

Temporal Probabilistic Relational Models and Beyond

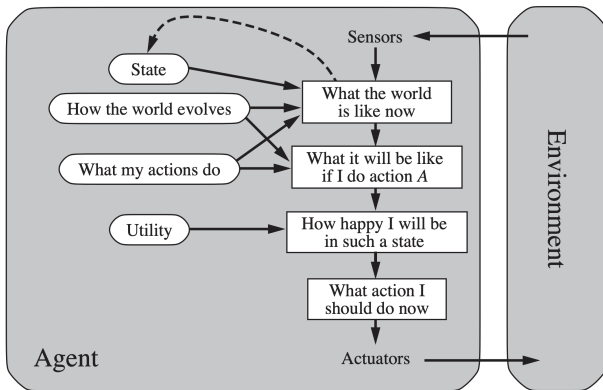
Marcel Gehrke

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University of Lübeck

January 30, 2023

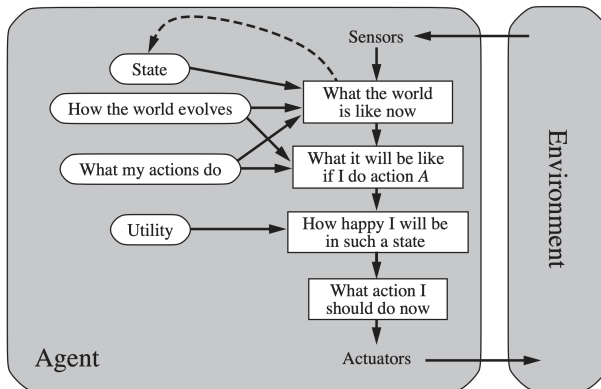
Artificial Intelligence: An Agent Perspective

Russell and Norvig (2020)



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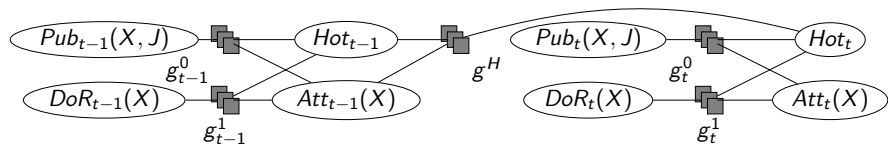


Knowledge representation and reasoning under uncertainty
→ Statistical Relational AI

Probabilistic Temporal Relational and Lifted Models

Murphy (2002), Poole (2003), Ahmadi et al. (2013)

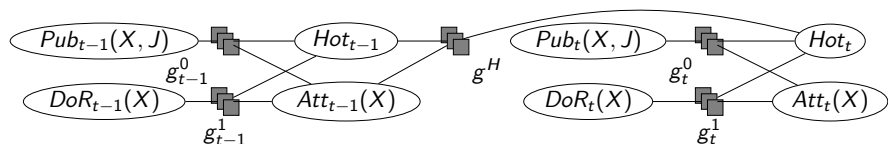
Parfactor graph G : **Compact encoding** of full joint d. $P_G = \frac{1}{Z} \prod_{f \in gr(u(G))} f$



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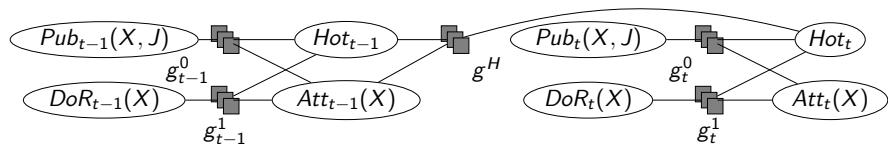
Marginal distribution query: $P(A_{\pi}^i | E_{0:t})$ w.r.t. the model:

- Prediction: $\pi > t$ (is the topic hot in $\pi - t$ days?)
- Filtering: $\pi = t$ (is the topic hot today?)
- Hindsight: $\pi < t$ (was the topic hot $t - \pi$ days ago?)

Probabilistic Temporal Relational and Lifted Models

Murphy (2002), Poole (2003), Ahmadi et al. (2013)

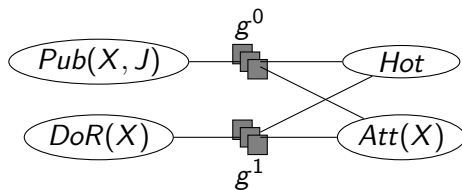
Parfactor graph G : Compact encoding of full joint d. $P_G = \frac{1}{Z} \prod_{f \in \text{gr}(u(G))} f$



QA: Eliminate all non-query variables
while **avoiding grounding and unrolling G** as well as building P_G

QA: Lifted Variable Elimination (LVE)

Poole (2003), de Salvo Braz et al. (2005), Milch et al. (2008), Taghipour et al. (2013)

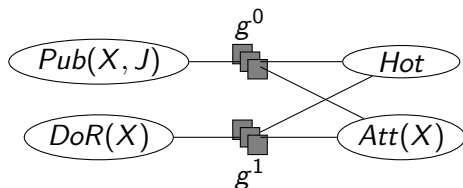


$$P(\text{DoR}(\text{eve}))$$

\sum_V indicates a sum over the values of V , $|X|$ a domain size

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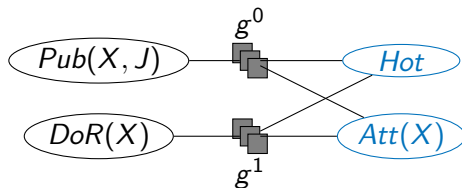


$$P(\text{DoR}(\text{eve})) \propto \sum_{\text{Hot}} \left(\sum_{\substack{\text{DoR}(X) \\ X \neq \text{eve}}} \sum_{\text{Att}(X)} g^1 \left(\sum_{\text{Pub}(X, J)} g^0 \right)^{|J|} \right)^{|\text{X}|_{X \neq \text{eve}}}$$

\sum_V indicates a sum over the values of V , $|\text{X}|$ a domain size

QA: Lifted Junction Tree Algorithm (LJT)

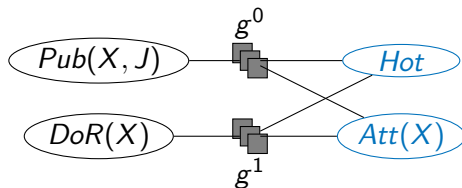
Lauritzen and Spiegelhalter (1988), Braun and Möller (2016)



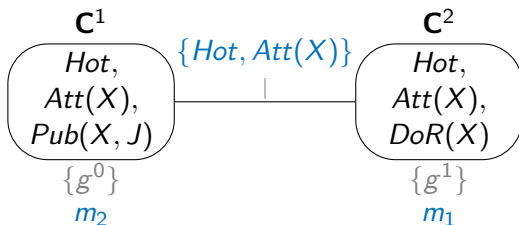
QA based on submodels
ensured to be independent

QA: Lifted Junction Tree Algorithm (LJT)

Lauritzen and Spiegelhalter (1988), Braun and Möller (2016)

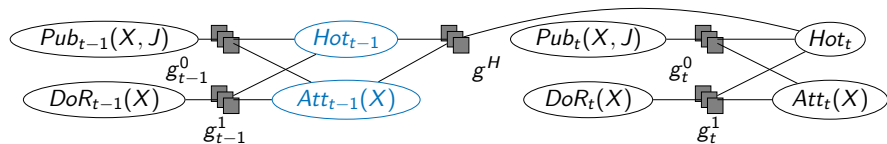


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Lifting + Temporal Conditional Independences

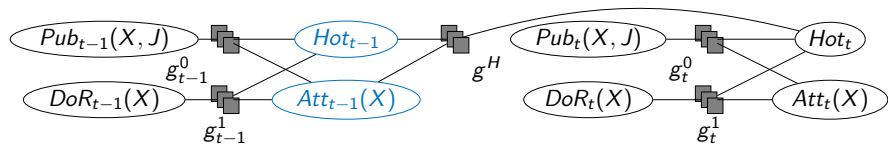
Braun and Möller (2016), Murphy (2002), Gehrke et al. (2018)



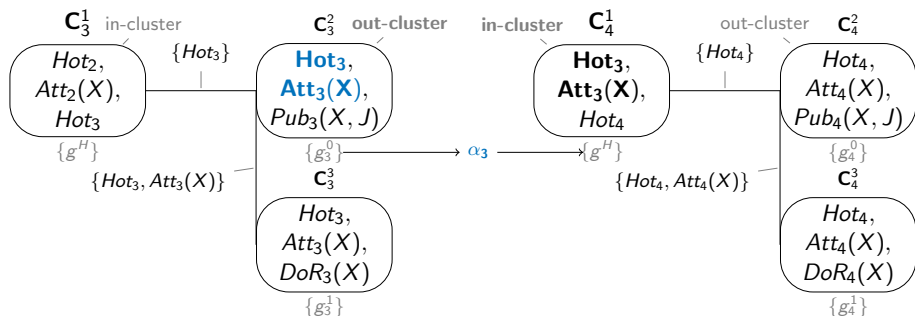
QA based on submodels and time slices
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Lifting + Temporal Conditional Independences

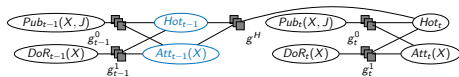
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QA based on submodels and time slices
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Lifting + Temporal Conditional Independences and Beyond



QA based on submodels
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Lifted Dynamic Junction Tree Algorithm (LDJT)

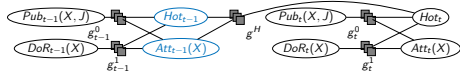
Gehrke et al. (2018)

Answer multiple temporal queries efficiently

Filtering: $P(\text{DoR}_5(\text{eve}) | \text{Hot}_5 = 1)$



Lifting + Temporal Conditional Independences and Beyond



Lifted Dynamic Junction Tree Algorithm (LDJT)

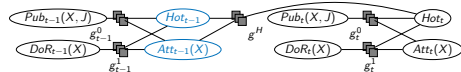
Complexity & Completeness

Polynomial w.r.t. domain size
 Linear w.r.t. # time steps
 Classes of **liftable** temporal models

QA based on submodels
 and time slices
 ensured to be independent



Lifting + Temporal Conditional Independences and Beyond



Lifted Dynamic Junction Tree Algorithm (LDJT)

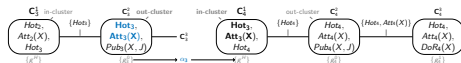
Complexity & Completeness

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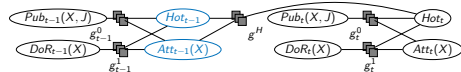
Decision making

Gehrke et al. (2019b,a)

LJT and LDJT to solve the
Maximum Expected Utility problem



Lifting + Temporal Conditional Independences and Beyond



Lifted Dynamic Junction Tree Algorithm (LDJT)

Complexity & Completeness

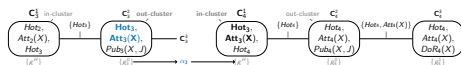
Decision making

Taming temporal reasoning

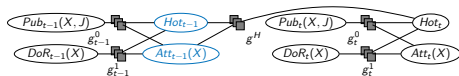
Gehrke et al. (2020)

Approximate symmetries over time to retain tractability

QA based on submodels
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Lifted Inference Continued...



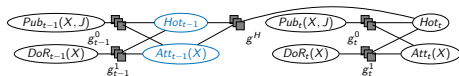
Who did it?

Identifying the most likely source to exhibit an event (combinatorial problem)

QA based on submodels
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Lifted Inference Continued...

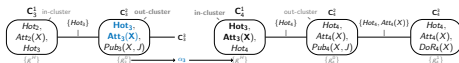


QA based on submodels
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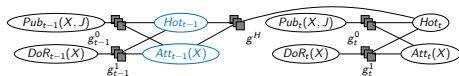
Who did it?

Causality

Started to have a look at lifting
causality with Malte



Lifted Inference Continued...



QA based on submodels
and time slices
ensured to be independent

Who did it?

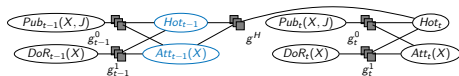
Causality

Preserving Privacy

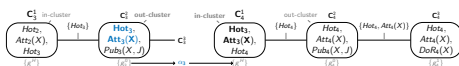
Its complicated



Lifted Inference Continued...



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Who did it?

Causality

Preserving Privacy

Text Understanding

Lightweight text understanding
using PGMs with Magnus.

References I

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Nima Taghipour, Daan Fierens, Jesse Davis, and Hendrik Blockeel. Lifted Variable Elimination: Decoupling the Operators from the Constraint Language. *Journal of Artificial Intelligence Research*, 47(1):393–439, 2013.