Adversarial Unsupervised Representation Learning for Activity Time-Series

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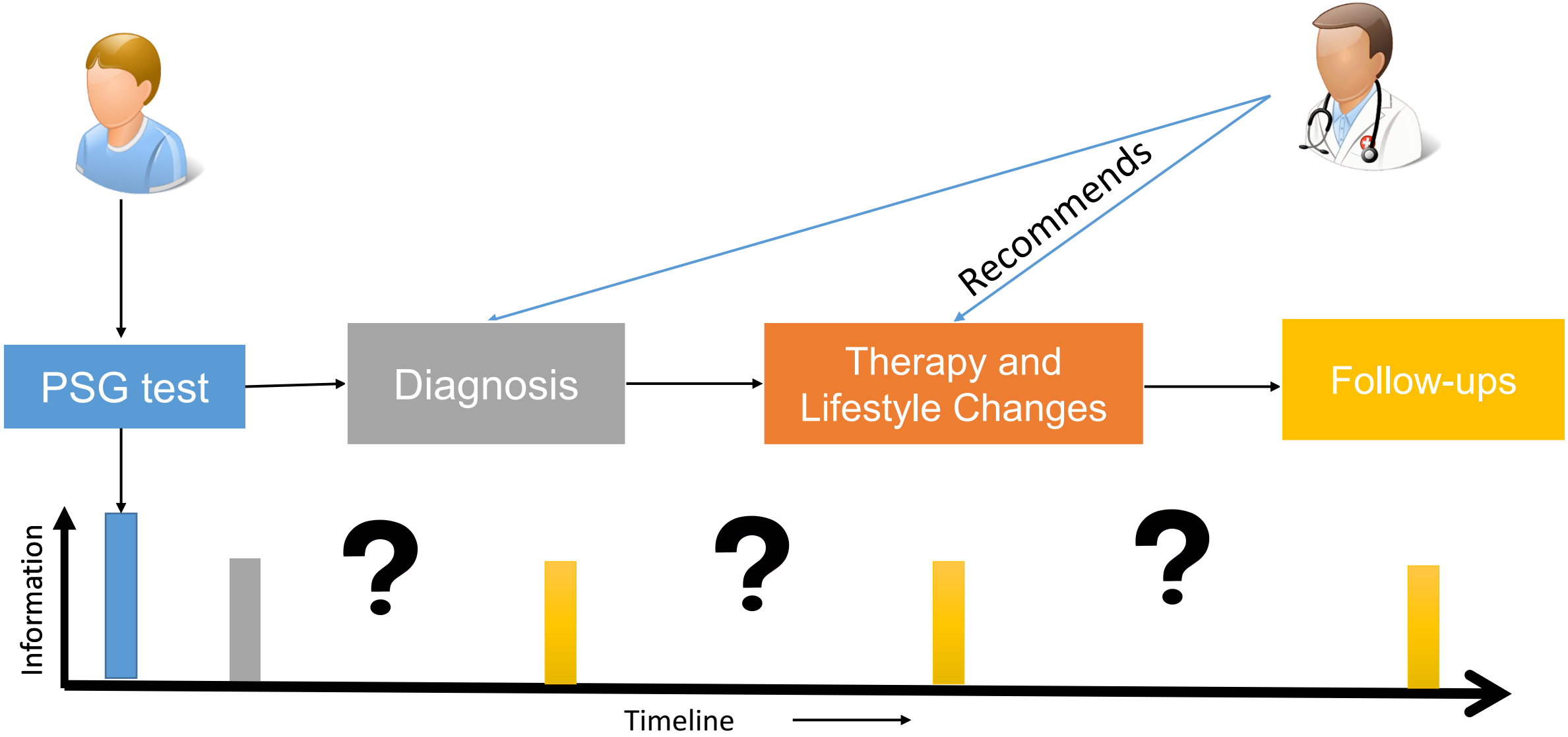
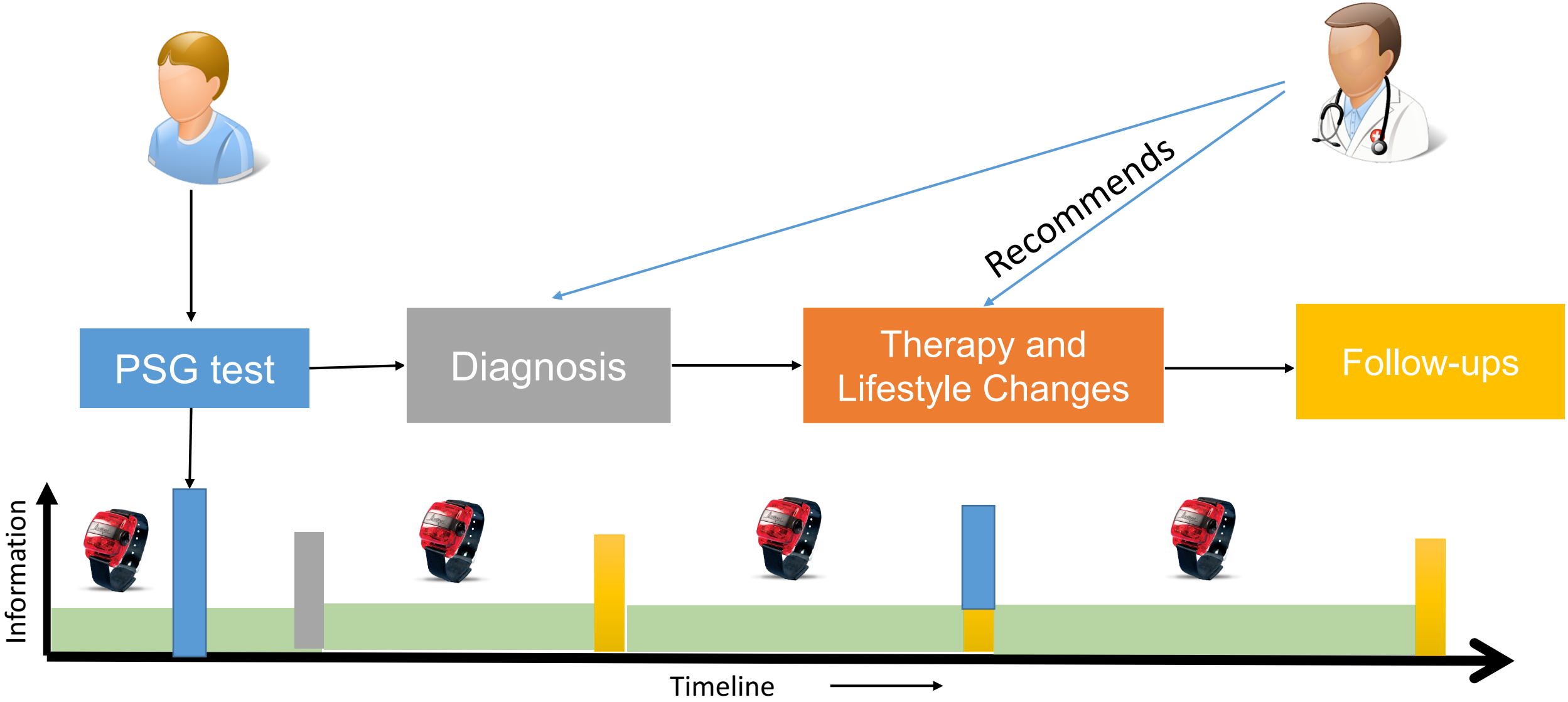
Motivation: Contemporary Regime

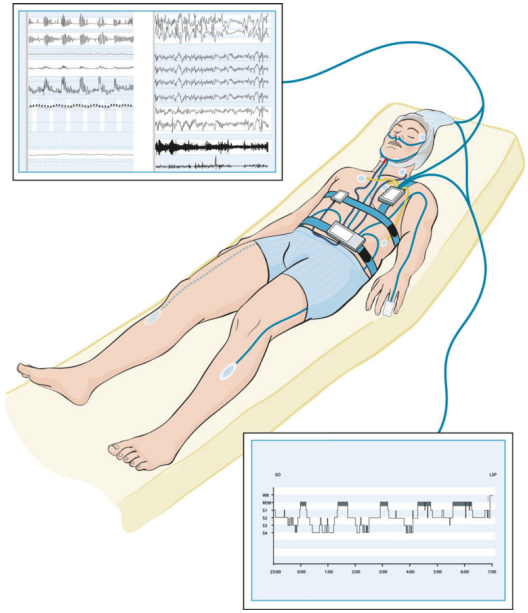


Motivation: New Regime

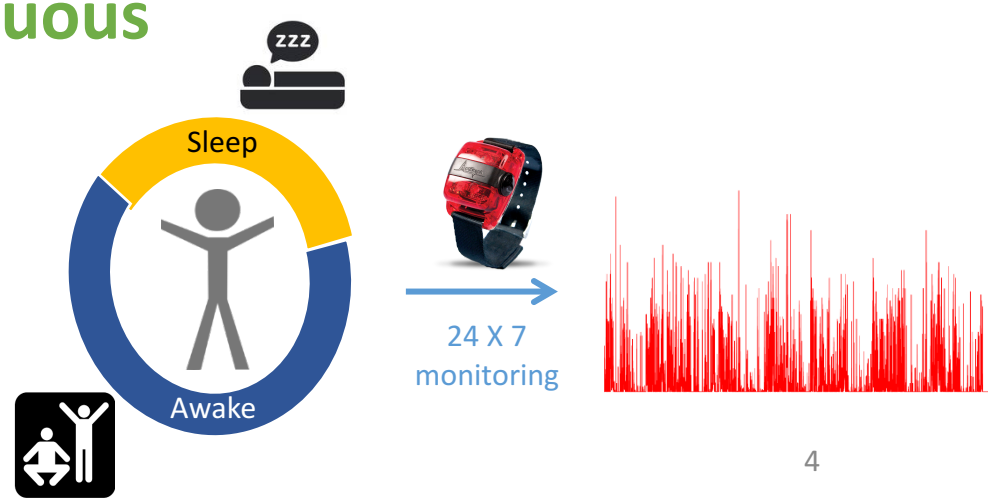


Motivation

- Current disorder screening requires various diagnosis tests and an **overnight lab** stay for polysomnography (PSG) test
- Long **waiting** for PSG
- Extremely **difficult** to do longitudinal tracking, patient has to show up often at the lab
- Wearable devices provide **real time** and **continuous stream** of **lower quality** activity data



Picture taken from https://aystesis.com/polysomnography/



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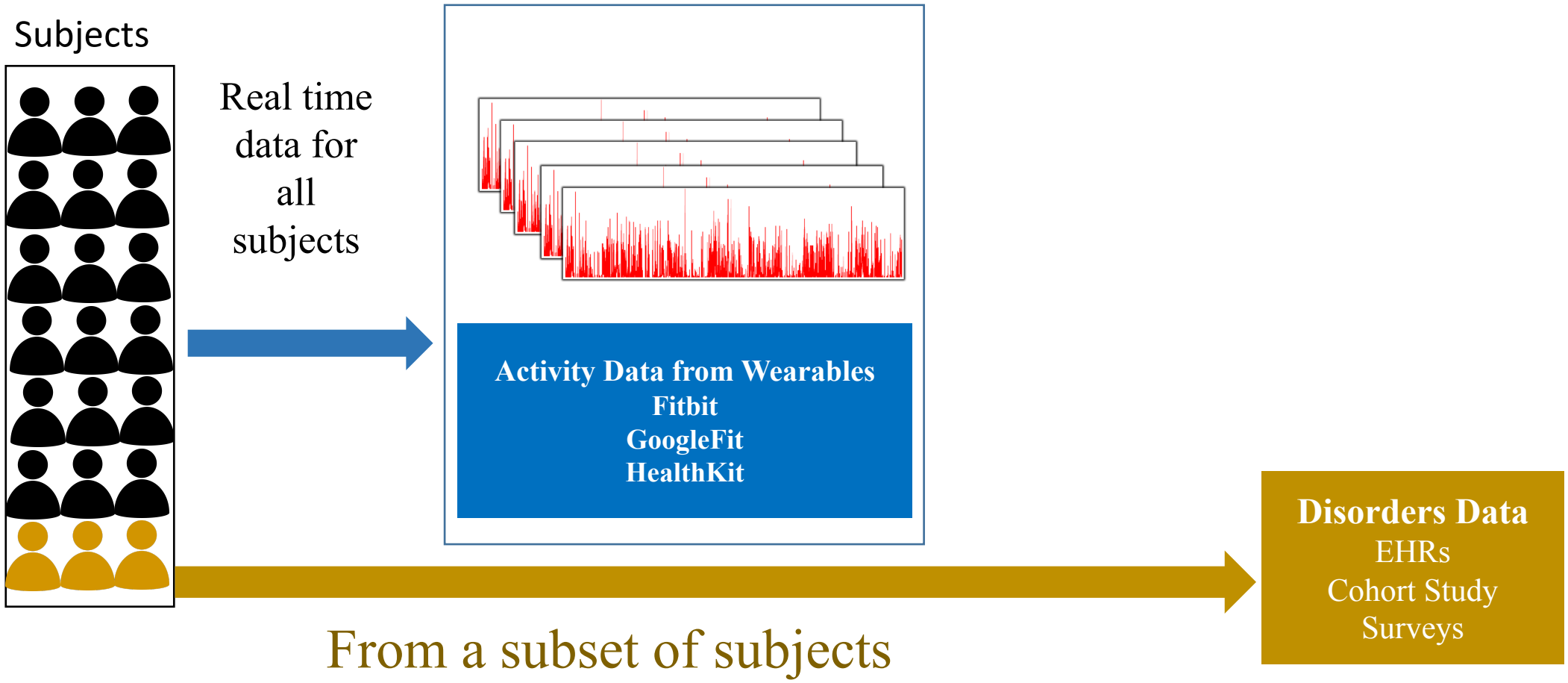
Subjects
Real time data for all subjects
Activity Data from Wearables
Fitbit
GoogleFit
HealthKit
Disorders Data
EHRs
Cohort Study
Surveys
From a subset of subjects

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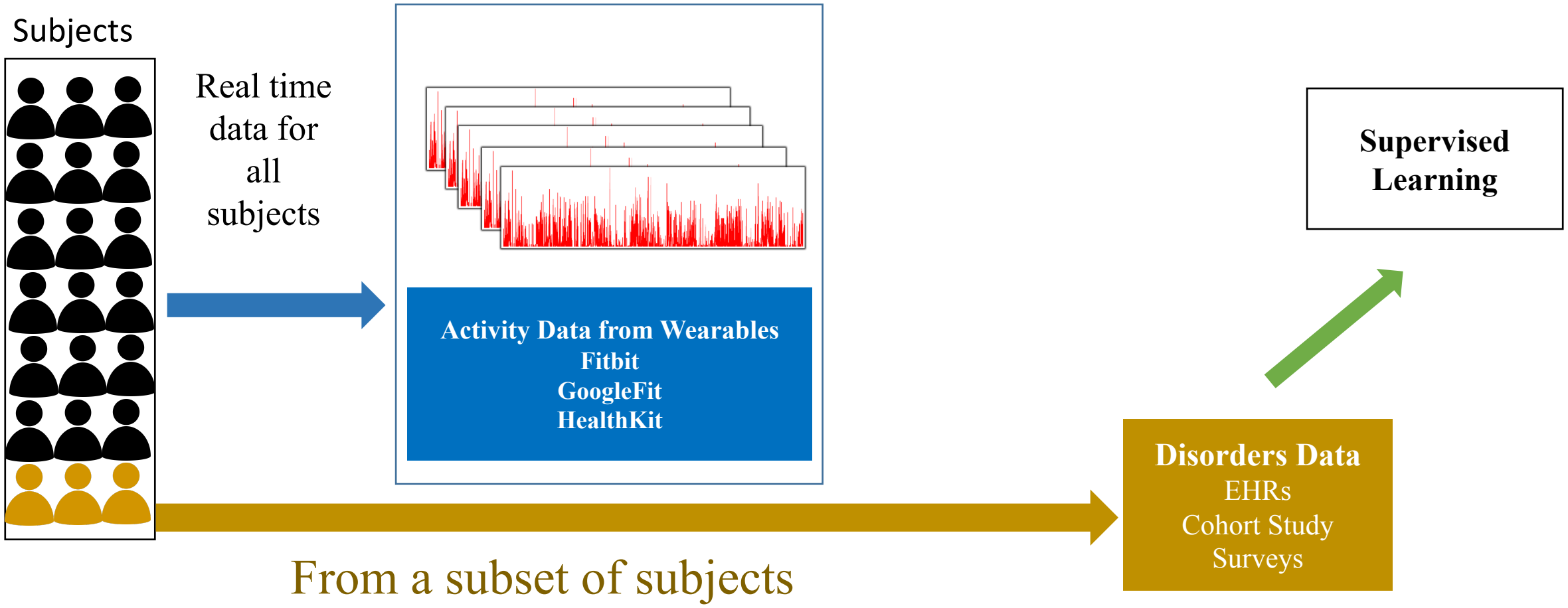
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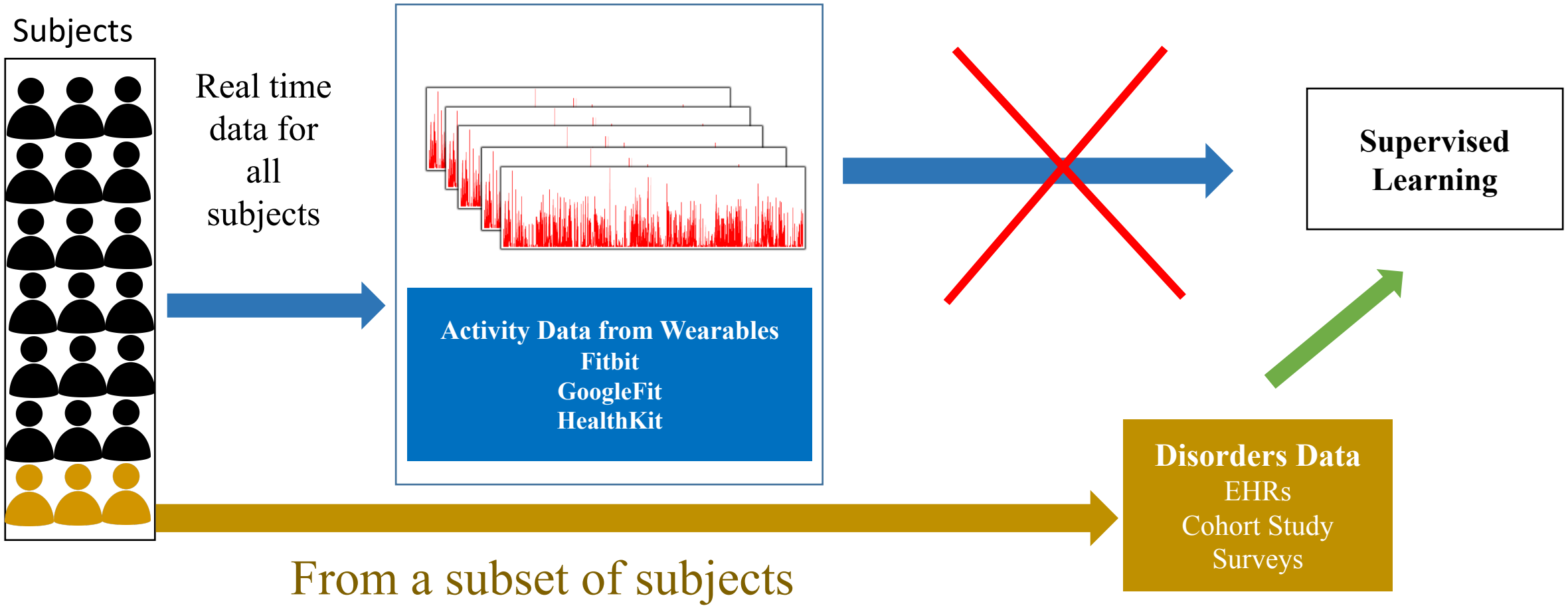
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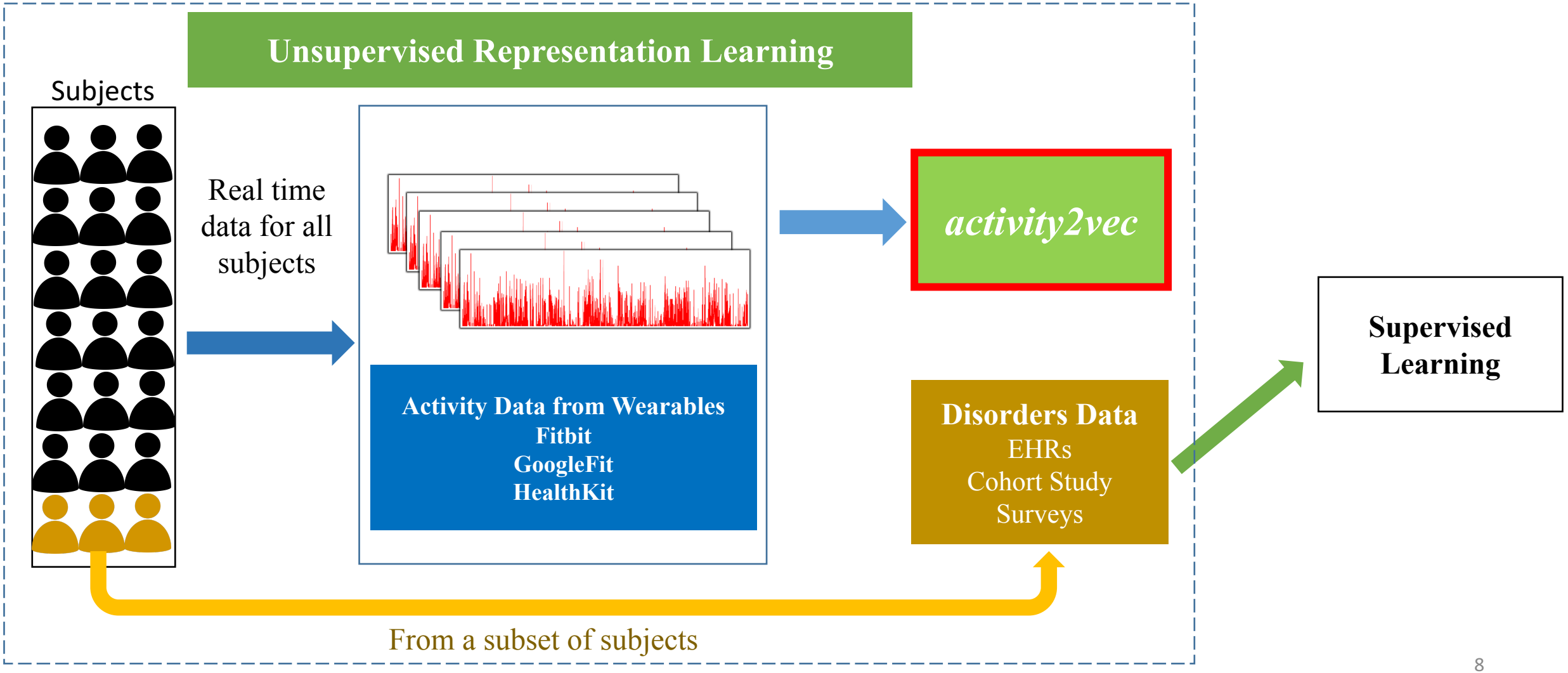
Proposed Approach



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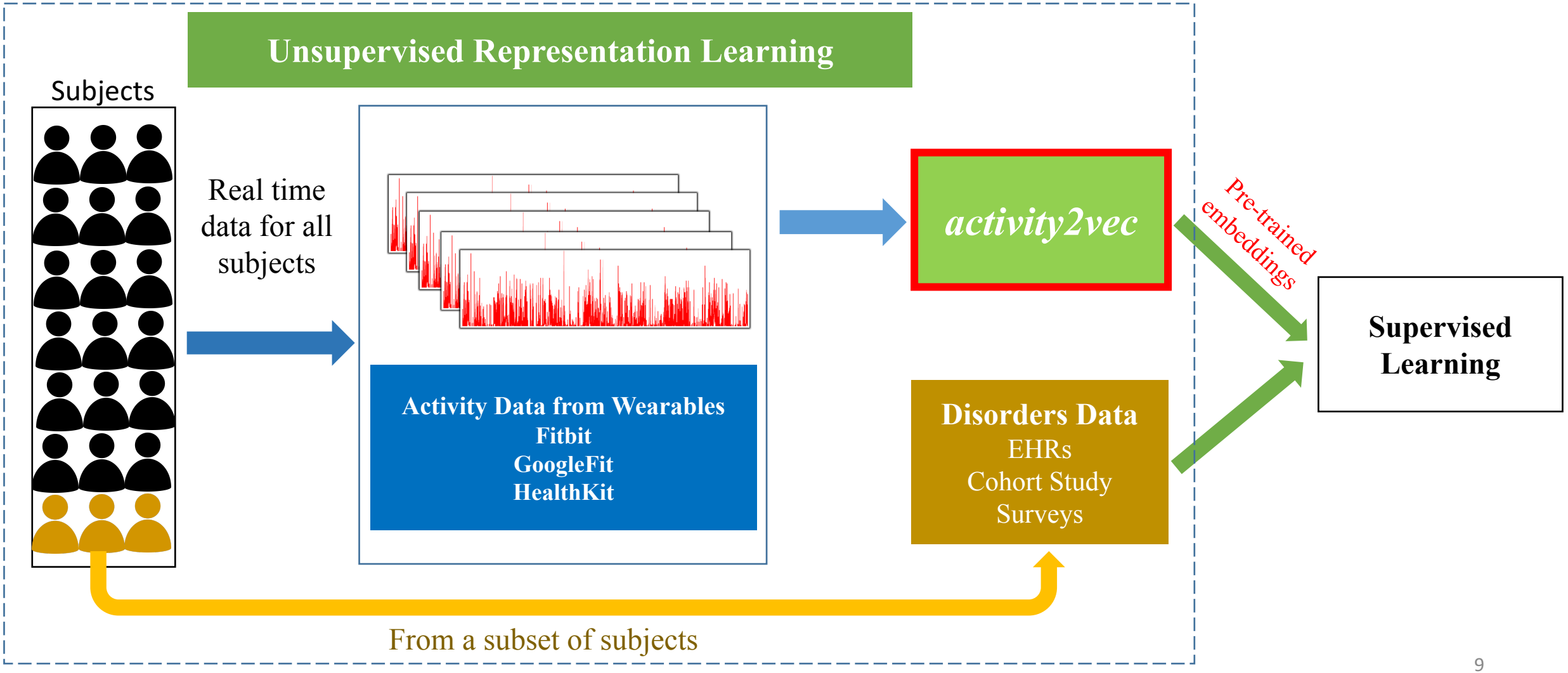


Proposed Approach & Challenges

Convert the time-series S into segments = $(T_1, T_2, T_3, \ldots\ldots, T_m)$

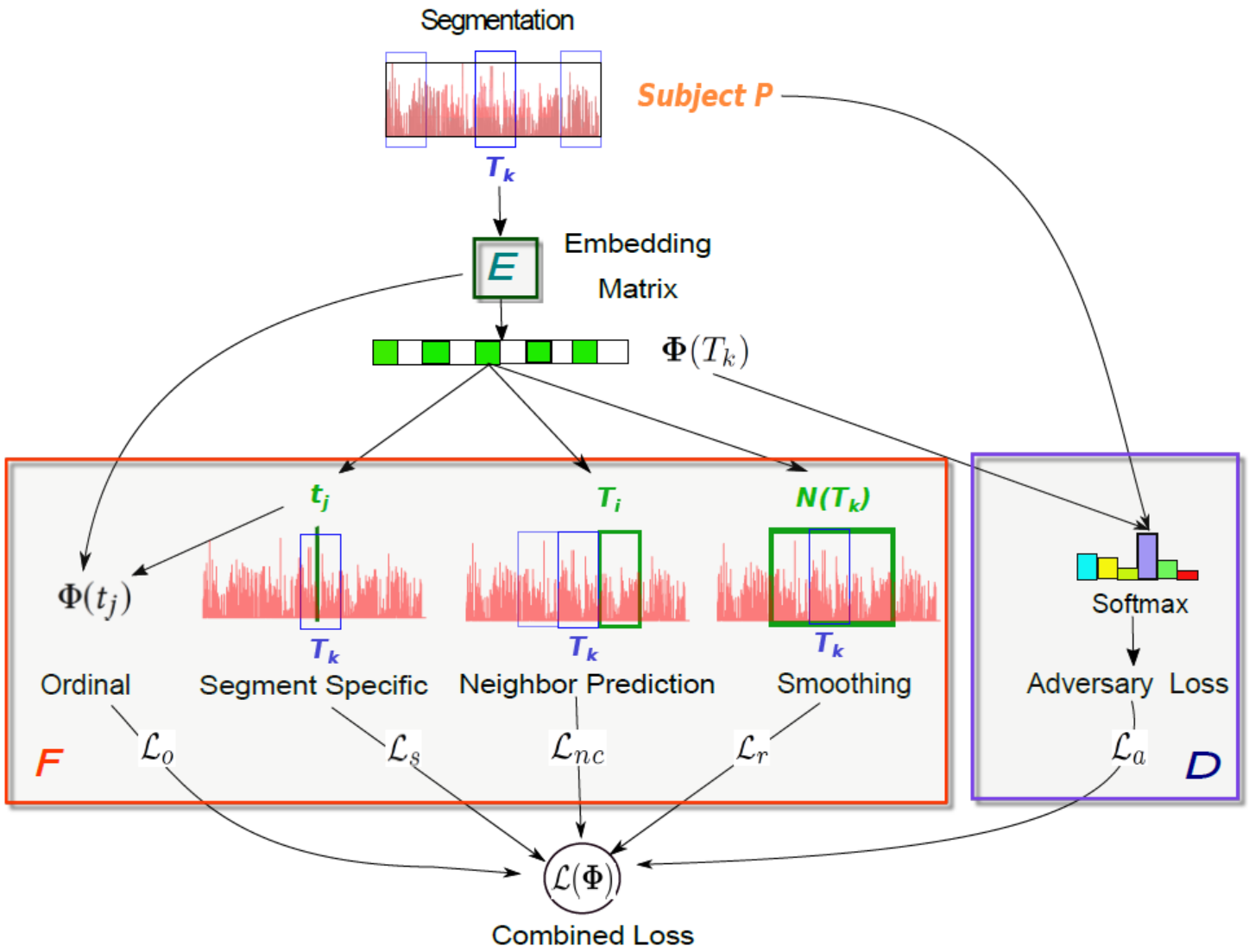
Learn mapping function $\Phi: T_k \longrightarrow R^d$ for each segment T_k

Activity time-series is a discrete valued time series like number of steps, activity levels

Challenges:

- Accounting for the **magnitude** of time-series values in the segment (*e.g.*, 25>24)
- Capturing the **dependencies** between the segments
- Accounting for the subject's **environment specific noise** that wearables suffers from

Proposed Approach



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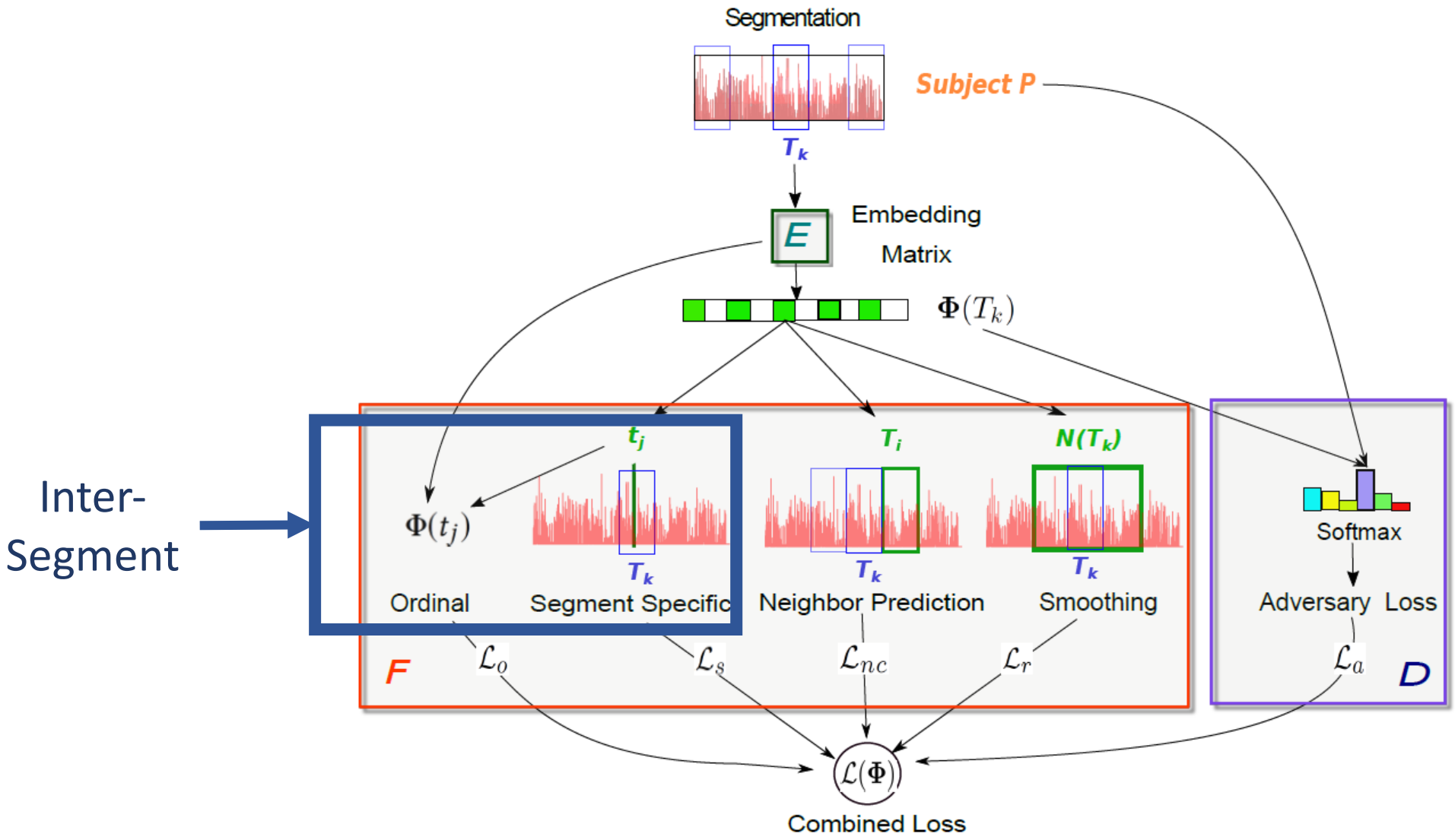

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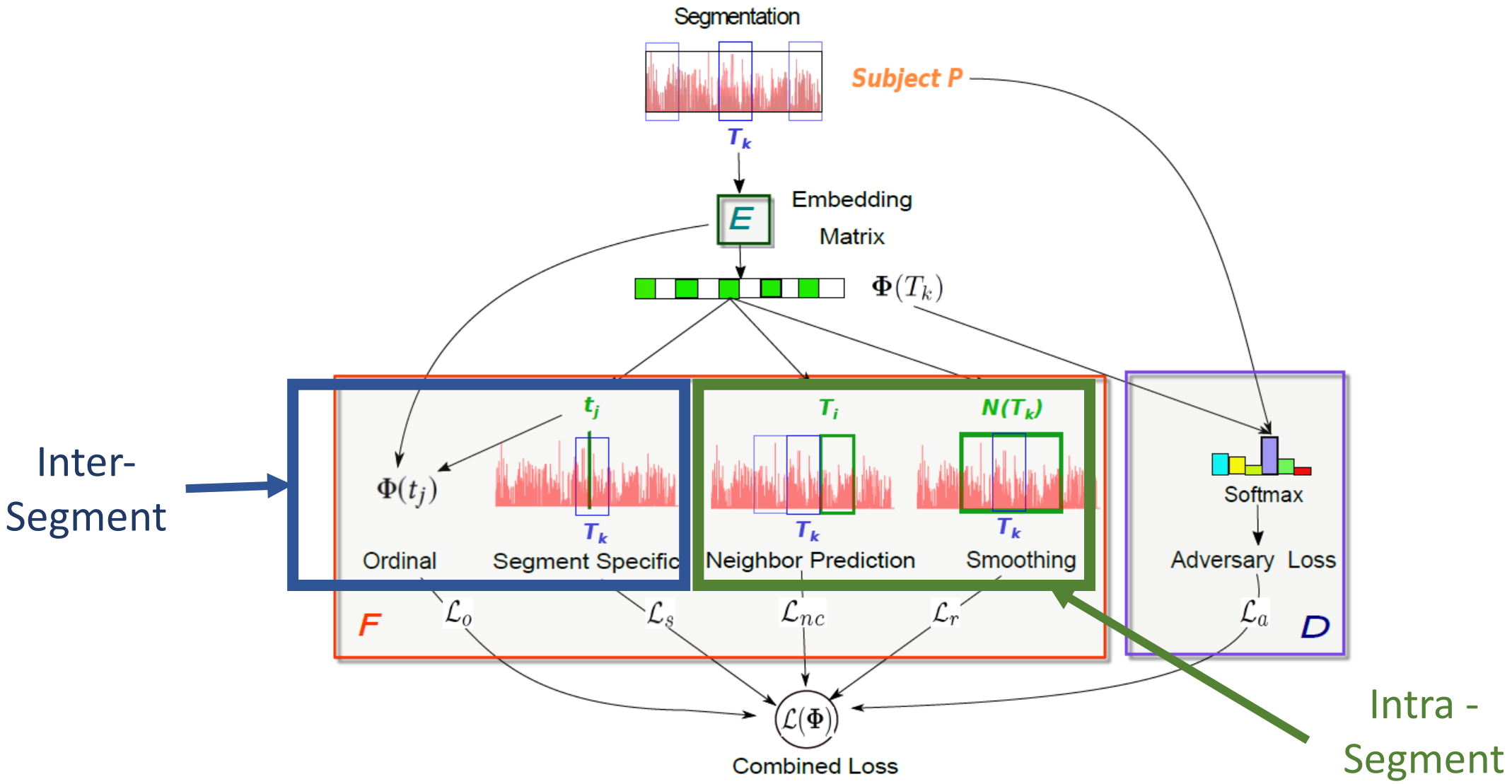

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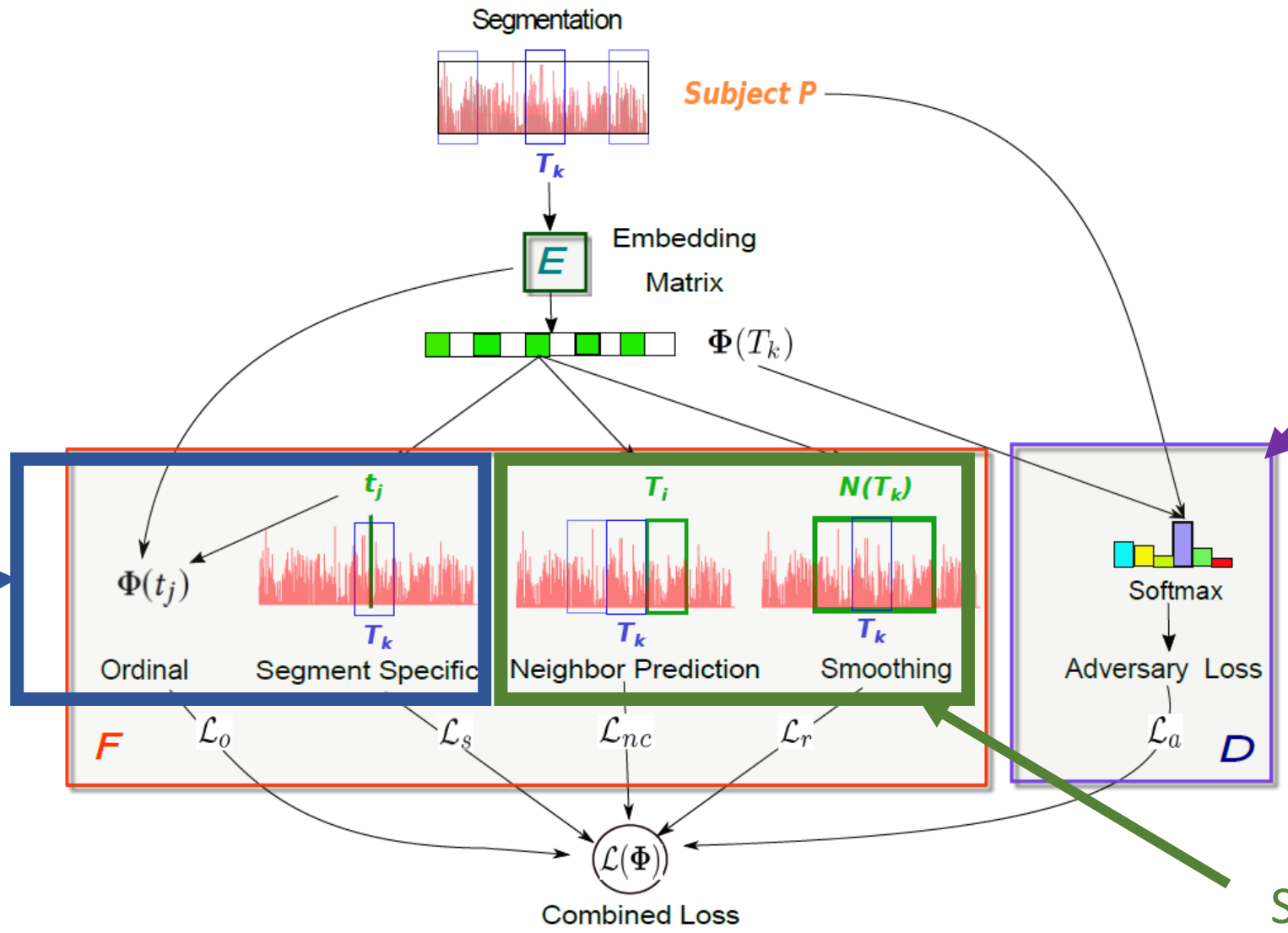
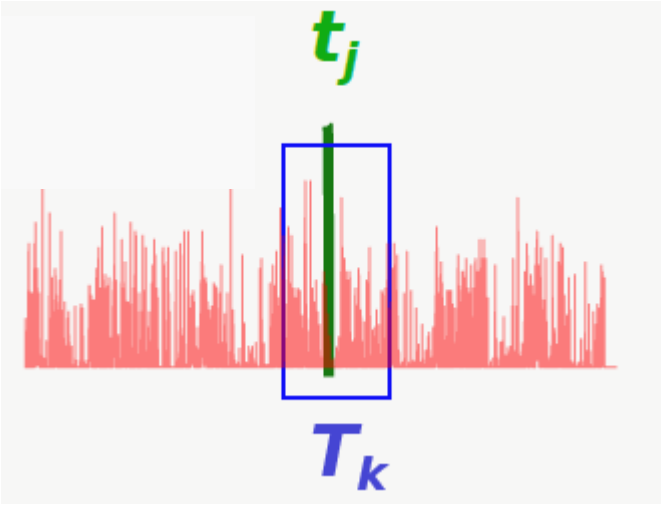


Inter-Segment

Subject Environment Invariance

Intra - Segment

Segment Content



1) Noise Contrastive Estimation for time-segment values

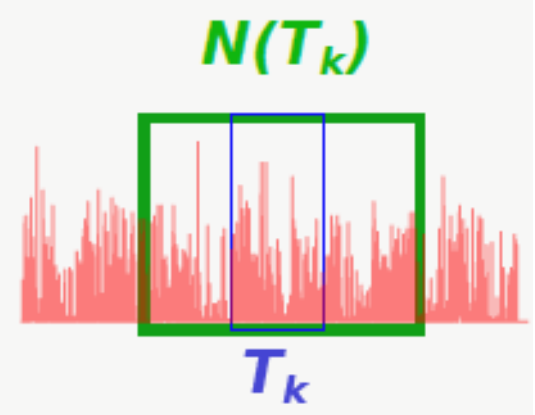
$$\mathcal{L}_s(\mathbf{\Phi}, \mathbf{W_s}|T_k, t_j) = -\log\sigma(\mathbf{w}_{t_j}^\top \mathbf{\Phi}(T_k)) - \sum_{m=1}^{M} \mathbb{E}_{t_m \sim \nu(t)} \log\sigma(-\mathbf{w}_{t_m}^\top \mathbf{\Phi}(T_k))$$

Noise distribution

2) Ordinal Regression for magnitude of time-series values

$$\mathcal{L}_o(\mathbf{\Phi}, \theta, \mathbf{w}_o|t_j) = -\sum_{c=1}^{v} \mathbb{I}(t_j = c) \log\Big[\sigma(\theta_{\mathbf{c}} - \mathbf{w}_o^\top \Phi(c)) - \sigma(\theta_{\mathbf{c-1}} - \mathbf{w}_o^\top \Phi(c))\Big]$$

Segment Context



3) Noise Contrastive Estimation for segment neighbors

$$\mathcal{L}_{nc}(\mathbf{\Phi}, \mathbf{W_{nc}}|T_k, T_i) = -\log\sigma(\mathbf{w}_{T_i}^{\top}\mathbf{\Phi}(T_k))$$
$$-\sum_{m=1}^{M}\mathbb{E}_{T_m\sim\nu(T)}\log\sigma(-\mathbf{w}_{T_m}^{\top}\mathbf{\Phi}(T_k))$$

Noise distribution

4) Smoothing with Neighbors

$$\mathcal{L}_r(\mathbf{\Phi}|T_k, \mathcal{N}(T_k)) = \frac{\eta}{|\mathcal{N}(T_k)|}\sum_{T_c\in\mathcal{N}(T_k)}\|\mathbf{\Phi}(T_k) - \mathbf{\Phi}(T_c)\|^2$$

Subject Invariance

The idea is to remove the subject's environment noise using adversarial learning over subject, i.e., producing subject invariant representations.

Discriminator Loss:

$$\mathcal{L}_d(\mathbf{U}|\mathbf{\Phi}, T_k, s = p) = -\sum_{s=1}^{P} \mathbb{I}(s = p) \log p(s = p|\Phi(T_k), \mathbf{U})$$

Predicting subject from representation $\Phi(T_k)$

Adversary Loss:

$$\mathcal{L}_a(\mathbf{\Phi}|\mathbf{U}, T_k, s = p) = \sum_{s=1}^{P} \mathbb{I}(s = p) \log p(s = p|\Phi(T_k), \mathbf{U})$$

Total Loss

$$\mathcal{L}(\mathbf{\Phi}) = \sum_{n=1}^{N} \sum_{T_k \in S_n} \sum_{\substack{t_j \in T_k \\ T_i \in \mathcal{N}(T_k)}} \Big[\underbrace{\mathcal{L}_s(\mathbf{\Phi}, \mathbf{W} | T_k, t_j) + \beta \mathcal{L}_o(\mathbf{\Phi}, \theta, \mathbf{w}_o | t_j)}_{\text{Segment Content}} +$$

$$\underbrace{\mathcal{L}_{nc}(\mathbf{\Phi}, \mathbf{W} | T_k, T_i) + \mathcal{L}_r(\mathbf{\Phi} | T_k, \mathcal{N}(T_k))}_{\text{Segment Context}} + \underbrace{\lambda \mathcal{L}_a(\mathbf{\Phi} | \mathbf{U}, T_k, s)}_{\text{Adversarial}} \Big]$$

Experimental Materials

- Datasets:
  - Hispanic Community Health Study (HCHS): 1887 subjects
  - Multi-Ethnic Study of Atherosclerosis (MESA): 2237 subjects

7 days of actigraphy data per subject

- Disorder Identification Tasks:
  - Sleep Apnea
  - Insomnia
  - Diabetes
  - Hypertension

We only have labels from HCHS but no labels from MESA

Baselines

- **Traditional time-series classification:**

- SAX-VSM
- BOSS
- BOSS-VSM
- HCTSA

- **Deep Learning Methods:**

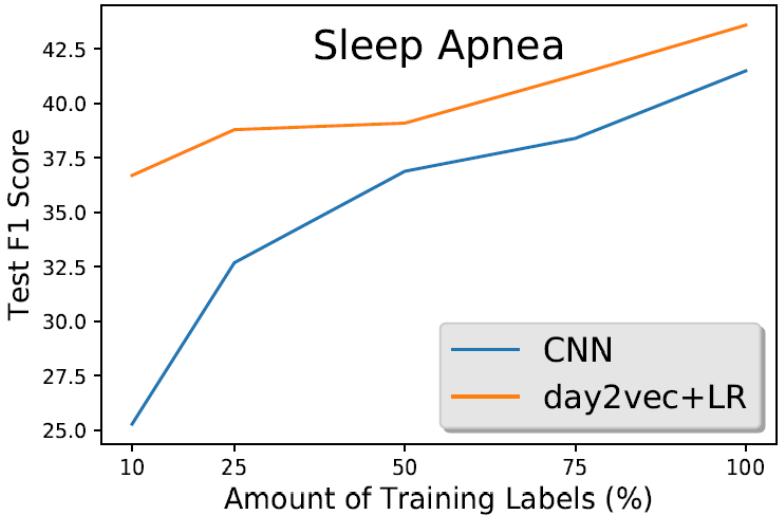
- Supervised CNN
- Semi-supervised LSTM

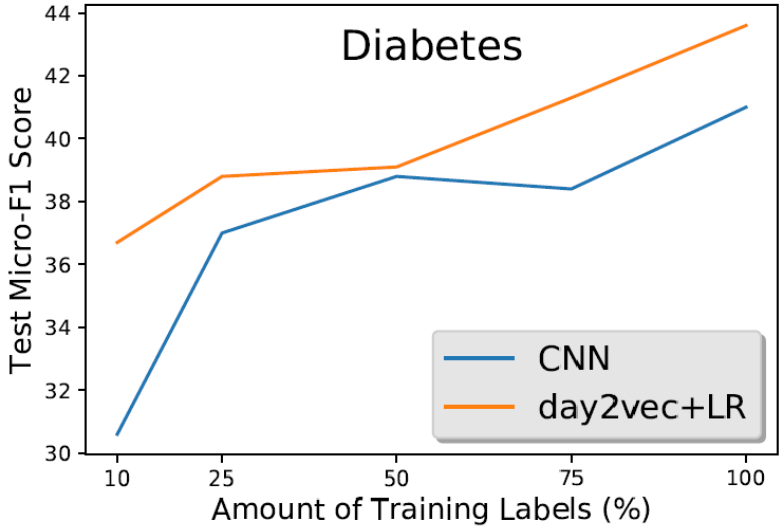
Results

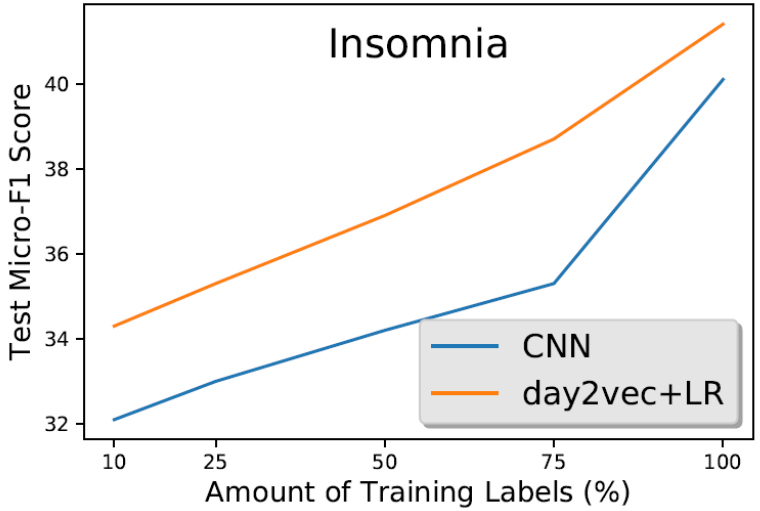
Different time-segment granularities

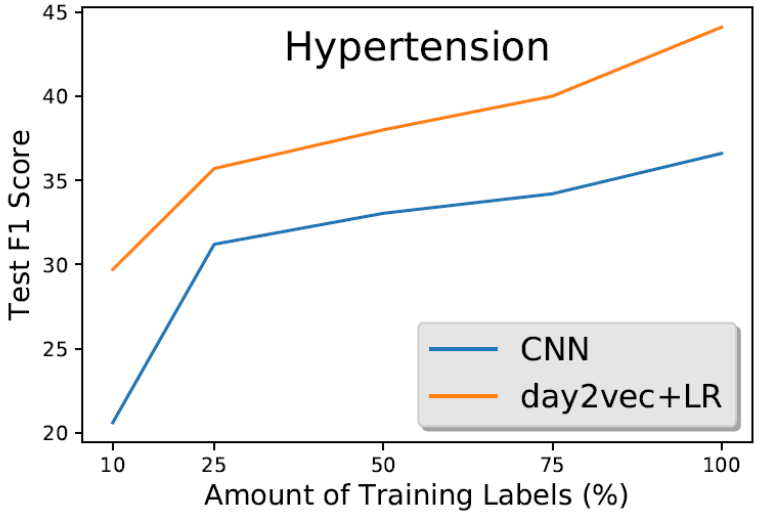
	Method	Clf.	Sleep Apnea	Diabetes		Insomnia		Hypertension	Speed
			F_1	F_1-macro	F_1-micro	F_1-macro	F_1-micro	F_1	
Supervised	Majority	0-R	00.0	21.7	31.9	47.4	25.5	00.0	-
	Random		33.9	34.3	31.3	36.2	30.0	33.4	-
	SAX-VSM		00.0	38.6	24.3	47.4	25.5	00.0	-
	BOSS		17.6	38.9	31.5	49.8	34.9	29.6	-
	BOSSVS		11.7	40.1	32.7	47.5	33.1	31.3	-
	Task-specific	CNN	41.5	45.2	41.0	50.7	40.1	36.6	2.0x
Unsupervised	sample2vec	LR	36.7	40.0	36.7	42.4	35.3	39.4	-
	hour2vec	LR	30.0	41.4	33.3	44.6	28.5	24.4	-
	hour2vec+Reg	LR	20.5	42.1	32.0	43.5	28.7	23.1	-
	day2vec	LR	36.8	40.9	38.0	45.2	35.8	40.3	0.3x
	day2vec+Reg	LR	**38.9**	41.8	**39.5**	46.6	**39.7**	**43.4**	0.3x
	week2vec	LR	14.5	40.6	34.1	44.2	31.5	18.7	-
	HCTSA	LR	20.3	40.0	35.0	46.7	33.7	22.0	8.2x
	LSTM	LSTM	32.2	41.4	33.3	46.1	30.4	37.8	10.5x
	day2vec+Reg+O	LR	40.5	45.3	40.2	50.9	40.3	43.6	0.4x
	day2vec+Reg+O+A	LR	**43.6**	45.8	**42.5**	55.7	**41.4**	**44.1**	**1.0x**

Results: Supervised vs Unsupervised







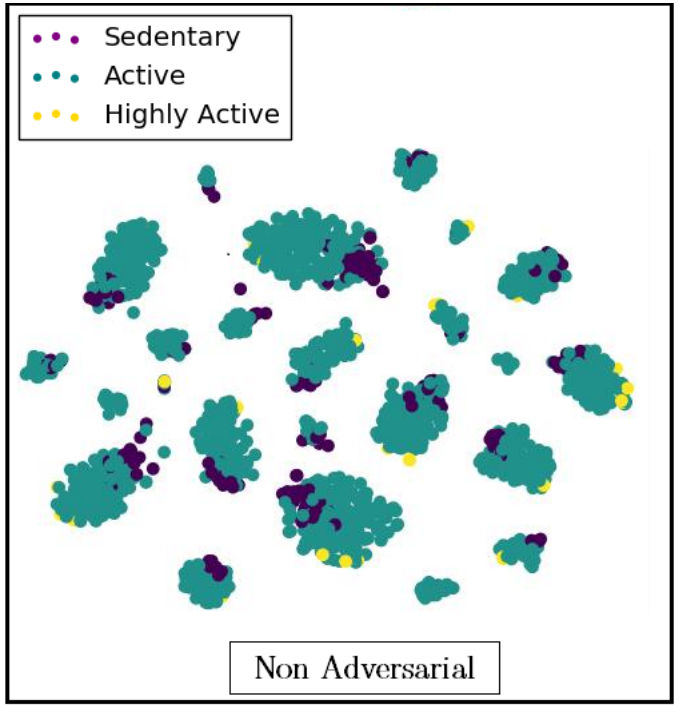


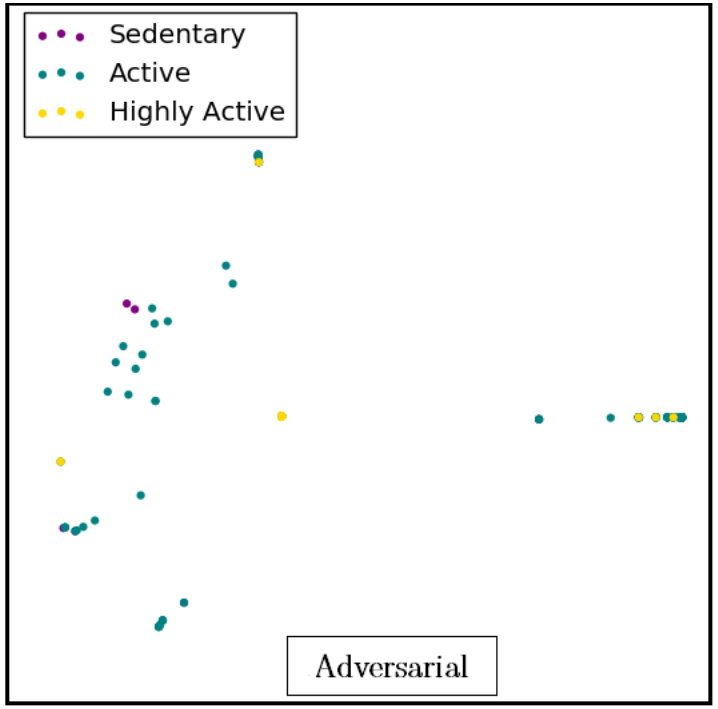
Conclusions

- **Novel model** for learning representations of human activity time-series for utilizing large amount of unlabeled data
- ***activity2vec*** encodes human activity time-series by modeling local (inter-segment) and global activity (intra-segment) patterns
- **Day-level granularity** preserves the best representations since human activities are structured around daily routines usually
- **Adversarial loss** promotes subject invariance reducing the effect of environmental noise on the representations

Thank you!

Results

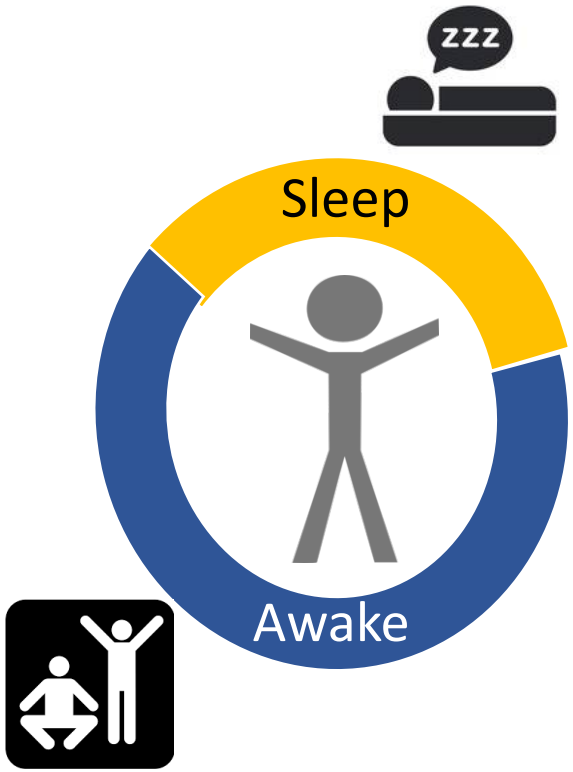




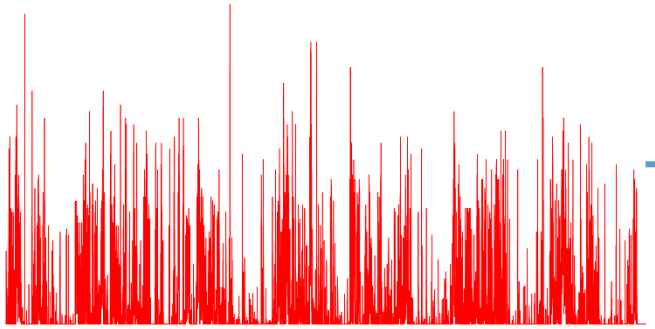
Clusters collapse with in-cluster class separations giving way to global class separations

t-SNE plots of HCHS subjects

Motivation



24 X 7
monitoring



Traditional Problems

Activity Tracking

Sleep Quality

Disorder Monitoring

Our focus

Insufficient sleep and/or activity lead to chronic disorders → can be uncovered by analyzing the actigraphy data

Motivation

Polysomnography (gold standard)

Multi-sensor input
Expensive
In-clinic monitoring
High Fidelity

Actigraphy

24X7 Monitoring
Wearable
Noisy

Wearable devices provide real time and continuous stream of lower quality activity data – can be used for real-time monitoring?