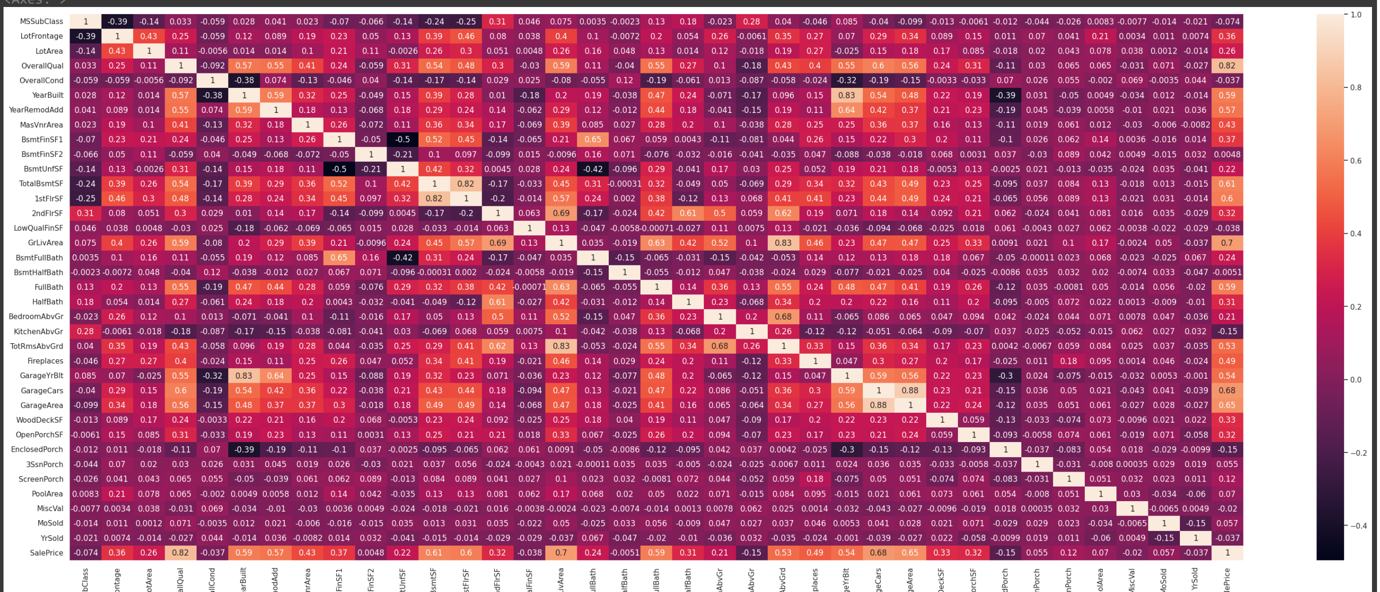
```
train_corr.shape
```

```
(1460, 38)
```

```
train_corr = train_corr.drop(columns = 'Id')
```

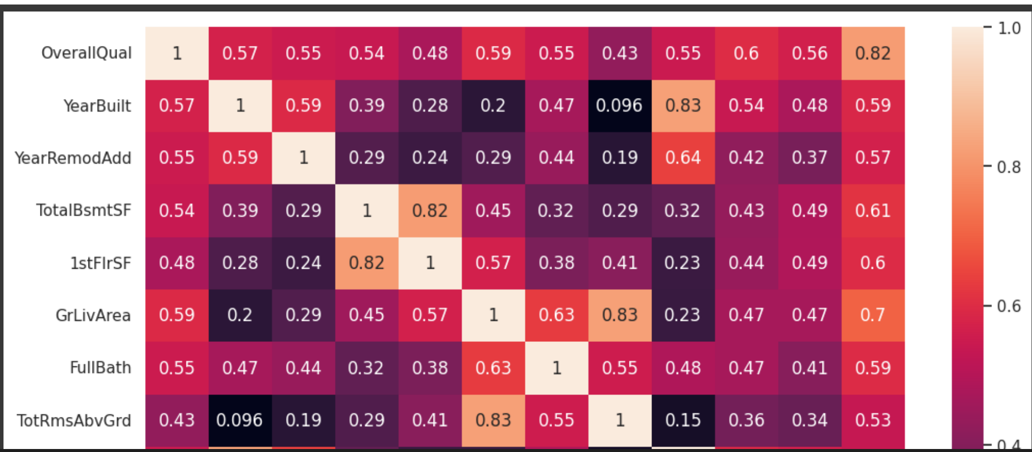
```
#Coralation plot
corr = train_corr.corr()
plt.subplots(figsize=(40,15))
sns.heatmap(corr, annot=True)
```

<Axes: >



```
thres = (corr['SalePrice'] > 0.5) | (corr['SalePrice'] < -0.5)
top_feature = corr.index[abs(thres)]

plt.subplots(figsize=(12, 8))
top_corr = hou[top_feature].corr()
sns.heatmap(top_corr, annot=True)
plt.show()
```




```
print("Find most important features relative to target")
corr = hou.corr()
corr.sort_values(['SalePrice'], ascending=False, inplace=True)
corr.SalePrice
```

```
Find most important features relative to target
SalePrice        1.000000
OverallQual      0.817185
GrLivArea        0.700927
GarageCars       0.680625
GarageArea       0.650888
TotalBsmtSF      0.612134
1stFlrSF         0.596981
FullBath         0.594771
YearBuilt        0.586570
YearRemodAdd     0.565608
GarageYrBlt      0.541073
TotRmsAbvGrd     0.534422
Fireplaces       0.489450
MasVnrArea       0.430809
BsmtFinSF1       0.372023
LotFrontage      0.355879
WoodDeckSF       0.334135
OpenPorchSF      0.321053
2ndFlrSF         0.319300
HalfBath         0.313982
LotArea          0.257320
BsmtFullBath     0.236224
BsmtUnfSF        0.221985
BedroomAbvGr     0.209043
ScreenPorch      0.121208
PoolArea         0.069798
MoSold           0.057330
3SsnPorch        0.054900
BsmtFinSF2       0.004832
BsmtHalfBath    -0.005149
Id              -0.017942
MiscVal         -0.020021
OverallCond     -0.036868
YrSold          -0.037263
LowQualFinSF    -0.037963
MSSubClass      -0.073959
KitchenAbvGr    -0.147548
EnclosedPorch   -0.149050
Name: SalePrice, dtype: float64
```

Handling Missing Values

```
hou['MiscFeature'] = hou['MiscFeature'].fillna('None')
hou['Alley'] = hou['Alley'].fillna('None')
hou['Fence'] = hou['Fence'].fillna('None')
hou['FireplaceQu'] = hou['FireplaceQu'].fillna('None')

#GarageType, GarageFinish, GarageQual and GarageCond these are replacing with None
for col in ['GarageType', 'GarageFinish', 'GarageQual', 'GarageCond']:
    hou[col] = hou[col].fillna('None')

#GarageYrBlt, GarageArea and GarageCars these are replacing with zero
for col in ['GarageYrBlt', 'GarageArea', 'GarageCars']:
    hou[col] = hou[col].fillna(int(0))

#BsmtFinType2, BsmtExposure, BsmtFinType1, BsmtCond, BsmtQual these are replacing with None
for col in ('BsmtFinType2', 'BsmtExposure', 'BsmtFinType1', 'BsmtCond', 'BsmtQual'):
    hou[col] = hou[col].fillna('None')

hou['Electrical'] = hou['Electrical'].fillna(hou['Electrical']).mode()[0]

hou['MasVnrArea'] = hou['MasVnrArea'].fillna(int(0))

hou['MasVnrType'] = hou['MasVnrType'].fillna('None')

hou['LotFrontage'] = hou['LotFrontage'].fillna(hou['LotFrontage'].mean())

hou = hou.drop('PoolQC', axis = 1)
```

```
hou.isnull().sum()
```

```
Id              0
MSSubClass      0
MSZoning        0
LotFrontage     0
LotArea         0
               ..
MoSold          0
YrSold          0
```

```
SaleType         0
SaleCondition    0
SalePrice        0
Length: 80, dtype: int64
```

```
hou.shape
```

```
(1460, 80)
```

```
hou.duplicated().sum()
```

```
0
```

Dealing With Categorical Features, Label Encoding, Train_Test_Split

```
from sklearn.preprocessing import LabelEncoder
```

```
# Extracting categorical columns:
catFeatures= [col for col in hou.columns if col in
              hou.select_dtypes(include=object).columns]

# Encoding Categorical Data
labelEncode = LabelEncoder()

# Iterating Over each categorial features:
for col in catFeatures:
    # storing its numerical value:
    hou[col] = labelEncode.fit_transform(hou[col])
```

```
y = hou['SalePrice']
#Take their values in X and y
X = hou.drop('SalePrice', axis = 1).values
y = y.values
```

```
X.shape
```

```
(1460, 79)
```

```
y.shape
```

```
(1460,)
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=7)
```

```
#This command shows the order pair of test and train

print("shape of X_train: ", X_train.shape)
print("shape of Y_train: ", y_train.shape)
print("shape of X_test: ", X_test.shape)
print("shape of Y_test: ", y_test.shape)
```

```
shape of X_train:  (1168, 79)
shape of Y_train:  (1168,)
shape of X_test:  (292, 79)
shape of Y_test:  (292,)
```

Model: Linear Regression

```
from sklearn.linear_model import LinearRegression
```

```
model = LinearRegression()
#Fit the model
model.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

```
#Prediction
print("Predict value " + str(model.predict([X_test[150]])))
print("Real value " + str(y_test[150]))
```

```
Predict value [11.8883059]
Real value 12.103491596905931
```

```
#Score/Accuracy
print("Accuracy --> ", model.score(X_test, y_test)*100)
```

```
Accuracy -->  89.62154463970859
```

Model: Random Forest Regressor

```
from sklearn.ensemble import RandomForestRegressor
```

```
model = RandomForestRegressor(n_estimators=1000)
#Fit
model.fit(X_train, y_train)
```

```
▾ RandomForestRegressor
```

```
#Prediction
print("Predict value " + str(model.predict([X_test[142]])))
print("Real value " + str(y_test[142]))
```

```
Predict value [11.70925155]
Real value 11.767187766223199
```

```
#Score/Accuracy
print("Accuracy --> ", model.score(X_test, y_test)*100)
```

```
Accuracy -->  89.51357514717174
```

Model: Grading Bosting Regressor

```
from sklearn.ensemble import GradientBoostingRegressor
```

```
GBR = GradientBoostingRegressor(n_estimators=100, max_depth=4)
#Fit
GBR.fit(X_train, y_train)
```

```
▾ GradientBoostingRegressor
GradientBoostingRegressor(max_depth=4)
```

```
#Prediction
print("Predict value " + str(model.predict([X_test[142]])))
print("Real value " + str(y_test[142]))
```

```
Predict value [11.70925155]
Real value 11.767187766223199
```

```
#Score/Accuracy
print("Accuracy --> ", GBR.score(X_test, y_test)*100)
```

```
Accuracy -->  91.77837512693186
```