Human Activity Segmentation Challenge

AALTD'23, 18.09.2023, Turin, Italy

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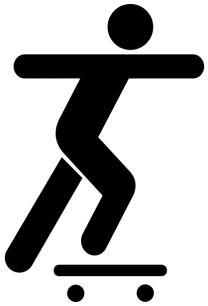
Human Activity Recognition (HAR)

Gait analysis



Activity Monitoring

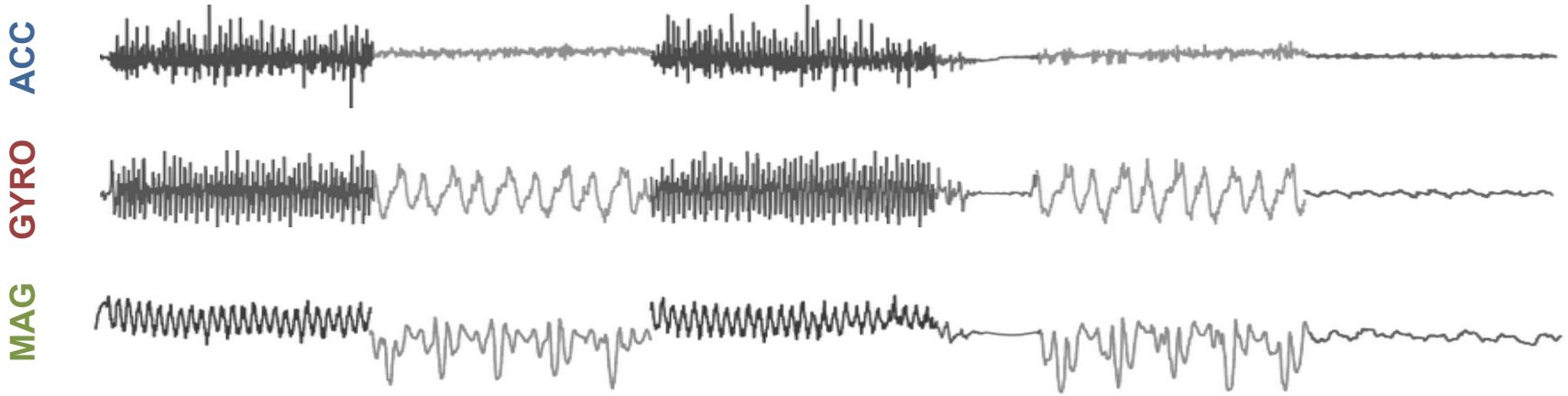
Fall detection

...

- Human activity recognition (HAR) is a research area, goal: **identify human motions** with machine learning (ML) workflows
- Recordings with cameras, environmental sensors or wearable devices, capture and process the behaviour
- Valuable **insights into health status, fitness or personal security**, relevant in many domains

Lara, O. D., & Labrador, M. A. (2012). A survey on human activity recognition using wearable sensors. IEEE communications surveys & tutorials, 15(3), 1192-1209.

Time Series Data from Wearable Devices

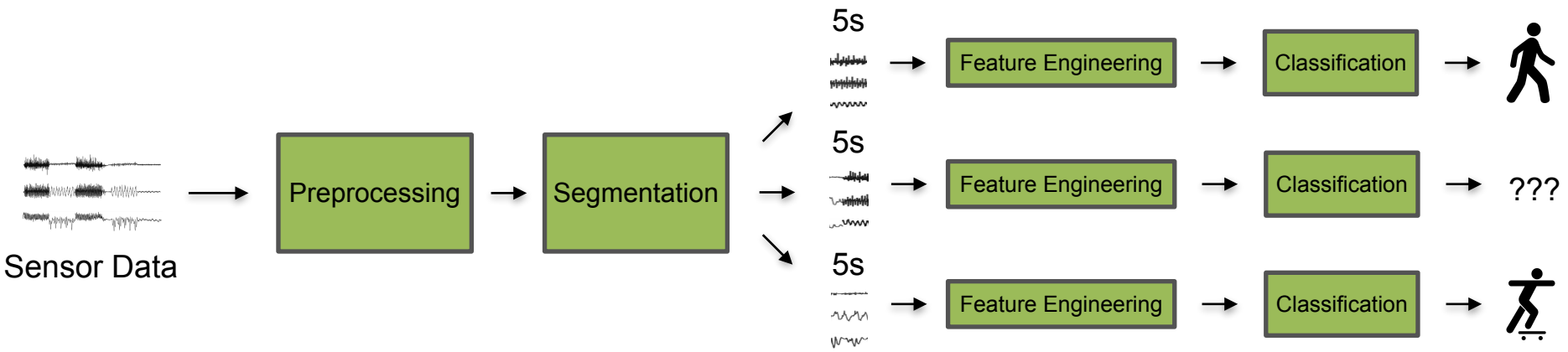


- Mobile devices contain **sensors that observe human behaviour** in long high-resolution time series (TS) data
- Interesting for HAR: Activity data from wearable sensors; **informative, comparable and readily available**
- Accelerometer (**ACC**), gyroscope (**GYRO**) and magnetometer (**MAG**) capture acceleration, angular velocity and orientation

Elkader, S. A., Barlow, M., & Lakshika, E. (2018, October). Wearable sensors for recognizing individuals undertaking daily activities. In Proceedings of the 2018 ACM International Symposium on Wearable Computers (pp. 64-67).

HAR workflows for Mobile Sensing Data

- HAR systems: sequence of complex processing steps, **classify small segments of sensor data** with activities
- Classification quality depends on size of the sensor segment, from which characteristic features are learned
- Problem: **optimal segment size depends on the captured activity,** should be adaptable in HAR systems

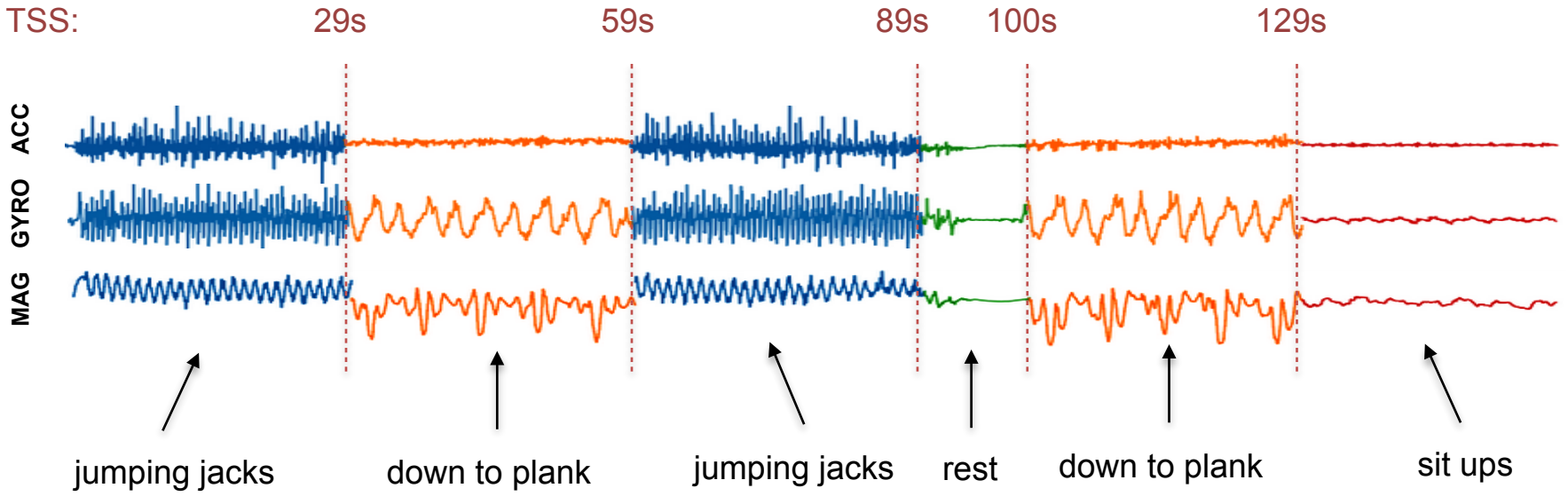


Ahad, M. A. R., Antar, A. D., & Ahmed, M. (2021). IoT Sensor-based Activity Recognition: Human Activity Recognition. Springer.

Problem: Which segment size should you choose?

Time Series Segmentation (TSS)

- TSS: unsupervised learning task, **splits a (multivariate) TS at increasing offsets** into *meaningful* partitions which form the segmentation
- HAR systems can use TSS to learn variable-sized segments, constitute single activities with characteristic properties
- Impact: HAR can **learn features from single activity segments** and in-between transitions (instead of fixed windows of 1-10s)



Selective Literature Overview

Algorithm	Publication
BOCD	arXiv (2007)
PELT	Journal of the American Statistical Association (2012)
AutoPlait	SIGMOD (2014)
Wild Binseg	The Annals of Statistics (2014)
HOG-1D	WACV (2016)
IGTS	Pervasive and Mobile Computing (2017)
FLUSS	ICDM (2017)
ESPRESSO	Interact. Mob. Wearable Ubiquitous Technol. (2020)
TS-CP2	WWW (2021)
ClaSP	CIKM (2021)
…	…

… and some more

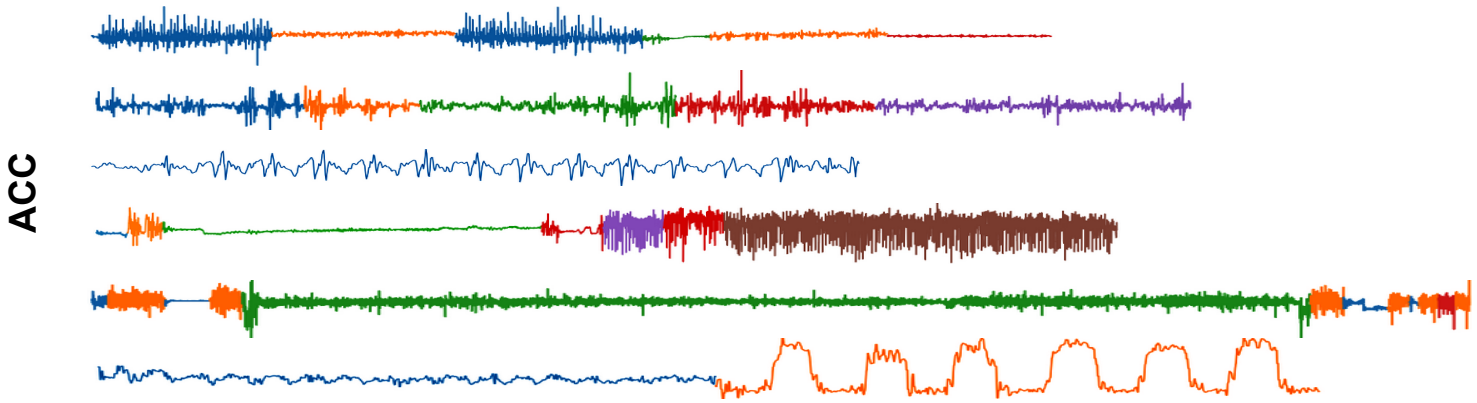
Most TSS algorithms can only handle medium-sized **preprocessed data sets**

Data Set	Publication
PAMAP	*ISWC (2012)*
MHEALTH	*ISWC (2012)*
Opportunity	Pattern Recognit. Lett. (2013)
…	…

… and many more

Most HAR data sets use a **laboratory setup** with intrusive specialised devices

Human Activity Segmentation Challenge

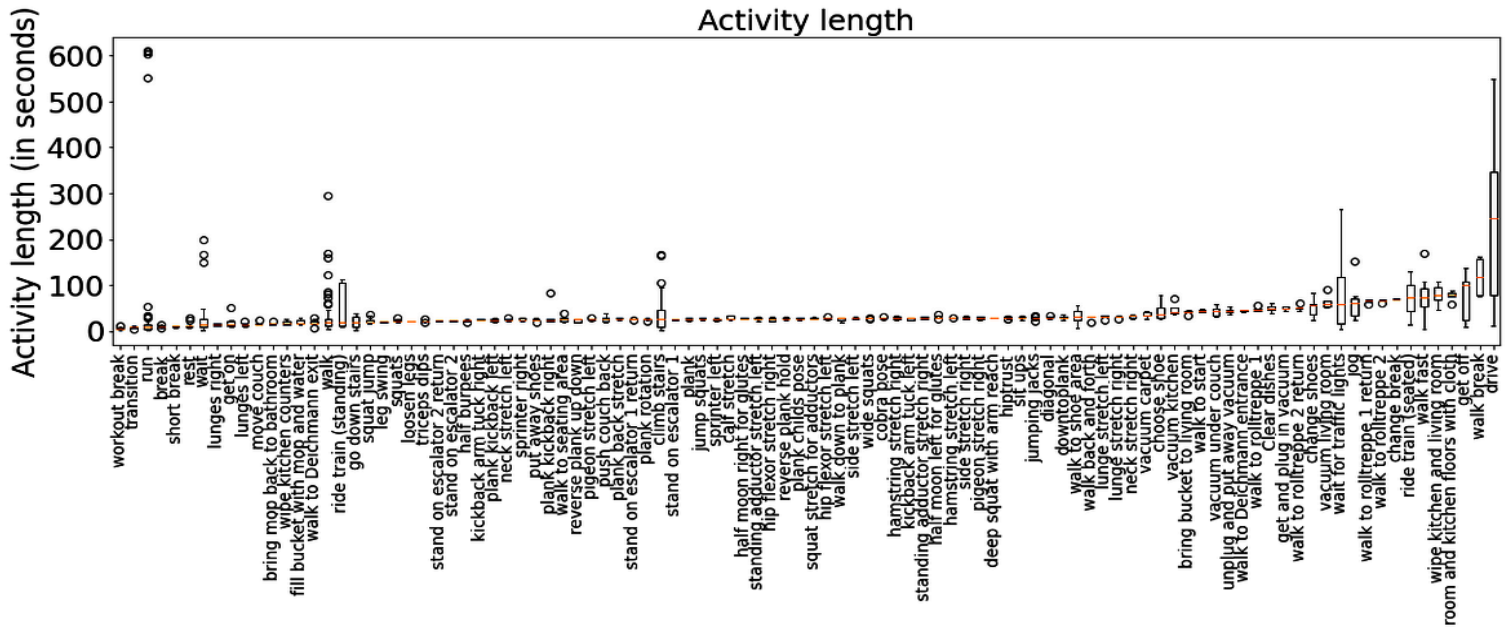


- New data set: **10.7 hours of multivariate real-world sensor data** (250 TS) from 15 bachelor students, diverse motion sequences
- Daily setting with ordinary smartphones, capture **100 activities in variety of behaviours**, realistic setting, sensor noise
- ECML Discovery Challenge: **Partition multivariate sensor signals** into unknown amount of variable-sized activity segments

Ermshaus, A., Schäfer, P., Leser, U., Bagnall, A., Tavenard, R., Leverger, C., Lemaire, V., Malinowski, S., Guyet, T. & Ifrim, G. (2023, April). Human Activity Segmentation Challenge. ECML/PKDD 2023 Discovery Challenge. Turin, Italy.

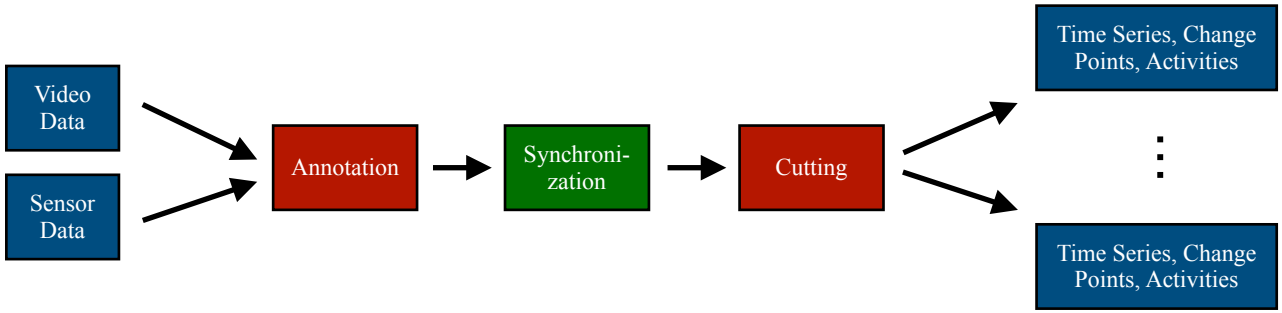
Data Set Design

- Participants: 2 groups of 8 and 7 CS bachelor students, semester project at HU Berlin, 10 males, 5 females between 21 and 42 years old
- 3 long motion sequences (per group): sport (indoor / outdoor), household, mall shopping, commuting to uni (train / bike)
- Technical setup: 5 smartphones, each worn in front right pocket, recording ACC, GYRO, MAG, LAT, LONG, speed with [Physics Toolbox Sensor Suit] app



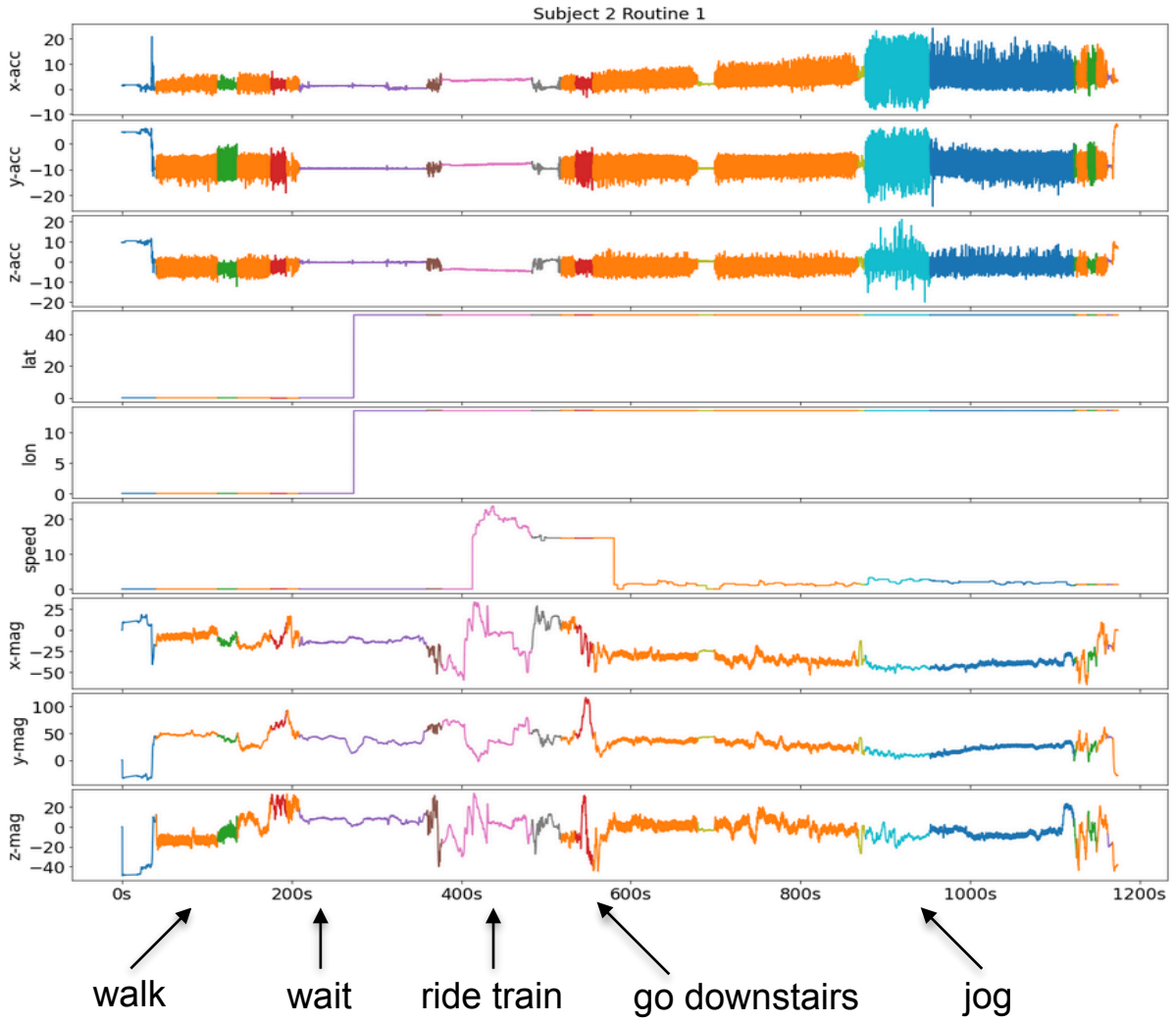
Data Collection and Preprocessing

- Data Collection: preparation phase, recording, follow-up phase, ground truth activities captured by another camera
- Preprocessing workflow: retrieve annotated, cut and resampled recordings at 50 Hertz
- 1 recording includes: 12-dimensional sensor signals, list of activities and transitions, meta information
- Challenge data: 250 cut recordings + sample rate, no labels, no meta information

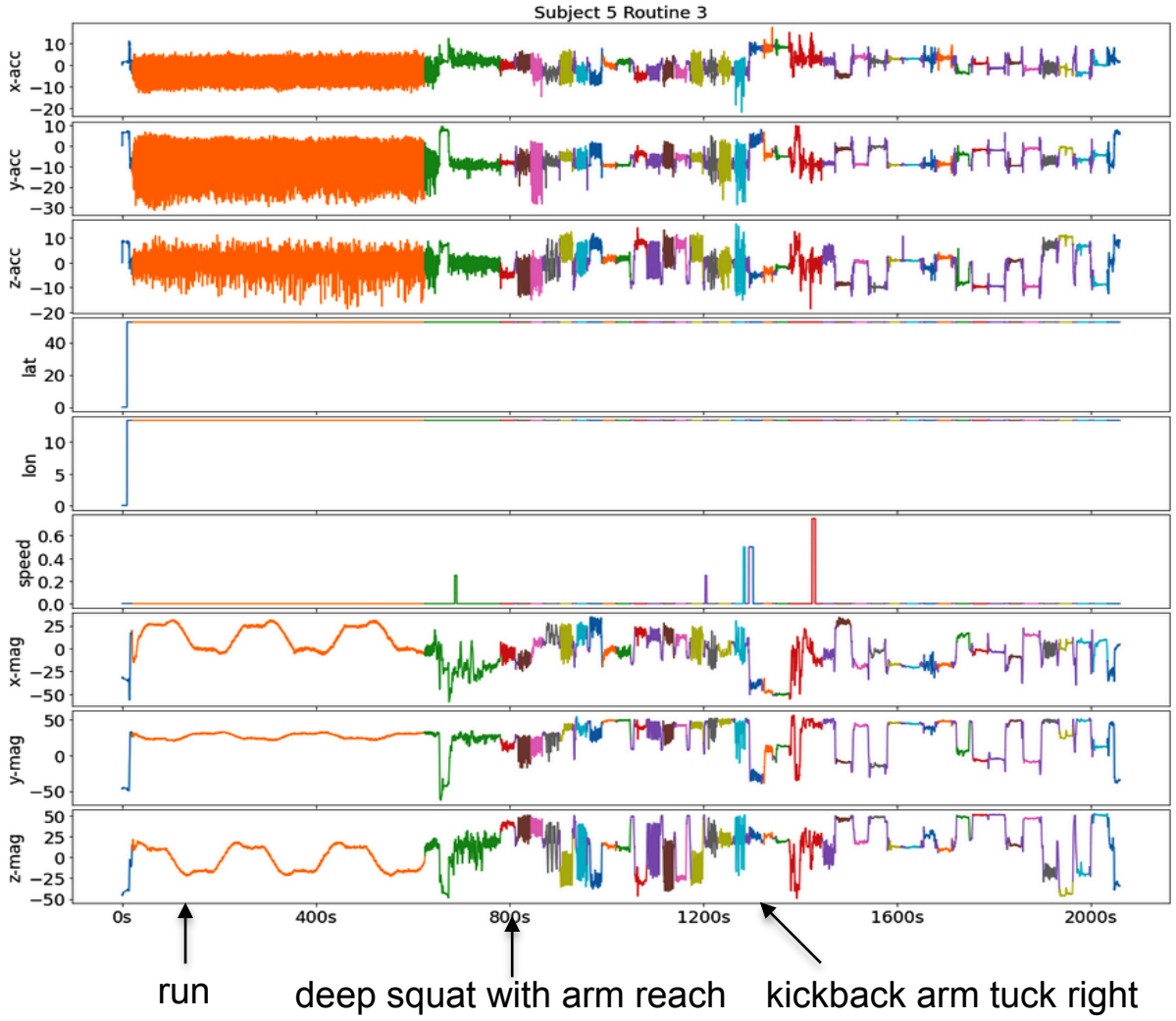


Preprocessing Workflow

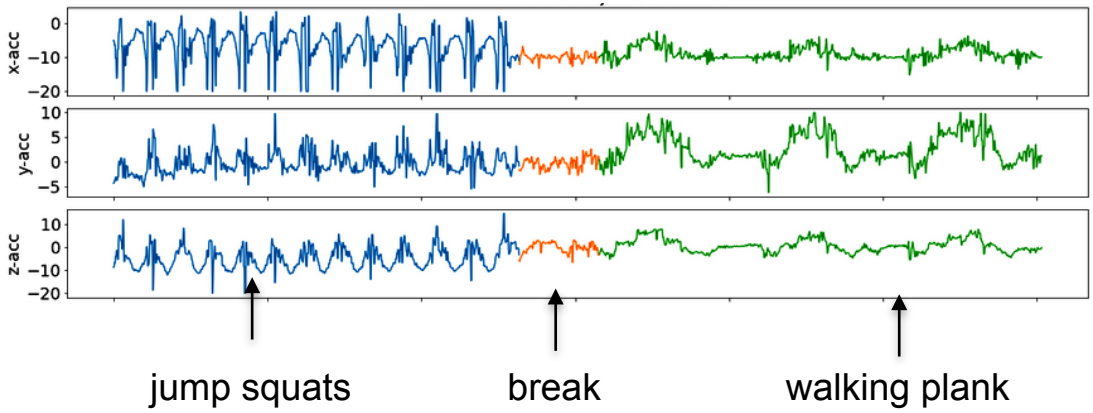
Train Commute Recording Example

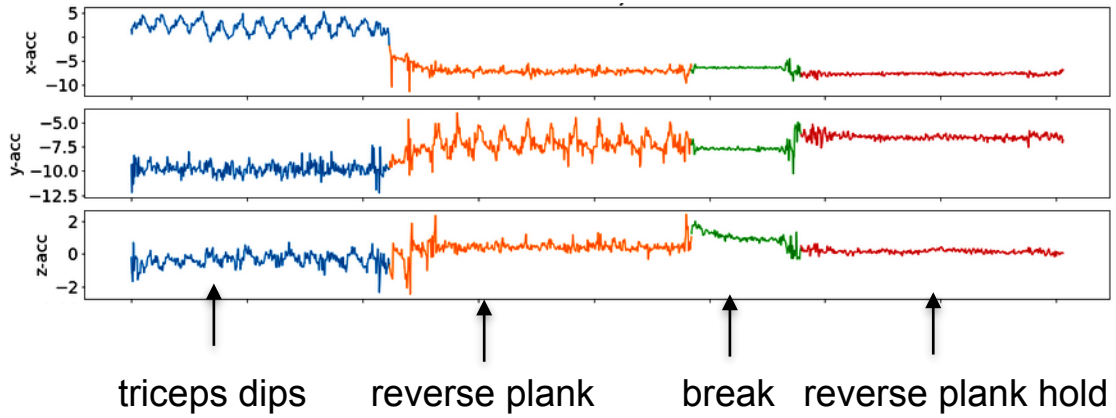


Outdoor Sport Recording Example



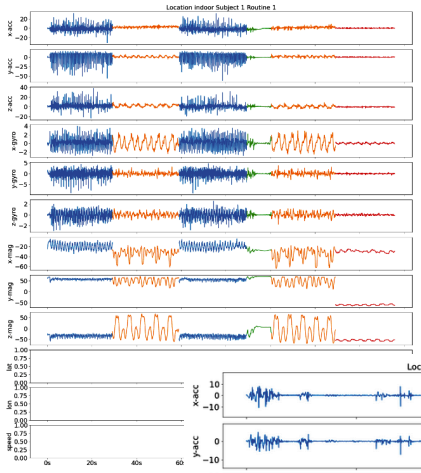
Outdoor Sport Cuts Example



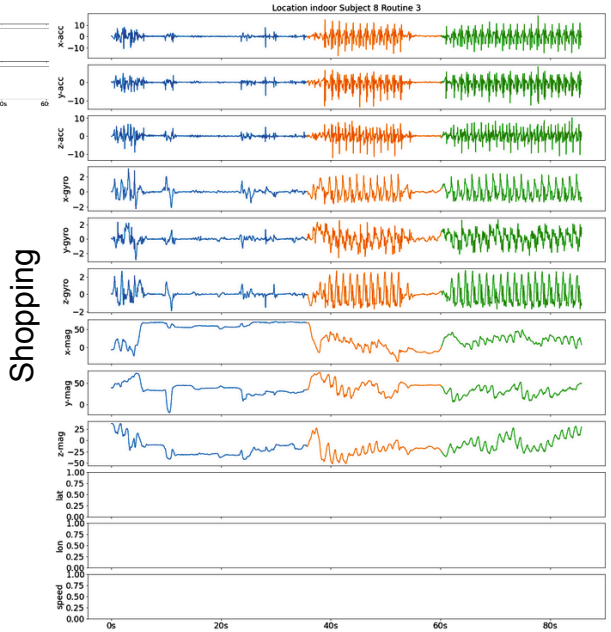


Data Set Examples

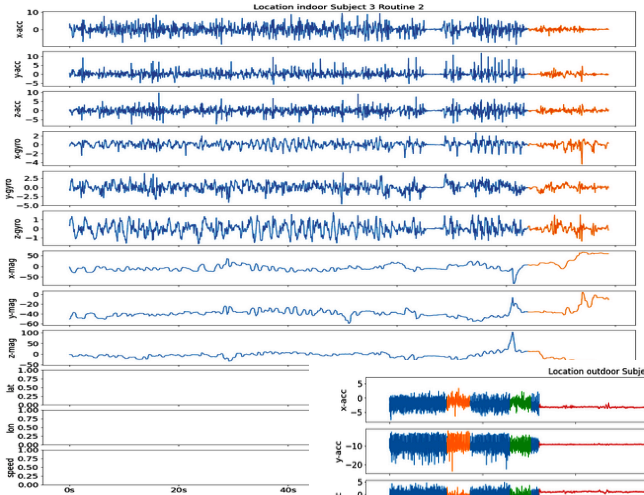
Sport



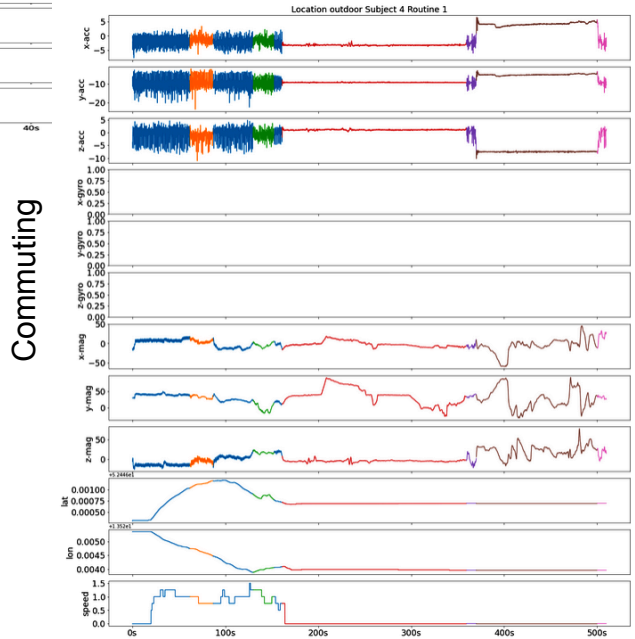
Shopping



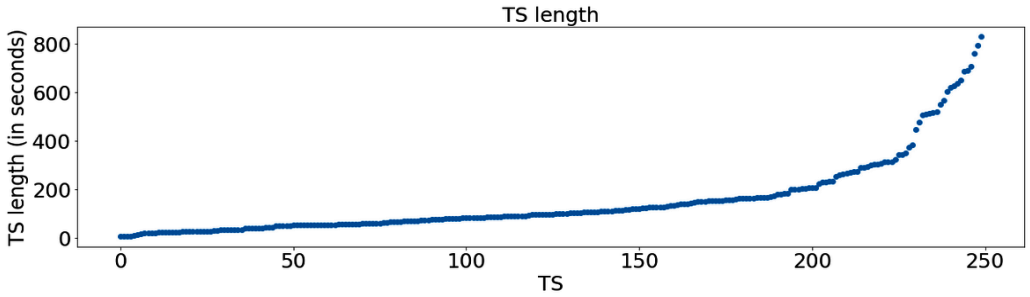
Household

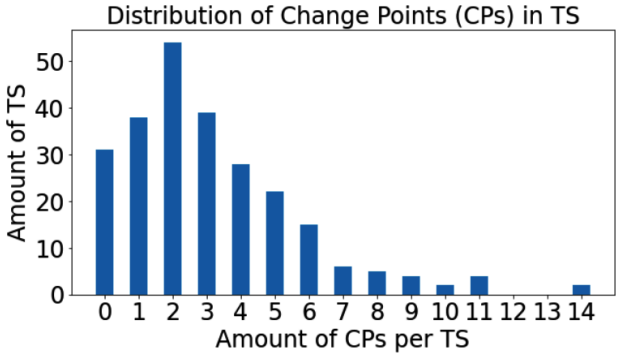


Commuting



Data Set Overview



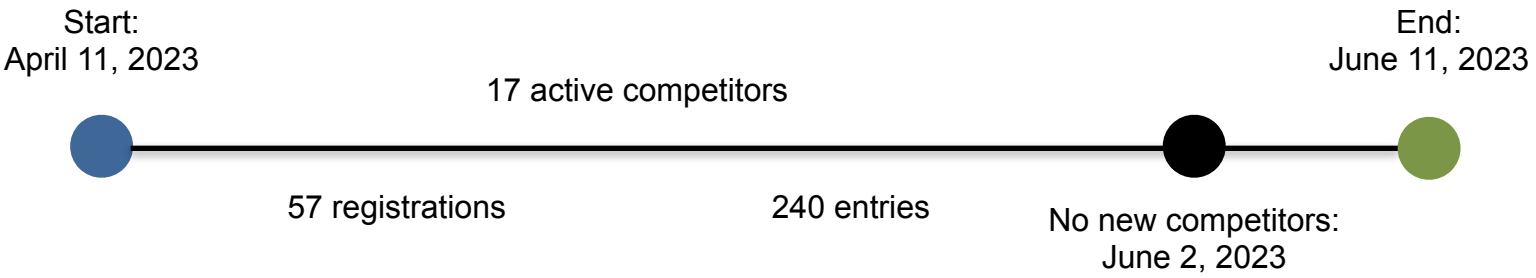


- In total: **10.7 hours of 100 activities** (250 12-dimensional TS at 50 Hz) from 16 participants performing 6 motion sequences
- TS capture between **7s and 14 min (median 100s) of data**; 1 to 15 potentially recurring activities
- Challenge data is freely available on GitHub: https://github.com/patrickzib/human_activity_segmentation_challenge

Challenge data

Challenge Organisation

- Kaggle community competition: information, communication and leaderboard; GitHub Repo for data, code and baselines
- Submissions: CSV files with predicted activity transitions for each of 250 TS, automatically scored/ranked by Kaggle
- Co-located with AALTD@ECML workshop, top-3 competitors rewarded with workshop publication, talk and free tickets

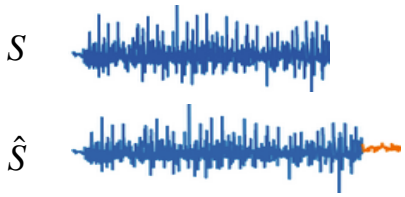


Powered by: aeon *tslearn*

Submission Evaluation

- Challenge: Predict amount and location of activity transition offsets for 250 12-dimensional TS
- Besides TS / sample rate, no additional information provided, fully unsupervised setting, no hand-labelling / training or external data
- public / private leaderboard (with 125 TS each), solutions ranked by F1 score, 3 submissions per day

$$IoU(S, \hat{S}) = \frac{S \cap \hat{S}}{S \cup \hat{S}}$$



Compute intersection over union for actual S and predicted $\hat{S}$ activities

$$IoU(S, \hat{S}) > t$$

TP	FN
FP	TN

Determine confusion matrix for given threshold $t \in [0{,}5 \ldots 1]$

$$F_1(t) = 2 \cdot \frac{precision(t) \cdot recall(t)}{precision(t) + recall(t)}$$

$$F_1 = \frac{1}{|thresholds|} \cdot \sum_t F_1(t)$$

Calculate F1-score for each threshold t and report average

Private Leaderboard Results

#	△	Team	Members	Score	Entries	Last	Solution
1	▲ 4	gh		0.51455	46	3mo	
2	▼ 1	Koular		0.50709	12	3mo	
3	▲ 7	Panos		0.49811	14	4mo	
4	▲ 4	infoxin		0.49811	15	4mo	
5	▲ 4	kojimar		0.49811	7	4mo	
6	▲ 1	Shayekh Islam		0.49811	4	5mo	
7	▲ 4	fuge		0.49811	5	4mo	
8	▼ 2	laffrent		0.49811	11	4mo	
		ClaSP		0.49602			
9	▼ 6	pjmathematician		0.49569	16	4mo	
10	▲ 2	ALLAccept		0.49094	11	3mo	

- Top-8 approaches improve on best baseline ClaSP
- Competition winners (top-2) reach over 50% F1-score
- Very hard unsupervised problem: More research needed (data available!)

Challenge Winners

Rank	F1-Score	Name	Country	Publication
1	51,46 %	Grzegorz Haranczyk	Poland	Change points detection in multivariate signal applied to human activity segmentation
2	50,71 %	Qi-Le Zhou	China	Change Point Detection via Synthetic Signals

Winning solutions will be published in this year's AALTD proceedings

Challenge Conclusion

- **New mobile sensing data set,** 250 multivariate motion recordings of 15 human subjects performing 100 daily activities
- Challenge winners outperform current baselines, performance increase is however limited, papers and code are online
- Performance must still be improved, future work should study multivariate segmentation of large real-world TS

Data and Python loader are available on our challenge website:

/patrickzib/human_activity_segmentation_challenge

TSS algorithms are implemented in open source libraries:

ruptures

aeon

stumpy

ClaSPy

Thanks for listening!

Any questions? Feel free to contact me at
ermshaua@informatik.hu-berlin.de