

# Uncertain Data Management Querying Probabilistic Databases

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## Credits

Structure, flow, and examples are based on the book **Probabilistic Databases** by D. Suciu, D. Olteanu, C. Ré, C. Koch (Morgan&Claypool, 2011)

PDFs of the slides available at <http://silviu.maniu.info/teaching/>

# Introduction

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0712	Antoine	C42	$x_2$	C42	none	$\neg y_1$
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- SQL: SELECT DISTINCT 1 FROM B, R WHERE B.room=R.room AND R.equipment='none'
- calculus:  $Q() : \exists d, t, r. B(d, t, r) \wedge R(r, 'none')$

# Query Evaluation Problem

## Definition

For a fixed query  $Q$ , a database  $\mathcal{D}$ , and a possible answer tuple  $a$ , compute its **marginal probability**  $P(a \in Q)$ .

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$$Q() \iff x_1 \neg y_1 \vee x_2 \neg y_1 \vee x_3 \neg y_2 \vee x_4 \neg y_2$$

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- $\Phi_{\text{true}} = \text{true}$ ,  $\Phi_{\text{false}} = \text{false}$

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- the query evaluation problem reduces to computing the **probability of its lineage**

### Proposition

*For  $Q(\bar{x})$  and  $\mathcal{D}$  a pc-database, the probability of a possible answer  $\bar{a}$  to  $Q$  is equal to the probability of its lineage formula:*

$$P(\bar{a} \in Q) = P(\Phi_{Q(\bar{a}/\bar{x})})$$

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The Query Problem

Query Complexity

## Possible Worlds Semantics

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- inefficient even prohibitive; can we do better?
- **not in the general case!**

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- problem known as  $\#\text{SAT}$ , in complexity class  $\#\text{P}$  (given a polynomial-time, non-deterministic Turing machine, compute the number of accepting computations)

# Probability Computation

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- hence, computing  $N \cdot P(\Phi)$  is in  $\#P$

# Probability Computation In Probabilistic Databases

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## What about probability computation in probabilistic databases?

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Example class of intractable (or **unsafe**) queries:

$$H_0 = R(x), S(x, y), T(y)$$

$$H_1 = R(x_0), S(x_0, y_0) \vee S(x_1, y_1), T(y_1)$$

...

## Probability Computation In Probabilistic Databases

<b>R</b>		<b>S</b>			<b>T</b>	
$x_1$	0.5	$x_1$	$y_1$	1	$y_1$	0.5
$x_2$	0.5	$x_1$	$y_2$	1	$y_2$	0.5
...		...			...	
		$x_2$	$y_1$	1		
		$x_2$	$y_2$	1		
		...				

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...		...			...	
		$x_2$	$y_1$	1		
		$x_2$	$y_2$	1		
		...				

Let us analyze  $H_0 = R(x), S(x, y), T(y)$  on a **tuple-independent database**

## Probability Computation In Probabilistic Databases

		<b>S</b>				
	<b>R</b>					<b>T</b>
		$x_1$	$y_1$	1		
	$x_1$ 0.5	$x_1$	$y_2$	1	$y_1$ 0.5	
	$x_2$ 0.5	...			$y_2$ 0.5	
	...	$x_2$	$y_1$	1	...	
		$x_2$	$y_2$	1		
		...				

- each possible tuple is of the form  $W = \langle R^W, S, T^W \rangle$ ,  
 $\Phi(X_i) = \text{true} \iff X_i \in R^W$ , similarly for  $\Phi(Y_i)$



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		<b>S</b>				
	<b>R</b>	$x_1$	$y_1$	1	<b>T</b>	
	$x_1$ 0.5	$x_1$	$y_2$	1	$y_1$ 0.5	
	$x_2$ 0.5	...			$y_2$ 0.5	
	...	$x_2$	$y_1$	1	...	
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 $\Phi(X_i) = \text{true} \iff X_i \in R^W$ , similarly for  $\Phi(Y_j)$
- $H_0$  true iff  $\exists x_i, x_j. R^W(x_i)S(x_i, y_j)T^W(y_j) = \text{true}$ ; 1-1  
 correspondence with possible worlds

## Probability Computation In Probabilistic Databases

		<b>S</b>				
	<b>R</b>	$x_1$	$y_1$	$1$	<b>T</b>	
	$x_1$ $0.5$	$x_1$	$y_2$	$1$	$y_1$ $0.5$	
	$x_2$ $0.5$	$\dots$			$y_2$ $0.5$	
	$\dots$	$x_2$	$y_1$	$1$	$\dots$	
	$\dots$	$x_2$	$y_2$	$1$	$\dots$	
		$\dots$				
		$\dots$				

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 $\Phi(X_i) = \text{true} \iff X_i \in R^W$ , similarly for  $\Phi(Y_i)$
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correspondence with possible worlds
- $\#\Phi = 2^n P(H_0)$  – an oracle for computing  $P(H_0)$  can be used  
to compute  $\#\Phi \rightsquigarrow P(H_0)$  is hard for  $\#P$

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$H_k$  are used as **primitives** for finding intractable queries

$H_k$  are not the only queries that are intractable, and there exist **safe** (tractable) queries

Next:

- **extensional query evaluation**: reasoning on the query  $Q$  directly
- **intensional query evaluation**: reasoning on the lineage of the query  $\Phi_Q$