CS Project - Calories Burnt Prediction Regression Model

XGBoost is a powerful approach for building supervised regression models. It tells about the difference between actual values and predicted values, i.e how far the model results are from the real values. There are several metrics involved in regression like root-mean-squared error (RMSE) and mean-squared-error (MAE).

A) RMSE: It is the square root of mean squared error (MSE). B) MAE: It is an absolute sum of actual and predicted differences, but it lacks mathematically, that’s why it is rarely used, as compared to other metrics.

1. Importing the Libraries

```
import numpy as np                                    # arrays
import pandas as pd                                   # dataframes
import matplotlib.pyplot as plt                       # plots
import seaborn as sns                                 # plots and graphs
from sklearn.model_selection import train_test_split # splitting the data
from xgboost import XGBRegressor                      # XGBoost Regressor
from sklearn import metrics                           # metrics used to evaluate the model
from yellowbrick.regressor import prediction_error
```

2. Data Collection and Processing

```
calories = pd.read_csv('/content/calories.csv')   # loading the data from csv file to pand
```

```
calories.head()  # print the first 5 rows of the data frame
```

	User_ID	Calories
0	14733363	231.0
1	14861698	66.0
2	11179863	26.0
3	16180408	71.0
4	17771927	35.0

```
exercise = pd.read_csv('/content/exercise.csv')   # loading the data from csv file to pand
```

```
exercise.head()  # print the first 5 rows of the data frame
```

	User_ID	Gender	Age	Height	Weight	Duration	Heart_Rate	Body_Temp
0	14733363	male	68	190.0	94.0	29.0	105.0	40.8
1	14861698	female	20	166.0	60.0	14.0	94.0	40.3
2	11179863	male	69	179.0	79.0	5.0	88.0	38.7
3	16180408	female	34	179.0	71.0	13.0	100.0	40.5
4	17771927	female	27	154.0	58.0	10.0	81.0	39.8

The heart rate is the indirect measurement of intensity of the exercise that the person is doing. Hence based on this we can find the calories burnt

3. Combining both the Data Frames

```
calories_data = pd.concat([exercise, calories['Calories']], axis=1) # concat is used for c
                                                                    # axis = 1 is for addi
```

```
calories_data.head()
```

	User_ID	Gender	Age	Height	Weight	Duration	Heart_Rate	Body_Temp	Calories
0	14733363	male	68	190.0	94.0	29.0	105.0	40.8	231.0
1	14861698	female	20	166.0	60.0	14.0	94.0	40.3	66.0
2	11179863	male	69	179.0	79.0	5.0	88.0	38.7	26.0
3	16180408	female	34	179.0	71.0	13.0	100.0	40.5	71.0
4	17771927	female	27	154.0	58.0	10.0	81.0	39.8	35.0

```
calories_data.shape  # checking the number of rows and columns
                     # here there are 15000 rows i.e no.of people and 9 columns i.e differ
```

```
(15000, 9)
```

```
calories_data.info() # getting some information about the datatypes of the data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15000 entries, 0 to 14999
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   User_ID     15000 non-null  int64
 1   Gender      15000 non-null  object
 2   Age         15000 non-null  int64
 3   Height      15000 non-null  float64
```

```
 4   Weight      15000 non-null  float64
 5   Duration    15000 non-null  float64
 6   Heart_Rate  15000 non-null  float64
 7   Body_Temp   15000 non-null  float64
 8   Calories    15000 non-null  float64
dtypes: float64(6), int64(2), object(1)
memory usage: 1.0+ MB
```

```
calories_data.isnull().sum() # checking for missing values
                             # 0 means there are no missing values; data is complete
```

```
User_ID       0
Gender        0
Age           0
Height        0
Weight        0
Duration      0
Heart_Rate    0
Body_Temp     0
Calories      0
dtype: int64
```

4. Data Analysis

```
calories_data.describe()  # get some statistical measures about the data
                          # (mean, standard deviation, minimum, maximum, 25,50,75 percenti
                          # if the heart rate & body temp is more then the person is doing
```

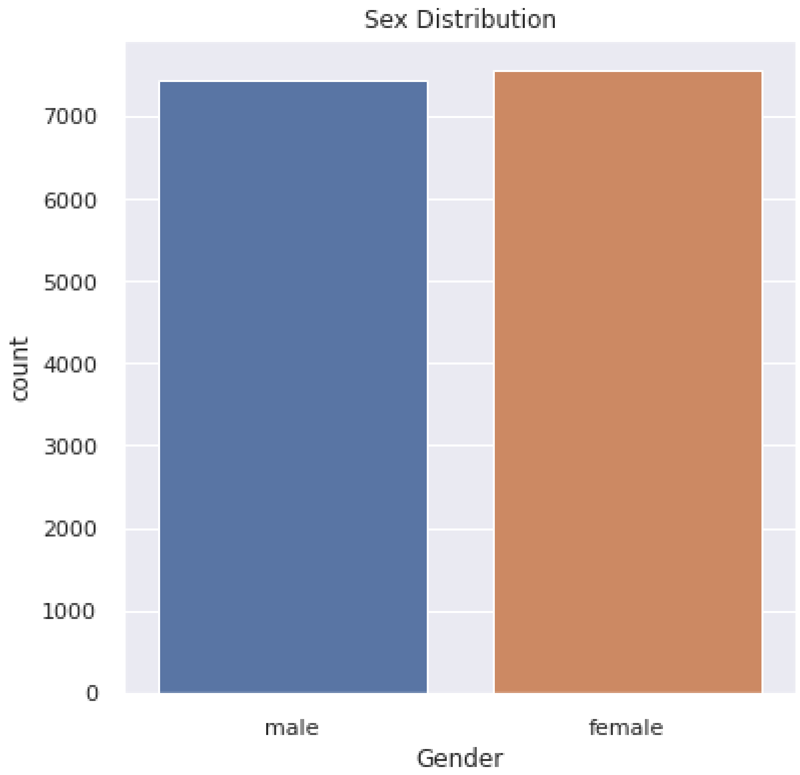
	User_ID	Age	Height	Weight	Duration	Heart_Ra
count	1.500000e+04	15000.000000	15000.000000	15000.000000	15000.000000	15000.000
mean	1.497736e+07	42.789800	174.465133	74.966867	15.530600	95.518
std	2.872851e+06	16.980264	14.258114	15.035657	8.319203	9.583
min	1.000116e+07	20.000000	123.000000	36.000000	1.000000	67.000
25%	1.247419e+07	28.000000	164.000000	63.000000	8.000000	88.000
50%	1.499728e+07	39.000000	175.000000	74.000000	16.000000	96.000
75%	1.744928e+07	56.000000	185.000000	87.000000	23.000000	103.000
max	1.999965e+07	79.000000	222.000000	132.000000	30.000000	128.000

5. Data Visualization

```
sns.set() # it will give basic theme for the plots
```

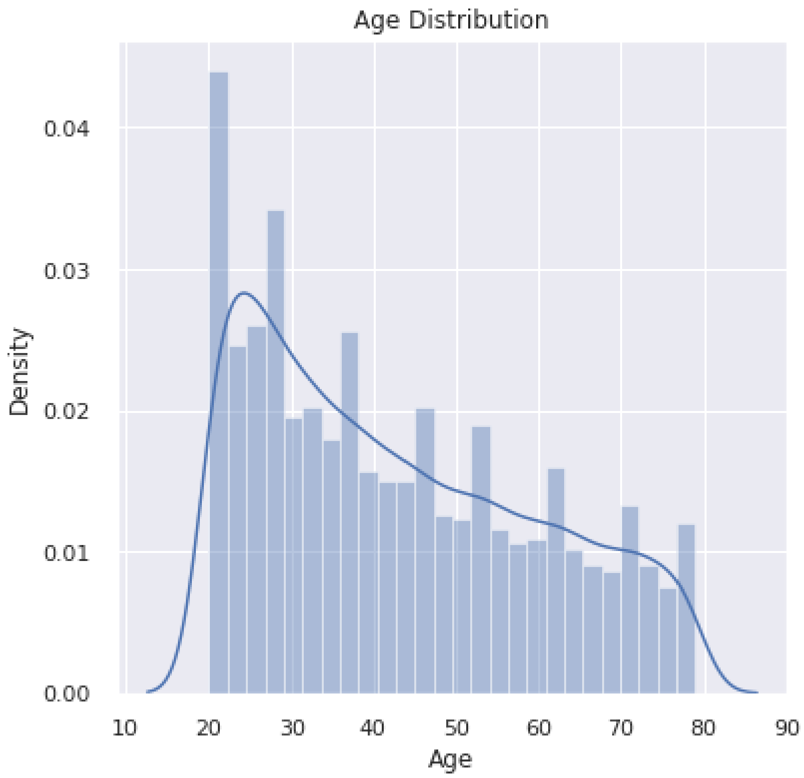
```
plt.figure(figsize=(6,6))
sns.countplot(x='Gender', data=calories_data)
```

```
plt.title('Sex Distribution')
plt.show() # plotting the Gender column in count plot
```



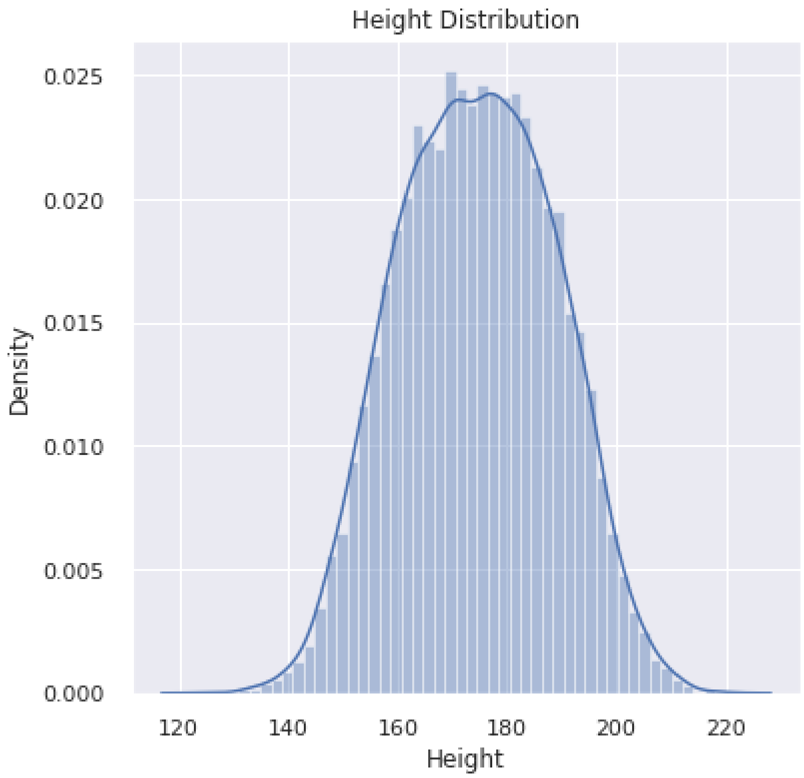

```
plt.figure(figsize=(6,6))
sns.distplot(calories_data['Age'])
plt.title('Age Distribution')
plt.show()  # plotting the Age column in dist plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```



```
plt.figure(figsize=(6,6))
sns.distplot(calories_data['Height'])
plt.title('Height Distribution')
plt.show()  # plotting the Height column in dist plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```

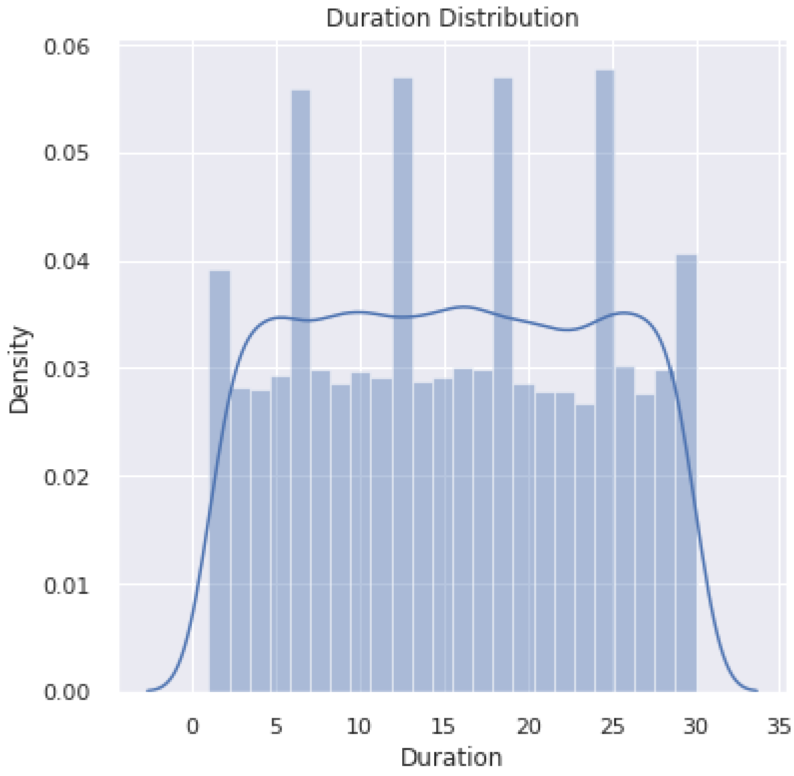



```
plt.figure(figsize=(6,6))
sns.distplot(calories_data['Weight'])
plt.title('Weight Distribution')
plt.show()  # plotting the Weight column in count plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```


```
plt.figure(figsize=(6,6))
sns.distplot(calories_data['Duration'])
plt.title('Duration Distribution')
plt.show()   # plotting the Duration column in count plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```

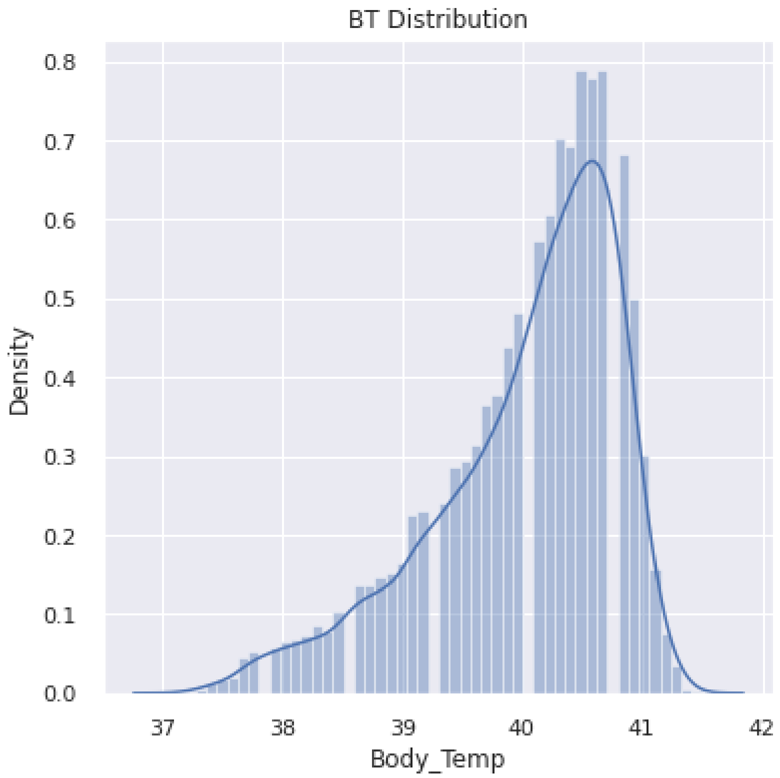



```
plt.figure(figsize=(6,6))
sns.distplot(calories_data['Heart_Rate'])
plt.title('HR Distribution')
plt.show() # plotting the Heart rate column in count plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```

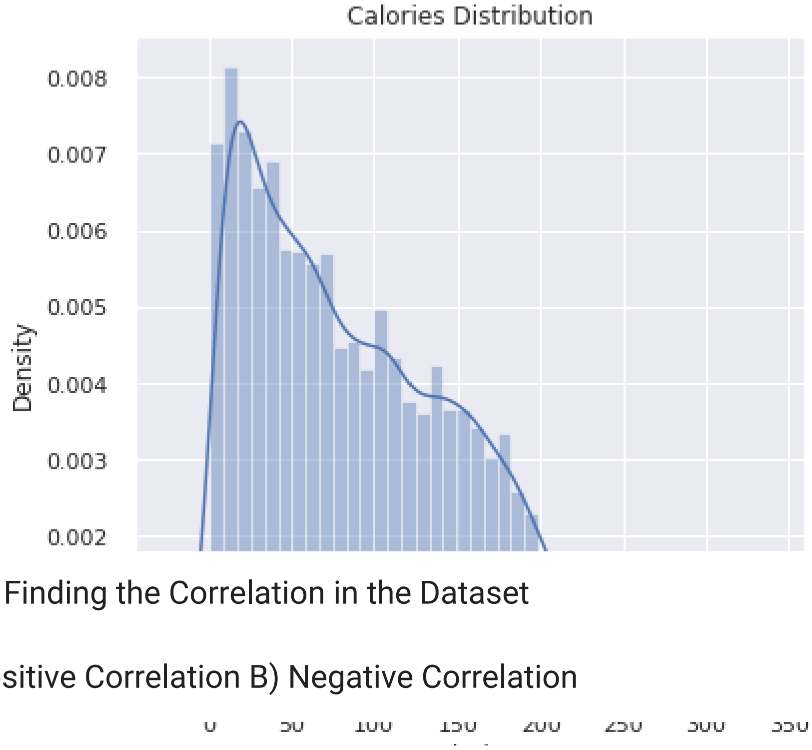

```
plt.figure(figsize=(6,6))
sns.distplot(calories_data['Body_Temp'])
plt.title('BT Distribution')
plt.show()  # plotting the Body temperature column in count plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```




```
plt.figure(figsize=(6,6))
sns.distplot(calories_data['Calories'])
plt.title('Calories Distribution')
plt.show()   # plotting the Calories column in count plot
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning:
  warnings.warn(msg, FutureWarning)
```



6. Finding the Correlation in the Dataset

A) Positive Correlation B) Negative Correlation

```
correlation = calories_data.corr()
```

```
plt.figure(figsize=(8,8))  # constructing a heatmap to understand the correlation
sns.heatmap(correlation, cbar=True, square=True, fmt='.1f', annot=True, annot_kws={'size':
# 1 means positive correlation and 0 means negative correlation
# Here, (Height,Weight), (Duration,Calories) are positively correlated whereas (Height,Age
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f67a6c9a810>
```

7. Coverting Text data to Numeric values

```
calories_data.replace({"Gender":{'male':0,'female':1}}, inplace=True)
# replacing men,female to 0,1 (numeric values) as machine cannot understand texts
```

```
calories_data.head()
```

	User_ID	Gender	Age	Height	Weight	Duration	Heart_Rate	Body_Temp	Calories
0	14733363	0	68	190.0	94.0	29.0	105.0	40.8	231.0
1	14861698	1	20	166.0	60.0	14.0	94.0	40.3	66.0
2	11179863	0	69	179.0	79.0	5.0	88.0	38.7	26.0
3	16180408	1	34	179.0	71.0	13.0	100.0	40.5	71.0
4	17771927	1	27	154.0	58.0	10.0	81.0	39.8	35.0

8. Separating Features -> (Categories) & Target -> (Calories)

```
X = calories_data.drop(columns=['User_ID','Calories'], axis=1) # drop is used to remove th
Y = calories_data['Calories']
```

```
print(X)
```

```
       Gender  Age  Height  Weight  Duration  Heart_Rate  Body_Temp
0           0   68   190.0    94.0      29.0       105.0       40.8
1           1   20   166.0    60.0      14.0        94.0       40.3
2           0   69   179.0    79.0       5.0        88.0       38.7
3           1   34   179.0    71.0      13.0       100.0       40.5
4           1   27   154.0    58.0      10.0        81.0       39.8
...       ...  ...     ...     ...       ...         ...        ...
14995       1   20   193.0    86.0      11.0        92.0       40.4
14996       1   27   165.0    65.0       6.0        85.0       39.2
14997       1   43   159.0    58.0      16.0        90.0       40.1
14998       0   78   193.0    97.0       2.0        84.0       38.3
14999       0   63   173.0    79.0      18.0        92.0       40.5

[15000 rows x 7 columns]
```

```
print(Y)
```

```
0        231.0
1         66.0
2         26.0
3         71.0
```

```
4         35.0
         ...
14995     45.0
14996     23.0
14997     75.0
14998     11.0
14999     98.0
Name: Calories, Length: 15000, dtype: float64
```

9. Splitting the data into Training Data & Test Data

```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=2)
```

```
print(X.shape, X_train.shape, X_test.shape)
```

```
(15000, 7) (12000, 7) (3000, 7)
```

10. Model Training

XGBoost Regression

```
# loading the XGBoost Regression model
# Instantiate an XGBoost object with hyperparameters
model = XGBRegressor(max_depth=3, n_estimators=100, n_jobs=1,
                           objectvie='reg:squarederror', booster='gbtree',
                           random_state=0, learning_rate=0.1)
```

1) max_depth=3: Here, the XGBoost uses decision trees as base learners. By setting max_depth=3, each tree will make 3 times of splits and stop there. 2) n_estimators=100: There are 100 trees in the ensemble. 3) objective='reg:squarederror': A name for the loss function used in our model. reg:squarederror is the standard option for regression in XGBoost. 4) booster='gbtree': The 'gbtree' is the XGBoost default base learner. With booster='gbtree', the XGBoost model uses decision trees, which is the best option for non-linear data. 5) n_jobs=2: Use 2 cores of the processor for doing parallel computations to run XGBoost. 6) random_state=1: Controls the randomness involved in creating trees. You may use any integer. By specifying a value for random_state, you will get the same result at different executions of your code. 7) learning_rate=0.05: Shrinks the weights of trees for each round of boosting. Decreasing learning_rate prevents overfitting.

```
model.fit(X_train, Y_train)
```

```
[03:44:47] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
XGBRegressor(objectvie='reg:squarederror')
```

11. Model Evaluation

Prediction on Test **Data**

```
test_data_prediction = model.predict(X_test)
#testing X data (features of the data) which will find the number of calories different fr
```

```
print(test_data_prediction) #predicted calories values
```

```
[129.06204  223.79721   39.181965 ... 145.59767   22.53474   92.29064 ]
```

12. Mean Absolute Error

Comparing Y test and the test data predicted by using the metric -> Mean Absolute Error

```
mae = metrics.mean_absolute_error(Y_test, test_data_prediction)
```

```
print("Mean Absolute Error = ", mae) #mean of the difference between aactual value and pre
```

```
Mean Absolute Error =  2.7159012502233186
```

13. Mean Squared Error & Root Mean Squared Error

```
MSE = metrics.mean_squared_error(Y_test, test_data_prediction)
RMSE = np.sqrt(MSE)
```

```
print("Mean Squared Error = ", MSE)
```

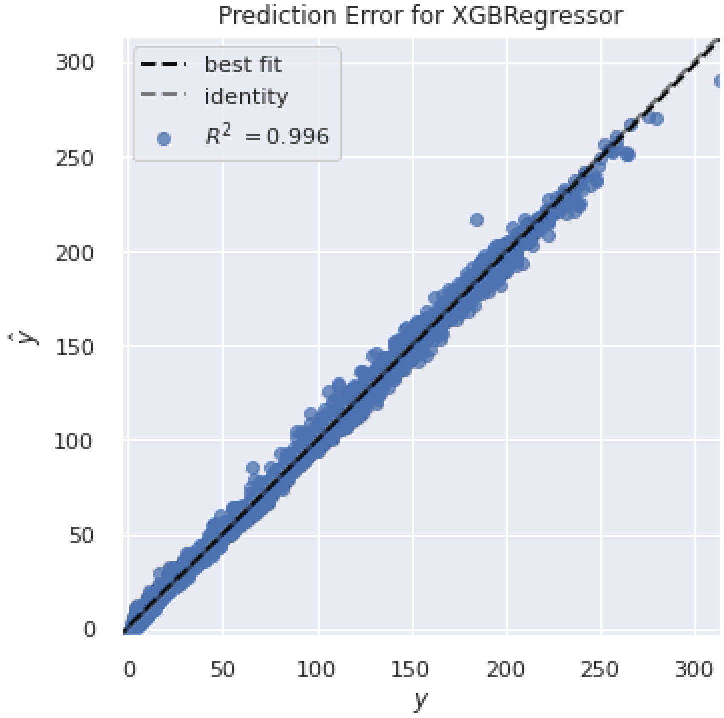
```
Mean Squared Error =  14.506464988228966
```

```
print("Root Mean Squared Error = ", RMSE)
```

```
Root Mean Squared Error =  3.8087353528735712
```

```
# Making the Prediction Error Plot
print("\nPrediction Error Plot")
print(prediction_error(model, X_train, Y_train, X_test, Y_test))
```

```
Prediction Error Plot
```




```
PredictionError(ax=<matplotlib.axes._subplots.AxesSubplot object at 0x7f538880c9d0>,
```

Our model returns an MAE value of ~ 2.71 and RMSE value of ~ 3.80 for the test data. Is that a good value? To find out, let's look at some statistical measures of the target column (Calories).

```
calories_data.describe().T #Transpose
```

	count	mean	std	min	25%	50%
User_ID	15000.0	1.497736e+07	2.872851e+06	10001159.0	12474190.75	14997285.0
Gender	15000.0	5.035333e-01	5.000042e-01	0.0	0.00	1.0
Age	15000.0	4.278980e+01	1.698026e+01	20.0	28.00	39.0
Height	15000.0	1.744651e+02	1.425811e+01	123.0	164.00	175.0
Weight	15000.0	7.496687e+01	1.503566e+01	36.0	63.00	74.0
Duration	15000.0	1.553060e+01	8.319203e+00	1.0	8.00	16.0
Heart_Rate	15000.0	9.551853e+01	9.583328e+00	67.0	88.00	96.0
Body_Temp	15000.0	4.002545e+01	7.792299e-01	37.1	39.60	40.2
Calories	15000.0	8.953953e+01	6.245698e+01	1.0	35.00	79.0

With Mean and Standard Deviation to be 89.53 and 62.45 respectively, the RMSE value that we got is considered good (3.80). The smaller the MAE & RMSE value, the better is the fit of the model.

On average, the calories predictions of our model are 3 units away from the actual values.