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

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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 epidemiological 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

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

Results

- 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 been learnt and how to extend AoT from segment level to sequence level.

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References:


Fig 1: Example of forward and backward time flow

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Downstream perf vs SSL subject count

Downstream perf vs pre-training layer

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