

Lifted Junction Tree Algorithm

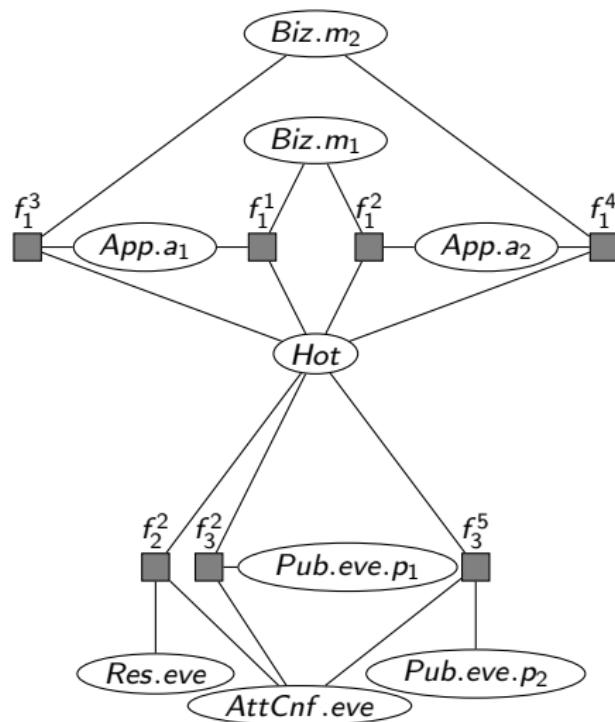
Counting and Conjunctive Queries

Tanya Braun, Ralf Möller

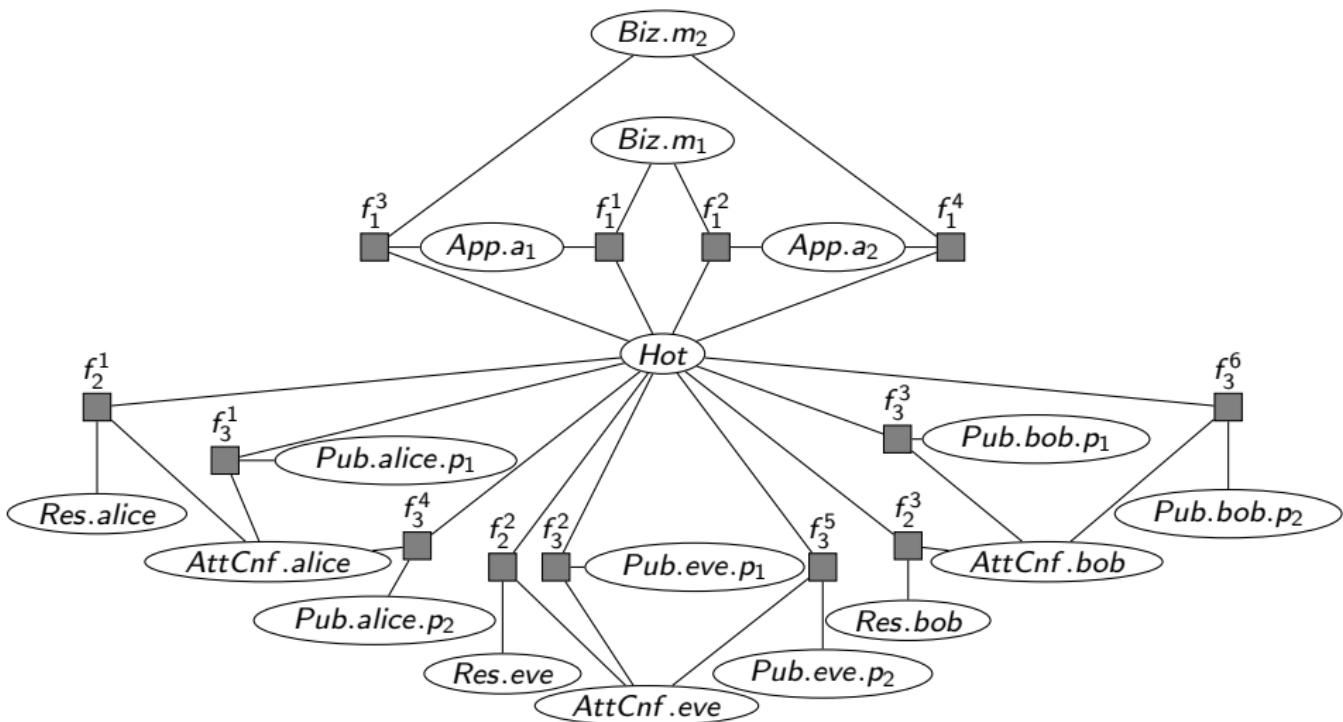
Institute of Information Systems
University of Lübeck

August 21, 2017

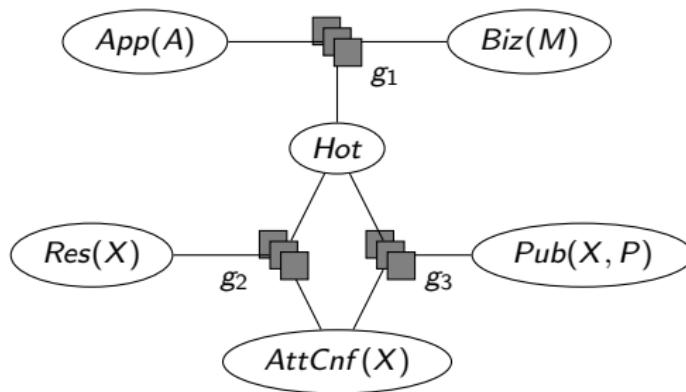
Problem: Propositional Models Explode



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Approach: Parameterization and Lifted Inference for Query Answering (QA)



Propositional

- 17 random variables
- 13 factors

Lifted

- 6 (parameterized) random variables
- 4 domains \mathcal{D} of logical variables
- 3 parametric factors

Next Problem: Make Query Answering More Practical

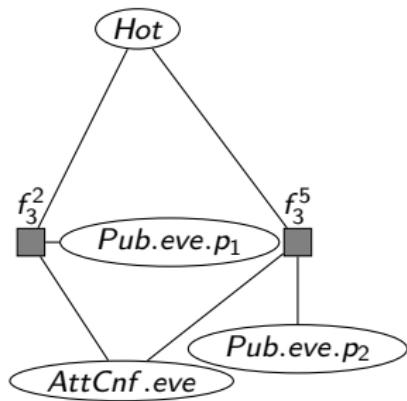
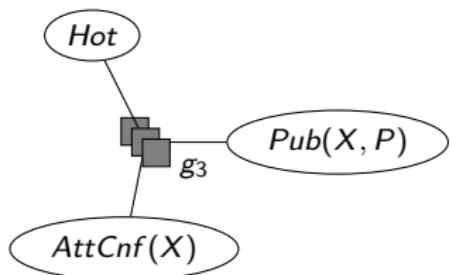
Workshop Contribution

Extensions to
Lifted Junction Tree Algorithm (LJT)
[Braun & Möller, 2016]

- Fewer groundings by exploiting technique of **counting**
- From multiple atomic queries to multiple **conjunctive queries**

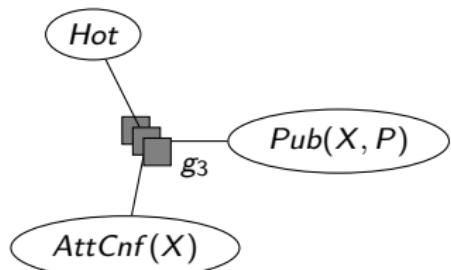
Lifted Variable Elimination (LVE) – Single Queries

Poole (2003), de Salvo Braz (2007), Milch et al. (2008), Taghipour (2013)



Lifted Variable Elimination (LVE) – Single Queries

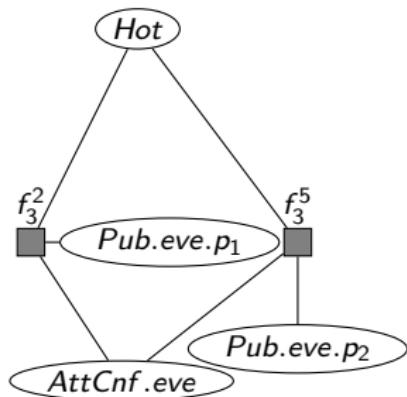
Poole (2003), de Salvo Braz (2007), Milch et al. (2008), Taghipour (2013)



$$f_3^2 = \phi(Hot, AttCnf.eve, Pub.eve.p_1)$$

<i>Hot</i>	<i>AttCnf.eve</i>	<i>Pub.eve.p₁</i>	ϕ
<i>true</i>	<i>true</i>	<i>true</i>	0.4
<i>true</i>	<i>true</i>	<i>false</i>	0.2
\vdots			

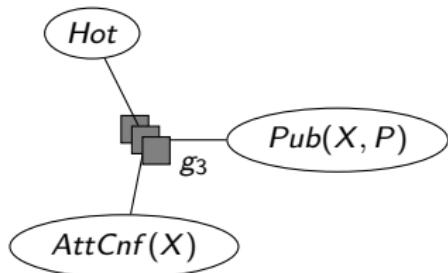
Overall, 8 cases



$$\sum_{v \in \text{range}(Pub.eve.p_1)} \phi(Hot, AttCnf.eve, v)$$

LVE: Avoiding Grounding by Exponentiation

$$g_3 = \phi(Hot, AttCnf(X), Pub(X, P))$$



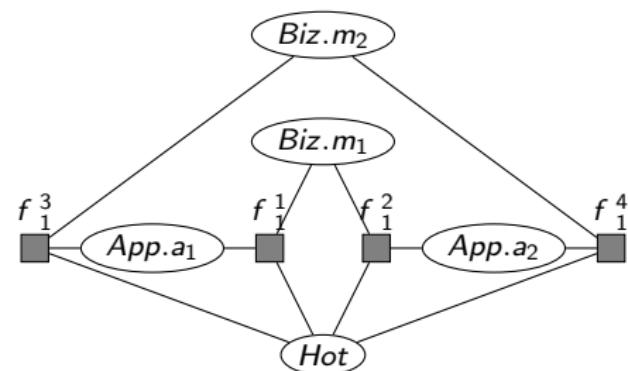
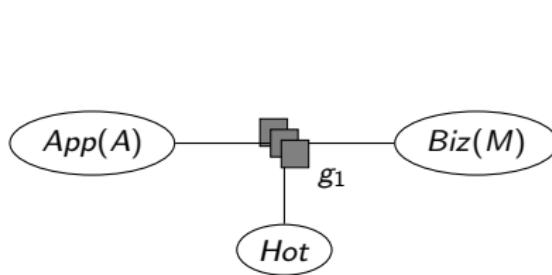
<i>Hot</i>	<i>AttCnf(X)</i>	<i>Pub(X, P)</i>	ϕ
<i>true</i>	<i>true</i>	<i>true</i>	0.4
<i>true</i>	<i>true</i>	<i>false</i>	0.2
:			

Overall, 8 entries

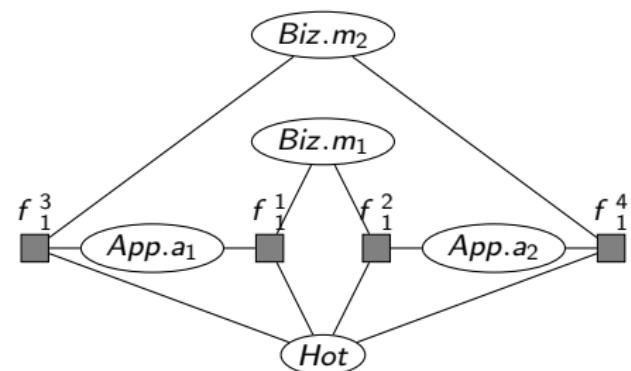
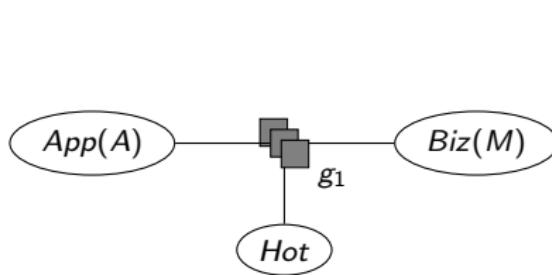
$$\sum_{Pub(X,P)} g_3 := \left(\sum_{v \in range(Pub(X,P))} \phi(Hot, AttCnf(X), v) \right)^{|\mathcal{D}(P)|}$$

$Pub(X, P)$ contains all logical variables in g_3 .

LVE: Avoiding Grounding by Counting



LVE: Avoiding Grounding by Counting



$$\begin{aligned}
 & \sum_{v \in \text{range}(App.a_1)} \phi(Hot, v, Biz.m_1, Biz.m_2) \rightarrow 16 \text{ cases} \\
 = & \sum_{v \in \text{range}(App.a_1)} \phi(Hot, v, \#_M[Biz(M)])
 \end{aligned}$$

LVE: Count-conversion

$$g_1 = \phi(Hot, App(A), Biz(M))$$

$$g'_1 = \phi(Hot, App(A), \#_M[Biz(M)])$$

<i>Hot</i>	<i>App(A)</i>	<i>Biz(M)</i>	ϕ
<i>true</i>	<i>true</i>	<i>true</i>	0.4
<i>true</i>	<i>true</i>	<i>false</i>	0.2
:			

<i>Hot</i>	<i>App(A)</i>	$\#$	ϕ
<i>true</i>	<i>true</i>	[2, 0]	0.4^2
<i>true</i>	<i>true</i>	[1, 1]	$0.4 \cdot 0.2$
<i>true</i>	<i>true</i>	[0, 2]	0.2^2
:			

Overall, 8 cases

Overall, 12 cases (instead of 16)

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Overall, 8 cases

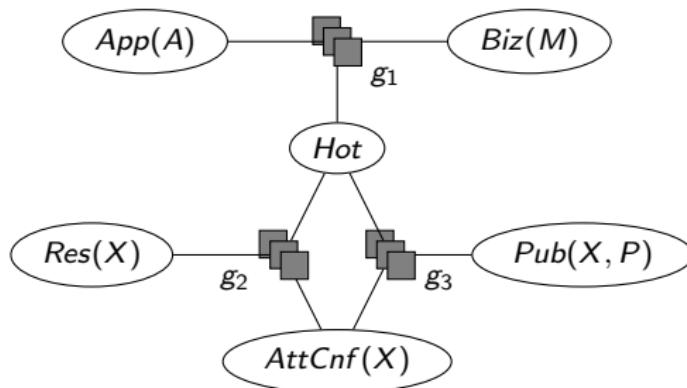
Overall, 12 cases (instead of 16)

$$\sum_{App(A)} g_1 := \left(\sum_{\substack{v \in \\ range(App(A))}} \phi(Hot, v, \#_M[Biz(M)]) \right)^{|\mathcal{D}(A)|}$$

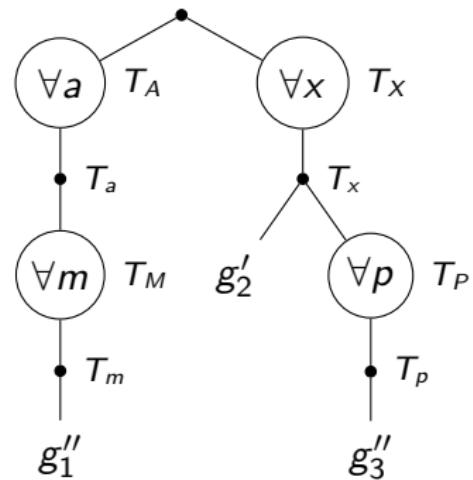
First-order Decomposition Trees (FO Dtrees)

Darwiche (2001), Taghipour (2013)

Model

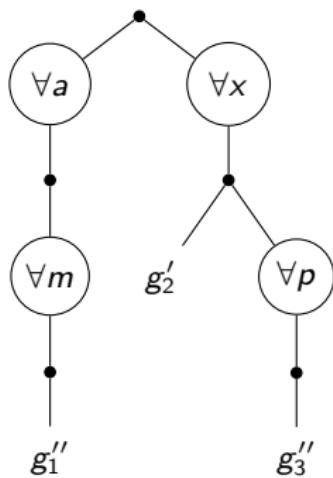


FO dtree

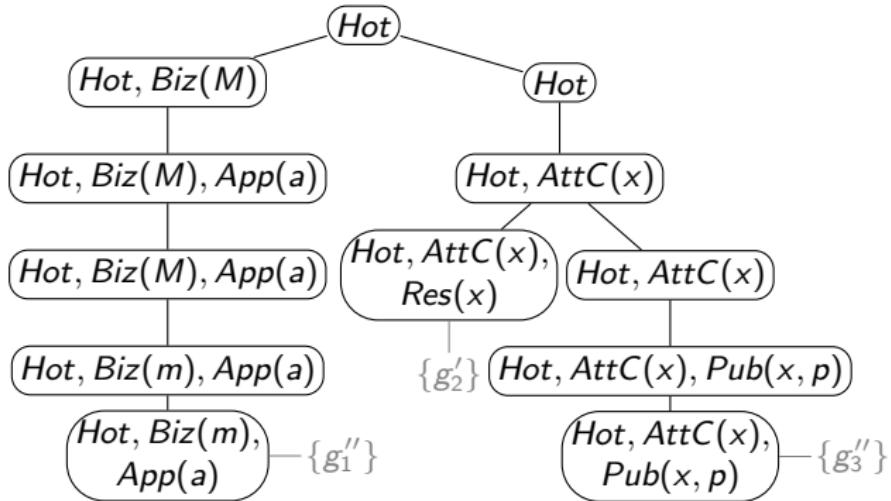


First-order Junction Trees (FO Jtrees)

FO dtree

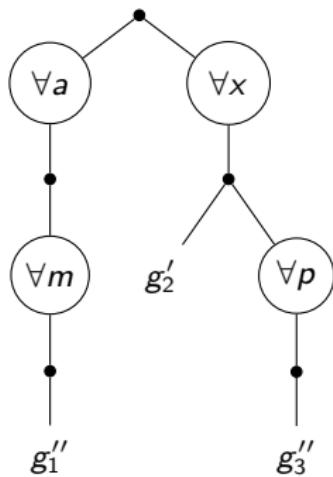


Clusters

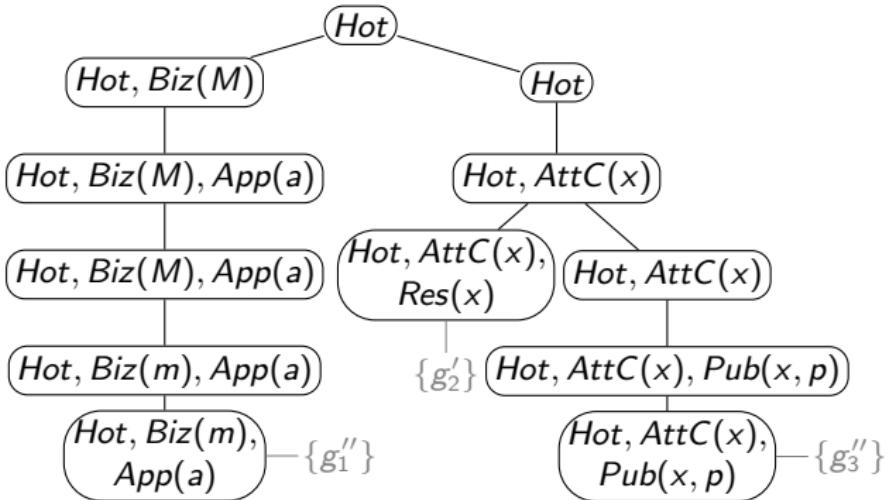


First-order Junction Trees (FO Jtrees)

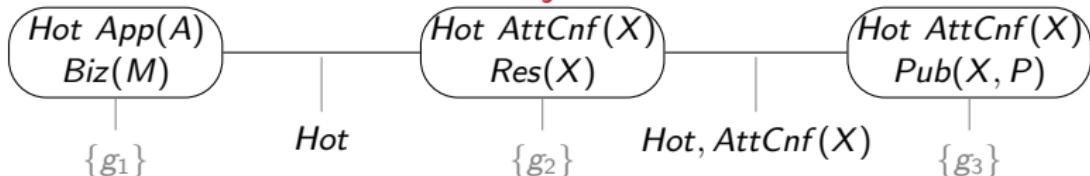
FO dtree



Clusters

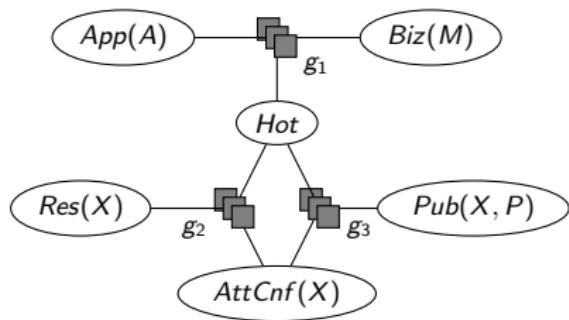


FO jtree

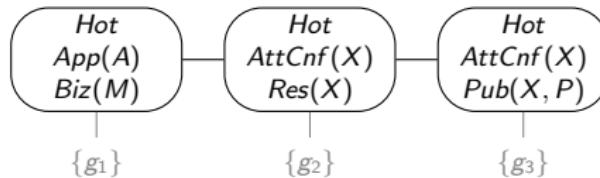


LJT – Multiple Queries

Lauritzen & Spiegelhalter (1988), Koller & Friedman (2009), Braun & Möller (2016)



Atomic queries on ground random variables, e.g., $Res.eve$, $Pub.eve.p_1$



Input

- Model G
- Queries \mathbf{Q}

Algorithm

- ① Build FO jtree for G .
- ② Pass messages
 - inbound
 - outbound
- ③ Answer queries \mathbf{Q} .
(without evidence)

Extended LJT: Example

Input + Construction

Model $G = \{g_1, g_2, g_3\}$,

- $g_1 = \phi_1(Hot, App(A), Biz(M))$
- $g_2 = \phi_2(Hot, AttCnf(X), Res(X))$
- $g_3 = \phi_3(Hot, AttCnf(X), Pub(X, P))$

Queries $\mathbf{Q} = \{Q_1, Q_2\}$

- $Q_1 = P(Pub(eve, p_1))$ (atomic query)
- $Q_2 = P(Pub(eve, p_1), Res(eve))$ (conjunctive query)

Extended LJT: Example

Input + Construction

Model $G = \{g_1, g_2, g_3\}$,

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Queries $Q = \{Q_1, Q_2\}$

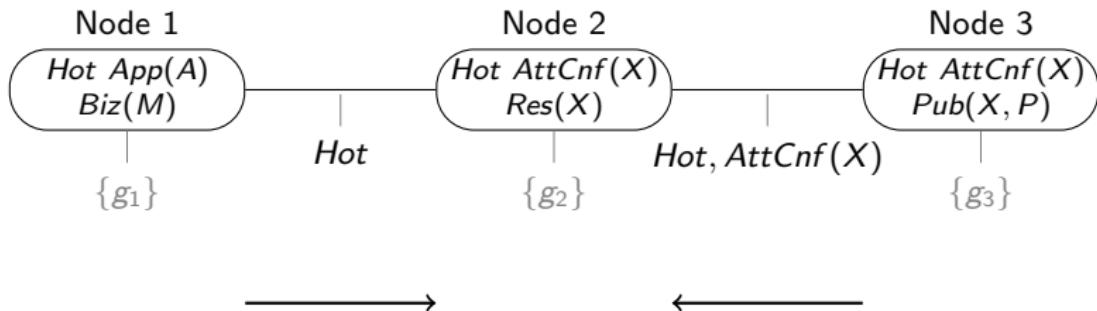
- $Q_1 = P(Pub(eve, p_1))$ (atomic query)
- $Q_2 = P(Pub(eve, p_1), Res(eve))$ (conjunctive query)

Constructed FO jtree



Extended LJT: Example Continued

Message Passing

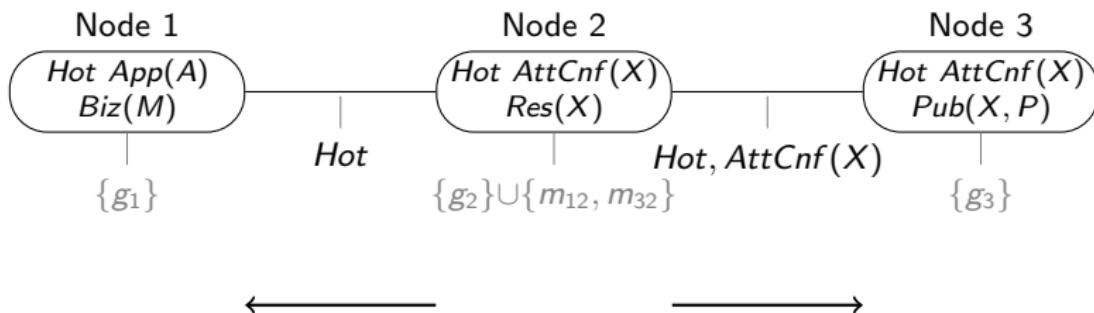


$$m_{12} = \sum_{\#_M[Biz(M)]} \sum_{App(A)} g_1$$

$$m_{32} = \sum_{Pub(X,P)} g_3$$

Extended LJT: Example Continued

Message Passing

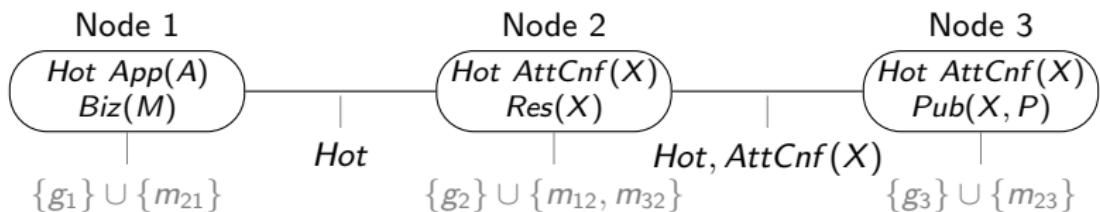


$$m_{21} = \sum_{AttCnf(X)} m_{32} \sum_{Res(X)} g_2$$

$$m_{23} = m_{12} \sum_{Res(X)} g_2$$

Extended LJT: Example Continued

Query Answering



Query

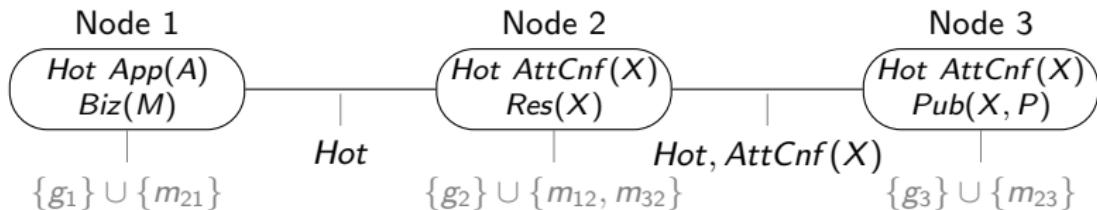
$$Q = P(Pub(eve, p_1))$$

Submodel

$$G^Q = \{g_3\} \cup \{m_{23}\}$$

Extended LJT: Example Continued

Query Answering



Query

$$Q = P(Pub(eve, p_1))$$

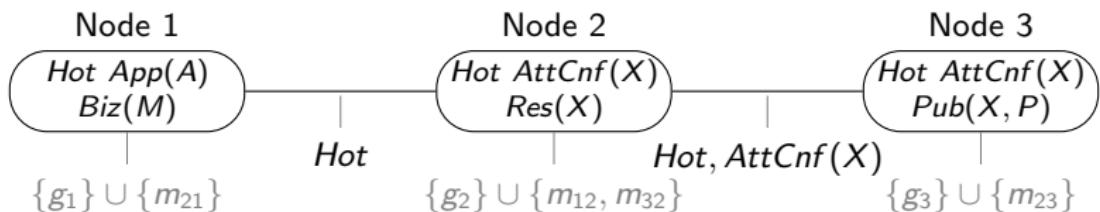
Submodel

$$G^Q = \{g_3\} \cup \{m_{23}\}$$

$$Q \propto \sum_{Hot} \sum_{AttCnf(X)} m_{23} \sum_{\substack{Pub(X, P), \\ X \neq eve, \\ P \neq p_1}} g_3$$

Extended LJT: Example Continued

Query Answering



Query

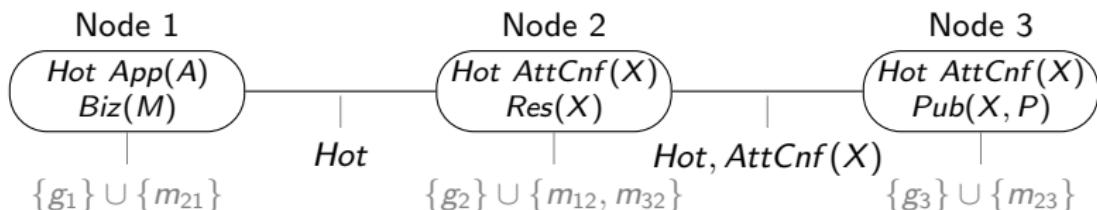
$$Q = P(Pub(eve, p_1), Res(eve))$$

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$$G^Q = \{g_2\} \cup \{g_3\} \cup \{m_{12}\}$$

Extended LJT: Example Continued

Query Answering



Query

$$Q = P(Pub(eve, p_1), Res(eve))$$

Submodel

$$G^Q = \{g_2\} \cup \{g_3\} \cup \{m_{12}\}$$

$$Q \propto \sum_{Hot} m_{12} \sum_{AttCnf(X)} \sum_{Res(X), X \neq eve} g_2 \sum_{Pub(X, P), X \neq eve, P \neq p_1} g_3$$

Analysis: LVE vs. LJT

LVE

- Eliminates complete model for each query
- Influence on QA: number of PRVs in **model**

LJT

- Finds subtree, eliminates smaller model in subtree
- Influence on QA: number of PRVs in **submodel**

Analysis: LVE vs. LJT

LVE

- Eliminates complete model for each query
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LJT

- Finds subtree, eliminates smaller model in subtree
- Influence on QA: number of PRVs in **submodel**

LJT preprocessing necessary → Static overhead

- New construction if structure changes
- New message passing if domain sizes or values change

PRV = parameterized random variable

Test Run: LVE vs. LJT

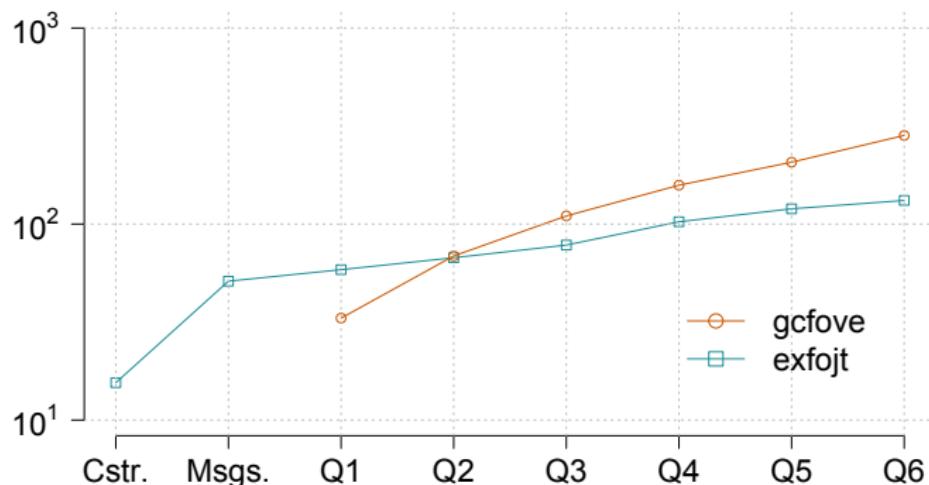


Figure: Accumulated Runtimes [ms] over 6 queries (points connected for readability)

gcfove: Implementation of LVE by Taghipour (2013)
exfojt: Own implementation of extended LJT

Problem: Make Query Answering More Practical

Workshop Contribution

Extensions to
Lifted Junction Tree Algorithm (LJT)
[Braun & Möller, 2016]

- Fewer groundings by exploiting technique of **counting**
- From multiple atomic queries to multiple **conjunctive queries**

Problem: Make Query Answering More Practical

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Future Directions

- Incrementally changing models
- Dynamic variant

Cutset, Context, Cluster

Darwiche (2001), Taghipour (2013)

$$\text{cutset}(T) = \bigcup_{T_i, T_j \in \text{child}(T)} RV(T_i) \cap RV(T_j) \setminus \text{acutset}(T)$$

$$\text{acutset}(T) = \bigcup_{T' \in \text{ancestor}(T)} \text{cutset}(T')$$

$$\text{context}(T) = RV(T) \cap \text{acutset}(T)$$

$$\text{cluster}(T) = \text{cutset}(T) \cup \text{context}(T)$$

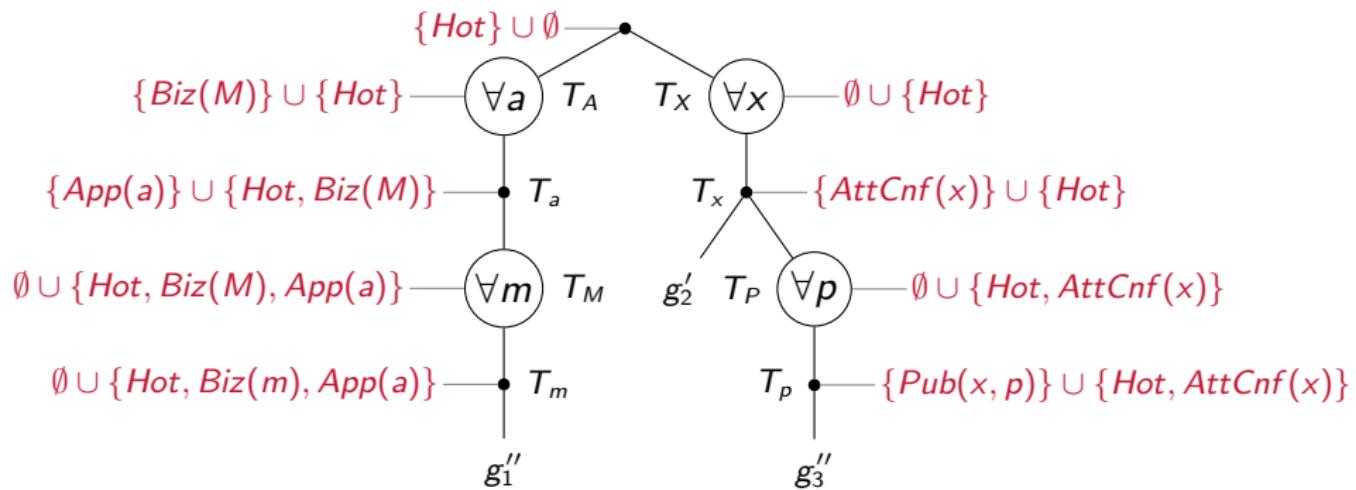
$$\text{cluster}(L) = RV(\phi_L), L \text{ leaf}$$

$$RV(T) = \bigcup_{T' \in \text{child}(T)} RV(T')$$

$$RV(L) = RV(\phi_L), L \text{ leaf}$$

Cutset, Context, Cluster

Darwiche (2001), Taghipour (2013)



Cutset, Context, Cluster

Darwiche (2001), Taghipour (2013), Labels: $\text{cutset}(N) \cup \text{context}(N)$

$$\text{cutset}(T) = \bigcup_{T_i, T_j \in \text{child}(T)} RV(T_i) \cap RV(T_j) \setminus \text{acutset}(T), \text{acutset}(T) = \bigcup_{T' \in \text{ancestor}(T)} \text{cutset}(T')$$

$$\text{context}(T) = RV(T) \cap \text{acutset}(T), RV(T) = \bigcup_{T' \in \text{child}(T)} RV(T'), RV(L) = RV(\phi_L), L \text{ leaf}$$

$$\text{cluster}(T) = \text{cutset}(T) \cup \text{context}(T), \text{cluster}(L) = RV(\phi_L), L \text{ leaf}$$

