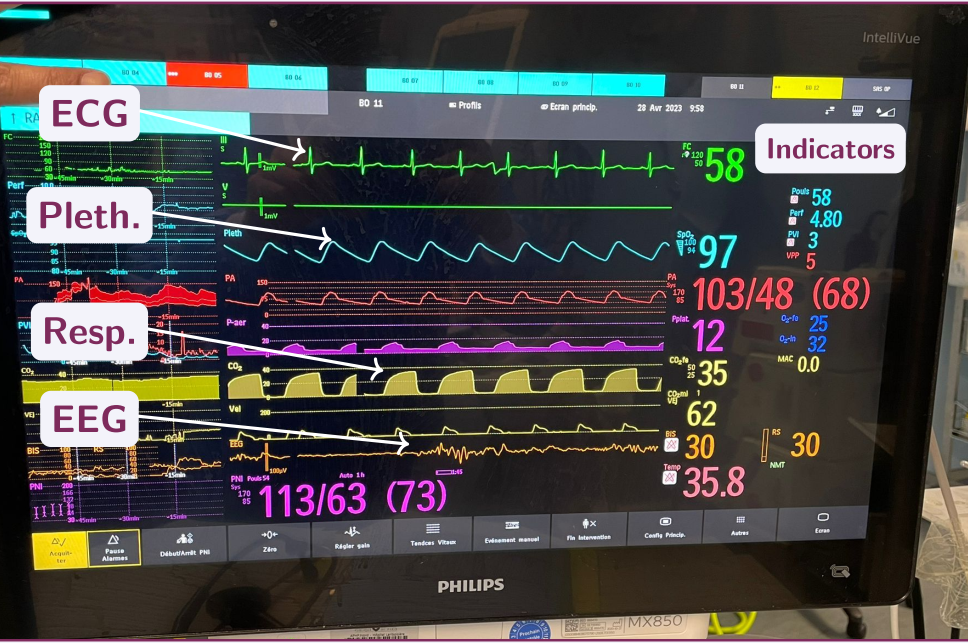
EULPS: Event-based Unsupervised Learning for Physiological Signals

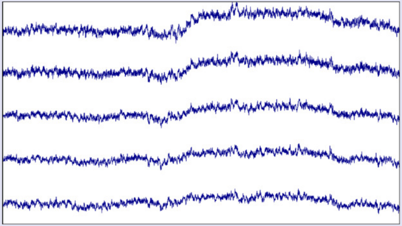
Thomas Moreau Inria Saclay

Audition ERC StG 2023 – PE6

General Anesthesia Monitoring

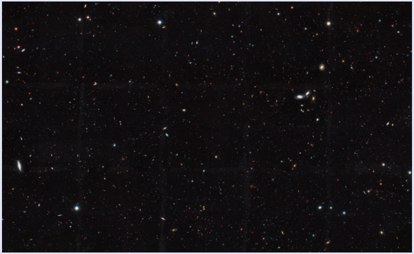


Large Scale Multivariate Physical Signals

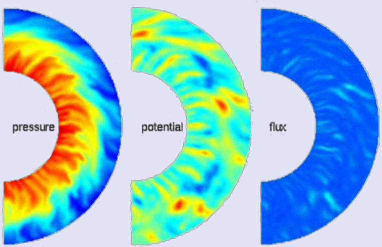


Neuroscience (MEG)

General Anesthesia

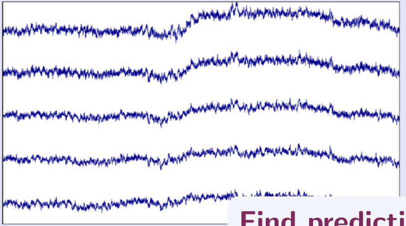


Astronomy



Physical Simulation

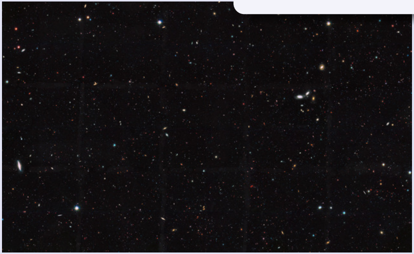
Large Scale Multivariate Physical Signals



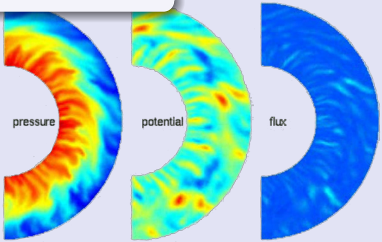
Neuroscience

Anesthesia

Find predictive representations of multivariate signals using AI.



Astronomy



Physical Simulation

Recent breakthrough in AI: Foundation Models

ChatGPT **Midjourney**

What do they have in common?

Recent breakthrough in AI: Foundation Models

ChatGPT **Midjourney**

What do they have in common?

Tokens **Self-supervised pretraining**

Capture the input distribution $\mathbb{P}(X)$ with interaction between tokens.

Recent breakthrough in AI: Foundation Models

ChatGPT **Midjourney**

What do they have in common?

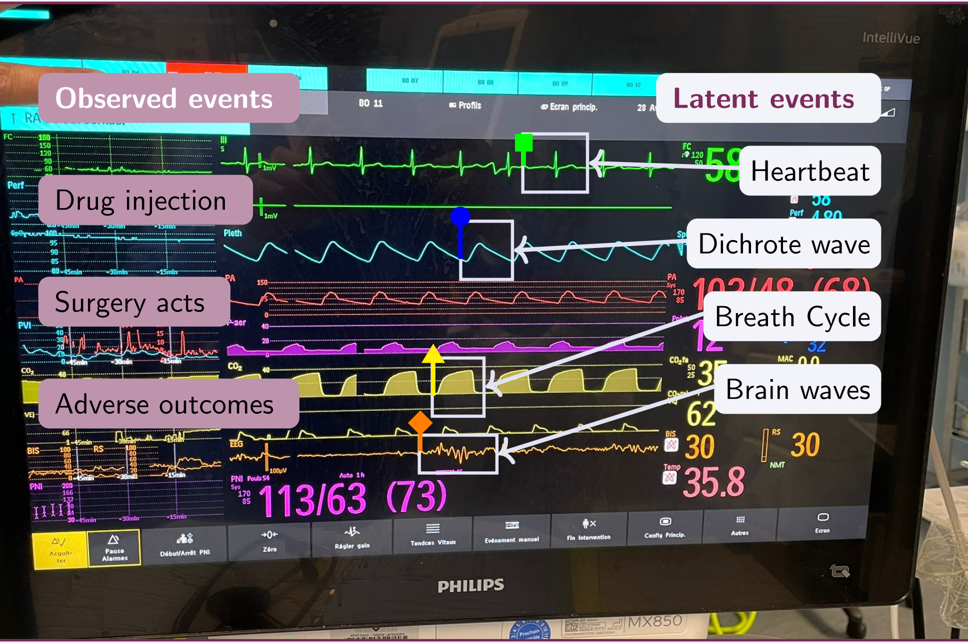
Tokens **Self-supervised pretraining**

Capture the input distribution $\mathbb{P}(X)$ with interaction between tokens.

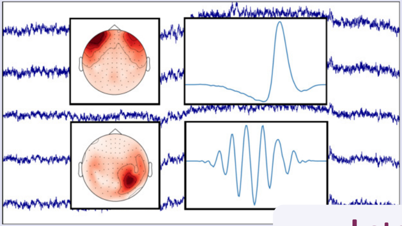
Challenges for signals:

- What are the tokens of the signals?
- How to derive more interpretable models?

Signals’ Tokens: Events



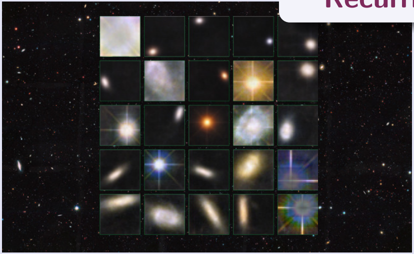
Signals' Tokens: Events



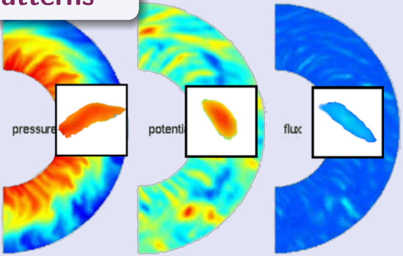
Neuroscience (M

eral Anesthesia

Latent Events are characterized by Recurring Patterns



Astronomy



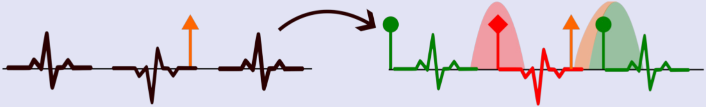
Physics Simulation

EULPS Goal

Model the Distribution of Events for Physiological Signals.

Hyp.: Events' time distribution $\mathbb{P}(\{t_k\}_k)$ is much simpler than $\mathbb{P}(X)$.

Challenge: Need to transform signals into events and model their distribution jointly.



EULPS: Event-based Unsupervised Learning for Physiological Signals

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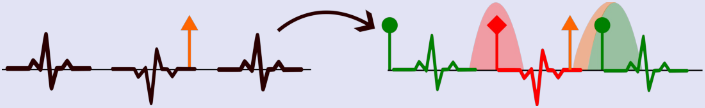


Events' distribution models

Joint Modeling of Signals and Events

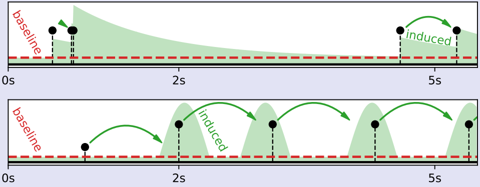
Task-specific Fine-tuning Algo.

Challenge 1

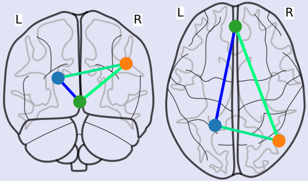
Which models for Physiological Signals Events?

Idea: use Point Processes to model the events' distribution $\mathbb{P}(\{t_k\}_k)$.

Current models (short latency)
Markovian kernels



Novel models (longer range interactions)



Spatial events interactions in the brain

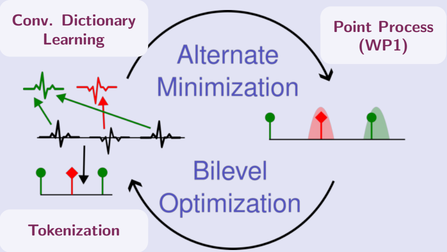
Development: Parametric models beyond Markovian kernels to capture complex events' dependencies and uncertainty in space and time.

Preliminary Study: [Staerman, Allain, Gramfort & **M.** ICML 2023]

Challenge 2

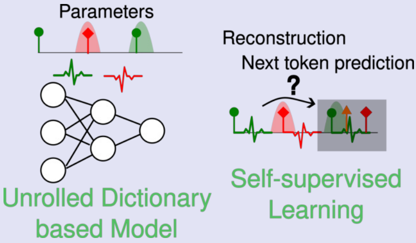
Can we jointly discover the Events and capture their distribution?

Dictionary-based approach



- Interpretable

Deep Learning approach



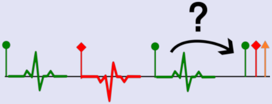
- Easy to fine-tune.

WP3: Validating Representations with Practical Tasks

Challenge 3

How to use event-based representations for machine learning on signals?

Detect adverse events in GA in real time.

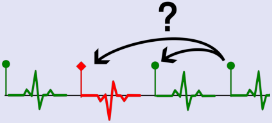


Event Prediction

Characterize atypical records

Anomaly Detection

Link stimuli and brain responses in Neuroscience.



Causality

Idea: Leverage differentiable architectures and model likelihood.

EULPS: Event-based Unsupervised Learning for Physiological Signals

Goal: Propose a new Signal Processing methodology based on Events.

2018-2023
17 papers in top ML conf.

GA Database
46k recordings; 25Tb

Several Domains
Neuroscience
Physics Simulation
Astrophysics

Core ML

Impact

Thomas Moreau

Open Source

Downloads: 26M/month

Contributor

Joblib

Loky

@tommoral

BenchOpt

αcsc

Downloads: 1k/month

References

[ICLR2022] Allain, C., Gramfort, A. & **Moreau, T.** *DriPP: Driven Point Process to Model Stimuli Induced Patterns in M/EEF Signals.* in ICLR 2022.

[ICLR2022a] Malézieux, B., **Moreau, T.** & Kowalski, M. *Understanding approximate and Unrolled Dictionary Learning for Pattern Recovery.* in ICLR 2022.

[NeurIPS2022] Dagréou, M., Ablin, P., Vaiter, S. & **Moreau, T.** *A framework for bilevel optimization that enables stochastic and global variance reduction algorithms.* in NeurIPS 2022.

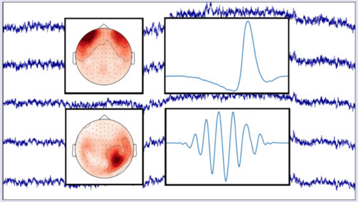
[ICML2023] Staerman, G., Allain, C., Gramfort, A. & **Moreau, T.** *FaDIn: Fast Discretized Inference for Hawkes Processes with General Parametric Kernels.* in ICML 2023.

[NImg 2023] Power, L., Allain, C., **Moreau, T.**, Gramfort, A. & Bardouille, T. *Using convolutional dictionary learning to detect task-related neuromagnetic transients and ageing trends in a large open-access dataset.* NeuroImage 2023.

Task Table

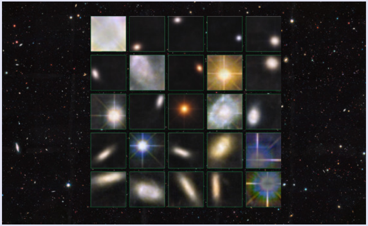
	WP1			WP2		WP3		WP4
	T-1.1 Parametric TPPs	T-1.2 Marked PPs	T-1.3 Spatial PPs	T-2.1 Joint estimation	T-2.2 Unrolled models	T-3.1 Validation	T-3.2 What if?	Open Source Code
Risk	$(\star)$	$(\star\star)$	$(\star\star\star)$	$(\star\star)$	$(\star\star)$	$(\star)$	$(\star\star\star)$	$(\star)$
Thomas Moreau								
PhD#1								
PhD#2								
PhD#3								
PhD#4								
Postdoc#1								
Postdoc#2								
Engineer#1								

Application domains

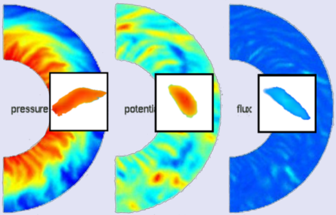


Neuroscience (MEG)
[Dupré*, **M.*** et al. NeurIPS 2018]

General Anesthesia
[Collaboration with Paris Hospitals]



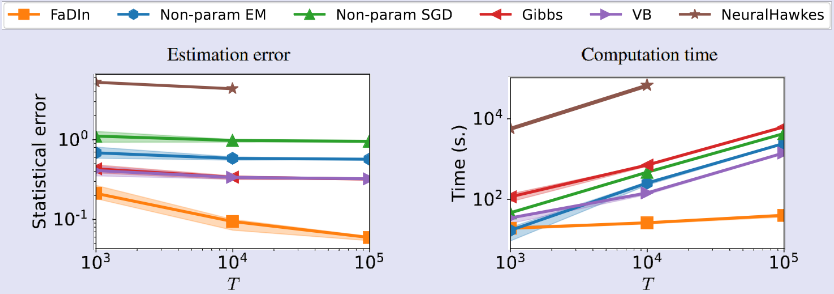
Astronomy
[**M.** & Gramfort, PAMI 2020]



Physics Simulation
[Collaboration with NumPEx Project]

FaDIn – PP framework for novel parametric models

- Opens the way for general parametric PP models
- Based on discretization and finite support kernel.
- Efficient inference thanks to pre-computations,
- Low statistical error,



[Staerman, Allain, Gramfort & **M.** ICML 2023]