# On the Complexity of Managing Probabilistic XML Data 

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## Outline

(1) Introduction

- Motivation
- Probabilistic Data Management
- Complexity Issues
(2) Prob-Trees
(3) Equivalence of Prob-Trees
(4) Prob-Trees with Additional ConstraintsConclusion


## Imprecise Data and Imprecise Tasks

## Observations

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## A Probabilistic XML Warehouse



## A Probabilistic XML Warehouse (Hidden Web)



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Topic crawler
Form analyzer
Inf. Extractor


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## Probabilistic Trees

## Framework - Unordered data trees

## - Details: no attributes, no mixed content. .

## (multiset semantics)

Sample space: Set of all such data trees.
Probabilistic tree (prob-tree): Representation of a discrete probability distribution over this sample space.

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Prob-tree model defined in [Abiteboul \& Senellart 2006]. Here, we tackle complexity questions about it:

- What is the complexity of queries and updates?
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## The Prob-Tree Model

- Data tree with event conditions (conjunction of probabilistic events or negations of probabilistic events) assigned to each node.
- Probabilistic events are boolean random variables, assumed to be independent, with their own probability distribution.
- Representation à la [Imieliński \& Lipksi 1984].



## Semantics of Prob-Trees

Semantics of a Prob-Tree $T$ : Set of Possible Worlds $\llbracket T \rrbracket$ (probability distribution over the set of data trees).

$p_{1}=0.06 \quad p_{2}=0.70 \quad p_{3}=0.24$

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Actually, fully expressive.

## Locally Monotone Queries

Query: function that maps a data tree $t$ to a set of subtrees of $t$ containing its root.

## Definition

A query $Q$ is locally monotone if, for any data trees $u, t^{\prime}$ and $t$ such that $u \leqslant t^{\prime} \leqslant t, u \in Q(t) \Longleftrightarrow u \in Q\left(t^{\prime}\right)$.

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Underlying data tree.

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## Consistence of Queries on Prob-Trees

## Theorem



## What about updates?

- We consider sets of elementary insertions and deletions.
- Defined with respect to a query (mapping between nodes of the query and nodes to insert/delete).
- More involved definitions.
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## Complexity Results

$T$ : prob-tree with underlying data tree $t$. time $(Q(t))$ : complexity of the query $Q$ over the data tree $t$.

Upper bounds for operations on $T$ :

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- Two Notions of Equivalence
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## Two Notions of Equivalence

What does it mean for two prob-trees to represent the same information?

Two different notions:

Structural Equivalence: we keep the same event variables.
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Two prob-trees $T$ and $T^{\prime}$ are structurally equivalent ( $T \equiv_{\text {struct }} T^{\prime}$ ) if they have the same event variables, the same probability distribution, and if they define the same possible world for every valuation of the event variables.

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## Complexity of Structural Equivalence

## Theorem

Structural Equivalence is a coRP problem: there exists a randomized polynomial-time algorithm that returns true if two prob-trees are equivalent, and false with probability $\geqslant 1 / 2$ otherwise.

Based on the notion of count-equivalence:
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Two propositional formulas $\psi, \psi^{\prime}$ in DNF are count-equivalent $\left(\psi \equiv \psi^{\prime}\right)$ if, for every valuation of the variables of $\psi$ and $\psi^{\prime}$, the same number of disjuncts of $\psi$ and $\psi^{\prime}$ are satisfied.


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$$
A \equiv A \vee(A \wedge B) \quad \text { but } \quad A \not \equiv A \vee(A \wedge B)
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## Idea behind the Probabilistic Algorithm

In a very simple case:

$\left(w_{1} \wedge w_{2} \wedge-w_{3}\right) \vee\left(w_{1} \wedge w_{2}\right) \vee$ $\left(w_{1} \wedge-w_{2}\right) \vee\left(-w_{1} \wedge w_{2} \wedge-w_{3}\right)$

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X_{2}\left(1-X_{3}\right)+X_{1} X_{2}+
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(see [Green, Karvounarakis \& Tannen 2007]).

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- Summary
- Perspectives


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- Polynomial complexity for queries and insertions.
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## Merci.

## Proof of the Exponential Complexity of Deletion

## Proof.

Deletion d: "If the root has a C-child, then delete all B-children of the root."


Then, it can be shown that if $T^{\prime} \equiv$ struct $d(T)$, at least $2^{n}$ literals appear in $T^{\prime}$.

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