Outline

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

• Relational models = the vast majority of data today, plus probabilistic Databases
• Weighted Model Counting = Uniform approach to Probabilistic Inference
• Lifted Inference = really simple rules
• The Power of Lifted Inference = we can prove that lifted inference is better
Challenges for the Future

Dealing with uncertainty

Reasoning with high-level structure

Learning
Challenges for the Future

Dealing with uncertainty

Reasoning with high-level structure
- logic
- databases
- programming
- ...

Learning
Challenges for the Future

Dealing with uncertainty
- probability theory
- graphical models
- ...

Reasoning with high-level structure
- logic
- databases
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- ...

Learning
Challenges for the Future

Dealing with uncertainty
• probability theory
• graphical models
• ...

Reasoning with high-level structure
• logic
• databases
• programming
• ...

Learning
• parameters
• structure
Challenges for the Future

Dealing with uncertainty
- probability theory
- graphical models
- ...

Reasoning with high-level structure
- logic
- databases
- programming
- ...

Learning
- parameters
- structure

Statistical relational learning, probabilistic logic learning, probabilistic programming, probabilistic databases, ...
Datalog

**Edge**

<table>
<thead>
<tr>
<th>x</th>
<th>y</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>c</td>
</tr>
<tr>
<td>a</td>
<td>b</td>
</tr>
<tr>
<td>b</td>
<td>c</td>
</tr>
<tr>
<td>c</td>
<td>d</td>
</tr>
</tbody>
</table>

\[
\begin{align*}
\text{path}(X,Y) & : \neg \text{edge}(X,Y). \\
\text{path}(X,Y) & : \neg \text{edge}(X,Z), \ \text{path}(Z,Y).
\end{align*}
\]

\[
\text{path}(a,d) = \text{Yes}
\]
**Probabilistic Datalog**

Edge

<table>
<thead>
<tr>
<th>x</th>
<th>y</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td>c</td>
<td>0.3</td>
</tr>
<tr>
<td>a</td>
<td>b</td>
<td>0.9</td>
</tr>
<tr>
<td>b</td>
<td>c</td>
<td>0.4</td>
</tr>
<tr>
<td>c</td>
<td>d</td>
<td>0.5</td>
</tr>
</tbody>
</table>

\[ P(\text{path}(a, d)) = ?? \]

\[ \text{path}(X, Y) : \neg \text{edge}(X, Y). \]
\[ \text{path}(X, Y) : \neg \text{edge}(X, Z), \ \text{path}(Z, Y). \]

[De Raedt'07, Fierens'15]
Probabilistic Programming

- Programming language + random variables
- Reason about distribution over executions

As going from hardware circuits to programming languages

```prolog
sample(L,N,S) :- permutation(S,T), sample_ordered(L,N,T).

sample_ordered(_, 0, []).
sample_ordered([X|L], N, [X|S]) :-
    N > 0, sample_now([X|L],N), N2 is N-1,
    sample_ordered(L,N2,S).
sample_ordered([H|L], N, S) :-
    N > 0, \+ sample_now([H|L],N), sample_ordered(L,N,S).

P::sample_now(L,N) :- length(L, M), M >= N, P is N/M.
```

\[
P(\text{sample([c,a,c,t,u,s],3,[c,a,t]))) = 0.1
\]

[De Raedt'07, Fierens’15]
Approximate Symmetries

• What if not liftable? Asymmetric graph?
• Exploit approximate symmetries:
  – Exact symmetry $g$: $\Pr(x) = \Pr(x^g)$
    E.g. Ising model without external field
  – Approximate symmetry $g$: $\Pr(x) \approx \Pr(x^g)$
    E.g. Ising model with external field

$P \approx P$

[VdB’13,’15,Gogate’14]
Example: Statistical Relational Model

- WebKB: Classify pages given links and words
- Very large Markov logic network

\[
\begin{align*}
1.3 \quad & \text{Page}(x, \text{Faculty}) \Rightarrow \text{HasWord}(x, \text{Hours}) \\
1.5 \quad & \text{Page}(x, \text{Faculty}) \land \text{Link}(x, y) \Rightarrow \text{Page}(y, \text{Course})
\end{align*}
\]

and 5000 more ...

- No symmetries with evidence on Link or Word
- Where do approx. symmetries come from?

[VdB’13,’15]
Over-Symmetric Approximations

- OSA makes model more symmetric
- E.g., low-rank Boolean matrix factorization

\[
\text{google.com and } \text{ibm.com become symmetric!}
\]

[VdB’13,’15]
Experiments: WebKB

KL Divergence

Time [s]

OSA-5-6
OSA-10-10
OSA-50-15
OSA-150-15
Gibbs
LMH

[VdB’13,’15]
Lifted Weight Learning

• Given: A set of first-order logic formulas

\[ w \text{ FacultyPage}(x) \land \text{Linked}(x,y) \Rightarrow \text{CoursePage}(y) \]

A set of training databases

• Learn: The associated maximum-likelihood weights

\[ \frac{\partial}{\partial w_j} \log \Pr_w(db) = n_j(db) - \mathbb{E}_w[n_j] \]

Count in databases Efficient

Expected counts Requires inference

\[ \mathbb{E}_w[n_F] = \Pr(F\theta_1) + \cdots + \Pr(F\theta_m) \]

• Idea: Lift the computation of \[ \mathbb{E}_w[n_j] \]

[Van Haaren’16]
Learning Time

$w \text{ Smokes}(x) \land \text{Friends}(x,y) \Rightarrow \text{Smokes}(y)$

Big data

Learns a model over 900,030,000 random variables

[Van Haaren’16]
Learning Time

\[
\text{w } \text{Smokes}(x) \land \text{Friends}(x,y) \Rightarrow \text{Smokes}(y)
\]

Big models

Learns a model over 900,030,000 random variables

[Van Haaren’16]
More Lifted Algorithms

- Exact Inference (AI)
  - First-Order Variable Elimination
    [Poole’03, deSalvoBraz’05, Milch’08, Taghipour’13]
  - First-Order Knowledge Compilation
    [V.d.Broeck’11,’12,’13]
  - Probabilistic Theorem Proving
    [Gogate’11]
  - MPE/MAP Inference
    [deSalvoBraz’06,Apsel’12,Sarkhel’14,Kopp’15]
More Lifted Algorithms

- Approximate Inference (AI)
  - Lifted Belief Propagation
    [Jaimovich’07, Singla’08, Kersting’09]
  - Lifted Bisimulation/Mini-buckets [Sen’08, ‘09]
  - Lifted Importance Sampling [Gogate’11,’12]
  - Lifted Relax, Compensate & Recover
    [V.d.Broeck’12]
  - Lifted MCMC [Niepert’13, Venugopal’12, VdB’15]
  - Lifted Variational Inference [Choi’12, Bui’12]
  - Lifted MAP-LP [Mladenov’14, Apsel’14]
More Lifted Algorithms

- Other Tasks (AI)
  - Lifted Kalman Filter [Ahmadi’11, Choi’11]
  - Lifted Linear Programming [Mladenov’12]
- Surveys [Kersting’12, Kimmig’15]
- Approximate Query Evaluation (DB)
  - Dissociation [Gatterbauer’13, ’14, ’15]
  - Collapsed Sampling [Gribkoff’15]
  - Approximate Compilation [Olteanu’10, Dylla’13]
Conclusions

- A radically new reasoning paradigm
- Lifted inference is **frontier and integration** of AI, KR, ML, DBs, theory, etc.
- We need
  - relational databases and logic
  - probabilistic models and statistical learning
  - algorithms that scale
- Many theoretical open problems
- Recently cool practical applications
Symmetric Open Problems

- Rules are complete beyond FO$^2$?
- Lifted approximations
  - Over-symmetric approx. with guarantees
  - Combined with Learning
- Mixed symmetric and asymmetric
- Theoretical computer science connections
  - Understanding #P1
- More SRL applications
- More expressive logics and programs
- Continuous random variables + Logic
Asymmetric Open Problems

• Extensions of the Dichotomy theorem
  – For 0, ½, 1 probabilities
  – FDs, Deterministic tables
  – Negations: ∀FO, ∃FO, or full FO
• Lifted approximation algorithms
• Characterize queries with tractable compilation to: FBDD, SDD, d-DNNF
• Circuit language supporting dichotomy
• Characterize queries with tractable most likely world (MAP = maximum a posteriori)
Long-Term Outlook

Probabilistic inference and learning exploit

~ 1988: conditional independence

~ 2000: contextual independence (local structure)
Probabilistic inference and learning exploit

~ 1988: conditional independence
~ 2000: contextual independence (local structure)
~ 201?: \textit{symmetry} \& \textit{exchangeability} \& first-order
If you want more…

• Books
  – Probabilistic Databases
  – Statistical Relational AI
  – (Lifted Inference Book)

• StarAI workshop on Monday
  http://www.starai.org

• Main conference papers
Thank You!

Questions?
References


References


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