imporingt dependencies

#libaries or function that r required for this project import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns from sklearn.model_selection import train_test_split from xgboost import XGBRegressor from sklearn import metrics

#numpy is used to make arrays (list of numbers or values) and np is the abbreviation.

#pandas is used to make DataFrames (structured tables) makes it easy to analyze and process the data.

#(the files are inform of CSV (comma separated values).we can't analyze them like this so we convert them into dataframe using pandas) #matplotlib is used to create plots(for data analysis we do some visualization) so it is for data visualization .

#seaborn is also for the data visualization.

#train_test_split is used to split the data we are importing it from sklearn .

#sklearn is one of the important machine learning libraries.

 $\mbox{\#XGBRgressor}$ we are using this regressor in this project .

#metrices is used to evaluate the data. to know how well our model is working..

Data Collection and Data Processing

#loading data from csv file to Pandas DataFrame
calories = pd.read_csv('/content/calories.csv')

#print the first 5 rows of the DataFrame
calories.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('/content/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

Combining two DataFrames

#combining the Calories col from calories dataframe into exercise_data dataframe.
#the calories burnt will be dependent of the Hear_Rate of an individual.
calories_data = pd.concat([exercise_data, calories['Calories']],axis=1) #axis=1 is for col and 0 is for rows

calories_data.head()

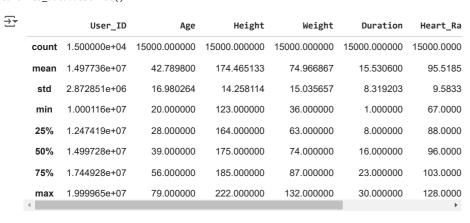
_										
₹		User_ID	Gender	Age	Height	Weight	Duration	Heart_Rate	Body_Temp	Calories
	0	14733363	male	68	190.0	94.0	29.0	105.0	40.8	231.0
	1	14861698	female	20	166.0	60.0	14.0	94.0	40.3	66.0
	2	11179863	male	69	179.0	79.0	5.0	88.0	38.7	26.0
	3	16180408	female	34	179.0	71.0	13.0	100.0	40.5	71.0
	4	17771927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

```
5/29/24, 10:47 PM
   #cheacking the no.of rows nd col
   calories_data.shape
    → (15000, 9)
   #getting some information about the data (useful for checking missing values)
   calories_data.info()
    <<class 'pandas.core.frame.DataFrame'>
        RangeIndex: 15000 entries, 0 to 14999
        Data columns (total 9 columns):
         # Column
                        Non-Null Count Dtype
        ---
                        15000 non-null int64
         0 User ID
         1
             Gender
                        15000 non-null
                                        object
                        15000 non-null int64
             Age
             Height
                        15000 non-null
                                        float64
                        15000 non-null float64
             Weight
             Duration
                        15000 non-null float64
             Heart_Rate 15000 non-null float64
             Body_Temp
                        15000 non-null float64
                        15000 non-null float64
             Calories
        dtypes: float64(6), int64(2), object(1)
        memory usage: 1.0+ MB
   #cheacking the missing values
   calories_data.isnull().sum()
    → User_ID
        Gender
                     0
        Age
                     0
        Height
        Weight
                     0
        Duration
                     0
        Heart Rate
                     0
        Body_Temp
                     0
        Calories
                      0
        dtype: int64
```

#if there are any missing values we need to preprocess the data . #AND HERE WE DON'T HAVE ANY NULL VALUES.

Data Analysis

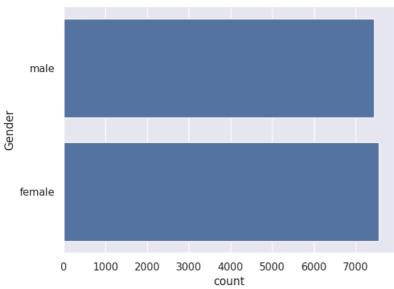
#get some statical measurement of the data calories_data.describe()



Data Visualization

```
#gives baisc theme for the plots like grids and Background colour.
#Plotting the gender col in countplot
sns.countplot(calories data['Gender'])
```

<a> <Axes: xlabel='count', ylabel='Gender'>



#as the distribution of gender are equal it means that the data is very good distributed dataset.

#we can use countplot only for categorical cols like male or female, Yes or NO. can't useful for numerical cols.

#for numerical cols we use distplot for visualization of the data.

#finding the distribution of the 'AGE' col.
sns.distplot(calories_data['Age'])

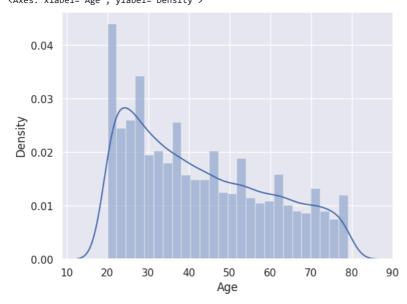
<ipython-input-17-d69e6e018a56>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(calories_data['Age'])
<Axes: xlabel='Age', ylabel='Density'>



#finding the distribution of the 'Height' col.
sns.distplot(calories_data['Height'])

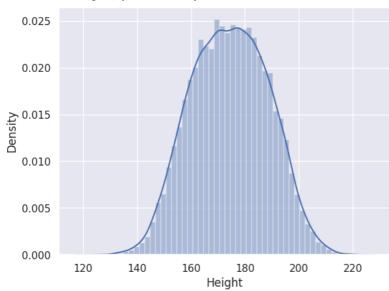
<ipython-input-18-8e8a5e46a286>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see $\frac{\text{https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751}}{\text{https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751}}$

sns.distplot(calories_data['Height'])
<Axes: xlabel='Height', ylabel='Density'>



#finding the distribution of the 'Weight' col.
sns.distplot(calories_data['Weight'])

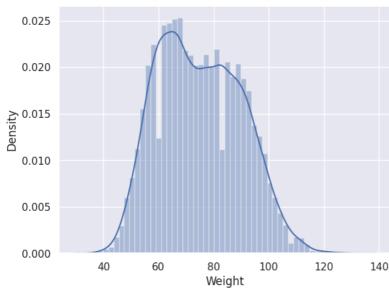
→ <ipython-input-19-5ad90a9eb752>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(calories_data['Weight'])
<Axes: xlabel='Weight', ylabel='Density'>



Converting text data into numerical data

#we are coverting the text col of "GENDER" into numerical col becoz we can't feed a textdata to a ML model #for that purpose we need to covert into numerical values.

#categorical convertion

calories_data["Gender"].replace({"male": 0, "female": 1}, inplace=True)

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

Finding the Correaltion in the Dataset

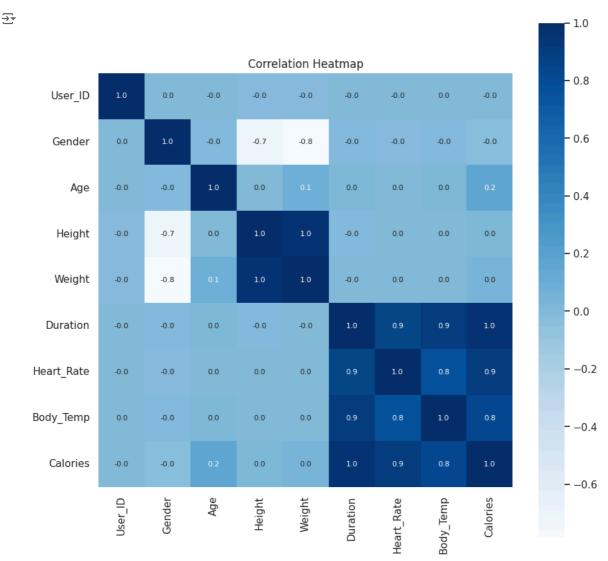
1. Positive Correlation. 2. Negative Correaltion.

```
#Positive corealtion: when 2 cols are directly proportional i.e
#example: when Duration increases the Calories Burnt are also increases.
#Negative correaltion: When they r indirectly proportional.
#AND "corr" function is used to calculate the correaltion
```

correlation = calories_data.corr()

#constructing a heatmat to understand the correlation

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



```
5/29/24, 10:47 PM
                                                                   Calories Burnt Prediction.ipynb - Colab
   #the HEATMAP gives colors according to the values.
   #each col is copared to other col if the value is large than is gives "1" and if it is less it gives "0"
   #1.0 means that the relation btw them is "Positively Correlations".
   #if the val is very less then it is "Negatively Correlations".
   #if the val is 0 then there is no correlations.
   #Height and Weight are compared and are positive are correlated (if a person is v.height then that weight will be more).
   #Duration, Heart_rate, Body_Temp and Calories are correlated (if a person spends more time then they will get increase in heart_rate, body
   #burn more calories).
   Separating Features and target
   #dividing the dataset into two parts.
   #we need to predict calories so taking into a diff Y variable.
   #and rest of cols into X variable.
   X= calories data.drop(columns=['User ID', 'Calories'], axis=1)
   Y= calories_data['Calories']
   print(X)
    \overline{2}
                Gender Age Height Weight Duration Heart_Rate Body_Temp
                              190.0
                                                             105.0
                                                                         40.8
                     0
                        68
                                       94.0
                                                  29.0
         1
                        20
                              166.0
                                       60.0
                                                  14.0
                                                              94.0
                                                                         40.3
                     1
                              179.0
                                                              88.0
         2
                     0
                        69
                                       79.0
                                                  5.0
                                                                         38.7
                         34
                              179.0
                                       71.0
                                                             100.0
                                                                         40.5
         3
                     1
                                                 13.0
                         27
                                                              81.0
        4
                    1
                              154.0
                                       58.0
                                                 10.0
                                                                         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
                         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
                              173.0
                                       79.0
                                                 18.0
                                                              92.0
                                                                         40.5
                        63
        [15000 rows x 7 columns]
   print(Y)
    ₹
        0
                  231.0
                   66.0
        2
                   26.0
         3
                   71.0
                   35.0
         14995
                  45.0
         14996
                   23.0
        14997
                   75.0
         14998
                   11.0
        14999
                   98.0
        Name: Calories, Length: 15000, dtype: float64
   Splitting dataset into training and testing
   #X_train consist all the traning data of X
   \#X\_\text{test} contains all the tests data of X
   \#Y\_train contain the corresponding calories of X\_train are stored.
```

```
#Y_test contains the corresponding calories of X_train are stored.
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2,random_state=2)
#0.2 means 20% of testing data we are considering as testing data.
#80% as training data to train the model.
print(X.shape, X_train.shape, X_test.shape)
→ (15000, 7) (12000, 7) (3000, 7)
Modelling training
XGBoost Regression
```

#Loading the model

model = XGBRegressor()

#training the model with X_train

```
model.fit(X train,Y train)
```



```
XGBRegressor

XGBRegressor(base_score=None, booster=None, callbacks=None, colsample_bylevel=None, colsample_bynode=None, colsample_bytree=None, device=None, early_stopping_rounds=None, enable_categorical=False, eval_metric=None, feature_types=None, gamma=None, grow_policy=None, importance_type=None, interaction_constraints=None, learning_rate=None, max_bin=None, max_cat_threshold=None, max_cat_to_onehot=None, max_delta_step=None, max_depth=None, max_leaves=None, min_child_weight=None, missing=nan, monotone_constraints=None, multi_strategy=None, n_estimators=None, n_jobs=None, num_parallel_tree=None, random_state=None, ...)
```

this training model if given to XGBoost regression model it finds the pattern btw the models
#the model will automatically will learn that if duration is more the calories burnt will be more
#or if the heart_rate is more then the calories burnt will be more like that this will be understand by the model through this
#training data . NOW THE MODEL HAS LEARNT FROM THE DATA.

Evaluation

```
predicting on testing data
```

```
test_data_prediction = model.predict (X_test)
```

#it will verfiy the corresponding calories burnt from the X_test features like:Duration, Heart_rate etc...
#save those calories in the test_data_prediction.
#Now compare this values with Y_test.

```
print(test_data_prediction)
```

```
→ [125.58828 222.11377 38.725952 ... 144.3179 23.425894 90.100494]
```

Mean Absolute Error

#Here we compare the original calories values with test_data_prediction .

#if we see the above there is 38.7259 and if the original is 33.873 then we will subtract the and we will take the mean

#so like this we will consider the overall values and will predict the MEAN Error.

mae=metrics.mean_absolute_error(Y_test,test_data_prediction)

```
print("Mean Absolute Error:",mae)
```

Mean Absolute Error: 1.4833678883314132

#As the mean is very low our model is good....

Buliding a Predictive System

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

#chaning input_data into numpy array
input_data_as_numpy_array = np.asarray(input_data)

#reshaping the array

input_data_reshape = input_data_as_numpy_array.reshape(1,-1)

prediction = model.predict(input_data_reshape)
print(prediction)

→ [236.13371]

#we changing the input_Data into numpy array becoz it is easy to some processing on NUMPY rather than tuples

#we are using reshape to tell the model that we are considering single row or data.

#the output we got is 236 which is near to the orginal val(231) so that means the model is working perfectly .