Mobile Health

Human Activity through Deep Learning

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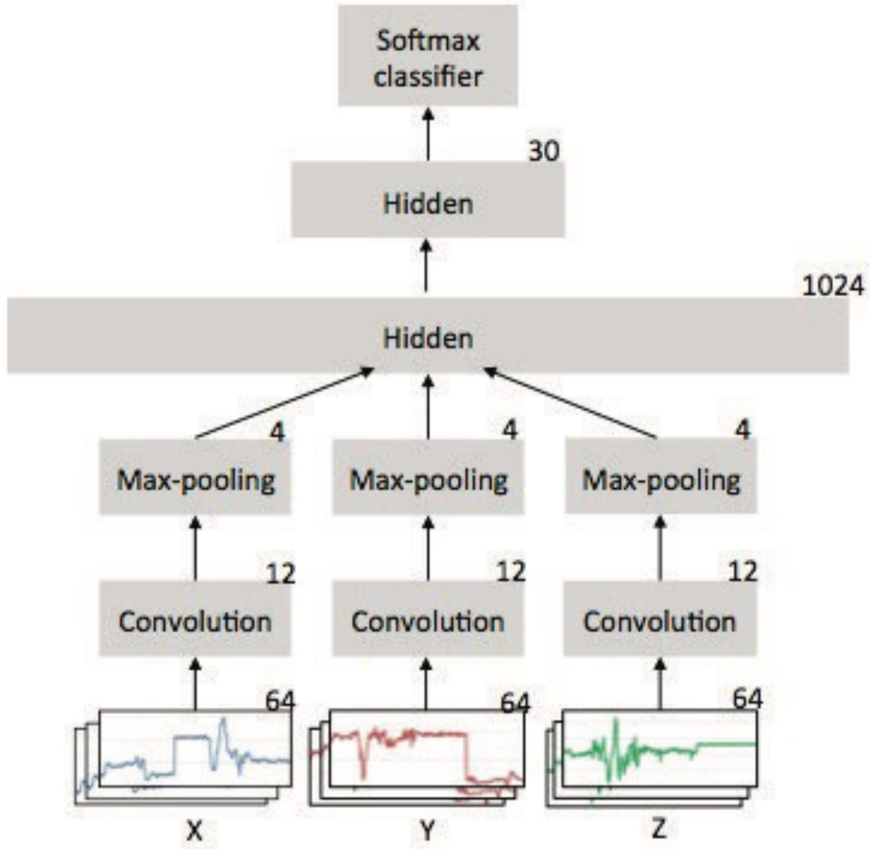
ML beyond Features for Activity Recognition



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,

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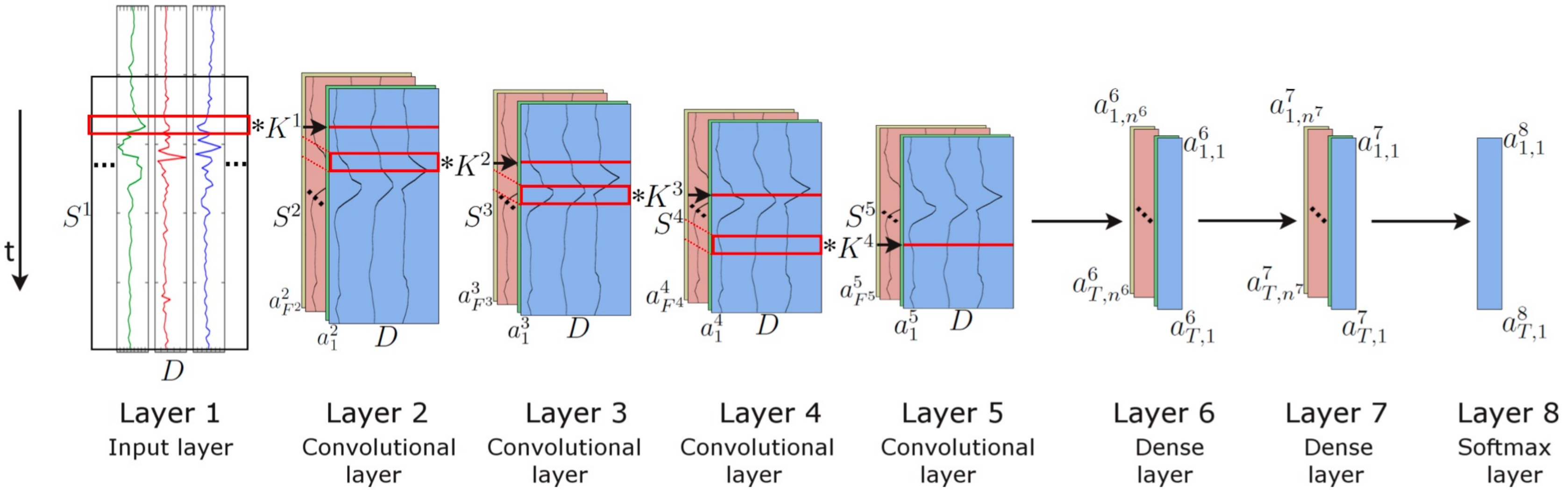
CNN+LSTMs for HAR



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

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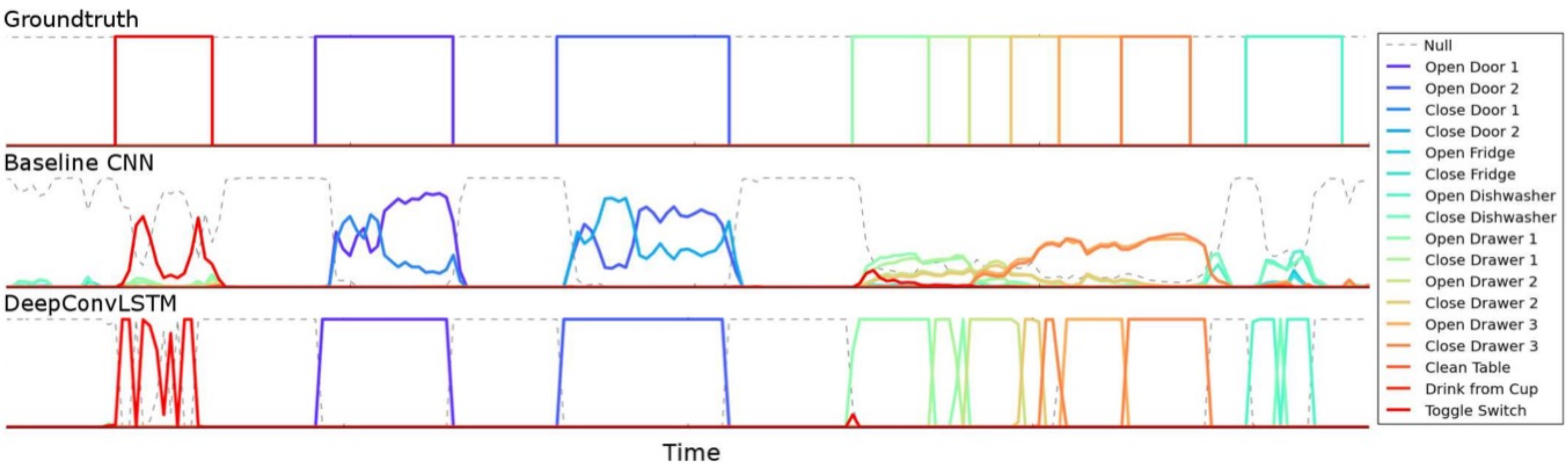
Visualization of Goodness of this Approach



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

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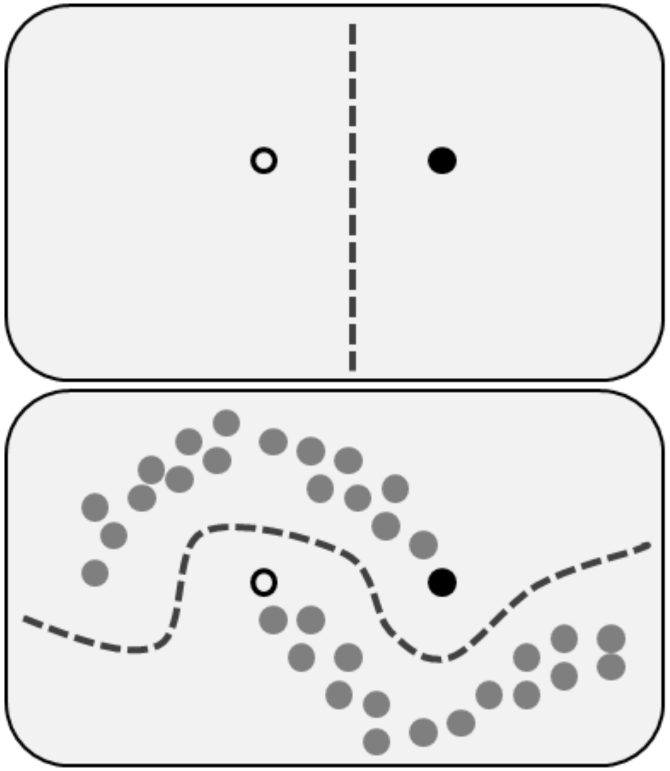
Deep Learning and HAR: Issues

- 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



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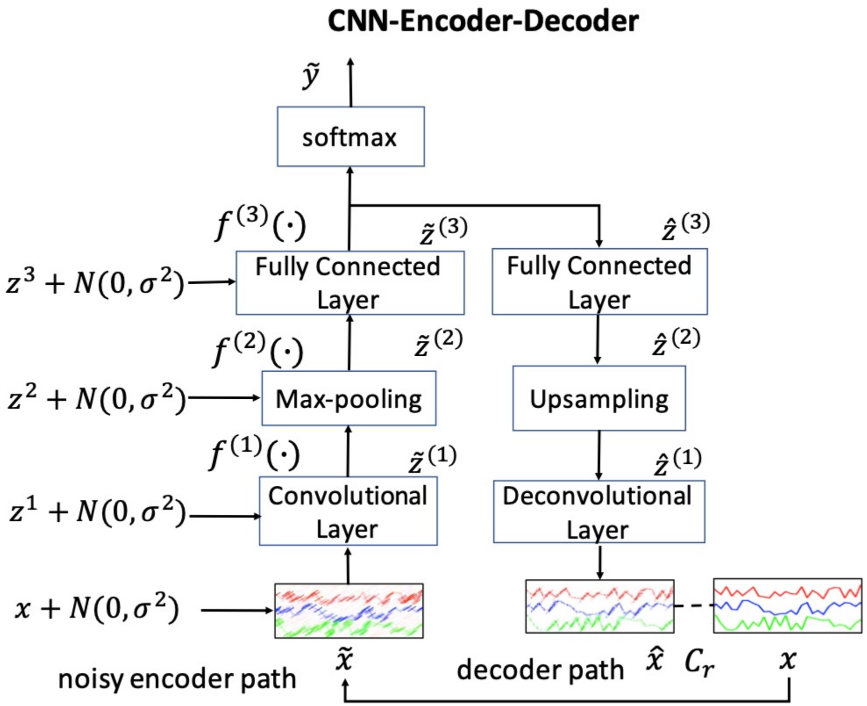
An Example of Semi Supervised HAR



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.

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Semi Supervised Approaches for HAR

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

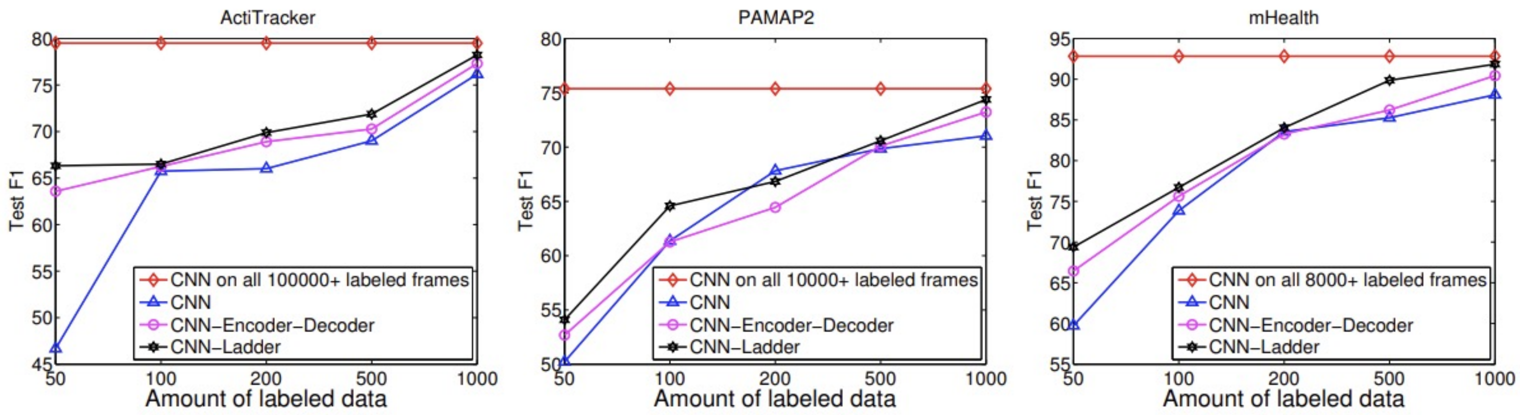

Figure 2: The F_m scores of CNN, CNN-Encoder-Decoder, and CNN-Ladder, with varying number of labeled examples. The F_m scores of supervised CNN on all labeled training examples are also shown as red lines.

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.

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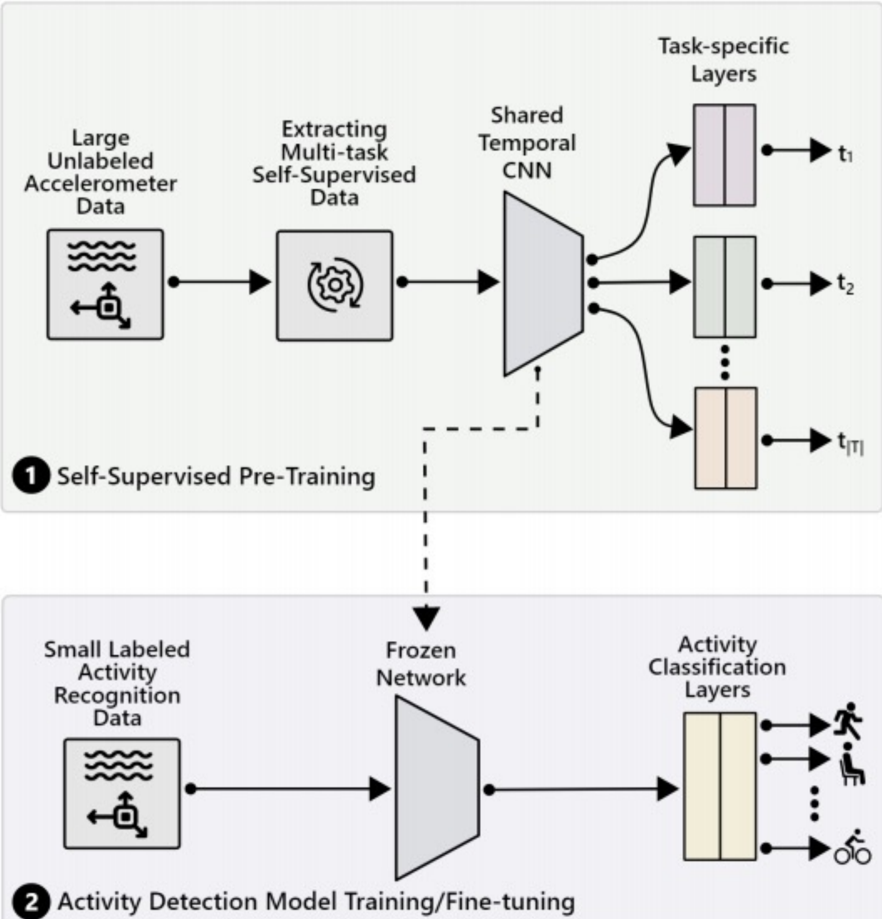
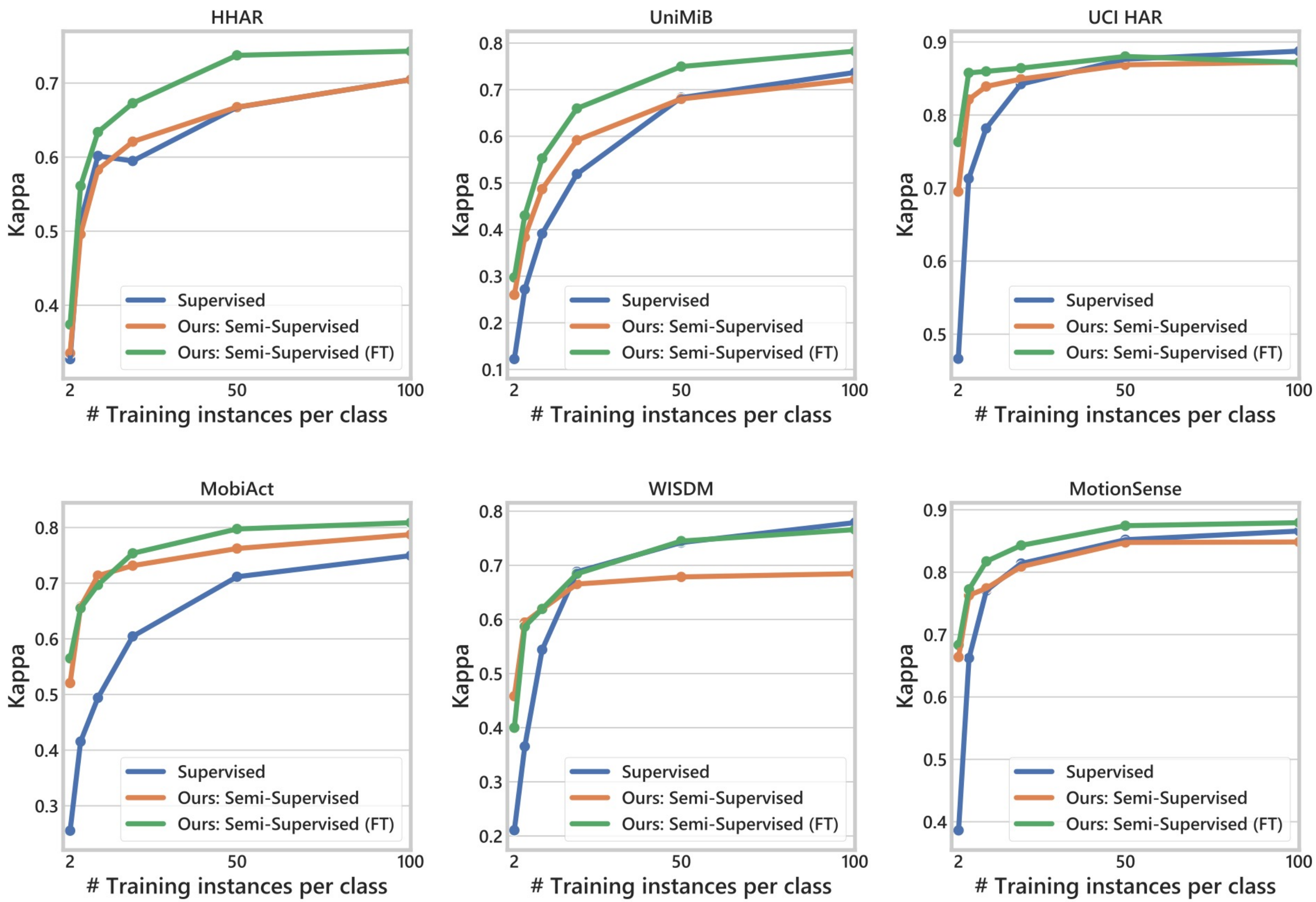
Self Supervision using Transformation Recognition



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

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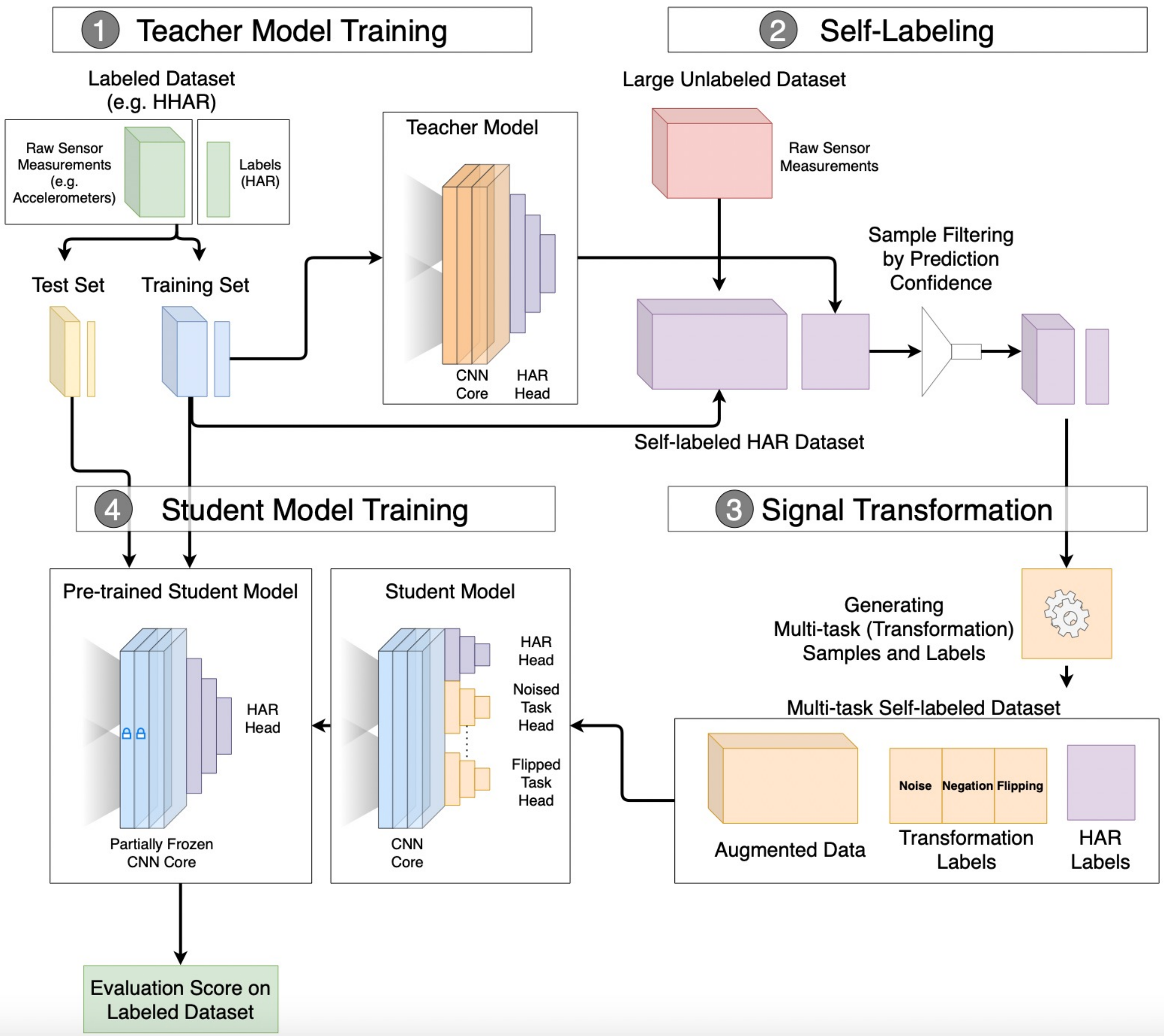
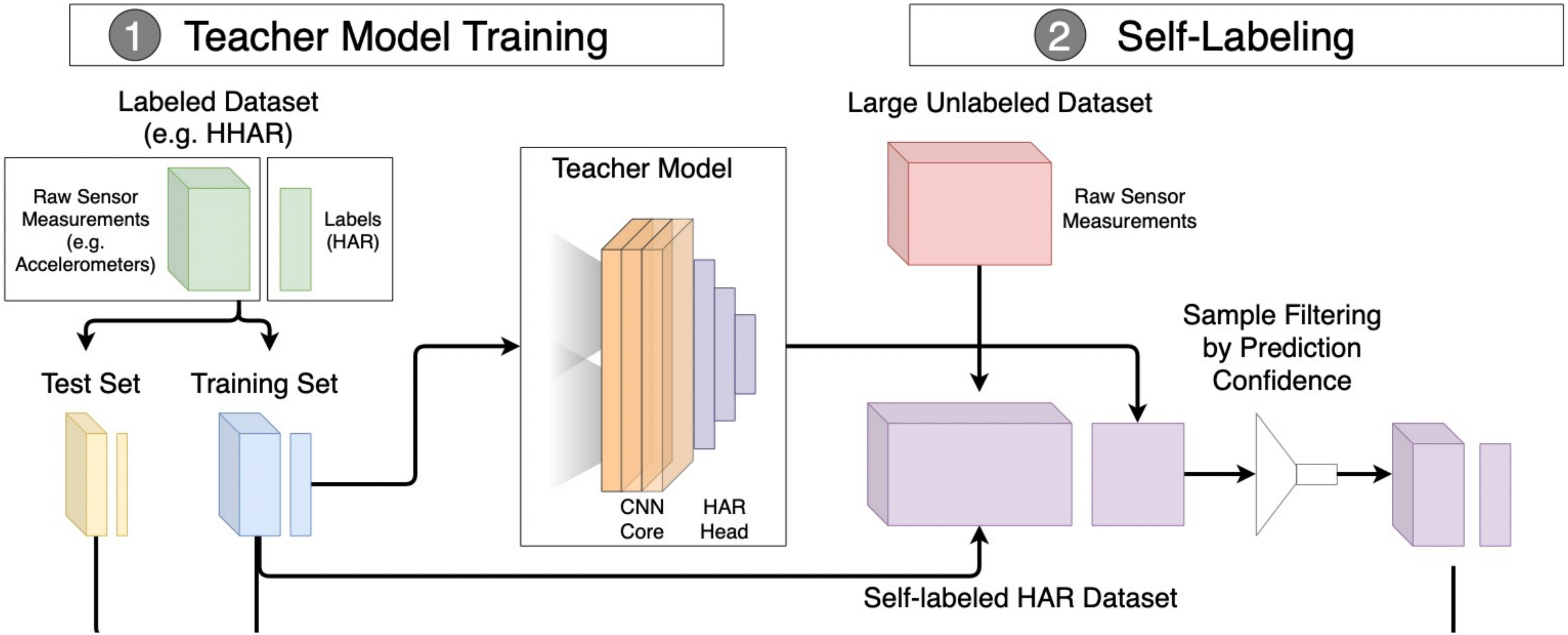
Self-training

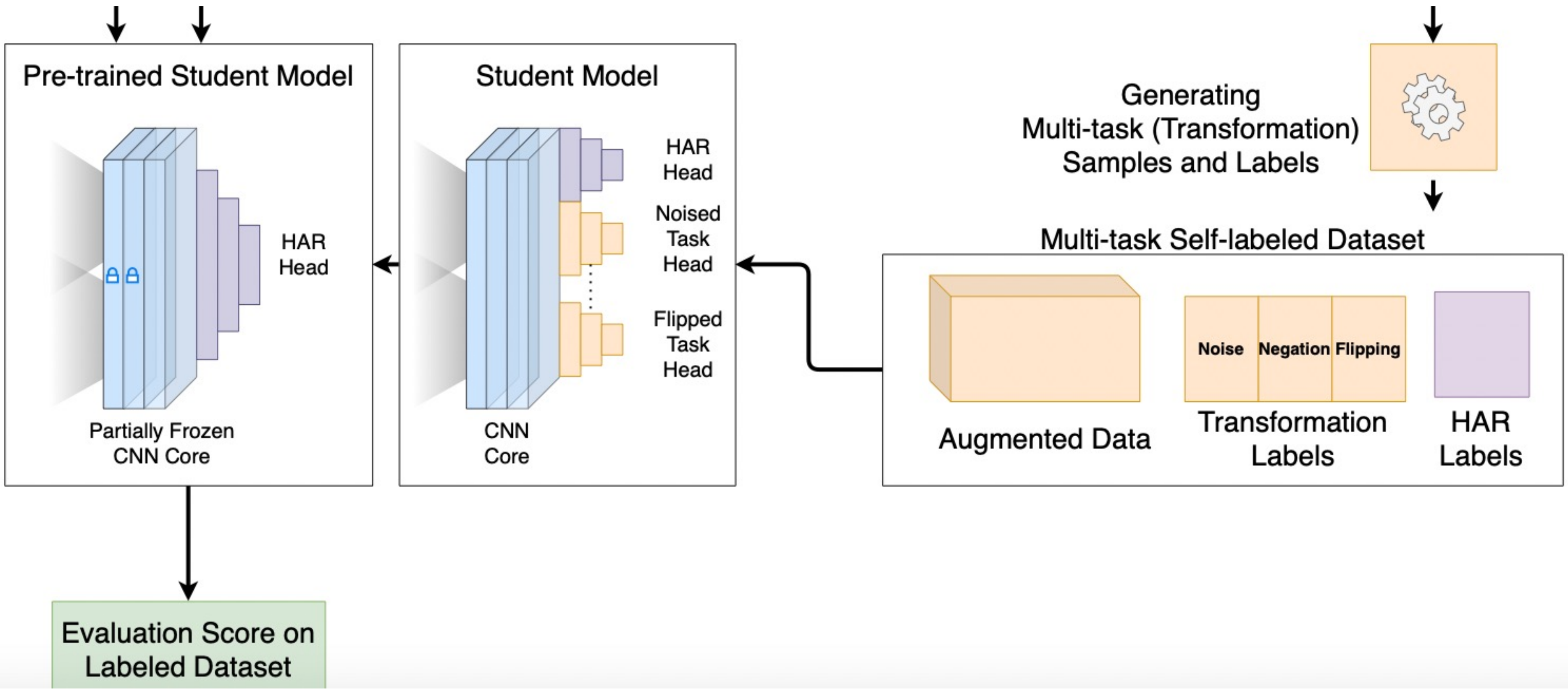


SelfHAR: Improving Human Activity Recognition through Self-training with Unlabeled Data. I. Tang, D. Spathis, I. Perez-Pozuelo, S. Brage, N. Wareham, C. Mascolo. In Procs of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT). Volume 5 Issue 1. 2021.

Teacher Model



Student Model



Performance

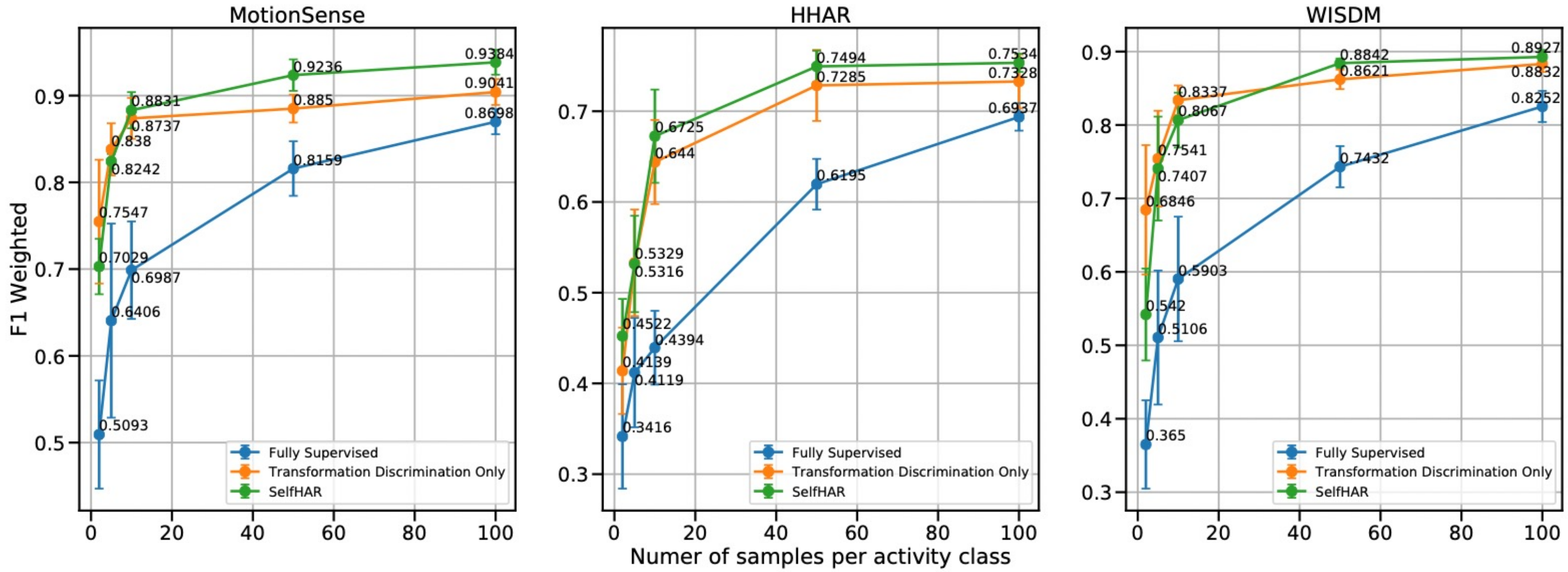


Fig. 4. Assessing classification performance as a function of limited training data. *SelfHAR* achieves high performance with significantly less training data and outperforms the variant with *no* teacher-student training in most cases.

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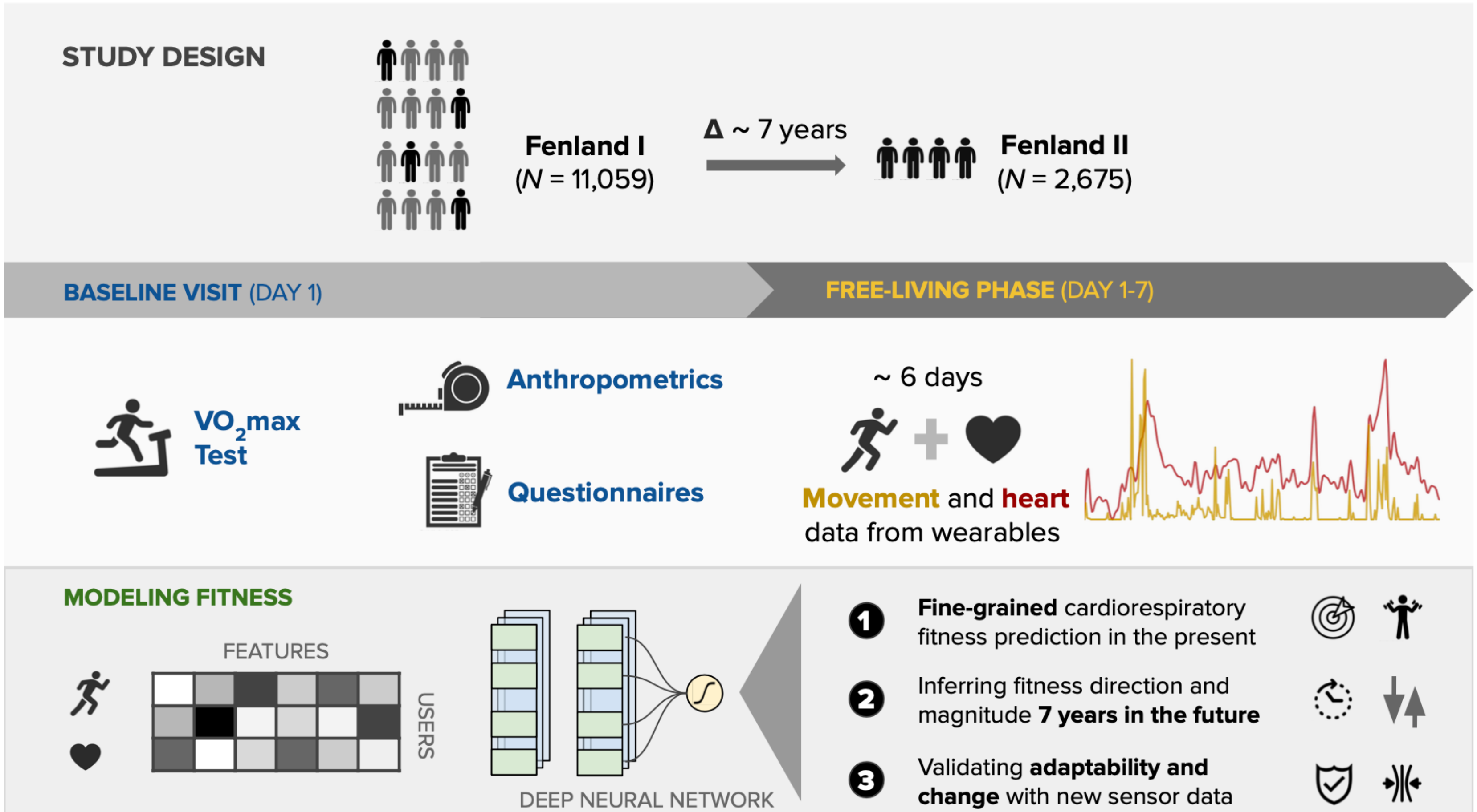
Another example of Self Supervision Application: Cardiorespiratory Fitness

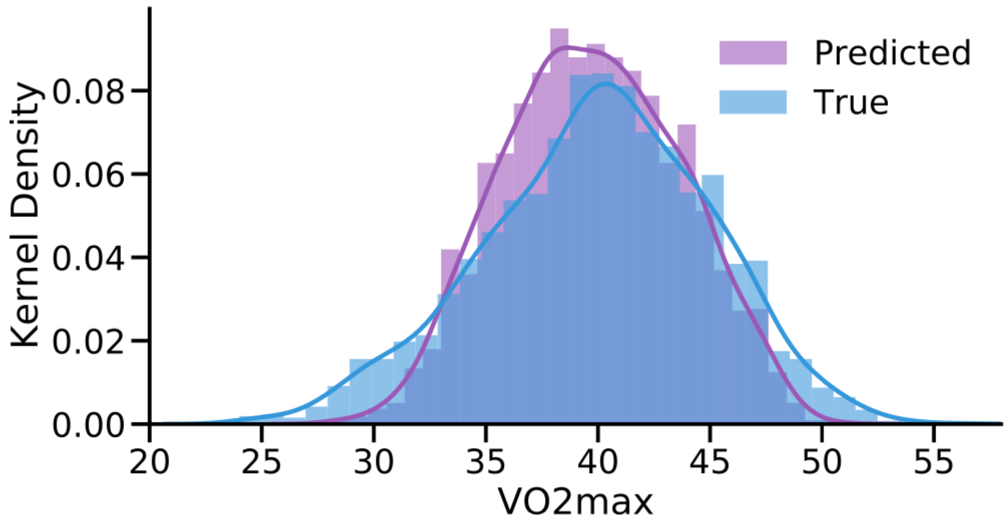
CRF through Wearable Data in Free Living

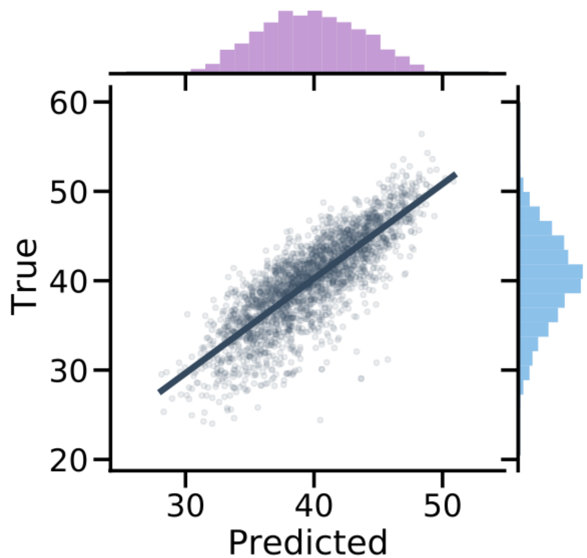


Longitudinal cardio-respiratory fitness prediction through wearables in free living environment. D. Spathis, I. Perez-Pozuelo, T. Gonzales, Y. Wu, S. Brage, N. Wareham, C. Mascolo. In Npj Digital Medicine. November 2022.

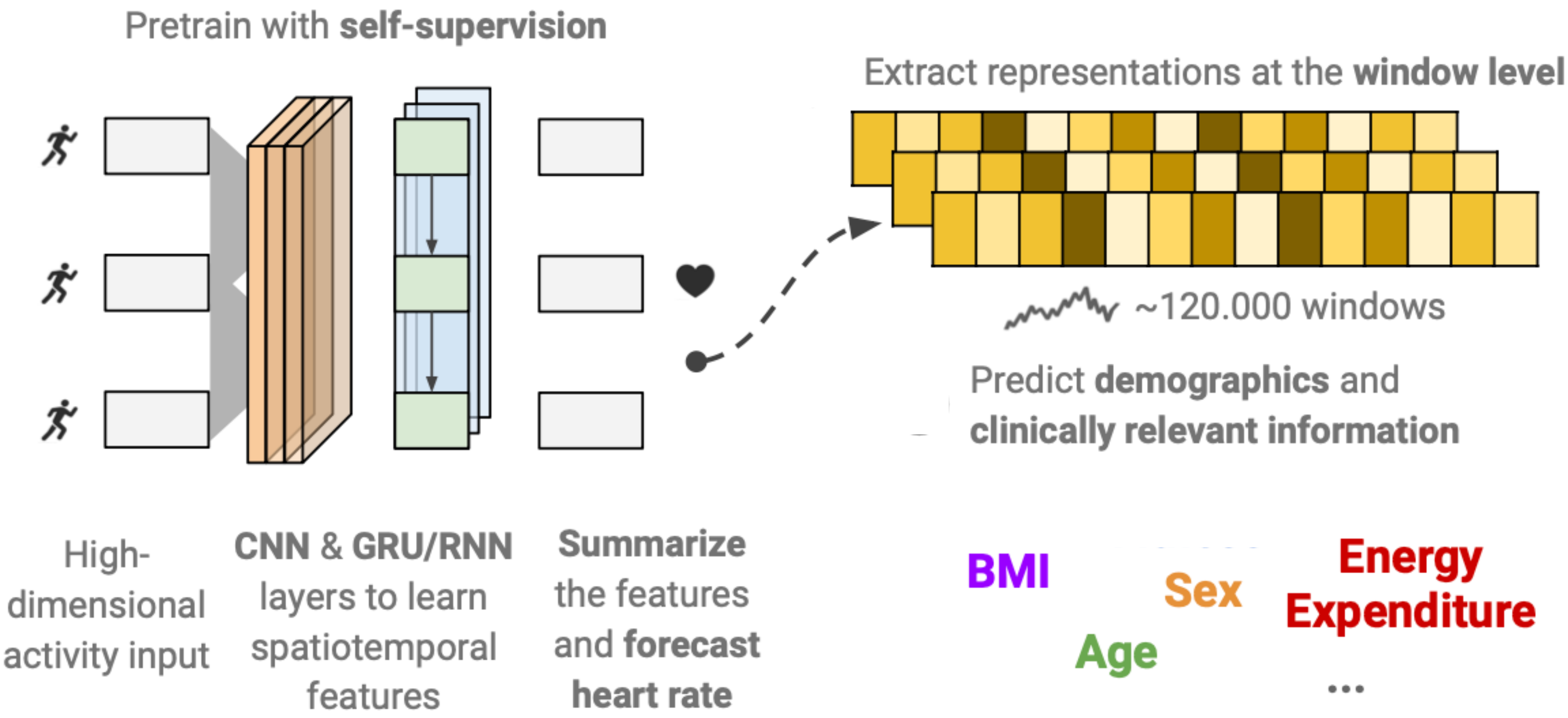
VO_2Max Prediction

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





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
Step2Heart$_A$	144.61 (0.62)	12.02 (0.02)	9.23 (0.03)
Step2Heart$_{A/T}$	143.65 (0.28)	11.98 (0.01)	9.21 (0.03)
Step2Heart$_{A/R}$	91.76 (0.12)	9.57 (0.00)	6.92 (0.03)
Step2Heart$_{A/R/T}$	**91.11** (0.37)	**9.54** (0.01)	**6.88** (0.02)
Baselines			
Global mean	250.99	15.84	12.46
User mean	186.05	13.64	10.40
XGBoost$_A$	162.92 (0.20)	12.76 (0.00)	9.83 (0.00)

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

Questions