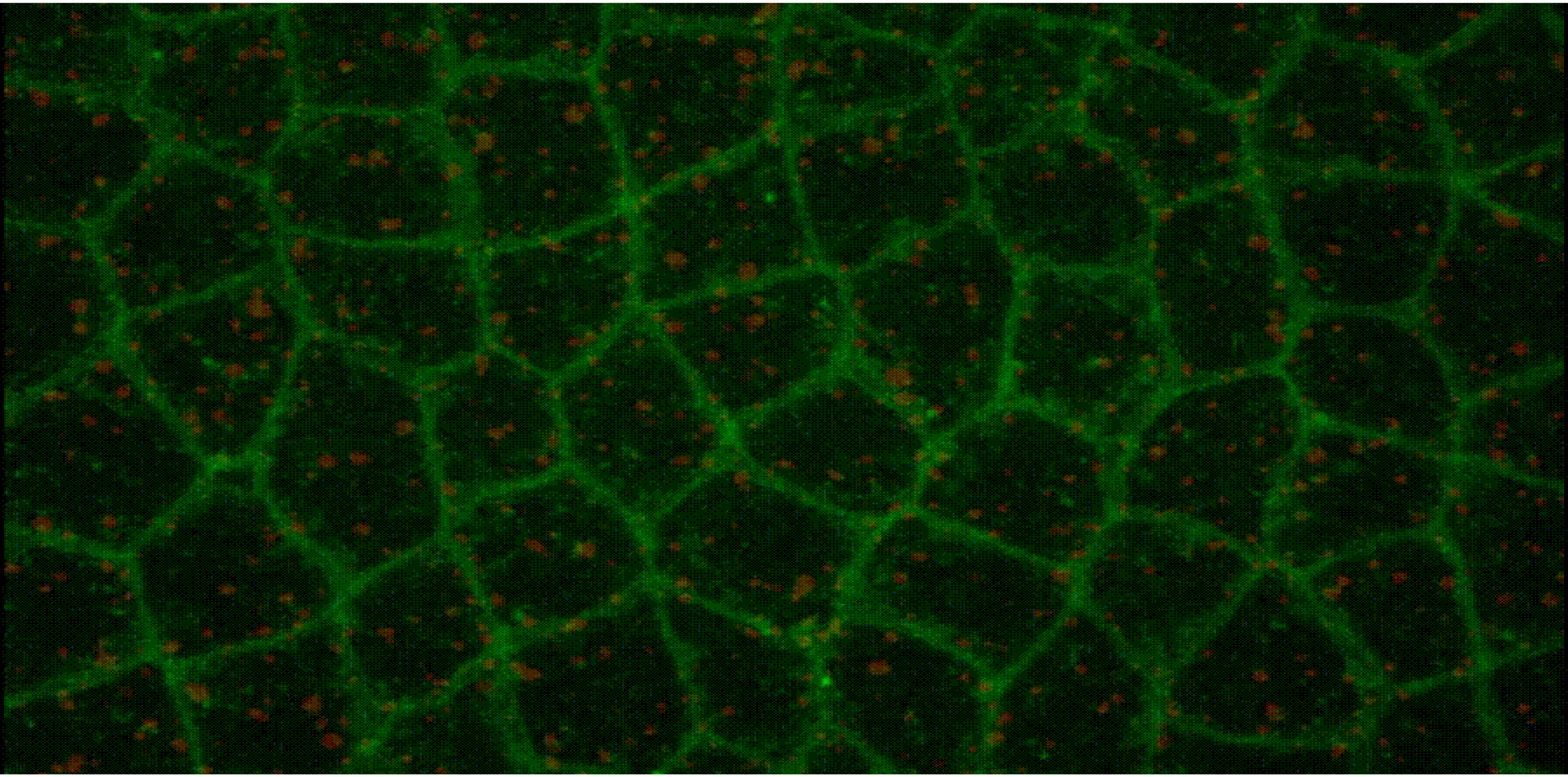
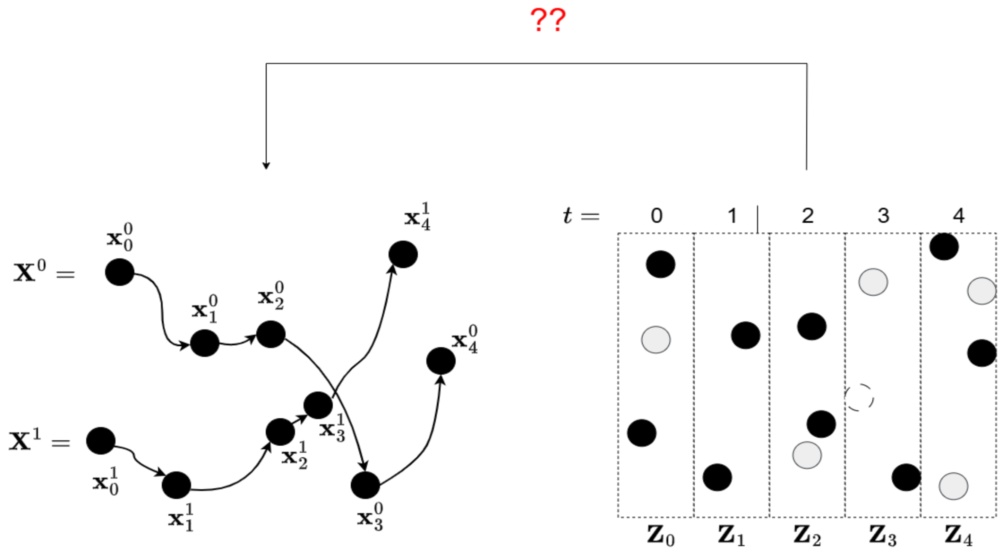
Measuring intracellular dynamics in dense in vivo environments through the combination of large language and stochastic modelling



Team Endotrack,
Centuri Hackathon 2024,
Claudio Collinet, IBDM

Piyush Mishra
Institut de Mathématiques de Marseille,
Institut Fresnel

Particle tracking is an inverse problem



$\mathbf{X} = \{\mathbf{X}^{\mathbf{p}}\}_{p=0:N-1}$

states

$\mathbf{Z} = \{\mathbf{Z}_t\}_{t=0:T-1}$

measurements

corruption

$$\mathbf{Z} = \mathbf{\Lambda} \cdot \mathbf{X} + \epsilon$$

Bayesian filtering provides an iterative approach to track particles

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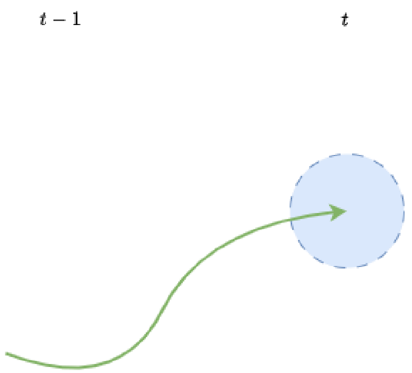

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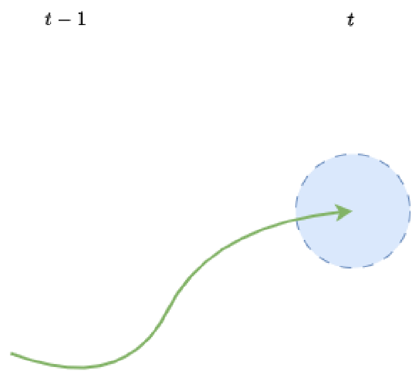

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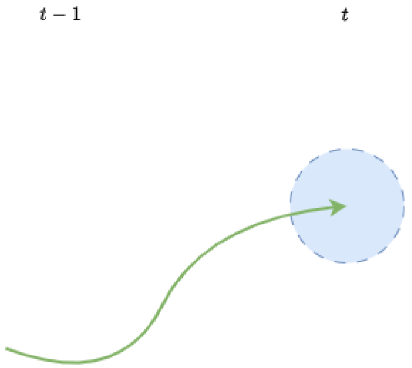

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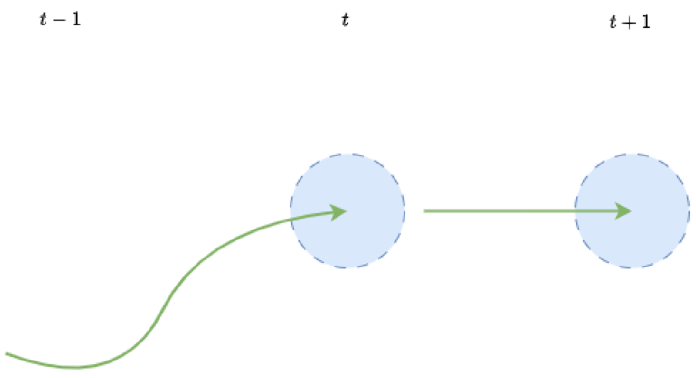
state extrapolate



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association

motion modelling $\mathcal{N}(\mathbf{F}\mu_{t-1}, \mathbf{Q})$

previous evidence $\mathcal{N}(\mu_{t-1}, \Sigma_{t-1})$

$\sum_{\eta_i^t \in \mathbf{H}_t'} p(\mathbf{z}_t|\mathbf{x}_t, \eta_i^t) p(\eta_i^t|\mathbf{x}_t)$

$\mathcal{N}(\mu_t^p, \Sigma_t^p)$

??

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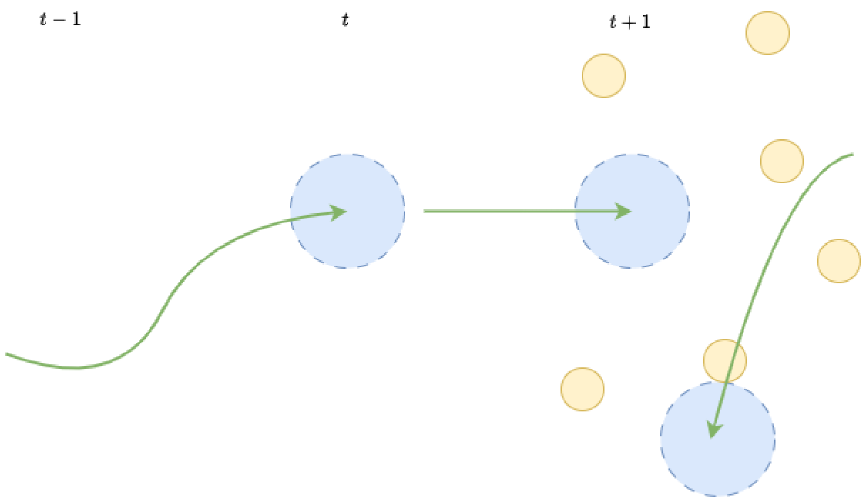
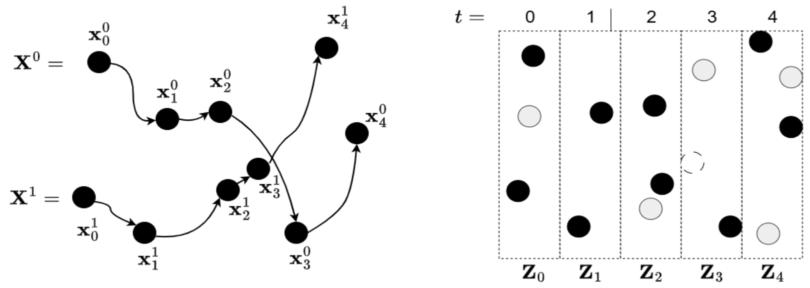


The decision of which hypotheses to eliminate is not trivial

??



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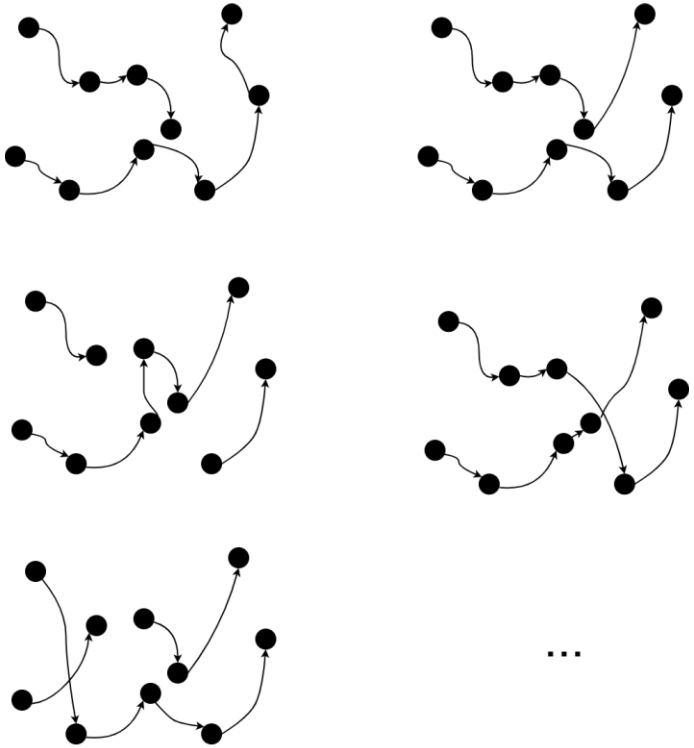
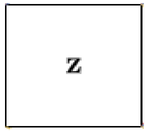


$|\eta_i| \propto N!^t$

hypotheses

Learn particle-interactions instead of assuming them



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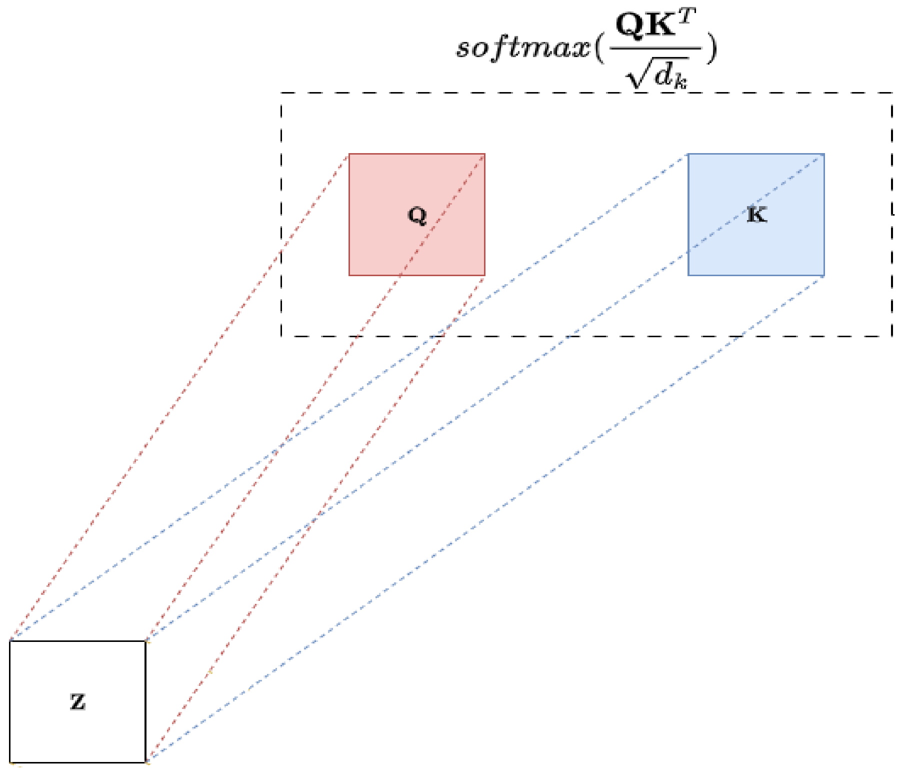

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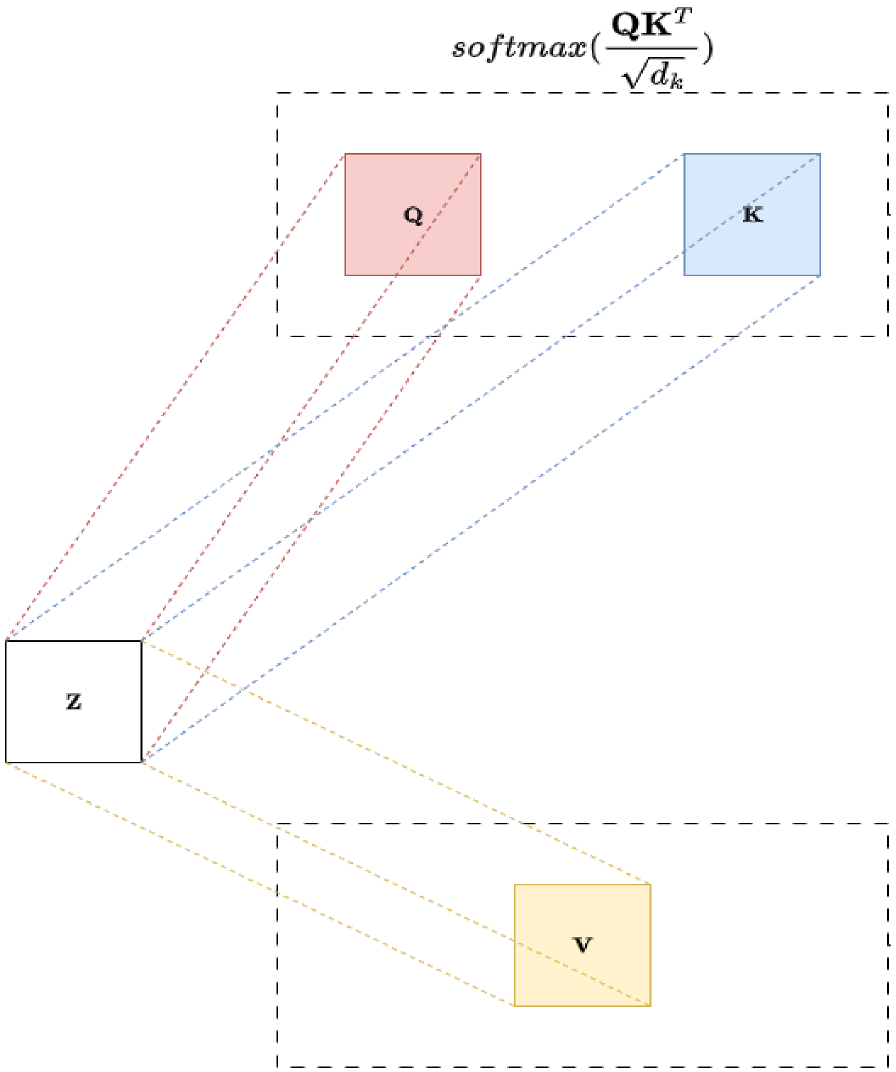

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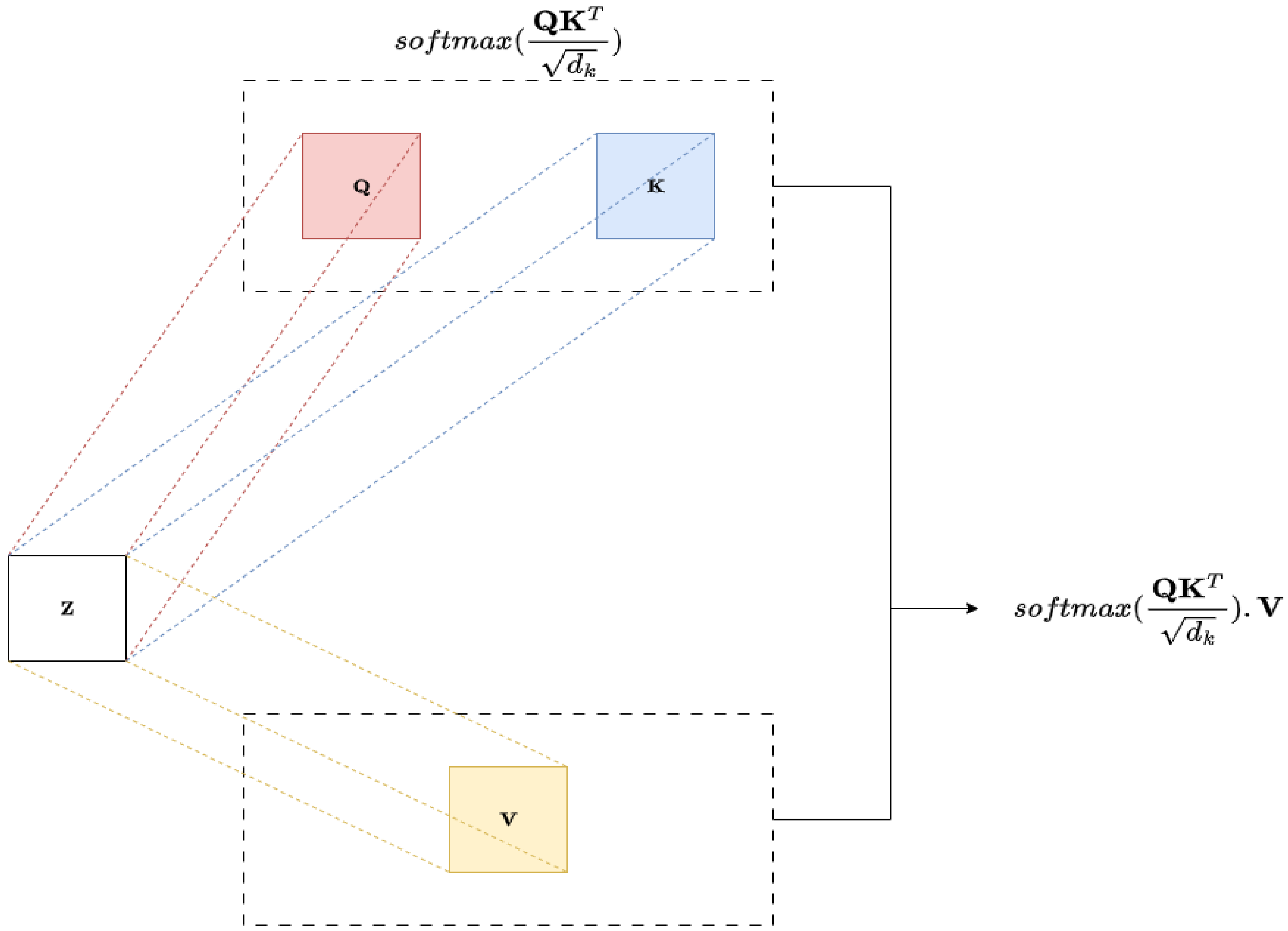


We tested a basic attention scheme for proof-of-concept

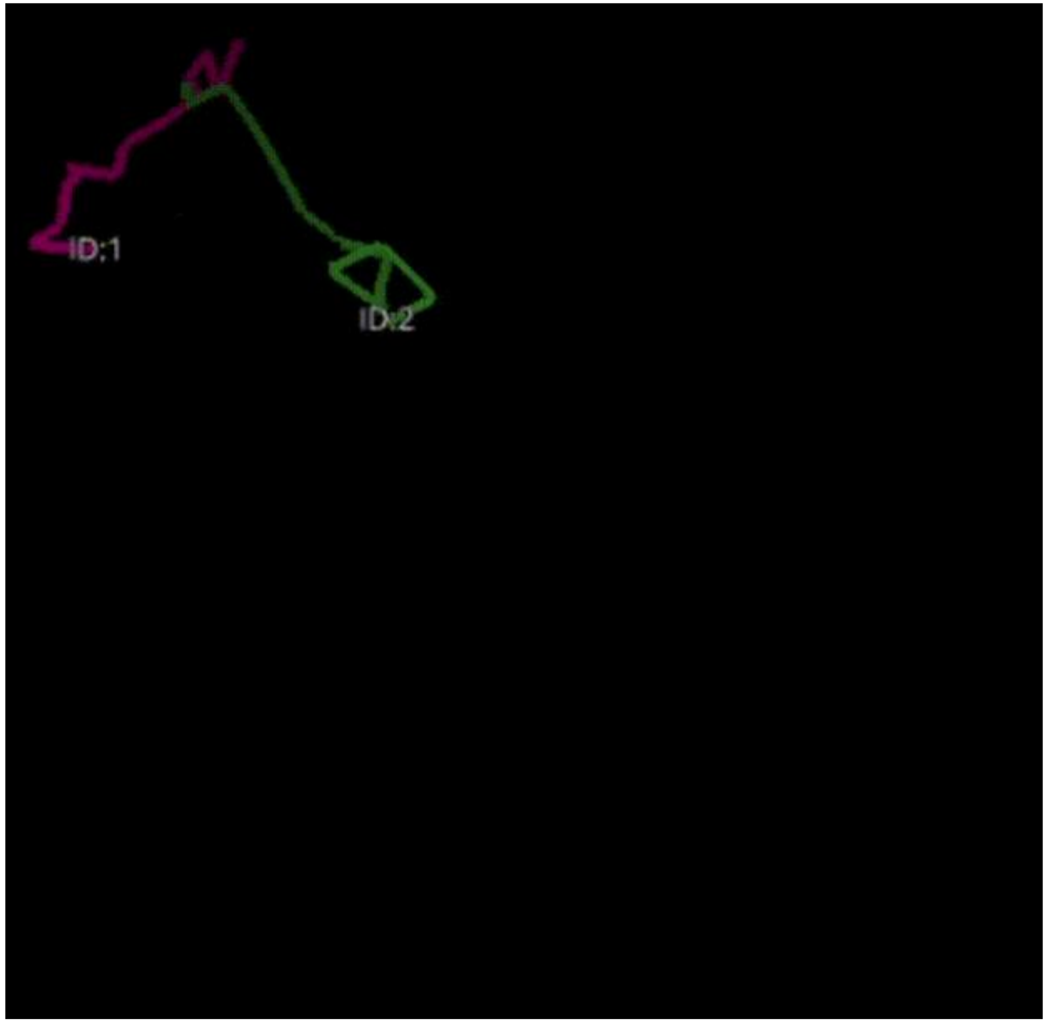
$$y^{t,p} = y^{t-1,p} + \varepsilon^{t,p} + \delta^{p}$$

drift

randomness with
process noise

$$z^{t,p} = y^{t,p} + \omega^{p}$$

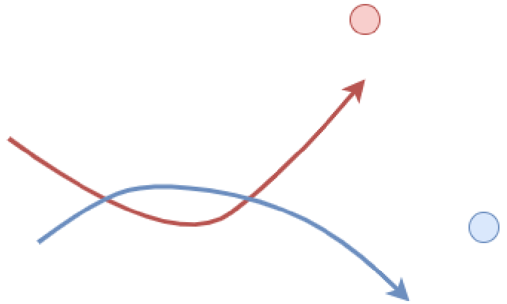
measurement noise



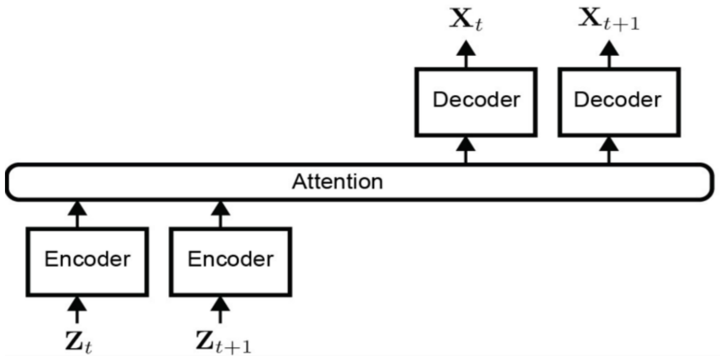
Mishra, Roudot, **Comparative study of transformer robustness for multiple particle tracking without clutter**, EUSIPCO 2024

We tested a basic attention scheme for proof-of-concept

Bayesian approach
Multiple hypothesis tracking (MHT)
Greedy association

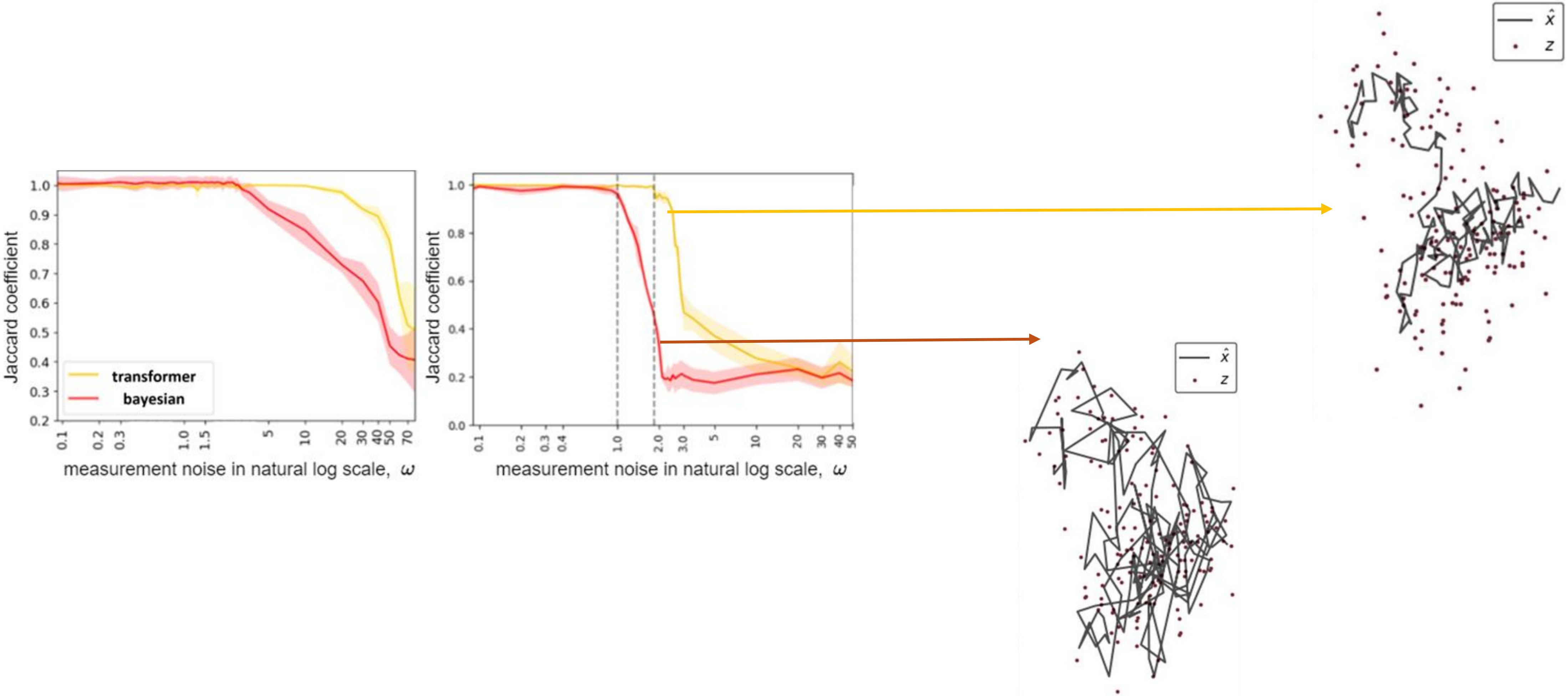


Transformer
Non-iterative learning & iterative prediction



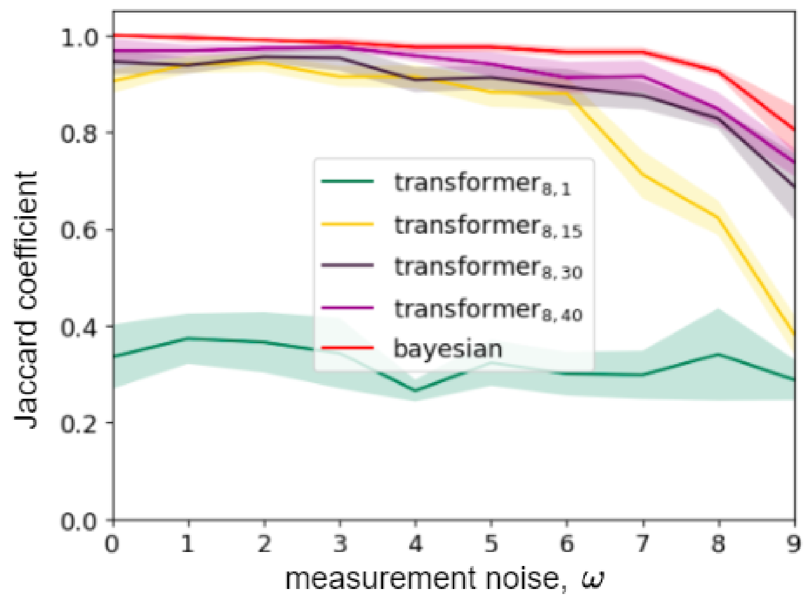
Mishra, Roudot, EUSIPCO 2024

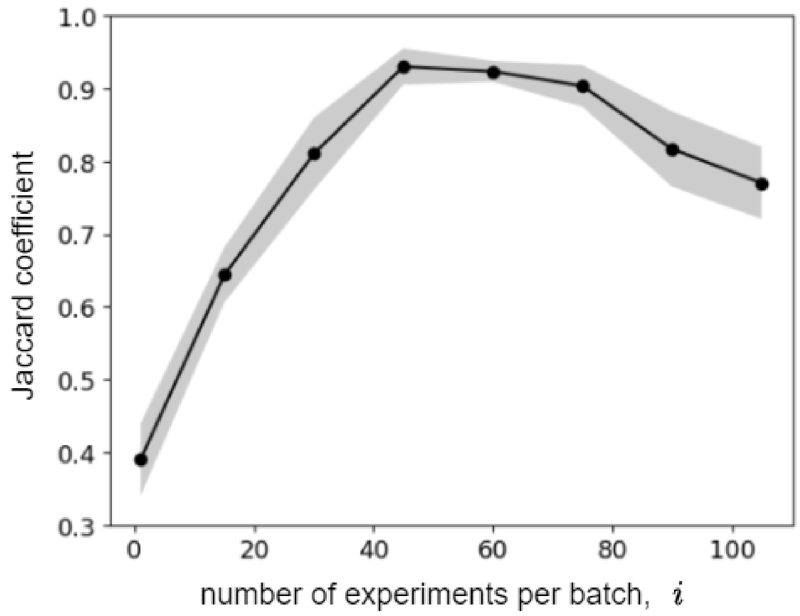
Attention is robust to increasing measurement noise



Mishra, Roudot, EUSIPCO 2024

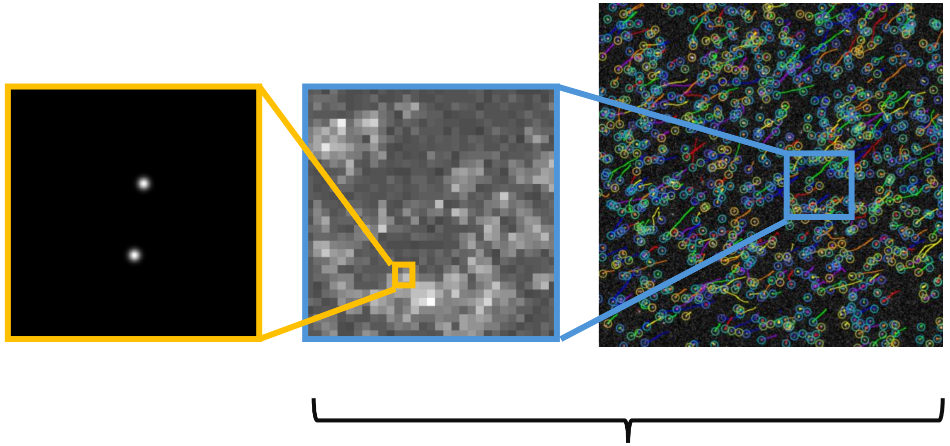
Bayesian filtering is optimal for small hypothesis sets





Mishra, Roudot, EUSIPCO 2024

Scaling up: split the problem into specialised tasks



- Proof of concept
- Only measurement noise
- No detection errors

- Tracking specific architecture
- False positives and negatives along with measurement noise

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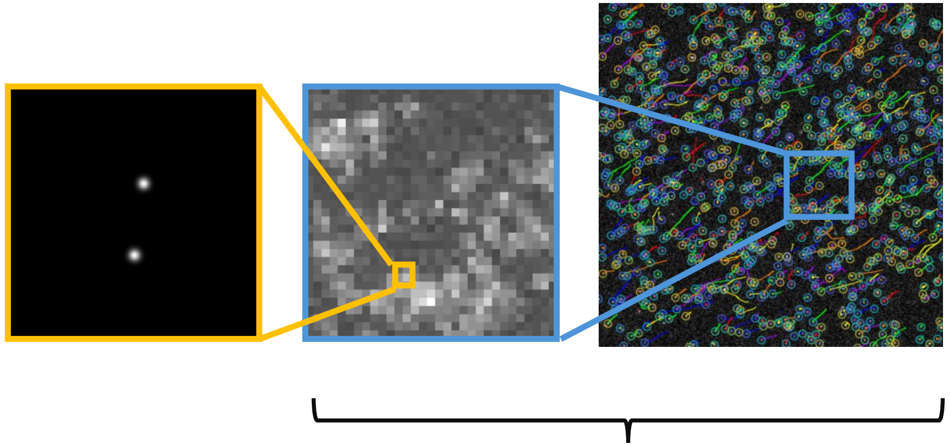

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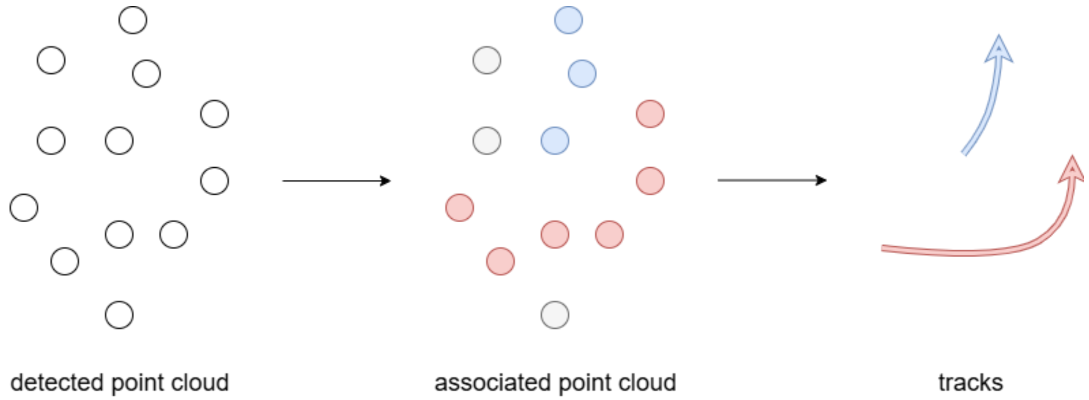
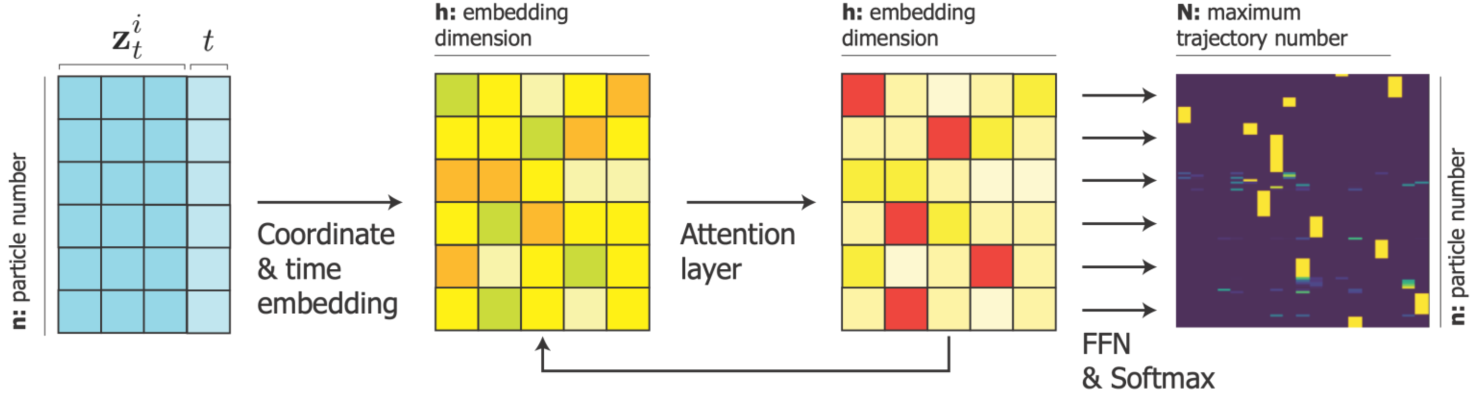


Mishra, Roudot, **Attention-Bayesian Hybrid Approach for Modular Multiple Particle Tracking**, 2025

ABHA first prunes the hypothesis-set, then filters each set individually

Stage 1:

Attention assigns each detection to a class of potential trajectory



Mishra, Roudot, 2025

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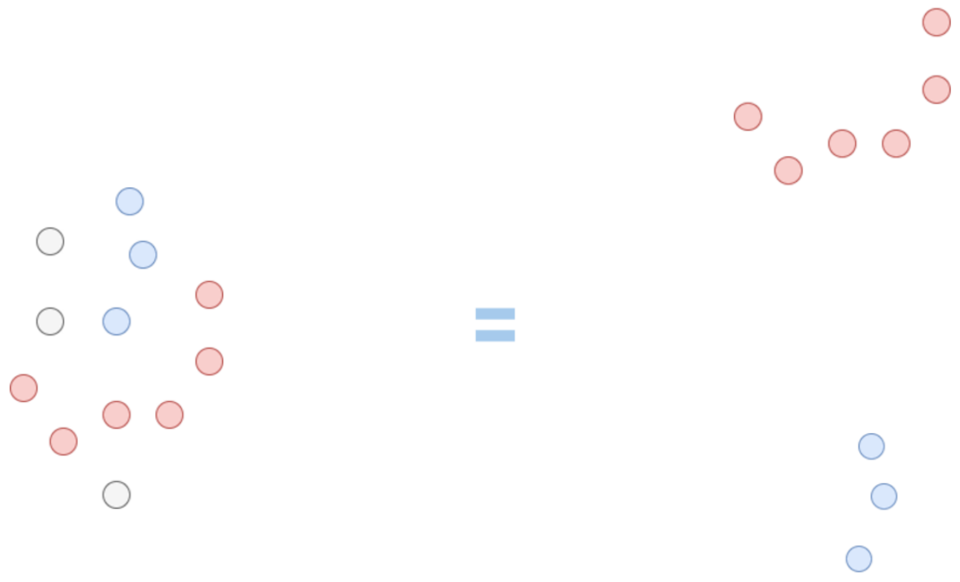
Stage 1:

Attention assigns each detection to a class of potential trajectory

Stage 2:

Each class is isolated and filtered using the Bayesian approach



Mishra, Roudot, 2025

Once pruned, there is only one measurement to associate: Kalman filtering

$$p(\mathbf{x}_t|\mathbf{z}_{1:t}) \propto \quad \text{likelihood} \quad \times \quad \text{prior}$$

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association — motion modelling — previous evidence

$\mathcal{N}(\mathbf{F}\mu_{t-1}, \mathbf{Q})$ $\quad \mathcal{N}(\mu_{t-1}, \Sigma_{t-1})$

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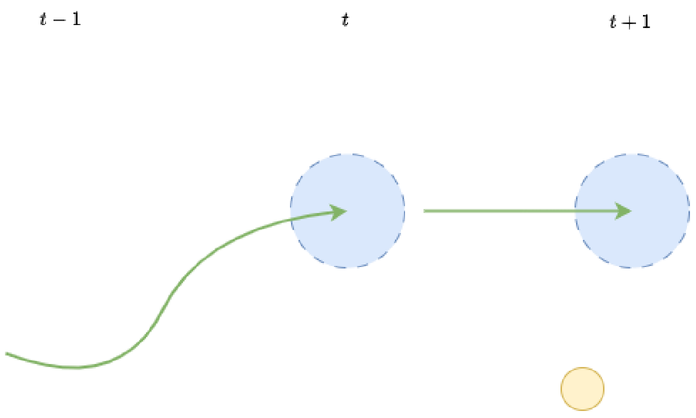

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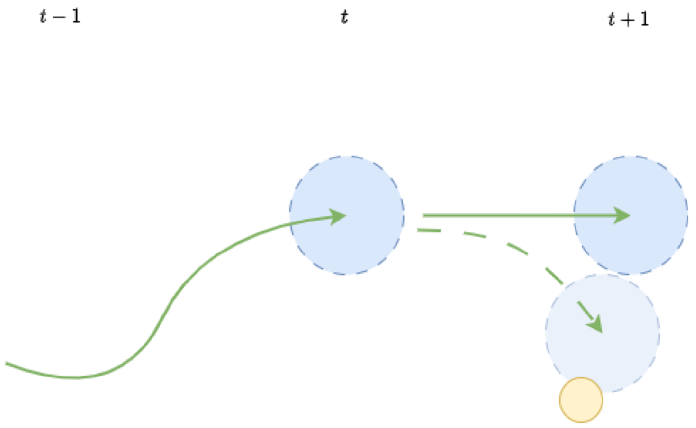
state extrapolate

$$\mathcal{N}(\mathbf{x}_t, \Sigma_t)$$

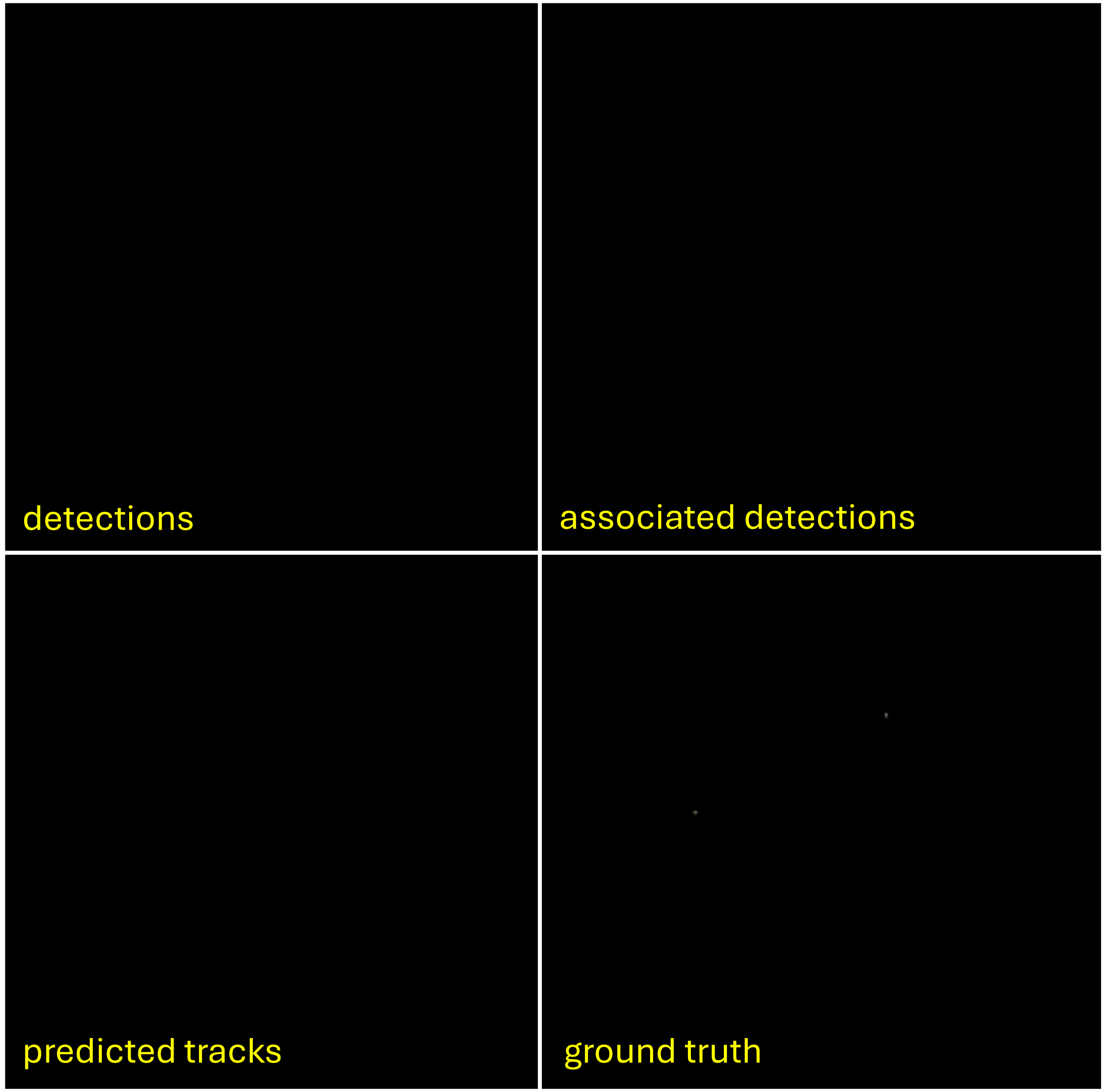
$$\mathbf{x}_t = \mu_t^p + \mathbf{K}_t(\mathbf{z}_t - \mathbf{H}\mu_t^p)$$

$$\Sigma_t = (\mathbf{I} - \mathbf{K}_t\mathbf{H})\Sigma_t^p$$

state update



Promising qualitative results on aggressively blinking detections



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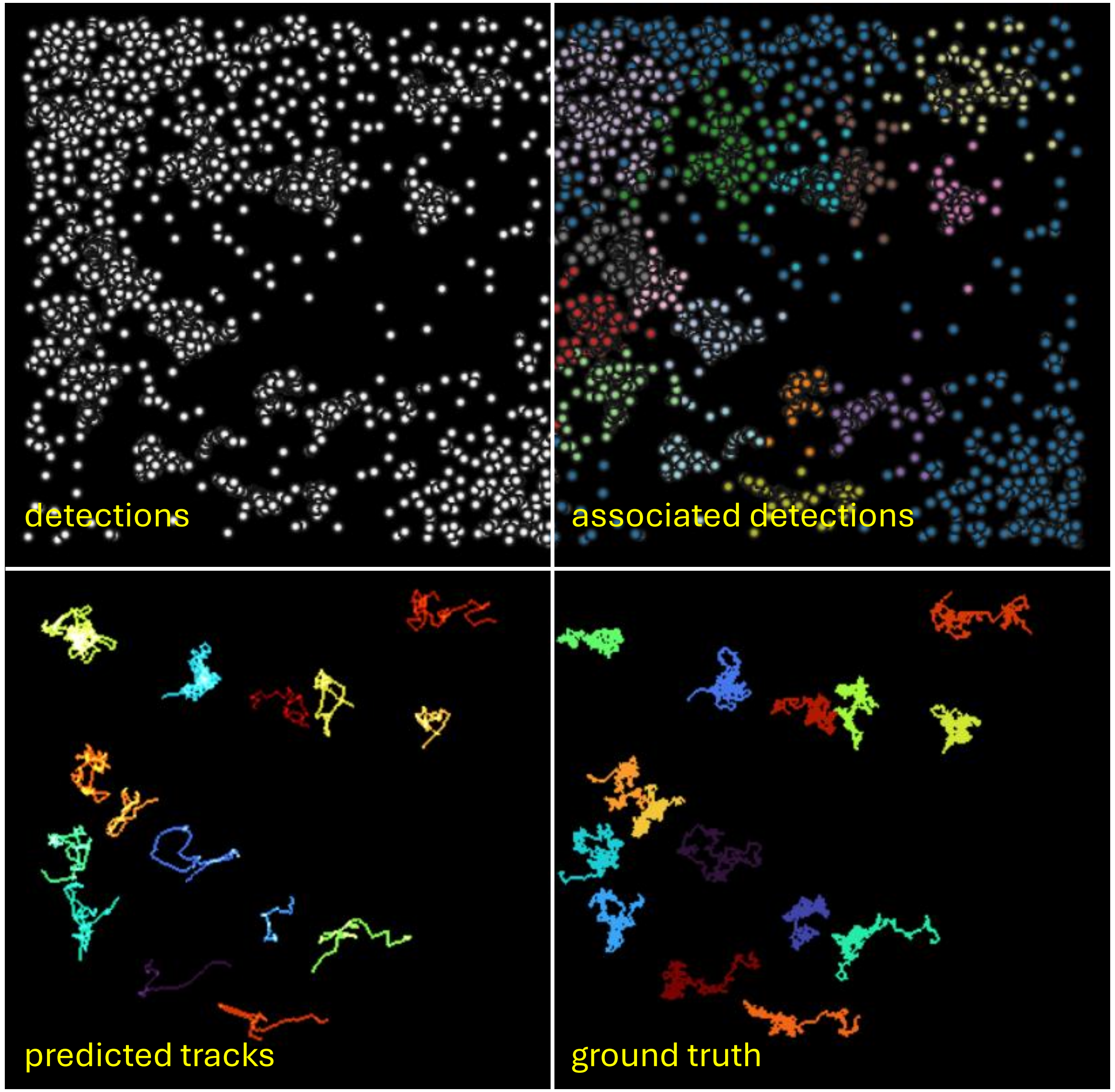
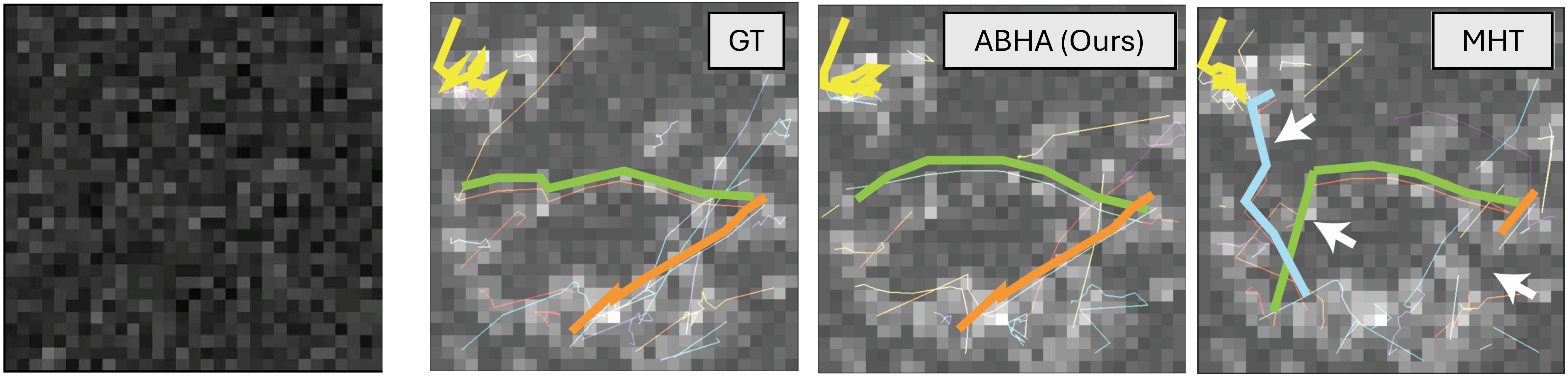


Both qualitative & quantitative reduction of tracking artifacts by ABHA on virus trafficking data

TGOSPA score (**lower is better**) captures:
- location errors
- missed & false detection error
- identity switches
- track fragmentation

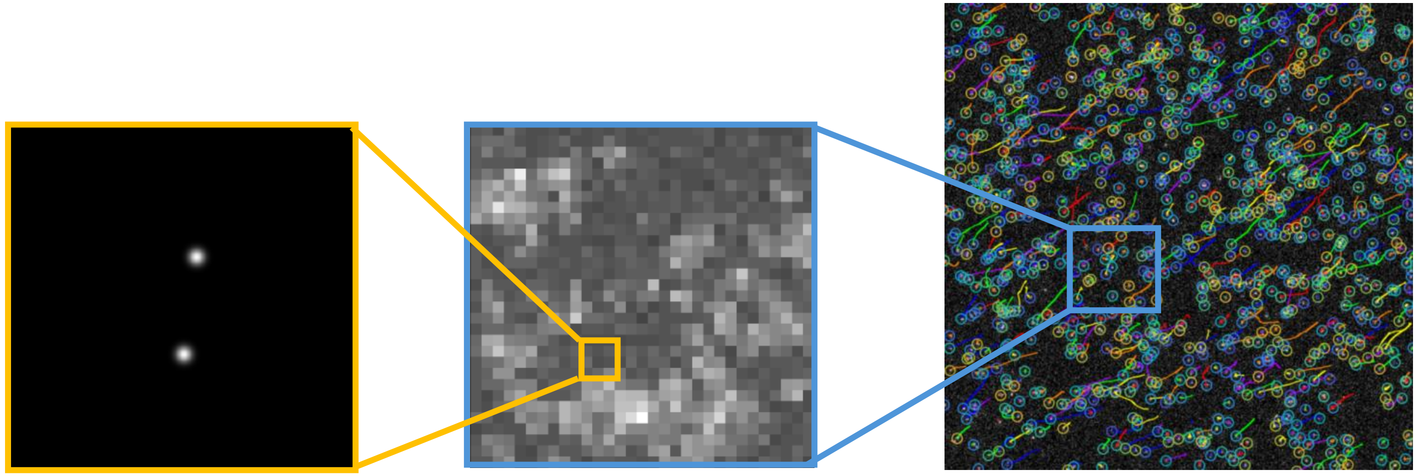


TGOSPA = 2.116 +- 0.094

TGOSPA = 5.743 +- 0.103

Mishra, Roudot, 2025

Ongoing work: prove it small, then go big



Proof-of-concept for robustness of attention, Mishra, Roudot, 2024

Proof-of-concept for hybridisation (ABHA), Mishra, Roudot, 2025

A scaled tool to track a large bulk of particles

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- A conservative yet precise tracker
- Ongoing work: scaling for a large number of particles

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FOR LIVING SYSTEMS

Thank you ☺

Philippe Roudot

Jules Vanaret

Sophie Carneiro-Esteves

Elhamou Ali

Guillaume Hermitte

Laura Neschen

INSTITUT FRESNEL MARSEILLE

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