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SIT225: Data Capture Technologies

Activity 7.1: Data analysis and interpretation

Data analysis is a broad term that covers a wide range of techniques that enable you to reveal any insights and relationships that may exist within raw data. As you might expect, Python lends itself readily to data analysis. Once Python has analyzed your data, you can then use your findings to make good business decisions, improve procedures, and even make informed predictions based on what you've discovered.

You have done data wrangling using Python Pandas module already in activity 5.2. In this activity, you will learn Data science statistics and linear regression models.

Hardware Required

No hardware is required.

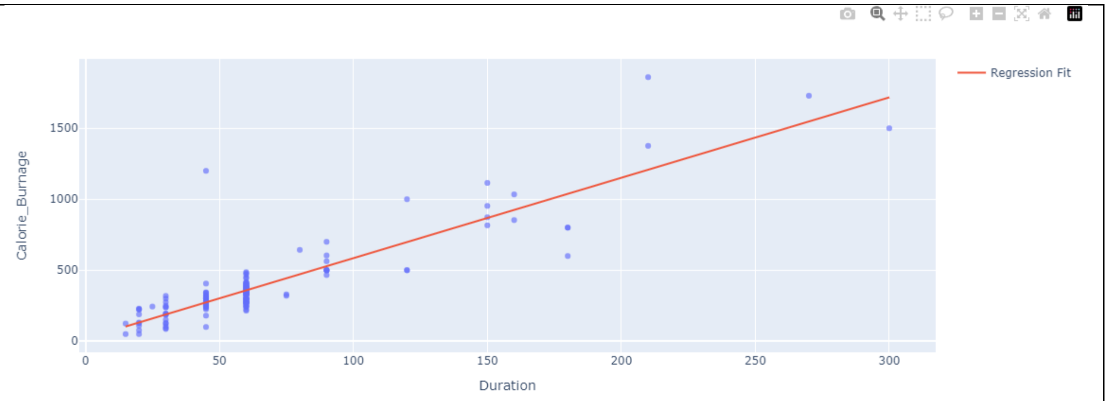
Software Required

Python 3
Python packages including Pandas, Numpy, Scikit-learn, seaborn, plotly

Steps:

Step	Action
1	A Jupyter Notebook is provided for Data Science exploration here (https://github.com/deakin-deep-dreamer/sit225/tree/main/week_7). You will need to fill in your student ID and name and run all the cells to observe the output. Convert the Notebook into PDF and merge with this activity sheet which needs to be combined with this week's task for OnTrack submission.

	Question: There are sections in the Notebook. After running the cells and observing the outputs, provide your reflection in brief on the topic items for each section of the Notebook. Answer: ok
2	Question: In the 1.1 Percentile subsection of **Descriptive statistics** section in the Notebook, you have calculated 10%, 25%, 50% and 75% percentiles for *Max_Pulse*. Compare these percentiles with *Average_Pulse* percentiles for any trend, if exists. Answer: We can observe that 50% the `Average_Pulse` is in quantile 25 to 75 or 100 to 111 beats per minute. Using quantile can be a great way to identify outliers by setting the boundary for data points below Q1 - 1.5IQR or above Q3 + 1.5IQR.
3	Question: In the "Correlation Does not imply Causality" section answer the question regarding the increase of ice cream sale in your own understanding. Answer: Causation relationship means a cause-and-effect relationship. In our case, it means that the sale of ice cream is causing more drowning cases, which is in no way correct. The positive correction between them indicates that both values increase during the summer, and it might be due to a third factor. A third factor can be hot weather, which causes people to visit the beach more often and leads to higher ice cream sales and drowning accidents.
4	Question: In the **1.7 Linear Regression** section in the Notebook, a linear regression model was used to predict Calorie_Burnage from attributes such as Average_Pulse. The Duration value was predicted from the model for all the value range of Average_Pulse and a regression line was drawn. You will need to answer the follow up question next to 1.7 section where it is required to generate a linear regression model for Duration instead of Average_Pulse to predict the Calorie_Burnage. Take a screenshot of the regression line and paste it here. Also, comment on both the regression lines. Answer:



Using `Duration` as predictor to predict ` Burnage` shows an overall better performance than using `Average_Pulse`. For ` Average_Pulse` the Mean Squared Error shows for 74716, so the square difference between actual values and predicted values is 74716, which is very large. Couple with an R^2, an indicator of goodness of fit, with only 0.0003, meaning that this model is useless. For the ` Duration` model, the mse is 15796.8, and R^2 is 0.79, which shows an acceptable performance.

Weekly task

Q2.

Up until step 7, my analysis is similar to the example given by the unit chair. I use the Temperature as the predictor and Humidity as the response variable. I plot the scatterplot, and the min/max temperature is similar to the example. However, I used IQR method to remove outliers, since if I just remove the 5 highest and lowest temperature, I will just be repeating myself. Also, after the outliers is removed, I noticed that our data might not have a linear relationship, and using linear model might not capture everything, so I use a non-linear one, which shows higher performance on the metrics, indicating my guesses are correct. To improve the predictions, I have also added new features deriving from Temperature and Humidity.

Q3.

https://www.youtube.com/watch?v=yvDXZyV92n8

Q4.

https://github.com/tomadonna1/SIT225_2024T2/tree/main/Pass%20Task%20Data%20analysis%20and%20interpretation

SIT225: Data Analysis & interpretation

Run each cell to generate output and finally convert this notebook to PDF.

```
# Fill in student ID and name
#
student_id = "s223128143"
student_first_last_name = "Hoang Long Tran"
print(student_id, student_first_last_name)
```

```
s223128143 Hoang Long Tran
```

1. Descriptive Statistics

Descriptive statistics summarizes important features of a data set such as: * Count * Sum * Standard deviation * Percentile * Average

```
# Make sure necessary packages are already installed.

import pandas as pd
import numpy as np
import seaborn as sns

full_health_data = pd.read_csv("full_health_data.csv", header=0, sep=",")
full_health_data.describe()
```

	Duration	Average_Pulse	Max_Pulse	Calorie_Burnage	Hours_Work	Hours_Sleep
count	163.000000	163.000000	163.000000	163.000000	163.000000	163.000000
mean	64.263804	107.723926	134.226994	382.368098	4.386503	7.680982
std	42.994520	14.625062	16.403967	274.227106	3.923772	0.663934

	Duration	Average_Pulse	Max_Pulse	Calorie_Burnage	Hours_Work	Hours_Sleep
min	15.000000	80.000000	100.000000	50.000000	0.000000	5.000000
25%	45.000000	100.000000	124.000000	256.500000	0.000000	7.500000
50%	60.000000	105.000000	131.000000	320.000000	5.000000	8.000000
75%	60.000000	111.000000	141.000000	388.500000	8.000000	8.000000
max	300.000000	159.000000	184.000000	1860.000000	11.000000	12.000000

1.1 Percentile

25%, 50% and 75% - Percentiles

Observe the output of the above cell for 25%, 50% and 75% of all the columns. Let's explain for Average_Pulse: * 25% of all of the training sessions have an average pulse of 100 beats per minute or lower. If we flip the statement, it means that 75% of all of the training sessions have an average pulse of 100 beats per minute or higher. * 75% of all the training session have an average pulse of 111 or lower. If we flip the statement, it means that 25% of all of the training sessions have an average pulse of 111 beats per minute or higher.

```
avg_pulse = full_health_data["Average_Pulse"]
print("parcentile_10", np.percentile(avg_pulse, 10) )
print("parcentile_25", np.percentile(avg_pulse, 25) )
print("parcentile_50", np.percentile(avg_pulse, 50) )
print("parcentile_75", np.percentile(avg_pulse, 75) )
```

```
parcentile_10 92.2
parcentile_25 100.0
parcentile_50 105.0
parcentile_75 111.0
```

Question: Calculate percentiles for Max_Pulse.

We can observe that 50% the `Average_Pulse` is in quantile 25 to 75 or 100 to 111 beats per minute. Using quantile can be a great way to identify outliers by setting the boundary for data points below Q1 - 1.5IQR or above Q3 + 1.5IQR.

1.2 Standard Deviation

Standard deviation is a number that describes how spread out the observations are.

A mathematical function will have difficulties in predicting precise values, if the observations are "spread". Standard deviation is a measure of uncertainty.

A low standard deviation means that most of the numbers are close to the mean (average) value.

A high standard deviation means that the values are spread out over a wider range.

```
import numpy as np

# We can use the std() function from Numpy to find the standard deviation of a variable:

std = np.std(full_health_data)
print(std)
```

```
Duration            42.862432
Average_Pulse       14.580131
Max_Pulse           16.353571
Calorie_Burnage    273.384624
Hours_Work           3.911718
Hours_Sleep          0.661895
dtype: float64
```

```
c:\Users\tomde\AppData\Local\Programs\Python\Python311\Lib\site-packages\numpy\core\fromnume
  return std(axis=axis, dtype=dtype, out=out, ddof=ddof, **kwargs)
```

1.2.1 Coefficient of variation

In the above cell, what does standard deviation numbers mean?

The coefficient of variation is used to get an idea of how large the standard deviation is.

Mathematically, the coefficient of variation is defined as:

$$CoefficientofVariation = StandardDeviation/Mean$$

```
cv = np.std(full_health_data) / np.mean(full_health_data)
print(cv)

# We see that the variables Duration and Calorie_Burnage has
# a high Standard Deviation compared to Max_Pulse, Average_Pulse and Hours_Sleep.
#
```

```
Duration           0.367051
Average_Pulse      0.124857
Max_Pulse          0.140043
Calorie_Burnage    2.341122
Hours_Work         0.033498
Hours_Sleep        0.005668
dtype: float64
```

1.3 Variance

Variance is another number that indicates how spread out the values are.

In fact, if you take the square root of the variance, you get the standard deviation. Or the other way around, if you multiply the standard deviation by itself, you get the variance!

```
var = np.var(full_health_data)
print(var)
```

```
Duration            1837.188076
Average_Pulse        212.580225
Max_Pulse            267.439271
Calorie_Burnage    74739.152847
Hours_Work            15.301536
Hours_Sleep            0.438105
dtype: float64
```

```
c:\Users\tomde\AppData\Local\Programs\Python\Python311\Lib\site-packages\numpy\core\fromnume
  return var(axis=axis, dtype=dtype, out=out, ddof=ddof, **kwargs)
```

1.4 Correlation

Correlation measures the relationship between two variables.

A function has a purpose to predict a value, by converting input (x) to output (f(x)). We can say also say that a function uses the relationship between two variables for prediction.

Correlation Coefficient

The correlation coefficient measures the relationship between two variables.

The correlation coefficient can never be less than -1 or higher than 1. * 1 = there is a perfect linear relationship between the variables * 0 = there is no linear relationship between the variables * -1 = there is a perfect negative linear relationship between the variables

Perfect Linear Relationship (Correlation Coefficient = 1)

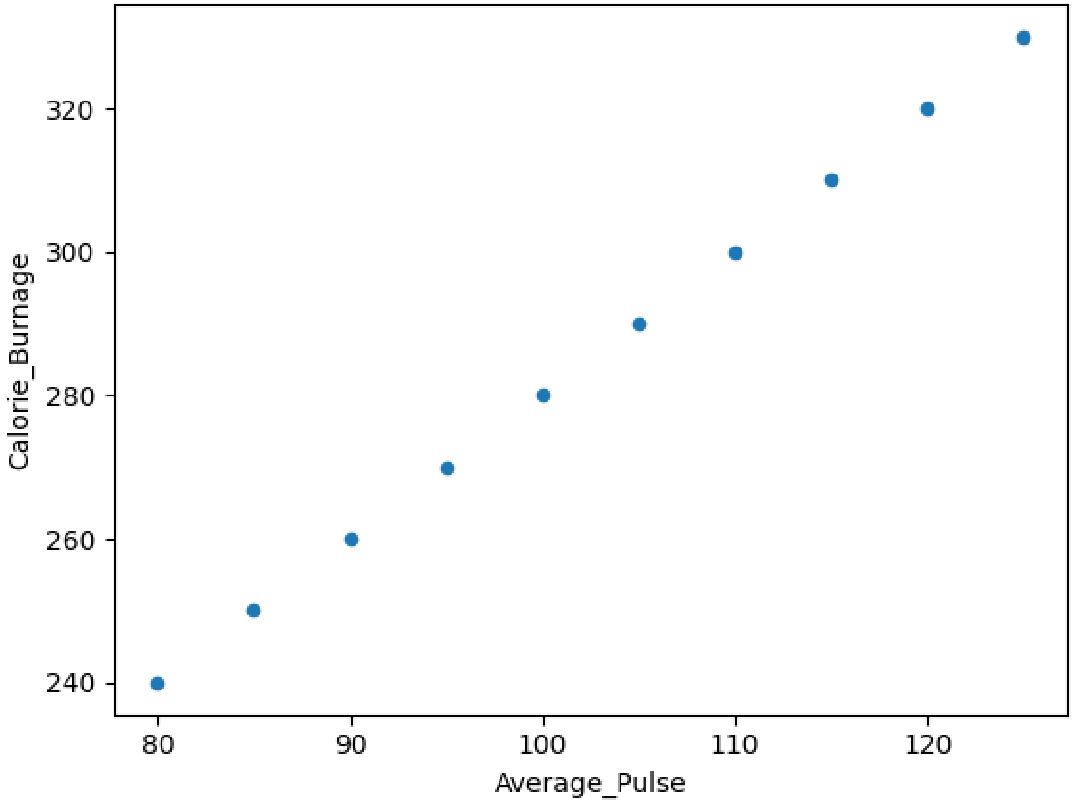
it exists a perfect linear relationship between Average_Pulse and Calorie_Burnage.

```
# Positive correlation
#

import matplotlib.pyplot as plt

def create_linear_health_data():
    data = [
        {'Duration':30, 'Average_Pulse':80, 'Max_Pulse':120,'Calorie_Burnage':240,'Hours_Worl
        {'Duration':45, 'Average_Pulse':85, 'Max_Pulse':120,'Calorie_Burnage':250,'Hours_Worl
        {'Duration':45, 'Average_Pulse':90, 'Max_Pulse':130,'Calorie_Burnage':260,'Hours_Worl
        {'Duration':60, 'Average_Pulse':95, 'Max_Pulse':130,'Calorie_Burnage':270,'Hours_Worl
        {'Duration':60, 'Average_Pulse':100, 'Max_Pulse':140,'Calorie_Burnage':280,'Hours_Wo
        {'Duration':60, 'Average_Pulse':105, 'Max_Pulse':140,'Calorie_Burnage':290,'Hours_Wo
        {'Duration':60, 'Average_Pulse':110, 'Max_Pulse':145,'Calorie_Burnage':300,'Hours_Wo
        {'Duration':45, 'Average_Pulse':115, 'Max_Pulse':145,'Calorie_Burnage':310,'Hours_Wo
        {'Duration':60, 'Average_Pulse':120, 'Max_Pulse':150,'Calorie_Burnage':320,'Hours_Wo
        {'Duration':45, 'Average_Pulse':125, 'Max_Pulse':150,'Calorie_Burnage':330,'Hours_Wo
    ]
    return data

health_data = pd.DataFrame.from_dict(create_linear_health_data())
health_data.plot(x ='Average_Pulse', y='Calorie_Burnage', kind='scatter')
plt.show()
```



Perfect Negative Linear Relationship (Correlation Coefficient = -1)

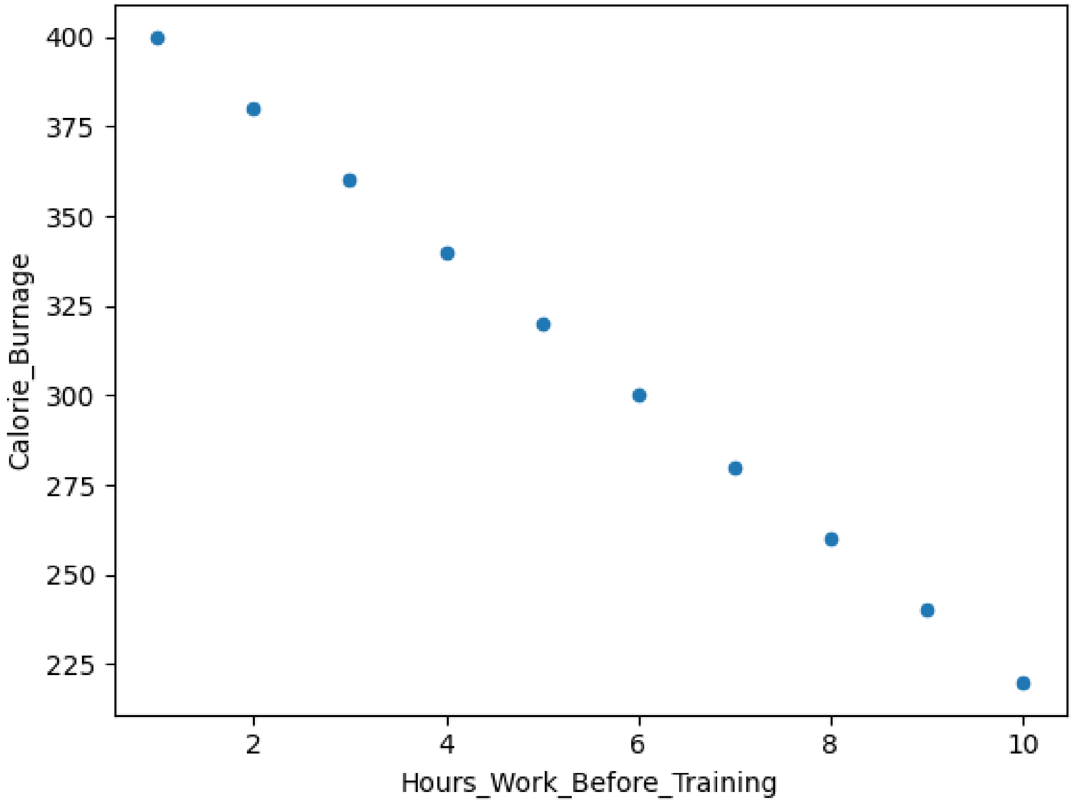
We have plotted fictional data here. The x-axis represents the amount of hours worked at our job before a training session. The y-axis is Calorie_Burnage.

If we work longer hours, we tend to have lower calorie burnage because we are exhausted before the training session.

The correlation coefficient here is -1.

```
# Negative correlation
#
negative_corr = {'Hours_Work_Before_Training': [10,9,8,7,6,5,4,3,2,1],
'Calorie_Burnage': [220,240,260,280,300,320,340,360,380,400]}
negative_corr = pd.DataFrame(data=negative_corr)

negative_corr.plot(x ='Hours_Work_Before_Training', y='Calorie_Burnage', kind='scatter')
plt.show()
```

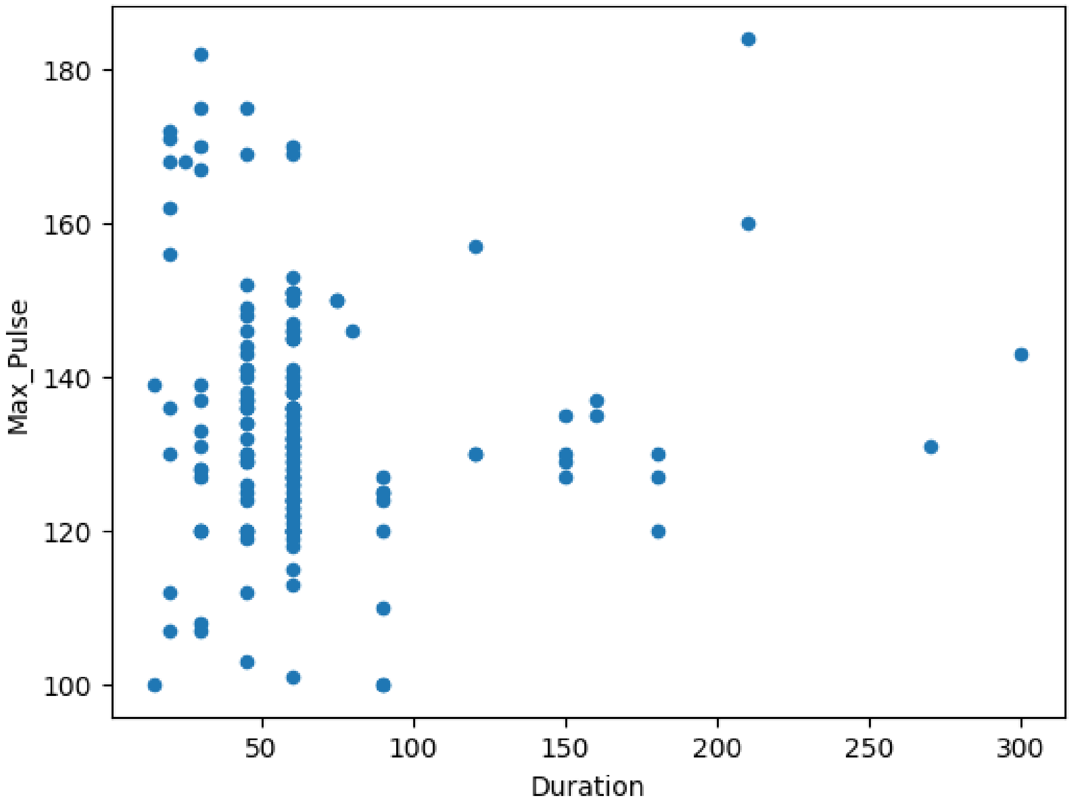


No Linear Relationship (Correlation coefficient = 0)

As you can see, there is no linear relationship between the two variables. It means that longer training session does not lead to higher Max_Pulse.

The correlation coefficient here is 0.

```
full_health_data.plot(x ='Duration', y='Max_Pulse', kind='scatter')
plt.show()
```



1.5 Correlation Matrix

A matrix is an array of numbers arranged in rows and columns.

A correlation matrix is simply a table showing the correlation coefficients between variables.

We can use the corr() function in Python to create a correlation matrix. We also use the round() function to round the output to two decimals:

```
Corr_Matrix = round(full_health_data.corr(),2)
display(Corr_Matrix)

# Drop 2 columns - Hours_Work and Hours_Sleep to view the matrix nice.
#
health_part = full_health_data.drop(columns=['Hours_Work', 'Hours_Sleep'])
Corr_Matrix = round(health_part.corr(),2)
Corr_Matrix
```

	Duration	Average_Pulse	Max_Pulse	Calorie_Burnage	Hours_Work	Hours_Sleep
Duration	1.00	-0.17	0.00	0.89	-0.12	0.07
Average_Pulse	-0.17	1.00	0.79	0.02	-0.28	0.03
Max_Pulse	0.00	0.79	1.00	0.20	-0.27	0.09
Calorie_Burnage	0.89	0.02	0.20	1.00	-0.14	0.08
Hours_Work	-0.12	-0.28	-0.27	-0.14	1.00	-0.14
Hours_Sleep	0.07	0.03	0.09	0.08	-0.14	1.00

	Duration	Average_Pulse	Max_Pulse	Calorie_Burnage
Duration	1.00	-0.17	0.00	0.89
Average_Pulse	-0.17	1.00	0.79	0.02
Max_Pulse	0.00	0.79	1.00	0.20
Calorie_Burnage	0.89	0.02	0.20	1.00

Using a Heatmap

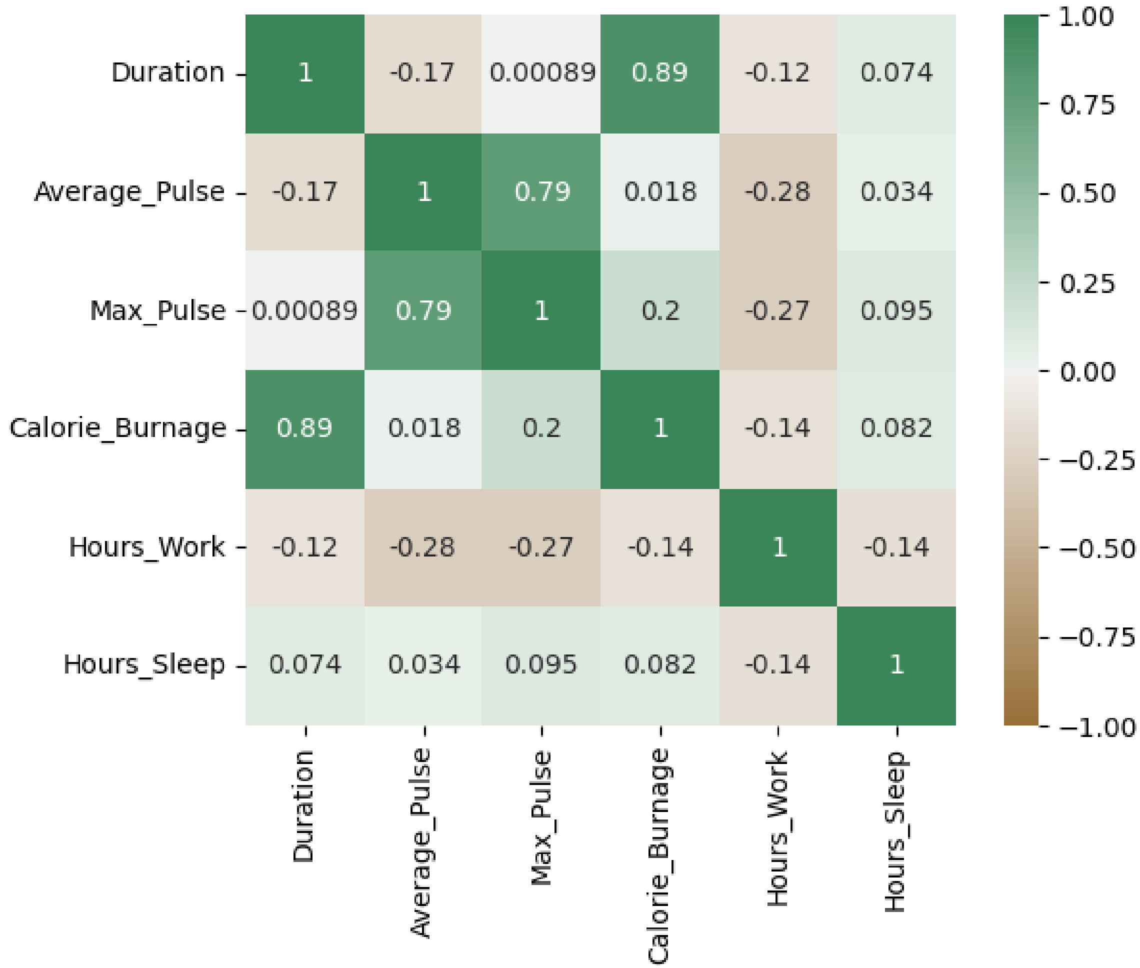
We can use a Heatmap to Visualize the Correlation Between Variables:

```
import matplotlib.pyplot as plt
import seaborn as sns

correlation_full_health = full_health_data.corr()

axis_corr = sns.heatmap(
    correlation_full_health,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(50, 500, n=500),
    square=True,
    annot=True
)

plt.show()
```



1.6 Correlation Does not imply Causality

Correlation measures the numerical relationship between two variables.

A high correlation coefficient (close to 1), does not mean that we can for sure conclude an actual relationship between two variables.

A classic example:

- During the summer, the sale of ice cream at a beach increases
- Simultaneously, drowning accidents also increase as well

Question: Does this mean that increase of ice cream sale is a direct cause of increased drowning accidents?

Causation relationship means a cause-and-effect relationship. In our case, it means that the sale of ice cream is causing more drowning cases, which is in no way correct. The positive correction between them indicates that both values increase during the summer, and it might be due to a third factor. A third factor can be hot weather, which causes people to visit the beach more often and leads to higher ice cream sales and drowning accidents.

1.7 Linear Regression

The term regression is used when you try to find the relationship between variables.

In Machine Learning and in statistical modeling, that relationship is used to predict the outcome of events.

We will use Scikit-learn to train various regression models. Scikit-learn is a popular Machine Learning (ML) library that offers various tools for creating and training ML algorithms, feature engineering, data cleaning, and evaluating and testing models. It was designed to be accessible, and to work seamlessly with popular libraries like NumPy and Pandas.

We see how to apply a simple regression model for predicting Calorie_Burnage on various factors such as Average_Pulse or Duration.

```python
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
from sklearn.linear_model import LinearRegression

df = full_health_data
X = df.Average_Pulse.values.reshape(-1, 1)

model = LinearRegression()
model.fit(X, df.Calorie_Burnage)

x_range = np.linspace(X.min(), X.max(), 100)
y_range = model.predict(x_range.reshape(-1, 1))

fig = px.scatter(df, x='Average_Pulse', y='Calorie_Burnage', opacity=0.65)
fig.add_traces(go.Scatter(x=x_range, y=y_range, name='Regression Fit'))
fig.show()
```

```
Unable to display output for mime type(s): application/vnd.plotly.v1+json
```

```python
from sklearn.metrics import mean_squared_error, r2_score
y_pred = model.predict(df.Average_Pulse.values.reshape(-1, 1))

# Calculate Mean Squared Error
mse = mean_squared_error(df.Calorie_Burnage, y_pred)
print(f"Mean Squared Error: {mse}")

# Calculate R-squared
r2 = r2_score(df.Calorie_Burnage, y_pred)
print(f"R-squared: {r2}")
```

```
Mean Squared Error: 74716.0640662176
R-squared: 0.00030892484335254267
```

Question:

We have seen earlier how to apply a simple regression model for predicting Calorie_Burnage from Average_Pulse. There might be another candidate Duration in addition to Average_Pulse. You will need to repeat the above linear regression process to find relationsthip between Calorie_Burnage and Duration.

Comment on the both regression lines: Calorie_Burnage - Average_Pulse and Calorie_Burnage - Duration.

```python
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
from sklearn.linear_model import LinearRegression

df = full_health_data
X = df.Duration.values.reshape(-1, 1)

model = LinearRegression()
model.fit(X, df.Calorie_Burnage)

x_range = np.linspace(X.min(), X.max(), 100)
y_range = model.predict(x_range.reshape(-1, 1))

fig = px.scatter(df, x='Duration', y='Calorie_Burnage', opacity=0.65)
fig.add_traces(go.Scatter(x=x_range, y=y_range, name='Regression Fit'))
fig.show()
```

```
Unable to display output for mime type(s): application/vnd.plotly.v1+json
```

```python
from sklearn.metrics import mean_squared_error, r2_score
y_pred = model.predict(df.Duration.values.reshape(-1, 1))

# Calculate Mean Squared Error
mse = mean_squared_error(df.Calorie_Burnage, y_pred)
print(f"Mean Squared Error: {mse}")

# Calculate R-squared
r2 = r2_score(df.Calorie_Burnage, y_pred)
print(f"R-squared: {r2}")
```

```
Mean Squared Error: 15796.80553979413
R-squared: 0.788640826956281
```