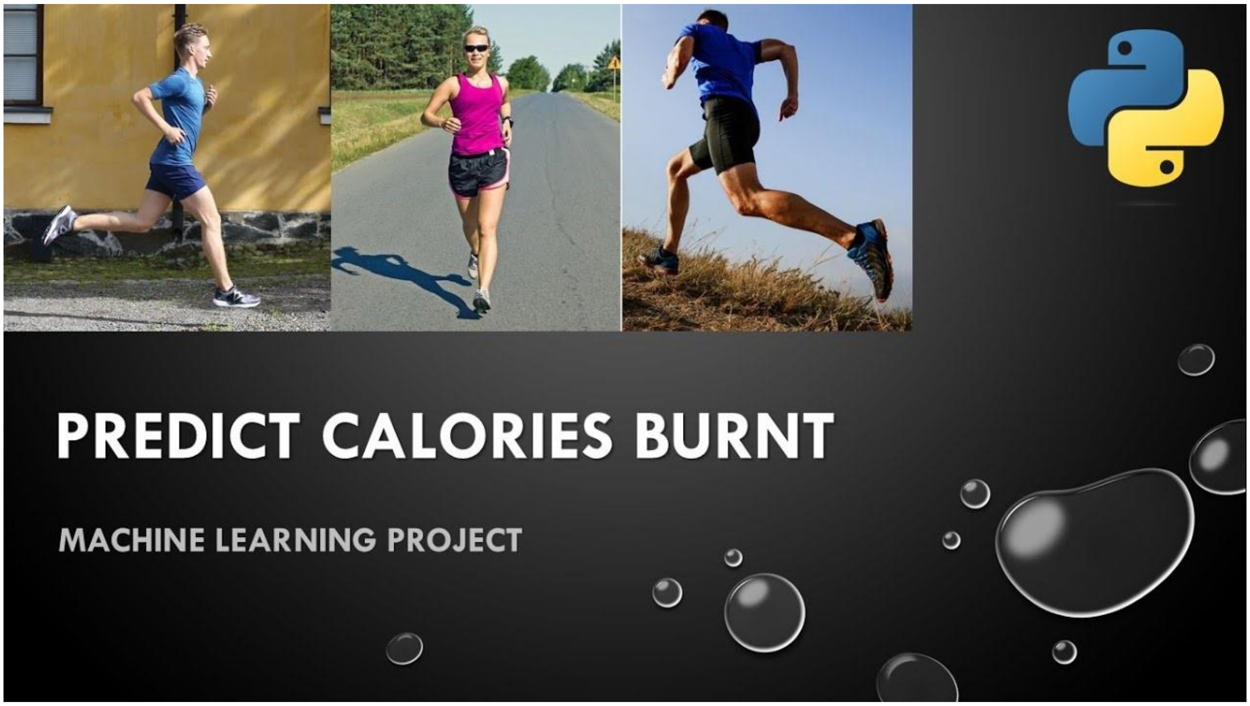
Project Name : Prediction of Calories Burnt using XGBoost

Prediction of calories burnt Using Machine Learning

This project aims to predict the calories burnt during various physical activities using machine learning techniques. The dataset used for this project includes various features such as age, weight, duration of activity, etc.

Project Introduction

The project titled "Prediction of Calories Burnt using XGBoost" focuses on utilizing machine learning techniques to estimate the number of calories burnt during physical activities. Caloric expenditure is a key factor in weight management and overall health. Traditional methods of estimating calories burnt, such as using heart rate monitors or metabolic equations, can be cumbersome and often lack precision. This project aims to provide a more accurate and efficient method by leveraging the power of XGBoost, a scalable and high-performance gradient boosting framework.



Problem Statement

Accurate prediction of calories burnt during physical activities is crucial for individuals who are keen on managing their weight, fitness, and overall health. Existing methods either require specialized equipment or depend on generalized equations that may not account for individual variability in metabolism and activity levels. The challenge is to develop a machine learning model that can predict calories burnt based on readily available data inputs, such as age, weight, height, gender, duration of activity, and type of activity

According to Jessica Simpson,"LAUGH A LOT. IT BURNS A LOT OF CALORIES"

- In this notebook, let's predict ✍ the calories burnt using XGBoost & let's have a healthy & a happier life.

DataSet Story

- User_ID : Unique identifier for each individual in the datasets
- Gender: Gender of the individual (e.g., 'Male' or 'Female').* Age: Age of the individual.iv Height: Height of the individua
- Weight: Weight of the individual.
- Duration: Duration of the physical activity or exercise session.
- Heart_Rate: Heart rate of the individual during the activity.
- Body_Temp: Body temperature of the individual.
- Calories: Calories burnt by an individual.
  y.*. .**

IMPORTING LIBRARIES

```
import numpy as np import pandas as pd
import matplotlib.pyplot as plt import ydata_profiling as pp
import warnings
warnings.filterwarnings('ignore') import seaborn as sns
from sklearn.model_selection import train_test_split import xgboost
from xgboost import XGBRegressor from sklearn import metrics
```

LOADING THE DATA & PREPROCESSING THE DATA

```
calories_data = pd.read_csv("calories.csv") calories_data.head()
```

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

```
exercise_data = pd.read_csv("exercise.csv") exercise_data.head()
```

```
   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
```

Inference:

- We can observe an Indirect relationship between heart rate & body temperature with respect to the excercise the individual does.

COMBINING THE EXCERCISE DATA & CALORIES DATA

```
combined_data = pd.concat([exercise_data,calories_data['Calories']], axis=1) combined_data.head()

   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

   Calories
0         231.0
1         66.0
2         26.0
3         71.0
4         35.0

#checking the number of rows & columns
combined_data.shape (15000, 9)
```

Hence our combined_data has 15,000 people with 9 different features

```
#getting the information about the data most importantly to know about any missing values
combined_data.info()

< 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
```

```
#checking the missing values combined_data.isnull().sum()
```

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

ANALYSING THE DATA

```
#To get stastical measures about the data combined_data.describe()
```

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

         Heart_Rate     Body_Temp      Calories  count  15000.000000
15000.000000  15000.000000  mean      95.518533     40.025453
89.539533  std        9.583328      0.779230     62.456978  min       67.000000
37.100000      1.000000
25%       88.000000     39.600000     35.000000
```

```
50%       96.000000     40.200000     79.000000  75%      103.000000
40.600000    138.000000  max      128.000000     41.500000    314.000000
```

Important inference

- Heart rate & body temperature is more when the person is doing excercise

```
pp.ProfileReport(combined_data)
```

{"model_id":"f837aa292b9d4795a178dc83a484fb02","version_major":2,"vers ion_minor":0}

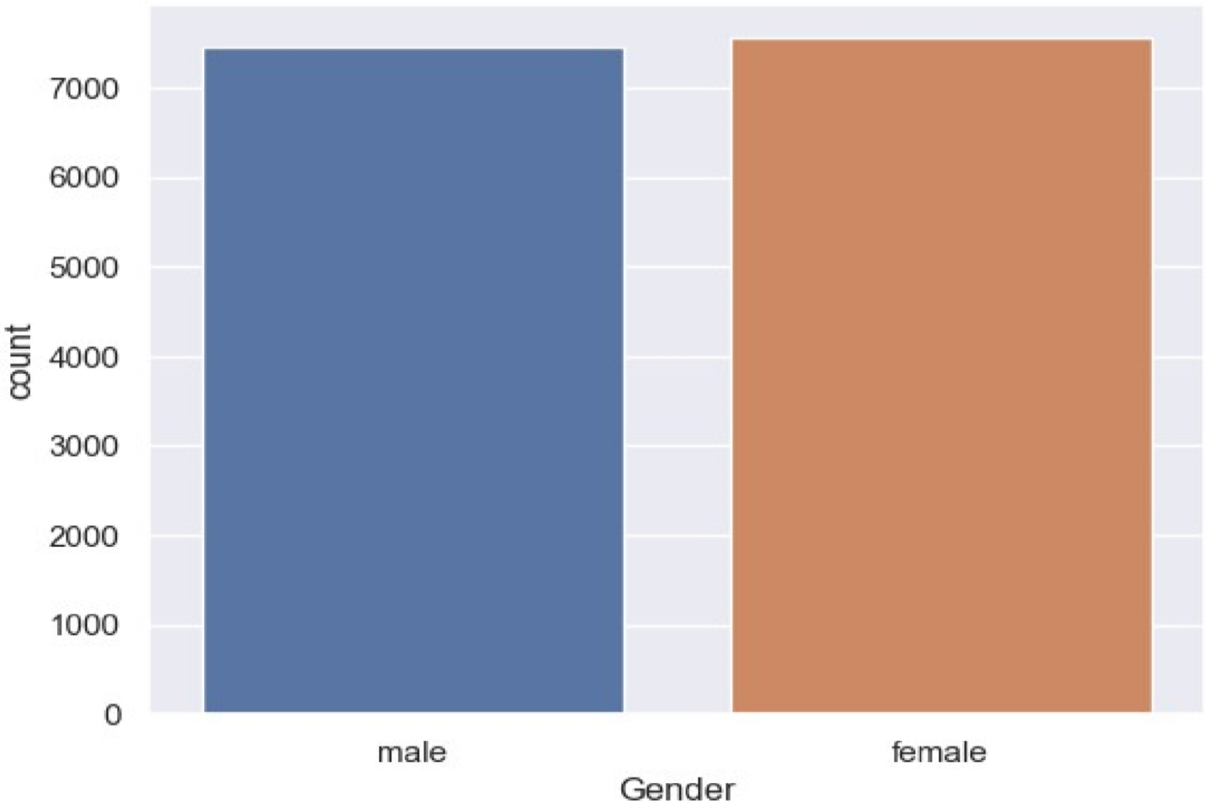
{"model_id":"cb048e6a2879499ca0c22fa667c8e550","version_major":2,"vers ion_minor":0}

{"model_id":"5e2701fbfc7f42e293d2ef9f9a85d6d5","version_major":2,"vers ion_minor":0}

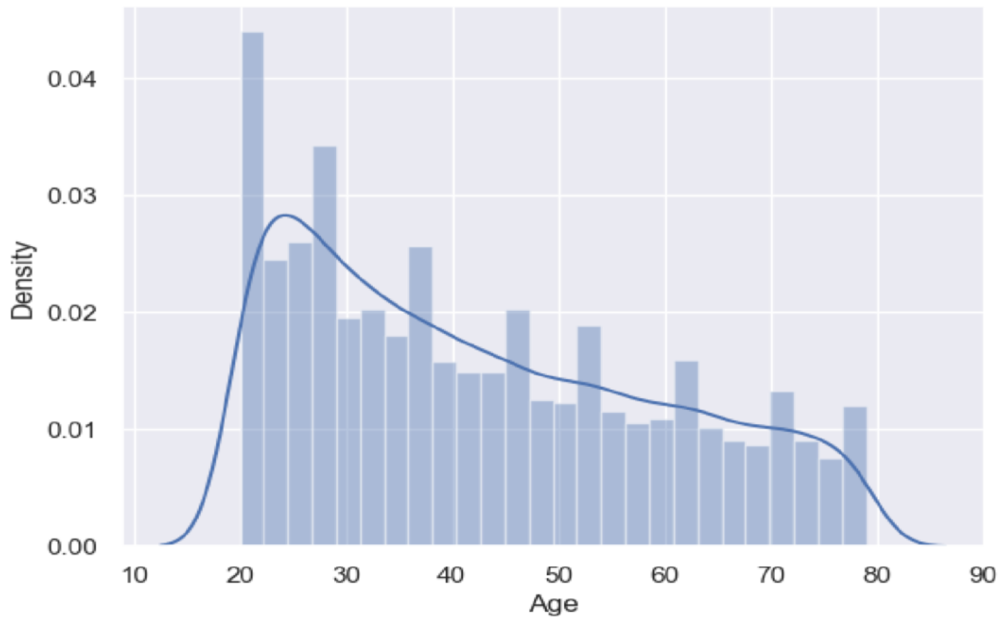
< IPython.core.display.HTML object >

VISUALIZATION OF DATA

```
sns.set()

%matplotlib inline
sns.countplot(data=combined_data, x='Gender')

# Show the plot plt.show()
```



From the above plot, we can observe that the data is evenly distributed(almost 7000) for both males and females.

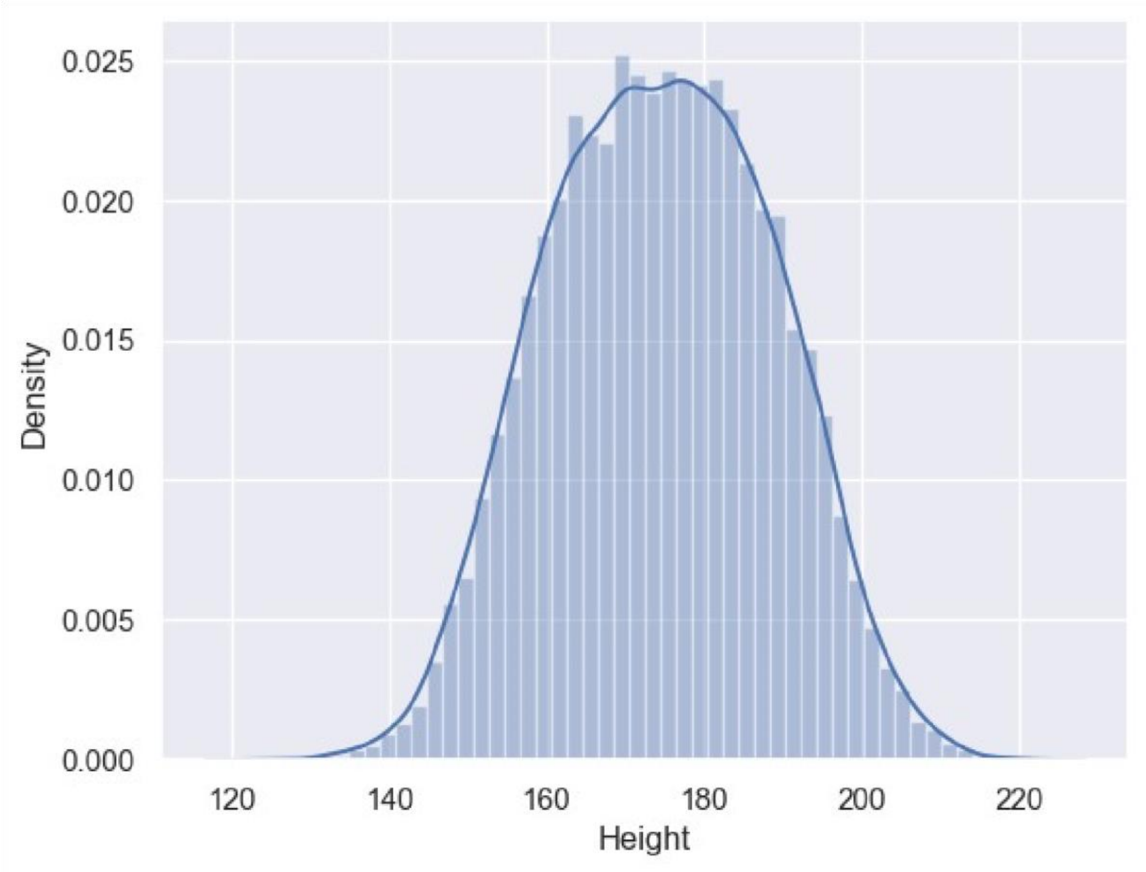


#inorder to find the distribution of age column sns.distplot(combined_data['Age'])

From the above plot, we can observe that the Age column has the mean value of 42 and the data is positively skewed & most of the datapoints are in between 20 to 50.

```
#inorder to find the distribution of height column sns.distplot(combined_data['Height'])
```

< Axes: xlabel='Height', ylabel='Density' >



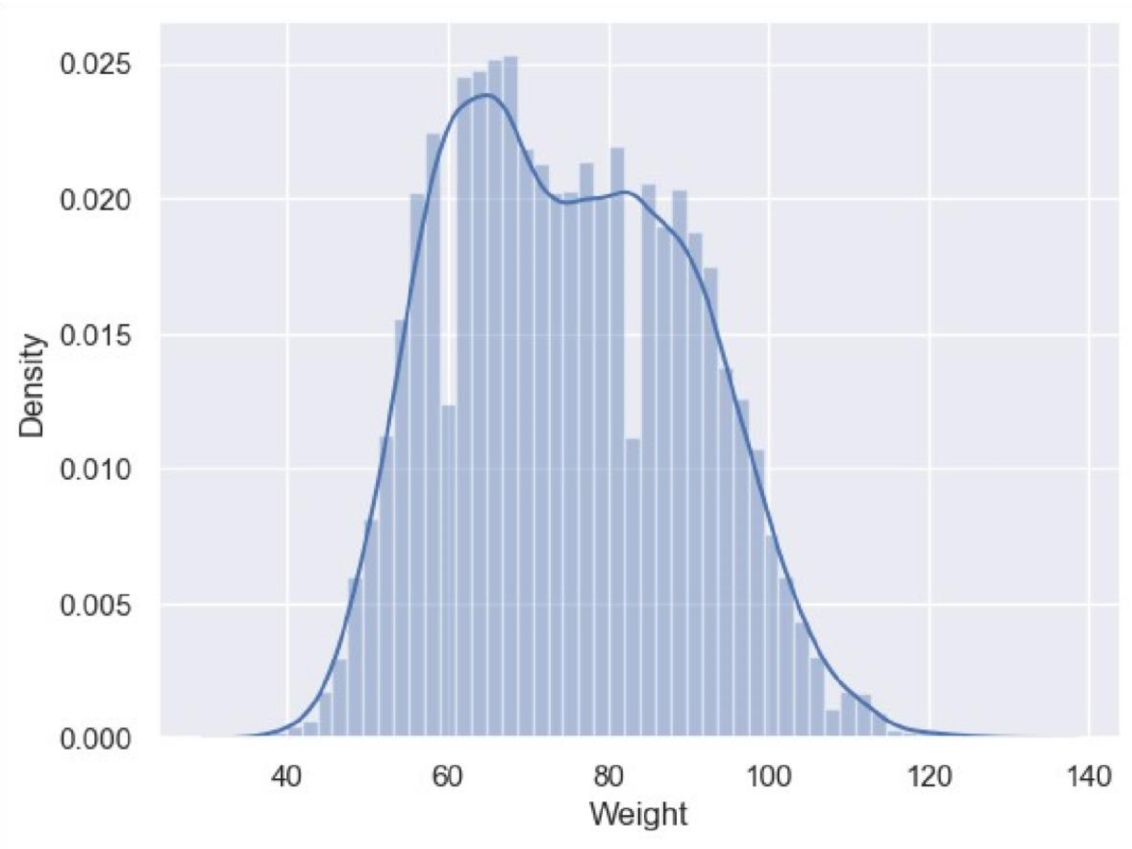
Hence,from the above plot we can observe that the height data is normally distributed with mean of 174cm.

#inorder to find the distribution of age column sns.distplot(combined_data['Age'])

< Axes: xlabel='Age', ylabel='Density' >

```
#inorder to find the distribution of weight column sns.distplot(combined_data['Weight'])
```

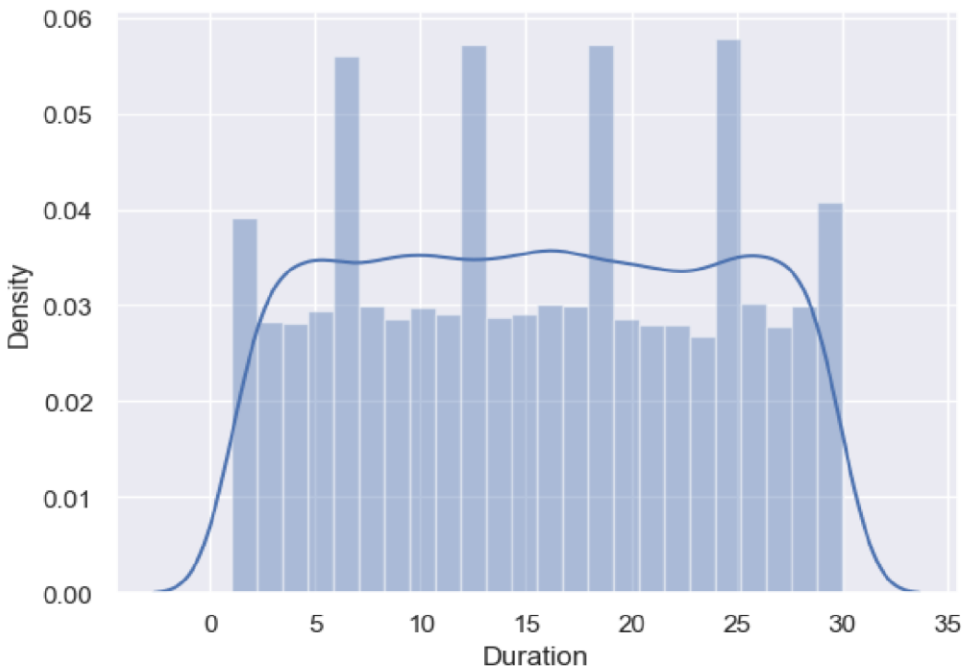
< Axes: xlabel='Weight', ylabel='Density' >



Hence,from the above plot we can observe that the weight data is also normally distributed with mean of 74 kg

```
sns.distplot(combined_data['Duration'])
```

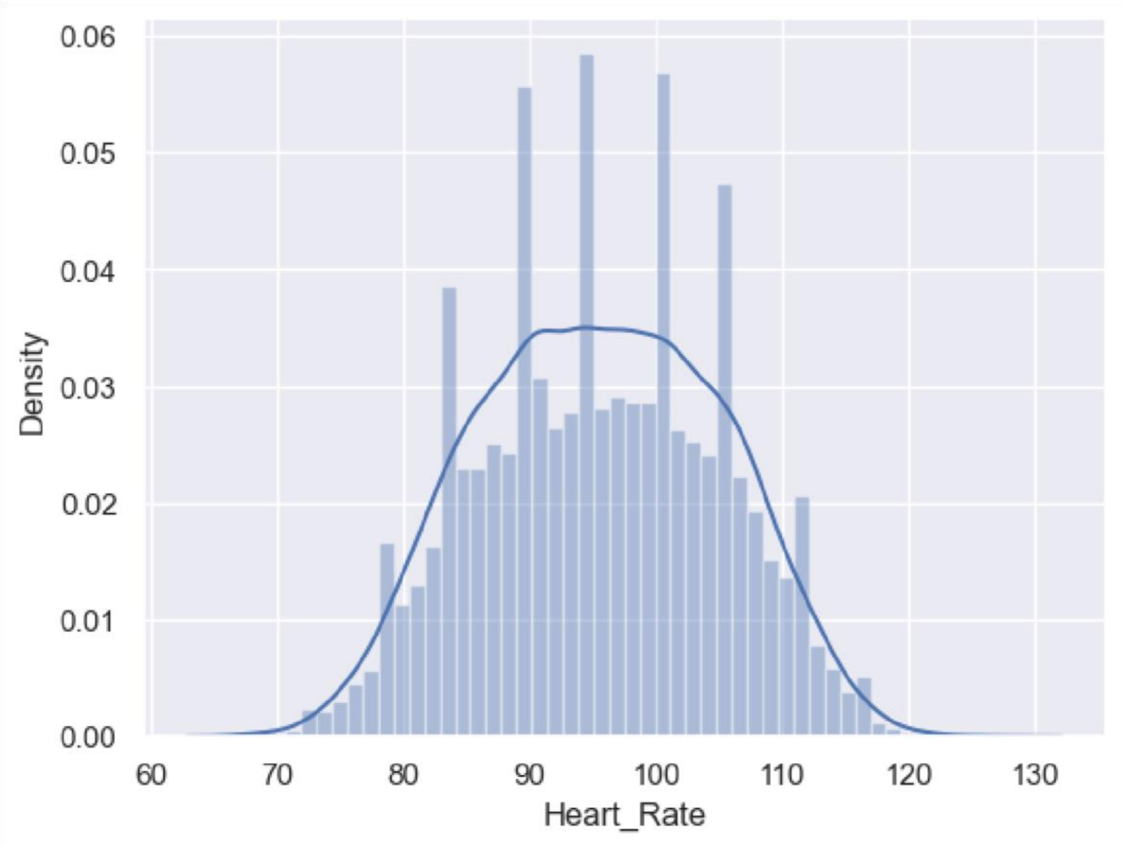
< Axes: xlabel='Duration', ylabel='Density' >



Hence, from the above plot we can observe that the duration data is a low peaked data with mean of 15mins

```
sns.distplot(combined_data['Heart_Rate'])
```

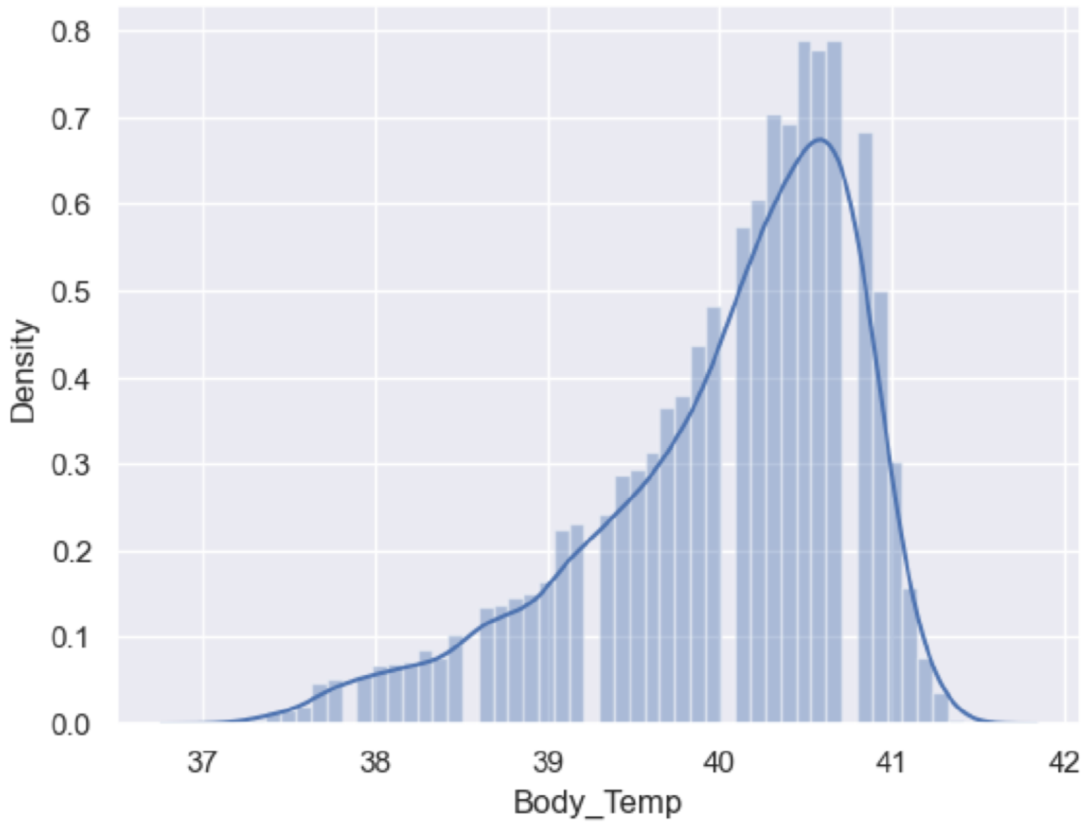
< Axes: xlabel='Heart_Rate', ylabel='Density' >



Hence,from the above plot we can observe that the heart rate column is normally distributed with mean of 95 heart beats with several outliers.

```
sns.distplot(combined_data['Body_Temp'])
```

< Axes: xlabel='Body_Temp', ylabel='Density' >

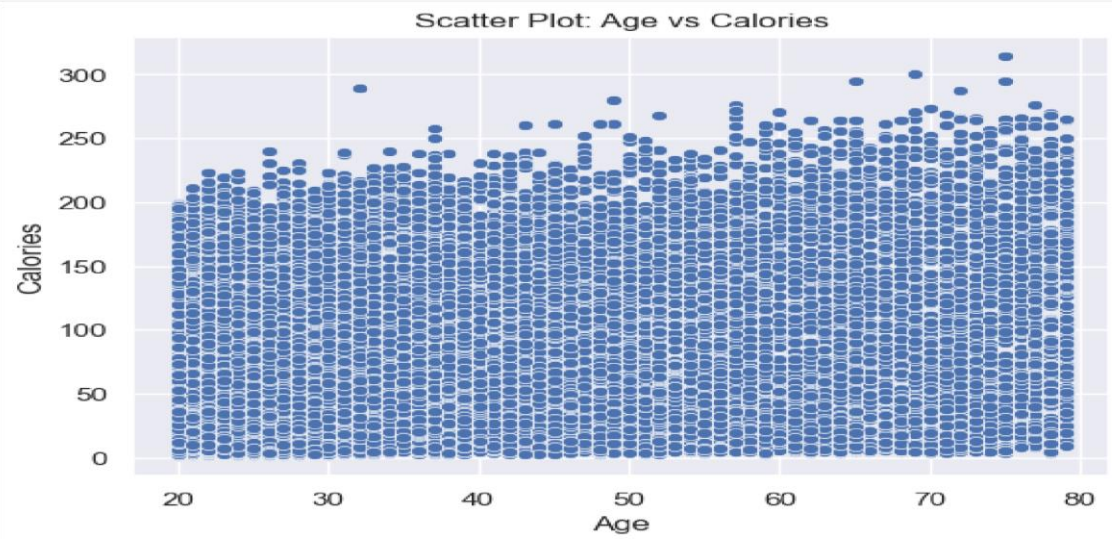


Hence,from the above plot we can observe that the temperature column is negatively skewed with mean of 40.

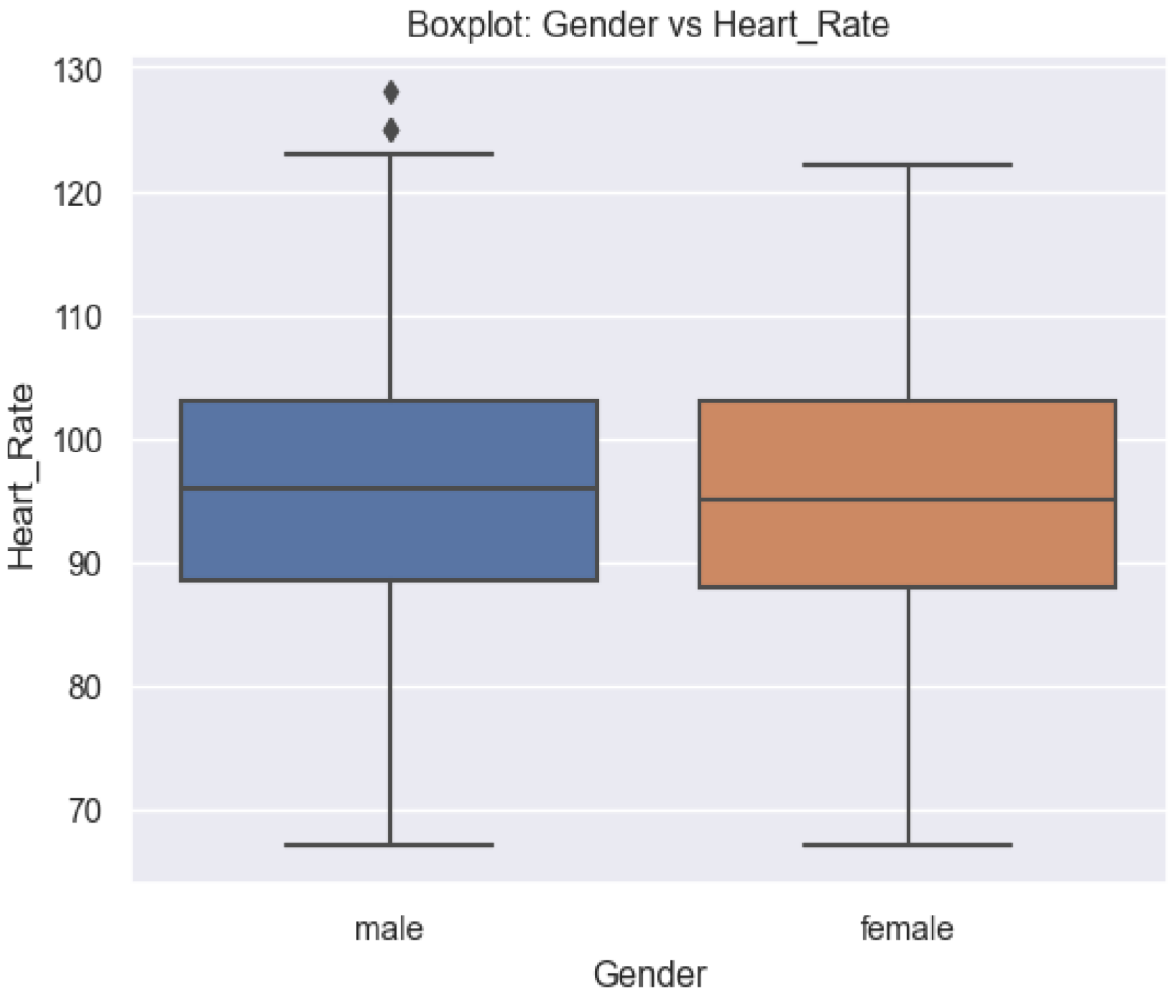
TO FIND THE CORRELATION IN THE DATA

Duration & calories are directly proportional=positively correlated

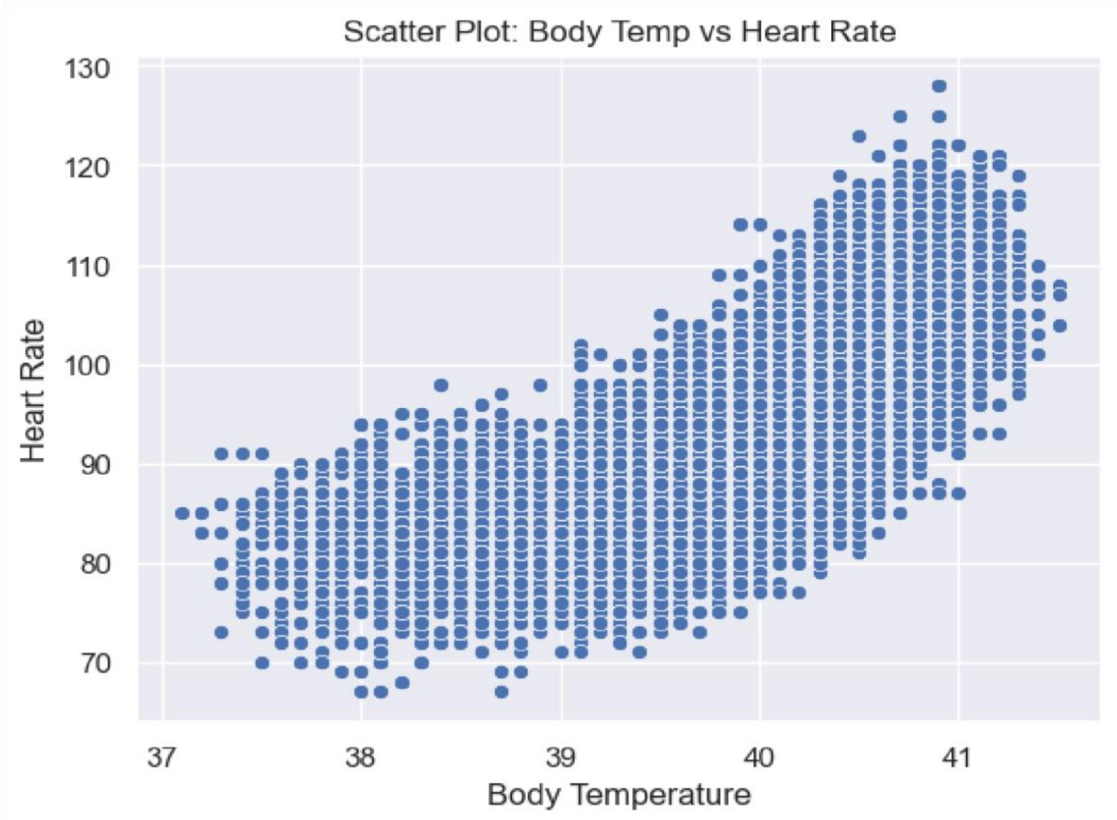
```
# Scatter plot for Age vs Calories
sns.scatterplot(x='Age', y='Calories', data=combined_data) plt.title('Scatter Plot: Age
vs Calories') plt.show()
```



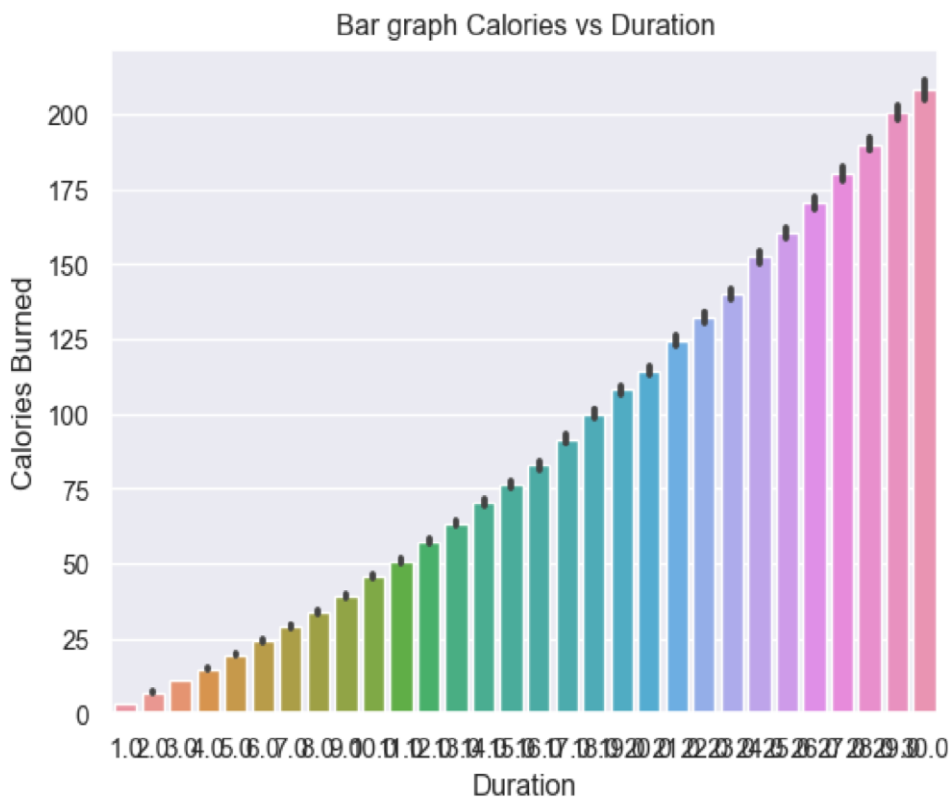

```
sns.boxplot(x='Gender',y='Heart_Rate',data=combined_data) plt.title("Boxplot: Gender vs
Heart_Rate") plt.show()
```




```
# Scatter plot for Body Temp vs Heart Rate
sns.scatterplot(x='Body_Temp', y='Heart_Rate', data=combined_data) plt.title('Scatter Plot: Body Temp vs Heart Rate') plt.xlabel('Body Temperature') plt.ylabel('Heart Rate') plt.show()
```

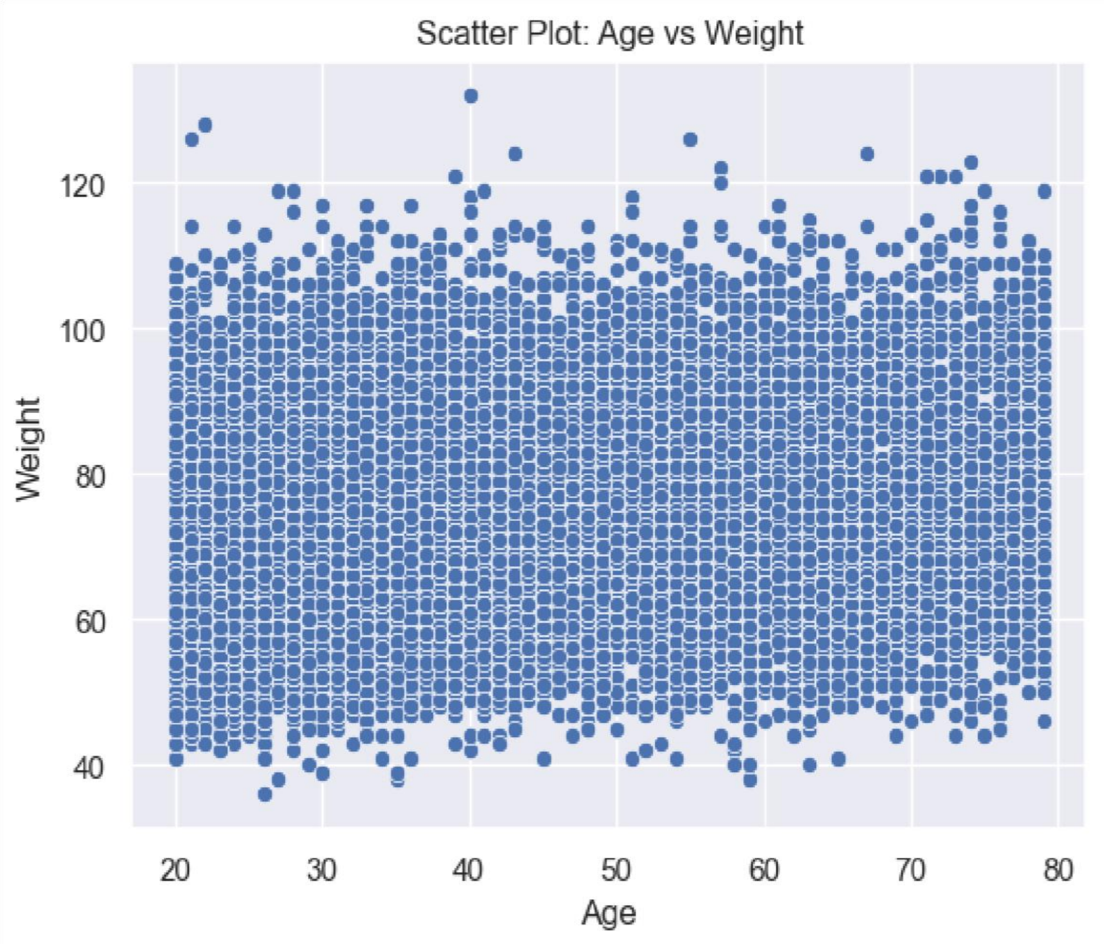



```
# Bar plot for Duration vs Calories
sns.barplot(x='Duration',y='Calories',data=combined_data) plt.title("Bar graph
Calories vs Duration") plt.xlabel('Duration') plt.ylabel('Calories Burned') plt.show()
```

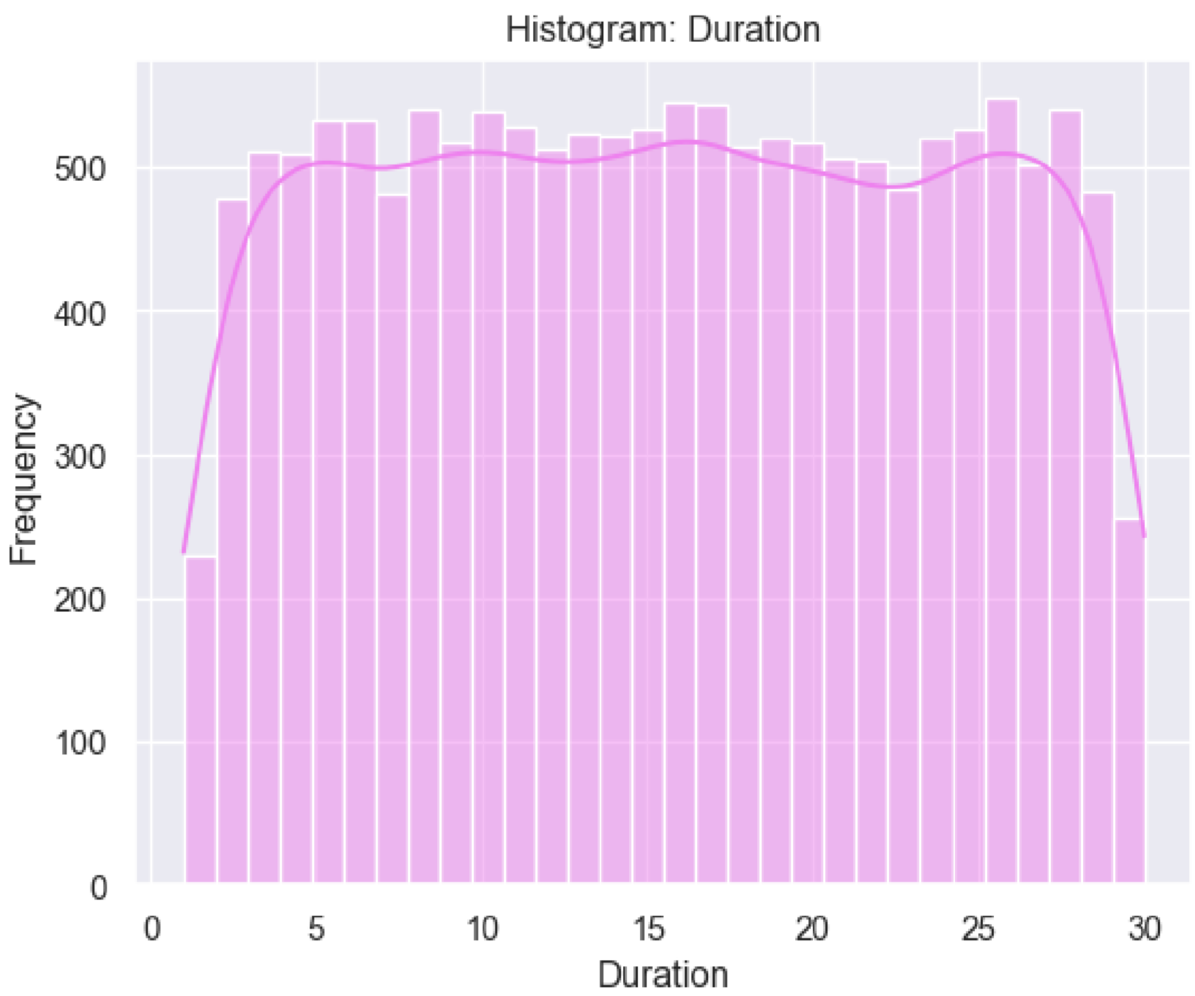



```
# Scatter plot for Age vs Weight
```

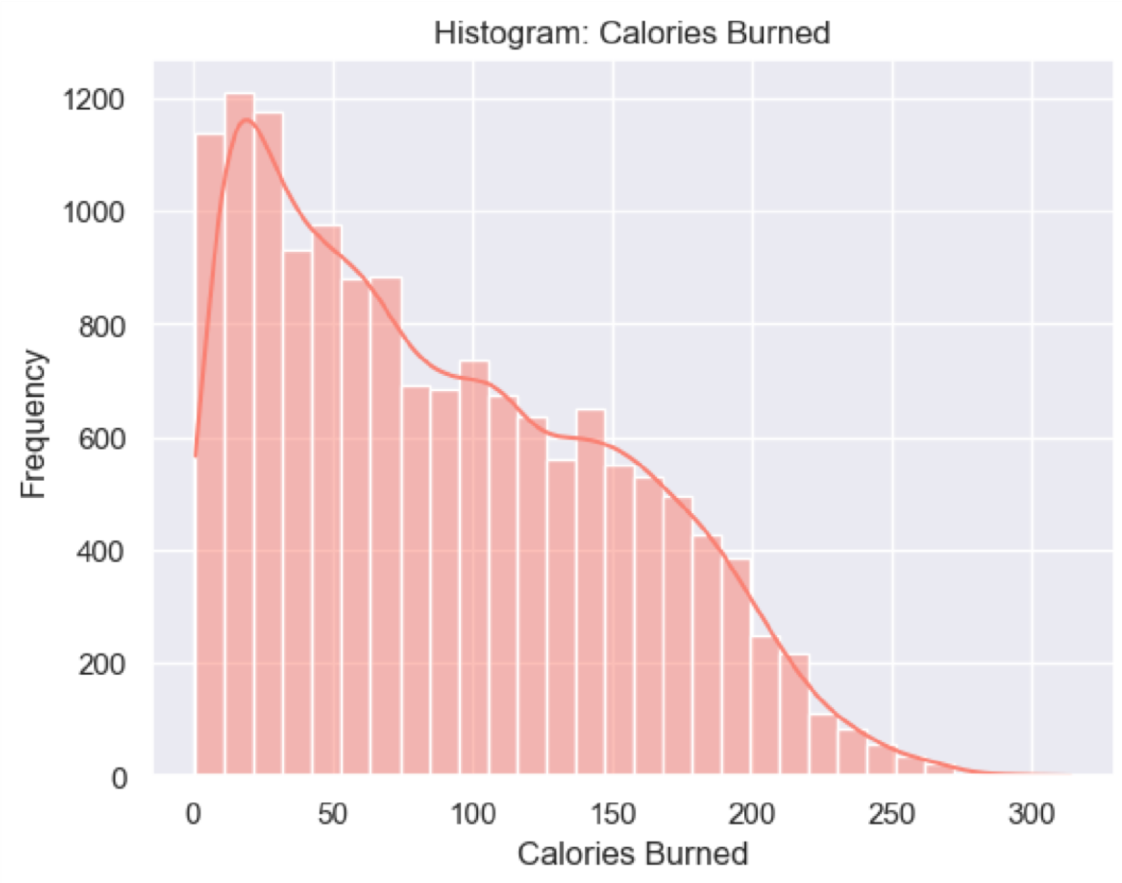
```
sns.scatterplot(x='Age', y='Weight', data=combined_data) plt.title('Scatter Plot: Age
vs Weight') plt.show()
```




```
# Histogram for Duration
sns.histplot(combined_data['Duration'], bins=30, kde=True, color='violet')
plt.title('Histogram: Duration')
plt.xlabel('Duration') plt.ylabel('Frequency')
plt.show()
```




```
# Histogram for Calories Burned
sns.histplot(combined_data['Calories'], bins=30, kde=True, color='salmon')
plt.title('Histogram: Calories Burned') plt.xlabel('Calories
Burned') plt.ylabel('Frequency') plt.show()
```




```
#converting gender string data type to float
gender_mapping={'male':0,'female':1}

combined_data["Gender"]=combined_data["Gender"].map(gender_mapping)
combined_data
```

```
         User_ID  Gender  Age  Height  Weight  Duration  Heart_Rate
Body_Temp  \
0       14733363       0   68   190.0    94.0      29.0       105.0
40.8
1       14861698       1   20   166.0    60.0      14.0        94.0
40.3
2       11179863       0   69   179.0    79.0       5.0        88.0
38.7
3       16180408       1   34   179.0    71.0      13.0       100.0
40.5
4       17771927       1   27   154.0    58.0      10.0        81.0
39.8
...          ...     ...  ...     ...     ...       ...         ...
...
14995   15644082       1   20   193.0    86.0      11.0        92.0
40.4
14996   17212577       1   27   165.0    65.0       6.0        85.0
```

39.2

14997 17271188 1 43 159.0 58.0 16.0 90.0
40.1
14998 18643037 0 78 193.0 97.0 2.0 84.0
38.3
14999 11751526 0 63 173.0 79.0 18.0 92.0
40.5

Calories
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

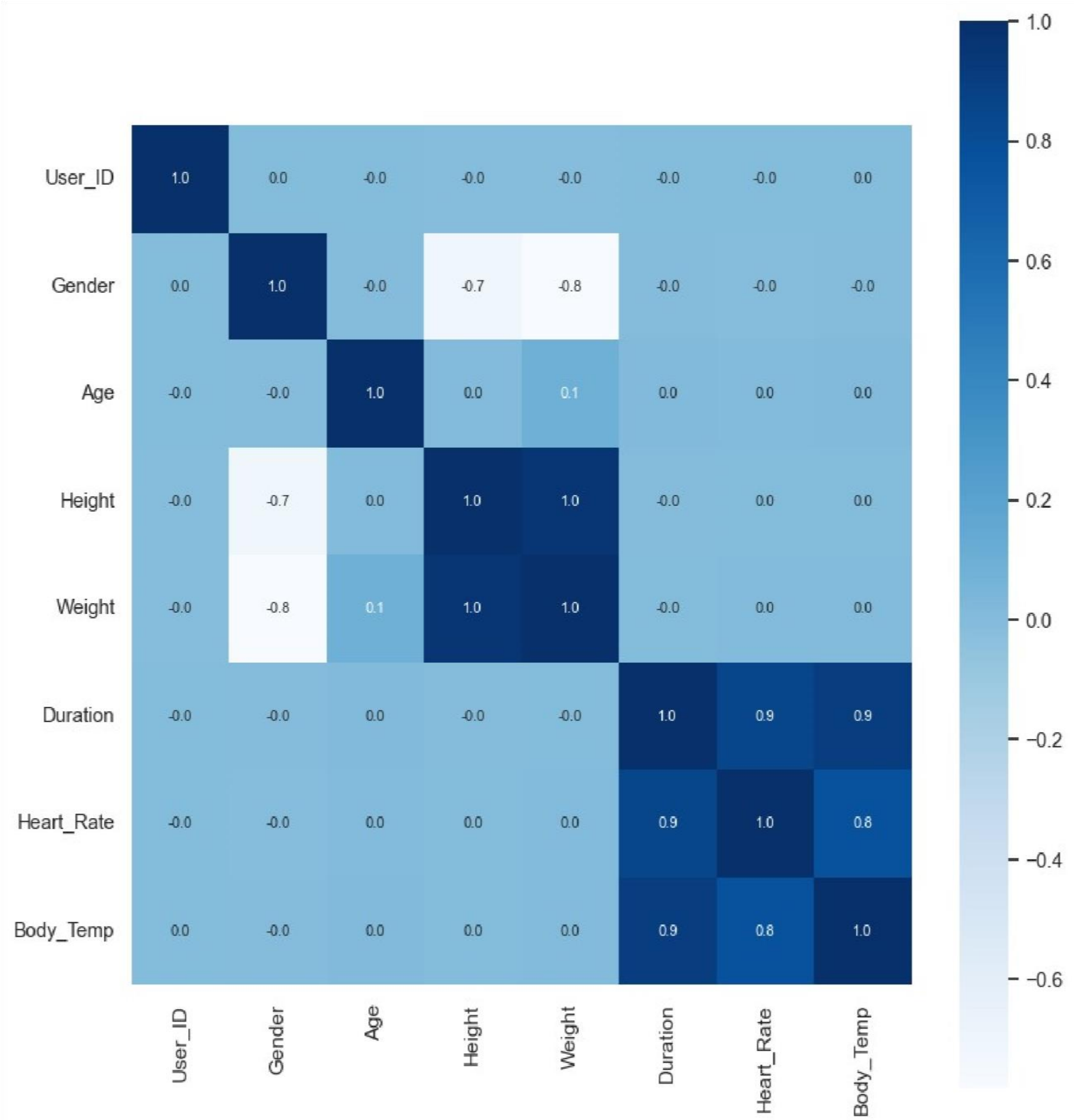
[15000 rows x 9 columns]

```
# df_numeric = combined_data[['Age', 'Height', 'Weight', 'Duration',
'Heart_Rate', 'Body_Temp']].copy()
# correlation_matrix = df_numeric.corr() correlation =
combined_data[['User_ID','Gender','Age','Height','Weight','Duration',' Heart_Rate','Body_Temp']]
.corr ()
```

Construction of heat map for the understanding of correlation

```
plt.figure(figsize=(10,10))
sns.heatmap(correlation, cbar=True, square=True, fmt='.1f', annot=True, annot_kws={'size':8},
cmap='Blues')
```

< Axes: >



CONVERSION OF TEXT DATA TO NUMERICAL VALUES

```
#combined_data.replace({'Gender':{'male':0,'female':1}},inplace=True) combined_data.head()
```

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

  Calories
0            231.0
1            66.0
2            26.0
3            71.0
4            35.0
```

SEPARATION OF FEATURES AND TARGET

```
X=combined_data.drop(['User_ID','Calories'],axis=1)
Y=combined_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
```

SPLIT 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)
```

Hence, we can observe that

- X contains the orignal amount of data which is 15000
- X_train contains 80% of the data which is 12000
- X_test contains 20% of the data which is 3000 **MODEL IMPLEMENTATION : XGBoost**

Regressor

```
#loading the model model =
XGBRegressor()

#training the model with X_train model.fit(X_train,Y_train)

XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,        colsample_bylevel=1,
colsample_bynode=1,
colsample_bytree=1,
        early_stopping_rounds=None, enable_categorical=False,
        eval_metric=None, gamma=0, gpu_id=-1,
grow_policy='depthwise',
        importance_type=None, interaction_constraints='',        learning_rate=0.300000012,
max_bin=256,
max_cat_to_onehot=4,
        max_delta_step=0, max_depth=6, max_leaves=0,
min_child_weight=1,
        missing=nan, monotone_constraints='()', n_estimators=100, n_jobs=0,
        num_parallel_tree=1, predictor='auto', random_state=0,
reg_alpha=0,        reg_lambda=1, ...)
```

EVALUATION

Evaluation is done by test data

PREDICTION OF THE DATA

```
calories_burnt_prediction = model.predict(X_test) print( calories_burnt_prediction )


[127.823784 226.00154   38.66253  ... 144.3636    22.767195
89.87375 ]
```

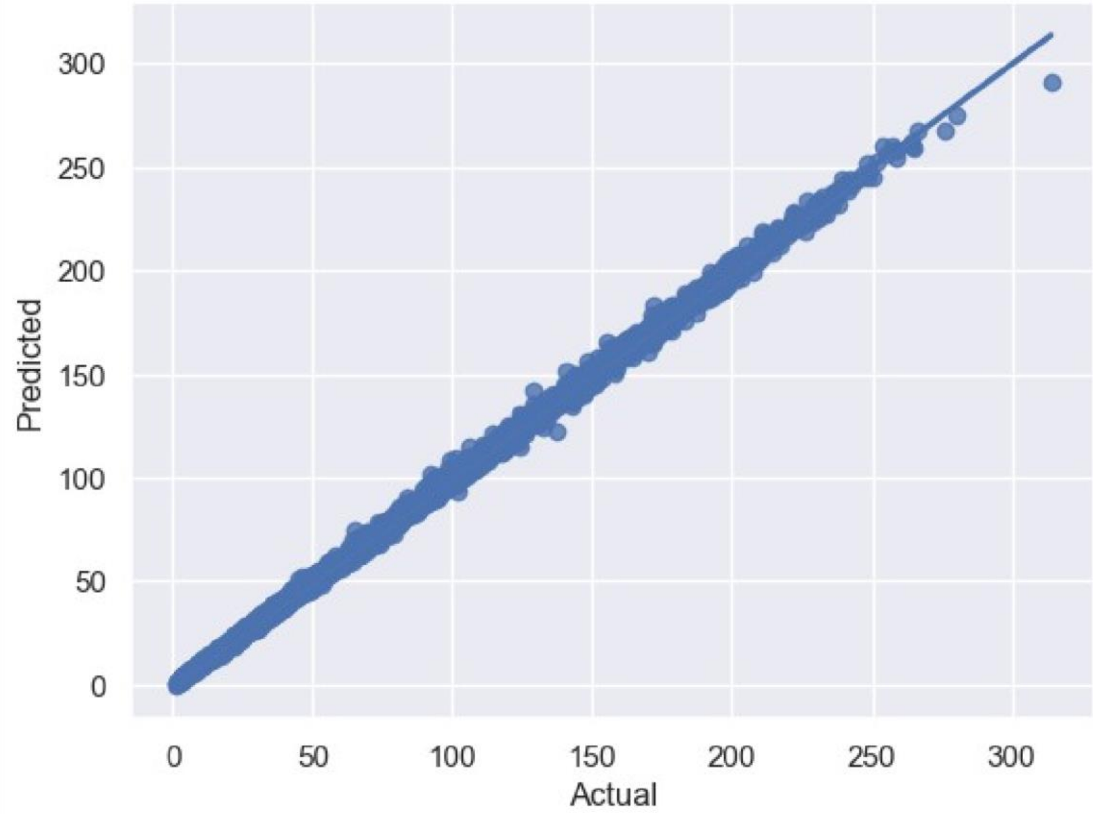
MEAN ABSOLUTE ERROR

```
MAE = metrics.mean_absolute_error(Y_test, calories_burnt_prediction) print("Mean Absolute Error
= ",MAE)


Mean Absolute Error =  1.4807048829992613
```

BUILDING A PREDICTIVE SYSTEM

- Building a predictive system inorder to find the calories burnt for the first individual from the dataset

```
input_data = (0,68,190.0,94.0,29.0,105.0,40.8,231)

print("The calories burnt for the first individual in the dataset is predicted as ",
calories_burnt_prediction[0])

The calories burnt for the first individual in the dataset is predicted as  127.823784

print("Thus we have successfully predicted the calories burnt using XGBoost")

Thus we have successfully predicted the calories burnt using XGBoost sns.regplot(x=Y_test,

y=calories_burnt_prediction)


plt.xlabel('Actual') plt.ylabel('Predicted')
plt.show()
```



STAY SAFE

STAY HEALTHY