



Probabilistic XML Data Management

Pierre Senellart





Uncertain data

Numerous sources of **uncertain data**:

- Measurement errors
- Data integration from contradicting sources
- Imprecise mappings between heterogeneous schemata
- Imprecise automatic process (information extraction, natural language processing, etc.)
- Imperfect human judgment



Managing this imprecision

Objective

Not to pretend this imprecision does not exist, and manage it as rigorously as possible throughout a long, automatic and human, potentially complex, process.

Especially:

- Use **probabilities** to represent the confidence in the data
- Query data and retrieve **probabilistic** results
- Allow adding, deleting, modifying data in a **probabilistic** way
- (If possible) Keep throughout the process **lineage/provenance** information, so as to ensure **traceability**



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Uncertainty is Everywhere

Modeling Probabilistic Data

Tables (Relational Data)

Trees (Semistructured Model)

Probabilistic XML

Challenges



Outline

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The relational model

- Data stored into **tables**
- Every table has a precise **schema** (**type** of columns)
- Adapted when the information is very **structured**

Patient	Examin. 1	Examin. 2	Diagnosis
A	23	12	α
B	10	23	β
C	2	4	γ
D	15	15	α
E	15	17	β



Simple probabilistic annotations

Patient	Examin. 1	Examin. 2	Diagnosis	Probability
A	23	12	α	0.9
B	10	23	β	0.8
C	2	4	γ	0.2
C	2	14	γ	0.4
D	15	15	α	0.6
D	15	15	β	0.4
E	15	17	β	0.7
E	15	17	α	0.3

- Allow representation of the **confidence** in each row of the table
- **Efficient** algorithms to compute the probability of a query answer
- Impossible to express **dependencies** across rows

Annotations + constraints

Patient	Examin. 1	Examin. 2	Diagnosis	Probability
A	23	12	α	0.9
B	10	23	β	0.8
C	2	4	γ	0.2
C	2	14	γ	0.4
D	15	15	β	0.6
D	15	15	α	0.4
E	15	17	β	0.7
E	15	17	α	0.3

- Still **efficient** algorithms for query answering
- Simple **dependencies** (exclusion) can be expressed, but not more complex ones



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Modeling Probabilistic Data

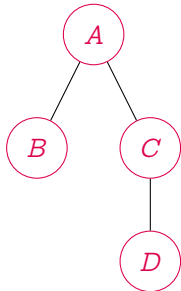
Tables (Relational Data)

Trees (Semistructured Model)

Probabilistic XML

Challenges

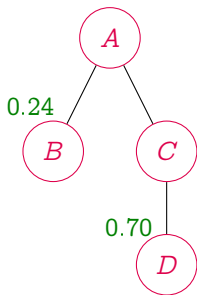
The semistructured model and XML



```
<a>  
  <b>...</b>  
  <c>  
    <d>...</d>  
  </c>  
</a>
```

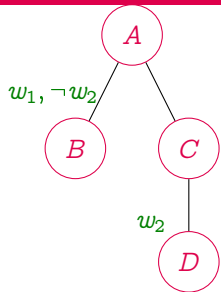
- **Tree-like** structuring of data
- **No** (or less) schema **constraints**
- Allow mixing **tags** (structured data) and text (unstructured content)
- Particularly adapted to **tagged** or **heterogeneous** content

Simple probabilistic annotations



- **Probabilities** associated to tree nodes
- Express parent/child dependencies
- Impossible to express more complex dependencies
- \Rightarrow some **sets of possible worlds** are not expressible this way!

Annotations with event variables



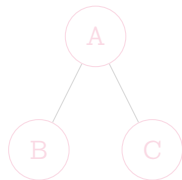
semantics \rightarrow



$$p_1 = 0.06$$



$$p_2 = 0.70$$

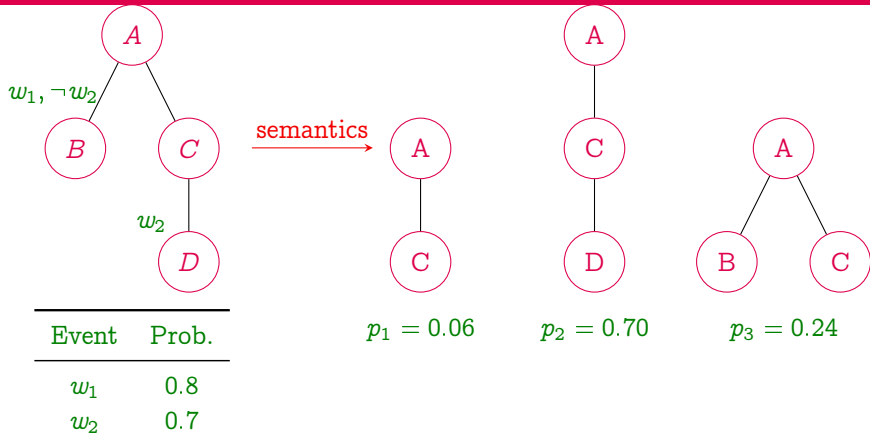


$$p_3 = 0.24$$

Event	Prob.
w_1	0.8
w_2	0.7

- Expresses arbitrarily complex dependencies
- Obviously, has an equivalent in the relational case

Annotations with event variables



- Expresses **arbitrarily complex** dependencies
- Obviously, has an equivalent in the relational case



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Why XML?

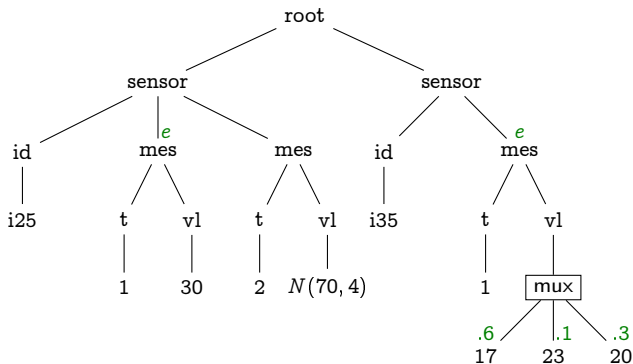
- Extensive literature about probabilistic relational databases
[Dalvi et al., 2009, Widom, 2005, Koch, 2009]
- Cases where a tree-like model might be appropriate:
 - No schema or few constraints on the schema (Web data!)
 - Independent modules **annotating** freely a content warehouse
 - Inherently tree-like data (e.g., mailing lists, parse trees)
- Different typical querying languages: SQL vs XPath/XQuery, conjunctive queries vs tree-pattern queries

Remark

Some results can be transferred from one model to the other. In other cases, connection much trickier! (See later.)

A general probabilistic XML model

[Abiteboul et al., 2009]



- e : event “it did not rain” at time 1
- mux : mutually exclusive options
- $N(70, 4)$: normal distribution

- Compact representation of a **set of possible worlds**
- Two kinds of dependencies: global (e) and local (mux)
- Generalizes **all previously proposed models** of the literature



Events and lineage

- Event variables: can represent the **provenance** of data
- Typically:
 1. At each (probabilistic) update, a **new** event variable is introduced
 2. Query results are given with probabilities, but also with the **lineage** of the query [Foster et al., 2008]
- Allow to keep **track**, with no additional cost, of the provenance of data!



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Querying probabilistic XML

Semantics of a (Boolean) query = **probability**:

1. Generate **all possible worlds** of a given probabilistic document
2. In each world, **evaluate the query**
3. **Add up** the probabilities of the worlds that make the query true

EXPTIME algorithm! Can we do better, i.e., can we apply directly the algorithm on the probabilistic document?

We shall talk about **data complexity** of query answering.



Querying probabilistic XML

Semantics of a (Boolean) query = **probability**:

1. Generate **all possible worlds** of a given probabilistic document (possibly exponentially many)
2. In each world, **evaluate the query**
3. **Add up** the probabilities of the worlds that make the query true

EXPTIME algorithm! Can we do better, i.e., can we apply directly the algorithm on the probabilistic document?

We shall talk about **data complexity** of query answering.

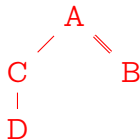


Boolean query languages on trees

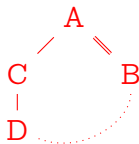
Single-path queries (SP) (no branching)



Tree-pattern queries (TP)



Tree-pattern queries with joins (TPJ)



Monadic second-order queries (MSO) generalization of TP, do not cover TPJ unless the size of the alphabet is bounded



The $\#P$ and $FP^{\#P}$ complexity classes

- A (counting) problem is in $\#P$ if there is a $PTIME$ non-deterministic Turing machine whose number of accepting paths, given as input the input of the problem, is the output of the problem.
- A problem is $\#P$ -hard if any $\#P$ problem can be $PTIME$ -reduced to it (via a Turing reduction). $\#2DNF$, the problem of counting the number of assignments satisfying a formula in 2-DNF, is $\#P$ -complete.
- A (computation) problem is in $FP^{\#P}$ if it is computable by a $PTIME$ Turing machine with access to a $\#P$ oracle.
- A problem is $FP^{\#P}$ -hard if any $FP^{\#P}$ problem can be $PTIME$ -reduced to it (via a Turing reduction). Equivalently, a computation problem is $FP^{\#P}$ -hard if it is $\#P$ -hard.



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Complexity of query evaluation

	Local dependencies	Arbitrary dependencies
SP	PTIME	FP ^{#P} -complete [Kimelfeld et al., 2008]
TP	PTIME [Kimelfeld and Sagiv, 2007, Kimelfeld et al., 2008, 2009]	FP ^{#P} -complete
TPJ	FP ^{#P} -complete [Abiteboul et al., 2010]	FP ^{#P} -complete
MSO	PTIME [Cohen et al., 2009]	FP ^{#P} -complete

Remark

Project-free queries are tractable with arbitrary dependencies. [Senellart and Abiteboul, 2007]



Complexity of query evaluation

Local dependencies

Arbitrary dependencies

TP

PTIME [Kimelfeld and Sagiv,
2007, Kimelfeld et al., 2008, 2009]

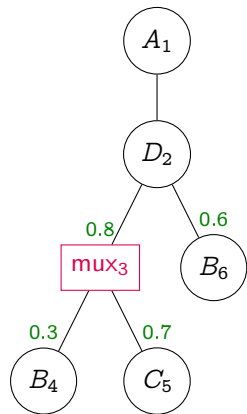
TPJ

FP^{#P}-complete
[Abiteboul et al., 2010]

TP PTIME for local dependencies

[Kimelfeld and Sagiv, 2007]

Bottom-up dynamic programming algorithm. Query: /A//B



	A_1	D_2	mux_3	B_4	C_5	B_6
/B				1	0	1
//B				1	0	1
/A//B				0	0	0

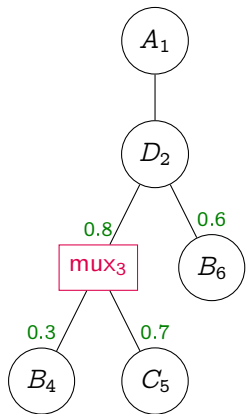
mux convex sum

ordinary inclusion-exclusion

TP PTIME for local dependencies

[Kimelfeld and Sagiv, 2007]

Bottom-up dynamic programming algorithm. Query: $/A//B$



	A_1	D_2	mux_3	B_4	C_5	B_6
$/B$			0.3	1	0	1
$//B$			0.3	1	0	1
$/A//B$			0	0	0	0

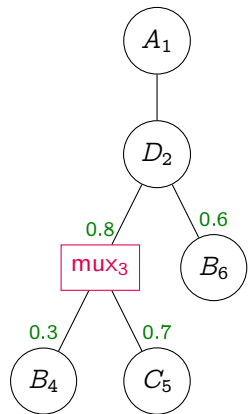
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TP PTIME for local dependencies

[Kimelfeld and Sagiv, 2007]

Bottom-up dynamic programming algorithm. Query: /A//B



	A_1	D_2	mux_3	B_4	C_5	B_6
/B		0	0.3	1	0	1
//B		0.696	0.3	1	0	1
/A//B		0	0	0	0	0

mux convex sum

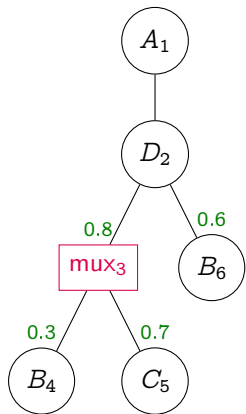
ordinary inclusion-exclusion

$$\begin{aligned}\Pr(D_2 \models //B) &= 1 - (1 - 0.8 \times \Pr(\text{mux}_3 \models //B)) \times (1 - 0.6 \times \Pr(B_6 \models //B)) \\ &= 1 - (1 - 0.8 \times 0.3) \times (1 - 0.6) = 0.696\end{aligned}$$

TP PTIME for local dependencies

[Kimelfeld and Sagiv, 2007]

Bottom-up dynamic programming algorithm. Query: $/A//B$

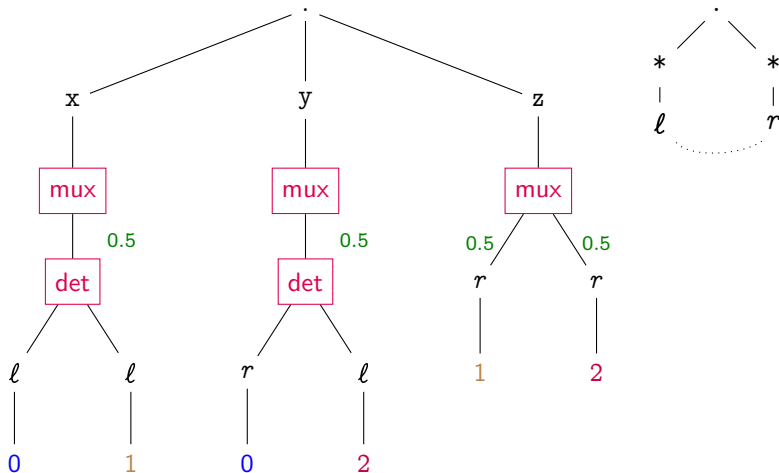


	A_1	D_2	mux_3	B_4	C_5	B_6
$/B$	0	0	0.3	1	0	1
$//B$	0.696	0.696	0.3	1	0	1
$/A//B$	0.696	0	0	0	0	0

mux convex sum

ordinary inclusion-exclusion

Reduction from #2DNF. Example: $\varphi = xy \vee x\neg z \vee yz$.





Approximating the probability of a query

In some sense, all variants of probabilistic XML are tractable: [Kimelfeld et al., 2009]

- **Additive approximation**: simple **Monte Carlo** sampling
- ... but additive approximation is not good enough for low probabilities
- (Slower) **multiplicative approximation** for TP queries: minor rewriting then biased Monte Carlo
- In practice, possible to automatically choose an **appropriate approximation method** [Senellart and Souihli, 2010].



Aggregate Queries [Cohen et al., 2008, Abiteboul et al., 2010]

Aggregate Queries: sum, count, avg, countd, min, max, etc.
Distributions? Possible values? Expected value?

- Computing **HAVING** queries is **tractable** for count, max, min, ratio.
- Computing expected values of sum and count **tractable** with arbitrary dependencies. Everything else **intractable**.
- Computing expected values of every of these aggregate functions is **tractable** with local dependencies.
- Computing distributions and possible values is **tractable** for count, min, max, **intractable** for the others.

Continuous distributions do not add any more complexity!

Updates defined by a query (cf. XUpdate, XQuery Update).

Semantics: for all matches of a query, insert or delete a node in the tree at a place located by the query.

Results

- Most updates are **intractable** with local dependencies: the result of an update can require an exponentially larger representation size
- Insertions with a for-all-match semantics are **tractable** with arbitrary dependencies; deletions are **intractable**.
- Some insert-if-there-is-a-match operations **tractable** for local dependencies but not for arbitrary dependencies.



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Tractable extensions of the local dependency model

- Arbitrary dependencies: **not tractable**
- Local dependencies: **not practical**
- Somewhere in between?
 - What makes the arbitrary dependency model hard?
 - How can the local dependency model be generalized, while remaining tractable?
- And can we go further? cf. XML schemas
 - Trees of unbounded depth
 - Trees of unbounded width
 - Infinite trees?

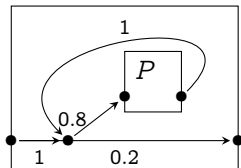
Prob. DTDs via rec. Markov chains

[Benedikt et al., 2010]

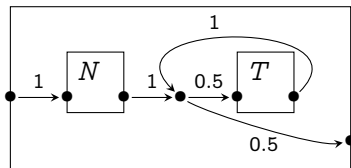
```
<!ELEMENT directory (person*)>
```

```
<!ELEMENT person (name,phone*)>
```

D: directory



P: person



N: name

T: phone



Such simple **tree-like** RMCs generalize probabilistic XML, and **MSO queries** are tractable!



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Link with probabilistic relational models

Relational case

(Block-independent disjoint model, [Dalvi and Suciu, 2007])

- Some conjunctive queries are **P**TIME
- Others are **#P**-hard
- Complex conditions to separate the two

XML case (Local dependencies)

- Tree pattern queries are **P**TIME
- Tree pattern queries with (non-trivial) joins are **#P**-hard

- Why does the XML case seem simpler?
- Is there some insight to be gained from one case to the other?
- Translating XML data and queries to the relational case yields queries with self-joins, a less well-understood setting



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But where do probabilities come from?!

- Do the numbers assigned as probabilities in PDBMS really make sense?
- In some cases, sources of “good” probabilities:
 - Statistics
 - Conditional Random Fields [Lafferty et al., 2001]
 - Parse Trees of Stochastic Context-Free Grammars [Cohen and Kimelfeld, 2010]
 - Uncertain Schema Matching [Dong et al., 2009, Fagin et al., 2010]
 - Representing a Corpus with a Probabilistic Documents?
- What about the rest? Does it really make sense to model uncertainty with probabilities?



A system that just works

- Nothing else than toy systems exist for probabilistic XML
- What should it be based upon:
 - a probabilistic relational DBMS? [Hollander and van Keulen, 2010]
 - a native XML DBMS? [Senellart and Souihli, 2010]
- Systems issue: distribution, indexing, etc.
- And need for a killer application!
 - Probabilistic content warehouse?
 - Parse trees of natural language sentences?
 - Concise representation of a large corpus of XML documents?

Merci.

Wabdam



DataRing Project: P2P Data Sharing for Online Communities

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Michael Benedikt, Evgeny Kharlamov, Dan Olteanu, and Pierre Senellart. Probabilistic XML via Markov chains. *Proceedings of the VLDB Endowment*, 3(1):770–781, September 2010. Presented at the VLDB 2010 conference, Singapore.

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Jennifer Widom. Trio: A system for integrated management of data, accuracy, and lineage. In *Proc. CIDR*, Asilomar, CA, USA, January 2005.