About me

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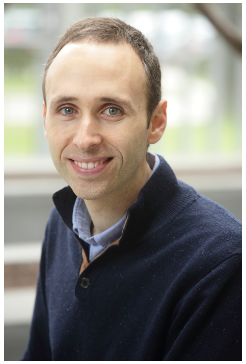
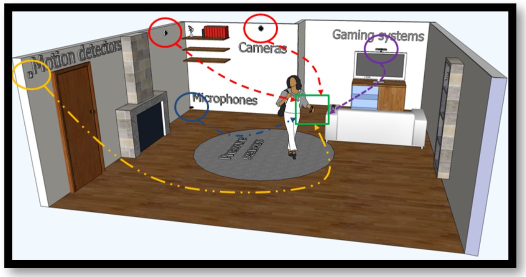
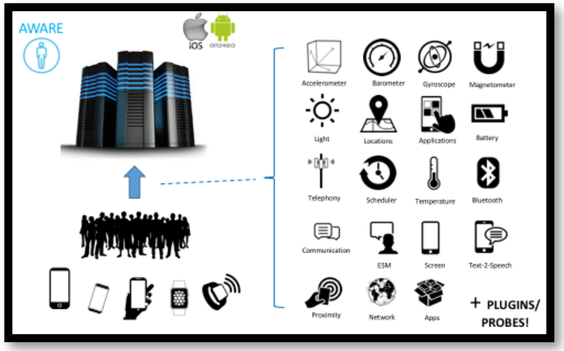
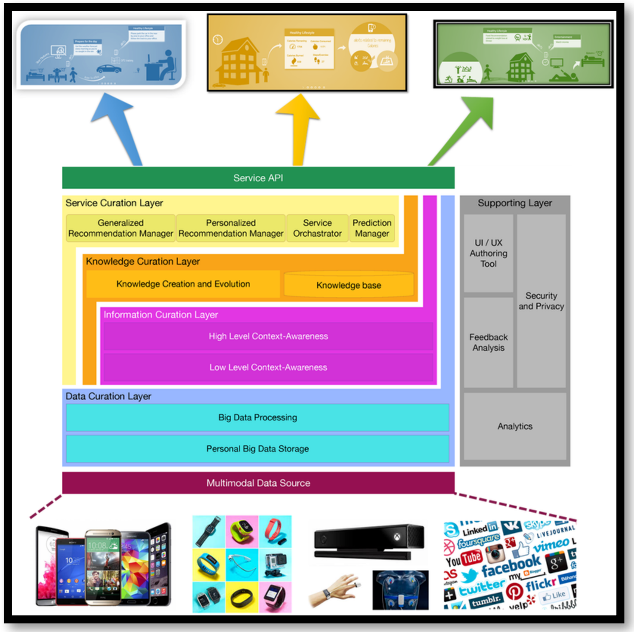


Research:

- smart mobile sensing
- behaviour and context modelling
- virtual coaching systems



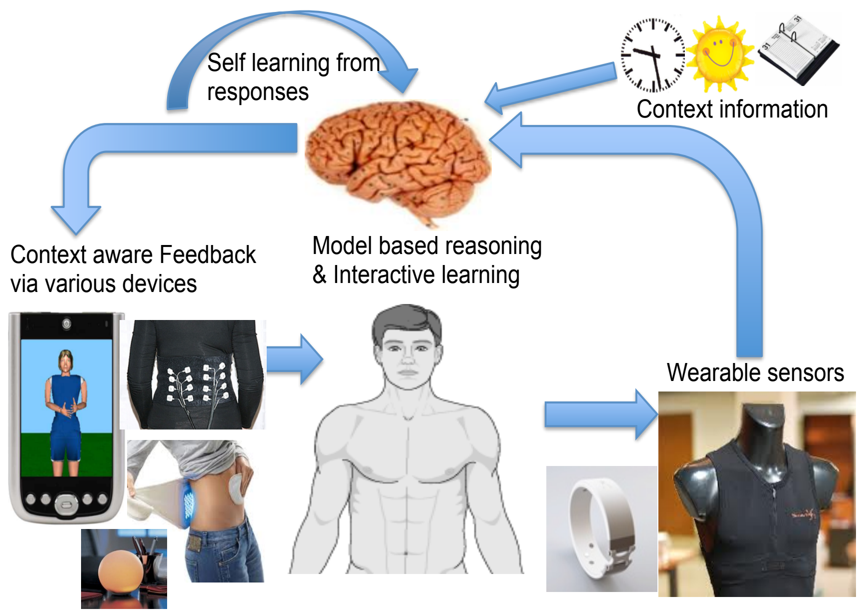




Center for Monitoring and Coaching:
“High Tech Care with a Human Touch”

Application domains:
Frailty, Stroke, Diabetes, Pain
Parkinson’s, Alzheimer’s, Autism

Human Behaviour Modeling
- Artificial intelligence
- Machine learning
- Behaviour change frameworks
- Persuasive tech



Multimodal Sensing
- Wearables
- Textiles
- Ambient sensors
- SNS
- ESM

Human-Computer Interaction
- Haptic interfaces
- (Emboddied) Virtual agents
- Natural language processing

https://www.utwente.nl/ctit/cmc/

We are hiring!

H2020-SC1-PM-15-2017: Personalised coaching for well-being and care of people as they age

Council of Coaches

PhD position #1: Smart Behavior Mining

PhD position #2: Human-Computer Interfaces

PhD position #3: Coaching Strategies and Knowledge Base

http://www.utwente.nl//en/organization/careers/vacancies/phd/

UNIVERSITY OF TWENTE.

Connected Health Summer School

Processing Sensor Data

Oresti Banos

June 28, 2017

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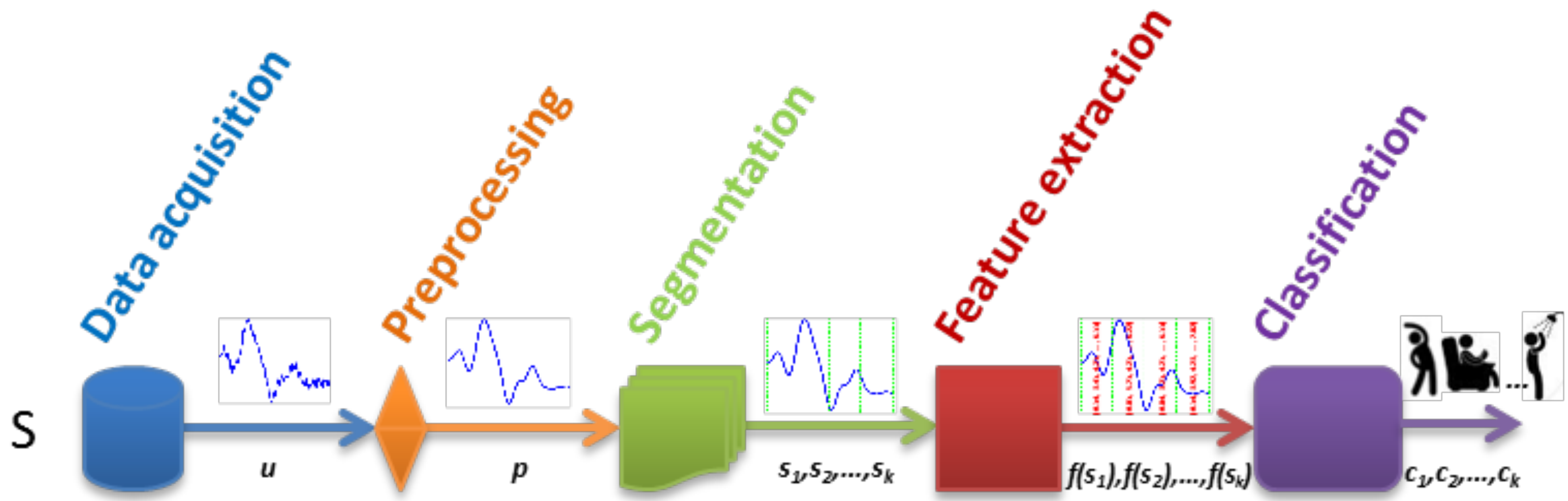
Learning Objectives

At the end of this course you should be able to:

- Identify the different stages of the activity recognition chain and their purpose
- Apply regular segmentation techniques to split sensor data streams
- Utilise common feature extraction techniques to characterise segments of sensor data
- Represent feature spaces for anticipating classification capacity

Activity recognition chain

- Multistage process combining computational techniques to automatically extract information and develop decisions on a given data set



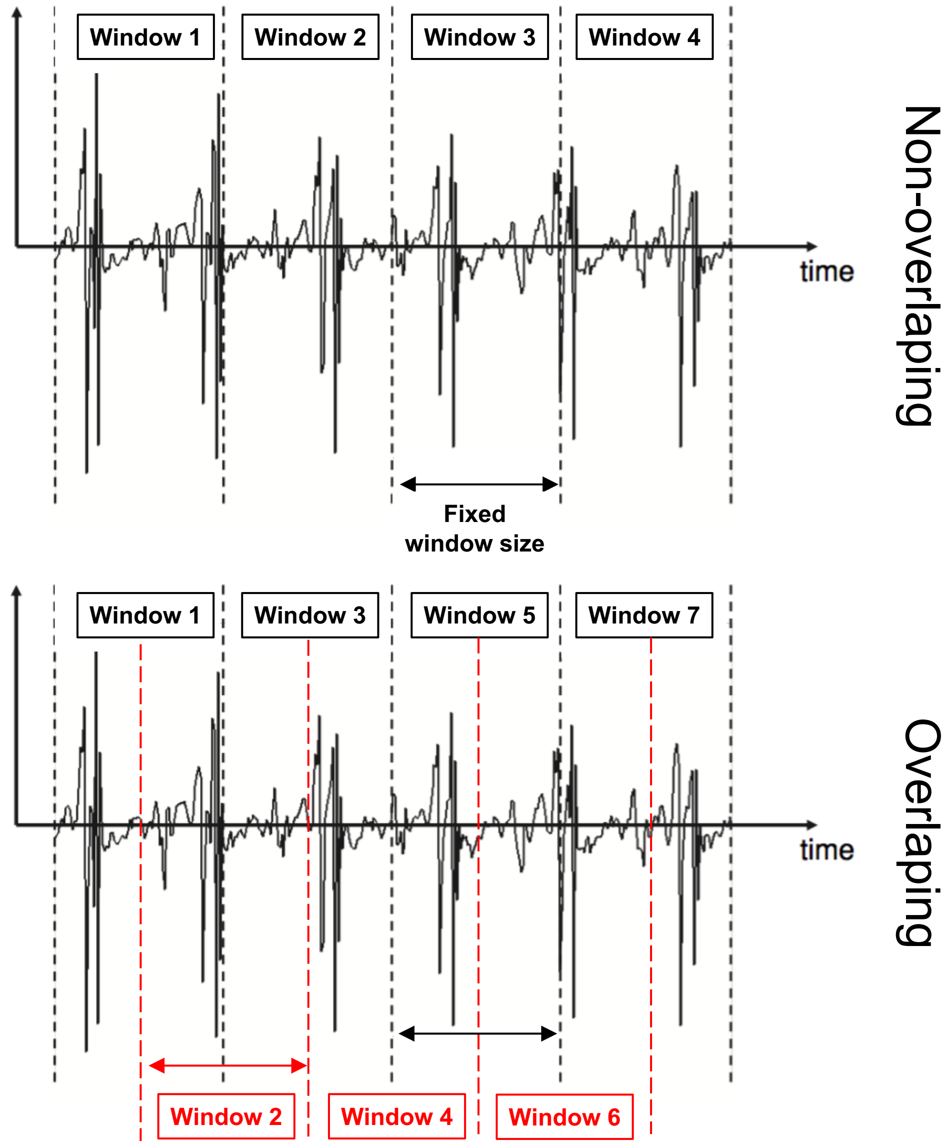
S = data source (sensor) *u = raw/unprocessed data* *p = preprocessed data*
s_i *= segment of data* $f(s_i)$ *= feature vector* c_i *= class/label*

Segmentation

- Process to divide the sensor data stream into smaller time segments or **data windows**
- The segmentation process is frequently called "windowing" as each segment represents a data window or frame
- In real-time applications, windows are defined concurrently with data acquisition and processing, so data streams can be effectively analysed "on-the-fly"

Segmentation

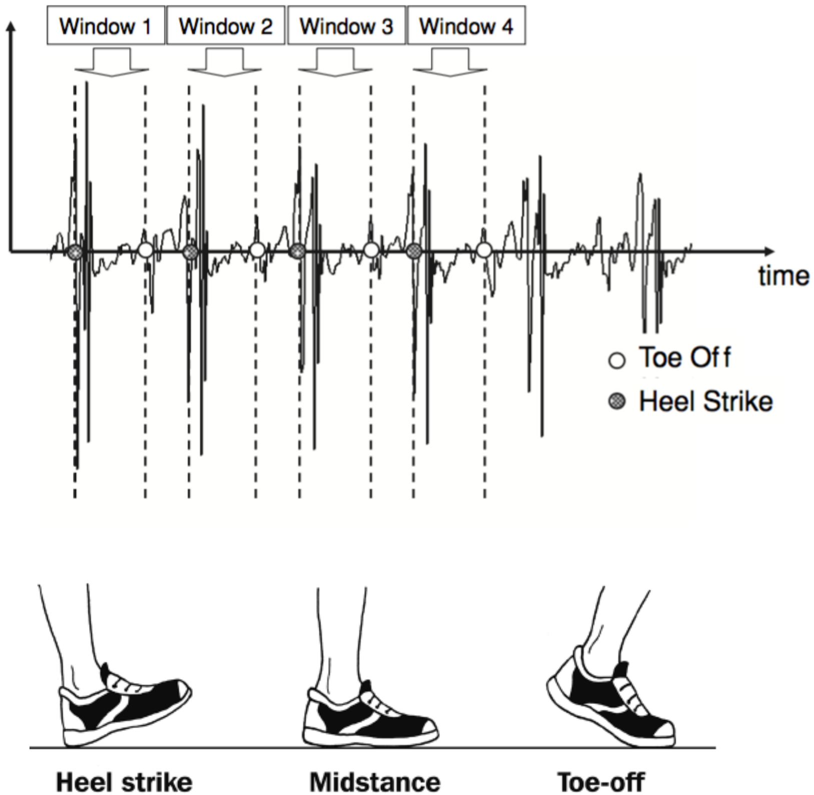
- Sliding window
  - Signals are split into windows of a fixed size and with no inter-window gaps
  - An overlap between adjacent windows is sometimes tolerated
  - Most widely used approach



Segmentation

- Event-defined window
  - The segment start and end is defined by a detected event
  - Additional processing is required to identify the events of interest
  - Example: toe offs and heel strikes based on the differentiation of the acceleration signal (derivative)

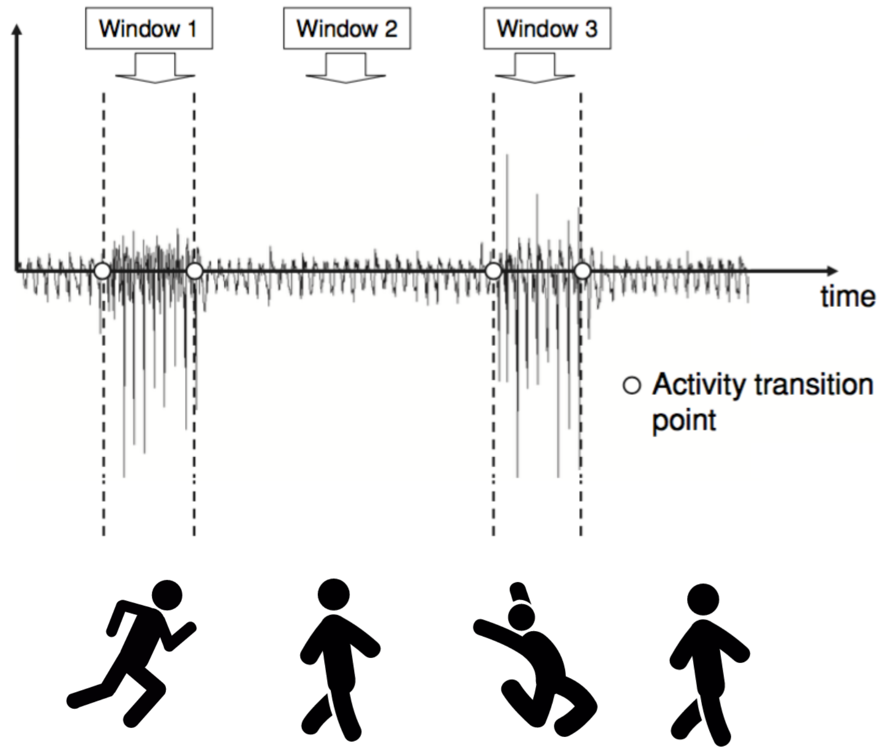
Data windows (normally) of variable size



Segmentation

- Class-defined window
  - The window start and end is defined by a change in the context or class (also spotting)
  - Example: activity transition detected from significant variations in the energy or statistical properties of the acceleration signal (e.g., variance)

Data windows (normally) of variable size



Featuring or characterisation

- How do you differentiate between these two persons? What do they have in common?

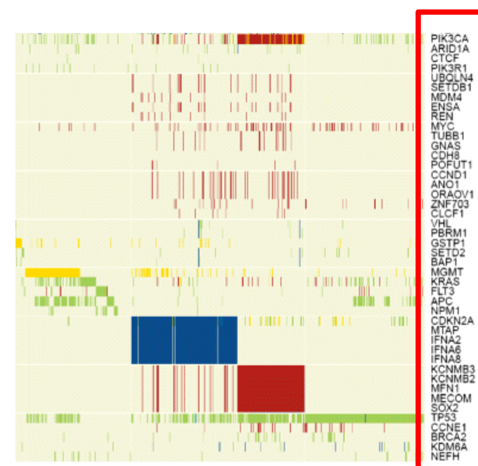
Featuring or characterisation

- Sometimes it becomes difficult to tell…

Feature extraction

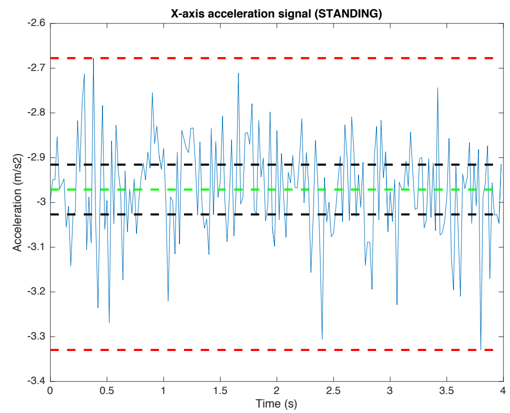
- Process of (numerically) characterising or transforming raw data into more descriptive or informative data
- Intended to facilitate the subsequent learning and generalization steps, and in some cases lead to better human interpretations

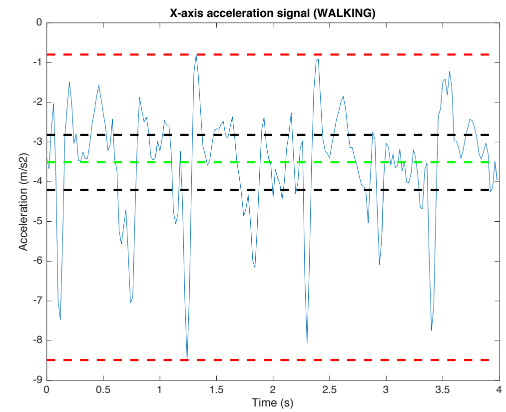
Location=prefrontal,
Size=3cm,
Density=60g/cm3, …

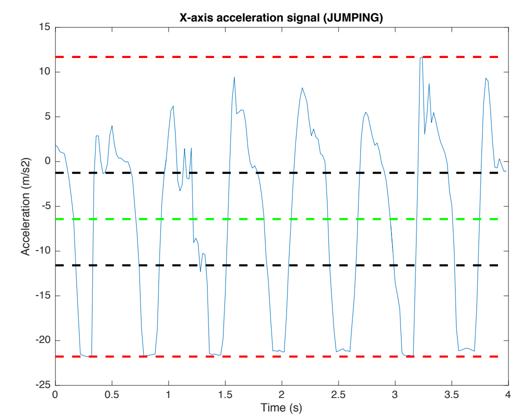


Feature extraction

- Time-domain features: statistical values derived directly from data window
- Examples:
  - Max
  - Min
  - Mean
  - Median
  - Variance
  - Skewness
  - Kurtosis



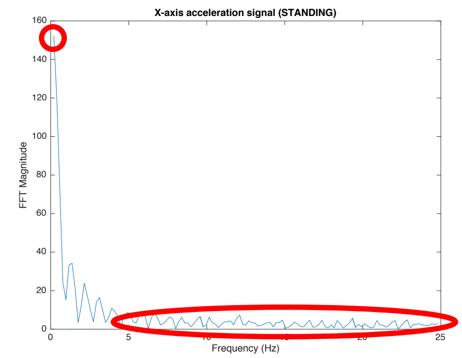


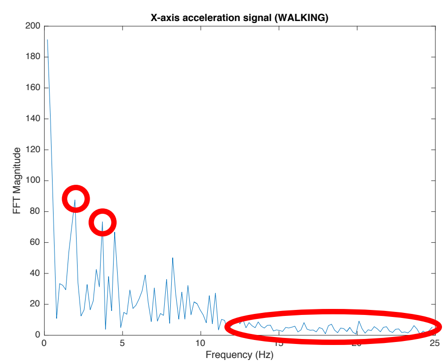


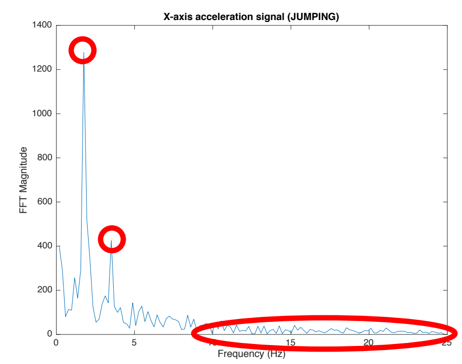
MATLAB: max, min, mean, median, var, skewness, kurtosis

Feature extraction

- Frequency-domain features: derived from a transformed version of the data window in the frequency domain
- Examples:
  - Fundamental frequency
  - N-order harmonics
  - Mean/Median/Mode frequency
  - Spectral power/energy
  - Entropy
  - Cepstrum coefficients



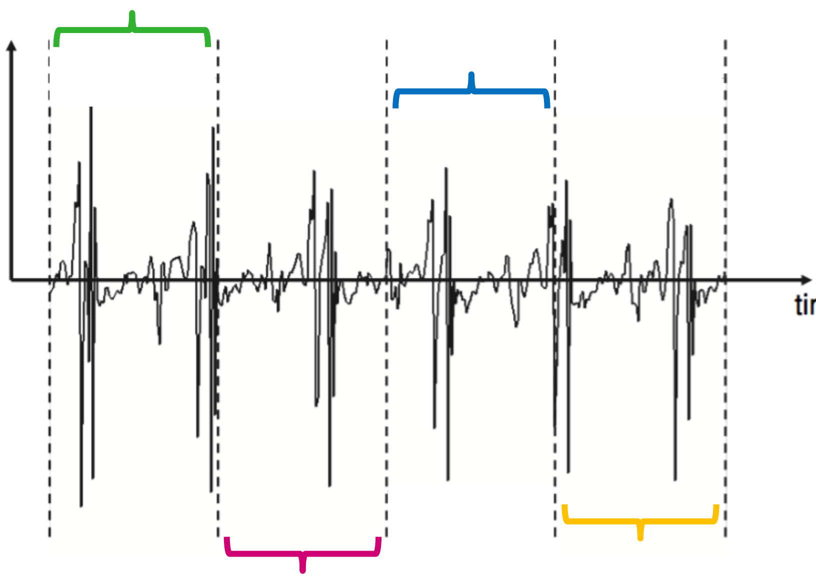




MATLAB: fft, pwelch, meanfreq, medfreq, rceps

Feature extraction

- Process of (numerically) characterising or transforming raw data into more informative data
- The outcome of the feature extraction process is normally a feature matrix
  - Rows represent each data instance, chunk or segment
  - Columns refer to the mathematical function (feature)



$$\begin{array}{cc} \textit{F1: Mean} & \textit{F2: Variance} \\ \end{array}$$

$$\begin{pmatrix} 0.18 & 0.35 \\ -0.26 & 0.15 \\ -0.05 & 0.21 \\ -0.19 & 0.18 \end{pmatrix}$$

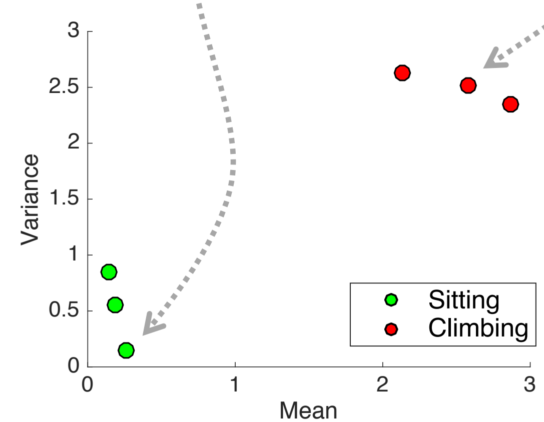
Feature matrix

Feature extraction

- Feature space:
  - Total number of features extracted from the data
  - Normally described as an array (also known as feature matrix) in which rows represent each instance and columns the feature type
  - The dimensions (D) of the feature space are given by the number of features (N)

Feature matrix

$$\begin{array}{cc} \textit{Mean} & \textit{Variance} \end{array}$$
$$\begin{pmatrix} 0.18 & 0.55 \\ 0.26 & 0.15 \\ 0.15 & 0.85 \\ 2.13 & 2.62 \\ 2.86 & 2.35 \\ 2.58 & 2.51 \end{pmatrix}$$

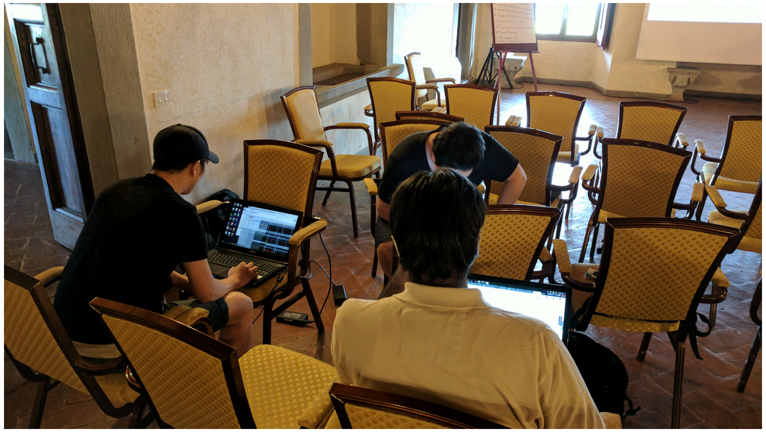


Feature space

MATLAB: scatter

Materials available here: https://goo.gl/6QQf6K

TUTORIAL TIME!



Datasets

- Activity recognition datasets (http://orestibanos.com/datasets.htm)

MHEALTH dataset

The MHEALTH (Mobile HEALTH) dataset comprises body motion and vital signs recordings for ten volunteers of diverse profile while performing several physical activities. Sensors placed on the subject's chest, right wrist and left ankle are used to measure the motion experienced by diverse body parts, namely, the acceleration, the rate of turn and the magnetic field orientation. The sensor positioned on the chest also provides 2-lead ECG measurements, which can be potentially used for basic heart monitoring, checking for various arrhythmias or looking at the effects of exercise on the ECG.

The dataset is available here and at the UCI Machine Learning Repository.

REALDISP dataset

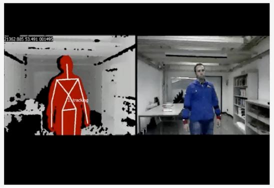
The REALDISP (REAListic sensor DISPlacement) dataset has been originally collected to investigate the effects of sensor displacement in the activity recognition process in real-world settings. It builds on the concept of ideal-placement, self-placement and induced-displacement. The ideal and mutual-displacement conditions represent extreme displacement variants and thus could represent boundary conditions for recognition algorithms. In contrast, self-placement reflects a users perception of how sensors could be attached, e.g., in a sports or lifestyle application. The dataset includes a wide range of physical activities (warm up, cool down and fitness exercises), sensor modalities (acceleration, rate of turn, magnetic field and quaternions) and participants (17 subjects). Apart from investigating sensor displacement, the dataset lend itself for benchmarking activity recognition techniques in ideal conditions.

The dataset is available here and at the UCI Machine Learning Repository.

Multimodal Kinect-IMU dataset

This dataset has been originally collected to investigate transfer learning (see reference below) among ambient sensing and wearable sensing systems. Nevertheless, the dataset may be also used for gesture spotting and continuous activity recognition. It includes data for three activity recognition scenarios, namely HCI (gesture recognition), fitness (continuous recognition) and background (unrelated events). The dataset comprises synchronized 3D coordinates of 15 body joints, measured by a vision-based skeleton tracking system (Microsoft Kinect) and the readings of 10 body-worn inertial measurement units (IMUs): acceleration, rate of turn, magnetic field and orientation (quaternions).

The dataset is available here.



References

Bulling, Andreas, Ulf Blanke, and Bernt Schiele. "A tutorial on human activity recognition using body-worn inertial sensors." ACM Computing Surveys (CSUR) 46.3 (2014): 33.

Lara, Oscar D., and Miguel A. Labrador. "A survey on human activity recognition using wearable sensors." IEEE Communications Surveys and Tutorials 15.3 (2013): 1192-1209.

Preece, Stephen J., et al. "Activity identification using body-mounted sensors—a review of classification techniques." Physiological measurement 30.4 (2009): R1.