IFN646 - Biomedical Data Science — Wearables Project

Import of necessary packages

In [1]:

```
import matplotlib.pyplot as plt
import numpy
import seaborn as sns
import pandas as pd
from sklearn.metrics import confusion_matrix, f1_score, accuracy_score, precision_score, recall_score
from preprocess import load_data, inform, __handle_missing_values
import warnings

# create image directory
from pathlib import Path
Path("img").mkdir(parents=True, exist_ok=True)
warnings.filterwarnings('ignore')
```

Load the data

In [2]:

```
full, train, test = load_data()
```

```
Loading cached files.
```

Print statistics of the datasets

In [3]:

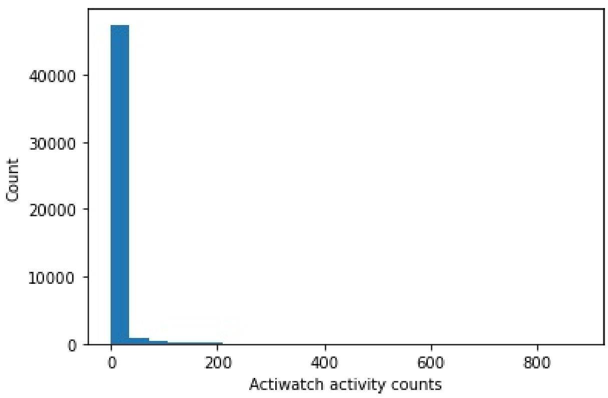
```
print("Full data:")
inform(full)
print("Training data:")
inform(train)
print("Test data:")
inform(test)
```

```
Full data:
Shape of data: (49100, 5)
There are 90.74% 0 values in column 'Actiware classification'.
There are 92.14 0 values in column 'Actiwatch activity counts'.
Training data:
Shape of data: (40761, 5)
There are 91.03% 0 values in column 'Actiware classification'.
There are 92.13 0 values in column 'Actiwatch activity counts'.
Test data:
Shape of data: (8339, 5)
There are 89.29% 0 values in column 'Actiware classification'.
There are 92.18 0 values in column 'Actiwatch activity counts'.
```

Gain overview of data

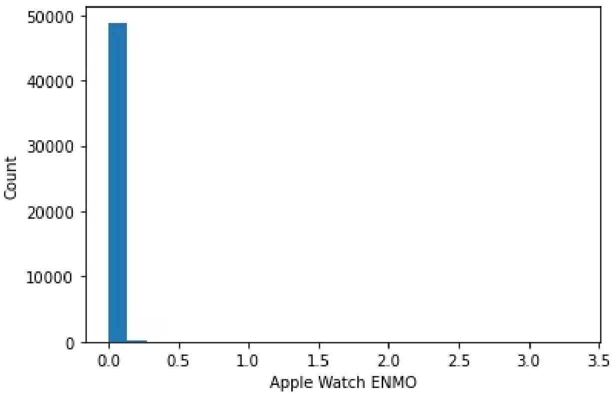
In [4]:

```
# plot histogram of Actiwatch activity counts for the whole data set
plt.hist(full['Actiwatch activity counts'], bins=25)
plt.ylabel('Count')
plt.xlabel('Actiwatch activity counts');
plt.savefig('img/actiwatch_histogram.pdf', bbox='tight')
```



In [5]:

```
# plot histogram of Apple Watch ENMO for the whole data set
plt.hist(full['Apple Watch ENMO'], bins=25)
plt.ylabel('Count')
plt.xlabel('Apple Watch ENMO');
plt.savefig('img/apple_watch_histogram.pdf', bbox='tight')
```



Function to calculate total counts according to Philips' Actiware software specification

In [6]:

```
def total_counts(df, src_col, dest_col):
    day = df['day'].values
    cts = df[src_col].values
    total = []
    for i in range(len(cts)):
        div_by_25_sum = 0
        div_by_5_sum = 0
        for j in range(-8, -4):
            if i + j >= 0 and day[i + j] == day[i]:
                div_by_25_sum += cts[i + j]
        for j in range(-4, 0):
            if i + j >= 0 and day[i + j] == day[i]:
                div_by_5_sum += cts[i + j]
        for j in range(1, 5):
            if i + j < len(cts) and day[i + j] == day[i]:
                div_by_5_sum += cts[i + j]
        for j in range(5, 9):
            if i + j < len(cts) and day[i + j] == day[i]:
                div_by_25_sum += cts[i + j]
        calculation = 0.04 * div_by_25_sum + 0.20 * div_by_5_sum + 4.00 * cts[i]
        total.append(calculation)
    df[dest_col] = total
```

In [7]:

```
# call total_counts function and add a column for total counts from Actiwatch
total_counts(train, 'Actiwatch activity counts', 'Actiwatch Total Counts')

# print first 30 items
train.head(30)
```

Out[7]:

	day	Actiwatch activity counts	Actiware classification	Apple Watch ENMO	time	Actiwatch Total Counts
1	1	109.0	1.0	0.227648	20:58:15	555.20
2	1	170.0	1.0	0.217089	20:58:30	812.40
3	1	91.0	1.0	0.267528	20:58:45	548.68
4	1	101.0	1.0	0.222397	20:59:00	607.12
5	1	125.0	1.0	0.262205	20:59:15	727.64
6	1	105.0	1.0	0.283417	20:59:30	673.96
7	1	176.0	1.0	0.314253	20:59:45	954.84
8	1	105.0	1.0	0.328872	21:00:00	689.72
9	1	159.0	1.0	0.444264	21:00:15	897.32
10	1	215.0	1.0	0.521921	21:00:30	1110.12
11	1	208.0	1.0	0.515725	21:00:45	1095.32
12	1	91.0	1.0	0.318492	21:01:00	637.72
13	1	97.0	1.0	0.348385	21:01:15	651.84
14	1	134.0	1.0	0.301678	21:01:30	773.68
15	1	125.0	1.0	0.292101	21:01:45	762.48
16	1	117.0	1.0	0.306116	21:02:00	692.08
17	1	76.0	1.0	0.273415	21:02:15	517.52
18	1	73.0	1.0	0.242683	21:02:30	484.24
19	1	385.0	1.0	0.276460	21:02:45	1639.80
20	1	2.0	1.0	0.004816	21:03:00	156.08
21	1	0.0	1.0	0.002099	21:03:15	126.12
22	1	0.0	1.0	0.002393	21:03:30	110.08
23	1	0.0	1.0	0.002089	21:03:45	93.04
24	1	0.0	1.0	0.002052	21:04:00	26.44
25	1	0.0	1.0	0.001939	21:04:15	21.44
26	1	0.0	1.0	0.001993	21:04:30	18.40
27	1	0.0	1.0	0.002051	21:04:45	15.48
28	1	0.0	1.0	0.001956	21:05:00	0.08
29	1	0.0	1.0	0.002015	21:05:15	0.00
30	1	0.0	1.0	0.001976	21:05:30	0.00

Helper functions that classifies into sleep/wake according to threshold 40

In [8]:

```
def classify(row, col):
    if row[col] > 40:
        return 1
    else:
        return 0
```

Plausibility Check

Perform classification of actiwatch total counts for plausibility check

In [9]:

```
train['Actiware classification calculated'] = train.apply(lambda x: classify(x, 'Actiwatch Total Counts'), axis

# set uninterrupted sleep values
train = __handle_missing_values(train, 'Actiware classification calculated')

#print first 30 elements
train.head(30)
```

```
0 rows were dropped where both activity counts and classification were missing.
That is roughly 0.00% of the dataset.

1125 classifications were set to 1 for the first and last 5 minutes of uninterrupted sleep.
That is roughly 2.76% of the dataset.
```

Out[9]:

	day	Actiwatch activity counts	Actiware classification	Apple Watch ENMO	time	Actiwatch Total Counts	Actiware classification calculated
1	1	109.0	1.0	0.227648	20:58:15	555.20	1
2	1	170.0	1.0	0.217089	20:58:30	812.40	1
3	1	91.0	1.0	0.267528	20:58:45	548.68	1
4	1	101.0	1.0	0.222397	20:59:00	607.12	1
5	1	125.0	1.0	0.262205	20:59:15	727.64	1
6	1	105.0	1.0	0.283417	20:59:30	673.96	1
7	1	176.0	1.0	0.314253	20:59:45	954.84	1
8	1	105.0	1.0	0.328872	21:00:00	689.72	1
9	1	159.0	1.0	0.444264	21:00:15	897.32	1
10	1	215.0	1.0	0.521921	21:00:30	1110.12	1
11	1	208.0	1.0	0.515725	21:00:45	1095.32	1
12	1	91.0	1.0	0.318492	21:01:00	637.72	1
13	1	97.0	1.0	0.348385	21:01:15	651.84	1
14	1	134.0	1.0	0.301678	21:01:30	773.68	1
15	1	125.0	1.0	0.292101	21:01:45	762.48	1
16	1	117.0	1.0	0.306116	21:02:00	692.08	1
17	1	76.0	1.0	0.273415	21:02:15	517.52	1
18	1	73.0	1.0	0.242683	21:02:30	484.24	1
19	1	385.0	1.0	0.276460	21:02:45	1639.80	1
20	1	2.0	1.0	0.004816	21:03:00	156.08	1
21	1	0.0	1.0	0.002099	21:03:15	126.12	1
22	1	0.0	1.0	0.002393	21:03:30	110.08	1
23	1	0.0	1.0	0.002089	21:03:45	93.04	1
24	1	0.0	1.0	0.002052	21:04:00	26.44	1
25	1	0.0	1.0	0.001939	21:04:15	21.44	1
26	1	0.0	1.0	0.001993	21:04:30	18.40	1
27	1	0.0	1.0	0.002051	21:04:45	15.48	1
28	1	0.0	1.0	0.001956	21:05:00	0.08	1
29	1	0.0	1.0	0.002015	21:05:15	0.00	1
30	1	0.0	1.0	0.001976	21:05:30	0.00	1

Compare classification to calculated classification

In [10]:

```
classification_stats = train.groupby(["Actiware classification", "Actiware classification calculated"]).size()
print(classification_stats)
```

```
Actiware classification  Actiware classification calculated
0.0                      0                                      37106
1.0                      0                                         19
                         1                                       3632
dtype: int64
```

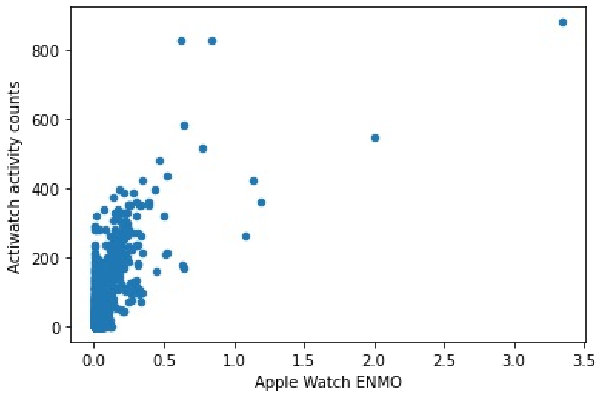
The plausibility check in which we re-classified the sleep/wake state according to Philip's software specification almost yielded a perfect result. Merely 19 values are misclassified. This might be due to some NA values handled improperly or a bug in the uninterrupted sleep algorithm. We will investigate that further in the next iteration.

Fit Machine Learning Model

Draw scatter plot from Apple Watch and Actiwatch

In [11]:

```
train.plot.scatter(x='Apple Watch ENMO', y='Actiwatch activity counts')
plt.savefig('img/scatter_plot.pdf', bbox='tight')
```

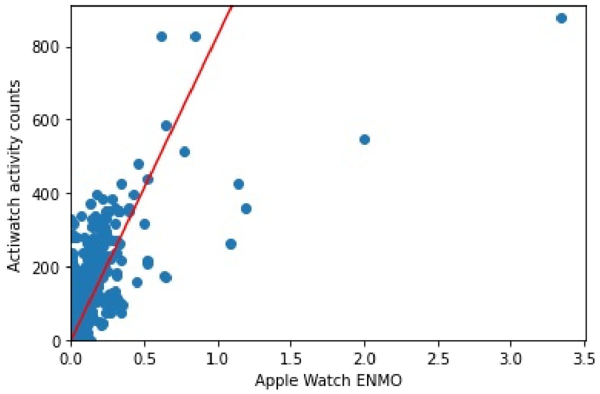


Fit linear Regression Model

In [12]:

```
# declare x and y for the model
x = train['Apple Watch ENMO']
y = train['Actiwatch activity counts']

x.fillna(0, inplace=True)
y.fillna(0, inplace=True)
x = x.tolist()
y = y.tolist()

x_removed_high_values = []
y_removed_high_values = []

# only focus on finding a regression line for smaller values, as high activity
# counts are likely to be awake anyway
for i in range(len(x)):
    if y[i] < 160:
        x_removed_high_values.append(x[i])
        y_removed_high_values.append(y[i])

# fit linear model
model = numpy.poly1d(numpy.polyfit(x_removed_high_values, y_removed_high_values, 1))

# create linspace to draw scatter plot in next step
line = numpy.linspace(0, 3.5, 1000)

# scatter plot
plt.scatter(x, y)

# draw regression graph into plot
plt.plot(line, model(line), color='red')

# set limits
plt.xlim([0,3.51])
plt.ylim([0,910])

# set labels
plt.xlabel("Apple Watch ENMO")
plt.ylabel("Actiwatch activity counts")

plt.savefig('img/scatter_plot_with_regression_line.pdf', bbox='tight')

print('The function of the regression line is:\nf(x) =', str(model).strip())
```

```
The function of the regression line is:
f(x) = 830.1 x - 1.774
```



Predict if sleep or awake for test data

In [13]:

```
# predict activity counts
```

```
test['Predicted activity counts'] = model(test['Apple Watch ENMO'])

# calculate total counts from prediction
total_counts(test, 'Predicted activity counts', 'Predicted Total Counts')

# print first 15 rows
test.head(15)
```

Out[13]:

	day	Actiwatch activity counts	Actiware classification	Apple Watch ENMO	time	Predicted activity counts	Predicted Total Counts
7789	5	91.0	1.0	0.049485	22:11:15	39.301102	442.111665
7790	5	62.0	1.0	0.047339	22:11:30	37.520075	450.677075
7791	5	58.0	1.0	0.069403	22:11:45	55.834148	530.042896
7792	5	154.0	1.0	1.066049	22:12:00	883.105176	3673.955762
7793	5	164.0	1.0	0.503060	22:12:15	415.792924	1898.819150
7794	5	159.0	1.0	0.117267	22:12:30	95.563985	675.876534
7795	5	94.0	1.0	0.075325	22:12:45	60.749480	537.821826
7796	5	0.0	1.0	0.003893	22:13:00	1.457241	303.842708
7797	5	6.0	1.0	0.006534	22:13:15	3.649144	171.210781
7798	5	0.0	1.0	0.003435	22:13:30	1.076835	93.540957
7799	5	0.0	1.0	0.003716	22:13:45	1.310717	77.808235
7800	5	0.0	1.0	0.003637	22:14:00	1.245012	65.899504
7801	5	0.0	1.0	0.004128	22:14:15	1.652067	32.204541
7802	5	0.0	1.0	0.003439	22:14:30	1.080816	12.950007
7803	5	0.0	1.0	0.003159	22:14:45	0.847705	8.196882

In [14]:

```
# classify
test['Predicted wake'] = test.apply(lambda x: classify(x, 'Predicted Total Counts'), axis=1)

# set uninterrupted sleep values
test = __handle_missing_values(test, 'Predicted wake')

# print first 15 rows
test.head(15)
```

```
0 rows were dropped where both activity counts and classification were missing.
That is roughly 0.00% of the dataset.

273 classifications were set to 1 for the first and last 5 minutes of uninterrupted sleep.
That is roughly 3.27% of the dataset.
```

Out[14]:

	day	Actiwatch activity counts	Actiware classification	Apple Watch ENMO	time	Predicted activity counts	Predicted Total Counts	Predicted wake
7789	5	91.0	1.0	0.049485	22:11:15	39.301102	442.111665	1
7790	5	62.0	1.0	0.047339	22:11:30	37.520075	450.677075	1
7791	5	58.0	1.0	0.069403	22:11:45	55.834148	530.042896	1
7792	5	154.0	1.0	1.066049	22:12:00	883.105176	3673.955762	1
7793	5	164.0	1.0	0.503060	22:12:15	415.792924	1898.819150	1
7794	5	159.0	1.0	0.117267	22:12:30	95.563985	675.876534	1
7795	5	94.0	1.0	0.075325	22:12:45	60.749480	537.821826	1
7796	5	0.0	1.0	0.003893	22:13:00	1.457241	303.842708	1
7797	5	6.0	1.0	0.006534	22:13:15	3.649144	171.210781	1
7798	5	0.0	1.0	0.003435	22:13:30	1.076835	93.540957	1
7799	5	0.0	1.0	0.003716	22:13:45	1.310717	77.808235	1
7800	5	0.0	1.0	0.003637	22:14:00	1.245012	65.899504	1
7801	5	0.0	1.0	0.004128	22:14:15	1.652067	32.204541	1
7802	5	0.0	1.0	0.003439	22:14:30	1.080816	12.950007	1
7803	5	0.0	1.0	0.003159	22:14:45	0.847705	8.196882	1

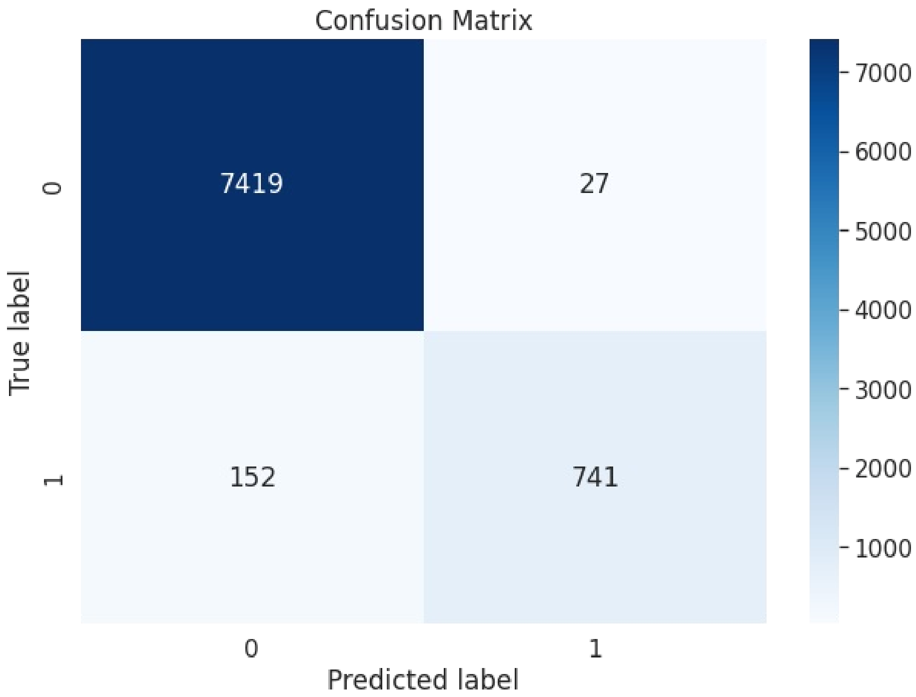
Print statistics of classification

Confusion matrix

In [15]:

```
# create matrix
```

```python
# create matrix
conf_mat = confusion_matrix(test['Actiware classification'], test['Predicted wake'])

# put matrix into data frame
df_cm = pd.DataFrame(conf_mat, range(2), range(2))

# plot matrix with blues color style
plt.figure(figsize=(10,7))
sns.set(font_scale=1.4)

s = sns.heatmap(df_cm, annot=True, cmap='Blues', fmt='g')
s.set(xlabel='Predicted label', ylabel='True label', title='Confusion Matrix')

fig = s.get_figure()
fig.savefig("img/confusion_matrix.pdf", bbox='tight')
```



Metrics: Accuracy, Misclassification Rate, Precision, Recall, F1-score

Note: As we are trying to classify sleep, we consider 0 as the positive class

In [16]:

```python
# Accuracy
acc = round(accuracy_score(test['Actiware classification'], test['Predicted wake'])*100, 2)
print("Accuracy score: \t", acc, '%')

# Misclassification Rate
print("Misclassification rate:\t", round(100-acc, 2), '%')

# Precision
print("Precision score:\t",
      round(precision_score(test['Actiware classification'], test['Predicted wake'], pos_label=0)*100, 2), '%')

# Recall
print("Recall: \t\t",
      round(recall_score(test['Actiware classification'], test['Predicted wake'], pos_label=0)*100, 2), '%')

# F1-Score
print("F1 score: \t\t",
      round(f1_score(test['Actiware classification'], test['Predicted wake'], pos_label=0)*100, 2), '%')
```

```
Accuracy score:         97.85 %
Misclassification rate:  2.15 %
Precision score:        97.99 %
Recall:                 99.64 %
F1 score:               98.81 %
```

Further metrics like total sleep time, awakenings during night

In [17]:

```python
# extract days
days = test['day'].unique()

# consider every day separately
for day in days:
    subset = test[test['day'] == day]

    # calc fall asleep time for actiware
    fall_asleep_id_acti = subset['Actiware classification'].idxmin()
```

```python
    # calc wake up time for actiware
    wake_up_id_acti = subset.iloc[::-1]['Actiware classification'].idxmin()+1

    # calc sleep time for actiware
    sleep_time_acti = (wake_up_id_acti - fall_asleep_id_acti) / 4 / 60

    # calc fall asleep time for predicted
    fall_asleep_id_pred = subset['Predicted wake'].idxmin()

    # calc wake up time for predicted
    wake_up_id_pred = subset.iloc[::-1]['Predicted wake'].idxmin()+1

    # calc sleep time for predicted
    sleep_time_pred = (wake_up_id_pred - fall_asleep_id_pred) / 4 / 60


    # calc awakenings during night for actiware
    awakening_ids = []
    # iterate over all ids of night period
    for i in range(fall_asleep_id_acti, wake_up_id_acti):
        # append all ids where wearer is awake
        if subset.loc[i]['Actiware classification'] == 1:
            awakening_ids.append(i)
    # calculate distinct wake ups
    distinct_awakenings = 0
    for i in range(1, len(awakening_ids)):
        # just consider new wake ups, i.e., where prior epoch is not already set to wake
        if awakening_ids[i-1] != awakening_ids[i]-1:
            distinct_awakenings += 1
    awakenings_acti = distinct_awakenings

    # calc awakenings during night for predicted
    awakening_ids = []
    # iterate over all ids of night period
    for i in range(fall_asleep_id_pred, wake_up_id_pred):
        # append all ids where wearer is awake
        if subset.loc[i]['Predicted wake'] == 1:
            awakening_ids.append(i)
    # calculate distinct wake ups
    distinct_awakenings = 0
    for i in range(1, len(awakening_ids)):
        # just consider new wake ups, i.e., where prior epoch is not already set to wake
        if awakening_ids[i-1] != awakening_ids[i]-1:
            distinct_awakenings += 1
    awakenings_pred = distinct_awakenings

    print("day", day, ": \t", "sleep time:\t", round(sleep_time_acti, 2),
          "h  \t", "pred. sleep time:\t", round(sleep_time_pred, 2), "h ")
    print("\t\t awakenings:\t", awakenings_acti, "\t\t pred. awakenings:\t", awakenings_pred)

    print()
```

```
day 5 :         sleep time:     6.75 h          pred. sleep time:       6.78 h
                awakenings:     18              pred. awakenings:       18

day 14 :        sleep time:     8.57 h          pred. sleep time:       8.58 h
                awakenings:     59              pred. awakenings:       50

day 15 :        sleep time:     5.5 h           pred. sleep time:       5.52 h
                awakenings:     33              pred. awakenings:       36

day 17 :        sleep time:     6.78 h          pred. sleep time:       6.83 h
                awakenings:     24              pred. awakenings:       22

day 25 :        sleep time:     5.85 h          pred. sleep time:       5.83 h
                awakenings:     44              pred. awakenings:       40
```