Comparative study of transformer robustness for multiple particle tracking without clutter

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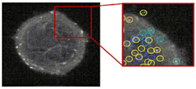
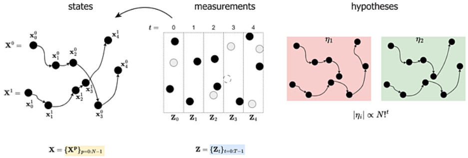
Motivation Fluorescent particle tracking poses a challenging inverse problem

Fluorescence microscopy images nanoscale particles that must be detected and tracked over time





Challenges

1. Biological processes are stochastic, leading to highly variable dynamics despite similar particle appearances.
2. Low rate of photonic emission leads to noisy images or low framerate. We consider the second scenario in this work.
3. Combinatorial explosion of the number of possible trajectories

Related work Conventional methods use a two-step estimator for the particle state and trajectory link

The Bayesian filtering equation provides a general framework for the problem of particle tracking:

$$p(\mathbf{X}_t|\mathbf{Z}_{1:t}) = p(\mathbf{Z}_t|\mathbf{X}_t)\int p(\mathbf{X}_t|\mathbf{X}_{t-1})p(\mathbf{X}_{t-1}|\mathbf{Z}_{1:t-1})d\mathbf{X}$$

representing the a priori knowledge on molecular dynamics, the state transition probability (e.g. predicting the position and speed at the next time step) and the likelihood of the set of measurement, that can be computed considering trajectory-to-measurement association

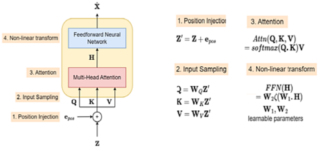
$$p(\mathbf{Z}_t|\mathbf{X}_t) = \sum_{\eta_p^t \in \mathbf{H}_t^t} p(\mathbf{Z}_t|\mathbf{X}_t, \eta_p^t)p(\eta_p^t|\mathbf{X}_t)$$

When all the hypotheses can be computed, a priori models are known and all probability computations are tractable, this estimator is optimal. However, most methods have to prematurely prune hypotheses to save on computations (a.k.a. gating), leading to a suboptimal solution. We perform our comparison in both scenarios.

RNNs have been used for motion prediction (Spilger et. al, 2021), but couldn't outperform Bayesian filtering (Roudot et. al, 2023). Recent work on transformers have focused on complex motion only with little combinatorial challenges (Pinto et. al, 2022).

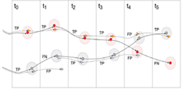
Method A transformer-based joint estimator of both particle state and trajectory linking

The transformer (Vaswani, 2017) architecture can be used to make decisions on both states and hypotheses simulatenously, as well as considering multiple state together. We trained our model using simulations of 2-particle systems (Brownian motion).



Results Transformer outperforms the Bayesian filter in long sequences but cannot match its optimal properties in short sequences

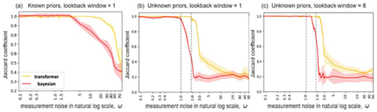
A. Jaccard coefficient gives accuracy



$$JC = \frac{TP}{TP+FP+FN} = \frac{8}{8+3+2} = 61.5\%$$

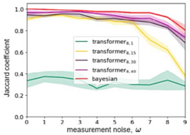
B. Transformer is robust to increasing noise in long sequences

Accuracy on increasing the measurement noise using exact or approximated priors for both filtering and simulation. Lookback window refers to the number of previous frame used to select the best trajectory hypothesis.

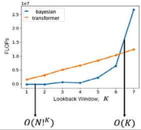


C. When Bayesian filtering is optimal, transformer remains sub-optimal

For short sequences, increasing the training size leads to to increasing performance for the transformer, until a a plateau is reached. Increasing training size further decreases the transformer performances.

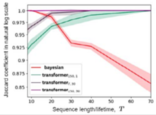


D. Transformer is significantly more efficient when increasing the lookback window



E. Transformer is robust to increasing sequence length

Two regimes: short sequences benefit from B.F. accuracy, whiile long sequences benefit from the transformer robustness.



Take-away

1. Transformers exhibit **improved robustness** & **computational efficiency on long sequences.**
2. Transformers are beneficial even when motions are elementary and a priori is known, thanks to its ability to handle complex combinatorial problems.

References

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