Outline

- Part 1: Motivation
- Part 2: Probabilistic Databases
- Part 3: Weighted Model Counting
- Part 4: Lifted Inference for WFOMC

\bigcup

- Part 5: Completeness of Lifted Inference
- Part 6: Query Compilation
- Part 7: Symmetric Lifted Inference Complexity
- Part 8: Open-World Probabilistic Databases
- Part 9: Discussion & Conclusions

Defining Lifted Inference

Informal:

Exploit symmetries, Reason at first-order level, Reason about groups of objects, Scalable inference, High-level probabilistic reasoning, etc.

• A formal definition: **Domain-lifted inference**

Inference runs in time polynomial in the number of objects in the domain.

- Polynomial in #people, #webpages, #cards
- <u>Not</u> polynomial in #predicates, #formulas, #logical variables
- Related to data complexity in databases

Defining Lifted Inference

Informal:

Exploit symmetries, Reason at first-order level, Reason about groups of objects, Scalable inference, High-level probabilistic reasoning, etc. [Poole'03, etc.]

A formal definition: Domain-lifted inference



Defining Lifted Inference

Informal:

Exploit symmetries, Reason at first-order level, Reason about groups of objects, Scalable inference, High-level probabilistic reasoning, etc. [Poole'03, etc.]

A formal definition: Domain-lifted inference



• Alternative in this tutorial:

Lifted inference = \exists Query Plan = \exists FO Compilation









• Simplification to *independent project*:

If $\Delta[C_1/x]$, $\Delta[C_2/x]$, ... are independent WMC($\exists z \Delta$) = Z - (Z_{C1}-WMC($\Delta[C_1/z]$)^{|Domain|} WMC($\forall z \Delta$) = WMC($\Delta[C_1/z]$)^{|Domain|}

• Simplification to *independent project*:

If $\Delta[C_1/x]$, $\Delta[C_2/x]$, ... are independent WMC($\exists z \Delta$) = Z - (Z_{C1}-WMC($\Delta[C_1/z]$)^{|Domain|} WMC($\forall z \Delta$) = WMC($\Delta[C_1/z]$)^{|Domain|}

A powerful new inference rule: *atom counting* Only possible with symmetric weights [°].
Intuition: **Remove unary relations** [°]



- FO-Model Counting: $w(R) = w(\neg R) = 1$
- Apply inference rules backwards (step 4-3-2-1)

- FO-Model Counting: $w(R) = w(\neg R) = 1$
- Apply inference rules backwards (step 4-3-2-1)

4.
$$\Delta = (\text{Stress}(\text{Alice}) \Rightarrow \text{Smokes}(\text{Alice}))$$

Domain = {Alice}

- FO-Model Counting: $w(R) = w(\neg R) = 1$
- Apply inference rules backwards (step 4-3-2-1)

4.
$$\Delta = (\text{Stress}(\text{Alice}) \Rightarrow \text{Smokes}(\text{Alice}))$$

Domain = {Alice}

 \rightarrow 3 models

- FO-Model Counting: $w(R) = w(\neg R) = 1$
- Apply inference rules backwards (step 4-3-2-1)

4. $\Delta = (\text{Stress}(\text{Alice}) \Rightarrow \text{Smokes}(\text{Alice}))$

Domain = {Alice}

WMC(\neg Stress(Alice) \lor Smokes(Alice))) = = Z - WMC(Stress(Alice)) × WMC(\neg Smokes(Alice)) = 4 - 1 × 1 = 3 models

- FO-Model Counting: $w(R) = w(\neg R) = 1$
- Apply inference rules backwards (step 4-3-2-1)

 $\Delta = (Stress(Alice) \Rightarrow Smokes(Alice))$

4.

Domain = {Alice}

 $WMC(\neg Stress(Alice) \lor Smokes(Alice))) =$ = Z - WMC(Stress(Alice)) × WMC(¬Smokes(Alice)) = 4 - 1 × 1 = 3 models

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

Domain = {n people}

- FO-Model Counting: $w(R) = w(\neg R) = 1$
- Apply inference rules backwards (step 4-3-2-1)

 $\Delta = (Stress(Alice) \Rightarrow Smokes(Alice))$

4.

Domain = {Alice}

 $WMC(\neg Stress(Alice) \lor Smokes(Alice))) =$ = Z - WMC(Stress(Alice)) × WMC(¬Smokes(Alice)) = 4 - 1 × 1 = 3 models

3. $\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$

Domain = {n people}

 \rightarrow 3ⁿ models

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

 \rightarrow 3ⁿ models

Domain = {n people}

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

 \rightarrow 3ⁿ models

2. $\Delta = \forall y$, (ParentOf(y) \land Female \Rightarrow MotherOf(y))

Domain = {n people}

D = {n people}

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

 \rightarrow 3ⁿ models

2. $\Delta = \forall y$, (ParentOf(y) \land Female \Rightarrow MotherOf(y))

D = {n people}

Domain = {n people}

If Female = true? $\Delta = \forall y$, (ParentOf(y) \Rightarrow MotherOf(y)) $\rightarrow 3^n$ models

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

 \rightarrow 3ⁿ models

2. $\Delta = \forall y, (ParentOf(y) \land Female \Rightarrow MotherOf(y))$

 $D = \{n \text{ people}\}$

Domain = {n people}

 \rightarrow 3ⁿ models If Female = true? $\Delta = \forall y, (ParentOf(y) \Rightarrow MotherOf(y))$

If Female = false? $\Delta = true$

 $\rightarrow 4^{n}$ models

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

 \rightarrow 3ⁿ models

2. $\Delta = \forall y$, (ParentOf(y) \land Female \Rightarrow MotherOf(y))

 $D = \{n \text{ people}\}$

If Female = true? $\Delta = \forall y$, (ParentOf(y) \Rightarrow MotherOf(y)) $\Rightarrow 3^{n}$ models If Female = false? $\Delta = true$ $\Rightarrow 4^{n}$ models

 \rightarrow 3ⁿ + 4ⁿ models

Domain = {n people}

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

 \rightarrow 3ⁿ models

2. $\Delta = \forall y$, (ParentOf(y) \land Female \Rightarrow MotherOf(y))

D = {n people}

WMC(Δ) = WMC(¬ Female ∨ ∀y, (ParentOf(y) ⇒ MotherOf(y))) = 2 * 2ⁿ * 2ⁿ - (2 - 1) * (2ⁿ * 2ⁿ - WMC(∀y, (ParentOf(y) ⇒ MotherOf(y)))) = 2 * 4ⁿ - (4ⁿ - 3ⁿ)

 \rightarrow 3ⁿ + 4ⁿ models

Domain = {n people}

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

 \rightarrow 3ⁿ models

2. $\Delta = \forall y$, (ParentOf(y) \land Female \Rightarrow MotherOf(y))

D = {n people}

WMC(Δ) = WMC(¬ Female ∨ ∀y, (ParentOf(y) ⇒ MotherOf(y))) = 2 * 2ⁿ * 2ⁿ - (2 - 1) * (2ⁿ * 2ⁿ - WMC(∀y, (ParentOf(y) ⇒ MotherOf(y)))) = 2 * 4ⁿ - (4ⁿ - 3ⁿ)

 \rightarrow 3ⁿ + 4ⁿ models

Domain = {n people}

1. $\Delta = \forall x, y, (ParentOf(x, y) \land Female(x) \Rightarrow MotherOf(x, y))$

D = {n people}

3.
$$\Delta = \forall x, (Stress(x) \Rightarrow Smokes(x))$$

 \rightarrow 3ⁿ models

2. $\Delta = \forall y$, (ParentOf(y) \land Female \Rightarrow MotherOf(y))

D = {n people}

WMC(Δ) = WMC(¬ Female ∨ ∀y, (ParentOf(y) ⇒ MotherOf(y))) = 2 * 2ⁿ * 2ⁿ - (2 - 1) * (2ⁿ * 2ⁿ - WMC(∀y, (ParentOf(y) ⇒ MotherOf(y)))) = 2 * 4ⁿ - (4ⁿ - 3ⁿ)

 \rightarrow 3ⁿ + 4ⁿ models

Domain = {n people}

1.

 $\Delta = \forall x, y, (ParentOf(x, y) \land Female(x) \Rightarrow MotherOf(x, y))$

D = {n people}

 \rightarrow (3ⁿ + 4ⁿ)ⁿ models

 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

...



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

$$\rightarrow 2^{n^2 - k(n-k)}$$
 models



 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?

Database:

Smokes(Alice) = 1 Smokes(Bob) = 0 Smokes(Charlie) = 0 Smokes(Dave) = 1 Smokes(Eve) = 0 ... $\rightarrow 2^{n^2 - k(n-k)}$ models



• If we know that there are *k* smokers?
Atom Counting: Example

 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

• If we know precisely who smokes, and there are k smokers?



Smokes(Alice) = 1Smokes(Bob) = 0Smokes(Charlie) = 0 Smokes(Dave) = 1 Smokes(Eve) = 0... $\rightarrow 2^{n^2 - k(n-k)}$ models



Atom Counting: Example

 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Domain = {n people}

models

• If we know precisely who smokes, and there are k smokers?



In total...

•

Smokes(Alice) = 1 Smokes(Bob) = 0 Smokes(Charlie) = 0 Smokes(Dave) = 1 Smokes(Eve) = 0 ... $\rightarrow 2^{n^2 - k(n-k)}$ models



• If we know that there are *k* smokers?

Atom Counting: Example

 $\Delta = \forall x, y, (Smokes(x) \land Friends(x, y) \Rightarrow Smokes(y))$

Smokes

• If we know precisely who smokes, and there are k smokers?

Smokes



• If we know that there are *k* smokers?



Friends

models

 $\rightarrow \sum_{k=0}^n \binom{n}{k} 2^{n^2 - k(n-k)} \text{ models}$

• In total...

1. Remove constants (shattering)

 $\Delta = \forall x \text{ (Friend(Alice, x) \lor Friend(x, Bob))}$

1. Remove constants (shattering)

 $\Delta = \forall x \text{ (Friend(Alice, x) } \lor \text{ Friend(x, Bob))}$

 $F_1(x) = Friend(Alice, x)$ $F_2(x) = Friend(x, Bob)$ $F_3 = Friend(Alice, Alice)$ $F_4 = Friend(Alice, Bob)$ $F_5 = Friend(Bob, Bob)$

 $| \Delta = \forall x (F_1(x) \lor F_2(x)) \land (F_3 \lor F_4) \land (F_4 \lor F_5)$

1. Remove constants (shattering)

 $\Delta = \forall x \text{ (Friend(Alice, x) } \lor \text{ Friend(x, Bob))}$

 $F_{1}(x) = Friend(Alice, x)$ $F_{2}(x) = Friend(x, Bob)$ $F_{3} = Friend(Alice, Alice)$ $F_{4} = Friend(Alice, Bob)$ $F_{5} = Friend(Bob, Bob)$

 $| \Delta = \forall x (F_1(x) \lor F_2(x)) \land (F_3 \lor F_4) \land (F_4 \lor F_5)$

2. "Rank" variables (= occur in the same order in each atom)

 $\Delta = (Friend(x,y) \lor Enemy(x,y)) \land (Friend(x,y) \lor Enemy(y,x))$

Wrong order ••••

1. Remove constants (shattering)

 $\Delta = \forall x \text{ (Friend(Alice, x) } \lor \text{ Friend(x, Bob))}$

 $F_{1}(x) = Friend(Alice, x)$ $F_{2}(x) = Friend(x, Bob)$ $F_{3} = Friend(Alice, Alice)$ $F_{4} = Friend(Alice, Bob)$ $F_{5} = Friend(Bob, Bob)$

 $| \Delta = \forall x (F_1(x) \lor F_2(x)) \land (F_3 \lor F_4) \land (F_4 \lor F_5)$



[Suciu'11]

3. Perform Resolution [Gribkoff'14]

 $\Delta = \forall x \forall y \ (\mathsf{R}(x) \ \lor \neg \mathsf{S}(x,y)) \land \forall x \forall y \ (\mathsf{S}(x,y) \ \lor \ \mathsf{T}(y))$

Rules stuck...



Now apply I/E!

4. Skolemization [VdB'14]

 $\Delta = \forall p, \exists c, Card(p,c)$

Inference rules assume one type of quantifier!

Mix ∀/∃ in encodings of MLNs with quantifiers and probabilistic programs



BUT: cannot introduce Skolem constants or functions!



 $\Delta = \forall p, \exists c, Card(p,c)$

 $\Delta = \forall p, \exists c, Card(p,c) \qquad Skolemization$ $\Delta' = \forall p, \forall c, Card(p,c) \Rightarrow S(p)$



$$\Delta = \forall p, \exists c, Card(p,c) \qquad Skolemization$$
$$\Delta' = \forall p, \forall c, Card(p,c) \Rightarrow S(p) \qquad w(S) =$$

Consider one position p:

∃c, Card(p,c) = true

$$w(S) = 1$$
 and $w(\neg S) = -1$
Skolem predicate

$$\Delta = \forall p, \exists c, Card(p,c)$$
 Skolemization
$$\Delta' = \forall p, \forall c, Card(p,c) \Rightarrow S(p)$$
 w(S) =

Consider one position p:

∃c, Card(p,c) = true S(p) = true

∃c, Card(p,c) = <mark>false</mark>

$$w(S) = 1$$
 and $w(\neg S) = -1$
Skolem predicate

→ S(p) = true Also model of Δ , weight * 1

$$\Delta = \forall p, \exists c, Card(p,c)$$
Skolemization
$$\Delta' = \forall p, \forall c, Card(p,c) \Rightarrow S(p)$$
Consider one position p:
$$\exists c, Card(p,c) = true$$

$$\exists c, Card(p,c) = true$$

$$\exists c, Card(p,c) = false$$

$$derivat$$
Also model of Δ , weight * 1
$$\exists c, Card(p,c) = false$$
No model of Δ , weight * 1
$$\exists c, Card(p,c) = false$$
No model of Δ , weight * 1
$$\exists c, Card(p,c) = false$$
No model of Δ , weight * 1
$$derivat$$

* /

*

[VdB'14]

Markov Logic

3.14 Smokes(x) \land Friends(x,y) \Rightarrow Smokes(y)





 \neg Friends(x, y)

 $\neg F(x,y)$

Friends(x, y)

Evaluation in time polynomial in domain size

Evaluation in time polynomial in domain size

[Vdb'11,'13]

Domain-lifted!

Negation Normal Form

Decomposable NNF

[Darwiche'01]

Deterministic Decomposable NNF

[Darwiche'01]

Deterministic Decomposable NNF

Deterministic Decomposable NNF

Weighted Model Counting and much more!

First-Order NNF

First-Order Decomposability

First-Order Decomposability

First-Order Determinism

First-Order NNF = Query Plan

Deterministic Decomposable FO NNF

 $\forall X, X \in \mathsf{People} : \mathsf{belgian}(X) \Rightarrow \mathsf{likes}(X, \mathsf{chocolate})$

Deterministic Decomposable FO NNF

 $\forall X, X \in \mathsf{People} : \mathsf{belgian}(X) \Rightarrow \mathsf{likes}(X, \mathsf{chocolate})$

Deterministic Decomposable FO NNF

 $\forall X, X \in \mathsf{People} : \mathsf{belgian}(X) \Rightarrow \mathsf{likes}(X, \mathsf{chocolate})$

Symmetric WFOMC on FO NNF

$$U(\alpha) = \begin{cases} 0 & \text{when } \alpha = \mathsf{false} \\ 1 & \text{when } \alpha = \mathsf{true} \\ 0.5 & \text{when } \alpha \text{ is a literal} \\ U(\ell_1) \times \cdots \times U(\ell_n) & \text{when } \alpha = \ell_1 \wedge \cdots \wedge \ell_n \\ U(\ell_1) + \cdots + U(\ell_n) & \text{when } \alpha = \ell_1 \vee \cdots \vee \ell_n \\ \prod_{i=1}^n U(\beta\{X/x_i\}) & \text{when } \alpha = \forall X \in \tau, \beta \text{ and } x_1, \dots, x_n \text{ are the objects in } \tau. \\ \sum_{i=1}^n U(\beta\{X/x_i\}) & \text{when } \alpha = \exists X \in \tau, \beta \text{ and } x_1, \dots, x_n \text{ are the objects in } \tau. \\ \prod_{i=0}^{|\tau|} U(\beta\{X/x_i\}) & \text{when } \alpha = \exists X \in \tau, \beta, \text{ and } x_i \text{ is any subset of } \tau \text{ such that } |\mathbf{x}_i| = i. \\ \sum_{i=0}^{|\tau|} {|\tau| \choose i} \cdot U(\beta\{\mathbf{X}/\mathbf{x}_i\}) & \text{when } \alpha = \exists \mathbf{X} \subseteq \tau, \beta, \text{ and } \mathbf{x}_i \text{ is any subset of } \tau \text{ such that } |\mathbf{x}_i| = i. \end{cases}$$

Complexity polynomial in domain size! Polynomial in NNF size for bounded depth.
How to do first-order knowledge compilation?











Compilation Rules

- Standard rules
 - Shannon decomposition (DPLL)
 - Detect decomposability
 - Etc.
- FO Shannon decomposition:





Let us automate this:

- Relational model

 $\begin{array}{l} \forall p, \ \exists c, \ Card(p,c) \\ \forall c, \ \exists p, \ Card(p,c) \\ \forall p, \ \forall c, \ \forall c', \ Card(p,c) \land \ Card(p,c') \Rightarrow c = c' \end{array}$

- Lifted probabilistic inference algorithm

Why not do propositional WMC?

Reduce to propositional model counting:

Why not do propositional WMC?

Reduce to propositional model counting:

$$\begin{split} & \Delta = \operatorname{Card}(A \bigstar, p_1) \lor \dots \lor \operatorname{Card}(2 \bigstar, p_1) \\ & \operatorname{Card}(A \bigstar, p_2) \lor \dots \lor \operatorname{Card}(2 \bigstar, p_2) \\ & \dots \\ & \operatorname{Card}(A \bigstar, p_1) \lor \dots \lor \operatorname{Card}(A \blacktriangledown, p_{52}) \\ & \operatorname{Card}(K \blacktriangledown, p_1) \lor \dots \lor \operatorname{Card}(K \blacktriangledown, p_{52}) \\ & \dots \\ & \neg \operatorname{Card}(A \blacktriangledown, p_1) \lor \neg \operatorname{Card}(A \blacktriangledown, p_2) \\ & \neg \operatorname{Card}(A \blacktriangledown, p_1) \lor \neg \operatorname{Card}(A \blacktriangledown, p_3) \\ & \dots \\ & \end{matrix}$$

Why not do propositional WMC?

Reduce to propositional model counting:

 $\Delta = \operatorname{Card}(A \Psi, p_1) \vee \ldots \vee \operatorname{Card}(2 \Phi, p_1)$ Card(A \Psi, p_2) $\vee \ldots \vee \operatorname{Card}(2 \Phi, p_2)$

 $\begin{array}{l} Card(A \blacklozenge, p_1) \lor \ldots \lor Card(A \blacklozenge, p_{52}) \\ Card(K \blacklozenge, p_1) \lor \ldots \lor Card(K \blacklozenge, p_{52}) \end{array}$

$$\neg Card(A \Psi, p_1) \lor \neg Card(A \Psi, p_2) \\ \neg Card(A \Psi, p_1) \lor \neg Card(A \Psi, p_3)$$

What will happen?







One model/perfect matching







Model counting: How many perfect matchings?



What if I set w(Card(K Ψ ,p₅₂)) = 0?



What if I set w(Card(K Ψ ,p₅₂)) = 0?



What if I set can set any asymmetric weight function?

Observations

- Asymmetric weight function can remove edge
 Encode any bigraph
- Counting models = perfect matchings
- Problem is **#P-complete**! ③
- All non-lifted WMC solvers efficiently handle asymmetric weights
- No solver does cards problem efficiently!

Later: Power of lifted vs. ground inference and complexities



Let us automate this:

- Relational model

 $\begin{array}{l} \forall p, \ \exists c, \ Card(p,c) \\ \forall c, \ \exists p, \ Card(p,c) \\ \forall p, \ \forall c, \ \forall c', \ Card(p,c) \land \ Card(p,c') \Rightarrow c = c' \end{array}$

- Lifted probabilistic inference algorithm

 $\begin{array}{l} \forall p, \ \exists c, \ Card(p,c) \\ \forall c, \ \exists p, \ Card(p,c) \\ \forall p, \ \forall c, \ \forall c', \ Card(p,c) \land \ Card(p,c') \Rightarrow c = c' \end{array}$



















Let us automate this:

- Lifted probabilistic inference algorithm

$$\#SAT = \sum_{k=0}^{n} {n \choose k} \sum_{l=0}^{n} {n \choose l} (l+1)^{k} (-1)^{2n-k-l} = n!$$

Computed in time polynomial in n

Summary Lifted Inference

- By definition: PTIME data complexity Also: ∃ FO compilation = ∃ Query Plan
- However: only works for "liftable" queries
- Preprocessing based on logical rewriting
- The rules: Deceptively simple: the only surprising rules are I/E and atom counting
- Rules are captured by a query plan or first-order NNF circuit