Challenges and opportunities in personal sensing for mood disorders

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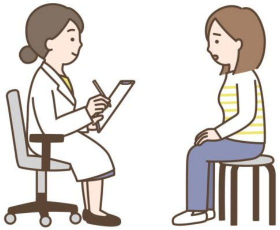
april

Biomedical Ai
UKRI CENTRE FOR DOCTORAL TRAINING

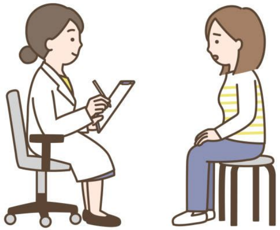
THE UNIVERSITY OF EDINBURGH

A new paradigm?

Present



Some months later…



A new paradigm?

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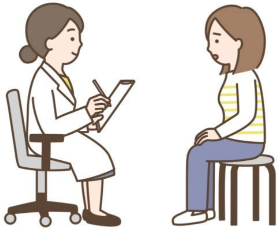

?

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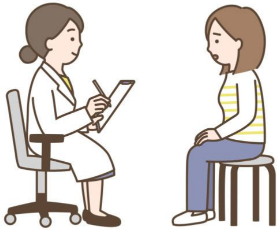
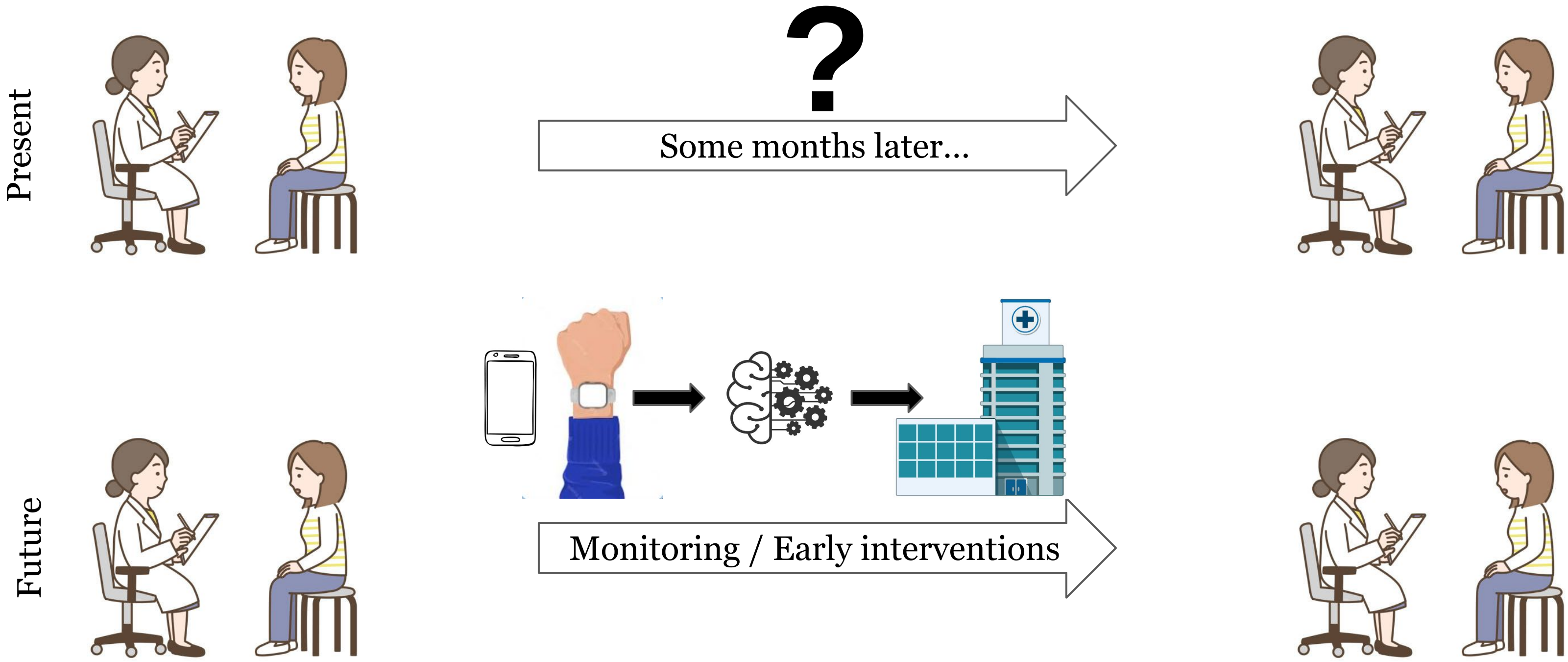
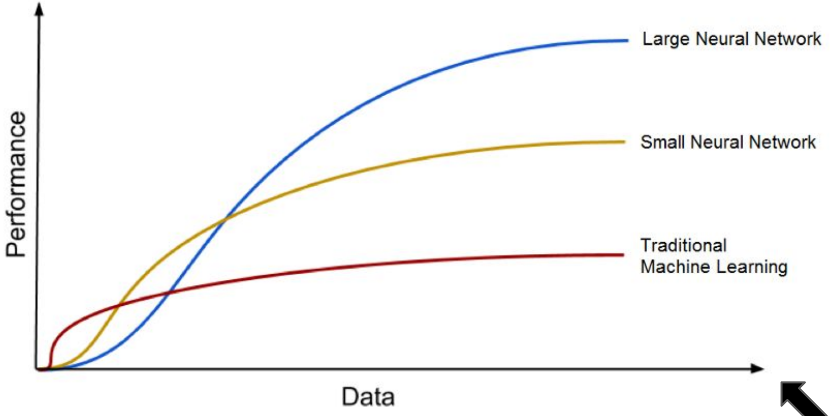


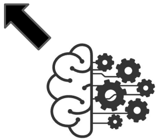
A new paradigm?



Challenge

Supervised Learning





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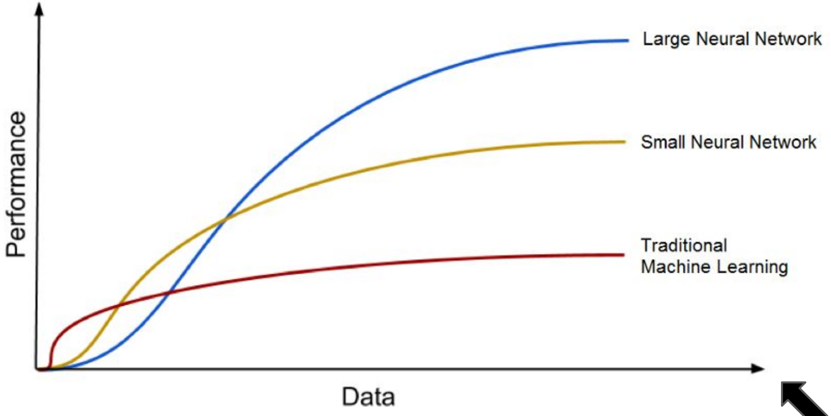
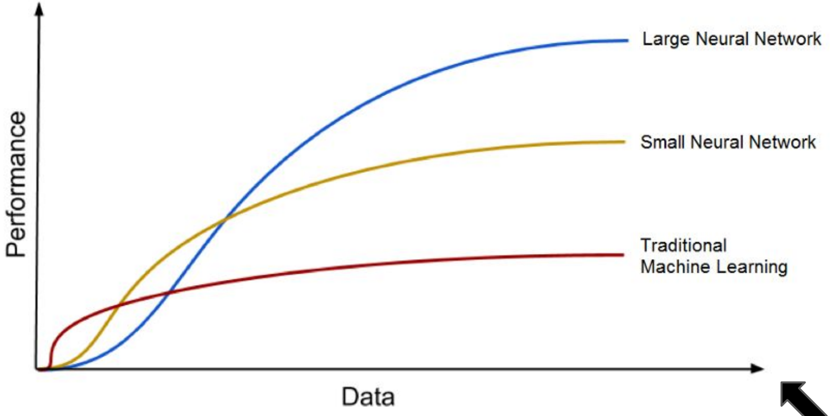


Labelling data is very resource-intensive

↳ psychiatrist assessment

Challenge

Supervised Learning



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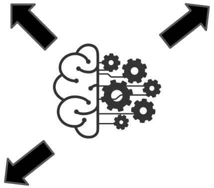

Unlabelled data is easier to source

data not collected for other purposes

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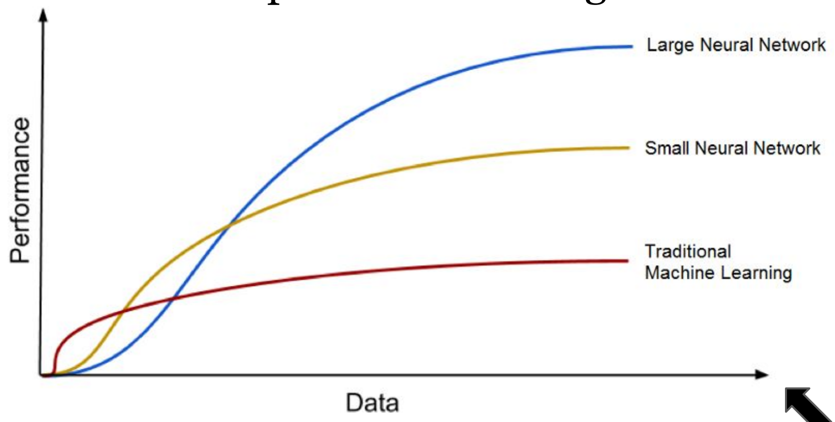

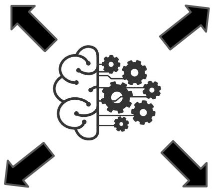

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Is it possible to learn from unlabelled data
something useful towards our goals?

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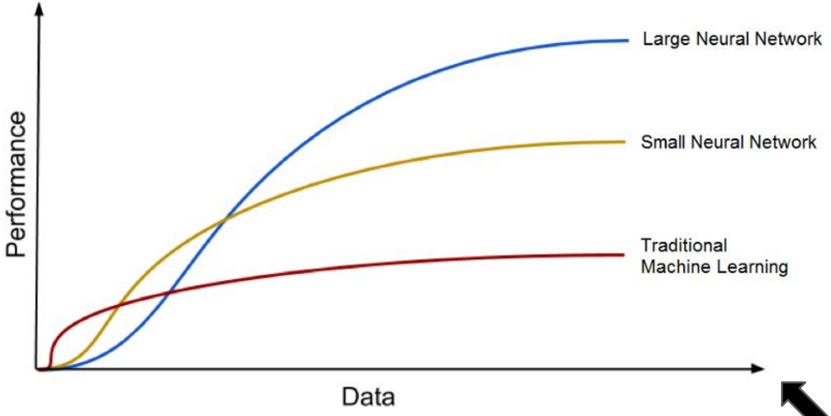

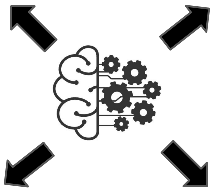

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↳ psychiatrist assessment

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⬇

Self-Supervised Learning

Mood Disorders

Global prevalence: depression 4.4%, bipolar disorder 2.4%

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Depression is the second leading cause of chronic disease burden

(Years Lived with Disability)

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Depression is the second leading cause of chronic disease burden

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Population-level economic burden: £6.43 billion

(UK-based estimate for 2018-2019)

Mood Disorders

Relapsing remitting course

Mood Disorders

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Euthymia

Mood Disorders

Relapsing remitting course

- Euthymia
- Mood, energy levels, neurovegetative functions, sleep

Mood Disorders

Relapsing remitting course

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Binary classification as the simplest yet useful scenario

Personal Sensing

Mood disorders' symptoms translate into changes in physiological parameters

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Wearable technology and AI

↳ near-continuous, passive, ecological monitoring ➡ early interventions

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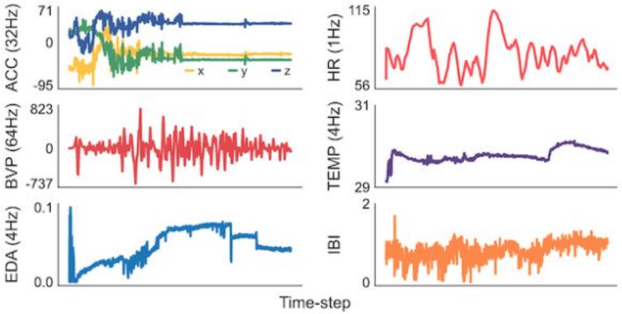
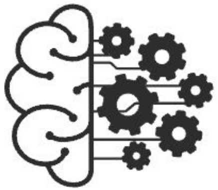
Empatica E4





Euthymia
Vs
Acute Episode

Motivation

Annotation* is resource-intensive

*Annotation: mood state of the person wearing the device as given by a specialist

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Studies have limited sample size (dozens)

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Self-supervised Learning

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Self-Supervised Learning

Pre-train model with **unlabelled data** on **surrogate task**

Step 1

Self-Supervised Learning

Pre-train model with **unlabelled data** on **surrogate task** Step 1

Model learns about the data

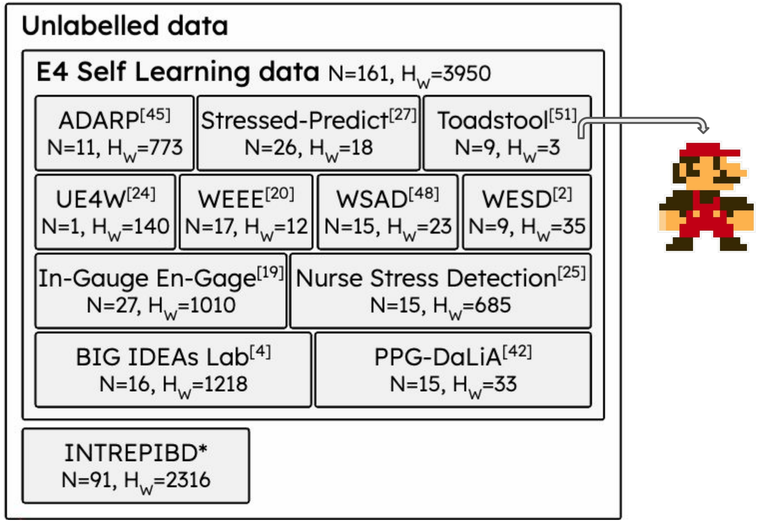
Self-Supervised Learning

Pre-train model with **unlabelled data** on **surrogate task** Step 1

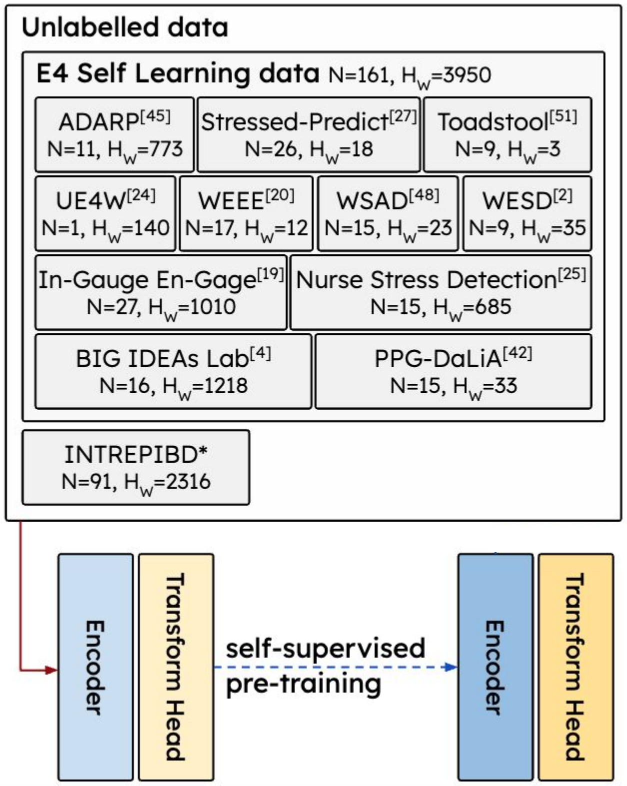
Model learns about the data

Fine-tune model on **target task** with **labelled data** Step 2

E4 Self Learning



Analyses Pipeline



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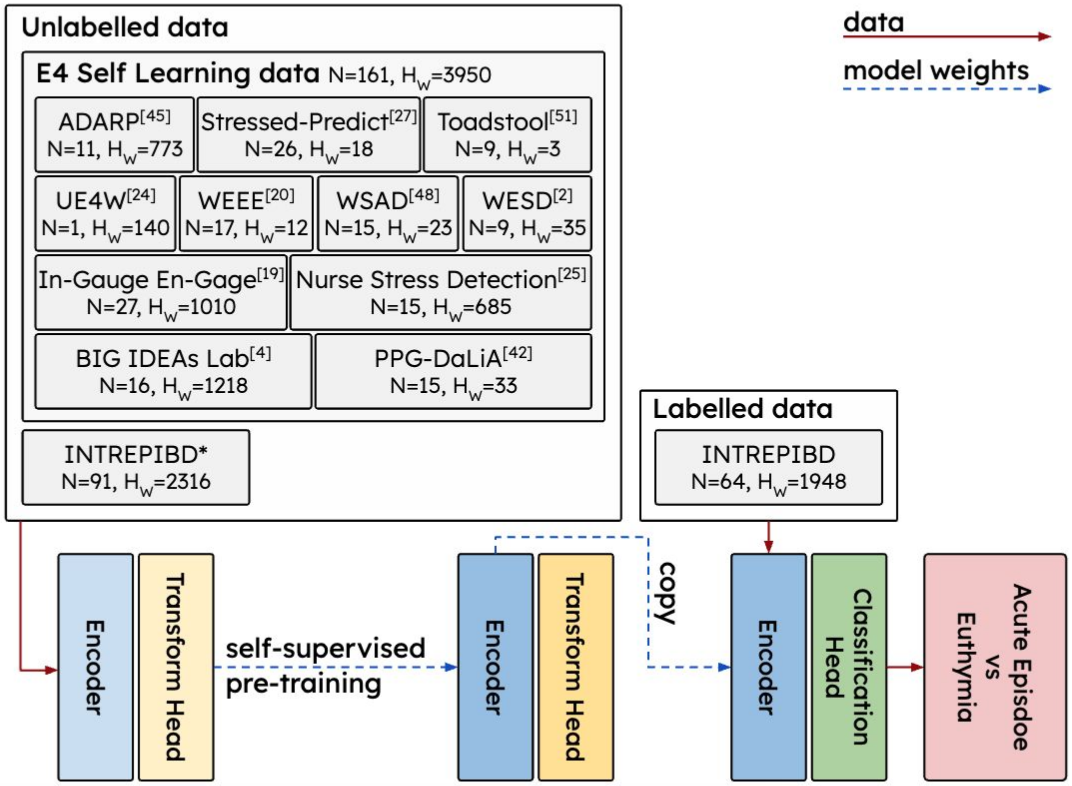
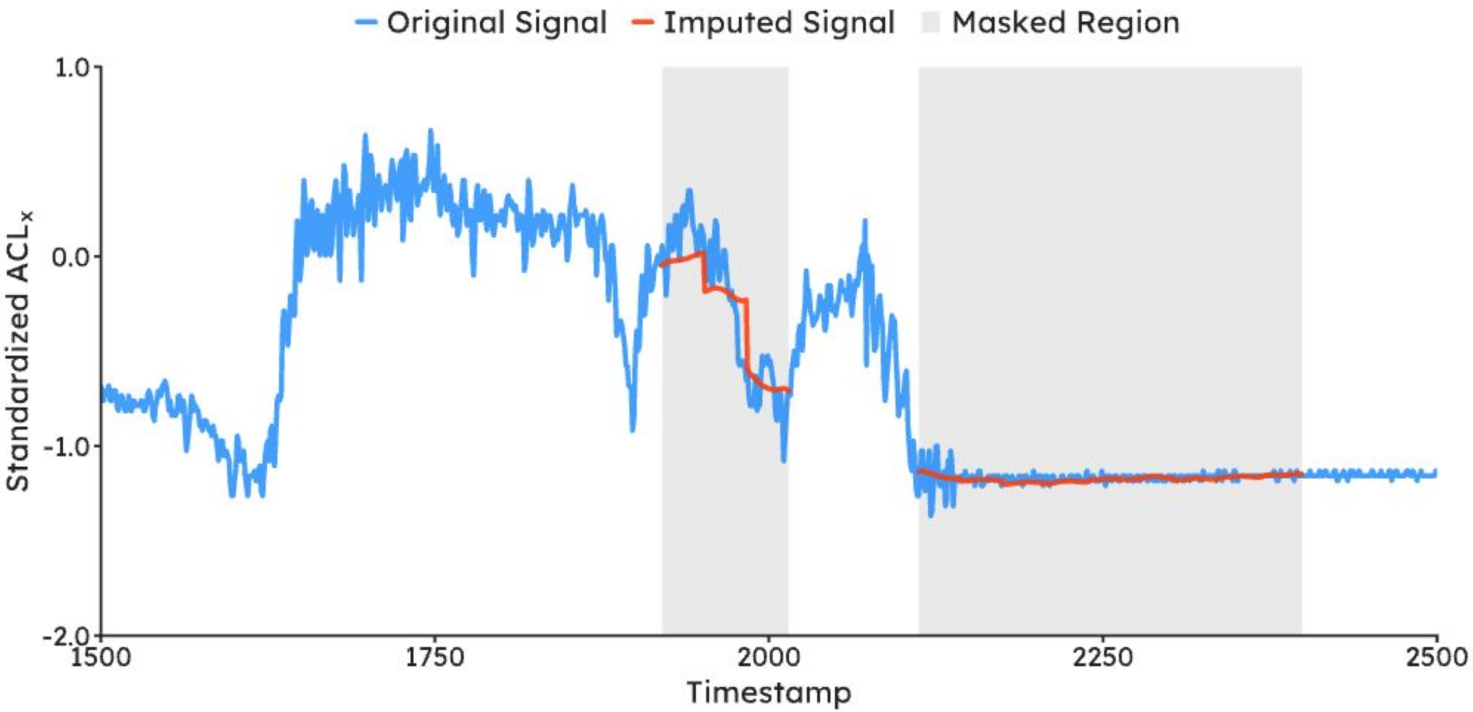
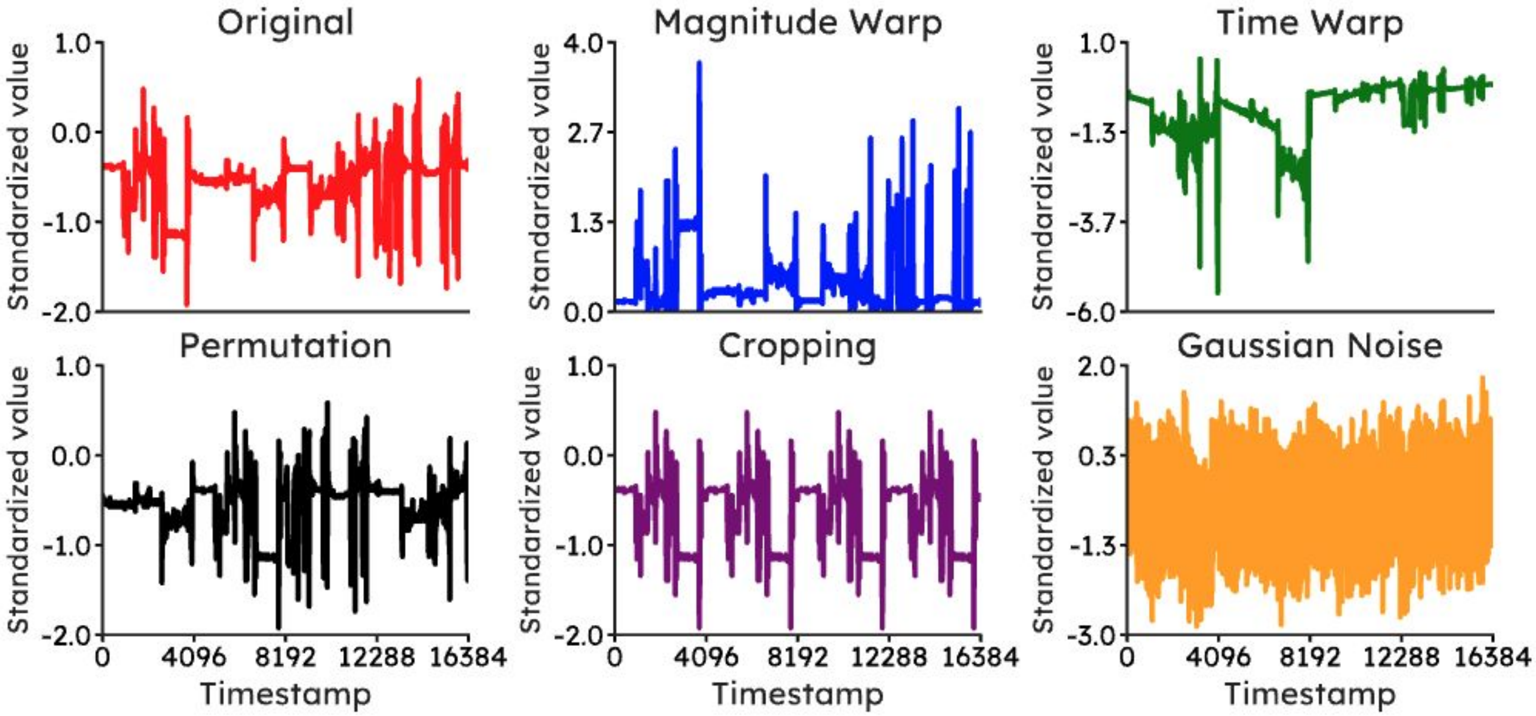


Surrogate Tasks



Masked Prediction

Surrogate Tasks



Transformation Prediction

INTREPIBD Cohort

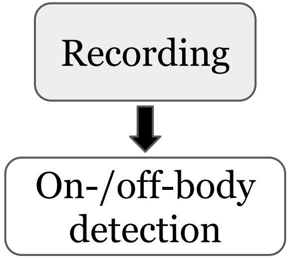
	Age mean (std)	Females n (percentage)	Diagnosis	HDRS mean (std)	YMRS mean (std)
Euthymia	47.22 (16.06)	14 (43.75%)	BD (N=26)	2.93 (1.73)	1.3 (1.61)
N=32			MDD (N=6)	3.14 (1.95)	0.29 (0.76)
Acute episode	50.56 (13.05)	15 (46.88%)	MDE-BD (N=9)	20.22 (6.34)	2.56 (3.94)
N=32			MDE-MDD (N=7)	25.14 (4.78)	1.86 (2.41)
			ME (N=14)	5.67 (4.37)	20.13 (6.28)
			MX (N=2)	16 (4.24)	13.5 (4.95)

Target task dataset

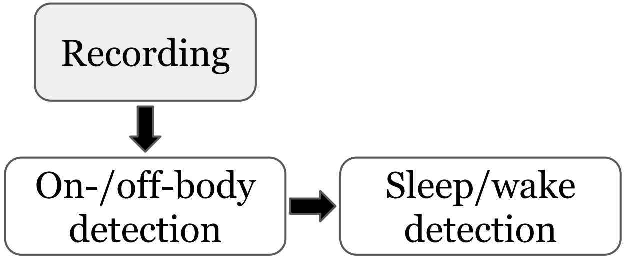
Pre-processing

Recording

Pre-processing



Pre-processing



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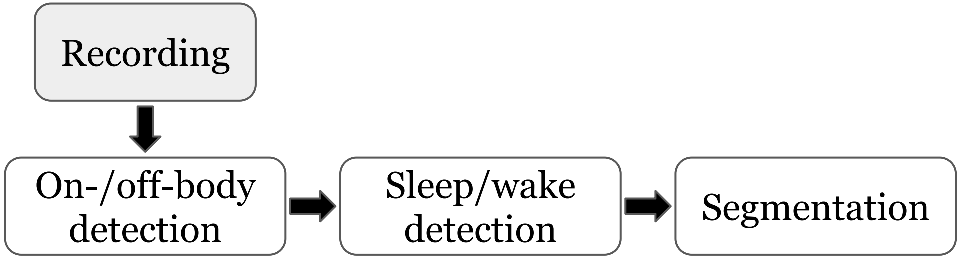

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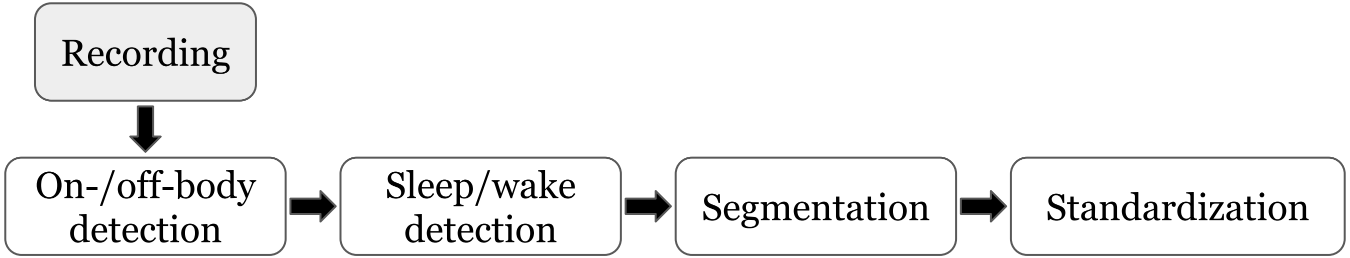

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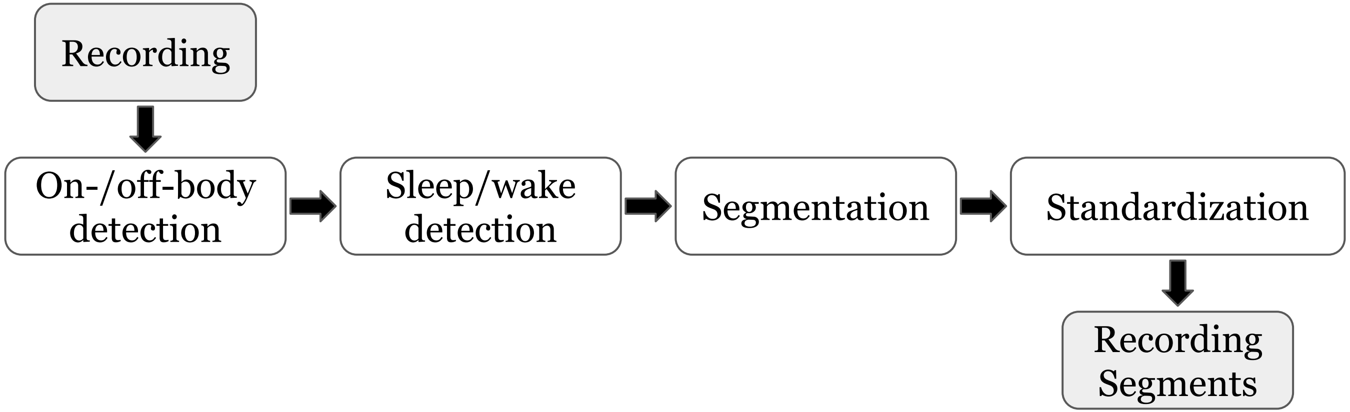

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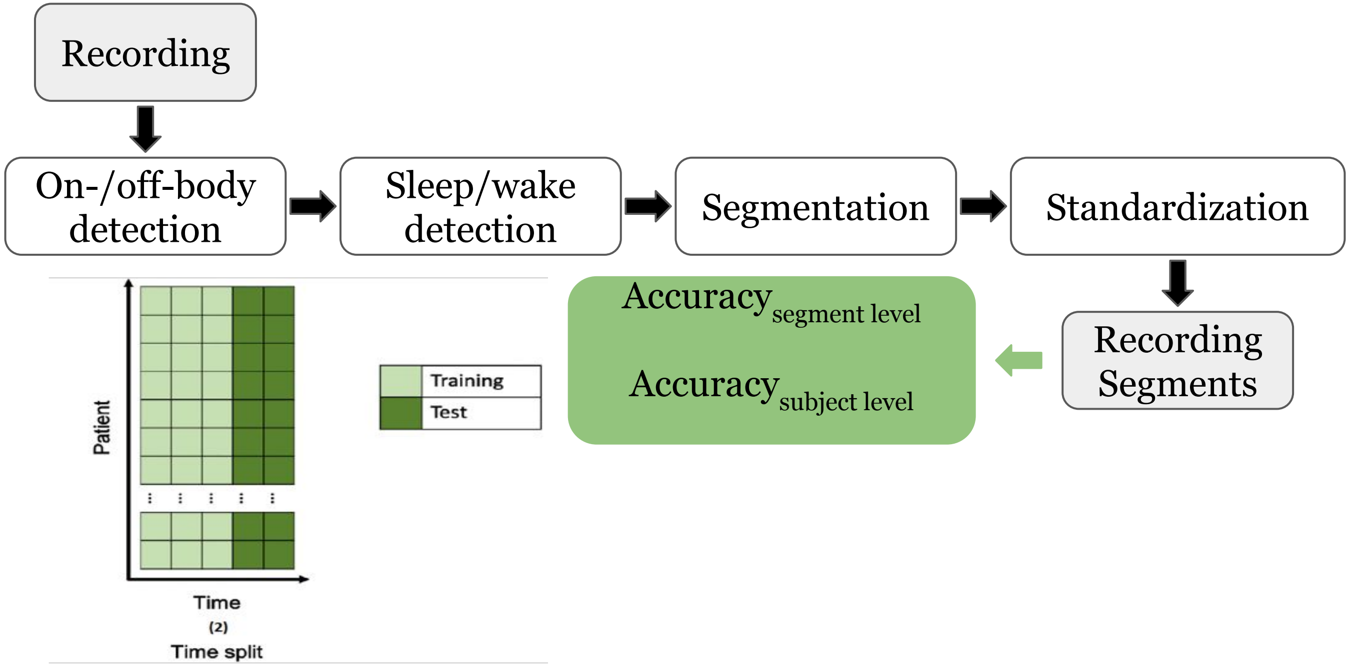
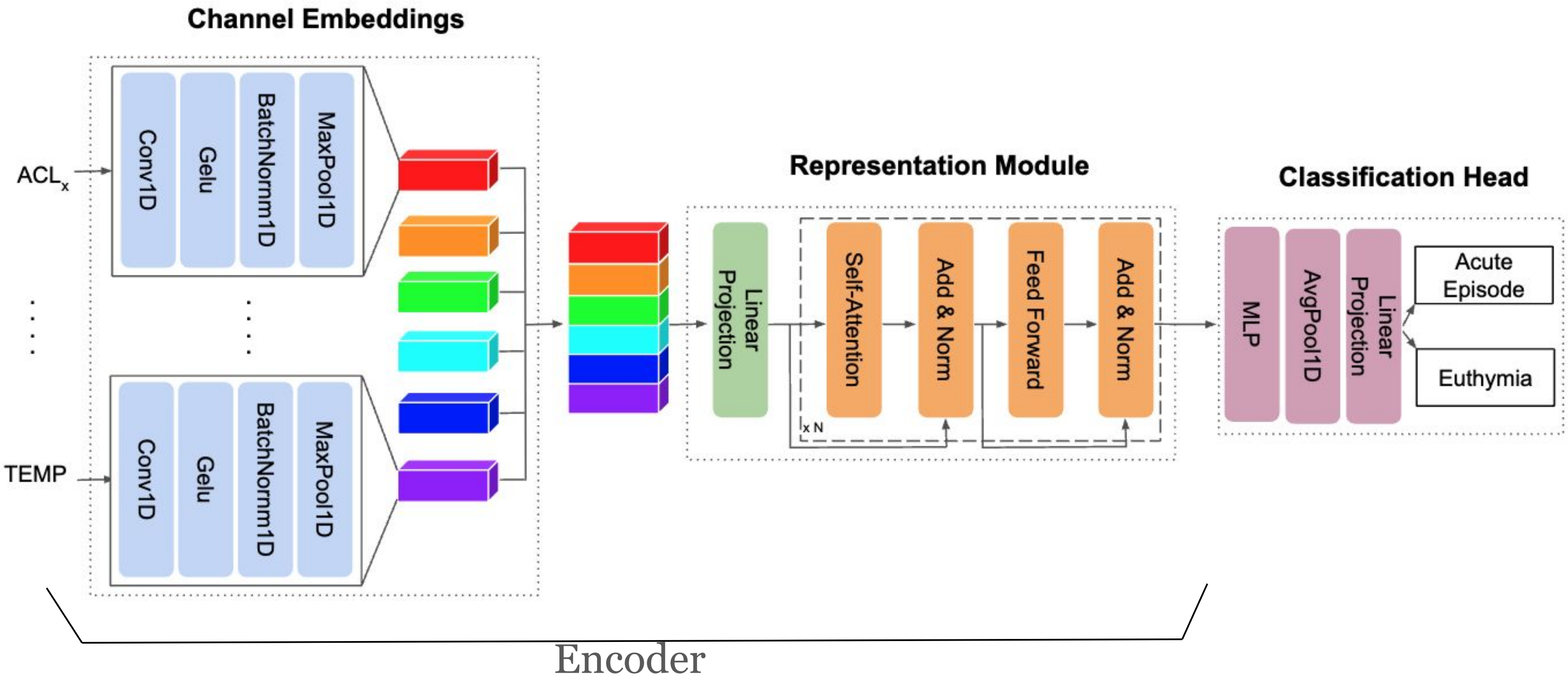


E4mer



Channel Embeddings
ACL$_x$
TEMP
Conv1D
Gelu
BatchNorm1D
MaxPool1D
Conv1D
Gelu
BatchNorm1D
MaxPool1D
Representation Module
Linear Projection
Self-Attention
Add & Norm
Feed Forward
Add & Norm
x N
Classification Head
MLP
AvgPool1D
Linear Projection
Acute Episode
Euthymia
Encoder

Results

	Model	ACC		Precision		Recall		F_1 score		AUROC	
		Segment	Subject	Segment	Subject	Segment	Subject	Segment	Subject	Segment	Subject
SL	XGBoost	72.02	82.81	71.33	83	72.11	81.1	71.72	82.03	72.44	83.17

XGBoost: traditional machine learning with extracted features

Results

	Model	ACC		Precision		Recall		F_1 Score		AUROC	
		Segment	Subject	Segment	Subject	Segment	Subject	Segment	Subject	Segment	Subject
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	E4mer	75.35	81.25	73.46	80.55	75.34	82.14	74.39	81.33	75.68	82.22

XGBoost and a modern deep learning pipeline perform on a similar level

Results

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	E4mer	75.35	81.25	73.46	80.55	75.34	82.14	74.39	81.33	75.68	82.22
SSL	MP (LR)	77.53	87.50	78.34	88.6	77.41	88	77.87	88.3	78.02	89.2
	MP (FT)	**81.23**	**90.63**	**80.91**	**90.11**	**82.00**	**92.87**	**81.45**	**91.47**	**82.02**	**93.11**

Self-supervised learning confidently outperforms baselines on all metrics

Results

Model		ACC		precision		recall		F_1 score		AUROC	
		segment	subject	segment	subject	segment	subject	segment	subject	segment	subject
SL	XGBoost	72.02	82.81	71.33	83	72.11	81.1	71.72	82.03	72.44	83.17
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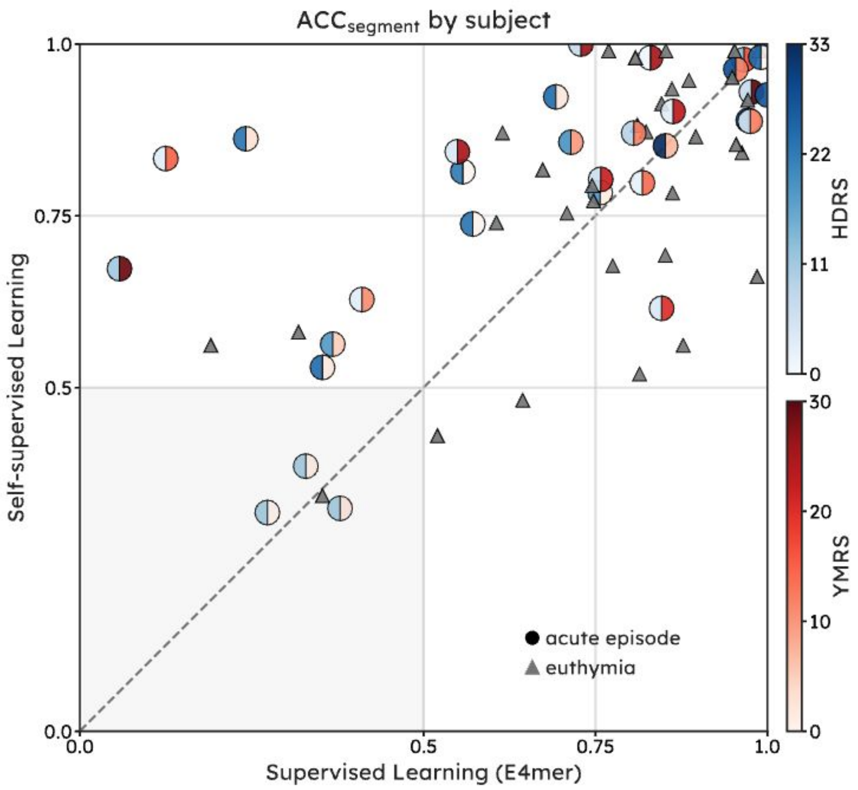
	TP (LR)	71.16	81.25	72.12	82.44	72.01	82.31	72.06	82.37	71.89	84.12
	TP (FT)	75.69	84.38	75.41	82.11	74.79	83.90	75.10	X 83	75.21	84.32

Surrogate task makes a difference

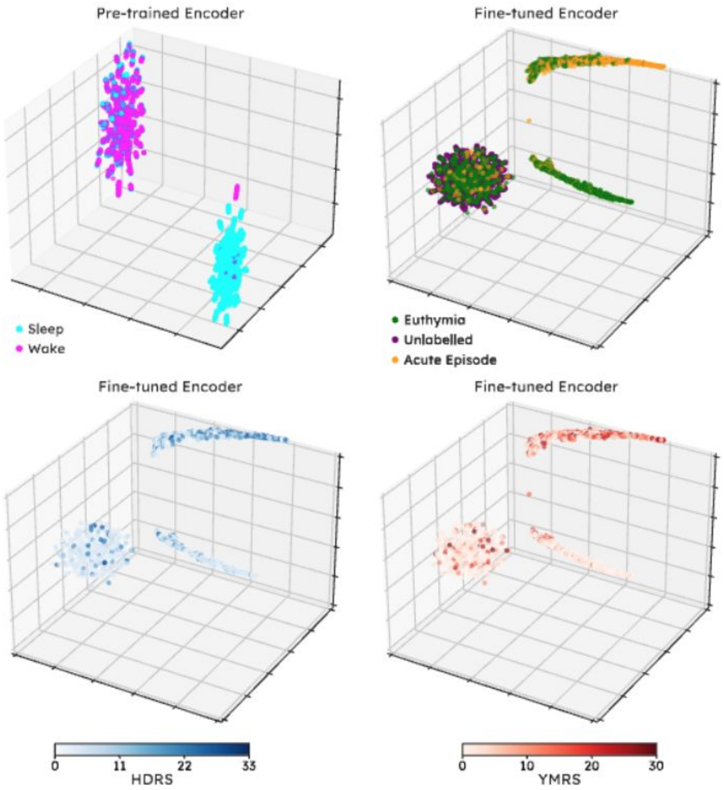
Results



ACC$_{segment}$ by subject
Self-supervised Learning
Supervised Learning (E4mer)
1.0
0.75
0.5
0.0
0.0
0.5
0.75
1.0
acute episode
euthymia
HDRS
33
22
11
0
YMRS
30
20
10
0

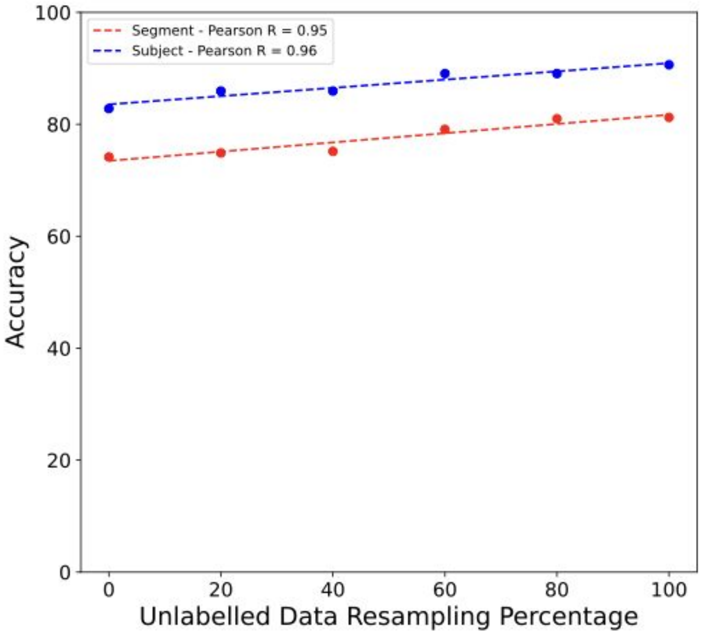
Results

Embeddings



Results

Ablation analysis



Is euthymia vs acute episode the whole story?

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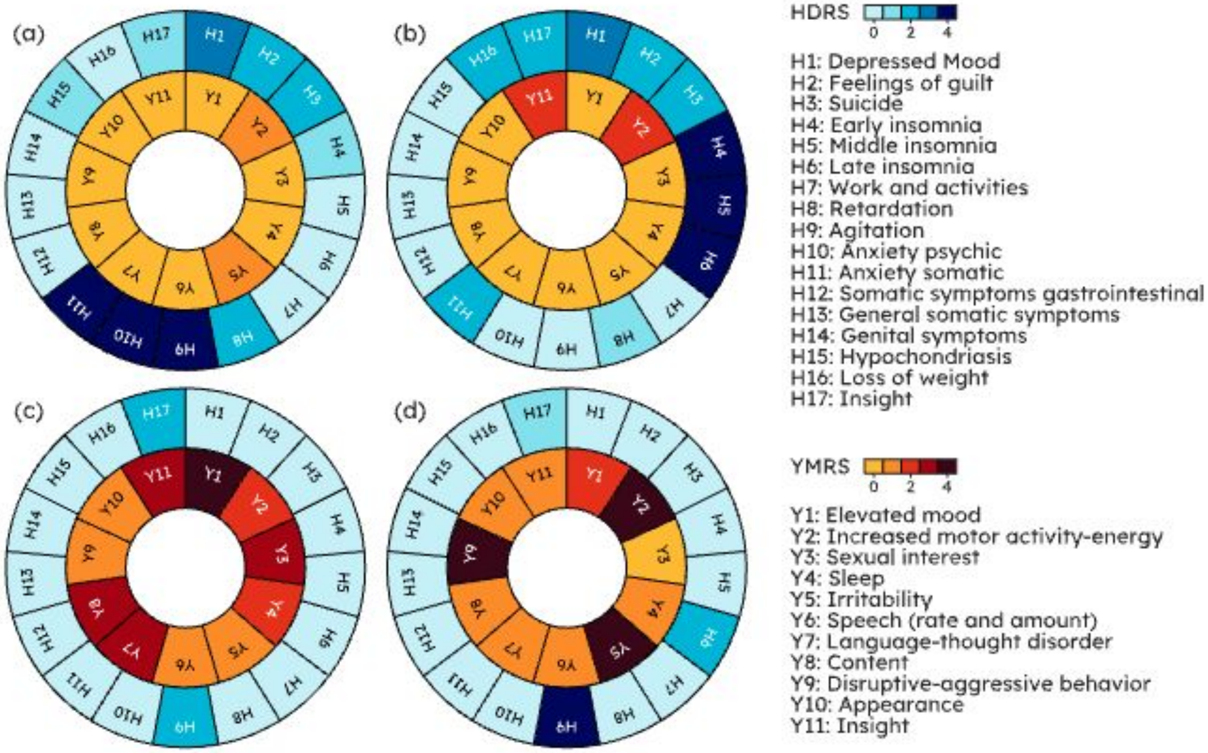

(Li M. B, Corponi F., et al. NeurIPS 2022. Corponi F., Li M. B., et al. 2023 medRxiv.)

Challenges

Mood disorders are highly heterogeneous

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Mood disorders are highly heterogeneous ➡ Generalization across subjects and within subject

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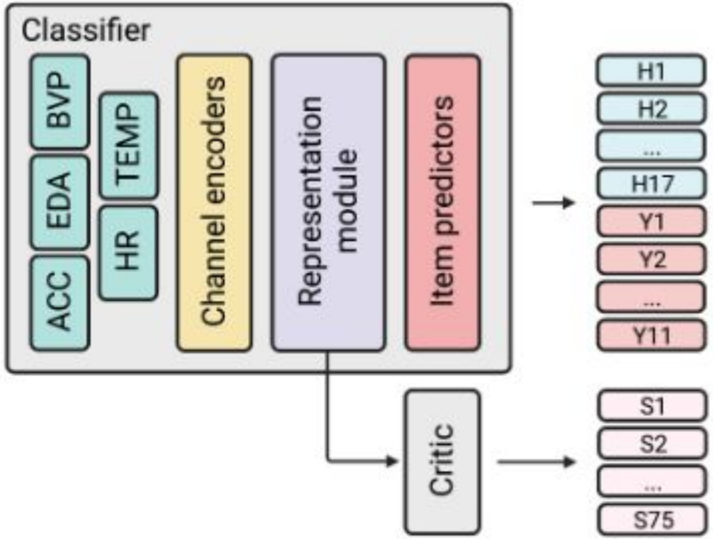

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Personal sensing data is noisy

Challenges

Mood disorders are highly heterogeneous

Personal sensing data is noisy ➡ More variability in the signal down to physiological rather than illness-related factors

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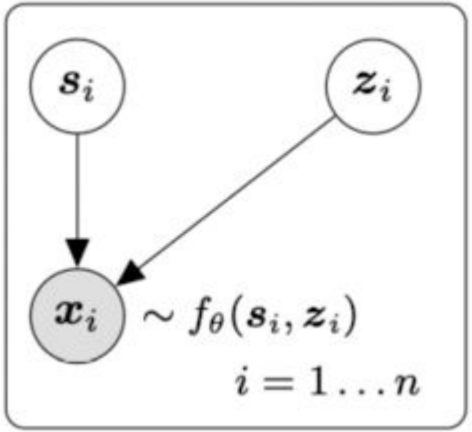

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Optimal windowing

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Explainability

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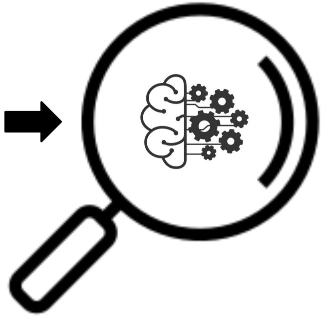

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Personal sensing data is noisy

Optimal windowing

Explainability

Action policy and uncertainty

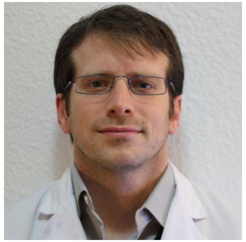
Thanks for your attention

Bipolar Disorders Unit, Hospital clinic, Barcelona

Questions? Feedback?

Antonio Vergari, PhD

Bryan Li, MSc



Diego Hidalgo-Mazzei, MD, PhD