Integration of Foundation Models and Gaussian Processes for Supporting the Diagnosis and Treatment of Mental Disorders based on EEG Signals

An Stochastic Approach

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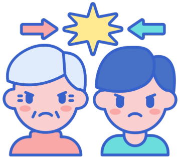
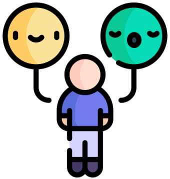
July 30, 2025

Motivation

Mental disorders affect cognition, behavior, and emotions of millions of people worldwide. Around 350 million individuals suffer from a mental disorder [Dehghan-Bonari et al., 2023].



Oppositional Defiant Disorder



Bipolar Disorder

Attention Deficit Hyperactivity Disorder

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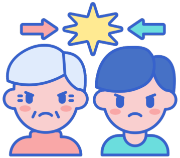
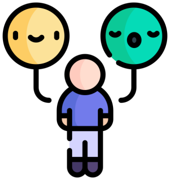


Oppositional Defiant Disorder



Bipolar Disorder

Attention Deficit Hyperactivity Disorder

Challenges: lengthy follow-up, subjective interpretations, inefficient criteria, and limited access to clinical care.

Problem Statement and Research Question

Model \ Challenge	Complex Patterns	High Labeled Data Volume	Stochasticity	Data Shift
Machine Learning [Salari et al., 2023]	✗	✓	✓	✗
Deep Learning [Lohani and Rana, 2023]	✓	✗	✓	✓
Foundation [Sibley, 2021]	✓	✓	✗	✓

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Research Question How to develop a stochastic foundational model for inference from biological signals that integrates Gaussian processes to support clinical practice through EEG signal analysis, considering the variability and inconsistencies present in the datasets?

Objectives

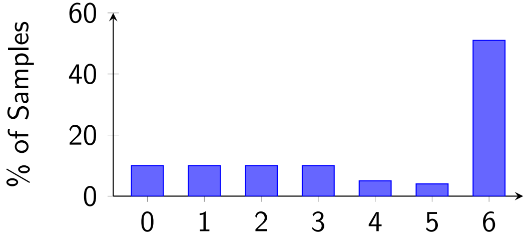
General Objective Develop a stochastic learning methodology related to EEG recordings based on a foundational model that integrates labeled and unlabeled databases using self-learning and fine-tuning techniques.

Specific Objectives

1. Develop a foundational model for the classification of biological signals related to EEG recordings, leveraging unlabeled data during the self-learning phase and labeled data for fine-tuning.
2. Implement a stochastic prediction tool based on Gaussian processes to model uncertainty in the foundational model's predictions.
3. Design a strategy to manage variability and inconsistency in EEG recording datasets, enabling the effective integration of databases with diverse standards.

Toadstool 2 Dataset

The dataset consists of video, sensor, and demographic data collected from 10 participants playing a Super Mario Bros.



0	Anger	3	Happy	6	Neutral
1	Disgust	4	Sad		
2	Fear	5	Surprised		

Signal	**Rate (Hz)**	**Channels**
BVP	64	1
ACC	32	3
EDA	4	1
HR	1	1

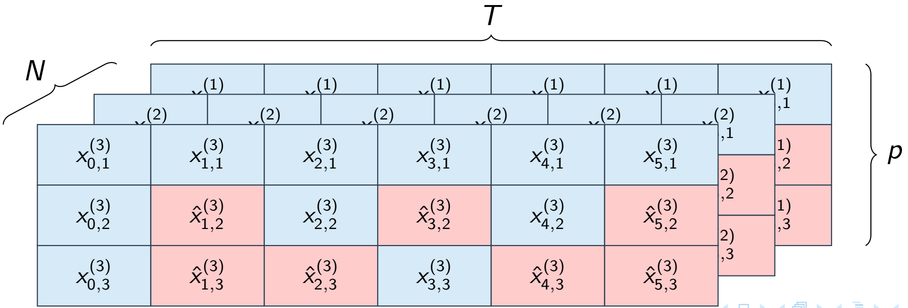
20.970 sensor-only samples (4 s windows)

Problem Setting

Let $\{(\boldsymbol{X}^{(i)}, y^{(i)})\}_{i=1}^{N}$ be the training dataset, where $\boldsymbol{X}^{(i)} \in \mathcal{X}$ and $y^{(i)} \in \{0, 1, \ldots, 6\}$. Here $\mathcal{X}$ is the space of vector sequences of length $T = 256$:

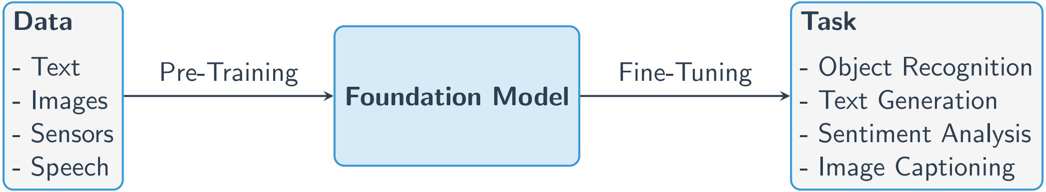
$$\boldsymbol{X}^{(i)} = \left[\boldsymbol{x}_1^{(i)}, \ldots, \boldsymbol{x}_t^{(i)}, \ldots, \boldsymbol{x}_T^{(i)}\right].$$

$\boldsymbol{x}_t^{(i)}$ has $p = 6$ elements by channels, denoted $x_{t,j}^{(i)} \in \mathbb{R}$ or be a missing value $\hat{x}_{t,j}^{(i)}$.



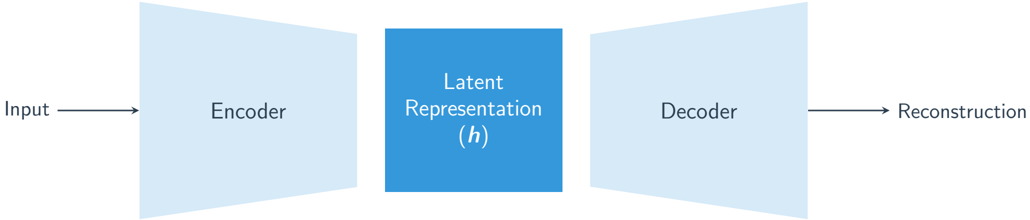
Objective 1: Foundation Model

We aims to train a general model using large amounts of data and tasks that can be fine-tuned easily in different downstream applications.

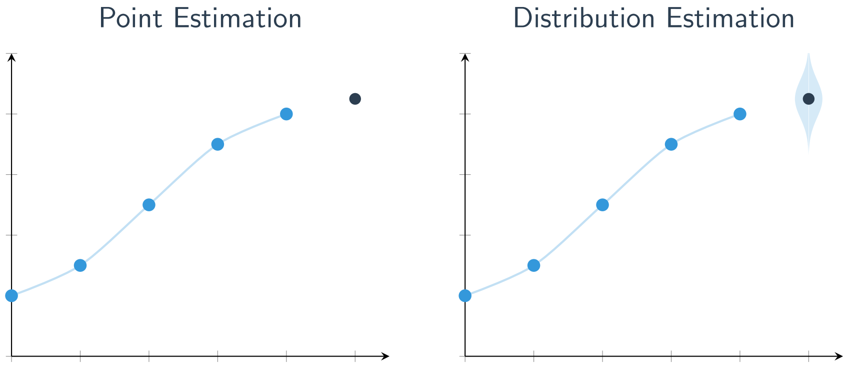


Architecture

We can leverage large amounts of unlabeled data to learn hidden-state representations without committing to any specific downstream task.

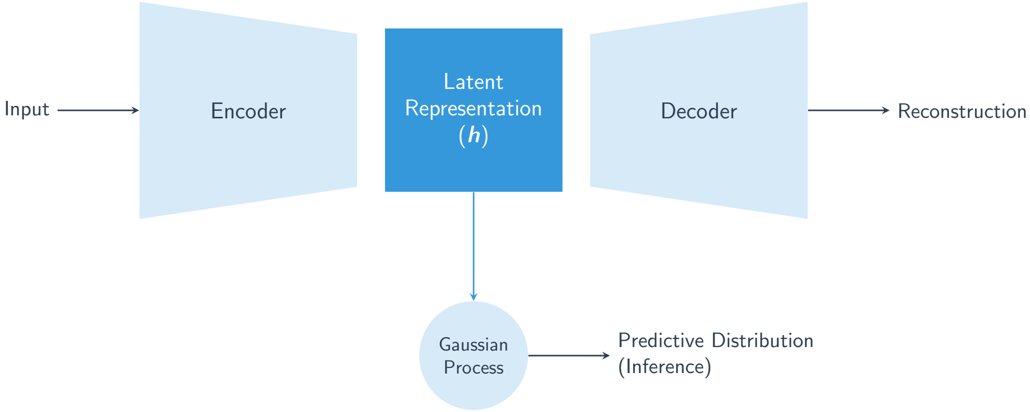


Objetive 2: Gaussian Process

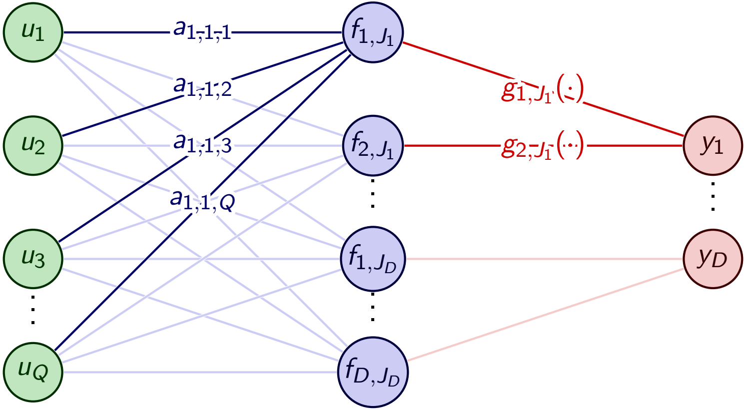


Sometimes, a single point prediction is not enough. How confident is the model in its prediction?

Architecture



Chained Correlated GP



Independent Process

$u_q(\mathbf{h}) \sim \mathcal{GP}(0, k_q(\mathbf{h}, \mathbf{h}'))$

Latent Process

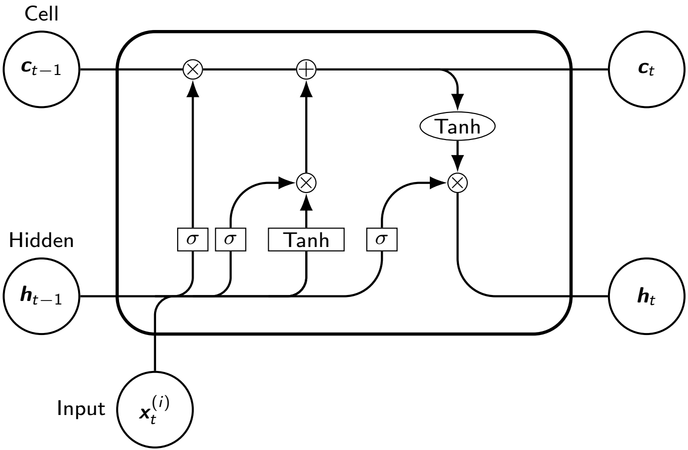
$$f_{d,j}(\mathbf{h}) = \sum_{q=1}^{Q} a_{d,j,q} u_q(\mathbf{h})$$

Likelihood

$$\mathbf{y} \mid \mathbf{f} \sim \prod_{d=1}^{D} p(\theta_{d,1}, \cdots, \theta_{d,J_d})$$

$$\theta_{d,j} = g_{d,j}(f_{d,j})$$

Objective 3: Long Short-Term Memory (LSTM) Architecture



$$
\begin{aligned}
\boldsymbol{i}_t &= \sigma\left(\boldsymbol{W}_{ii}\, \boldsymbol{x}_t^{(i)} + \boldsymbol{W}_{hi}\, \boldsymbol{h}_{t-1} + \boldsymbol{b}_i\right),\\
\boldsymbol{f}_t &= \sigma\left(\boldsymbol{W}_{if}\, \boldsymbol{x}_t^{(i)} + \boldsymbol{W}_{hf}\, \boldsymbol{h}_{t-1} + \boldsymbol{b}_f\right),\\
\boldsymbol{g}_t &= \tanh\left(\boldsymbol{W}_{ig}\, \boldsymbol{x}_t^{(i)} + \boldsymbol{W}_{hg}\, \boldsymbol{h}_{t-1} + \boldsymbol{b}_g\right),\\
\boldsymbol{o}_t &= \sigma\left(\boldsymbol{W}_{io}\, \boldsymbol{x}_t^{(i)} + \boldsymbol{W}_{ho}\, \boldsymbol{h}_{t-1} + \boldsymbol{b}_o\right),\\
\boldsymbol{C}_t &= \boldsymbol{f}_t \odot \boldsymbol{C}_{t-1} + \boldsymbol{i}_t \odot \boldsymbol{g}_t,\\
\boldsymbol{h}_t &= \boldsymbol{o}_t \odot \tanh\left(\boldsymbol{C}_t\right).
\end{aligned}
$$

$\odot$ is the Hadamard product, and σ the sigmoid function.

Missing-Value Imputation

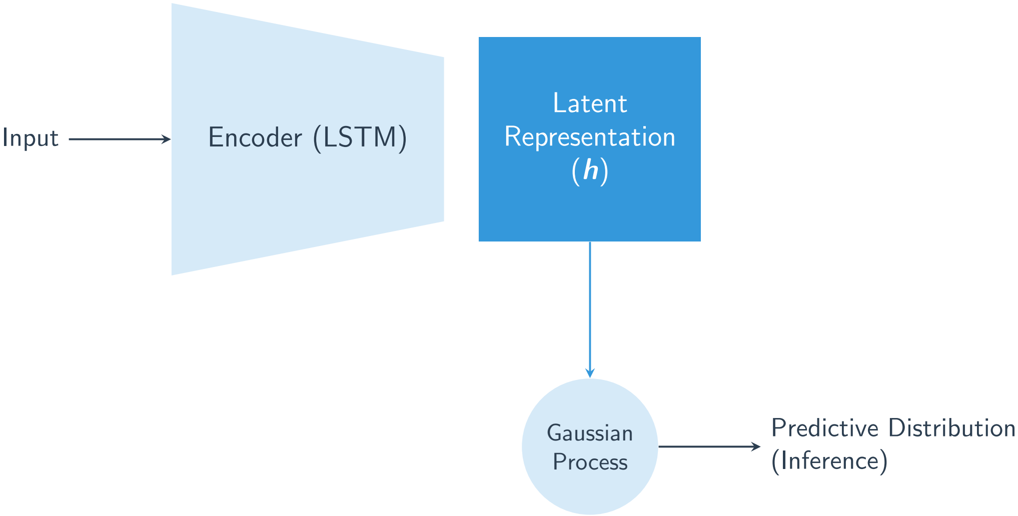
At each time step t, missing channel entries in $\boldsymbol{x}_t^{(i)}$ can be imputed sequentially from the hidden state via an affine map:

$$\hat{x}_{t,j}^{(i)} = \boldsymbol{w}_j^\top \boldsymbol{h}_t + b_j, \quad j = 1, \ldots, p.$$

$$\begin{aligned} \{\boldsymbol{W}_{ii}, \boldsymbol{W}_{if}, \boldsymbol{W}_{ig}, \boldsymbol{W}_{io}\} &\in \mathbb{R}^{H\times p}, \\ \{\boldsymbol{W}_{hi}, \boldsymbol{W}_{hf}, \boldsymbol{W}_{hg}, \boldsymbol{W}_{ho}\} &\in \mathbb{R}^{H\times H}, \\ \{\boldsymbol{b}_i, \boldsymbol{b}_f, \boldsymbol{b}_g, \boldsymbol{b}_o\} &\in \mathbb{R}^{H}, \\ \boldsymbol{w}_j &\in \mathbb{R}^{H}, \\ b_j &\in \mathbb{R}, \\ \boldsymbol{h}_t, \boldsymbol{C}_t &\in \mathbb{R}^{H}. \end{aligned}$$

Here H denotes the dimensionality of the hidden state.

Architecture



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PMID: 33949916.