Introduction

The following project documentation was written as work assignment for the module "Multivariate Analysis" of the Master in Statistics for Data Science at the Universidad Carlos III de Madrid. It contains the Multivariate Analysis of a Kaggel dataset on Sleep Health and Lifestyle (https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset). The work is split into two parts, where in a first part a exploratory data analysis is performed, where required, data preprocessing steps are performed and a Prinicipal Component Analysis (PCA) is performed. In the second part, based on the learnings of part one, a (XXXXXXXXXXX) is performed to (XXXXXXXXX).

The dataset at hand is composed out of the collumns shown in the table below. It has been modified compared to the kaggle source data by turning the "Sleep Disorder" Variable into a binary variable (yes/no) and by seperating the blood pressure variables into the two variables blood pressure systolic and blood pressure diastolic.

Variable	Description
Person ID	An identifier for each individual.
Gender	The gender of the person (Male/Female).
Age	The age of the person in years.
Occupation	The occupation or profession of the person.
Sleep Duration (hours)	The number of hours the person sleeps per day.
Quality of Sleep (scale: 1-10)	A subjective rating of the quality of sleep, ranging from 1 to 10.
Physical Activity Level (minutes/day)	The number of minutes the person engages in physical activity daily.
Stress Level (scale: 1-10)	A subjective rating of the stress level experienced by the person, ranging from 1 to 10.
BMI Category	The BMI category of the person (e.g., Underweight, Normal, Overweight).
Blood Pressure (systolic)	The blood pressure measurement of the person (systolic pressure)
Blood Pressure (diastolic)	The blood pressure measurement of the person (diastolic pressure)
Heart Rate (bpm)	The resting heart rate of the person in beats per minute.
Daily Steps	The number of steps the person takes per day.

Variable	Description
Sleep Disorder	The presence or absence of a sleep disorder in the person (Binary)

Furthermore some variable renaming and data type modifications are performed. All these preprocessing steps are performed in the following code chunk.

Based on the value counts and the variable description, the numeric and categorical variables are identified as:

Type	Variables
Numeric Variables	age, sleep_duration, physical_activity_level, heart_rate, daily_steps, blood_pressure_systolic, blood_pressure_diastolic
Categorical Variables	gender, occupation, quality_of_sleep, stress_level, bmi_category, sleep_disorder

Reviewing the unique values of the identified categorical values, a duplicate in bmi_category for "Normal" and "Normal Weight" can be identified. This is solved by replacing all instances of "Normal Weight" with "Normal"

Out[73]:

	bmi_category
0	Overweight
1	Normal
2	Obese

Doing so concludes the required preprocessing steps and allows to begin with the first part of this project work.

Part 1 - Exploratory Analysis and Dimension Reduction via PCA

The first part of this work contains the initial exploratory analysis of the dataset as well as a Principal Component Analysis (PCA) of the dataset.

Explortary Data Analysis

The Exploratory Data Analysis contains a general overview of the datasets structure and correlations. To begin, the first 5 rows of the data Set are shown to give a first insight into the structure of the dataset.

Out[74]:

	person_id	gender	age	occupation	sleep_duration	quality_of_sleep	physical_activity
0	1	Male	27	Software Engineer	6.1	6	
1	2	Male	28	Doctor	6.2	6	
2	3	Male	28	Doctor	6.2	6	
3	4	Male	28	Sales Representative	5.9	4	
4	5	Male	28	Sales Representative	5.9	4	

The categorical Variables can be sperated into the following categories with:

One Binary variable:

- gender
- sleep disorder

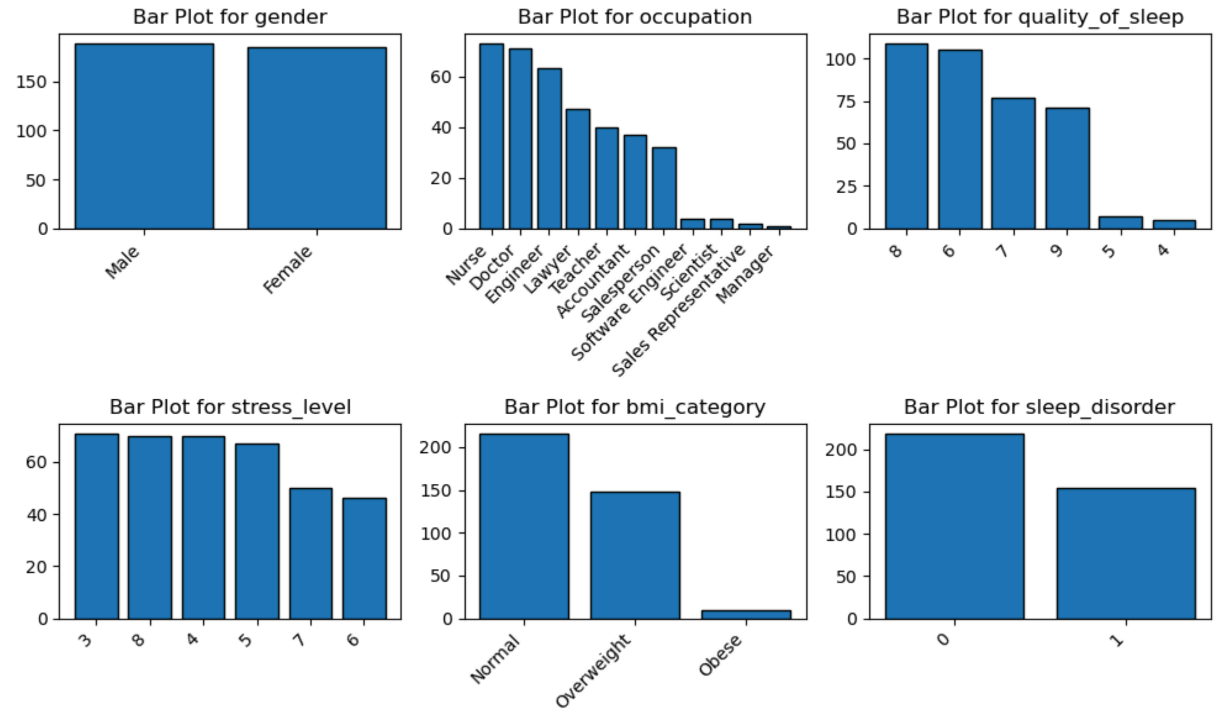
Three ordinal variables:

- quality of sleep
- stress level
- bmi_category

And one nominal variables:

- occupation

Plotting barplots for the categorical variables, beginning with the binary variables of gender and sleep disorder shows an even distribution between male and female and a fairly even distribution between observations with and without sleep disorder. In the meantime, stress level shows a dicrease in observations towards higher stress level, and equally quality of sleep and body mass index (bmi) show a continious decrease in observations for quality of sleep from 8 to 4 and for a bmi categories from normal to obese. Lastly, the variable occupation shows a somewhat uneven distribution of observations between the different occupations, with the two occupations with the individually biggest contribution to the overall dataset are Nurses and Doctors. The bias a potential overrepresentation of the medical field with irregular working ours in shifts can not be futhere anaylzed in this work, but has to be taken into account in later conclusions.



Of the seven numerical variables, all are continious. Plotting histograms and boxplots side by side, two categories emerge:

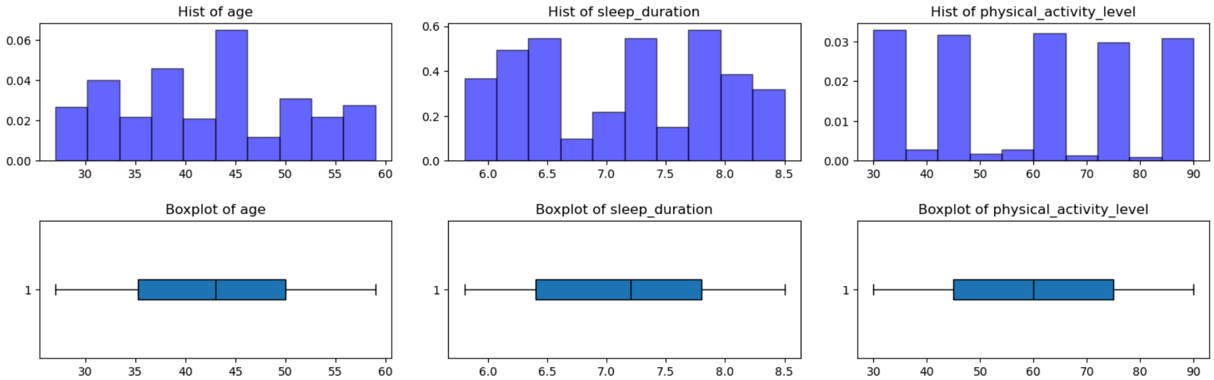
- measured variables
- estimated/rounded variables (variables that probably where estimated as part of a questioneer by its participants)

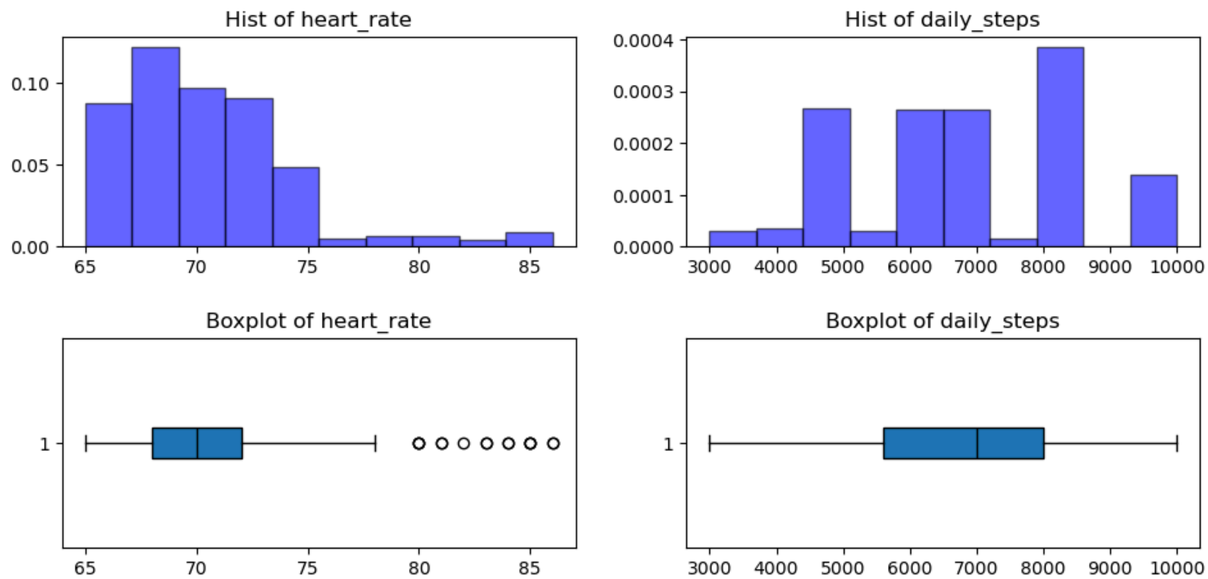
For the measured variables age, haert rate and sleep duration, a more or less continious distribution can be identified for age, with while showing variance still is somewhat uniformly distributed in between the limits of around 30 to 60. Furthermore, appears to show three groups with one group having very little sleep (up to 6,5 hours) and one group sleeping for longer times (more than 8 hours) , while in between these two a dip in sleeping time can be observed. As last variable of this group, the heart rate is shown to have the majority of its observations inbetween 65 and 75 with visual hints to a normal distributions, but shows both in histogram and boxplot significant outliers for higher hartrates which will have to be adressed in the preprocessing step.

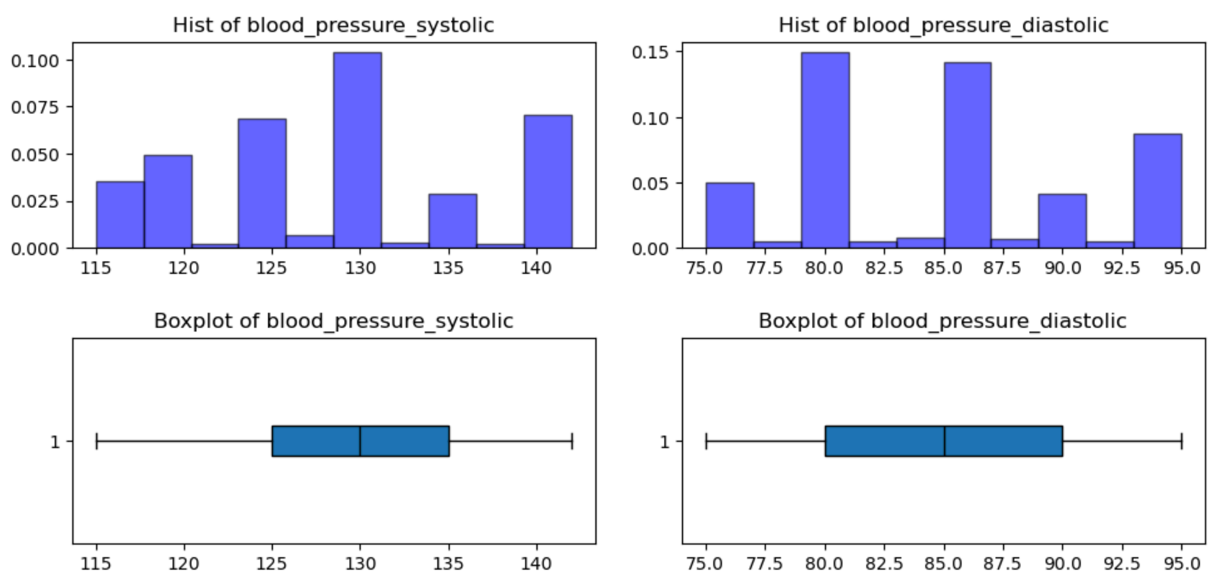
The estimated/rounded variables (physical activity level, daily steps, blood_pressure_systolic/diastolic) shows a specific characteristic with a back and forth between highs and lows which can be attributed to the way people estimate numeric values in increments, like evaluating the physical activity level (mins/day) mostly in increments of 15 min (half an hour, 45 min, one hour, etc.) The lows inbetween then show observations with more specific anwser like 42 min, leading to the somewhat irregular apperance of the histograms. Taking this into account, the phyiscal activity level shows a fairly uniform distribution of observation, while dailty steps tends more into the direction of a right skewed uniform distribution, leading to an overall potentially above average fit sample of people.

The high percentage of medical workers with a great walking distances as part of their profession might further contribute to this. Meanwhile, the blood preassure systolic/diastolic appears to both be more or less evenly distributed.

Out[76]: 'blood_pressure_diastolic'







As a first attempt to evaluate the correlations found in this dataset, the following set of Metrics is applied and plotted.

$$q_1 = \left(1 - \frac{\min \lambda_j}{\max \lambda_j}\right)^{p+2},$$

$$q_2 = 1 - \frac{p}{\sum_{j=1}^{p}(1/\lambda_j)},$$

$$q_3 = 1 - \sqrt{|R|},$$

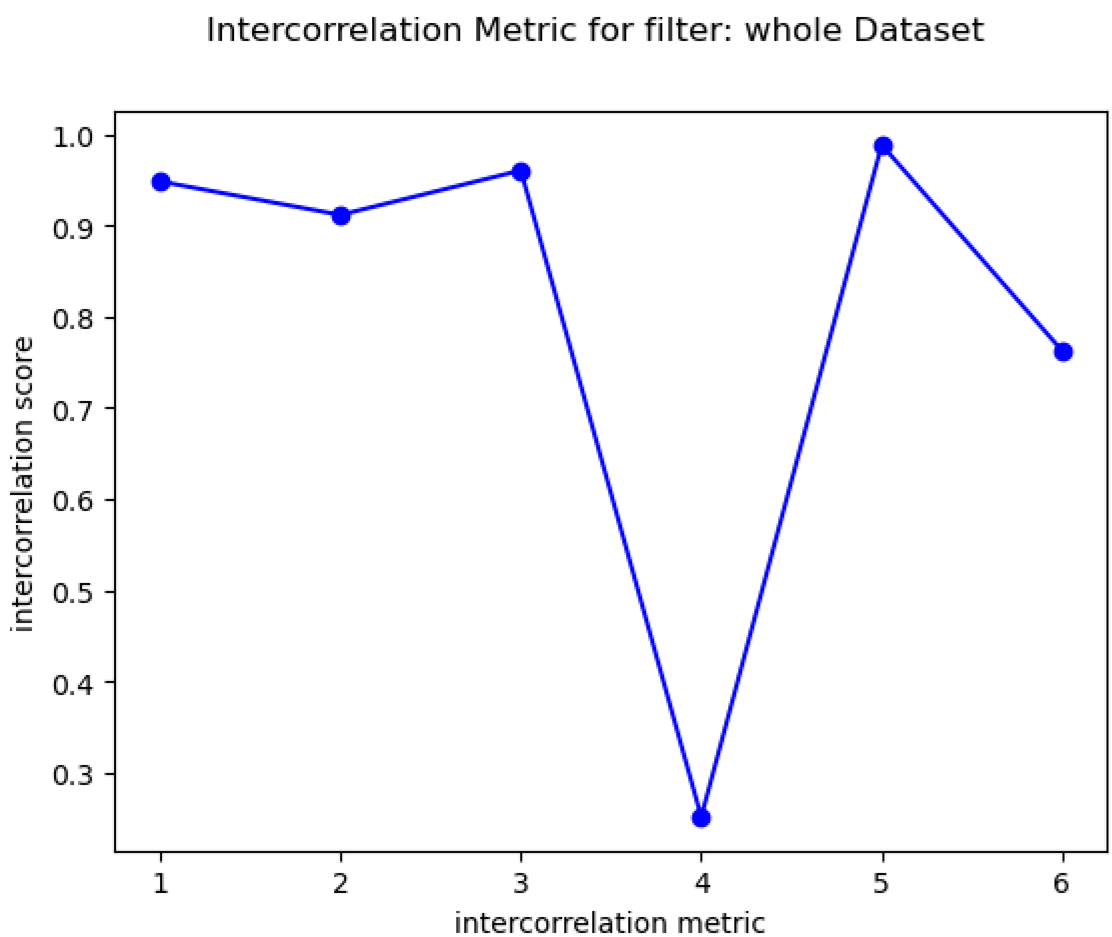
$$q_4 = \left(\frac{\max \lambda_j}{p}\right)^{3/2},$$

$$q_5 = \left(1 - \frac{\min \lambda_j}{p}\right)^{5},$$

$$q_6 = \sum_{j=1}^{p} \frac{1 - 1/r_{ij}}{p}$$

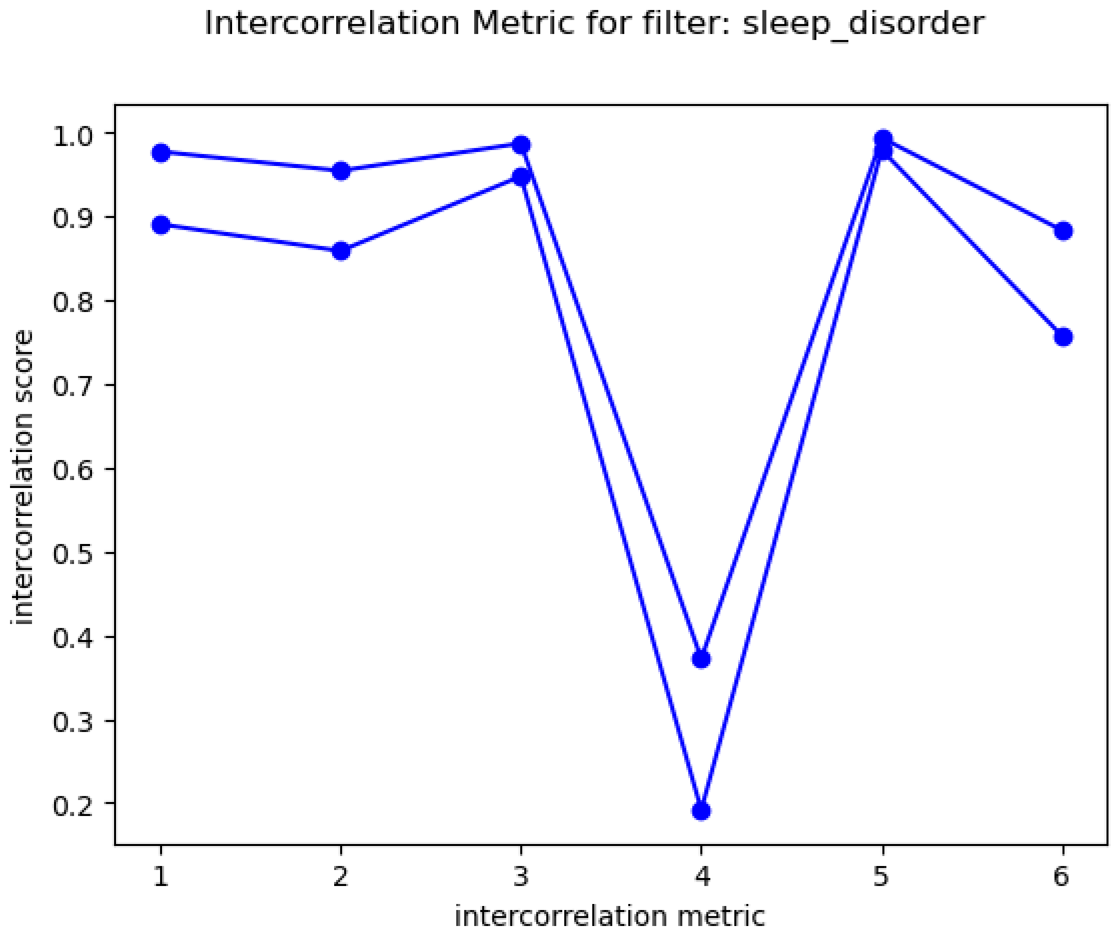
The resulting plot shows high correlation metric scores for all metric except for metric 4.

```
[0.948209   0.9115284  0.96033816 0.25164604 0.98831354 0.76247781]
```

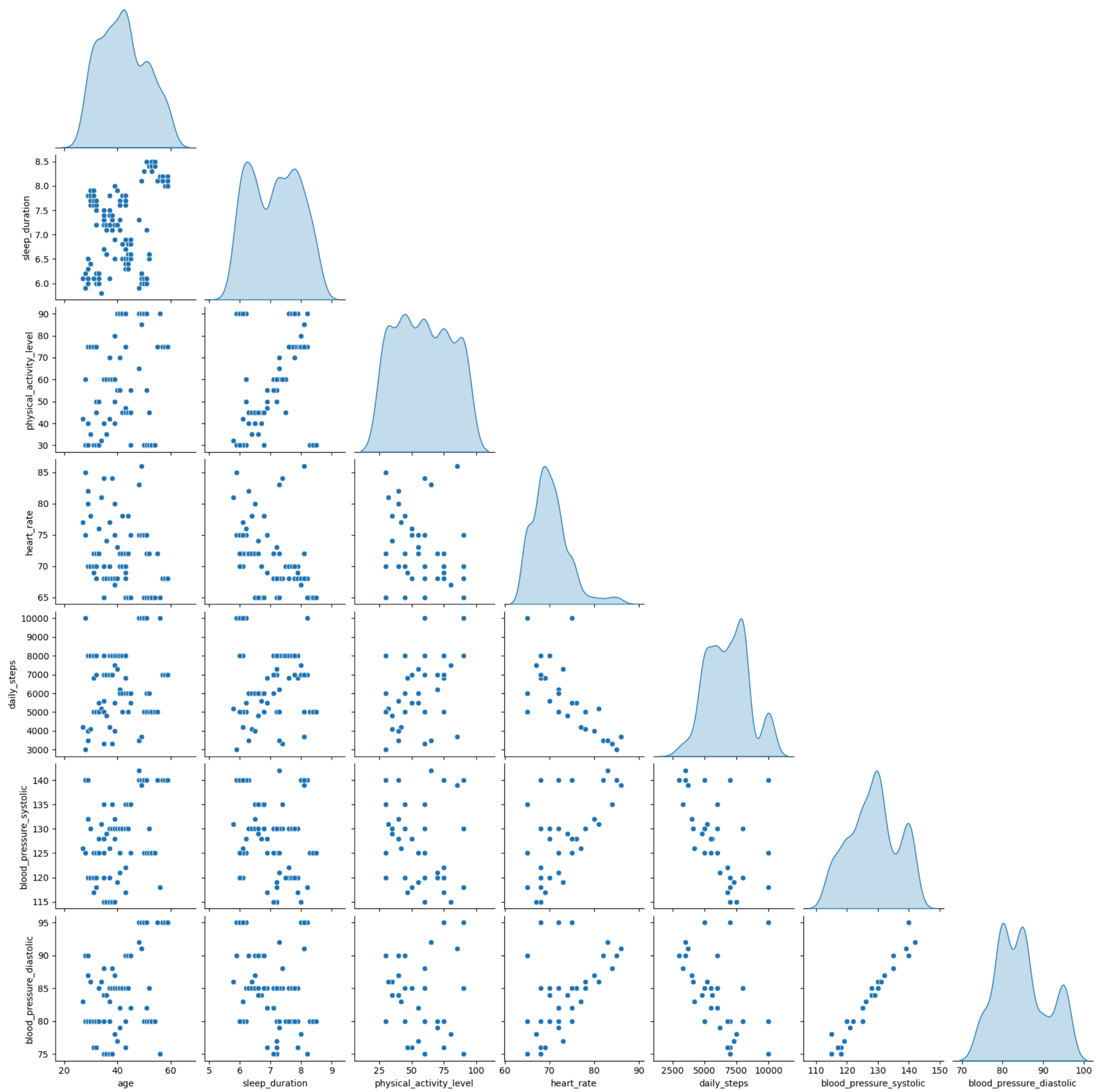


Applying the same method to a dataset filtered on the binary variable sleep disorder shows an overall higher than before correlation in the subset for (??????) while the subset for (???????) shows lower correlation metrics than the joined dataset.

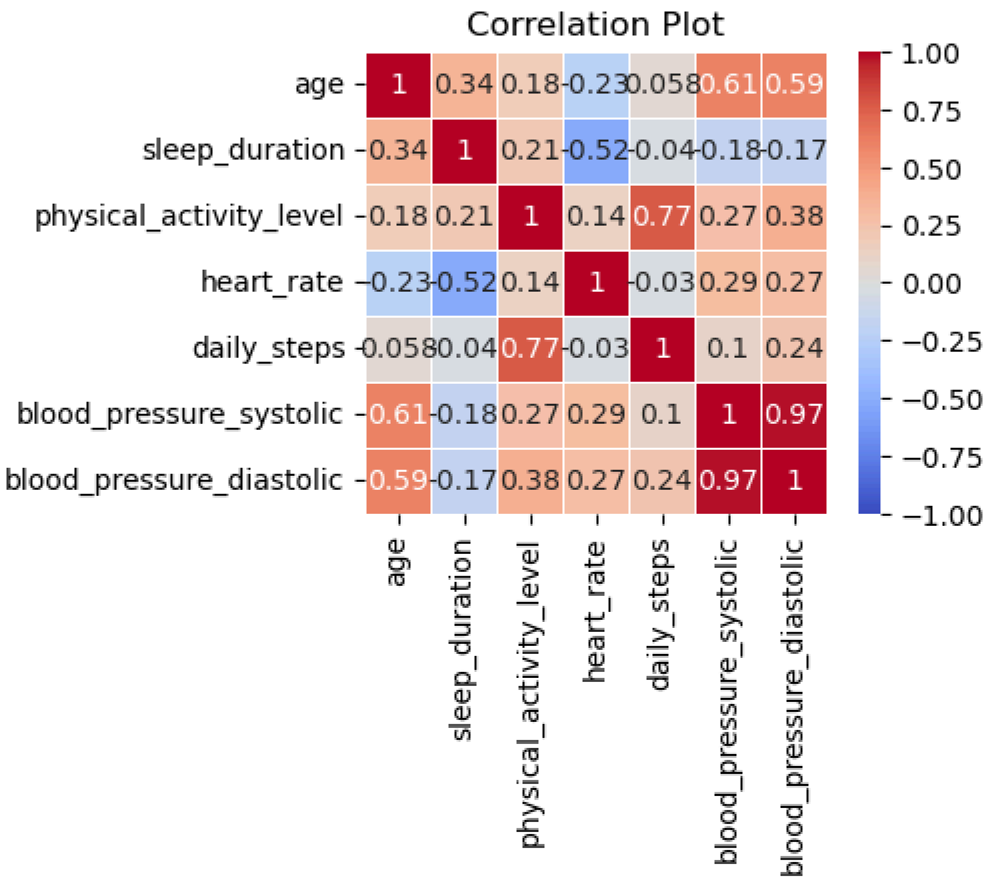
```
[0.89043129 0.85848947 0.9475162  0.19168981 0.97888426 0.75689052]
[0.97710909 0.95408716 0.98689285 0.37193839 0.99337259 0.88299737]
```



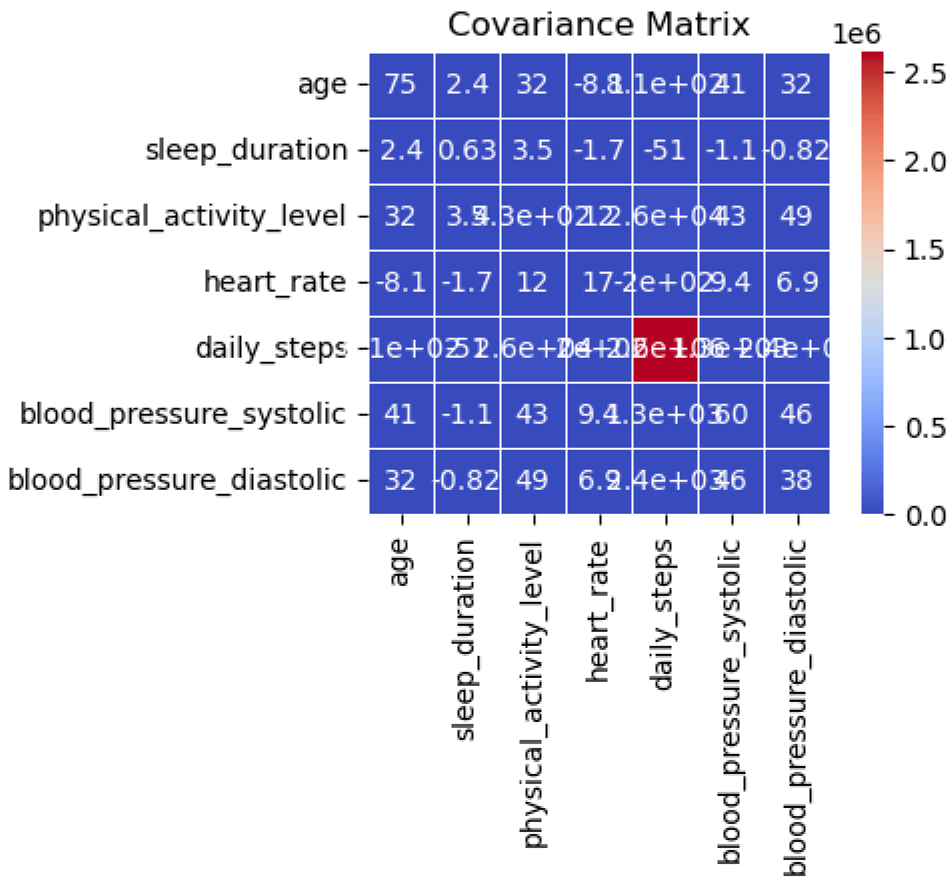
Expandning the coreelation analysis with a paiplot shows a veriaty of potential correlations between variables, the most notable being between the linear correlation betwen blood pressure systolic and diastolic as well as between daily steps and heart rate/ blood pressure. Further correlation can bee seen inbetween physical activity level and sleep duration while the plot age vs sleep duration appears to show certain clusters that may be further analyzed in the second part of this work.



Plotting the correlation corresponding matrix reflects some of the observations made in the pairplot, with the verious near 100% correlation between blood pressure systolic and diastolic very aparent. Two previously less apparent correlations are the ones between age and blood pressure as well as the correlation between physical activity and daily steps.



Plotting the covariance matrix however shows an issue with the current format of the data, where daily steps outweighs all other variances due to its scale (3000 - 10000). This issue will be adressed in the next section of part one of this work.



Having a general overview of structure and correlation in the data, the next step is to scaling and outlier issues in the next subsection.

Preprocessing

The following two issues in the current data set:

- Outliers in variable "heart rate"
- Scaling issue to (among others) variable "daily steps"

This section corrects outliers, validates skewness and standardizes the numeric variables.

Outliers and Skewness

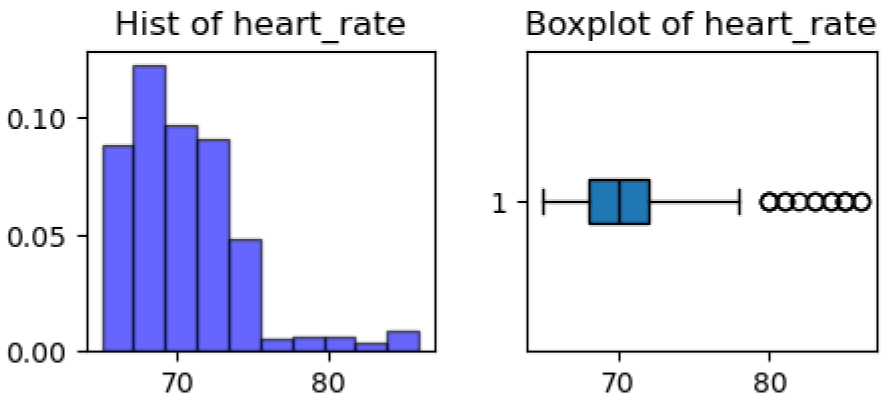
The aim of this part of the preprocessing, is to obtain symmetric variables without outliers in order to apply in a correct form the PCA.

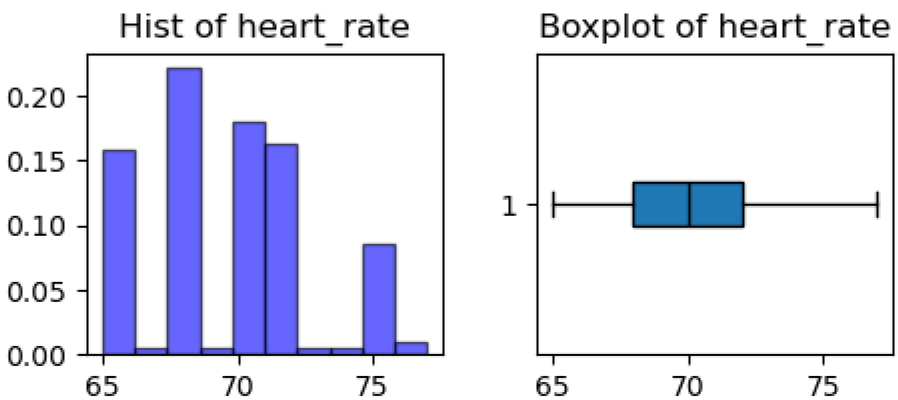
It is observed that only one variable has outliers and positive skewness problems (heart rate). Therefore, the first step is to cut the outliers (4% of the dataframe), and then, check if the skewness problem is also corrected.

```
Skewness of age : 0.2561893511793312
Skewness of sleep_duration : 0.037403602518975176
Skewness of physical_activity_level : 0.07418782500797434
Skewness of heart_rate : 1.2199056700731632
Skewness of daily_steps : 0.17756151681455
Skewness of blood_pressure_systolic : -0.03552565092220491
Skewness of blood_pressure_diastolic : 0.37705009626387237

                  Variable  Count     Min         Mean  Percentile 90%  \
0                      age    374    27.0    42.184492            54.0
1           sleep_duration    374     5.8     7.132086             8.2
2  physical_activity_level    374    30.0    59.171123            90.0
3               heart_rate    374    65.0    70.165775            75.0
4              daily_steps    374  3000.0  6816.844920          8000.0
5  blood_pressure_systolic    374   115.0   128.553476           140.0
6 blood_pressure_diastolic    374    75.0    84.649733            95.0

   Percentile 95%  Percentile 99%      Max      Variance
0            58.0            59.0     59.0  7.522324e+01
1             8.4             8.5      8.5  6.330696e-01
2            90.0            90.0     90.0  4.339224e+02
3            78.0            85.0     86.0  1.710381e+01
4         10000.0         10000.0  10000.0  2.617651e+06
5           140.0           140.0    142.0  6.003333e+01
6            95.0            95.0     95.0  3.796546e+01

The threshold for age upper outliers is  72.125
 then there are 0 outliers in this variable, representing the 0.0 % of the dataset
The threshold for sleep_duration upper outliers is  9.899999999999999
 then there are 0 outliers in this variable, representing the 0.0 % of the dataset
The threshold for physical_activity_level upper outliers is  120.0
 then there are 0 outliers in this variable, representing the 0.0 % of the dataset
The threshold for heart_rate upper outliers is  78.0
 then there are 15 outliers in this variable, representing the 4.01 % of the dataset
The threshold for daily_steps upper outliers is  11600.0
 then there are 0 outliers in this variable, representing the 0.0 % of the dataset
The threshold for blood_pressure_systolic upper outliers is  150.0
 then there are 0 outliers in this variable, representing the 0.0 % of the dataset
The threshold for blood_pressure_diastolic upper outliers is  105.0
 then there are 0 outliers in this variable, representing the 0.0 % of the dataset
```

We can see that the skewness was also corrected by cutting the oultiers observations. For that reason, there is not needed another type of transformation.

```
Skewness of heart_rate : 0.207482395234077
```



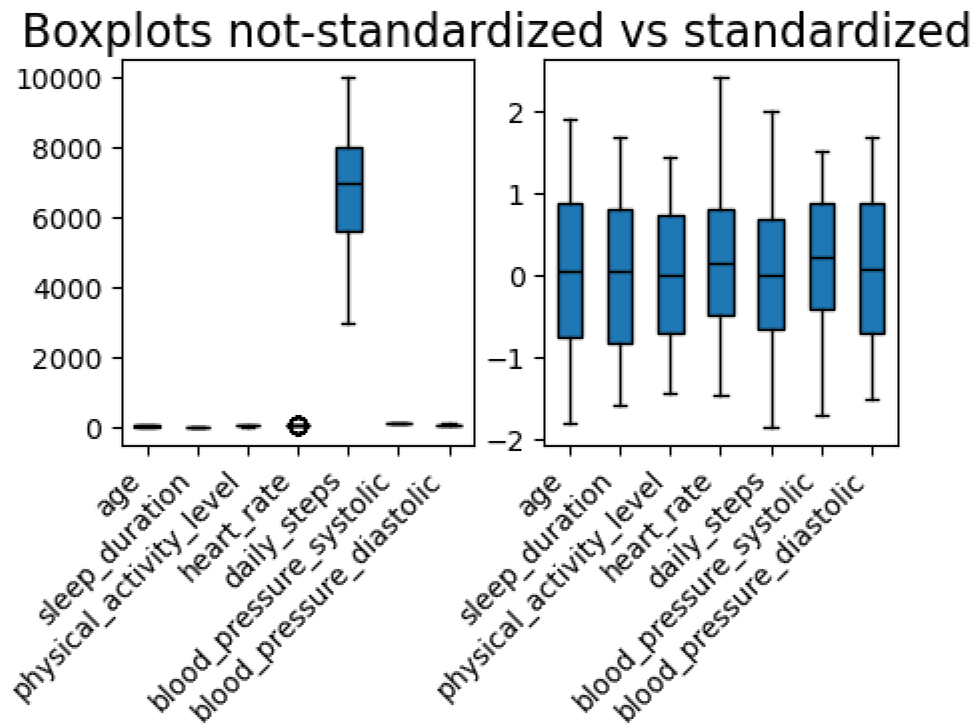


Standardize numeric variables

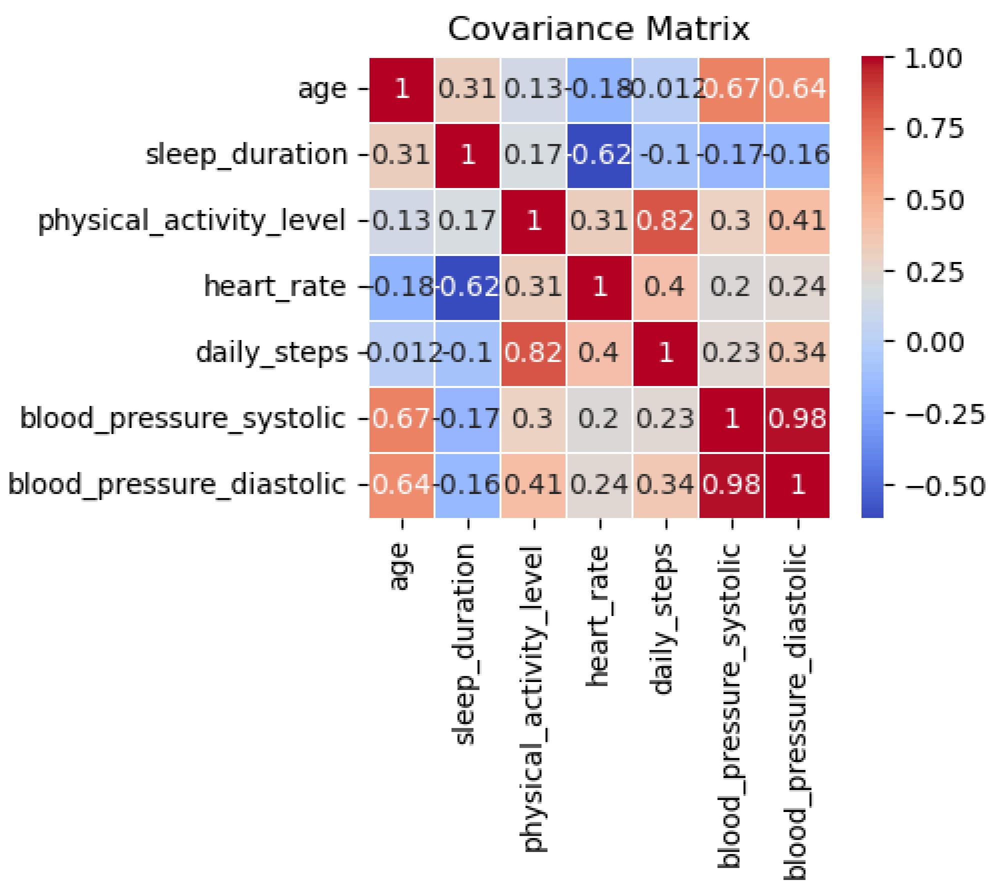
Having seen in the exploratory data analysis that there exists a strong imbalance in scale between numerical variables in the dataset, the dataset is standardized in this step to mean 0 and scaled on its standarddeviation.

Comparing the boxplots pre-standardized and post-standardized shows the major impact the rescaling has, where daily steps previously dominated and now an even distribution for all numeric variables can be seen.

```
Out[89]: Text(0.5, 0.98, 'Boxplots not-standardized vs standardized')
```



As a result from scaling, now the covariance matrix can be constructed, showing similar results compared to the previously analyzed correlation matrix.



PCA

Having analyzed the data and its characteristic and highly correlated variables identified, as well as having eliminated outliers as well as having standardized the numeric variables, principal component analysis can now be applied in an attempt to reduce dimensionality.

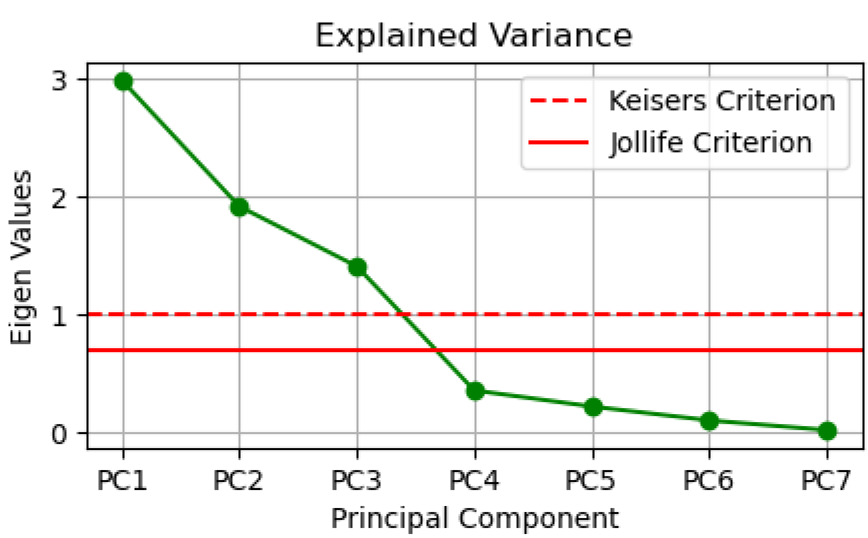
Number of Principal Components

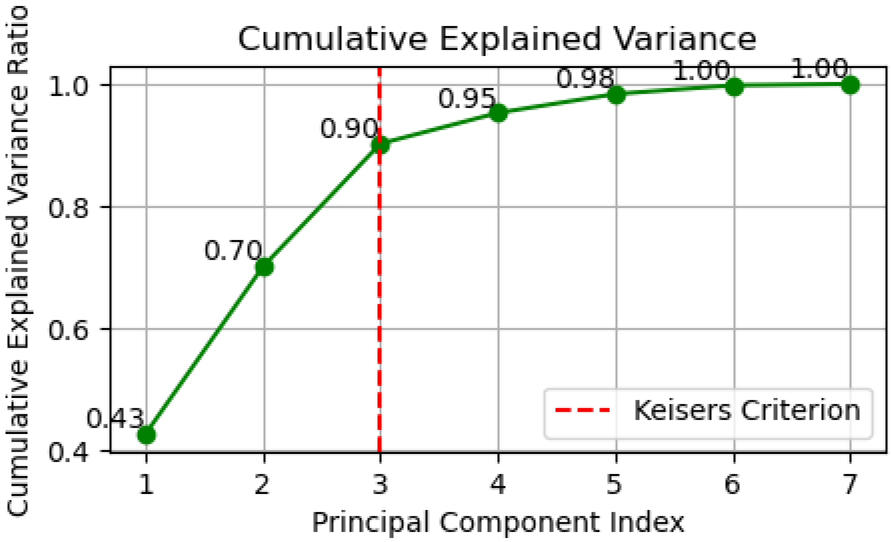
By analysing the Explained Variance (eigenvalues) trend, and the Joliffe´s and Kaiser´s criterion, for this project there are selected 3 Principal components that explain the 90% of the variability.

Out[91]:

```
▾ PCA
PCA()
```

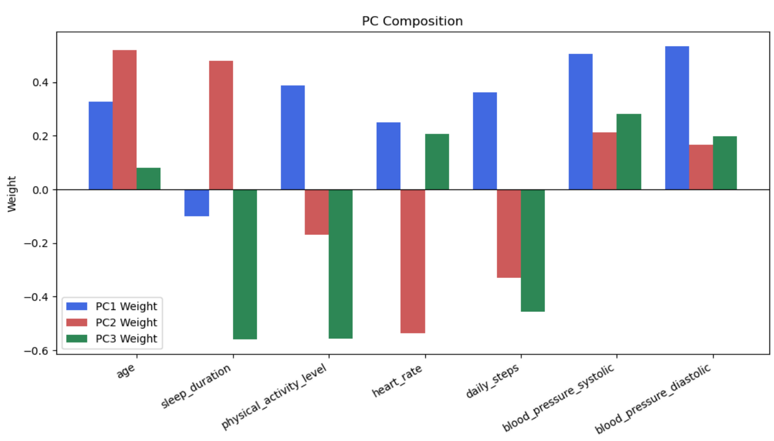
```
Explained Variance:  [2.98968211 1.91745272 1.4083181  0.35319134 0.21650964 0.09865
361
 0.0161925 ]
Singular Values:  [32.4862707  26.01654875 22.29655327 11.16586514  8.74230527  5.90
124756
  2.39080551]
trace:  7.000000000000005
```

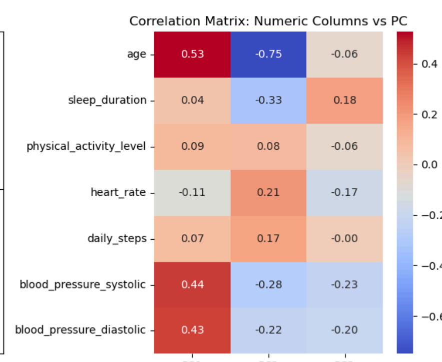




Contribution of Variables to Principal Components and Interpretation

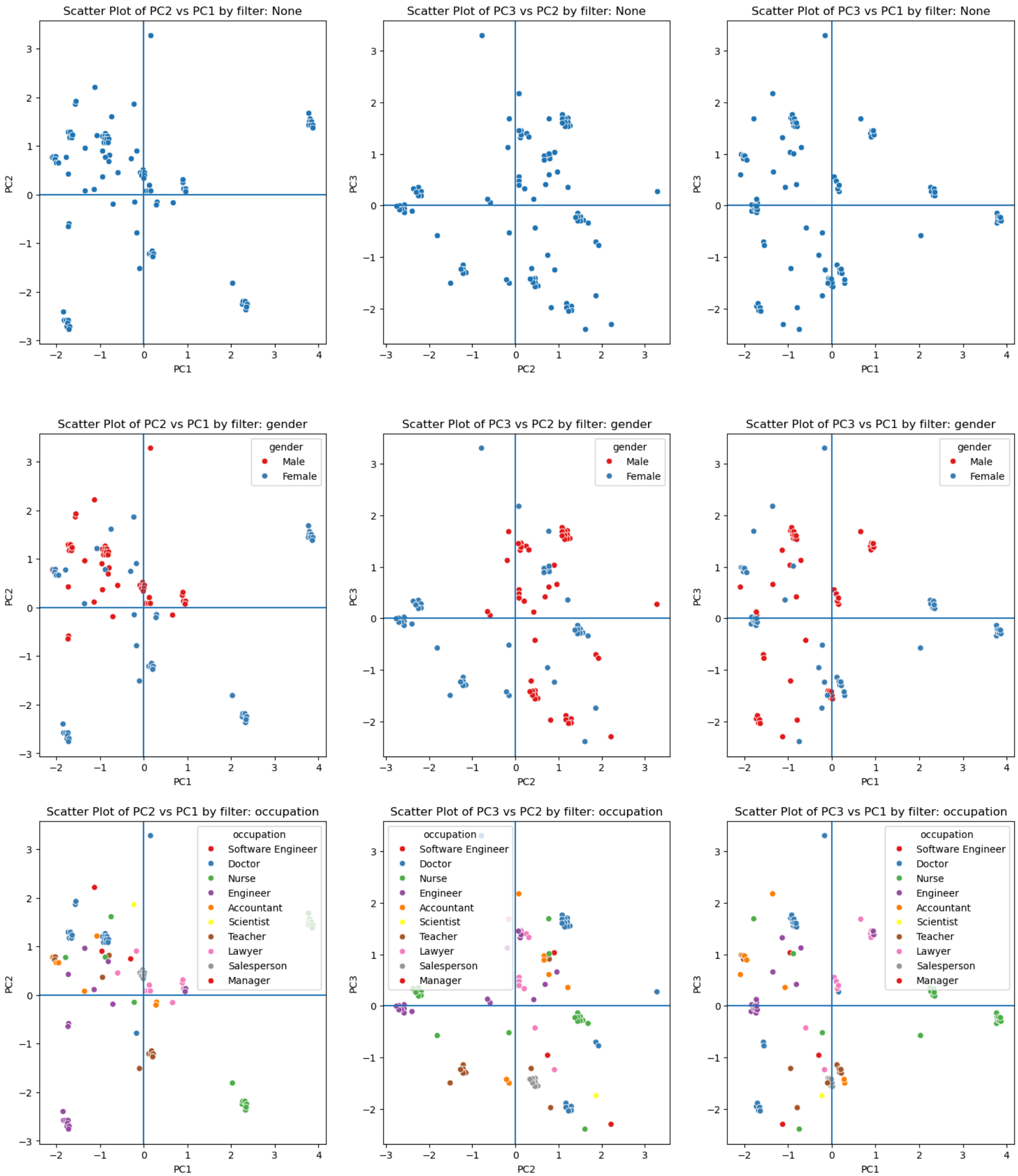
Plotting the Composition of the Principal Components as a Barplot shows a general overlap in the contribution of all variables to the new found principle components, making a very clear seperation into characteristics that are described by the prinicipal components a more dificult task. Since all outliers and scale differences have been treated in the preprocessing steps, the dataset simply seems not to have directly obvious meaningfull interpretation of its principal components. While interpreability in more general terms is one of the challenges associated to PCA, an attempt is made to give some intuition to the three principal component dimensions selected to represent this data set. The first principal component PC1 can be interpreted as overall characteristics of a person, with all variables except for sleep_duration somewhat evenly related. PC2 could be interpreted as the dimension of age, with age, leep duration and heart rate mainly contributing. Simelarly, PC3 could be interpreted as the physical condition dimension, with physical activity level, daily steps and sleep duration primarily contributing.

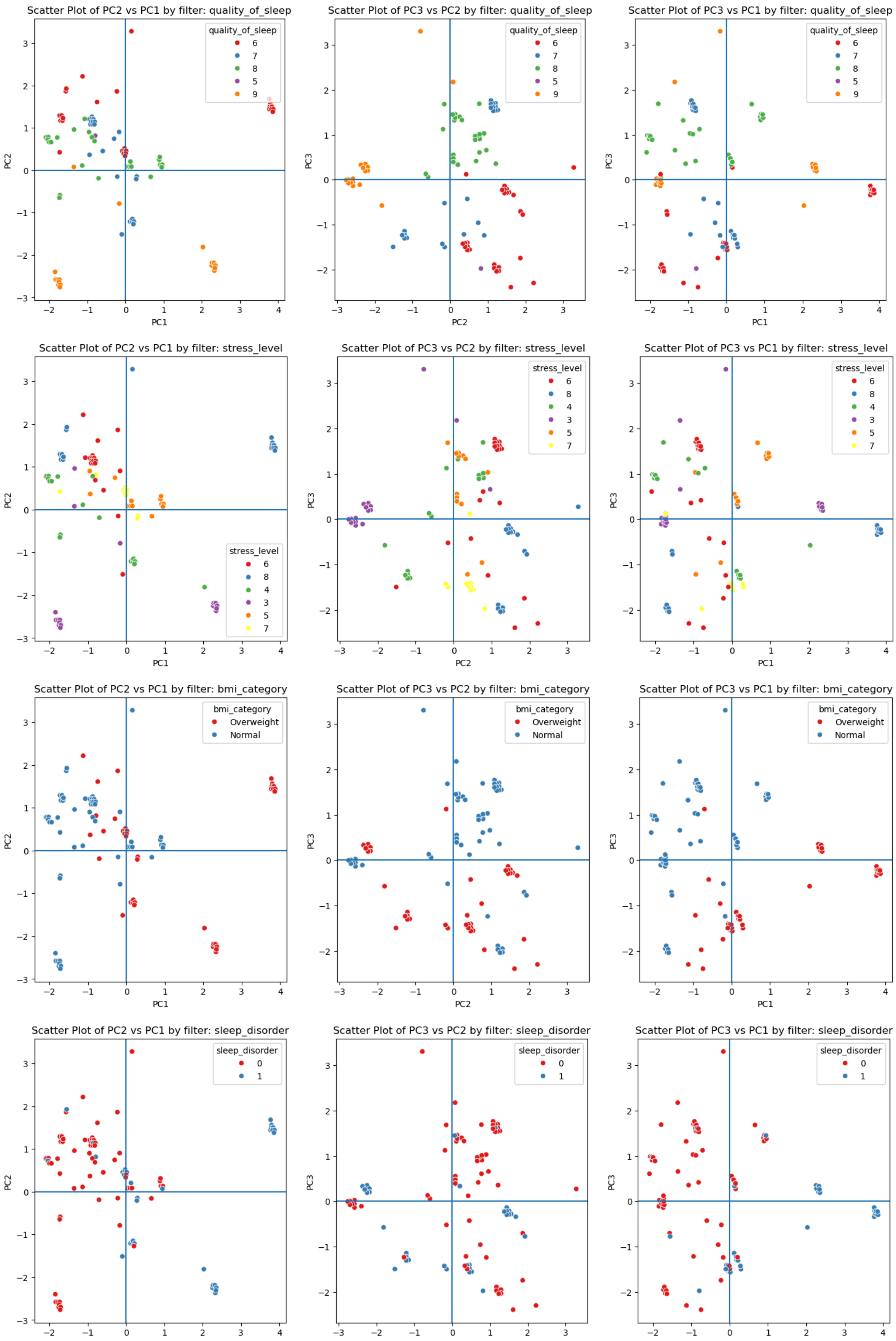




Plotting the data transformed into the three first principal components shows a similarly entangled image image as already shown in the barplots, with no obious interpretation.

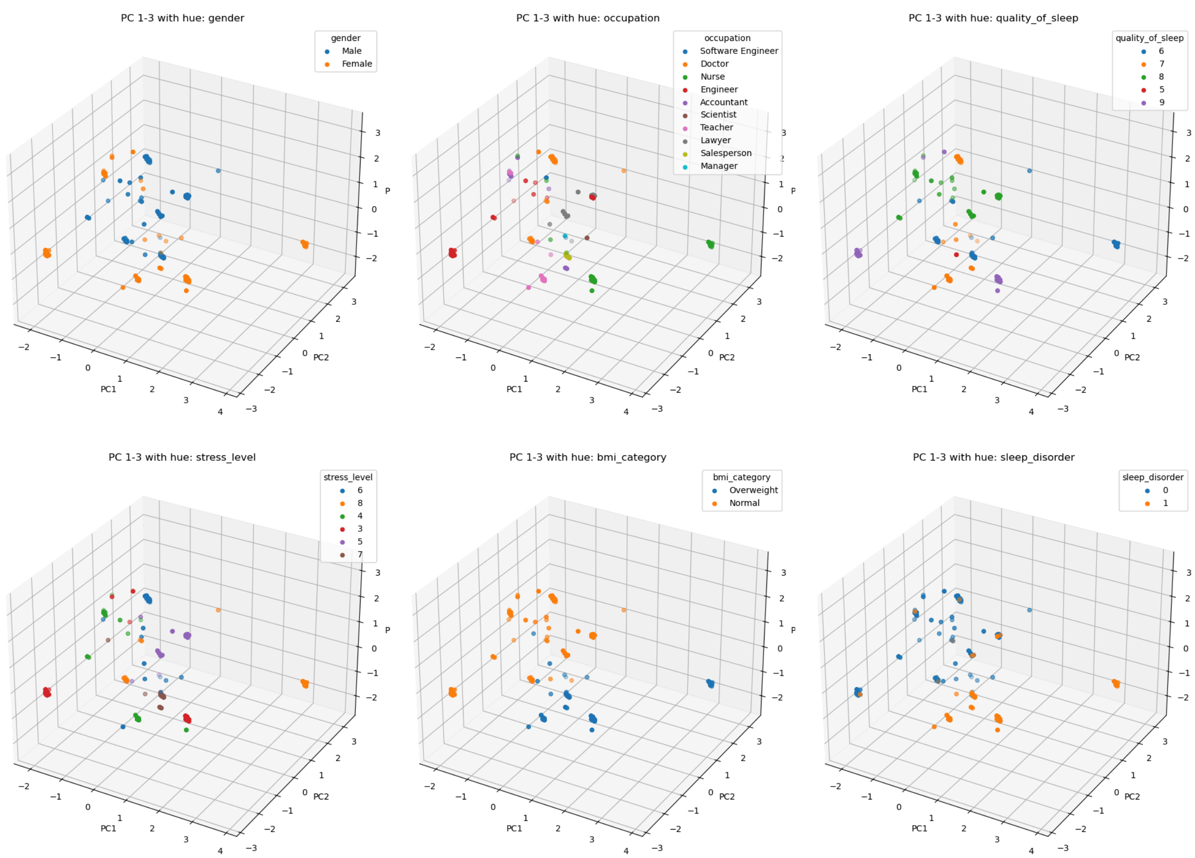
```
C:\Users\flore\AppData\Local\Temp\ipykernel_5052\1258635817.py:4: UserWarning: Ignor
ing `palette` because no `hue` variable has been assigned.
  sns.scatterplot(data=df, x=x_col, y=y_col, hue=hue_col, palette='Set1',ax=ax)
C:\Users\flore\AppData\Local\Temp\ipykernel_5052\1258635817.py:4: UserWarning: Ignor
ing `palette` because no `hue` variable has been assigned.
  sns.scatterplot(data=df, x=x_col, y=y_col, hue=hue_col, palette='Set1',ax=ax)
C:\Users\flore\AppData\Local\Temp\ipykernel_5052\1258635817.py:4: UserWarning: Ignor
ing `palette` because no `hue` variable has been assigned.
  sns.scatterplot(data=df, x=x_col, y=y_col, hue=hue_col, palette='Set1',ax=ax)
```




Scatter Plot of PC2 vs PC1 by filter: quality_of_sleep
Scatter Plot of PC3 vs PC2 by filter: quality_of_sleep
Scatter Plot of PC3 vs PC1 by filter: quality_of_sleep
quality_of_sleep
6
7
8
5
9
Scatter Plot of PC2 vs PC1 by filter: stress_level
Scatter Plot of PC3 vs PC2 by filter: stress_level
Scatter Plot of PC3 vs PC1 by filter: stress_level
stress_level
6
8
4
3
5
7
Scatter Plot of PC2 vs PC1 by filter: bmi_category
Scatter Plot of PC3 vs PC2 by filter: bmi_category
Scatter Plot of PC3 vs PC1 by filter: bmi_category
bmi_category
Overweight
Normal
Scatter Plot of PC2 vs PC1 by filter: sleep_disorder
Scatter Plot of PC3 vs PC2 by filter: sleep_disorder
Scatter Plot of PC3 vs PC1 by filter: sleep_disorder
sleep_disorder
0
1
PC1
PC2
PC3

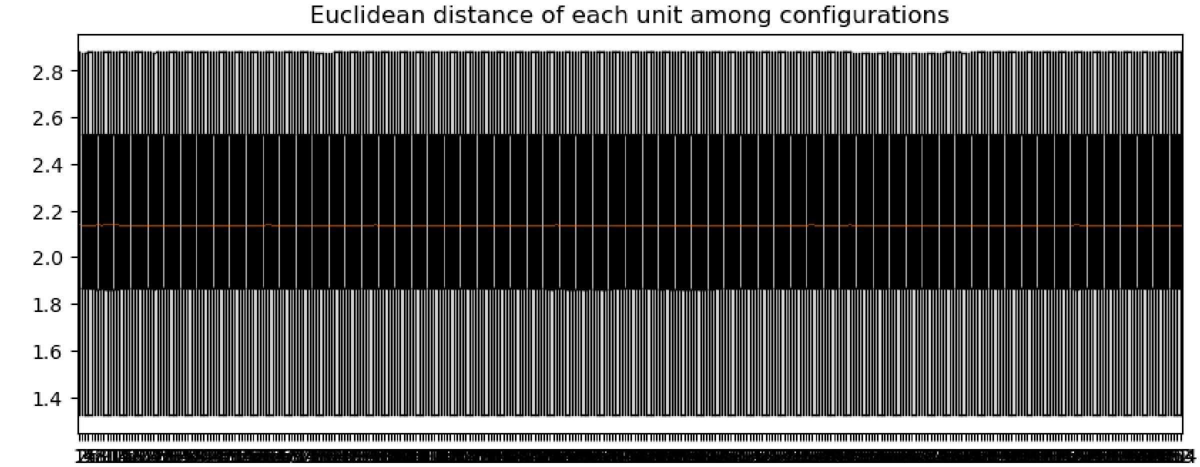
A first glance at possible meaning behind the principal components is only found when plotting the transformed data in three dimensions with a colorcoding for the categorical features. Doing so, first patterns emerge. Some observable pattern include:

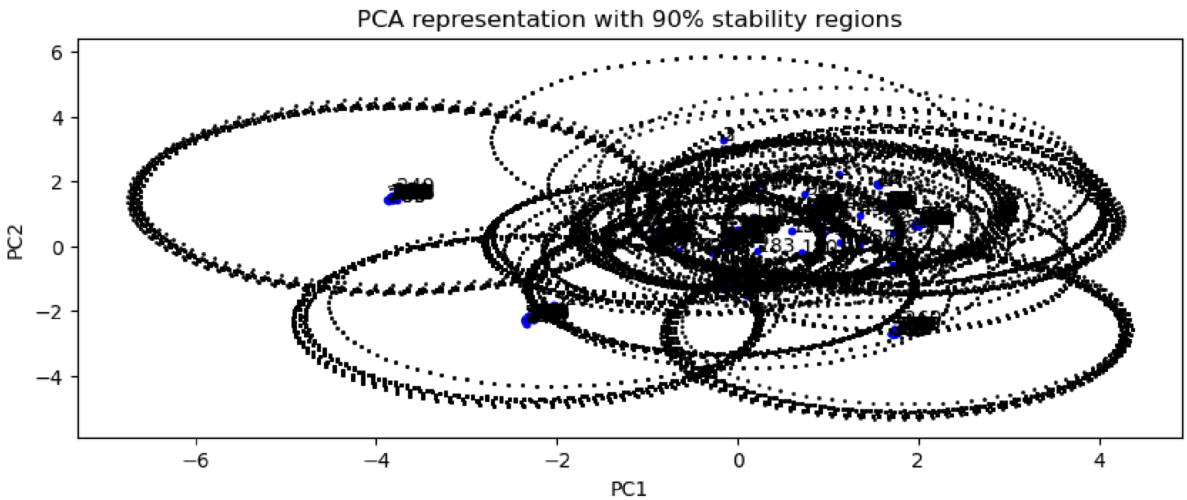
- male data points being closer to the origin and female values data points
- clusters of occupations visible, sometimes in combination with stress level like two clusters for nurses, one with low and one with high stress level
- non-sleep disorder and normal weight for PC1 in negative area



These emerging patterns between the principal components, the numerical and categorical variables and more specifically sleep disorder show an apparent clustering potential that can be further investigated in the second part of this project via distance based metrics.

Stability of the Principal components





Out[101…

	Mean	Standard Deviation	Median	Mean Absolute Deviation (MAD)
PCA 1	2.169042	0.396796	2.139104	0.306660
PCA 2	2.170711	0.396445	2.140058	0.305647
PCA 3	2.169899	0.396737	2.139598	0.306719
PCA 4	2.169952	0.396728	2.139642	0.306678
PCA 5	2.170067	0.396691	2.139747	0.306680
PCA 6	2.170119	0.396667	2.139757	0.306644

To perform the stability analysis using the leave-one-out method, we obtained 354 different outputs, which makes it challenging to interpret the results visually.

The values in the table are quite consistent across the different PCAs, indicating that they all exhibit similar average Euclidean distances and very low standard deviations. This suggests that the principal components are stable, remaining unaffected by changes in the data. Consequently, this implies that the PCA captures the underlying structure of the data reliably, providing confidence in the robustness of the results. In general, this suggests that the PCA model is likely to generalize well to new data.

Conclusion Part 1

In the first Part of this project work, an exploratory data analysis has been performed in support of a principal component analysis. The principal component analysis has been shown to deliver three principal components that explain the datas variance well and are stable when genaralizing to new data, while attributing intuitive characteristics to the new dimensions has shown to be challanging. Only when visualizing the categorical variables together with the data in the new dimensions, patterns and cluster emerge. To further understand the in this analysis discovered patterns will be the task of the second part of this work.