Importing the necessary libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings, pdftables_api, joblib
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split, cross_val_score, RepeatedKFold, Ra
from sklearn.linear_model import LinearRegression, LassoCV, PassiveAggressiveRegressor,
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR, LinearSVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, ExtraTree
from sklearn.neural network import MLPRegressor
from scipy.stats import probplot
from sklearn.preprocessing import FunctionTransformer, StandardScaler, OrdinalEncoder
from sklearn.impute import KNNImputer
from xgboost import XGBRegressor
from catboost import CatBoostRegressor
from lightgbm import LGBMRegressor
from sklearn.metrics import mean_squared_error, mean_squared_log_error, r2_score, mean_a
from sklearn.feature_selection import SelectKBest, SelectPercentile, SelectFromModel, f_
```

In [2]:

```
## Converting the dataset contained in PDF into a CSV file
# conversion = pdftables_api.Client('zf1l3ni5vlkx')
# conversion.csv('Assignment Dataset - Brandintelle - dataset.pdf','dataset.csv')
```

Loading the dataset

```
In [3]:
```

```
df = pd.read_csv('dataset.csv',usecols=lambda x: x != 'Sr No')
df.head()
```

Out[3]:

	DATE	Sales	TV_Spends	OOH_Spends	Print_Spends	FB_Impressions	Paid_Searc
0	2015- 11-23	2754371.667	167687.6	0	95463.66667	7.290385e+07	
1	2015- 11-30	2584276.667	214600.9	0	0.00000	1.658110e+07	295
2	2015- 12-07	2547386.667	0.0	248022	3404.00000	4.995477e+07	361
3	2015- 12-14	2875220.000	625877.3	0	132600.00000	3.164930e+07	368
4	2015- 12-21	2215953.333	0.0	520005	0.00000	8.802269e+06	284
4							•

Understanding the shape and structure of the dataset

```
In [4]:

df.shape

Out[4]:
(208, 11)

In [5]:

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 208 entries, 0 to 207
Data columns (total 11 columns):
```

#	Column	Non-Null Count	υτype
0	DATE	208 non-null	object
1	Sales	208 non-null	float64
2	TV_Spends	208 non-null	float64
3	OOH_Spends	208 non-null	int64
4	Print_Spends	208 non-null	float64
5	FB_Impressions	208 non-null	float64
6	Paid_Search_Clicks	208 non-null	float64
7	Search_Spends	208 non-null	int64
8	competitor_sales_B	208 non-null	int64
9	FB_Spends	208 non-null	float64
10	events	208 non-null	object
d+\(\n)	oc. float(1/6) inte	1(2) object(2)	

dtypes: float64(6), int64(3), object(2)

memory usage: 18.0+ KB

In [6]:

df.describe()

Out[6]:

	Sales	TV_Spends	OOH_Spends	Print_Spends	FB_Impressions	Paid_Sea
count	2.080000e+02	2.080000e+02	208.000000	208.000000	2.080000e+02	1
mean	1.822143e+06	1.113277e+05	81033.639423	27964.741987	2.446024e+07	50
std	7.162286e+05	2.141877e+05	157483.924979	48623.026739	3.509738e+07	40
min	6.722500e+05	0.000000e+00	0.000000	0.000000	0.000000e+00	
25%	1.165211e+06	0.000000e+00	0.000000	0.000000	0.000000e+00	18
50%	1.874514e+06	0.000000e+00	0.000000	0.000000	0.000000e+00	42
75%	2.378407e+06	1.380503e+05	95359.000000	35758.750002	4.121226e+07	75
max	3.827520e+06	1.185349e+06	938178.000000	239417.333300	1.782983e+08	156
4						•

In [7]:

```
df.isna().sum()
```

Out[7]:

DATE 0 Sales 0 TV_Spends 0 00H_Spends 0 Print_Spends FB_Impressions 0 Paid_Search_Clicks Search_Spends 0 competitor_sales_B FB_Spends 0 events dtype: int64

In [8]:

```
df.duplicated().sum()
```

Out[8]:

0

Exploratory Data Analysis

Kurtosis of TV Spends: 8.654882533891652

<Figure size 640x480 with 0 Axes>

Univariate Analysis

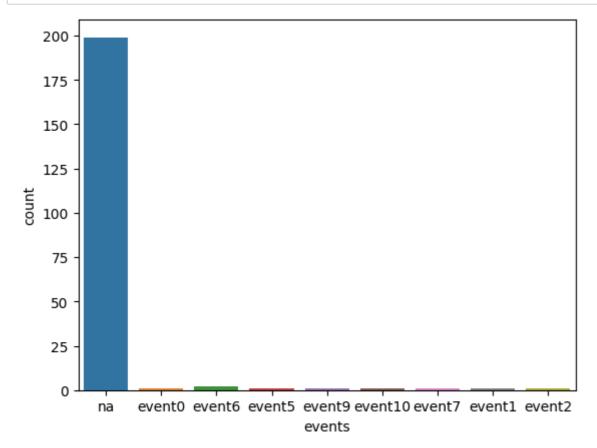
In [9]:

```
for col in df.columns:
    if isinstance(df[col][0],np.number):
        print(f"Skewness of {col}:",df[col].skew())
        print(f"Kurtosis of {col}:",df[col].kurtosis())
        plt.figure(figsize=(14,4))
        plt.subplot(131)
        sns.distplot(df[col])
        plt.subplot(132)
        sns.boxplot(df[col])
        plt.subplot(133)
        probplot(df[col],rvalue=True,plot=plt,dist='norm')
        plt.suptitle(col)
        plt.show()
        plt.tight_layout()
Skewness of Sales: 0.24521570453575126
Kurtosis of Sales: -0.8304394212678265
                                      Sales
                                                               Probability Plot
                                                      3.5
                                                      3.0
                                                      2.5
                                                     Valu
                                                      2.0
                                                      1.5
                                                      1.0
                                                                        R^2 = 0.9644
                                                      0.0
                                      2.0
                                         2.5 3.0
Skewness of TV_Spends: 2.777197561438994
```

The features "TV_Spends", "OOH_Spends", "Print_Spends", "FB_Impressions" and "FB_Spends" have highly right-skewed distributions due to the presence of outliers.

In [10]:

```
sns.countplot(df.events);
```



Bivariate Analysis

In [11]:

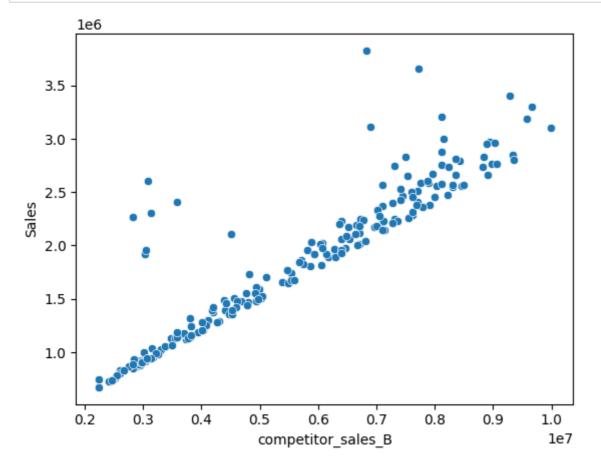
```
df.corr()['Sales'].sort_values(ascending=False)[1:]
```

Out[11]:

competitor_sales_B	0.916454
Search_Spends	0.442774
Paid_Search_Clicks	0.427513
TV_Spends	0.419869
FB_Spends	0.317594
FB_Impressions	0.315126
Print_Spends	0.230415
00H_Spends	0.095279
Name: Sales, dtype:	float64

In [12]:

```
sns.scatterplot(x='competitor_sales_B',y='Sales',data=df);
```



There is a substantially high correlation between competitor sales and the local sales.

In [13]:

```
df.DATE = pd.to_datetime(df.DATE,errors='coerce')
```

In [14]:

```
df['month'] = df.DATE.dt.month_name()
df['day'] = df.DATE.dt.day_name()
df['year'] = df.DATE.dt.year
df['hour'] = df.DATE.dt.hour
df['daysinmonth'] = df.DATE.dt.daysinmonth
df['dayofweek'] = df.DATE.dt.dayofweek
```

In [15]:

```
df.describe()
```

Out[15]:

	Sales	TV_Spends	OOH_Spends	Print_Spends	FB_Impressions	Paid_Sea
count	2.080000e+02	2.080000e+02	208.000000	208.000000	2.080000e+02	1
mean	1.822143e+06	1.113277e+05	81033.639423	27964.741987	2.446024e+07	50
std	7.162286e+05	2.141877e+05	157483.924979	48623.026739	3.509738e+07	40
min	6.722500e+05	0.000000e+00	0.000000	0.000000	0.000000e+00	
25%	1.165211e+06	0.000000e+00	0.000000	0.000000	0.000000e+00	18
50%	1.874514e+06	0.000000e+00	0.000000	0.000000	0.000000e+00	42
75%	2.378407e+06	1.380503e+05	95359.000000	35758.750002	4.121226e+07	75
max	3.827520e+06	1.185349e+06	938178.000000	239417.333300	1.782983e+08	156
4						•

In [16]:

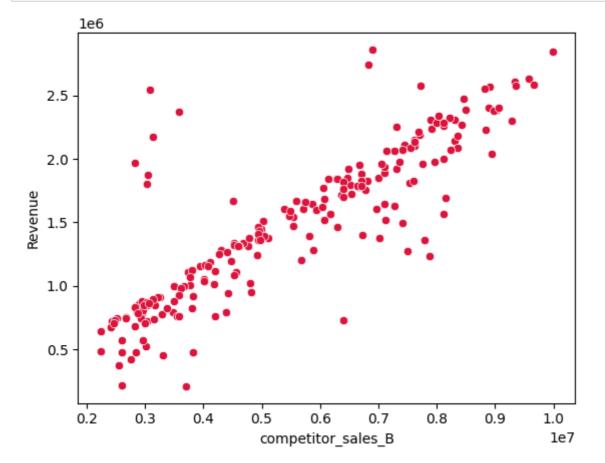
```
df.drop(['hour','dayofweek'],axis=1,inplace=True) # Since the variance of these features
```

In [17]:

```
df['Cost'] = df.TV_Spends + df.OOH_Spends + df.Print_Spends + df.Search_Spends + df.FB_S
df['Revenue'] = df.Sales - df.Cost
df.Revenue = df.Revenue.apply(abs)
df['CPM'] = (df.FB_Spends / df.FB_Impressions) * 1000 # Cost Per Thousand Impressions
df['CPC'] = df.Search_Spends / df.Paid_Search_Clicks # Cost Per Click
df['CPS'] = df.Cost / df.Sales # Cost Per Sale
df['ROI'] = (df.Revenue - df.Cost) / (df.Cost+0.0000001) * 100 # Return on Investment
```

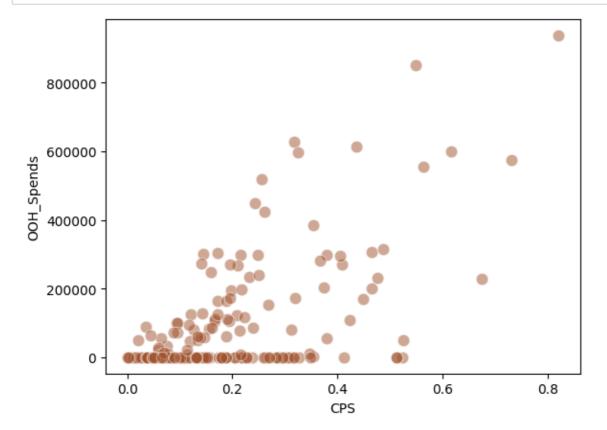
```
In [18]:
```

```
sns.scatterplot(x='competitor_sales_B',y='Revenue',data=df,color='crimson');
```



There is a significant positive correlation between total revenue and competitor sales.

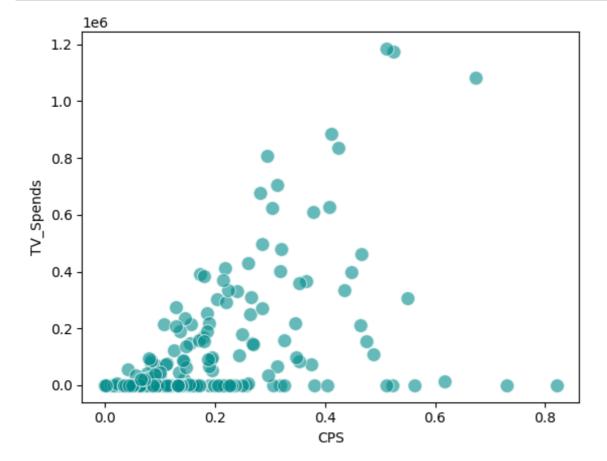
In [19]:



There is a strong positive correlation between spends on Outdoor medium and Cost per Sale.

In [20]:

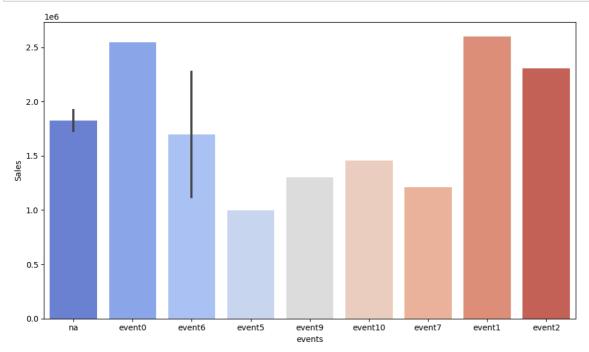
sns.scatterplot(x='CPS',y='TV_Spends',data=df,s=100,alpha=0.6,color='darkcyan');



There is a strong positive correlation between TV_Spends and Cost Per Sale. Cost per Sale can be minimized by lowering the TV spends.

In [21]:

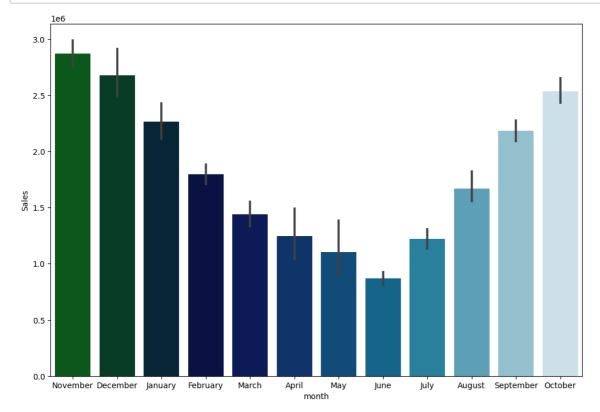
```
plt.figure(figsize=(10,6))
sns.barplot(x='events',y='Sales',data=df,palette='coolwarm')
plt.tight_layout();
```



Event 1 generates the maximum sales whereas event 5 generates the least sales. Moreover, event 0 generates really high sales, less than only event 1. Event 1 and event 0 must be conducted as many times as possible throughout the marketing campaigns to enhance the overall sales.

In [22]:

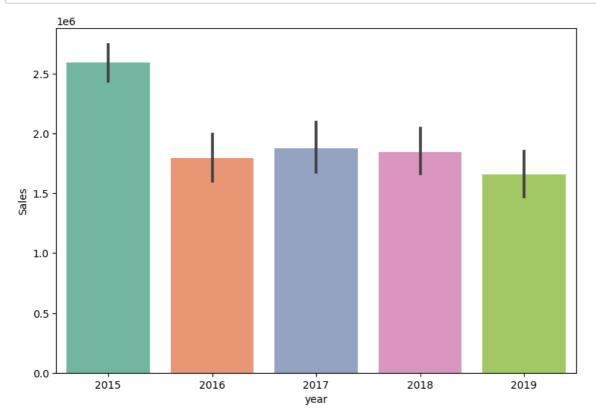
```
plt.figure(figsize=(12,8))
sns.barplot(x='month',y='Sales',data=df,palette='ocean');
```



The highest amount of sales are obtained during the final quarter of a year, in the months of October, November and December. A potential reason may be the festive shopping season when people do a lot of shopping due to reasonable discounts and affordable prices. On the other hand, the summer months of April, May and June generate the lowest amount of sales.

In [23]:

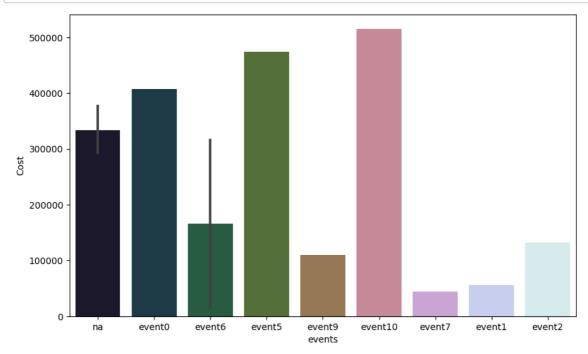
```
plt.figure(figsize=(9,6))
sns.barplot(x='year',y='Sales',data=df,palette='Set2');
```



The year of 2015 recorded the largest sales while the years of 2016 and 2019 observed the lowest sales.

In [24]:

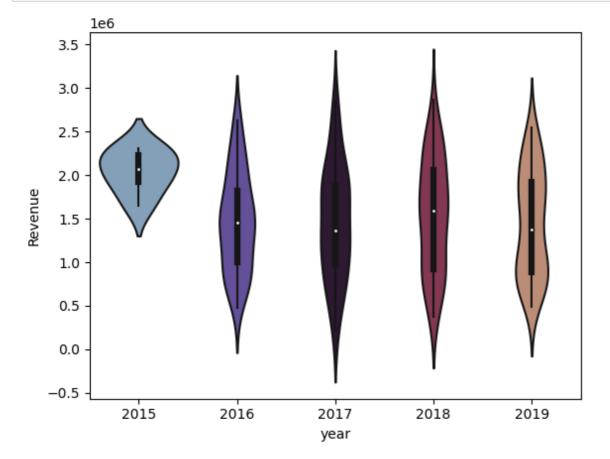
```
plt.figure(figsize=(10,6))
sns.barplot(x='events',y='Cost',data=df,palette='cubehelix');
```



The highest amount was spent in event 10 whereas the lowest amount was expended in event 7.

In [25]:

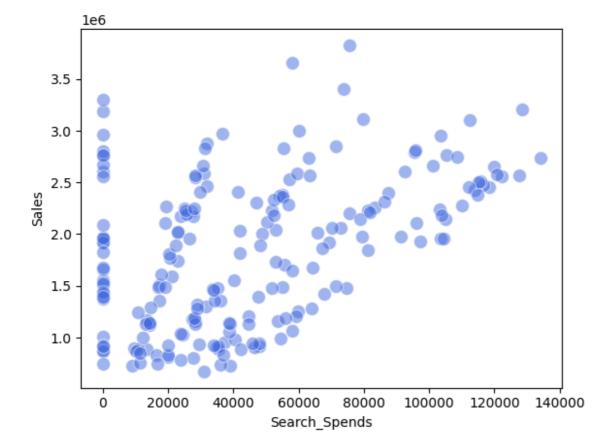
```
sns.violinplot(x='year',y='Revenue',data=df,palette='twilight');
```



The year 2015 generated the most revenue whereas 2017 and 2019 were the least profitable years.

In [26]:

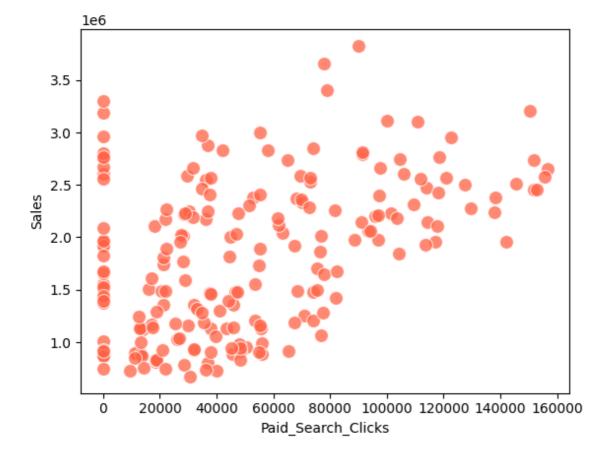
 $sns.scatterplot(x='Search_Spends',y='Sales',data=df,color='royalblue',s=100,alpha=0.5);$



There is a mild positive correlation between spendings done on getting the paid advertisements on the search results and sales i.e. more the amount spent on the paid search results, more will be the total sales.

In [27]:

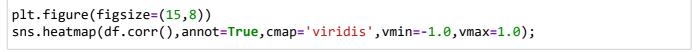
 $sns.scatterplot(x='Paid_Search_Clicks',y='Sales',data=df,color='tomato',s=100,alpha=0.76)$

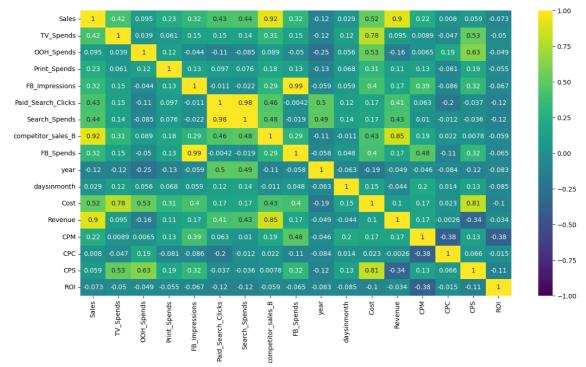


There is a mild positive correlation between sales and the number of user clicks on the paid advertisements posted on the search results i.e. more the user clicks on the paid search results, more will be the gross sales.

Multivariate Analysis

In [28]:



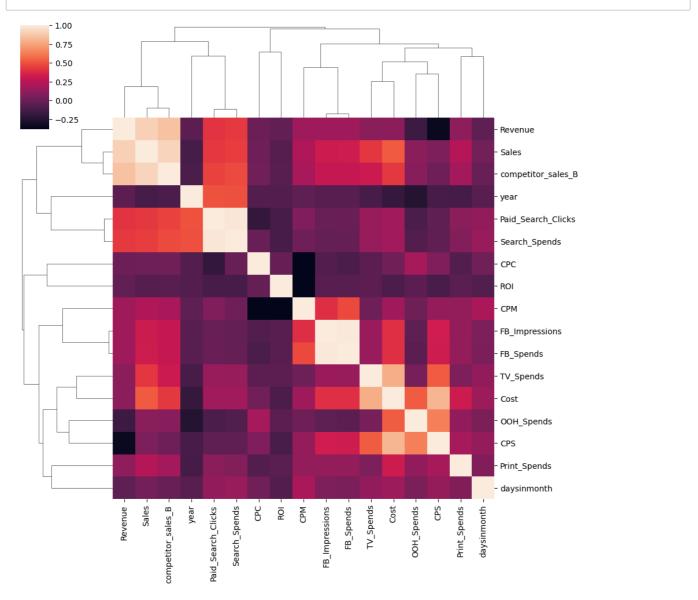


There is a perfect positive correlation between the features "FB_impressions" and "FB_Spends" i.e. more the spendings done on the FB advertisements, more will be the total number of user impressions. In addition, there is an almost perfect positive correlation between the features "Paid_Search_Clicks" and "Search_Spends" i.e. more the spendings done on the paid advertisements to place them in the search results, more will be the number of clicks.

There is a mild positive correlation between competitor sales and the spendings done on paid advertisements to get them on the search results as well as number of user clicks on the paid advertisements.

In [29]:

sns.clustermap(df.corr());



Feature Engineering

Feature Transformation

```
In [30]:
for col in df.columns:
    if isinstance(df[col][0],np.number):
        print(f"Skewness of {col}:",df[col].skew())
        print(f"Kurtosis of {col}:",df[col].kurtosis())
        plt.figure(figsize=(14,4))
        plt.subplot(131)
        sns.distplot(df[col])
        plt.subplot(132)
        sns.boxplot(df[col])
        plt.subplot(133)
        probplot(df[col],rvalue=True,plot=plt,dist='norm')
        plt.suptitle(col)
        plt.show()
        plt.tight_layout()
Skewness of Sales: 0.24521570453575126
Kurtosis of Sales: -0.8304394212678265
                                      Sales
                                                               Probability Plot
                                                      3.5
                                                      3.0
                                                      2.5
                                                     Valu
                                                      2.0
                                                      1.5
                                                      1.0
                                                                       R^2 = 0.9644
```

Skewness of TV_Spends: 2.777197561438994 Kurtosis of TV Spends: 8.654882533891652

<Figure size 640x480 with 0 Axes>

In [31]:

```
outlier_cols = ['TV_Spends','OOH_Spends','Print_Spends','FB_Impressions','Search_Spends'
```

2.0

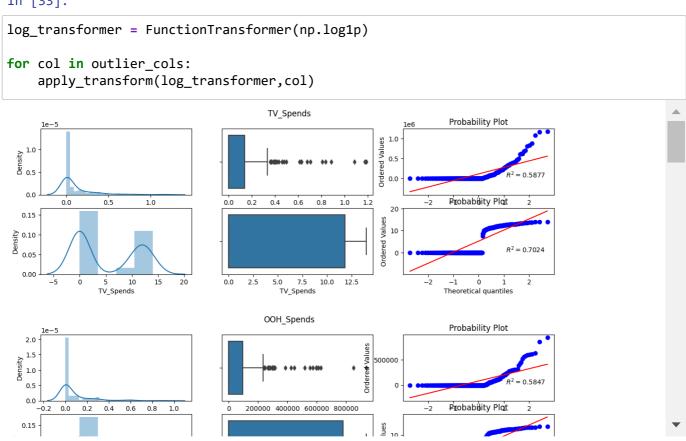
2.5 3.0

0.0

In [32]:

```
def apply transform(transformer,col):
   plt.figure(figsize=(14,4))
   plt.subplot(231)
   sns.distplot(df[col])
   plt.subplot(232)
   sns.boxplot(df[col])
   plt.subplot(233)
   probplot(df[col],plot=plt,rvalue=True,dist='norm')
   plt.suptitle(col)
   tf_col = transformer.fit_transform(df[col])
   plt.subplot(234)
   sns.distplot(tf col)
   plt.subplot(235)
   sns.boxplot(tf_col)
   plt.subplot(236)
   probplot(tf_col,plot=plt,rvalue=True,dist='norm')
   plt.show();
```

In [33]:



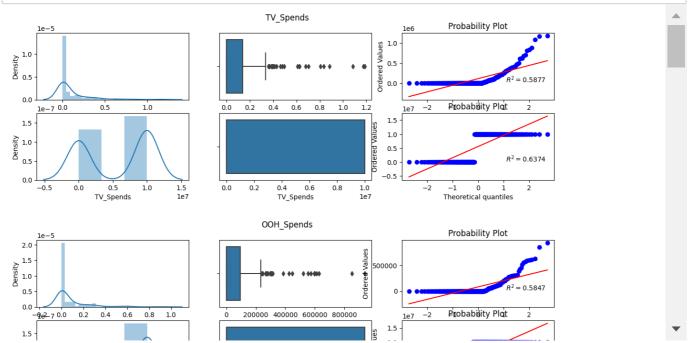
In [34]:

```
sqrt_transformer = FunctionTransformer(np.sqrt)
for col in outlier_cols:
      apply_transform(sqrt_transformer,col)
                                                             TV_Spends
                                                                                                       Probability Plot
                                                                                       Ordered Values
   Density
0.5
                                                                                         0.5
                                                                                         0.0
     0.0
                                1.0
                                                                                                       Probability Plot
                       0.5
                                                   0.0
                                                        0.2
                                                             0.4
                                                                   0.6
                                                                        0.8
                                                                             1.0
                                                                                       1000
   0.004
 Density
   0.002
   0.000
                                 1000
                                                        200
                                                              400 600
TV_Spends
                                                                                                                        2
                      TV_Spends
                                                            OOH_Spends
                                                                                                       Probability Plot
                                                                                   Ordered Values
   1.5
1.0
                                                                                      500000
     0.5
                                                                                                       Probability Plot
                       0.4
                            0.6
                                 0.8
                                                        200000 400000 600000 800000
                                                                                       1000
```

In [35]:

reciprocal_transformer = FunctionTransformer(lambda x: 1/(x+0.0000001))

for col in outlier_cols:
 apply_transform(reciprocal_transformer,col)



In [36]:

```
square_transformer = FunctionTransformer(lambda x: x**2)
for col in outlier_cols:
      apply_transform(square_transformer,col)
                                                          TV Spends
                                                                                                   Probability Plot
                                                                                   Ordered Values
0.0
 Density
0.5
                                                                                                   Probability Plot
                                                     0.2
                                                           0.4
                     0.5
                              1.0
                                                0.0
                                                                0.6
                                                                     0.8
                                                                          1.0
                                                                                   ed Values
                                                                                     1.0
                                                                                     0.5
                                                                                     0.0
                                                                           1.25
le12
          0.0
                                               0.00
                                                     0.25
                                                           0.50
                                                                0.75
                                                                                                  Theoretical quantiles
                                                             TV_Spends
                                                         OOH_Spends
                                                                                                   Probability Plot
                                                                                Ordered Values
   1.5
 1.5
                    0.4
                         0.6
                              0.8
                                   1.0
                                                     200000 400000 600000 800000
                                                                                                   Probability Plot
               0.2
                                                                                   s 7.5
In [37]:
cube_transformer = FunctionTransformer(lambda x: x**3)
for col in outlier_cols:
      apply_transform(cube_transformer,col)
                                                          TV_Spends
                                                                                                   Probability Plot
                                                                                   Ordered Values
 Density
0.5
                                                                                     0.0
       1e-17<sup>0.0</sup>
                                                                                                   Probability Plot
                     0.5
                              1.0
                                                     0.2
                                                          0.4
                                                               0.6
                                                                     0.8
                                                                          1.0
                                                                               1.2
                                                                                         1e18 -2
                                                                                     1.5
                                                                                   Ordered Values
                                                                                     1.0
                                                                                     0.5
                                                                                     0.0
                                                                            1.5
le18
          0.0
                                 1.5
                                                0.0
                                     1e18
                                                             TV_Spends
                    TV Spends
                                                                                                  Theoretical quantiles
                                                         OOH_Spends
                                                                                                   Probability Plot
                                                                                         1e17 -2
                                                                                                   Probability Plot
                0.2
                     0.4
                         0.6
                               0.8
                                    1.0
                                                     200000 400000 600000 800000
      -0-2-170.0
                                                                                     nes
```

Log Transform: None

Sqrt Transform: TV_Spends, OOH_Spends, Print_Spends, FB_Impressions, Search_Spends, FB_Spends,

Cost, CPS

Reciprocal Transform: ROI

```
In [38]:
```

```
df.ROI = reciprocal_transformer.fit_transform(df.ROI)
```

```
In [39]:
```

```
sqrt_cols = ['TV_Spends','OOH_Spends','Print_Spends','FB_Impressions','Search_Spends','F

for col in sqrt_cols:
    df[col] = sqrt_transformer.fit_transform(df[col])
```

In [40]:

```
cube_cols = ['daysinmonth','CPM']

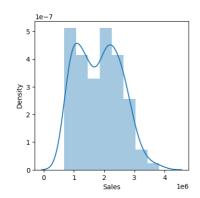
for col in cube_cols:
    df[col] = cube_transformer.fit_transform(df[col])
```

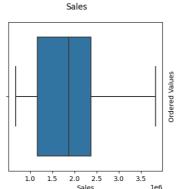
Treatment of Outliers

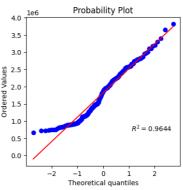
In [41]:

```
for col in df.columns:
    if isinstance(df[col][0],np.number):
        print(f"Skewness of {col}:",df[col].skew())
        print(f"Kurtosis of {col}:",df[col].kurtosis())
        plt.figure(figsize=(14,4))
        plt.subplot(131)
        sns.distplot(df[col])
        plt.subplot(132)
        sns.boxplot(df[col])
        plt.subplot(133)
        probplot(df[col],rvalue=True,plot=plt,dist='norm')
        plt.suptitle(col)
        plt.show()
        plt.tight_layout()
```

Skewness of Sales: 0.24521570453575126 Kurtosis of Sales: -0.8304394212678265







Skewness of TV_Spends: 1.2843203253105715 Kurtosis of TV_Spends: 0.8062730021064808

<Figure size 640x480 with 0 Axes>

In [42]:

```
outlier_cols = ['TV_Spends','OOH_Spends','Print_Spends','daysinmonth','Cost','CPS','ROI'
```

In [43]:

```
def remove_outliers(col):
    lower_limit, upper_limit = df[col].quantile([0.25,0.75])
    IQR = upper_limit - lower_limit
    lower_whisker = lower_limit - 1.5 * IQR
    upper_whisker = upper_limit + 1.5 * IQR
    return np.where(df[col]>upper_whisker,upper_whisker,np.where(df[col]<lower_whisker,l</pre>
```

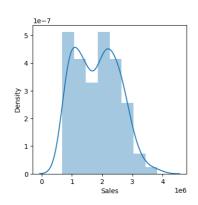
In [44]:

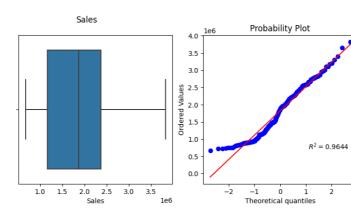
```
for col in outlier_cols:
    df[col] = remove_outliers(col)
```

In [45]:

```
for col in df.columns:
    if isinstance(df[col][0],np.number):
        print(f"Skewness of {col}:",df[col].skew())
        print(f"Kurtosis of {col}:",df[col].kurtosis())
        plt.figure(figsize=(14,4))
        plt.subplot(131)
        sns.distplot(df[col])
        plt.subplot(132)
        sns.boxplot(df[col])
        plt.subplot(133)
        probplot(df[col],rvalue=True,plot=plt,dist='norm')
        plt.suptitle(col)
        plt.show()
        plt.tight_layout()
```

Skewness of Sales: 0.24521570453575126 Kurtosis of Sales: -0.8304394212678265





Skewness of TV_Spends: 1.1787652374584585 Kurtosis of TV_Spends: 0.2947058456459817

<Figure size 640x480 with 0 Axes>

Categorical Encoding

```
In [46]:
```

```
events_encoded = pd.get_dummies(df.events)
df = pd.concat([df,events_encoded],axis=1)
df.head()
```

Out[46]:

	DATE	Sales	TV_Spends	OOH_Spends	Print_Spends	FB_Impressions	Paid_Searc
0	2015- 11-23	2754371.667	409.496764	0.000000	308.971951	8538.375297	
1	2015- 11-30	2584276.667	463.250364	0.000000	0.000000	4071.989630	295
2	2015- 12-07	2547386.667	0.000000	498.018072	58.343809	7067.869104	361
3	2015- 12-14	2875220.000	791.124074	0.000000	364.142829	5625.770794	368
4	2015- 12-21	2215953.333	0.000000	721.113722	0.000000	2966.861891	284

5 rows × 30 columns

In [47]:

```
df.drop(['DATE','events'],axis=1,inplace=True) # Dropping the encoded features
```

```
In [48]:
```

```
oe = OrdinalEncoder(categories=[['January','February','March','April','May','June','July
df.month = oe.fit_transform(df[['month']])
df.month = df.month.astype(int)
```

In [49]:

```
df.day.unique()
```

Out[49]:

```
array(['Monday'], dtype=object)
```

In [50]:

```
df.drop('day',axis=1,inplace=True)
```

Splitting the dataset into independent and dependent features

```
In [51]:

X = df.drop('Sales',axis=1)
y = df.Sales
```

Dividing the dataset into training and test sets

```
In [52]:

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=101,s)
```

Feature Selection

In [53]:

```
# Imputing the missing values of features "CPM" and "CPC" using KNN Imputer
knn = KNNImputer()
X_train.CPM = knn.fit_transform(X_train[['CPM']])
X_test.CPM = knn.transform(X_test[['CPM']])
X_train.CPC = knn.fit_transform(X_train[['CPC']])
X_test.CPC = knn.transform(X_test[['CPC']])
```

In [54]:

```
kbest = SelectKBest(k=10,score_func=f_regression)
kbest.fit(X_train,y_train)
```

Out[54]:

SelectKBest(score_func=<function f_regression at 0x000002D852B68C10>)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [55]:
```

```
selected_features = kbest.get_feature_names_out()
selected_features

Out[55]:
```

```
In [56]:
p values = sorted(kbest.pvalues )[-11:-1]
p_values
Out[56]:
[0.29621362809634305,
0.4117374290552849,
0.4854282592677701,
0.5191069637621774,
0.5240722060102341,
 0.5260145210689713,
0.5610557516486525,
0.6247269979130835,
0.7174908169529665,
0.8149251225529097]
In [57]:
percentile = SelectPercentile(percentile=40,score_func=mutual_info_regression)
percentile.fit(X_train,y_train)
Out[57]:
SelectPercentile(percentile=40,
                 score_func=<function mutual_info_regression at 0x000002D8</pre>
52B6B640>)
In a Jupyter environment, please rerun this cell to show the HTML representation or
trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page
with nbviewer.org.
In [58]:
selected_features = percentile.get_feature_names_out()
selected_features
Out[58]:
array(['FB_Impressions', 'Paid_Search_Clicks', 'Search_Spends',
       'competitor_sales_B', 'FB_Spends', 'month', 'daysinmonth', 'Cost',
       'Revenue', 'CPC'], dtype=object)
In [59]:
scores = percentile.scores_
scores
Out[59]:
array([7.23428038e-02, 0.00000000e+00, 0.0000000e+00, 1.38218084e-01,
       2.26453768e-01, 3.91721631e-01, 1.85563034e+00, 1.40362830e-01,
       1.03035418e+00, 0.00000000e+00, 2.08168839e-01, 1.57324862e-01,
       9.97497534e-01, 7.60956266e-02, 7.85898066e-02, 2.71179576e-03,
       0.00000000e+00, 1.11022302e-16, 2.22044605e-16, 2.29885057e-03,
       2.29885057e-03, 0.00000000e+00, 0.00000000e+00, 6.89655172e-03,
       0.0000000e+00, 1.11484289e-02])
```

In [60]:

```
sfm = SelectFromModel(estimator=RandomForestRegressor(),threshold='median',max_features=
sfm.fit(X_train,y_train)
```

Out[60]:

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

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In [61]:

```
selected_features = sfm.get_feature_names_out()
selected_features
```

Out[61]:

In [62]:

rfe = RFECV(estimator=RandomForestRegressor(),step=2,min_features_to_select=10,cv=Repeat
rfe.fit(X_train,y_train)

```
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
```

```
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Fitting estimator with 26 features.
Fitting estimator with 24 features.
Fitting estimator with 22 features.
Fitting estimator with 20 features.
Fitting estimator with 18 features.
Fitting estimator with 16 features.
Fitting estimator with 14 features.
Fitting estimator with 12 features.
Out[62]:
RFECV(cv=RepeatedKFold(n_repeats=2, n_splits=5, random_state=None),
      estimator=RandomForestRegressor(), min_features_to_select=10, step=
2,
      verbose=1)
```

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```
In [63]:
```

In [64]:

```
cv_results = pd.DataFrame(rfe.cv_results_)
cv_results
```

Out[64]:

	mean_test_score	std_test_score	split0_test_score	split1_test_score	split2_test_score	sp
0	0.953846	0.025036	0.934461	0.952460	0.940314	
1	0.952678	0.024481	0.930628	0.952234	0.948455	
2	0.949106	0.026685	0.936129	0.947903	0.933233	
3	0.949527	0.023309	0.927902	0.955995	0.933202	
4	0.950482	0.025952	0.931175	0.948924	0.935897	
5	0.950338	0.027089	0.933802	0.956256	0.925562	
6	0.948114	0.024669	0.938335	0.944549	0.923984	
7	0.947927	0.027466	0.930386	0.943013	0.924109	
8	0.951625	0.027313	0.923922	0.952528	0.942030	
4						•

In [65]:

```
sfs = Sequential Feature Selector (estimator = Random Forest Regressor (), direction = \begin{tabular}{l} backward ', n \\ sfs.fit (X_train, y_train) \end{tabular}
```

Out[65]:

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

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In [66]:

```
selected_features = sfs.get_feature_names_out()
selected_features
```

Out[66]:

In [67]:

```
lasso = SelectFromModel(estimator=LassoCV(),max_features=10,threshold='median')
lasso.fit(X_train,y_train)
```

Out[67]:

SelectFromModel(estimator=LassoCV(), max_features=10, threshold='median')

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [68]:

```
selected_features = lasso.get_feature_names_out()
selected_features
```

Out[68]:

In [69]:

```
rf = RandomForestRegressor()
rf.fit(X_train,y_train)
```

Out[69]:

RandomForestRegressor()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [70]:

```
feat_imp = pd.DataFrame({'feature': X_train.columns, 'importance': rf.feature_importance
feat_imp = feat_imp.sort_values('importance',ascending=False)
feat_imp.head(10)
```

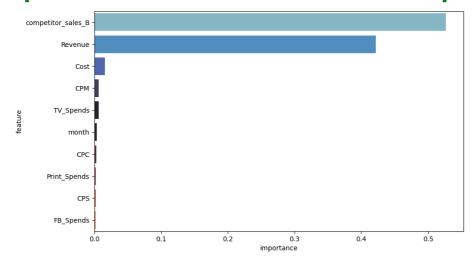
Out[70]:

	feature	importance
6	competitor_sales_B	0.526396
12	Revenue	0.421944
11	Cost	0.015886
13	СРМ	0.006584
0	TV_Spends	0.006431
8	month	0.004104
14	CPC	0.002922
2	Print_Spends	0.002623
15	CPS	0.002502
7	FB_Spends	0.002249

In [71]:

```
plt.figure(figsize=(10,6))
sns.barplot(x='importance',y='feature',data=feat_imp[:10],orient='horizontal',palette='i
plt.title('Top 10 Features based on Feature Importances',fontsize=32,fontweight='bold',c
```

Top 10 Features based on Feature Importances



Final selected features: TV_Spends, Print_Spends, FB_Impressions, Paid_Search_Clicks, Search_Spends, competitor sales B, FB Spends, month, Cost, Revenue

In [72]:

```
selected_features = kbest.get_feature_names_out()
selected_features
```

Out[72]:

In [73]:

```
X_train_final = X_train[selected_features]
X_test_final = X_test[selected_features]
```

Feature Scaling and Normalization

In [74]:

```
scaler = StandardScaler()
features = X_train_final.columns
X_train_final = scaler.fit_transform(X_train_final)
X_train_final = pd.DataFrame(X_train_final,columns=features)
X_test_final = scaler.transform(X_test_final)
X_test_final = pd.DataFrame(X_test_final,columns=features)
X_train_final.head()
```

Out[74]:

	TV_Spends	Print_Spends	FB_Impressions	Paid_Search_Clicks	Search_Spends	competite
0	-0.783061	-0.664231	-0.848186	-0.858039	-0.695131	
1	2.711955	1.312909	0.890787	-0.573911	-0.296307	
2	-0.783061	-0.664231	-0.848186	0.618792	0.527713	
3	-0.219207	0.466012	-0.848186	2.490902	1.796331	
4	-0.783061	0.620425	1.103090	0.549877	0.798168	
4						•

In [75]:

```
X_test_final.head()
```

Out[75]:

	TV_Spends	Print_Spends	FB_Impressions	Paid_Search_Clicks	Search_Spends	competite
0	-0.783061	0.428265	-0.848186	0.332446	0.310150	
1	1.254396	1.819061	-0.848186	1.097669	0.874541	
2	0.979124	0.564416	-0.848186	-1.296380	-1.903236	
3	-0.475982	-0.664231	-0.848186	1.120051	0.984434	
4	-0.783061	-0.664231	-0.848186	-0.294711	0.094439	
4						•

Model Training & Evaluation

```
In [76]:
models = []
r2\_scores = []
rmse_scores = []
mape_scores = []
rmsle_scores = []
In [77]:
# Custom function for training and evaluating the performance of machine learning algori
def train_and_evaluate_model(model):
    models.append(model)
    model.fit(X_train_final,y_train)
    pred = model.predict(X test final)
    mape = mean_absolute_percentage_error(y_test,pred)
    print("Mean Absolute Percentage Error:",mape)
    mape_scores.append(mape)
    rmse = np.sqrt(mean_squared_error(y_test,pred))
    print("Root Mean Squared Error:",rmse)
    rmse_scores.append(rmse)
    rmsle = np.sqrt(mean_squared_log_error(y_test,pred))
    print("Root Mean Squared Log Error:",rmsle)
    rmsle_scores.append(rmsle)
    r2 = r2_score(y_test,pred)
    print("R2 Score:",r2)
    r2_scores.append(r2)
In [78]:
train_and_evaluate_model(LinearRegression())
Mean Absolute Percentage Error: 0.037602824334626514
Root Mean Squared Error: 95719.65932929565
Root Mean Squared Log Error: 0.054083587741203705
R2 Score: 0.9776935128173896
In [79]:
train and evaluate model(RidgeCV())
Mean Absolute Percentage Error: 0.037576727144972885
Root Mean Squared Error: 95459.3213232264
Root Mean Squared Log Error: 0.05398820597383878
R2 Score: 0.9778146860267136
In [80]:
train and evaluate model(LassoCV())
Mean Absolute Percentage Error: 0.03783084232199294
Root Mean Squared Error: 94616.6682867993
```

Root Mean Squared Log Error: 0.05441759560536869

R2 Score: 0.9782046324533435

In [81]:

```
train_and_evaluate_model(ElasticNetCV())
```

Mean Absolute Percentage Error: 0.387978940632649

Root Mean Squared Error: 637848.9992897833 Root Mean Squared Log Error: 0.3986055426448395

R2 Score: 0.009476800952389897

In [82]:

train_and_evaluate_model(PassiveAggressiveRegressor())

Mean Absolute Percentage Error: 0.907267207643512

Root Mean Squared Error: 1796564.495941118 Root Mean Squared Log Error: 2.4916878409008674

R2 Score: -6.8580451575580055

In [83]:

train_and_evaluate_model(SGDRegressor())

Mean Absolute Percentage Error: 0.037566835227451675

Root Mean Squared Error: 94392.6483730361

Root Mean Squared Log Error: 0.0537273258228889

R2 Score: 0.9783077182264387

In [84]:

train_and_evaluate_model(HuberRegressor())

Mean Absolute Percentage Error: 0.03257423090991409

Root Mean Squared Error: 97713.81345166509

Root Mean Squared Log Error: 0.05412793580298358

R2 Score: 0.9767543968080068

In [85]:

train_and_evaluate_model(GammaRegressor())

Mean Absolute Percentage Error: 0.12822104797443734

Root Mean Squared Error: 226768.91995867676 Root Mean Squared Log Error: 0.1575623544267843

R2 Score: 0.8748024132026497

In [86]:

train and evaluate model(PoissonRegressor())

Mean Absolute Percentage Error: 0.06294067286451101

Root Mean Squared Error: 135480.1809989763

Root Mean Squared Log Error: 0.08324090746272196

In [87]:

```
train and evaluate model(QuantileRegressor())
```

Mean Absolute Percentage Error: 0.39378914922931957

Root Mean Squared Error: 641197.4596635281 Root Mean Squared Log Error: 0.4024142776336646

R2 Score: -0.000950223165545161

In [88]:

```
train_and_evaluate_model(TweedieRegressor())
```

Mean Absolute Percentage Error: 0.12217514530929383

Root Mean Squared Error: 203452.77840820202

Root Mean Squared Log Error: 0.15316495344984618

R2 Score: 0.8992242254554426

In [89]:

```
train_and_evaluate_model(RANSACRegressor())
```

Mean Absolute Percentage Error: 0.03760282433462657

Root Mean Squared Error: 95719.65932929545

Root Mean Squared Log Error: 0.05408358774120371

R2 Score: 0.9776935128173897

In [90]:

```
train_and_evaluate_model(TheilSenRegressor())
```

Mean Absolute Percentage Error: 0.030573411988741174

Root Mean Squared Error: 100104.28013287541

Root Mean Squared Log Error: 0.051124515831031954

R2 Score: 0.9756031257114411

In [91]:

train_and_evaluate_model(ARDRegression())

Mean Absolute Percentage Error: 0.3897500536465553

Root Mean Squared Error: 640895.4233972202

Root Mean Squared Log Error: 0.40018403325881324

R2 Score: -7.4494259607593705e-06

In [92]:

train and evaluate model(KNeighborsRegressor())

Mean Absolute Percentage Error: 0.09621601222885663

Root Mean Squared Error: 194296.93162217078 Root Mean Squared Log Error: 0.11857938575928037

In [93]:

```
train and evaluate model(SVR())
```

Mean Absolute Percentage Error: 0.3937790005193053

Root Mean Squared Error: 641184.4895068462

Root Mean Squared Log Error: 0.40240644405243603

R2 Score: -0.0009097290877075892

In [94]:

```
train_and_evaluate_model(LinearSVR())
```

Mean Absolute Percentage Error: 0.9999072672076434

Root Mean Squared Error: 1932579.9619044955 Root Mean Squared Log Error: 9.369523419245049

R2 Score: -8.092929816658131

In [95]:

```
train_and_evaluate_model(DecisionTreeRegressor())
```

Mean Absolute Percentage Error: 0.05747376450124135

Root Mean Squared Error: 178053.0501159588

Root Mean Squared Log Error: 0.08933740009013505

R2 Score: 0.9228159203428141

In [96]:

train_and_evaluate_model(RandomForestRegressor())

Mean Absolute Percentage Error: 0.031220698049212087

Root Mean Squared Error: 94152.49581950194

Root Mean Squared Log Error: 0.04413921764540404

R2 Score: 0.9784179562594475

In [97]:

train_and_evaluate_model(BaggingRegressor())

Mean Absolute Percentage Error: 0.03229415620859832

Root Mean Squared Error: 93314.61261437052

Root Mean Squared Log Error: 0.0459340413587151

R2 Score: 0.9788003734975818

In [98]:

train and evaluate model(ExtraTreesRegressor())

Mean Absolute Percentage Error: 0.020760607330991044

Root Mean Squared Error: 80884.65690320772

Root Mean Squared Log Error: 0.04130882721501735

In [99]:

```
train and evaluate model(GradientBoostingRegressor())
```

Mean Absolute Percentage Error: 0.025872045660698333

Root Mean Squared Error: 79388.0408617185

Root Mean Squared Log Error: 0.04022760523143929

R2 Score: 0.9846559832574224

In [100]:

```
train_and_evaluate_model(AdaBoostRegressor())
```

Mean Absolute Percentage Error: 0.06038815051975686

Root Mean Squared Error: 130780.25885881713

Root Mean Squared Log Error: 0.07690470681856508

R2 Score: 0.958359754639006

In [101]:

```
train_and_evaluate_model(HistGradientBoostingRegressor())
```

Mean Absolute Percentage Error: 0.04854479957493201

Root Mean Squared Error: 133895.73833799115 Root Mean Squared Log Error: 0.0674887118995013

R2 Score: 0.9563521955001669

In [102]:

train_and_evaluate_model(MLPRegressor())

Mean Absolute Percentage Error: 0.9999917598610703

Root Mean Squared Error: 1932698.5618114949 Root Mean Squared Log Error: 11.735067605729451

R2 Score: -8.09404589334577

In [103]:

train_and_evaluate_model(XGBRegressor())

Mean Absolute Percentage Error: 0.042062524512644826

Root Mean Squared Error: 128363.67129137942 Root Mean Squared Log Error: 0.06035237338180336

R2 Score: 0.959884412763658

In [104]:

train and evaluate model(CatBoostRegressor(silent=True))

Mean Absolute Percentage Error: 0.03515162308993974

Root Mean Squared Error: 108755.73903371001

Root Mean Squared Log Error: 0.061378420723152506

In [105]:

```
train_and_evaluate_model(LGBMRegressor())
```

Mean Absolute Percentage Error: 0.04485766673147905 Root Mean Squared Error: 126248.80450768779 Root Mean Squared Log Error: 0.06491580174683761

R2 Score: 0.9611953792536151

In [106]:

```
train_and_evaluate_model(VotingRegressor(estimators=[
    ('CAT',CatBoostRegressor(silent=True)),
    ('LR',LinearRegression()),
    ('SGD',SGDRegressor()),
    ('GB',GradientBoostingRegressor()),
    ('ET',ExtraTreesRegressor()),
    ('BAG',BaggingRegressor()),
    ('RF',RandomForestRegressor()),
    ('THEIL',TheilSenRegressor()),
    ('RANSAC',RANSACRegressor()),
    ('HUBER',HuberRegressor()),
    ('LASSO',LassoCV()),
    ('RIDGE',RidgeCV())
]))
```

Mean Absolute Percentage Error: 0.02410496728707758

Root Mean Squared Error: 74835.45294225398

Root Mean Squared Log Error: 0.03774425811193272

Baseline Model Performance Comparison

In [107]:

```
model_perfs = pd.DataFrame({'Model': models, 'MAPE': mape_scores, 'RMSE': rmse_scores, '
model_perfs = model_perfs.sort_values('R2',ascending=False)
model_perfs
```

Out[107]:

	Model	MAPE	RMSE	RMSLE	
28	VotingRegressor(estimators=[('CAT',\n	0.024105	7.483545e+04	0.037744	0.98
21	$([Decision Tree Regressor (criterion = 'friedman_ms$	0.025872	7.938804e+04	0.040228	0.98
20	(ExtraTreeRegressor(random_state=2090432581),	0.020761	8.088466e+04	0.041309	0.98
19	(DecisionTreeRegressor(random_state=174724458)	0.032294	9.331461e+04	0.045934	0.97
18	(DecisionTreeRegressor(max_features=1.0, rando	0.031221	9.415250e+04	0.044139	0.97
5	SGDRegressor()	0.037567	9.439265e+04	0.053727	0.97
2	LassoCV()	0.037831	9.461667e+04	0.054418	0.97
1	RidgeCV()	0.037577	9.545932e+04	0.053988	0.97
11	RANSACRegressor()	0.037603	9.571966e+04	0.054084	0.97
0	LinearRegression()	0.037603	9.571966e+04	0.054084	0.97
6	HuberRegressor()	0.032574	9.771381e+04	0.054128	0.97
12	TheilSenRegressor()	0.030573	1.001043e+05	0.051125	0.97
26	<pre><catboost.core.catboostregressor 0x0<="" at="" object="" pre=""></catboost.core.catboostregressor></pre>	0.035152	1.087557e+05	0.061378	0.97
27	LGBMRegressor()	0.044858	1.262488e+05	0.064916	0.96
25	XGBRegressor(base_score=None, booster=None, ca	0.042063	1.283637e+05	0.060352	0.95
22	$(Decision Tree Regressor (max_depth=3, random_sta$	0.060388	1.307803e+05	0.076905	0.95
23	HistGradientBoostingRegressor()	0.048545	1.338957e+05	0.067489	0.95
8	PoissonRegressor()	0.062941	1.354802e+05	0.083241	0.95
17	DecisionTreeRegressor()	0.057474	1.780531e+05	0.089337	0.92
14	KNeighborsRegressor()	0.096216	1.942969e+05	0.118579	0.90
10	TweedieRegressor()	0.122175	2.034528e+05	0.153165	0.89
7	GammaRegressor()	0.128221	2.267689e+05	0.157562	0.87
3	ElasticNetCV()	0.387979	6.378490e+05	0.398606	0.00
13	ARDRegression()	0.389750	6.408954e+05	0.400184	-0.00
15	SVR()	0.393779	6.411845e+05	0.402406	-0.00
9	QuantileRegressor()	0.393789	6.411975e+05	0.402414	-0.00
4	PassiveAggressiveRegressor()	0.907267	1.796564e+06	2.491688	-6.85
16	LinearSVR()	0.999907	1.932580e+06	9.369523	-8.09
24	MLPRegressor()	0.999992	1.932699e+06	11.735068	-8.09
4					•

Among the baseline models, the Voting Regressor produced the best performance by achieving the maximum r2 score of more than 98.5%, closely followed by Extra Trees Regressor and Decision Tree Regressor, which obtained r2 scores of 98.47% and 98.32% respectively.

Cross Validation and Model Optimization using Hyperparameter Tuning

In [108]:

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END bootstrap=False, criterion=squared_error, max_features=sqrt, n_es
timators=400, oob_score=False; total time=
                                             1.1s
[CV] END bootstrap=False, criterion=squared_error, max_features=sqrt, n_es
timators=400, oob_score=False; total time=
                                             1.1s
[CV] END bootstrap=False, criterion=squared_error, max_features=sqrt, n_es
timators=400, oob_score=False; total time=
                                             1.1s
[CV] END bootstrap=False, criterion=squared_error, max_features=sqrt, n_es
timators=400, oob_score=False; total time= 1.1s
[CV] END bootstrap=False, criterion=squared_error, max_features=sqrt, n_es
timators=400, oob_score=False; total time=
                                             1.1s
[CV] END bootstrap=True, criterion=absolute_error, max_features=auto, n_es
timators=600, oob_score=True; total time=
                                           5.0s
[CV] END bootstrap=True, criterion=absolute_error, max_features=auto, n_es
timators=600, oob_score=True; total time=
                                            5.2s
[CV] END bootstrap=True, criterion=absolute_error, max_features=auto, n_es
timators=600, oob_score=True; total time=
                                            5.0s
[CV] END bootstrap=True, criterion=absolute_error, max_features=auto, n_es
timators=600, oob_score=True; total time=
                                            4.9s
[CV] END bootstrap=True, criterion=absolute_error, max_features=auto, n_es
timators=600, oob_score=True; total time=
                                            5.0s
[CV] END bootstrap=False, criterion=squared_error, max_features=log2, n_es
timators=200, oob_score=False; total time=
                                             0.5s
[CV] END bootstrap=False, criterion=squared_error, max_features=log2, n_es
timators=200, oob_score=False; total time=
                                             0.5s
[CV] END bootstrap=False, criterion=squared_error, max_features=log2, n_es
timators=200, oob_score=False; total time=
                                             0.5s
[CV] END bootstrap=False, criterion=squared_error, max_features=log2, n_es
timators=200, oob_score=False; total time=
                                             0.5s
[CV] END bootstrap=False, criterion=squared_error, max_features=log2, n_es
timators=200, oob score=False; total time=
                                             0.5s
[CV] END bootstrap=False, criterion=squared_error, max_features=auto, n_es
timators=1000, oob_score=True; total time=
                                             0.0s
[CV] END bootstrap=False, criterion=squared_error, max_features=auto, n_es
timators=1000, oob_score=True; total time=
                                             0.0s
[CV] END bootstrap=False, criterion=squared_error, max_features=auto, n_es
timators=1000, oob_score=True; total time=
                                             0.0s
[CV] END bootstrap=False, criterion=squared_error, max_features=auto, n_es
timators=1000, oob_score=True; total time=
                                             0.0s
[CV] END bootstrap=False, criterion=squared_error, max_features=auto, n_es
timators=1000, oob_score=True; total time=
                                             0.0s
[CV] END bootstrap=True, criterion=absolute error, max features=log2, n es
timators=800, oob_score=True; total time=
                                            4.5s
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=800, oob_score=True; total time=
                                            4.8s
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=800, oob_score=True; total time=
                                            5.1s
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=800, oob score=True; total time=
                                            4.4s
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=800, oob score=True; total time=
[CV] END bootstrap=False, criterion=poisson, max_features=sqrt, n_estimato
rs=400, oob_score=True; total time=
                                      0.0s
[CV] END bootstrap=False, criterion=poisson, max features=sqrt, n estimato
rs=400, oob score=True; total time=
                                      0.0s
[CV] END bootstrap=False, criterion=poisson, max_features=sqrt, n_estimato
rs=400, oob_score=True; total time=
                                      0.0s
[CV] END bootstrap=False, criterion=poisson, max_features=sqrt, n_estimato
rs=400, oob_score=True; total time=
                                      0.0s
[CV] END bootstrap=False, criterion=poisson, max features=sqrt, n estimato
rs=400, oob_score=True; total time=
                                      0.0s
```

```
[CV] END bootstrap=True, criterion=friedman_mse, max_features=log2, n_esti
mators=200, oob_score=False; total time=
                                           0.6s
[CV] END bootstrap=True, criterion=friedman mse, max features=log2, n esti
mators=200, oob_score=False; total time=
                                           0.7s
[CV] END bootstrap=True, criterion=friedman mse, max features=log2, n esti
mators=200, oob_score=False; total time=
                                           0.6s
[CV] END bootstrap=True, criterion=friedman_mse, max_features=log2, n_esti
mators=200, oob_score=False; total time=
                                           0.6s
[CV] END bootstrap=True, criterion=friedman_mse, max_features=log2, n_esti
mators=200, oob_score=False; total time=
                                           0.7s
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=200, oob_score=False; total time=
                                             1.0s
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=200, oob_score=False; total time=
                                             1.0s
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=200, oob score=False; total time=
                                             1.05
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=200, oob_score=False; total time=
                                             0.9s
[CV] END bootstrap=True, criterion=absolute_error, max_features=log2, n_es
timators=200, oob_score=False; total time= 0.9s
[CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, n_es
timators=600, oob_score=False; total time=
                                             3.0s
[CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, n_es
timators=600, oob_score=False; total time=
                                             3.0s
[CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, n_es
timators=600, oob_score=False; total time=
                                             2.9s
[CV] END bootstrap=True, criterion=absolute error, max features=sqrt, n es
timators=600, oob_score=False; total time=
                                             3.0s
[CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, n_es
timators=600, oob_score=False; total time=
                                            3.0s
[CV] END bootstrap=False, criterion=friedman_mse, max_features=auto, n_est
imators=600, oob_score=False; total time=
                                            2.1s
[CV] END bootstrap=False, criterion=friedman_mse, max_features=auto, n_est
imators=600, oob_score=False; total time=
                                            2.1s
[CV] END bootstrap=False, criterion=friedman_mse, max_features=auto, n_est
imators=600, oob_score=False; total time=
                                            2.1s
[CV] END bootstrap=False, criterion=friedman_mse, max_features=auto, n_est
imators=600, oob_score=False; total time=
                                            2.1s
[CV] END bootstrap=False, criterion=friedman_mse, max_features=auto, n_est
imators=600, oob score=False; total time=
Mean Absolute Percentage Error: 0.03207742438582975
Root Mean Squared Error: 96287.085641307
Root Mean Squared Log Error: 0.04740284868926336
R2 Score: 0.9774282631485722
```

In [109]:

```
grid_rf.best_params_
```

Out[109]:

```
{'oob_score': True,
 'n_estimators': 600,
 'max_features': 'auto',
 'criterion': 'absolute_error',
 'bootstrap': True}
```

In [110]:

```
param_grid = {'n_neighbors': [2,5,8,12,20],
              'weights': ['uniform','distance'],
              'algorithm': ['ball_tree', 'kd_tree', 'brute'],
              'metric': ['minkowski', 'manhattan', 'euclidean', 'chebyshev']
             }
grid_knn = RandomizedSearchCV(KNeighborsRegressor(),param_grid,cv=RepeatedKFold(n_splits
train_and_evaluate_model(grid_knn)
Fitting 15 folds for each of 10 candidates, totalling 150 fits
[CV] END algorithm=brute, metric=minkowski, n_neighbors=5, weights=unif
orm; total time=
[CV] END algorithm=brute, metric=minkowski, n_neighbors=5, weights=unif
orm; total time=
                   0.0s
[CV] END algorithm=brute, metric=minkowski, n_neighbors=5, weights=unif
orm; total time=
                   0.0s
[CV] END algorithm=brute, metric=minkowski, n_neighbors=5, weights=unif
orm; total time=
[CV] END algorithm=brute, metric=minkowski, n_neighbors=5, weights=unif
orm; total time=
                   0.0s
[CV] END algorithm=brute, metric=minkowski, n_neighbors=5, weights=unif
orm; total time=
                   0.0s
[CV] END algorithm=brute, metric=minkowski, n neighbors=5, weights=unif
orm; total time=
                   0.0s
[CV] END algorithm=brute, metric=minkowski, n_neighbors=5, weights=unif
orm; total time=
                   0.0s
[CV] END algorithm=brute, metric=minkowski, n_neighbors=5, weights=unif
orm; total time=
                   0.0s
In [111]:
grid_knn.best_params_
Out[111]:
{'weights': 'uniform',
 'n_neighbors': 5,
 'metric': 'manhattan',
 'algorithm': 'kd_tree'}
```

In [112]:

Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=quantile, max bins=100; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=quantile, max_bins=100; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=quantile, max bins=100; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=quantile, max_bins=100; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=quantile, max_bins=100; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=absolute_ error, max_bins=150; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=absolute_ error, max_bins=150; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=absolute_ error, max_bins=150; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=absolute_ error, max_bins=150; total time= 0.0s [CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=absolute_ error, max_bins=150; total time= 0.0s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max_bins=100; total time= 0.2s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max_bins=100; total time= 0.2s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max_bins=100; total time= 0.2s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max_bins=100; total time= 0.2s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max bins=100; total time= 0.2s [CV] END interaction_cst=pairwise, learning_rate=0.8, loss=poisson, max_bi ns=250; total time= 0.1s [CV] END interaction_cst=pairwise, learning_rate=0.8, loss=poisson, max_bi ns=250; total time= 0.1s [CV] END interaction_cst=pairwise, learning_rate=0.8, loss=poisson, max_bi ns=250; total time= 0.1s [CV] END interaction_cst=pairwise, learning_rate=0.8, loss=poisson, max_bi ns=250; total time= 0.1s [CV] END interaction_cst=pairwise, learning_rate=0.8, loss=poisson, max_bi ns=250; total time= 0.1s [CV] END interaction cst=pairwise, learning rate=0.2, loss=absolute error, max bins=0; total time= 0.0s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max bins=0; total time= 0.0s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max_bins=0; total time= 0.0s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max bins=0; total time= 0.0s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=absolute_error, max bins=0; total time= 0.0s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=poisson, max_bi ns=0; total time= 0.0s [CV] END interaction cst=pairwise, learning rate=0.2, loss=poisson, max bi ns=0; total time= 0.0s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=poisson, max_bi ns=0; total time= 0.0s [CV] END interaction_cst=pairwise, learning_rate=0.2, loss=poisson, max_bi ns=0; total time= 0.0s [CV] END interaction cst=pairwise, learning rate=0.2, loss=poisson, max bi ns=0; total time= 0.0s

```
[CV] END interaction_cst=no_interaction, learning_rate=0.8, loss=poisson,
max_bins=250; total time=
                            0.0s
[CV] END interaction cst=no interaction, learning rate=0.8, loss=poisson,
max_bins=250; total time=
                            0.0s
[CV] END interaction cst=no interaction, learning rate=0.8, loss=poisson,
max_bins=250; total time=
                            0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.8, loss=poisson,
max_bins=250; total time=
                            0.0s
[CV] END interaction cst=no interaction, learning rate=0.8, loss=poisson,
max bins=250; total time=
                            0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.8, loss=squared_error,
max_bins=0; total time=
                          0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.8, loss=squared_error,
max_bins=0; total time=
                          0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.8, loss=squared_error,
max bins=0; total time=
                          0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.8, loss=squared_error,
max bins=0; total time=
                          0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.8, loss=squared_error,
max_bins=0; total time=
                          0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=absolute_
error, max_bins=250; total time=
                                   0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=absolute_
error, max_bins=250; total time=
                                   0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=absolute_
error, max_bins=250; total time=
                                   0.0s
[CV] END interaction cst=no interaction, learning rate=0.2, loss=absolute
error, max_bins=250; total time=
                                   0.0s
[CV] END interaction cst=no interaction, learning rate=0.2, loss=absolute
error, max_bins=250; total time=
                                   0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=absolute_
error, max_bins=50; total time=
                                  0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=absolute_
error, max_bins=50; total time=
                                  0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=absolute_
error, max_bins=50; total time=
                                  0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=absolute_
error, max_bins=50; total time=
                                  0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=absolute_
error, max_bins=50; total time=
                                  0.0s
Mean Absolute Percentage Error: 0.05068667357430494
Root Mean Squared Error: 137696.6523488204
Root Mean Squared Log Error: 0.07847529290656403
R2 Score: 0.9538389521789743
```

In [113]:

```
grid_hgb.best_params_
```

Out[113]:

```
{'max_bins': 100,
  'loss': 'absolute_error',
  'learning_rate': 0.2,
  'interaction cst': 'pairwise'}
```

In [114]:

```
param grid = \{'C': [0.001, 0.01, 0.1, 1, 5],
             'gamma': ['scale','auto'],
             'epsilon': np.linspace(0.001,1,5),
             'kernel': ['linear','poly','rbf','sigmoid'],
             'degree': [2,3,4,5],
             'shrinking': [True,False]
grid_svr = RandomizedSearchCV(SVR(),param_grid,verbose=2,cv=RepeatedKFold(n_splits=5,n_r
train_and_evaluate_model(grid_svr)
Fitting 15 folds for each of 10 candidates, totalling 150 fits
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
[CV] END C=5, degree=3, epsilon=1.0, gamma=scale, kernel=linear, shrink
ing=True; total time=
                        0.0s
In [115]:
```

```
grid svr.best params
```

Out[115]:

```
{'shrinking': True,
  'kernel': 'linear',
  'gamma': 'scale',
  'epsilon': 1.0,
  'degree': 3,
  'C': 5}
```

In [116]:

```
param grid = {'loss': ['epsilon insensitive','squared epsilon insensitive'],
             'C': [0.0001,0.001,0.01,0.1,1],
             'epsilon': np.linspace(0.001,1,5)}
grid_lsvr = RandomizedSearchCV(LinearSVR(),param_grid,cv=RepeatedKFold(n_splits=6,n_repe
train_and_evaluate_model(grid_lsvr)
Fitting 12 folds for each of 10 candidates, totalling 120 fits
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
al time=
           0.0s
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
al time=
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
al time=
           0.0s
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
al time=
           0.0s
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
al time=
           0.0s
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
           0.0s
al time=
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
al time=
           0.0s
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
al time=
           0.0s
[CV] END C=0.01, epsilon=0.75025, loss=squared_epsilon_insensitive; tot
al time=
           0.0s
In [117]:
```

```
grid_lsvr.best_params_
```

Out[117]:

```
{'loss': 'squared_epsilon_insensitive', 'epsilon': 0.25075, 'C': 0.1}
```

In [118]:

```
param_grid = {'criterion': ['squared_error','friedman_mse','absolute_error','poisson'],
              'splitter': ['best','random'],
              'max_features': ['auto','sqrt','log2']
grid_dt = RandomizedSearchCV(DecisionTreeRegressor(),param_grid,verbose=2,cv=RepeatedKFo
train_and_evaluate_model(grid_dt)
Fitting 18 folds for each of 10 candidates, totalling 180 fits
[CV] END criterion=squared error, max features=sqrt, splitter=random; t
otal time=
             0.0s
[CV] END criterion=squared_error, max_features=sqrt, splitter=random; t
otal time=
[CV] END criterion=squared_error, max_features=sqrt, splitter=random; t
otal time=
             0.0s
[CV] END criterion=squared_error, max_features=sqrt, splitter=random; t
otal time=
             0.0s
[CV] END criterion=squared_error, max_features=sqrt, splitter=random; t
otal time=
[CV] END criterion=squared_error, max_features=sqrt, splitter=random; t
otal time=
             0.0s
[CV] END criterion=squared_error, max_features=sqrt, splitter=random; t
otal time=
             0.0s
[CV] END criterion=squared_error, max_features=sqrt, splitter=random; t
otal time=
[CV] END criterion=squared_error, max_features=sqrt, splitter=random; t
otal time= 0.0s
FA./1 END
In [119]:
```

```
grid_dt.best_params_
```

Out[119]:

```
{'splitter': 'best', 'max_features': 'auto', 'criterion': 'absolute_erro
r'}
```

In [120]:

```
param grid = {'loss': ['squared error','absolute error','huber','quantile'],
              'n_estimators': [100,400,700,1000],
              'learning_rate': [0.2,0.4,0.7,1],
              'criterion': ['friedman_mse','squared_error'],
              'max_features': ['auto','sqrt','log2']
grid_gb = RandomizedSearchCV(GradientBoostingRegressor(),param_grid,verbose=3,cv=6)
train_and_evaluate_model(grid_gb)
Fitting 6 folds for each of 10 candidates, totalling 60 fits
[CV 1/6] END criterion=friedman_mse, learning_rate=0.7, loss=squared er
ror, max_features=sqrt, n_estimators=100;, score=0.941 total time=
[CV 2/6] END criterion=friedman_mse, learning_rate=0.7, loss=squared_er
ror, max features=sqrt, n estimators=100;, score=0.934 total time=
[CV 3/6] END criterion=friedman_mse, learning_rate=0.7, loss=squared_er
ror, max_features=sqrt, n_estimators=100;, score=0.834 total time=
[CV 4/6] END criterion=friedman_mse, learning_rate=0.7, loss=squared_er
ror, max_features=sqrt, n_estimators=100;, score=0.691 total time=
[CV 5/6] END criterion=friedman_mse, learning_rate=0.7, loss=squared_er
ror, max features=sqrt, n estimators=100;, score=0.872 total time=
0s
[CV 6/6] END criterion=friedman_mse, learning_rate=0.7, loss=squared_er
ror, max_features=sqrt, n_estimators=100;, score=0.908 total time=
FOU 4 /67 END
               . . . . . .
In [121]:
```

```
grid_gb.best_params_
```

Out[121]:

```
{'n_estimators': 100,
  'max_features': 'auto',
  'loss': 'absolute_error',
  'learning_rate': 0.4,
  'criterion': 'squared_error'}
```

In [122]:

Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV 1/5] END learning_rate=0.4, n_estimators=700;, score=0.927 total time= 2.2s [CV 2/5] END learning_rate=0.4, n_estimators=700;, score=0.961 total time= 2.1s [CV 3/5] END learning_rate=0.4, n_estimators=700;, score=0.884 total time= 2.0s [CV 4/5] END learning_rate=0.4, n_estimators=700;, score=0.975 total time= [CV 5/5] END learning_rate=0.4, n_estimators=700;, score=0.941 total time= 3.0s [CV 1/5] END .learning_rate=1, n_estimators=100;, score=0.887 total time= 1.1s [CV 2/5] END .learning_rate=1, n_estimators=100;, score=0.919 total time= 1.2s [CV 3/5] END .learning_rate=1, n_estimators=100;, score=0.815 total time= 1.0s [CV 4/5] END .learning_rate=1, n_estimators=100;, score=0.935 total time= 0.9s [CV 5/5] END .learning_rate=1, n_estimators=100;, score=0.920 total time= 1.0s [CV 1/5] END learning_rate=0.4, n_estimators=400;, score=0.927 total time= 1.7s [CV 2/5] END learning_rate=0.4, n_estimators=400;, score=0.961 total time= 1.6s [CV 3/5] END learning_rate=0.4, n_estimators=400;, score=0.884 total time= [CV 4/5] END learning_rate=0.4, n_estimators=400;, score=0.975 total time= 1.7s [CV 5/5] END learning_rate=0.4, n_estimators=400;, score=0.941 total time= [CV 1/5] END learning_rate=0.2, n_estimators=1000;, score=0.904 total time [CV 2/5] END learning_rate=0.2, n_estimators=1000;, score=0.967 total time 2.8s [CV 3/5] END learning_rate=0.2, n_estimators=1000;, score=0.930 total time 2.6s [CV 4/5] END learning_rate=0.2, n_estimators=1000;, score=0.973 total time 3.4s [CV 5/5] END learning rate=0.2, n estimators=1000;, score=0.970 total time 2.8s [CV 1/5] END learning rate=0.2, n estimators=100;, score=0.902 total time= 1.1s [CV 2/5] END learning_rate=0.2, n_estimators=100;, score=0.967 total time= 0.9s [CV 3/5] END learning_rate=0.2, n_estimators=100;, score=0.929 total time= 1.2s [CV 4/5] END learning rate=0.2, n estimators=100;, score=0.972 total time= 1.0s [CV 5/5] END learning_rate=0.2, n_estimators=100;, score=0.969 total time= 0.9s [CV 1/5] END learning_rate=0.7, n_estimators=700;, score=0.925 total time= [CV 2/5] END learning rate=0.7, n estimators=700;, score=0.927 total time= 2.5s [CV 3/5] END learning_rate=0.7, n_estimators=700;, score=0.899 total time= 2.2s [CV 4/5] END learning_rate=0.7, n_estimators=700;, score=0.959 total time= 2.3s [CV 5/5] END learning rate=0.7, n estimators=700;, score=0.931 total time= 3.0s

```
[CV 1/5] END learning_rate=0.4, n_estimators=1000;, score=0.927 total time
    2.7s
[CV 2/5] END learning rate=0.4, n estimators=1000;, score=0.961 total time
    3.5s
[CV 3/5] END learning rate=0.4, n estimators=1000;, score=0.884 total time
    2.9s
[CV 4/5] END learning_rate=0.4, n_estimators=1000;, score=0.975 total time
   3.5s
[CV 5/5] END learning rate=0.4, n estimators=1000;, score=0.941 total time
    2.9s
[CV 1/5] END learning_rate=1, n_estimators=1000;, score=0.887 total time=
[CV 2/5] END learning_rate=1, n_estimators=1000;, score=0.919 total time=
2.3s
[CV 3/5] END learning_rate=1, n_estimators=1000;, score=0.815 total time=
[CV 4/5] END learning_rate=1, n_estimators=1000;, score=0.935 total time=
2.7s
[CV 5/5] END learning_rate=1, n_estimators=1000;, score=0.920 total time=
[CV 1/5] END learning rate=0.4, n estimators=100;, score=0.927 total time=
0.9s
[CV 2/5] END learning_rate=0.4, n_estimators=100;, score=0.961 total time=
1.1s
[CV 3/5] END learning_rate=0.4, n_estimators=100;, score=0.884 total time=
1.0s
[CV 4/5] END learning rate=0.4, n estimators=100;, score=0.975 total time=
0.9s
[CV 5/5] END learning rate=0.4, n estimators=100;, score=0.941 total time=
0.9s
[CV 1/5] END .learning_rate=1, n_estimators=700;, score=0.887 total time=
2.1s
[CV 2/5] END .learning_rate=1, n_estimators=700;, score=0.919 total time=
2.1s
[CV 3/5] END .learning_rate=1, n_estimators=700;, score=0.815 total time=
2.2s
[CV 4/5] END .learning_rate=1, n_estimators=700;, score=0.935 total time=
2.3s
[CV 5/5] END .learning_rate=1, n_estimators=700;, score=0.920 total time=
2.3s
Mean Absolute Percentage Error: 0.04412554970177765
Root Mean Squared Error: 134966.0300207573
Root Mean Squared Log Error: 0.0697660248534803
R2 Score: 0.9556516116917408
```

In [123]:

```
grid_cat.best_params_
```

Out[123]:

```
{'n_estimators': 1000, 'learning_rate': 0.2}
```

In [124]:

Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV] END bootstrap=False, max features=0.0, max samples=0.58, n estimators =800, oob score=False; total time= 0.0s [CV] END bootstrap=False, max_features=0.0, max_samples=0.58, n_estimators =800, oob_score=False; total time= 0.0s [CV] END bootstrap=False, max_features=0.0, max_samples=0.58, n_estimators =800, oob score=False; total time= 0.0s [CV] END bootstrap=False, max_features=0.0, max_samples=0.58, n_estimators =800, oob_score=False; total time= 0.0s [CV] END bootstrap=False, max_features=0.0, max_samples=0.58, n_estimators =800, oob_score=False; total time= 0.0s [CV] END bootstrap=False, max_features=0.5, max_samples=0.24, n_estimators =500, oob_score=False; total time= 2.0s [CV] END bootstrap=False, max_features=0.5, max_samples=0.24, n_estimators =500, oob_score=False; total time= 1.8s [CV] END bootstrap=False, max_features=0.5, max_samples=0.24, n_estimators =500, oob_score=False; total time= 1.9s [CV] END bootstrap=False, max_features=0.5, max_samples=0.24, n_estimators =500, oob_score=False; total time= 1.8s [CV] END bootstrap=False, max_features=0.5, max_samples=0.24, n_estimators =500, oob_score=False; total time= 1.8s [CV] END bootstrap=False, max_features=1.0, max_samples=0.58, n_estimators =1000, oob_score=False; total time= 4.7s [CV] END bootstrap=False, max_features=1.0, max_samples=0.58, n_estimators =1000, oob_score=False; total time= 4.7s [CV] END bootstrap=False, max_features=1.0, max_samples=0.58, n_estimators =1000, oob_score=False; total time= 4.8s [CV] END bootstrap=False, max_features=1.0, max_samples=0.58, n_estimators =1000, oob_score=False; total time= 4.7s [CV] END bootstrap=False, max_features=1.0, max_samples=0.58, n_estimators =1000, oob score=False; total time= 4.9s [CV] END bootstrap=False, max_features=0.0, max_samples=0.58, n_estimators =500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, max_features=0.0, max_samples=0.58, n_estimators =500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, max_features=0.0, max_samples=0.58, n_estimators =500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, max_features=0.0, max_samples=0.58, n_estimators =500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, max features=0.0, max samples=0.58, n estimators =500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, max features=0.75, max samples=0.24, n estimator s=300, oob score=False; total time= 1.3s [CV] END bootstrap=False, max_features=0.75, max_samples=0.24, n_estimator s=300, oob score=False; total time= 1.2s [CV] END bootstrap=False, max_features=0.75, max_samples=0.24, n_estimator s=300, oob_score=False; total time= 1.1s [CV] END bootstrap=False, max_features=0.75, max_samples=0.24, n_estimator s=300, oob score=False; total time= 1.1s [CV] END bootstrap=False, max_features=0.75, max_samples=0.24, n_estimator s=300, oob score=False; total time= 1.1s [CV] END bootstrap=False, max_features=0.75, max_samples=0.71, n_estimator s=500, oob score=True; total time= 0.0s [CV] END bootstrap=False, max features=0.75, max samples=0.71, n estimator s=500, oob score=True; total time= 0.0s [CV] END bootstrap=False, max features=0.75, max samples=0.71, n estimator s=500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, max_features=0.75, max_samples=0.71, n_estimator s=500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, max features=0.75, max samples=0.71, n estimator s=500, oob score=True; total time= 0.0s

```
[CV] END bootstrap=True, max_features=0.0, max_samples=0.24, n_estimators=
800, oob score=True; total time=
                                   0.0s
[CV] END bootstrap=True, max features=0.0, max samples=0.24, n estimators=
800, oob score=True; total time=
                                   0.0s
[CV] END bootstrap=True, max features=0.0, max samples=0.24, n estimators=
800, oob_score=True; total time=
                                   0.0s
[CV] END bootstrap=True, max_features=0.0, max_samples=0.24, n_estimators=
800, oob_score=True; total time=
                                   0.0s
[CV] END bootstrap=True, max features=0.0, max samples=0.24, n estimators=
800, oob score=True; total time=
                                   0.0s
[CV] END bootstrap=True, max_features=0.75, max_samples=0.58, n_estimators
=800, oob_score=False; total time=
                                     3.5s
[CV] END bootstrap=True, max_features=0.75, max_samples=0.58, n_estimators
=800, oob_score=False; total time=
                                     3.7s
[CV] END bootstrap=True, max_features=0.75, max_samples=0.58, n_estimators
=800, oob score=False; total time=
                                     3.6s
[CV] END bootstrap=True, max_features=0.75, max_samples=0.58, n_estimators
=800, oob_score=False; total time=
                                     3.4s
[CV] END bootstrap=True, max_features=0.75, max_samples=0.58, n_estimators
=800, oob_score=False; total time=
                                     3.4s
[CV] END bootstrap=True, max_features=0.5, max_samples=0.96, n_estimators=
500, oob_score=False; total time=
                                    2.2s
[CV] END bootstrap=True, max_features=0.5, max_samples=0.96, n_estimators=
500, oob_score=False; total time=
                                    2.2s
[CV] END bootstrap=True, max_features=0.5, max_samples=0.96, n_estimators=
500, oob_score=False; total time=
                                    2.2s
[CV] END bootstrap=True, max features=0.5, max samples=0.96, n estimators=
500, oob_score=False; total time=
                                    2.1s
[CV] END bootstrap=True, max features=0.5, max samples=0.96, n estimators=
500, oob_score=False; total time=
                                    2.2s
[CV] END bootstrap=True, max_features=0.0, max_samples=0.58, n_estimators=
800, oob_score=False; total time=
                                    0.0s
[CV] END bootstrap=True, max features=0.0, max samples=0.58, n estimators=
800, oob_score=False; total time=
                                    0.0s
[CV] END bootstrap=True, max_features=0.0, max_samples=0.58, n_estimators=
800, oob_score=False; total time=
                                    0.0s
[CV] END bootstrap=True, max_features=0.0, max_samples=0.58, n_estimators=
800, oob_score=False; total time=
                                    0.0s
[CV] END bootstrap=True, max_features=0.0, max_samples=0.58, n_estimators=
800, oob score=False; total time=
Mean Absolute Percentage Error: 0.031812137397857515
Root Mean Squared Error: 94700.60976805227
Root Mean Squared Log Error: 0.04551408853916175
R2 Score: 0.978165942716579
```

In [125]:

```
grid_bag.best_params_
```

Out[125]:

```
{'oob_score': False,
 'n_estimators': 1000,
 'max_samples': 0.58,
 'max_features': 1.0,
 'bootstrap': False}
```

In [126]:

Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV 1/5] END boosting_type=goss, importance_type=gain, learning_rate=1.0, min_split_gain=1, n_estimators=300;, score=0.786 total time= [CV 2/5] END boosting_type=goss, importance_type=gain, learning_rate=1.0, min_split_gain=1, n_estimators=300;, score=0.846 total time= [CV 3/5] END boosting_type=goss, importance_type=gain, learning_rate=1.0, min_split_gain=1, n_estimators=300;, score=0.665 total time= [CV 4/5] END boosting_type=goss, importance_type=gain, learning_rate=1.0, min_split_gain=1, n_estimators=300;, score=0.811 total time= [CV 5/5] END boosting_type=goss, importance_type=gain, learning_rate=1.0, min_split_gain=1, n_estimators=300;, score=0.802 total time= [CV 1/5] END boosting_type=goss, importance_type=split, learning_rate=0.4, min_split_gain=0.68, n_estimators=1000;, score=0.663 total time= [CV 2/5] END boosting_type=goss, importance_type=split, learning_rate=0.4, min_split_gain=0.68, n_estimators=1000;, score=0.740 total time= [CV 3/5] END boosting_type=goss, importance_type=split, learning_rate=0.4, min_split_gain=0.68, n_estimators=1000;, score=0.708 total time= [CV 4/5] END boosting_type=goss, importance_type=split, learning_rate=0.4, min_split_gain=0.68, n_estimators=1000;, score=0.801 total time= [CV 5/5] END boosting_type=goss, importance_type=split, learning_rate=0.4, min_split_gain=0.68, n_estimators=1000;, score=0.763 total time= [CV 1/5] END boosting_type=dart, importance_type=split, learning_rate=0.2, min_split_gain=0.87, n_estimators=500;, score=0.931 total time= [CV 2/5] END boosting_type=dart, importance_type=split, learning_rate=0.2, min_split_gain=0.87, n_estimators=500;, score=0.955 total time= [CV 3/5] END boosting_type=dart, importance_type=split, learning_rate=0.2, min_split_gain=0.87, n_estimators=500;, score=0.953 total time= [CV 4/5] END boosting_type=dart, importance_type=split, learning_rate=0.2, min_split_gain=0.87, n_estimators=500;, score=0.963 total time= [CV 5/5] END boosting_type=dart, importance_type=split, learning_rate=0.2, min_split_gain=0.87, n_estimators=500;, score=0.964 total time= [CV 1/5] END boosting_type=gbdt, importance_type=gain, learning_rate=0.2, min_split_gain=0.79, n_estimators=300;, score=0.940 total time= [CV 2/5] END boosting_type=gbdt, importance_type=gain, learning_rate=0.2, min_split_gain=0.79, n_estimators=300;, score=0.957 total time= [CV 3/5] END boosting_type=gbdt, importance_type=gain, learning_rate=0.2, min_split_gain=0.79, n_estimators=300;, score=0.942 total time= [CV 4/5] END boosting_type=gbdt, importance_type=gain, learning_rate=0.2, min_split_gain=0.79, n_estimators=300;, score=0.955 total time= [CV 5/5] END boosting_type=gbdt, importance_type=gain, learning_rate=0.2, min_split_gain=0.79, n_estimators=300;, score=0.957 total time= [CV 1/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0, min_split_gain=0.79, n_estimators=500;, score=0.954 total time= [CV 2/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0, min_split_gain=0.79, n_estimators=500;, score=0.953 total time= [CV 3/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0, min_split_gain=0.79, n_estimators=500;, score=0.873 total time= [CV 4/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0, min_split_gain=0.79, n_estimators=500;, score=0.898 total time= [CV 5/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0, min_split_gain=0.79, n_estimators=500;, score=0.942 total time= [CV 1/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.79, n_estimators=800;, score=0.942 total time= [CV 2/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.79, n_estimators=800;, score=0.964 total time= [CV 3/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.79, n_estimators=800;, score=0.909 total time= [CV 4/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.79, n_estimators=800;, score=0.914 total time= [CV 5/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.79, n_estimators=800;, score=0.958 total time=

[CV 1/5] END boosting_type=gbdt, importance_type=gain, learning_rate=0.4, min_split_gain=0.87, n_estimators=100;, score=0.943 total time= [CV 2/5] END boosting type=gbdt, importance type=gain, learning rate=0.4, min_split_gain=0.87, n_estimators=100;, score=0.958 total time= [CV 3/5] END boosting type=gbdt, importance type=gain, learning rate=0.4, min_split_gain=0.87, n_estimators=100;, score=0.933 total time= [CV 4/5] END boosting_type=gbdt, importance_type=gain, learning_rate=0.4, min_split_gain=0.87, n_estimators=100;, score=0.946 total time= [CV 5/5] END boosting_type=gbdt, importance_type=gain, learning_rate=0.4, min_split_gain=0.87, n_estimators=100;, score=0.957 total time= [CV 1/5] END boosting_type=goss, importance_type=gain, learning_rate=0.4, min_split_gain=0.79, n_estimators=100;, score=0.663 total time= [CV 2/5] END boosting_type=goss, importance_type=gain, learning_rate=0.4, min_split_gain=0.79, n_estimators=100;, score=0.740 total time= [CV 3/5] END boosting_type=goss, importance_type=gain, learning_rate=0.4, min split gain=0.79, n estimators=100;, score=0.708 total time= [CV 4/5] END boosting_type=goss, importance_type=gain, learning_rate=0.4, min_split_gain=0.79, n_estimators=100;, score=0.801 total time= [CV 5/5] END boosting_type=goss, importance_type=gain, learning_rate=0.4, min_split_gain=0.79, n_estimators=100;, score=0.763 total time= [CV 1/5] END boosting_type=dart, importance_type=gain, learning_rate=0.8, min_split_gain=1, n_estimators=300;, score=0.949 total time= [CV 2/5] END boosting_type=dart, importance_type=gain, learning_rate=0.8, min_split_gain=1, n_estimators=300;, score=0.968 total time= [CV 3/5] END boosting_type=dart, importance_type=gain, learning_rate=0.8, min_split_gain=1, n_estimators=300;, score=0.913 total time= [CV 4/5] END boosting type=dart, importance type=gain, learning rate=0.8, min_split_gain=1, n_estimators=300;, score=0.932 total time= [CV 5/5] END boosting_type=dart, importance_type=gain, learning_rate=0.8, min_split_gain=1, n_estimators=300;, score=0.959 total time= [CV 1/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.87, n_estimators=500;, score=0.944 total time= [CV 2/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.87, n_estimators=500;, score=0.963 total time= [CV 3/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.87, n_estimators=500;, score=0.908 total time= [CV 4/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min_split_gain=0.87, n_estimators=500;, score=0.911 total time= [CV 5/5] END boosting_type=dart, importance_type=gain, learning_rate=1.0, min split gain=0.87, n estimators=500;, score=0.956 total time= Mean Absolute Percentage Error: 0.05287068945686181 Root Mean Squared Error: 142237.58139948634 Root Mean Squared Log Error: 0.07440089741866754 R2 Score: 0.9507441733056884

In [127]:

grid_lgbm.best_params_

Out[127]:

```
{'n_estimators': 500,
 'min_split_gain': 0.87,
 'learning_rate': 0.2,
 'importance_type': 'split',
 'boosting_type': 'dart'}
```

In [128]:

Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV] END bootstrap=False, criterion=poisson, max features=log2, max sample s=0.7, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=poisson, max_features=log2, max_sample s=0.7, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=poisson, max_features=log2, max_sample s=0.7, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=poisson, max_features=log2, max_sample s=0.7, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=poisson, max_features=log2, max_sample s=0.7, n_estimators=300, oob_score=False; total time= 0.0s [CV] END bootstrap=False, criterion=friedman_mse, max_features=log2, max_s amples=0.45, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=friedman_mse, max_features=log2, max_s amples=0.45, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=friedman_mse, max_features=log2, max_s amples=0.45, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=friedman_mse, max_features=log2, max_s amples=0.45, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=friedman_mse, max_features=log2, max_s amples=0.45, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.7, n_estimators=1000, oob_score=True; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.7, n_estimators=1000, oob_score=True; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.7, n_estimators=1000, oob_score=True; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.7, n_estimators=1000, oob_score=True; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.7, n_estimators=1000, oob_score=True; total time= [CV] END bootstrap=True, criterion=squared_error, max_features=auto, max_s amples=0.95, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=True, criterion=squared_error, max_features=auto, max_s amples=0.95, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=True, criterion=squared_error, max_features=auto, max_s amples=0.95, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=True, criterion=squared_error, max_features=auto, max_s amples=0.95, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=True, criterion=squared error, max features=auto, max s amples=0.95, n_estimators=300, oob_score=False; total time= [CV] END bootstrap=False, criterion=absolute error, max features=sqrt, max _samples=0.2, n_estimators=800, oob_score=False; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=sqrt, max _samples=0.2, n_estimators=800, oob_score=False; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=sqrt, max _samples=0.2, n_estimators=800, oob_score=False; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=sqrt, max samples=0.2, n estimators=800, oob score=False; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=sqrt, max _samples=0.2, n_estimators=800, oob_score=False; total time= [CV] END bootstrap=False, criterion=friedman_mse, max_features=sqrt, max_s amples=0.7, n_estimators=300, oob_score=True; total time= [CV] END bootstrap=False, criterion=friedman mse, max features=sqrt, max s amples=0.7, n_estimators=300, oob_score=True; total time= [CV] END bootstrap=False, criterion=friedman_mse, max_features=sqrt, max_s amples=0.7, n_estimators=300, oob_score=True; total time= [CV] END bootstrap=False, criterion=friedman_mse, max_features=sqrt, max_s amples=0.7, n_estimators=300, oob_score=True; total time= [CV] END bootstrap=False, criterion=friedman mse, max features=sqrt, max s amples=0.7, n_estimators=300, oob_score=True; total time= 0.0s

[CV] END bootstrap=False, criterion=absolute_error, max_features=sqrt, max _samples=0.95, n_estimators=500, oob_score=True; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=sqrt, max _samples=0.95, n_estimators=500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, criterion=absolute error, max features=sqrt, max _samples=0.95, n_estimators=500, oob_score=True; total time= 0.0s [CV] END bootstrap=False, criterion=absolute_error, max_features=sqrt, max _samples=0.95, n_estimators=500, oob_score=True; total time= [CV] END bootstrap=False, criterion=absolute error, max features=sqrt, max _samples=0.95, n_estimators=500, oob_score=True; total time= [CV] END bootstrap=False, criterion=squared_error, max_features=log2, max_ samples=0.7, n_estimators=500, oob_score=False; total time= [CV] END bootstrap=False, criterion=squared_error, max_features=log2, max_ samples=0.7, n_estimators=500, oob_score=False; total time= [CV] END bootstrap=False, criterion=squared_error, max_features=log2, max_ samples=0.7, n estimators=500, oob score=False; total time= [CV] END bootstrap=False, criterion=squared_error, max_features=log2, max_ samples=0.7, n_estimators=500, oob_score=False; total time= [CV] END bootstrap=False, criterion=squared_error, max_features=log2, max_ samples=0.7, n_estimators=500, oob_score=False; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.2, n_estimators=800, oob_score=True; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.2, n_estimators=800, oob_score=True; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.2, n_estimators=800, oob_score=True; total time= [CV] END bootstrap=True, criterion=absolute error, max features=sqrt, max samples=0.2, n_estimators=800, oob_score=True; total time= [CV] END bootstrap=True, criterion=absolute_error, max_features=sqrt, max_ samples=0.2, n_estimators=800, oob_score=True; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=auto, max _samples=0.45, n_estimators=100, oob_score=False; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=auto, max _samples=0.45, n_estimators=100, oob_score=False; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=auto, max _samples=0.45, n_estimators=100, oob_score=False; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=auto, max _samples=0.45, n_estimators=100, oob_score=False; total time= [CV] END bootstrap=False, criterion=absolute_error, max_features=auto, max _samples=0.45, n_estimators=100, oob_score=False; total time= Mean Absolute Percentage Error: 0.024177768172682246 Root Mean Squared Error: 77496.62330560893 Root Mean Squared Log Error: 0.039356923308345025 R2 Score: 0.9853784149714498

In [129]:

grid_et.best_params_

Out[129]:

```
{'oob_score': False,
 'n_estimators': 300,
 'max_samples': 0.95,
 'max_features': 'auto',
 'criterion': 'squared_error',
 'bootstrap': True}
```

In [130]:

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END booster=gbtree, grow_policy=0, importance_type=gain, learning_
rate=0.6, n_estimators=900, sampling_method=uniform; total time=
[CV] END booster=gbtree, grow_policy=0, importance_type=gain, learning_
rate=0.6, n estimators=900, sampling method=uniform; total time=
[CV] END booster=gbtree, grow_policy=0, importance_type=gain, learning_
rate=0.6, n_estimators=900, sampling_method=uniform; total time=
[CV] END booster=gbtree, grow_policy=0, importance_type=gain, learning_
rate=0.6, n_estimators=900, sampling_method=uniform; total time=
[CV] END booster=gbtree, grow_policy=0, importance_type=gain, learning_
rate=0.6, n_estimators=900, sampling_method=uniform; total time=
[CV] END booster=gbtree, grow policy=0, importance type=total cover, le
arning_rate=0.4, n_estimators=700, sampling_method=uniform; total time=
[CV] END booster=gbtree, grow_policy=0, importance_type=total_cover, le
arning_rate=0.4, n_estimators=700, sampling_method=uniform; total time=
0.0s
[CV] END booster=gbtree, grow policy=0, importance type=total cover, le
```

arning_rate=0.4, n_estimators=700, sampling_method=uniform; total time=

In [131]:

```
grid_xgb.best_params_
```

Out[131]:

```
{'sampling_method': 'uniform',
  'n_estimators': 1000,
  'learning_rate': 0.4,
  'importance_type': 'weight',
  'grow_policy': 0,
  'booster': 'gblinear'}
```

In [132]:

```
param_grid = {'loss': ['squared_error', 'huber', 'epsilon_insensitive', 'squared_epsilon_in
              'penalty': ['12', '11', 'elasticnet'],
              'l1_ratio': [0.15,0.45,0.68,0.81,0.97],
              'alpha': [0.0001,0.001,0.01,0.1,1],
              'shuffle': [True, False],
              'learning_rate': ['adaptive','constant','optimal','invscaling'],
              'epsilon': np.linspace(0.001,100,10),
              'average': [True,False]
grid_sgd = RandomizedSearchCV(SGDRegressor(),param_grid,verbose=2,cv=5)
train and evaluate model(grid sgd)
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END alpha=0.0001, average=False, epsilon=77.7779999999999, l1_rat
io=0.81, learning_rate=invscaling, loss=squared_epsilon_insensitive, pe
nalty=elasticnet, shuffle=False; total time=
                                               0.0s
[CV] END alpha=0.0001, average=False, epsilon=77.7779999999999, l1_rat
io=0.81, learning_rate=invscaling, loss=squared_epsilon_insensitive, pe
nalty=elasticnet, shuffle=False; total time=
                                               0.0s
[CV] END alpha=0.0001, average=False, epsilon=77.7779999999999, l1_rat
io=0.81, learning_rate=invscaling, loss=squared_epsilon_insensitive, pe
nalty=elasticnet, shuffle=False; total time=
[CV] END alpha=0.0001, average=False, epsilon=77.7779999999999, l1_rat
io=0.81, learning_rate=invscaling, loss=squared_epsilon_insensitive, pe
nalty=elasticnet, shuffle=False; total time=
                                               0.0s
[CV] END alpha=0.0001, average=False, epsilon=77.7779999999999, l1_rat
io=0.81, learning_rate=invscaling, loss=squared_epsilon_insensitive, pe
nalty=elasticnet, shuffle=False; total time=
[CV] END alpha=0.1, average=False, epsilon=33.33399999999999, l1_ratio
=0.15, learning_rate=optimal, loss=huber, penalty=elasticnet, shuffle=T
rue; total time= 0.0s
In [133]:
grid_sgd.best_params_
Out[133]:
{'shuffle': False,
 'penalty': 'elasticnet',
 'loss': 'squared epsilon insensitive',
 'learning_rate': 'invscaling',
 'l1 ratio': 0.81,
 'epsilon': 77.77799999999999999,
 'average': False,
 'alpha': 0.0001}
```

In [134]:

Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV] ENDalpha=10.0, epsilon=10.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=10.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=10.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=10.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=10.0; 0.0s	total	time=
[CV] ENDalpha=7.7777999999999, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=7.77779999999999, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=7.7777999999999, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=7.7777999999999, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=7.7777999999999, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=3.3334, epsilon=2.0; 0.0s	total	time=
[CV] ENDalpha=3.3334, epsilon=2.0; 0.0s	total	time=
[CV] ENDalpha=3.3334, epsilon=2.0; 0.0s	total	time=
[CV] ENDalpha=3.3334, epsilon=2.0; 0.0s	total	time=
[CV] ENDalpha=3.3334, epsilon=2.0; 0.0s	total	time=
[CV] ENDalpha=8.8889, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=8.8889, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=8.8889, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=8.8889, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=8.8889, epsilon=6.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=1.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=1.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=1.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=1.0; 0.0s	total	time=
[CV] ENDalpha=10.0, epsilon=1.0; 0.0s	total	time=
[CV] ENDalpha=4.4445, epsilon=8.0; 0.0s	total	time=
[CV] ENDalpha=4.4445, epsilon=8.0; 0.0s	total	time=
[CV] ENDalpha=4.4445, epsilon=8.0; 0.0s	total	time=
[CV] ENDalpha=4.4445, epsilon=8.0; 0.0s	total	time=
[CV] ENDalpha=4.4445, epsilon=8.0; 0.0s	total	time=
0.03		

```
4/12/23, 9:13 PM
                         Sales Prediction Using Supervised Machine Learning - Jupyter Notebook
 [CV] END .....alpha=8.8889, epsilon=5.0; total time=
 0.0s
 [CV] END ......alpha=8.8889, epsilon=5.0; total time=
 0.0s
 [CV] END .....alpha=10.0, epsilon=4.0; total time=
 0.0s
 [CV] END .....alpha=10.0, epsilon=4.0; total time=
 0.0s
 [CV] END ......alpha=10.0, epsilon=4.0; total time=
 0.0s
 [CV] END .....alpha=10.0, epsilon=4.0; total time=
 0.0s
 [CV] END .....alpha=10.0, epsilon=4.0; total time=
 0.0s
 [CV] END .....alpha=4.4445, epsilon=3.0; total time=
 0.0s
 [CV] END .....alpha=8.8889, epsilon=7.0; total time=
 0.0s
 Mean Absolute Percentage Error: 0.3882166185318009
 Root Mean Squared Error: 640842.613070887
 Root Mean Squared Log Error: 0.39938931342570616
 R2 Score: 0.00015734670766076597
 In [135]:
 grid_huber.best_params_
```

Out[135]:

```
{'epsilon': 2.0, 'alpha': 3.3334}
```

In [136]:

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END alpha=10.0, link=identity, power=(1, 2), solver=newton-cholesky;
total time=
             0.0s
[CV] END alpha=10.0, link=identity, power=(1, 2), solver=newton-cholesky;
total time=
             0.0s
[CV] END alpha=10.0, link=identity, power=(1, 2), solver=newton-cholesky;
total time=
              0.0s
[CV] END alpha=10.0, link=identity, power=(1, 2), solver=newton-cholesky;
total time=
             0.0s
[CV] END alpha=10.0, link=identity, power=(1, 2), solver=newton-cholesky;
total time=
             0.0s
[CV] END alpha=2.2223, link=auto, power=3, solver=newton-cholesky; total t
ime=
      0.0s
[CV] END alpha=2.2223, link=auto, power=3, solver=newton-cholesky; total t
ime=
      0.0s
[CV] END alpha=2.2223, link=auto, power=3, solver=newton-cholesky; total t
ime=
      0.0s
[CV] END alpha=2.2223, link=auto, power=3, solver=newton-cholesky; total t
ime=
      0.0s
[CV] END alpha=2.2223, link=auto, power=3, solver=newton-cholesky; total t
ime=
      0.0s
[CV] END alpha=5.5556, link=log, power=2, solver=newton-cholesky; total ti
me=
      0.0s
[CV] END alpha=5.5556, link=log, power=2, solver=newton-cholesky; total ti
me=
      0.0s
[CV] END alpha=5.5556, link=log, power=2, solver=newton-cholesky; total ti
      0.0s
[CV] END alpha=5.5556, link=log, power=2, solver=newton-cholesky; total ti
[CV] END alpha=5.5556, link=log, power=2, solver=newton-cholesky; total ti
[CV] END alpha=7.77779999999999, link=identity, power=(1, 2), solver=lbfg
s; total time=
                0.0s
[CV] END alpha=7.777799999999999, link=identity, power=(1, 2), solver=lbfg
s; total time=
               0.0s
[CV] END alpha=7.77779999999999, link=identity, power=(1, 2), solver=lbfg
s; total time=
                 0.0s
[CV] END alpha=7.777799999999999, link=identity, power=(1, 2), solver=lbfg
s; total time=
                 0.0s
[CV] END alpha=7.777799999999999, link=identity, power=(1, 2), solver=lbfg
s; total time=
                 0.0s
[CV] END alpha=4.4445, link=log, power=(1, 2), solver=newton-cholesky; tot
al time=
           0.0s
[CV] END alpha=4.4445, link=log, power=(1, 2), solver=newton-cholesky; tot
al time=
           0.0s
[CV] END alpha=4.4445, link=log, power=(1, 2), solver=newton-cholesky; tot
al time=
           0.0s
[CV] END alpha=4.4445, link=log, power=(1, 2), solver=newton-cholesky; tot
al time=
           0.0s
[CV] END alpha=4.4445, link=log, power=(1, 2), solver=newton-cholesky; tot
al time=
[CV] END alpha=2.2223, link=auto, power=(1, 2), solver=lbfgs; total time=
0.0s
[CV] END alpha=2.2223, link=auto, power=(1, 2), solver=lbfgs; total time=
0.0s
[CV] END alpha=2.2223, link=auto, power=(1, 2), solver=lbfgs; total time=
0.0s
[CV] END alpha=2.2223, link=auto, power=(1, 2), solver=lbfgs; total time=
0.0s
[CV] END alpha=2.2223, link=auto, power=(1, 2), solver=lbfgs; total time=
0.0s
```

```
[CV] END alpha=6.6667, link=identity, power=3, solver=newton-cholesky; tot
al time=
           0.0s
[CV] END alpha=6.6667, link=identity, power=3, solver=newton-cholesky; tot
al time=
           0.0s
[CV] END alpha=6.6667, link=identity, power=3, solver=newton-cholesky; tot
al time=
           0.0s
[CV] END alpha=6.6667, link=identity, power=3, solver=newton-cholesky; tot
al time=
           0.0s
[CV] END alpha=6.6667, link=identity, power=3, solver=newton-cholesky; tot
           0.0s
al time=
[CV] END alpha=7.77779999999999, link=identity, power=3, solver=newton-ch
olesky; total time=
                      0.0s
[CV] END alpha=7.77779999999999, link=identity, power=3, solver=newton-ch
olesky; total time=
                      0.0s
[CV] END alpha=7.77779999999999, link=identity, power=3, solver=newton-ch
olesky; total time=
                      0.0s
[CV] END alpha=7.77779999999999, link=identity, power=3, solver=newton-ch
olesky; total time=
                      0.0s
[CV] END alpha=7.77779999999999, link=identity, power=3, solver=newton-ch
olesky; total time=
                      0.0s
[CV] END .....alpha=0.0001, link=auto, power=1, solver=lbfgs; total time=
0.0s
[CV] END .....alpha=0.0001, link=auto, power=1, solver=lbfgs; total time=
0.0s
[CV] END .....alpha=0.0001, link=auto, power=1, solver=lbfgs; total time=
0.0s
[CV] END .....alpha=0.0001, link=auto, power=1, solver=lbfgs; total time=
0.0s
[CV] END .....alpha=0.0001, link=auto, power=1, solver=lbfgs; total time=
0.0s
[CV] END alpha=0.0001, link=auto, power=2, solver=newton-cholesky; total t
      0.0s
ime=
[CV] END alpha=0.0001, link=auto, power=2, solver=newton-cholesky; total t
      0.0s
[CV] END alpha=0.0001, link=auto, power=2, solver=newton-cholesky; total t
      0.0s
[CV] END alpha=0.0001, link=auto, power=2, solver=newton-cholesky; total t
      0.0s
[CV] END alpha=0.0001, link=auto, power=2, solver=newton-cholesky; total t
ime=
Mean Absolute Percentage Error: 0.0591406631966941
Root Mean Squared Error: 136080.82844277137
Root Mean Squared Log Error: 0.07777764320505613
R2 Score: 0.9549159644382277
```

In [137]:

```
grid_tweedie.best_params_
```

Out[137]:

```
{'solver': 'newton-cholesky', 'power': 2, 'link': 'auto', 'alpha': 0.0001}
```

In [138]:

- Fitting 5 folds for each of 10 candidates, totalling 50 fits
- [CV] END C=0.1, average=False, epsilon=0.25075, loss=squared_epsilon_insen sitive, shuffle=True; total time= 0.0s
- [CV] END C=0.1, average=False, epsilon=0.25075, loss=squared_epsilon_insen sitive, shuffle=True; total time= 0.0s
- [CV] END C=0.1, average=False, epsilon=0.25075, loss=squared_epsilon_insen sitive, shuffle=True; total time= 0.0s
- [CV] END C=0.1, average=False, epsilon=0.25075, loss=squared_epsilon_insen sitive, shuffle=True; total time= 0.0s
- [CV] END C=0.1, average=False, epsilon=0.25075, loss=squared_epsilon_insen sitive, shuffle=True; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.75025, loss=epsilon_insensitive, shuffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.75025, loss=epsilon_insensitive, shuffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.75025, loss=epsilon_insensitive, shuffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.75025, loss=epsilon_insensitive, shuffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.75025, loss=epsilon_insensitive, shuffle=False; total time= 0.0s
- [CV] END C=1, average=True, epsilon=0.75025, loss=epsilon_insensitive, shu ffle=False; total time= 0.0s
- [CV] END C=1, average=True, epsilon=0.75025, loss=epsilon_insensitive, shu ffle=False; total time= 0.0s
- [CV] END C=1, average=True, epsilon=0.75025, loss=epsilon_insensitive, shu ffle=False; total time= 0.0s
- [CV] END C=1, average=True, epsilon=0.75025, loss=epsilon_insensitive, shu ffle=False; total time= 0.0s
- [CV] END C=1, average=True, epsilon=0.75025, loss=epsilon_insensitive, shu ffle=False; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.25075, loss=epsilon_insensitive, sh uffle=False; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.25075, loss=epsilon_insensitive, sh uffle=False; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.25075, loss=epsilon_insensitive, sh uffle=False; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.25075, loss=epsilon_insensitive, sh uffle=False; total time= 0.0s $^{\circ}$
- [CV] END C=10, average=True, epsilon=0.25075, loss=epsilon_insensitive, sh uffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.25075, loss=squared_epsilon_ins ensitive, shuffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.25075, loss=squared_epsilon_ins ensitive, shuffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.25075, loss=squared_epsilon_ins ensitive, shuffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.25075, loss=squared_epsilon_ins ensitive, shuffle=False; total time= 0.0s
- [CV] END C=0.0001, average=True, epsilon=0.25075, loss=squared_epsilon_ins ensitive, shuffle=False; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.001, loss=squared_epsilon_insensiti
 ve, shuffle=True; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.001, loss=squared_epsilon_insensiti
 ve, shuffle=True; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.001, loss=squared_epsilon_insensiti
 ve, shuffle=True; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.001, loss=squared_epsilon_insensitive, shuffle=True; total time= 0.0s
- [CV] END C=10, average=True, epsilon=0.001, loss=squared_epsilon_insensitive, shuffle=True; total time= 0.0s

```
4/12/23, 9:13 PM
                                 Sales Prediction Using Supervised Machine Learning - Jupyter Notebook
 [CV] END C=1, average=True, epsilon=1.0, loss=epsilon_insensitive, shuffle
 =True; total time=
                       0.0s
 [CV] END C=1, average=True, epsilon=1.0, loss=epsilon insensitive, shuffle
 =True; total time=
                       0.0s
 [CV] END C=1, average=True, epsilon=1.0, loss=epsilon insensitive, shuffle
 =True; total time=
                       0.0s
 [CV] END C=1, average=True, epsilon=1.0, loss=epsilon_insensitive, shuffle
 =True; total time=
                       0.0s
 [CV] END C=1, average=True, epsilon=1.0, loss=epsilon insensitive, shuffle
 =True; total time=
                       0.0s
 [CV] END C=0.01, average=False, epsilon=0.75025, loss=epsilon_insensitive,
 shuffle=False; total time=
                               0.0s
 [CV] END C=0.01, average=False, epsilon=0.75025, loss=epsilon_insensitive,
 shuffle=False; total time=
                               0.0s
 [CV] END C=0.01, average=False, epsilon=0.75025, loss=epsilon_insensitive,
 shuffle=False; total time=
                               0.0s
 [CV] END C=0.01, average=False, epsilon=0.75025, loss=epsilon_insensitive,
 shuffle=False; total time=
                               0.0s
 [CV] END C=0.01, average=False, epsilon=0.75025, loss=epsilon_insensitive,
 shuffle=False; total time= 0.0s
 [CV] END C=1, average=False, epsilon=0.25075, loss=squared epsilon insensi
 tive, shuffle=True; total time=
                                    0.0s
 [CV] END C=1, average=False, epsilon=0.25075, loss=squared_epsilon_insensi
 tive, shuffle=True; total time=
                                    0.0s
 [CV] END C=1, average=False, epsilon=0.25075, loss=squared_epsilon_insensi
 tive, shuffle=True; total time=
                                    0.0s
 [CV] END C=1, average=False, epsilon=0.25075, loss=squared epsilon insensi
 tive, shuffle=True; total time=
                                    0.0s
 [CV] END C=1, average=False, epsilon=0.25075, loss=squared epsilon insensi
 tive, shuffle=True; total time=
                                    0.0s
 [CV] END C=0.001, average=True, epsilon=0.5005, loss=epsilon_insensitive,
 shuffle=True; total time=
                              0.0s
 [CV] END C=0.001, average=True, epsilon=0.5005, loss=epsilon insensitive,
 shuffle=True; total time=
                              0.0s
 [CV] END C=0.001, average=True, epsilon=0.5005, loss=epsilon_insensitive,
 shuffle=True; total time=
                              0.0s
 [CV] END C=0.001, average=True, epsilon=0.5005, loss=epsilon_insensitive,
 shuffle=True; total time=
                              0.0s
 [CV] END C=0.001, average=True, epsilon=0.5005, loss=epsilon_insensitive,
 shuffle=True; total time=
                              0.0s
 Mean Absolute Percentage Error: 0.0341132425926999
 Root Mean Squared Error: 103082.83496662248
```

Root Mean Squared Log Error: 0.05185352883288553

R2 Score: 0.9741296918089055

In [139]:

```
grid_pa.best_params_
```

```
Out[139]:
```

```
{'shuffle': True,
 'loss': 'squared epsilon insensitive',
 'epsilon': 0.25075,
 'average': False,
 'C': 0.1}
```

In [140]:

```
param_grid = {
    'eps': [0.0001,0.001,0.1,1],
    'positive': [True,False],
    'selection': ['cyclic','random']
}
grid_lasso = RandomizedSearchCV(LassoCV(),param_grid,verbose=2,cv=5)
train_and_evaluate_model(grid_lasso)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END .....eps=0.001, positive=False, selection=cyclic; total time=
0.0s
[CV] END .....eps=1, positive=True, selection=random; total time=
0.0s
[CV] END .....eps=1, positive=True, selection=cyclic; total time=
0.0s
[CV] END .....eps=0.1, positive=True, selection=cyclic; total time=
0.0s
[CV] END .....eps=0.0001, positive=False, selection=random; total time=
0.1s
```

[CV] ENDeps=0.001, positive=True, selection=random; total time=

0.0s [CV] ENDeps=0.1, positive=True, selection=random; total time=

0.0s [CV] ENDeps=0.1, positive=True, selection=random; total time=

0.0s [CV] ENDeps=0.1, positive=True, selection=random; total time= 0.0s

[CV] ENDeps=0.1, positive=True, selection=random; total time= 0.0s [CV] ENDeps=0.1, positive=True, selection=random; total time=

0.0s

Mean Absolute Percentage Error: 0.03607362447546001 Root Mean Squared Error: 89480.54698845446

Root Mean Squared Log Error: 0.052034517531026246

R2 Score: 0.9805066646085272

In [141]:

```
grid_lasso.best_params_
```

Out[141]:

```
{'selection': 'random', 'positive': True, 'eps': 0.01}
```

In [142]:

```
param_grid = {
    'alphas': [(0.1, 1.0, 10.0),(0.01,0.1,1),(0.001,0.01,0.1)],
    'gcv_mode': ['auto', 'svd', 'eigen'],
    'store_cv_values': [True,False],
    'alpha_per_target': [True,False]
}
grid_ridge = RandomizedSearchCV(RidgeCV(),param_grid,verbose=2,cv=5)
train_and_evaluate_model(grid_ridge)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END alpha per target=True, alphas=(0.001, 0.01, 0.1), gcv mode=svd, s
tore cv values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd, s
tore_cv_values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd, s
tore cv values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd, s
tore_cv_values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd, s
tore_cv_values=False; total time=
                                    0.0s
[CV] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
store_cv_values=False; total time=
                                     0.0s
[CV] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
store_cv_values=False; total time=
                                     0.0s
[CV] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
store_cv_values=False; total time=
                                     0.0s
[CV] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
store_cv_values=False; total time=
                                     0.0s
[CV] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
store_cv_values=False; total time=
                                     0.0s
[CV] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True; total time=
                                    0.0s
[CV] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True; total time=
                                    0.0s
[CV] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True; total time=
                                    0.0s
[CV] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True; total time=
                                    0.0s
[CV] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store cv values=True; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto, st
ore_cv_values=True; total time=
                                  0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto, st
ore_cv_values=True; total time=
                                  0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto, st
ore_cv_values=True; total time=
                                  0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto, st
ore_cv_values=True; total time=
                                  0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto, st
ore_cv_values=True; total time=
                                  0.0s
[CV] END alpha per target=True, alphas=(0.01, 0.1, 1), gcv mode=eigen, sto
re cv values=False; total time=
                                  0.0s
[CV] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=eigen, sto
re_cv_values=False; total time=
                                  0.0s
[CV] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=eigen, sto
re_cv_values=False; total time=
                                  0.0s
[CV] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=eigen, sto
re cv values=False; total time=
                                  0.0s
[CV] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=eigen, sto
re cv values=False; total time=
                                  0.0s
[CV] END alpha_per_target=False, alphas=(0.01, 0.1, 1), gcv_mode=eigen, st
ore cv values=False; total time=
                                   0.0s
[CV] END alpha per target=False, alphas=(0.01, 0.1, 1), gcv mode=eigen, st
ore cv values=False; total time=
                                   0.0s
[CV] END alpha_per_target=False, alphas=(0.01, 0.1, 1), gcv_mode=eigen, st
ore_cv_values=False; total time=
                                   0.0s
[CV] END alpha_per_target=False, alphas=(0.01, 0.1, 1), gcv_mode=eigen, st
ore_cv_values=False; total time=
                                   0.0s
[CV] END alpha per target=False, alphas=(0.01, 0.1, 1), gcv mode=eigen, st
ore cv values=False; total time=
                                   0.0s
```

```
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore_cv_values=True; total time=
                                   0.0s
[CV] END alpha per target=True, alphas=(0.1, 1.0, 10.0), gcv mode=eigen, s
tore cv values=True; total time=
                                   0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore_cv_values=True; total time=
                                   0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore_cv_values=True; total time=
                                   0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore_cv_values=True; total time=
                                   0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore_cv_values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore_cv_values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore cv values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore_cv_values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen, s
tore_cv_values=False; total time=
                                    0.0s
[CV] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=auto, stor
e_cv_values=False; total time=
                                 0.0s
[CV] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=auto, stor
e_cv_values=False; total time=
                                 0.0s
[CV] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=auto, stor
e_cv_values=False; total time=
                                 0.0s
[CV] END alpha per target=True, alphas=(0.01, 0.1, 1), gcv mode=auto, stor
e_cv_values=False; total time=
                                 0.0s
[CV] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=auto, stor
e_cv_values=False; total time=
                                 0.05
[CV] END alpha_per_target=False, alphas=(0.01, 0.1, 1), gcv_mode=svd, stor
e_cv_values=False; total time=
                                 0.0s
[CV] END alpha_per_target=False, alphas=(0.01, 0.1, 1), gcv_mode=svd, stor
e_cv_values=False; total time=
                                 0.05
[CV] END alpha_per_target=False, alphas=(0.01, 0.1, 1), gcv_mode=svd, stor
e_cv_values=False; total time=
                                 0.0s
[CV] END alpha_per_target=False, alphas=(0.01, 0.1, 1), gcv_mode=svd, stor
e_cv_values=False; total time=
                                 0.0s
[CV] END alpha per target=False, alphas=(0.01, 0.1, 1), gcv mode=svd, stor
e_cv_values=False; total time=
                                 0.0s
Mean Absolute Percentage Error: 0.03757672714457013
Root Mean Squared Error: 95459.32132352471
Root Mean Squared Log Error: 0.053988205973587854
R2 Score: 0.977814686026575
```

In [143]:

```
grid_ridge.best_params_
```

Out[143]:

```
{'store_cv_values': True,
  'gcv_mode': 'eigen',
  'alphas': (0.1, 1.0, 10.0),
  'alpha per target': False}
```

In [144]:

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END .....l1 ratio=0.3, positive=True, selection=random; total time=
0.0s
[CV] END .....l1_ratio=0.3, positive=False, selection=random; total time=
0.0s
[CV] END .....l1_ratio=0.1, positive=False, selection=random; total time=
0.0s
[CV] END .....l1_ratio=0.3, positive=False, selection=cyclic; total time=
0.0s
[CV] END .....l1 ratio=0.5, positive=False, selection=random; total time=
0.0s
[CV] END .....l1_ratio=0.5, positive=False, selection=random; total time=
0.0s
[CV] END .....l1_ratio=0.5, positive=False, selection=random; total time=
0.0s
[CV] END .....l1 ratio=0.5, positive=False, selection=random; total time=
0.0s
[CV] END .....l1_ratio=0.5, positive=False, selection=random; total time=
0.0s
[CV] END .....l1_ratio=1, positive=False, selection=cyclic; total time=
0.0s
[CV] END .....l1 ratio=1, positive=False, selection=cyclic; total time=
0.0s
[CV] END ......l1_ratio=1, positive=False, selection=cyclic; total time=
0.0s
[CV] END .....l1_ratio=1, positive=False, selection=cyclic; total time=
0.0s
[CV] END .....l1 ratio=1, positive=False, selection=cyclic; total time=
0.0s
```

```
[CV] END ......l1_ratio=1, positive=True, selection=cyclic; total time=
0.0s
[CV] END ......l1 ratio=1, positive=True, selection=cyclic; total time=
0.0s
[CV] END ......l1_ratio=1, positive=True, selection=cyclic; total time=
0.0s
[CV] END ......l1_ratio=1, positive=True, selection=cyclic; total time=
0.0s
[CV] END ......l1 ratio=1, positive=True, selection=cyclic; total time=
0.0s
[CV] END .....l1_ratio=1, positive=False, selection=random; total time=
0.0s
[CV] END .....l1 ratio=0.3, positive=True, selection=cyclic; total time=
0.0s
[CV] END .....l1_ratio=0.3, positive=True, selection=cyclic; total time=
0.0s
[CV] END .....l1_ratio=0.3, positive=True, selection=cyclic; total time=
0.0s
[CV] END .....l1 ratio=0.3, positive=True, selection=cyclic; total time=
0.0s
[CV] END .....l1_ratio=0.3, positive=True, selection=cyclic; total time=
0.0s
[CV] END .....l1_ratio=0.8, positive=False, selection=random; total time=
0.0s
[CV] END .....l1 ratio=0.8, positive=False, selection=random; total time=
0.0s
Mean Absolute Percentage Error: 0.03754926308061059
Root Mean Squared Error: 89235.81748679242
Root Mean Squared Log Error: 0.05393519130217834
R2 Score: 0.9806131474279399
```

In [145]:

```
grid_elasticnet.best_params_
```

```
Out[145]:
```

```
{'selection': 'cyclic', 'positive': True, 'l1_ratio': 1}
```

In [146]:

Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV] END ..learning_rate=0.8, loss=linear, n_estimators=1000; total time= 3.4s [CV] END ..learning_rate=0.8, loss=linear, n_estimators=1000; total time= 3.3s [CV] END ..learning_rate=0.8, loss=linear, n_estimators=1000; total time= 3.4s [CV] END ..learning_rate=0.8, loss=linear, n_estimators=1000; total time= 3.4s [CV] END ..learning_rate=0.8, loss=linear, n_estimators=1000; total time= 3.4s [CV] END ...learning_rate=0.8, loss=square, n_estimators=100; total time= 0.2s [CV] END ...learning_rate=0.8, loss=square, n_estimators=100; total time= 0.2s [CV] END ...learning_rate=0.8, loss=square, n_estimators=100; total time= 0.3s [CV] END ...learning_rate=0.8, loss=square, n_estimators=100; total time= 0.3s [CV] END ...learning_rate=0.8, loss=square, n_estimators=100; total time= 0.2s [CV] END learning_rate=0.6, loss=exponential, n_estimators=1000; total tim e= 3.5s [CV] END learning_rate=0.6, loss=exponential, n_estimators=1000; total tim 3.8s [CV] END learning_rate=0.6, loss=exponential, n_estimators=1000; total tim [CV] END learning_rate=0.6, loss=exponential, n_estimators=1000; total tim [CV] END learning_rate=0.6, loss=exponential, n_estimators=1000; total tim [CV] END learning_rate=0.1, loss=exponential, n_estimators=1000; total tim e= 3.4s [CV] END learning_rate=0.1, loss=exponential, n_estimators=1000; total tim e= [CV] END learning_rate=0.1, loss=exponential, n_estimators=1000; total tim 3.4s 6= [CV] END learning_rate=0.1, loss=exponential, n_estimators=1000; total tim [CV] END learning rate=0.1, loss=exponential, n estimators=1000; total tim 3.4s e= [CV] END ...learning rate=0.8, loss=square, n estimators=700; total time= 2.2s [CV] END ...learning_rate=0.8, loss=square, n_estimators=700; total time= 2.3s [CV] END ...learning_rate=0.8, loss=square, n_estimators=700; total time= 2.3s [CV] END ...learning rate=0.8, loss=square, n estimators=700; total time= 2.3s [CV] END ...learning_rate=0.8, loss=square, n_estimators=700; total time= 2.5s [CV] END learning_rate=0.8, loss=exponential, n_estimators=100; total time 0.2s [CV] END learning rate=0.8, loss=exponential, n estimators=100; total time 0.3s [CV] END learning rate=0.8, loss=exponential, n estimators=100; total time 0.3s [CV] END learning_rate=0.8, loss=exponential, n_estimators=100; total time 0.3s [CV] END learning rate=0.8, loss=exponential, n estimators=100; total time 0.3s

```
[CV] END ...learning_rate=0.8, loss=linear, n_estimators=400; total time=
1.3s
[CV] END ...learning rate=0.8, loss=linear, n estimators=400; total time=
1.3s
[CV] END ...learning_rate=0.8, loss=linear, n_estimators=400; total time=
1.3s
[CV] END ...learning_rate=0.8, loss=linear, n_estimators=400; total time=
1.3s
[CV] END ...learning rate=0.8, loss=linear, n estimators=400; total time=
1.3s
[CV] END ...learning_rate=0.8, loss=linear, n_estimators=700; total time=
2.3s
[CV] END .....learning_rate=1, loss=linear, n_estimators=700; total time=
2.3s
[CV] END .....learning_rate=1, loss=linear, n_estimators=700; total time=
2.4s
[CV] END .....learning_rate=1, loss=linear, n_estimators=700; total time=
2.6s
[CV] END .....learning rate=1, loss=linear, n estimators=700; total time=
2.4s
[CV] END .....learning_rate=1, loss=linear, n_estimators=700; total time=
2.3s
[CV] END ...learning_rate=0.8, loss=square, n_estimators=400; total time=
1.4s
[CV] END ...learning_rate=0.8, loss=square, n_estimators=400; total time=
1.5s
[CV] END ...learning_rate=0.8, loss=square, n_estimators=400; total time=
[CV] END ...learning_rate=0.8, loss=square, n_estimators=400; total time=
1.3s
[CV] END ...learning rate=0.8, loss=square, n estimators=400; total time=
1.3s
Mean Absolute Percentage Error: 0.06382350157680054
Root Mean Squared Error: 125385.84798589497
Root Mean Squared Log Error: 0.0759745650968994
R2 Score: 0.9617240536246201
```

In [147]:

```
grid_ab.best_params_
```

Out[147]:

```
{'n_estimators': 400, 'loss': 'square', 'learning_rate': 0.8}
```

In [148]:

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END alpha=1, fit intercept=True, solver=lbfgs, warm start=False; tota
1 time=
          0.0s
[CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=False; tota
1 time=
          0.0s
[CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=False; tota
1 time=
          0.0s
[CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=False; tota
l time=
          0.0s
[CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=False; tota
1 time=
          0.0s
[CV] END alpha=1, fit_intercept=False, solver=lbfgs, warm_start=False; tot
al time=
           0.0s
[CV] END alpha=1, fit_intercept=False, solver=lbfgs, warm_start=False; tot
al time=
           0.0s
[CV] END alpha=1, fit_intercept=False, solver=lbfgs, warm_start=False; tot
al time=
           0.0s
[CV] END alpha=1, fit_intercept=False, solver=lbfgs, warm_start=False; tot
al time=
           0.0s
[CV] END alpha=1, fit_intercept=False, solver=lbfgs, warm_start=False; tot
al time=
           0.0s
[CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=False;
total time=
             0.0s
[CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=False;
total time=
             0.0s
[CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=False;
total time=
             0.0s
[CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=False;
total time=
[CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=False;
total time=
             0.0s
[CV] END alpha=1, fit_intercept=False, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=1, fit_intercept=False, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=1, fit_intercept=False, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=1, fit_intercept=False, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=1, fit_intercept=False, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=10, fit intercept=True, solver=newton-cholesky, warm start=
True; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
True; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=True, solver=lbfgs, warm_start=True; tota
1 time=
[CV] END alpha=10, fit intercept=True, solver=lbfgs, warm start=True; tota
1 time=
          0.0s
[CV] END alpha=10, fit_intercept=True, solver=lbfgs, warm_start=True; tota
l time=
[CV] END alpha=10, fit_intercept=True, solver=lbfgs, warm_start=True; tota
1 time=
          0.0s
[CV] END alpha=10, fit intercept=True, solver=lbfgs, warm start=True; tota
1 time=
          0.0s
```

```
[CV] END alpha=0.001, fit_intercept=False, solver=lbfgs, warm_start=False;
total time=
              0.0s
[CV] END alpha=0.001, fit intercept=False, solver=lbfgs, warm start=False;
total time=
              0.0s
[CV] END alpha=0.001, fit intercept=False, solver=lbfgs, warm start=False;
total time=
             0.0s
[CV] END alpha=0.001, fit_intercept=False, solver=lbfgs, warm_start=False;
total time=
              0.0s
[CV] END alpha=0.001, fit intercept=False, solver=lbfgs, warm start=False;
total time=
              0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
False; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
False; total time=
                   0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
False; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
False; total time=
                     0.0s
[CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start=
False; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=False, solver=newton-cholesky, warm_start
=True; total time=
                    0.0s
[CV] END alpha=10, fit_intercept=False, solver=newton-cholesky, warm_start
=True; total time=
                     0.0s
[CV] END alpha=10, fit_intercept=False, solver=newton-cholesky, warm_start
=True; total time=
                    0.0s
[CV] END alpha=10, fit intercept=False, solver=newton-cholesky, warm start
=True; total time= 0.0s
[CV] END alpha=10, fit_intercept=False, solver=newton-cholesky, warm_start
=True; total time=
                    0.0s
[CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=True; total
time=
        0.0s
[CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm start=True; total
time=
       0.0s
[CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=True; total
time=
[CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=True; total
time=
[CV] END alpha=1, fit intercept=True, solver=lbfgs, warm start=True; total
time=
        0.0s
Mean Absolute Percentage Error: 0.06294123795511576
Root Mean Squared Error: 135479.5624858958
Root Mean Squared Log Error: 0.08324169711154629
R2 Score: 0.9553134871395782
```

In [149]:

```
grid_poisson.best_params_
```

Out[149]:

```
{'warm_start': True,
 'solver': 'newton-cholesky',
 'fit_intercept': True,
 'alpha': 10}
```

In [150]:

- Fitting 5 folds for each of 10 candidates, totalling 50 fits
- [CV] END alpha=0.001, fit_intercept=True, solver=newton-cholesky, warm_start=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=newton-cholesky, warm_start=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=newton-cholesky, warm_start=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=newton-cholesky, warm_sta
 rt=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=newton-cholesky, warm_start=True; total time= 0.0s
- [CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=True; total time= 0.0s
- [CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=True; total time= 0.0s
- [CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=True; total time= 0.0s
- [CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=True; total time= 0.0s
- [CV] END alpha=1, fit_intercept=True, solver=lbfgs, warm_start=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=True; t
 otal time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=True; t otal time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=True; t
 otal time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=True; t otal time= 0.0s
- [CV] END alpha=0.001, fit_intercept=True, solver=lbfgs, warm_start=True; t
 otal time= 0.0s
- [CV] END alpha=0.1, fit_intercept=True, solver=newton-cholesky, warm_start
 =True; total time= 0.0s
- [CV] END alpha=0.1, fit_intercept=True, solver=newton-cholesky, warm_start =True; total time= 0.0s
- [CV] END alpha=0.1, fit_intercept=True, solver=newton-cholesky, warm_start =True; total time= 0.0s
- [CV] END alpha=0.1, fit_intercept=True, solver=newton-cholesky, warm_start =True; total time= 0.0s
- [CV] END alpha=0.1, fit_intercept=True, solver=newton-cholesky, warm_start =True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=False, solver=newton-cholesky, warm_st art=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=False, solver=newton-cholesky, warm_st art=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=False, solver=newton-cholesky, warm_st
 art=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=False, solver=newton-cholesky, warm_st
 art=True; total time= 0.0s
- [CV] END alpha=0.001, fit_intercept=False, solver=newton-cholesky, warm_st art=True; total time= 0.0s
- [CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start= False; total time= 0.0s
- [CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start= False; total time= 0.0s
- [CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start= False; total time= 0.0s
- [CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start= False; total time= 0.0s
- [CV] END alpha=10, fit_intercept=True, solver=newton-cholesky, warm_start= False; total time= 0.0s

```
[CV] END alpha=0.1, fit_intercept=True, solver=lbfgs, warm_start=False; to
tal time=
            0.0s
[CV] END alpha=0.1, fit intercept=True, solver=lbfgs, warm start=False; to
tal time=
            0.0s
[CV] END alpha=0.1, fit intercept=True, solver=lbfgs, warm start=False; to
tal time=
            0.0s
[CV] END alpha=0.1, fit_intercept=True, solver=lbfgs, warm_start=False; to
tal time=
            0.0s
[CV] END alpha=0.1, fit intercept=True, solver=lbfgs, warm start=False; to
tal time=
            0.0s
[CV] END alpha=0.01, fit_intercept=True, solver=newton-cholesky, warm_star
t=True; total time=
                      0.0s
[CV] END alpha=0.01, fit_intercept=True, solver=newton-cholesky, warm_star
t=True; total time=
                      0.0s
[CV] END alpha=0.01, fit_intercept=True, solver=newton-cholesky, warm_star
t=True; total time=
                      0.0s
[CV] END alpha=0.01, fit_intercept=True, solver=newton-cholesky, warm_star
t=True; total time=
                      0.0s
[CV] END alpha=0.01, fit_intercept=True, solver=newton-cholesky, warm_star
t=True; total time=
                      0.0s
[CV] END alpha=0.01, fit_intercept=True, solver=lbfgs, warm_start=False; t
otal time=
             0.0s
[CV] END alpha=0.01, fit_intercept=True, solver=lbfgs, warm_start=False; t
otal time=
             0.0s
[CV] END alpha=0.01, fit_intercept=True, solver=lbfgs, warm_start=False; t
             0.0s
otal time=
[CV] END alpha=0.01, fit intercept=True, solver=lbfgs, warm start=False; t
otal time=
             0.0s
[CV] END alpha=0.01, fit intercept=True, solver=lbfgs, warm start=False; t
otal time=
             0.0s
[CV] END alpha=0.001, fit_intercept=False, solver=lbfgs, warm_start=False;
total time=
             0.0s
[CV] END alpha=0.001, fit_intercept=False, solver=lbfgs, warm start=False;
total time=
             0.0s
[CV] END alpha=0.001, fit_intercept=False, solver=lbfgs, warm_start=False;
total time=
             0.0s
[CV] END alpha=0.001, fit_intercept=False, solver=lbfgs, warm_start=False;
total time=
             0.0s
[CV] END alpha=0.001, fit_intercept=False, solver=lbfgs, warm_start=False;
total time=
Mean Absolute Percentage Error: 0.05874172503527488
Root Mean Squared Error: 135231.56435136718
Root Mean Squared Log Error: 0.07756227647474297
R2 Score: 0.9554769365713998
```

In [151]:

```
grid_gamma.best_params_
```

Out[151]:

```
{'warm_start': True, 'solver': 'lbfgs', 'fit_intercept': True, 'alpha': 0.
001}
```

In [152]:

Fitting 5 folds for each of 10 candidates, totalling 50 fits [CV] END alpha 1=1e-05, alpha 2=1e-07, compute score=False, fit intercept= False, lambda_1=1e-05, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-05, alpha_2=1e-07, compute_score=False, fit_intercept= False, lambda_1=1e-05, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-05, alpha_2=1e-07, compute_score=False, fit_intercept= False, lambda_1=1e-05, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-05, alpha_2=1e-07, compute_score=False, fit_intercept= False, lambda_1=1e-05, lambda_2=1e-07; total time= [CV] END alpha_1=1e-05, alpha_2=1e-07, compute_score=False, fit_intercept= False, lambda_1=1e-05, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-07; total time= 0.1s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-07; total time= 0.2s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-07; total time= 0.1s [CV] END alpha_1=1e-08, alpha_2=1e-08, compute_score=False, fit_intercept= False, lambda_1=1e-05, lambda_2=1e-06; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-08, compute_score=False, fit_intercept= False, lambda_1=1e-05, lambda_2=1e-06; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-08, compute_score=False, fit_intercept= False, lambda_1=1e-05, lambda_2=1e-06; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-08, compute_score=False, fit_intercept= False, lambda_1=1e-05, lambda_2=1e-06; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-08, compute_score=False, fit_intercept= False, lambda 1=1e-05, lambda 2=1e-06; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-06; total time= 0.2s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-06; total time= 0.0s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-06; total time= [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-06; total time= 0.2s [CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept= True, lambda_1=1e-08, lambda_2=1e-06; total time= 0.0s [CV] END alpha 1=1e-05, alpha 2=1e-06, compute score=False, fit intercept= False, lambda_1=1e-07, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-05, alpha_2=1e-06, compute_score=False, fit_intercept= False, lambda_1=1e-07, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-05, alpha_2=1e-06, compute_score=False, fit_intercept= False, lambda_1=1e-07, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-05, alpha_2=1e-06, compute_score=False, fit_intercept= False, lambda 1=1e-07, lambda 2=1e-07; total time= 0.0s [CV] END alpha_1=1e-05, alpha_2=1e-06, compute_score=False, fit_intercept= False, lambda_1=1e-07, lambda_2=1e-07; total time= 0.0s [CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=True, fit_intercept=F alse, lambda_1=1e-06, lambda_2=1e-06; total time= 0.0s [CV] END alpha 1=1e-07, alpha 2=1e-05, compute score=True, fit intercept=F alse, lambda 1=1e-06, lambda 2=1e-06; total time= 0.0s [CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=True, fit_intercept=F alse, lambda_1=1e-06, lambda_2=1e-06; total time= 0.0s [CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=True, fit_intercept=F alse, lambda_1=1e-06, lambda_2=1e-06; total time= 0.0s [CV] END alpha 1=1e-07, alpha 2=1e-05, compute score=True, fit intercept=F alse, lambda 1=1e-06, lambda 2=1e-06; total time= 0.0s

```
[CV] END alpha_1=1e-08, alpha_2=1e-05, compute_score=True, fit_intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
[CV] END alpha 1=1e-08, alpha 2=1e-05, compute score=True, fit intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
                                                    0.0s
[CV] END alpha 1=1e-08, alpha 2=1e-05, compute score=True, fit intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
                                                    0.0s
[CV] END alpha_1=1e-08, alpha_2=1e-05, compute_score=True, fit_intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
                                                    0.0s
[CV] END alpha 1=1e-08, alpha 2=1e-05, compute score=True, fit intercept=F
alse, lambda 1=1e-07, lambda 2=1e-06; total time=
                                                    0.0s
[CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=True, fit_intercept=T
rue, lambda_1=1e-05, lambda_2=1e-06; total time=
[CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=True, fit_intercept=T
rue, lambda_1=1e-05, lambda_2=1e-06; total time=
[CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=True, fit_intercept=T
rue, lambda 1=1e-05, lambda 2=1e-06; total time=
[CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=True, fit_intercept=T
rue, lambda_1=1e-05, lambda_2=1e-06; total time=
[CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=True, fit_intercept=T
rue, lambda_1=1e-05, lambda_2=1e-06; total time=
[CV] END alpha_1=1e-08, alpha_2=1e-06, compute_score=True, fit_intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
                                                    0.0s
[CV] END alpha_1=1e-08, alpha_2=1e-06, compute_score=True, fit_intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
[CV] END alpha_1=1e-08, alpha_2=1e-06, compute_score=True, fit_intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
                                                    0.0s
[CV] END alpha 1=1e-08, alpha 2=1e-06, compute score=True, fit intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
                                                    0.0s
[CV] END alpha_1=1e-08, alpha_2=1e-06, compute_score=True, fit_intercept=F
alse, lambda_1=1e-07, lambda_2=1e-06; total time=
                                                    0.0s
[CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept=
True, lambda_1=1e-06, lambda_2=1e-07; total time=
                                                    0.0s
[CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept=
True, lambda_1=1e-06, lambda_2=1e-07; total time=
                                                    0.05
[CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept=
True, lambda_1=1e-06, lambda_2=1e-07; total time=
                                                    0.0s
[CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept=
True, lambda_1=1e-06, lambda_2=1e-07; total time=
[CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept=
True, lambda 1=1e-06, lambda 2=1e-07; total time=
Mean Absolute Percentage Error: 0.03767929032989868
Root Mean Squared Error: 92664.15716479663
Root Mean Squared Log Error: 0.054885830451669886
R2 Score: 0.9790948901271462
```

In [153]:

```
grid_ard.best_params_
```

Out[153]:

```
{'lambda_2': 1e-06,
  'lambda_1': 1e-08,
  'fit_intercept': True,
  'compute_score': False,
  'alpha_2': 1e-07,
  'alpha_1': 1e-08}
```

In [154]:

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits
[CV] END .....fit_intercept=True, positive=True; total time=
0.0s
[CV] END .....fit_intercept=True, positive=False; total time=
0.0s
[CV] END .....fit_intercept=False, positive=True; total time=
0.0s
[CV] END .....fit_intercept=False, positive=True; total time=
0.0s
[CV] END .....fit_intercept=False, positive=True; total time=
0.0s
[CV] END .....fit intercept=False, positive=True; total time=
0.0s
[CV] END .....fit_intercept=False, positive=True; total time=
0.0s
[CV] END .....fit_intercept=False, positive=False; total time=
0.0s
[CV] END .....fit intercept=False, positive=False; total time=
0.0s
[CV] END .....fit_intercept=False, positive=False; total time=
0.0s
[CV] END .....fit_intercept=False, positive=False; total time=
0.0s
[CV] END .....fit intercept=False, positive=False; total time=
0.0s
Mean Absolute Percentage Error: 0.037602824334626514
Root Mean Squared Error: 95719.65932929565
Root Mean Squared Log Error: 0.054083587741203705
R2 Score: 0.9776935128173896
```

```
In [155]:
grid_lr.best_params_
Out[155]:
{'positive': False, 'fit_intercept': True}
```

Hyperparameter-Optimized Model Performance Comparison

```
In [156]:

model_perfs = pd.DataFrame({'Model': models, 'MAPE': mape_scores, 'RMSE': rmse_scores, '
model_perfs = model_perfs.sort_values('R2',ascending=False)
model_perfs
```

Out[156]:

	Model	MAPE	RMSE	RMSLE	
28	VotingRegressor(estimators=[('CAT',\n	0.024105	7.483545e+04	0.037744	0
39	RandomizedSearchCV(estimator=ExtraTreesRegress	rchCV(estimator=ExtraTreesRegress 0.024178 7.749662e+04 0.03		0.039357	0
21	([DecisionTreeRegressor(criterion='friedman_ms	0.025872	7.938804e+04	0.040228	0
20	(ExtraTreeRegressor(random_state=2090432581),	0.020761	8.088466e+04	0.041309	0
47	RandomizedSearchCV(cv=5, estimator=ElasticNetC	0.037549	8.923582e+04	0.053935	0
45	$Randomized Search CV (cv=5,\ estimator=Lasso CV (), \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\$	0.036074	8.948055e+04	0.052035	0
51	RandomizedSearchCV(cv=5, estimator=ARDRegressi	0.037679	9.266416e+04	0.054886	0
19	(DecisionTreeRegressor(random_state=174724458)	0.032294	9.331461e+04	0.045934	0
18	(DecisionTreeRegressor(max_features=1.0, rando	0.031221	9.415250e+04	0.044139	0
5	SGDRegressor()	0.037567	9.439265e+04	0.053727	0
2	LassoCV()	0.037831	9.461667e+04	0.054418	0
37	RandomizedSearchCV(cv=5, estimator=BaggingRegr	0.031812	9.470061e+04	0.045514	0
1	RidgeCV()	0.037577	9.545932e+04	0.053988	0
46	$Randomized Search CV (cv=5,\ estimator=Ridge CV (), \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\$	0.037577	9.545932e+04	0.053988	0
11	RANSACRegressor()	0.037603	9.571966e+04	0.054084	0
0	LinearRegression()	0.037603	9.571966e+04	0.054084	0
52	Randomized Search CV (cv=5,estimator=Linear Regre	0.037603	9.571966e+04	0.054084	0
40	RandomizedSearchCV(cv=5,\n e	0.037618	9.574424e+04	0.054104	0
41	$Randomized Search CV (cv=5,\ estimator=SGDR egresso$	0.037189	9.587206e+04	0.053823	0
29	$Randomized Search CV (cv=5,\ estimator=Random Fores$	0.032077	9.628709e+04	0.047403	0
6	HuberRegressor()	0.032574	9.771381e+04	0.054128	0
12	TheilSenRegressor()	0.030573	1.001043e+05	0.051125	0
33	$Randomized Search CV (cv=Repeated KFold (n_repeats=$	0.043065	1.029213e+05	0.062062	0
44	Randomized Search CV (cv=5, estimator=Passive Aggr	0.034113	1.030828e+05	0.051854	0
26	<pre><catboost.core.catboostregressor 0x0<="" at="" object="" pre=""></catboost.core.catboostregressor></pre>	0.035152	1.087557e+05	0.061378	0
35	Randomized Search CV (cv=6,estimator=Gradient Boo	0.049553	1.244436e+05	0.064934	0
48	Randomized Search CV (cv=5,estimator=AdaBoost Reg	0.063824	1.253858e+05	0.075975	0
27	LGBMRegressor()	0.044858	1.262488e+05	0.064916	0
34	$Randomized Search CV (cv=Repeated KFold (n_repeats=$	0.044681	1.281810e+05	0.067728	0
25	XGBRegressor(base_score=None, booster=None, ca	0.042063	1.283637e+05	0.060352	0
22	(DecisionTreeRegressor(max_depth=3, random_sta	0.060388	1.307803e+05	0.076905	0
23	HistGradientBoostingRegressor()	0.048545	1.338957e+05	0.067489	0
36	RandomizedSearchCV(cv=5,\n e	0.044126	1.349660e+05	0.069766	0
50	RandomizedSearchCV(cv=5, estimator=GammaRegres	0.058742	1.352316e+05	0.077562	0
49	Randomized Search CV (cv=5,estimator=Poisson Regr	0.062941	1.354796e+05	0.083242	0
8	PoissonRegressor()	0.062941	1.354802e+05	0.083241	0
43	RandomizedSearchCV(cv=5, estimator=TweedieRegr	0.059141	1.360808e+05	0.077778	0

	Model	MAPE	RMSE	RMSLE	
31	RandomizedSearchCV(cv=5, estimator=HistGradien	0.050687	1.376967e+05	0.078475	0
38	$Randomized Search CV (estimator = LGBMR egressor (), \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\ \\$	0.052871	1.422376e+05	0.074401	0
30	$Randomized Search CV (cv=Repeated KFold (n_repeats=$	0.081620	1.754687e+05	0.105170	0
17	DecisionTreeRegressor()	0.057474	1.780531e+05	0.089337	0
14	KNeighborsRegressor()	0.096216	1.942969e+05	0.118579	0
10	TweedieRegressor()	0.122175	2.034528e+05	0.153165	0
7	GammaRegressor()	0.128221	2.267689e+05	0.157562	0
3	ElasticNetCV()	0.387979	6.378490e+05	0.398606	0
32	$Randomized Search CV (cv=Repeated KFold (n_repeats=$	0.392319	6.393462e+05	0.401252	0
42	RandomizedSearchCV(cv=5, estimator=HuberRegres	0.388217	6.408426e+05	0.399389	0
13	ARDRegression()	0.389750	6.408954e+05	0.400184	-0
15	SVR()	0.393779	6.411845e+05	0.402406	-0
9	QuantileRegressor()	0.393789	6.411975e+05	0.402414	-0
4	PassiveAggressiveRegressor()	0.907267	1.796564e+06	2.491688	-6
16	LinearSVR()	0.999907	1.932580e+06	9.369523	-8
24 Afte	MLPRegressor() r completion of the entire hyperparameter tuning pr	0.999992 ocess, it is	1.932699e+06 s clearly evider	11.735068 nt that the \	

or outperforms all the other models by obtaining an astounding r2 score of approximately 98.64%.

Saving the best performing model for future use

```
In [158]:
```

```
vc = VotingRegressor(estimators=[
    ('CAT', CatBoostRegressor(silent=True)),
    ('LR', LinearRegression()),
    ('SGD', SGDRegressor()),
    ('GB', GradientBoostingRegressor()),
    ('ET', ExtraTreesRegressor()),
    ('BAG', BaggingRegressor()),
    ('RF', RandomForestRegressor()),
    ('THEIL', TheilSenRegressor()),
    ('THEIL', TheilSenRegressor()),
    ('RANSAC', RANSACRegressor()),
    ('HUBER', HuberRegressor()),
    ('LASSO', LassoCV()),
    ('RIDGE', RidgeCV())
])
vc.fit(X_train_final,y_train)
```

Out[158]:

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [159]:
```

```
vc_pred = vc.predict(X_test_final)
print("R2:",r2_score(y_test,vc_pred))

R2: 0.9851030297616545

In [160]:
joblib.dump(vc,'sales_predictor.h5')

Out[160]:
['sales_predictor.h5']
```

```
In [161]:
```

```
model = joblib.load('sales_predictor.h5')
model
```

Out[161]:

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

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