

### Probabilistic XML: A Data Model for the Web

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Nebdam

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### An Uncertain World





#### An Uncertain World

#### Uncertainty is Everywhere

Probabilistic Databases Probabilistic XML Applications

Probabilistic XML: Models and Complexity

Reconciling Web Data Models with the Actual Web





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, graph mining, etc.)
- Imperfect human judgment
- Lies, opinions, rumors





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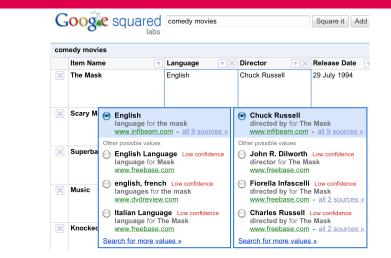
### **Ward Use case: Web information extraction**

instance	iteration	date learned	confidence
arabic, egypt	406	08-sep-2011	(Seed) 100.0
chinese, republic of china	439	24-oct-2011	100.0
chinese, singapore	421	21-sep-2011	(Seed) 100.0
english, britain	439	24-oct-2011	100.0
english, canada	439	24-oct-2011	(Seed) 100.0
english, england001	439	24-oct-2011	100.0
arabic, morocco	422	23-sep-2011	100.0
cantonese, hong kong	406	08-sep-2011	100.0
<u>english, uk</u>	436	19-oct-2011	100.0
english, south vietnam	427	27-sep-2011	99.9
french, morocco	422	23-sep-2011	99.9
greek, turkey	430	07-oct-2011	99.9

Never-ending Language Learning (NELL, CMU), http://rtw.ml.cmu.edu/rtw/kbbrowser/



## Use case: Web information extraction



Google Squared (terminated), screenshot from [Fink et al., 2011]

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# **With Use case: Web information extraction**

Subject	Predicate	Object	Confidence
0	diedOnDate		97.91%
5	influences	Priscilla Presley Carlo Wolff	97.29% 96.25%

YAGO, http://www.mpi-inf.mpg.de/yago-naga/yago [Suchanek et al., 2007]



## **Uncertainty in Web information extraction**

- The information extraction system is imprecise
- The system has some confidence in the information extracted, which can be:
  - a probability of the information being true (e.g., conditional random fields)
  - an ad-hoc numeric confidence score
  - a rough discrete level of confidence (low, medium, high)
- What if this uncertain information is not seen as something final, but is used as a source of, e.g., a query answering system?





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## Managing uncertainty

#### 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:

- Represent different forms of uncertainty
- Probabilities are used to measure uncertainty in the data
- Query data and retrieve uncertain results
- Allow adding, deleting, modifying data in an uncertain way



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### Why probabilities?

- Not the only option: fuzzy set theory [Galindo et al., 2005], Dempster-Shafer theory [Zadeh, 1986]
- Mathematically rich theory, nice semantics with respect to traditional database operations (e.g., joins)
- Some applications already generate probabilities (e.g., statistical information extraction or natural language probabilities)
- Naturally arising in case of conflicting information, based on the trust in the sources
- In other cases, we "cheat" and pretend that (normalized) confidence scores are probabilities: see this as a first-order approximation



## Probabilistic relational DBMSs

Numerous studies on the modeling and querying of probabilistic relations:

block-independent disjoint (BIDs) databases [Dalvi et al., 2009] tuples either mutually exclusive or independent, depending on key values

probabilistic c-tables [Imieliński and Lipski, 1984, Green and Tannen, 2006, Senellart, 2007], tuples annotated with arbitrary probabilistic formulas

Two main probabilistic relational DBMS:

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Trio [Widom, 2005] Various uncertainty operators: unknown value, uncertain tuple, choice between different possible values, with probabilistic annotations

MayBMS [Koch, 2009] Uncertain tables can be constructed using a REPAIR-KEY operator, similar to BIDs, and more elaborate correlations can result from querying

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### Probabilistic relational DBMSs

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	test=# select * from R;			
	dummy   weather   ground   p			
Numero	dummy   rain   wet   0.35	ons:		
block-in	dummy   rain   dry   0.05 dummy   no rain   wet   0.1 dummy   no rain   dry   0.5	ither		
	dummy   no rain   dry   0.5 (4 rows)	lues		
probabi test=# create table S as repair key Dummy in R weight by P; SELECT Two matest=# select Ground, conf() from S group by Ground; ground   conf				
	dry   0.55 wet   0.45 (2 rows)	ılue, , with		
MayBMS [Koch, 2009] Uncertain tables can be constructed using a				
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		TELECOM ParisTech		

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### **副 ※ 認知** Why probabilistic XML?

- Different typical querying languages: SQL and conjunctive queries vs XPath and tree-pattern queries (possibly with joins)
- Cases where a tree-like model might be appropriate:
  - No schema or few constraints on the schema
  - Independent modules annotating freely a content warehouse
  - Inherently tree-like data (e.g., mailing lists, parse trees) with naturally occurring queries involving the descendant axis

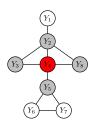
#### Remark

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



### Web information extraction [Senellart et al., 2008]

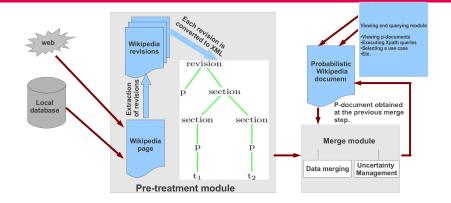




- Annotate HTML Web pages with possible labels
- Labels can be learned from a corpus of annotated documents
- Conditional random fields for XML: estimate probabilities of annotations given annotations of neighboring nodes
- Provides probabilistic labeling of Web pages



# [Abdessalem et al., 2011, Ba et al., 2011]



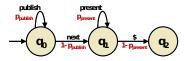
Use trees with probabilistic annotations to represent the uncertainty in the correctness of a document under open version control (e.g., Wikipedia articles)

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#### Probabilistic summaries of XML corpora [Abiteboul et al., 2012a,b]





- Transform an XML schema (deterministic top-down tree automaton) into a probabilistic generator (probabilistic tree automaton) of XML documents
- Probability distribution optimal with respect to a given corpus
- Application: Optimal auto-completions in an XML editor



### Probabilistic XML: Models and Complexity





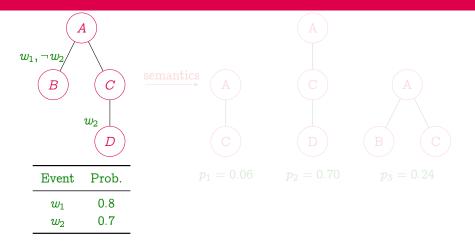
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#### Probabilistic XML: Models and Complexity Modeling Querying Undating

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#### A general discrete Probabilistic XML Model [Abiteboul and Senellart, 2006, Senellart, 2007, Abiteboul et al., 2009]



Expresses arbitrarily complex dependencies

Analogous to probabilistic c-tables

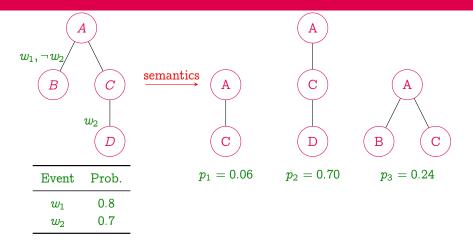
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joint work with



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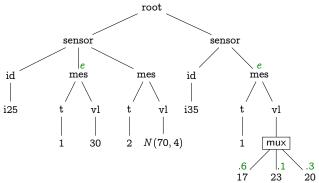
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### Continuous distributions [Abiteboul et al., 2011]

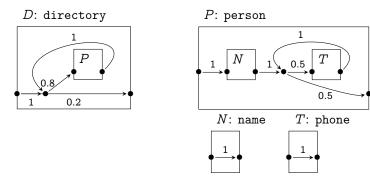


- e: event "it did not rain" at time 1
- mux: mutually exclusive options
- N(70, 4): normal distribution
- Two kinds of dependencies in discrete probabilistic XML: global
   (e) and local (mux)
- Addcontinuous leaves; non-obvious semantics issues



### Recursive Markov chains [Benedikt et al., 2010]

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



Probabilistic model that subsumes local discrete models

Allows generating documents of unbounded width or depth



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#### An Uncertain World

#### Probabilistic XML: Models and Complexity

Modeling Querying

Reconciling Web Data Models with the Actual Web



### 

Semantics of a (Boolean) query = probability the query is true:

- 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.



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Semantics of a (Boolean) query = probability the query is true:

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- Tree-pattern queries are evaluable in linear time over local dependencies with a bottom-up, dynamic programming algorithm
- Indeed, any monadic second-order query is tractable over local dependencies
- Even trivial queries are **#P-hard** over global dependencies
- Monte-Carlo sampling works
- Multiplicative approximation is also tractable (existence of a FPRAS)



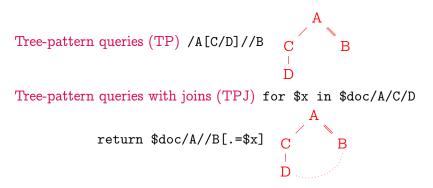
Aggregate Queries: sum, count, avg, countd, min, max, etc. Distributions? Possible values? Expected value?

- Computing expected values of sum and count tractable with global dependencies; everything else intractable
- Computing expected values of every of these aggregate functions tractable with local dependencies
- Computing distributions and possible values tractable for count, min, max, intractable for the others

Continuous distributions do not add any more complexity!



### Queries with joins are hard [Kharlamov et al., 2011]



Over local dependencies, dichotomy for queries with a single join:

- If equivalent to a join-free query, linear-time
- Otherwise, #P-hard

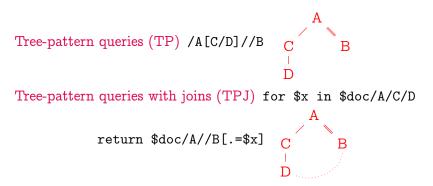
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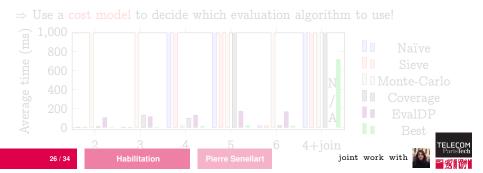
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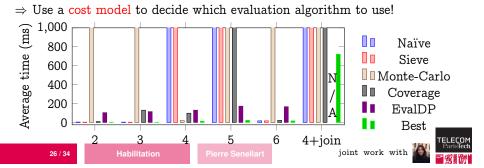


- Monte-Carlo is very good at approximating high probabilities
- Sometimes the structure of a query makes the probability of a query easy to evaluate
- For small formulas, naïve evaluation techniques good enough
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### Probabilistic XML: Models and Complexity

Modeling Querying Updating

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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-each-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



### Reconciling Web Data Models with the Actual Web





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Probabilistic XML: Models and Complexity

### Reconciling Web Data Models with the Actual Web Applying Probabilistic XML to Web data Formal Models for Web Content Acquisition



# Applying Probabilistic XML to Web data

- Current mismatch (in my research, but also in general) between:
  - Applications that produce and have to deal with uncertainty:
    - Information extraction
    - Graph mining
    - Natural language parsing
    - Data integration

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- etc.
- Probabilistic database management systems
- Analogy to data management in the 1960's:
  - Each data management application (accounting, cataloging, etc.) was developing its own way of managing data
  - Each application dealing with imprecise data is developing its own way of managing imprecision

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Probabilistic DBMSs are becoming more and more mature – time to put them to use for real applications?

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# Formal Models for Web Content Acquisition

#### Current mismatch between:

- Actual Web mining and Web data management applications:
  - Web graph mining
  - wrapper induction
  - Web crawling
- Research on the foundations of Web data management

### Plan: bridge the two

- Use formal models for data exchange [Senellart and Gottlob, 2008, Gottlob and Senellart, 2010] to perform wrapper induction or ontology matching
- Use static analysis techniques for JavaScript to perform deep Web data extraction [Benedikt et al., 2012b]
- Use results of formal studies of the containment of recursive query languages [Benedikt et al., 2011, 2012a] to optimize query answering over the deep Web



# Formal Models for Web Content Acquisition

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### Questions?



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