21BDS0340

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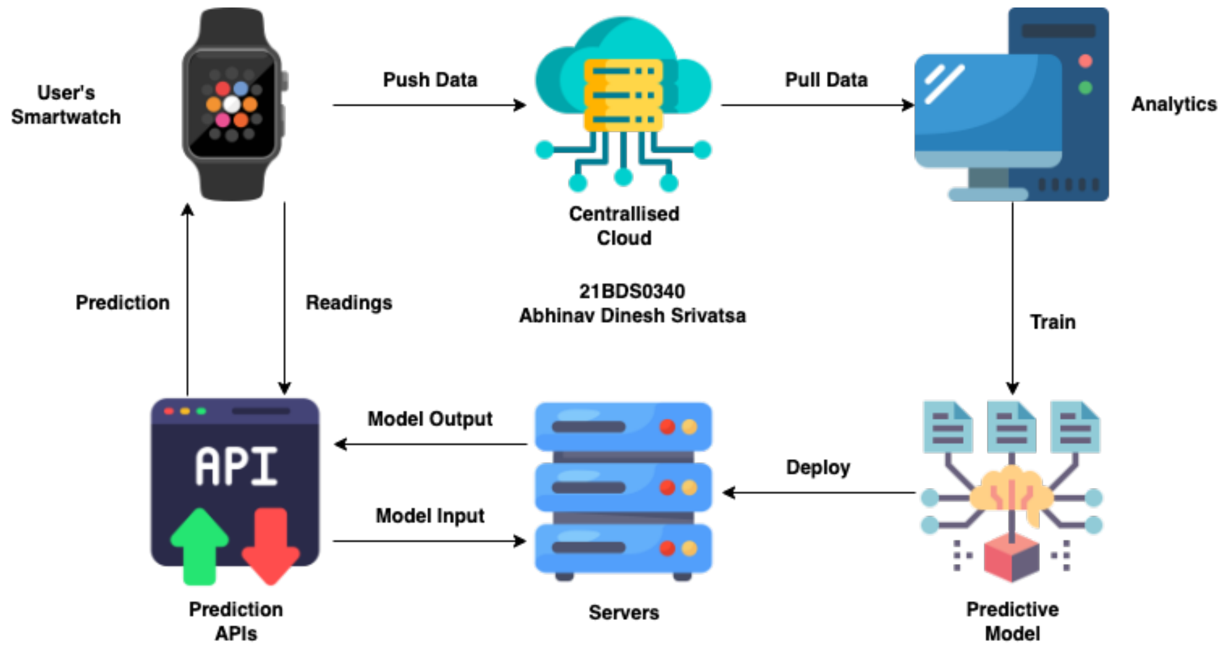
Predictive Analysis

Digital Assignment – II

System Design and Implementation



User Smartwatches

Contains various sensors to measure users' data, sensors include:

- Heart rate monitors to measure heart rate
- Oximetry sensors to measure blood oxygen levels
- Ambient light sensors to measure surrounding lighting conditions
- Accelerometers to measure velocity and acceleration
- Gyroscopes to measure changes in direction angularly
- Barometers to measure atmospheric pressure
- Ambient temperature sensors to measure the environments temperature
- Magnetometer to measure nearby magnetic fields strengths and direction
- Skin conductance sensors to measure the skins electrical conductivity
- Skin temperature sensors to measure body temperature
- GPS (Global Positioning System) to measure current location globally

The smartwatch takes the data measured and pushes it to the cloud for analytics to use.

Centrallised Cloud

Pools data and store it to be used by analytics teams, technologies for stream processing will shine here.

Analytics
Uses data stored by the data ingestion in the cloud to perform exploratory data analysis and find patterns in data, model building and testing happens here.

Predictive Model
A model is developed by analysis of the data to create steady relationships between the independent variables and predicting (dependent) variable in the data.

Servers
The predictive model can be deployed on servers on the cloud or locally to allow users to be able to access predictions and test accuracy.

Prediction APIs
APIs can be developed for users to access the model in the servers with better security and rate limiting. This completes the cycle for predictions for users utilizing data that they have provided.

<u>Activity Recognition and Fitness Metrics</u>

Activities Tracked
1. Bicycling
2. Sitting/standing
3. Sleep
4. Vehicle travelling
5. Walking
6. Any other actions (mixed)

<u>Expected Deliverables start on the next page:</u>

In [1]:
```
!wget https://ora.ox.ac.uk/objects/uuid:99d7c092-d865-4a19-b096-cc16440cd
```

```
--2024-11-06 06:24:02--  https://ora.ox.ac.uk/objects/uuid:99d7c092-d865-4
a19-b096-cc16440cd001/files/rpr76f381b
Resolving ora.ox.ac.uk (ora.ox.ac.uk)... 129.67.246.216
Connecting to ora.ox.ac.uk (ora.ox.ac.uk)|129.67.246.216|:443... connecte
d.
HTTP request sent, awaiting response... 200 OK
Length: unspecified [application/zip]
Saving to: ‘rpr76f381b’

rpr76f381b              [                <=> ]   6.43G  27.0MB/s    in 4m
11s

2024-11-06 06:28:14 (26.3 MB/s) - ‘rpr76f381b’ saved [6902652480]
```

In [2]:
```
!unzip rpr76f381b -d data >> /dev/null
```

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
import scipy.signal as signal
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
```

In [4]:
```
def extract_features(xyz, sample_rate=100):
    ''' Extract commonly used HAR time-series features. xyz is a window o

    feats = {}

    x, y, z = xyz.T

    feats['xmin'], feats['xq25'], feats['xmed'], feats['xq75'], feats['xm
        x, (0, .25, .5, .75, 1))
    feats['ymin'], feats['yq25'], feats['ymed'], feats['yq75'], feats['ym
        y, (0, .25, .5, .75, 1))
    feats['zmin'], feats['zq25'], feats['zmed'], feats['zq75'], feats['zm
        z, (0, .25, .5, .75, 1))

    with np.errstate(divide='ignore', invalid='ignore'):  # ignore div by
        # xy, xy, zx correlation
        feats['xycorr'] = np.nan_to_num(np.corrcoef(x, y)[0, 1])
        feats['yzcorr'] = np.nan_to_num(np.corrcoef(y, z)[0, 1])
        feats['zxcorr'] = np.nan_to_num(np.corrcoef(z, x)[0, 1])

    v = np.linalg.norm(xyz, axis=1)

    feats['min'], feats['q25'], feats['med'], feats['q75'], feats['max']
        v, (0, .25, .5, .75, 1))

    with np.errstate(divide='ignore', invalid='ignore'):  # ignore div by
        # 1s autocorrelation
        feats['corr1s'] = np.nan_to_num(np.corrcoef(
            v[:-sample_rate], v[sample_rate:]))[0, 1]
```

```
    # Angular features
    feats.update(angular_features(xyz, sample_rate))

    # Spectral features
    feats.update(spectral_features(v, sample_rate))

    # Peak features
    feats.update(peak_features(v, sample_rate))

    return feats


def spectral_features(v, sample_rate):
    """ Spectral entropy, 1st & 2nd dominant frequencies """

    feats = {}

    # Spectrum using Welch's method with 3s segment length
    # First run without detrending to get the true spectrum
    freqs, powers = signal.welch(v, fs=sample_rate,
                                 nperseg=3 * sample_rate,
                                 noverlap=2 * sample_rate,
                                 detrend=False,
                                 average='median')

    with np.errstate(divide='ignore', invalid='ignore'):  # ignore div by
        feats['pentropy'] = np.nan_to_num(stats.entropy(powers + 1e-16))

    # Spectrum using Welch's method with 3s segment length
    # Now do detrend to focus on the relevant freqs
    freqs, powers = signal.welch(v, fs=sample_rate,
                                 nperseg=3 * sample_rate,
                                 noverlap=2 * sample_rate,
                                 detrend='constant',
                                 average='median')

    peaks, _ = signal.find_peaks(powers)
    peak_powers = powers[peaks]
    peak_freqs = freqs[peaks]
    peak_ranks = np.argsort(peak_powers)[::-1]
    if len(peaks) >= 2:
        feats['f1'] = peak_freqs[peak_ranks[0]]
        feats['f2'] = peak_freqs[peak_ranks[1]]
        feats['p1'] = peak_powers[peak_ranks[0]]
        feats['p2'] = peak_powers[peak_ranks[1]]
    elif len(peaks) == 1:
        feats['f1'] = feats['f2'] = peak_freqs[peak_ranks[0]]
        feats['p1'] = feats['p2'] = peak_powers[peak_ranks[0]]
    else:
        feats['f1'] = feats['f2'] = 0
        feats['p1'] = feats['p2'] = 0

    return feats


def peak_features(v, sample_rate):
    """ Features of the signal peaks. A proxy to step counts. """

    feats = {}
    u = butterfilt(v, (.6, 5), fs=sample_rate)
```

```
    peaks, peak_props = signal.find_peaks(
        u, distance=0.2 * sample_rate, prominence=0.25)
    feats['numPeaks'] = len(peaks)
    if len(peak_props['prominences']) > 0:
        feats['peakPromin'] = np.median(peak_props['prominences'])
    else:
        feats['peakPromin'] = 0

    return feats


def angular_features(xyz, sample_rate):
    """ Roll, pitch, yaw.
    Hip and Wrist Accelerometer Algorithms for Free-Living Behavior
    Classification, Ellis et al.
    """

    feats = {}

    # Raw angles
    x, y, z = xyz.T

    roll = np.arctan2(y, z)
    pitch = np.arctan2(x, z)
    yaw = np.arctan2(y, x)

    feats['avgroll'] = np.mean(roll)
    feats['avgpitch'] = np.mean(pitch)
    feats['avgyaw'] = np.mean(yaw)
    feats['sdroll'] = np.std(roll)
    feats['sdpitch'] = np.std(pitch)
    feats['sdyaw'] = np.std(yaw)

    # Gravity angles
    xyz = butterfilt(xyz, 0.5, fs=sample_rate)

    x, y, z = xyz.T

    roll = np.arctan2(y, z)
    pitch = np.arctan2(x, z)
    yaw = np.arctan2(y, x)

    feats['rollg'] = np.mean(roll)
    feats['pitchg'] = np.mean(pitch)
    feats['yawg'] = np.mean(yaw)

    return feats


def butterfilt(x, cutoffs, fs, order=10, axis=0):
    nyq = 0.5 * fs
    if isinstance(cutoffs, tuple):
        hicut, lowcut = cutoffs
        if hicut > 0:
            btype = 'bandpass'
            Wn = (hicut / nyq, lowcut / nyq)
        else:
            btype = 'low'
            Wn = lowcut / nyq
    else:
```

```
        btype = 'low'
        Wn = cutoffs / nyq
    sos = signal.butter(order, Wn, btype=btype, analog=False, output='sos
    y = signal.sosfiltfilt(sos, x, axis=axis)
    return y


def get_feature_names():
    """ Hacky way to get the list of feature names """

    feats = extract_features(np.zeros((1000, 3)), 100)
    return list(feats.keys())
```

In [5]:
```
data = pd.read_csv(
    "data/capture24/P001.csv.gz", compression="gzip",
    index_col="time", parse_dates=["time"],
    dtype={"x": "f4", "y": "f4", "z": "f4", "annotation": "string"}
    )
data
```

Out[5]:

time	x	y	z	annotation
2016-11-13 02:18:00.000	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95
2016-11-13 02:18:00.010	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95
2016-11-13 02:18:00.020	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95
2016-11-13 02:18:00.030	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95
2016-11-13 02:18:00.040	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95
...	...	...	...	...
2016-11-14 06:07:59.960	0.049416	-0.797846	0.565700	7030 sleeping;MET 0.95
2016-11-14 06:07:59.970	0.049416	-0.782285	0.565700	7030 sleeping;MET 0.95
2016-11-14 06:07:59.980	0.049416	-0.782285	0.565700	7030 sleeping;MET 0.95
2016-11-14 06:07:59.990	0.049416	-0.782285	0.565700	7030 sleeping;MET 0.95
2016-11-14 06:08:00.000	0.049416	-0.782285	0.565700	7030 sleeping;MET 0.95

10020001 rows × 4 columns

In [6]:
```
annot = pd.read_csv("data/capture24/annotation-label-dictionary.csv", ind
annot
```

Out[6]:

annotation	label:WillettsSpecific2018	label:WillettsMET2018
7030 sleeping;MET 0.95	sleep	sleep
occupation;office and administrative support;11580 office/computer work general;MET 1.5	sitting	sitstand+lowactivity
home activity;household chores;preparing meals/cooking/washing dishes;5035 kitchen activity general cooking/washing/dishes/cleaning up;MET 3.3	household-chores	sitstand+activity
occupation;office and administrative support;11580 office wok/computer work general;MET 1.5	sitting	sitstand+lowactivity
home activity;miscellaneous;sitting;9060 sitting/lying reading or without observable/identifiable activities;MET 1.3	sitting	sitstand+lowactivity
...	...	...
transportation;walking;17250 walking as the single means to a destination not to work or class;MET 3.0	mixed-activity	walking
transportation;walking;17270 walking as the single means to work or class (not from);MET 3.5	walking	walking
transportation;public transportation;16016 riding in a bus or train;MET 1.3	vehicle	vehicle
household-chores;sitstand+lowactivity;MET 2.8	household-chores	sitstand+lowactivity
vehicle;MET 1.3	vehicle	vehicle

206 rows × 6 columns

In [7]:

```
# using Willetts2018
annot["label:Willetts2018"]
```

Out[7]:

	label:Willetts2018
annotation	
7030 sleeping;MET 0.95	sleep
occupation;office and administrative support;11580 office/computer work general;MET 1.5	sit-stand
home activity;household chores;preparing meals/cooking/washing dishes;5035 kitchen activity general cooking/washing/dishes/cleaning up;MET 3.3	mixed
occupation;office and administrative support;11580 office wok/computer work general;MET 1.5	sit-stand
home activity;miscellaneous;sitting;9060 sitting/lying reading or without observable/identifiable activities;MET 1.3	sit-stand
...	...
transportation;walking;17250 walking as the single means to a destination not to work or class;MET 3.0	mixed
transportation;walking;17270 walking as the single means to work or class (not from);MET 3.5	walking
transportation;public transportation;16016 riding in a bus or train;MET 1.3	vehicle
household-chores;sitstand+lowactivity;MET 2.8	mixed
vehicle;MET 1.3	vehicle

206 rows × 1 columns

dtype: object

In [8]:

```
# mapping data to low dimension annotation
data["label"] = annot["label:Willetts2018"].reindex(data["annotation"]).t
data
```

Out[8]:

time	x	y	z	annotation	label
2016-11-13 02:18:00.000	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95	sleep
2016-11-13 02:18:00.010	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95	sleep
2016-11-13 02:18:00.020	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95	sleep
2016-11-13 02:18:00.030	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95	sleep
2016-11-13 02:18:00.040	-0.466690	-0.533341	0.658472	7030 sleeping;MET 0.95	sleep
...	...	...	...	...	...
2016-11-14 06:07:59.960	0.049416	-0.797846	0.565700	7030 sleeping;MET 0.95	sleep
2016-11-14 06:07:59.970	0.049416	-0.782285	0.565700	7030 sleeping;MET 0.95	sleep
2016-11-14 06:07:59.980	0.049416	-0.782285	0.565700	7030 sleeping;MET 0.95	sleep
2016-11-14 06:07:59.990	0.049416	-0.782285	0.565700	7030 sleeping;MET 0.95	sleep
2016-11-14 06:08:00.000	0.049416	-0.782285	0.565700	7030 sleeping;MET 0.95	sleep

10020001 rows × 5 columns

In [9]:
```
data.label.unique()
```

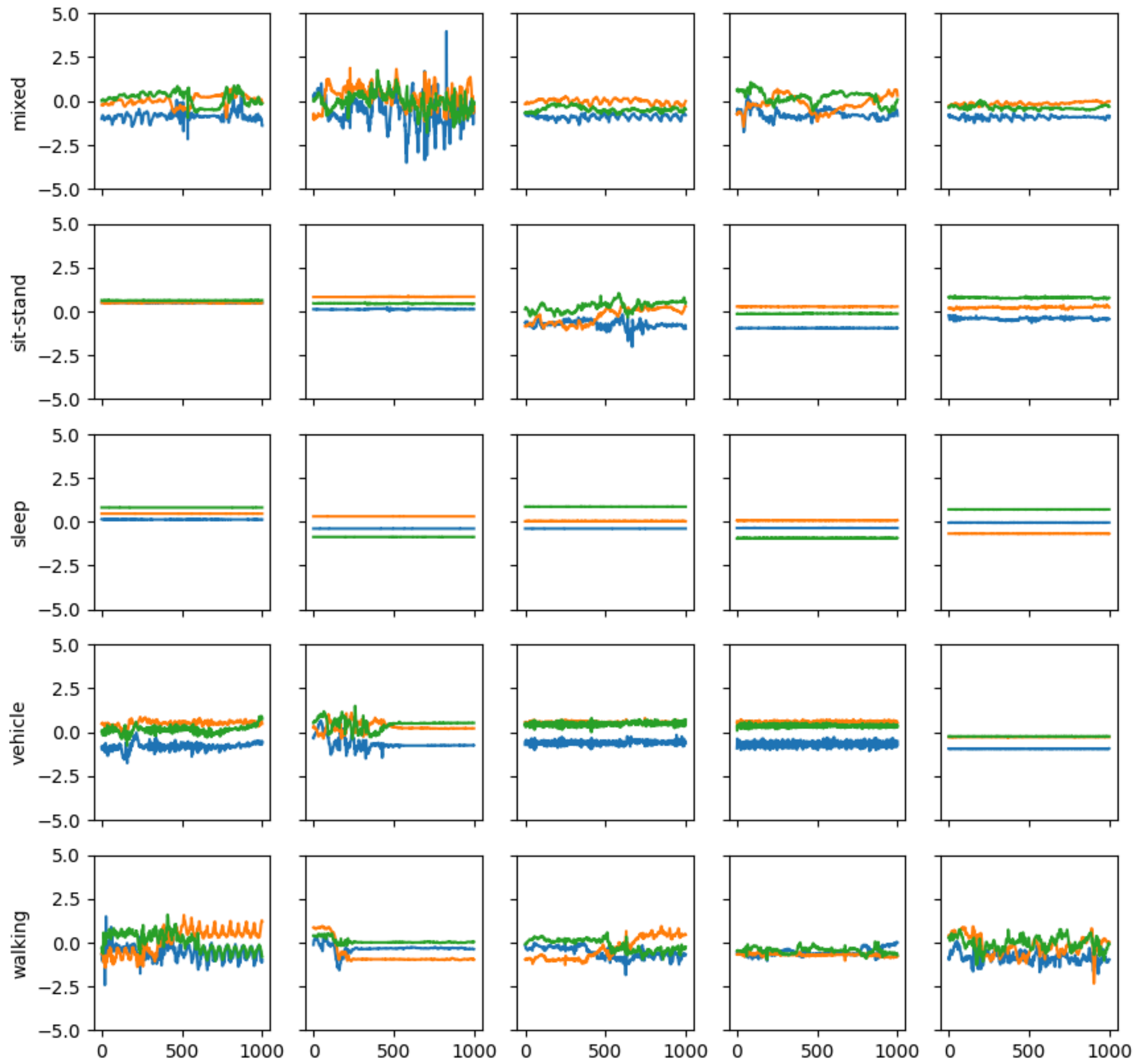
Out[9]:
```
array(['sleep', nan, 'mixed', 'walking', 'vehicle', 'sit-stand'],
      dtype=object)
```

In [10]:
```
def window(data, size = "10s"):
  X, Y = [], []
  for time, d in data.resample(size, origin='start'):
      if d.isna().any().any() or len(d) != 1000:
          continue

      x = d[["x", "y", "z"]].to_numpy()
      y = d["label"].mode(dropna=False).item()

      X.append(x)
      Y.append(y)

  X = np.stack(X)
  Y = np.stack(Y)

  return X, Y
```

In [11]:
```
# creating the windows
```

```
X, Y = window(data)
```

In [12]:
```
# plotting the activities
plots = 5
unique_labels = np.unique(Y)
fig, ax = plt.subplots(len(unique_labels), plots, sharex = True, sharey =
for label, row in zip(unique_labels, ax):
    i = np.random.choice(np.where(Y == label)[0], size = plots)
    row[0].set_ylabel(label)
    for feature, x in zip(X[i], row):
        x.plot(feature)
        x.set_ylim(-5, 5)
fig.show()
```



In [13]:
```
# training model to predict activity
Xf = pd.DataFrame([extract_features(x) for x in X])
Xf
```

Out[13]:

	xmin	xq25	xmed	xq75	xmax	ymin	yq
0	-0.482334	-0.466690	-0.466690	-0.466690	-0.466690	-0.548902	-0.5489
1	-0.482334	-0.466690	-0.466690	-0.466690	-0.466690	-0.548902	-0.5489
2	-0.482334	-0.482334	-0.466690	-0.466690	-0.466690	-0.548902	-0.5333
3	-0.482398	-0.482334	-0.466690	-0.466690	-0.466690	-0.548902	-0.5333
4	-0.482398	-0.482334	-0.466690	-0.466690	-0.466626	-0.548902	-0.5333
...	...	...	...	...	...	...	
7347	0.033708	0.033772	0.049416	0.049416	0.049416	-0.813407	-0.7978
7348	0.033708	0.033772	0.049416	0.049416	0.065059	-0.813407	-0.7978
7349	0.033772	0.049416	0.049416	0.049416	0.049416	-0.797846	-0.7978
7350	0.033708	0.033772	0.049352	0.049416	0.049416	-0.797846	-0.7978
7351	0.033708	0.033772	0.049416	0.049416	0.049416	-0.797846	-0.7978

7352 rows × 40 columns

In [14]:

```
# training model
rfc = RandomForestClassifier(
    n_estimators=100,
    n_jobs=4,
    random_state=42
)
rfc.fit(Xf, Y)
```

Out[14]:

```
RandomForestClassifier
RandomForestClassifier(n_jobs=4, random_state=42)
```

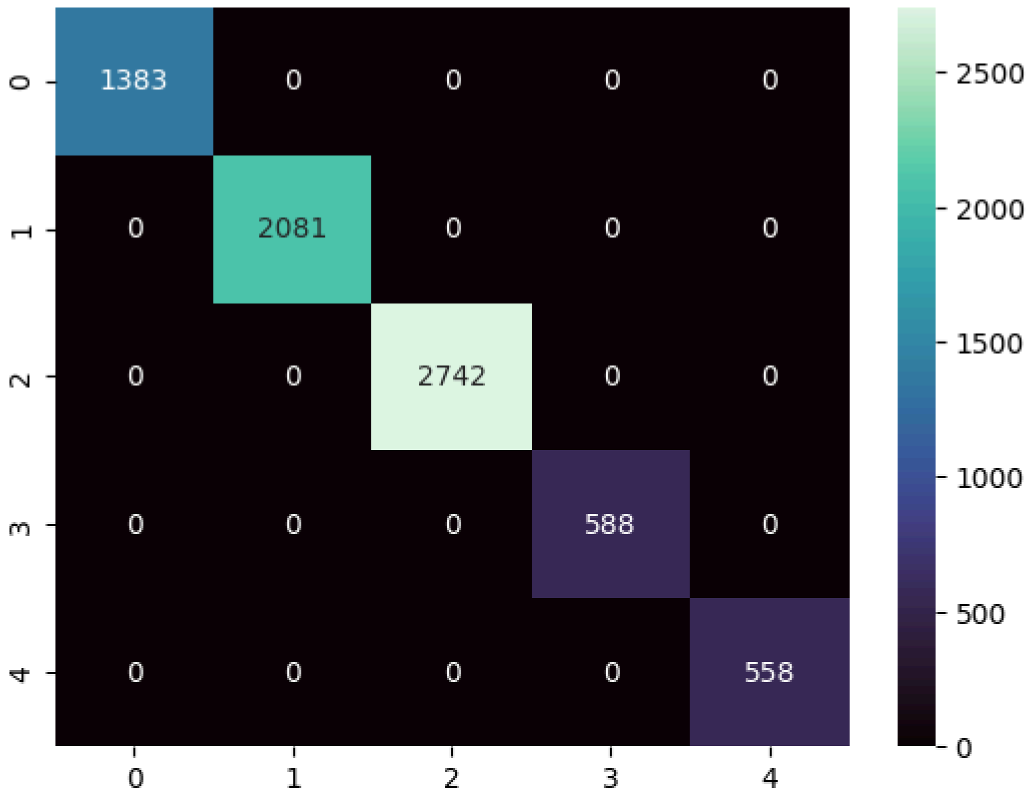
In [15]:

```
print(classification_report(Y, rfc.predict(Xf), zero_division=0))
```

```
              precision    recall  f1-score   support

       mixed       1.00      1.00      1.00      1383
   sit-stand       1.00      1.00      1.00      2081
       sleep       1.00      1.00      1.00      2742
     vehicle       1.00      1.00      1.00       588
     walking       1.00      1.00      1.00       558

    accuracy                           1.00      7352
   macro avg       1.00      1.00      1.00      7352
weighted avg       1.00      1.00      1.00      7352
```

In [16]:

```
Yp = rfc.predict(Xf)
sns.heatmap(confusion_matrix(Y, Yp), cmap = "mako", annot = True, fmt = "
plt.show()
```



In [17]:

```
# trying to extend model to another person
data = pd.read_csv(
    "data/capture24/P002.csv.gz", compression="gzip",
    index_col="time", parse_dates=["time"],
    dtype={"x": "f4", "y": "f4", "z": "f4", "annotation": "string"}
    )
data["label"] = annot["label:Willetts2018"].reindex(data["annotation"]).t
X, Y = window(data)
Xf = pd.DataFrame([extract_features(x) for x in X])
Xf
```

Out[17]:

	xmin	xq25	xmed	xq75	xmax	ymin	yq2
0	-0.394386	-0.378620	-0.378620	-0.362854	-0.331323	0.444236	0.4599
1	-0.410152	-0.378620	-0.378620	-0.378620	-0.347089	0.444236	0.4599
2	-0.410152	-0.394386	-0.378620	-0.378620	-0.347089	0.444236	0.4599
3	-0.410152	-0.394386	-0.378620	-0.378620	-0.347089	0.444236	0.4599
4	-0.410152	-0.394386	-0.378620	-0.378620	-0.347089	0.444236	0.4599
...	...	...	...	...	...	...	
5581	-0.360339	-0.344573	-0.344573	-0.344573	-0.328807	-0.732336	-0.7166
5582	-0.344933	-0.344933	-0.344573	-0.344573	-0.328807	-0.717062	-0.7013
5583	-0.344933	-0.344933	-0.344573	-0.344573	-0.328807	-0.717062	-0.7013
5584	-0.344933	-0.344933	-0.344933	-0.344933	-0.329167	-0.717062	-0.7013
5585	-0.344933	-0.344933	-0.344933	-0.344933	-0.329167	-0.717062	-0.7013

5586 rows × 40 columns

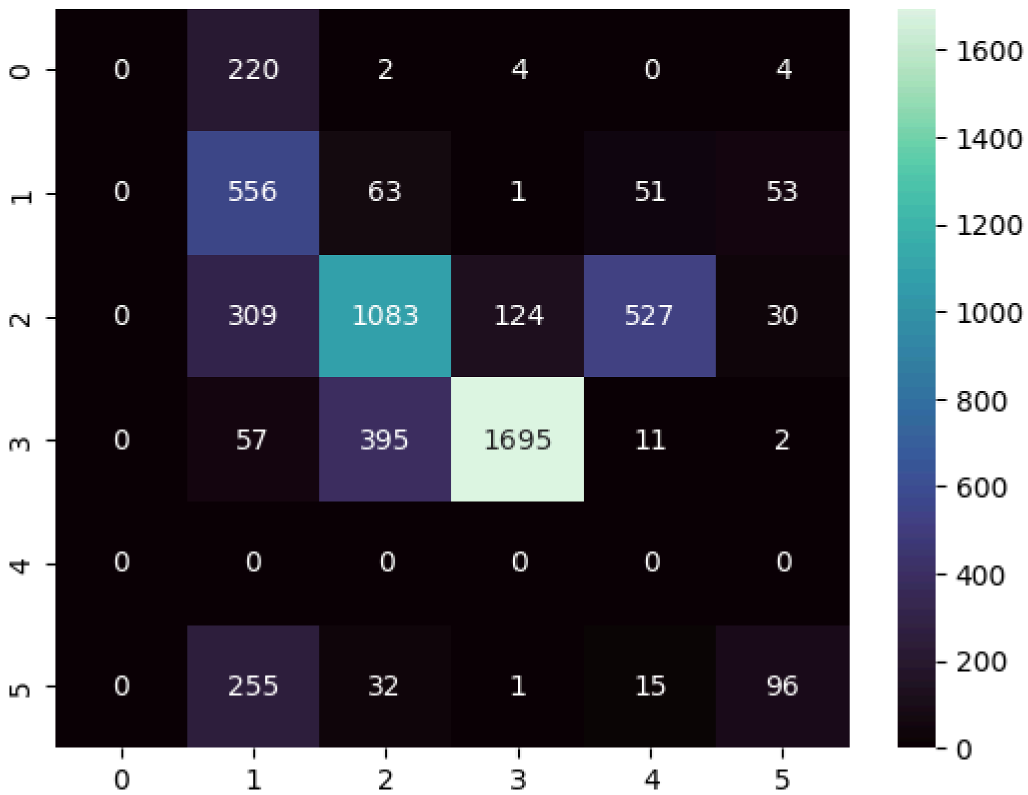
In [18]:

```
# checking metrics
print(classification_report(Y, rfc.predict(Xf), zero_division=0))
```

```
              precision    recall  f1-score   support

   bicycling       0.00      0.00      0.00       230
       mixed       0.40      0.77      0.52       724
   sit-stand       0.69      0.52      0.59      2073
       sleep       0.93      0.78      0.85      2160
     vehicle       0.00      0.00      0.00         0
     walking       0.52      0.24      0.33       399

    accuracy                           0.61      5586
   macro avg       0.42      0.39      0.38      5586
weighted avg       0.70      0.61      0.64      5586
```

In [19]:

```
# plotting prediction heatmap
Yp = rfc.predict(Xf)
sns.heatmap(confusion_matrix(Y, Yp), cmap = "mako", annot = True, fmt = "
plt.show()
```


0
220
2
4
0
4
0
556
63
1
51
53
0
309
1083
124
527
30
0
57
395
1695
11
2
0
0
0
0
0
0
0
255
32
1
15
96
0
1
2
3
4
5
1600
1400
1200
1000
800
600
400
200
0