```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from sklearn.tree import DecisionTreeRegressor
```

Data Acquring

```
df=pd.read_csv("../input/motorcycle-dataset/BIKE DETAILS.csv")
```

```
df
```

```
                                     name  selling_price  year 
seller_type  \
0               Royal Enfield Classic 350         175000  2019 
Individual   
1                               Honda Dio          45000  2017 
Individual   
2     Royal Enfield Classic Gunmetal Grey         150000  2018 
Individual   
3       Yamaha Fazer FI V 2.0 [2016-2018]          65000  2015 
Individual   
4                   Yamaha SZ [2013-2014]          20000  2011 
Individual   
...                                   ...            ...   ... 
...   
1056                             Activa 3g          17000  2010 
Individual   
1057                      Honda CB twister          16000  2012 
Individual   
1058                     Bajaj Discover 125         15000  2013 
Individual   
1059                        Honda CB Shine          12000  2009 
Individual   
1060                      Bajaj Pulsar 150          10000  2008 
Individual   

          owner  km_driven  ex_showroom_price  
0     1st owner        350                NaN  
1     1st owner       5650                NaN  
2     1st owner      12000           148114.0  
3     1st owner      23000            89643.0  
4     2nd owner      21000                NaN  
...         ...        ...                ...  
1056  1st owner     500000            52000.0  
1057  1st owner      33000            51000.0  
```

```
1058  2nd owner      35000            57000.0
1059  1st owner      53000            58000.0
1060  1st owner      92233            75000.0

[1061 rows x 7 columns]
```

```
df.isnull().sum()
```

```
name                   0
selling_price          0
year                   0
seller_type            0
owner                  0
km_driven              0
ex_showroom_price    435
dtype: int64
```

```
df.describe()
```

```
       selling_price         year      km_driven  ex_showroom_price
count    1061.000000  1061.000000    1061.000000       6.260000e+02
mean    59638.151744  2013.867107   34359.833176       8.795871e+04
std     56304.291973     4.301191   51623.152702       7.749659e+04
min      5000.000000  1988.000000     350.000000       3.049000e+04
25%     28000.000000  2011.000000   13500.000000       5.485200e+04
50%     45000.000000  2015.000000   25000.000000       7.275250e+04
75%     70000.000000  2017.000000   43000.000000       8.703150e+04
max    760000.000000  2020.000000  880000.000000       1.278000e+06
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1061 entries, 0 to 1060
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   name               1061 non-null   object 
 1   selling_price      1061 non-null   int64  
 2   year               1061 non-null   int64  
 3   seller_type        1061 non-null   object 
 4   owner              1061 non-null   object 
 5   km_driven          1061 non-null   int64  
 6   ex_showroom_price  626 non-null    float64
dtypes: float64(1), int64(3), object(3)
memory usage: 58.1+ KB
```

Data Cleaning

**** Handling the Missing values

```
df['ex_showroom_price'].isnull().sum()
```

```
435
```

```
df['ex_showroom_price'].fillna(np.round(df['ex_showroom_price'].median
(),2),inplace=True)
df['ex_showroom_price']
```

```
0        72752.5
1        72752.5
2       148114.0
3        89643.0
4        72752.5
          ...
1056     52000.0
1057     51000.0
1058     57000.0
1059     58000.0
1060     75000.0
Name: ex_showroom_price, Length: 1061, dtype: float64
```

```
np.round(df['ex_showroom_price'],2)
```

```
0        72752.5
1        72752.5
2       148114.0
3        89643.0
4        72752.5
          ...
1056     52000.0
1057     51000.0
1058     57000.0
1059     58000.0
1060     75000.0
Name: ex_showroom_price, Length: 1061, dtype: float64
```

```
df['name'].value_counts().head(15)
```

```
Bajaj Pulsar 150                 41
Royal Enfield Classic 350        27
Honda Activa [2000-2015]         23
Honda CB Hornet 160R             22
Bajaj Pulsar 180                 20
Royal Enfield Thunderbird 350    19
Hero Honda Splendor Plus         17
Bajaj Discover 125               16
Yamaha FZ S V 2.0                16
Honda Activa 3G                  15
Honda Shine                      15
Honda CB Unicorn 150             14
TVS Apache RTR 160               14
Bajaj Pulsar 135 LS              13
```

```
Honda Activa 5G                  12
Name: name, dtype: int64
```

```
df['owner'].value_counts()
```

```
1st owner    924
2nd owner    123
3rd owner     11
4th owner      3
Name: owner, dtype: int64
```

```
df['seller_type'].value_counts()
```

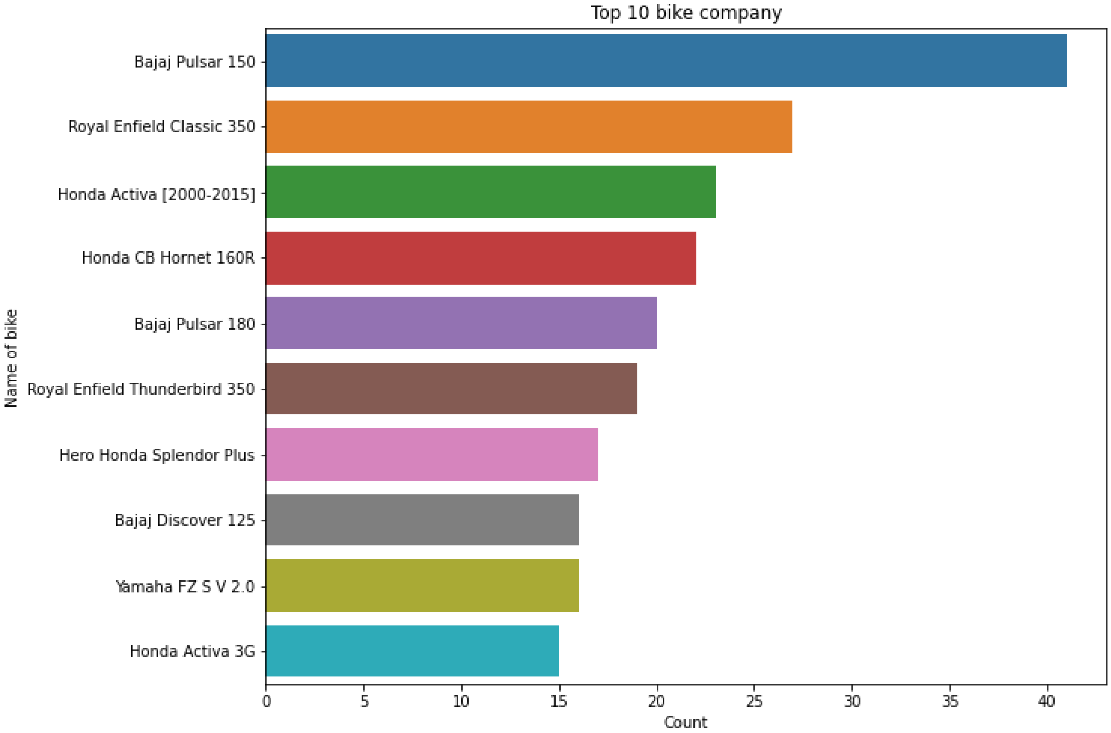
```
Individual    1055
Dealer           6
Name: seller_type, dtype: int64
```

Data Processing

Explorative Data Analysis

```
top_bike_company = df['name'].value_counts().head(10)
plt.figure(figsize=(10, 8))
sns.barplot(x = top_bike_company, y = top_bike_company.index)
plt.ylabel('Name of bike')
plt.title('Top 10 bike company')
plt.xlabel('Count')
```

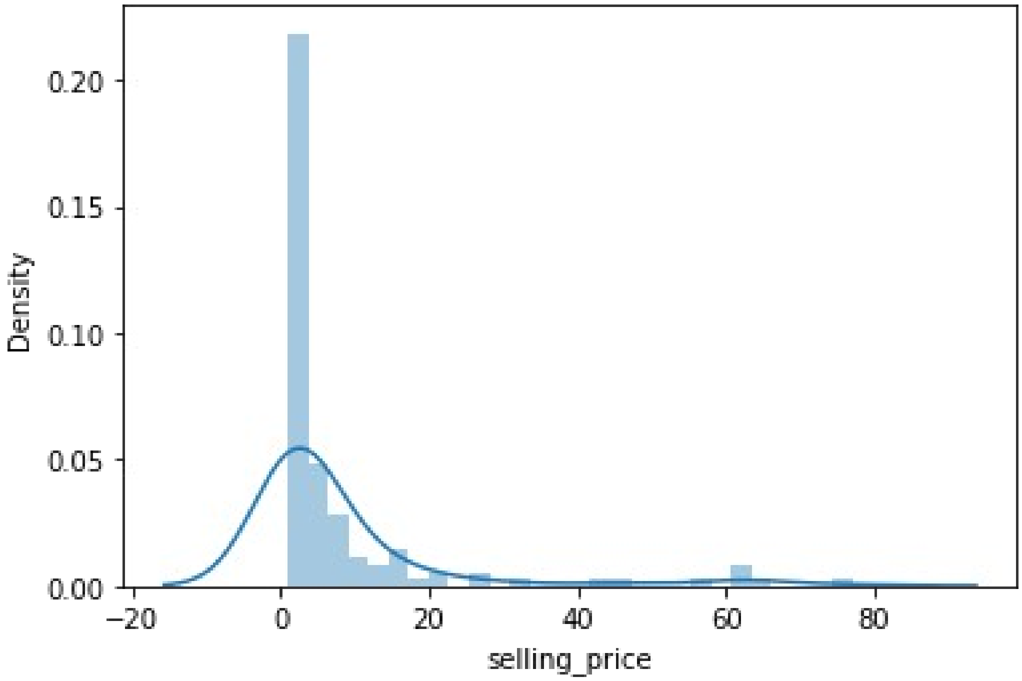
```
Text(0.5, 0, 'Count')
```



```
sns.distplot(df['selling_price'].value_counts())
```

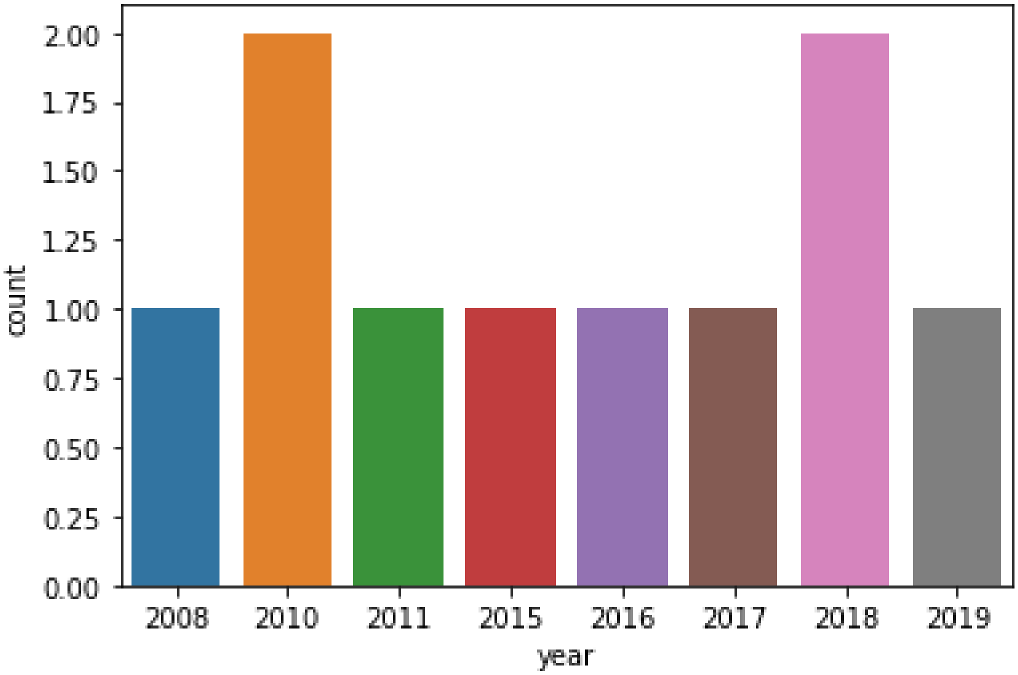
```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a
figure-level function with similar flexibility) or `histplot` (an
axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

```
<AxesSubplot:xlabel='selling_price', ylabel='Density'>
```



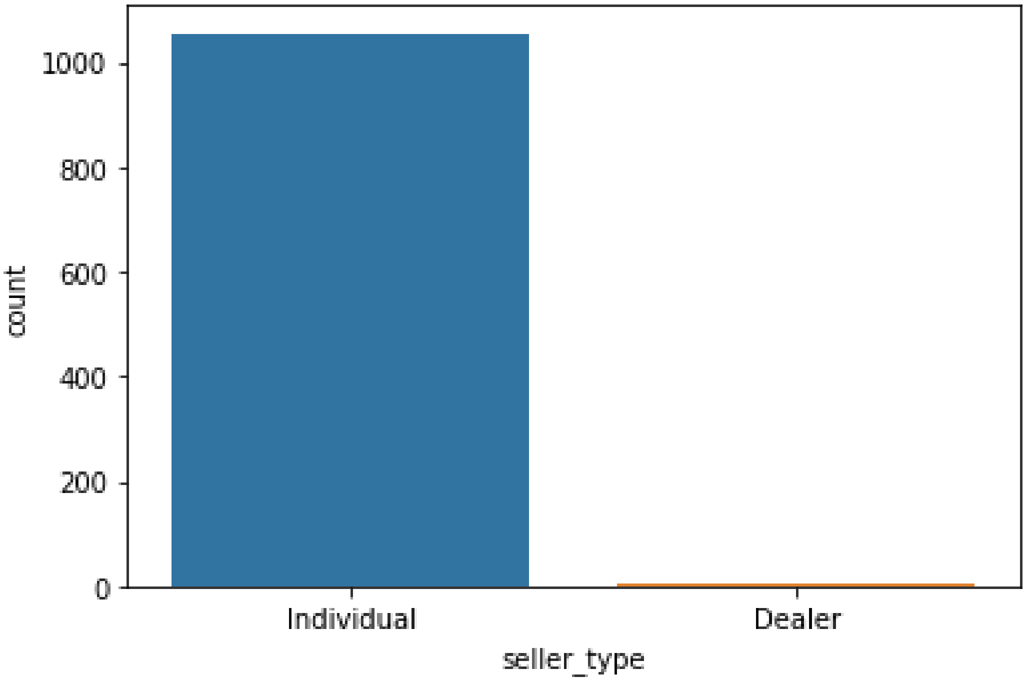
```
sns.countplot(x=df['year'].head(10))
```

```
<AxesSubplot:xlabel='year', ylabel='count'>
```



```
sns.countplot(x=df['seller_type'], data=df)
```

```
<AxesSubplot:xlabel='seller_type', ylabel='count'>
```



Handling the Categorical values

```
# we can convert categorical data to binary data through OneHotEncoder method or get_dummies method

df=pd.get_dummies(df,columns=['owner','seller_type'],drop_first=True)
'''
or
from sklearn.preprocessing import OneHotEncoder
encoder=OneHotEncoder(drop='first')
enc=pd.DataFrame(encoder.fit_transform(df[['owner']]).toarray())
'''
```

```
"\nor\nfrom sklearn.preprocessing import OneHotEncoder\
nencoder=OneHotEncoder(drop='first')\
nenc=pd.DataFrame(encoder.fit_transform(df[['owner']]).toarray())\n"
```

```
def bike_model(model_name, excl_honda_hero=False):
    model_list = []
    if excl_honda_hero:
        for i in df['name']:
            if model_name in i and 'Hero' not in i:
                model_list.append(i)
        return model_list
    else:
        for i in df['name']:
            if model_name in i:
                model_list.append(i)
        return model_list
```

```
royal_enfield = bike_model('Royal Enfield')
honda = bike_model('Honda',excl_honda_hero=True)
bajaj = bike_model('Bajaj')
yamaha = bike_model('Yamaha')
suzuki = bike_model('Suzuki')
hero = bike_model('Hero')
tvs = bike_model('TVS')
ktm = bike_model('KTM')

def brand(i):
    if i in royal_enfield:
        return 'Royal Enfield'
    elif i in honda:
        return 'Honda'
    elif i in bajaj:
        return 'Bajaj'
    elif i in yamaha:
        return 'Yamaha'
    elif i in hero:
        return 'Hero'
    elif i in tvs:
        return 'TVS'
    elif i in suzuki:
        return 'Suzuki'
    elif i in ktm:
        return 'KTM'
    else:
        return 'Other'

df['brand'] = df['name'].apply(lambda x:brand(x))
df.head()
```

```
                                  name  selling_price  year  km_driven
\
0            Royal Enfield Classic 350         175000  2019        350

1                            Honda Dio          45000  2017       5650

2  Royal Enfield Classic Gunmetal Grey         150000  2018      12000

3    Yamaha Fazer FI V 2.0 [2016-2018]          65000  2015      23000

4                Yamaha SZ [2013-2014]          20000  2011      21000


   ex_showroom_price  owner_2nd owner  owner_3rd owner  owner_4th
owner  \
0            72752.5                0                0
0
1            72752.5                0                0
```

```
0
2           148114.0               0                0
0
3            89643.0               0                0
0
4            72752.5               1                0
0

   seller_type_Individual          brand
0                       1  Royal Enfield
1                       1          Honda
2                       1  Royal Enfield
3                       1         Yamaha
4                       1         Yamaha
```

```
df=df.drop('name',axis='columns')
```

```
df= pd.get_dummies(df, columns=['brand'], drop_first=True)
```

```
x=df.drop('selling_price',axis='columns')
y=df['selling_price']
```

Train Test Split

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
```

Data Modeling

```
lin_reg=LinearRegression()
lin_reg.fit(x_train,y_train)
```

```
LinearRegression()
```

```
print("Model Intercept: ",lin_reg.intercept_)
print("Model Coefficient: ",lin_reg.coef_)
print("Model Coefficient: ",sum(lin_reg.coef_))
```

```
Model Intercept:  -7378244.053604637
Model Coefficient:  [ 3.67555304e+03 -4.31636574e-02  5.31133013e-01 -
5.68265614e+03
  1.97106293e+04  1.78218123e+04 -1.41637480e+04 -3.77752986e+03
 -3.14007480e+03  8.45983695e+04  2.08886295e+04  5.98193684e+04
 -1.08881358e+03  3.21982099e+03  5.13215333e+03]
Model Coefficient:  187014.0018849024
```

```
y_pred_test=lin_reg.predict(x_test)
y_pred_train=lin_reg.predict(x_train)
```

```
lin_reg
```

```
LinearRegression()
```

```
lin_reg.predict([[2019,350,72752.5,0,0,0,1,0,0,0,0,1,0,0,0]])
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/base.py:451:
UserWarning: X does not have valid feature names, but LinearRegression
was fitted with feature names
  "X does not have valid feature names, but"
```

```
array([126979.29749026])
```

```
sum(y_pred_train)
```

```
46420892.00000158
```

```
train_res=y_train-y_pred_train
test_res=y_test-y_pred_test
```

```
train_res
```

```
950    -1056.951098
782    -1069.378083
749   -19049.202127
381   -24245.328807
958    15516.206691
           ...
337    -4168.860505
502    17390.550009
675     1370.210492
853     9162.222489
866   -70408.846196
Name: selling_price, Length: 795, dtype: float64
```

```
test_res
```

```
105    18128.875915
971   -48972.025308
461    -3816.790146
754    22255.880623
230     1717.231501
           ...
662   -18087.661904
519     5830.945276
635     2090.762243
194   -16176.087586
916   -15137.524791
Name: selling_price, Length: 266, dtype: float64
```

```
from sklearn.metrics import
mean_squared_error,mean_absolute_error,r2_score
```

Mean Squared error and Root Mean Squared error

```
mse=mean_squared_error(y_test,y_pred_test)
mse
```

```
1064870473.0227611
```

```
mse_train=mean_squared_error(y_train,y_pred_train)
mse_train
```

```
528138316.53659874
```

```
rmse=np.sqrt(mse)
rmse
```

```
32632.353164041986
```

```
rmse=np.sqrt(mse_train)
rmse
```

```
22981.2601163774
```

```
lin_reg.score(x_train,y_train)
```

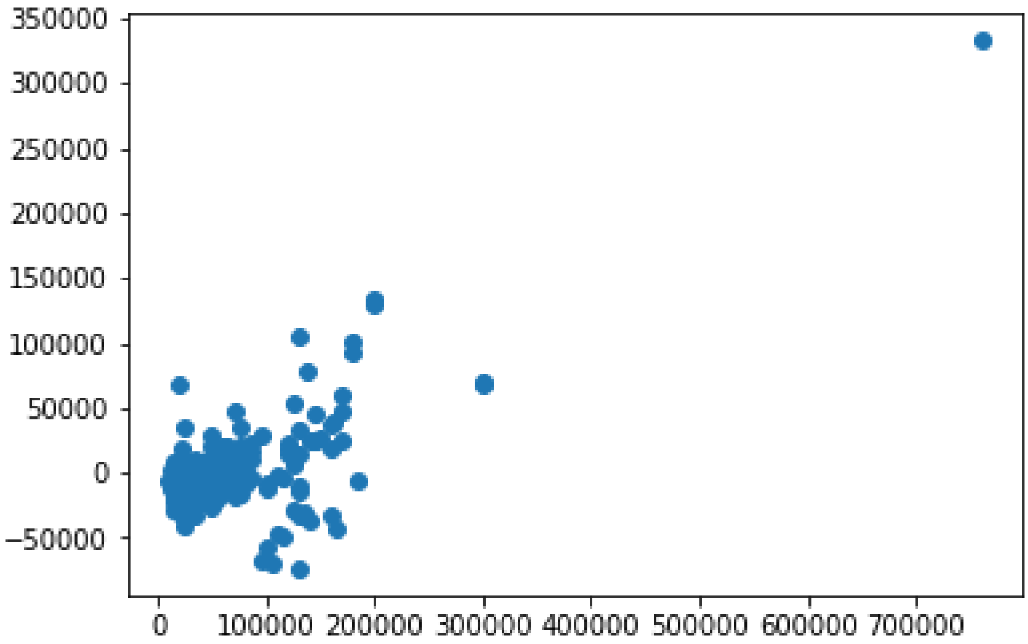
```
0.818041848370445
```

```
lin_reg.score(x_test,y_test)
```

```
0.7297034397025874
```

```
plt.scatter(y_test,test_res)
```

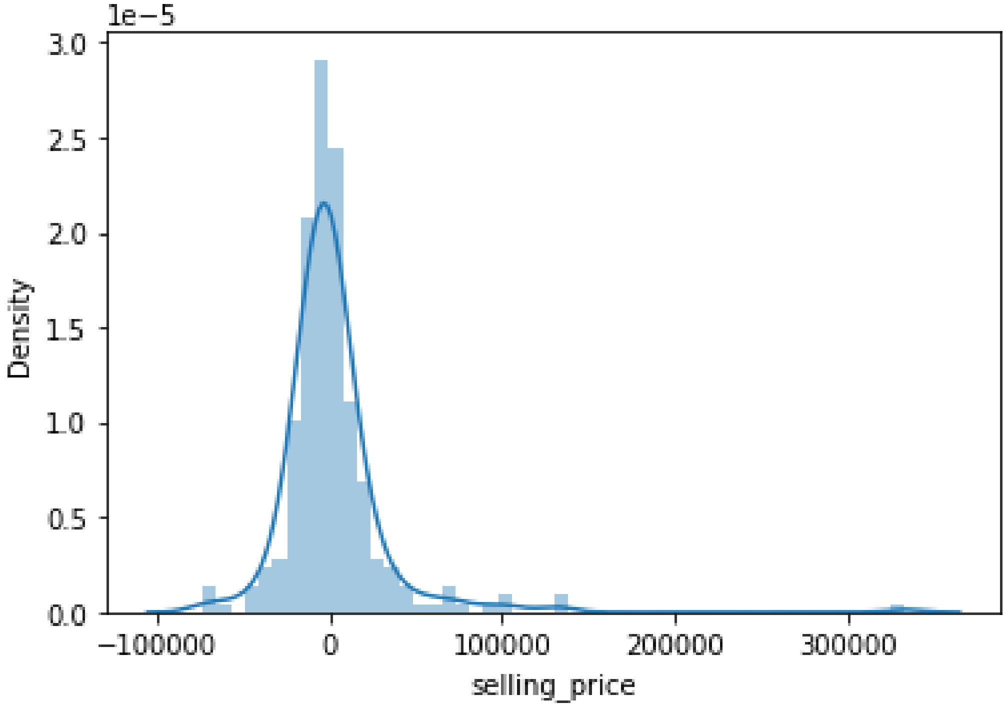
```
<matplotlib.collections.PathCollection at 0x7fc55da0de90>
```



```
sns.distplot(test_res,kde=True)
```

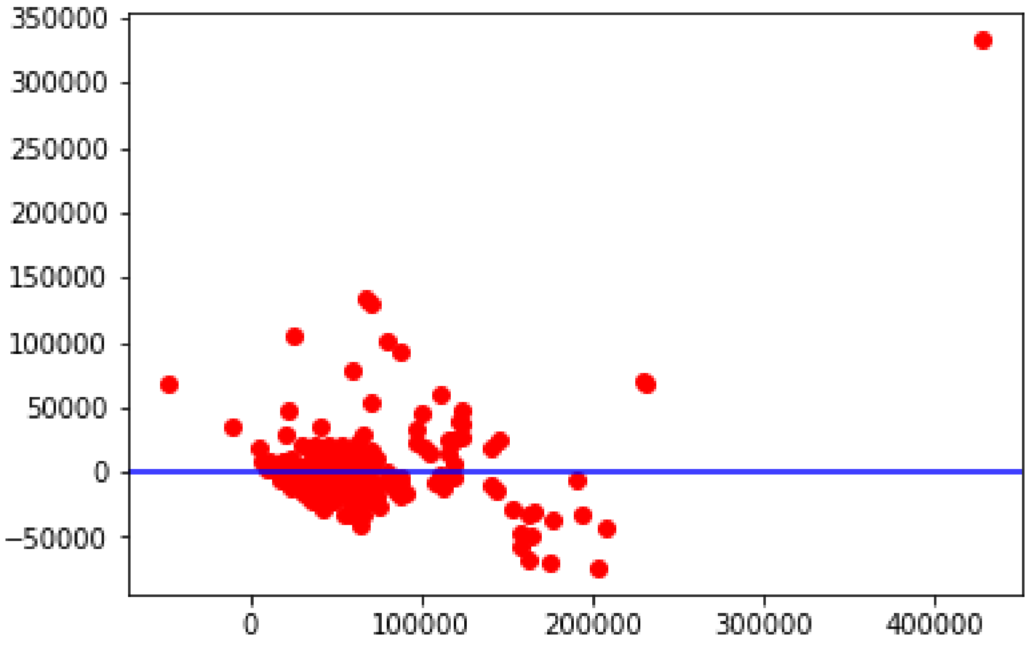
```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed
in a future version. Please adapt your code to use either `displot` (a
figure-level function with similar flexibility) or `histplot` (an
axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

```
<AxesSubplot:xlabel='selling_price', ylabel='Density'>
```



```
plt.scatter(y_pred_test,test_res,c='r')
plt.axhline(y=0,color='blue')
```

```
<matplotlib.lines.Line2D at 0x7fc55da8a9d0>
```



```
import statsmodels.formula.api as smf
model1=smf.ols('y~x',data=df).fit()
model1.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                      y   R-squared:
0.796
Model:                            OLS   Adj. R-squared:
0.794
Method:                 Least Squares   F-statistic:
272.6
Date:                Thu, 21 Jul 2022   Prob (F-statistic):
0.00
Time:                        17:11:10   Log-Likelihood:
-12266.
No. Observations:                1061   AIC:
2.456e+04
Df Residuals:                    1045   BIC:
2.464e+04
Df Model:                          15

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
Intercept  -7.201e+06   4.06e+05    -17.715      0.000      -8e+06
-6.4e+06
x[0]        3582.7039    201.943     17.741      0.000    3186.444
3978.964
x[1]          -0.0364      0.017     -2.179      0.030      -0.069
-0.004
x[2]           0.5959      0.015     40.585      0.000       0.567
0.625
x[3]       -5577.7978   2512.229     -2.220      0.027   -1.05e+04
-648.211
x[4]        2.029e+04   7915.992      2.563      0.011    4754.873
3.58e+04
x[5]        6203.1532   1.57e+04      0.395      0.693   -2.46e+04
3.7e+04
x[6]       -8504.5739   1.05e+04     -0.808      0.419   -2.91e+04
1.21e+04
x[7]       -5210.9224   2322.398     -2.244      0.025   -9768.016
-653.828
x[8]       -3935.8774   2418.645     -1.627      0.104   -8681.831
810.076
x[9]          7.6e+04   5529.175     13.745      0.000    6.51e+04
8.68e+04
x[10]       1.672e+04   5289.319      3.160      0.002    6337.309
2.71e+04
x[11]       5.675e+04   2982.476     19.029      0.000    5.09e+04
6.26e+04
x[12]       7952.5339   4961.751      1.603      0.109   -1783.595
1.77e+04
x[13]       3307.3299   3476.214      0.951      0.342   -3513.825
1.01e+04
x[14]       2101.5975   3023.855      0.695      0.487   -3831.922
8035.117
======================================================================
========
Omnibus:                      728.287   Durbin-Watson:
1.730
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
23729.204
Skew:                           2.687   Prob(JB):
0.00
Kurtosis:                      25.536   Cond. No.
5.47e+07
======================================================================
========

Notes:
```

```
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 5.47e+07. This might indicate that
there are
strong multicollinearity or other numerical problems.
"""
```

Saving model and Converting

```
from joblib import dump, load
```

```
dump(lin_reg,"motor_cycle_prediction.joblib")
```

```
['motor_cycle_prediction.joblib']
```

```
#Deployment
```

```
loaded_lin=load("motor_cycle_prediction.joblib")
```

```
loaded_model=load("motor_cycle_prediction.joblib")
```

```
loaded_model.predict([[2019,350,72752.5,0,0,0,1,0,0,0,0,1,0,0,0]])
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/base.py:451:
UserWarning: X does not have valid feature names, but LinearRegression
was fitted with feature names
  "X does not have valid feature names, but"
```

```
array([126979.29749026])
```