

Black Friday Sales Prediction

April 29, 2023

0.1 Importing the relevant libraries

```
[157]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings, joblib
warnings.filterwarnings('ignore')
from sklearn.preprocessing import LabelEncoder, StandardScaler, OrdinalEncoder,
    ↳OneHotEncoder, FunctionTransformer, PowerTransformer
from sklearn.model_selection import train_test_split, RandomizedSearchCV,
    ↳RepeatedKfold
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.linear_model import Lasso, LinearRegression, LassoCV, RidgeCV,
    ↳ElasticNetCV, PassiveAggressiveRegressor, SGDRegressor, ARDRegression,
    ↳RANSACRegressor, TweedieRegressor, HuberRegressor
from sklearn.svm import LinearSVR
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor,
    ↳ExtraTreesRegressor, BaggingRegressor, AdaBoostRegressor,
    ↳HistGradientBoostingRegressor, VotingRegressor
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from catboost import CatBoostRegressor
from lightgbm import LGBMRegressor
from sklearn.metrics import mean_squared_error, r2_score,
    ↳mean_absolute_percentage_error
from scipy.stats import probplot
from sklearn.feature_selection import SelectKBest, SelectFromModel,
    ↳SelectPercentile, f_regression, r_regression, RFE
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,
    ↳ModelCheckpoint
```

```
from tensorflow.keras.utils import plot_model
from tensorflow_addons.metrics import RSquare
```

```
[2]: plt.rcParams['figure.figsize'] = (12,8) # Overwriting the default figure size
```

0.2 Loading the dataset

```
[3]: train = pd.read_csv('train.csv')
train_copy = train.copy()
train.head()
```

```
[3]:
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	\
0	1000001	P00069042	F	0-17	10	A	
1	1000001	P00248942	F	0-17	10	A	
2	1000001	P00087842	F	0-17	10	A	
3	1000001	P00085442	F	0-17	10	A	
4	1000002	P00285442	M	55+	16	C	

	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	\
0	2	0	3	
1	2	0	1	
2	2	0	12	
3	2	0	12	
4	4+	0	8	

	Product_Category_2	Product_Category_3	Purchase
0	NaN	NaN	8370
1	6.0	14.0	15200
2	NaN	NaN	1422
3	14.0	NaN	1057
4	NaN	NaN	7969

0.3 Understanding the features and dimensions of the dataset

```
[4]: train.shape
```

```
[4]: (550068, 12)
```

```
[5]: train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 12 columns):
#   Column                Non-Null Count  Dtype
---  -
0   User_ID                550068 non-null int64
1   Product_ID             550068 non-null object
2   Gender                 550068 non-null object
```

```

3   Age                                550068 non-null object
4   Occupation                        550068 non-null int64
5   City_Category                     550068 non-null object
6   Stay_In_Current_City_Years       550068 non-null object
7   Marital_Status                    550068 non-null int64
8   Product_Category_1                550068 non-null int64
9   Product_Category_2                376430 non-null float64
10  Product_Category_3                166821 non-null float64
11  Purchase                          550068 non-null int64

```

dtypes: float64(2), int64(5), object(5)

memory usage: 50.4+ MB

```
[6]: train.describe()
```

```

[6]:      User_ID      Occupation  Marital_Status  Product_Category_1  \
count  5.500680e+05  550068.000000  550068.000000  550068.000000
mean    1.003029e+06    8.076707    0.409653    5.404270
std     1.727592e+03    6.522660    0.491770    3.936211
min     1.000001e+06    0.000000    0.000000    1.000000
25%     1.001516e+06    2.000000    0.000000    1.000000
50%     1.003077e+06    7.000000    0.000000    5.000000
75%     1.004478e+06   14.000000    1.000000    8.000000
max     1.006040e+06   20.000000    1.000000   20.000000

      Product_Category_2  Product_Category_3  Purchase
count      376430.000000      166821.000000  550068.000000
mean           9.842329           12.668243   9263.968713
std            5.086590            4.125338   5023.065394
min            2.000000            3.000000   12.000000
25%            5.000000            9.000000   5823.000000
50%            9.000000           14.000000   8047.000000
75%           15.000000           16.000000  12054.000000
max           18.000000           18.000000  23961.000000

```

```
[7]: train.duplicated().sum()
```

```
[7]: 0
```

```
[8]: train.isnull().sum()
```

```

[8]: User_ID      0
     Product_ID   0
     Gender      0
     Age         0
     Occupation   0
     City_Category 0
     Stay_In_Current_City_Years 0
     Marital_Status 0

```

```

Product_Category_1      0
Product_Category_2    173638
Product_Category_3    383247
Purchase                0
dtype: int64

```

```
[9]: train['Gender'].value_counts()
```

```

[9]: M    414259
     F    135809
     Name: Gender, dtype: int64

```

0.4 Exploratory Data Analysis

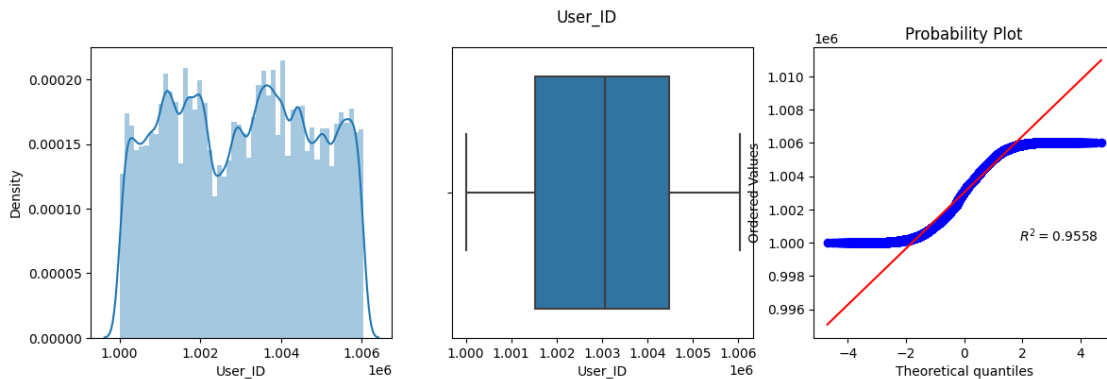
```

[10]: for col in train.select_dtypes(np.number):
        print("Skewness:".format(col),train[col].skew())
        print("Kurtosis:".format(col),train[col].kurtosis())
        plt.figure(figsize=(14,4))
        plt.subplot(131)
        sns.distplot(train[col])
        plt.subplot(132)
        sns.boxplot(train[col])
        plt.subplot(133)
        probplot(train[col],rvalue=True,plot=plt)
        plt.suptitle(col)
        plt.show();

```

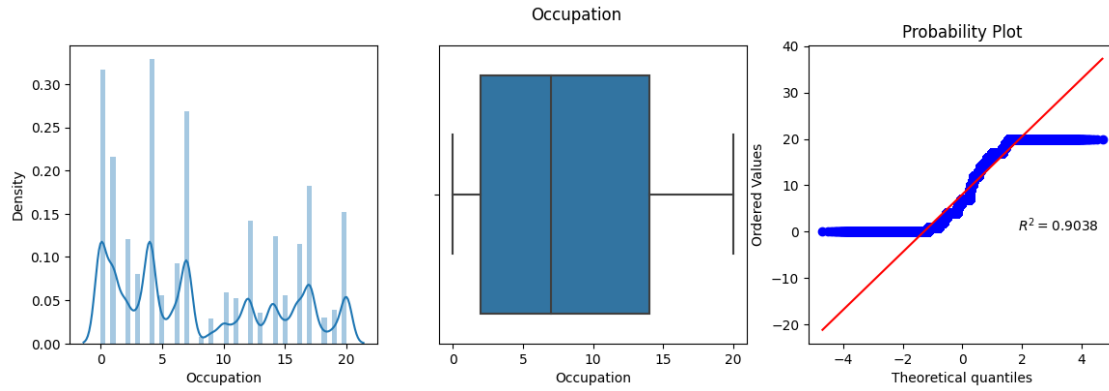
Skewness: 0.0030655518513462644

Kurtosis: -1.1955007812357379

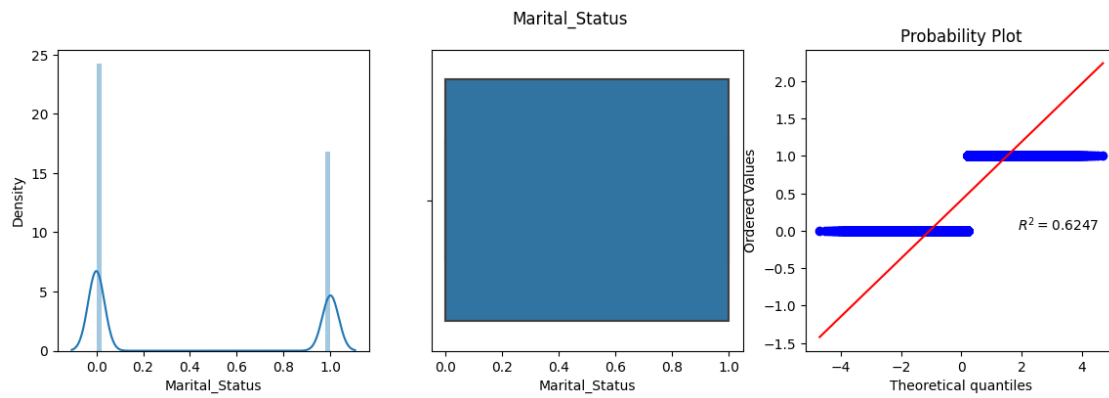


Skewness: 0.40014010986184784

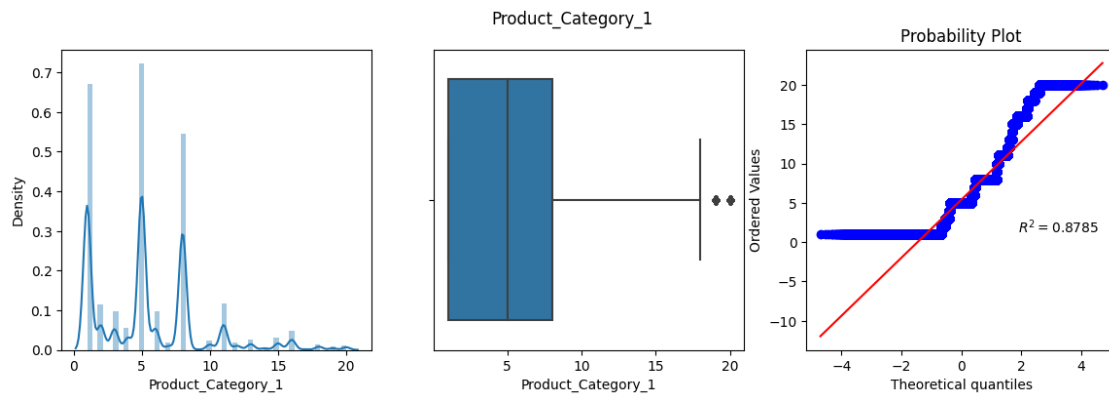
Kurtosis: -1.21611364874086



Skewness: 0.3674372854404167
Kurtosis: -1.8649966222489232



Skewness: 1.0257349338538029
Kurtosis: 1.2347569716913842

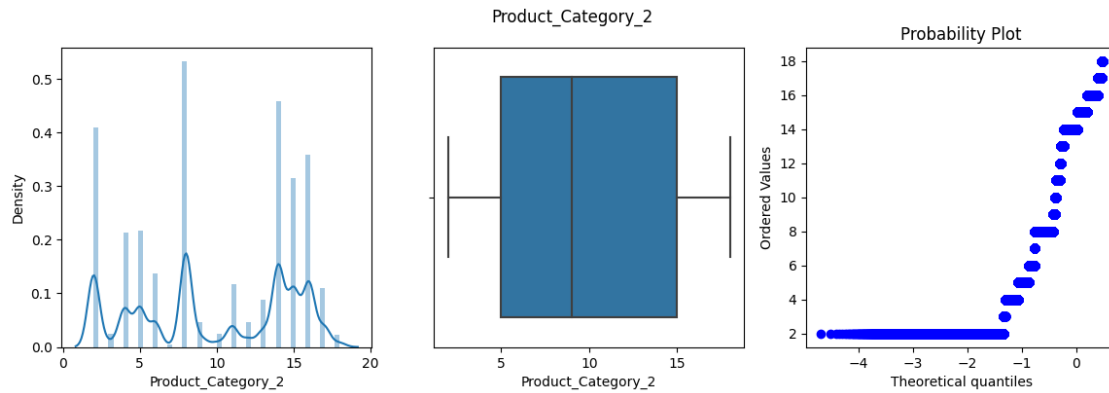


Skewness: -0.1627577144156097

Kurtosis: -1.4322668993429908

posx and posy should be finite values

posx and posy should be finite values

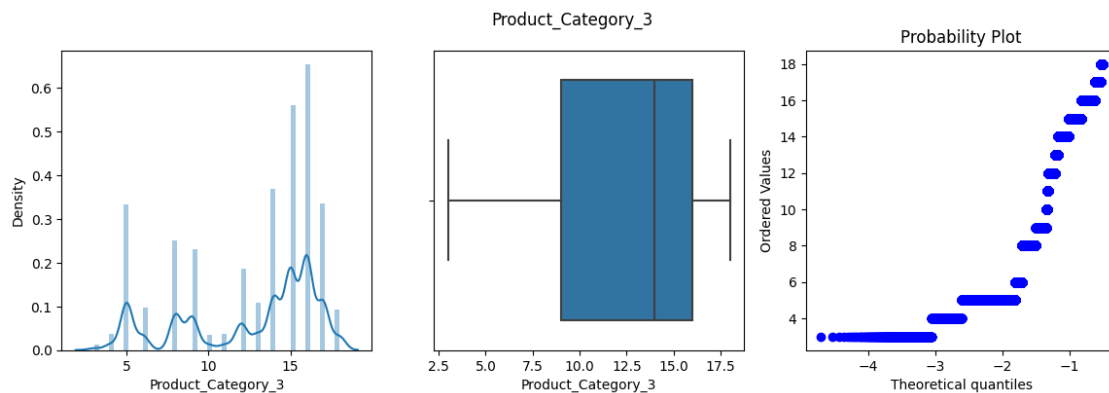


Skewness: -0.7654458894373977

Kurtosis: -0.8080661150996602

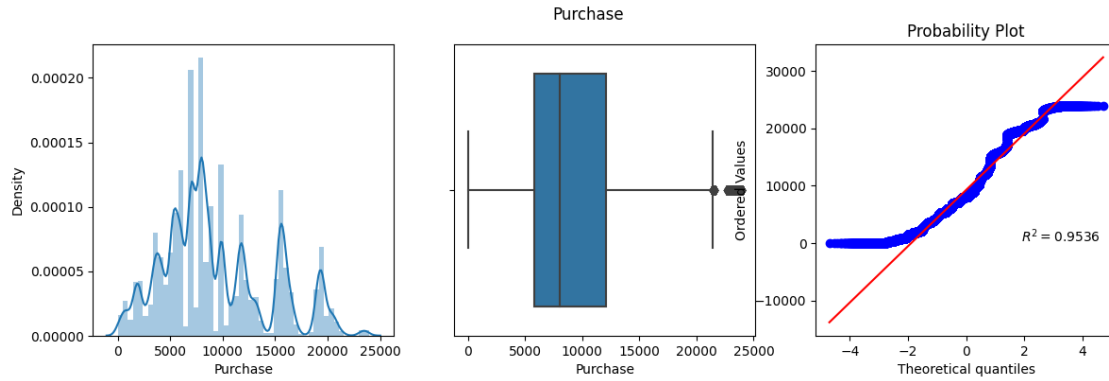
posx and posy should be finite values

posx and posy should be finite values

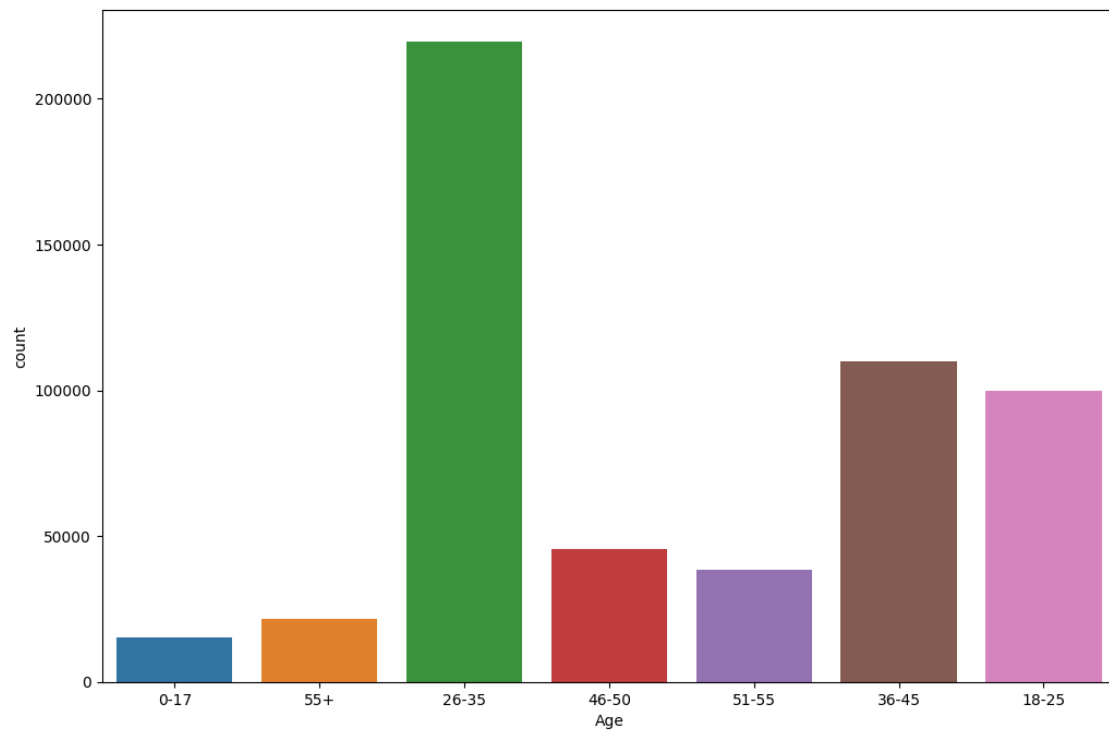


Skewness: 0.6001400037087128

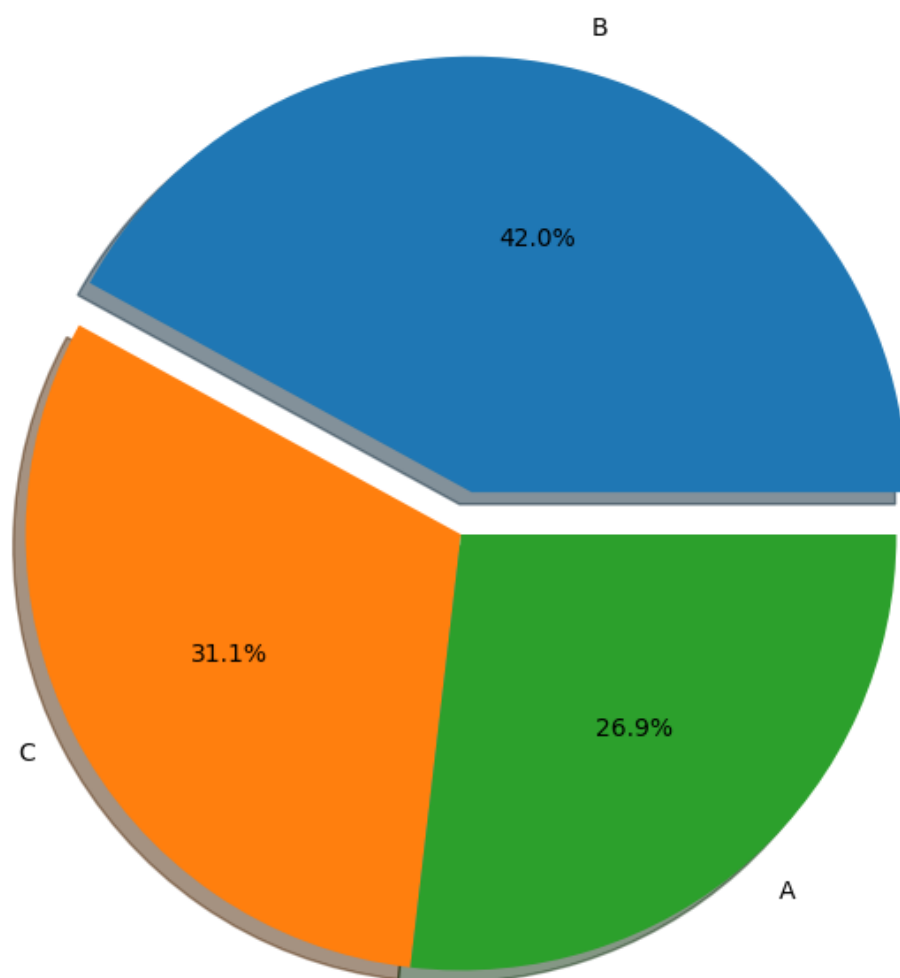
Kurtosis: -0.3383775655851702



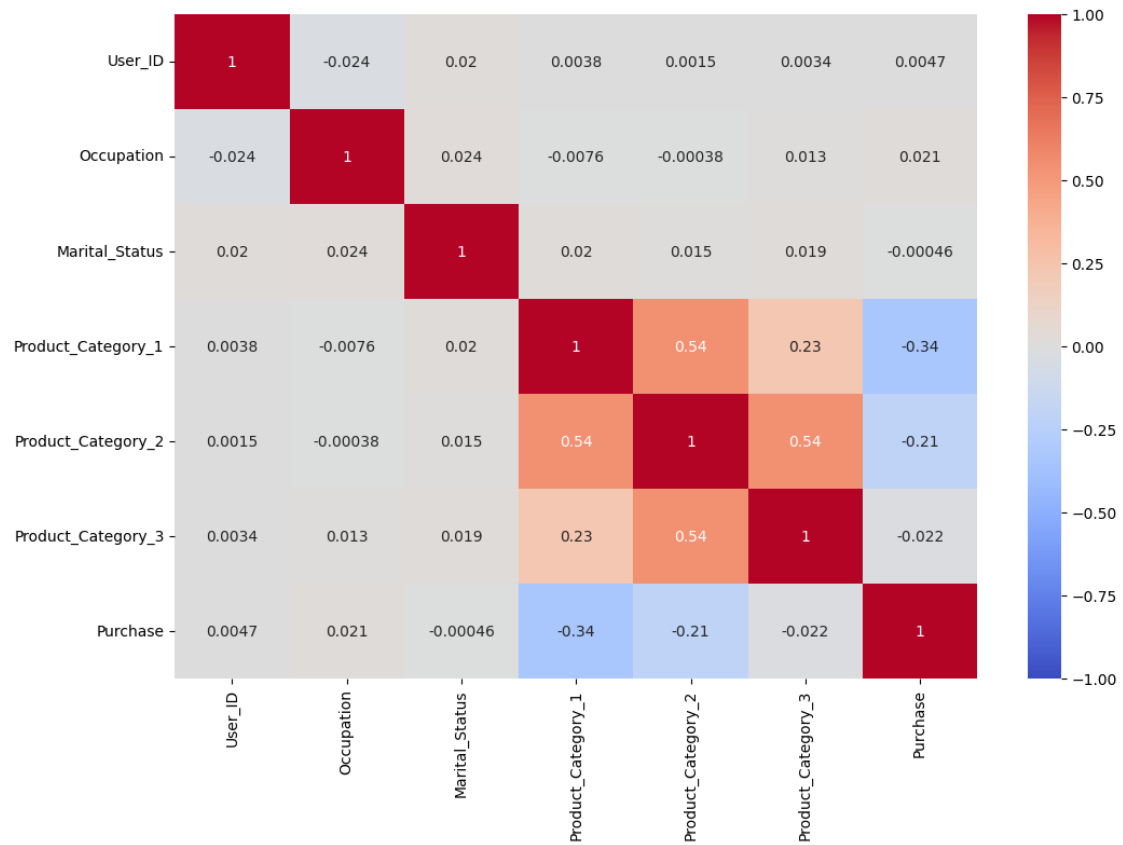
```
[11]: sns.countplot(train['Age']);
```



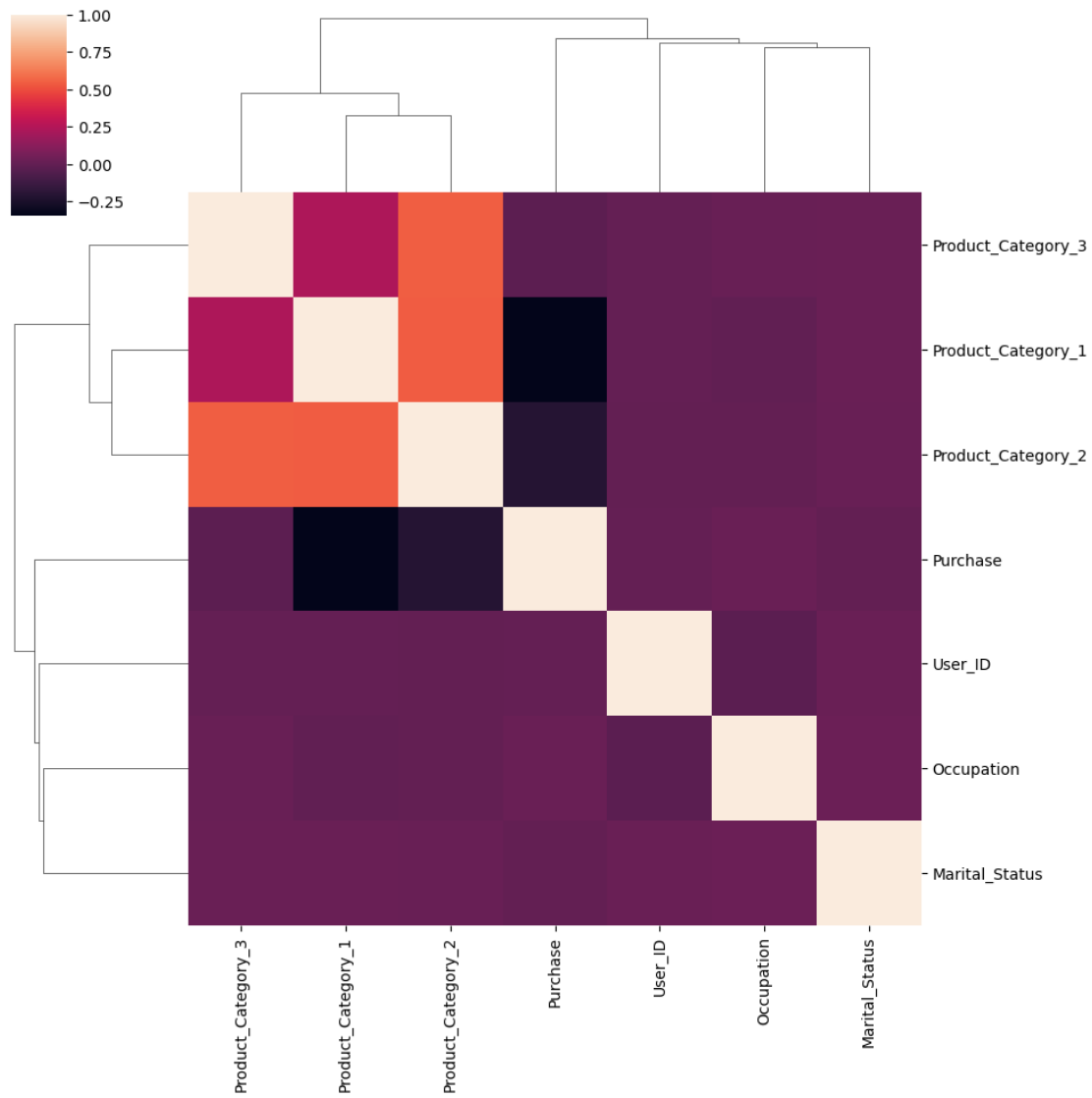
```
[12]: plt.figure(figsize=(12,8))
values = train['City_Category'].value_counts().values
labels = train['City_Category'].value_counts().keys()
explode = (0.1,0,0)
plt.pie(values,labels=labels,explode=explode,shadow=True,autopct='%1.1f%%');
```



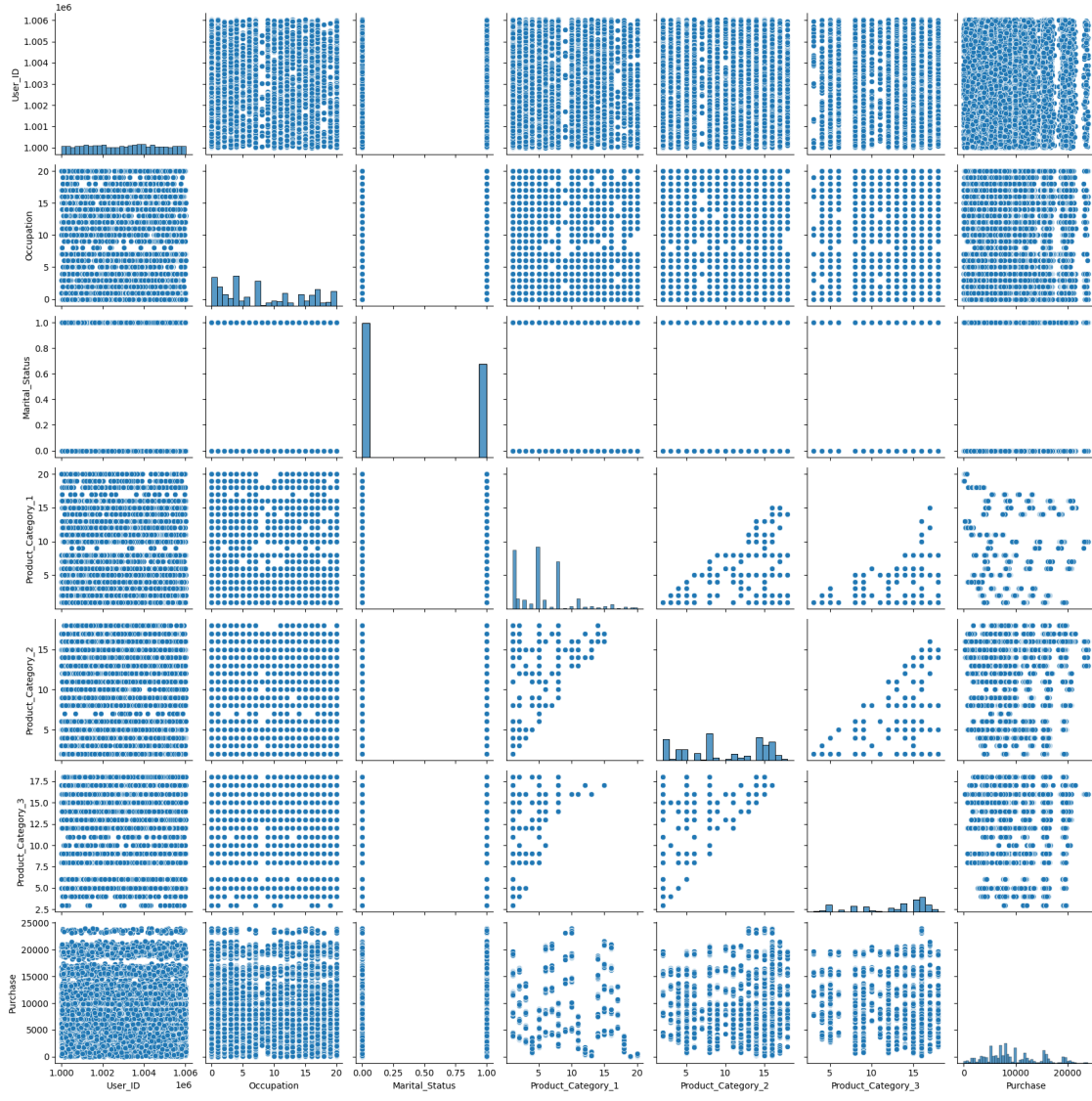
```
[13]: sns.heatmap(train.corr(),annot=True,cmap='coolwarm',vmin=-1,vmax=1);
```

```
[14]: sns.clustermap(train.corr());
```



```
[15]: sns.pairplot(train.sample(20000),palette='winter');
```



0.5 Feature Engineering

0.5.1 Missing Values Imputation

```
[16]: train.Product_Category_2.isna().sum() / len(train.Product_Category_2)
```

```
[16]: 0.3156664266963357
```

```
[17]: train.Product_Category_3.isna().sum() / len(train.Product_Category_3)
```

```
[17]: 0.6967265865311197
```

```
[18]: # Using Iterative Imputation technique to impute the missing values of features
imputer = IterativeImputer()
missing_cols = ['Product_Category_2', 'Product_Category_3']

for col in missing_cols:
    train[col] = imputer.fit_transform(train[[col]])
```

0.5.2 Treatment of Outliers

```
[19]: def remove_outliers(data,col):
    lower_limit, upper_limit = data[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(data[col]<lower_whisker,lower_whisker,np.
    ↳where(data[col]>upper_whisker,upper_whisker,data[col]))
```

```
[20]: outlier_cols = ['Purchase', 'Product_Category_1']

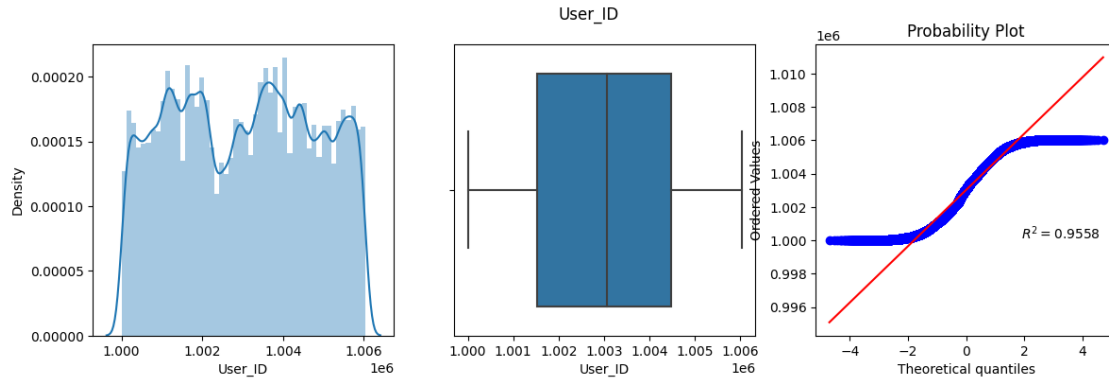
for col in outlier_cols:
    train[col] = remove_outliers(train,col)
```

0.5.3 Feature Transformation

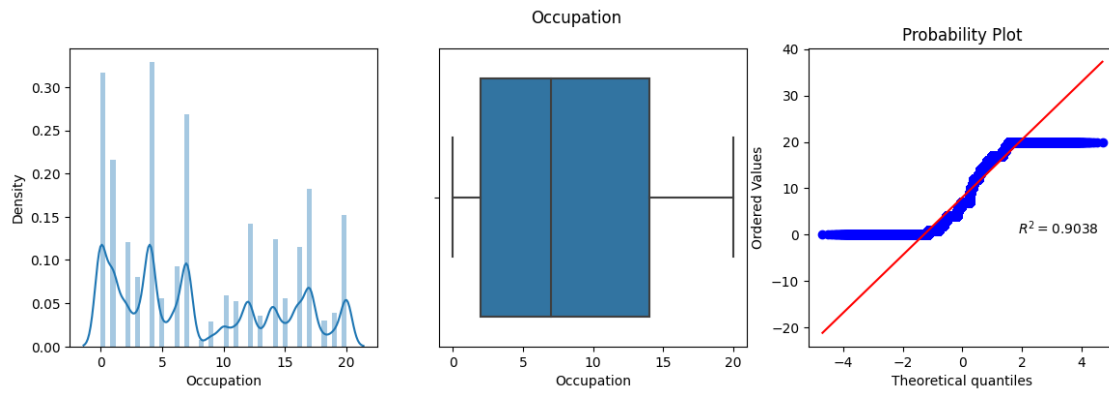
```
[21]: for col in train.select_dtypes(np.number):
    print("Skewness:".format(col),train[col].skew())
    print("Kurtosis:".format(col),train[col].kurtosis())
    plt.figure(figsize=(14,4))
    plt.subplot(131)
    sns.distplot(train[col])
    plt.subplot(132)
    sns.boxplot(train[col])
    plt.subplot(133)
    probplot(train[col],rvalue=True,plot=plt)
    plt.suptitle(col)
    plt.show();
```

Skewness: 0.0030655518513462644

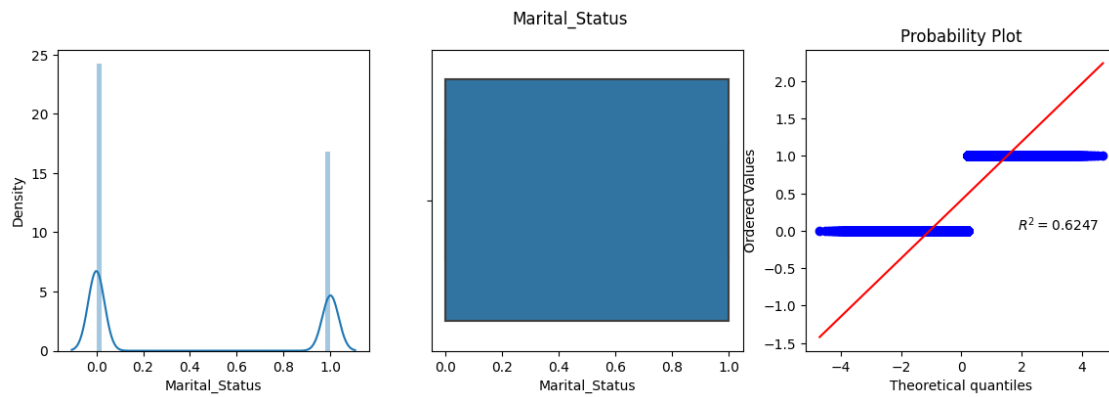
Kurtosis: -1.1955007812357379



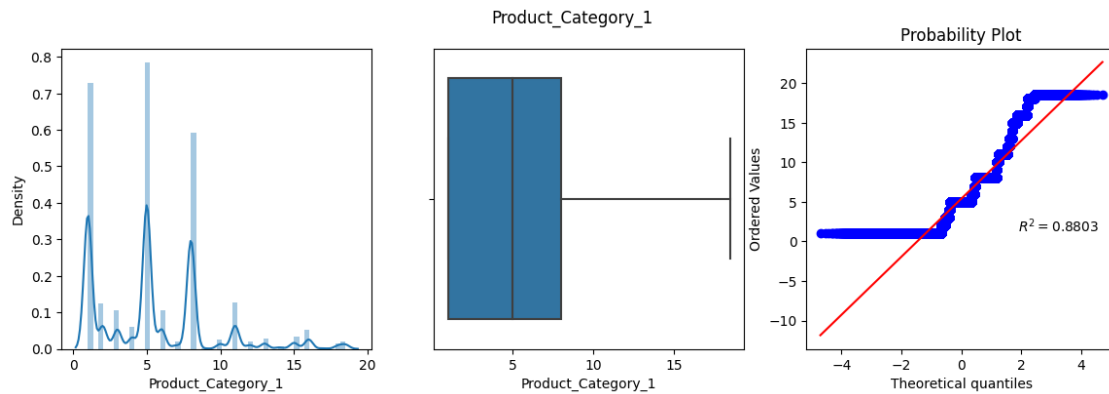
Skewness: 0.40014010986184784
Kurtosis: -1.21611364874086



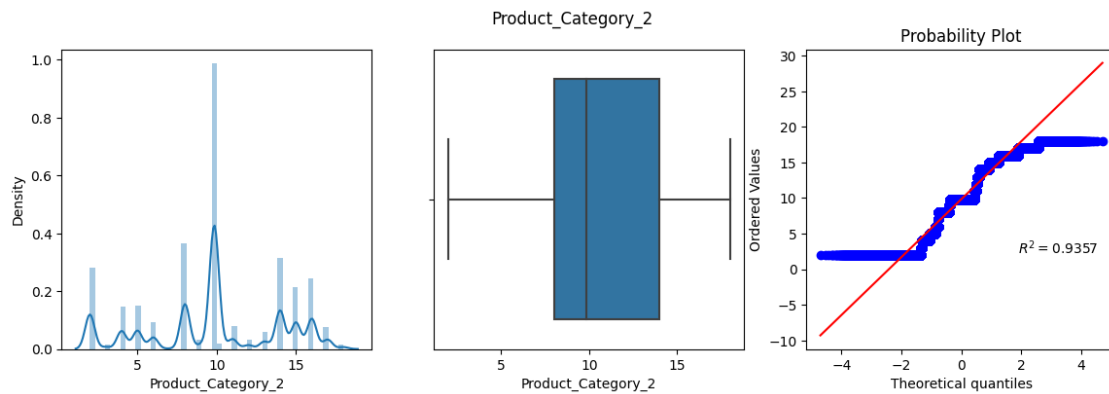
Skewness: 0.3674372854404167
Kurtosis: -1.8649966222489232



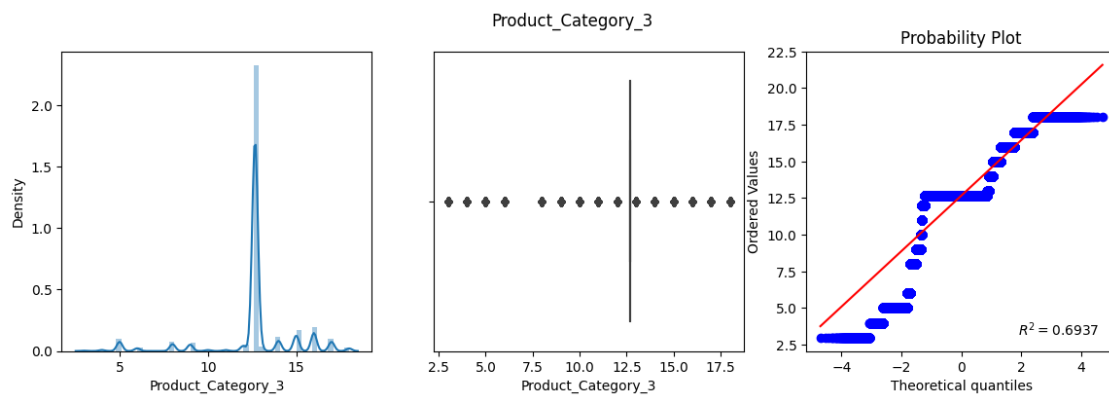
Skewness: 0.9754247200563484
Kurtosis: 0.9952049593382419



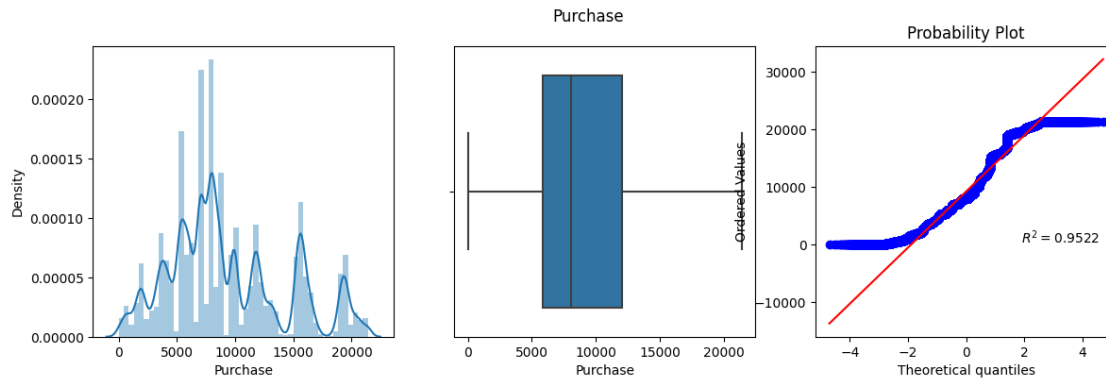
Skewness: -0.19674654415192747
Kurtosis: -0.7091007945191348



Skewness: -1.3899353636558347
Kurtosis: 4.227593988084336



Skewness: 0.5765871650473653
Kurtosis: -0.4160743828298181

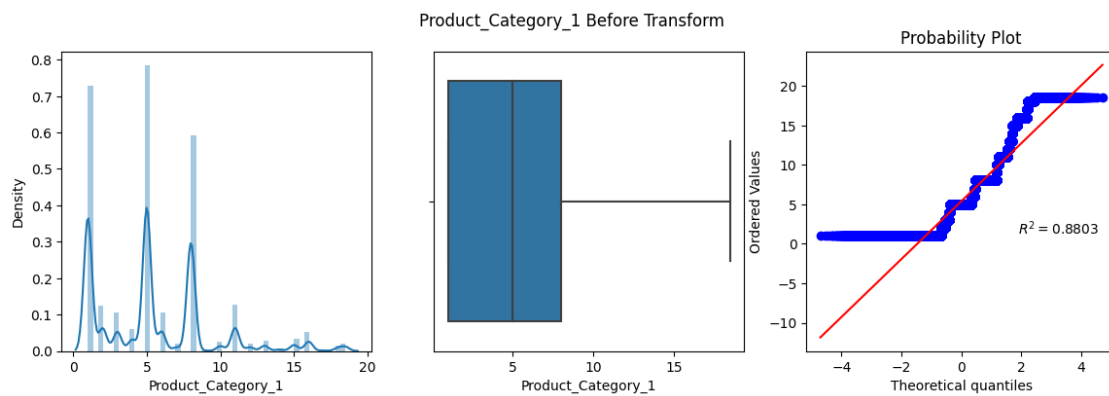
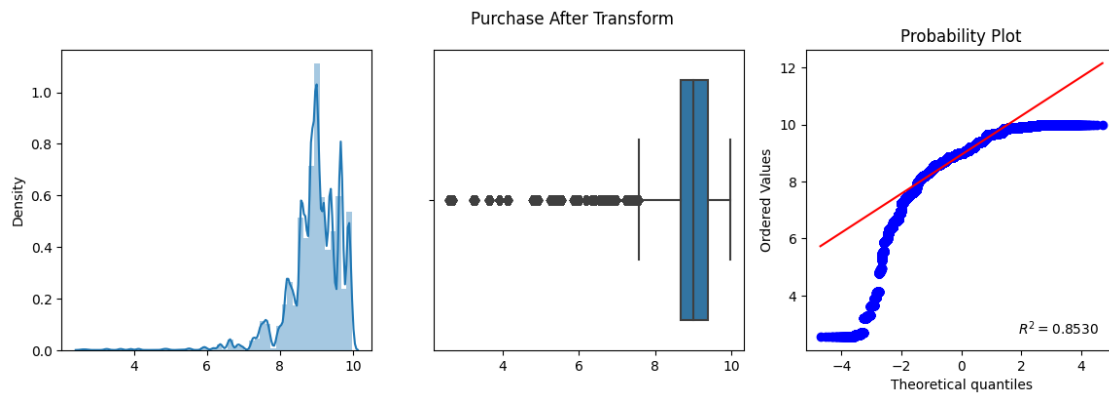
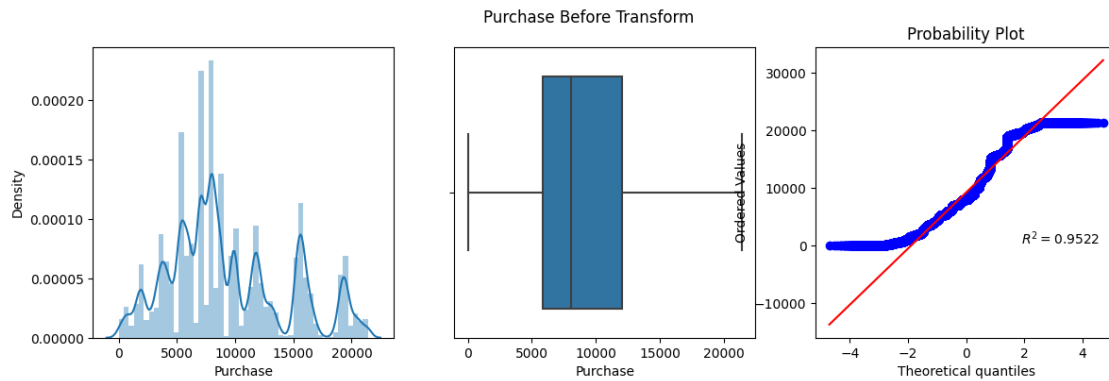


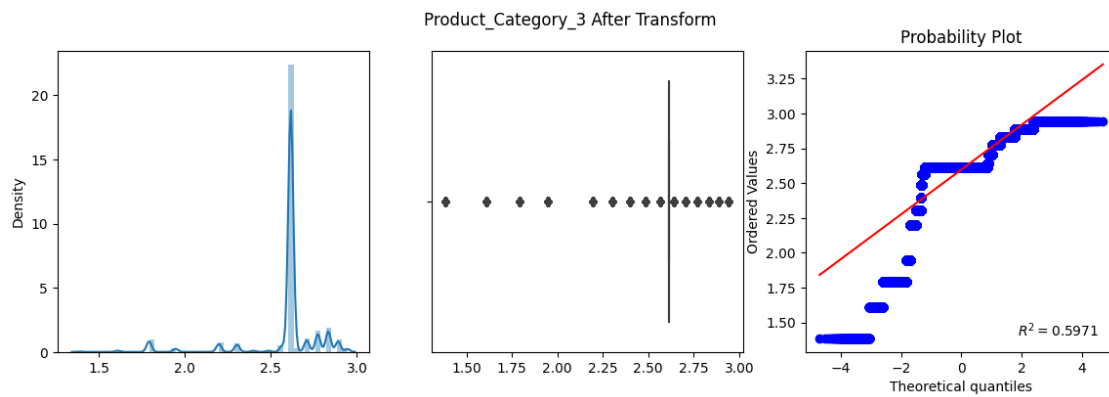
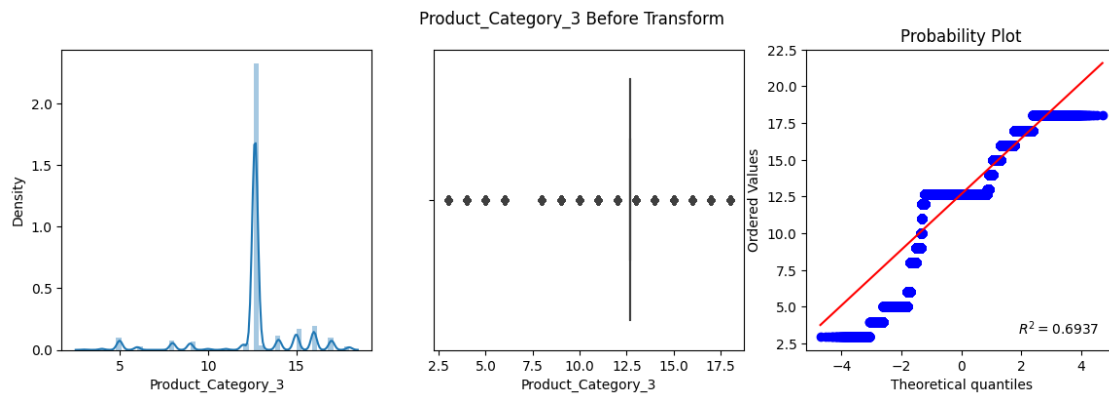
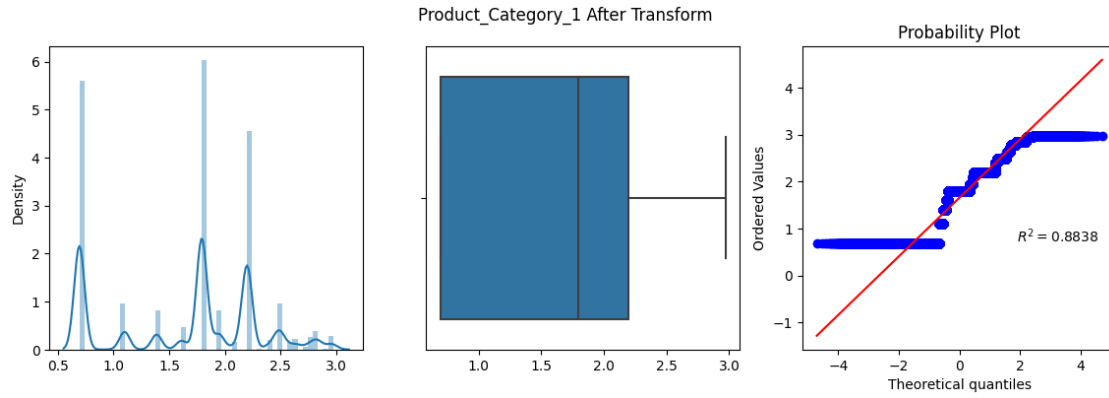
Left Skewed Distribution: Product_Category_3 Right Skewed Distribution: Purchase, Product_Category_1 Normal Distribution: Product_Category_2, Occupation, User_ID

```
[22]: def apply_transform(transform,col):  
    plt.figure(figsize=(14,4))  
    plt.subplot(131)  
    sns.distplot(train[col])  
    plt.subplot(132)  
    sns.boxplot(train[col])  
    plt.subplot(133)  
    probplot(train[col],rvalue=True,dist='norm',plot=plt)  
    plt.suptitle(f'{col} Before Transform')  
    plt.show()  
    col_tf = transform.fit_transform(train[[col]])  
    col_tf = np.array(col_tf).reshape(col_tf.shape[0])  
    plt.figure(figsize=(14,4))  
    plt.subplot(131)  
    sns.distplot(col_tf)  
    plt.subplot(132)  
    sns.boxplot(col_tf)  
    plt.subplot(133)  
    probplot(col_tf,rvalue=True,dist='norm',plot=plt)  
    plt.suptitle(f'{col} After Transform')  
    plt.show();
```

```
[23]: skewed_cols = ['Purchase','Product_Category_1','Product_Category_3']  
  
for col in skewed_cols:
```

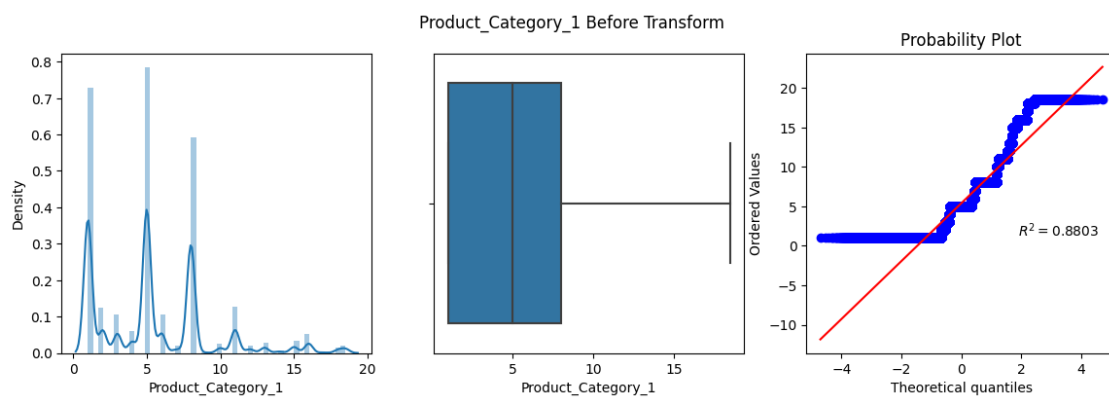
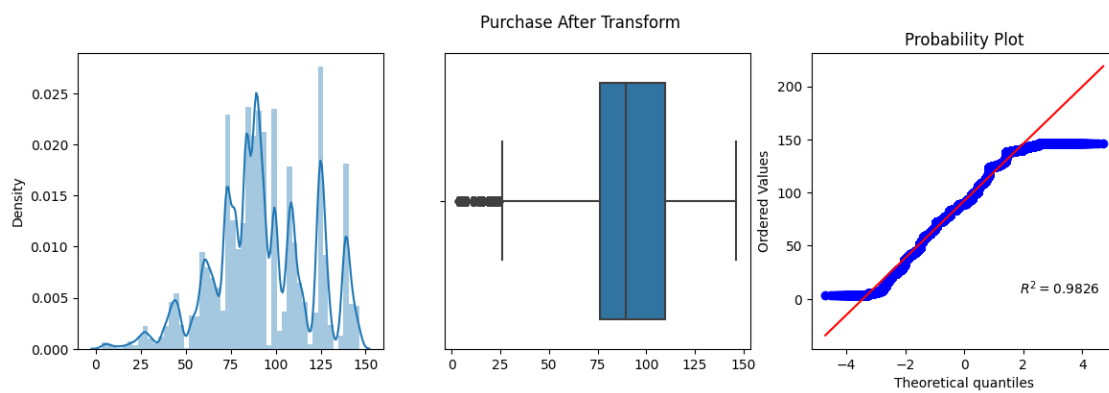
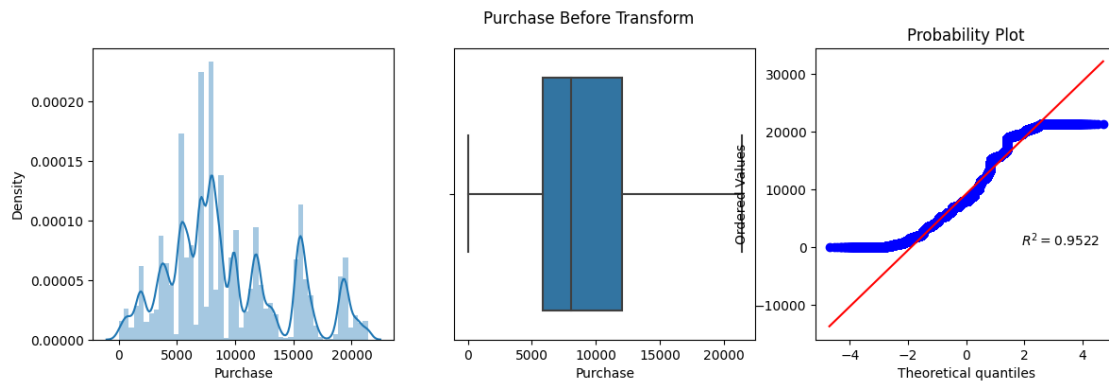
```
apply_transform(FunctionTransformer(np.log1p), col)
```

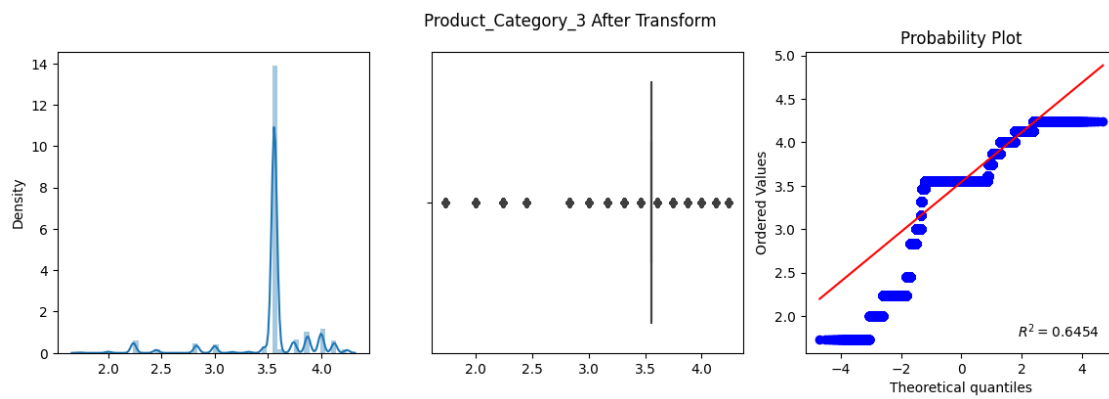
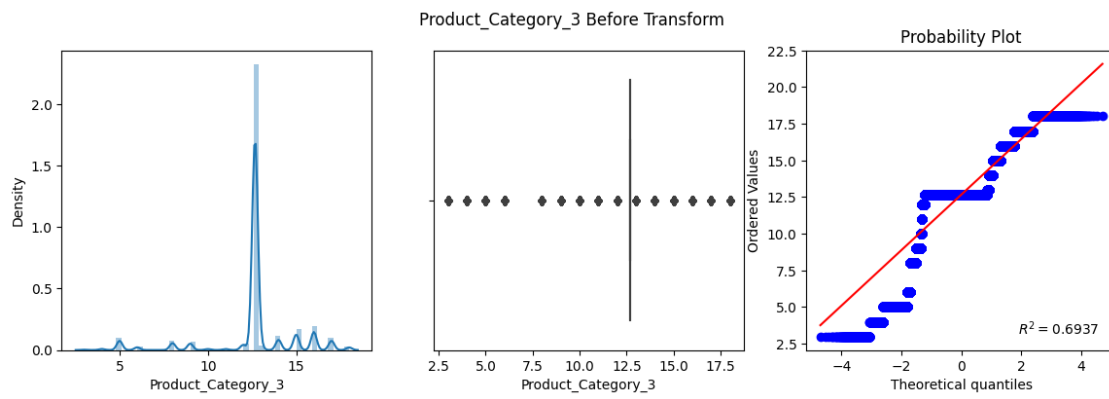
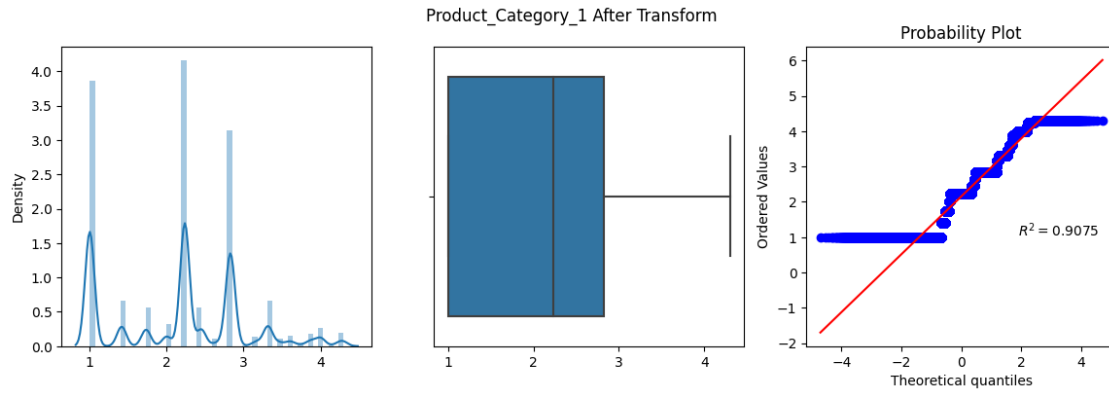




```
[24]: skewed_cols = ['Purchase', 'Product_Category_1', 'Product_Category_3']

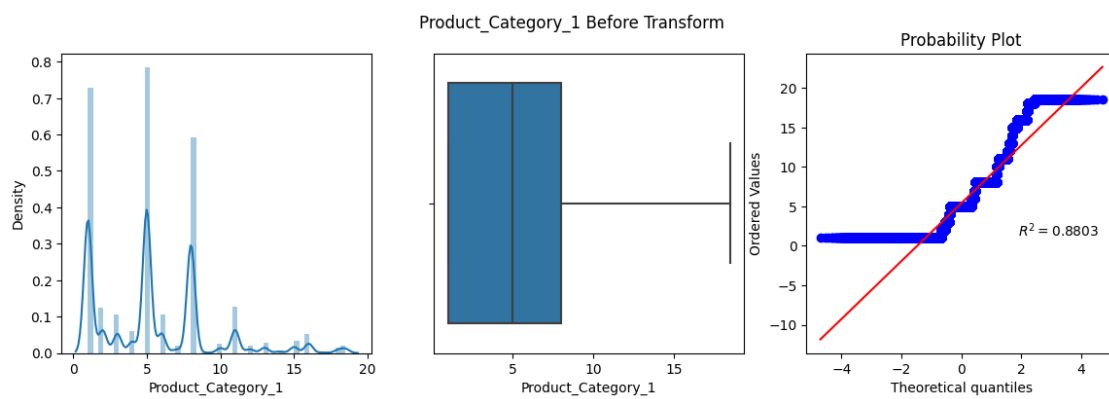
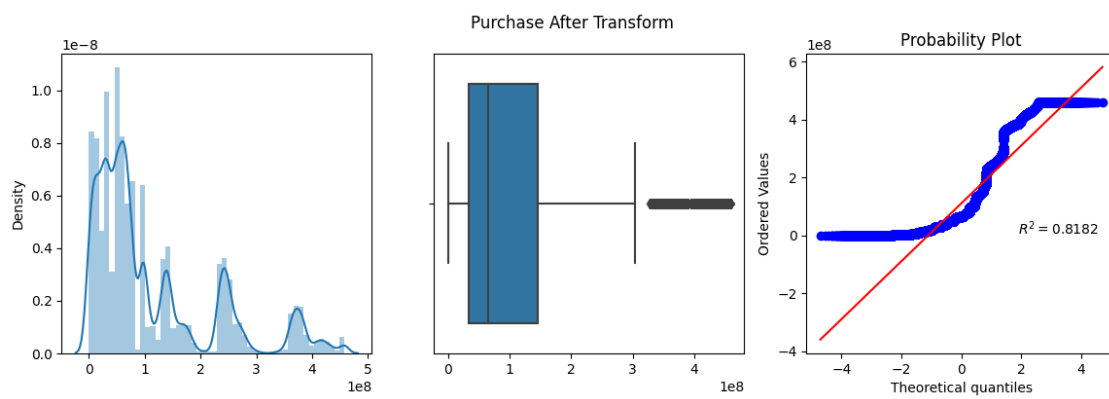
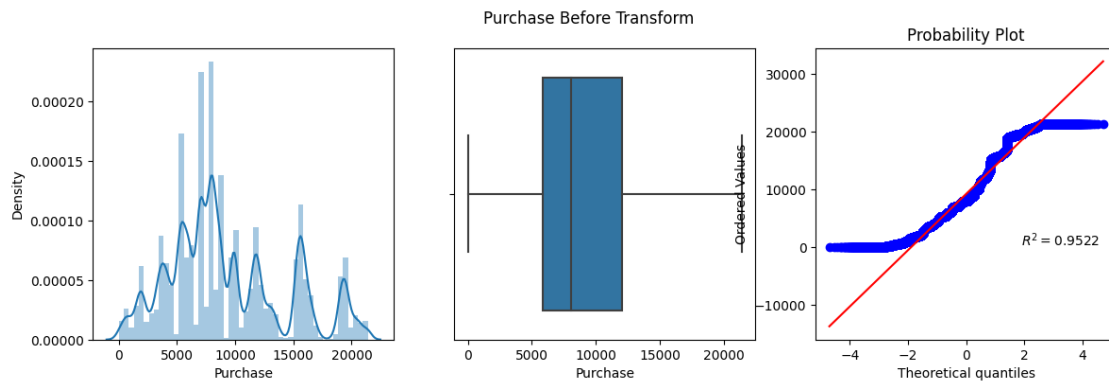
for col in skewed_cols:
    apply_transform(FunctionTransformer(np.sqrt), col)
```

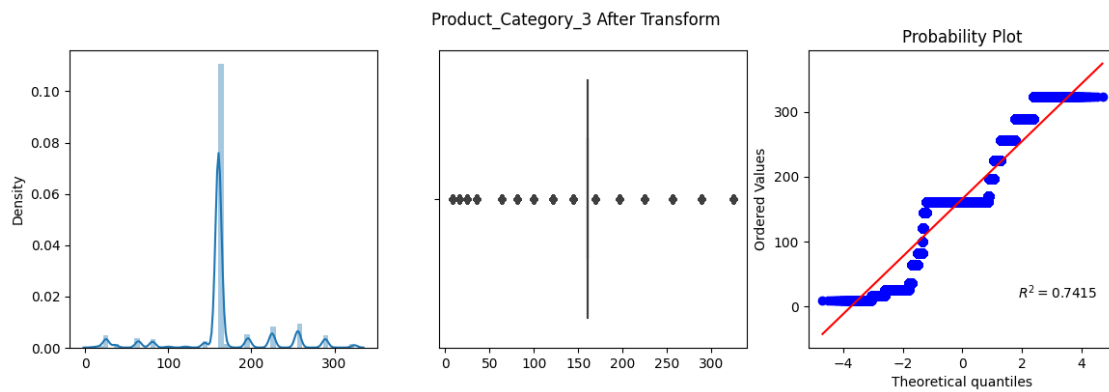
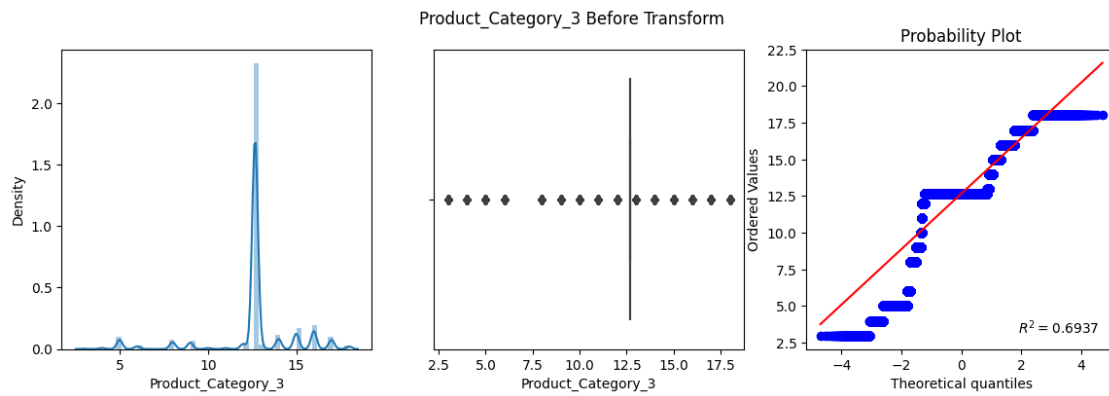
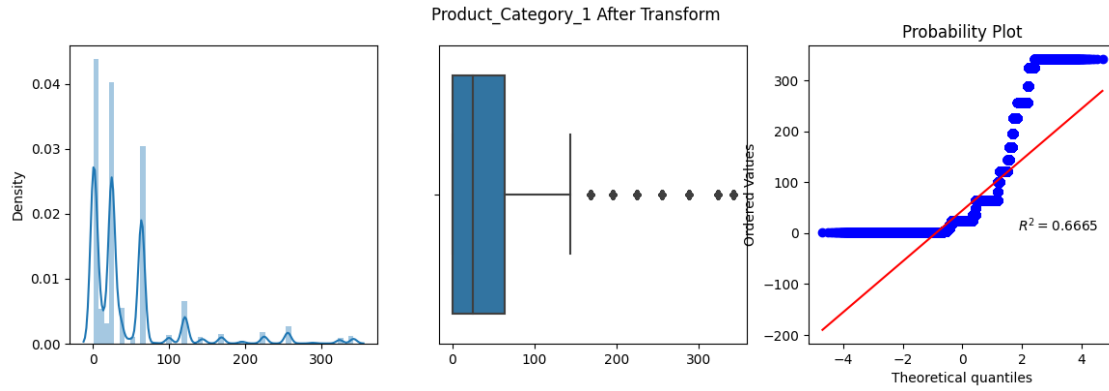




```
[25]: skewed_cols = ['Purchase', 'Product_Category_1', 'Product_Category_3']

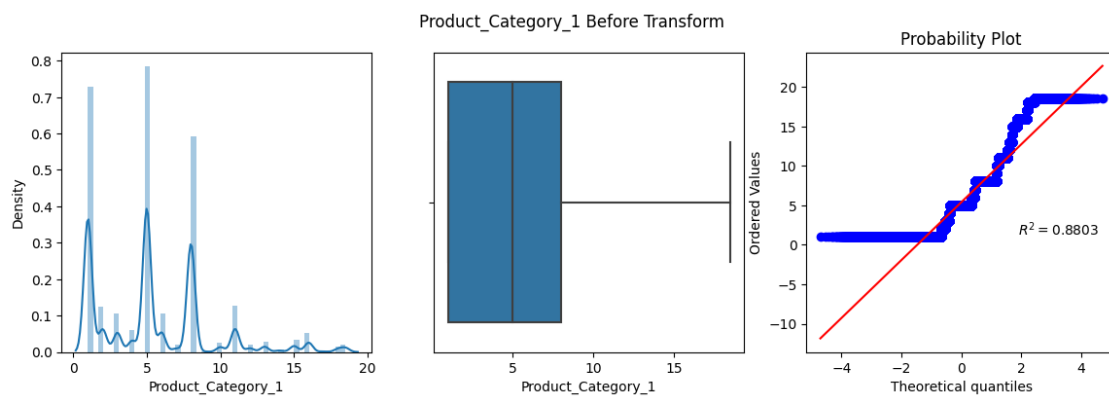
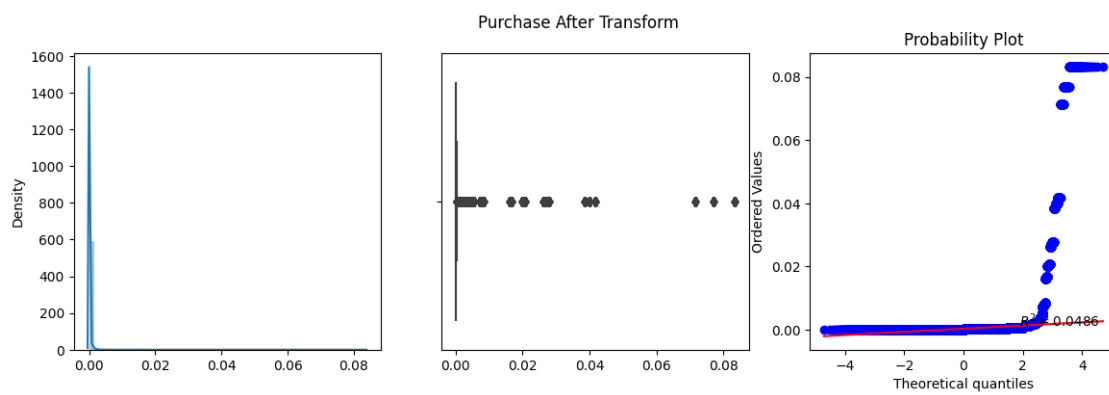
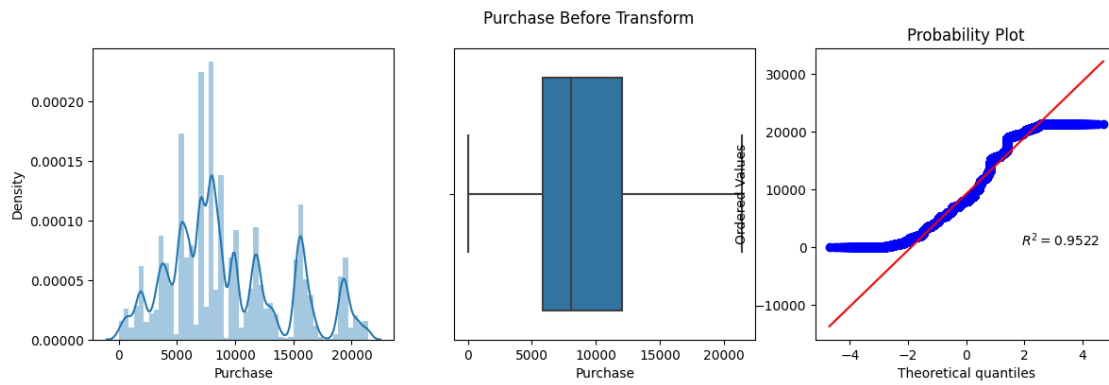
for col in skewed_cols:
    apply_transform(FunctionTransformer(lambda x: x**2), col)
```

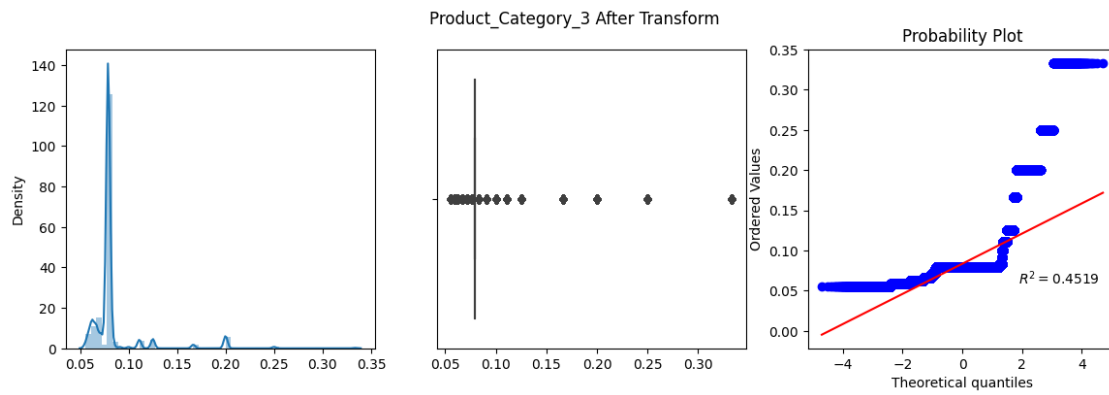
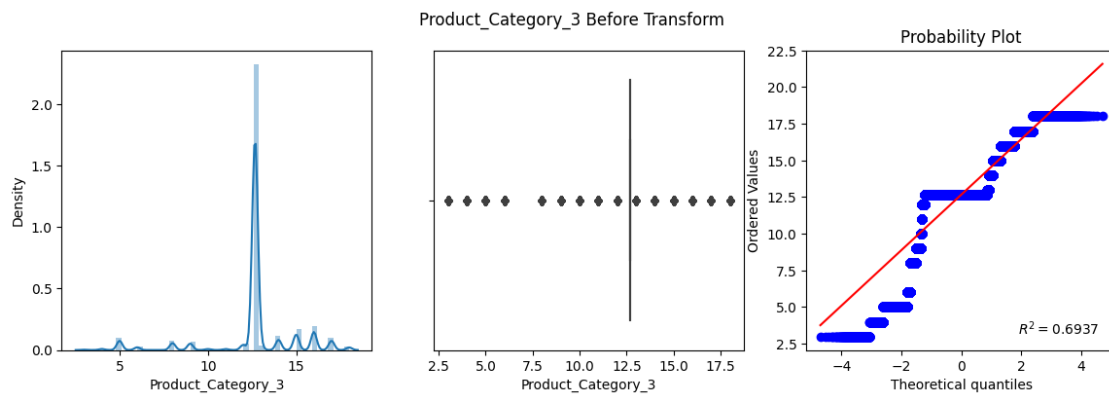
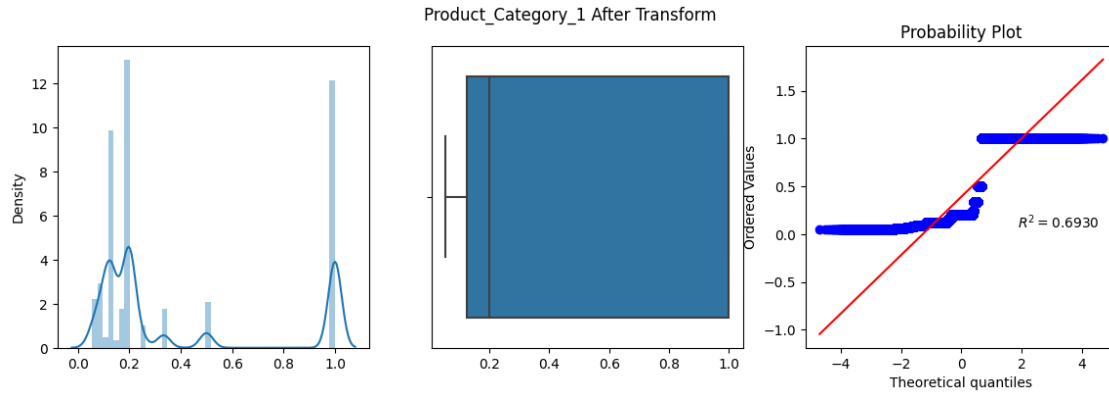




```
[26]: skewed_cols = ['Purchase', 'Product_Category_1', 'Product_Category_3']

for col in skewed_cols:
    apply_transform(FunctionTransformer(lambda x: 1/(x+0.000001)), col)
```

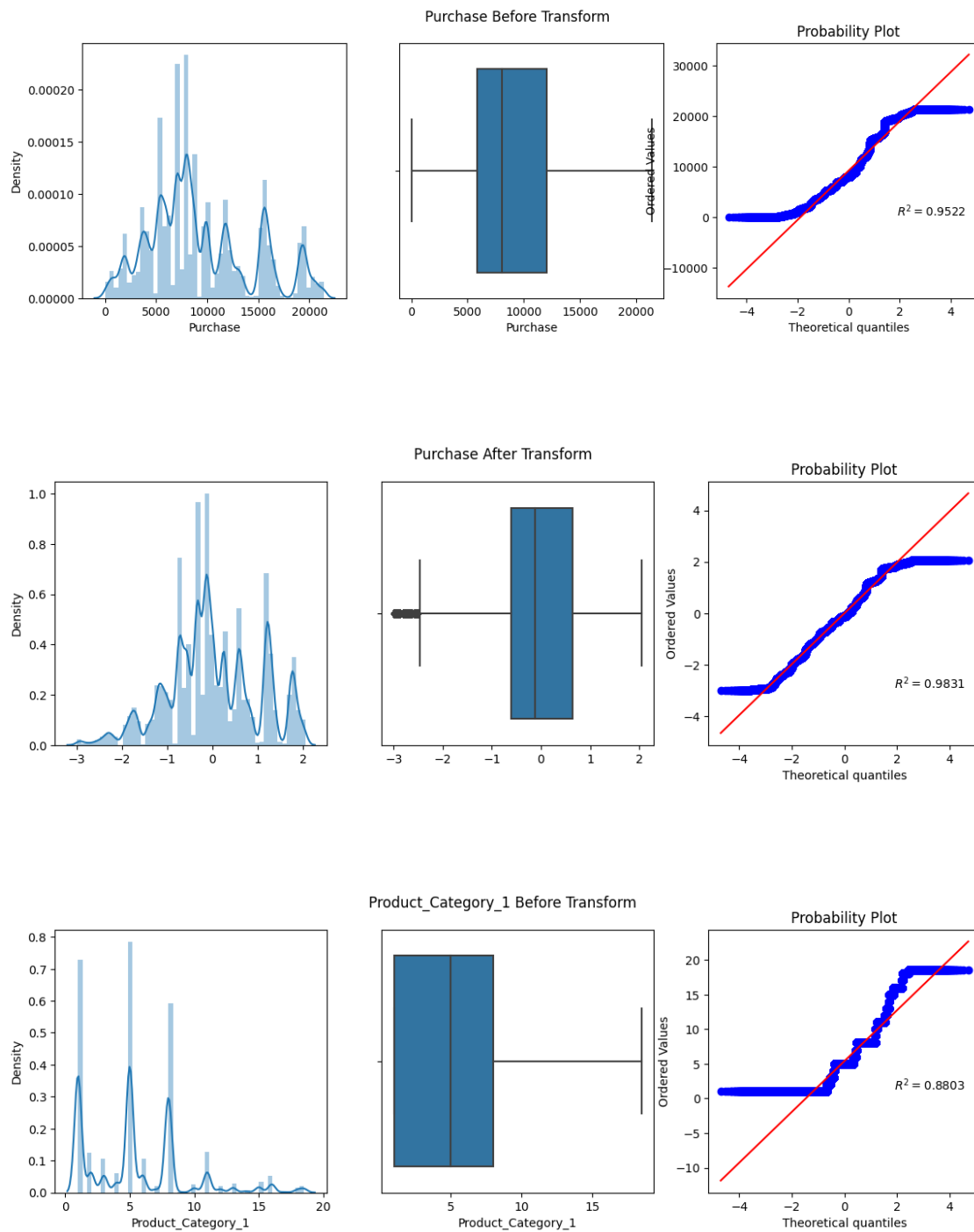


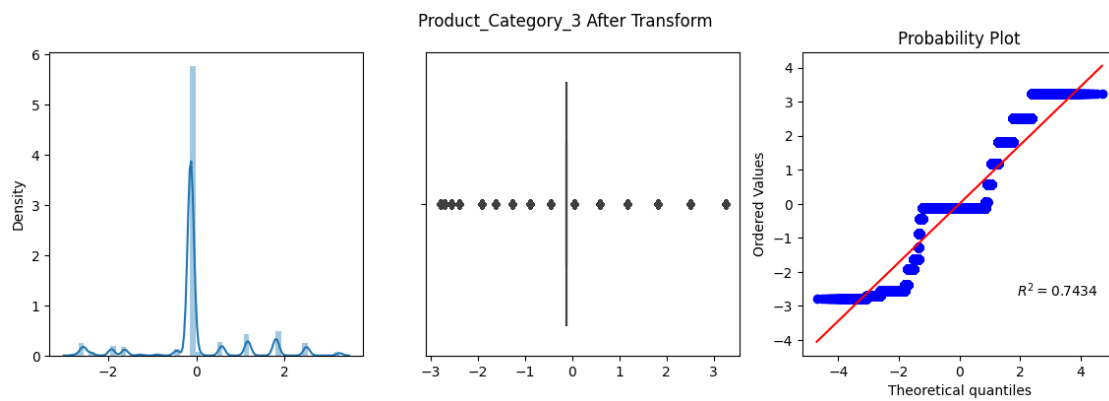
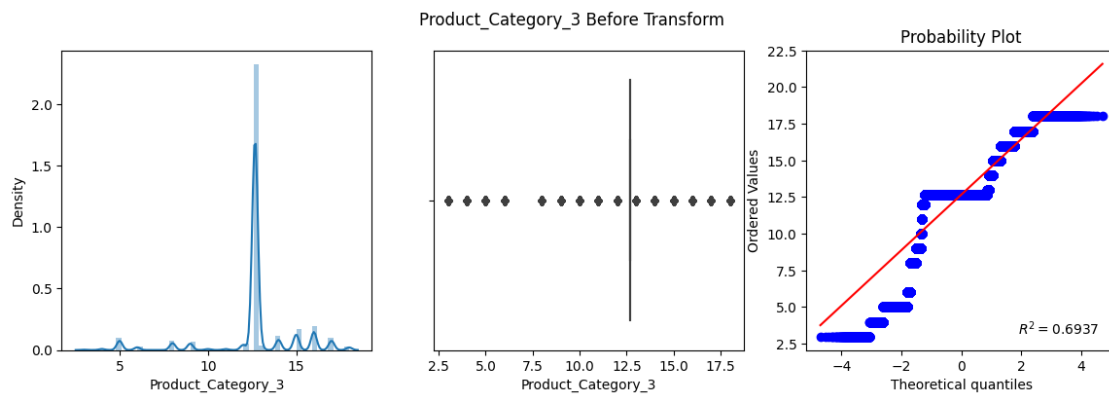
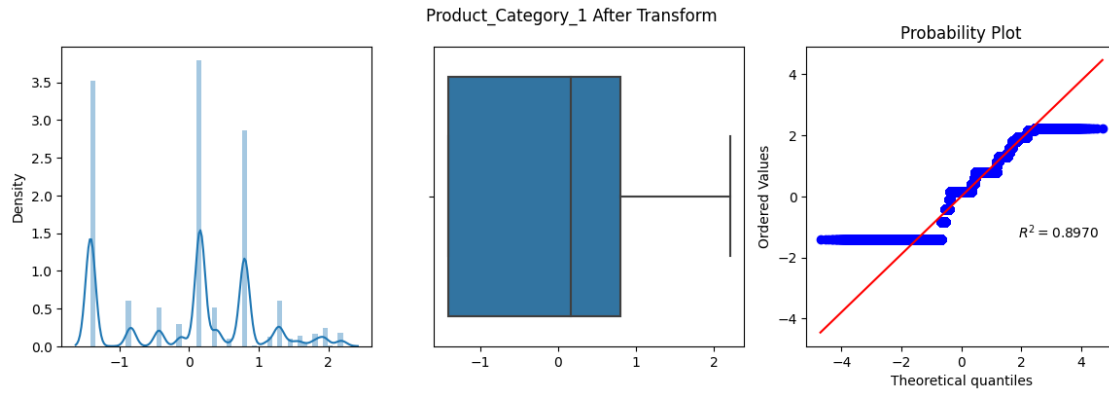


```
[27]: # Applying Box-Cox Transform
skewed_cols = ['Purchase', 'Product_Category_1', 'Product_Category_3']

for col in skewed_cols:
```

```
apply_transform(PowerTransformer(method='box-cox'),col)
```

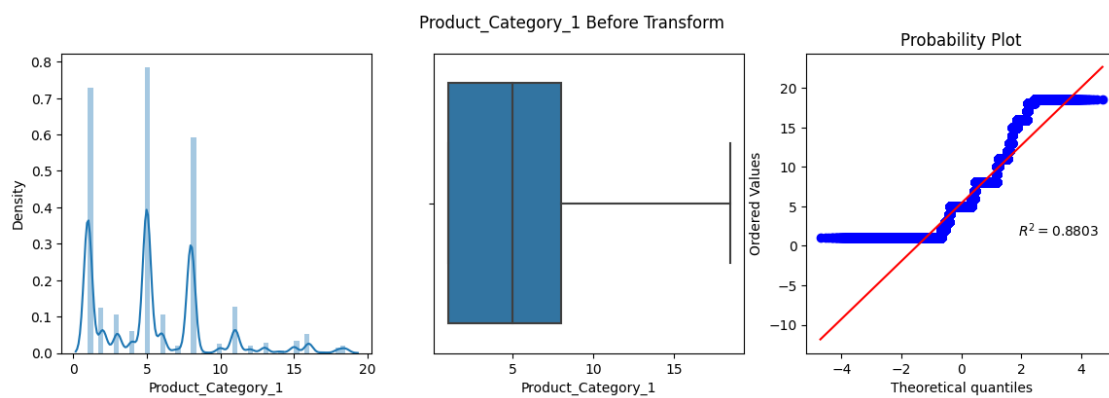
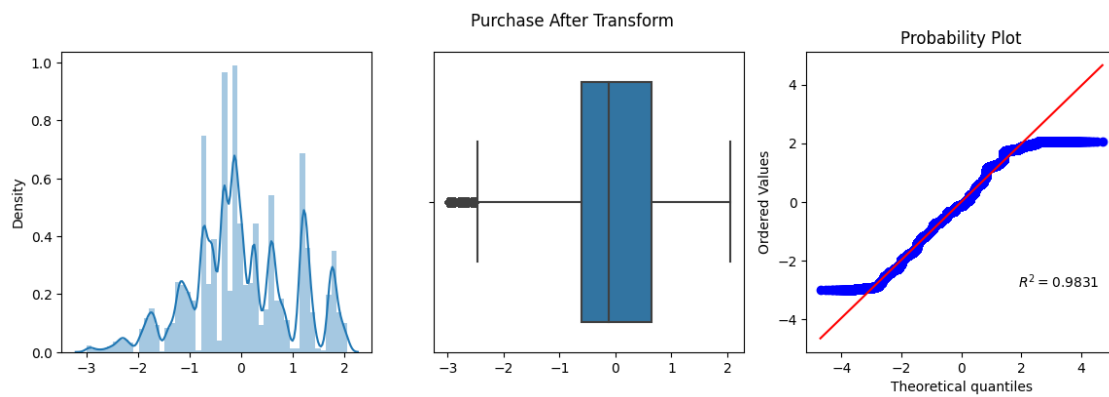
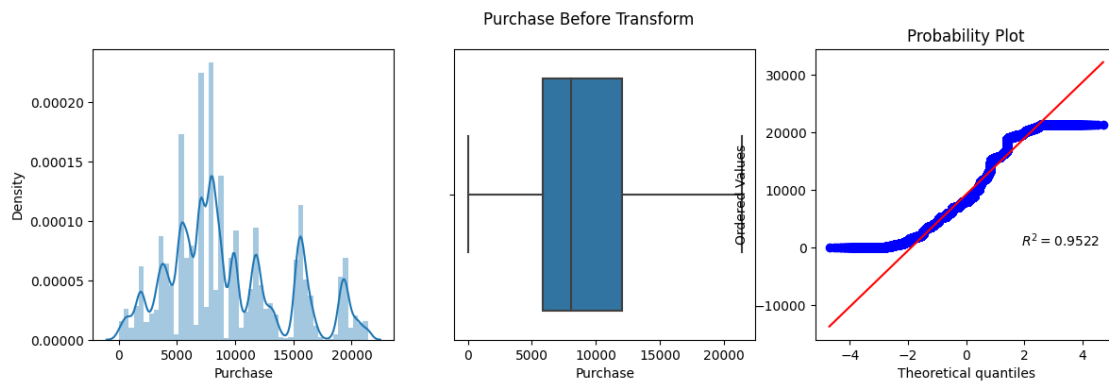


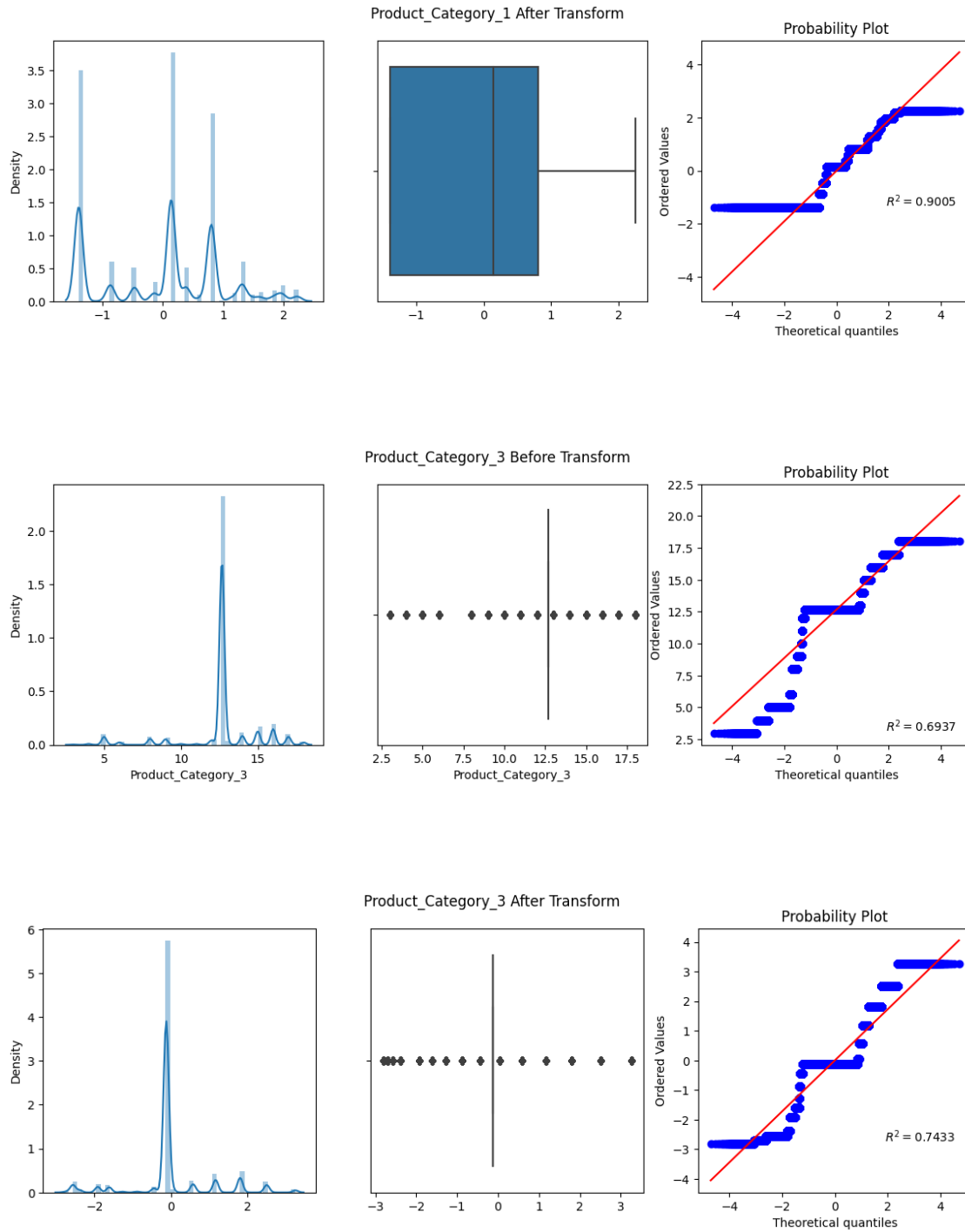


```
[28]: # Applying Yeo-Johnson Transform
skewed_cols = ['Purchase', 'Product_Category_1', 'Product_Category_3']

for col in skewed_cols:
```

```
apply_transform(PowerTransformer(),col)
```





Power Transform (Box-Cox): `Product_Category_3` Power Transform (Yeo-Johnson): `Purchase`
 Log Transform: `None` Reciprocal Transform: `None` Square Transform: `None` Sqrt Transform: `Product_Category_1`

```

[29]: pt = PowerTransformer()
      train.Purchase = pt.fit_transform(train[['Purchase']])

[30]: st = FunctionTransformer(np.sqrt)
      train.Product_Category_1 = st.fit_transform(train[['Product_Category_1']])

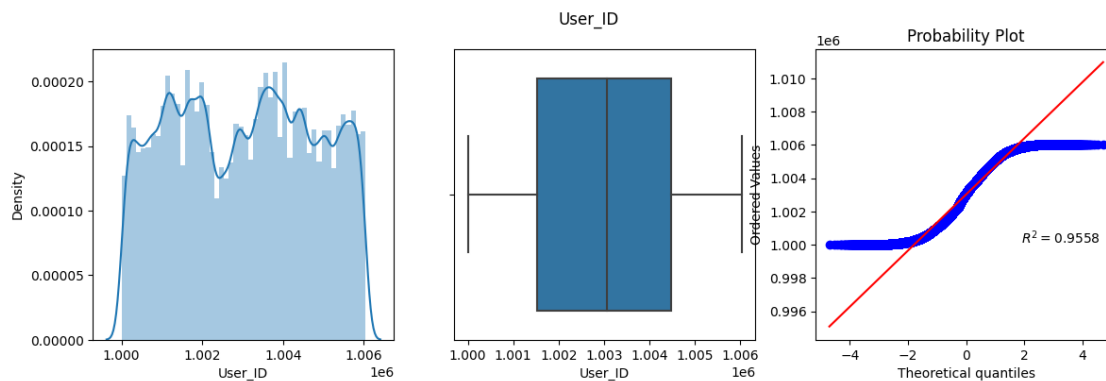
[31]: box_cox_transform = PowerTransformer(method='box-cox')
      train.Product_Category_3 = box_cox_transform.
      ↪fit_transform(train[['Product_Category_3']])

[32]: for col in train.select_dtypes(np.number):
      print("Skewness:".format(col),train[col].skew())
      print("Kurtosis:".format(col),train[col].kurtosis())
      plt.figure(figsize=(14,4))
      plt.subplot(131)
      sns.distplot(train[col])
      plt.subplot(132)
      sns.boxplot(train[col])
      plt.subplot(133)
      probplot(train[col],rvalue=True,plot=plt)
      plt.suptitle(col)
      plt.show();

```

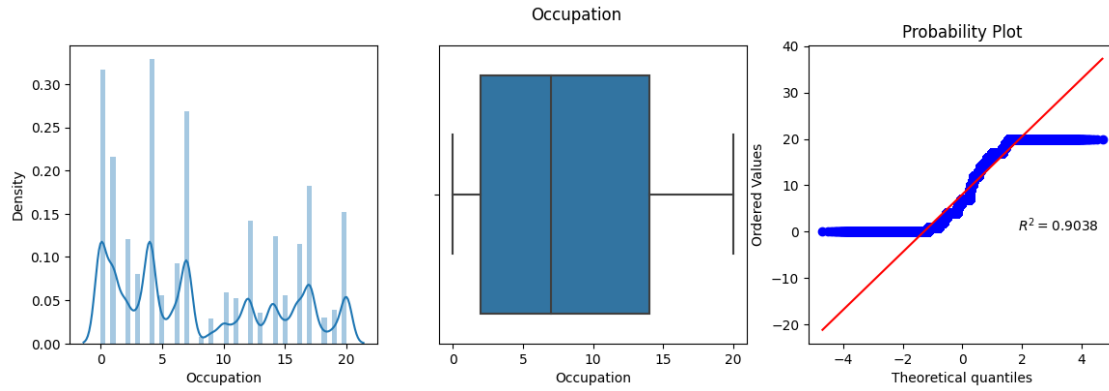
Skewness: 0.0030655518513462644

Kurtosis: -1.1955007812357379

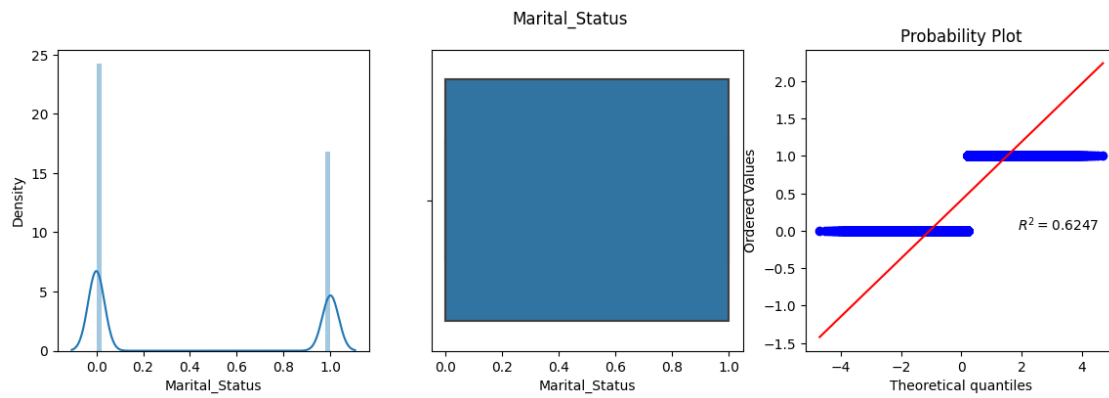


Skewness: 0.40014010986184784

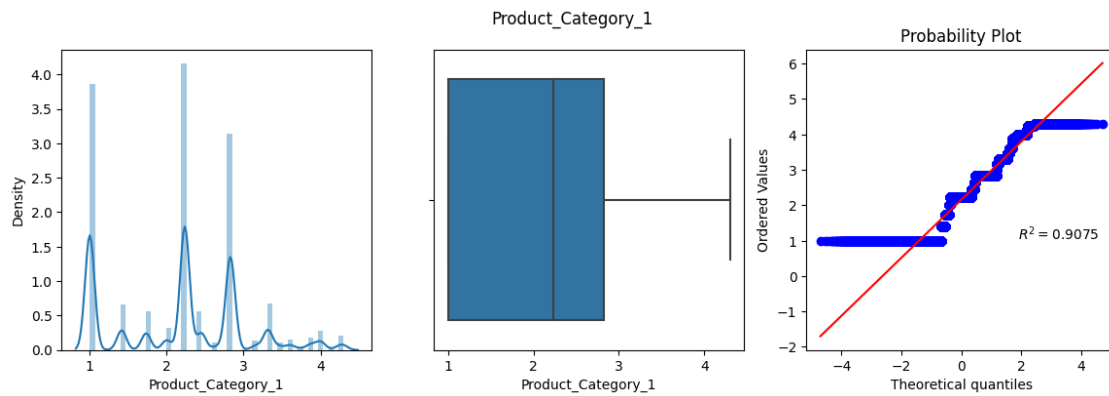
Kurtosis: -1.21611364874086



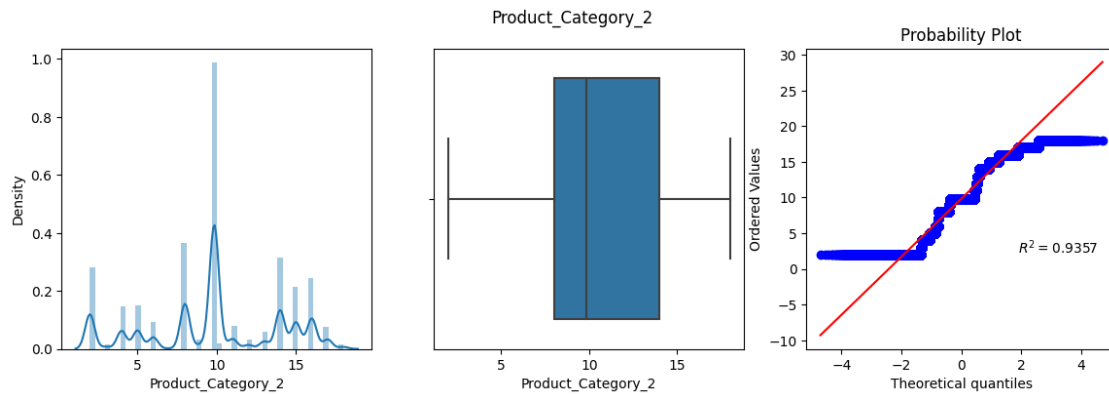
Skewness: 0.3674372854404167
Kurtosis: -1.8649966222489232



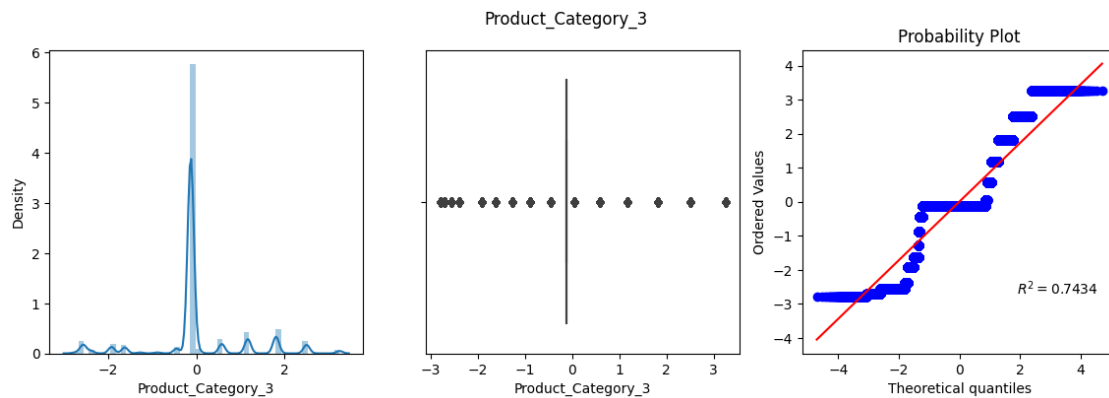
Skewness: 0.13674486545923803
Kurtosis: -0.6728419506381202



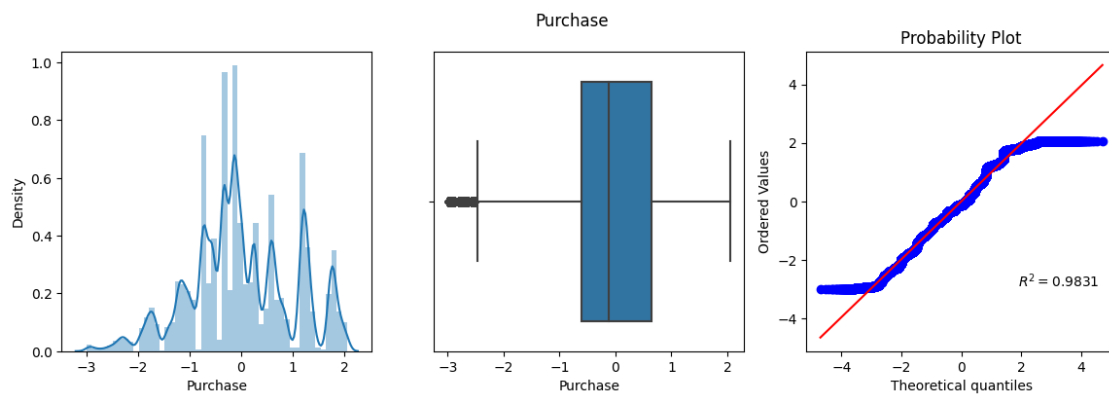
Skewness: -0.19674654415192747
Kurtosis: -0.7091007945191348



Skewness: 0.2200486348089301
Kurtosis: 2.1892090657986714



Skewness: -0.03376206852197367
Kurtosis: -0.2756737456256291



0.5.4 Categorical Encoding

Ordinal Encoding the features with only a few categories

```
[33]: train.Product_ID.nunique() / len(train)

[33]: 0.006601002057927383

[34]: train.Age.unique()

[34]: array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
          dtype=object)

[35]: age_encoder = OrdinalEncoder(categories=[['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']])
      train.Age = age_encoder.fit_transform(train[['Age']])

[36]: train.Age = train.Age.astype(int)

[37]: train.City_Category.unique()

[37]: array(['A', 'C', 'B'], dtype=object)

[38]: city_category_encoder = OrdinalEncoder(categories=[['A', 'B', 'C']])
      train.City_Category = city_category_encoder.
      ↪fit_transform(train[['City_Category']])

[39]: train.City_Category = train.City_Category.astype(int)

[40]: train.Stay_In_Current_City_Years.unique()

[40]: array(['2', '4+', '3', '1', '0'], dtype=object)

[41]: city_stay_years_encoder = OrdinalEncoder(categories=[['0', '1', '2', '3', '4+']])
      train.Stay_In_Current_City_Years = city_stay_years_encoder.
      ↪fit_transform(train[['Stay_In_Current_City_Years']])

[42]: train.Stay_In_Current_City_Years = train.Stay_In_Current_City_Years.astype(int)

[43]: gender_encoder = OrdinalEncoder(categories=[['F', 'M']])
      train.Gender = gender_encoder.fit_transform(train[['Gender']])
      train.Gender = train.Gender.astype(int)
```

One Hot Encoding Product_ID feature with high cardinality

```
[44]: product_id_cnts = train.Product_ID.value_counts()
      product_id_cnts
```

```
[44]: P00265242    1880
      P00025442    1615
      P00110742    1612
      P00112142    1562
      P00057642    1470
      ...
      P00314842     1
      P00298842     1
      P00231642     1
      P00204442     1
      P00066342     1
      Name: Product_ID, Length: 3631, dtype: int64
```

```
[45]: threshold = 1000
      remaining_categories = product_id_cnts[product_id_cnts <= threshold].index
      product_ids_data = pd.get_dummies(train.Product_ID,
      ↪replace(remaining_categories, 'Others'),drop_first=True,sparse=False)
      train = pd.concat([train,product_ids_data],axis=1)
      train.head()
```

```
[45]:   User_ID Product_ID Gender Age Occupation City_Category \
0  1000001  P00069042     0   0         10             0
1  1000001  P00248942     0   0         10             0
2  1000001  P00087842     0   0         10             0
3  1000001  P00085442     0   0         10             0
4  1000002  P00285442     1   6         16             2

      Stay_In_Current_City_Years  Marital_Status  Product_Category_1 \
0                               2                0             1.732051
1                               2                0             1.000000
2                               2                0             3.464102
3                               2                0             3.464102
4                               4                0             2.828427

      Product_Category_2  ... P00184942  P00220442  P00237542  P00242742 \
0          9.842329  ...          0          0          0          0
1          6.000000  ...          0          0          0          0
2          9.842329  ...          0          0          0          0
3         14.000000  ...          0          0          0          0
4          9.842329  ...          0          0          0          0

      P00251242  P00255842  P00265242  P00270942  P00278642  P00334242
0              0          0          0          0          0          0
1              0          0          0          0          0          0
2              0          0          0          0          0          0
3              0          0          0          0          0          0
4              0          0          0          0          0          0
```


[5 rows x 47 columns]

```
[46]: train.drop('Product_ID',axis=1,inplace=True)
```

```
[47]: train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 46 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   User_ID                              550068 non-null  int64
1   Gender                               550068 non-null  int32
2   Age                                  550068 non-null  int32
3   Occupation                           550068 non-null  int64
4   City_Category                        550068 non-null  int32
5   Stay_In_Current_City_Years          550068 non-null  int32
6   Marital_Status                       550068 non-null  int64
7   Product_Category_1                   550068 non-null  float64
8   Product_Category_2                   550068 non-null  float64
9   Product_Category_3                   550068 non-null  float64
10  Purchase                             550068 non-null  float64
11  P00000142                            550068 non-null  uint8
12  P00010742                            550068 non-null  uint8
13  P00025442                            550068 non-null  uint8
14  P00028842                            550068 non-null  uint8
15  P00031042                            550068 non-null  uint8
16  P00034742                            550068 non-null  uint8
17  P00044442                            550068 non-null  uint8
18  P00046742                            550068 non-null  uint8
19  P00051442                            550068 non-null  uint8
20  P00057642                            550068 non-null  uint8
21  P00058042                            550068 non-null  uint8
22  P00059442                            550068 non-null  uint8
23  P00080342                            550068 non-null  uint8
24  P00102642                            550068 non-null  uint8
25  P00110742                            550068 non-null  uint8
26  P00110842                            550068 non-null  uint8
27  P00110942                            550068 non-null  uint8
28  P00111142                            550068 non-null  uint8
29  P00112142                            550068 non-null  uint8
30  P00112542                            550068 non-null  uint8
31  P00114942                            550068 non-null  uint8
32  P00117442                            550068 non-null  uint8
33  P00117942                            550068 non-null  uint8
34  P00145042                            550068 non-null  uint8
35  P00148642                            550068 non-null  uint8
```

```

36 P00184942          550068 non-null uint8
37 P00220442          550068 non-null uint8
38 P00237542          550068 non-null uint8
39 P00242742          550068 non-null uint8
40 P00251242          550068 non-null uint8
41 P00255842          550068 non-null uint8
42 P00265242          550068 non-null uint8
43 P00270942          550068 non-null uint8
44 P00278642          550068 non-null uint8
45 P00334242          550068 non-null uint8
dtypes: float64(4), int32(4), int64(3), uint8(35)
memory usage: 56.1 MB

```

0.5.5 Feature Splitting

```
[48]: X = train.drop('Purchase',axis=1)
      y = train.Purchase
```

```
[49]: X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.
      ↪3,random_state=101,shuffle=True)
```

0.5.6 Feature Selection

```
[50]: kbest = SelectKBest(score_func=f_regression,k=10)
      kbest.fit(X_train,y_train)
```

```
[50]: SelectKBest(score_func=<function f_regression at 0x000002D653D63B50>)
```

```
[51]: selected_features = kbest.get_feature_names_out()
      selected_features
```

```
[51]: array(['Product_Category_1', 'Product_Category_2', 'P00025442',
      'P00059442', 'P00102642', 'P00110742', 'P00110942', 'P00184942',
      'P00237542', 'P00255842'], dtype=object)
```

```
[52]: percentile = SelectPercentile(score_func=r_regression,percentile=25)
      percentile.fit(X_train,y_train)
```

```
[52]: SelectPercentile(percentile=25,
      score_func=<function r_regression at 0x000002D653D63AC0>)
```

```
[53]: selected_features = percentile.get_feature_names_out()
      selected_features
```

```
[53]: array(['P00025442', 'P00028842', 'P00059442', 'P00080342', 'P00110742',
      'P00110842', 'P00110942', 'P00148642', 'P00184942', 'P00237542',
      'P00255842'], dtype=object)
```

```
[54]: sfm = SelectFromModel(estimator=Lasso(),max_features=10,threshold='median')
      sfm.fit(X_train,y_train)
```

```
[54]: SelectFromModel(estimator=Lasso(), max_features=10, threshold='median')
```

```
[55]: selected_features = sfm.get_feature_names_out()
      selected_features
```

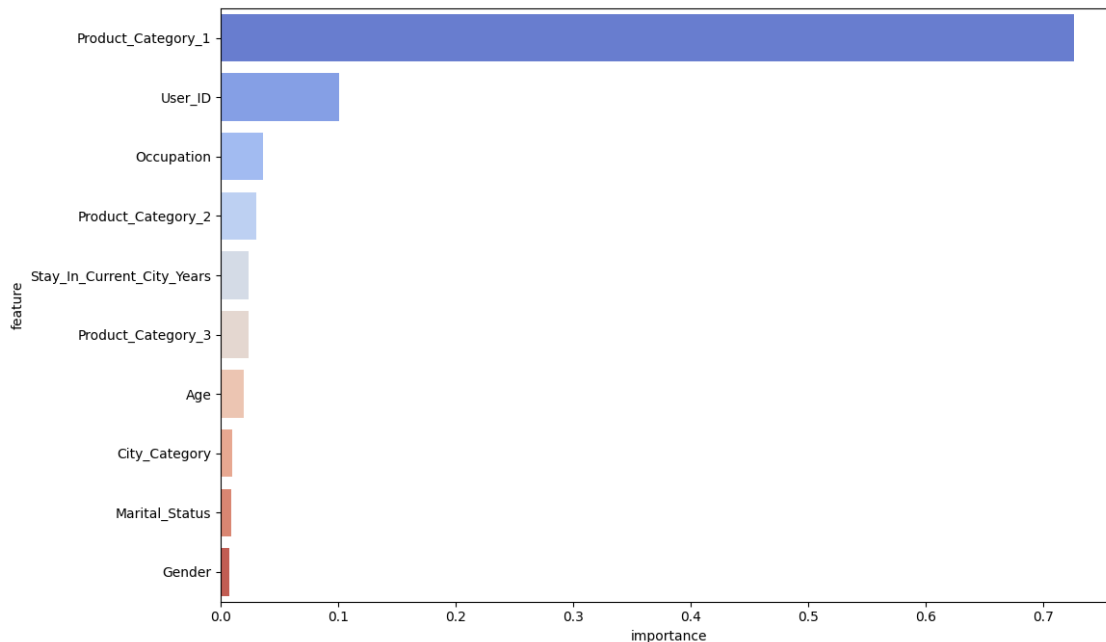
```
[55]: array(['User_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
        'Stay_In_Current_City_Years', 'Marital_Status',
        'Product_Category_1', 'Product_Category_2', 'Product_Category_3'],
      dtype=object)
```

```
[56]: rf = RandomForestRegressor()
      rf.fit(X_train,y_train)
```

```
[56]: RandomForestRegressor()
```

```
[57]: featimps = pd.DataFrame({'feature': X_train.columns, 'importance': rf.
      ↪feature_importances_}).sort_values('importance',ascending=False).
      ↪reset_index()
      sns.barplot(x='importance',y='feature',data=featimps[:
      ↪10],palette='coolwarm',orient='horizontal')
      plt.title('Top 10 Most Significant_
      ↪Features',fontsize=32,fontweight='bold',color='crimson',pad=20);
```

Top 10 Most Significant Features



```
[58]: rfe = <sklearn.feature_selection.RFE object at 0x0000000000000000>
      ↪ RFE(estimator=DecisionTreeRegressor(), n_features_to_select=10, step=2, verbose=1)
      rfe.fit(X_train, y_train)
```

```
Fitting estimator with 45 features.
Fitting estimator with 43 features.
Fitting estimator with 41 features.
Fitting estimator with 39 features.
Fitting estimator with 37 features.
Fitting estimator with 35 features.
Fitting estimator with 33 features.
Fitting estimator with 31 features.
Fitting estimator with 29 features.
Fitting estimator with 27 features.
Fitting estimator with 25 features.
Fitting estimator with 23 features.
Fitting estimator with 21 features.
Fitting estimator with 19 features.
Fitting estimator with 17 features.
Fitting estimator with 15 features.
Fitting estimator with 13 features.
Fitting estimator with 11 features.
```

```
[58]: RFE(estimator=DecisionTreeRegressor(), n_features_to_select=10, step=2,
          verbose=1)
```

```
[59]: selected_features = rfe.get_feature_names_out()
      selected_features
```

```
[59]: array(['User_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
            'Stay_In_Current_City_Years', 'Marital_Status',
            'Product_Category_1', 'Product_Category_2', 'Product_Category_3'],
          dtype=object)
```

Final selected features: User_ID, Gender, Product_Category_1, Product_Category_2, Product_Category_3, Occupation, Age, Stay_In_Current_City_Years, City_Category, Marital_Status

```
[60]: # Saving the original train and test sets with all features
      X_train_orig = X_train
      X_test_orig = X_test
```

```
[61]: selected_features = <list of str>
      ↪ ['User_ID', 'Gender', 'Product_Category_1', 'Product_Category_2', 'Product_Category_3', 'Occupat
      X_train = X_train[selected_features]
      X_test = X_test[selected_features]
```

0.5.7 Feature Scaling and Normalization

```
[62]: scaler = StandardScaler()
features = X_train.columns
X_train = scaler.fit_transform(X_train)
X_train = pd.DataFrame(X_train, columns=features)
X_test = scaler.transform(X_test)
X_test = pd.DataFrame(X_test, columns=features)
X_train.head()
```

```
[62]:      User_ID    Gender  Product_Category_1  Product_Category_2  \
0 -1.150879  0.572005         0.089372         -0.438020
1  0.665463  0.572005        -1.346979         -0.913589
2  1.694356  0.572005        -1.346979         0.275334
3  1.393852  0.572005        -1.346979         -0.438020
4  1.670038  0.572005        -1.346979         -0.913589

      Product_Category_3  Occupation      Age  Stay_In_Current_City_Years  \
0         -0.123780     0.448026 -0.366457             -0.665696
1          1.811159     1.368064  0.372141              0.110560
2          1.170506     0.448026  1.110739              0.110560
3          2.504494     1.521403  1.110739              1.663072
4          1.170506    -1.085370 -0.366457              0.110560

      City_Category  Marital_Status
0          1.259217          1.201445
1          1.259217         -0.832331
2         -1.372375          1.201445
3          1.259217         -0.832331
4          1.259217         -0.832331
```

```
[63]: X_test.head()
```

```
[63]:      User_ID    Gender  Product_Category_1  Product_Category_2  \
0  0.403173  0.572005         0.777712         1.702042
1  0.833375 -1.748236         0.777712         0.988688
2 -1.230203  0.572005         1.345013         1.464257
3 -0.539449 -1.748236         0.089372         0.988688
4 -1.546919  0.572005         0.777712         1.464257

      Product_Category_3  Occupation      Age  Stay_In_Current_City_Years  \
0         -0.12378    -0.318672  0.372141             1.663072
1         -0.12378    -0.318672  1.849336              0.110560
2         -0.12378     0.754705  2.587934              0.110560
3         -0.12378     1.368064 -0.366457             -0.665696
4         -0.12378     1.828083  2.587934             -1.441953

      City_Category  Marital_Status
```

0	-0.056579	-0.832331
1	1.259217	1.201445
2	1.259217	1.201445
3	1.259217	1.201445
4	1.259217	1.201445

0.6 Model Training and Evaluation

```
[64]: models = []
      mape_scores = []
      rmse_scores = []
      r2_scores = []
```

```
[65]: def train_and_evaluate_model(model):
      model.fit(X_train,y_train)
      y_pred = model.predict(X_test)
      mape = mean_absolute_percentage_error(y_test,y_pred)
      print("Mean Absolute Percentage Error:",mape)
      mape_scores.append(mape)
      rmse = np.sqrt(mean_squared_error(y_test,y_pred))
      print("Root Mean Squared Error:",rmse)
      rmse_scores.append(rmse)
      r2 = r2_score(y_test,y_pred)
      print("R2 Score:",r2)
      r2_scores.append(r2)
      models.append(str(model))
```

```
[66]: train_and_evaluate_model(LinearRegression())
```

```
Mean Absolute Percentage Error: 2.8234008250550833
Root Mean Squared Error: 0.892663406287973
R2 Score: 0.20032474031957914
```

```
[67]: train_and_evaluate_model(PassiveAggressiveRegressor())
```

```
Mean Absolute Percentage Error: 14.310156538727036
Root Mean Squared Error: 1.3983747386520378
R2 Score: -0.9623900646180061
```

```
[68]: train_and_evaluate_model(LassoCV())
```

```
Mean Absolute Percentage Error: 2.812867333547169
Root Mean Squared Error: 0.892664185594689
R2 Score: 0.20032334406525076
```

```
[69]: train_and_evaluate_model(RidgeCV())
```

```
Mean Absolute Percentage Error: 2.8233581573545994
Root Mean Squared Error: 0.8926634055078709
```

R2 Score: 0.2003247417172579

[70]: `train_and_evaluate_model(ElasticNetCV())`

Mean Absolute Percentage Error: 2.8121501826077413

Root Mean Squared Error: 0.8926642822761707

R2 Score: 0.2003231708446166

[71]: `train_and_evaluate_model(SGDRegressor())`

Mean Absolute Percentage Error: 2.7202018625514937

Root Mean Squared Error: 0.8931740126472111

R2 Score: 0.19940964499918323

[72]: `train_and_evaluate_model(ARDRegression())`

Mean Absolute Percentage Error: 2.8297385560973485

Root Mean Squared Error: 0.8927136736891901

R2 Score: 0.20023467562411568

[73]: `train_and_evaluate_model(RANSACRegressor())`

Mean Absolute Percentage Error: 11.936712173922304

Root Mean Squared Error: 1.245035838215126

R2 Score: -0.5556142114505327

[74]: `train_and_evaluate_model(TweedieRegressor())`

Mean Absolute Percentage Error: 2.0143316242632388

Root Mean Squared Error: 0.9181377683924193

R2 Score: 0.1540320647972323

[75]: `train_and_evaluate_model(HuberRegressor())`

Mean Absolute Percentage Error: 3.325187379446081

Root Mean Squared Error: 0.8998930716525829

R2 Score: 0.1873191748327313

[76]: `train_and_evaluate_model(KNeighborsRegressor())`

Mean Absolute Percentage Error: 8.719461644697752

Root Mean Squared Error: 0.7662208462255327

R2 Score: 0.4108225404184672

[77]: `train_and_evaluate_model(LinearSVR())`

Mean Absolute Percentage Error: 3.8023761824714395

Root Mean Squared Error: 0.8991850291168946

R2 Score: 0.18859751831781946

[78]: `train_and_evaluate_model(DecisionTreeRegressor())`

Mean Absolute Percentage Error: 8.496325234246056
Root Mean Squared Error: 0.6688305545412612
R2 Score: 0.5510784987847512

[79]: `train_and_evaluate_model(RandomForestRegressor())`

Mean Absolute Percentage Error: 8.446763523066489
Root Mean Squared Error: 0.5767442604473769
R2 Score: 0.6661858368303517

[80]: `train_and_evaluate_model(BaggingRegressor())`

Mean Absolute Percentage Error: 8.594595292246996
Root Mean Squared Error: 0.5886268374012141
R2 Score: 0.6522890922558543

[81]: `train_and_evaluate_model(AdaBoostRegressor())`

Mean Absolute Percentage Error: 11.01367780559405
Root Mean Squared Error: 0.6927129761062139
R2 Score: 0.5184461685271473

[82]: `train_and_evaluate_model(GradientBoostingRegressor())`

Mean Absolute Percentage Error: 10.125410208044876
Root Mean Squared Error: 0.5793988118363351
R2 Score: 0.6631059063418037

[83]: `train_and_evaluate_model(HistGradientBoostingRegressor())`

Mean Absolute Percentage Error: 9.876981695725544
Root Mean Squared Error: 0.5616787976630642
R2 Score: 0.6833975601880338

[84]: `train_and_evaluate_model(ExtraTreesRegressor())`

Mean Absolute Percentage Error: 8.372041827291929
Root Mean Squared Error: 0.6093903320447405
R2 Score: 0.627325809902322

[85]: `train_and_evaluate_model(XGBRegressor())`

Mean Absolute Percentage Error: 9.51036370349967
Root Mean Squared Error: 0.5457647134984077
R2 Score: 0.7010840411107506

[86]: `train_and_evaluate_model(MLPRegressor())`

Mean Absolute Percentage Error: 9.539762827939755
Root Mean Squared Error: 0.5833922163030351
R2 Score: 0.6584459358340025


```
[87]: train_and_evaluate_model(CatBoostRegressor(silent=True))
```

```
Mean Absolute Percentage Error: 9.56680928275904
Root Mean Squared Error: 0.5476492163446818
R2 Score: 0.6990161884230746
```

```
[88]: train_and_evaluate_model(LGBMRegressor())
```

```
Mean Absolute Percentage Error: 9.851481978998917
Root Mean Squared Error: 0.561846711372876
R2 Score: 0.6832082354822013
```

```
[89]: train_and_evaluate_model(VotingRegressor([
    ('XGB',XGBRegressor()),
    ('HIST',HistGradientBoostingRegressor()),
    ('GB',GradientBoostingRegressor()),
    ('LGBM',LGBMRegressor()),
    ('CAT',CatBoostRegressor(silent=True))
]))
```

```
Mean Absolute Percentage Error: 9.77223625121511
Root Mean Squared Error: 0.5558328621173839
R2 Score: 0.6899536407626163
```

0.7 Baseline Models Performance Comparison

```
[90]: model_perfs = pd.DataFrame({'Model': models, 'MAPE': mape_scores, 'RMSE': rmse_scores, 'R2': r2_scores}).sort_values('R2',ascending=False).
    reset_index()
model_perfs
```

```
[90]:
```

	index	Model	MAPE \
0	19	XGBRegressor(base_score=None, booster=None, ca...	9.510364
1	21	<catboost.core.CatBoostRegressor object at 0x0...	9.566809
2	23	VotingRegressor(estimators=[('XGB',\n ...	9.772236
3	17	HistGradientBoostingRegressor()	9.876982
4	22	LGBMRegressor()	9.851482
5	13	RandomForestRegressor()	8.446764
6	16	GradientBoostingRegressor()	10.125410
7	20	MLPRegressor()	9.539763
8	14	BaggingRegressor()	8.594595
9	18	ExtraTreesRegressor()	8.372042
10	12	DecisionTreeRegressor()	8.496325
11	15	AdaBoostRegressor()	11.013678
12	10	KNeighborsRegressor()	8.719462
13	3	RidgeCV()	2.823358
14	0	LinearRegression()	2.823401
15	2	LassoCV()	2.812867
16	4	ElasticNetCV()	2.812150

17	6	ARDRegression()	2.829739
18	5	SGDRegressor()	2.720202
19	11	LinearSVR()	3.802376
20	9	HuberRegressor()	3.325187
21	8	TweedieRegressor()	2.014332
22	7	RANSACRegressor()	11.936712
23	1	PassiveAggressiveRegressor()	14.310157

	RMSE	R2
0	0.545765	0.701084
1	0.547649	0.699016
2	0.555833	0.689954
3	0.561679	0.683398
4	0.561847	0.683208
5	0.576744	0.666186
6	0.579399	0.663106
7	0.583392	0.658446
8	0.588627	0.652289
9	0.609390	0.627326
10	0.668831	0.551078
11	0.692713	0.518446
12	0.766221	0.410823
13	0.892663	0.200325
14	0.892663	0.200325
15	0.892664	0.200323
16	0.892664	0.200323
17	0.892714	0.200235
18	0.893174	0.199410
19	0.899185	0.188598
20	0.899893	0.187319
21	0.918138	0.154032
22	1.245036	-0.555614
23	1.398375	-0.962390

Among the baseline models, the XGBoost Regressor has produced the best performance by achieving a decent r2 score of more than 70%. It is closely followed by the Cat Boost Regressor which obtained an r2 score of nearly 70%.

0.8 Hyperparameter Optimization and Cross Validation

```
[91]: 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=5,verbose=2)
train_and_evaluate_model(grid_knn)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```

[CV] END algorithm=ball_tree, metric=manhattan, n_neighbors=8, weights=uniform;
total time= 2.5min
[CV] END algorithm=ball_tree, metric=manhattan, n_neighbors=8, weights=uniform;
total time= 2.4min
[CV] END algorithm=ball_tree, metric=manhattan, n_neighbors=8, weights=uniform;
total time= 2.5min
[CV] END algorithm=ball_tree, metric=manhattan, n_neighbors=8, weights=uniform;
total time= 2.3min
[CV] END algorithm=ball_tree, metric=manhattan, n_neighbors=8, weights=uniform;
total time= 2.3min
[CV] END algorithm=brute, metric=euclidean, n_neighbors=20, weights=distance;
total time= 0.6s
[CV] END algorithm=brute, metric=euclidean, n_neighbors=20, weights=distance;
total time= 0.0s
[CV] END algorithm=brute, metric=euclidean, n_neighbors=20, weights=distance;
total time= 0.0s
[CV] END algorithm=brute, metric=euclidean, n_neighbors=20, weights=distance;
total time= 0.0s
[CV] END algorithm=brute, metric=euclidean, n_neighbors=20, weights=distance;
total time= 0.0s
[CV] END algorithm=kd_tree, metric=chebyshev, n_neighbors=5, weights=distance;
total time= 32.5s
[CV] END algorithm=kd_tree, metric=chebyshev, n_neighbors=5, weights=distance;
total time= 33.0s
[CV] END algorithm=kd_tree, metric=chebyshev, n_neighbors=5, weights=distance;
total time= 32.3s
[CV] END algorithm=kd_tree, metric=chebyshev, n_neighbors=5, weights=distance;
total time= 32.5s
[CV] END algorithm=kd_tree, metric=chebyshev, n_neighbors=5, weights=distance;
total time= 32.0s
[CV] END algorithm=ball_tree, metric=chebyshev, n_neighbors=8, weights=uniform;
total time=10.2min
[CV] END algorithm=ball_tree, metric=chebyshev, n_neighbors=8, weights=uniform;
total time=10.2min
[CV] END algorithm=ball_tree, metric=chebyshev, n_neighbors=8, weights=uniform;
total time=10.2min
[CV] END algorithm=ball_tree, metric=chebyshev, n_neighbors=8, weights=uniform;
total time=10.2min
[CV] END algorithm=ball_tree, metric=chebyshev, n_neighbors=8, weights=uniform;
total time=12.3min
[CV] END algorithm=brute, metric=manhattan, n_neighbors=20, weights=uniform;
total time= 0.0s
[CV] END algorithm=brute, metric=manhattan, n_neighbors=20, weights=uniform;
total time= 0.0s
[CV] END algorithm=brute, metric=manhattan, n_neighbors=20, weights=uniform;
total time= 0.0s
[CV] END algorithm=brute, metric=manhattan, n_neighbors=20, weights=uniform;

```

```

total time= 0.0s
[CV] END algorithm=brute, metric=manhattan, n_neighbors=20, weights=uniform;
total time= 0.0s
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=12, weights=uniform;
total time= 5.8min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=12, weights=uniform;
total time= 4.2min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=12, weights=uniform;
total time= 4.1min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=12, weights=uniform;
total time= 4.1min
[CV] END algorithm=brute, metric=chebyshev, n_neighbors=8, weights=distance;
total time= 0.0s
[CV] END algorithm=brute, metric=chebyshev, n_neighbors=8, weights=distance;
total time= 0.0s
[CV] END algorithm=brute, metric=chebyshev, n_neighbors=8, weights=distance;
total time= 0.0s
[CV] END algorithm=brute, metric=chebyshev, n_neighbors=8, weights=distance;
total time= 0.0s
[CV] END algorithm=brute, metric=chebyshev, n_neighbors=8, weights=distance;
total time= 0.0s
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=2, weights=uniform;
total time= 2.6min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=2, weights=uniform;
total time= 2.6min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=2, weights=uniform;
total time= 2.6min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=2, weights=uniform;
total time= 2.6min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=2, weights=uniform;
total time= 2.6min
[CV] END algorithm=kd_tree, metric=minkowski, n_neighbors=12, weights=distance;
total time= 26.3s
[CV] END algorithm=kd_tree, metric=minkowski, n_neighbors=12, weights=distance;
total time= 26.5s
[CV] END algorithm=kd_tree, metric=minkowski, n_neighbors=12, weights=distance;
total time= 26.4s
[CV] END algorithm=kd_tree, metric=minkowski, n_neighbors=12, weights=distance;
total time= 25.9s
[CV] END algorithm=kd_tree, metric=minkowski, n_neighbors=12, weights=distance;
total time= 27.5s
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=8, weights=uniform;
total time= 3.7min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=8, weights=uniform;
total time= 3.6min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=8, weights=uniform;

```

```

total time= 3.6min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=8, weights=uniform;
total time= 3.6min
[CV] END algorithm=ball_tree, metric=euclidean, n_neighbors=8, weights=uniform;
total time= 3.6min
Mean Absolute Percentage Error: 8.127303527261052
Root Mean Squared Error: 0.7344649448280902
R2 Score: 0.4586472577584031

```

```
[92]: grid_knn.best_params_
```

```
[92]: {'weights': 'distance',
      'n_neighbors': 12,
      'metric': 'minkowski',
      'algorithm': 'kd_tree'}
```

```
[93]: param_grid = {'learning_rate': [0.2,0.4,0.5,0.8,1.0],
                  'loss': ['squared_error','absolute_error','poisson','quantile'],
                  'max_bins': np.arange(0,255,50),
                  'interaction_cst': ['pairwise','no_interaction']}

grid_hgb =
↳ RandomizedSearchCV(HistGradientBoostingRegressor(),param_grid,cv=5,verbose=2)
train_and_evaluate_model(grid_hgb)
```

```

Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END interaction_cst=pairwise, learning_rate=1.0, loss=absolute_error,
max_bins=100; total time= 2.8s
[CV] END interaction_cst=pairwise, learning_rate=1.0, loss=absolute_error,
max_bins=100; total time= 1.9s
[CV] END interaction_cst=pairwise, learning_rate=1.0, loss=absolute_error,
max_bins=100; total time= 2.7s
[CV] END interaction_cst=pairwise, learning_rate=1.0, loss=absolute_error,
max_bins=100; total time= 2.7s
[CV] END interaction_cst=pairwise, learning_rate=1.0, loss=absolute_error,
max_bins=100; total time= 3.4s
[CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=squared_error,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=squared_error,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=squared_error,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.5, loss=squared_error,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.2, loss=squared_error,
max_bins=250; total time= 0.0s

```

[illegible]

```

[CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=absolute_error,
max_bins=50; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=absolute_error,
max_bins=50; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=absolute_error,
max_bins=50; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=absolute_error,
max_bins=50; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=1.0, loss=absolute_error,
max_bins=50; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.4, loss=quantile,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.4, loss=quantile,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.4, loss=quantile,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.4, loss=quantile,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=no_interaction, learning_rate=0.4, loss=quantile,
max_bins=100; total time= 0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.5, loss=poisson,
max_bins=200; total time= 0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.5, loss=poisson,
max_bins=200; total time= 0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.5, loss=poisson,
max_bins=200; total time= 0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.5, loss=poisson,
max_bins=200; total time= 0.0s
[CV] END interaction_cst=pairwise, learning_rate=0.5, loss=poisson,
max_bins=200; total time= 0.0s
Mean Absolute Percentage Error: 8.077690119738152
Root Mean Squared Error: 0.5717884864685593
R2 Score: 0.6718979008972392

```

```
[94]: grid_hgb.best_params_
```

```
[94]: {'max_bins': 100,
      'loss': 'absolute_error',
      'learning_rate': 1.0,
      'interaction_cst': 'pairwise'}
```

```
[95]: 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_lsrv = RandomizedSearchCV(LinearSVR(), param_grid, cv=5, verbose=2)
train_and_evaluate_model(grid_lsrv)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```

[CV] END C=0.001, epsilon=0.25075, loss=squared_epsilon_insensitive; total time=
0.7s
[CV] END C=0.001, epsilon=0.25075, loss=squared_epsilon_insensitive; total time=
0.8s
[CV] END C=0.001, epsilon=0.25075, loss=squared_epsilon_insensitive; total time=
0.7s
[CV] END C=0.001, epsilon=0.25075, loss=squared_epsilon_insensitive; total time=
0.7s
[CV] END C=0.001, epsilon=0.25075, loss=squared_epsilon_insensitive; total time=
0.7s
[CV] END C=0.1, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
1.8s
[CV] END C=0.1, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
1.7s
[CV] END C=0.1, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
1.8s
[CV] END C=0.1, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
1.8s
[CV] END C=0.1, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
1.7s
[CV] END ...C=0.01, epsilon=0.5005, loss=epsilon_insensitive; total time=    0.6s
[CV] END ...C=0.01, epsilon=0.5005, loss=epsilon_insensitive; total time=    0.6s
[CV] END ...C=0.01, epsilon=0.5005, loss=epsilon_insensitive; total time=    0.7s
[CV] END ...C=0.01, epsilon=0.5005, loss=epsilon_insensitive; total time=    0.6s
[CV] END ...C=0.01, epsilon=0.5005, loss=epsilon_insensitive; total time=    0.6s
[CV] END ...C=1, epsilon=0.75025, loss=epsilon_insensitive; total time=   13.5s
[CV] END ...C=1, epsilon=0.75025, loss=epsilon_insensitive; total time=   13.3s
[CV] END ...C=1, epsilon=0.75025, loss=epsilon_insensitive; total time=   13.4s
[CV] END ...C=1, epsilon=0.75025, loss=epsilon_insensitive; total time=   13.6s
[CV] END ...C=1, epsilon=0.75025, loss=epsilon_insensitive; total time=   13.9s
[CV] END C=1, epsilon=0.001, loss=squared_epsilon_insensitive; total time=
29.5s
[CV] END C=1, epsilon=0.001, loss=squared_epsilon_insensitive; total time=
30.4s
[CV] END C=1, epsilon=0.001, loss=squared_epsilon_insensitive; total time=
29.5s
[CV] END C=1, epsilon=0.001, loss=squared_epsilon_insensitive; total time=
29.4s
[CV] END C=1, epsilon=0.001, loss=squared_epsilon_insensitive; total time=
29.8s
[CV] END ...C=1, epsilon=0.25075, loss=epsilon_insensitive; total time=   24.5s
[CV] END ...C=1, epsilon=0.25075, loss=epsilon_insensitive; total time=   24.7s
[CV] END ...C=1, epsilon=0.25075, loss=epsilon_insensitive; total time=   24.2s
[CV] END ...C=1, epsilon=0.25075, loss=epsilon_insensitive; total time=   24.6s
[CV] END ...C=1, epsilon=0.25075, loss=epsilon_insensitive; total time=   24.4s
[CV] END C=0.01, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
0.6s

```



```

[CV] END C=0.01, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
0.6s
[CV] END C=0.01, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
0.6s
[CV] END C=0.01, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
0.6s
[CV] END C=0.01, epsilon=1.0, loss=squared_epsilon_insensitive; total time=
0.6s
[CV] END ...C=0.01, epsilon=1.0, loss=epsilon_insensitive; total time=    0.5s
[CV] END ...C=0.01, epsilon=1.0, loss=epsilon_insensitive; total time=    0.5s
[CV] END ...C=0.01, epsilon=1.0, loss=epsilon_insensitive; total time=    0.5s
[CV] END ...C=0.01, epsilon=1.0, loss=epsilon_insensitive; total time=    0.5s
[CV] END ...C=0.01, epsilon=1.0, loss=epsilon_insensitive; total time=    0.5s
[CV] END C=0.001, epsilon=0.75025, loss=squared_epsilon_insensitive; total time=
0.5s
[CV] END C=0.001, epsilon=0.75025, loss=squared_epsilon_insensitive; total time=
0.5s
[CV] END C=0.001, epsilon=0.75025, loss=squared_epsilon_insensitive; total time=
0.5s
[CV] END C=0.001, epsilon=0.75025, loss=squared_epsilon_insensitive; total time=
0.5s
[CV] END C=0.001, epsilon=0.75025, loss=squared_epsilon_insensitive; total time=
0.5s
[CV] END .C=1, epsilon=1.0, loss=squared_epsilon_insensitive; total time= 12.0s
[CV] END .C=1, epsilon=1.0, loss=squared_epsilon_insensitive; total time= 12.1s
[CV] END .C=1, epsilon=1.0, loss=squared_epsilon_insensitive; total time= 12.1s
[CV] END .C=1, epsilon=1.0, loss=squared_epsilon_insensitive; total time= 12.2s
[CV] END .C=1, epsilon=1.0, loss=squared_epsilon_insensitive; total time= 11.8s
Mean Absolute Percentage Error: 2.8237898951889937
Root Mean Squared Error: 0.8926635273733877
R2 Score: 0.20032452337550755

```

```
[96]: grid_lsvr.best_params_
```

```
[96]: {'loss': 'squared_epsilon_insensitive', 'epsilon': 0.001, 'C': 1}
```

```

[97]: param_grid = {'learning_rate': [0.2,0.4,0.5,0.7,1],
                    'n_estimators': [100,400,700,800,1000]
                  }
grid_cat =
↳ RandomizedSearchCV(CatBoostRegressor(silent=True),param_grid,verbose=5,cv=5)
train_and_evaluate_model(grid_cat)

```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```

[CV 1/5] END learning_rate=0.7, n_estimators=700;, score=0.704 total time=
19.3s
[CV 2/5] END learning_rate=0.7, n_estimators=700;, score=0.710 total time=
19.2s

```

[CV 3/5] END learning_rate=0.7, n_estimators=700;, score=0.701 total time= 20.3s
 [CV 4/5] END learning_rate=0.7, n_estimators=700;, score=0.706 total time= 21.2s
 [CV 5/5] END learning_rate=0.7, n_estimators=700;, score=0.707 total time= 20.0s
 [CV 1/5] END learning_rate=1, n_estimators=1000;, score=0.699 total time= 28.3s
 [CV 2/5] END learning_rate=1, n_estimators=1000;, score=0.703 total time= 29.4s
 [CV 3/5] END learning_rate=1, n_estimators=1000;, score=0.694 total time= 28.6s
 [CV 4/5] END learning_rate=1, n_estimators=1000;, score=0.699 total time= 29.5s
 [CV 5/5] END learning_rate=1, n_estimators=1000;, score=0.699 total time= 28.9s
 [CV 1/5] END learning_rate=0.5, n_estimators=100;, score=0.691 total time= 3.8s
 [CV 2/5] END learning_rate=0.5, n_estimators=100;, score=0.696 total time= 4.0s
 [CV 3/5] END learning_rate=0.5, n_estimators=100;, score=0.685 total time= 3.8s
 [CV 4/5] END learning_rate=0.5, n_estimators=100;, score=0.690 total time= 3.7s
 [CV 5/5] END learning_rate=0.5, n_estimators=100;, score=0.693 total time= 3.3s
 [CV 1/5] END learning_rate=0.4, n_estimators=100;, score=0.688 total time= 4.0s
 [CV 2/5] END learning_rate=0.4, n_estimators=100;, score=0.694 total time= 3.9s
 [CV 3/5] END learning_rate=0.4, n_estimators=100;, score=0.683 total time= 3.8s
 [CV 4/5] END learning_rate=0.4, n_estimators=100;, score=0.687 total time= 4.2s
 [CV 5/5] END learning_rate=0.4, n_estimators=100;, score=0.690 total time= 3.7s
 [CV 1/5] END learning_rate=0.5, n_estimators=800;, score=0.707 total time= 23.7s
 [CV 2/5] END learning_rate=0.5, n_estimators=800;, score=0.711 total time= 23.1s
 [CV 3/5] END learning_rate=0.5, n_estimators=800;, score=0.703 total time= 24.2s
 [CV 4/5] END learning_rate=0.5, n_estimators=800;, score=0.708 total time= 23.3s
 [CV 5/5] END learning_rate=0.5, n_estimators=800;, score=0.708 total time= 27.5s
 [CV 1/5] END learning_rate=0.7, n_estimators=100;, score=0.693 total time= 4.2s
 [CV 2/5] END learning_rate=0.7, n_estimators=100;, score=0.698 total time= 5.1s
 [CV 3/5] END learning_rate=0.7, n_estimators=100;, score=0.690 total time= 4.1s
 [CV 4/5] END learning_rate=0.7, n_estimators=100;, score=0.694 total time=

3.9s
 [CV 5/5] END learning_rate=0.7, n_estimators=100;, score=0.696 total time=4.0s
 [CV 1/5] END learning_rate=0.2, n_estimators=700;, score=0.702 total time=23.9s
 [CV 2/5] END learning_rate=0.2, n_estimators=700;, score=0.708 total time=24.6s
 [CV 3/5] END learning_rate=0.2, n_estimators=700;, score=0.698 total time=24.3s
 [CV 4/5] END learning_rate=0.2, n_estimators=700;, score=0.702 total time=23.5s
 [CV 5/5] END learning_rate=0.2, n_estimators=700;, score=0.704 total time=25.8s
 [CV 1/5] END learning_rate=0.4, n_estimators=800;, score=0.707 total time=26.4s
 [CV 2/5] END learning_rate=0.4, n_estimators=800;, score=0.712 total time=28.5s
 [CV 3/5] END learning_rate=0.4, n_estimators=800;, score=0.703 total time=27.5s
 [CV 4/5] END learning_rate=0.4, n_estimators=800;, score=0.707 total time=27.5s
 [CV 5/5] END learning_rate=0.4, n_estimators=800;, score=0.708 total time=28.6s
 [CV 1/5] END learning_rate=0.7, n_estimators=1000;, score=0.704 total time=33.8s
 [CV 2/5] END learning_rate=0.7, n_estimators=1000;, score=0.708 total time=35.6s
 [CV 3/5] END learning_rate=0.7, n_estimators=1000;, score=0.701 total time=34.9s
 [CV 4/5] END learning_rate=0.7, n_estimators=1000;, score=0.705 total time=35.3s
 [CV 5/5] END learning_rate=0.7, n_estimators=1000;, score=0.706 total time=35.2s
 [CV 1/5] END learning_rate=0.4, n_estimators=1000;, score=0.708 total time=34.9s
 [CV 2/5] END learning_rate=0.4, n_estimators=1000;, score=0.712 total time=34.3s
 [CV 3/5] END learning_rate=0.4, n_estimators=1000;, score=0.704 total time=35.3s
 [CV 4/5] END learning_rate=0.4, n_estimators=1000;, score=0.708 total time=34.8s
 [CV 5/5] END learning_rate=0.4, n_estimators=1000;, score=0.708 total time=36.2s
 Mean Absolute Percentage Error: 9.178925449737434
 Root Mean Squared Error: 0.5385006580059473
 R2 Score: 0.7089881504192195

```
[98]: grid_cat.best_params_
```

```
[98]: {'n_estimators': 1000, 'learning_rate': 0.4}
```

```
[99]: param_grid = {'boosting_type': ['gbdt', 'dart', 'goss', 'rf'],  
                  'learning_rate': np.linspace(0,1,6)[1:],  
                  'n_estimators': [100,300,500,800,1000],  
                  'importance_type': ['split', 'gain'],  
                  'min_split_gain': [0.68,0.79,0.87,1]}  
grid_lgbm = RandomizedSearchCV(LGBMRegressor(),param_grid,verbose=3,cv=5)  
train_and_evaluate_model(grid_lgbm)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```
[CV 1/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0,  
min_split_gain=1, n_estimators=500;; score=0.686 total time= 2.3s  
[CV 2/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0,  
min_split_gain=1, n_estimators=500;; score=0.692 total time= 2.2s  
[CV 3/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0,  
min_split_gain=1, n_estimators=500;; score=0.683 total time= 1.5s  
[CV 4/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0,  
min_split_gain=1, n_estimators=500;; score=0.687 total time= 1.2s  
[CV 5/5] END boosting_type=gbdt, importance_type=split, learning_rate=1.0,  
min_split_gain=1, n_estimators=500;; score=0.684 total time= 2.0s  
[CV 1/5] END boosting_type=rf, importance_type=split,  
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=100;; score=nan  
total time= 0.3s  
[CV 2/5] END boosting_type=rf, importance_type=split,  
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=100;; score=nan  
total time= 0.2s  
[CV 3/5] END boosting_type=rf, importance_type=split,  
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=100;; score=nan  
total time= 0.2s  
[CV 4/5] END boosting_type=rf, importance_type=split,  
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=100;; score=nan  
total time= 0.3s  
[CV 5/5] END boosting_type=rf, importance_type=split,  
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=100;; score=nan  
total time= 0.2s  
[CV 1/5] END boosting_type=goss, importance_type=gain, learning_rate=0.8,  
min_split_gain=0.87, n_estimators=300;; score=0.679 total time= 3.8s  
[CV 2/5] END boosting_type=goss, importance_type=gain, learning_rate=0.8,  
min_split_gain=0.87, n_estimators=300;; score=0.684 total time= 4.5s  
[CV 3/5] END boosting_type=goss, importance_type=gain, learning_rate=0.8,  
min_split_gain=0.87, n_estimators=300;; score=0.675 total time= 4.7s  
[CV 4/5] END boosting_type=goss, importance_type=gain, learning_rate=0.8,  
min_split_gain=0.87, n_estimators=300;; score=0.680 total time= 4.2s  
[CV 5/5] END boosting_type=goss, importance_type=gain, learning_rate=0.8,  
min_split_gain=0.87, n_estimators=300;; score=0.679 total time= 4.4s
```

```

[CV 1/5] END boosting_type=goss, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=1000;,
score=0.678 total time= 15.7s
[CV 2/5] END boosting_type=goss, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=1000;,
score=0.679 total time= 16.6s
[CV 3/5] END boosting_type=goss, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=1000;,
score=0.674 total time= 13.5s
[CV 4/5] END boosting_type=goss, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=1000;,
score=0.676 total time= 13.7s
[CV 5/5] END boosting_type=goss, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=1000;,
score=0.677 total time= 13.5s
[CV 1/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=0.68, n_estimators=100;, score=nan total time= 0.2s
[CV 2/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=0.68, n_estimators=100;, score=nan total time= 0.3s
[CV 3/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=0.68, n_estimators=100;, score=nan total time= 0.2s
[CV 4/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=0.68, n_estimators=100;, score=nan total time= 0.2s
[CV 5/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=0.68, n_estimators=100;, score=nan total time= 0.1s
[CV 1/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=500;, score=nan
total time= 0.1s
[CV 2/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=500;, score=nan
total time= 0.1s
[CV 3/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=500;, score=nan
total time= 0.1s
[CV 4/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=500;, score=nan
total time= 0.1s
[CV 5/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=1, n_estimators=500;, score=nan
total time= 0.1s
[CV 1/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.79, n_estimators=300;,
score=nan total time= 0.3s
[CV 2/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.79, n_estimators=300;,
score=nan total time= 0.3s
[CV 3/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.79, n_estimators=300;,

```

```

score=nan total time= 0.3s
[CV 4/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.79, n_estimators=300;,
score=nan total time= 0.3s
[CV 5/5] END boosting_type=rf, importance_type=gain,
learning_rate=0.6000000000000001, min_split_gain=0.79, n_estimators=300;,
score=nan total time= 0.3s
[CV 1/5] END boosting_type=rf, importance_type=split,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=300;,
score=nan total time= 0.3s
[CV 2/5] END boosting_type=rf, importance_type=split,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=300;,
score=nan total time= 0.3s
[CV 3/5] END boosting_type=rf, importance_type=split,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=300;,
score=nan total time= 0.2s
[CV 4/5] END boosting_type=rf, importance_type=split,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=300;,
score=nan total time= 0.1s
[CV 5/5] END boosting_type=rf, importance_type=split,
learning_rate=0.6000000000000001, min_split_gain=0.68, n_estimators=300;,
score=nan total time= 0.1s
[CV 1/5] END boosting_type=rf, importance_type=split, learning_rate=0.8,
min_split_gain=0.79, n_estimators=300;, score=nan total time= 0.1s
[CV 2/5] END boosting_type=rf, importance_type=split, learning_rate=0.8,
min_split_gain=0.79, n_estimators=300;, score=nan total time= 0.1s
[CV 3/5] END boosting_type=rf, importance_type=split, learning_rate=0.8,
min_split_gain=0.79, n_estimators=300;, score=nan total time= 0.1s
[CV 4/5] END boosting_type=rf, importance_type=split, learning_rate=0.8,
min_split_gain=0.79, n_estimators=300;, score=nan total time= 0.1s
[CV 5/5] END boosting_type=rf, importance_type=split, learning_rate=0.8,
min_split_gain=0.79, n_estimators=300;, score=nan total time= 0.1s
[CV 1/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=1, n_estimators=100;, score=nan total time= 0.2s
[CV 2/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=1, n_estimators=100;, score=nan total time= 0.3s
[CV 3/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=1, n_estimators=100;, score=nan total time= 0.2s
[CV 4/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=1, n_estimators=100;, score=nan total time= 0.2s
[CV 5/5] END boosting_type=rf, importance_type=gain, learning_rate=0.2,
min_split_gain=1, n_estimators=100;, score=nan total time= 0.3s
Mean Absolute Percentage Error: 9.67618640428579
Root Mean Squared Error: 0.5599833082311786
R2 Score: 0.6853060741071018

```

[100]: `grid_lgbm.best_params_`

```
[100]: {'n_estimators': 500,
        'min_split_gain': 1,
        'learning_rate': 1.0,
        'importance_type': 'split',
        'boosting_type': 'gbdt'}
```

```
[ ]: param_grid = {'n_estimators': [100,400,700,900,1000],
                   'grow_policy': [0,1],
                   'learning_rate': [0.1,0.4,0.6,0.8,1],
                   'booster': ['gbtree','gblinear','dart'],
                   'sampling_method': ['uniform','gradient_based'],
                   'importance_type': ['gain','weight','cover','total_gain','total_cover']}

grid_xgb = RandomizedSearchCV(XGBRegressor(),param_grid,verbose=3,cv=5)
train_and_evaluate_model(grid_xgb)
```

```
[ ]: grid_xgb.best_params_
```

```
[104]: param_grid = {'loss':
                    ↳ ['squared_error','huber','epsilon_insensitive','squared_epsilon_insensitive'],
                    'penalty': ['l2', 'l1', '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=3,cv=5)
train_and_evaluate_model(grid_sgd)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```
[CV 1/5] END alpha=0.001, average=False, epsilon=55.55599999999999,
l1_ratio=0.81, learning_rate=invscaling, loss=epsilon_insensitive,
penalty=elasticnet, shuffle=True;; score=-0.000 total time= 0.4s
[CV 2/5] END alpha=0.001, average=False, epsilon=55.55599999999999,
l1_ratio=0.81, learning_rate=invscaling, loss=epsilon_insensitive,
penalty=elasticnet, shuffle=True;; score=-0.000 total time= 0.3s
[CV 3/5] END alpha=0.001, average=False, epsilon=55.55599999999999,
l1_ratio=0.81, learning_rate=invscaling, loss=epsilon_insensitive,
penalty=elasticnet, shuffle=True;; score=-0.000 total time= 0.3s
[CV 4/5] END alpha=0.001, average=False, epsilon=55.55599999999999,
l1_ratio=0.81, learning_rate=invscaling, loss=epsilon_insensitive,
penalty=elasticnet, shuffle=True;; score=-0.000 total time= 0.3s
[CV 5/5] END alpha=0.001, average=False, epsilon=55.55599999999999,
l1_ratio=0.81, learning_rate=invscaling, loss=epsilon_insensitive,
penalty=elasticnet, shuffle=True;; score=-0.000 total time= 0.3s
```

```

[CV 1/5] END alpha=1, average=False, epsilon=100.0, l1_ratio=0.81,
learning_rate=constant, loss=squared_error, penalty=l2, shuffle=True;,
score=0.141 total time= 0.3s
[CV 2/5] END alpha=1, average=False, epsilon=100.0, l1_ratio=0.81,
learning_rate=constant, loss=squared_error, penalty=l2, shuffle=True;,
score=0.160 total time= 0.3s
[CV 3/5] END alpha=1, average=False, epsilon=100.0, l1_ratio=0.81,
learning_rate=constant, loss=squared_error, penalty=l2, shuffle=True;,
score=0.132 total time= 0.3s
[CV 4/5] END alpha=1, average=False, epsilon=100.0, l1_ratio=0.81,
learning_rate=constant, loss=squared_error, penalty=l2, shuffle=True;,
score=0.062 total time= 0.3s
[CV 5/5] END alpha=1, average=False, epsilon=100.0, l1_ratio=0.81,
learning_rate=constant, loss=squared_error, penalty=l2, shuffle=True;,
score=0.133 total time= 0.3s
[CV 1/5] END alpha=1, average=False, epsilon=88.889, l1_ratio=0.15,
learning_rate=optimal, loss=huber, penalty=elasticnet, shuffle=False;,
score=0.114 total time= 0.1s
[CV 2/5] END alpha=1, average=False, epsilon=88.889, l1_ratio=0.15,
learning_rate=optimal, loss=huber, penalty=elasticnet, shuffle=False;,
score=0.113 total time= 0.2s
[CV 3/5] END alpha=1, average=False, epsilon=88.889, l1_ratio=0.15,
learning_rate=optimal, loss=huber, penalty=elasticnet, shuffle=False;,
score=0.113 total time= 0.1s
[CV 4/5] END alpha=1, average=False, epsilon=88.889, l1_ratio=0.15,
learning_rate=optimal, loss=huber, penalty=elasticnet, shuffle=False;,
score=0.113 total time= 0.2s
[CV 5/5] END alpha=1, average=False, epsilon=88.889, l1_ratio=0.15,
learning_rate=optimal, loss=huber, penalty=elasticnet, shuffle=False;,
score=0.112 total time= 0.2s
[CV 1/5] END alpha=1, average=False, epsilon=33.333999999999996, l1_ratio=0.97,
learning_rate=constant, loss=huber, penalty=elasticnet, shuffle=False;,
score=-0.000 total time= 0.2s
[CV 2/5] END alpha=1, average=False, epsilon=33.333999999999996, l1_ratio=0.97,
learning_rate=constant, loss=huber, penalty=elasticnet, shuffle=False;,
score=-0.000 total time= 0.2s
[CV 3/5] END alpha=1, average=False, epsilon=33.333999999999996, l1_ratio=0.97,
learning_rate=constant, loss=huber, penalty=elasticnet, shuffle=False;,
score=-0.000 total time= 0.2s
[CV 4/5] END alpha=1, average=False, epsilon=33.333999999999996, l1_ratio=0.97,
learning_rate=constant, loss=huber, penalty=elasticnet, shuffle=False;,
score=-0.000 total time= 0.2s
[CV 5/5] END alpha=1, average=False, epsilon=33.333999999999996, l1_ratio=0.97,
learning_rate=constant, loss=huber, penalty=elasticnet, shuffle=False;,
score=-0.001 total time= 0.2s
[CV 1/5] END alpha=0.0001, average=True, epsilon=77.77799999999999,
l1_ratio=0.15, learning_rate=invscaling, loss=huber, penalty=l2, shuffle=True;,
score=0.202 total time= 0.5s

```


[CV 2/5] END alpha=0.0001, average=True, epsilon=77.77799999999999,
l1_ratio=0.15, learning_rate=invscaling, loss=huber, penalty=l2, shuffle=True;;
score=0.199 total time= 0.4s

[CV 3/5] END alpha=0.0001, average=True, epsilon=77.77799999999999,
l1_ratio=0.15, learning_rate=invscaling, loss=huber, penalty=l2, shuffle=True;;
score=0.200 total time= 0.3s

[CV 4/5] END alpha=0.0001, average=True, epsilon=77.77799999999999,
l1_ratio=0.15, learning_rate=invscaling, loss=huber, penalty=l2, shuffle=True;;
score=0.200 total time= 0.3s

[CV 5/5] END alpha=0.0001, average=True, epsilon=77.77799999999999,
l1_ratio=0.15, learning_rate=invscaling, loss=huber, penalty=l2, shuffle=True;;
score=0.197 total time= 0.4s

[CV 1/5] END alpha=0.01, average=True, epsilon=88.889, l1_ratio=0.97,
learning_rate=constant, loss=squared_error, penalty=l1, shuffle=False;;
score=-67460.297 total time= 0.2s

[CV 2/5] END alpha=0.01, average=True, epsilon=88.889, l1_ratio=0.97,
learning_rate=constant, loss=squared_error, penalty=l1, shuffle=False;;
score=-68099.544 total time= 0.2s

[CV 3/5] END alpha=0.01, average=True, epsilon=88.889, l1_ratio=0.97,
learning_rate=constant, loss=squared_error, penalty=l1, shuffle=False;;
score=-69191.629 total time= 0.2s

[CV 4/5] END alpha=0.01, average=True, epsilon=88.889, l1_ratio=0.97,
learning_rate=constant, loss=squared_error, penalty=l1, shuffle=False;;
score=-71982.763 total time= 0.2s

[CV 5/5] END alpha=0.01, average=True, epsilon=88.889, l1_ratio=0.97,
learning_rate=constant, loss=squared_error, penalty=l1, shuffle=False;;
score=-65447.485 total time= 0.2s

[CV 1/5] END alpha=0.01, average=False, epsilon=88.889, l1_ratio=0.68,
learning_rate=adaptive, loss=squared_error, penalty=elasticnet, shuffle=True;;
score=0.201 total time= 2.7s

[CV 2/5] END alpha=0.01, average=False, epsilon=88.889, l1_ratio=0.68,
learning_rate=adaptive, loss=squared_error, penalty=elasticnet, shuffle=True;;
score=0.198 total time= 2.5s

[CV 3/5] END alpha=0.01, average=False, epsilon=88.889, l1_ratio=0.68,
learning_rate=adaptive, loss=squared_error, penalty=elasticnet, shuffle=True;;
score=0.199 total time= 2.4s

[CV 4/5] END alpha=0.01, average=False, epsilon=88.889, l1_ratio=0.68,
learning_rate=adaptive, loss=squared_error, penalty=elasticnet, shuffle=True;;
score=0.200 total time= 2.6s

[CV 5/5] END alpha=0.01, average=False, epsilon=88.889, l1_ratio=0.68,
learning_rate=adaptive, loss=squared_error, penalty=elasticnet, shuffle=True;;
score=0.197 total time= 2.5s

[CV 1/5] END alpha=0.1, average=True, epsilon=66.667, l1_ratio=0.68,
learning_rate=invscaling, loss=squared_error, penalty=elasticnet, shuffle=True;;
score=-6080079220288757.000 total time= 0.4s

[CV 2/5] END alpha=0.1, average=True, epsilon=66.667, l1_ratio=0.68,
learning_rate=invscaling, loss=squared_error, penalty=elasticnet, shuffle=True;;
score=-6024078978513247.000 total time= 0.4s

```

[CV 3/5] END alpha=0.1, average=True, epsilon=66.667, l1_ratio=0.68,
learning_rate=invscaling, loss=squared_error, penalty=elasticnet, shuffle=True;,
score=-6297130631828823.000 total time= 0.4s
[CV 4/5] END alpha=0.1, average=True, epsilon=66.667, l1_ratio=0.68,
learning_rate=invscaling, loss=squared_error, penalty=elasticnet, shuffle=True;,
score=-6217647599143482.000 total time= 0.4s
[CV 5/5] END alpha=0.1, average=True, epsilon=66.667, l1_ratio=0.68,
learning_rate=invscaling, loss=squared_error, penalty=elasticnet, shuffle=True;,
score=-5979207886954764.000 total time= 0.4s
[CV 1/5] END alpha=0.01, average=False, epsilon=11.111999999999998,
l1_ratio=0.97, learning_rate=constant, loss=epsilon_insensitive, penalty=l2,
shuffle=False;, score=-0.000 total time= 0.0s
[CV 2/5] END alpha=0.01, average=False, epsilon=11.111999999999998,
l1_ratio=0.97, learning_rate=constant, loss=epsilon_insensitive, penalty=l2,
shuffle=False;, score=-0.000 total time= 0.0s
[CV 3/5] END alpha=0.01, average=False, epsilon=11.111999999999998,
l1_ratio=0.97, learning_rate=constant, loss=epsilon_insensitive, penalty=l2,
shuffle=False;, score=-0.000 total time= 0.0s
[CV 4/5] END alpha=0.01, average=False, epsilon=11.111999999999998,
l1_ratio=0.97, learning_rate=constant, loss=epsilon_insensitive, penalty=l2,
shuffle=False;, score=-0.000 total time= 0.0s
[CV 5/5] END alpha=0.01, average=False, epsilon=11.111999999999998,
l1_ratio=0.97, learning_rate=constant, loss=epsilon_insensitive, penalty=l2,
shuffle=False;, score=-0.000 total time= 0.0s
[CV 1/5] END alpha=1, average=True, epsilon=88.889, l1_ratio=0.45,
learning_rate=constant, loss=huber, penalty=l1, shuffle=True;,
score=-25400275.322 total time= 0.4s
[CV 2/5] END alpha=1, average=True, epsilon=88.889, l1_ratio=0.45,
learning_rate=constant, loss=huber, penalty=l1, shuffle=True;,
score=-25838165.254 total time= 0.4s
[CV 3/5] END alpha=1, average=True, epsilon=88.889, l1_ratio=0.45,
learning_rate=constant, loss=huber, penalty=l1, shuffle=True;,
score=-25502413.758 total time= 0.4s
[CV 4/5] END alpha=1, average=True, epsilon=88.889, l1_ratio=0.45,
learning_rate=constant, loss=huber, penalty=l1, shuffle=True;,
score=-25637219.163 total time= 0.4s
[CV 5/5] END alpha=1, average=True, epsilon=88.889, l1_ratio=0.45,
learning_rate=constant, loss=huber, penalty=l1, shuffle=True;,
score=-25582429.714 total time= 0.4s
Mean Absolute Percentage Error: 2.82223803400594
Root Mean Squared Error: 0.8926630101569394
R2 Score: 0.20032545005208235

```

```
[105]: grid_sgd.best_params_
```

```
[105]: {'shuffle': True,
        'penalty': 'l2',
```

```

'loss': 'huber',
'learning_rate': 'invscaling',
'l1_ratio': 0.15,
'epsilon': 77.77799999999999,
'average': True,
'alpha': 0.0001}

```

```

[106]: param_grid = {'epsilon': np.linspace(1,10,10),
'alpha': np.linspace(0.0001,10,10)}
grid_huber = RandomizedSearchCV(HuberRegressor(),param_grid,verbose=3,cv=5)
train_and_evaluate_model(grid_huber)

```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```

[CV 1/5] END ...alpha=2.2223, epsilon=4.0;, score=0.202 total time= 0.6s
[CV 2/5] END ...alpha=2.2223, epsilon=4.0;, score=0.199 total time= 0.4s
[CV 3/5] END ...alpha=2.2223, epsilon=4.0;, score=0.200 total time= 0.4s
[CV 4/5] END ...alpha=2.2223, epsilon=4.0;, score=0.200 total time= 0.4s
[CV 5/5] END ...alpha=2.2223, epsilon=4.0;, score=0.197 total time= 0.4s
[CV 1/5] END ...alpha=5.5556, epsilon=5.0;, score=0.202 total time= 0.4s
[CV 2/5] END ...alpha=5.5556, epsilon=5.0;, score=0.199 total time= 0.4s
[CV 3/5] END ...alpha=5.5556, epsilon=5.0;, score=0.200 total time= 0.4s
[CV 4/5] END ...alpha=5.5556, epsilon=5.0;, score=0.200 total time= 0.5s
[CV 5/5] END ...alpha=5.5556, epsilon=5.0;, score=0.197 total time= 0.4s
[CV 1/5] END ...alpha=5.5556, epsilon=6.0;, score=0.202 total time= 0.4s
[CV 2/5] END ...alpha=5.5556, epsilon=6.0;, score=0.199 total time= 0.4s
[CV 3/5] END ...alpha=5.5556, epsilon=6.0;, score=0.200 total time= 0.4s
[CV 4/5] END ...alpha=5.5556, epsilon=6.0;, score=0.200 total time= 0.4s
[CV 5/5] END ...alpha=5.5556, epsilon=6.0;, score=0.197 total time= 0.4s
[CV 1/5] END ...alpha=0.0001, epsilon=1.0;, score=0.191 total time= 0.6s
[CV 2/5] END ...alpha=0.0001, epsilon=1.0;, score=0.187 total time= 0.6s
[CV 3/5] END ...alpha=0.0001, epsilon=1.0;, score=0.188 total time= 0.6s
[CV 4/5] END ...alpha=0.0001, epsilon=1.0;, score=0.190 total time= 0.6s
[CV 5/5] END ...alpha=0.0001, epsilon=1.0;, score=0.186 total time= 0.6s
[CV 1/5] END alpha=7.777999999999999, epsilon=2.0;, score=0.199 total time=
0.4s
[CV 2/5] END alpha=7.777999999999999, epsilon=2.0;, score=0.195 total time=
0.5s
[CV 3/5] END alpha=7.777999999999999, epsilon=2.0;, score=0.196 total time=
0.4s
[CV 4/5] END alpha=7.777999999999999, epsilon=2.0;, score=0.197 total time=
0.4s
[CV 5/5] END alpha=7.777999999999999, epsilon=2.0;, score=0.194 total time=
0.4s
[CV 1/5] END ...alpha=5.5556, epsilon=4.0;, score=0.202 total time= 0.4s
[CV 2/5] END ...alpha=5.5556, epsilon=4.0;, score=0.199 total time= 0.4s
[CV 3/5] END ...alpha=5.5556, epsilon=4.0;, score=0.200 total time= 0.5s
[CV 4/5] END ...alpha=5.5556, epsilon=4.0;, score=0.200 total time= 0.4s
[CV 5/5] END ...alpha=5.5556, epsilon=4.0;, score=0.197 total time= 0.4s

```

```

[CV 1/5] END ...alpha=10.0, epsilon=1.0;; score=0.191 total time= 0.6s
[CV 2/5] END ...alpha=10.0, epsilon=1.0;; score=0.187 total time= 0.6s
[CV 3/5] END ...alpha=10.0, epsilon=1.0;; score=0.188 total time= 0.7s
[CV 4/5] END ...alpha=10.0, epsilon=1.0;; score=0.190 total time= 0.7s
[CV 5/5] END ...alpha=10.0, epsilon=1.0;; score=0.186 total time= 0.6s
[CV 1/5] END ...alpha=8.8889, epsilon=7.0;; score=0.202 total time= 0.4s
[CV 2/5] END ...alpha=8.8889, epsilon=7.0;; score=0.199 total time= 0.4s
[CV 3/5] END ...alpha=8.8889, epsilon=7.0;; score=0.200 total time= 0.4s
[CV 4/5] END ...alpha=8.8889, epsilon=7.0;; score=0.200 total time= 0.4s
[CV 5/5] END ...alpha=8.8889, epsilon=7.0;; score=0.197 total time= 0.4s
[CV 1/5] END alpha=7.777799999999999, epsilon=1.0;; score=0.191 total time=
0.6s
[CV 2/5] END alpha=7.777799999999999, epsilon=1.0;; score=0.187 total time=
0.6s
[CV 3/5] END alpha=7.777799999999999, epsilon=1.0;; score=0.188 total time=
0.6s
[CV 4/5] END alpha=7.777799999999999, epsilon=1.0;; score=0.190 total time=
0.6s
[CV 5/5] END alpha=7.777799999999999, epsilon=1.0;; score=0.186 total time=
0.6s
[CV 1/5] END ...alpha=0.0001, epsilon=3.0;; score=0.202 total time= 0.4s
[CV 2/5] END ...alpha=0.0001, epsilon=3.0;; score=0.199 total time= 0.4s
[CV 3/5] END ...alpha=0.0001, epsilon=3.0;; score=0.200 total time= 0.4s
[CV 4/5] END ...alpha=0.0001, epsilon=3.0;; score=0.200 total time= 0.4s
[CV 5/5] END ...alpha=0.0001, epsilon=3.0;; score=0.197 total time= 0.4s
Mean Absolute Percentage Error: 2.8234145756086915
Root Mean Squared Error: 0.8926634016243036
R2 Score: 0.20032474867529548

```

```
[107]: grid_huber.best_params_
```

```
[107]: {'epsilon': 7.0, 'alpha': 8.8889}
```

```
[108]: param_grid = {'link': ['auto', 'identity', 'log'],
'solver': ['lbfgs', 'newton-cholesky'],
'alpha': np.linspace(0.0001,10,10)}
grid_tweedie = RandomizedSearchCV(TweedieRegressor(),param_grid,verbose=3,cv=5)
train_and_evaluate_model(grid_tweedie)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```

[CV 1/5] END alpha=6.6667, link=identity, solver=newton-cholesky;; score=0.055
total time= 0.2s
[CV 2/5] END alpha=6.6667, link=identity, solver=newton-cholesky;; score=0.054
total time= 0.0s
[CV 3/5] END alpha=6.6667, link=identity, solver=newton-cholesky;; score=0.055
total time= 0.0s
[CV 4/5] END alpha=6.6667, link=identity, solver=newton-cholesky;; score=0.055
total time= 0.0s

```

```

[CV 5/5] END alpha=6.6667, link=identity, solver=newton-cholesky;, score=0.054
total time= 0.0s
[CV 1/5] END alpha=4.4445, link=auto, solver=newton-cholesky;, score=0.074 total
time= 0.0s
[CV 2/5] END alpha=4.4445, link=auto, solver=newton-cholesky;, score=0.073 total
time= 0.0s
[CV 3/5] END alpha=4.4445, link=auto, solver=newton-cholesky;, score=0.073 total
time= 0.0s
[CV 4/5] END alpha=4.4445, link=auto, solver=newton-cholesky;, score=0.073 total
time= 0.1s
[CV 5/5] END alpha=4.4445, link=auto, solver=newton-cholesky;, score=0.073 total
time= 0.0s
[CV 1/5] END alpha=4.4445, link=log, solver=lbgfs;, score=nan total time= 0.9s
[CV 2/5] END alpha=4.4445, link=log, solver=lbgfs;, score=nan total time= 0.9s
[CV 3/5] END alpha=4.4445, link=log, solver=lbgfs;, score=nan total time= 1.0s
[CV 4/5] END alpha=4.4445, link=log, solver=lbgfs;, score=nan total time= 0.9s
[CV 5/5] END alpha=4.4445, link=log, solver=lbgfs;, score=nan total time= 0.9s
[CV 1/5] END alpha=5.5556, link=log, solver=lbgfs;, score=nan total time= 0.9s
[CV 2/5] END alpha=5.5556, link=log, solver=lbgfs;, score=nan total time= 0.9s
[CV 3/5] END alpha=5.5556, link=log, solver=lbgfs;, score=nan total time= 1.1s
[CV 4/5] END alpha=5.5556, link=log, solver=lbgfs;, score=nan total time= 1.2s
[CV 5/5] END alpha=5.5556, link=log, solver=lbgfs;, score=nan total time= 1.0s
[CV 1/5] END alpha=5.5556, link=auto, solver=newton-cholesky;, score=0.063 total
time= 0.1s
[CV 2/5] END alpha=5.5556, link=auto, solver=newton-cholesky;, score=0.062 total
time= 0.2s
[CV 3/5] END alpha=5.5556, link=auto, solver=newton-cholesky;, score=0.063 total
time= 0.1s
[CV 4/5] END alpha=5.5556, link=auto, solver=newton-cholesky;, score=0.063 total
time= 0.1s
[CV 5/5] END alpha=5.5556, link=auto, solver=newton-cholesky;, score=0.062 total
time= 0.1s
[CV 1/5] END alpha=4.4445, link=identity, solver=newton-cholesky;, score=0.074
total time= 0.2s
[CV 2/5] END alpha=4.4445, link=identity, solver=newton-cholesky;, score=0.073
total time= 0.1s
[CV 3/5] END alpha=4.4445, link=identity, solver=newton-cholesky;, score=0.073
total time= 0.0s
[CV 4/5] END alpha=4.4445, link=identity, solver=newton-cholesky;, score=0.073
total time= 0.0s
[CV 5/5] END alpha=4.4445, link=identity, solver=newton-cholesky;, score=0.073
total time= 0.1s
[CV 1/5] END alpha=2.2223, link=auto, solver=lbgfs;, score=0.112 total time=
0.0s
[CV 2/5] END alpha=2.2223, link=auto, solver=lbgfs;, score=0.111 total time=
0.0s
[CV 3/5] END alpha=2.2223, link=auto, solver=lbgfs;, score=0.111 total time=
0.0s

```

```

[CV 4/5] END alpha=2.2223, link=auto, solver=lbfgs;, score=0.112 total time=
0.0s
[CV 5/5] END alpha=2.2223, link=auto, solver=lbfgs;, score=0.110 total time=
0.1s
[CV 1/5] END alpha=7.777799999999999, link=identity, solver=newton-cholesky;,
score=0.049 total time= 0.0s
[CV 2/5] END alpha=7.777799999999999, link=identity, solver=newton-cholesky;,
score=0.048 total time= 0.0s
[CV 3/5] END alpha=7.777799999999999, link=identity, solver=newton-cholesky;,
score=0.048 total time= 0.1s
[CV 4/5] END alpha=7.777799999999999, link=identity, solver=newton-cholesky;,
score=0.048 total time= 0.1s
[CV 5/5] END alpha=7.777799999999999, link=identity, solver=newton-cholesky;,
score=0.048 total time= 0.0s
[CV 1/5] END alpha=5.5556, link=identity, solver=newton-cholesky;, score=0.063
total time= 0.0s
[CV 2/5] END alpha=5.5556, link=identity, solver=newton-cholesky;, score=0.062
total time= 0.0s
[CV 3/5] END alpha=5.5556, link=identity, solver=newton-cholesky;, score=0.063
total time= 0.0s
[CV 4/5] END alpha=5.5556, link=identity, solver=newton-cholesky;, score=0.063
total time= 0.1s
[CV 5/5] END alpha=5.5556, link=identity, solver=newton-cholesky;, score=0.062
total time= 0.1s
[CV 1/5] END alpha=0.0001, link=identity, solver=newton-cholesky;, score=0.202
total time= 0.1s
[CV 2/5] END alpha=0.0001, link=identity, solver=newton-cholesky;, score=0.199
total time= 0.0s
[CV 3/5] END alpha=0.0001, link=identity, solver=newton-cholesky;, score=0.200
total time= 0.1s
[CV 4/5] END alpha=0.0001, link=identity, solver=newton-cholesky;, score=0.200
total time= 0.1s
[CV 5/5] END alpha=0.0001, link=identity, solver=newton-cholesky;, score=0.197
total time= 0.2s
Mean Absolute Percentage Error: 2.8232365443066776
Root Mean Squared Error: 0.892663404201744
R2 Score: 0.2003247440573952


```

```
[109]: grid_tweedie.best_params_
```

```
[109]: {'solver': 'newton-cholesky', 'link': 'identity', 'alpha': 0.0001}
```

```
[110]: param_grid = {'C': [0.0001,0.001,0.01,0.1,1,10],
'loss': ['epsilon_insensitive','squared_epsilon_insensitive'],
'epsilon': np.linspace(0.001,1,5),
'shuffle': [True,False],
'average': [True,False]}
```

```

grid_pa = 
↳ RandomizedSearchCV(PassiveAggressiveRegressor(), param_grid, verbose=3, cv=5)
train_and_evaluate_model(grid_pa)

```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```

[CV 1/5] END C=0.1, average=False, epsilon=1.0, loss=epsilon_insensitive,
shuffle=False;; score=-0.014 total time= 0.2s
[CV 2/5] END C=0.1, average=False, epsilon=1.0, loss=epsilon_insensitive,
shuffle=False;; score=-0.014 total time= 0.2s
[CV 3/5] END C=0.1, average=False, epsilon=1.0, loss=epsilon_insensitive,
shuffle=False;; score=-0.013 total time= 0.1s
[CV 4/5] END C=0.1, average=False, epsilon=1.0, loss=epsilon_insensitive,
shuffle=False;; score=-0.013 total time= 0.0s
[CV 5/5] END C=0.1, average=False, epsilon=1.0, loss=epsilon_insensitive,
shuffle=False;; score=-0.199 total time= 0.1s
[CV 1/5] END C=10, average=True, epsilon=0.001,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.196 total time= 0.3s
[CV 2/5] END C=10, average=True, epsilon=0.001,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.193 total time= 0.3s
[CV 3/5] END C=10, average=True, epsilon=0.001,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.194 total time= 0.4s
[CV 4/5] END C=10, average=True, epsilon=0.001,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.195 total time= 0.4s
[CV 5/5] END C=10, average=True, epsilon=0.001,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.192 total time= 0.3s
[CV 1/5] END C=0.0001, average=False, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.191 total time= 0.4s
[CV 2/5] END C=0.0001, average=False, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.184 total time= 0.4s
[CV 3/5] END C=0.0001, average=False, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.190 total time= 0.4s
[CV 4/5] END C=0.0001, average=False, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.190 total time= 0.4s
[CV 5/5] END C=0.0001, average=False, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.182 total time= 0.4s
[CV 1/5] END C=0.1, average=True, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.197 total time= 0.3s
[CV 2/5] END C=0.1, average=True, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.193 total time= 0.4s
[CV 3/5] END C=0.1, average=True, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.195 total time= 0.5s
[CV 4/5] END C=0.1, average=True, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.196 total time= 0.4s
[CV 5/5] END C=0.1, average=True, epsilon=0.001, loss=epsilon_insensitive,
shuffle=True;; score=0.192 total time= 0.3s
[CV 1/5] END C=0.0001, average=False, epsilon=0.75025,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.186 total time= 0.1s
[CV 2/5] END C=0.0001, average=False, epsilon=0.75025,

```

```

loss=squared_epsilon_insensitive, shuffle=False;; score=0.185 total time= 0.1s
[CV 3/5] END C=0.0001, average=False, epsilon=0.75025,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.185 total time= 0.1s
[CV 4/5] END C=0.0001, average=False, epsilon=0.75025,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.185 total time= 0.1s
[CV 5/5] END C=0.0001, average=False, epsilon=0.75025,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.183 total time= 0.1s
[CV 1/5] END C=1, average=True, epsilon=0.25075, loss=epsilon_insensitive,
shuffle=True;; score=0.197 total time= 0.4s
[CV 2/5] END C=1, average=True, epsilon=0.25075, loss=epsilon_insensitive,
shuffle=True;; score=0.194 total time= 0.3s
[CV 3/5] END C=1, average=True, epsilon=0.25075, loss=epsilon_insensitive,
shuffle=True;; score=0.195 total time= 0.3s
[CV 4/5] END C=1, average=True, epsilon=0.25075, loss=epsilon_insensitive,
shuffle=True;; score=0.195 total time= 0.3s
[CV 5/5] END C=1, average=True, epsilon=0.25075, loss=epsilon_insensitive,
shuffle=True;; score=0.193 total time= 0.3s
[CV 1/5] END C=0.0001, average=False, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.173 total time= 0.0s
[CV 2/5] END C=0.0001, average=False, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.172 total time= 0.0s
[CV 3/5] END C=0.0001, average=False, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.172 total time= 0.0s
[CV 4/5] END C=0.0001, average=False, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.172 total time= 0.0s
[CV 5/5] END C=0.0001, average=False, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.169 total time= 0.0s
[CV 1/5] END C=1, average=False, epsilon=0.5005, loss=epsilon_insensitive,
shuffle=True;; score=-0.236 total time= 0.3s
[CV 2/5] END C=1, average=False, epsilon=0.5005, loss=epsilon_insensitive,
shuffle=True;; score=-0.217 total time= 0.4s
[CV 3/5] END C=1, average=False, epsilon=0.5005, loss=epsilon_insensitive,
shuffle=True;; score=-0.755 total time= 0.5s
[CV 4/5] END C=1, average=False, epsilon=0.5005, loss=epsilon_insensitive,
shuffle=True;; score=-0.447 total time= 0.3s
[CV 5/5] END C=1, average=False, epsilon=0.5005, loss=epsilon_insensitive,
shuffle=True;; score=-0.174 total time= 0.3s
[CV 1/5] END C=0.01, average=True, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.172 total time= 0.1s
[CV 2/5] END C=0.01, average=True, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.172 total time= 0.1s
[CV 3/5] END C=0.01, average=True, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.171 total time= 0.1s
[CV 4/5] END C=0.01, average=True, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.171 total time= 0.1s
[CV 5/5] END C=0.01, average=True, epsilon=1.0,
loss=squared_epsilon_insensitive, shuffle=False;; score=0.169 total time= 0.1s
[CV 1/5] END C=1, average=True, epsilon=0.5005,

```



```

loss=squared_epsilon_insensitive, shuffle=True;; score=0.197 total time= 0.3s
[CV 2/5] END C=1, average=True, epsilon=0.5005,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.194 total time= 0.5s
[CV 3/5] END C=1, average=True, epsilon=0.5005,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.195 total time= 0.3s
[CV 4/5] END C=1, average=True, epsilon=0.5005,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.195 total time= 0.3s
[CV 5/5] END C=1, average=True, epsilon=0.5005,
loss=squared_epsilon_insensitive, shuffle=True;; score=0.193 total time= 0.3s
Mean Absolute Percentage Error: 3.0829306687352838
Root Mean Squared Error: 0.89554858676565
R2 Score: 0.19514712018188363

```

```
[111]: grid_pa.best_params_
```

```
[111]: {'shuffle': True,
        'loss': 'squared_epsilon_insensitive',
        'epsilon': 0.5005,
        'average': True,
        'C': 1}
```

```
[112]: param_grid = {
        'eps': [0.0001,0.001,0.01,0.1,1],
        'positive': [True,False],
        'selection': ['cyclic','random']
      }
grid_lasso = RandomizedSearchCV(LassoCV(),param_grid,verbose=3,cv=5)
train_and_evaluate_model(grid_lasso)
```

```

Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV 1/5] END eps=0.1, positive=True, selection=random;; score=0.003 total time=
1.6s
[CV 2/5] END eps=0.1, positive=True, selection=random;; score=0.003 total time=
1.4s
[CV 3/5] END eps=0.1, positive=True, selection=random;; score=0.003 total time=
1.4s
[CV 4/5] END eps=0.1, positive=True, selection=random;; score=0.003 total time=
1.4s
[CV 5/5] END eps=0.1, positive=True, selection=random;; score=0.003 total time=
1.4s
[CV 1/5] END eps=1, positive=True, selection=cyclic;; score=-0.000 total time=
1.4s
[CV 2/5] END eps=1, positive=True, selection=cyclic;; score=-0.000 total time=
1.4s
[CV 3/5] END eps=1, positive=True, selection=cyclic;; score=-0.000 total time=
1.4s
[CV 4/5] END eps=1, positive=True, selection=cyclic;; score=-0.000 total time=
1.4s

```

[CV 5/5] END eps=1, positive=True, selection=cyclic;; score=-0.000 total time=1.4s
 [CV 1/5] END eps=0.01, positive=True, selection=cyclic;; score=0.009 total time=1.4s
 [CV 2/5] END eps=0.01, positive=True, selection=cyclic;; score=0.010 total time=1.4s
 [CV 3/5] END eps=0.01, positive=True, selection=cyclic;; score=0.009 total time=1.4s
 [CV 4/5] END eps=0.01, positive=True, selection=cyclic;; score=0.009 total time=1.4s
 [CV 5/5] END eps=0.01, positive=True, selection=cyclic;; score=0.009 total time=1.5s
 [CV 1/5] END eps=0.001, positive=True, selection=random;; score=0.009 total time= 1.5s
 [CV 2/5] END eps=0.001, positive=True, selection=random;; score=0.010 total time= 1.5s
 [CV 3/5] END eps=0.001, positive=True, selection=random;; score=0.009 total time= 1.5s
 [CV 4/5] END eps=0.001, positive=True, selection=random;; score=0.009 total time= 1.4s
 [CV 5/5] END eps=0.001, positive=True, selection=random;; score=0.009 total time= 1.4s
 [CV 1/5] END eps=0.01, positive=True, selection=random;; score=0.009 total time=1.4s
 [CV 2/5] END eps=0.01, positive=True, selection=random;; score=0.010 total time=1.4s
 [CV 3/5] END eps=0.01, positive=True, selection=random;; score=0.009 total time=1.4s
 [CV 4/5] END eps=0.01, positive=True, selection=random;; score=0.009 total time=1.4s
 [CV 5/5] END eps=0.01, positive=True, selection=random;; score=0.009 total time=1.4s
 [CV 1/5] END eps=0.1, positive=False, selection=random;; score=0.194 total time=1.4s
 [CV 2/5] END eps=0.1, positive=False, selection=random;; score=0.190 total time=1.4s
 [CV 3/5] END eps=0.1, positive=False, selection=random;; score=0.192 total time=1.4s
 [CV 4/5] END eps=0.1, positive=False, selection=random;; score=0.193 total time=1.4s
 [CV 5/5] END eps=0.1, positive=False, selection=random;; score=0.189 total time=1.5s
 [CV 1/5] END eps=0.0001, positive=False, selection=random;; score=0.202 total time= 1.5s
 [CV 2/5] END eps=0.0001, positive=False, selection=random;; score=0.199 total time= 1.5s
 [CV 3/5] END eps=0.0001, positive=False, selection=random;; score=0.200 total time= 1.5s

```

[CV 4/5] END eps=0.0001, positive=False, selection=random;; score=0.200 total
time= 1.6s
[CV 5/5] END eps=0.0001, positive=False, selection=random;; score=0.197 total
time= 1.7s
[CV 1/5] END eps=1, positive=False, selection=random;; score=-0.000 total time=
1.5s
[CV 2/5] END eps=1, positive=False, selection=random;; score=-0.000 total time=
1.4s
[CV 3/5] END eps=1, positive=False, selection=random;; score=-0.000 total time=
1.4s
[CV 4/5] END eps=1, positive=False, selection=random;; score=-0.000 total time=
1.4s
[CV 5/5] END eps=1, positive=False, selection=random;; score=-0.000 total time=
1.4s
[CV 1/5] END eps=0.001, positive=False, selection=cyclic;; score=0.202 total
time= 1.4s
[CV 2/5] END eps=0.001, positive=False, selection=cyclic;; score=0.199 total
time= 1.5s
[CV 3/5] END eps=0.001, positive=False, selection=cyclic;; score=0.200 total
time= 1.5s
[CV 4/5] END eps=0.001, positive=False, selection=cyclic;; score=0.200 total
time= 1.5s
[CV 5/5] END eps=0.001, positive=False, selection=cyclic;; score=0.197 total
time= 1.5s
[CV 1/5] END eps=0.01, positive=False, selection=cyclic;; score=0.202 total
time= 1.4s
[CV 2/5] END eps=0.01, positive=False, selection=cyclic;; score=0.199 total
time= 1.5s
[CV 3/5] END eps=0.01, positive=False, selection=cyclic;; score=0.200 total
time= 1.4s
[CV 4/5] END eps=0.01, positive=False, selection=cyclic;; score=0.200 total
time= 1.4s
[CV 5/5] END eps=0.01, positive=False, selection=cyclic;; score=0.197 total
time= 1.4s
Mean Absolute Percentage Error: 2.822343792405214
Root Mean Squared Error: 0.8926633657703132
R2 Score: 0.20032481291350235

```

```
[113]: grid_lasso.best_params_
```

```
[113]: {'selection': 'random', 'positive': False, 'eps': 0.0001}
```

```
[114]: 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=3,cv=5)
train_and_evaluate_model(grid_ridge)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```
[CV 1/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto,
store_cv_values=False;; score=0.202 total time= 0.4s
[CV 2/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto,
store_cv_values=False;; score=0.199 total time= 0.2s
[CV 3/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto,
store_cv_values=False;; score=0.200 total time= 0.2s
[CV 4/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto,
store_cv_values=False;; score=0.200 total time= 0.3s
[CV 5/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=auto,
store_cv_values=False;; score=0.197 total time= 0.2s
[CV 1/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True;; score=nan total time= 0.0s
[CV 2/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True;; score=nan total time= 0.0s
[CV 3/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True;; score=nan total time= 0.0s
[CV 4/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True;; score=nan total time= 0.0s
[CV 5/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=True;; score=nan total time= 0.0s
[CV 1/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=False;; score=nan total time= 0.0s
[CV 2/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=False;; score=nan total time= 0.0s
[CV 3/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=False;; score=nan total time= 0.0s
[CV 4/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=False;; score=nan total time= 0.0s
[CV 5/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=eigen,
store_cv_values=False;; score=nan total time= 0.0s
[CV 1/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=auto,
store_cv_values=False;; score=0.202 total time= 0.2s
[CV 2/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=auto,
store_cv_values=False;; score=0.199 total time= 0.3s
[CV 3/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=auto,
store_cv_values=False;; score=0.200 total time= 0.2s
[CV 4/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=auto,
store_cv_values=False;; score=0.200 total time= 0.2s
[CV 5/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=auto,
store_cv_values=False;; score=0.197 total time= 0.3s
[CV 1/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
store_cv_values=False;; score=0.202 total time= 0.2s
[CV 2/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
store_cv_values=False;; score=0.199 total time= 0.2s
```

[CV 3/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=False;; score=0.200 total time= 0.3s
 [CV 4/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=False;; score=0.200 total time= 0.2s
 [CV 5/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=False;; score=0.197 total time= 0.2s
 [CV 1/5] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=svd,
 store_cv_values=False;; score=0.202 total time= 0.3s
 [CV 2/5] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=svd,
 store_cv_values=False;; score=0.199 total time= 0.2s
 [CV 3/5] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=svd,
 store_cv_values=False;; score=0.200 total time= 0.2s
 [CV 4/5] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=svd,
 store_cv_values=False;; score=0.200 total time= 0.3s
 [CV 5/5] END alpha_per_target=True, alphas=(0.01, 0.1, 1), gcv_mode=svd,
 store_cv_values=False;; score=0.197 total time= 0.2s
 [CV 1/5] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.202 total time= 0.2s
 [CV 2/5] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.199 total time= 0.3s
 [CV 3/5] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.200 total time= 0.2s
 [CV 4/5] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.200 total time= 0.2s
 [CV 5/5] END alpha_per_target=False, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.197 total time= 0.3s
 [CV 1/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.202 total time= 0.2s
 [CV 2/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.199 total time= 0.3s
 [CV 3/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.200 total time= 0.2s
 [CV 4/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.200 total time= 0.2s
 [CV 5/5] END alpha_per_target=True, alphas=(0.001, 0.01, 0.1), gcv_mode=svd,
 store_cv_values=True;; score=0.197 total time= 0.3s
 [CV 1/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
 store_cv_values=False;; score=0.202 total time= 0.2s
 [CV 2/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
 store_cv_values=False;; score=0.199 total time= 0.2s
 [CV 3/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
 store_cv_values=False;; score=0.200 total time= 0.3s
 [CV 4/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
 store_cv_values=False;; score=0.200 total time= 0.2s
 [CV 5/5] END alpha_per_target=True, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
 store_cv_values=False;; score=0.197 total time= 0.2s
 [CV 1/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
 store_cv_values=False;; score=0.202 total time= 0.3s

```
[CV 2/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
store_cv_values=False;; score=0.199 total time= 0.2s
[CV 3/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
store_cv_values=False;; score=0.200 total time= 0.3s
[CV 4/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
store_cv_values=False;; score=0.200 total time= 0.3s
[CV 5/5] END alpha_per_target=False, alphas=(0.1, 1.0, 10.0), gcv_mode=svd,
store_cv_values=False;; score=0.197 total time= 0.3s
Mean Absolute Percentage Error: 2.8233581573545994
Root Mean Squared Error: 0.8926634055078709
R2 Score: 0.2003247417172579
```

```
[115]: grid_ridge.best_params_
```

```
[115]: {'store_cv_values': False,
'gcv_mode': 'auto',
'alphas': (0.1, 1.0, 10.0),
'alpha_per_target': True}
```

```
[116]: param_grid = {'selection': ['cyclic','random'],
'l1_ratio': [0.1,0.3,0.5,0.8,1],
'positive': [True,False]}
grid_elasticnet = RandomizedSearchCV(ElasticNetCV(),param_grid,verbose=2,cv=5)
train_and_evaluate_model(grid_elasticnet)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```
[CV] END ...l1_ratio=0.8, positive=True, selection=cyclic; total time= 1.5s
[CV] END ...l1_ratio=0.8, positive=True, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=True, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=True, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=True, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=0.3, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.3, positive=False, selection=random; total time= 1.4s
[CV] END ...l1_ratio=0.3, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.3, positive=False, selection=random; total time= 1.6s
[CV] END ...l1_ratio=0.3, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.8, positive=True, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.8, positive=True, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.8, positive=True, selection=random; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=True, selection=random; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=True, selection=random; total time= 1.6s
[CV] END ...l1_ratio=1, positive=True, selection=cyclic; total time= 1.5s
[CV] END ...l1_ratio=1, positive=True, selection=cyclic; total time= 1.5s
[CV] END ...l1_ratio=1, positive=True, selection=cyclic; total time= 1.6s
[CV] END ...l1_ratio=1, positive=True, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=1, positive=True, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=False, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=False, selection=cyclic; total time= 1.4s
```

```

[CV] END ...l1_ratio=0.8, positive=False, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=False, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=False, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=1, positive=True, selection=random; total time= 1.4s
[CV] END ...l1_ratio=1, positive=True, selection=random; total time= 1.5s
[CV] END ...l1_ratio=1, positive=True, selection=random; total time= 1.5s
[CV] END ...l1_ratio=1, positive=True, selection=random; total time= 1.4s
[CV] END ...l1_ratio=1, positive=True, selection=random; total time= 1.4s
[CV] END ...l1_ratio=1, positive=False, selection=cyclic; total time= 1.5s
[CV] END ...l1_ratio=1, positive=False, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=1, positive=False, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=1, positive=False, selection=cyclic; total time= 1.4s
[CV] END ...l1_ratio=1, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=1, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=1, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=1, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=1, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.5, positive=True, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.5, positive=True, selection=random; total time= 1.6s
[CV] END ...l1_ratio=0.5, positive=True, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.5, positive=True, selection=random; total time= 1.4s
[CV] END ...l1_ratio=0.5, positive=True, selection=random; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=False, selection=random; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=False, selection=random; total time= 1.4s
[CV] END ...l1_ratio=0.8, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.8, positive=False, selection=random; total time= 1.5s
[CV] END ...l1_ratio=0.8, positive=False, selection=random; total time= 1.5s
Mean Absolute Percentage Error: 2.8128598486398455
Root Mean Squared Error: 0.8926641867031345
R2 Score: 0.20032334207928992

```

```
[117]: grid_elasticnet.best_params_
```

```
[117]: {'selection': 'random', 'positive': False, 'l1_ratio': 1}
```

```

[118]: param_grid = {'alpha_1': [1e-5,1e-6,1e-7,1e-8],
'alpha_2': [1e-5,1e-6,1e-7,1e-8],
'lambda_1': [1e-5,1e-6,1e-7,1e-8],
'lambda_2': [1e-5,1e-6,1e-7,1e-8],
'fit_intercept': [True,False],
'compute_score': [True,False]}
grid_ard = RandomizedSearchCV(ARDRegression(),param_grid,verbose=2,cv=5)
train_and_evaluate_model(grid_ard)

```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```

[CV] END alpha_1=1e-07, alpha_2=1e-05, compute_score=False, fit_intercept=False,
lambda_1=1e-05, lambda_2=1e-07; total time= 0.1s

```

[illegible]

[illegible]

```
[CV] END alpha_1=1e-08, alpha_2=1e-07, compute_score=False, fit_intercept=False,
lambda_1=1e-06, lambda_2=1e-05; total time= 0.1s
Mean Absolute Percentage Error: 2.8176495204191436
Root Mean Squared Error: 0.8927101760905762
R2 Score: 0.20024094247695468
```

```
[119]: grid_ard.best_params_
```

```
[119]: {'lambda_2': 1e-05,
       'lambda_1': 1e-07,
       'fit_intercept': False,
       'compute_score': True,
       'alpha_2': 1e-06,
       'alpha_1': 1e-08}
```

```
[120]: param_grid = {'fit_intercept': [True, False],
                    'positive': [True, False]}
grid_lr = RandomizedSearchCV(LinearRegression(), param_grid, verbose=2, cv=5)
train_and_evaluate_model(grid_lr)
```

Fitting 5 folds for each of 4 candidates, totalling 20 fits

```
[CV] END ...fit_intercept=True, positive=True; total time= 0.2s
[CV] END ...fit_intercept=True, positive=True; total time= 0.1s
[CV] END ...fit_intercept=True, positive=True; total time= 0.1s
[CV] END ...fit_intercept=True, positive=True; total time= 0.3s
[CV] END ...fit_intercept=True, positive=True; total time= 0.1s
[CV] END ...fit_intercept=True, positive=False; total time= 0.2s
[CV] END ...fit_intercept=True, positive=False; total time= 0.1s
[CV] END ...fit_intercept=True, positive=False; total time= 0.2s
[CV] END ...fit_intercept=True, positive=False; total time= 0.1s
[CV] END ...fit_intercept=True, positive=False; total time= 0.1s
[CV] END ...fit_intercept=False, positive=True; total time= 0.1s
[CV] END ...fit_intercept=False, positive=True; total time= 0.1s
[CV] END ...fit_intercept=False, positive=True; total time= 0.2s
[CV] END ...fit_intercept=False, positive=True; total time= 0.1s
[CV] END ...fit_intercept=False, positive=True; total time= 0.1s
[CV] END ...fit_intercept=False, positive=False; total time= 0.1s
[CV] END ...fit_intercept=False, positive=False; total time= 0.1s
[CV] END ...fit_intercept=False, positive=False; total time= 0.1s
[CV] END ...fit_intercept=False, positive=False; total time= 0.1s
[CV] END ...fit_intercept=False, positive=False; total time= 0.1s
[CV] END ...fit_intercept=False, positive=False; total time= 0.1s
Mean Absolute Percentage Error: 2.8111217986582604
Root Mean Squared Error: 0.8926599124662851
R2 Score: 0.20033100005259452
```

```
[121]: grid_lr.best_params_
```

```
[121]: {'positive': False, 'fit_intercept': False}
```

0.9 Optimized Models Performance Comparison

```
[123]: model_perfs = pd.DataFrame({'model': models, 'MAPE': mape_scores, 'RMSE': rmse_scores, 'R2': r2_scores}).sort_values('R2', ascending=False).reset_index()
model_perfs
```

```
[123]:
```

	index	model	MAPE \
0	27	RandomizedSearchCV(cv=5,\n	e... 9.178925
1	19	XGBRegressor(base_score=None, booster=None, ca...	9.510364
2	21	<catboost.core.CatBoostRegressor object at 0x0...	9.566809
3	23	VotingRegressor(estimators=[('XGB',\n	... 9.772236
4	28	RandomizedSearchCV(cv=5, estimator=LGBMRegress...	9.676186
5	17	HistGradientBoostingRegressor()	9.876982
6	22	LGBMRegressor()	9.851482
7	25	RandomizedSearchCV(cv=5, estimator=HistGradien...	8.077690
8	13	RandomForestRegressor()	8.446764
9	16	GradientBoostingRegressor()	10.125410
10	20	MLPRegressor()	9.539763
11	14	BaggingRegressor()	8.594595
12	18	ExtraTreesRegressor()	8.372042
13	12	DecisionTreeRegressor()	8.496325
14	15	AdaBoostRegressor()	11.013678
15	24	RandomizedSearchCV(cv=5, estimator=KNeighborsR...	8.127304
16	10	KNeighborsRegressor()	8.719462
17	37	RandomizedSearchCV(cv=5, estimator=LinearRegre...	2.811122
18	29	RandomizedSearchCV(cv=5, estimator=SGDRegresso...	2.822238
19	33	RandomizedSearchCV(cv=5, estimator=LassoCV(),\n...	2.822344
20	30	RandomizedSearchCV(cv=5, estimator=HuberRegres...	2.823415
21	31	RandomizedSearchCV(cv=5, estimator=TweedieRegr...	2.823237
22	34	RandomizedSearchCV(cv=5, estimator=RidgeCV(),\n...	2.823358
23	3	RidgeCV()	2.823358
24	0	LinearRegression()	2.823401
25	26	RandomizedSearchCV(cv=5, estimator=LinearSVR()...	2.823790
26	2	LassoCV()	2.812867
27	35	RandomizedSearchCV(cv=5, estimator=ElasticNetC...	2.812860
28	4	ElasticNetCV()	2.812150
29	36	RandomizedSearchCV(cv=5, estimator=ARDRegressi...	2.817650
30	6	ARDRegression()	2.829739
31	5	SGDRegressor()	2.720202
32	32	RandomizedSearchCV(cv=5, estimator=PassiveAggr...	3.082931
33	11	LinearSVR()	3.802376
34	9	HuberRegressor()	3.325187
35	8	TweedieRegressor()	2.014332
36	7	RANSACRegressor()	11.936712
37	1	PassiveAggressiveRegressor()	14.310157

	RMSE	R2
0	0.538501	0.708988
1	0.545765	0.701084
2	0.547649	0.699016
3	0.555833	0.689954
4	0.559983	0.685306
5	0.561679	0.683398
6	0.561847	0.683208
7	0.571788	0.671898
8	0.576744	0.666186
9	0.579399	0.663106
10	0.583392	0.658446
11	0.588627	0.652289
12	0.609390	0.627326
13	0.668831	0.551078
14	0.692713	0.518446
15	0.734465	0.458647
16	0.766221	0.410823
17	0.892660	0.200331
18	0.892663	0.200325
19	0.892663	0.200325
20	0.892663	0.200325
21	0.892663	0.200325
22	0.892663	0.200325
23	0.892663	0.200325
24	0.892663	0.200325
25	0.892664	0.200325
26	0.892664	0.200323
27	0.892664	0.200323
28	0.892664	0.200323
29	0.892710	0.200241
30	0.892714	0.200235
31	0.893174	0.199410
32	0.895549	0.195147
33	0.899185	0.188598
34	0.899893	0.187319
35	0.918138	0.154032
36	1.245036	-0.555614
37	1.398375	-0.962390

```
[125]: model_perfs.iloc[0]['model']
```

```
[125]: "RandomizedSearchCV(cv=5,\n
estimator=<catboost.core.CatBoostRegressor object at 0x000002D60CBAC1C0>,\n
param_distributions={'learning_rate': [0.2, 0.4, 0.5, 0.7,\n
1],\n
'n_estimators': [100, 400, 700,\n
800,\n
1000]}],\n
```

```
verbose=5)"
```

0.10 Deep Learning using Artificial Neural Networks (ANN)

```
[158]: ann = Sequential()
ann.add(Dense(units=32,activation='relu',input_shape=(X_train.shape[1],)))
ann.add(Dense(units=64,activation='relu'))
ann.add(Dropout(0.1))
ann.add(Dense(units=128,activation='relu'))
ann.add(Dropout(0.2))
ann.add(Dense(units=256,activation='relu'))
ann.add(Dropout(0.3))
ann.add(Dense(units=1))
ann.compile(loss='mean_squared_error',optimizer='adam',metrics=RSquare())
ann.summary()
```

Model: "sequential_7"

Layer (type)	Output Shape	Param #
dense_31 (Dense)	(None, 32)	352
dense_32 (Dense)	(None, 64)	2112
dropout_18 (Dropout)	(None, 64)	0
dense_33 (Dense)	(None, 128)	8320
dropout_19 (Dropout)	(None, 128)	0
dense_34 (Dense)	(None, 256)	33024
dropout_20 (Dropout)	(None, 256)	0
dense_35 (Dense)	(None, 1)	257

=====
Total params: 44,065
Trainable params: 44,065
Non-trainable params: 0
=====

```
[159]: plot_model(ann, 'ann.png', show_shapes=True, dpi=100, show_layer_names=True)
```

[159]:

dense_31_input	input:	[(None, 10)]
InputLayer	output:	[(None, 10)]



dense_31	input:	(None, 10)
Dense	output:	(None, 32)



dense_32	input:	(None, 32)
Dense	output:	(None, 64)



dropout_18	input:	(None, 64)
Dropout	output:	(None, 64)



dense_33	input:	(None, 64)
Dense	output:	(None, 128)



dropout_19	input:	(None, 128)
Dropout	output:	(None, 128)



dense_34	input:	(None, 128)
Dense	output:	(None, 256)



dropout_20	input:	(None, 256)
Dropout	output:	(None, 256)



dense_35	input:	(None, 256)
Dense	output:	(None, 1)

```
[163]: es = EarlyStopping(monitor='val_r_square',mode='max',patience=20,verbose=1,restore_best_weights=True)
rl = ReduceLROnPlateau(monitor='val_r_square',mode='max',patience=20,factor=0.1,min_lr=1e-3,verbose=1)
mc = ModelCheckpoint('black_friday_sales_predictor.h5',monitor='val_r_square',mode='max',verbose=1,save_best_only=True)

r = ann.fit(X_train,
            y_train,
            epochs=100,
            batch_size=32,
            callbacks=[es,mc,rl],
            validation_data=(X_test,y_test))
```

```
Epoch 1/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.5752 -
r_square: 0.4256
Epoch 1: val_r_square improved from -inf to 0.44221, saving model to
black_friday_sales_predictor.h5
12033/12033 [=====] - 32s 3ms/step - loss: 0.5753 -
r_square: 0.4256 - val_loss: 0.5558 - val_r_square: 0.4422 - lr: 0.0010
Epoch 2/100
12025/12033 [=====>.] - ETA: 0s - loss: 0.4716 -
r_square: 0.5292
Epoch 2: val_r_square improved from 0.44221 to 0.62176, saving model to
black_friday_sales_predictor.h5
12033/12033 [=====] - 33s 3ms/step - loss: 0.4715 -
r_square: 0.5292 - val_loss: 0.3769 - val_r_square: 0.6218 - lr: 0.0010
Epoch 3/100
12026/12033 [=====>.] - ETA: 0s - loss: 0.3860 -
r_square: 0.6145
Epoch 3: val_r_square improved from 0.62176 to 0.62972, saving model to
black_friday_sales_predictor.h5
12033/12033 [=====] - 33s 3ms/step - loss: 0.3860 -
r_square: 0.6146 - val_loss: 0.3690 - val_r_square: 0.6297 - lr: 0.0010
Epoch 4/100
12019/12033 [=====>.] - ETA: 0s - loss: 0.3740 -
r_square: 0.6266
Epoch 4: val_r_square improved from 0.62972 to 0.63633, saving model to
black_friday_sales_predictor.h5
12033/12033 [=====] - 35s 3ms/step - loss: 0.3739 -
r_square: 0.6266 - val_loss: 0.3624 - val_r_square: 0.6363 - lr: 0.0010
Epoch 5/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3673 -
r_square: 0.6333
```

Epoch 5: val_r_square improved from 0.63633 to 0.64068, saving model to black_friday_sales_predictor.h5
12033/12033 [=====] - 34s 3ms/step - loss: 0.3673 - r_square: 0.6333 - val_loss: 0.3581 - val_r_square: 0.6407 - lr: 0.0010
Epoch 6/100
12023/12033 [=====>.] - ETA: 0s - loss: 0.3646 - r_square: 0.6360
Epoch 6: val_r_square did not improve from 0.64068
12033/12033 [=====] - 36s 3ms/step - loss: 0.3645 - r_square: 0.6360 - val_loss: 0.3609 - val_r_square: 0.6379 - lr: 0.0010
Epoch 7/100
12019/12033 [=====>.] - ETA: 0s - loss: 0.3634 - r_square: 0.6371
Epoch 7: val_r_square did not improve from 0.64068
12033/12033 [=====] - 34s 3ms/step - loss: 0.3634 - r_square: 0.6371 - val_loss: 0.3602 - val_r_square: 0.6385 - lr: 0.0010
Epoch 8/100
12020/12033 [=====>.] - ETA: 0s - loss: 0.3600 - r_square: 0.6405
Epoch 8: val_r_square did not improve from 0.64068
12033/12033 [=====] - 36s 3ms/step - loss: 0.3600 - r_square: 0.6405 - val_loss: 0.3641 - val_r_square: 0.6346 - lr: 0.0010
Epoch 9/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3595 - r_square: 0.6411
Epoch 9: val_r_square did not improve from 0.64068
12033/12033 [=====] - 37s 3ms/step - loss: 0.3595 - r_square: 0.6411 - val_loss: 0.3587 - val_r_square: 0.6400 - lr: 0.0010
Epoch 10/100
12024/12033 [=====>.] - ETA: 0s - loss: 0.3578 - r_square: 0.6427
Epoch 10: val_r_square did not improve from 0.64068
12033/12033 [=====] - 35s 3ms/step - loss: 0.3578 - r_square: 0.6428 - val_loss: 0.3634 - val_r_square: 0.6353 - lr: 0.0010
Epoch 11/100
12020/12033 [=====>.] - ETA: 0s - loss: 0.3575 - r_square: 0.6430
Epoch 11: val_r_square did not improve from 0.64068
12033/12033 [=====] - 35s 3ms/step - loss: 0.3575 - r_square: 0.6430 - val_loss: 0.3770 - val_r_square: 0.6216 - lr: 0.0010
Epoch 12/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.3571 - r_square: 0.6435
Epoch 12: val_r_square did not improve from 0.64068
12033/12033 [=====] - 36s 3ms/step - loss: 0.3571 - r_square: 0.6435 - val_loss: 0.3728 - val_r_square: 0.6259 - lr: 0.0010
Epoch 13/100
12031/12033 [=====>.] - ETA: 0s - loss: 0.3563 -


```

r_square: 0.6443
Epoch 13: val_r_square did not improve from 0.64068
12033/12033 [=====] - 35s 3ms/step - loss: 0.3563 -
r_square: 0.6443 - val_loss: 0.3603 - val_r_square: 0.6384 - lr: 0.0010
Epoch 14/100
12013/12033 [=====>.] - ETA: 0s - loss: 0.3562 -
r_square: 0.6443
Epoch 14: val_r_square did not improve from 0.64068
12033/12033 [=====] - 40s 3ms/step - loss: 0.3562 -
r_square: 0.6443 - val_loss: 0.3672 - val_r_square: 0.6315 - lr: 0.0010
Epoch 15/100
12014/12033 [=====>.] - ETA: 0s - loss: 0.3554 -
r_square: 0.6452
Epoch 15: val_r_square did not improve from 0.64068
12033/12033 [=====] - 34s 3ms/step - loss: 0.3554 -
r_square: 0.6451 - val_loss: 0.3605 - val_r_square: 0.6382 - lr: 0.0010
Epoch 16/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3552 -
r_square: 0.6453
Epoch 16: val_r_square did not improve from 0.64068
12033/12033 [=====] - 34s 3ms/step - loss: 0.3552 -
r_square: 0.6453 - val_loss: 0.3605 - val_r_square: 0.6383 - lr: 0.0010
Epoch 17/100
12021/12033 [=====>.] - ETA: 0s - loss: 0.3543 -
r_square: 0.6463
Epoch 17: val_r_square did not improve from 0.64068
12033/12033 [=====] - 35s 3ms/step - loss: 0.3543 -
r_square: 0.6462 - val_loss: 0.3629 - val_r_square: 0.6358 - lr: 0.0010
Epoch 18/100
12019/12033 [=====>.] - ETA: 0s - loss: 0.3539 -
r_square: 0.6466
Epoch 18: val_r_square improved from 0.64068 to 0.64385, saving model to
black_friday_sales_predictor.h5
12033/12033 [=====] - 33s 3ms/step - loss: 0.3539 -
r_square: 0.6466 - val_loss: 0.3549 - val_r_square: 0.6439 - lr: 0.0010
Epoch 19/100
12027/12033 [=====>.] - ETA: 0s - loss: 0.3540 -
r_square: 0.6465
Epoch 19: val_r_square did not improve from 0.64385
12033/12033 [=====] - 35s 3ms/step - loss: 0.3540 -
r_square: 0.6465 - val_loss: 0.3626 - val_r_square: 0.6361 - lr: 0.0010
Epoch 20/100
12022/12033 [=====>.] - ETA: 0s - loss: 0.3544 -
r_square: 0.6462
Epoch 20: val_r_square improved from 0.64385 to 0.64504, saving model to
black_friday_sales_predictor.h5
12033/12033 [=====] - 36s 3ms/step - loss: 0.3543 -
r_square: 0.6462 - val_loss: 0.3537 - val_r_square: 0.6450 - lr: 0.0010

```

Epoch 21/100
12023/12033 [=====>.] - ETA: 0s - loss: 0.3533 -
r_square: 0.6472
Epoch 21: val_r_square did not improve from 0.64504
12033/12033 [=====] - 39s 3ms/step - loss: 0.3533 -
r_square: 0.6472 - val_loss: 0.3609 - val_r_square: 0.6378 - lr: 0.0010
Epoch 22/100
12031/12033 [=====>.] - ETA: 0s - loss: 0.3533 -
r_square: 0.6473
Epoch 22: val_r_square did not improve from 0.64504
12033/12033 [=====] - 55s 5ms/step - loss: 0.3533 -
r_square: 0.6473 - val_loss: 0.3690 - val_r_square: 0.6297 - lr: 0.0010
Epoch 23/100
12018/12033 [=====>.] - ETA: 0s - loss: 0.3527 -
r_square: 0.6478
Epoch 23: val_r_square did not improve from 0.64504
12033/12033 [=====] - 46s 4ms/step - loss: 0.3527 -
r_square: 0.6478 - val_loss: 0.3651 - val_r_square: 0.6336 - lr: 0.0010
Epoch 24/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3519 -
r_square: 0.6487
Epoch 24: val_r_square did not improve from 0.64504
12033/12033 [=====] - 46s 4ms/step - loss: 0.3518 -
r_square: 0.6487 - val_loss: 0.3671 - val_r_square: 0.6316 - lr: 0.0010
Epoch 25/100
12022/12033 [=====>.] - ETA: 0s - loss: 0.3521 -
r_square: 0.6484
Epoch 25: val_r_square did not improve from 0.64504
12033/12033 [=====] - 44s 4ms/step - loss: 0.3520 -
r_square: 0.6485 - val_loss: 0.3639 - val_r_square: 0.6348 - lr: 0.0010
Epoch 26/100
12030/12033 [=====>.] - ETA: 0s - loss: 0.3519 -
r_square: 0.6487
Epoch 26: val_r_square did not improve from 0.64504
12033/12033 [=====] - 45s 4ms/step - loss: 0.3519 -
r_square: 0.6486 - val_loss: 0.3616 - val_r_square: 0.6371 - lr: 0.0010
Epoch 27/100
12029/12033 [=====>.] - ETA: 0s - loss: 0.3525 -
r_square: 0.6480
Epoch 27: val_r_square did not improve from 0.64504
12033/12033 [=====] - 43s 4ms/step - loss: 0.3525 -
r_square: 0.6480 - val_loss: 0.3697 - val_r_square: 0.6290 - lr: 0.0010
Epoch 28/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.3515 -
r_square: 0.6490
Epoch 28: val_r_square did not improve from 0.64504
12033/12033 [=====] - 45s 4ms/step - loss: 0.3515 -
r_square: 0.6490 - val_loss: 0.3611 - val_r_square: 0.6376 - lr: 0.0010

Epoch 29/100
12031/12033 [=====>.] - ETA: 0s - loss: 0.3516 -
r_square: 0.6489
Epoch 29: val_r_square did not improve from 0.64504
12033/12033 [=====] - 44s 4ms/step - loss: 0.3516 -
r_square: 0.6490 - val_loss: 0.3619 - val_r_square: 0.6368 - lr: 0.0010
Epoch 30/100
12030/12033 [=====>.] - ETA: 0s - loss: 0.3505 -
r_square: 0.6500
Epoch 30: val_r_square did not improve from 0.64504
12033/12033 [=====] - 44s 4ms/step - loss: 0.3505 -
r_square: 0.6500 - val_loss: 0.3683 - val_r_square: 0.6304 - lr: 0.0010
Epoch 31/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3504 -
r_square: 0.6501
Epoch 31: val_r_square did not improve from 0.64504
12033/12033 [=====] - 41s 3ms/step - loss: 0.3504 -
r_square: 0.6501 - val_loss: 0.3713 - val_r_square: 0.6274 - lr: 0.0010
Epoch 32/100
12023/12033 [=====>.] - ETA: 0s - loss: 0.3510 -
r_square: 0.6496
Epoch 32: val_r_square did not improve from 0.64504
12033/12033 [=====] - 48s 4ms/step - loss: 0.3509 -
r_square: 0.6496 - val_loss: 0.3701 - val_r_square: 0.6286 - lr: 0.0010
Epoch 33/100
12025/12033 [=====>.] - ETA: 0s - loss: 0.3523 -
r_square: 0.6483
Epoch 33: val_r_square did not improve from 0.64504
12033/12033 [=====] - 70s 6ms/step - loss: 0.3523 -
r_square: 0.6483 - val_loss: 0.3686 - val_r_square: 0.6301 - lr: 0.0010
Epoch 34/100
12021/12033 [=====>.] - ETA: 0s - loss: 0.3503 -
r_square: 0.6502
Epoch 34: val_r_square did not improve from 0.64504
12033/12033 [=====] - 47s 4ms/step - loss: 0.3503 -
r_square: 0.6502 - val_loss: 0.3542 - val_r_square: 0.6445 - lr: 0.0010
Epoch 35/100
12026/12033 [=====>.] - ETA: 0s - loss: 0.3507 -
r_square: 0.6499
Epoch 35: val_r_square did not improve from 0.64504
12033/12033 [=====] - 40s 3ms/step - loss: 0.3507 -
r_square: 0.6498 - val_loss: 0.3621 - val_r_square: 0.6366 - lr: 0.0010
Epoch 36/100
12025/12033 [=====>.] - ETA: 0s - loss: 0.3499 -
r_square: 0.6506
Epoch 36: val_r_square did not improve from 0.64504
12033/12033 [=====] - 46s 4ms/step - loss: 0.3499 -
r_square: 0.6506 - val_loss: 0.3634 - val_r_square: 0.6353 - lr: 0.0010

Epoch 37/100
12024/12033 [=====>.] - ETA: 0s - loss: 0.3500 -
r_square: 0.6506
Epoch 37: val_r_square did not improve from 0.64504
12033/12033 [=====] - 41s 3ms/step - loss: 0.3500 -
r_square: 0.6506 - val_loss: 0.3668 - val_r_square: 0.6319 - lr: 0.0010
Epoch 38/100
12026/12033 [=====>.] - ETA: 0s - loss: 0.3500 -
r_square: 0.6505
Epoch 38: val_r_square did not improve from 0.64504
12033/12033 [=====] - 47s 4ms/step - loss: 0.3501 -
r_square: 0.6505 - val_loss: 0.3746 - val_r_square: 0.6241 - lr: 0.0010
Epoch 39/100
12017/12033 [=====>.] - ETA: 0s - loss: 0.3504 -
r_square: 0.6502
Epoch 39: val_r_square did not improve from 0.64504
12033/12033 [=====] - 38s 3ms/step - loss: 0.3504 -
r_square: 0.6502 - val_loss: 0.3769 - val_r_square: 0.6217 - lr: 0.0010
Epoch 40/100
12020/12033 [=====>.] - ETA: 0s - loss: 0.3495 -
r_square: 0.6511
Epoch 40: val_r_square did not improve from 0.64504
12033/12033 [=====] - 41s 3ms/step - loss: 0.3495 -
r_square: 0.6511 - val_loss: 0.3599 - val_r_square: 0.6388 - lr: 0.0010
Epoch 41/100
12013/12033 [=====>.] - ETA: 0s - loss: 0.3502 -
r_square: 0.6503
Epoch 41: val_r_square did not improve from 0.64504
12033/12033 [=====] - 39s 3ms/step - loss: 0.3502 -
r_square: 0.6503 - val_loss: 0.3660 - val_r_square: 0.6327 - lr: 0.0010
Epoch 42/100
12021/12033 [=====>.] - ETA: 0s - loss: 0.3495 -
r_square: 0.6510
Epoch 42: val_r_square did not improve from 0.64504
12033/12033 [=====] - 39s 3ms/step - loss: 0.3495 -
r_square: 0.6510 - val_loss: 0.3561 - val_r_square: 0.6427 - lr: 0.0010
Epoch 43/100
12026/12033 [=====>.] - ETA: 0s - loss: 0.3496 -
r_square: 0.6510
Epoch 43: val_r_square did not improve from 0.64504
12033/12033 [=====] - 40s 3ms/step - loss: 0.3495 -
r_square: 0.6510 - val_loss: 0.3625 - val_r_square: 0.6363 - lr: 0.0010
Epoch 44/100
12033/12033 [=====] - ETA: 0s - loss: 0.3499 -
r_square: 0.6507
Epoch 44: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 3ms/step - loss: 0.3499 -
r_square: 0.6507 - val_loss: 0.3627 - val_r_square: 0.6361 - lr: 0.0010

Epoch 45/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3500 -
r_square: 0.6505
Epoch 45: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 3ms/step - loss: 0.3499 -
r_square: 0.6506 - val_loss: 0.3659 - val_r_square: 0.6328 - lr: 0.0010
Epoch 46/100
12026/12033 [=====>.] - ETA: 0s - loss: 0.3497 -
r_square: 0.6508
Epoch 46: val_r_square did not improve from 0.64504
12033/12033 [=====] - 46s 4ms/step - loss: 0.3497 -
r_square: 0.6509 - val_loss: 0.3671 - val_r_square: 0.6316 - lr: 0.0010
Epoch 47/100
12026/12033 [=====>.] - ETA: 0s - loss: 0.3500 -
r_square: 0.6505
Epoch 47: val_r_square did not improve from 0.64504
12033/12033 [=====] - 45s 4ms/step - loss: 0.3499 -
r_square: 0.6506 - val_loss: 0.3678 - val_r_square: 0.6309 - lr: 0.0010
Epoch 48/100
12029/12033 [=====>.] - ETA: 0s - loss: 0.3494 -
r_square: 0.6511
Epoch 48: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 3ms/step - loss: 0.3494 -
r_square: 0.6511 - val_loss: 0.3700 - val_r_square: 0.6287 - lr: 0.0010
Epoch 49/100
12023/12033 [=====>.] - ETA: 0s - loss: 0.3488 -
r_square: 0.6517
Epoch 49: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 4ms/step - loss: 0.3488 -
r_square: 0.6517 - val_loss: 0.3656 - val_r_square: 0.6331 - lr: 0.0010
Epoch 50/100
12024/12033 [=====>.] - ETA: 0s - loss: 0.3498 -
r_square: 0.6507
Epoch 50: val_r_square did not improve from 0.64504
12033/12033 [=====] - 41s 3ms/step - loss: 0.3498 -
r_square: 0.6507 - val_loss: 0.3894 - val_r_square: 0.6092 - lr: 0.0010
Epoch 51/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3495 -
r_square: 0.6510
Epoch 51: val_r_square did not improve from 0.64504
12033/12033 [=====] - 39s 3ms/step - loss: 0.3495 -
r_square: 0.6510 - val_loss: 0.3623 - val_r_square: 0.6364 - lr: 0.0010
Epoch 52/100
12022/12033 [=====>.] - ETA: 0s - loss: 0.3488 -
r_square: 0.6517
Epoch 52: val_r_square did not improve from 0.64504
12033/12033 [=====] - 38s 3ms/step - loss: 0.3488 -
r_square: 0.6517 - val_loss: 0.3640 - val_r_square: 0.6347 - lr: 0.0010

Epoch 53/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.3498 -
r_square: 0.6507
Epoch 53: val_r_square did not improve from 0.64504
12033/12033 [=====] - 39s 3ms/step - loss: 0.3498 -
r_square: 0.6507 - val_loss: 0.3749 - val_r_square: 0.6238 - lr: 0.0010
Epoch 54/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.3498 -
r_square: 0.6507
Epoch 54: val_r_square did not improve from 0.64504
12033/12033 [=====] - 40s 3ms/step - loss: 0.3498 -
r_square: 0.6507 - val_loss: 0.3735 - val_r_square: 0.6252 - lr: 0.0010
Epoch 55/100
12023/12033 [=====>.] - ETA: 0s - loss: 0.3495 -
r_square: 0.6511
Epoch 55: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 3ms/step - loss: 0.3494 -
r_square: 0.6511 - val_loss: 0.3717 - val_r_square: 0.6270 - lr: 0.0010
Epoch 56/100
12013/12033 [=====>.] - ETA: 0s - loss: 0.3485 -
r_square: 0.6520
Epoch 56: val_r_square did not improve from 0.64504
12033/12033 [=====] - 38s 3ms/step - loss: 0.3485 -
r_square: 0.6520 - val_loss: 0.3731 - val_r_square: 0.6256 - lr: 0.0010
Epoch 57/100
12023/12033 [=====>.] - ETA: 0s - loss: 0.3506 -
r_square: 0.6499
Epoch 57: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 4ms/step - loss: 0.3506 -
r_square: 0.6499 - val_loss: 0.3629 - val_r_square: 0.6358 - lr: 0.0010
Epoch 58/100
12022/12033 [=====>.] - ETA: 0s - loss: 0.3495 -
r_square: 0.6510
Epoch 58: val_r_square did not improve from 0.64504
12033/12033 [=====] - 40s 3ms/step - loss: 0.3495 -
r_square: 0.6510 - val_loss: 0.3648 - val_r_square: 0.6339 - lr: 0.0010
Epoch 59/100
12031/12033 [=====>.] - ETA: 0s - loss: 0.3485 -
r_square: 0.6520
Epoch 59: val_r_square did not improve from 0.64504
12033/12033 [=====] - 40s 3ms/step - loss: 0.3485 -
r_square: 0.6520 - val_loss: 0.3633 - val_r_square: 0.6354 - lr: 0.0010
Epoch 60/100
12027/12033 [=====>.] - ETA: 0s - loss: 0.3483 -
r_square: 0.6522
Epoch 60: val_r_square did not improve from 0.64504
12033/12033 [=====] - 40s 3ms/step - loss: 0.3483 -
r_square: 0.6523 - val_loss: 0.3613 - val_r_square: 0.6374 - lr: 0.0010

Epoch 61/100
12029/12033 [=====>.] - ETA: 0s - loss: 0.3480 -
r_square: 0.6525
Epoch 61: val_r_square did not improve from 0.64504
12033/12033 [=====] - 41s 3ms/step - loss: 0.3480 -
r_square: 0.6525 - val_loss: 0.3691 - val_r_square: 0.6296 - lr: 0.0010
Epoch 62/100
12019/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6519
Epoch 62: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 3ms/step - loss: 0.3486 -
r_square: 0.6519 - val_loss: 0.3639 - val_r_square: 0.6348 - lr: 0.0010
Epoch 63/100
12017/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6520
Epoch 63: val_r_square did not improve from 0.64504
12033/12033 [=====] - 40s 3ms/step - loss: 0.3486 -
r_square: 0.6519 - val_loss: 0.3706 - val_r_square: 0.6281 - lr: 0.0010
Epoch 64/100
12019/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6520
Epoch 64: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 3ms/step - loss: 0.3485 -
r_square: 0.6520 - val_loss: 0.3680 - val_r_square: 0.6307 - lr: 0.0010
Epoch 65/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6520
Epoch 65: val_r_square did not improve from 0.64504
12033/12033 [=====] - 38s 3ms/step - loss: 0.3485 -
r_square: 0.6521 - val_loss: 0.3658 - val_r_square: 0.6329 - lr: 0.0010
Epoch 66/100
12027/12033 [=====>.] - ETA: 0s - loss: 0.3480 -
r_square: 0.6524
Epoch 66: val_r_square did not improve from 0.64504
12033/12033 [=====] - 41s 3ms/step - loss: 0.3480 -
r_square: 0.6525 - val_loss: 0.3642 - val_r_square: 0.6345 - lr: 0.0010
Epoch 67/100
12023/12033 [=====>.] - ETA: 0s - loss: 0.3483 -
r_square: 0.6522
Epoch 67: val_r_square did not improve from 0.64504
12033/12033 [=====] - 39s 3ms/step - loss: 0.3483 -
r_square: 0.6522 - val_loss: 0.3726 - val_r_square: 0.6261 - lr: 0.0010
Epoch 68/100
12029/12033 [=====>.] - ETA: 0s - loss: 0.3491 -
r_square: 0.6515
Epoch 68: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 3ms/step - loss: 0.3490 -
r_square: 0.6515 - val_loss: 0.3539 - val_r_square: 0.6448 - lr: 0.0010

Epoch 69/100
12022/12033 [=====>.] - ETA: 0s - loss: 0.3488 -
r_square: 0.6517
Epoch 69: val_r_square did not improve from 0.64504
12033/12033 [=====] - 42s 4ms/step - loss: 0.3489 -
r_square: 0.6516 - val_loss: 0.3700 - val_r_square: 0.6287 - lr: 0.0010
Epoch 70/100
12030/12033 [=====>.] - ETA: 0s - loss: 0.3491 -
r_square: 0.6514
Epoch 70: val_r_square did not improve from 0.64504
12033/12033 [=====] - 41s 3ms/step - loss: 0.3491 -
r_square: 0.6514 - val_loss: 0.3637 - val_r_square: 0.6350 - lr: 0.0010
Epoch 71/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.3482 -
r_square: 0.6523
Epoch 71: val_r_square improved from 0.64504 to 0.64824, saving model to
black_friday_sales_predictor.h5
12033/12033 [=====] - 41s 3ms/step - loss: 0.3482 -
r_square: 0.6523 - val_loss: 0.3505 - val_r_square: 0.6482 - lr: 0.0010
Epoch 72/100
12030/12033 [=====>.] - ETA: 0s - loss: 0.3491 -
r_square: 0.6515
Epoch 72: val_r_square did not improve from 0.64824
12033/12033 [=====] - 40s 3ms/step - loss: 0.3491 -
r_square: 0.6515 - val_loss: 0.3564 - val_r_square: 0.6424 - lr: 0.0010
Epoch 73/100
12031/12033 [=====>.] - ETA: 0s - loss: 0.3490 -
r_square: 0.6515
Epoch 73: val_r_square did not improve from 0.64824
12033/12033 [=====] - 38s 3ms/step - loss: 0.3490 -
r_square: 0.6515 - val_loss: 0.3646 - val_r_square: 0.6341 - lr: 0.0010
Epoch 74/100
12023/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6519
Epoch 74: val_r_square did not improve from 0.64824
12033/12033 [=====] - 42s 4ms/step - loss: 0.3487 -
r_square: 0.6518 - val_loss: 0.3733 - val_r_square: 0.6254 - lr: 0.0010
Epoch 75/100
12015/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6519
Epoch 75: val_r_square did not improve from 0.64824
12033/12033 [=====] - 41s 3ms/step - loss: 0.3486 -
r_square: 0.6519 - val_loss: 0.3644 - val_r_square: 0.6343 - lr: 0.0010
Epoch 76/100
12021/12033 [=====>.] - ETA: 0s - loss: 0.3483 -
r_square: 0.6523
Epoch 76: val_r_square did not improve from 0.64824
12033/12033 [=====] - 43s 4ms/step - loss: 0.3482 -


```

r_square: 0.6523 - val_loss: 0.3709 - val_r_square: 0.6278 - lr: 0.0010
Epoch 77/100
12027/12033 [=====>.] - ETA: 0s - loss: 0.3488 -
r_square: 0.6517
Epoch 77: val_r_square did not improve from 0.64824
12033/12033 [=====] - 42s 3ms/step - loss: 0.3488 -
r_square: 0.6517 - val_loss: 0.3655 - val_r_square: 0.6332 - lr: 0.0010
Epoch 78/100
12021/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6519
Epoch 78: val_r_square did not improve from 0.64824
12033/12033 [=====] - 37s 3ms/step - loss: 0.3486 -
r_square: 0.6519 - val_loss: 0.3662 - val_r_square: 0.6325 - lr: 0.0010
Epoch 79/100
12025/12033 [=====>.] - ETA: 0s - loss: 0.3485 -
r_square: 0.6521
Epoch 79: val_r_square did not improve from 0.64824
12033/12033 [=====] - 39s 3ms/step - loss: 0.3485 -
r_square: 0.6521 - val_loss: 0.3742 - val_r_square: 0.6245 - lr: 0.0010
Epoch 80/100
12021/12033 [=====>.] - ETA: 0s - loss: 0.3485 -
r_square: 0.6520
Epoch 80: val_r_square did not improve from 0.64824
12033/12033 [=====] - 39s 3ms/step - loss: 0.3485 -
r_square: 0.6520 - val_loss: 0.3746 - val_r_square: 0.6241 - lr: 0.0010
Epoch 81/100
12016/12033 [=====>.] - ETA: 0s - loss: 0.3487 -
r_square: 0.6518
Epoch 81: val_r_square did not improve from 0.64824
12033/12033 [=====] - 44s 4ms/step - loss: 0.3487 -
r_square: 0.6518 - val_loss: 0.3544 - val_r_square: 0.6443 - lr: 0.0010
Epoch 82/100
12017/12033 [=====>.] - ETA: 0s - loss: 0.3477 -
r_square: 0.6528
Epoch 82: val_r_square did not improve from 0.64824
12033/12033 [=====] - 42s 4ms/step - loss: 0.3477 -
r_square: 0.6528 - val_loss: 0.3570 - val_r_square: 0.6417 - lr: 0.0010
Epoch 83/100
12019/12033 [=====>.] - ETA: 0s - loss: 0.3485 -
r_square: 0.6521
Epoch 83: val_r_square did not improve from 0.64824
12033/12033 [=====] - 41s 3ms/step - loss: 0.3485 -
r_square: 0.6521 - val_loss: 0.3713 - val_r_square: 0.6274 - lr: 0.0010
Epoch 84/100
12031/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6519
Epoch 84: val_r_square did not improve from 0.64824
12033/12033 [=====] - 41s 3ms/step - loss: 0.3486 -

```

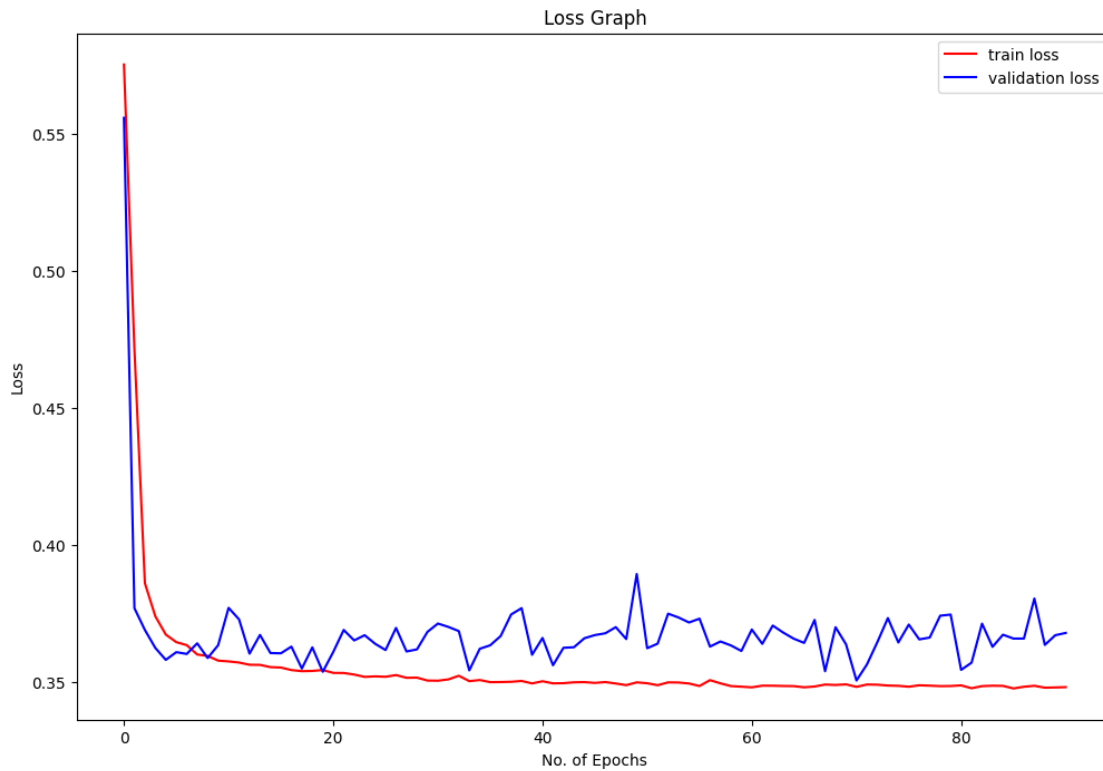
```

r_square: 0.6519 - val_loss: 0.3628 - val_r_square: 0.6359 - lr: 0.0010
Epoch 85/100
12018/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6520
Epoch 85: val_r_square did not improve from 0.64824
12033/12033 [=====] - 39s 3ms/step - loss: 0.3486 -
r_square: 0.6520 - val_loss: 0.3672 - val_r_square: 0.6315 - lr: 0.0010
Epoch 86/100
12017/12033 [=====>.] - ETA: 0s - loss: 0.3476 -
r_square: 0.6529
Epoch 86: val_r_square did not improve from 0.64824
12033/12033 [=====] - 39s 3ms/step - loss: 0.3476 -
r_square: 0.6529 - val_loss: 0.3658 - val_r_square: 0.6329 - lr: 0.0010
Epoch 87/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.3482 -
r_square: 0.6523
Epoch 87: val_r_square did not improve from 0.64824
12033/12033 [=====] - 39s 3ms/step - loss: 0.3482 -
r_square: 0.6523 - val_loss: 0.3658 - val_r_square: 0.6329 - lr: 0.0010
Epoch 88/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.3486 -
r_square: 0.6519
Epoch 88: val_r_square did not improve from 0.64824
12033/12033 [=====] - 40s 3ms/step - loss: 0.3486 -
r_square: 0.6519 - val_loss: 0.3804 - val_r_square: 0.6182 - lr: 0.0010
Epoch 89/100
12025/12033 [=====>.] - ETA: 0s - loss: 0.3479 -
r_square: 0.6526
Epoch 89: val_r_square did not improve from 0.64824
12033/12033 [=====] - 42s 3ms/step - loss: 0.3479 -
r_square: 0.6526 - val_loss: 0.3635 - val_r_square: 0.6352 - lr: 0.0010
Epoch 90/100
12015/12033 [=====>.] - ETA: 0s - loss: 0.3480 -
r_square: 0.6526
Epoch 90: val_r_square did not improve from 0.64824
12033/12033 [=====] - 39s 3ms/step - loss: 0.3480 -
r_square: 0.6525 - val_loss: 0.3670 - val_r_square: 0.6317 - lr: 0.0010
Epoch 91/100
12032/12033 [=====>.] - ETA: 0s - loss: 0.3481 -
r_square: 0.6524Restoring model weights from the end of the best epoch: 71.

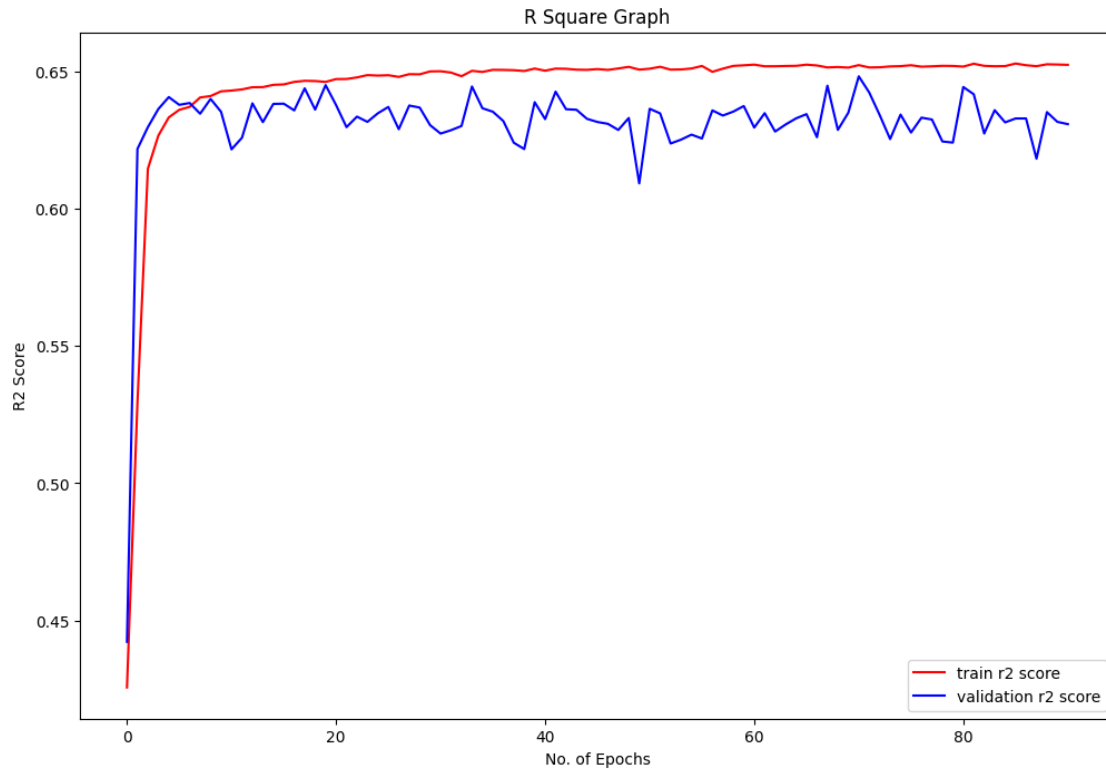
Epoch 91: val_r_square did not improve from 0.64824
12033/12033 [=====] - 39s 3ms/step - loss: 0.3481 -
r_square: 0.6524 - val_loss: 0.3679 - val_r_square: 0.6308 - lr: 0.0010
Epoch 91: early stopping

```

```
[164]: plt.plot(r.history['loss'],'r',label='train loss')
plt.plot(r.history['val_loss'],'b',label='validation loss')
plt.xlabel('No. of Epochs')
plt.ylabel('Loss')
plt.title('Loss Graph')
plt.legend();
```



```
[165]: plt.plot(r.history['r_square'],'r',label='train r2 score')
plt.plot(r.history['val_r_square'],'b',label='validation r2 score')
plt.xlabel('No. of Epochs')
plt.ylabel('R2 Score')
plt.title('R Square Graph')
plt.legend();
```



```
[166]: loss, r2 = ann.evaluate(X_test,y_test)
print("Validation Loss:",loss)
print("Validation R2 Score:",r2)
```

```
5157/5157 [=====] - 7s 1ms/step - loss: 0.3505 -
r_square: 0.6482
Validation Loss: 0.35051849484443665
Validation R2 Score: 0.6482372879981995
```

0.11 Saving the best performing model for future use

```
[168]: y_pred = grid_cat.predict(X_test)
print("R2 Score:",r2_score(y_test,y_pred))
```

```
R2 Score: 0.7089881504192195
```

```
[170]: joblib.dump(grid_cat,'model.h5')
```

```
[170]: ['model.h5']
```

```
[171]: model = joblib.load('model.h5')
model
```

```
[171]: RandomizedSearchCV(cv=5,  
                           estimator=<catboost.core.CatBoostRegressor object at  
0x000002D606DFC670>,  
                           param_distributions={'learning_rate': [0.2, 0.4, 0.5, 0.7,  
                                                                    1],  
                                                'n_estimators': [100, 400, 700, 800,  
                                                                    1000]}},  
                           verbose=5)
```