Exploiting Causality for Efficient Monitoring in DBNs

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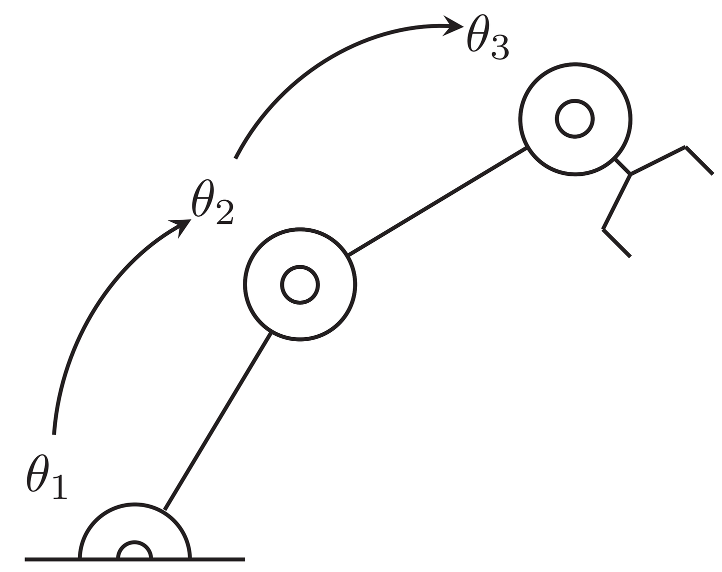
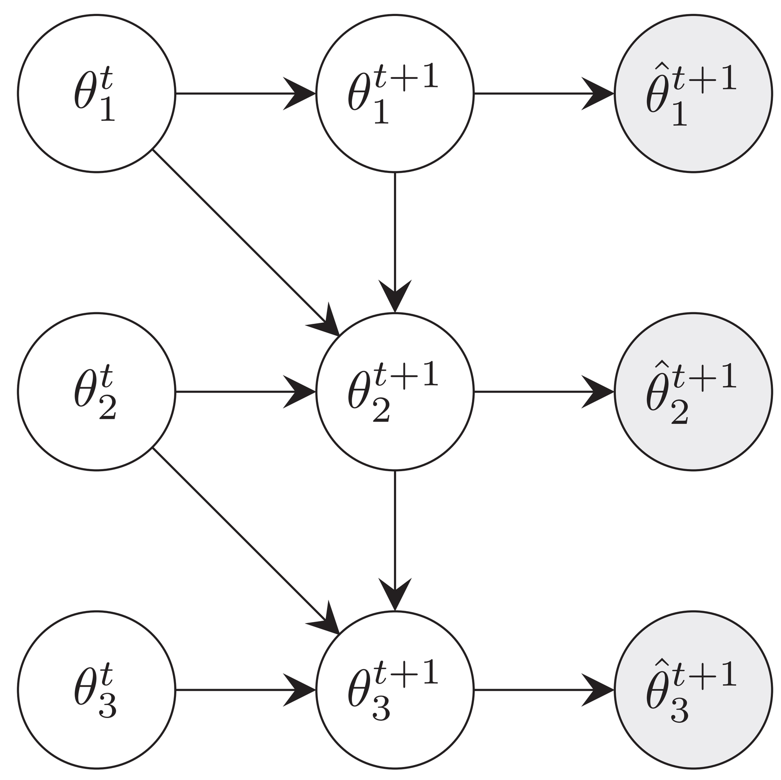
Introduction

- Dynamic Bayesian network (DBN) useful to model actions in decision process with partial observability
- Agent maintains belief state b^t which is a probability distribution over state space of process
- **Monitoring (filtering) task:** update belief state b^t to b^{t+1} based on stochastic observation o^{t+1}
  $\Rightarrow$ Difficult task in complex systems
- Existing methods do not exploit causal structure
  $\Rightarrow$ **Idea:** exploit *causality* to accelerate monitoring



Robot arm with absolute joint orientations θ_i



Passivity-based Monitoring

Active and Passive Variables:

- Each action a modelled as DBN Δ^a
- State variables in Δ^a are either active or passive

Passive variable x_i may only change value if any of its parents in Δ^a change value (else *active*)

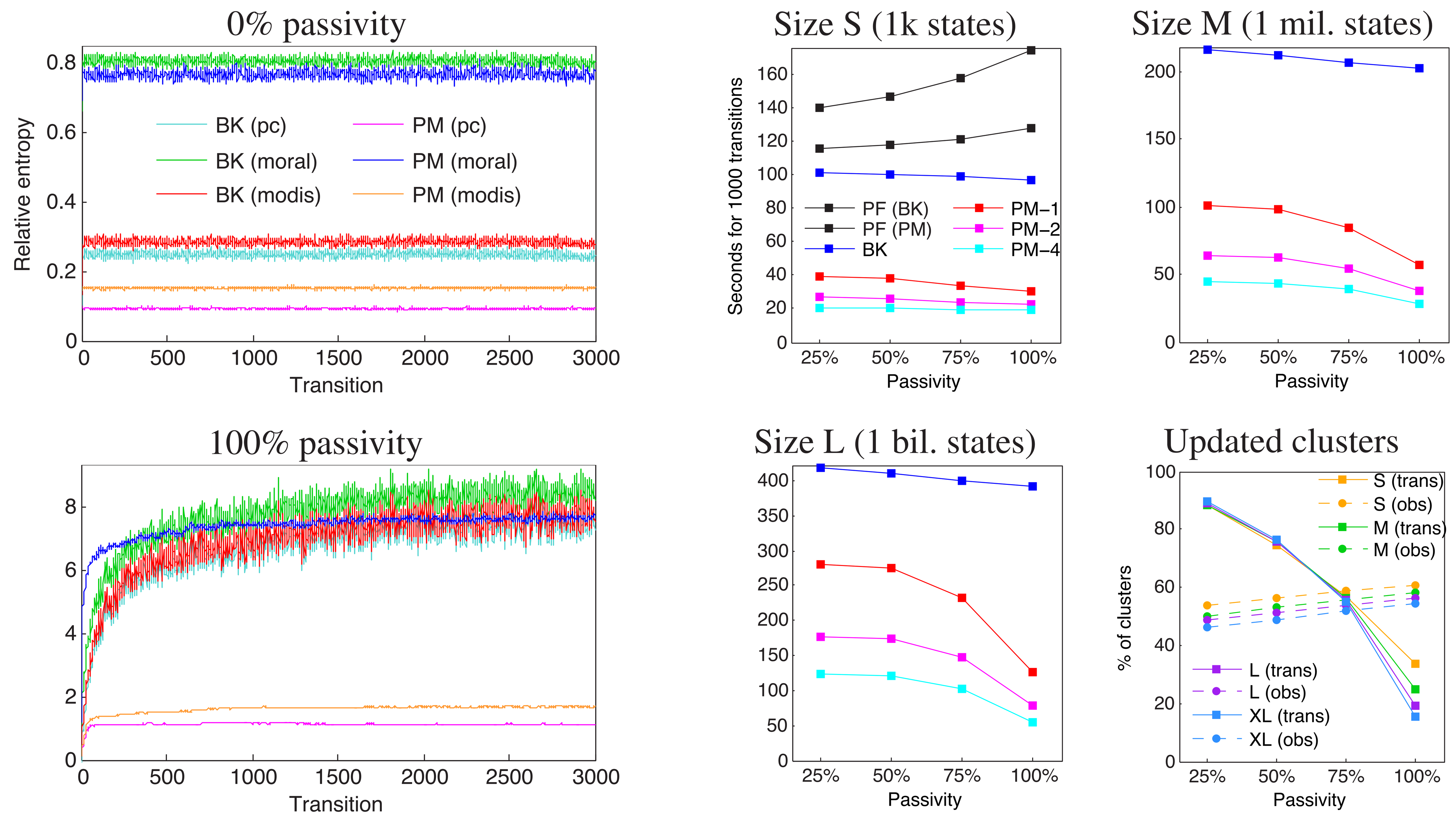
- Can be determined from Δ^a (edges and CPD)

Passivity-based Monitoring (PM):

1. Belief state b^t represented as product of K belief factors b_k^t, such that $b^t(s) = \prod_{k=1}^{K} b_k^t(s)$. Each belief factor b_k^t associated with cluster C_k of state variables.
2. Transition step $b_k^t \rightarrow \hat{b}_k^{t+1}$ performed for all clusters C_k which include active variables in Δ^{a^t}, or to which there is a causal path from an active variable.
3. Observation step $\hat{b}_k^{t+1} \rightarrow b_k^{t+1}$ performed for all clusters C_k which depend on observation variables, using only observation clusters $\hat{C}_l$ relevant for C_k.

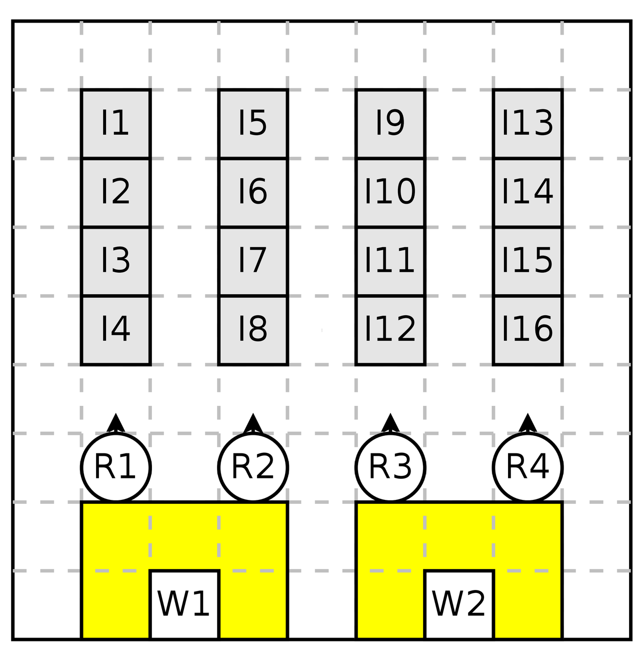
Experiment: Synthetic Processes

- Accuracy and timing in synthetic processes of 4 sizes:
  - S: n=10, m=3 *(n = # state vars, m = # obs. vars.)*
  - M: n=20, m=6
  - L: n=30, m=9
  - XL: n=40, m=12
- All state and observation variables binary
- Processes generated using Gaussian mixture models
- Three clustering methods: $\langle pc \rangle$, $\langle modis \rangle$, $\langle moral \rangle$
- Benchmark monitoring methods:
  - Particle filtering (PF) (Gordon et al., 1993)
  - Boyen-Koller (BK) (Boyen and Koller, 1998)
- **X% passivity:** X% of non-target variables were passive

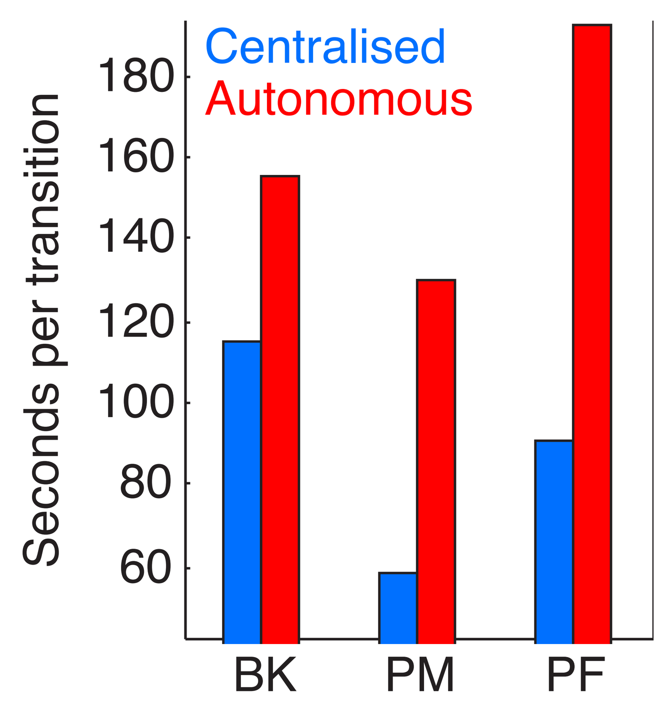


Experiment: Multi-robot Warehouse

- Simulation of complex multi-robot warehouse system
- **Actions:** move forward/backward, turn left/right, load/unload inventory pod, do nothing
- **Sensors:** which pod loaded (if any), direction facing
- Move/turn operations and direction sensor **stochastic** (i.e. small chance of incorrect result)
- Two control modes: centralised and autonomous
- Robot tasks generated by external scheduler



Initial state of warehouse simulation



References:

Gordon, N., Salmond, D., Smith, A. (1993). Novel approach to nonlinear/non-Gaussian Bayesian state estimation. In Radar and Signal Processing, IEE Proceedings F, Vol. 140, pp. 107–113.

Boyen, X., Koller, D. (1998). Tractable inference for complex stochastic processes. In Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence, pp. 33–42.

See full article for more details: http://arxiv.org/abs/1401.7941