

CALIBRATION SLIDE



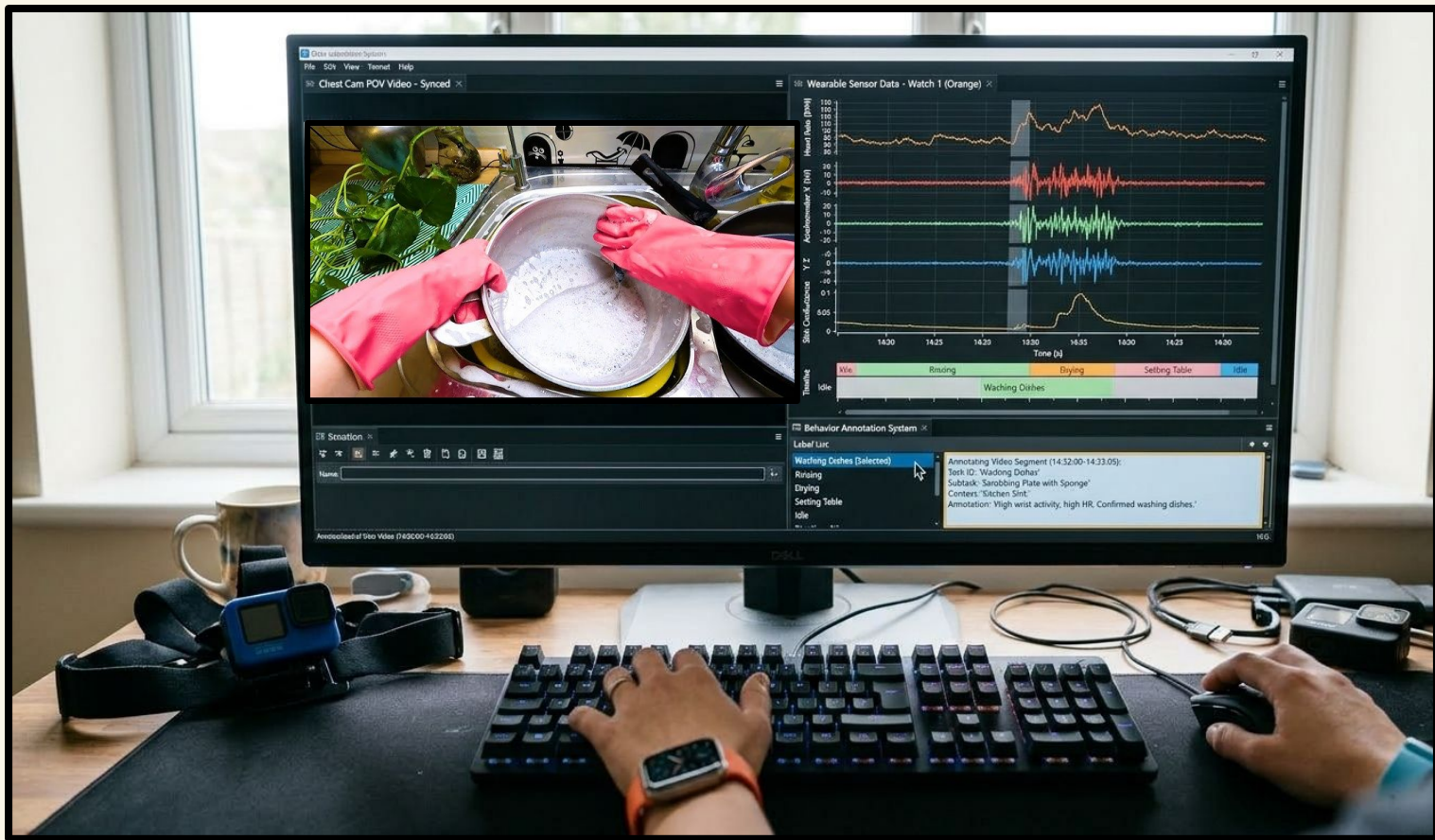
Wrist-based
wearable devices



First person view
camera

Wrist-based
wearable devices



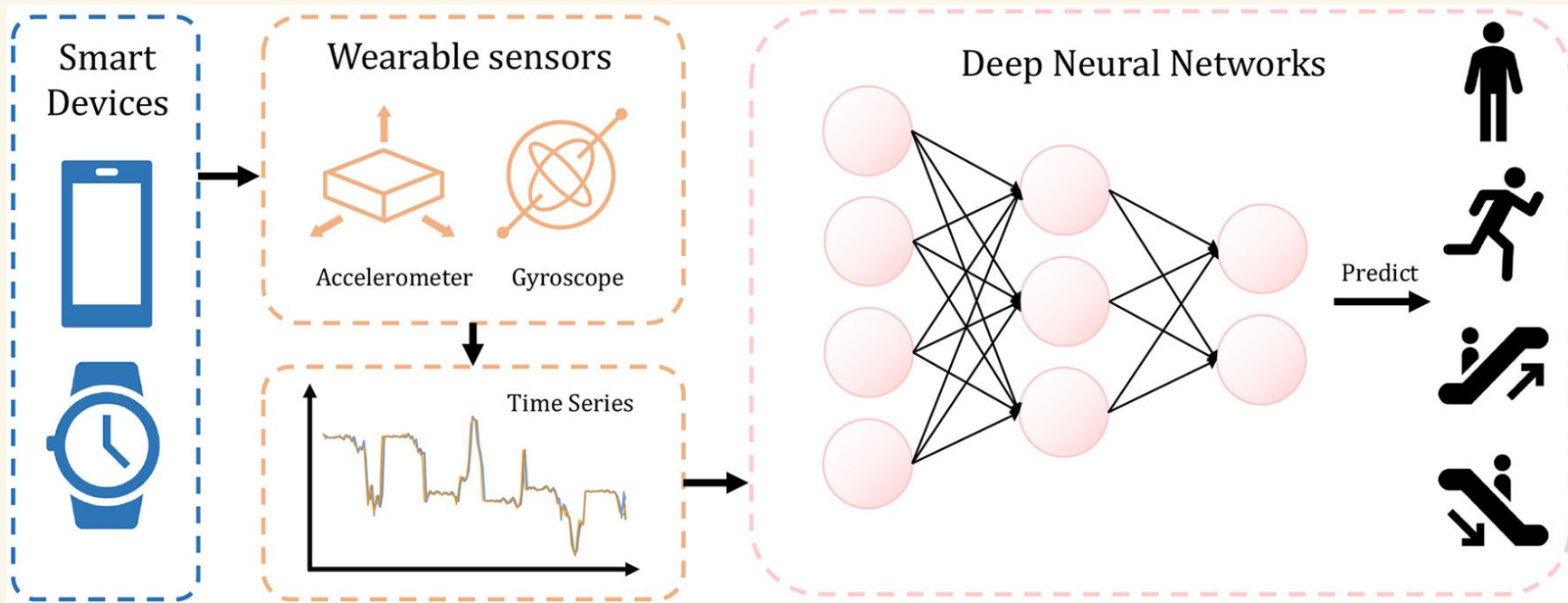




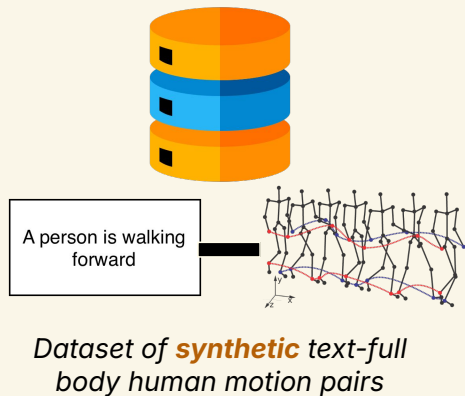
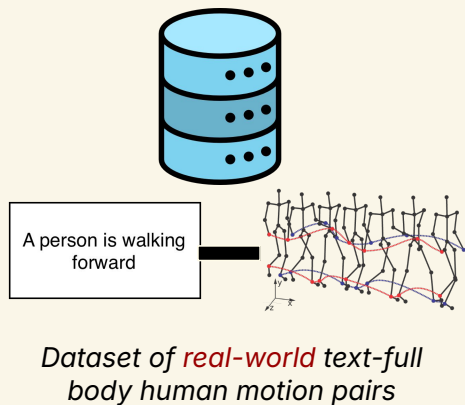
- This is **expensive**, **impractical**, and **difficult to scale**.
- Machine Learning runs on data (lots of data!) and needs **diverse**, **large** labelled datasets.

What if we use
synthetic data?

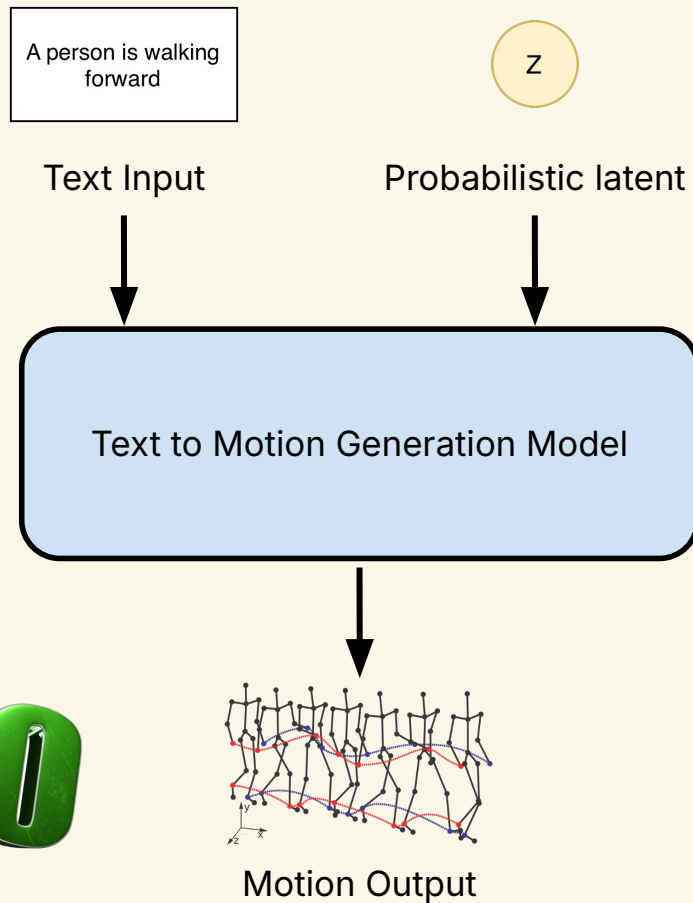
Human Activity Recognition:



Generating Synthetic Motion



Training



Generating **x10**

Pretraining Motion Time-Series Model

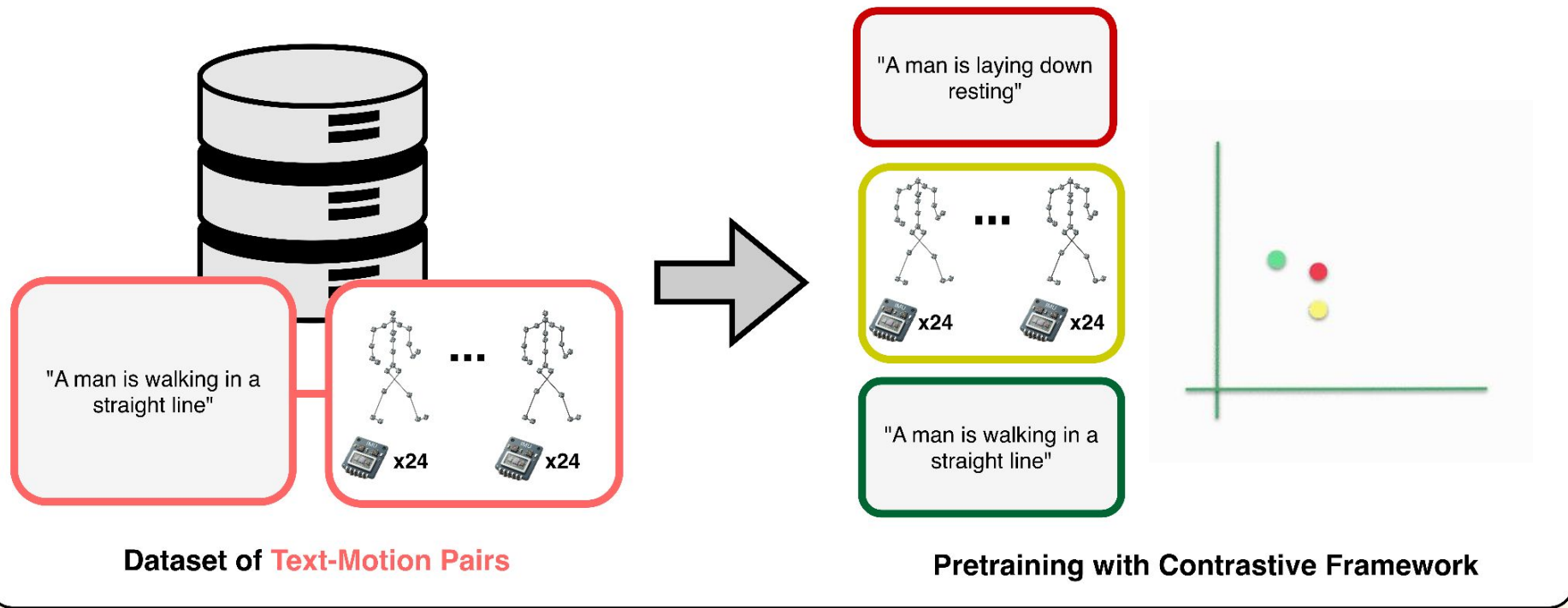


Table 2: Scaling synthetic data improves downstream HAR performance. At sufficient scale ($8\times$), synthetic pretraining outperforms real-world pretraining in all fine-tuned settings, with the exception of the 0-shot regime. Reported scores are mean macro-averaged F1 across datasets; **bold** and underlined values denote best and second-best results per column, respectively. All results are obtained using a fixed random seed across runs.

Method	0-shot	1-shot	2-shot	3-shot	5-shot	10-shot
Real-World Baseline	0.3070	0.5445	0.6243	0.6611	0.7041	0.7667
MDM (Synthetic)						
1 $\times$	0.2460	0.5120	0.6160	0.6559	0.6974	0.7653
2 $\times$	<u>0.2928</u>	0.5334	0.6089	0.6505	0.7008	0.7368
4 $\times$	0.2546	0.5299	0.6344	0.6749	0.7023	0.7663
8 $\times$	0.2654	0.5517	0.6266	0.6704	0.7165	0.7792
T2M (Synthetic)						
1 $\times$	0.2606	0.5229	0.6100	0.6551	0.7024	0.7649
2 $\times$	0.2462	0.5132	0.6062	0.6669	0.7226	0.7635
4 $\times$	0.2482	0.5256	0.6114	<u>0.6766</u>	0.7024	0.7719
8 $\times$	0.2123	<u>0.5491</u>	<u>0.6372</u>	0.6631	0.7050	0.7891
MotionDiffuse (Synthetic)						
1 $\times$	0.2738	0.5363	0.6060	0.6548	0.7053	0.7739
2 $\times$	0.2739	0.5233	0.6186	0.6725	0.6995	0.7907
4 $\times$	0.2566	0.5423	0.6472	0.6700	0.7150	0.7959
8 $\times$	0.2427	0.5460	0.6550	0.6893	<u>0.7213</u>	<u>0.7956</u>

- **Consistent gap** remains in the 0-shot setting!

- Suggests that **real-world data** induces representations that generalise more effectively **out-of-the-box**, whereas **synthetic pretraining** excels under **adaptation**.

- **Performance improves** as synthetic data scales but **trend is not strictly monotonic**

Thank you!

MOTION CAPTURE IS NOT THE TARGET DOMAIN: SCALING SYNTHETIC DATA FOR LEARNING MOTION REPRESENTATIONS

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ABSTRACT

Synthetic data offers a compelling path to scalable pretraining when real-world data is scarce, but models pretrained on synthetic data often fail to transfer reliably to deployment settings. We study this problem in full-body human motion, where large-scale data collection is infeasible but essential for wearable-based Human Activity Recognition (HAR), and where synthetic motion can be generated from motion-capture-derived representations. We pretrain motion time-series models using such synthetic data and evaluate their transfer across diverse downstream HAR tasks. Our results show that synthetic pretraining improves generalisation when mixed with real data or scaled sufficiently. We also demonstrate that large-scale motion-capture pretraining yields only marginal gains due to domain mismatch with wearable signals, clarifying key sim-to-real challenges and the limits and opportunities of synthetic motion data for transferable HAR representations.