```
# Importing libraries
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from sklearn.model_selection import train_test_split , GridSearchCV
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression


from sklearn import metrics


from IPython.display import HTML
import plotly.express as px

import warnings
warnings.filterwarnings('ignore')


calories = pd.read_csv("calories.csv")
exercise = pd.read_csv("exercise.csv")
```

Start coding or generate with AI.

General Overview of Dataset

```
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

Next steps: Generate code with calories View recommended plots New interactive sheet

```
exercise.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

Next steps: Generate code with exercise View recommended plots New interactive sheet

```
exercise_df = exercise.merge(calories , on = "User_ID")
exercise_df.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

Next steps: Generate code with exercise_df View recommended plots New interactive sheet

```
print("This dataset has " , exercise_df.shape[0] ," instances and ",  exercise_df.shape[1] , " columns.")
```

```
This dataset has  15000  instances and  9  columns.
```

```
print("Columns : ")
for i , column in zip(range(len(exercise_df.columns)) , exercise_df.columns):
  print("\t" , i + 1 , "." ,  column)
```

```
Columns :
         1 . User_ID
         2 . Gender
         3 . Age
         4 . Height
         5 . Weight
         6 . Duration
         7 . Heart_Rate
         8 . Body_Temp
         9 . Calories
```

1.**User_ID** : The ID of the person which is unique.
2.**Gender** : Gender of the person.
3.**Age** : Age of the person.
4.**Height** : Height of the person in cm.
5.**Weight** : Weight of the person in kg.
6.**Duration** : Duration of the person's exercise/activity.
7.**Heart_Rate** : Heart rate per min of the person.
8.**Body_Temp** : Body temperature of the person in C°.
9.**Calories** : Calories burned in kilo calories.

Dataset's Overall Statistic

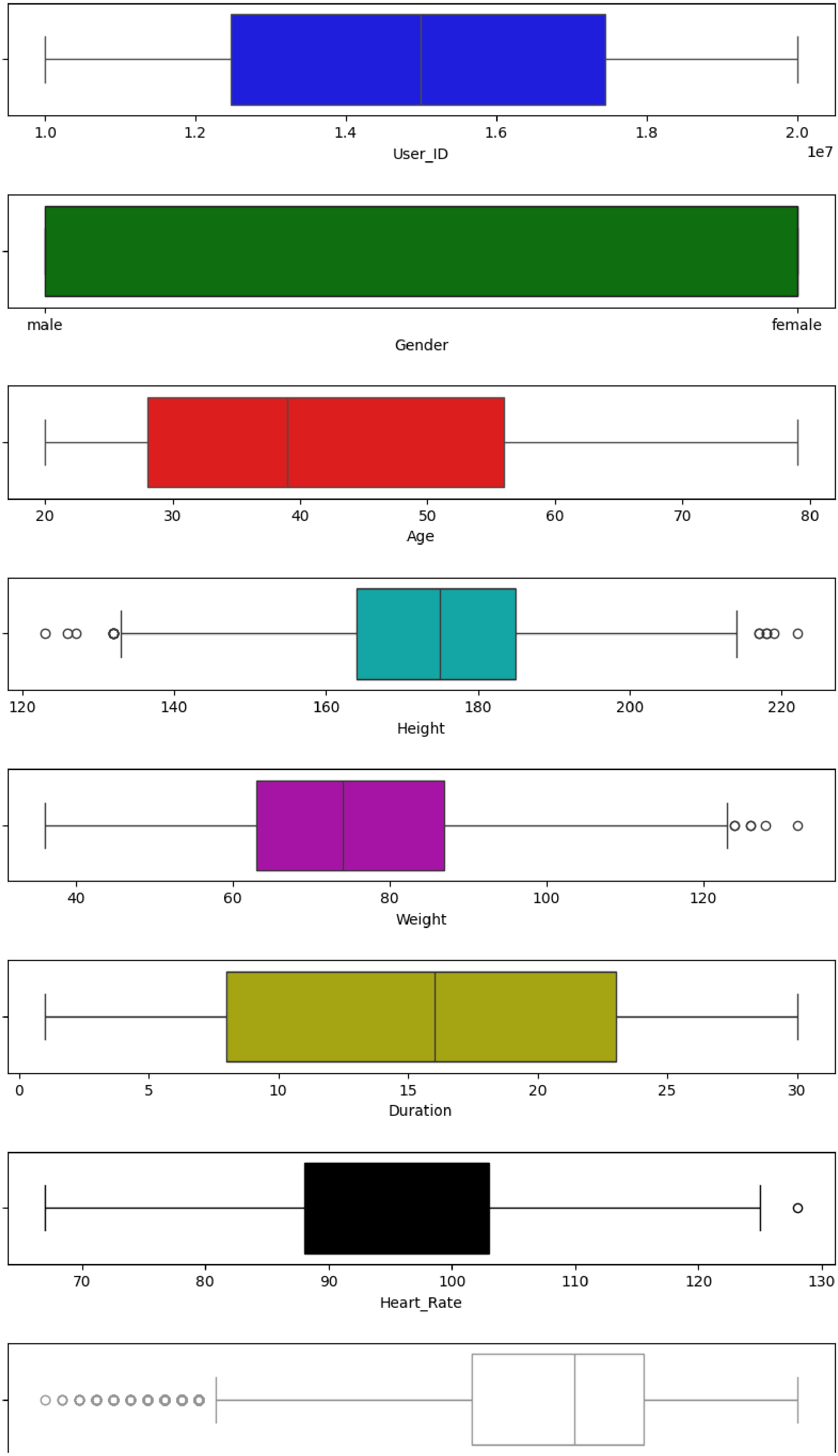
```
exercise_df.describe()
```

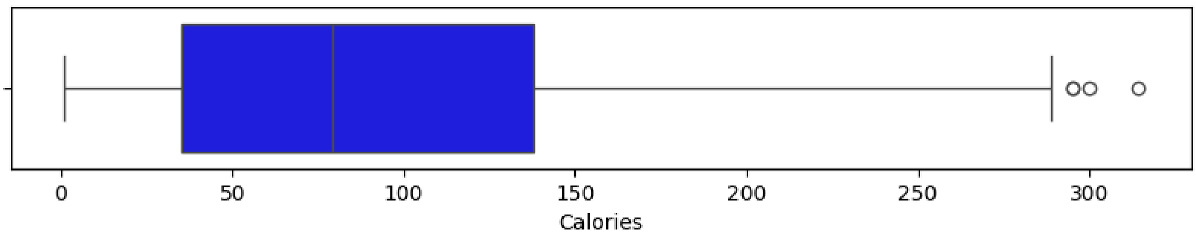
	User_ID	Age	Height	Weight	Duration	Heart_Rate	Body_Temp	Calories
count	1.500000e+04	15000.000000	15000.000000	15000.000000	15000.000000	15000.000000	15000.000000	15000.000000
mean	1.497736e+07	42.789800	174.465133	74.966867	15.530600	95.518533	40.025453	89.539533
std	2.872851e+06	16.980264	14.258114	15.035657	8.319203	9.583328	0.779230	62.456978
min	1.000116e+07	20.000000	123.000000	36.000000	1.000000	67.000000	37.100000	1.000000
25%	1.247419e+07	28.000000	164.000000	63.000000	8.000000	88.000000	39.600000	35.000000
50%	1.499728e+07	39.000000	175.000000	74.000000	16.000000	96.000000	40.200000	79.000000
75%	1.744928e+07	56.000000	185.000000	87.000000	23.000000	103.000000	40.600000	138.000000
max	1.999965e+07	79.000000	222.000000	132.000000	30.000000	128.000000	41.500000	314.000000

- As we can see, the table above shows the `Descriptive Statistics` (for example `centeral tendency`) of each column or feature.

- For example for `Age` column.%25 of the data lie between **20** and **28**, anohter %25 lie between **28** and **39**, and so on.The box plot shows the exact concept that I just mentioned.
- The outliers are shown with dots in box plots, which we will discuss about them in the next section.

```
c = ['b' , 'g' , 'r' , 'c' , 'm' , 'y' , 'k' , 'w' , 'b']
fig1 , axes = plt.subplots(len(exercise_df.columns) , 1 , figsize = (10 , 20))
plt.subplots_adjust(wspace = 0.3 , hspace = 0.7)
axes = axes.flatten()             #for using axes indeces with one dimention array instead of two dimension
for i , column in zip(range(len(exercise_df.columns)) , exercise_df.columns):
  try:
    sns.boxplot(data = exercise_df , x = column , color = c[i] , ax = axes[i])
  except:
    fig1.delaxes(axes[i])
    continue
```


1.0
1.2
1.4
1.6
1.8
2.0
1e7
User_ID
male
female
Gender
20
30
40
50
60
70
80
Age
120
140
160
180
200
220
Height
40
60
80
100
120
Weight
0
5
10
15
20
25
30
Duration
70
80
90
100
110
120
130
Heart_Rate



Overall information of dataset

```
exercise_df.info()
```

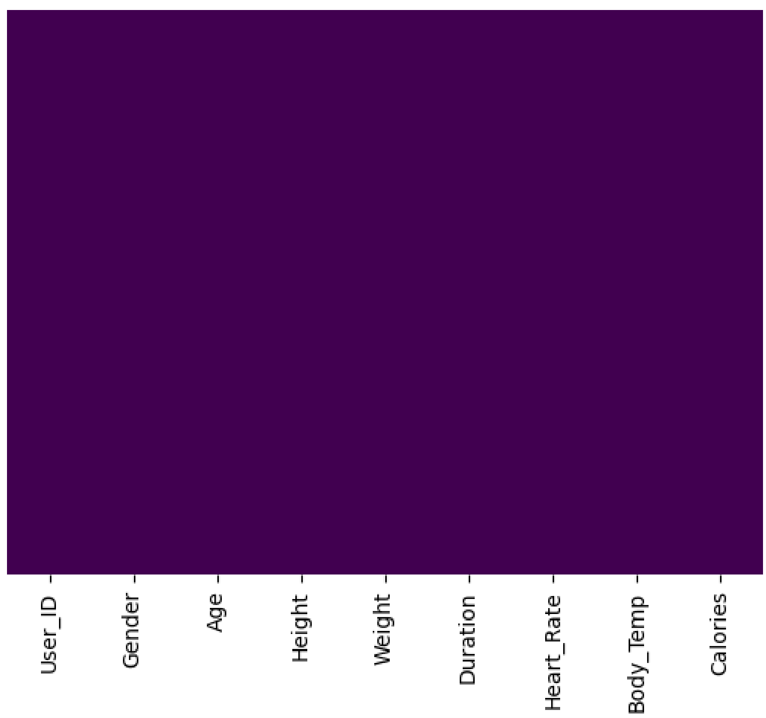
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15000 entries, 0 to 14999
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   User_ID     15000 non-null  int64  
 1   Gender      15000 non-null  object 
 2   Age         15000 non-null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

Null Values

In this section we are going to check whether this dataset has null values or not.We will check this with heatmap.Because it is easy to understand and we can see dataset's condition at a glance.

```
sns.heatmap(exercise_df.isnull() , yticklabels = False , cbar = False , cmap = "viridis")
```

```
<Axes: >
```



- As we can see, fortunately, this dataset does not have any null/NaN values, which is good and it is not necessary to do extra manipulations(for instance imputation , dropping or filling NaN values etc.) with this dataset.

Drop Duplicates

Lets assure that this dataset does not contain any duplicate values in `User_ID` column.

```
print("The shape of dataset before dropping duplicates : " , exercise_df.shape)
exercise_df.drop_duplicates(subset = ['User_ID'], keep='last' , inplace = True)    # Keeping the first example of dupl
print("The shape of dataset after dropping duplicates : " , exercise_df.shape)
```

```
The shape of dataset before dropping duplicates :  (15000, 9)
The shape of dataset after dropping duplicates :  (15000, 9)
```

- As we can see the shape of dataset before and after dropping duplicates is the same.It is a good sign, because we do not need to be worry about `Data Leakage`.

- In the next step we have to delete `User_ID` feature.Because it is a `low predictive feature`.In other words, it is not only a useless feature for our calorie burned prediction model but also has a negative impact on model's accuracy.

```
exercise_df.drop(columns = "User_ID" , inplace = True)
```

- For avoiding any `Data Leakage` in our model, let's split our data into training set and test set before doing any `feature engineering`.

```
exercise_train_data , exercise_test_data = train_test_split(exercise_df , test_size = 0.2 , random_state = 1)
print("Shape of training data : " , exercise_train_data.shape)
print("Shape of test data : " , exercise_test_data.shape)
```

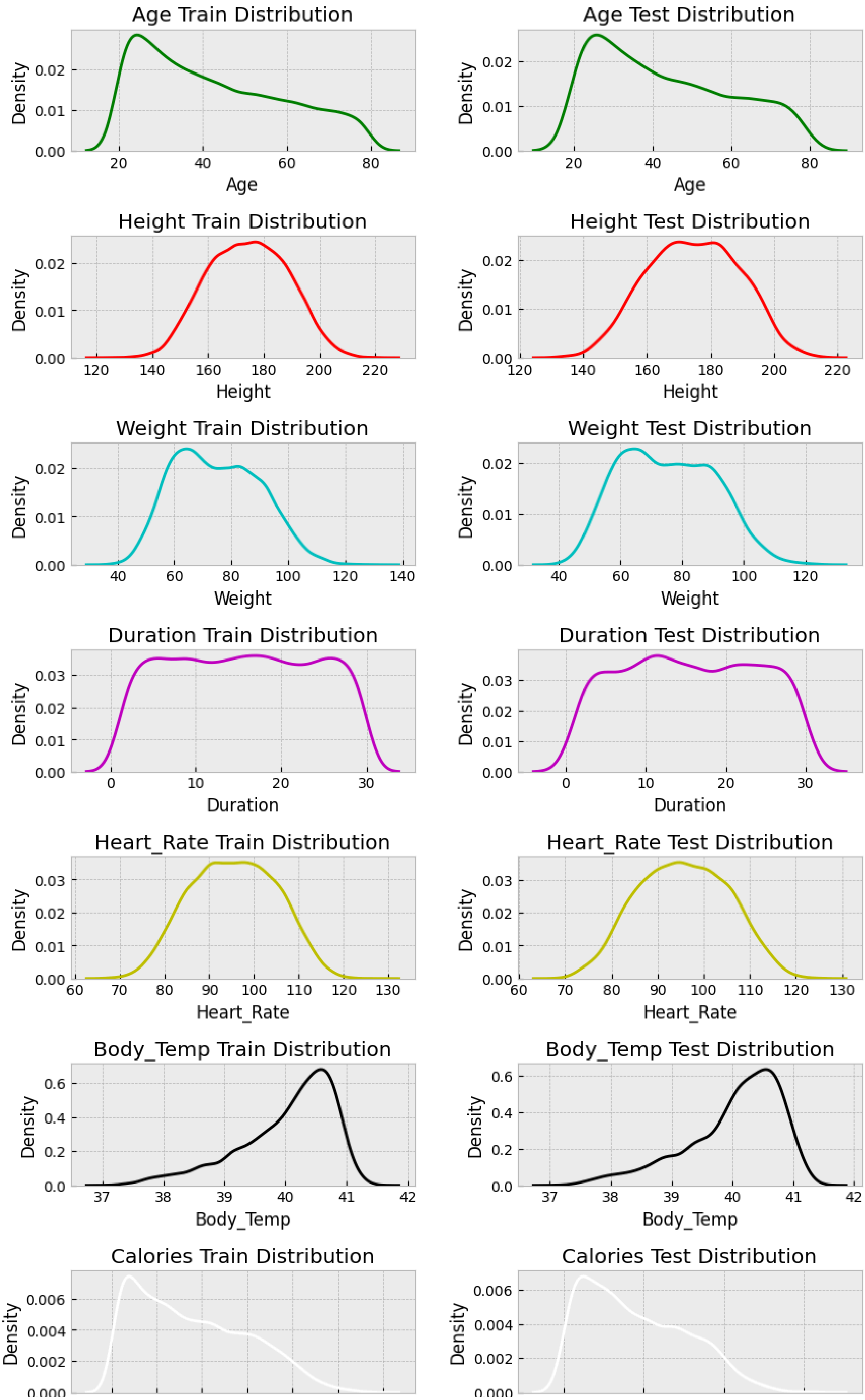
```
Shape of training data :  (12000, 8)
Shape of test data :  (3000, 8)
```

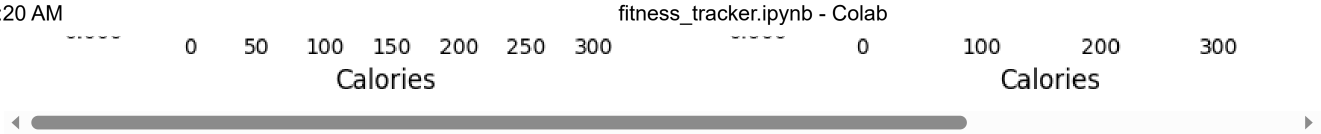
Dataset's Distribution

One of the main criterions that whether we will be able to deploy our model into production or not, is that **the distribution of features for both training set and test set must be similar**.This is because the model is fitting on the training set and the model keeps in mind the training set patterns.When the distribution of test set is different from the training set it means that the model can not predict very well on test set examples and unlike the training set accuracy, the testing set accuracy will be low.This is because, at first, we have to see and compare the distributions for both test set and training set and check whether both have the same distribution or not.

```
from matplotlib import style
style.use("bmh")


c = ['b' , 'g' , 'r' , 'c' , 'm' , 'y' , 'k' , 'w' , 'b']
fig1 , axes = plt.subplots(len(exercise_train_data.columns) , 2 , figsize = (10 , 20))
plt.subplots_adjust(wspace = 0.3 , hspace = 0.7)
axes = axes.flatten()             #for using axes indeces with one dimention array instead of two dimension

for i , column , color in zip(range(0 , len(exercise_train_data.columns) * 2 , 2) , exercise_train_data.columns , c):
  try:
    axes[i].title.set_text(column + " Train Distribution")
    sns.kdeplot(data = exercise_train_data , x = column , ax = axes[i] , color = color)
  except:
    fig1.delaxes(axes[i])
    continue

for i , column , color in zip(range(1 , len(exercise_train_data.columns) * 2 , 2) , exercise_train_data.columns , c):
  try:
    axes[i].title.set_text(column + " Test Distribution")
```

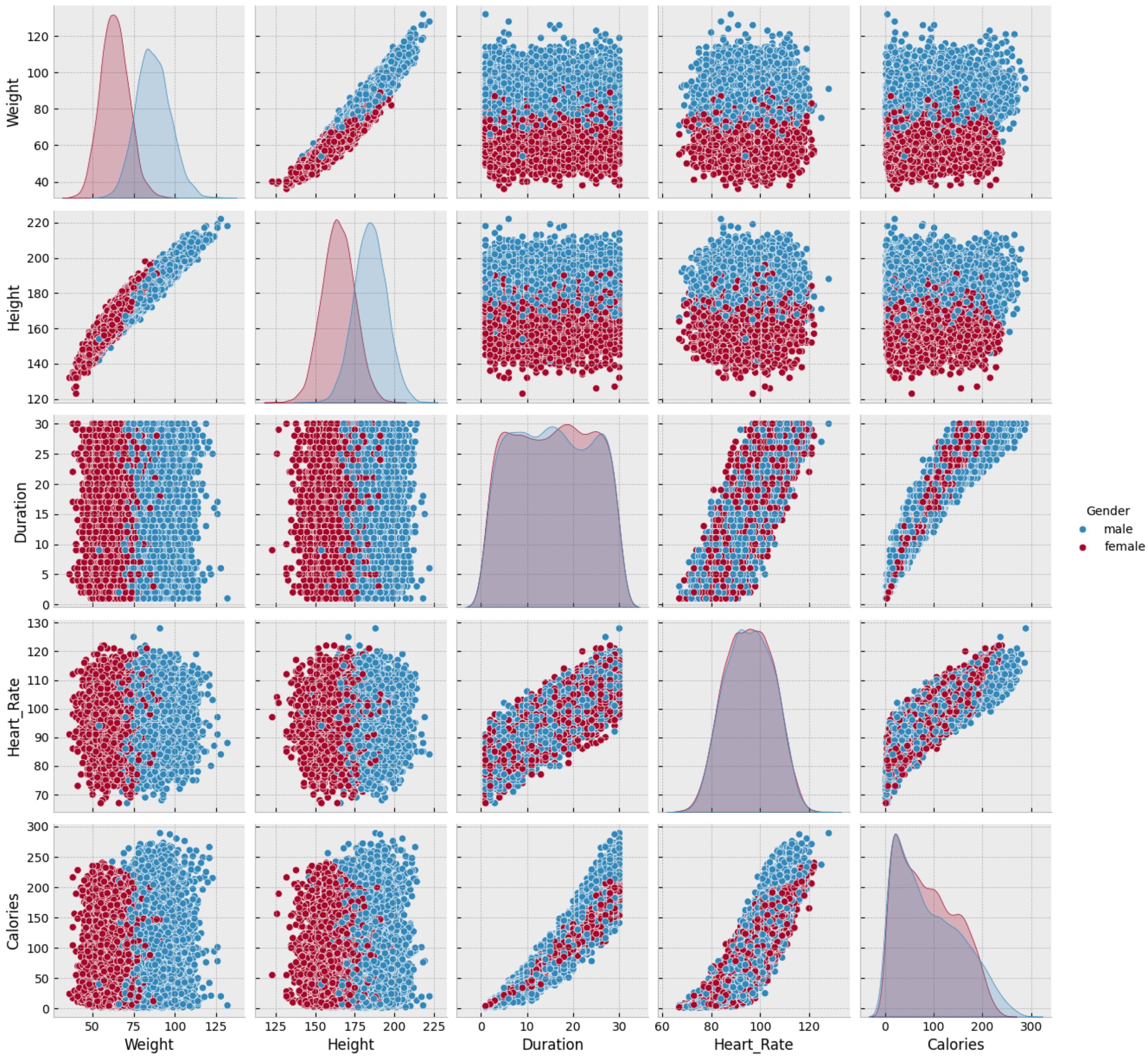
```
        sns.kdeplot(data = exercise_test_data , x = column , ax = axes[i] , color = color)
      except:
        fig1.delaxes(axes[i])
        continue
```


Age Train Distribution
Density
Age
Age Test Distribution
Density
Age
Height Train Distribution
Density
Height
Height Test Distribution
Density
Height
Weight Train Distribution
Density
Weight
Weight Test Distribution
Density
Weight
Duration Train Distribution
Density
Duration
Duration Test Distribution
Density
Duration
Heart_Rate Train Distribution
Density
Heart_Rate
Heart_Rate Test Distribution
Density
Heart_Rate
Body_Temp Train Distribution
Density
Body_Temp
Body_Temp Test Distribution
Density
Body_Temp
Calories Train Distribution
Density
Calories Test Distribution
Density




```
sns.pairplot(exercise_train_data[["Weight" , "Height" , "Duration" , "Heart_Rate" , "Calories" , "Gender"]] , hue = "G
```

```
<seaborn.axisgrid.PairGrid at 0x7955c652cc10>
```



- As we can see from graphs above, there is not a specific correlation or relationship between most of the features in the dataset.For example,there is not a specific relationship between `Duration` and `Weight` or between `Duration` and `Hight`.This is because exercisers may have different exercise duration no matter of their `Weight` and `Height`.
- In some cases, a featrue has a low relationship with another feature, like `Duration` and `Heart_Rate`.Somehow(with low confident) we can say that the more time somebody exercises the more 'Heart Rate' per minute he/she will have.
- In some cases , two featrues have a high relationship(in compare to last two cases), like `Height` and `Weight`.

- There are more informations and benefits that we can get from `Correlation` concept.But thats for now and we will go further in the next section.

Exploratory Data Analysis(EDA)

```
print('Minimum age in dataset is : ' , exercise_train_data["Age"].min())
print('Maximum age in dataset is : ' , exercise_train_data["Age"].max())
```

```
Minimum age in dataset is :  20
Maximum age in dataset is :  79
```

- As we can see the oldest person in dataset is 79 years old and the youngest is 20 years old.What we want to do is divide this range of ages into several named ranges.In other words we want to convert the continuous column into categorical column.
  The ranges are:

Name	Age
Young	[20 , 40)
Middle-Aged	[40 , 60)
Old	[60 , 80)

```
age_groups = ["Young" , "Middle-Aged" , "Old"]
exercise_train_data["age_groups"] = pd.cut(exercise_train_data["Age"] , bins = [20 , 40 ,60 , 80] , right = False , la
exercise_train_data["age_groups"].head()
```

	age_groups
2643	Old
13352	Old
13117	Old
2560	Old
14297	Middle-Aged

dtype: category

```
exercise_train_data["age_groups"].value_counts()
```

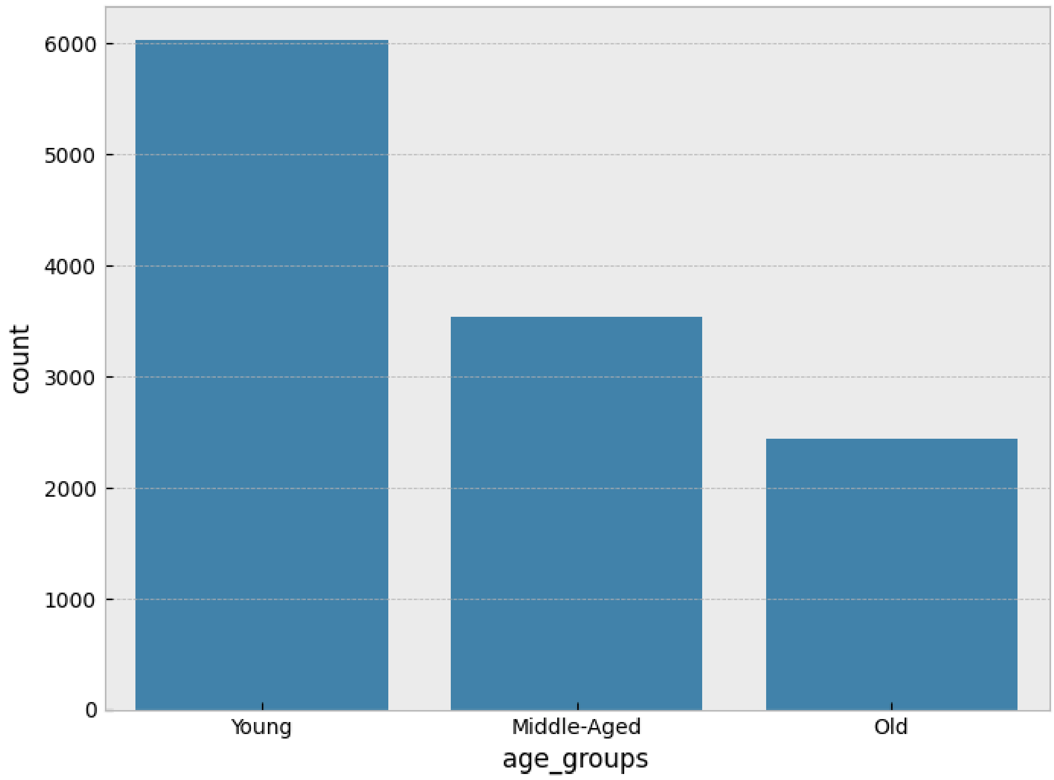
age_groups	count
Young	6029
Middle-Aged	3535
Old	2436

dtype: int64

- As we can see we have just converted a continuous column into a categorical column.Now its time to analyze `age_groups` column in terms of different aspects.

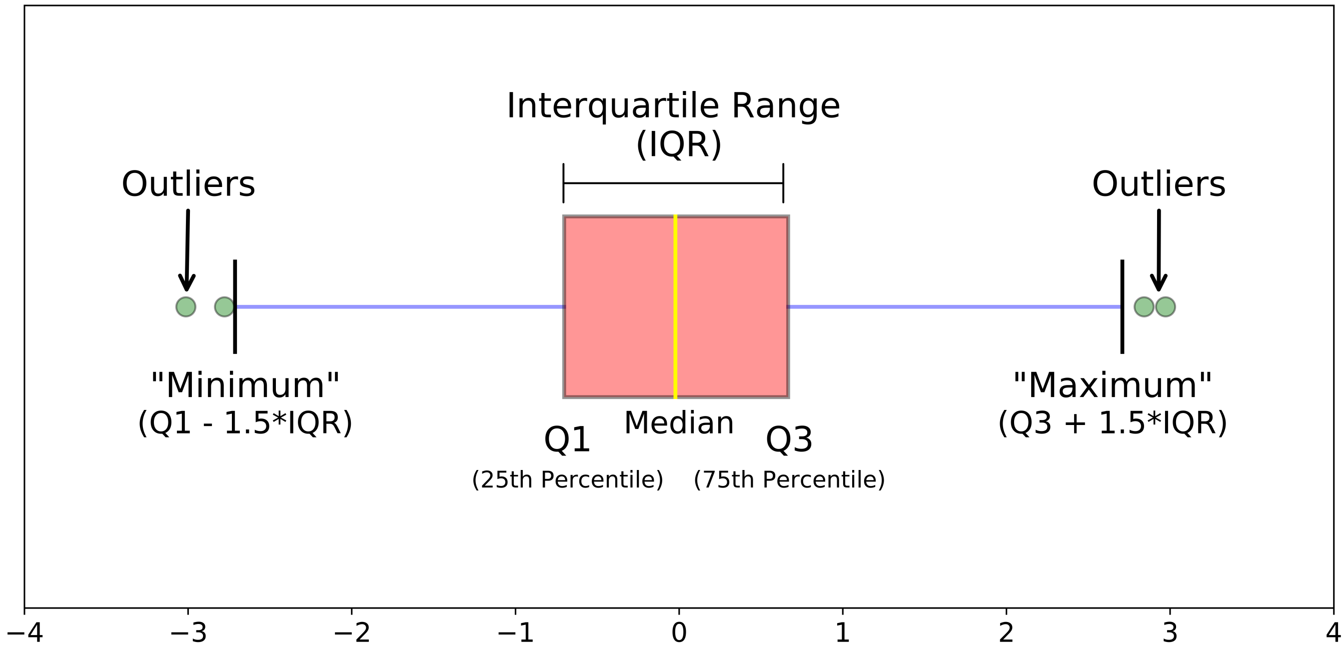
```
plt.rcParams["figure.figsize"] = 8 , 6
sns.countplot(data = exercise_train_data , x = "age_groups")
```

```
<Axes: xlabel='age_groups', ylabel='count'>
```

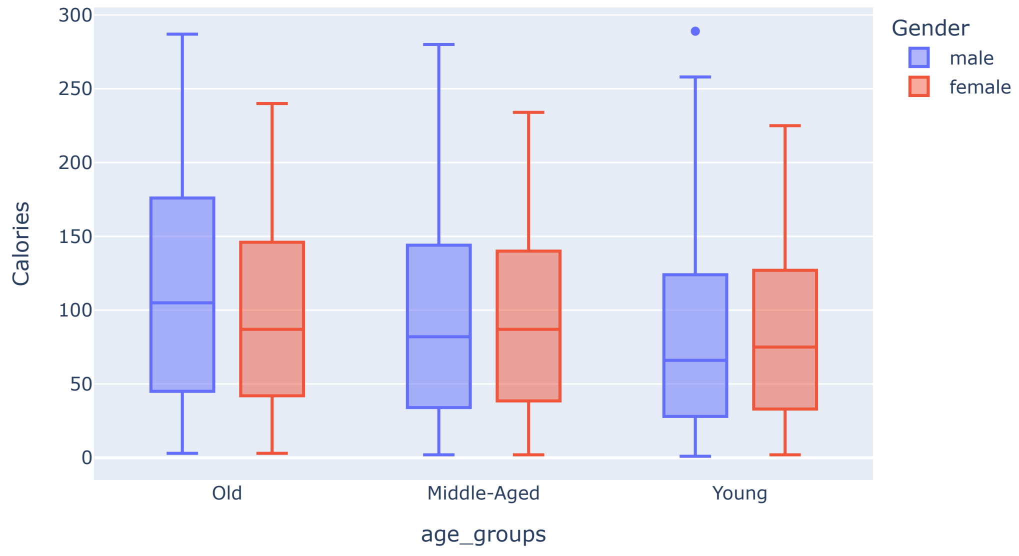


- As we expected, there is a significant difference between in counts of different age groups.Most of the people of this dataset are **young**.The second is **middle-aged** and the third one is **old**.

Lets analyze how many kilocalories each age groups burned.We will do this with `box plot` .Because `box plot` has a intuitive graph that we can extract **Median** , **Interquartile Range** , **Outliers** and etc.Just like the picture below shows.




```
fig = px.box(exercise_train_data , x= "age_groups" , y = "Calories" , color = "Gender")

fig.update_layout(
    width=700,
    height=450,
)

fig.show()
```



- As we can observe, old individuals have burned more kilocalories in compare of two other age groups.And the young persons are the least in burning kilocalories which is a surprise!
- Another interesting thing is, females in all age ranges performed very similar.In other words, they burned same amount of kilocalories in average.But for males, old group outperformed and the youth have the weakest performance.
- Also there is an outlier for young group which is shown by a point.This point has a value which is greater than third quartile value(Q3) plus 1.5 times of interquartile range magnitude.

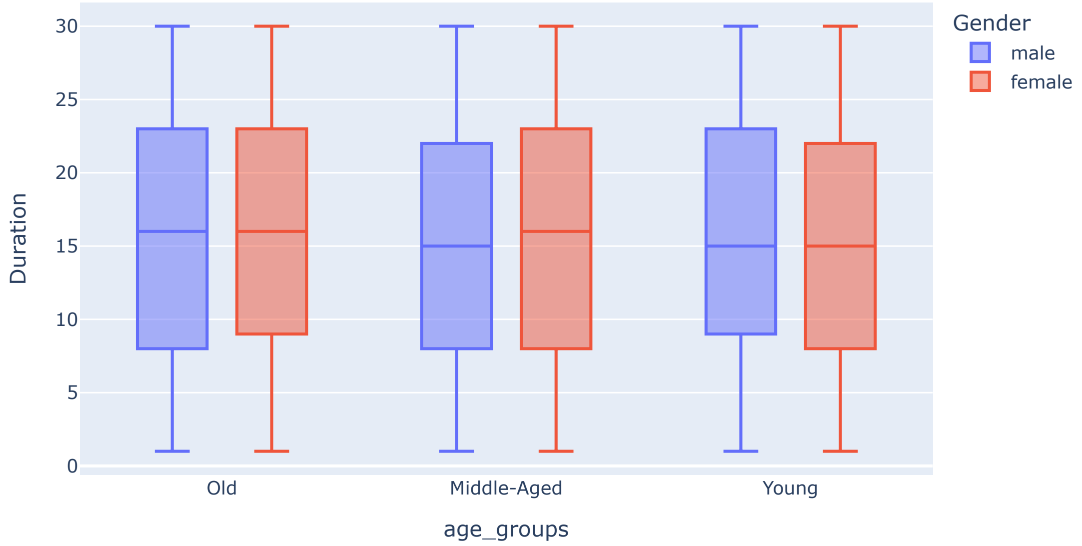
  `Outlier > Q3 + 1.5 * IQR`

  OR

  `Outlier < Q1 - 1.5 * IQR`

Now lets see which group have the most exercise duration in minutes.

```
fig = px.box(exercise_train_data , x= "age_groups" , y = "Duration" , color = "Gender")

fig.update_layout(
    width=750,
    height=450,
)

fig.show()
```



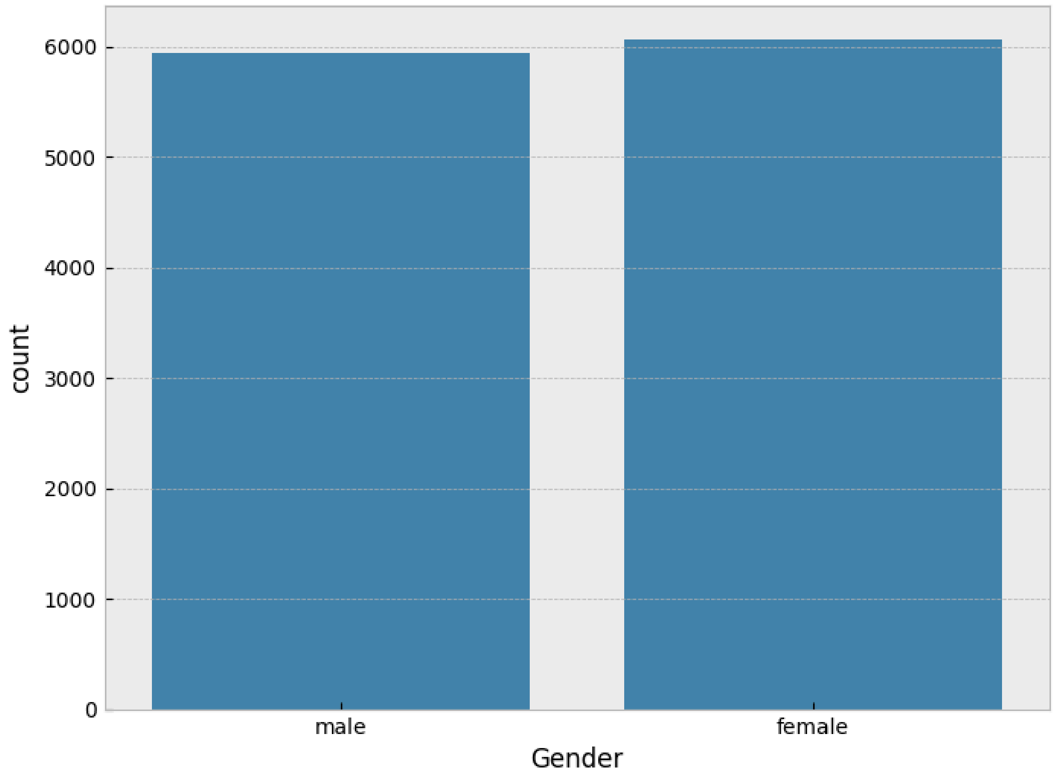
- As we can see , the exercise duration of each group is pretty identical.Every group have the same interquartile range , median and so on.
- In addition, the duration is very similar for males and females in `old` and `middle-aged` groups.But in `youth` , males outperformed.
- Another tip is, the median exercise duration of this dataset is about 15 minutes.We will assure this by the code bellow:

Gender

Lets plot the count plot of each gender to see how many exercisers are male and how many of them are female.

```
plt.rcParams["figure.figsize"] = 8 , 6
sns.countplot(data = exercise_train_data , x = "Gender")
```

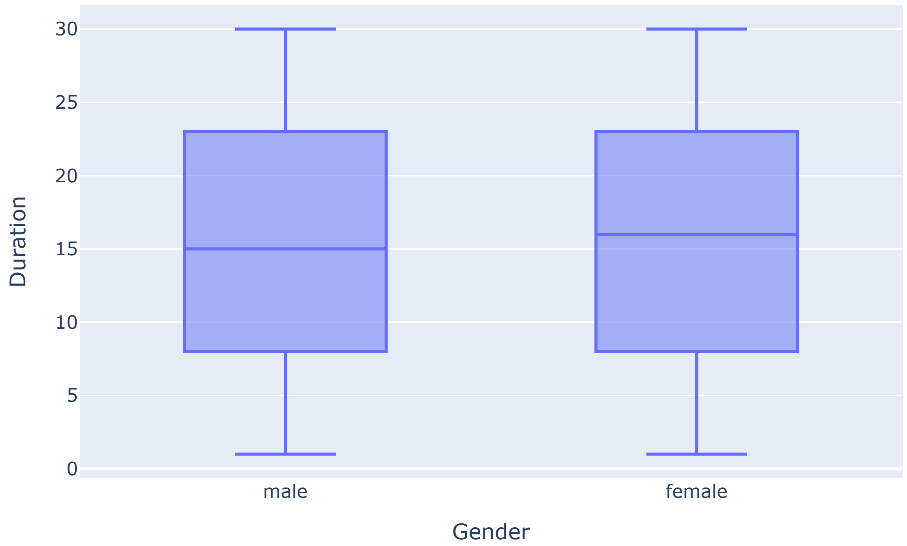
```
<Axes: xlabel='Gender', ylabel='count'>
```



- As we can see, number of females are slightly higher than man but this distinction is not significant.we can say, in general, they are equal.

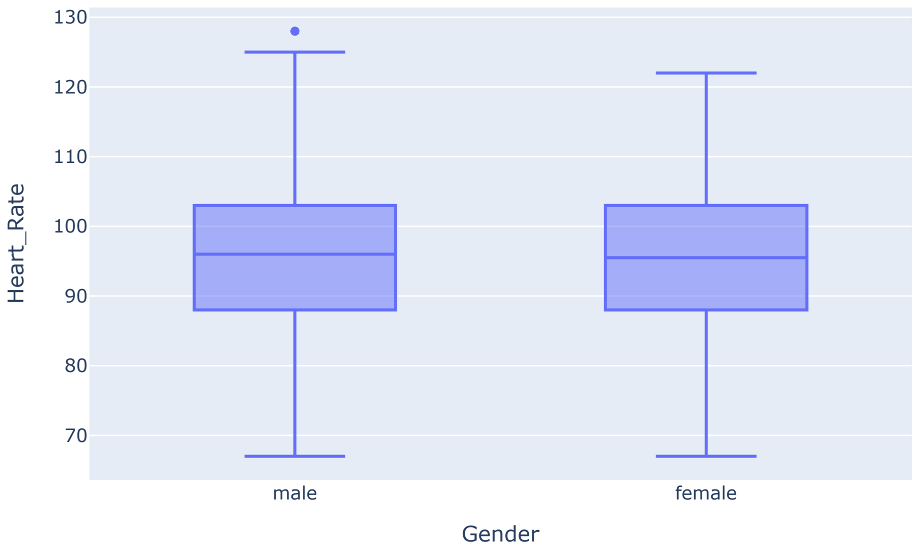
In this section, lets compare the exercise duration between males and females.

```
fig = px.box(exercise_train_data , x= "Gender" , y = "Duration")

fig.update_layout(
    width=700,
    height=450,
)

fig.show()
```



- As we can observe the median , IQR and etc. for both groups are overly identical.We proved this fact in the previous section.

```
fig = px.box(exercise_train_data , x= "Gender" , y = "Heart_Rate")

fig.update_layout(
    width=700,
    height=450,
)

fig.show()
```



- As we can see, again the overall heart rate of both male and female are similar.In addition to this, we have an outliers for the male.

In this section our purpose is combine the `Weight` column and the `Height` column values to perform a simple BMI calculation to classify individuals of this dataset into different groups according to their BMI value.

- The BMI(Body Mass Index) formula:

$$BMI = \frac{Weight(kg)}{Height(m)^2}$$

OR

$$BMI = \frac{Weight(Ib)}{Height(in)^2}$$

- The first formula will be used because the units for `Weight` and `Height` of this dataset is `kg` and `meter` in respect.
- According to [this page](#) we will classify instances according to below table:

Categoty	from	to
Very severely underweight	--	15
Severely underweight	15	16
Underweight	16	18.5
Normal (healthy weight)	18.5	25
Overweight	25	30
Obese Class I (Moderately obese)	30	35
Obese Class II (Severely obese)	35	40
Obese Class III (Very severely obese)	40	

- We will classify examples according to above category:

```
for data in [exercise_train_data , exercise_test_data]:         # adding BMI column to both training and test sets
  data["BMI"] = data["Weight"] / ((data["Height"] / 100) ** 2)
  data["BMI"] = round(data["BMI"] , 2)


# exercise_test_data["BMI"] = exercise_test_data["Weight"] / ((exercise_test_data["Height"] / 100) ** 2)
# exercise_test_data["BMI"] = round(exercise_test_data["BMI"] , 2)
# exercise_test_data.head()


bmi_category = ["Very severely underweight" , "Severely underweight" ,
                "Underweight" , "Normal" ,
                "Overweight" , "Obese Class I" ,
```

```
                  "Obese Class II" , "Obese Class III"]

exercise_train_data["Categorized_BMI"] = pd.cut(exercise_train_data["BMI"] , bins = [0 , 15 , 16 , 18.5 , 25 , 30 , 35
                                                , right = False , labels = bmi_category)

exercise_train_data["Categorized_BMI"] = exercise_train_data["Categorized_BMI"].astype("object") # converting 'categor
exercise_train_data.head()
```

	Gender	Age	Height	Weight	Duration	Heart_Rate	Body_Temp	Calories	age_groups	BMI	Categorized_BMI
2643	male	62	172.0	81.0	14.0	88.0	40.5	68.0	Old	27.38	Overweight
13352	male	77	182.0	83.0	28.0	108.0	40.8	241.0	Old	25.06	Overweight
13117	female	73	170.0	71.0	16.0	91.0	40.2	83.0	Old	24.57	Normal
2560	male	76	176.0	81.0	24.0	94.0	40.7	154.0	Old	26.15	Overweight
14297	male	42	183.0	77.0	7.0	93.0	39.8	32.0	Middle-	22.99	Normal

Next steps: Generate code with exercise_train_data View recommended plots New interactive sheet

Now lets see the `Categorized_BMI` distribution in this dataset.

```
ds = exercise_train_data["Categorized_BMI"].value_counts().reset_index()
ds.columns = ["Categorized_BMI" , "Count"]
ds
```

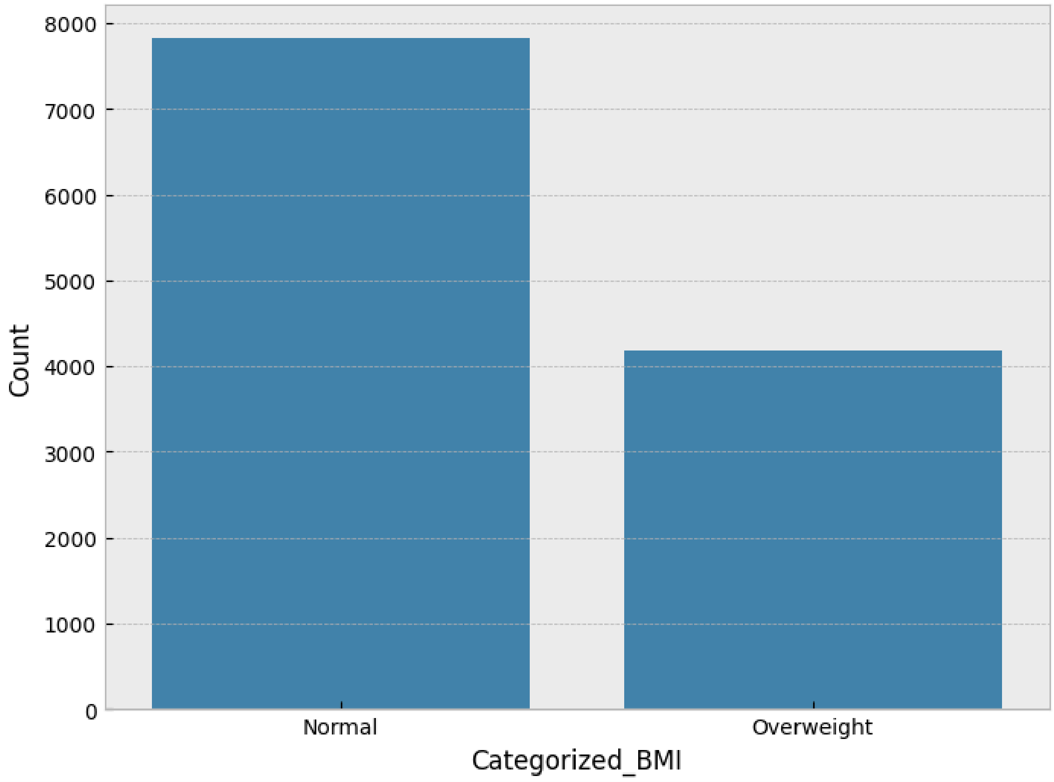
	Categorized_BMI	Count
0	Normal	7819
1	Overweight	4181

Next steps: Generate code with ds View recommended plots New interactive sheet

- As we can see, many parts of this dataset consists of `Normal` individuals.The second and last group is `Overweight` group.Other groups are not in the dataset which is normal.Because `Obese` and `Underweight` persons do not tend to do exercise.
- So lets plot the boxplot of the first two categories.

```
ds = ds[(ds["Categorized_BMI"] == "Normal") | (ds["Categorized_BMI"] == "Overweight")]
#ds["Categorized_BMI"] = ds["Categorized_BMI"].astype("object")

plt.rcParams["figure.figsize"] = 8 , 6
sns.barplot(data = ds , x = "Categorized_BMI" , y = "Count")
```

```
<Axes: xlabel='Categorized_BMI', ylabel='Count'>
```



- As we can see, many parts of this dataset consists of `Normal` individuals.The second and last group is `Overweight` group.Other groups are not in the dataset which is normal.Because `Obese` and `Underweight` persons do not tend to do exercise.

Lets get into details and see how many of each group are male and how many of them are female.

First of all lets prepare the dataset that shows the distributions of `Categorized_BMI` for each gender:

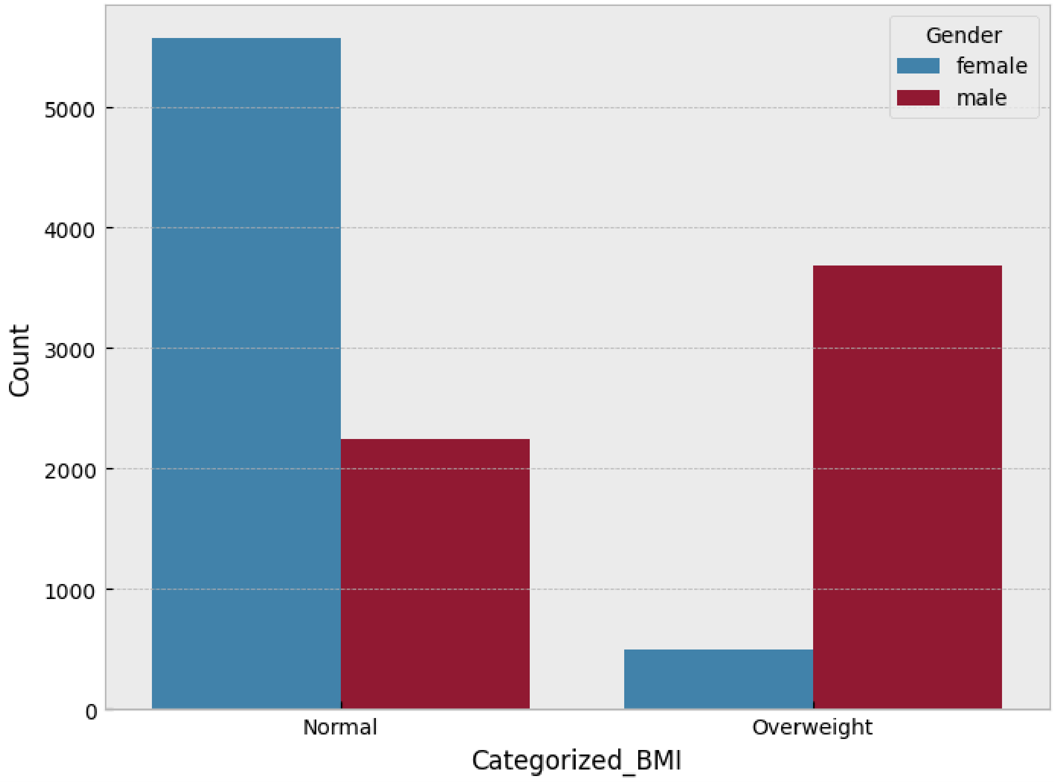
```
ds =exercise_train_data[["Gender" ,"Categorized_BMI"]].value_counts().reset_index().sort_values(by = ["Gender" , "Cate
ds.columns = ["Gender" , "Categorized_BMI" , "Count"]
ds
```

	Gender	Categorized_BMI	Count
0	female	Normal	5572
3	female	Overweight	496
2	male	Normal	2247
1	male	Overweight	3685

Next steps: Generate code with ds View recommended plots New interactive sheet

```
plt.rcParams["figure.figsize"] = 8 , 6
sns.barplot(data = ds , x = "Categorized_BMI" , y = "Count" , hue = "Gender")
```

<Axes: xlabel='Categorized_BMI', ylabel='Count'>



- An interesting thing that this graph shows is the `weight` distribution between each gender.the number of males who are overweight is way more than the number of females that have the similar situation.And the number of females that are in their ideal weight is really large in compare of other categories.In general, women have a better situation than men.

Now lets plot the `Categirized_BMI` distribution for each group ages.

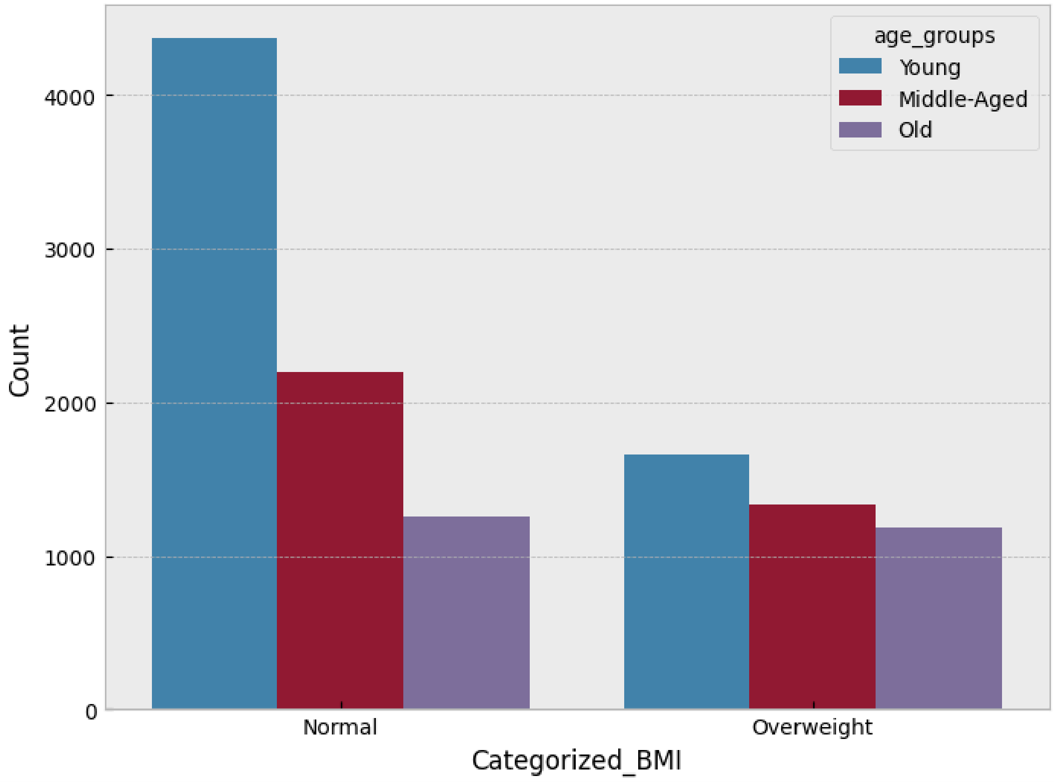
```
ds =exercise_train_data[["age_groups" ,"Categorized_BMI"]].value_counts().reset_index().sort_values(by = ["age_groups" ,
ds.columns = ["age_groups" , "Categorized_BMI" , "Count"]
ds
```

	age_groups	Categorized_BMI	Count
0	Young	Normal	4369
2	Young	Overweight	1660
1	Middle-Aged	Normal	2197
3	Middle-Aged	Overweight	1338
4	Old	Normal	1253
5	Old	Overweight	1183

Next steps: Generate code with ds | View recommended plots | New interactive sheet

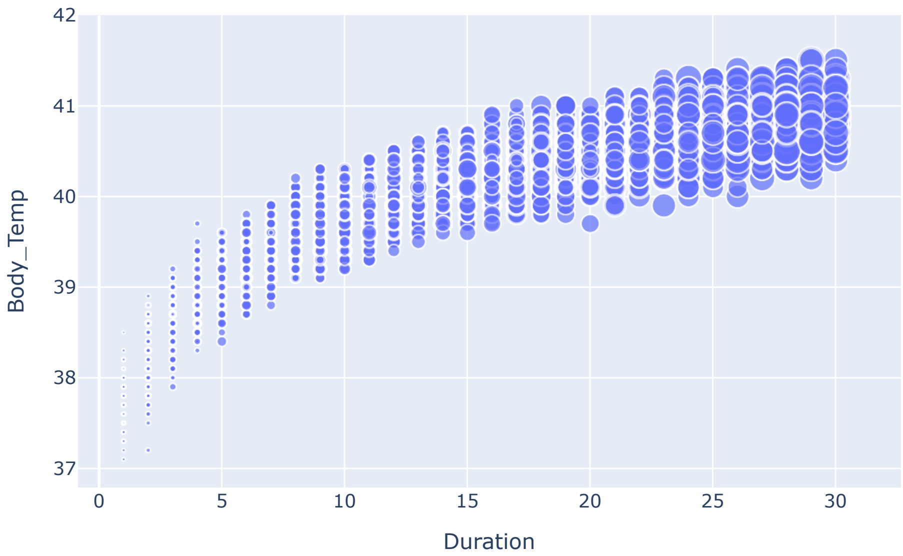
```
plt.rcParams["figure.figsize"] = 8 , 6
sns.barplot(data = ds , x = "Categorized_BMI" , y = "Count" , hue = "age_groups")
```

```
<Axes: xlabel='Categorized_BMI', ylabel='Count'>
```



- As we can see the `Categorized_BMI` is identically distributed between age groups(the sequence is identical, for example in both `Normal` and `Overweight` ; `Young` comes first , 'Middle-Aged` comes second , etc.)
- An interesting thing is , about `50%` of old individuals have `Normal` weight and another `50%` are `Overweight` .

```
fig = px.scatter(exercise_train_data , x = "Duration" , y = "Body_Temp" , size = "Calories")

fig.update_layout(
    width=700,
    height=450,
)

fig.show()
```



[Pearson] Corelation

In this section we are going to analyze the correlations between each two features.The corrlation helps us to see , how much this two features' relationship is strong.If the the relationship of this two features is extremely strong(In other words the correlation is equall to 1 or -1 or close to this two numbers) we will face `collinearity` problem in our model.This means that not only this two feature will not help us to build a better model but also they cause some problems for our model.One way is to remove one of these feaures.

- We use pearson correlation method:

Covariance : **COV(X , Y)** =

$$(\frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{N})$$

Correlation : **CORR(X , Y)** =

$$(\frac{COV(X,Y)}{\sigma_X \sigma_Y})$$

Where :

> 1. **Xi** : the values of the X-variable
>
> 2. **Yj** : the values of the Y-variable
>
> 3. **X̄** : the mean (average) of the X-variable
>
> 4. **Ȳ** : the mean (average) of the Y-variable
>
> 5. **N** : the number of data points
>
> 6. **σX** : the standard deviation of the X-variable
>
> 7. **σY** : the standard deviation of the Y-variable

So now lets plot the heatmap to analyze the correlation of features in this dataset.

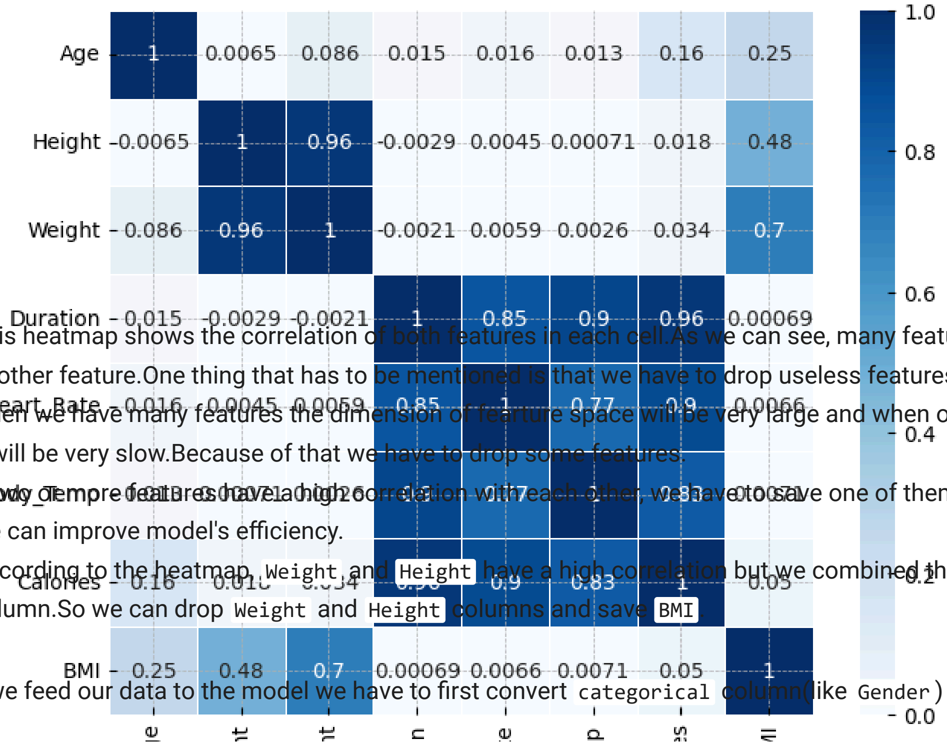
```
exercise_train_data.columns
```

```
Index(['Gender', 'Age', 'Height', 'Weight', 'Duration', 'Heart_Rate',
       'Body_Temp', 'Calories', 'age_groups', 'BMI', 'Categorized_BMI'],
      dtype='object')
```

```
Start coding or generate with AI.
```

```
plt.rcParams["figure.figsize"] = 8 , 6
corr = exercise_train_data.corr(numeric_only = True)
sns.heatmap(corr , annot = True , square = True , linewidth = .5 , vmin = 0 , vmax = 1 , cmap = 'Blues')
```

```
<Axes: >
```



- This heatmap shows the correlation of both features in each cell.As we can see, many features have high correlation with another feature.One thing that has to be mentioned is that we have to drop useless features as many as possible.Because when we have many features the dimension of fearture space will be very large and when our model runs on this features it will be very slow.Because of that we have to drop some features.
- If two or more features have high correlation with each other, we have to save one of them and drop the rest.In This way, we can improve model's efficiency.
- According to the heatmap, `Weight` and `Height` have a high correlation but we combined them and put them into the `BMI` column.So we can drop `Weight` and `Height` columns and save `BMI`

Before we feed our data to the model we have to first convert `categorical` column(like `Gender`) into `numerical` column.

```
exercise_train_data = exercise_train_data[["Gender" , "Age" , "BMI" , "Duration" , "Heart_Rate" , "Body_Temp" , "Calor
exercise_test_data = exercise_test_data[["Gender" , "Age" , "BMI"  , "Duration" , "Heart_Rate" , "Body_Temp" , "Calori
exercise_train_data = pd.get_dummies(exercise_train_data, drop_first = True)
exercise_test_data = pd.get_dummies(exercise_test_data, drop_first = True)
```

- So now let's seperate X and y for training set and test set.

```
X_train = exercise_train_data.drop("Calories" , axis = 1)
y_train = exercise_train_data["Calories"]

X_test = exercise_test_data.drop("Calories" , axis = 1)
y_test = exercise_test_data["Calories"]
```

```
# print(X_train.shape)
# print(X_test.shape)
# print(y_train.shape)
# print(y_test.shape)
```