Applications of System Identification

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Abstract

Learning linear dynamical systems (LDS) is a well-studied problem, with applications ranging from solving joint problems to identifying pathways of biochemistry. We presented globally convergent methods and EM heuristics to apply LDS on joint partitioning. The biggest advantage of our method is that the dimension of the hidden state does not need to be known ahead of time. Additionally, we simulated a dataset based on the Krebs cycle, which is a benchmark for methods in causal learning. One focus would be on the application of an iterated additive-noise model estimation via non-commutative polynomial optimization (IANN) in causal discovery. Computational experiments show benefits in certain applications, where the hidden state can be expected, but where its dimension is unknown. Such as in the Krebs cycle or modelling metabolism more broadly.

Problem Preliminaries

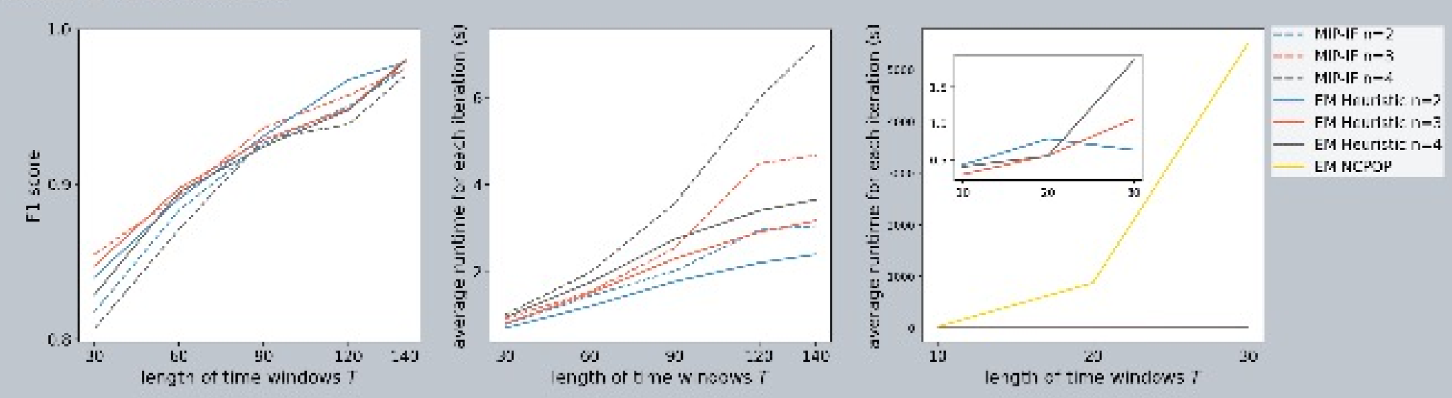
- To find the global optima of the objective function subject to the feasible constraints arising from the LDS.
- The optimal objective values can be bounded in non-convex **mixed-integer nonlinear programs (MINLPs).** However, a significant drawback of LDS-based methods is their reliance on a priori knowledge of the hidden state dimension.
- Extend research to a **Non-Commutative Polynomial Optimization (NCPOP)**, which is an operator-valued optimization problem. Given the input data p(x) and q_i (x), the standard form is

$$\begin{aligned} \underset{(\mathcal{H}, X, \psi)}{\text{minimize}} \quad & \langle \psi, p(X)\psi \rangle \\ \text{subject to} \quad & q_i(X) \succcurlyeq 0, i = 1, \ldots, m, \\ & \langle \psi, \psi \rangle = 1, \end{aligned}$$

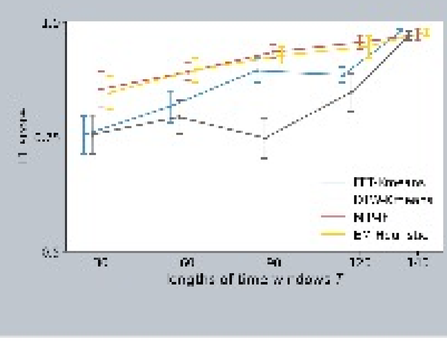
where q_i (x) are positive semidefinite.

EM Heuristic

- Finding an optimal trajectory for a set of trajectories is easier than clustering the trajectories. Therefore, as a complement to the NCPOP formulation, we provide an efficient Expectation-Maximization (EM) procedure for clustering time-series.
- **Experimental results:**



- **Baseline:**



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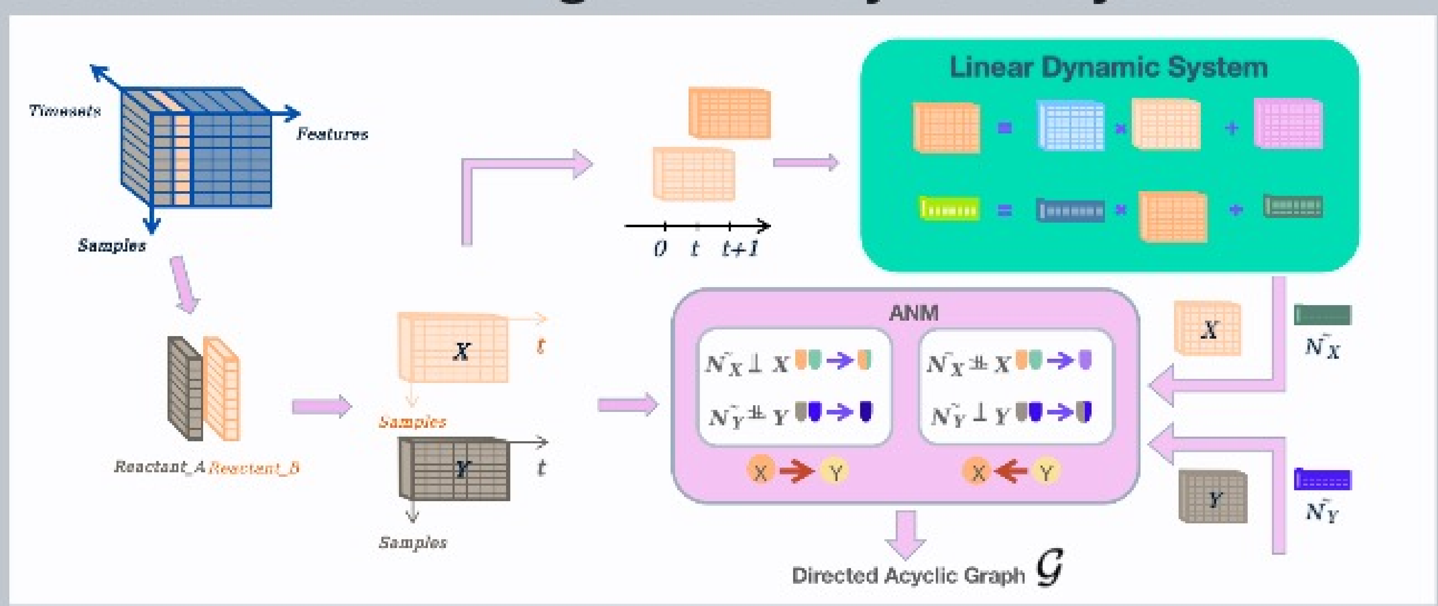
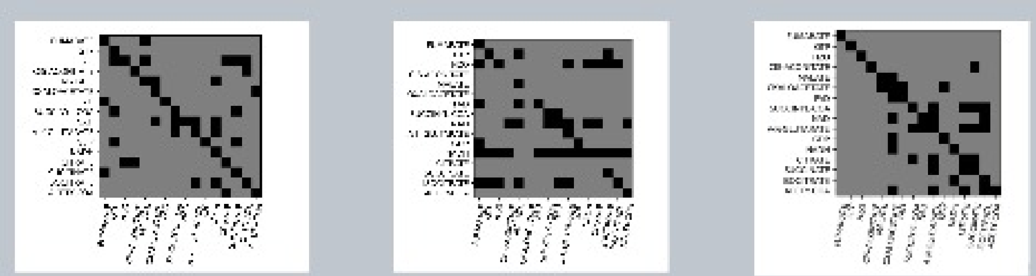
Causal Learning & Future Work

- The learning of Nonlinear causal discovery with additive noise models (ANM) can be reduced to the learning of linear dynamic systems.



- We consider training a rich class of causal models from time-series data and we suggest the use of the Krebs cycle and models of metabolism more broadly. Here are adjacency matrices produced by the ground truth and prediction.



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References

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