



Lifted Probabilistic Inference by First-Order Knowledge Compilation

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Lifted Inference in Probabilistic Logical Models - Tutorial - IJCAI11 18/07/11

Outline

- Overview Approach
- First-Order d-DNNF Circuits
- First-Order Knowledge Compilation
- Experiments
- Conclusions

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	Variable Elimination	Belief Propagation	Knowledge Compilation
Ground	[Zhang94]	[Pearl82]	[Darwiche03]
Lifted	[Poole03]	[Singla08]	Our approach

Advantages of Knowledge Compilation

- Compile once, then run polytime inference for multiple queries and evidence
- Efficient data structures
- Principled logical approach
- Exploits context-specific independences
- State of the art for exact inference in
 - Bayesian networks
 - Statistical relational learning
- Used in many domains, not just probabilistic reasoning

Question?

- Can we lift knowledge compilation to a first-order setting?
- First step taken: first-order d-DNNFs for
 - weighted first-order model counting
 - lifted probabilistic inference
- Many open questions remaining!

What is Lifted Inference?

2 friends $(X, Y) \land \operatorname{smokes}(X) \Rightarrow \operatorname{smokes}(Y)$

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2 friends $(X, Y) \land \operatorname{smokes}(X) \Rightarrow \operatorname{smokes}(Y)$

- Variables X,Y range over domain People
- Represents propositional model for given domain (50 people)
- Propositional inference in factor graph is expensive
- However: symmetries



What is Lifted Inference?

2 friends $(X, Y) \land \operatorname{smokes}(X) \Rightarrow \operatorname{smokes}(Y)$

- We compile to a circuit independent of |People|
- Inference linear in |People|
 - → Lifted Inference







• Step 1: Convert model to weighted CNF



- Step 1: Convert model to weighted CNF
- Step 2: Convert CNF to d-DNNF circuit



- Step 1: Convert model to weighted CNF
- Step 2: Convert CNF to d-DNNF circuit
- Step 3: Perform weighted model counting

First-Order Knowledge Compilation

Our Approach: First-Order Knowledge Compilation:



- Step 1: Convert model to weighted FO CNF
- Step 2: Convert CNF to FO d-DNNF circuit
- Step 3: Perform weighted FO model counting

First-Order Knowledge Compilation

Step 1: Converting to Weighted FO CNF



 $w: \operatorname{smokes}(X) \wedge \operatorname{friends}(X, Y) \Rightarrow \operatorname{smokes}(Y)$

Step 1: Converting to Weighted FO CNF



$$w:\operatorname{smokes}(X)\wedge\operatorname{friends}(X,Y)\Rightarrow\operatorname{smokes}(Y)$$

 $[\operatorname{smokes}(X) \wedge \operatorname{friends}(X, Y) \Rightarrow \operatorname{smokes}(Y)] \equiv f(X, Y)$

Step 1: Converting to Weighted FO CNF



• Weight function on ground atoms

 $w(\operatorname{smokes}(X)) = 2$ $w(\operatorname{friends}(X, Y)) = 5$

 $w(\neg \operatorname{smokes}(X)) = 10$ $w(\neg \operatorname{friends}(X, Y)) = 1$

Weight function on ground atoms

$$\begin{split} & \mathrm{w}(\mathrm{smokes}(X)) = 2 & \mathrm{w}(\neg\,\mathrm{smokes}(X)) = 10 \\ & \mathrm{w}(\mathrm{friends}(X,Y)) = 5 & \mathrm{w}(\neg\,\mathrm{friends}(X,Y)) = 1 \end{split}$$

• Weight of a model (possible world) $\{\underbrace{\operatorname{smokes}(alice)}_{2}, \underbrace{\neg \operatorname{smokes}(bob)}_{10}, \underbrace{\operatorname{friends}(alice, bob)}_{5}, \ldots\}$ $2:10:5:\ldots=100$

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- Weight of a model (possible world) $\{\underbrace{\operatorname{smokes}(alice)}_{2}, \underbrace{\neg \operatorname{smokes}(bob)}_{10}, \underbrace{\operatorname{friends}(alice, bob)}_{5}, \ldots\}$ $2 \cdot 10 \cdot 5 \cdot \ldots = 100$
- Weight of all models is $100 + \ldots = Z$

- Weight function on ground atoms
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- Weight of a model (possible world) $\{\underbrace{\operatorname{smokes}(alice)}_{2}, \underbrace{\neg \operatorname{smokes}(bob)}_{10}, \underbrace{\operatorname{friends}(alice, bob)}_{5}, \ldots\}$ $2 \cdot 10 \cdot 5 \cdot \ldots = 100$
- Weight of all models is $100 + \ldots = Z$ Weight of models where Alice smokes is $100 + \ldots = Q$

- Weight function on ground atoms
 - $$\begin{split} & \mathrm{w}(\mathrm{smokes}(X)) = 2 & \mathrm{w}(\neg\,\mathrm{smokes}(X)) = 10 \\ & \mathrm{w}(\mathrm{friends}(X,Y)) = 5 & \mathrm{w}(\neg\,\mathrm{friends}(X,Y)) = 1 \end{split}$$
- Weight of a model (possible world) $\{\underbrace{\operatorname{smokes}(alice)}_{2}, \underbrace{\neg \operatorname{smokes}(bob)}_{10}, \underbrace{\operatorname{friends}(alice, bob)}_{5}, \ldots\}$ $2 \cdot 10 \cdot 5 \cdot \ldots = 100$
- Weight of all models is 100 + ... = ZWeight of models where Alice smokes is 100 + ... = Q•₁₈ $P(smokes(alice)) = \frac{Q}{Z}$ rder Knowledge Compilation 22

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First-Order d-DNNF Circuits



First-Order d-DNNF Circuits



First-Order d-DNNF Circuits



- Deterministic disjunction
- Decomposable conjunction
- 3 additional first-order operators (inner nodes)

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Step 2: Our Compilation Algorithm

- Recursively apply
 - Unit Propagation
 - Independence
 - Inclusion-Exclusion (Shannon Decomposition)
 - Shattering
 - Independent Partial Grounding
 - Atom Counting
 - (Grounding)



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Generate first-order operators in inner nodes



Atom Counting • (Grounding)

- Independent Partial Grounding
- Shattering
- Inclusion-Exclusion (Shannon Decomposition)

Step 2: Our Compilation Algorithm

Independence

Recursively apply

Unit Propagation



Unit Propagation

 $\begin{aligned} & \operatorname{friends}(X,Y) \lor \operatorname{dislikes}(X,Y) \\ &\neg \operatorname{friends}(X,Y) \lor \operatorname{likes}(X,Y) \\ & \operatorname{friends}(X,X) \end{aligned}$








Step 2: Our Compilation Algorithm

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$$\begin{aligned} & \operatorname{fun}(X) \lor \neg \operatorname{friends}(X,Y) \\ & \operatorname{fun}(X) \lor \neg \operatorname{friends}(Y,X) \end{aligned}$$

Atom with one logical variable $X \in \{luc, jesse\}$

$$\begin{array}{l} \operatorname{fun}(X) \lor \neg \operatorname{friends}(X,Y) \\ \operatorname{fun}(X) \lor \neg \operatorname{friends}(Y,X) \end{array}$$





All partial interpretations for fun(X) - deterministic - 2^{|People|}





$$2^{|\text{People}|} \rightarrow |\text{People}|+1$$





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 $|People|+1 \rightarrow 1$

49



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Evaluated Models

- Sick Death [de Salvo Braz 2005]
- WebKB [Lowd 2007]
- Competing Workshops [Milch 2008]
- Workshop Attributes [Milch 2008]
- Friends Smoker [Singla 2008]
- Friends Smoker Drinker

Competing Workshops [Milch 2008]

Probabilistic Model:

- $-2: hot(W) \land attends(P)$
 - $3: \operatorname{attends}(P) \wedge \operatorname{series}$

Competing Workshops [Milch 2008]

Competing Workshops





Friends Smoker [Singla 2008]

Probabilistic Model:

 $1.2: \operatorname{smokes}(X) \wedge \operatorname{friends}(X, Y) \Rightarrow \operatorname{smokes}(Y)$ $1.2: \operatorname{smokes}(X) \wedge \operatorname{friends}(Y, X) \Rightarrow \operatorname{smokes}(Y)$ $2: \operatorname{smokes}(X) \Rightarrow \operatorname{cancer}(X)$

Friends Smoker [Singla 2008]

Friends Smoker



Friends Smoker Drinker

New Probabilistic Model:

 $1.2: \operatorname{smokes}(X) \wedge \operatorname{friends}(X, Y) \Rightarrow \operatorname{smokes}(Y)$ $1.2: \operatorname{drinks}(X) \wedge \operatorname{friends}(X, Y) \Rightarrow \operatorname{drinks}(Y)$

Friends Smoker Drinker

Friends Smoker Drinker



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Benefits of First-Order Knowledge Compilation?

- Compile once for a given set of evidence then run polytime inference
- Efficient data structure
- Principled logical approach
 - First model theoretic approach to lifted probabilistic inference
 - Uses concepts from logical inference: model counting, unit propagation, Shannon decomposition, etc.
- Exploits context-specific independences
- State of the art for exact lifted inference
 - Lifts more models than C-FOVE

Contributions

- We introduced first-order ...
 - knowledge compilation
 - d-DNNF circuits
 - weighted model counting
 - smoothing
- Algorithm to compile a first-order probabilistic model into FO d-DNNF circuits
- Closer to understanding the connection between lifted inference in first-order logic (resolution) and lifted inference in graphical models

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Poster

Wednesday 10:30 UAI session

• Talk

Thursday 10:30 UAI session



Extra Slides

Logic-based Probabilistic Inference



- DPLL Search Weighted Model Counting [Sang 2005]
- Knowledge Compilation [Darwiche]

First-Order Knowledge Compilation

Additional Operator Nodes



Auxiliary Operations

- Splitting w.r.t. an atom [Poole 2003]:
 - Similar to splitting in (C-)FOVE, but with domain constraints

Before Splitting	Atom	After Splitting
$\mathbf{p}(X,Y) \vee \mathbf{q}(X) \vee \mathbf{r}(Y)$	p(X, X)	$\mathbf{p}(X,X) \vee \mathbf{q}(X) \vee \mathbf{r}(X)$
		$\mathbf{p}(X,Y) \vee \mathbf{q}(X) \vee \mathbf{r}(Y), X \neq Y$
$\mathbf{p}(X) \lor \mathbf{q}(X), X \in D$	$p(X), X \in D_1$	$p(X) \lor q(X), X \in D_1$
		$p(X) \lor q(X), X \in D_2$

• Shattering [de Salvo Braz 2005] Splitting w.r.t. any atom in theory, until convergence



Independence

- Set of clauses independent from rest
- Independence when no unifying atoms



Inclusion-Exclusion

- Clause has set of literals that share no logical variables with rest
- Non-deterministic disjunction & intersection

 $\mathbf{p}(X) \vee \mathbf{r}(X, X) \vee \mathbf{q}(Y) \vee \mathbf{r}(Y, Z)$

Inclusion-Exclusion

- Clause has set of literals that share no logical variables with rest
- Non-deterministic disjunction & intersection


Independent Partial Grounding

- Single logical variable in every atom (position!)
- Different partial groundings are independent

 $\begin{aligned} \mathbf{p}(X) &\lor \mathbf{q}(X,Y) \\ \mathbf{r}(X) &\lor \mathbf{q}(X,Y) \end{aligned}$

Independent Partial Grounding

- Single logical variable in every atom (position!)
- Different partial groundings are independent



Special Inclusion Exclusion Case: Shannon Decomposition



First-Order Smoothing



First-Order Smoothing



First-Order Smoothing



Circuit Evaluation

- Propagate weighted model count to root node
- Propagate
 - + for disjunction
 - * for conjunction
 - $\sum_{s} {|D| \choose s} \operatorname{wmc}(c \wedge |D_1^\top| = s)$

for atom counting

Atom counting linear in domain size, others independent of



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