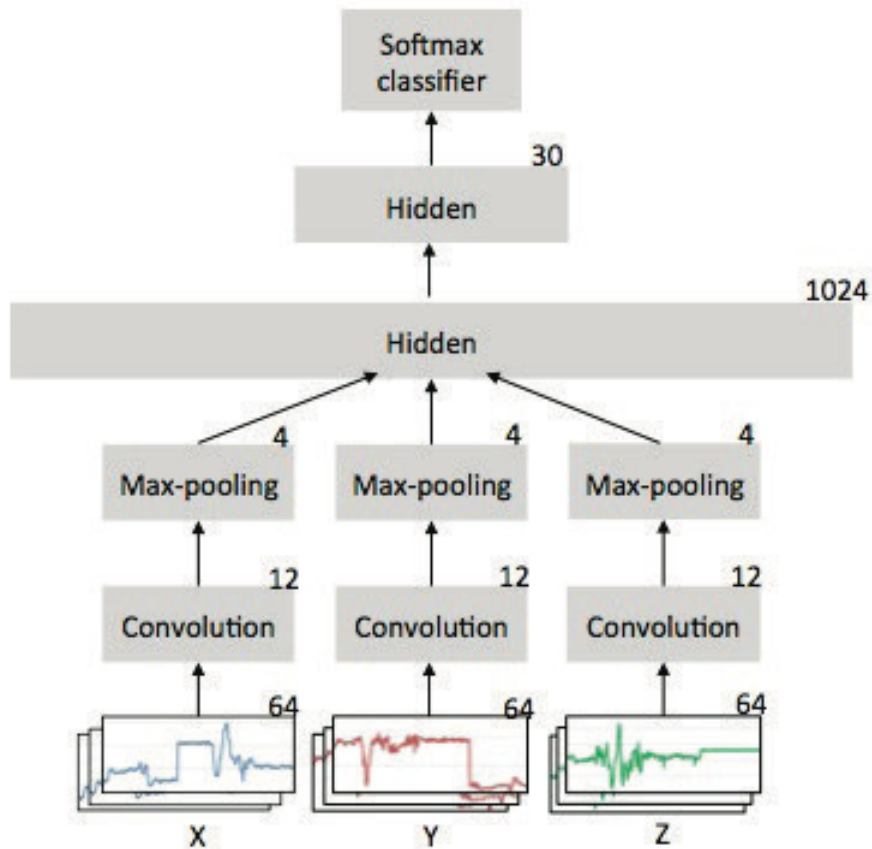


Mobile Health  
Lecture 8  
Human Activity through  
Deep Learning

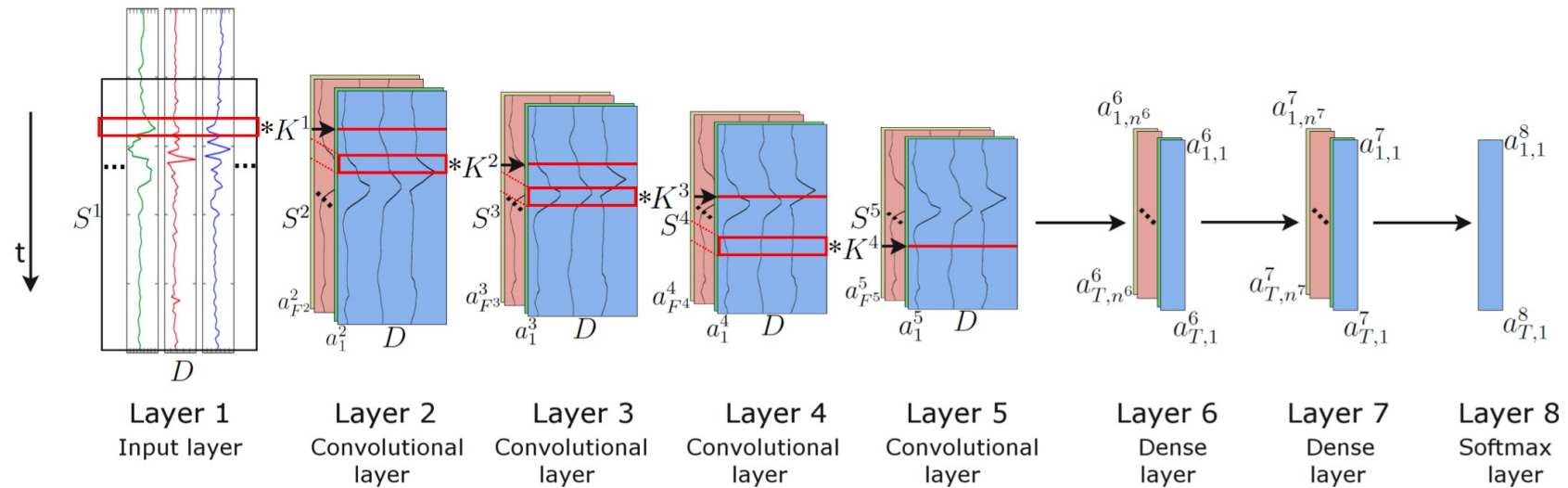
Cecilia Mascolo

# ML beyond Features for Activity Recognition



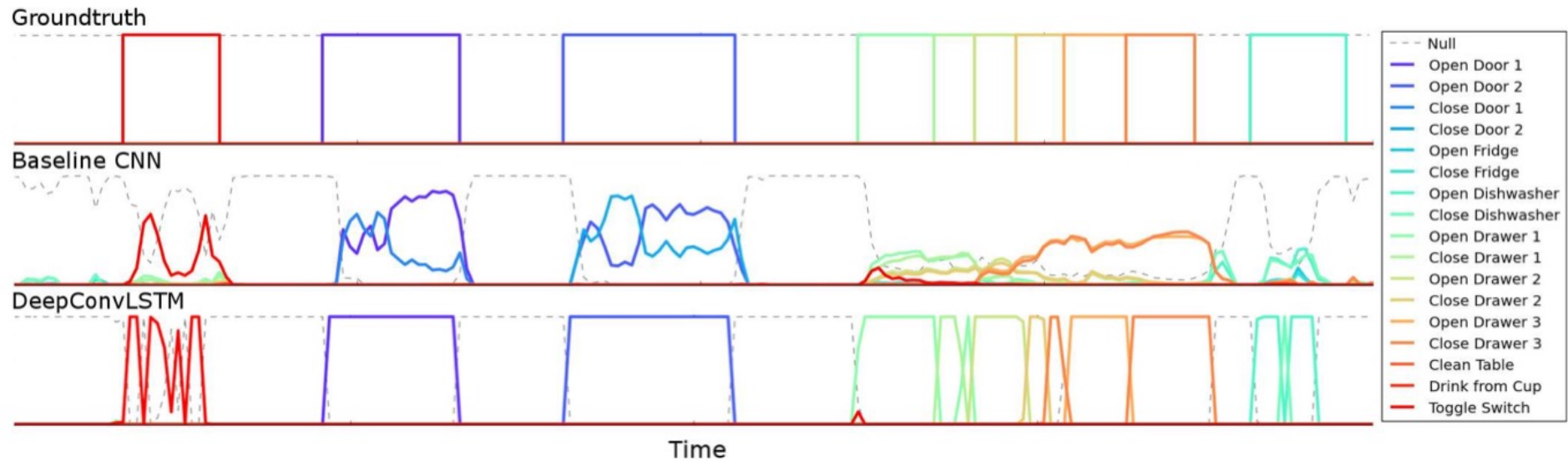
M. Zeng *et al.*, "Convolutional Neural Networks for human activity recognition using mobile sensors," *6th International Conference on Mobile Computing, Applications and Services*, 2014, pp. 197-205,

# CNN+LSTMs for HAR



Ordóñez, F.J.; Roggen, D. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. *Sensors* **2016**, *16*, 115.

# Visualization of Goodness of this Approach

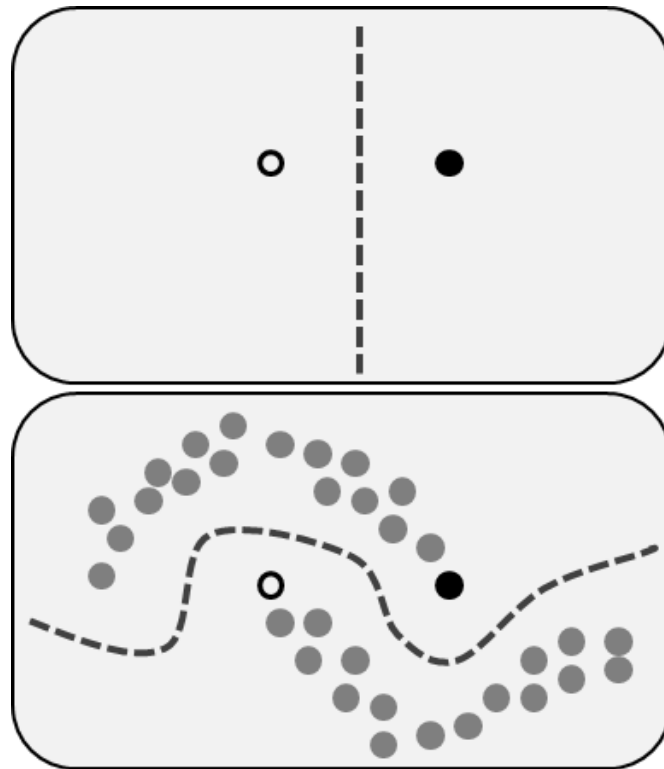


Ordóñez, F.J.; Roggen, D. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. *Sensors* **2016**, *16*, 115.

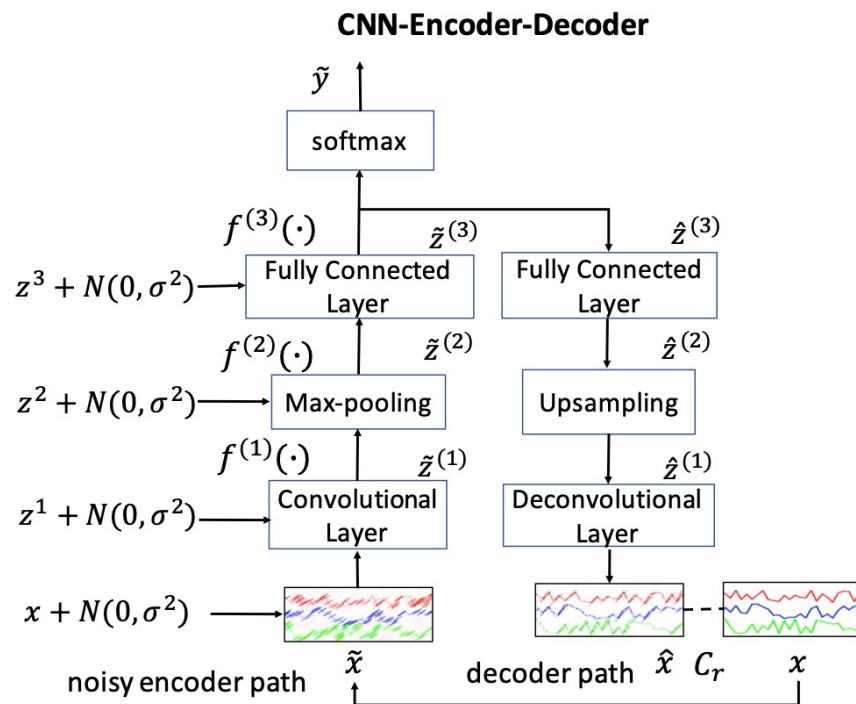
# Deep Learning and HAR: Issues

- Unlike other domains, sensor data often lacks large scale labelled datasets
  - Difficult to collect large scale ground truth
  - This can lead to overfitting! (DNN with many parameters will memorize small data)
- Solutions:
  - Semi supervised learning
  - Self learning
  - Self training
  - Transfer Learning

# Semi-Supervised Learning: A recap



# An Example of Semi Supervised HAR



Zeng, M., Yu, T., Wang, X., Nguyen, L. T., Mengshoel, O. J., & Lane, I. (2017, December). Semi-supervised convolutional neural networks for human activity recognition. In 2017 IEEE International Conference on Big Data (Big Data) (pp. 522-529). IEEE.

# Semi Supervised Approaches for HAR

- Semi-supervised learning methods can achieve similar performance to fully supervised ones using only a fraction of the labels

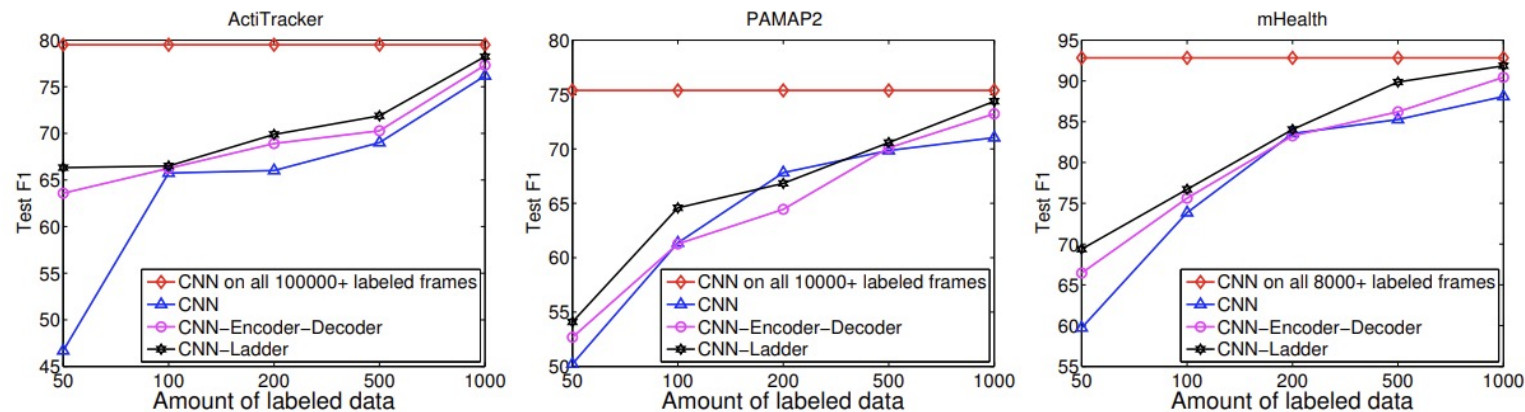
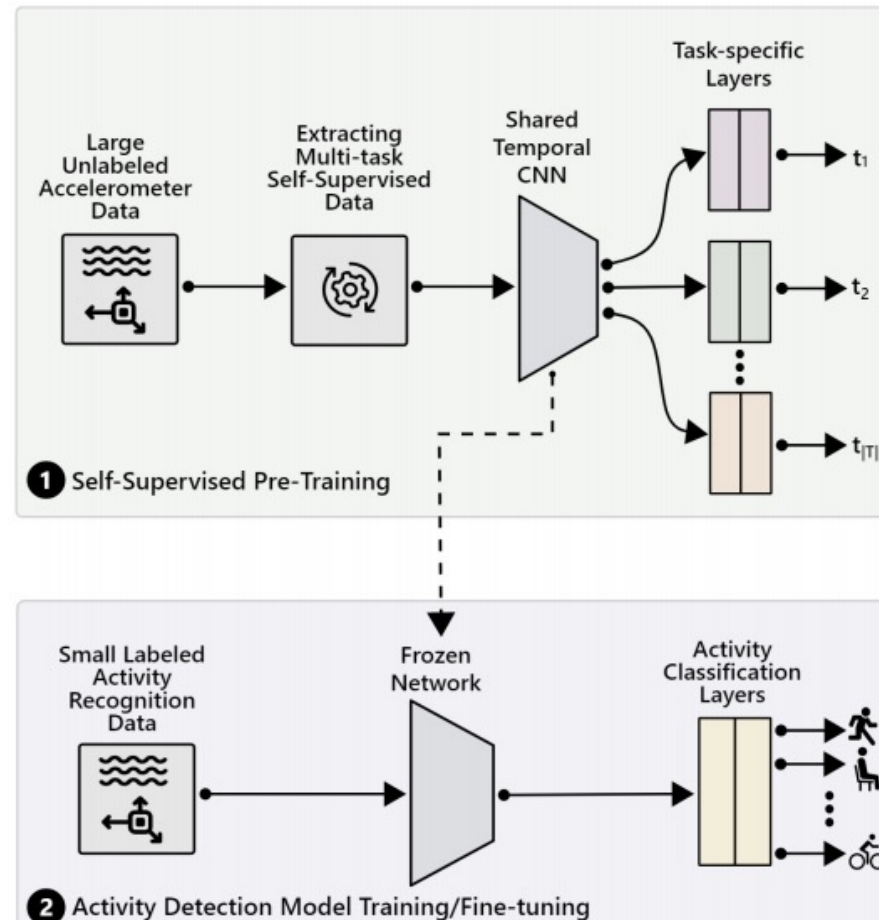


Figure 2: The  $F_m$  scores of CNN, CNN-Encoder-Decoder, and CNN-Ladder, with varying number of labeled examples. The  $F_m$  scores of supervised CNN on all labeled training examples are also shown as red lines.

Zeng, M., Yu, T., Wang, X., Nguyen, L. T., Mengshoel, O. J., & Lane, I. (2017, December). Semi-supervised convolutional neural networks for human activity recognition. In 2017 IEEE International Conference on Big Data (Big Data) (pp. 522-529). IEEE.

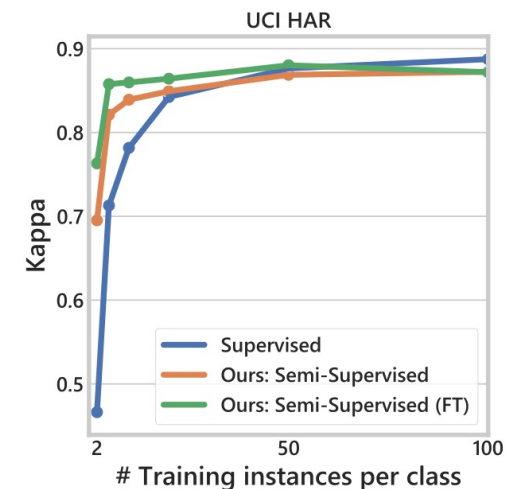
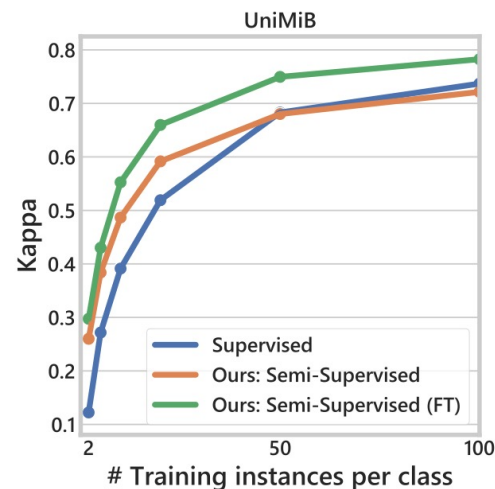
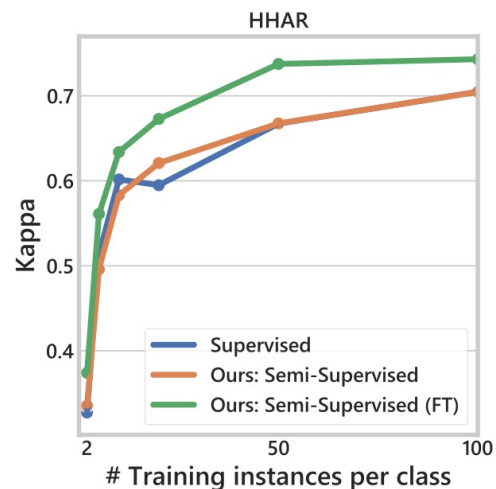


# Self Supervision using Transformation Recognition



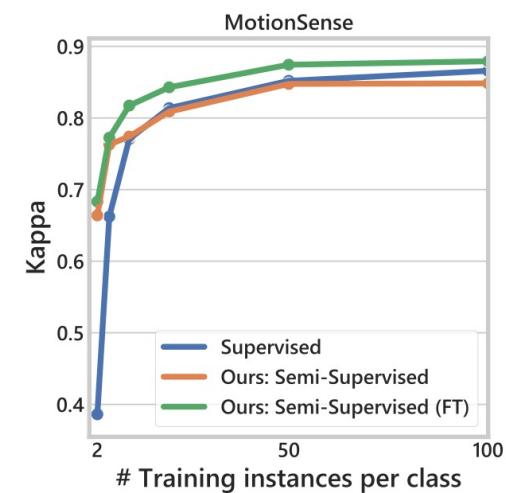
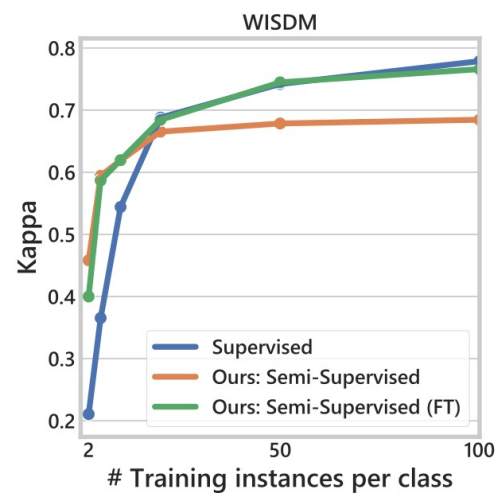
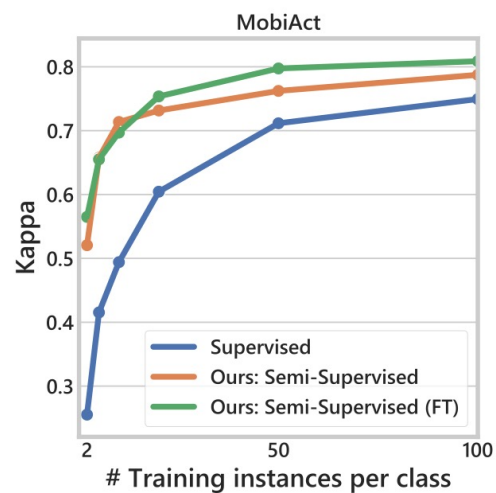
Saeed, A., Ozcelebi, T., & Lukkien, J. (2019). Multi-task self-supervised learning for human activity detection. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 3(2), 1-30.

# Results

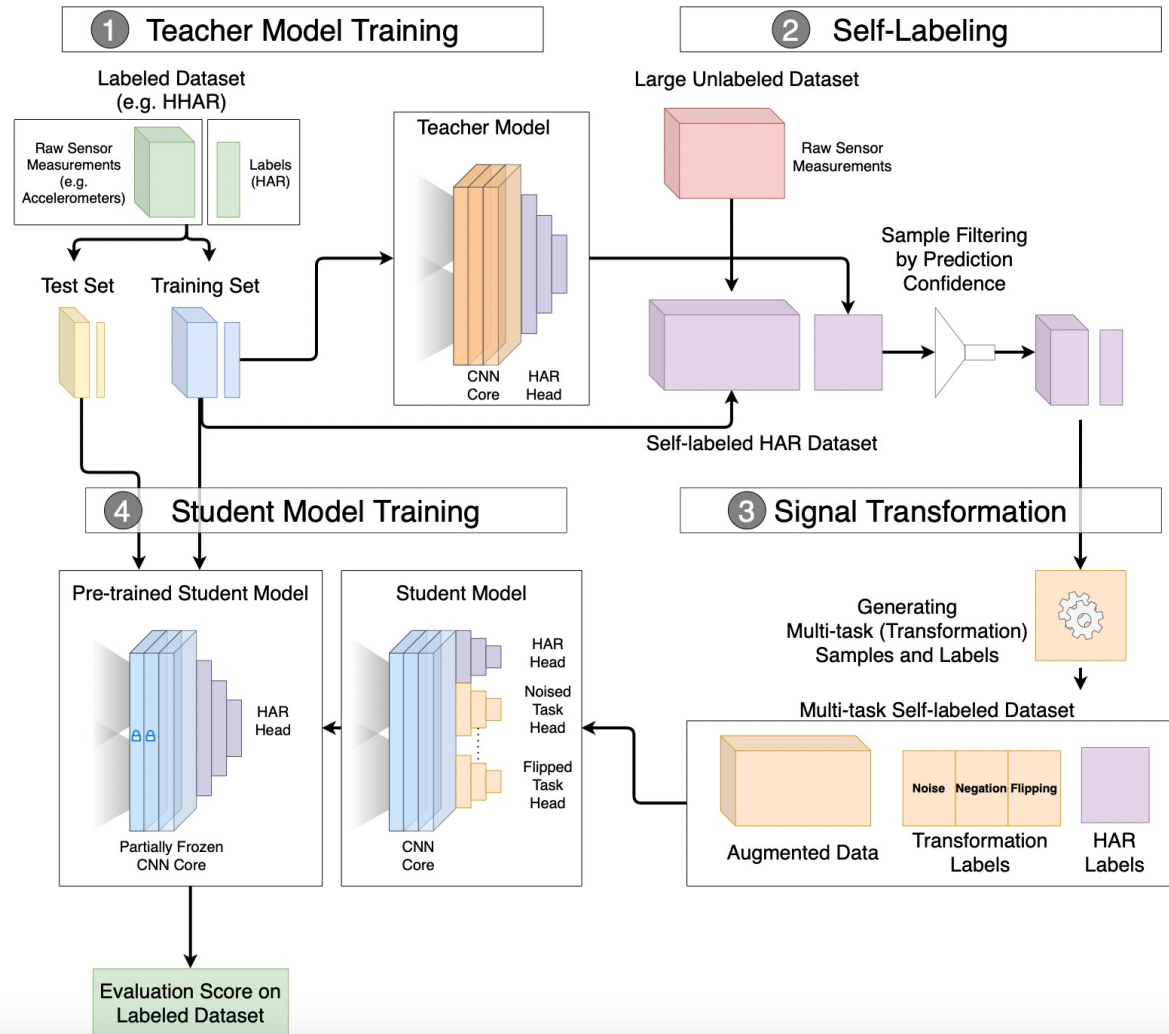


Cohen Kappa is a weighted version of precision, recall and f-score robust to imbalance.

SS-FT is fine tuned on HAR task

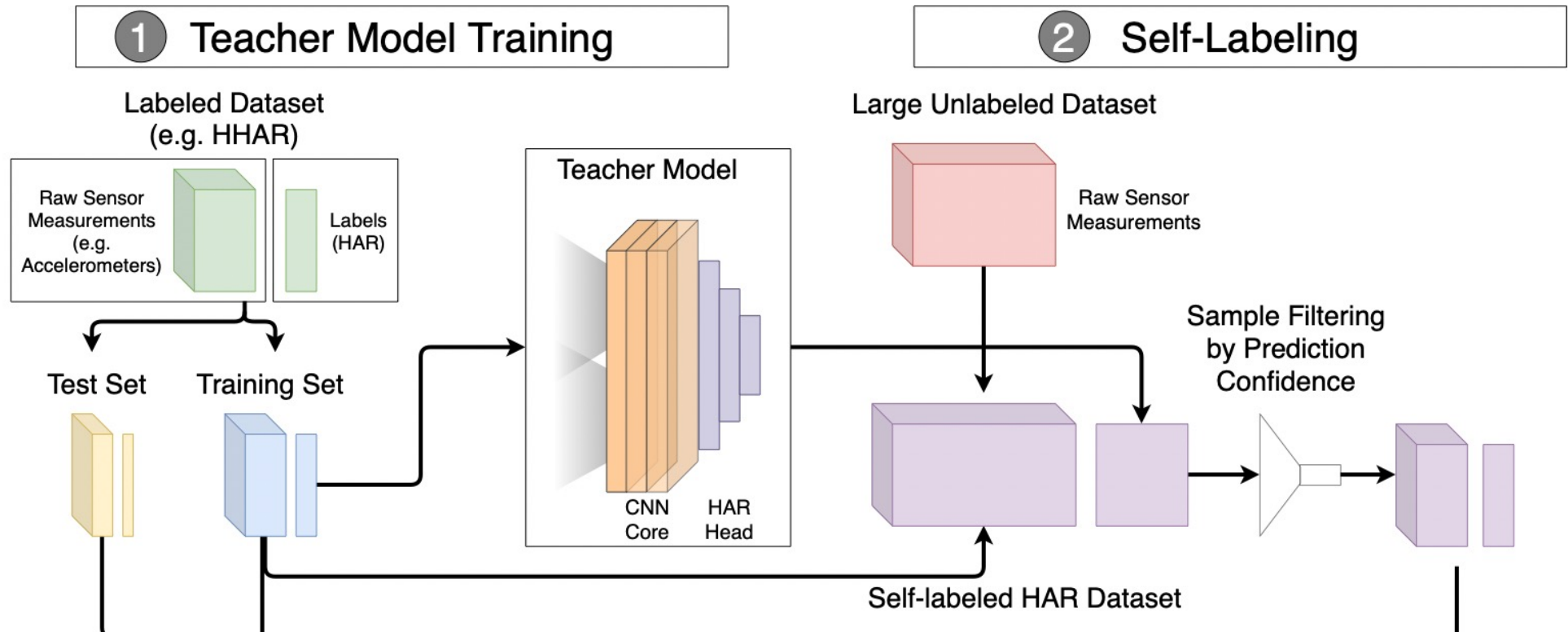


# Self-training

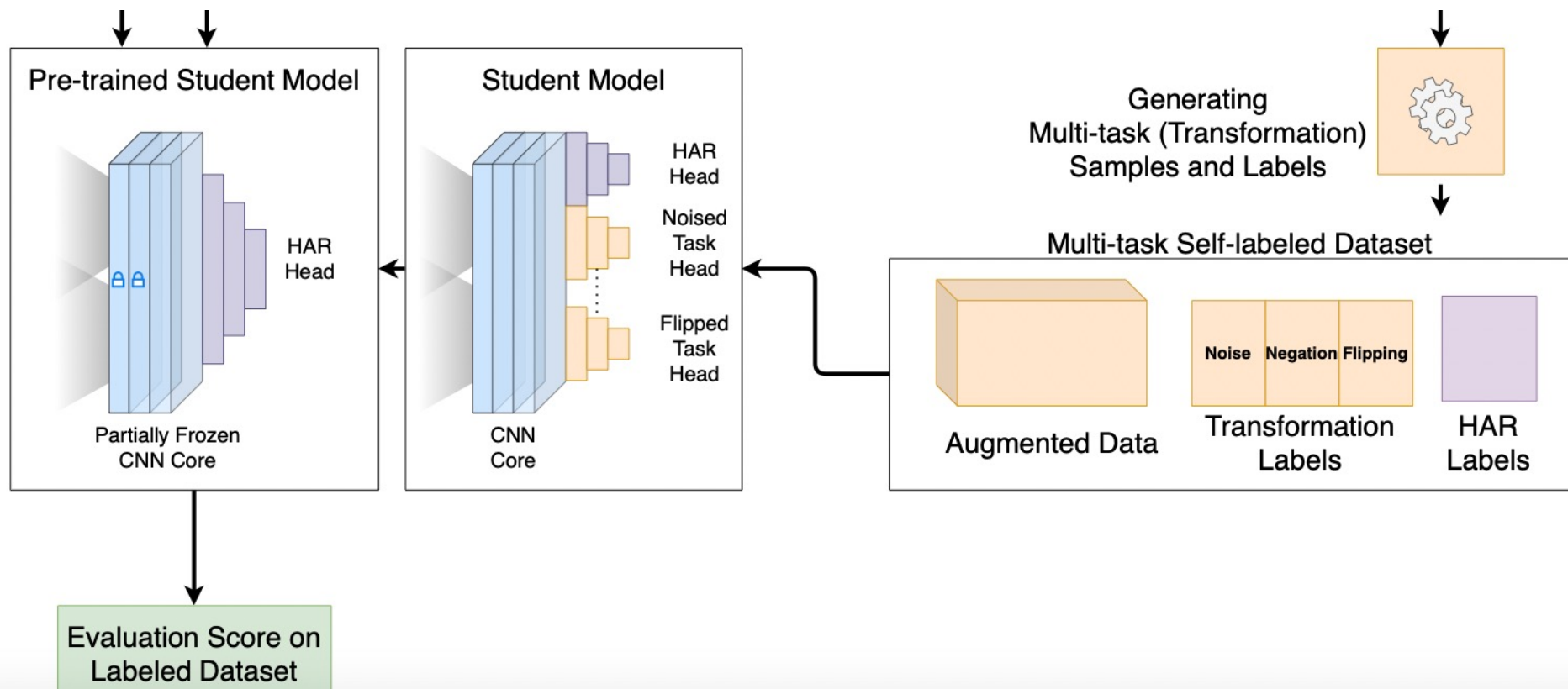


**SelfHAR: Improving Human Activity Recognition through Self-training with Unlabeled Data.** I. Tang, D. Spathis, I. Perez-Pozuelo, S. Brage, N. Wareham, C. Mascolo. In Procs of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT). Volume 5 Issue 1. 2021.

# Teacher Model



# Student Model



# Performance

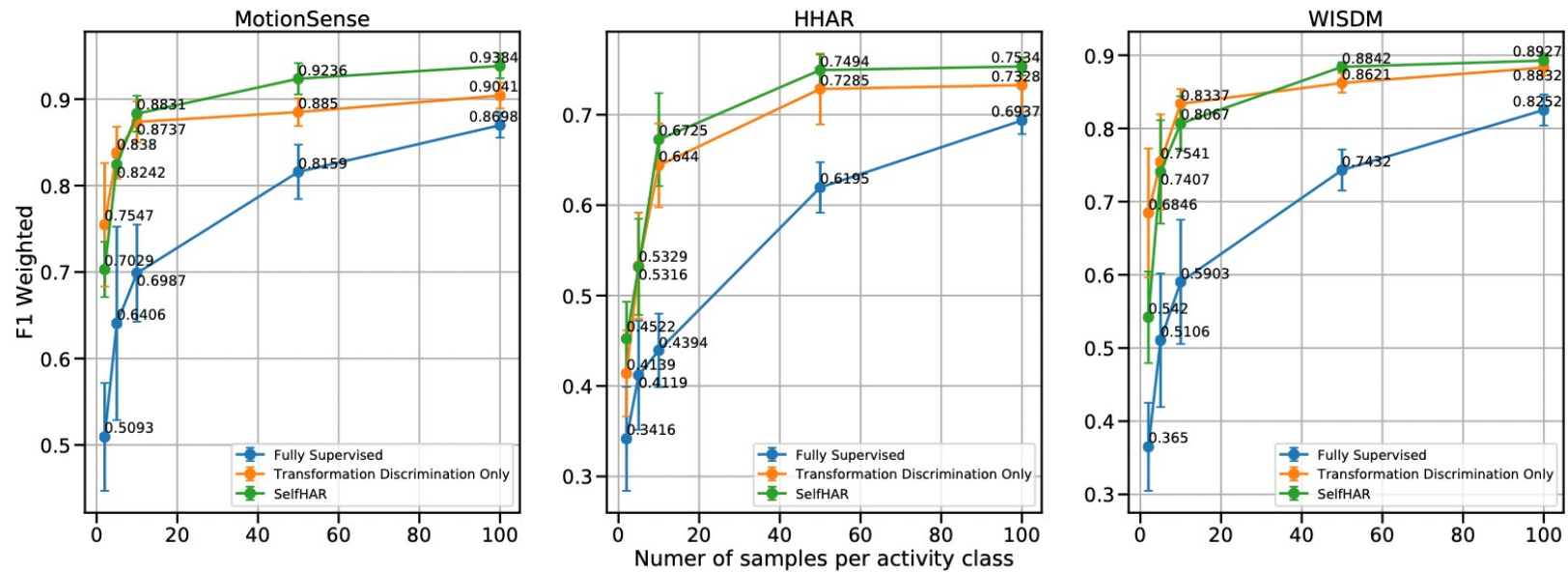
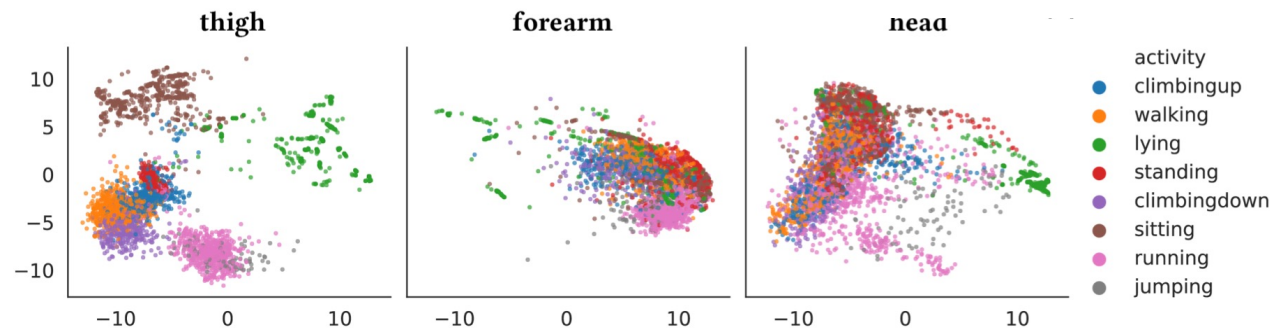
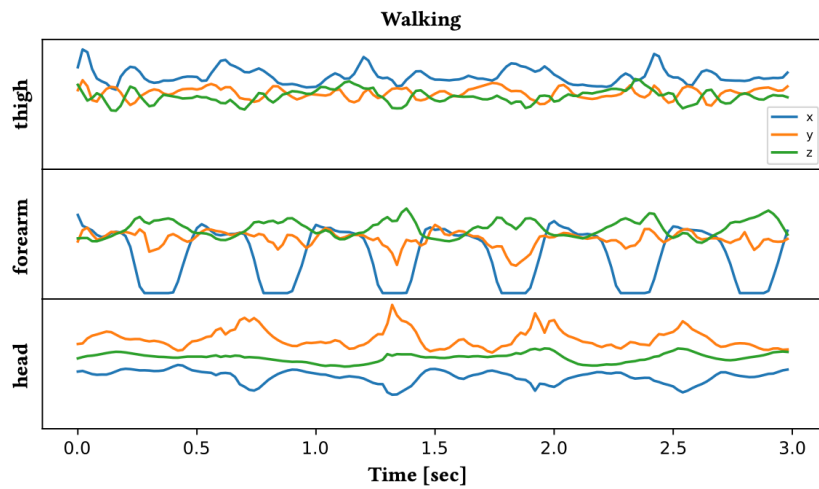


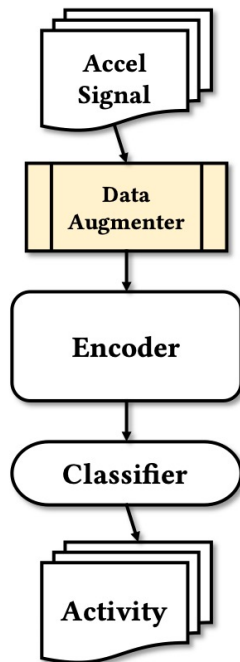
Fig. 4. Assessing classification performance as a function of limited training data. *SelfHAR* achieves high performance with significantly less training data and outperforms the variant with *no* teacher-student training in most cases.

# Domain Adaptation in HAR

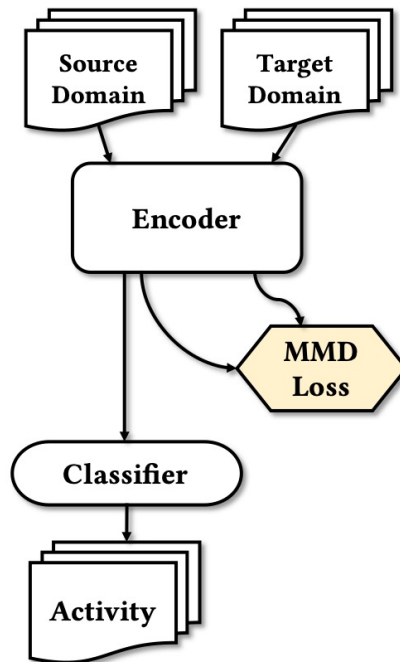


Youngjae Chang, Akhil Mathur, Anton Isopoussu, Junehwa Song, and Fahim Kawsar. 2020. A Systematic Study of Unsupervised Domain Adaptation for Robust Human-Activity Recognition. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 4, 1, Article 39.

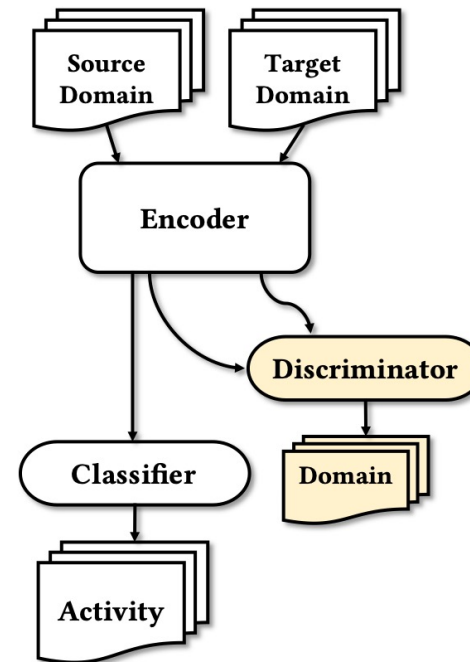
# Techniques for Domain Generalization



(a) Data augmentation



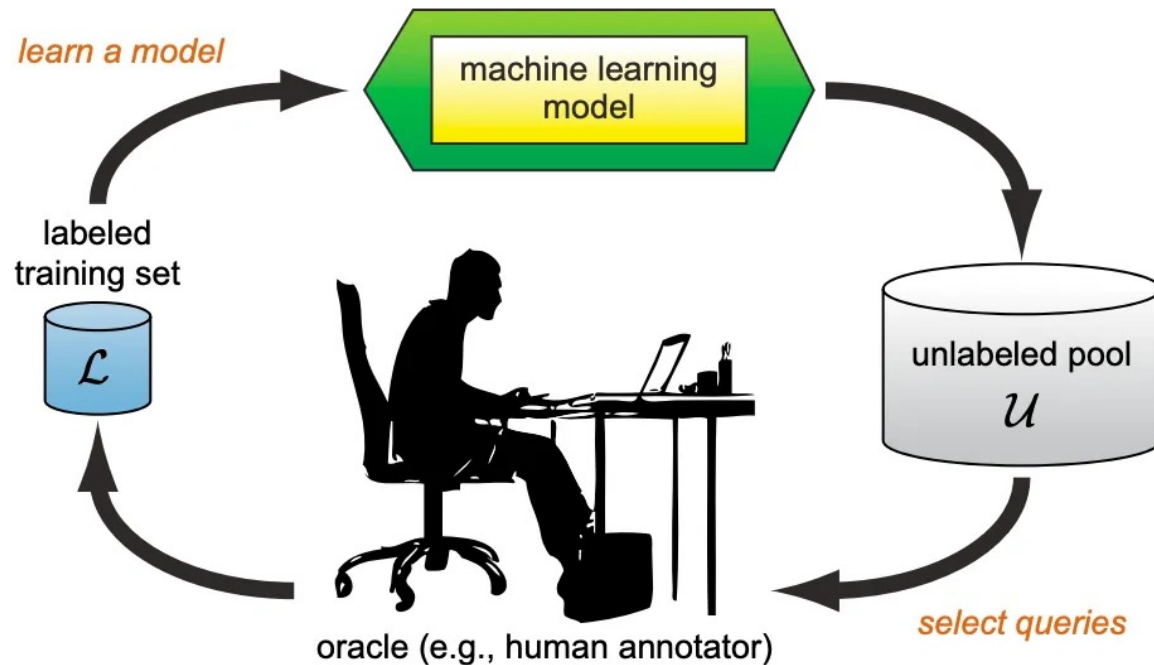
(b) Feature matching



(c) Confusion maximization



# Active Learning and HAR

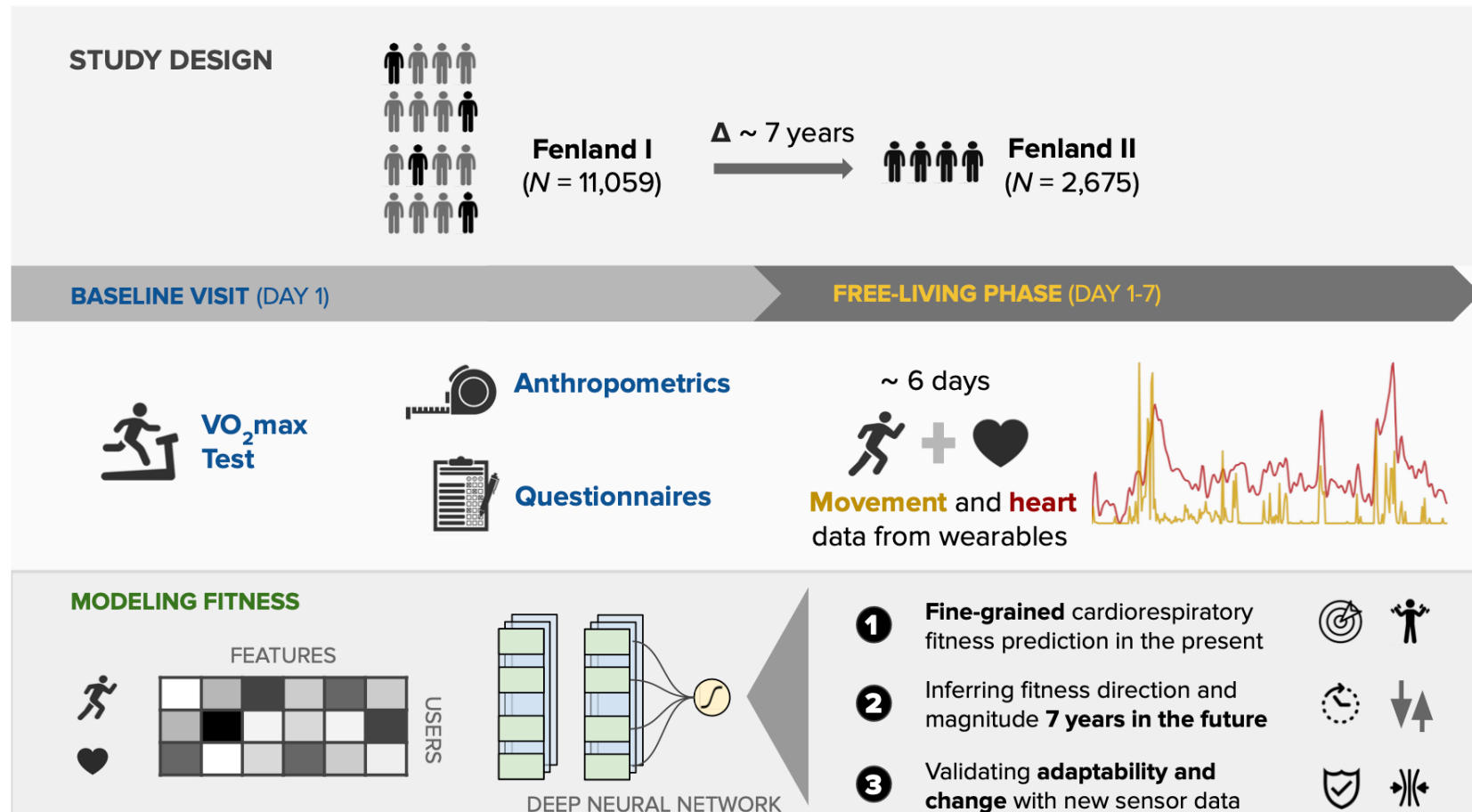


A. Vaith, B. Taetz and G. Bleser, "Uncertainty based active learning with deep neural networks for inertial gait analysis," *2020 IEEE 23rd International Conference on Information Fusion (FUSION)*.

## Another example of Self Supervision Application: Cardiorespiratory Fitness



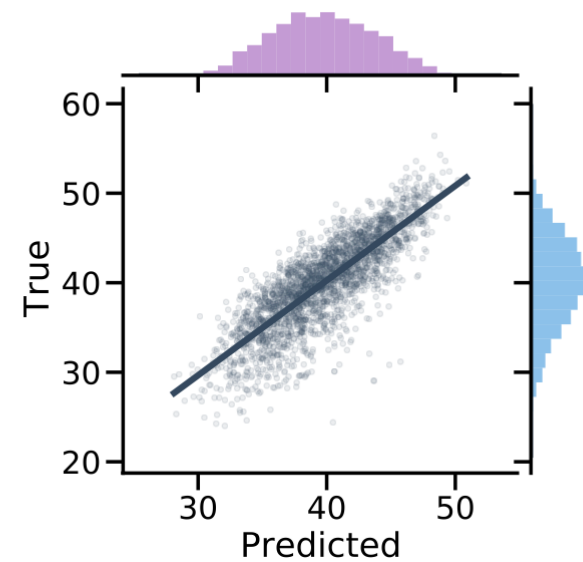
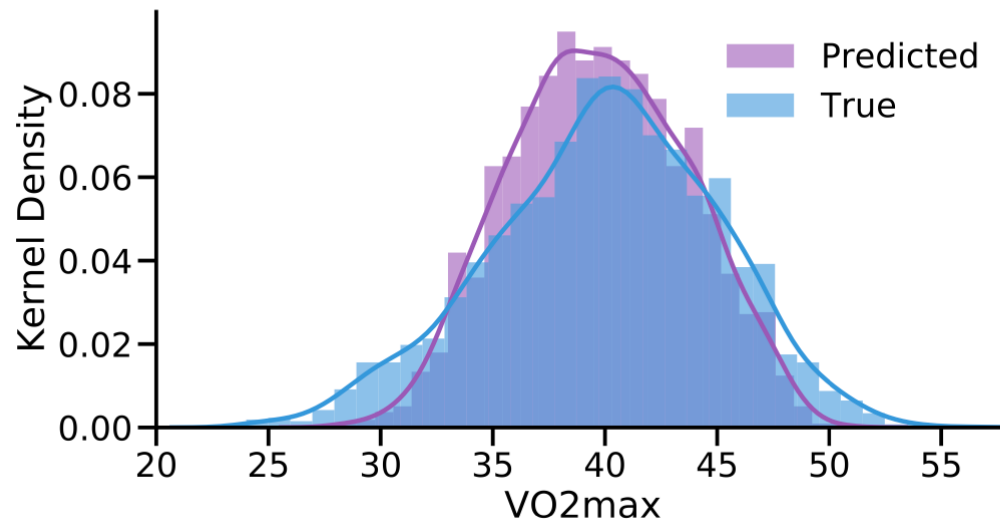
# CRF through Wearable Data in Free Living



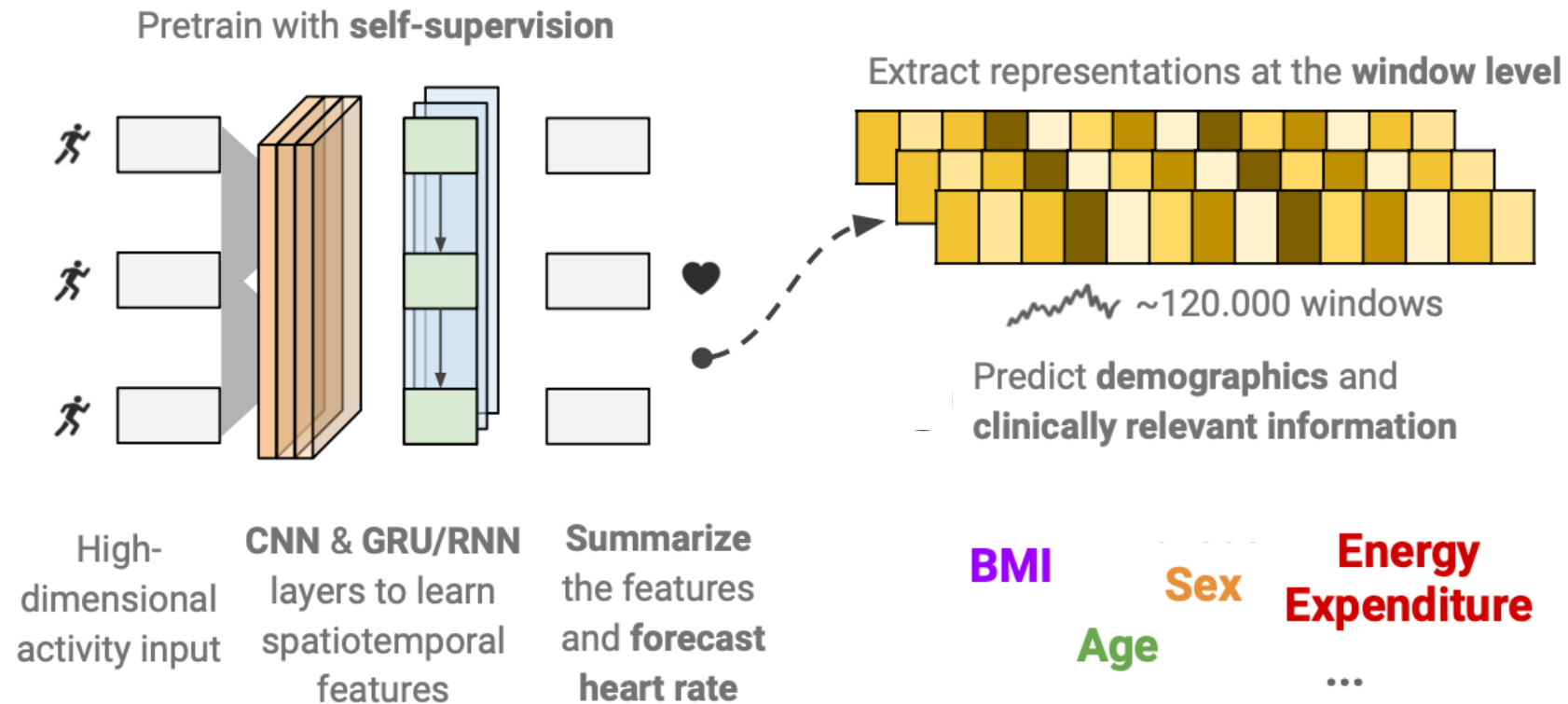
**Longitudinal cardio-respiratory fitness prediction through wearables in free living environment.** D. Spathis, I. Perez-Pozuelo, T. Gonzales, Y. Wu, S. Brage, N. Wareham, C. Mascolo. In Npj Digital Medicine. November 2022.

# VO<sub>2</sub>Max Prediction

Data modality	Evaluation Metrics [95% CI]			N (train+val / test set)
	R <sup>2</sup>	Corr	RMSE	
<b>Anthropometrics</b>				
Age/Sex/Weight/BMI/Height	0.362 [0.332-0.391]	0.604 [0.579-0.627]	4.043 [3.924-4.172]	
<b>Resting Heart Rate</b>				
RHR (Sensor-derived)	0.374 [0.344-0.403]	0.615 [0.589-0.639]	4.007 [3.891-4.117]	
<b>Anthropometrics + RHR</b>				11059
Age/Sex/Weight/BMI/Height/RHR	0.616 [0.588-0.641]	0.785 [0.767-0.802]	3.138 [3.031-3.237]	(8384/2675)
<b>Wearable Sensors + RHR + Anthro.</b>				
Acceleration/HR/HRV/MVPA	<b>0.671 [0.649-0.692]</b>	<b>0.822 [0.808-0.835]</b>	<b>2.903 [2.801-3.003]</b>	
Age/Sex/Weight/BMI/Height/RHR				



# Heart Rate Prediction from Wearable Data



**Self-supervised transfer learning of physiological representations from free-living wearable data.** D. Spathis, I. Perez-Pozuelo, S. Brage, N. Wareham, C. Mascolo. In Procs of ACM Conf. on Health, Inference, and Learning (CHIL21). April 2021

# Heart Rate Prediction & Downstream Tasks

	MSE	RMSE	MAE
<i>Step2Heart</i> <sub>A</sub>	144.61 (0.62)	12.02 (0.02)	9.23 (0.03)
<i>Step2Heart</i> <sub>A/T</sub>	143.65 (0.28)	11.98 (0.01)	9.21 (0.03)
<i>Step2Heart</i> <sub>A/R</sub>	91.76 (0.12)	9.57 (0.00)	6.92 (0.03)
<i>Step2Heart</i> <sub>A/R/T</sub>	<b>91.11 (0.37)</b>	<b>9.54 (0.01)</b>	<b>6.88 (0.02)</b>
<b>Baselines</b>			
Global mean	250.99	15.84	12.46
User mean	186.05	13.64	10.40
XGBoost <sub>A</sub>	162.92 (0.20)	12.76 (0.00)	9.83 (0.00)

Outcome	<i>Step2Heart</i> <sub>A/R/T</sub>			
PCA*	90%	95%	99%	99.9%
PAEE	78.2	79.2	<b>80.6</b>	79.7
Height	70.3	74	80.5	81.3
Weight	69.9	70.7	<b>77.4</b>	76.9
Sex	76.2	81.5	91.1	<b>93.4</b>
Age	61.1	63.8	67.3	<b>67.6</b>
BMI	64.7	66.1	67.8	<b>69.4</b>
Resting HR	N/A			

# Questions