# Dichotomies in the Complexity of Query Answering over Probabilistic Databases 

Open Problems in Database Theory, ICDT 2017

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## Tuple-Independent Probabilistic Databases

- A tuple-independent probabilistic database [DS04], or TID for short, is a pair $(D, p)$ where:
- $D$ is an ordinary relational database, viewed as a set of facts
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- Semantics: probability distribution over the subinstances $E \subseteq D$ :

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- Can simulate and facilitate common models in Statistical Relational Learning (SRL), such as Markov Logic Networks, if expressive classes of queries can be evaluated efficiently [JS12]


## Problem 1: Query Evaluation

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Let $Q$ be a boolean query. Evaluation of $Q$ over TIDs is the following problem. Given $(D, p)$, compute the probability $\pi_{Q}(D, p)$ that $Q$ is satisfied by a random database of $(D, p)$.

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$$
\pi_{Q}(D, p) \stackrel{\text { def }}{=} \sum_{E \subseteq D, E \models Q} \operatorname{Pr}(E \mid D, p)
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- Open: Dichotomy for (U)CQs on Block-Independent DBs (BID)?
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- Open: Dichotomies in the presence of FDs?


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- FPAS for $Q$ : Numerical algorithm $A(D, p, \epsilon)$ such that:

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\frac{\pi_{Q}(D, p)}{(1+\epsilon)}<A(D, p, \epsilon)<(1+\epsilon) \pi_{Q}(D, p)
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- Terminates in polynomial time in the size of $(D, p)$ and in $\frac{1}{\epsilon}$
- FPRAS for $Q$ : Randomized $A(D, p, \epsilon)$ such that:

$$
\operatorname{Pr}_{A}\left[\frac{\pi_{Q}(D, p)}{(1+\epsilon)}<A(D, p, \epsilon)<(1+\epsilon) \pi_{Q}(D, p)\right]>0.99
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- Some fragments of UCQ-minus-UCQ have FPRAS, while some are hard to approximate [KRT11]
- Open: Dichotomies for approximation in RA, or popular fragments with negation
- Important special cases (arise in translation from SRL, e.g., MLN): universal FO, full dependencies (e.g., full TGDs, EDGs)


## Problem 3: Most Probable Database (MPD)

- Let $Q$ be a boolean query (now viewed as a constraint)
- The MPD problem for $Q$ :

Given $(D, p)$, compute $\operatorname{argmax}_{E}\{\operatorname{Pr}(E \mid D, p) \mid E \models Q\}$

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- Open: Other / more expressive classes of constraints (e.g., universal FO, full dependencies)?


## Questions?

## References I

( Nilesh N. Dalvi and Dan Suciu, Efficient query evaluation on probabilistic databases, VLDB, Morgan Kaufmann, 2004, pp. 864-875.
囯 , The dichotomy of probabilistic inference for unions of conjunctive queries, J. ACM 59 (2012), no. 6, 30.
Robert Fink and Dan Olteanu, Dichotomies for queries with negation in probabilistic databases, ACM Trans. Database Syst. 41 (2016), no. 1, 4:1-4:47.

Eric Gribkoff, Guy Van den Broeck, and Dan Suciu, The most probable database problem, Proceedings of the First International Workshop on Big Uncertain Data (BUDA), 2014.

目 Abhay Kumar Jha and Dan Suciu, Probabilistic databases with markoviews, PVLDB 5 (2012), no. 11, 1160-1171.

## References II

R Richard M. Karp and Michael Luby, Monte-carlo algorithms for enumeration and reliability problems, 24th Annual Symposium on Foundations of Computer Science, Tucson, Arizona, USA, 7-9 November 1983, IEEE Computer Society, 1983, pp. 56-64.
Sanjeev Khanna, Sudeepa Roy, and Val Tannen, Queries with difference on probabilistic databases, PVLDB 4 (2011), no. 11, 1051-1062.

