Learning the Arrow of Time for Human Activity Recognition: A Study on 700,000 Person-days of Wearable Data

Hang Yuan, Shing Chan, Aiden Doherty

hang.yuan@cs.ox.ac.uk, shing.chan@ndph.ox.ac.uk, aiden.doherty@ndph.ox.ac.uk

Motivation

- Wearable devices allow us to monitor an individual's health and fitness continuously, potentially revolutionising personalised medicine.
- Wearable devices' noninvasive and highly scalable nature is good for large-scale population health and epi-demiological studies (Willetts et al., 2018).
- Lack of labelled datasets like the ImageNet makes deep-learning models inferior to models that are based on hand-crafted features
- Self-supervised-learning (SSL) could potentially utilise large-scale unlabelled dataset like the UK-biobank (Doherty et al., 2017)

Methods

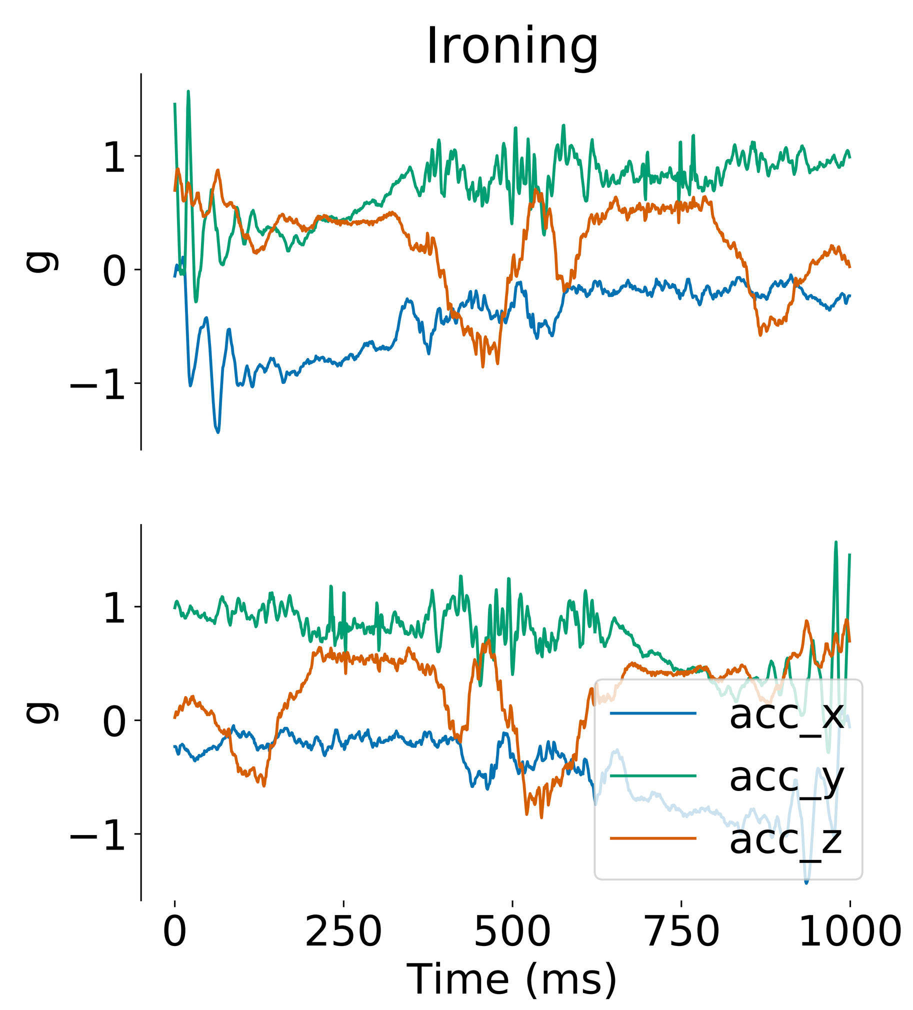


Fig 1: Example of forward and backward time flow

ResNet V2 with 18 layers on 700,000 person-day of wearable data (UK-biobank)

Task: Discriminate the arrow of time (AoT) in 10-second segment

- **Weighted sampling**: weighted sampling based on SD of each segment
- **Positive example ratio**: when the ratio of positive examples is greater than .5, it is easier for the model to converge

Downstream evaluation

Table 1. Wrist-worn accelerometer datasets used to evaluate human activity recognition tasks

Dataset	#Subjects	#Samples	#Labels	Environment
UK-Biobank	100K	-	-	free-living
Capture-24	152	573K	5	free-living
Rowlands	55	36K	13	lab
PAMAP2	8	2869	8	lab
OPPORTUNITY	4	3882	4	lab

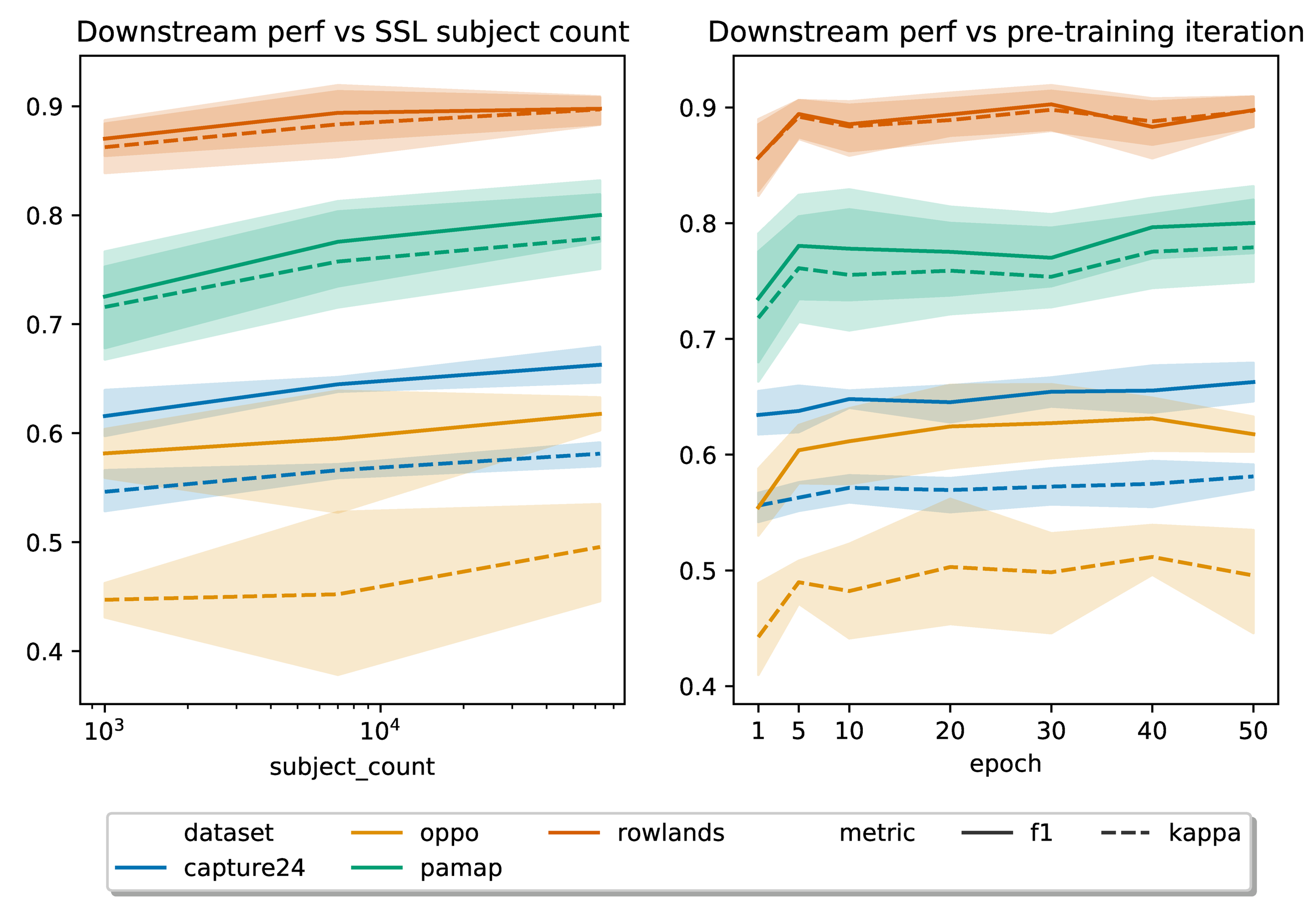
After the AoT training has converged on the UK-biobank. We evaluated the network on four downstream benchmark datasets in both lab and free-living environments.

Results

Table 2. F1 and Kappa (κ) for downstream human activity recognition tasks (mean $\pm$ SD)

Data		Random forest	From scratch	SSL fine-tune linear	SSL fine-tune all
Capture-24	F1	.559 $\pm$ .010	.625 $\pm$ .018	**.664 $\pm$ .014**	.663 $\pm$ .019
	κ	.493 $\pm$ .007	.545 $\pm$ .022	**.583 $\pm$ .014**	.581 $\pm$ .013
Rowlands	F1	.835 $\pm$ .018	.836$\pm$ .022	.846$\pm$ .031	**.884 $\pm$ .026**
	κ	.852 $\pm$ .016	.820 $\pm$ .027	.835 $\pm$ .031	**.880 $\pm$ .027**
PAMAP2	F1	.771 $\pm$ .084	.550 $\pm$ .076	.741 $\pm$ .046	**.807 $\pm$ .056**
	κ	.756 $\pm$ .091	.545 $\pm$ .086	.725 $\pm$ .055	**.786 $\pm$ .060**
OPPORTUNITY	F1	.456 $\pm$ .129	.401 $\pm$ .084	.579 $\pm$ .031	**.637 $\pm$ .013**
	κ	.347 $\pm$ .137	.236 $\pm$ .085	.468 $\pm$.033	**.519 $\pm$ .045**

- SSL model fine-tuned on all layers is the best on three out of four datasets.
- Biggest performance boost was observed on a small dataset with only four subjects.
- When pre-train data and downstream data is similar, fine-tuning linear layers yields better outcome.



- Performance gain diminishes exponentially w.r.t. the size of pre-train dataset.
- One does not see an obvious downstream performance improvement after the pre-trained model has converged.

Discussion

- We have developed a robust representation for wearable data using a large-scale pre-training dataset.
- The representation generalises well to an array of downstream applications.
- The fine-tuned model consistently beats random forest baseline and the network trained from scratch.

In the future, we will investigate what is be learnt and how to extend AoT from segment level to sequence level.

Acknowledgements

Funding bodies: Li Kai Shing Foundation, Novo Nordisk, Alan Turing Institute, the British Heart Foundation, Health Data Research UK, and the National Institute for Health Research.

References:

- Willetts, M., Hollowell, S., Aslett, L., Holmes, C., and Doherty, A. Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 ukbiobankparticipants. ScientificReports,8(1):1–10, 2018.
- Doherty, A., Jackson, D., Hammerla, N., Plo¨tz, T., Olivier, P., Granat, M. H., White, T., Van Hees, V. T., Trenell, M. I., Owen, C. G., et al. Large scale population assess- ment of physical activity using wrist worn accelerometers: The uk biobank study. PloS one, 12(2):e0169649, 2017.

Nuffield Department of POPULATION HEALTH

BIG DATA INSTITUTE

UNIVERSITY OF OXFORD

HEALTH DATA SCIENCE