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 <code>Average_Pulse</code> 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:

Coefficient of Variation = Standard Deviation / 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

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

dtype: float64

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

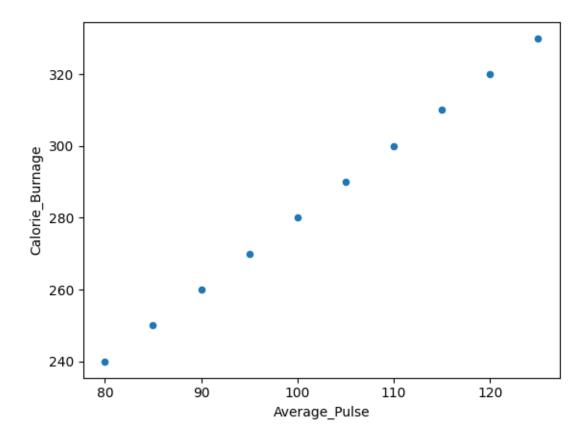
The correlation coefficient measures the relationship between two variables.

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_Wor'
                                     {'Duration': 45, 'Average_Pulse': 85, 'Max_Pulse': 120, 'Calorie_Burnage': 250, 'Hours_Wor'
                                     {'Duration': 45, 'Average_Pulse': 90, 'Max_Pulse': 130, 'Calorie_Burnage': 260, 'Hours_Work
                                      {'Duration':60, 'Average_Pulse':95, 'Max_Pulse':130,'Calorie_Burnage':270,'Hours_Wor
                                     {'Duration':60, 'Average_Pulse':100, 'Max_Pulse':140,'Calorie_Burnage':280,'Hours_World No. 140, 'Calorie_Burnage':280,'Hours_World No. 140, 'Calorie_Burnage':280, 'Hours_World No. 140, 'Hours_World No. 140
                                     {'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_World No. 145, 'Calorie_Burnage':300, 'Hours_World No. 145, 'Hours
                                      {'Duration': 45, 'Average_Pulse': 115, 'Max_Pulse': 145, 'Calorie_Burnage': 310, 'Hours_Woo
                                     {'Duration':60, 'Average_Pulse':120, 'Max_Pulse':150,'Calorie_Burnage':320,'Hours_Woo
                                     {'Duration': 45, 'Average_Pulse': 125, 'Max_Pulse': 150, 'Calorie_Burnage': 330, 'Hours_Woo
                   ]
                   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()
```



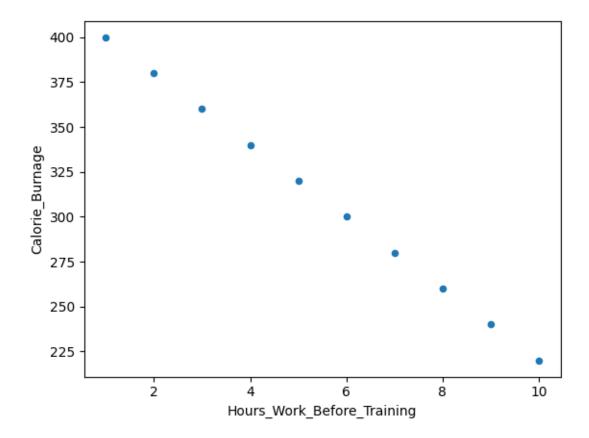
Perfect Negative Linear Relationship (Correlation Coefficient = -1)

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()
```

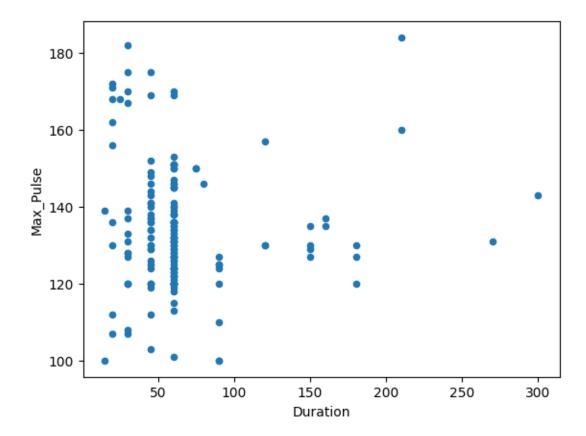


No Linear Relationship (Correlation coefficient = 0)

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

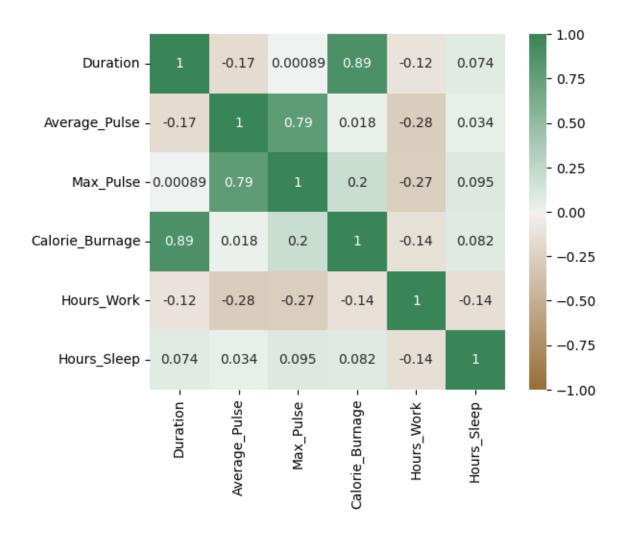
Using a Heatmap

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
)
```



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.

```
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()
```

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```
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.

```
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

```
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