Mobile Health
Lecture 7
IMU and
Human Activity

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Inertial Measurement Unit

- Accelerometer
- Gyroscope
- Magnetometer

Accelerometer

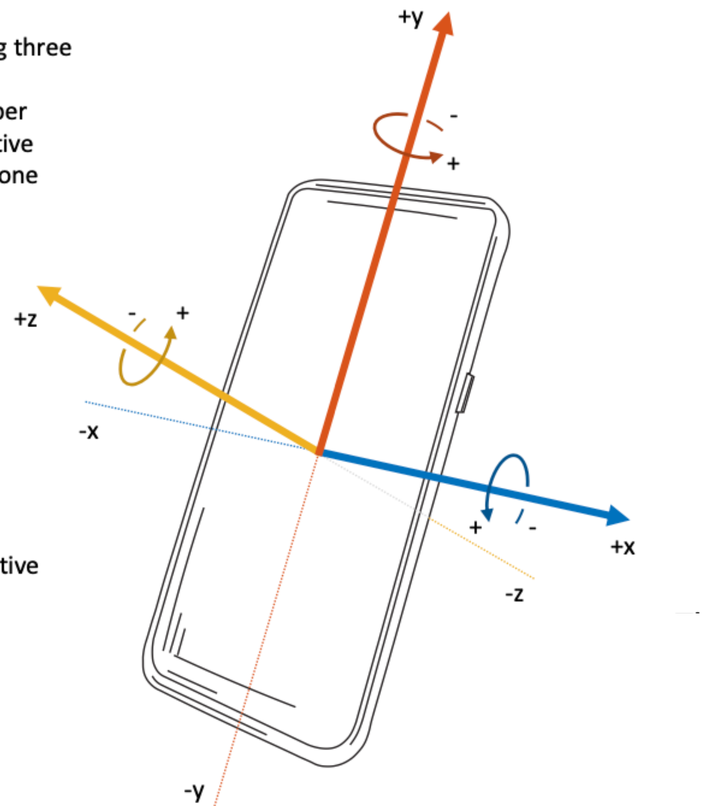
- Measures rate of change of velocity along three orthogonal axes of smartphone
- Output: gravitational units (g) or meters per seconds squared (m/s^2); positive or negative depending on the orientation of smartphone

Gyroscope

- Measures angular velocity around three orthogonal axes of smartphone
- Output: radians per second (rad/s); positive or negative depending on the direction of rotation

Magnetometer

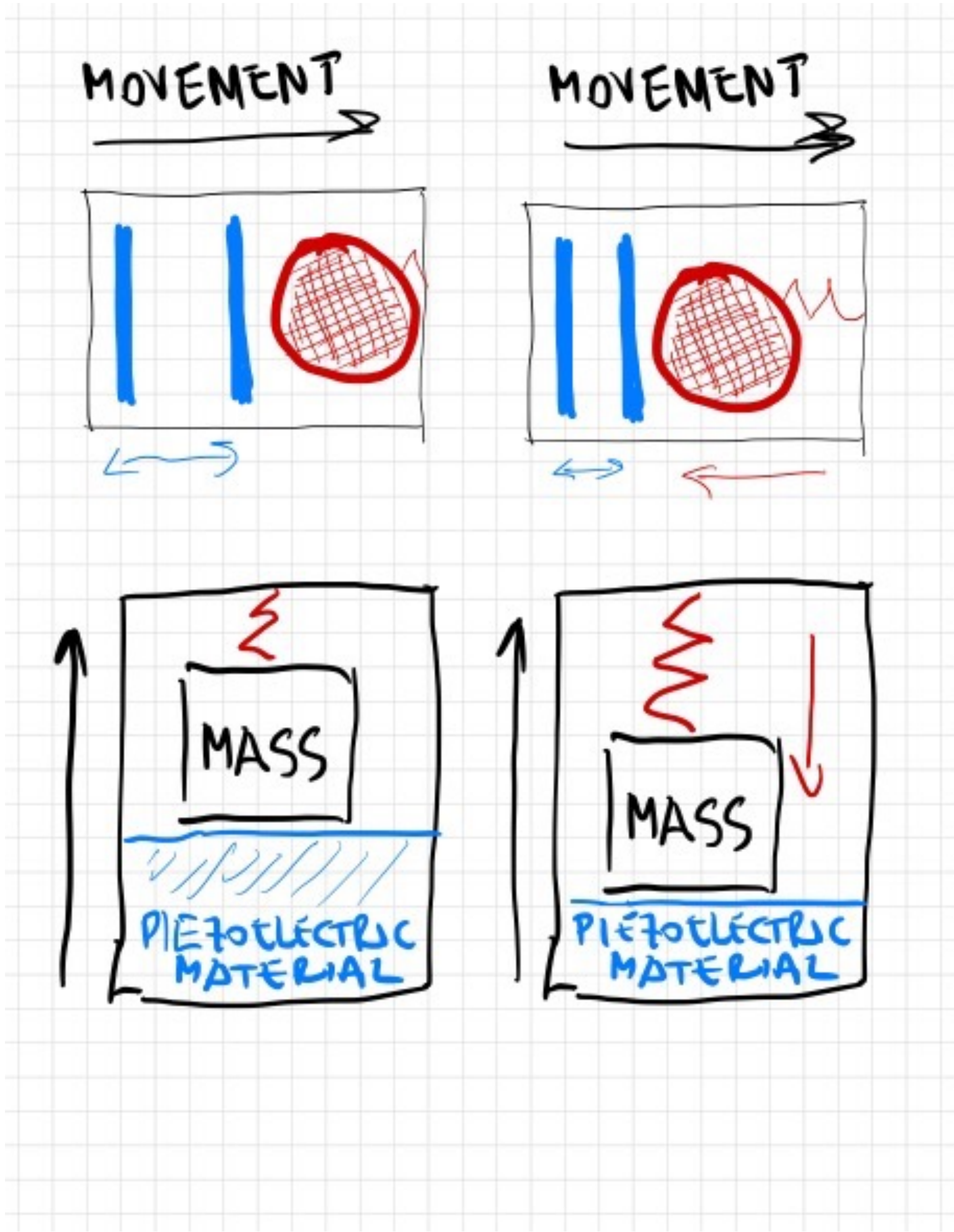
- Measures strength of Earth's magnetic field relative to three orthogonal axes of smartphone
- Output: microtesla (μT); positive or negative depending on the orientation of smartphone



From A systematic review of smartphone-based human activity recognition methods for health research. Marcin Straczkiewicz, Peter Jamess, Jukka-Pekka Onnela. Nature NPJ Digital Medicine.

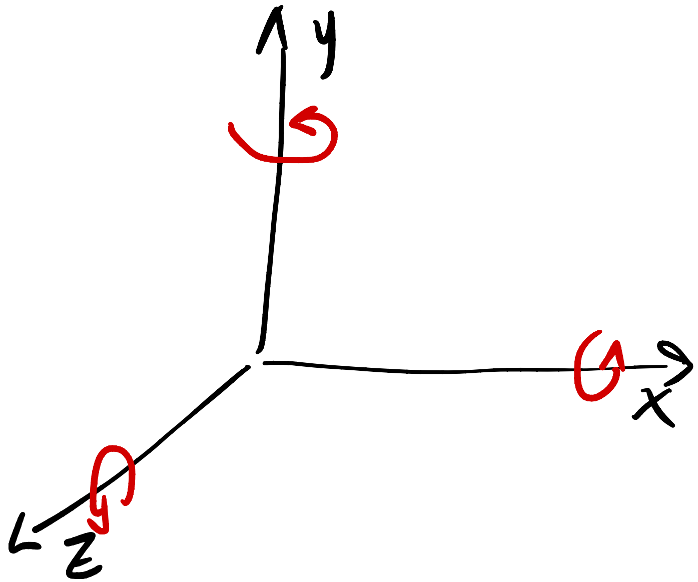
Accelerometer

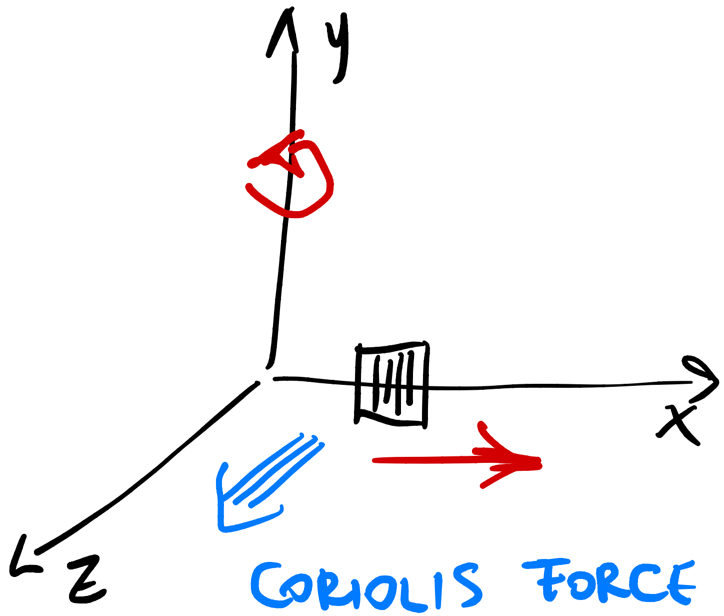
- Measures the change in speed with respect to time.
  - More informative than just speed.
  - Speed can be deduced.
- Capacitor (vibration)
- Piezoelectric
- Current devices have accelerometers measuring movement in the three orthogonal axis.



Gyroscope: an intuition

- Gyroscopes use vibration to measures the rate of rotation.
- In practice it measures the rate of rotation wrt to each axis
- Unit deg/s





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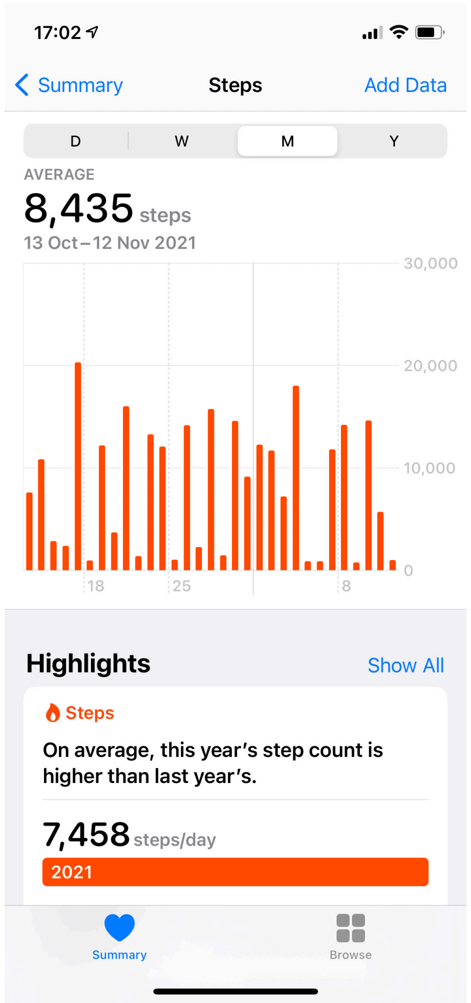
Step Count

- Wearables already use IMUs to offer activity indicators

- However no automatic (more refined) activity recognition in most cases…



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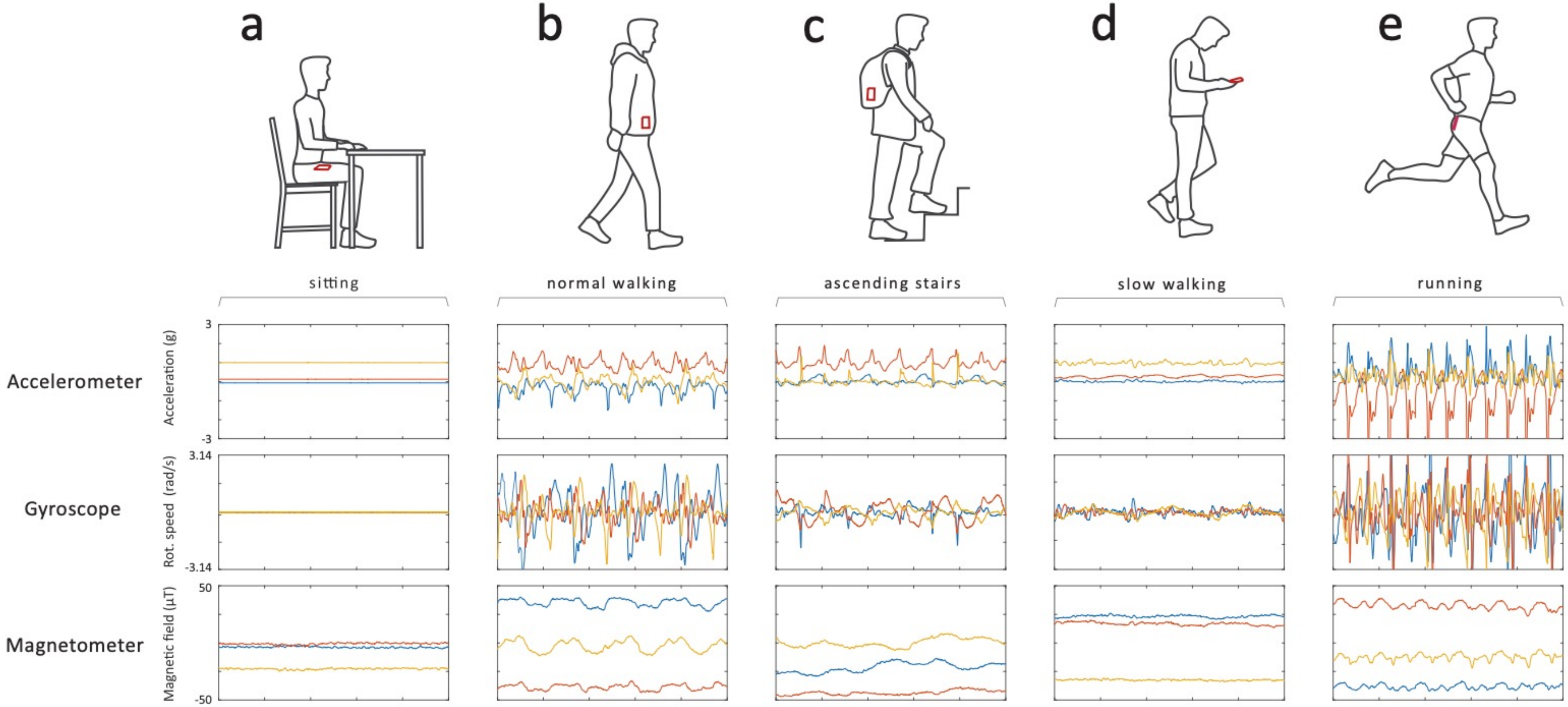
Activity Recognition



From A systematic review of smartphone-based human activity recognition methods for health research. Marcin Straczkiewicz, Peter Jamess, Jukka-Pekka Onnela. Nature NPJ Digital Medicine.

Considerations

- Position of the device might change the signals.
- Different sensors sense different patterns.
- Does it change from person to person.
- What about sampling?

Sampling

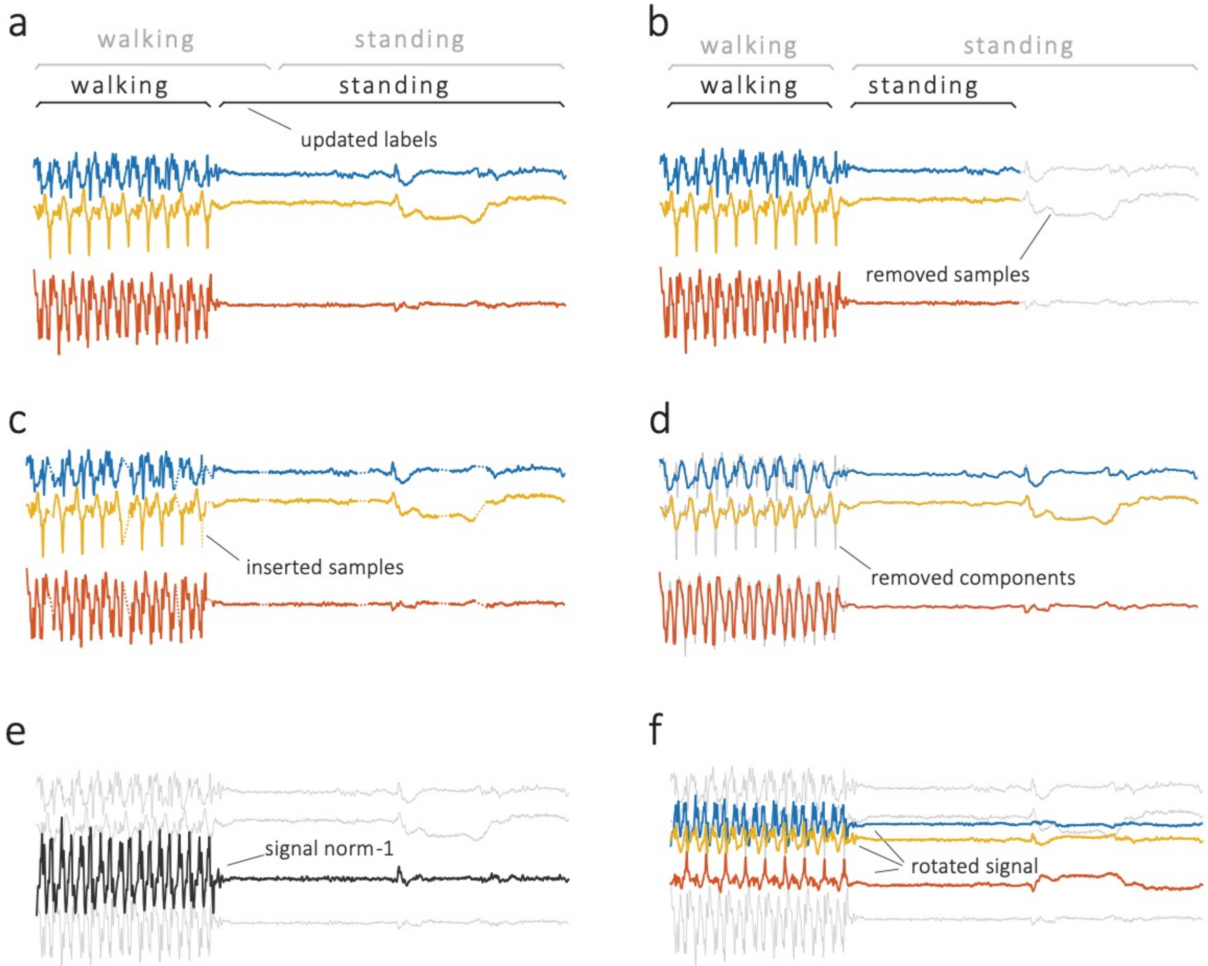
- Generally between 20 and 30 Hz.

- Some studies try to research the trade offs of sampling frequency and activity detection because sampling affects device battery…
  - 10Hz enough to distinguish activity from smartphone IMUs and 20Hz for mode of transport [1].

[1] From A systematic review of smartphone-based human activity recognition methods for health research. Marcin Straczkiewicz, Peter Jamess, Jukka-Pekka Onnela. Nature NPJ Digital Medicine.

Preprocessing

A labels are realigned (by eye)
B samples are removed to balance data
C missing data is filled with adjacent data
D removing components, denoising: high frequency noise cancellation.
E (see next slides ..magnitude): aggregation
F rotate to different coordinate system



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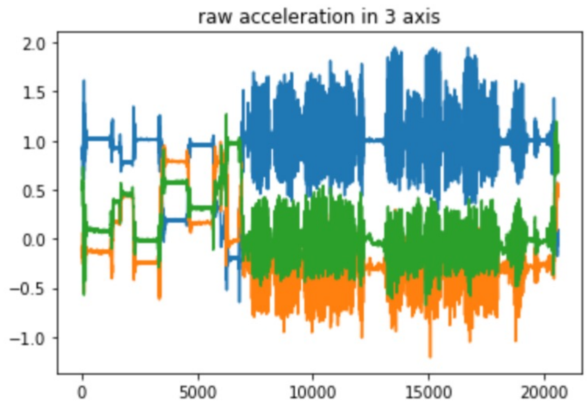
From A systematic review of smartphone-based human activity recognition methods for health research. Marcin Straczkiewicz, Peter Jamess, Jukka-Pekka Onnela. Nature NPJ Digital Medicine.

Signal Filtering

- Removing certain frequencies

- Example
  - Low pass filter: passes low frequencies and attenuates high frequencies.
  - Band-pass filter: only frequencies in a frequency band are passed.



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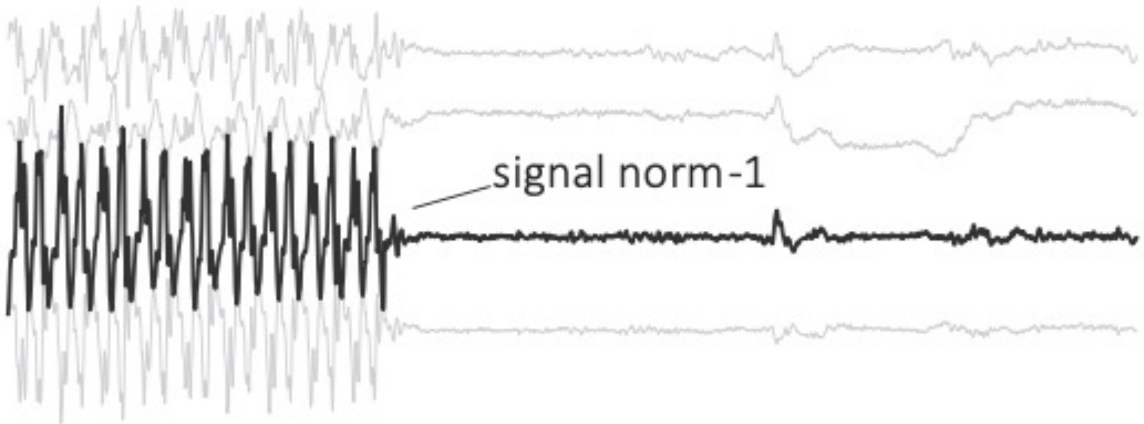
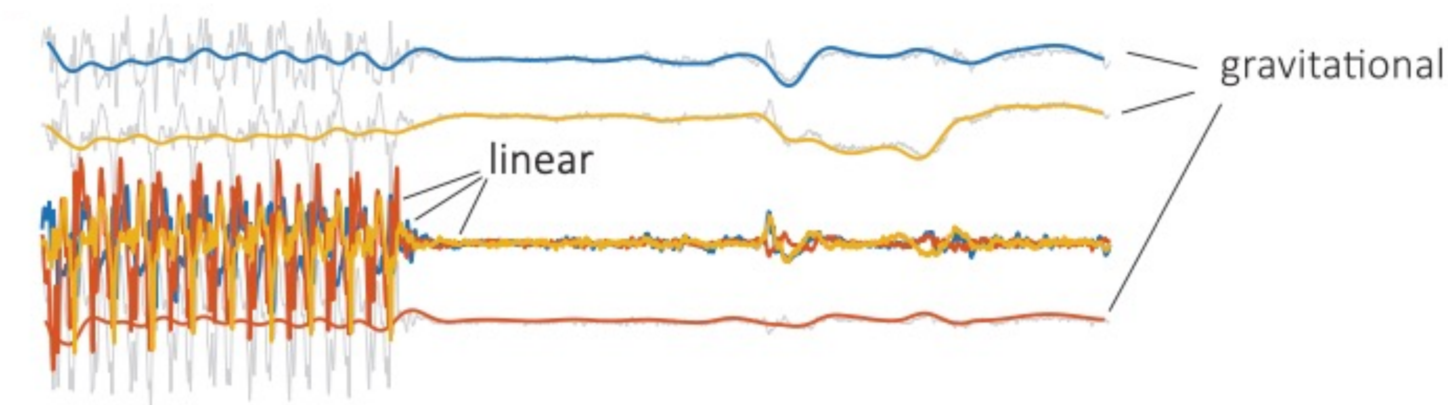
Preprocessing: Magnitude

$$\forall i : m_i = \sqrt{x^2 + y^2 + z^2}$$



Gravitational and Body Force Separation



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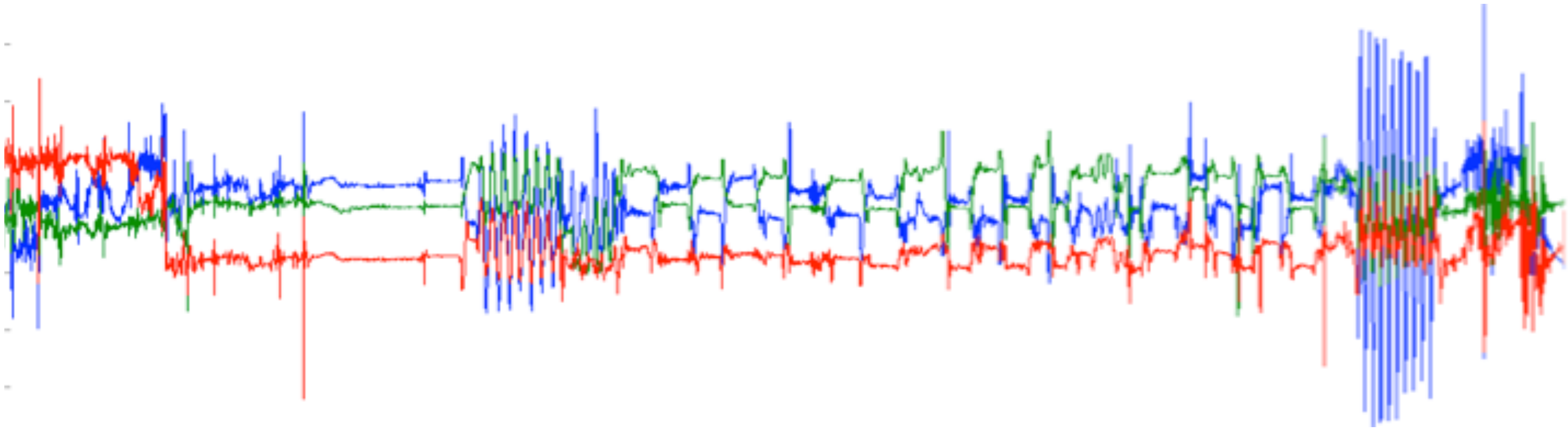
Data Segmentation

- Localize temporal patterns of interest
- But you do not know what/where these are…
- Sliding window approach
  - Issues: window length, overlap, window label choice…



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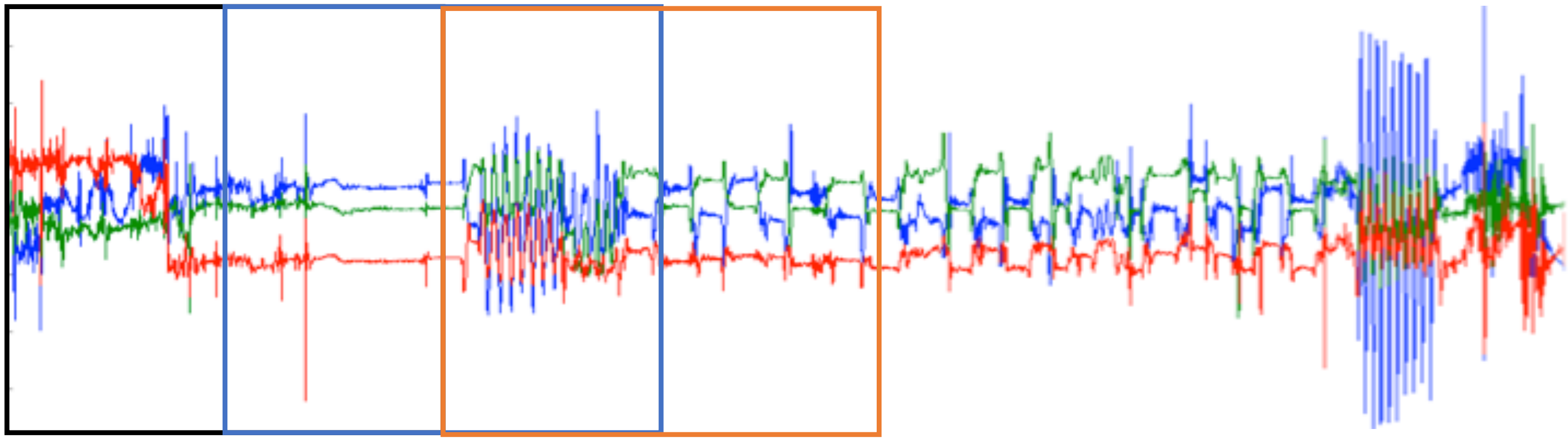
Sliding Window with 50% overlap

- Let’s fix the window size, define a 50% overlap
- One can change window size and overlap



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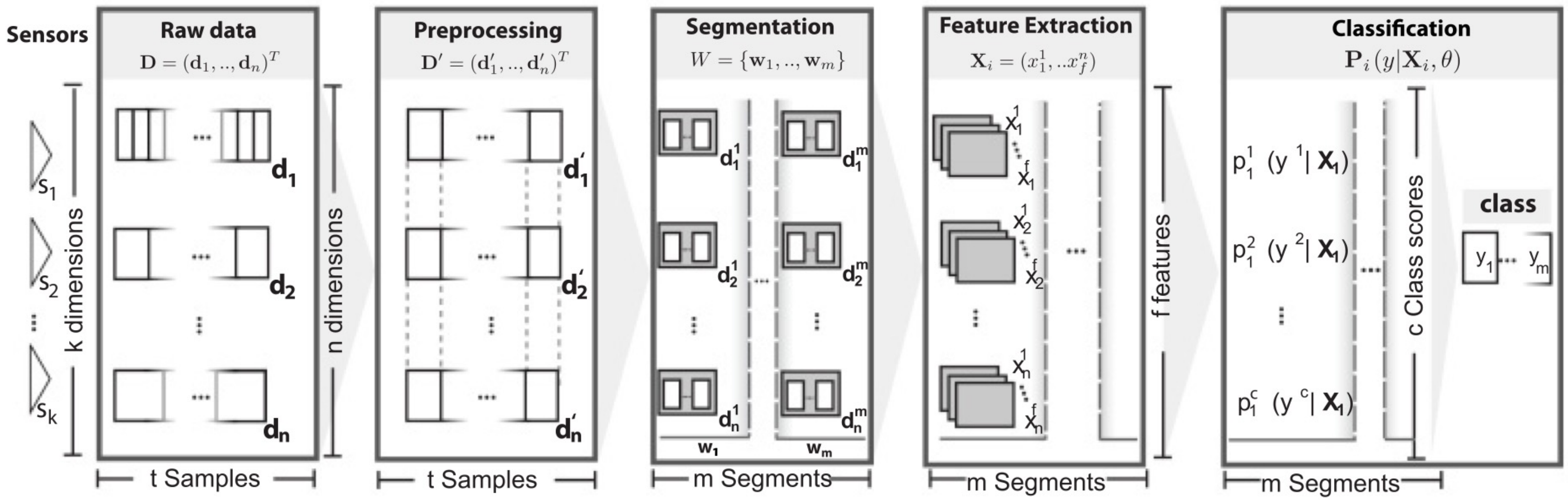
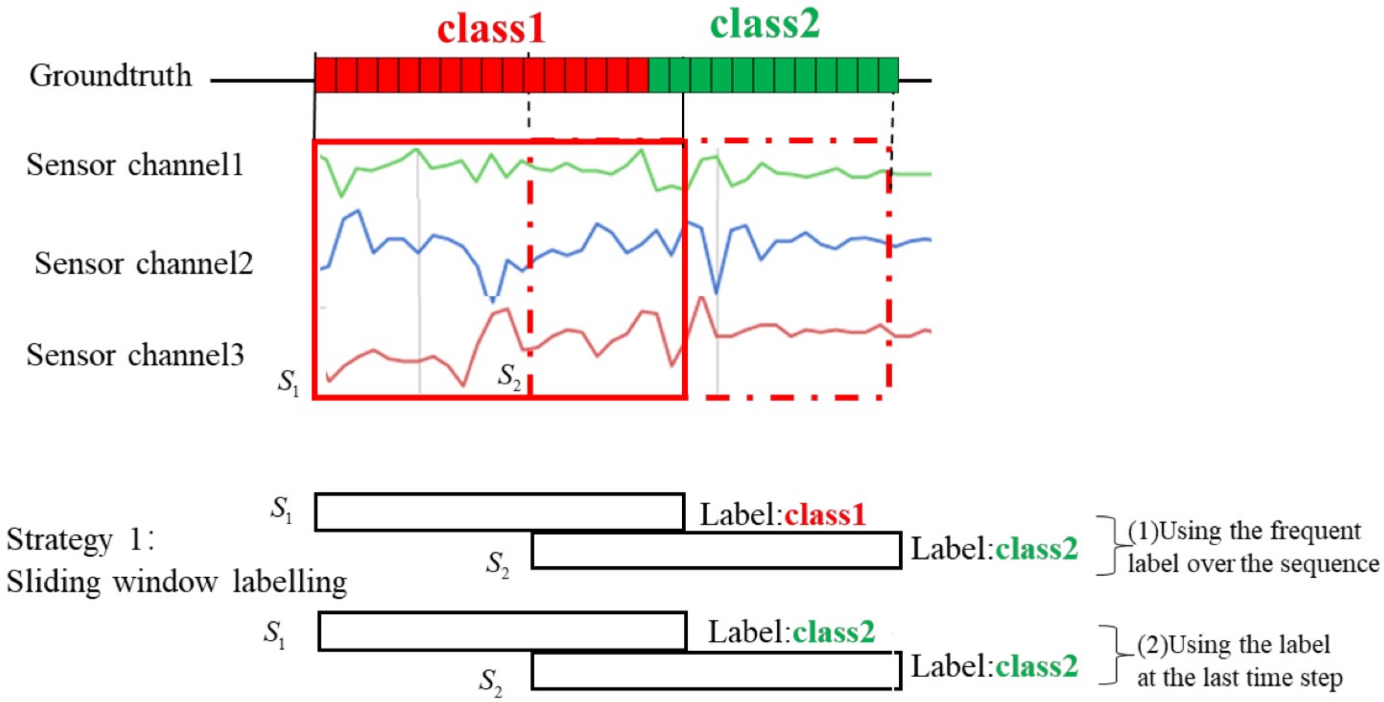
Segmented Samples to Prediction

- For each sample further analysis is applied to reach a prediction, for example:
  - A number of features are extracted on a sample and a classifier is used to use these to decide on the class label for a sample.
  - The sample raw data is fed into a deep learning network which gets to a softmax probability offering a classification output.

Traditional Inference Pipeline



Mapping Classes with Windows



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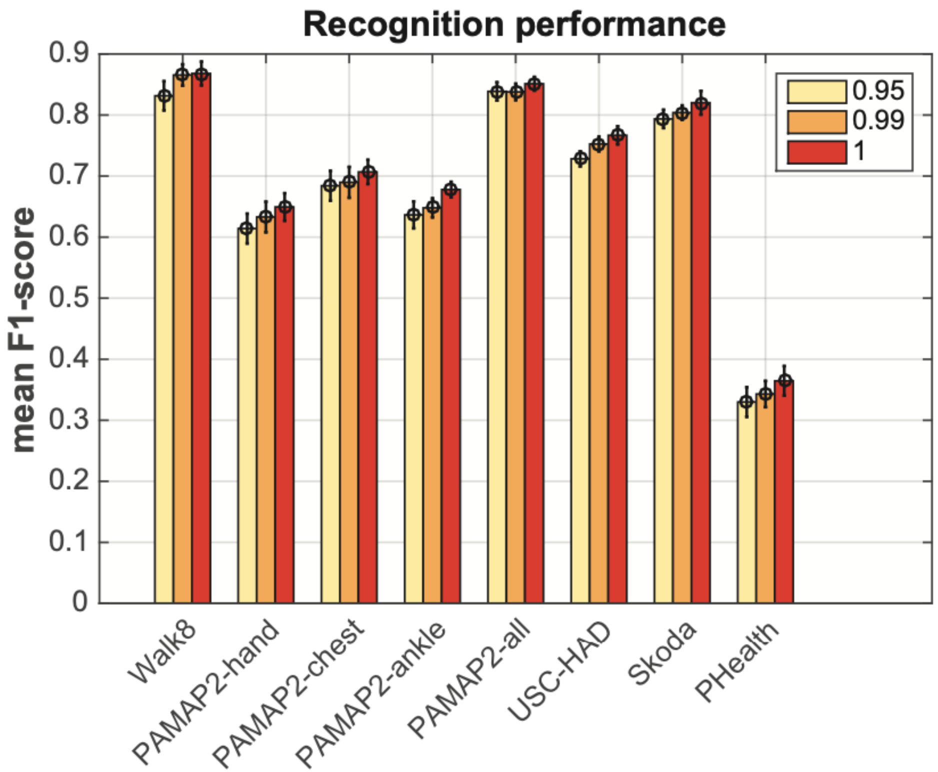
Zhang, Yong & Zhang, Yu & Zhang, Zhao & Bao, Jie & Song, Yunpeng. (2018). Human activity recognition based on time series analysis using U-Net.

Sampling Rate

Sampling rate has impact on battery
Here is an approach that defines a function to allow lowering sampling rate while keeping a similarity with the original curve.

Histogram shows that when using this method the performance are not affected much.

Dataset	#Classes	Original	Optimal sampling rates	
		$Q(Hz)$	$\hat{q}$ ($\mathcal{S} = 0.95$) (Hz)	$\hat{q}$ ($\mathcal{S} = 0.99$) (Hz)
Skoda	11	96	12	22
PAMAP2-Hand	13	100	32	56
PAMAP2-Chest			33	57
PAMAP2-Ankle			42	63
USC-HAD	12	100	17	30
PHealth	10	100	15	26
Walk8	4	250	18	35



[A. Khan, N. Hammerla, S. Mellor, and T. Ploetz, “Optimising sampling rates for accelerometer-based human activity recognition,” Pattern Recognition Letters, 2016.]

Class Prediction Problem

- Predict activity given a window of movement data.
- Predict activity given multiple windows of movement data.
- Predict the activity sequence given multiple windows of movement data.
- Predict activity given a sequence of movement data for a pre-segmented activity.
- Predict activity cessation or transition given a window of movement data.
- Predict a stationary or non-stationary activity given a window of movement data

Feature Extraction

- Distribution of x,y, z axis acceleration per window for various activities

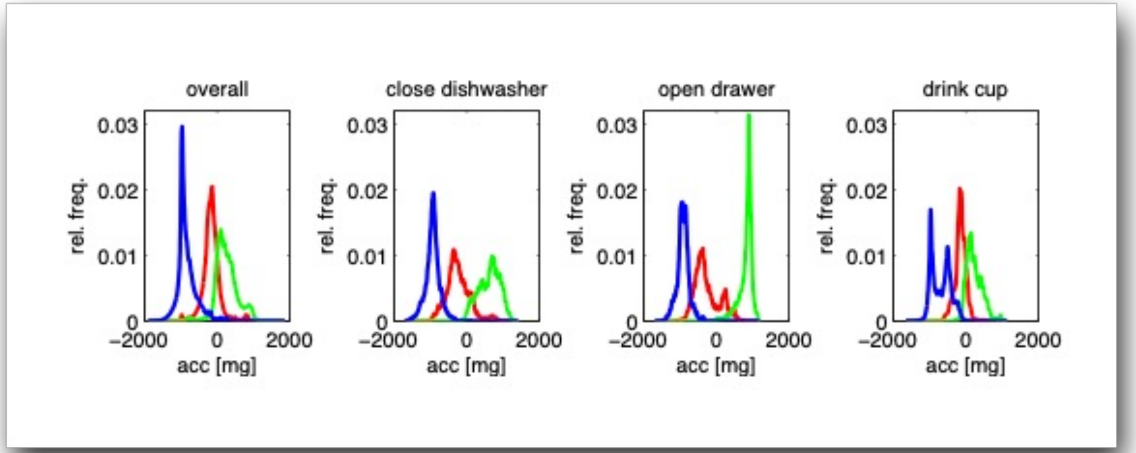
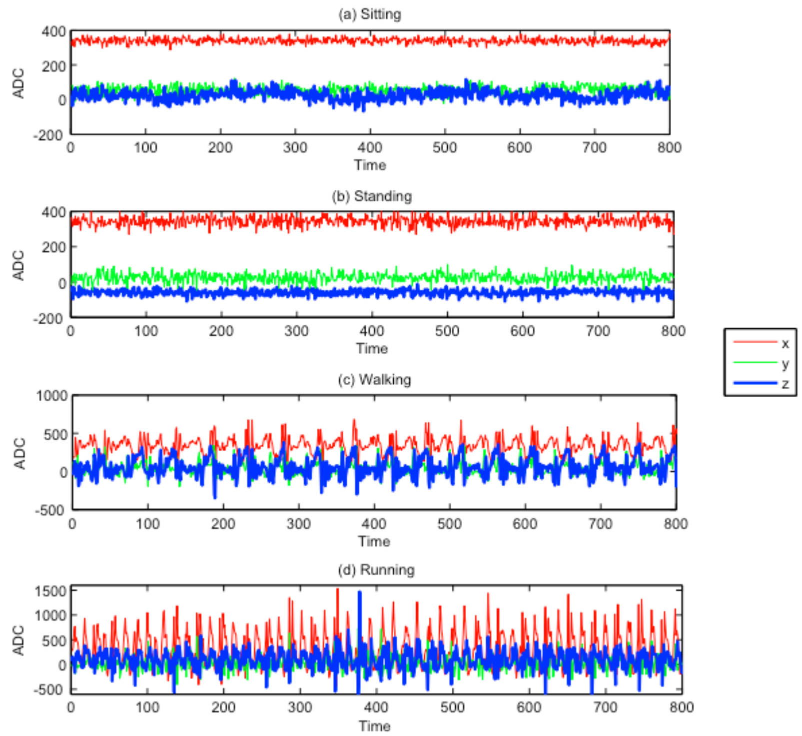


Figure by Thomas Ploetz

Physical Activity using Accelerometer

- Activities: sitting, standing, waking, running

- Feature examples:
  - **Mean** (can help distinguish between standing and sitting).
  - Standard deviation
  - **Number of peaks** (can help distinguish between waking and running).



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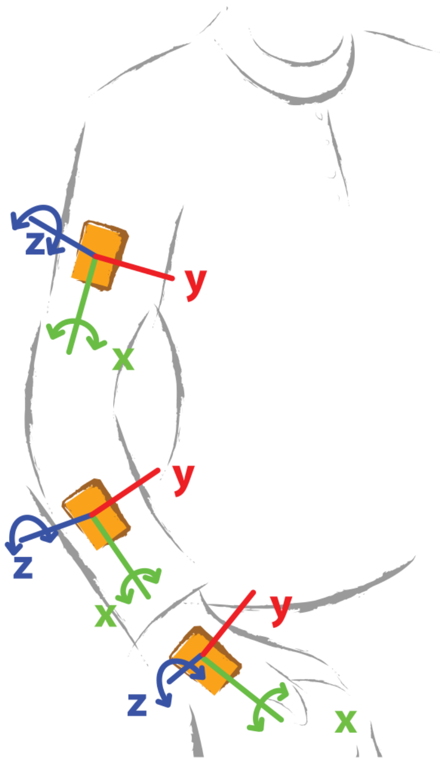
Classification: a Recap!

- Feature extraction produces a feature vector.
- The classification matches the feature vector to a pre-defined set of classes.
- The classification engine is typically based on machine-learning techniques and is trained using labelled training data.
- Common classification algorithms include:
  - K Nearest Neighbour.
  - Naive Bayes classifier.
  - Decision Trees.
  - Hidden Markov Models.

Activity Recognition Classification

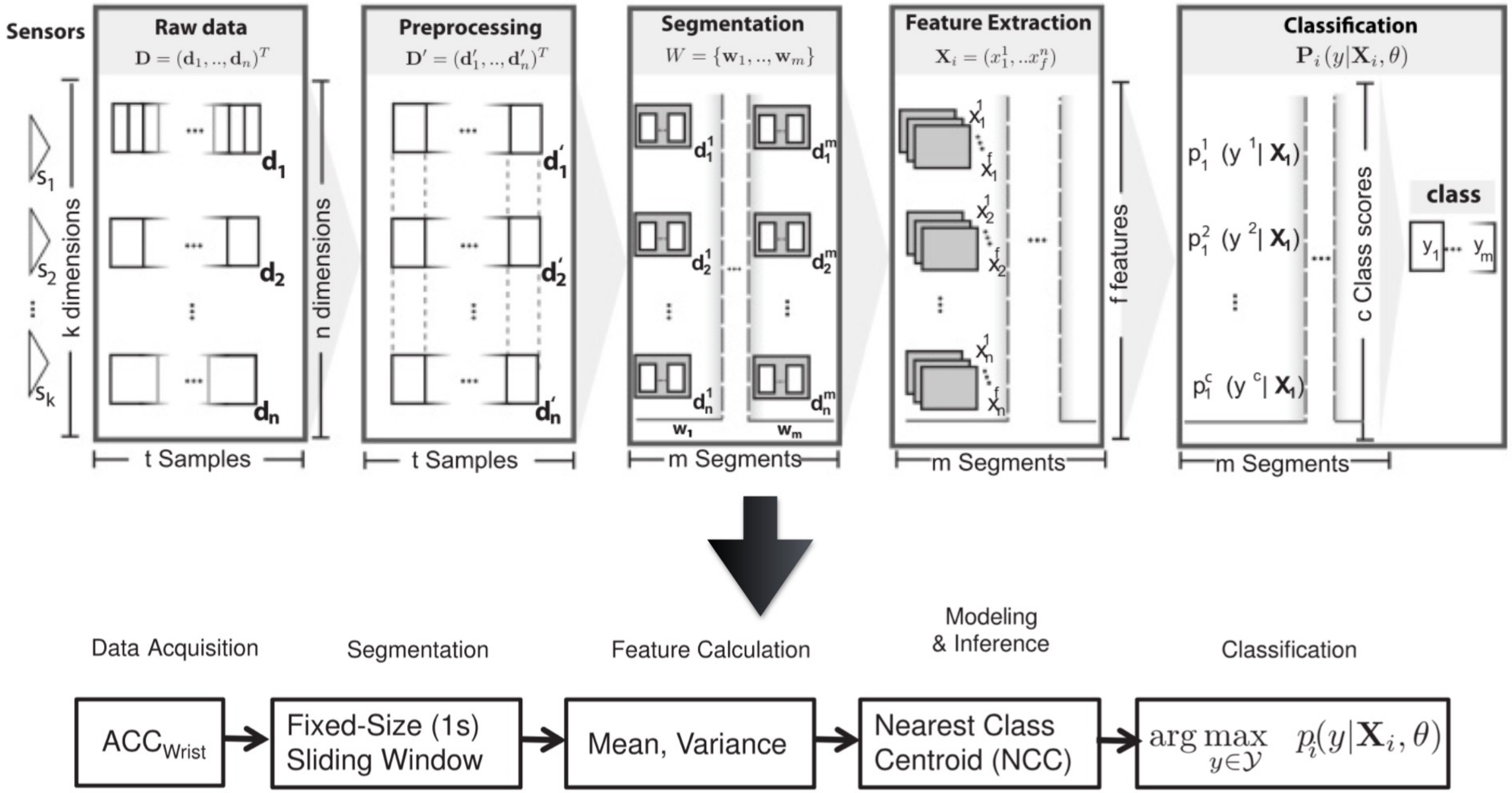


Activities

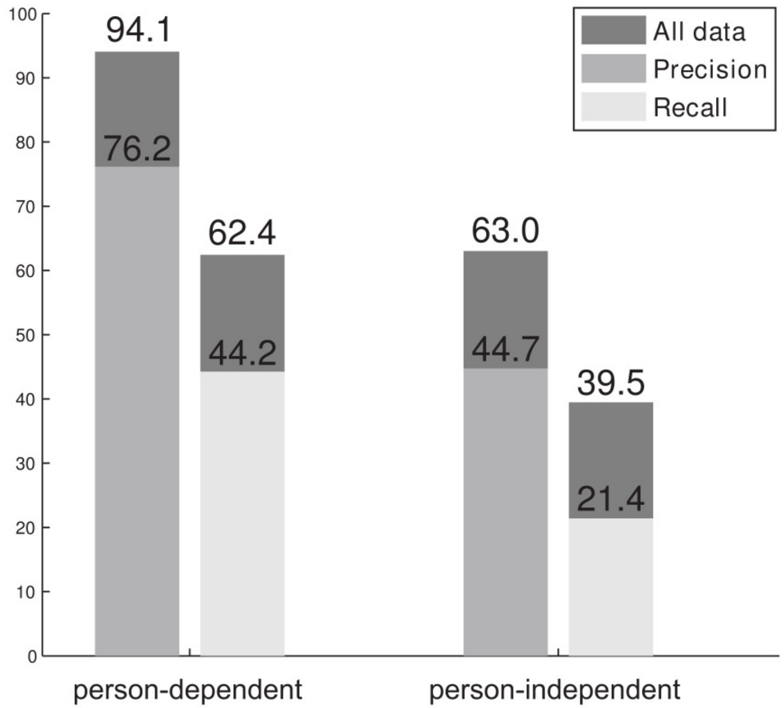
opening a window
closing a window
watering a plant
turning book pages

drinking from a bottle
cutting with a knife
chopping with a knife
stirring in a bowl

forehand
backhand
and smash


Sensors
Raw data
$D = (d_1, .., d_n)^T$
Preprocessing
$D' = (d'_1, .., d'_n)^T$
Segmentation
$W = \{w_1, .., w_m\}$
Feature Extraction
$X_i = (x_1^1, ..x_f^n)$
Classification
$P_i(y|X_i, \theta)$
k dimensions
n dimensions
f features
c Class scores
class
t Samples
t Samples
m Segments
m Segments
m Segments
Data Acquisition
Segmentation
Feature Calculation
Modeling & Inference
Classification
ACC_{Wrist}
Fixed-Size (1s) Sliding Window
Mean, Variance
Nearest Class Centroid (NCC)
$\arg\max_{y \in \mathcal{Y}} p_i(y|X_i, \theta)$

Classification Results: Person Dependence and Multiple Sensors



Confusion Matrix on Activities

classification

groundtruth

	NULL	Open window	Drink	Water plant	Close window	Cut	Chop	Stir	Book	Forehand	Backhand	Smash	*recall*
NULL	**24267**	216	444	3228	48	24	60	75	45		3		**85.42**
Open window	3849	**1938**	453	291	48	12	9		24				**29.26**
Drink	3984	927	**3780**	321	3	9							**41.89**
Water plant	3984	726	774	**3735**	21	57	15						**40.11**
Close window	3891	381	1173	945	**1533**								**19.35**
Cut	2940		264	450		**6585**	456		3				**61.55**
Chop	2895	168	435	153		909	**5742**		126				**55.06**
Stir	4947	39	135	42	21	474	561	**4392**	207				**40.60**
Book	4560	27	144	951		354	1725	60	**6687**				**46.09**
Forehand	3195	330		144	609	9	66		3	**969**	6	3	**18.17**
Backhand	3003	207	21		21	3	6	24	33		**1302**		**28.18**
Smash	1860	57		78	185		42	45		1567	137	**230**	**5.47**
precision	**38.29**	**38.64**	**49.59**	**36.13**	**61.59**	**78.06**	**66.14**	**95.56**	**93.81**	**38.21**	**89.92**	**98.71**	

Gait analysis

- Gait is indicative of musculoskeletal and neurological diseases such as Parkinson’s disease, Alzheimer’s disease, multiple sclerosis and osteoarthritis.

M. Ullrich, A. Kuderle, J. Hannink, S. Del Din, H. Gaßner, F. Marxreiter, J. Klucken, B. Eskofier,F. Kluge. Detection of Gait From Continuous Inertial Sensor Data Using Harmonic Frequencies. JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS. 2020.

The Sensor and the Setting…

- Training set: 150 gait analysis recordings of 121 patients in hospital
- Validation set: 203 gait recordings from 7 PD patients at their home
- Exercises:
  1. 2x10 m walk with a break at the turning point (*2x10m*) 2)
  2. 4x10 m walk without stops at turning points
  3. (*4x10m*) 3) 2-minute walk back and forth along a straight path of 25 m (*2min*)
  4. Tapping on the ground with the heel (*heel)*
  5. Tapping on the ground with heel and toes alternately (*heel-toe*)
  6. Circular movement of the foot (*circling*)

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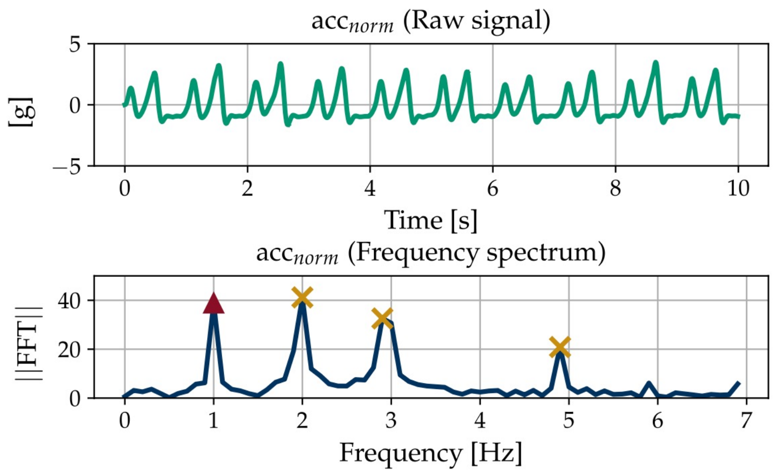
Data Processing

- Norm of accelerometer and gyroscope for window used to detect movement. If above a threshold accept sequence.
- Low pass filter (cut off 6Hz).
- Use FFT to find important frequencies.
- Uses autocorrelation to measure peaks (and harmonic frequencies)

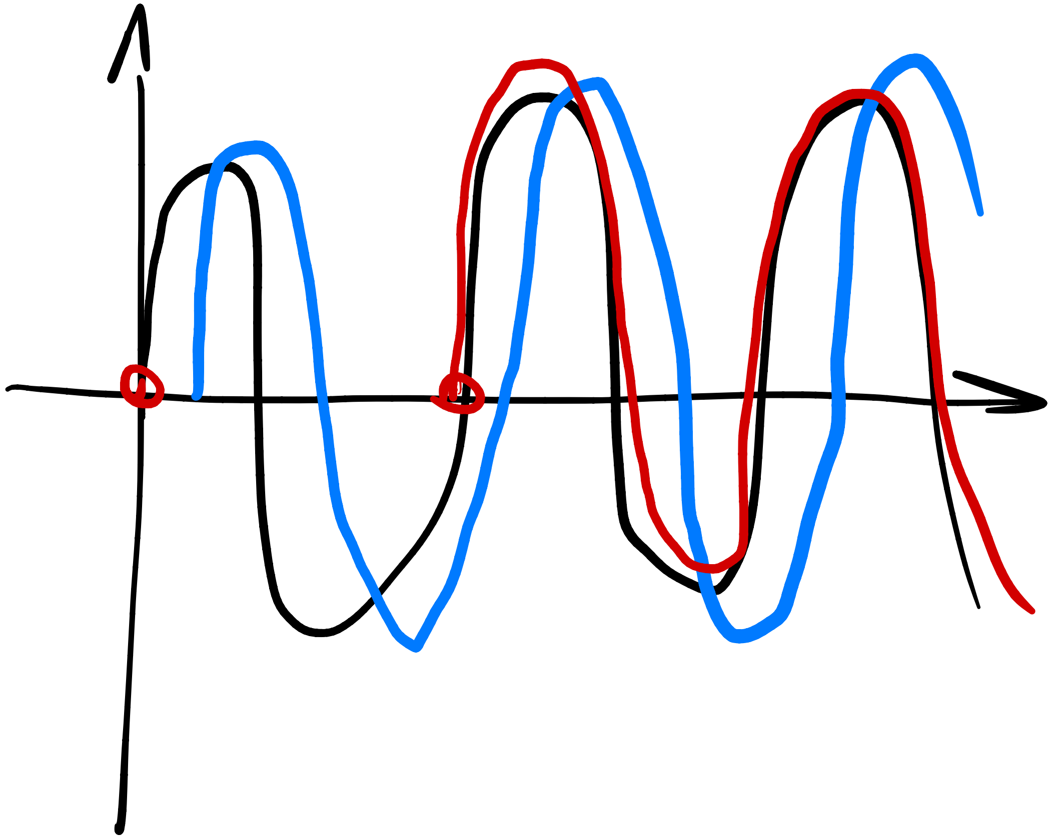
$$R(m) = \sum_{n=0}^{N-1-m} s(n)s(n+m)$$

- Use these to decide if to keep this window.

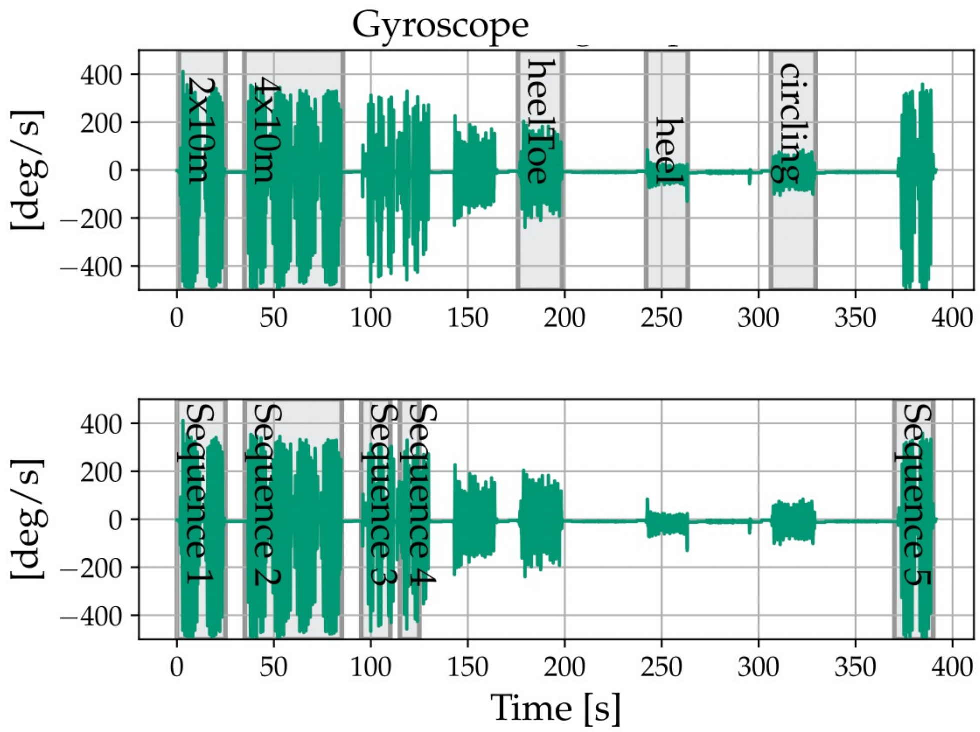
$$|s^{3d}| = \sqrt{s_x^2 + s_y^2 + s_z^2},$$



Autocorrelation to measure period



Some Results



	acc_v	acc_{norm}	gyr_{ml}	gyr_{norm}
Lab Data Set				
Sensitivity	0.97 (0.03)	0.94 (0.04)	0.98 (0.01)	0.89 (0.04)
Specificity	0.95 (0.02)	0.96 (0.01)	0.96 (0.02)	0.81 (0.04)
Youden index	0.92 (0.02)	0.90 (0.04)	0.94 (0.01)	0.70 (0.06)
Opt. Peak Prom.	8	13	17	11
Val. Data Set				
Sensitivity	0.50	0.70	0.97	0.89

Parkinson's and Wrist Worn Accelerometer

sensors

MDPI

Article

Detection of Parkinson's Disease Using Wrist Accelerometer Data and Passive Monitoring

Elham Rastegari [1,*], Hesham Ali [2] and Vivien Marmelat [3]

[1] Department of Business Intelligence and Analytics, Business College, Creighton University, Omaha, NE 68178, USA
[2] Department of Biomedical Informatics, College of Information Systems and Technology, University of Nebraska at Omaha, Omaha, NE 68182, USA
[3] Department of Biomechanics, College of Education, Health and Human Sciences, University of Nebraska at Omaha, Omaha, NE 68182, USA
[*] Correspondence: elhamrastegari@creighton.edu

Abstract: Parkinson's disease is a neurodegenerative disorder impacting patients' movement, causing a variety of movement abnormalities. It has been the focus of research studies for early detection based on wearable technologies. The benefit of wearable technologies in the domain rises by continuous monitoring of this population's movement patterns over time. The ubiquity of wrist-worn accelerometry and the fact that the wr
the accelerometer for continuous mor
choice for early detection of the disease
use a dataset consisting of one-week w
Parkinson's disease and healthy elderl
methods, including epoch-based statis
were used. Using various machine lea
using the document-of-words method

	Healthy Elderlies	PD
Subjects	32	28
Gender (M/F)	10/22	20/5
Age	64.2 ± 7	71 ± 6.2
H&Y	-	1.73 ± 0.83

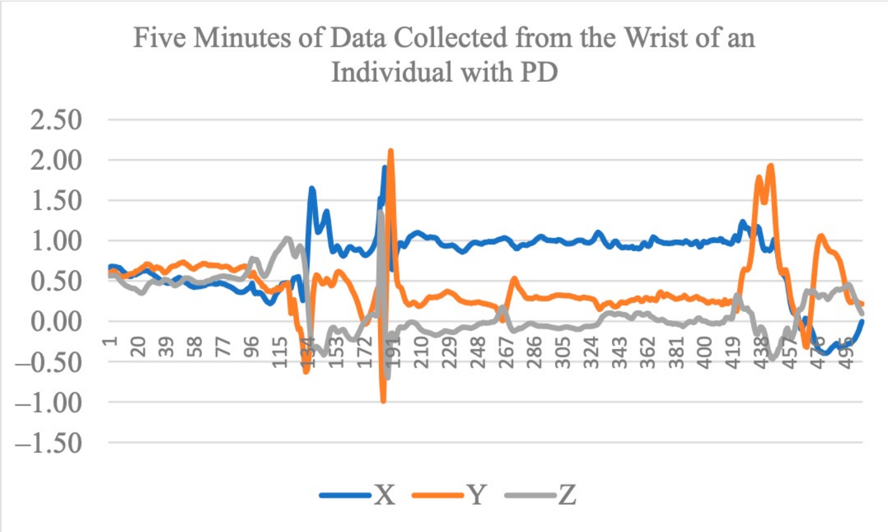
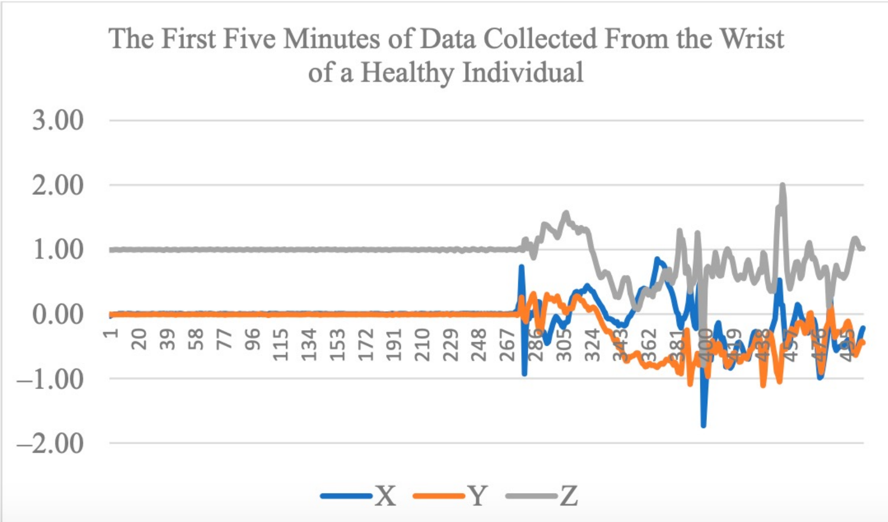


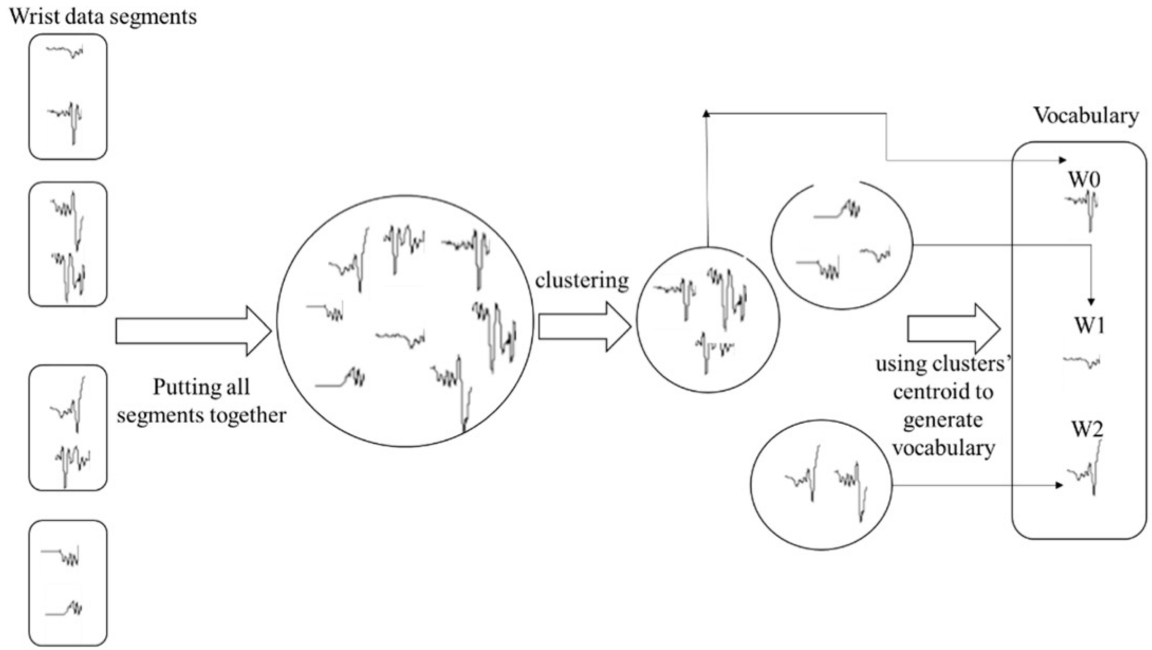
Figure 3. First five minutes of raw data collected from the wrist of an individual with PD.



Features: Two methods

1) Simple accelerometer features (such as magnitude)

2) A bag of words approach



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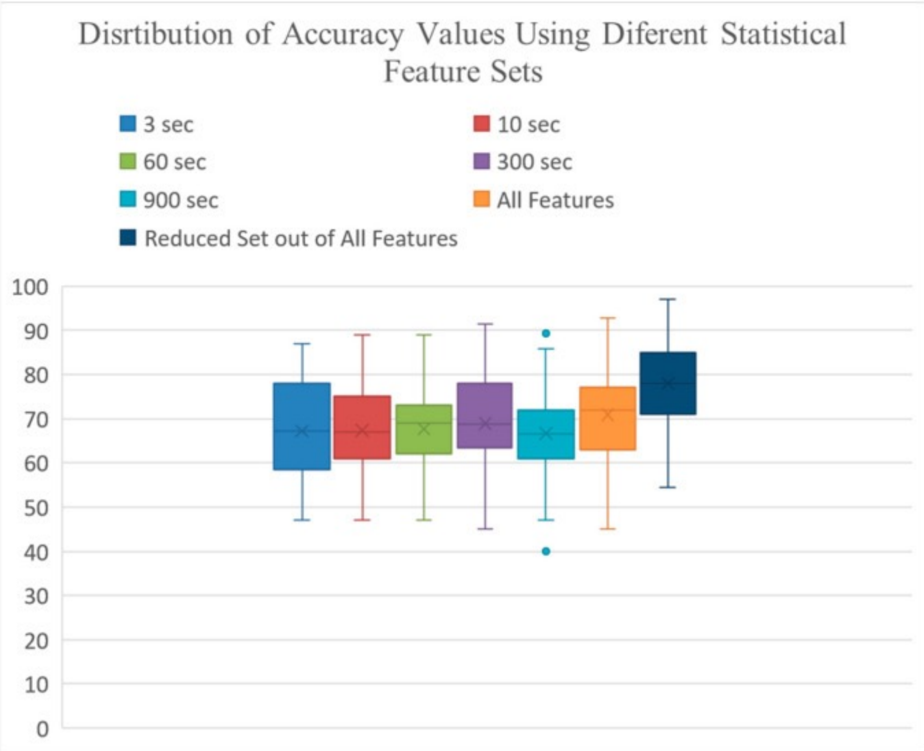
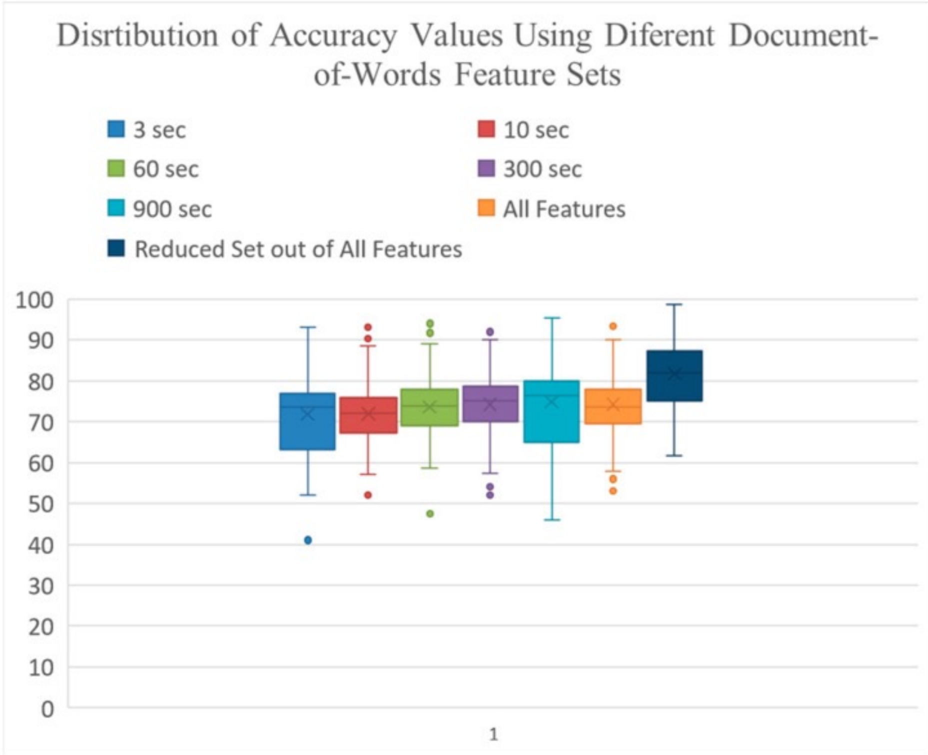
Comparison of methods





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How many days of data are needed?

- Battery on devices is important
- Can this classification be done with less data?

- It seems that “at least 3 days of data” are needed to obtain similar performance (wrt to 7 days tried).

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Public Health (1): Physical Activity

ARTICLE OPEN

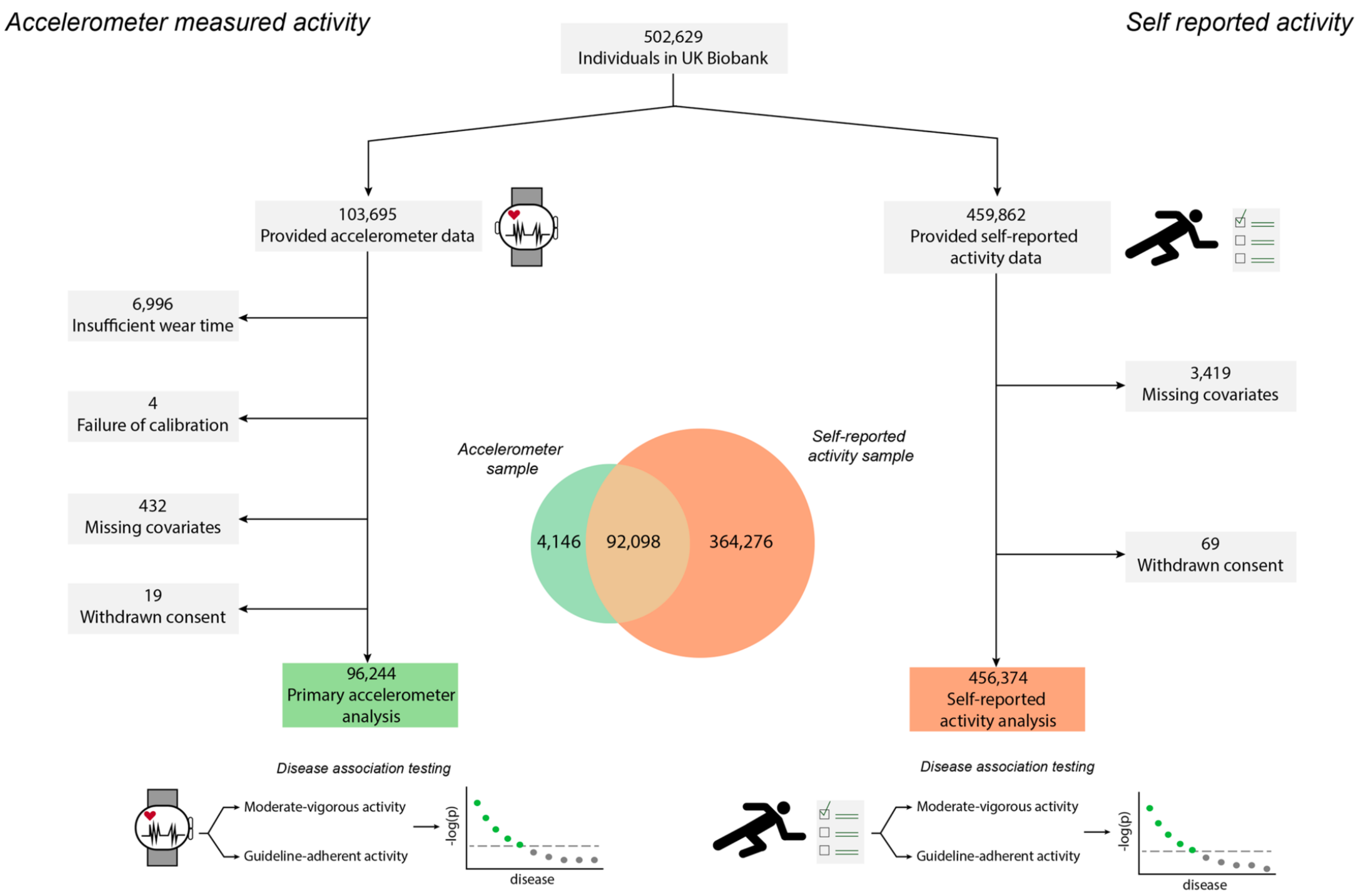
Check for updates

Wearable accelerometer-derived physical activity and incident disease

Shaan Khurshid[1,2,3], Lu-Chen Weng[1,2], Victor Nauffal[2,4], James P. Pirruccello[1,2,5], Rachael A. Venn[1,2,5], Mostafa A. Al-Alusi[1,2,5], Emelia J. Benjamin[6,7], Patrick T. Ellinor[1,2,3] and Steven A. Lubitz[1,2,3]✉

Physical activity is regarded as favorable to health but effects across the spectrum of human disease are poorly quantified. In contrast to self-reported measures, wearable accelerometers can provide more precise and reproducible activity quantification. Using wrist-worn accelerometry data from the UK Biobank prospective cohort study, we test associations between moderate-to-vigorous physical activity (MVPA) – both total MVPA minutes and whether MVPA is above a guideline-based threshold of ≥150 min/week—and incidence of 697 diseases using Cox proportional hazards models adjusted for age, sex, body mass index, smoking, Townsend Deprivation Index, educational attainment, diet quality, alcohol use, blood pressure, anti-hypertensive use. We correct for multiplicity at a false discovery rate of 1%. We perform analogous testing using self-reported MVPA. Among 96,244 adults wearing accelerometers for one week (age 62 ± 8 years), MVPA is associated with 373 (54%) tested diseases over a median 6.3 years of follow-up. Greater MVPA is overwhelmingly associated with lower disease risk (98% of associations) with hazard ratios (HRs) ranging 0.70–0.98 per 150 min increase in weekly MVPA, and associations spanning all 16 disease categories tested. Overall, associations with lower disease risk are enriched for cardiac (16%), digestive (14%), endocrine/metabolic (10%), and respiratory conditions (8%) (chi-square $p < 0.01$). Similar patterns are observed using the guideline-based threshold of ≥150 MVPA min/week. Some of the strongest associations with guideline-adherent activity include lower risks of incident heart failure (HR 0.65, 95% CI 0.55–0.77), type 2 diabetes (HR 0.64, 95% CI 0.58–0.71), cholelithiasis (HR 0.61, 95% CI 0.54–0.70), and chronic bronchitis (HR 0.42, 95% CI 0.33–0.54). When assessed within 456,374 individuals providing self-reported MVPA, effect sizes for guideline-adherent activity are substantially smaller (e.g., heart failure HR 0.84, 95% CI 0.80–0.88). Greater wearable device-based physical activity is robustly associated with lower disease incidence. Future studies are warranted to identify potential mechanisms linking physical activity and disease, and assess whether optimization of measured activity can reduce disease risk.

npj Digital Medicine (2022)5:131 ; https://doi.org/10.1038/s41746-022-00676-9



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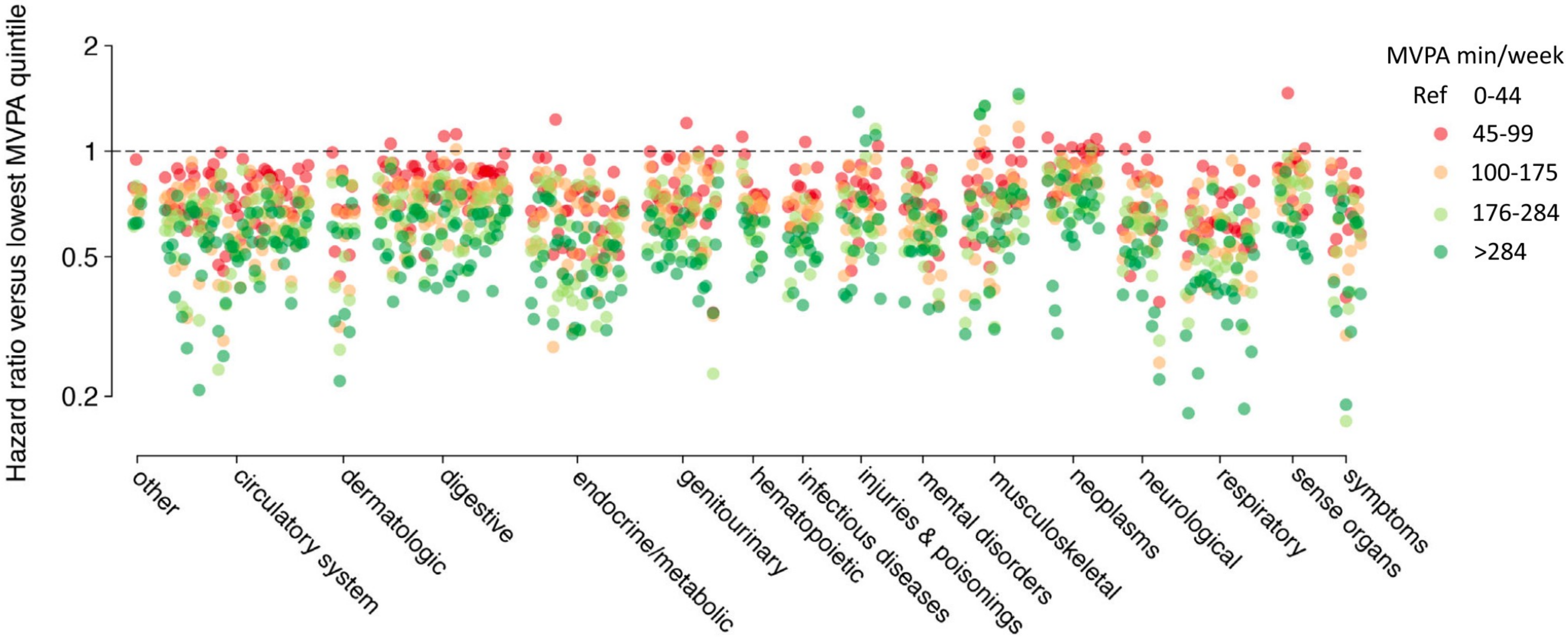
MVPA

- Minutes of **moderate-to vigorous physical activity (MVPA)** defined as the sum of 5-s epochs where **mean acceleration** was ≥100mg.



Public Health (2): Transport Mode Detection

Accelerometer-Based Transportation Mode Detection on Smartphones

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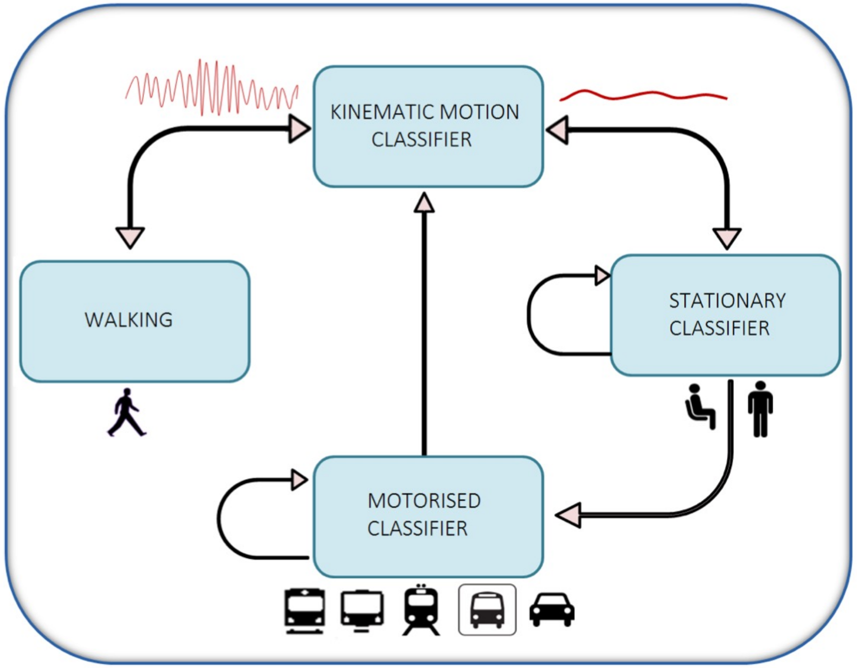

Method

- Low pass filter (retaining 90% of data)
- Sliding window of 50%, duration 1.2 secs
- Estimation of gravity component
- Feature extraction
- Classification(s)

Domain	**Features**
Statistical	Mean, STD, Variance, Median, Min, Max, Range, Interquartile range Kurtosis, Skewness, RMS
Time	Integral, Double integral, Auto-Correlation, Mean-Crossing Rate,
Frequency	FFT DC,1,2,3,4,5,6 Hz, Spectral Energy, Spectral Entropy, Spectrum peak position, Wavelet Entropy, Wavelet Magnitude
Peak	Volume (AuC), Intensity, Length, Kurtosis, Skewness
Segment	Variance of peak features (10 features), Peak frequency (2 features), Stationary duration, Stationary frequency

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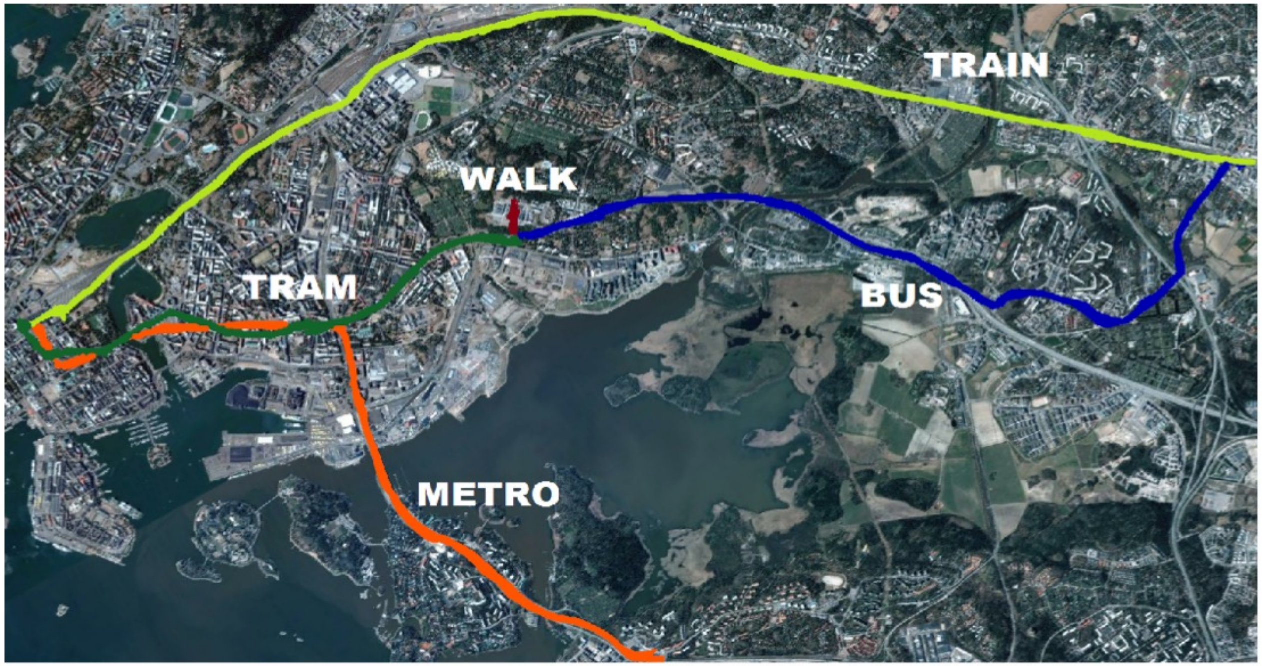
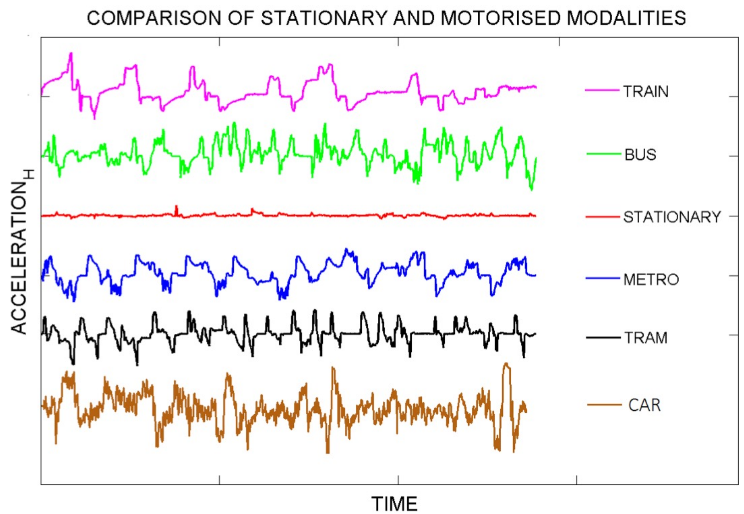
Scenarios and Patterns





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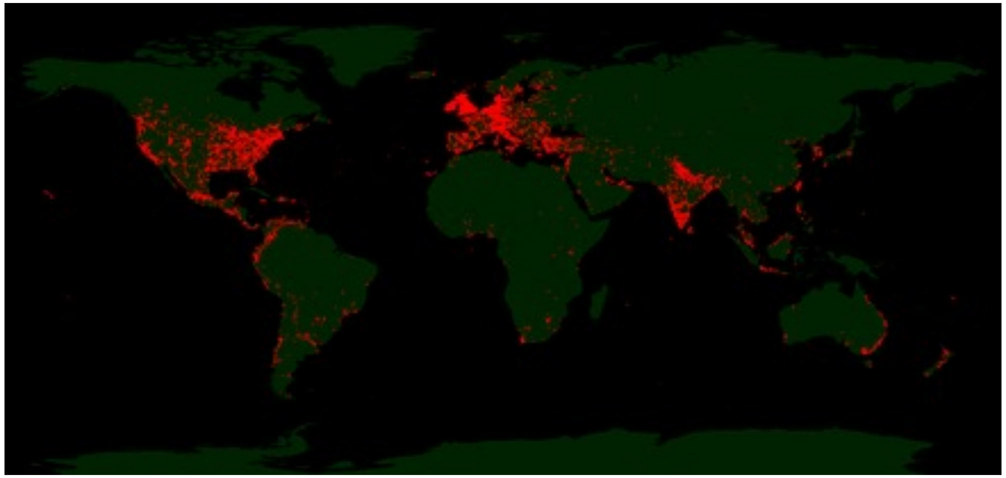
Public Health (3): Mood and Activity



Happier People Live More Active Lives: Using Smartphones to Link Happiness and Physical Activity. PLoS ONE. July 2016. N. Lathia, G. M. Sandstrom, C. Mascolo, P. J. Rentfrow.

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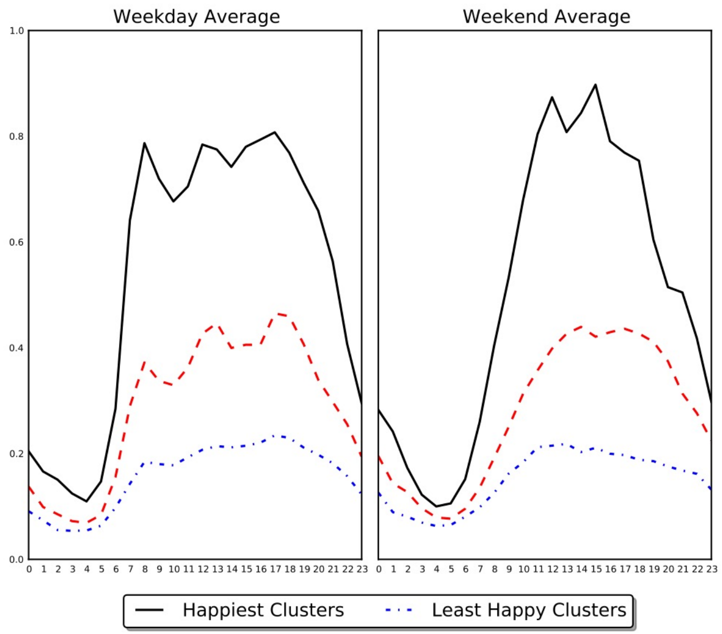
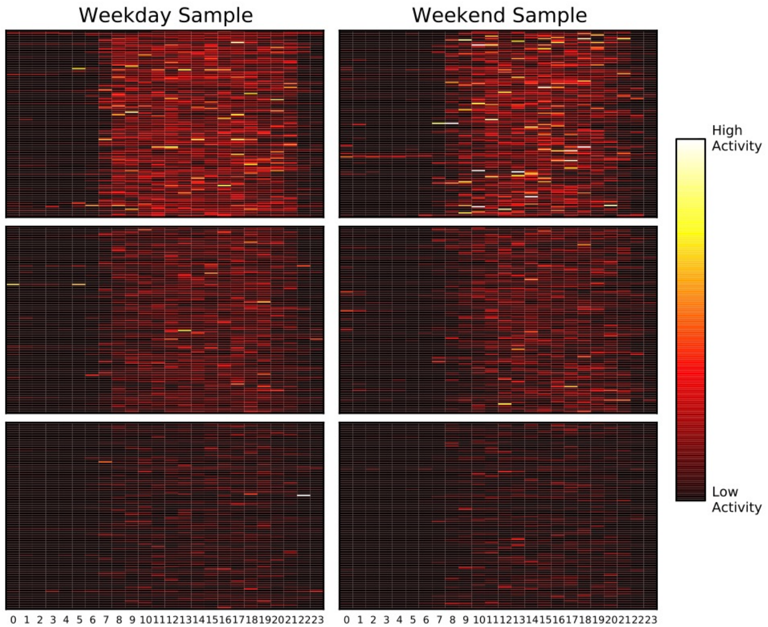
Happiness and Accelerometer





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Questions