FinalReport-ColibriWireless

January 6, 2024

Candidate Number: 277229

0.1 Trivisio IMU - Colibri Wireless Report

This report has been created to analyse the data provided by the company Trivisio, regarding their physical activity monitor. The main purpose of this analysis is to find out possible future improvements that can be added to the product to generate a better user experience, and in return, better profits.

The data collection was done by tracking the information gathered by Trivisio´s inertial measurement unit (IMU), Colibri Wireless, in 9 subjects that performed different types of activities.The data collectors have informed me that each subject also had a heart monitor, which kept track of their heart rate throughout the experiment.

The data from this experiment was given in 9 different files, with additional PDFs files providing information about the product, the type of data and the subjects, which have been used in this report and will be explained as necessary.

The first step in this report, is to clean and wrangle the data, and to do so, all 9 files must be added into one data frame.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
import warnings
warnings.filterwarnings('ignore')
from sklearn.cluster import KMeans
import statsmodels.api as sm
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
```

The product is equipped with different sensors that measure temperature, movement and orientation of hands, chest and ankles.

Following that information, I have named the columns of the data frame, to be as informative as possible, considering the similarities between all the different types of measurements.

Since the data has been given in separate files, I found that the most straightforward way to merge them was to create the structure of a complete data frame, that will then be filled with each subject´s file´s data.

[2]:

```
columnas=['timestamp','activityID', 'bpm',
          #hand
          'IMU_hand_temp', 'IMU_hand_acceleration_scale16g_1', 'IMU_hand_acceleration_scale16g_2',
          'IMU_hand_acceleration_scale16g_3',  'IMU_hand_acceleration_scale6g_1',
          'IMU_hand_acceleration_scale6g_2',  'IMU_hand_acceleration_scale6g_3',
          'IMU_hand_gyroscope_1','IMU_hand_gyroscope_2','IMU_hand_gyroscope_3',
          'IMU_hand_magnetometer_1','IMU_hand_magnetometer_2','IMU_hand_magnetometer_3',
          'IMU_hand_orientation_1', 'IMU_hand_orientation_2','IMU_hand_orientation_3',
          'IMU_hand_orientation_4',
          #chest
          'IMU_chest_temp','IMU_chest_acceleration_scale16g_1','IMU_chest_acceleration_scale16g_2',
          'IMU_chest_acceleration_scale16g_3','IMU_chest_acceleration_scale6g_1',
          'IMU_chest_acceleration_scale6g_2', 'IMU_chest_acceleration_scale6g_3',
          'IMU_chest_gyroscope_1','IMU_chest_gyroscope_2','IMU_chest_gyroscope_3',
          'IMU_chest_magnetometer_1','IMU_chest_magnetometer_2','IMU_chest_magnetometer_3',
          'IMU_chest_orientation_1','IMU_chest_orientation_2','IMU_chest_orientation_3',
          'IMU_chest_orientation_4',
          #ankle
          'IMU_ankle_temp','IMU_ankle_acceleration_scale16g_1','IMU_ankle_acceleration_scale16g_2',
          'IMU_ankle_acceleration_scale16g_3','IMU_ankle_acceleration_scale6g_1',
          'IMU_ankle_acceleration_scale6g_2', 'IMU_ankle_acceleration_scale6g_3',
          'IMU_ankle_gyroscope_1','IMU_ankle_gyroscope_2','IMU_ankle_gyroscope_3',
          'IMU_ankle_magnetometer_1','IMU_ankle_magnetometer_2','IMU_ankle_magnetometer_3',
          'IMU_ankle_orientation_1','IMU_ankle_orientation_2','IMU_ankle_orientation_3',
          'IMU_ankle_orientation_4',]
df_complete = pd.DataFrame(columns=columnas)
```

```
file_path1 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject101.dat'
file_path2 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject102.dat'
file_path3 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject103.dat'
file_path4 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject104.dat'
file_path5 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject105.dat'
file_path6 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject106.dat'
file_path7 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject107.dat'
file_path8 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject108.dat'
file_path9 = 'C://Users//Flor//Downloads//DS//Final//Dataset//Dataset//Protocol/
 ↪/subject109.dat'

data1 = pd.read_csv(file_path1, names=columnas, delimiter=" ")
data1.insert(loc=0, column='SubjectID', value=101)
data2 = pd.read_csv(file_path2, names=columnas, delimiter=" ")
data2.insert(loc=0, column='SubjectID', value=102)
data3 = pd.read_csv(file_path3, names=columnas, delimiter=" ")
data3.insert(loc=0, column='SubjectID', value=103)
data4 = pd.read_csv(file_path4, names=columnas, delimiter=" ")
data4.insert(loc=0, column='SubjectID', value=104)
data5 = pd.read_csv(file_path5, names=columnas, delimiter=" ")
data5.insert(loc=0, column='SubjectID', value=105)
data6 = pd.read_csv(file_path6, names=columnas, delimiter=" ")
data6.insert(loc=0, column='SubjectID', value=106)
data7 = pd.read_csv(file_path7, names=columnas, delimiter=" ")
data7.insert(loc=0, column='SubjectID', value=107)
data8 = pd.read_csv(file_path8, names=columnas, delimiter=" ")
data8.insert(loc=0, column='SubjectID', value=108)
data9 = pd.read_csv(file_path9, names=columnas, delimiter=" ")
data9.insert(loc=0, column='SubjectID', value=109)


df_complete = pd.concat([df_complete,␣
 ↪data1,data2,data3,data4,data5,data6,data7,data8,data9],
                        ignore_index=True)
```

Now, **df_complete** has the information that was provided to be of all 9 individuals. One thing to point out, there are a significant number of ´bpm´ (beats per minute, meaning heart rate) cells empty, which is something that needs to be resolved somehow.

[3]:

```
df_complete
```

[3]:

```
         timestamp  activityID    bpm  IMU_hand_temp  \
0             8.38           0  104.0        30.0000
1             8.39           0    NaN        30.0000
2             8.40           0    NaN        30.0000
3             8.41           0    NaN        30.0000
4             8.42           0    NaN        30.0000
…              …          …     …             …
2872528     100.19           0    NaN        25.1875
2872529     100.20           0    NaN        25.1875
2872530     100.21           0    NaN        25.1875
2872531     100.22           0    NaN        25.1875
2872532     100.23           0  161.0        25.1875

         IMU_hand_acceleration_scale16g_1  IMU_hand_acceleration_scale16g_2  \
0                                 2.37223                           8.60074
1                                 2.18837                           8.56560
2                                 2.37357                           8.60107
3                                 2.07473                           8.52853
4                                 2.22936                           8.83122
…                                   …                                 …
2872528                          -4.71493                          10.22250
2872529                          -4.95932                          10.37130
2872530                          -4.93997                           9.83615
2872531                          -4.64941                           9.11129
2872532                          -4.09726                           8.15642

         IMU_hand_acceleration_scale16g_3  IMU_hand_acceleration_scale6g_1  \
0                                 3.51048                          2.43954
1                                 3.66179                          2.39494
2                                 3.54898                          2.30514
3                                 3.66021                          2.33528
4                                 3.70000                          2.23055
…                                   …                                …
2872528                           4.66893                         -5.04654
2872529                           4.12594                         -4.96890
2872530                           3.70468                         -5.04613
2872531                           3.51904                         -5.06854
2872532                           3.29961                         -4.73244

         IMU_hand_acceleration_scale6g_2  IMU_hand_acceleration_scale6g_3  \
0                                8.76165                          3.35465
1                                8.55081                          3.64207
2                                8.53644                          3.73280
3                                8.53622                          3.73277
4                                8.59741                          3.76295
```

```
…                                     …                               …
2872528                         9.94944                         4.50736
2872529                        10.29620                         4.43102
2872530                        10.35690                         4.14405
2872531                         9.75268                         3.87359
2872532                         8.82870                         3.54305

         …  IMU_ankle_gyroscope_2  IMU_ankle_gyroscope_3  \
0        …               0.009250              -0.017580
1        …              -0.004638               0.000368
2        …               0.000148               0.022495
3        …              -0.020301               0.011275
4        …              -0.014303              -0.002823
…      …                     …                      …
2872528  …              -0.062676              -0.127084
2872529  …              -0.027006              -0.089808
2872530  …              -0.038024              -0.064709
2872531  …              -0.025796              -0.064357
2872532  …               0.011866              -0.042858

         IMU_ankle_magnetometer_1  IMU_ankle_magnetometer_2  \
0                        -61.1888                 -38.95990
1                        -59.8479                 -38.89190
2                        -60.7361                 -39.41380
3                        -60.4091                 -38.76350
4                        -61.5199                 -39.38790
…                             …                         …
2872528                  -46.5153                   3.58240
2872529                  -45.7474                   3.54453
2872530                  -46.3997                   4.22078
2872531                  -46.5282                   4.48593
2872532                  -46.2704                   4.21475

         IMU_ankle_magnetometer_3  IMU_ankle_orientation_1  \
0                      -58.143800                 1.000000
1                      -58.525300                 1.000000
2                      -58.399900                 1.000000
3                      -58.395600                 1.000000
4                      -58.269400                 1.000000
…                             …                        …
2872528                 -0.035995                 0.598531
2872529                  0.108583                 0.598428
2872530                  0.105504                 0.598233
2872531                  0.530240                 0.598116
2872532                  0.247798                 0.598119

         IMU_ankle_orientation_2  IMU_ankle_orientation_3  \
```

```
0                          0.000000                    0.000000
1                          0.000000                    0.000000
2                          0.000000                    0.000000
3                          0.000000                    0.000000
4                          0.000000                    0.000000
…                              …                         …
2872528                    0.033615                    0.799791
2872529                    0.033012                    0.799933
2872530                    0.033172                    0.800095
2872531                    0.033427                    0.800180
2872532                    0.033685                    0.800188

         IMU_ankle_orientation_4  SubjectID
0                          0.000000      101.0
1                          0.000000      101.0
2                          0.000000      101.0
3                          0.000000      101.0
4                          0.000000      101.0
…                              …          …
2872528                   -0.031075      109.0
2872529                   -0.030018      109.0
2872530                   -0.029416      109.0
2872531                   -0.029208      109.0
2872532                   -0.028602      109.0

[2872533 rows x 55 columns]
```

The data collector mentioned that the times in between the different physical activities, such as waiting time, walking to different rooms and travel time, were marked with a 0 value in the ActivityID column. Furthermore, two sensors have similar functions but different accuracy, which is why they advised disregarding the less accurate measurements since it wasn't precisely calibrated. Finally, there was a note in the columns marked as orientation, which mentioned that they were not to be used in this analysis.

As a result of all these notes, I had to remove all rows where ActivityID is 0, and all columns that utilized orientation and acceleration over 6g.

[4]:
```
df_complete = df_complete[df_complete['activityID'] != 0]
```

[5]:
```
df_complete = df_complete.drop(['IMU_hand_orientation_1', ␣
↪'IMU_hand_orientation_2',
             'IMU_hand_orientation_3', 'IMU_hand_orientation_4',
             'IMU_chest_orientation_1', 'IMU_chest_orientation_2',
             'IMU_chest_orientation_3', 'IMU_chest_orientation_4',
             'IMU_ankle_orientation_1', 'IMU_ankle_orientation_2',
             'IMU_ankle_orientation_3', 'IMU_ankle_orientation_4',
            ␣
↪'IMU_hand_acceleration_scale6g_1','IMU_hand_acceleration_scale6g_2',
```

```
                ␣
↪'IMU_hand_acceleration_scale6g_3','IMU_chest_acceleration_scale6g_1',
                ␣
↪'IMU_chest_acceleration_scale6g_2','IMU_chest_acceleration_scale6g_3',
                ␣
↪'IMU_ankle_acceleration_scale6g_1','IMU_ankle_acceleration_scale6g_2',
             'IMU_ankle_acceleration_scale6g_3'
            ], axis=1)
```

[6]:
```
df_complete.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1942872 entries, 2928 to 2872019
Data columns (total 34 columns):
 #   Column                           Dtype
---  ------                           -----
 0   timestamp                        float64
 1   activityID                       object
 2   bpm                              float64
 3   IMU_hand_temp                    float64
 4   IMU_hand_acceleration_scale16g_1  float64
 5   IMU_hand_acceleration_scale16g_2  float64
 6   IMU_hand_acceleration_scale16g_3  float64
 7   IMU_hand_gyroscope_1             float64
 8   IMU_hand_gyroscope_2             float64
 9   IMU_hand_gyroscope_3             float64
 10  IMU_hand_magnetometer_1          float64
 11  IMU_hand_magnetometer_2          float64
 12  IMU_hand_magnetometer_3          float64
 13  IMU_chest_temp                   float64
 14  IMU_chest_acceleration_scale16g_1 float64
 15  IMU_chest_acceleration_scale16g_2 float64
 16  IMU_chest_acceleration_scale16g_3 float64
 17  IMU_chest_gyroscope_1            float64
 18  IMU_chest_gyroscope_2            float64
 19  IMU_chest_gyroscope_3            float64
 20  IMU_chest_magnetometer_1         float64
 21  IMU_chest_magnetometer_2         float64
 22  IMU_chest_magnetometer_3         float64
 23  IMU_ankle_temp                   float64
 24  IMU_ankle_acceleration_scale16g_1 float64
 25  IMU_ankle_acceleration_scale16g_2 float64
 26  IMU_ankle_acceleration_scale16g_3 float64
 27  IMU_ankle_gyroscope_1            float64
 28  IMU_ankle_gyroscope_2            float64
 29  IMU_ankle_gyroscope_3            float64
 30  IMU_ankle_magnetometer_1         float64
```

```
 31   IMU_ankle_magnetometer_2           float64
 32   IMU_ankle_magnetometer_3           float64
 33   SubjectID                          float64
dtypes: float64(33), object(1)
memory usage: 518.8+ MB
```

The column **ActivityID** is currently only showing numbers, which don't mean a lot when trying to give meaning to the other measurements. That's why I created an **activity_dictionary**, which is, in turn, used to fill out a new column in the data frame, called **activityID_legend**

The idea behind this column is to give a clearer perspective and to help with the interpretation of the data representations.

[7]:
```
activity_dictonary = {
    1: 'lying',
    2: 'sitting',
    3: 'standing',
    4: 'walking',
    5: 'running',
    6: 'cycling',
    7: 'nordic walking',
    9: 'watching tv',
    10: 'computer work',
    11: 'car driving',
    12: 'ascending stairs',
    13: 'descending stairs',
    16: 'vacuum cleaning',
    17: 'ironing',
    18: 'folding laundry',
    19: 'house cleaning',
    20: 'playing soccer',
    24: 'rope jumping'

}

df_complete['activityID_legend'] = df_complete['activityID'].
 ↪map(activity_dictonary)
```

As I mentioned previously, several **bpm** empty values need to be addressed. However, we have 1942872 entries, and according to the following check on this column, there are 1765464 empty values in total. Removing these empty values would not be wise, since it would mean removing most of our data. As an alternative, we could look into another column, that may help bring a different solution.

The column **timestamp**, which is our given measure of time in seconds, shows very small variations between rows. That means that there are several rows which belong to the same subject, while they are conducting the same activity, in a relatively small amount of time. I have decided that it is safe to consider that, because the variations between rows consist of approximately 0,1 seconds each, it's safe to fill up the **bpm** column with its nearer value available, belonging to the same subject and the same activity.

[8]:
```
df_complete['bpm'].isna().sum()
```

[8]: 1765464

[9]:
```
def rellenar_bpm(group):
    group['bpm'] = group['bpm'].ffill().bfill()
    return group

df_complete = df_complete.groupby(['activityID', 'SubjectID']).
 ↪apply(rellenar_bpm)
```

After having extensively modified the data frame, it is important to make some checks, to see that everything is going according to plan. I'm checking the structure of the data frame again, double-checking that **activityID** does not present any 0 values and checking that there are no duplicate rows.

[10]:
```
df_complete['activityID'].unique()
```

[10]: array([1, 2, 3, 4, 5, 6, 7, 12, 13, 16, 17, 24], dtype=object)

[11]:
```
df_complete.describe()
```

[11]:
```
          timestamp           bpm  IMU_hand_temp  \
count  1.942872e+06  1.942871e+06   1.931748e+06
mean   1.705202e+03  1.074847e+02   3.275752e+01
std    1.093463e+03  2.699077e+01   1.791983e+00
min    3.120000e+01  5.700000e+01   2.487500e+01
25%    7.445400e+02  8.600000e+01   3.168750e+01
50%    1.480330e+03  1.040000e+02   3.318750e+01
75%    2.663610e+03  1.240000e+02   3.406250e+01
max    4.245680e+03  2.020000e+02   3.550000e+01

       IMU_hand_acceleration_scale16g_1  IMU_hand_acceleration_scale16g_2  \
count                      1.931748e+06                      1.931748e+06
mean                      -4.938311e+00                      3.580308e+00
std                        6.231142e+00                      6.887907e+00
min                       -1.453670e+02                     -1.043010e+02
25%                       -8.955800e+00                      1.048068e+00
50%                       -5.426670e+00                      3.523155e+00
75%                       -9.430042e-01                      6.454320e+00
max                        6.285960e+01                      1.556990e+02

       IMU_hand_acceleration_scale16g_3  IMU_hand_gyroscope_1  \
count                      1.931748e+06          1.931748e+06
mean                       3.609347e+00          6.470148e-04
std                        3.960176e+00          1.328472e+00
min                       -1.014520e+02         -2.813540e+01
25%                        1.161655e+00         -3.768683e-01
```

```
50%                        3.441330e+00         -6.076310e-03
75%                        6.538525e+00          3.323695e-01
max                        1.577600e+02          2.641580e+01

       IMU_hand_gyroscope_2  IMU_hand_gyroscope_3  IMU_hand_magnetometer_1  \
count          1.931748e+06          1.931748e+06             1.931748e+06
mean           3.990067e-02         -2.219538e-03             2.105412e+01
std            9.542155e-01          1.595544e+00             2.381242e+01
min           -1.784950e+01         -1.426470e+01            -1.039410e+02
25%           -2.224115e-01         -3.798985e-01             4.752860e+00
50%            5.905485e-03         -5.582015e-03             2.283745e+01
75%            2.655973e-01          3.648515e-01             3.929700e+01
max            2.307790e+01          1.433840e+01             1.375440e+02

       …  IMU_ankle_acceleration_scale16g_1  \
count  …                       1.934365e+06
mean   …                       9.404517e+00
std    …                       6.531695e+00
min    …                      -1.550680e+02
25%    …                       8.425630e+00
50%    …                       9.537770e+00
75%    …                       1.028620e+01
max    …                       1.572320e+02

       IMU_ankle_acceleration_scale16g_2  IMU_ankle_acceleration_scale16g_3  \
count                       1.934365e+06                       1.934365e+06
mean                       -1.555721e-01                      -2.592149e+00
std                         7.741951e+00                       3.938341e+00
min                        -1.574430e+02                      -1.589260e+02
25%                        -2.175540e+00                      -3.811010e+00
50%                        -2.907700e-01                      -2.418770e+00
75%                         1.780190e+00                      -1.042100e+00
max                         1.572930e+02                       1.588720e+02

       IMU_ankle_gyroscope_1  IMU_ankle_gyroscope_2  IMU_ankle_gyroscope_3  \
count           1.934365e+06           1.934365e+06           1.934365e+06
mean            1.062149e-02          -3.676710e-02           7.725809e-03
std             1.126987e+00           6.380790e-01           2.011906e+00
min            -2.399500e+01          -1.812690e+01          -1.401960e+01
25%            -2.062960e-01          -1.063010e-01          -4.368720e-01
50%             4.666780e-03          -3.971010e-03          -2.243400e-03
75%             1.307210e-01           1.154390e-01           9.160350e-02
max             1.742040e+01           1.358820e+01           1.652880e+01

       IMU_ankle_magnetometer_1  IMU_ankle_magnetometer_2  \
count              1.934365e+06              1.934365e+06
mean              -3.156858e+01              1.414712e+00
```

```
std                  1.835626e+01              2.168850e+01
min                 -1.728650e+02             -1.379080e+02
25%                 -4.170720e+01             -1.245170e+01
50%                 -3.397750e+01              8.009720e-01
75%                 -1.787670e+01              1.785610e+01
max                  9.155160e+01              9.424780e+01

       IMU_ankle_magnetometer_3     SubjectID
count              1.934365e+06  1.942872e+06
mean               1.724289e+01  1.045664e+02
std                1.972172e+01  2.333052e+00
min               -1.027160e+02  1.010000e+02
25%                3.761730e+00  1.020000e+02
50%                1.875760e+01  1.050000e+02
75%                3.120870e+01  1.070000e+02
max                1.469000e+02  1.090000e+02

[8 rows x 33 columns]
```

[12]:
```
df_complete.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 1942872 entries, (1, 101.0, 2928) to (24, 109.0, 2872019)
Data columns (total 35 columns):
 #   Column                              Dtype
---  ------                              -----
 0   timestamp                           float64
 1   activityID                          object
 2   bpm                                 float64
 3   IMU_hand_temp                       float64
 4   IMU_hand_acceleration_scale16g_1    float64
 5   IMU_hand_acceleration_scale16g_2    float64
 6   IMU_hand_acceleration_scale16g_3    float64
 7   IMU_hand_gyroscope_1                float64
 8   IMU_hand_gyroscope_2                float64
 9   IMU_hand_gyroscope_3                float64
 10  IMU_hand_magnetometer_1             float64
 11  IMU_hand_magnetometer_2             float64
 12  IMU_hand_magnetometer_3             float64
 13  IMU_chest_temp                      float64
 14  IMU_chest_acceleration_scale16g_1   float64
 15  IMU_chest_acceleration_scale16g_2   float64
 16  IMU_chest_acceleration_scale16g_3   float64
 17  IMU_chest_gyroscope_1               float64
 18  IMU_chest_gyroscope_2               float64
 19  IMU_chest_gyroscope_3               float64
 20  IMU_chest_magnetometer_1            float64
 21  IMU_chest_magnetometer_2            float64
```

```
 22  IMU_chest_magnetometer_3           float64
 23  IMU_ankle_temp                     float64
 24  IMU_ankle_acceleration_scale16g_1  float64
 25  IMU_ankle_acceleration_scale16g_2  float64
 26  IMU_ankle_acceleration_scale16g_3  float64
 27  IMU_ankle_gyroscope_1              float64
 28  IMU_ankle_gyroscope_2              float64
 29  IMU_ankle_gyroscope_3              float64
 30  IMU_ankle_magnetometer_1           float64
 31  IMU_ankle_magnetometer_2           float64
 32  IMU_ankle_magnetometer_3           float64
 33  SubjectID                          float64
 34  activityID_legend                  object
dtypes: float64(33), object(2)
memory usage: 609.2+ MB
```

[13]:
```
duplicados = df_complete.duplicated().sum()
duplicados
```

[13]: 0

[14]:
```
df_complete
```

[14]:
```
                                timestamp activityID    bpm  IMU_hand_temp  \
activityID SubjectID
1          101.0     2928           37.66          1  100.0         30.375
                     2929           37.67          1  100.0         30.375
                     2930           37.68          1  100.0         30.375
                     2931           37.69          1  100.0         30.375
                     2932           37.70          1  100.0         30.375
…                                   …         …     …              …
24         109.0     2872015        95.06         24  162.0         25.125
                     2872016        95.07         24  162.0         25.125
                     2872017        95.08         24  162.0         25.125
                     2872018        95.09         24  162.0         25.125
                     2872019        95.10         24  162.0         25.125

                                IMU_hand_acceleration_scale16g_1  \
activityID SubjectID
1          101.0     2928                                2.21530
                     2929                                2.29196
                     2930                                2.29090
                     2931                                2.21800
                     2932                                2.30106
…                                                          …
24         109.0     2872015                             4.99466
                     2872016                             5.02764
                     2872017                             5.06409
```

```
                    2872018                           5.13914
                    2872019                           5.00812

                              IMU_hand_acceleration_scale16g_2  \
activityID SubjectID
1          101.0    2928                              8.27915
                    2929                              7.67288
                    2930                              7.14240
                    2931                              7.14365
                    2932                              7.25857
…                                                       …
24         109.0    2872015                           6.01881
                    2872016                           5.90369
                    2872017                           5.71370
                    2872018                           5.63724
                    2872019                           5.40645

                              IMU_hand_acceleration_scale16g_3  \
activityID SubjectID
1          101.0    2928                              5.58753
                    2929                              5.74467
                    2930                              5.82342
                    2931                              5.89930
                    2932                              6.09259
…                                                       …
24         109.0    2872015                           5.59830
                    2872016                           5.48372
                    2872017                           5.48491
                    2872018                           5.48629
                    2872019                           5.02326

                              IMU_hand_gyroscope_1  IMU_hand_gyroscope_2  \
activityID SubjectID
1          101.0    2928                  -0.004750              0.037579
                    2929                  -0.171710              0.025479
                    2930                  -0.238241              0.011214
                    2931                  -0.192912              0.019053
                    2932                  -0.069961             -0.018328
…                                             …                     …
24         109.0    2872015               -0.289166             -0.110170
                    2872016               -0.275411             -0.128358
                    2872017               -0.289885             -0.126548
                    2872018               -0.234417             -0.101485
                    2872019               -0.260924             -0.093849

                              IMU_hand_gyroscope_3  …  \
activityID SubjectID                                …
```

```
1           101.0     2928                  -0.011145  …
                      2929                  -0.009538  …
                      2930                   0.000831  …
                      2931                   0.013374  …
                      2932                   0.004582  …
…                                                 …  …
24          109.0     2872015                0.238570  …
                      2872016                0.267409  …
                      2872017                0.281483  …
                      2872018                0.275497  …
                      2872019                0.266205  …

                               IMU_ankle_acceleration_scale16g_2  \
activityID SubjectID
1           101.0     2928                              -1.84761
                      2929                              -1.88438
                      2930                              -1.92203
                      2931                              -1.84714
                      2932                              -1.88582
…                                                          …
24          109.0     2872015                           -2.24401
                      2872016                           -2.28110
                      2872017                           -2.24313
                      2872018                           -2.24425
                      2872019                           -2.28286

                               IMU_ankle_acceleration_scale16g_3  \
activityID SubjectID
1           101.0     2928                              0.095156
                      2929                             -0.020804
                      2930                             -0.059173
                      2931                              0.094385
                      2932                              0.095775
…                                                          …
24          109.0     2872015                          -2.259740
                      2872016                          -2.337100
                      2872017                          -2.337340
                      2872018                          -2.259360
                      2872019                          -2.181920

                               IMU_ankle_gyroscope_1  IMU_ankle_gyroscope_2  \
activityID SubjectID
1           101.0     2928                  0.002908              -0.027714
                      2929                  0.020882               0.000945
                      2930                 -0.035392              -0.052422
                      2931                 -0.032514              -0.018844
                      2932                  0.001351              -0.048878
```

```
…                                      …                     …
24          109.0     2872015         0.021288              -0.012885
                      2872016         0.010715               0.003629
                      2872017        -0.016939              -0.035176
                      2872018        -0.028069              -0.036457
                      2872019        -0.013310              -0.030195

                              IMU_ankle_gyroscope_3  IMU_ankle_magnetometer_1  \
activityID SubjectID
1          101.0      2928            0.001752                  -61.1081
                      2929            0.006007                  -60.8916
                      2930           -0.004882                  -60.3407
                      2931            0.026950                  -60.7646
                      2932           -0.006328                  -60.2040
…                                      …                           …
24         109.0      2872015         0.005878                  -45.7855
                      2872016        -0.004235                  -46.0331
                      2872017        -0.002309                  -45.5140
                      2872018        -0.007076                  -45.9093
                      2872019         0.018229                  -46.1702

                              IMU_ankle_magnetometer_2  \
activityID SubjectID
1          101.0      2928                  -36.863600
                      2929                  -36.319700
                      2930                  -35.784200
                      2931                  -37.102800
                      2932                  -37.122500
…                                              …
24         109.0      2872015                -0.831734
                      2872016                -0.817288
                      2872017                -1.229410
                      2872018                -0.565555
                      2872019                -0.812965

                              IMU_ankle_magnetometer_3  SubjectID  \
activityID SubjectID
1          101.0      2928                  -58.369600      101.0
                      2929                  -58.365600      101.0
                      2930                  -58.611900      101.0
                      2931                  -57.879900      101.0
                      2932                  -57.884700      101.0
…                                              …          …
24         109.0      2872015                -0.170139      109.0
                      2872016                 0.538134      109.0
                      2872017                 0.540438      109.0
                      2872018                 0.680109      109.0
```

```
                    2872019                 -0.313346      109.0

                                 activityID_legend
activityID SubjectID
1          101.0     2928                    lying
                     2929                    lying
                     2930                    lying
                     2931                    lying
                     2932                    lying
…                                            …
24         109.0     2872015          rope jumping
                     2872016          rope jumping
                     2872017          rope jumping
                     2872018          rope jumping
                     2872019          rope jumping

[1942872 rows x 35 columns]
```

We have already dealt with the NaN for **bpm**, but we have not checked to see if there are any in the rest of the columns. Since the accuracy of the measurements is very important to the data collector, I have decided to check for the percentage of NaNs present in each column.

[15]:
```
df_complete.isna().mean() * 100
```

[15]:
```
timestamp                              0.000000
activityID                             0.000000
bpm                                    0.000051
IMU_hand_temp                          0.572554
IMU_hand_acceleration_scale16g_1       0.572554
IMU_hand_acceleration_scale16g_2       0.572554
IMU_hand_acceleration_scale16g_3       0.572554
IMU_hand_gyroscope_1                   0.572554
IMU_hand_gyroscope_2                   0.572554
IMU_hand_gyroscope_3                   0.572554
IMU_hand_magnetometer_1                0.572554
IMU_hand_magnetometer_2                0.572554
IMU_hand_magnetometer_3                0.572554
IMU_chest_temp                         0.124558
IMU_chest_acceleration_scale16g_1      0.124558
IMU_chest_acceleration_scale16g_2      0.124558
IMU_chest_acceleration_scale16g_3      0.124558
IMU_chest_gyroscope_1                  0.124558
IMU_chest_gyroscope_2                  0.124558
IMU_chest_gyroscope_3                  0.124558
IMU_chest_magnetometer_1               0.124558
IMU_chest_magnetometer_2               0.124558
IMU_chest_magnetometer_3               0.124558
IMU_ankle_temp                         0.437857
```

```
IMU_ankle_acceleration_scale16g_1    0.437857
IMU_ankle_acceleration_scale16g_2    0.437857
IMU_ankle_acceleration_scale16g_3    0.437857
IMU_ankle_gyroscope_1                0.437857
IMU_ankle_gyroscope_2                0.437857
IMU_ankle_gyroscope_3                0.437857
IMU_ankle_magnetometer_1             0.437857
IMU_ankle_magnetometer_2             0.437857
IMU_ankle_magnetometer_3             0.437857
SubjectID                            0.000000
activityID_legend                    0.000000
dtype: float64
```

[16]:
```
df_complete.dropna(inplace=True)
```

[17]:
```
df_complete
```

[17]:
```
                              timestamp activityID    bpm  IMU_hand_temp  \
activityID SubjectID
1          101.0     2928         37.66          1  100.0         30.375
                     2929         37.67          1  100.0         30.375
                     2930         37.68          1  100.0         30.375
                     2931         37.69          1  100.0         30.375
                     2932         37.70          1  100.0         30.375
…                                   …          …    …              …
24         109.0     2872015      95.06         24  162.0         25.125
                     2872016      95.07         24  162.0         25.125
                     2872017      95.08         24  162.0         25.125
                     2872018      95.09         24  162.0         25.125
                     2872019      95.10         24  162.0         25.125

                              IMU_hand_acceleration_scale16g_1  \
activityID SubjectID
1          101.0     2928                              2.21530
                     2929                              2.29196
                     2930                              2.29090
                     2931                              2.21800
                     2932                              2.30106
…                                                        …
24         109.0     2872015                           4.99466
                     2872016                           5.02764
                     2872017                           5.06409
                     2872018                           5.13914
                     2872019                           5.00812

                              IMU_hand_acceleration_scale16g_2  \
activityID SubjectID
```

```
1          101.0    2928                              8.27915
                    2929                              7.67288
                    2930                              7.14240
                    2931                              7.14365
                    2932                              7.25857
…                                                       …
24         109.0    2872015                           6.01881
                    2872016                           5.90369
                    2872017                           5.71370
                    2872018                           5.63724
                    2872019                           5.40645

                             IMU_hand_acceleration_scale16g_3  \
activityID SubjectID
1          101.0    2928                              5.58753
                    2929                              5.74467
                    2930                              5.82342
                    2931                              5.89930
                    2932                              6.09259
…                                                       …
24         109.0    2872015                           5.59830
                    2872016                           5.48372
                    2872017                           5.48491
                    2872018                           5.48629
                    2872019                           5.02326

                             IMU_hand_gyroscope_1  IMU_hand_gyroscope_2  \
activityID SubjectID
1          101.0    2928                -0.004750              0.037579
                    2929                -0.171710              0.025479
                    2930                -0.238241              0.011214
                    2931                -0.192912              0.019053
                    2932                -0.069961             -0.018328
…                                           …                     …
24         109.0    2872015             -0.289166             -0.110170
                    2872016             -0.275411             -0.128358
                    2872017             -0.289885             -0.126548
                    2872018             -0.234417             -0.101485
                    2872019             -0.260924             -0.093849

                             IMU_hand_gyroscope_3  …  \
activityID SubjectID                               …
1          101.0    2928                -0.011145  …
                    2929                -0.009538  …
                    2930                 0.000831  …
                    2931                 0.013374  …
                    2932                 0.004582  …
```

```
…                                                …   …
24         109.0    2872015                0.238570  …
                    2872016                0.267409  …
                    2872017                0.281483  …
                    2872018                0.275497  …
                    2872019                0.266205  …

                             IMU_ankle_acceleration_scale16g_2  \
activityID SubjectID
1          101.0    2928                              -1.84761
                    2929                              -1.88438
                    2930                              -1.92203
                    2931                              -1.84714
                    2932                              -1.88582
…                                                       …
24         109.0    2872015                           -2.24401
                    2872016                           -2.28110
                    2872017                           -2.24313
                    2872018                           -2.24425
                    2872019                           -2.28286

                             IMU_ankle_acceleration_scale16g_3  \
activityID SubjectID
1          101.0    2928                              0.095156
                    2929                             -0.020804
                    2930                             -0.059173
                    2931                              0.094385
                    2932                              0.095775
…                                                       …
24         109.0    2872015                          -2.259740
                    2872016                          -2.337100
                    2872017                          -2.337340
                    2872018                          -2.259360
                    2872019                          -2.181920

                             IMU_ankle_gyroscope_1  IMU_ankle_gyroscope_2  \
activityID SubjectID
1          101.0    2928                  0.002908              -0.027714
                    2929                  0.020882               0.000945
                    2930                 -0.035392              -0.052422
                    2931                 -0.032514              -0.018844
                    2932                  0.001351              -0.048878
…                                            …                     …
24         109.0    2872015               0.021288              -0.012885
                    2872016               0.010715               0.003629
                    2872017              -0.016939              -0.035176
                    2872018              -0.028069              -0.036457
```

```
                   2872019             -0.013310             -0.030195

                            IMU_ankle_gyroscope_3  IMU_ankle_magnetometer_1  \
activityID SubjectID
1          101.0     2928                0.001752                  -61.1081
                     2929                0.006007                  -60.8916
                     2930               -0.004882                  -60.3407
                     2931                0.026950                  -60.7646
                     2932               -0.006328                  -60.2040
…                                             …                         …
24         109.0     2872015             0.005878                  -45.7855
                     2872016            -0.004235                  -46.0331
                     2872017            -0.002309                  -45.5140
                     2872018            -0.007076                  -45.9093
                     2872019             0.018229                  -46.1702

                            IMU_ankle_magnetometer_2  \
activityID SubjectID
1          101.0     2928                 -36.863600
                     2929                 -36.319700
                     2930                 -35.784200
                     2931                 -37.102800
                     2932                 -37.122500
…                                              …
24         109.0     2872015               -0.831734
                     2872016               -0.817288
                     2872017               -1.229410
                     2872018               -0.565555
                     2872019               -0.812965

                            IMU_ankle_magnetometer_3  SubjectID  \
activityID SubjectID
1          101.0     2928                 -58.369600      101.0
                     2929                 -58.365600      101.0
                     2930                 -58.611900      101.0
                     2931                 -57.879900      101.0
                     2932                 -57.884700      101.0
…                                              …        …
24         109.0     2872015               -0.170139      109.0
                     2872016                0.538134      109.0
                     2872017                0.540438      109.0
                     2872018                0.680109      109.0
                     2872019               -0.313346      109.0

                            activityID_legend
activityID SubjectID
1          101.0     2928               lying
```

```
                    2929               lying
                    2930               lying
                    2931               lying
                    2932               lying
…                                      …
24       109.0      2872015     rope jumping
                    2872016     rope jumping
                    2872017     rope jumping
                    2872018     rope jumping
                    2872019     rope jumping

[1921430 rows x 35 columns]
```

Since none of the percentages shown in the code above are significant, I decided to remove them all and preserve the accuracy of the remaining data. From this decision, the number of entries in the data goes from 1942872 rows to 1921430 rows, which should not compromise the integrity of the analysis.

Now that the data has been sufficiently cleaned, I added a column to analyze the difference between the types of activities. To give value to this new column, I am utilizing the target values of heart rate for the type of exercise. According to research, the target heart rate for moderate exercise is 65%-75% of your maximum heart rate, and for intense exercise, it is 77%-93%. Another thing to point out is that the maximum heart rate of a person is determined by subtracting their age from 220. *This study is referenced at the end of this report if more information is needed.*

Taking these factors into consideration, I have created a function that utilizes the information we have on each subject and calculates their maximum heart rate and their corresponding level of exercise per activity. Which is then included in a column denominated **exercise_intensity**.

The four values that this new column takes are **Resting**, **Moderate**, **Vigorous** and **Extreme**. The following blocks of code detail how the calculations are done, and later on are applied into all rows, grouping by **SubjectID** and **activityID**, which in turn causes repetition in values, because the subjects are performing the same activity for a significant amount of time, which translates into several rows.

[18]:
```
#calculating each subject's maximum heart rate to check the level
#of intensity each exercise represents.

def maximosbpm(subject,bpm):
    subjects_age={
        '101.0':27,
        '102.0':25,
        '103.0':31,
        '104.0':24,
        '105.0':26,
        '106.0':26,
        '107.0':23,
        '108.0':32,
        '109.0':31,
```

```
    }
    edad=subjects_age.get(subject)
    maxbpm=220-edad
    moderate_min = maxbpm * 0.65
    vigorous_min = maxbpm * 0.77


    if moderate_min <= bpm < vigorous_min:
        return 'Moderate'
    elif bpm<moderate_min:
        return 'Resting'
    elif vigorous_min <= bpm < maxbpm:
        return 'Vigorous'
    elif bpm>=maxbpm:
        return 'Extreme'
```

[19]:
```
def usar_maximosbpm(row):
    subject = str(row['SubjectID'])
    bpm = row['bpm']
    return maximosbpm(subject, bpm)

df_complete['exercise_intensity'] = df_complete.apply(usar_maximosbpm, axis=1)
```

[20]:
```
df_complete
```

[20]:
```
                              timestamp activityID    bpm  IMU_hand_temp  \
activityID SubjectID
1          101.0     2928         37.66          1  100.0         30.375
                     2929         37.67          1  100.0         30.375
                     2930         37.68          1  100.0         30.375
                     2931         37.69          1  100.0         30.375
                     2932         37.70          1  100.0         30.375
…                                   …        …     …             …
24         109.0     2872015      95.06         24  162.0         25.125
                     2872016      95.07         24  162.0         25.125
                     2872017      95.08         24  162.0         25.125
                     2872018      95.09         24  162.0         25.125
                     2872019      95.10         24  162.0         25.125

                              IMU_hand_acceleration_scale16g_1  \
activityID SubjectID
1          101.0     2928                              2.21530
                     2929                              2.29196
                     2930                              2.29090
                     2931                              2.21800
                     2932                              2.30106
```

```
…                                                         …
24           109.0      2872015                     4.99466
                        2872016                     5.02764
                        2872017                     5.06409
                        2872018                     5.13914
                        2872019                     5.00812

                                 IMU_hand_acceleration_scale16g_2  \
activityID SubjectID
1           101.0       2928                        8.27915
                        2929                        7.67288
                        2930                        7.14240
                        2931                        7.14365
                        2932                        7.25857
…                                                         …
24           109.0      2872015                     6.01881
                        2872016                     5.90369
                        2872017                     5.71370
                        2872018                     5.63724
                        2872019                     5.40645

                                 IMU_hand_acceleration_scale16g_3  \
activityID SubjectID
1           101.0       2928                        5.58753
                        2929                        5.74467
                        2930                        5.82342
                        2931                        5.89930
                        2932                        6.09259
…                                                         …
24           109.0      2872015                     5.59830
                        2872016                     5.48372
                        2872017                     5.48491
                        2872018                     5.48629
                        2872019                     5.02326

                                 IMU_hand_gyroscope_1  IMU_hand_gyroscope_2  \
activityID SubjectID
1           101.0       2928                -0.004750              0.037579
                        2929                -0.171710              0.025479
                        2930                -0.238241              0.011214
                        2931                -0.192912              0.019053
                        2932                -0.069961             -0.018328
…                                                 …                     …
24           109.0      2872015             -0.289166             -0.110170
                        2872016             -0.275411             -0.128358
                        2872017             -0.289885             -0.126548
                        2872018             -0.234417             -0.101485
```

```
                    2872019              -0.260924             -0.093849

                                 IMU_hand_gyroscope_3  …  \
activityID SubjectID                                   …
1          101.0    2928                    -0.011145  …
                    2929                    -0.009538  …
                    2930                     0.000831  …
                    2931                     0.013374  …
                    2932                     0.004582  …
…                                                …  …
24         109.0    2872015                  0.238570  …
                    2872016                  0.267409  …
                    2872017                  0.281483  …
                    2872018                  0.275497  …
                    2872019                  0.266205  …

                                 IMU_ankle_acceleration_scale16g_3  \
activityID SubjectID
1          101.0    2928                                  0.095156
                    2929                                 -0.020804
                    2930                                 -0.059173
                    2931                                  0.094385
                    2932                                  0.095775
…                                                              …
24         109.0    2872015                              -2.259740
                    2872016                              -2.337100
                    2872017                              -2.337340
                    2872018                              -2.259360
                    2872019                              -2.181920

                                 IMU_ankle_gyroscope_1  IMU_ankle_gyroscope_2  \
activityID SubjectID
1          101.0    2928                      0.002908              -0.027714
                    2929                      0.020882               0.000945
                    2930                     -0.035392              -0.052422
                    2931                     -0.032514              -0.018844
                    2932                      0.001351              -0.048878
…                                                  …                      …
24         109.0    2872015                   0.021288              -0.012885
                    2872016                   0.010715               0.003629
                    2872017                  -0.016939              -0.035176
                    2872018                  -0.028069              -0.036457
                    2872019                  -0.013310              -0.030195

                                 IMU_ankle_gyroscope_3  IMU_ankle_magnetometer_1  \
activityID SubjectID
1          101.0    2928                      0.001752                  -61.1081
```

```
                       2929              0.006007              -60.8916
                       2930             -0.004882              -60.3407
                       2931              0.026950              -60.7646
                       2932             -0.006328              -60.2040
…                                             …                     …
24         109.0       2872015           0.005878              -45.7855
                       2872016          -0.004235              -46.0331
                       2872017          -0.002309              -45.5140
                       2872018          -0.007076              -45.9093
                       2872019           0.018229              -46.1702

                                 IMU_ankle_magnetometer_2  \
activityID SubjectID
1          101.0       2928                    -36.863600
                       2929                    -36.319700
                       2930                    -35.784200
                       2931                    -37.102800
                       2932                    -37.122500
…                                                   …
24         109.0       2872015                  -0.831734
                       2872016                  -0.817288
                       2872017                  -1.229410
                       2872018                  -0.565555
                       2872019                  -0.812965

                                 IMU_ankle_magnetometer_3  SubjectID  \
activityID SubjectID
1          101.0       2928                    -58.369600      101.0
                       2929                    -58.365600      101.0
                       2930                    -58.611900      101.0
                       2931                    -57.879900      101.0
                       2932                    -57.884700      101.0
…                                                   …         …
24         109.0       2872015                  -0.170139      109.0
                       2872016                   0.538134      109.0
                       2872017                   0.540438      109.0
                       2872018                   0.680109      109.0
                       2872019                  -0.313346      109.0

                                 activityID_legend  exercise_intensity
activityID SubjectID
1          101.0       2928                  lying             Resting
                       2929                  lying             Resting
                       2930                  lying             Resting
                       2931                  lying             Resting
                       2932                  lying             Resting
…                                            …                 …
```

```
24          109.0     2872015       rope jumping            Vigorous
                      2872016       rope jumping            Vigorous
                      2872017       rope jumping            Vigorous
                      2872018       rope jumping            Vigorous
                      2872019       rope jumping            Vigorous

[1921430 rows x 36 columns]
```

As a next step in the exploration of this dataset, I'm calculating the mean value of all columns that are taking measurements of similar factors. This is done in the hopes of clarifying the data for further analysis.

That is why I'm creating a new data frame with new columns, for acceleration, gyroscope and magnetometer for the three body parts, hand, chest and ankle, taking the mean of all the values provided by the data collector.

[21]:
```
df_medias=df_complete.select_dtypes(include=[np.number])
df_medias['mean_hand_acceleration'] =␣
 ↪df_medias[['IMU_hand_acceleration_scale16g_1',
                                      'IMU_hand_acceleration_scale16g_2',
                                      'IMU_hand_acceleration_scale16g_3']].
 ↪mean(axis=1)

df_medias['mean_ankle_acceleration'] =␣
 ↪df_medias[['IMU_ankle_acceleration_scale16g_1',
                                      'IMU_ankle_acceleration_scale16g_2',
                                      'IMU_ankle_acceleration_scale16g_3']].
 ↪mean(axis=1)

df_medias['mean_chest_acceleration'] =␣
 ↪df_medias[['IMU_chest_acceleration_scale16g_1',
                                      'IMU_chest_acceleration_scale16g_2',
                                      'IMU_chest_acceleration_scale16g_3']].
 ↪mean(axis=1)

df_medias['mean_hand_gyroscope'] = df_medias[['IMU_hand_gyroscope_1',
                                              'IMU_hand_gyroscope_2',
                                              'IMU_hand_gyroscope_3']].
 ↪mean(axis=1)

df_medias['mean_ankle_gyroscope'] = df_medias[['IMU_ankle_gyroscope_1',
                                              'IMU_ankle_gyroscope_2',
                                              'IMU_ankle_gyroscope_3']].
 ↪mean(axis=1)

df_medias['mean_chest_gyroscope'] = df_medias[['IMU_chest_gyroscope_1',
                                              'IMU_chest_gyroscope_2',
```

```
                                                'IMU_chest_gyroscope_3']].
↪mean(axis=1)

df_medias['mean_hand_magnetometer'] = df_medias[['IMU_hand_magnetometer_1',
                                                 'IMU_hand_magnetometer_2',
                                                 'IMU_hand_magnetometer_3']].
↪mean(axis=1)

df_medias['mean_ankle_magnetometer'] = df_medias[['IMU_ankle_magnetometer_1',
                                                  'IMU_ankle_magnetometer_2',
                                                  'IMU_ankle_magnetometer_3']].
↪mean(axis=1)

df_medias['mean_chest_magnetometer'] = df_medias[['IMU_chest_magnetometer_1',
                                                  'IMU_chest_magnetometer_2',
                                                  'IMU_chest_magnetometer_3']].
↪mean(axis=1)

df_medias['activityID']=df_complete['activityID']
df_medias['exercise_intensity']=df_complete['exercise_intensity']
```

[22]:
```
df_medias
```

[22]:
```
                              timestamp    bpm  IMU_hand_temp  \
activityID SubjectID
1          101.0     2928         37.66  100.0         30.375
                     2929         37.67  100.0         30.375
                     2930         37.68  100.0         30.375
                     2931         37.69  100.0         30.375
                     2932         37.70  100.0         30.375
…                                 …     …             …
24         109.0     2872015      95.06  162.0         25.125
                     2872016      95.07  162.0         25.125
                     2872017      95.08  162.0         25.125
                     2872018      95.09  162.0         25.125
                     2872019      95.10  162.0         25.125

                              IMU_hand_acceleration_scale16g_1  \
activityID SubjectID
1          101.0     2928                              2.21530
                     2929                              2.29196
                     2930                              2.29090
                     2931                              2.21800
                     2932                              2.30106
…                                                        …
24         109.0     2872015                           4.99466
                     2872016                           5.02764
```

```
                    2872017                             5.06409
                    2872018                             5.13914
                    2872019                             5.00812

                               IMU_hand_acceleration_scale16g_2  \
activityID SubjectID
1          101.0    2928                                8.27915
                    2929                                7.67288
                    2930                                7.14240
                    2931                                7.14365
                    2932                                7.25857
…                                                         …
24         109.0    2872015                             6.01881
                    2872016                             5.90369
                    2872017                             5.71370
                    2872018                             5.63724
                    2872019                             5.40645

                               IMU_hand_acceleration_scale16g_3  \
activityID SubjectID
1          101.0    2928                                5.58753
                    2929                                5.74467
                    2930                                5.82342
                    2931                                5.89930
                    2932                                6.09259
…                                                         …
24         109.0    2872015                             5.59830
                    2872016                             5.48372
                    2872017                             5.48491
                    2872018                             5.48629
                    2872019                             5.02326

                               IMU_hand_gyroscope_1  IMU_hand_gyroscope_2  \
activityID SubjectID
1          101.0    2928                  -0.004750              0.037579
                    2929                  -0.171710              0.025479
                    2930                  -0.238241              0.011214
                    2931                  -0.192912              0.019053
                    2932                  -0.069961             -0.018328
…                                             …                     …
24         109.0    2872015               -0.289166             -0.110170
                    2872016               -0.275411             -0.128358
                    2872017               -0.289885             -0.126548
                    2872018               -0.234417             -0.101485
                    2872019               -0.260924             -0.093849

                               IMU_hand_gyroscope_3  IMU_hand_magnetometer_1  \
```

```
activityID SubjectID
1          101.0     2928                -0.011145                8.93200
                     2929                -0.009538                9.58300
                     2930                 0.000831                9.05516
                     2931                 0.013374                9.92698
                     2932                 0.004582                9.15626
…                                            …                       …
24         109.0     2872015              0.238570               -4.79353
                     2872016              0.267409               -4.54101
                     2872017              0.281483               -4.17401
                     2872018              0.275497               -4.66091
                     2872019              0.266205               -5.05008

                               …  mean_ankle_acceleration  \
activityID SubjectID           …
1          101.0     2928      …                 2.662032
                     2929      …                 2.597479
                     2930      …                 2.571709
                     2931      …                 2.636982
                     2932      …                 2.661912
…                             …                     …
24         109.0     2872015   …                 1.634507
                     2872016   …                 1.583083
                     2872017   …                 1.595727
                     2872018   …                 1.647030
                     2872019   …                 1.660640

                               mean_chest_acceleration  mean_hand_gyroscope  \
activityID SubjectID
1          101.0     2928                     2.707567             0.007228
                     2929                     2.733360            -0.051923
                     2930                     2.703949            -0.075399
                     2931                     2.744582            -0.053495
                     2932                     2.796648            -0.027902
…                                                 …                    …
24         109.0     2872015                  2.304086            -0.053589
                     2872016                  2.253289            -0.045453
                     2872017                  2.316360            -0.044983
                     2872018                  2.314066            -0.020135
                     2872019                  2.355183            -0.029522

                               mean_ankle_gyroscope  mean_chest_gyroscope  \
activityID SubjectID
1          101.0     2928                 -0.007684              0.000145
                     2929                  0.009278             -0.021601
                     2930                 -0.030899             -0.003142
                     2931                 -0.008136             -0.035405
```

```
                    2932                 -0.017951           -0.017464
…                                            …                  …
24          109.0   2872015               0.004761           -0.072864
                    2872016               0.003369           -0.061935
                    2872017              -0.018141           -0.017922
                    2872018              -0.023868           -0.011660
                    2872019              -0.008425           -0.011241

                              mean_hand_magnetometer  mean_ankle_magnetometer  \
activityID SubjectID
1          101.0    2928                   -26.325367               -52.113767
                    2929                   -26.428167               -51.858967
                    2930                   -25.951613               -51.578933
                    2931                   -26.023973               -51.915767
                    2932                   -26.037313               -51.737067
…                                               …                        …
24         109.0    2872015                -23.730043               -15.595791
                    2872016                -23.828237               -15.437418
                    2872017                -23.496437               -15.400991
                    2872018                -23.992003               -15.264915
                    2872019                -23.602593               -15.765504

                              mean_chest_magnetometer  activityID  \
activityID SubjectID
1          101.0    2928                    -1.962178           1
                    2929                    -2.020103           1
                    2930                    -2.079840           1
                    2931                    -2.057705           1
                    2932                    -2.441961           1
…                                                …         …
24         109.0    2872015                  3.486200          24
                    2872016                  3.469400          24
                    2872017                  3.687233          24
                    2872018                  3.214000          24
                    2872019                  3.385633          24

                              exercise_intensity
activityID SubjectID
1          101.0    2928                 Resting
                    2929                 Resting
                    2930                 Resting
                    2931                 Resting
                    2932                 Resting
…                                          …
24         109.0    2872015             Vigorous
                    2872016             Vigorous
                    2872017             Vigorous
```

```
                     2872018           Vigorous
                     2872019           Vigorous

[1921430 rows x 44 columns]
```

To further analyze what each subject goes through during each activity, I calculated the time difference between the first and the last timestamp for each activity. This means that our new data frame has the total time that each person took to perform each activity, in the column **time_difference**. It's important to note that this column has a similar structure to column **exercise_intensity**, in the sense that the value will be repeated per subject per activity since it is taking into account a large number of rows.

[23]:

```python
df_medias.reset_index(drop=True, inplace=True)
def calculo_time_diff(group):
    return group['timestamp'].max() - group['timestamp'].min()

time_diffs = df_medias.groupby(['SubjectID', 'activityID']).
 ↪apply(calculo_time_diff).reset_index()
time_diffs.rename(columns={0: 'time_difference'}, inplace=True)

df_medias = pd.merge(df_medias, time_diffs, on=['SubjectID', 'activityID'],␣
 ↪how='left')
```

[24]:

```python
df_medias
```

[24]:

```
          timestamp    bpm  IMU_hand_temp  IMU_hand_acceleration_scale16g_1  \
0             37.66  100.0         30.375                           2.21530
1             37.67  100.0         30.375                           2.29196
2             37.68  100.0         30.375                           2.29090
3             37.69  100.0         30.375                           2.21800
4             37.70  100.0         30.375                           2.30106
…                 …      …              …                                 …
1921425       95.06  162.0         25.125                           4.99466
1921426       95.07  162.0         25.125                           5.02764
1921427       95.08  162.0         25.125                           5.06409
1921428       95.09  162.0         25.125                           5.13914
1921429       95.10  162.0         25.125                           5.00812

          IMU_hand_acceleration_scale16g_2  IMU_hand_acceleration_scale16g_3  \
0                                  8.27915                           5.58753
1                                  7.67288                           5.74467
2                                  7.14240                           5.82342
3                                  7.14365                           5.89930
4                                  7.25857                           6.09259
…                                        …                                 …
1921425                            6.01881                           5.59830
1921426                            5.90369                           5.48372
1921427                            5.71370                           5.48491
```

```
1921428                           5.63724                                  5.48629
1921429                           5.40645                                  5.02326

         IMU_hand_gyroscope_1  IMU_hand_gyroscope_2  IMU_hand_gyroscope_3  \
0                   -0.004750              0.037579             -0.011145
1                   -0.171710              0.025479             -0.009538
2                   -0.238241              0.011214              0.000831
3                   -0.192912              0.019053              0.013374
4                   -0.069961             -0.018328              0.004582
…                       …                     …                    …
1921425             -0.289166             -0.110170              0.238570
1921426             -0.275411             -0.128358              0.267409
1921427             -0.289885             -0.126548              0.281483
1921428             -0.234417             -0.101485              0.275497
1921429             -0.260924             -0.093849              0.266205

         IMU_hand_magnetometer_1  …  mean_chest_acceleration  \
0                        8.93200  …                 2.707567
1                        9.58300  …                 2.733360
2                        9.05516  …                 2.703949
3                        9.92698  …                 2.744582
4                        9.15626  …                 2.796648
…                            …   …                    …
1921425                 -4.79353  …                 2.304086
1921426                 -4.54101  …                 2.253289
1921427                 -4.17401  …                 2.316360
1921428                 -4.66091  …                 2.314066
1921429                 -5.05008  …                 2.355183

         mean_hand_gyroscope  mean_ankle_gyroscope  mean_chest_gyroscope  \
0                   0.007228             -0.007684              0.000145
1                  -0.051923              0.009278             -0.021601
2                  -0.075399             -0.030899             -0.003142
3                  -0.053495             -0.008136             -0.035405
4                  -0.027902             -0.017951             -0.017464
…                       …                    …                    …
1921425            -0.053589              0.004761             -0.072864
1921426            -0.045453              0.003369             -0.061935
1921427            -0.044983             -0.018141             -0.017922
1921428            -0.020135             -0.023868             -0.011660
1921429            -0.029522             -0.008425             -0.011241

         mean_hand_magnetometer  mean_ankle_magnetometer  \
0                    -26.325367               -52.113767
1                    -26.428167               -51.858967
2                    -25.951613               -51.578933
3                    -26.023973               -51.915767
```

```
4                    -26.037313          -51.737067
…                         …                   …
1921425              -23.730043          -15.595791
1921426              -23.828237          -15.437418
1921427              -23.496437          -15.400991
1921428              -23.992003          -15.264915
1921429              -23.602593          -15.765504

         mean_chest_magnetometer  activityID  exercise_intensity  \
0                      -1.962178           1             Resting
1                      -2.020103           1             Resting
2                      -2.079840           1             Resting
3                      -2.057705           1             Resting
4                      -2.441961           1             Resting
…                            …          …                  …
1921425                 3.486200          24            Vigorous
1921426                 3.469400          24            Vigorous
1921427                 3.687233          24            Vigorous
1921428                 3.214000          24            Vigorous
1921429                 3.385633          24            Vigorous

         time_difference
0                 271.86
1                 271.86
2                 271.86
3                 271.86
4                 271.86
…                    …
1921425            63.90
1921426            63.90
1921427            63.90
1921428            63.90
1921429            63.90

[1921430 rows x 45 columns]
```

Since these new columns were calculated using the original data, we must remove the original columns so that we are not duplicating the information. That is why this second data frame must not have the first measurements for hands, chest and ankles dedicated to acceleration, gyroscope and magnetometer, and it must also not have the **timestamp** column, since it has been replaced by the **time_difference** column.

[25]:
```
df_medias = df_medias.drop(['IMU_hand_acceleration_scale16g_1',
                            'IMU_hand_acceleration_scale16g_2',
                            'IMU_hand_acceleration_scale16g_3',
                            'IMU_ankle_acceleration_scale16g_1',
                            'IMU_ankle_acceleration_scale16g_2',
```

```
                             'IMU_ankle_acceleration_scale16g_3',
                             'IMU_chest_acceleration_scale16g_1',
                             'IMU_chest_acceleration_scale16g_2',
                             'IMU_chest_acceleration_scale16g_3',
                             'IMU_hand_gyroscope_1',
                             'IMU_hand_gyroscope_2',
                             'IMU_hand_gyroscope_3',
                             'IMU_ankle_gyroscope_1',
                             'IMU_ankle_gyroscope_2',
                             'IMU_ankle_gyroscope_3',
                             'IMU_chest_gyroscope_1',
                             'IMU_chest_gyroscope_2',
                             'IMU_chest_gyroscope_3',
                             'IMU_hand_magnetometer_1',
                             'IMU_hand_magnetometer_2',
                             'IMU_hand_magnetometer_3',
                             'IMU_ankle_magnetometer_1',
                             'IMU_ankle_magnetometer_2',
                             'IMU_ankle_magnetometer_3',
                             'IMU_chest_magnetometer_1',
                             'IMU_chest_magnetometer_2',
                             'IMU_chest_magnetometer_3',
                             'timestamp'
             ], axis=1)
```

As a result, we are left with a new data frame that has 1921430 entries and 17 columns.

[26]:
```
df_medias['activityID'] = df_medias['activityID'].astype(float)

df_medias.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1921430 entries, 0 to 1921429
Data columns (total 17 columns):
 #   Column                   Dtype
---  ------                   -----
 0   bpm                      float64
 1   IMU_hand_temp            float64
 2   IMU_chest_temp           float64
 3   IMU_ankle_temp           float64
 4   SubjectID                float64
 5   mean_hand_acceleration   float64
 6   mean_ankle_acceleration  float64
 7   mean_chest_acceleration  float64
 8   mean_hand_gyroscope      float64
 9   mean_ankle_gyroscope     float64
 10  mean_chest_gyroscope     float64
 11  mean_hand_magnetometer   float64
```

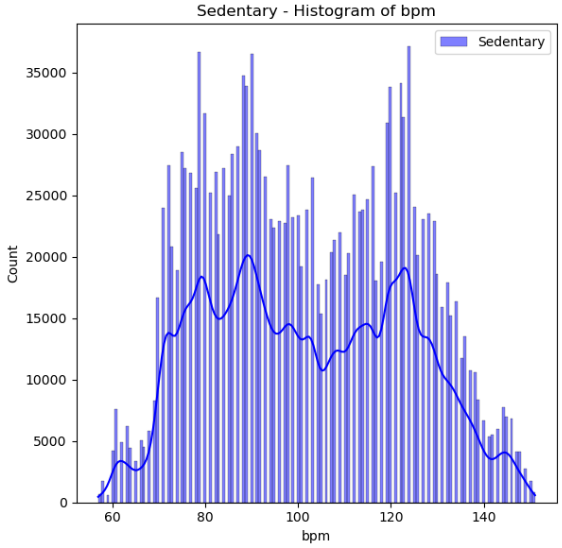
```
 12   mean_ankle_magnetometer   float64
 13   mean_chest_magnetometer   float64
 14   activityID                float64
 15   exercise_intensity        object
 16   time_difference           float64
dtypes: float64(16), object(1)
memory usage: 249.2+ MB
```

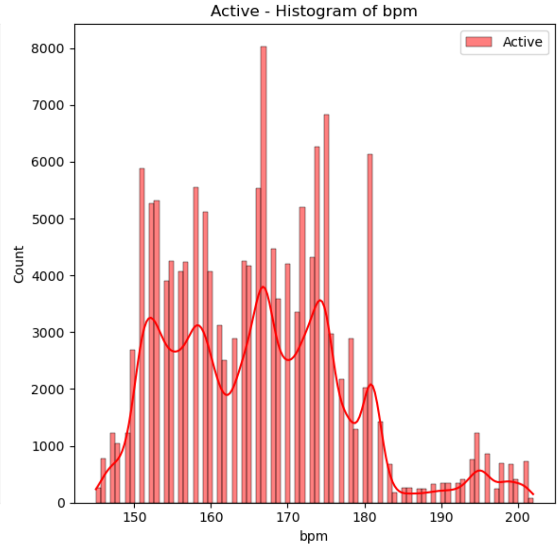
One thing we need to check before moving forward with the exploration is the distribution of the numerical columns because that will dictate the way we handle the data. To do that, I have used the column I created, **exercise_intensity**, to divide the data into **Sedentary** and **Active**.

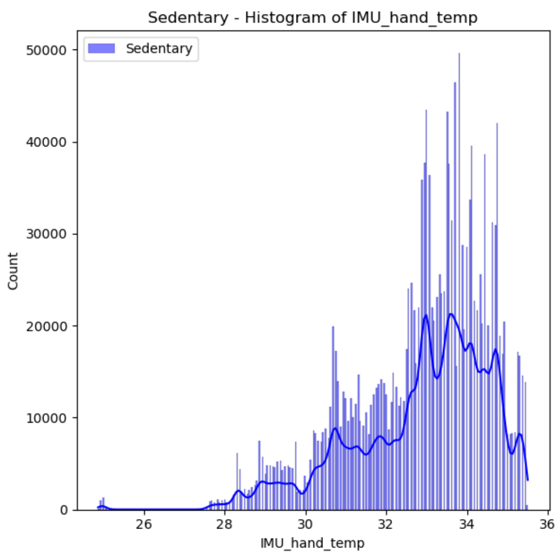
The following code shows the histoplots of every numerical column, comparing both data frames so that we can have a visual representation of each column. This approach will help us understand how the values of each numerical column differ between the Sedentary and Active activities.

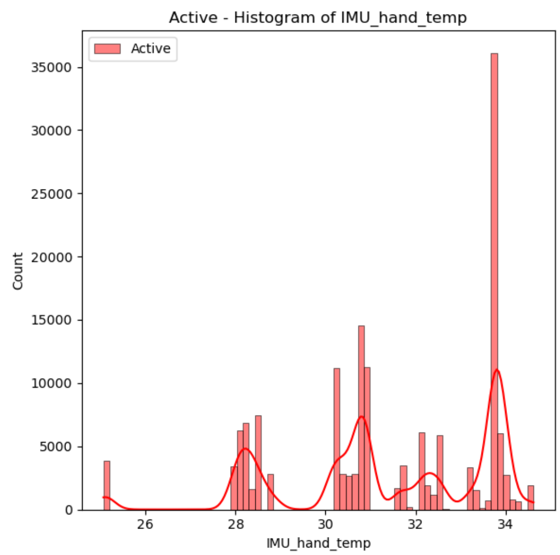
[27]:
```
sedentary_df = df_medias[(df_medias['exercise_intensity'] == 'Resting') |␣
 ↪(df_medias['exercise_intensity'] == 'Moderate')]
active_df = df_medias[(df_medias['exercise_intensity'] == 'Vigorous') |␣
 ↪(df_medias['exercise_intensity'] == 'Extreme')]
```

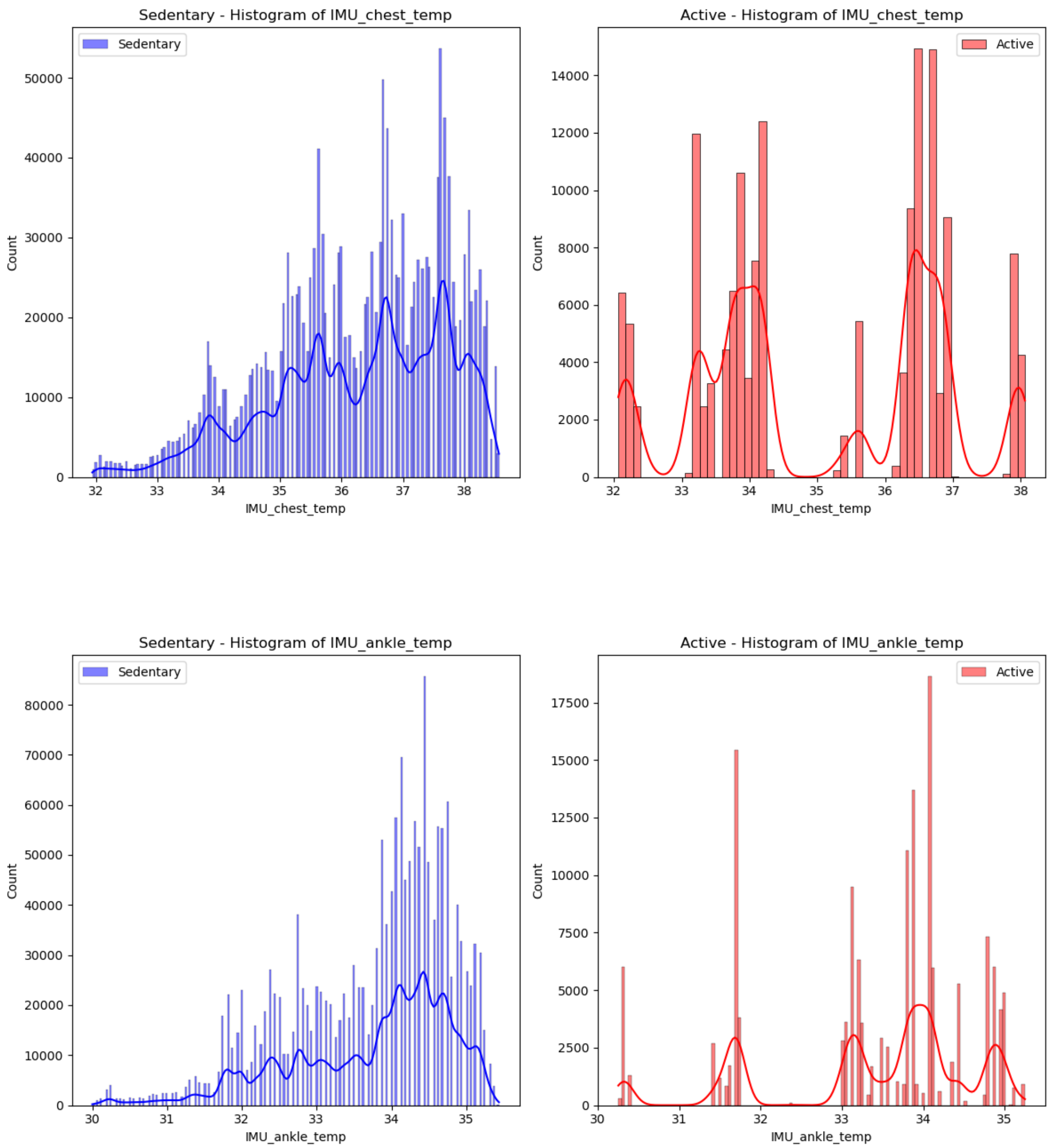
[28]:
```
numeric_cols = sedentary_df.select_dtypes(include=['float64', 'int64']).columns

for col in numeric_cols:
    plt.figure(figsize=(12, 6))

    plt.subplot(1, 2, 1)
    sns.histplot(sedentary_df[col], kde=True, color='blue', label='Sedentary')
    plt.title(f'Sedentary - Histogram of {col}')
    plt.legend()

    plt.subplot(1, 2, 2)
    sns.histplot(active_df[col], kde=True,color='red',label='Active')
    plt.title(f'Active - Histogram of {col}')
    plt.legend()

    plt.tight_layout()
    plt.show()
```

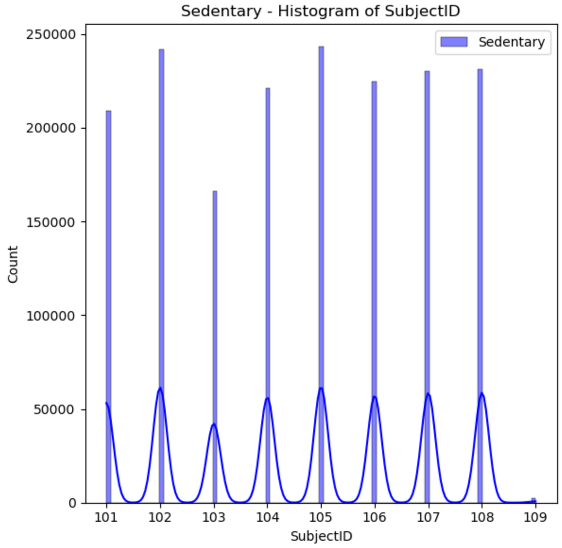

Sedentary - Histogram of bpm
Sedentary
Count
bpm

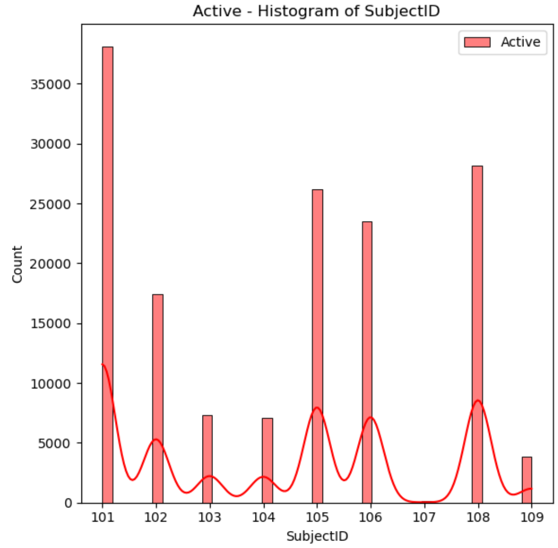

Active - Histogram of bpm
Active
Count
bpm

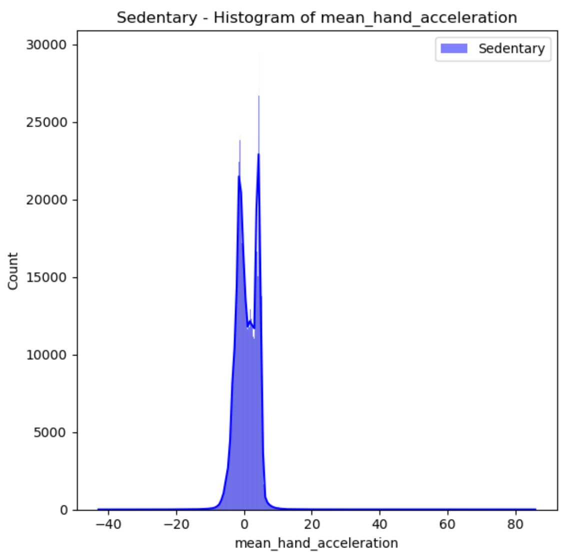

Sedentary - Histogram of IMU_hand_temp
Sedentary
Count
IMU_hand_temp

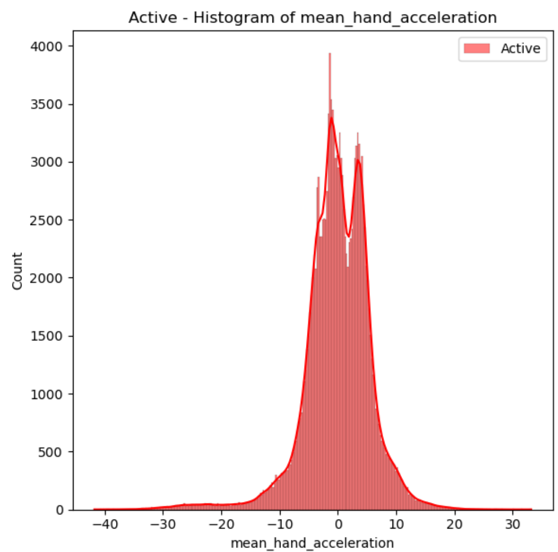

Active - Histogram of IMU_hand_temp
Active
Count
IMU_hand_temp

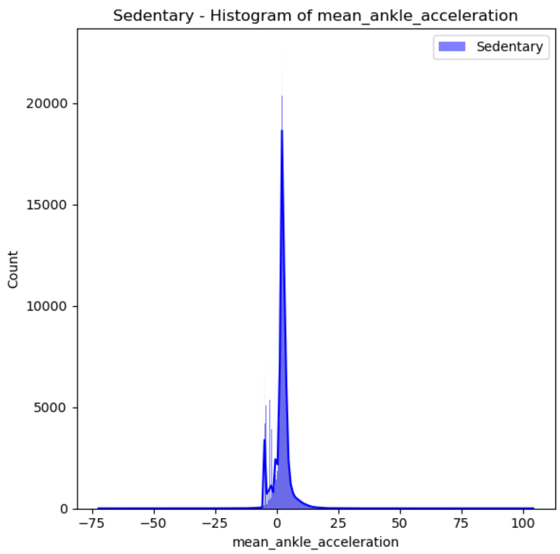
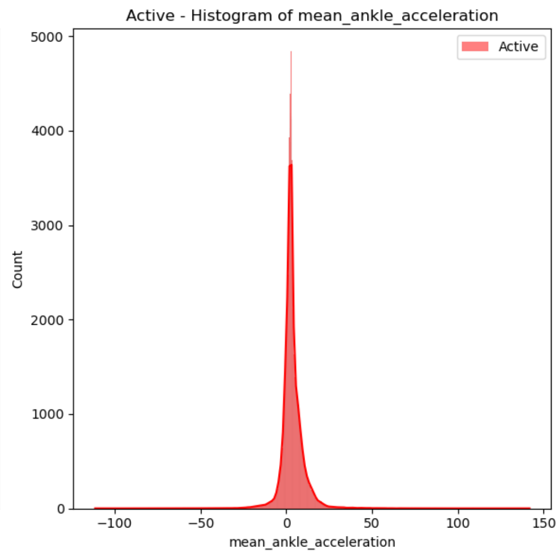
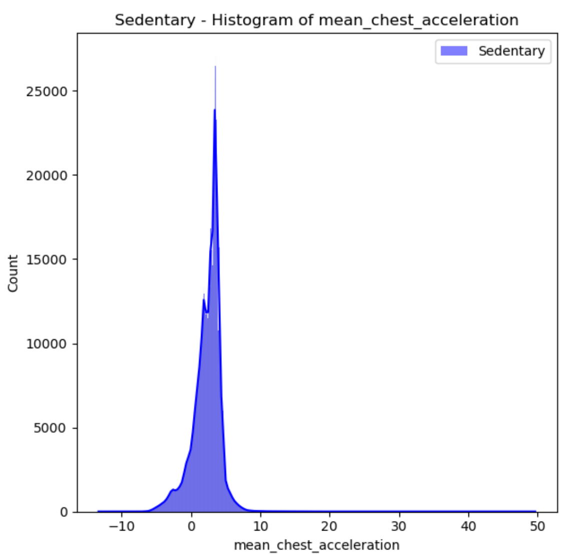
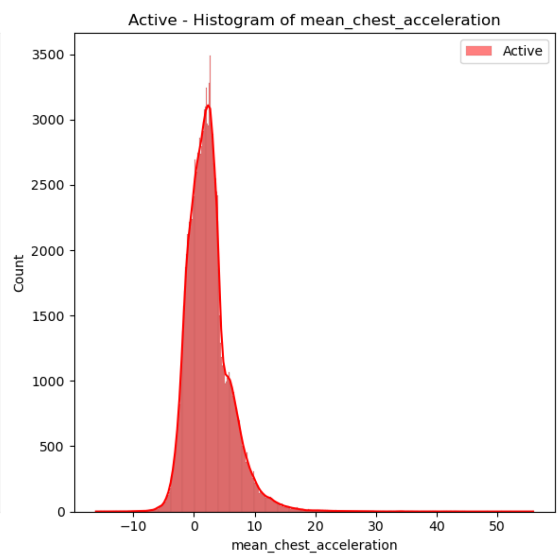

Sedentary - Histogram of IMU_chest_temp
Sedentary
Count
IMU_chest_temp
Active - Histogram of IMU_chest_temp
Active
Count
IMU_chest_temp
Sedentary - Histogram of IMU_ankle_temp
Sedentary
Count
IMU_ankle_temp
Active - Histogram of IMU_ankle_temp
Active
Count
IMU_ankle_temp

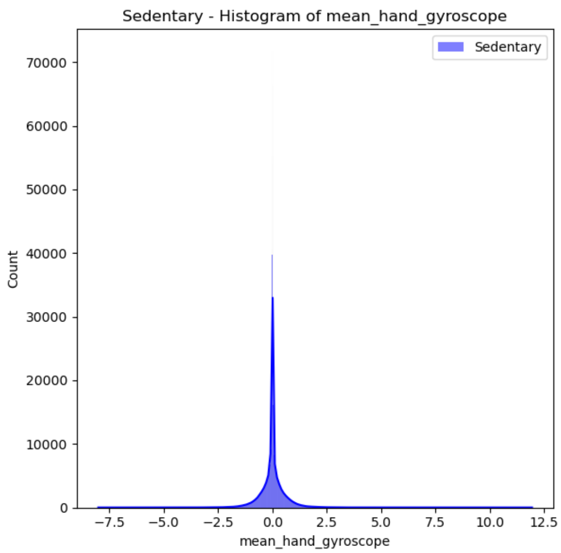

Sedentary - Histogram of SubjectID
Sedentary
Count
SubjectID
0
50000
100000
150000
200000
250000
101
102
103
104
105
106
107
108
109

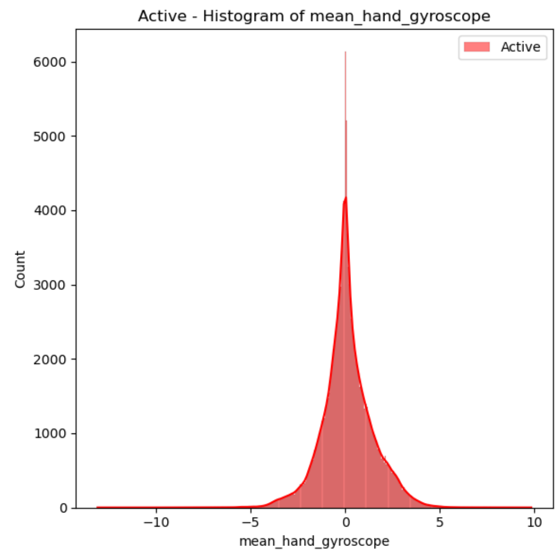

Active - Histogram of SubjectID
Active
Count
SubjectID
0
5000
10000
15000
20000
25000
30000
35000
101
102
103
104
105
106
107
108
109

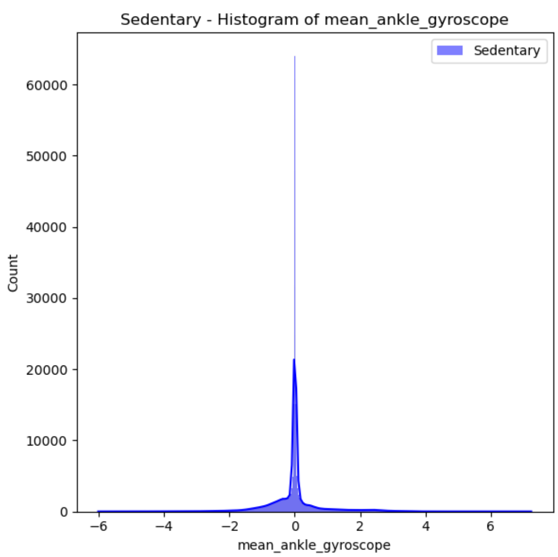

Sedentary - Histogram of mean_hand_acceleration
Sedentary
Count
mean_hand_acceleration
0
5000
10000
15000
20000
25000
30000
−40
−20
0
20
40
60
80

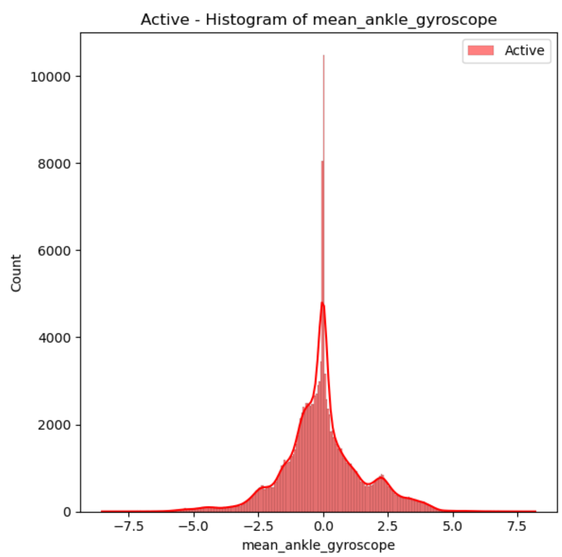

Active - Histogram of mean_hand_acceleration
Active
Count
mean_hand_acceleration
0
500
1000
1500
2000
2500
3000
3500
4000
−40
−30
−20
−10
0
10
20
30

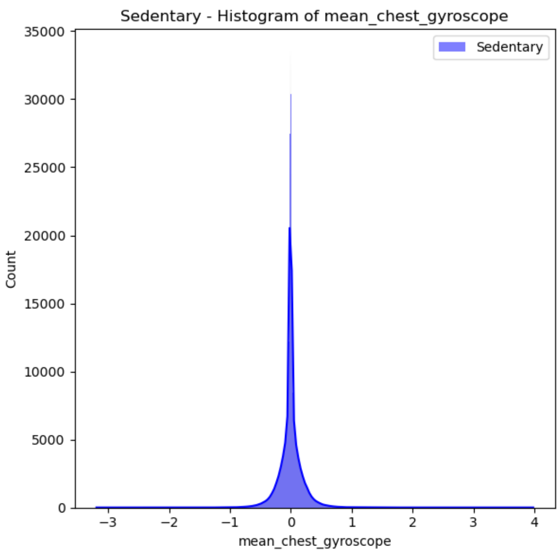

Sedentary - Histogram of mean_ankle_acceleration
Sedentary
Count
mean_ankle_acceleration

Active - Histogram of mean_ankle_acceleration
Active
Count
mean_ankle_acceleration

Sedentary - Histogram of mean_chest_acceleration
Sedentary
Count
mean_chest_acceleration

Active - Histogram of mean_chest_acceleration
Active
Count
mean_chest_acceleration

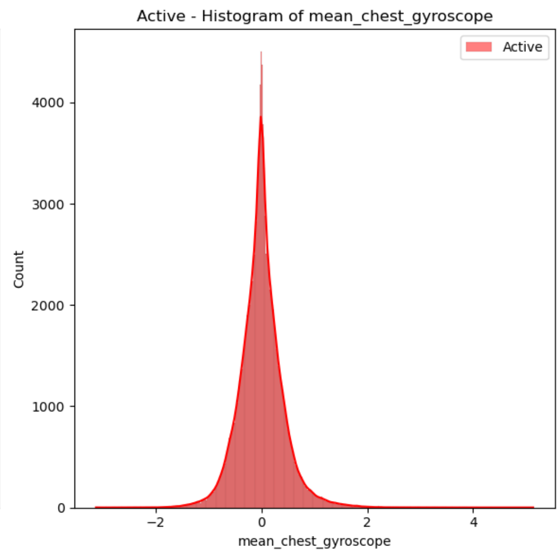

Sedentary - Histogram of mean_hand_gyroscope
Sedentary
Count
mean_hand_gyroscope
0
10000
20000
30000
40000
50000
60000
70000
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
12.5

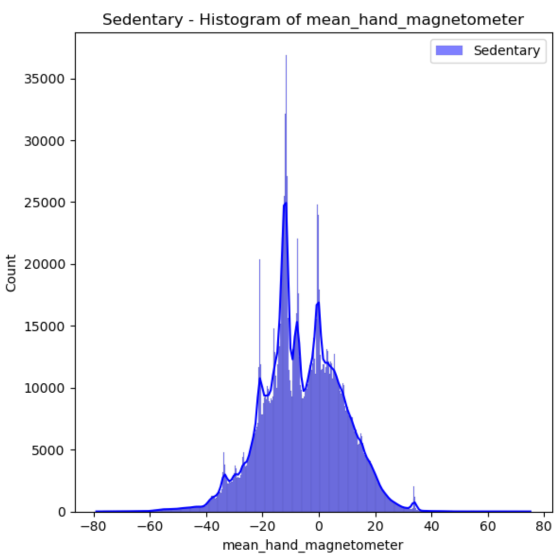

Active - Histogram of mean_hand_gyroscope
Active
Count
mean_hand_gyroscope
0
1000
2000
3000
4000
5000
6000
−10
−5
0
5
10

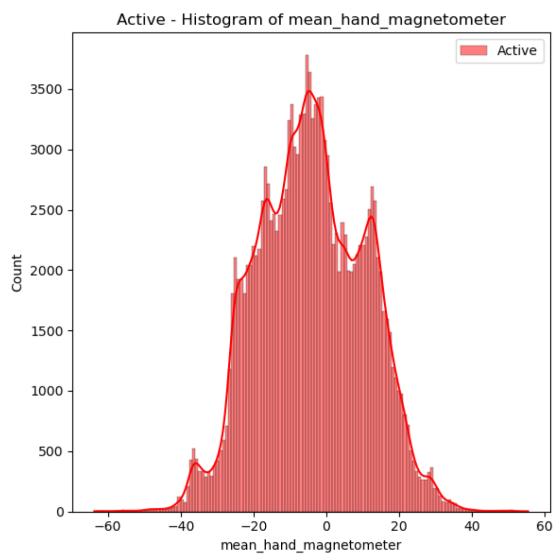

Sedentary - Histogram of mean_ankle_gyroscope
Sedentary
Count
mean_ankle_gyroscope
0
10000
20000
30000
40000
50000
60000
−6
−4
−2
0
2
4
6

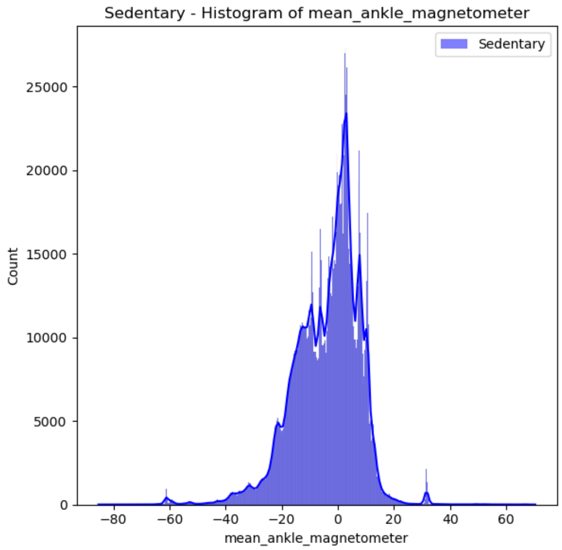

Active - Histogram of mean_ankle_gyroscope
Active
Count
mean_ankle_gyroscope
0
2000
4000
6000
8000
10000
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5

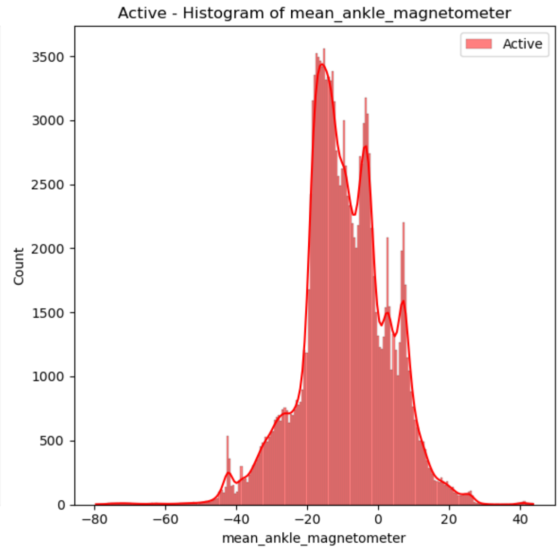

Sedentary - Histogram of mean_chest_gyroscope
Sedentary
Count
mean_chest_gyroscope
0
5000
10000
15000
20000
25000
30000
35000
−3
−2
−1
0
1
2
3
4

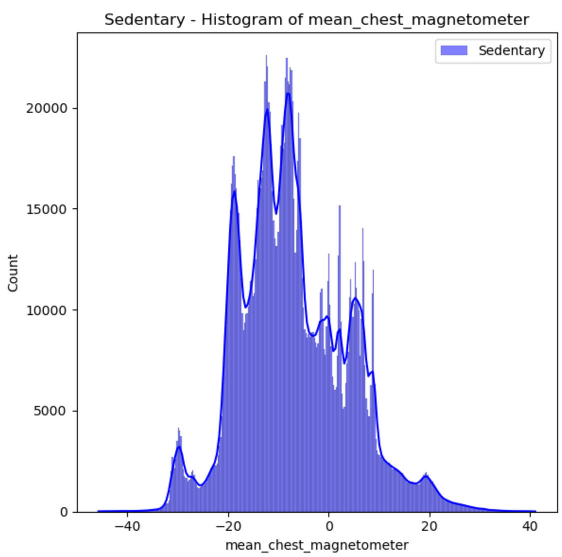

Active - Histogram of mean_chest_gyroscope
Active
Count
mean_chest_gyroscope
0
1000
2000
3000
4000
−2
0
2
4

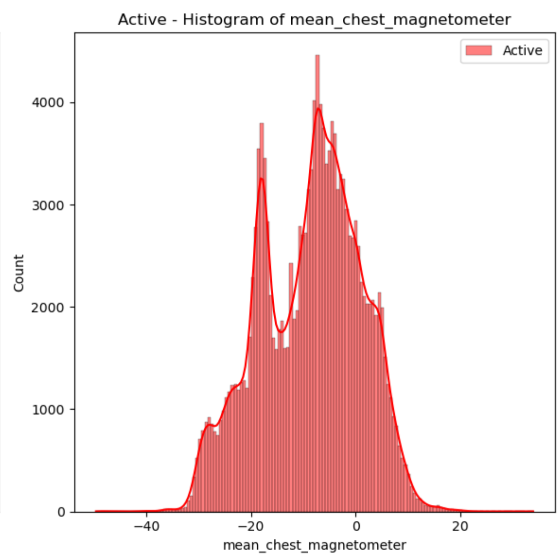

Sedentary - Histogram of mean_hand_magnetometer
Sedentary
Count
mean_hand_magnetometer
0
5000
10000
15000
20000
25000
30000
35000
−80
−60
−40
−20
0
20
40
60
80

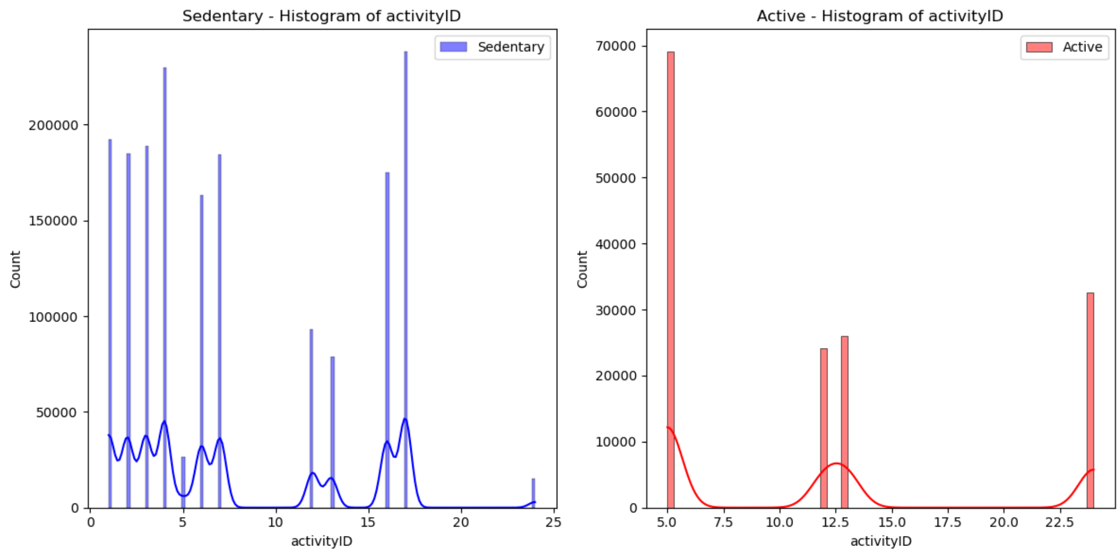

Active - Histogram of mean_hand_magnetometer
Active
Count
mean_hand_magnetometer
0
500
1000
1500
2000
2500
3000
3500
−60
−40
−20
0
20
40
60

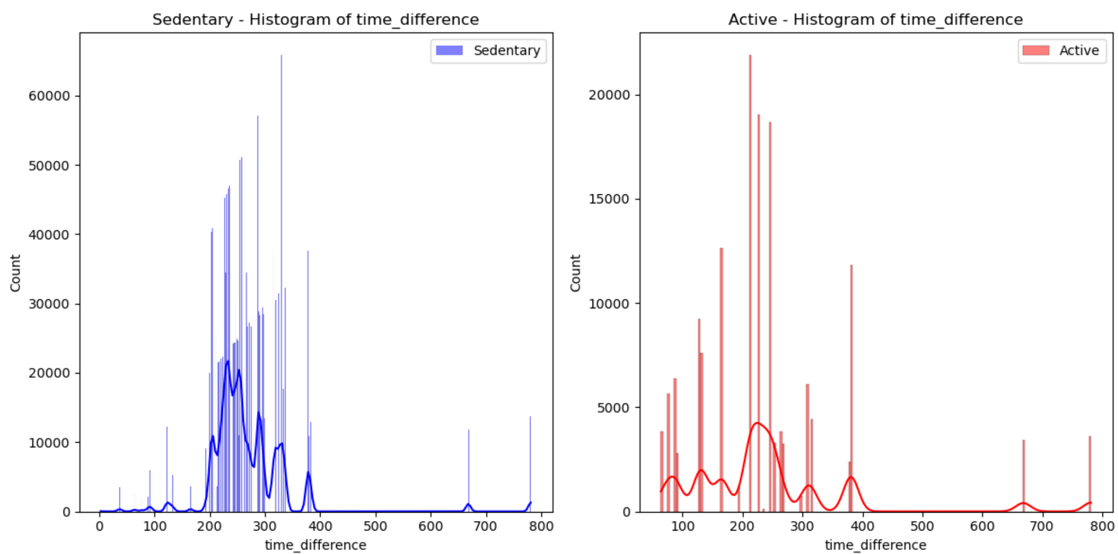

Sedentary - Histogram of mean_ankle_magnetometer
Sedentary
Count
0
5000
10000
15000
20000
25000
−80
−60
−40
−20
0
20
40
60
mean_ankle_magnetometer


Active - Histogram of mean_ankle_magnetometer
Active
Count
0
500
1000
1500
2000
2500
3000
3500
−80
−60
−40
−20
0
20
40
mean_ankle_magnetometer


Sedentary - Histogram of mean_chest_magnetometer
Sedentary
Count
0
5000
10000
15000
20000
−40
−20
0
20
40
mean_chest_magnetometer


Active - Histogram of mean_chest_magnetometer
Active
Count
0
1000
2000
3000
4000
−40
−20
0
20
mean_chest_magnetometer



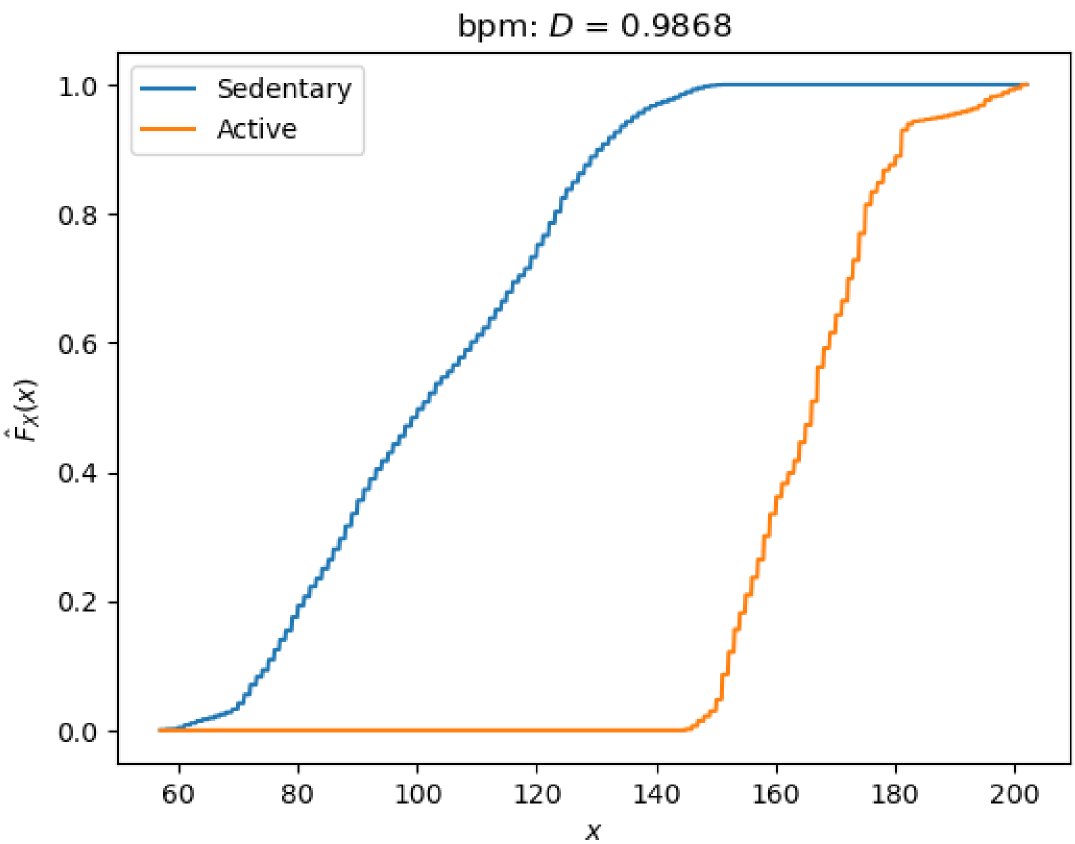


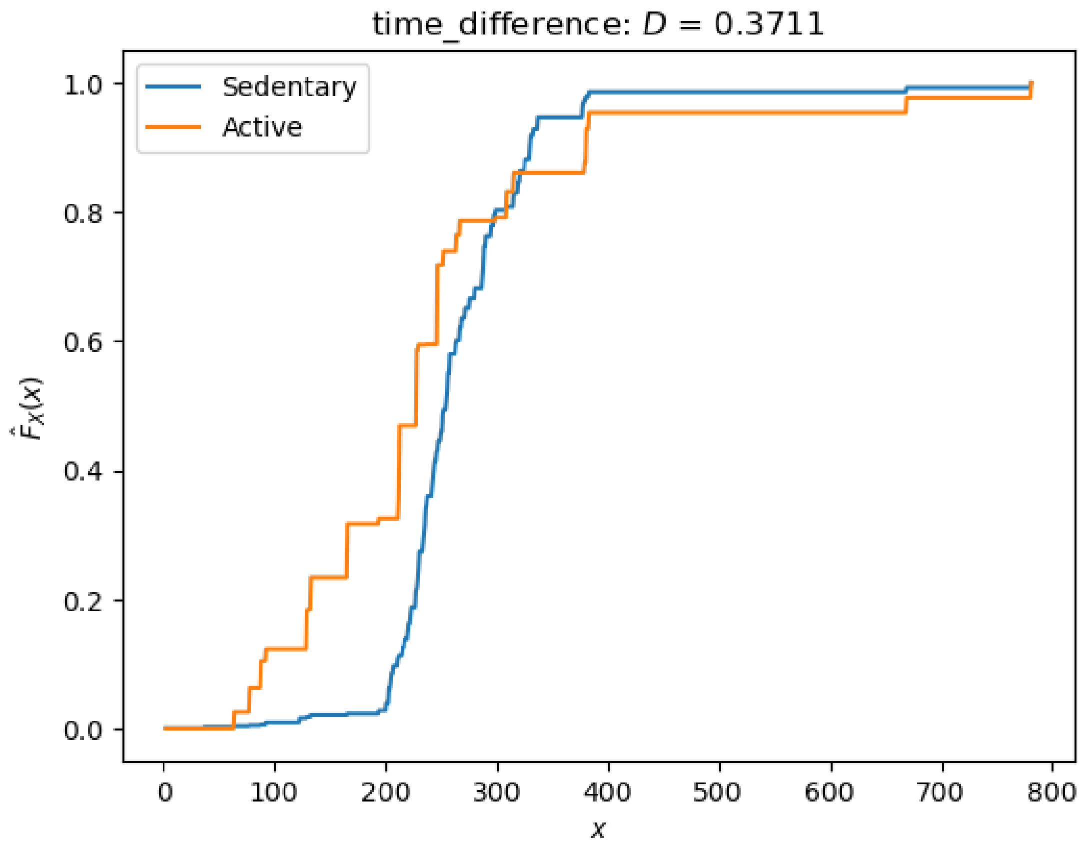
[29]:
```
cols = df_medias.columns
hist_plots = ["bpm","time_difference"]
bar_plots = [c for c in cols if (c not in hist_plots)]
```

As a following step, the code shows different ECDFs plots for the numerical features. These particular graphs are very good for interpreting differences in the behaviours of two sets of data. The further the two lines are apart from each other, the more significant the difference between the two groups is. The idea behind this analysis is that we will be able to focus our attention on specific features, according to how they behave in sedentary and active settings.

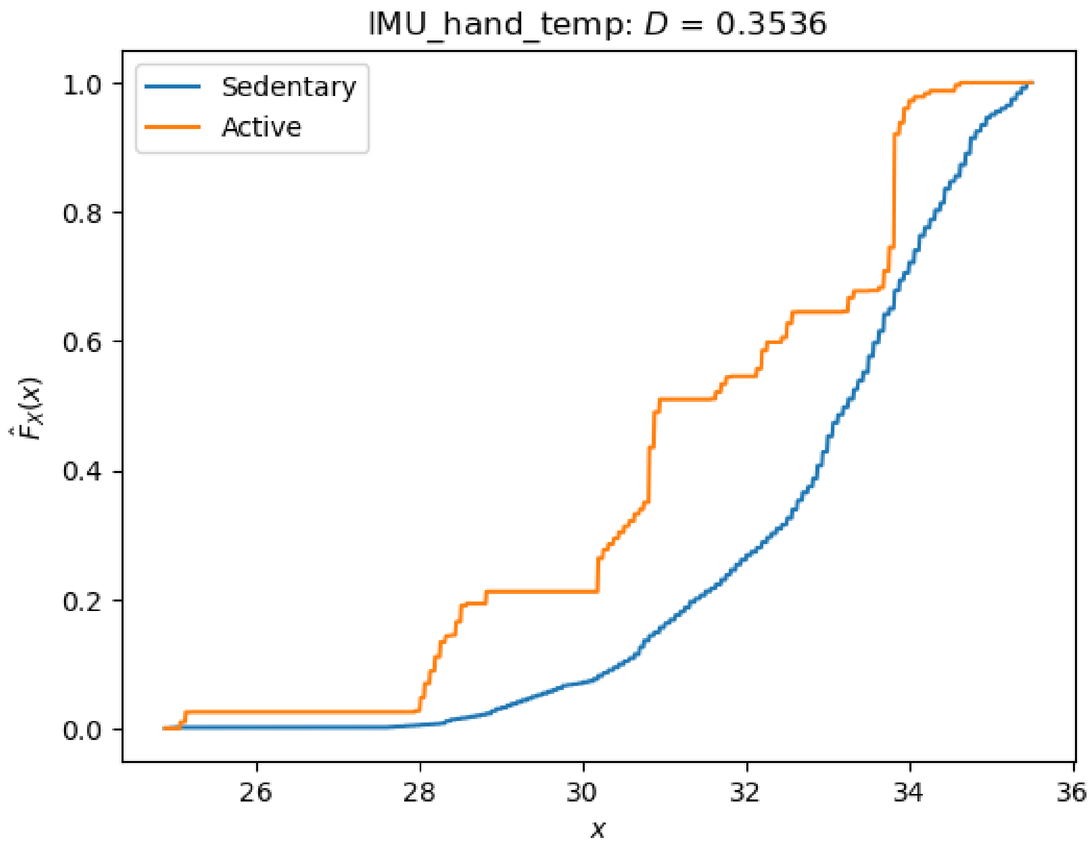
[30]:
```
#edited from Lab10 Solutions
from statsmodels.distributions.empirical_distribution import ECDF

numerical_cols = df_medias.select_dtypes(include=[np.number]).columns
bar_plots = [c for c in numerical_cols if c not in hist_plots]

def plot_ECDF(df_1, df_2, col, label_1, label_2, title=None):
    fig, ax = plt.subplots(nrows=1, ncols=1)

    values_1 = df_1[df_1[col].notna()][col].values
    values_2 = df_2[df_2[col].notna()][col].values

    if not values_1.size or not values_2.size:
        print(f"Skipping {col}: insufficient data")
        return

    if title is None:
        title = col

    ECDF_1 = ECDF(values_1)
    ECDF_2 = ECDF(values_2)
    xax = np.linspace(min(np.min(values_1),np.min(values_2)),max(np.
 ↪max(values_1),np.max(values_2)),1001)
    ax.plot(xax,ECDF_1(xax),label=label_1)
    ax.plot(xax,ECDF_2(xax),label=label_2)
    ax.legend(loc="best")

    D = np.max(np.abs(ECDF_2(xax) - ECDF_1(xax)))
    ax.set_title(fr"{title}: $D$ = {D:.4f}")
    ax.set_xlabel(r"$x$")
    ax.set_ylabel(r"$\hat{F}_{X}(x)$")
```

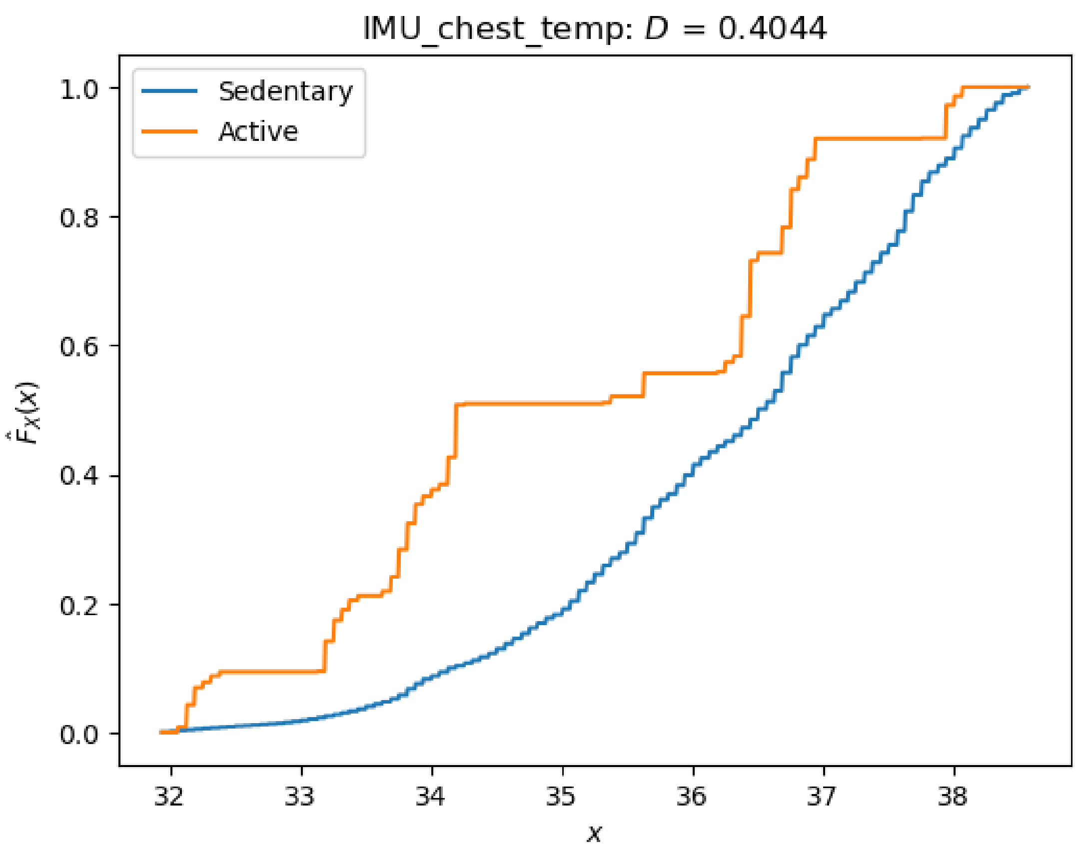
[31]:
```
for col in hist_plots + bar_plots:
    plot_ECDF(sedentary_df, active_df, col, "Sedentary", "Active")
```


bpm: D = 0.9868
Sedentary
Active
$\hat{F}_X(x)$
x
1.0
0.8
0.6
0.4
0.2
0.0
60
80
100
120
140
160
180
200

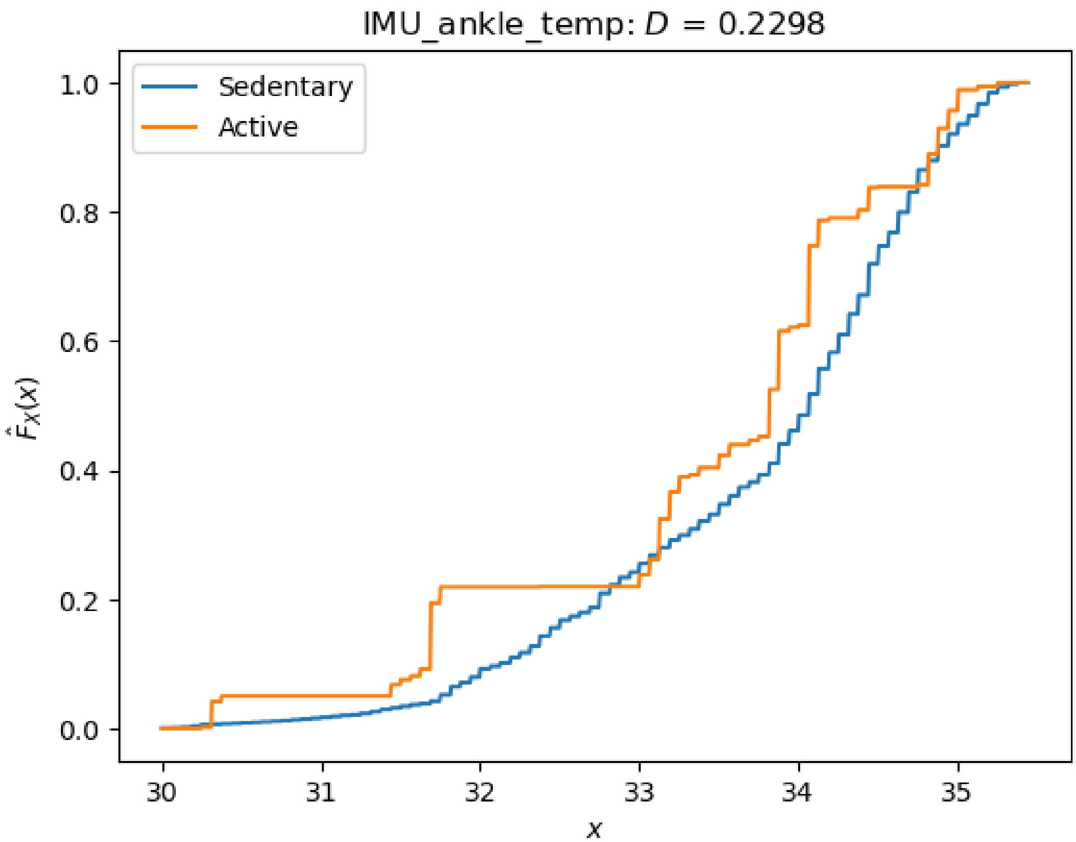


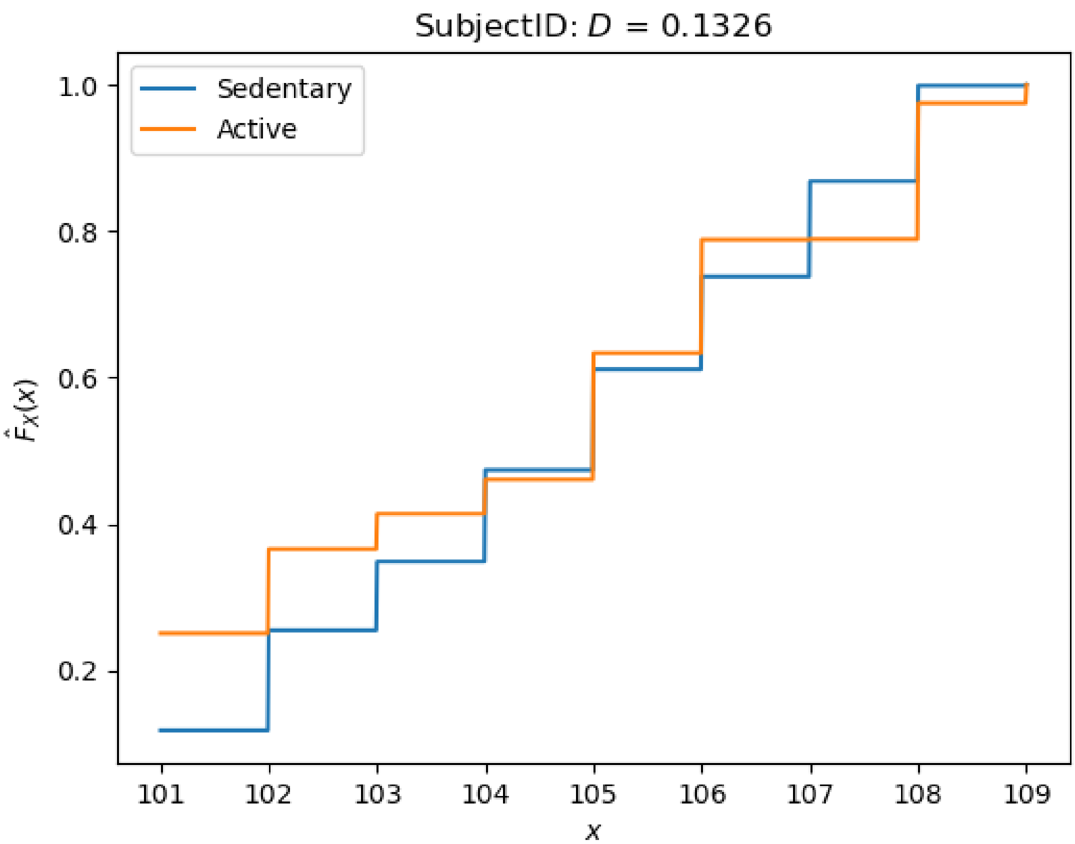
time_difference: D = 0.3711
Sedentary
Active
$\hat{F}_X(x)$
x
0.0
0.2
0.4
0.6
0.8
1.0
0
100
200
300
400
500
600
700
800

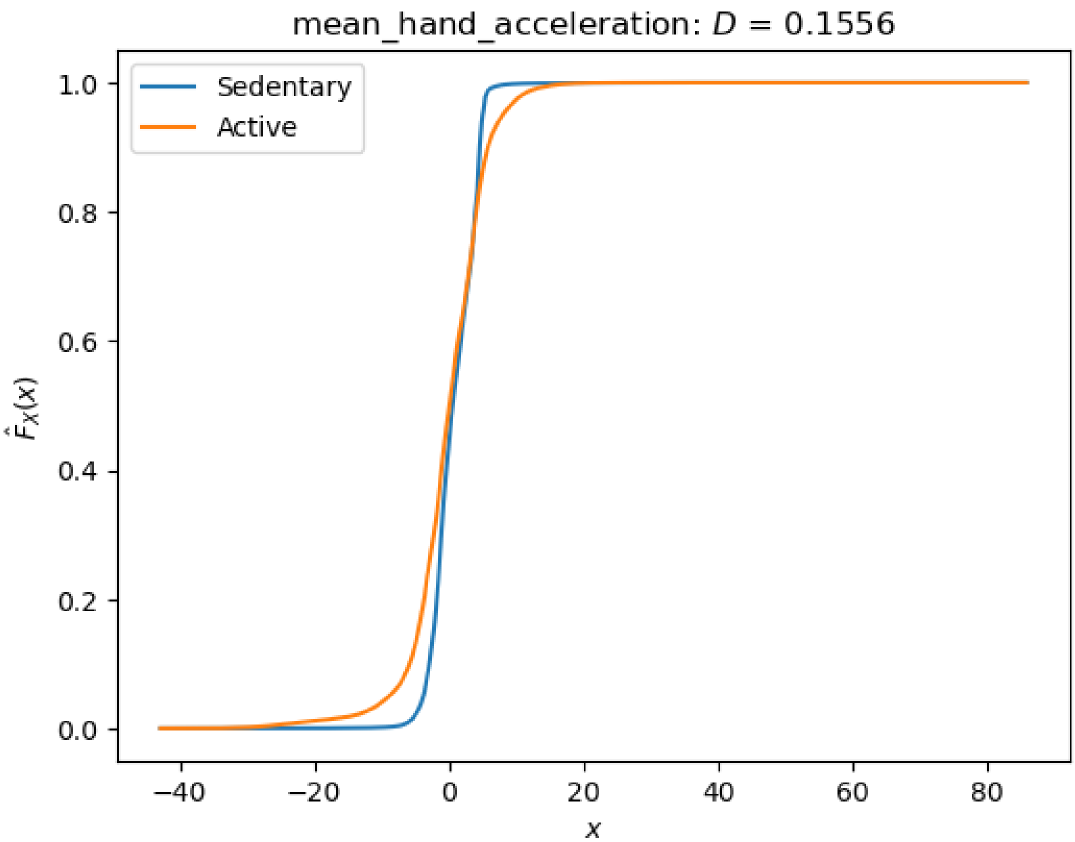

IMU_hand_temp: D = 0.3536
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
0.0
$\hat{F}_X(x)$
26
28
30
32
34
36
x

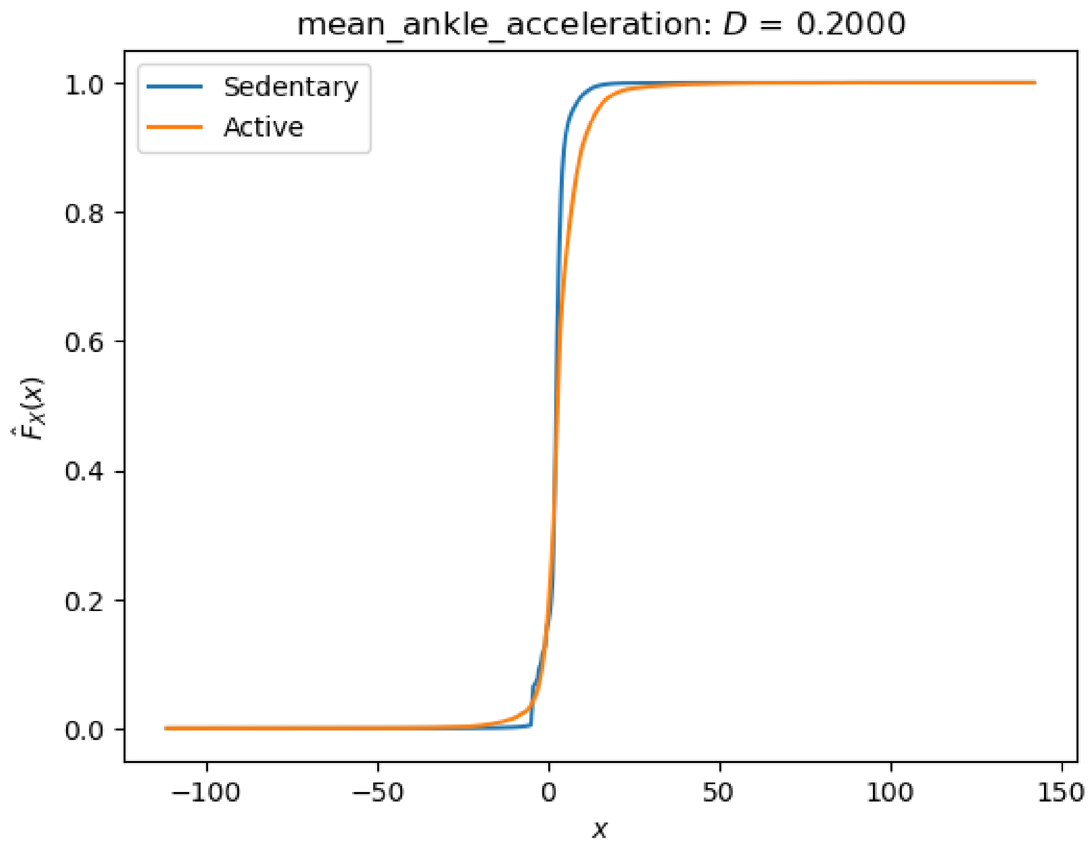


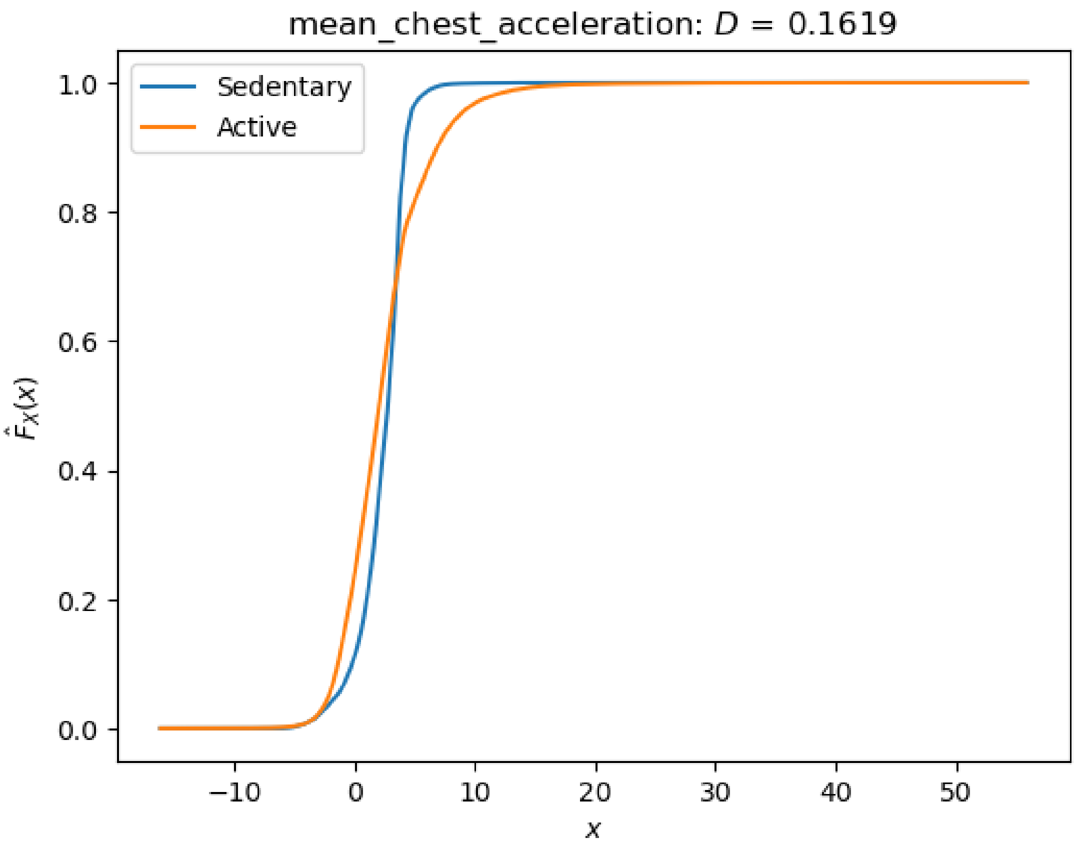
IMU_chest_temp: D = 0.4044
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
0.0
$\hat{F}_X(x)$
32
33
34
35
36
37
38
x


IMU_ankle_temp: D = 0.2298
Sedentary
Active
$\hat{F}_X(x)$
x
1.0
0.8
0.6
0.4
0.2
0.0
30
31
32
33
34
35

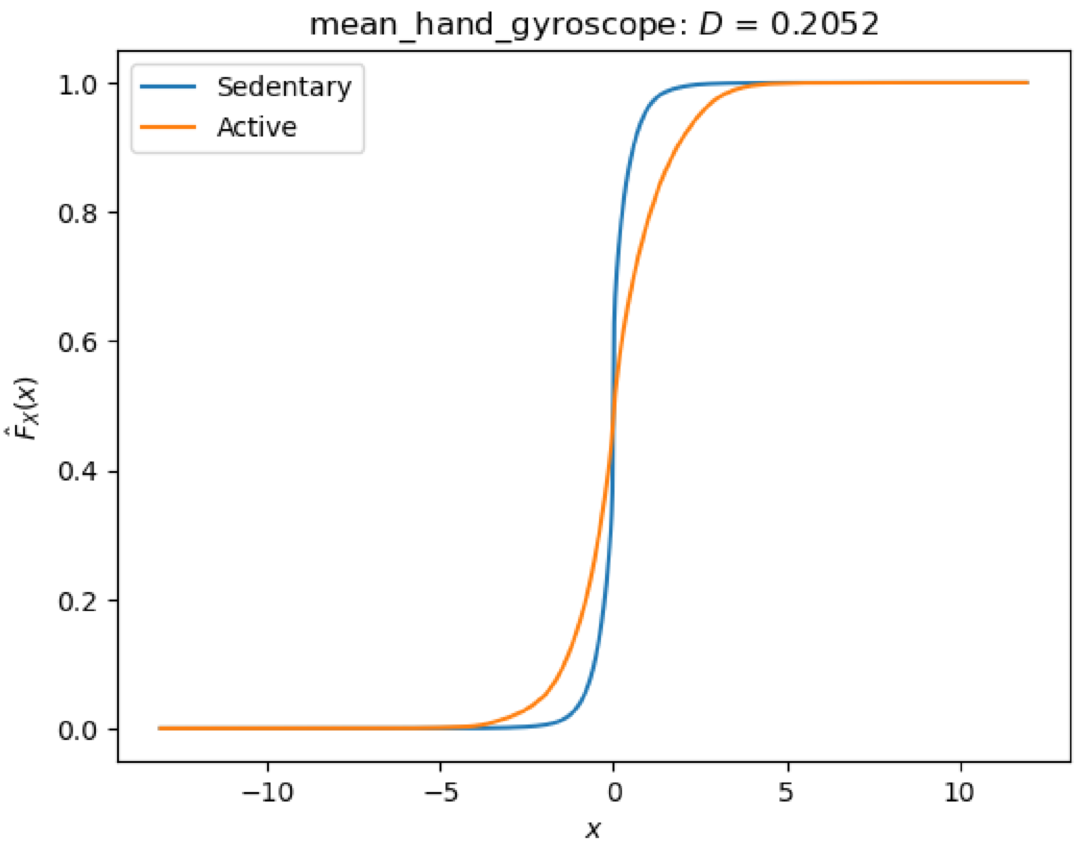

SubjectID: D = 0.1326
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
$\hat{F}_X(x)$
101
102
103
104
105
106
107
108
109
x

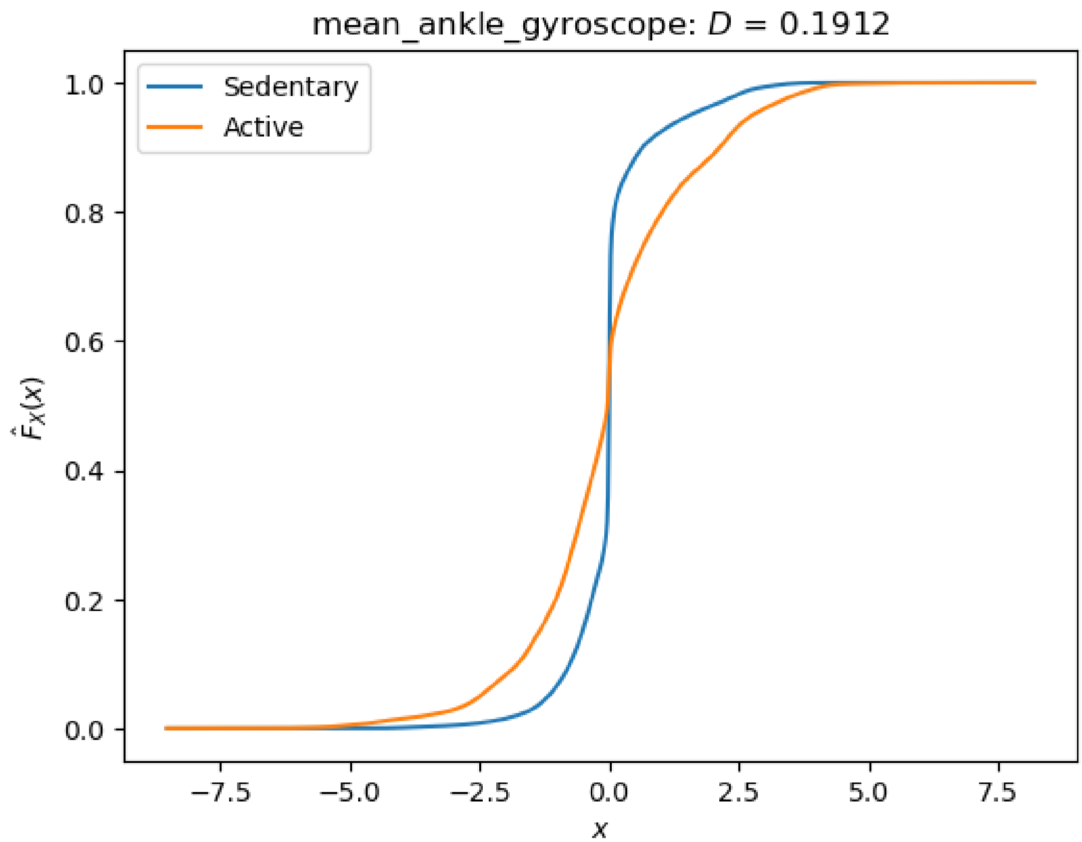

mean_hand_acceleration: D = 0.1556
Sedentary
Active
$\hat{F}_X(x)$
x
1.0
0.8
0.6
0.4
0.2
0.0
−40
−20
0
20
40
60
80

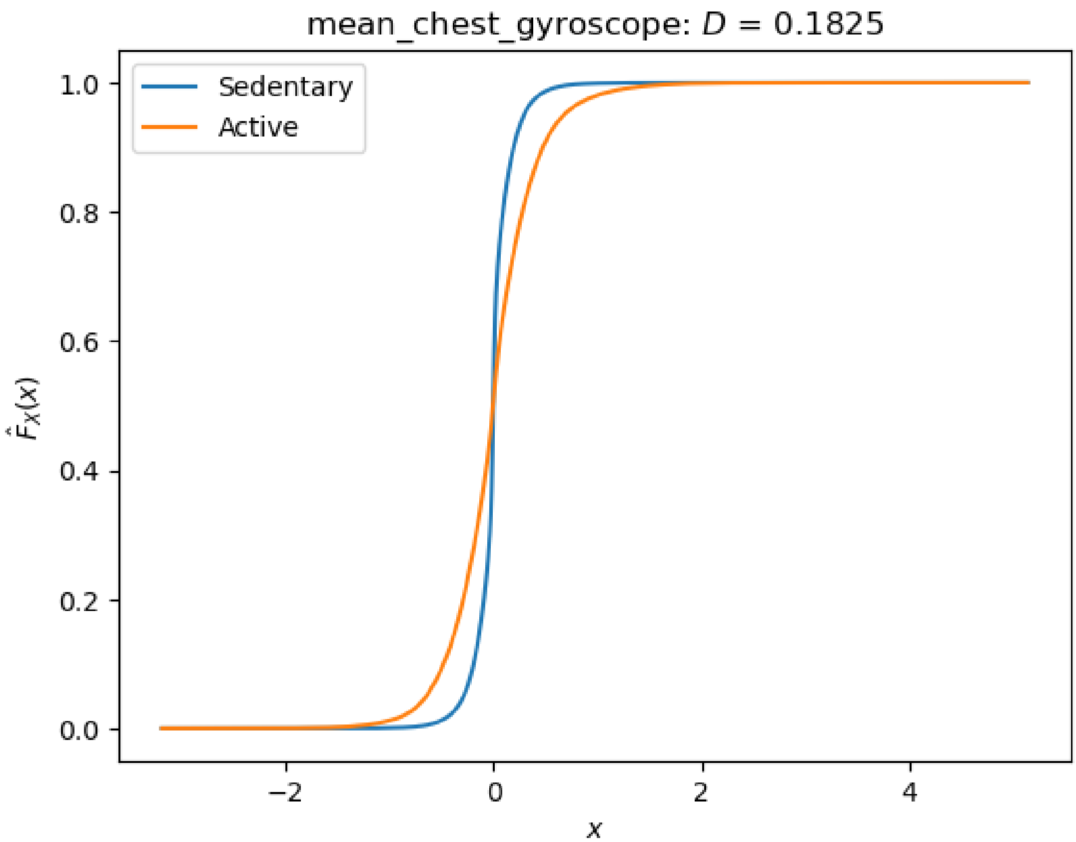

mean_ankle_acceleration: D = 0.2000
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
0.0
$\hat{F}_X(x)$
−100
−50
0
50
100
150
x

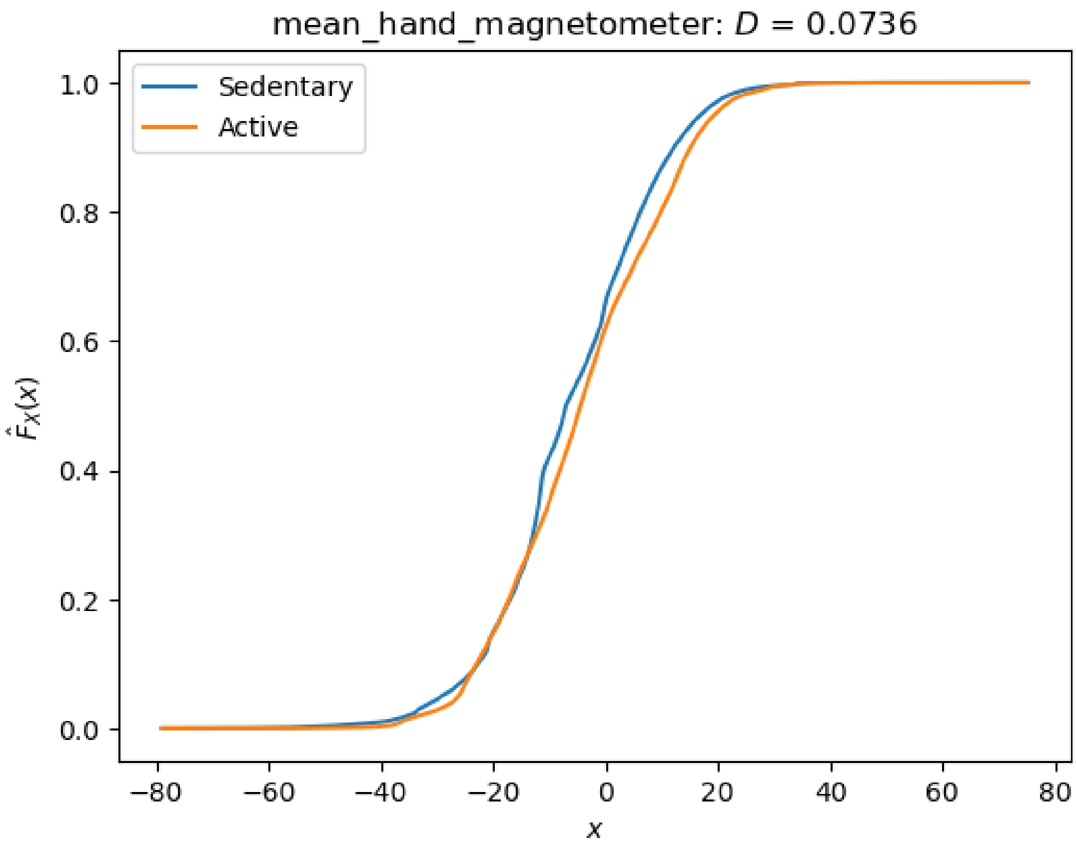


mean_chest_acceleration: D = 0.1619
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
0.0
$\hat{F}_X(x)$
−10
0
10
20
30
40
50
x

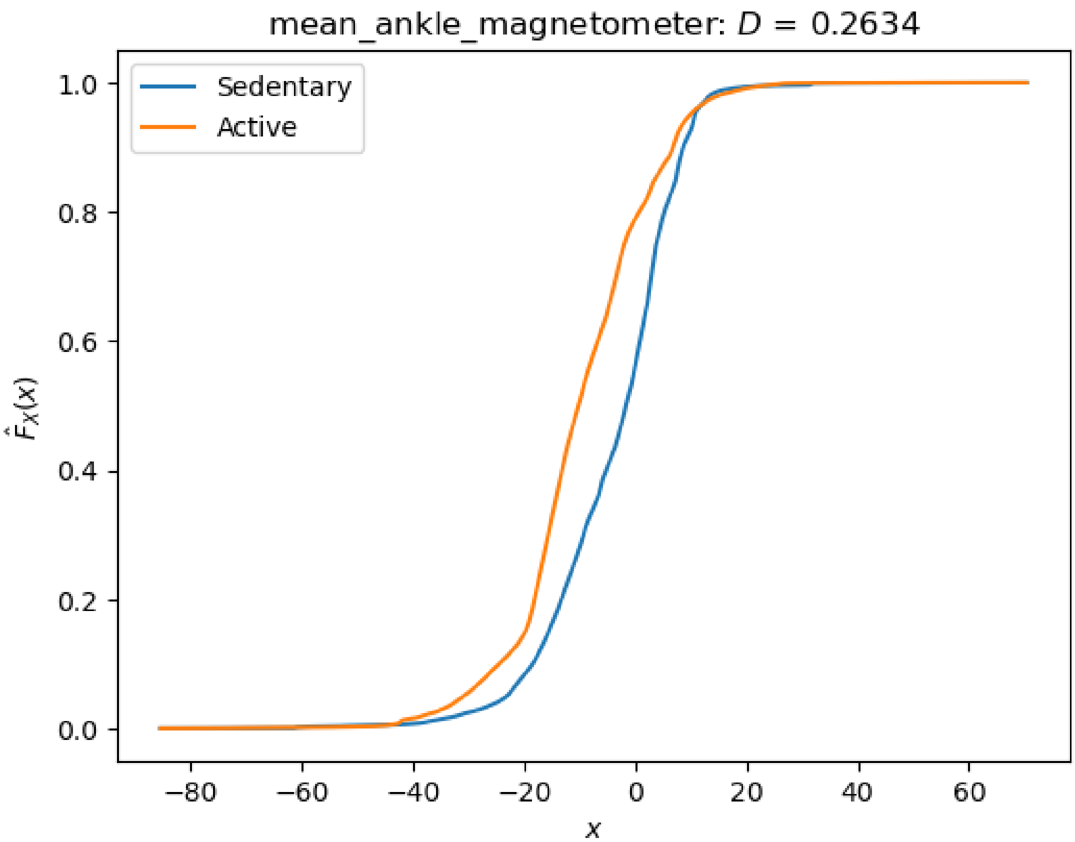

mean_hand_gyroscope: D = 0.2052
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
0.0
$\hat{F}_X(x)$
−10
−5
0
5
10
x

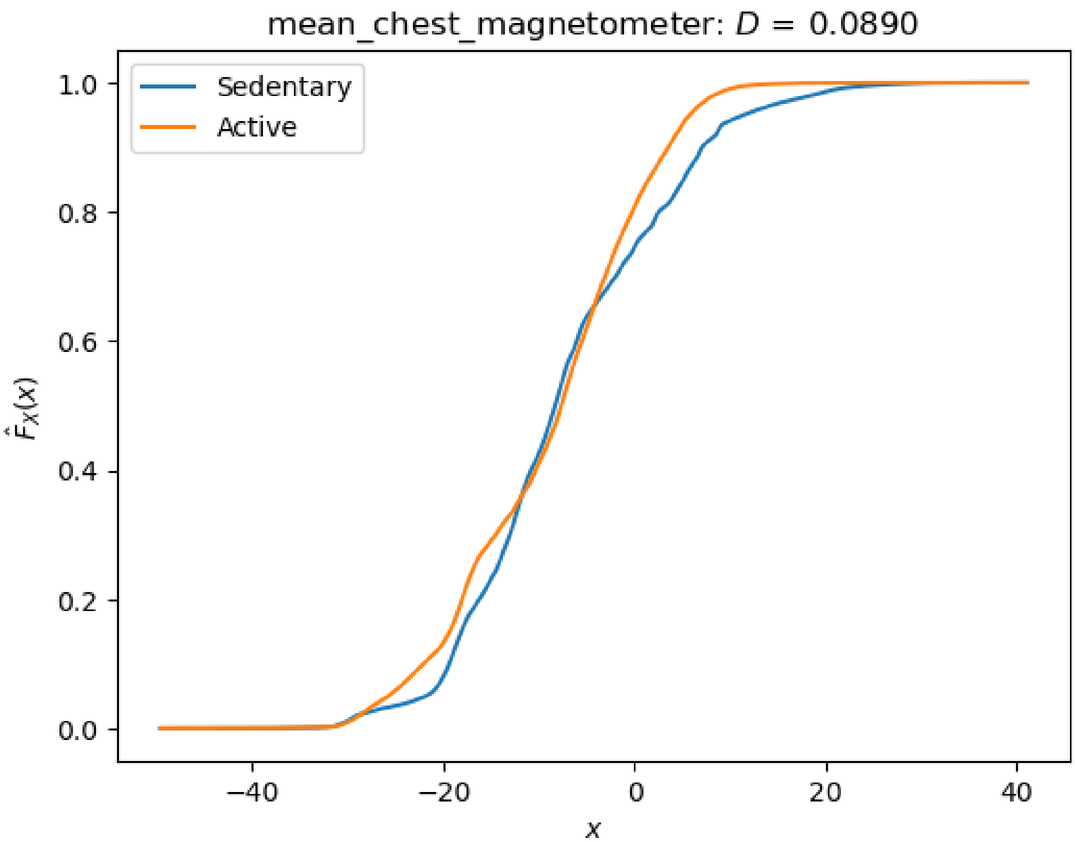

mean_ankle_gyroscope: D = 0.1912
Sedentary
Active
$\hat{F}_X(x)$
x
1.0
0.8
0.6
0.4
0.2
0.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5

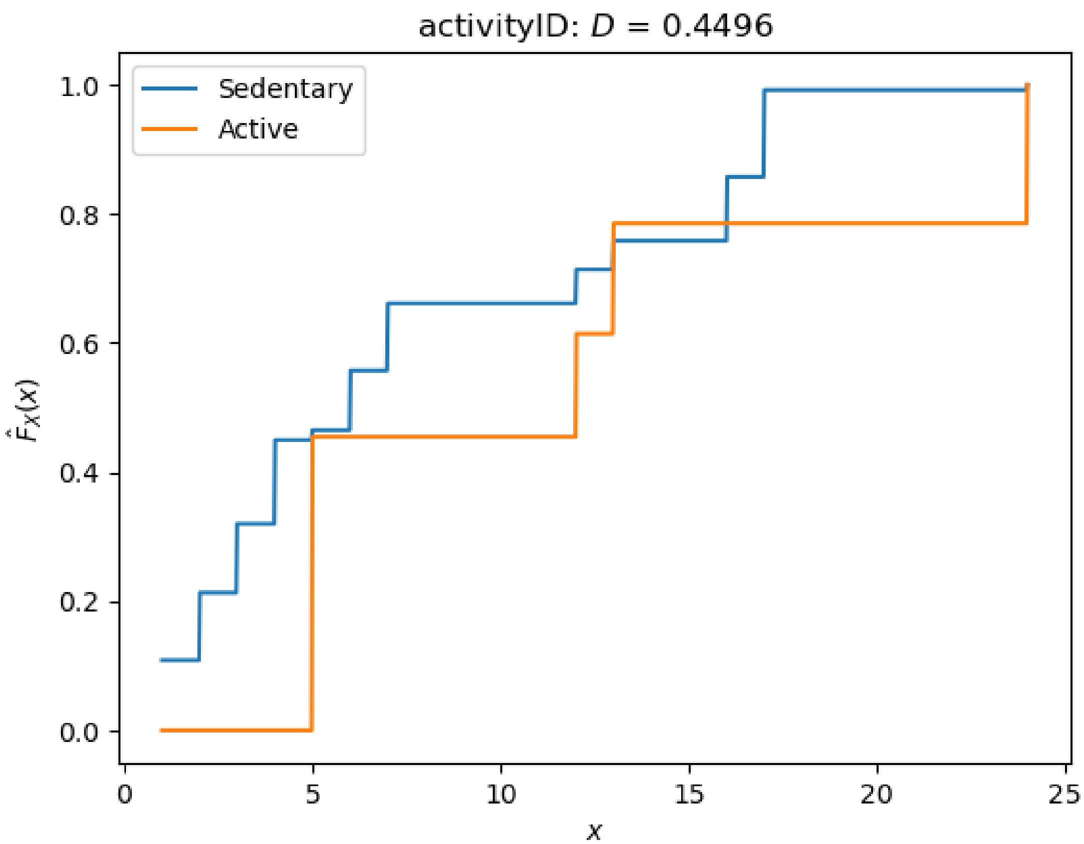

mean_chest_gyroscope: D = 0.1825
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
0.0
$\hat{F}_X(x)$
−2
0
2
4
x



mean_hand_magnetometer: D = 0.0736
Sedentary
Active
$\hat{F}_X(x)$
0.0
0.2
0.4
0.6
0.8
1.0
−80
−60
−40
−20
0
20
40
60
80
x


mean_ankle_magnetometer: D = 0.2634
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
0.0
$\hat{F}_X(x)$
−80
−60
−40
−20
0
20
40
60
x


mean_chest_magnetometer: D = 0.0890
Sedentary
Active
1.0
0.8
0.6
0.4
0.2
0.0
$\hat{F}_X(x)$
−40
−20
0
20
40
x

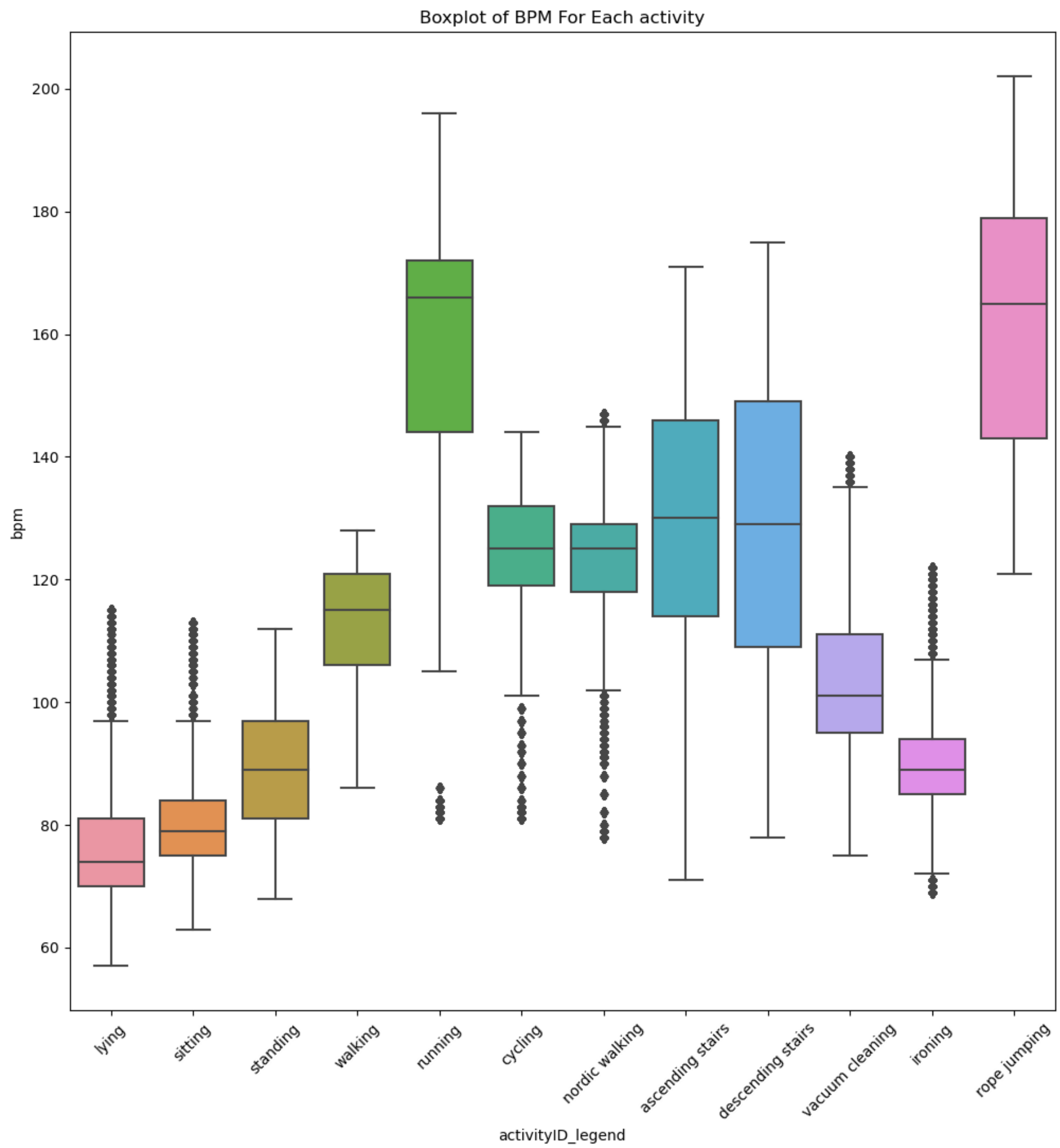


Following the values obtained in the ECDFs, we can see that **bpm** is the most significant feature that we need to focus on, because these readings for these two groups come from different distributions, indicating that active individuals have different heart rate characteristics compared to the sedentary individuals. Other features that have an interesting different behaviour are **time difference** and **chest temperature**, however, to continue this analysis I will be focusing only on heart rate and time difference.

[32]:
```
df_medias['activityID_legend'] = df_medias['activityID'].map(activity_dictonary)
```

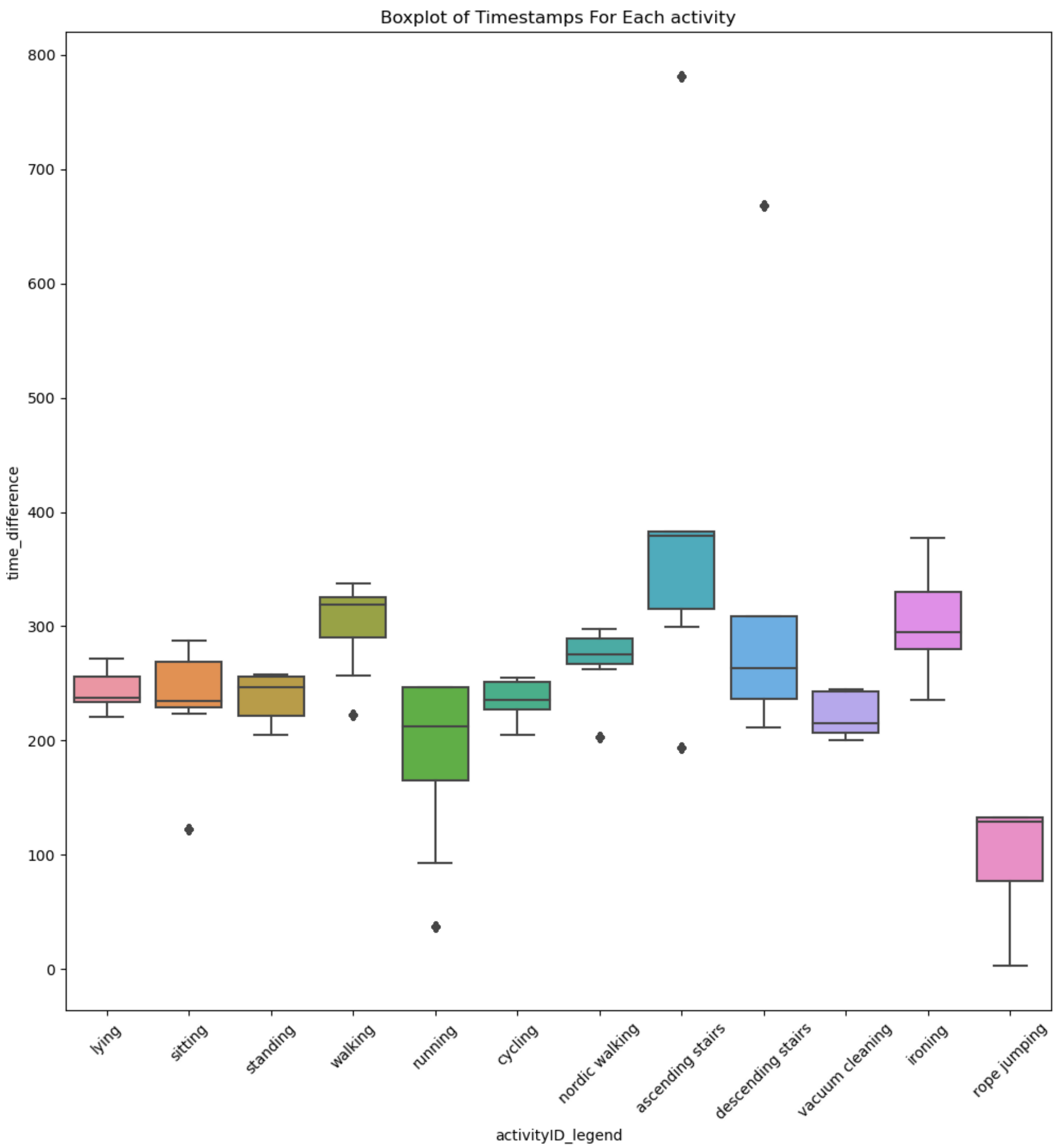
Since we are now going to be focusing on **bpm** and **time difference**, we need to take a look at their boxplots, regarding the activities. The reason behind this is that the data collector requested that the models and the possible improvements that we advise should be linked to the activities.

[33]:
```
plt.figure(figsize=(12,12))
sns.boxplot(x='activityID_legend',y='bpm',data=df_medias).set_title("Boxplot of␣
↪BPM For Each activity");
plt.xticks(rotation=45)
plt.show()
```



From the **bpm** boxplot, there are a few observations to be made. For instance, it is very clear to see that there are indicators that show that less vigorous activities carry lower heart rates. Another thing to point out is that there are some outliers, particularly in walking, standing and running. Outliers indicate that the data behaves differently in these points, meaning that some subjects have presented an abnormal value, in comparison to the rest, for these activities. Finally, the activities show different levels of variability, rope jumping and running have a wide IQR, suggesting a high variability among participants during these activities. Conversely, activities like lying and sitting have a much narrower IQR, suggesting less variability.

[34]:
```
plt.figure(figsize=(12,12))
sns.boxplot(x='activityID_legend',y='time_difference',data=df_medias).
    ↪set_title("Boxplot of Timestamps For Each activity");
plt.xticks(rotation=45)
plt.show()
```

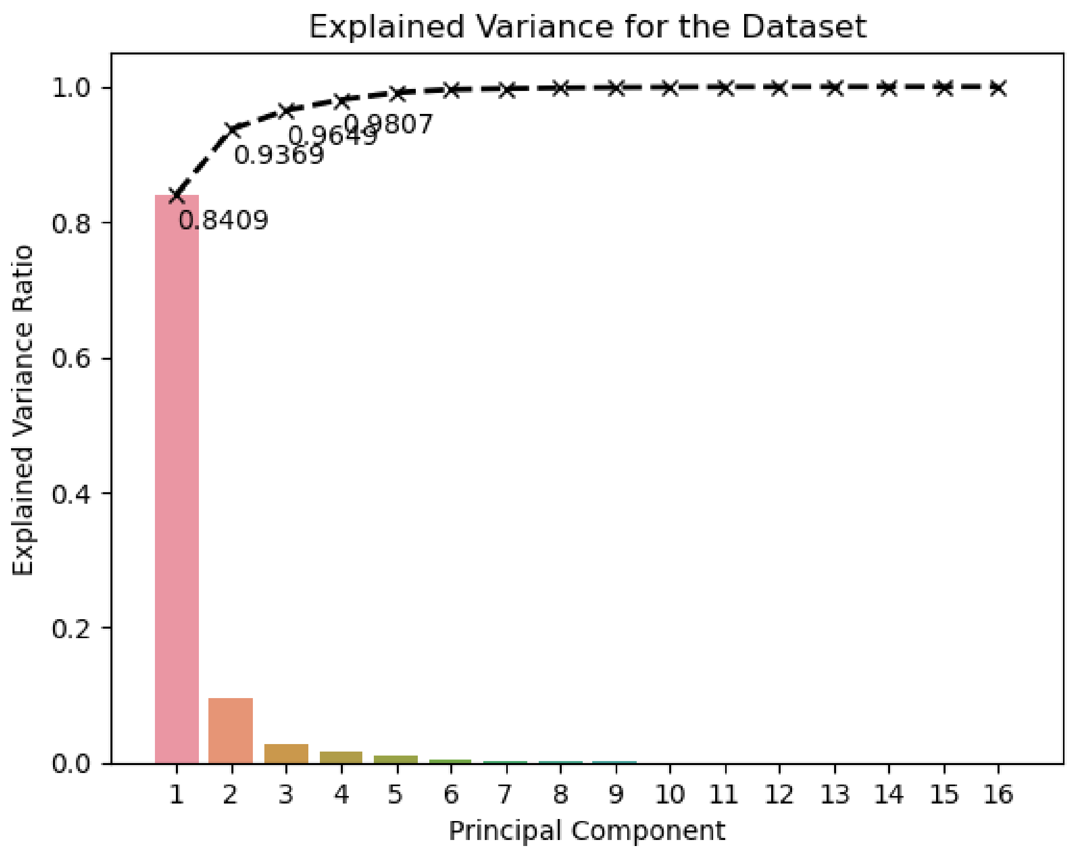


From the **time difference** boxplot, there are a few observations to be made. Firstly, in activities like lying, sitting, and rope jumping, there are outliers that indicate anomalies in the data. Secondly, rope jumping has a smaller box and lower median, which indicates that subjects spent less time during this activity. On the other hand, activities like vacuuming and cycling took longer, which can be attributed to the activity itself, but also can be related to the toll each activity takes on the body. This last observation is a very interesting point to consider for this report, taking into account that we are looking at an IMU.

Continuing with the exploratory data analysis, the next step I decided to take is Principal Component Analysis. PCA is a statistical procedure that can reveal the structure of the data, to understand the relationship among variables. As its name mentions, the principal component is selected, reflecting the data's variance.

[35]:
```
#edited from Lab10 Solutions
from sklearn.decomposition import PCA
df_numeros = df_medias.select_dtypes(include=[np.number])
pca = PCA().fit(df_numeros)
comps = pca.components_
ev_ratio = pca.explained_variance_ratio_
cumul_ev_ratio = np.cumsum(ev_ratio)
pcs = np.arange(1,len(df_numeros.columns)+1)
loadings = pd.DataFrame(data=comps,columns=[f"PC{pc}" for pc in␣
 ↪pcs],index=df_numeros.columns)

fig,ax = plt.subplots(nrows=1,ncols=1)
sns.barplot(x=pcs,y=ev_ratio)
ax.plot(pcs-1,cumul_ev_ratio,ls="--",marker="x",lw=2,c="k")
for pc,cer in zip(pcs,cumul_ev_ratio):
    ax.annotate(f"{cer:.4f}",xy=(pc-1,cer-0.05))
    if cer > 0.98:
        break
ax.set_xlabel("Principal Component")
ax.set_ylabel("Explained Variance Ratio")
ax.set_title("Explained Variance for the Dataset")
```

[35]:
```
Text(0.5, 1.0, 'Explained Variance for the Dataset')
```



[36]:
```
#Used ChatGPT. Prompted: having a PCA plot, how do I know which one is the
↪principal component
from sklearn.decomposition import PCA

pca = PCA().fit(df_numeros)
ev_ratio = pca.explained_variance_ratio_
first_component = pca.components_[0]
loadings_df = pd.DataFrame(pca.components_, columns=df_numeros.columns)
first_component_loadings = loadings_df.iloc[0]

significant_features = first_component_loadings.abs().
↪sort_values(ascending=False)
print("Most significant features for the First Principal Component:")
print(significant_features.head())
```

```
Most significant features for the First Principal Component:
time_difference            0.999860
mean_chest_magnetometer    0.008692
mean_hand_magnetometer     0.007868
bpm                        0.005917
```

```
IMU_chest_temp           0.005485
Name: 0, dtype: float64
```

From the PCA plot, and the written explanation, it is clear that the feature **time_difference** explains a large part of the variation of the dataset. Something that is congruent with the previous analysis done with ECDFs.

A final thing to point out is that the following features that explain variation in the dataset are **mean_chest_magnetometer**, **mean_hand_magnetometer** and **bpm**. These last three correspond to a significantly smaller portion of the variation, but the presence of heart rate as one of the principal features helps us move along with this analysis.

Having identified the principal component of the dataset, it's time to add some more information provided by the data collector, that is not entirely included in the original dataset but that will give valuable insights into possible improvements of the product.

Amongst the information provided to me, there was a detailed chart about the subjects and there was also a chart that mentioned METs and their relationship to each activity. METs stands for **Metabolic Equivalent of Task**, it's a measurement that is based on the amount of energy that is used, based on the notion that only 1 MET is used when a person is sitting calmly. This scale is used to measure the intensity of different exercises, giving a clear view of how active a person is. Additionally, there is a scientific consensus on how many METs an adult human should be utilizing per week. It is recommended that a healthy adult expends between 450 and 750 METs per week.

The following code generates a **df_subjects** with the information that we have of the subjects, and then goes into creating a **df_calculos** that takes this information, activity, bpm, exercise intensity and time difference, and calculates the corresponding METs expended by each subject in each activity.

[37]:
```
data = {
    "SubjectID": [101, 102, 103, 104, 105, 106, 107, 108, 109],
    "Sex": ["Male", "Female", "Male", "Male", "Male", "Male", "Male", "Male",␣
 ↪"Male"],
    "Age": [27, 25, 31, 24, 26, 26, 23, 32, 31],
    "Height": [182, 169, 187, 194, 180, 183, 173, 179, 168],
    "Weight": [83, 78, 92, 95, 73, 69, 86, 87, 65],
    "bpm": [75, 74, 68, 58, 70, 60, 60, 66, 54],
    "Maxbpm": [193, 195, 189, 196, 194, 194, 197, 188, 189],
    "Dominant hand": ["right", "right", "right", "right", "right", "right",␣
 ↪"right", "left", "right"]
}

df_subjects = pd.DataFrame(data)
df_subjects
```

[37]:

	SubjectID	Sex	Age	Height	Weight	bpm	Maxbpm	Dominant hand
0	101	Male	27	182	83	75	193	right
1	102	Female	25	169	78	74	195	right
2	103	Male	31	187	92	68	189	right
3	104	Male	24	194	95	58	196	right

```
4        105     Male    26     180      73    70      194           right
5        106     Male    26     183      69    60      194           right
6        107     Male    23     173      86    60      197           right
7        108     Male    32     179      87    66      188            left
8        109     Male    31     168      65    54      189           right
```

[38]:
```
df_medias
```

[38]:
```
           bpm  IMU_hand_temp  IMU_chest_temp  IMU_ankle_temp  SubjectID  \
0        100.0         30.375         32.1875           30.75      101.0
1        100.0         30.375         32.1875           30.75      101.0
2        100.0         30.375         32.1875           30.75      101.0
3        100.0         30.375         32.1875           30.75      101.0
4        100.0         30.375         32.1875           30.75      101.0
…          …             …              …               …            …
1921425  162.0         25.125         32.3750           31.50      109.0
1921426  162.0         25.125         32.3750           31.50      109.0
1921427  162.0         25.125         32.3750           31.50      109.0
1921428  162.0         25.125         32.3750           31.50      109.0
1921429  162.0         25.125         32.3750           31.50      109.0

         mean_hand_acceleration  mean_ankle_acceleration  \
0                      5.360660                 2.662032
1                      5.236503                 2.597479
2                      5.085573                 2.571709
3                      5.086983                 2.636982
4                      5.217407                 2.661912
…                          …                       …
1921425                5.537257                 1.634507
1921426                5.471683                 1.583083
1921427                5.420900                 1.595727
1921428                5.420890                 1.647030
1921429                5.145943                 1.660640

         mean_chest_acceleration  mean_hand_gyroscope  mean_ankle_gyroscope  \
0                       2.707567             0.007228             -0.007684
1                       2.733360            -0.051923              0.009278
2                       2.703949            -0.075399             -0.030899
3                       2.744582            -0.053495             -0.008136
4                       2.796648            -0.027902             -0.017951
…                           …                    …                     …
1921425                 2.304086            -0.053589              0.004761
1921426                 2.253289            -0.045453              0.003369
1921427                 2.316360            -0.044983             -0.018141
1921428                 2.314066            -0.020135             -0.023868
1921429                 2.355183            -0.029522             -0.008425
```

```
         mean_chest_gyroscope  mean_hand_magnetometer  \
0                    0.000145              -26.325367
1                   -0.021601              -26.428167
2                   -0.003142              -25.951613
3                   -0.035405              -26.023973
4                   -0.017464              -26.037313
…                         …                     …
1921425             -0.072864              -23.730043
1921426             -0.061935              -23.828237
1921427             -0.017922              -23.496437
1921428             -0.011660              -23.992003
1921429             -0.011241              -23.602593

         mean_ankle_magnetometer  mean_chest_magnetometer  activityID  \
0                     -52.113767                -1.962178         1.0
1                     -51.858967                -2.020103         1.0
2                     -51.578933                -2.079840         1.0
3                     -51.915767                -2.057705         1.0
4                     -51.737067                -2.441961         1.0
…                           …                       …          …
1921425               -15.595791                 3.486200        24.0
1921426               -15.437418                 3.469400        24.0
1921427               -15.400991                 3.687233        24.0
1921428               -15.264915                 3.214000        24.0
1921429               -15.765504                 3.385633        24.0

        exercise_intensity  time_difference activityID_legend
0                  Resting           271.86             lying
1                  Resting           271.86             lying
2                  Resting           271.86             lying
3                  Resting           271.86             lying
4                  Resting           271.86             lying
…                    …                 …               …
1921425           Vigorous            63.90      rope jumping
1921426           Vigorous            63.90      rope jumping
1921427           Vigorous            63.90      rope jumping
1921428           Vigorous            63.90      rope jumping
1921429           Vigorous            63.90      rope jumping

[1921430 rows x 18 columns]
```

[39]:
```
grouped_medias = df_medias.groupby(['SubjectID', 'activityID']).agg({
    'bpm': 'mean',
    'time_difference': 'first',
    'exercise_intensity': 'first'
}).reset_index()
```

```python
df_calculos = grouped_medias.merge(
    df_subjects[['SubjectID', 'Sex', 'Age', 'Weight']],
    on='SubjectID',
    how='left'
)

df_calculos['time_difference'] = df_calculos['time_difference'] / 60


activity_details = {
    1: (1.0, 3),
    2: (1.8, 3),
    3: (1.8, 3),
    4: (3.3, 3),
    5: (7.0, 3),
    6: (4.0, 3),
    7: (5.0, 3),
    9: (1.0, 3),
    10: (1.8, 3),
    11: (1.8, 3),
    12: (8.0, 1),
    13: (3.0, 1),
    16: (3.5, 3),
    17: (2.3, 3),
    18: (1.8, 3),
    19: (3.8, 3),
    20: (8.0,3),
    24: (10.0,2)

}

def calculo_METs(row):
    activity_id = row['activityID']
    if activity_id in activity_details:
        valor_met, duracion_estandar = activity_details[activity_id]
        duracion_real = row['time_difference']
        return (duracion_real / duracion_estandar) * valor_met
    return 0



df_calculos['METs'] = df_calculos.apply(calculo_METs, axis=1)
df_calculos = df_calculos[['SubjectID', 'activityID', 'bpm',␣
 ↪'exercise_intensity', 'time_difference', 'METs']]

df_calculos.head()
```

```
[39]:    SubjectID  activityID         bpm exercise_intensity  time_difference  \
0      101.0         1.0   87.530925            Resting         4.531000
1      101.0         2.0   91.180737            Resting         3.913167
2      101.0         3.0  103.411105            Resting         3.619333
3      101.0         4.0  120.484216            Resting         3.708667
4      101.0         5.0  161.355976            Resting         3.544000

       METs
0  1.510333
1  2.347900
2  2.171600
3  4.079533
4  8.269333
```

```
[40]: df_calculos['bpm'] = df_calculos['bpm'].round(2)
      df_calculos['METs'] = df_calculos['METs'].round(2)
      df_calculos['time_difference'] = df_calculos['time_difference'].round(2)
```

The new data frame grouped information that was repetitive in the previous data frame, such as time difference, activity, and exercise intensity; however, it was necessary to calculate the average heart rate per person per activity to properly calculate the METs column. This reduction may seem drastic, but it's still preserving the original information provided to us, and I decided that the calculation of the METs used per activity should be the main focus at this point.

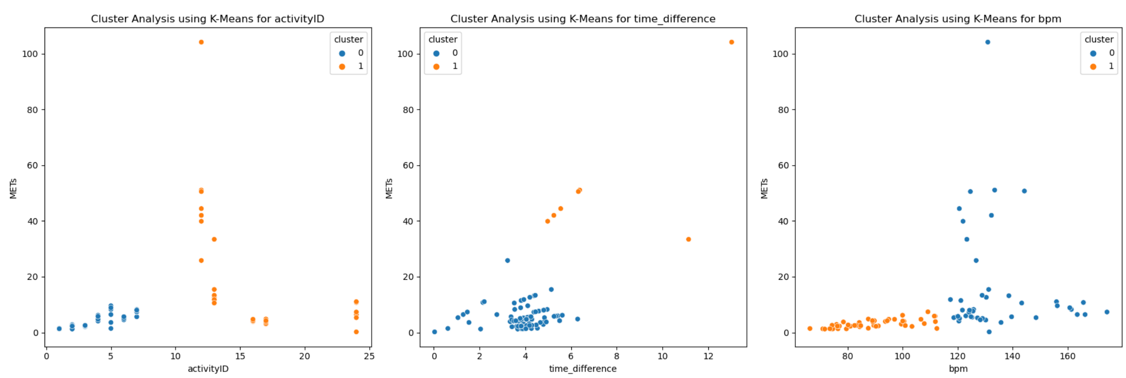
```
[41]: df_calculos
```

```
[41]:     SubjectID  activityID     bpm exercise_intensity  time_difference   METs
0       101.0         1.0   87.53            Resting             4.53   1.51
1       101.0         2.0   91.18            Resting             3.91   2.35
2       101.0         3.0  103.41            Resting             3.62   2.17
3       101.0         4.0  120.48            Resting             3.71   4.08
4       101.0         5.0  161.36            Resting             3.54   8.27
..        …          …     …                …                …     …
85      108.0        13.0  143.31            Resting             3.52  10.56
86      108.0        16.0  106.68            Resting             4.05   4.72
87      108.0        17.0   89.04            Resting             5.50   4.22
88      108.0        24.0  174.31           Moderate             1.47   7.34
89      109.0        24.0  148.51           Moderate             1.06   5.32

[90 rows x 6 columns]
```

Presently, it's time to perform a K-Means clustering model. Following the same path that we have through this report, the purpose is to see how much the principal components that we detected, time difference and bpm, plus the component that was requested of us by the data collector, acitivityID, are related to METs value.

K-Means clustering is an unsupervised mathematical model that assigns data points to a cluster such that the sum of the squared distance between the data points and the cluster's centroid is minimized. The main purpose of this technique is to group similar data points and discover patterns that show similarity. Finding patterns amongst the data gives us insight into its behaviour and helps us predict how it will continue to behave.

[42]:
```
#edited from Lab10 Solutions
fig, axes = plt.subplots(1, 3, figsize=(18, 6))

n_clusters = 2
features = ['activityID', 'time_difference', 'bpm']

for i, feature in enumerate(features):
    df_numeros = df_calculos[[feature, 'METs']].copy()
    scaler = StandardScaler()
    df_numeros_scaled = scaler.fit_transform(df_numeros)

    kmeans = KMeans(n_clusters=n_clusters, random_state=42).
 ↪fit(df_numeros_scaled)
    df_numeros['cluster'] = kmeans.labels_

    sns.scatterplot(data=df_numeros, x=feature, y="METs", hue='cluster',␣
 ↪ax=axes[i])
    axes[i].set_title(f"Cluster Analysis using K-Means for {feature}")

plt.tight_layout()
plt.show()
```



Activity ID: this graphic shows that the model was able to identify two clusters and it shows that the data was divided by the scale of the activity. The vertical lines in this cluster model reflect the nature of this column, which is not a continuous value. This point will need to be studied further.

Time Difference: this graph shows that shorter activities are grouped together, leaving the longer activities in a different cluster. This is congruent with the idea that the longer someone exercises, the more energy they will spend.

BPM: this graph shows that lower bpm values are clustered together while higher ones are grouped in a different cluster. This suggests a correlation between the heart rate and the value of METS.

The separation of the clusters for all features highly suggests a correlation between these three columns and METs, although, it is important to point out that the activityID needs to be revisited since the vertical lines indicate a categorical feature.

[43]:
```
df_calculos.info()
```

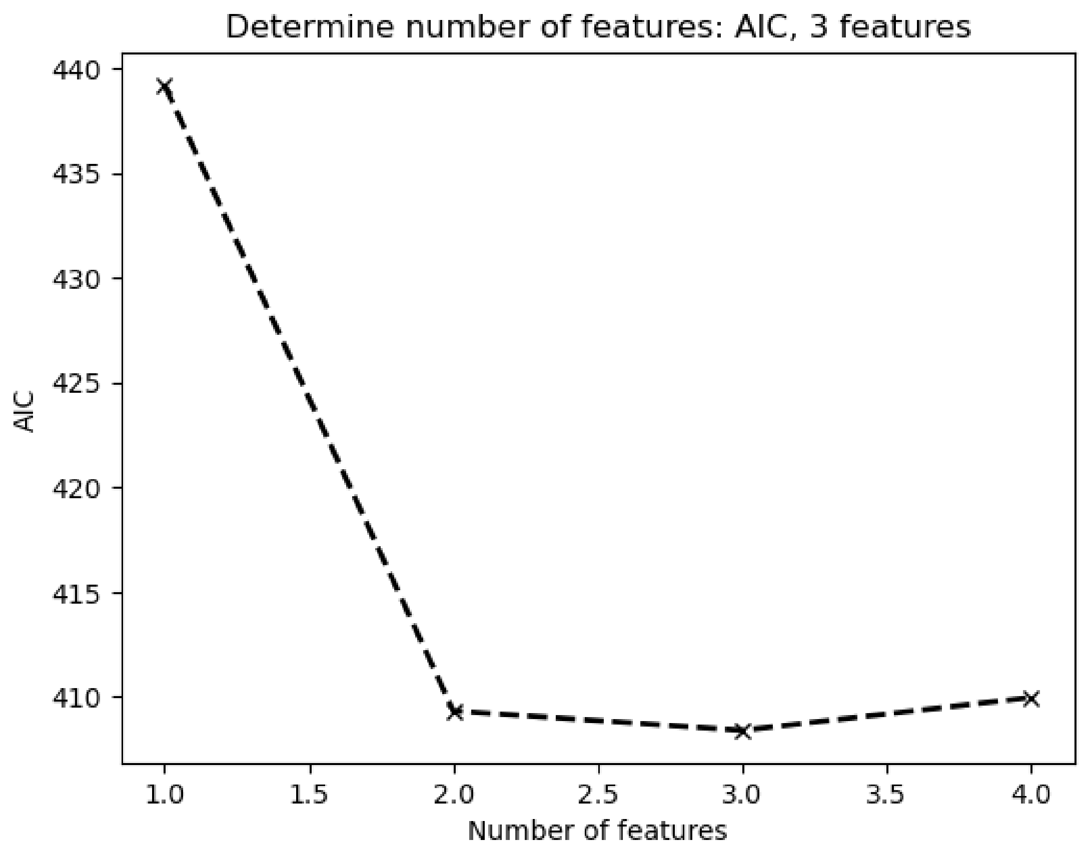
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90 entries, 0 to 89
Data columns (total 6 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   SubjectID           90 non-null     float64
 1   activityID          90 non-null     float64
 2   bpm                 90 non-null     float64
 3   exercise_intensity  90 non-null     object
 4   time_difference     90 non-null     float64
 5   METs                90 non-null     float64
dtypes: float64(5), object(1)
memory usage: 4.3+ KB
```

Continuing with the model creation, I wanted to test if one of the features would be better to create a model that could predict the behavior of METs. That's why the next code shows an **AIC feature selection**, with a linear regression model.

AIC is a measurement used in model selection to quantify the quality of fit of a model, given the model a score. Through this process, the best feature, or features, to predict METs is chosen. The **Linear Regression** model uses all the features selected and tries to predict the values of METs, generating an **R-squared** value that gives the model a score.

[44]:
```
#edited from Lab10 solutions

df_calculos = df_calculos.select_dtypes(include=[np.number])
y = df_calculos['METs']
X = df_calculos.drop(columns=['METs'])


AIC = np.zeros(len(X.columns))
lm = LinearRegression()
num_features = np.arange(1, len(X.columns) + 1)
sfs_features = {nf: {} for nf in num_features[:-1]}


for idx, nf in enumerate(num_features[:-1]):
    sfs = SequentialFeatureSelector(lm, n_features_to_select=nf,␣
 ↪direction='forward').fit(X, y)
    features = sfs.get_feature_names_out()
    new_X = X[list(features)]
    nf_lm = lm.fit(new_X, y)
    score = nf_lm.score(new_X, y)
```

```
    y_pred = nf_lm.predict(new_X)
    mse = mean_squared_error(y, y_pred)
    AIC[idx] = len(y) * np.log(mse) + 2 * nf
    sfs_features[nf] = {"score": score, "features": features, "model": nf_lm}


nf_lm = lm.fit(X, y)
score = nf_lm.score(X, y)
y_pred = nf_lm.predict(X)
mse = mean_squared_error(y, y_pred)
AIC[-1] = len(y) * np.log(mse) + 2 * num_features[-1]

aic_features = np.argmin(AIC) + 1

fig, ax = plt.subplots(nrows=1, ncols=1)
ax.set_xlabel("Number of features")
ax.set_ylabel("AIC")
ax.set_title(f"Determine number of features: AIC, {aic_features} features")
ax.plot(num_features, AIC, ls="--", lw=2, marker="x", c="k")
plt.show()

best_features = sfs_features[aic_features]["features"]
best_score = sfs_features[aic_features]["score"]
print(f"Best number of features: {aic_features}")
print(f"Best features: {best_features}")
print(f"Best model score: {best_score}")
```




```
Best number of features: 3
Best features: ['activityID' 'bpm' 'time_difference']
Best model score: 0.6171299201242995
```

The results show that the AIC is minimized when all three features are used, and the resulting R-Square value is reasonably high to consider following this direction in future models.

As a next step, we are going to apply an Ordinary Least Square regression model to our data. The OLS method is used when trying to estimate the relationships between a dependent variable and independent variables. The main goal is to find a linear model that describes this relationship. OLS estimates the coefficients by minimizing the sum of the squares of the errors, meaning the difference between the value that was predicted and the one that was observed.

[45]:
```
#edited from Lab10 solutions
features = sfs_features[aic_features]["features"]

X2 = X[features]
feature = sm.add_constant(X2)

model = sm.OLS(y, feature)
results = model.fit()
```

```python
results.summary(slim=True)
```

[45]:

Dep. Variable:	METs	**R-squared:**	0.617
Model:	OLS	**Adj. R-squared:**	0.604
No. Observations:	90	**F-statistic:**	46.21
Covariance Type:	nonrobust	**Prob (F-statistic):**	6.96e-18

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-43.0165	5.337	-8.060	0.000	-53.626	-32.406
activityID	0.2843	0.169	1.687	0.095	-0.051	0.619
bpm	0.2041	0.043	4.782	0.000	0.119	0.289
time_difference	6.4582	0.609	10.598	0.000	5.247	7.670

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The OLS model that was used tries to predict the value of METs based on the activity, time and heart rate. The results show an R-squared value, which measures the accuracy of the model, of 0.617 indicating that the model is relatively good.

The **p-value** obtained for **activityID** indicates that this feature is not a significant predictor for METs. However, the **p-values** for both **bpm** and **time difference** suggest a strong relationship between these features and the MET values.

After obtaining results for the OLS model, it's important to validate it. The best way to achieve this validation is by splitting the data into training and testing data. This method trains a linear regression model into the training data and then evaluates the performance of the model on the test data.

[46]:

```python
mejores_features = sfs_features[aic_features]["features"]

X = df_calculos[mejores_features]
y = df_calculos['METs']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪shuffle=True)

lm = LinearRegression()
lm.fit(X_train, y_train)

y_pred = lm.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)


print(f"Mean Squared Error (MSE) on Test Set: {mse}")
print(f"R-squared Score on Test Set: {r2}")
coeficientes_modelo= dict(zip(mejores_features, lm.coef_))
print("Feature Coefficients in the Best Model:")
```

```
coeficientes_df = pd.DataFrame(list(coeficientes_modelo.items()),␣
↪columns=['Feature', 'Coefficient'])
coeficientes_df
```

```
Mean Squared Error (MSE) on Test Set: 93.56287541947589
R-squared Score on Test Set: 0.3807106417017889
Feature Coefficients in the Best Model:
```

[46]:

	Feature	Coefficient
0	activityID	0.167984
1	bpm	0.225066
2	time_difference	6.375244

These results show that some aspects of the model remain the same, after its validation. For example, **time difference** remains the strongest feature involved in the METs, which is following the reality that the longer someone practices an activity, the more energy they will spend. Another aspect that remains, is that **bpm** is closely related as well, which also makes sense since activities that elevate the heart rate tend to be the ones that require more energy.

There are two aspects of this validation where we should be focusing, one is that activity remains the feature that is least related to METs, however, as I mentioned before in this report, this feature has the added difficulty that it's a categorical variable. That being said, we need to make sure to treat it as such. The final observation is the R-square value, which is now significantly lower than the original model. This indicates that the model is not performing as well as it was predicted, when dealing with unseen data.

I believe these last two points are related, considering that **activityID** must be treated as a categorical variable, which is probably the reason why the model is doing badly when tested. To fix this, we need to normalize the values of this column.

The data collector mentioned that they wanted **activityID** as part of the models, which is why I have decided to try **one-hot encoding** to see if the model can be improved. This technique is used to turn categorical variables into numerical forms that can be used more effectively in linear regression models.

[47]:

```
one_hot_encoder = OneHotEncoder()
activityID_codificado = one_hot_encoder.
↪fit_transform(df_calculos[['activityID']]).toarray()
columnas_codificadas = one_hot_encoder.get_feature_names_out(['activityID'])
activityID_codificado_df = pd.DataFrame(activityID_codificado,␣
↪columns=columnas_codificadas)
resto_df = df_calculos[['time_difference', 'bpm']].reset_index(drop=True)
X_combinado = pd.concat([activityID_codificado_df, resto_df], axis=1)

y = df_calculos['METs'].reset_index(drop=True)
X_combinado_con_constante = sm.add_constant(X_combinado)

model = sm.OLS(y, X_combinado_con_constante).fit()
model_summary = model.summary()
```

```
model_summary
```

[47]:

Dep. Variable:	METs	**R-squared:**	0.950
Model:	OLS	**Adj. R-squared:**	0.941
Method:	Least Squares	**F-statistic:**	110.2
Date:	Sat, 06 Jan 2024	**Prob (F-statistic):**	9.67e-44
Time:	04:17:57	**Log-Likelihood:**	-237.63
No. Observations:	90	**AIC:**	503.3
Df Residuals:	76	**BIC:**	538.3
Df Model:	13		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-9.8951	4.336	-2.282	0.025	-18.530	-1.260
activityID__1.0	-8.4172	1.750	-4.809	0.000	-11.903	-4.931
activityID__2.0	-6.6664	1.630	-4.089	0.000	-9.913	-3.420
activityID__3.0	-7.0644	1.422	-4.968	0.000	-9.896	-4.232
activityID__4.0	-8.9439	1.338	-6.683	0.000	-11.609	-6.278
activityID__5.0	3.2350	2.355	1.374	0.174	-1.455	7.926
activityID__6.0	-3.9005	1.562	-2.497	0.015	-7.012	-0.789
activityID__7.0	-4.4508	1.553	-2.866	0.005	-7.544	-1.358
activityID__12.0	29.7283	1.752	16.969	0.000	26.239	33.218
activityID__13.0	0.3787	1.623	0.233	0.816	-2.853	3.610
activityID__16.0	-3.6159	1.255	-2.881	0.005	-6.115	-1.116
activityID__17.0	-10.6744	1.454	-7.340	0.000	-13.571	-7.778
activityID__24.0	10.4963	2.747	3.820	0.000	5.024	15.968
time_difference	4.9661	0.326	15.243	0.000	4.317	5.615
bpm	-0.0035	0.041	-0.086	0.932	-0.085	0.078

Omnibus:	61.752	**Durbin-Watson:**	2.699
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	769.797
Skew:	1.728	**Prob(JB):**	6.93e-168
Kurtosis:	16.905	**Cond. No.**	1.88e+18

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 3.37e-31. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

After converting the **activityID** column through one-hot encoding, I ran another OLS model to see if we would get better results. As seen above, the new **R-square** value is higher than before, and it suggests that this new model predicts the behaviour of METs better than the previous one.

Additionally, the coefficients obtained are now indicating some relationship between certain types of activities and the METs values. This makes sense since we know that some of the activities that took place in the experiment require more energy than others.

As I did with the previous model, this one too needs to be validated. This is why I'm performing yet another train and test split technique, to see if the new model stands.

[48]:
```python
X_train, X_test, y_train, y_test = train_test_split(X_combinado, y, test_size=0.
 ↪3, shuffle=True)

lm = LinearRegression()
lm.fit(X_train, y_train)

y_pred = lm.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)


print(f"Mean Squared Error (MSE) on Test Set: {mse}")
print(f"R-squared Score on Test Set: {r2}")
nombre_features = list(columnas_codificadas) + ['time_difference', 'bpm']
coeficientes_modelo = dict(zip(nombre_features, lm.coef_))
print("Feature Coefficients in the Best Model:")
coeficientes_df = pd.DataFrame(list(coeficientes_modelo.items()),␣
 ↪columns=['Feature', 'Coefficient'])
coeficientes_df
```

```
Mean Squared Error (MSE) on Test Set: 60.70243627400725
R-squared Score on Test Set: 0.8606404694662707
Feature Coefficients in the Best Model:
```

[48]:

	Feature	Coefficient
0	activityID_1.0	-6.810532
1	activityID_2.0	-5.843352
2	activityID_3.0	-5.597211
3	activityID_4.0	-5.975531
4	activityID_5.0	0.086274
5	activityID_6.0	-3.788619
6	activityID_7.0	-2.860114
7	activityID_12.0	33.952219
8	activityID_13.0	3.089649
9	activityID_16.0	-3.359851
10	activityID_17.0	-6.979503
11	activityID_24.0	4.086571
12	time_difference	2.729026
13	bpm	0.025489

The final results of this validation show that the **R-square** value is significantly higher for this model than it was before performing one-hot encoding. This result indicates that 86% of the variability in METS can be explained by the model.

The coefficients are now indicating a relationship between time, certain activities, and, in some cases, heart rate, with the values obtained for METs. Meaning that the three features are related to this variable.

In general, these results indicate that this model is better equipped to predict the data's behaviour, compared to the previous one.

0.2 Conclusion

This report was created to analyze the given data and to come up with possible improvements to the Colibri Wireless IMU. The data collector provided a lot of additional information regarding how the data was obtained, as well as information about subjects and the product itself.

After carefully reading all these recommendations and clarifications, I conducted the data analysis stage known as cleaning and wrangling. At this point, all the irrelevant information was dropped, and some columns were added to provide more clarity regarding some aspects, particularly for the different activities. This is why I focused on adding a legend to interpret the numbers given to the activities, as well as a new column clarifying the intensity of each exercise.

The heart rate column needed a particular treatment, given that its nature is crucial for analyzing exercises, but it presented a lot of empty values. To fix this, I decided to fill out the rows with the data closest to them, that belong to the same subject while performing the same activity.

It's important to always know the distribution of the data that you are dealing with, as well as how the features interact amongst themselves. This is why I created a series of graphs detailing these behaviours, and why I split the data into two groups, to see the difference between sedentary and active data.

Amongst the added data, there is the column MET, which is a measurement of energy spent by human beings. The intention behind this column is directly related to the improvement that can be added to the product.

At the end of this report, several models aim to predict the behaviour of the MET values, because I wanted to see if this variable could be calculated and added to the product. Before performing them, I applied a series of techniques to see which variables would be more appropriate to include in the models, which is how I concluded that time, heart rate and activity could work best.

The final model proves that these three variables are closely related to METs. Considering that those values are already being measured by the product, I'm able to provide advice regarding possible improvements.

0.2.1 Improvements

Time tracking: currently, the device is keeping track of time by creating a series of timestamps with the different measurements provided by the sensors. This is helpful when it comes to technology, however, it is not easy for the person to read. I suggest including additional software that lets the user know how long they spent during each activity, for a prolonged amount of time. In other words, provide the user with the possibility to see exactly how much time they spent on each activity in a day, in a week, and in a month.

Heart rate: the data provider clarified that the bpm values were obtained by an extra sensor that is not part of the product. Given the importance of this particular variable, I would suggest including its measurement in the original device, to avoid using a second one, which can be more costly and bothersome for the user.

METs: considering the information that the product is already capturing and considering the results of the models obtained in this report, I believe it would be very beneficial to include the measurements of energy in the product. Adding this software to the device is going to add great value to the user since this is exactly what they want to know. The final user is tracking how much exercise they are doing, and how it's affecting their health. By giving them an exact number of METs, and by giving these values alongside a tracker of longer periods of time (days, weeks and months), we would be providing a holistic picture of their exercise routine which is clear and concise, and which represents something they can understand.

0.2.2 References:

- https://www.hsph.harvard.edu/nutritionsource/staying-active/
- https://www.aafp.org/pubs/afp/issues/2008/0215/p513.html