Probabilistic Databases: Models and Applications to Web Data

Pierre Senellart

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Part I: Uncertainty in the Real World

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
- Lies, opinions, rumors

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- Imperfect human judgment
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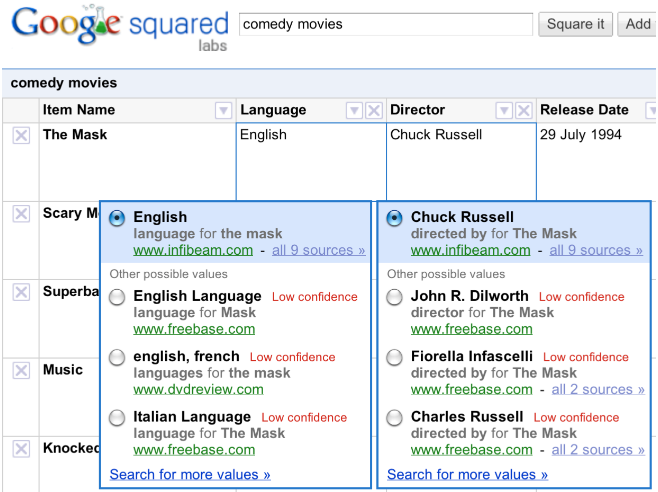
Use case: Web information extraction

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
english, uk	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]

Use case: Web information extraction

Subject	Predicate	Object	Confidence
Elvis Presley	diedOnDate	1977-08-16	97.91%
Elvis Presley	isMarriedTo	Priscilla Presley	97.29%
Elvis Presley	influences	Carlo Wolff	96.25%

YAGO, `http://www.mpi-inf.mpg.de/yago-naga/yago`

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 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?

Different types of uncertainty

Two dimensions:

- Different types:
  - Unknown value: NULL in an RDBMS
  - Alternative between several possibilities: either A or B or C
  - Imprecision on a numeric value: a sensor gives a value that is an approximation of the actual value
  - Confidence in a fact as a whole: cf. information extraction
  - Structural uncertainty: the schema of the data itself is uncertain
- Qualitative (NULL) or Quantitative (95%, low-confidence, etc.) uncertainty

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.

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Especially:

- Represent all different forms of uncertainty
- Use probabilities to represent quantitative information on the confidence in the data
- Query data and retrieve uncertain results
- Allow adding, deleting, modifying data in an uncertain way
- Bonus (if possible): Keep as well lineage/provenance information, so as to ensure traceability

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)
- In other cases, we "cheat" and pretend that (normalized) confidence scores are probabilities: see this as a first-order approximation

Objective of this talk

- Present data models for uncertain data management in general, and probabilistic data management in particular:
  - relational
  - XML
- Briefly discuss querying of probabilistic data

Part II: Probabilistic Models of Uncertainty

- Probabilistic Relational Models
- Probabilistic XML

Possible worlds semantics

Possible world: A regular (deterministic) relational or XML database

Incomplete database: (Compact) representation of a set of possible worlds

Probabilistic database: (Compact) representation of a probability distribution over possible worlds, either:

- finite: a set of possible worlds, each with their probability
- continuous: more complicated, requires defining a σ-algebra, and a measure for the sets of this σ-algebra

Part II: Probabilistic Models of Uncertainty

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- Probabilistic XML

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

Codd tables, a.k.a. SQL NULLs

Patient	Examin. 1	Examin. 2	Diagnosis
A	23	12	α
B	10	23	$\perp_1$
C	2	4	γ
D	15	15	$\perp_2$
E	$\perp_3$	17	β

- Most simple form of incomplete database
- Widely used in practice, in DBMS since the mid-1970s!
- All NULLs ($\perp$) are considered distinct
- Possible world semantics: all (infinitely many under the open world assumption) possible completions of the table
- In SQL, three-valued logic, weird semantics:

```
SELECT * FROM Tel WHERE tel_nr = '333' OR tel_nr <> '333'
```

C-tables [Imielinski and Lipski, 1984]

Patient	Examin. 1	Examin. 2	Diagnosis	Condition
A	23	12	α	
B	10	23	$\perp_1$	
C	2	4	γ	
D	$\perp_2$	15	$\perp_1$	
E	$\perp_3$	17	β	$18 < \perp_3 < \perp_2$

- NULLs are labeled, and can be reused inside and across tuples
- Arbitrary correlations across tuples
- Closed under the relational algebra (Codd tables only closed under projection and union)
- Every set of possible worlds can be represented as a database with c-tables

Tuple-independent databases (TIDs)

[Lakshmanan et al., 1997, Dalvi and Suciu, 2007]

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
- Impossible to express dependencies across rows
- Very simple model, well understood

Block-independent databases (BIDs)

[Barbará et al., 1992, Ré and Suciu, 2007]

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

- The table has a primary key: tuples sharing a primary key are mutually exclusive (probabilities must sum up to ≤ 1)
- Simple dependencies (exclusion) can be expressed, but not more complex ones

Probabilistic c-tables [Green and Tannen, 2006]

Patient	Examin. 1	Examin. 2	Diagnosis	Condition
A	23	12	α	w_1
B	10	23	β	w_2
C	2	4	γ	w_3
C	2	14	γ	$\neg w_3 \wedge w_4$
D	15	15	β	w_5
D	15	15	α	$\neg w_5 \wedge w_6$
E	15	17	β	w_7
E	15	17	α	$\neg w_7$

- The w_i's are Boolean random variables
- Each w_i has a probability of being true (e.g., $\Pr(w_1) = 0.9$)
- The w_i's are independent
- Any finite probability distribution of tables can be represented using probabilistic c-tables

Two actual PRDBMS: Trio and MayBMS

Two main probabilistic relational DBMS:

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

MayBMS [Koch, 2009] Implementation of the probabilistic c-tables model. In addition, uncertain tables can be constucted using a `REPAIR-KEY` operator, similar to BIDs.

Two actual PRDBMS: Trio and MayBMS

Two m

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Ma

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d using

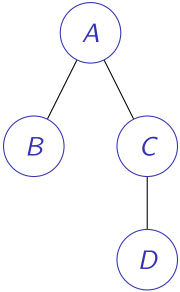
```
test=# select * from R;
 dummy | weather | ground |  p
-------+---------+--------+------
 dummy | rain    | wet    | 0.35
 dummy | rain    | dry    | 0.05
 dummy | no rain | wet    |  0.1
 dummy | no rain | dry    |  0.5
(4 rows)

test=# create table S as
repair key Dummy in R weight by P;
SELECT
test=# select Ground, conf() from S group by Ground;
 ground | conf
--------+------
 dry    | 0.55
 wet    | 0.45
(2 rows)
```

Part II: Probabilistic Models of Uncertainty

- Probabilistic Relational Models
- Probabilistic XML

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

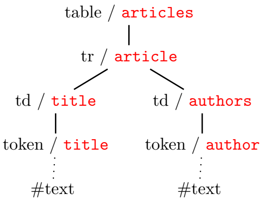
Why Probabilistic XML?

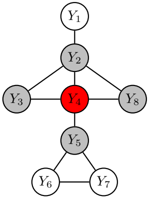
- Extensive literature about probabilistic relational databases [Dalvi et al., 2009, Widom, 2005, Koch, 2009]
- Different typical querying languages: conjunctive queries vs XPath and tree-pattern queries (possibly with joins)
- Cases where a tree-like model might be appropriate:
  - No schema or few 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! [Amarilli and Senellart, 2013]

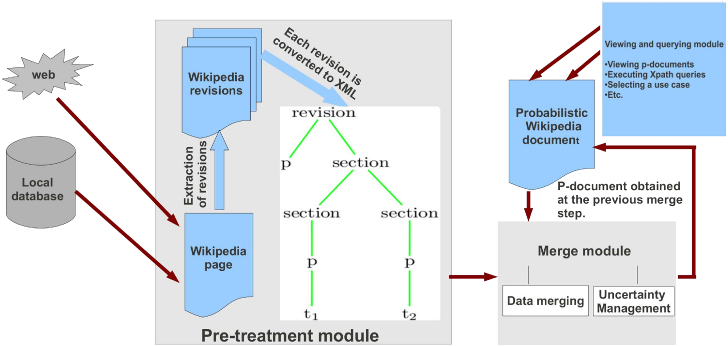
Web information extraction [Senellart et al., 2008]





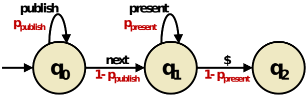
- Annotate HTML Web pages with possible labels
- Labels can be learned from a corpus of annotated documents
- Conditional random fields for XML: estimate probabilities of annotations given annotations of neighboring nodes
- Provides probabilistic labeling of Web pages

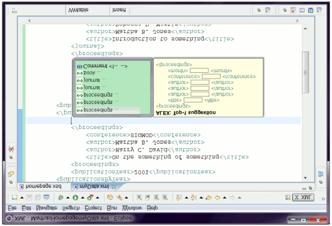
Uncertain version control
[Abdessalem et al., 2011, Ba et al., 2013]



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

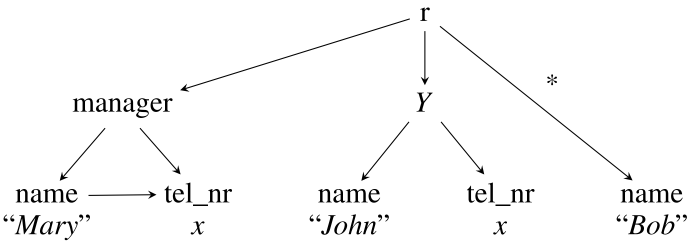
Probabilistic summaries of XML corpora
[Abiteboul et al., 2012a,b]





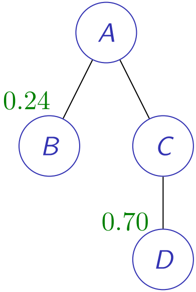
- Transform an XML schema (deterministic top-down tree automaton) into a probabilistic generator (probabilistic tree automaton) of XML documents
- Probability distribution optimal with respect to a given corpus
- Application: Optimal auto-completions in an XML editor

Incomplete XML [Barceló et al., 2009]



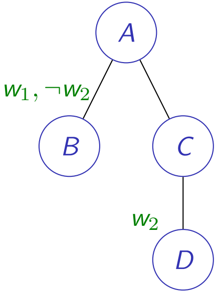
- Models all XML documents where these patterns exist (i.e., this subtree can be matched)
- Can be used for query answering, etc.

Simple probabilistic annotations



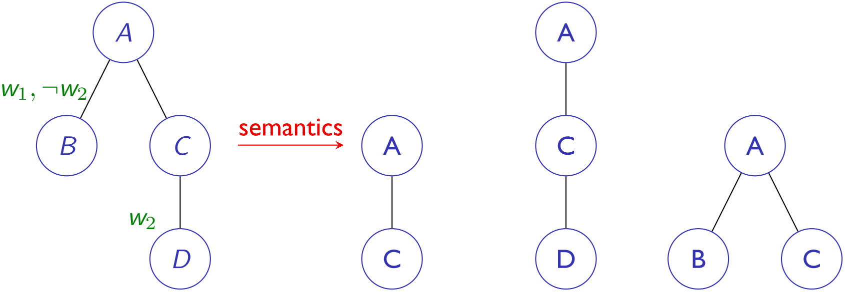
- Probabilities associated to tree nodes
- Express parent/child dependencies
- Impossible to express more complex dependencies
- $\Rightarrow$ some sets of possible worlds are not expressible this way!

Annotations with event variables



Event	Prob.
w_1	0.8
w_2	0.7

Annotations with event variables



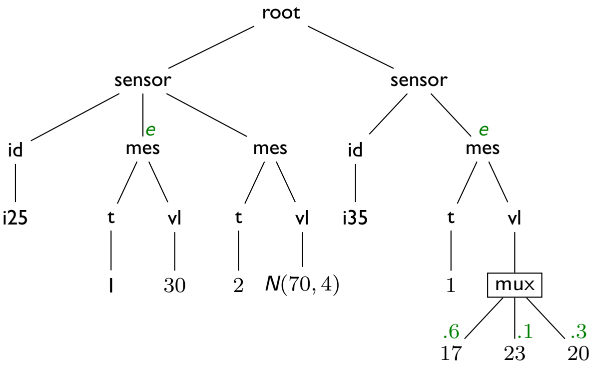
$p_1 = 0.06$ $\quad p_2 = 0.70$ $\quad p_3 = 0.24$

Event	Prob.
w_1	0.8
w_2	0.7

- Expresses arbitrarily complex dependencies
- Obviously, analogous to probabilstic c-tables

A general probabilistic XML model

[Abiteboul et al., 2009]



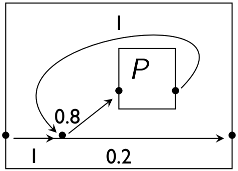
- *e*: event "it did not rain" at time 1
- mux: mutually exclusive options
- $N(70, 4)$: normal distribution

- 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

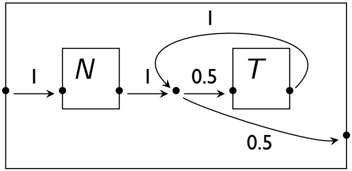
Recursive Markov chains [Benedikt et al., 2010]

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

D: `directory`



P: `person`



- Probabilistic model that extends PXML with local dependencies
- Allows generating documents of unbounded width or depth

Part III: Querying Probabilistic Databases

- Semantics
- Lineage computation and #P-Hardness
- Special tractable case within Probabilistic XML

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Semantics Of Query Answering: Example

Person

name	city	probability
Ivan	Moscow	0.3
Jean	Paris	0.8
Pedro	Madrid	0.4

Query:
SELECT name FROM Person

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SELECT name FROM Person

Pr = 0.3*0.8*0.4

name	city
Ivan	Moscow
Jean	Paris
Pedro	Madrid

Pr = 0.3*0.2*0.4

name	city
Ivan	Moscow
Pedro	Madrid

...

Semantics Of Query Answering: Example

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Pr = 0.3*0.8*0.4

name	city
Ivan	Moscow
Jean	Paris
Pedro	Madrid

Pr = 0.3*0.2*0.4

name	city
Ivan	Moscow
Pedro	Madrid

...

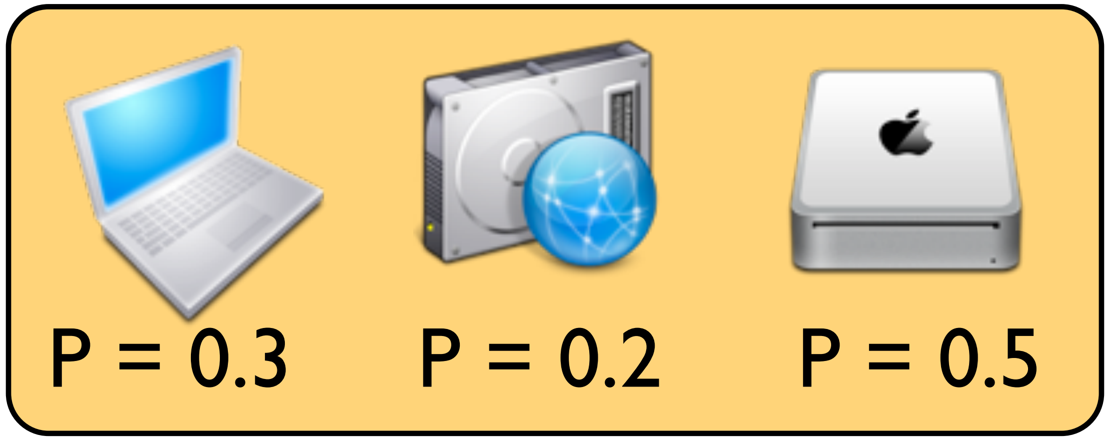
Possible answers: ({Ivan, Juan, Pedro}, 0.3*0.8*0.4),
({Ivan, Pedro}, 0.3*0.2*0.4), ...

Possible tuples: (Ivan, 0.3), (Jean, 0.8), (Pedro, 0.4)

Semantics Of Query Answering

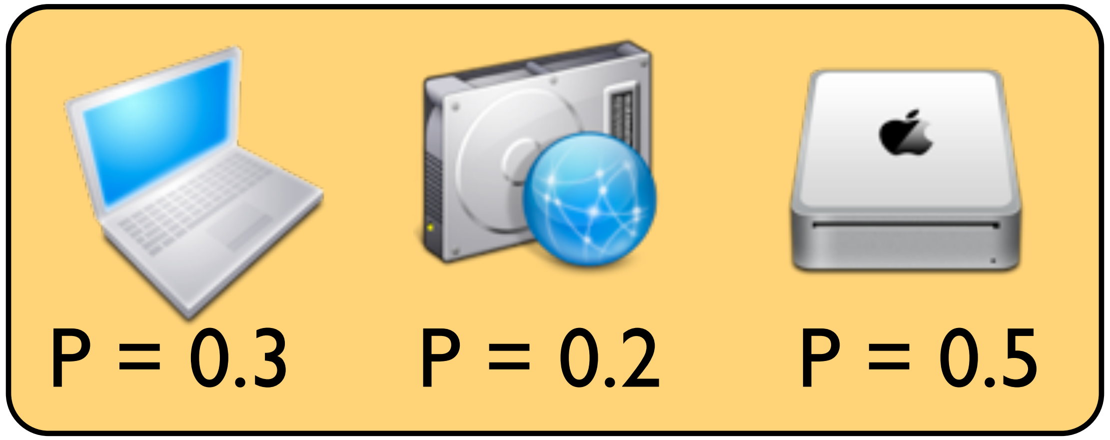
Possible Answers Semantics

Probabilistic DB:



Possible Tuples Semantics

Probabilistic DB:



Semantics Of Query Answering

Possible Answers Semantics

Probabilistic DB:

P = 0.3 P = 0.2 P = 0.5

Q Q Q

{a} {a,b}

Possible Tuples Semantics

Probabilistic DB:

P = 0.3 P = 0.2 P = 0.5

Semantics Of Query Answering

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{a} {a,b}

Answer: ({a}, 0.3); ({a,b}, 0.5)

Possible Tuples Semantics

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Semantics Of Query Answering

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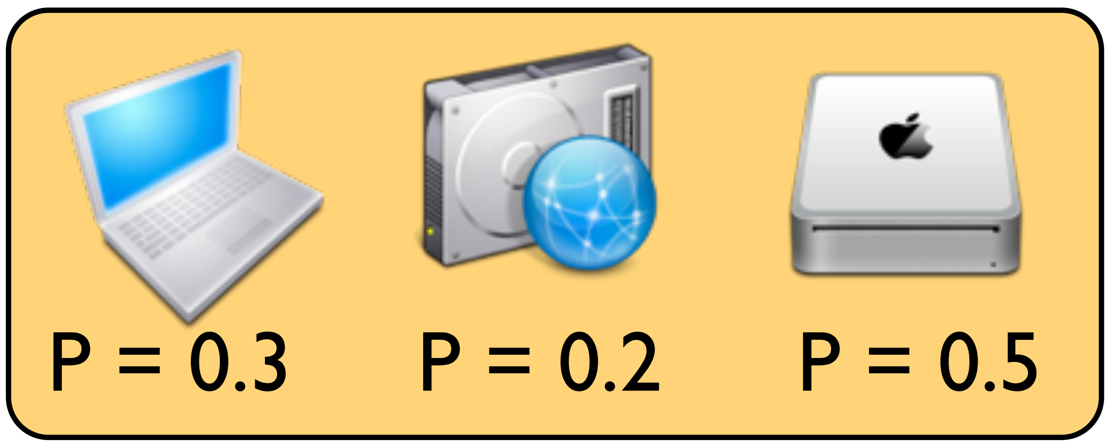

Q Q Q

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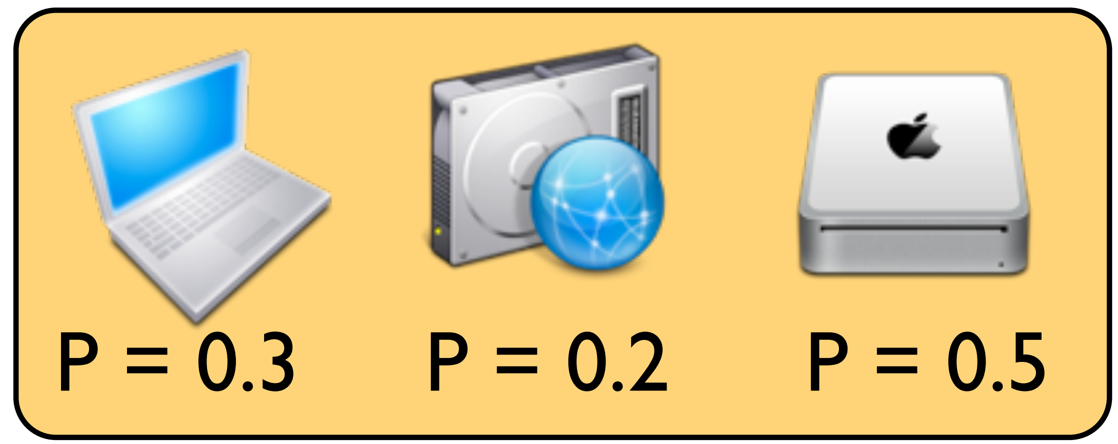
Answer: ({a}, 0.3); ({a,b}, 0.5)

Probability distribution on sets of tuples

Possible Tuples Semantics

Probabilistic DB:



Semantics Of Query Answering

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Answer: ({a}, 0.3); ({a,b}, 0.5)

Probability distribution on
sets of tuples

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Semantics Of Query Answering

Possible Answers Semantics

Probabilistic DB:

P = 0.3 P = 0.2 P = 0.5

Q Q Q

{a} {a,b}

Answer: ({a}, 0.3); ({a,b}, 0.5)

Probability distribution on
sets of tuples

Possible Tuples Semantics

Probabilistic DB:

P = 0.3 P = 0.2 P = 0.5

Q Q Q

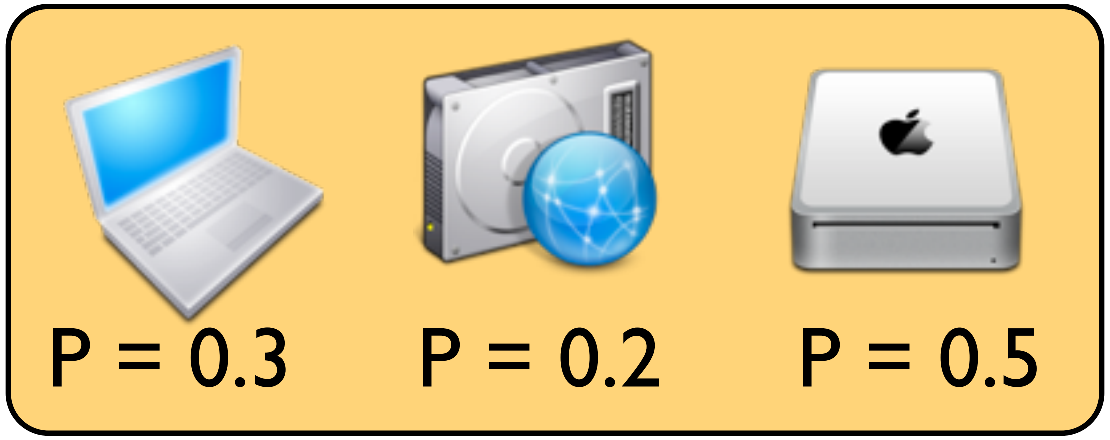
{a} {a,b}

Answer: (a, 0.8), (b, 0.5)

Semantics Of Query Answering

Possible Answers Semantics

Probabilistic DB:



Q Q Q

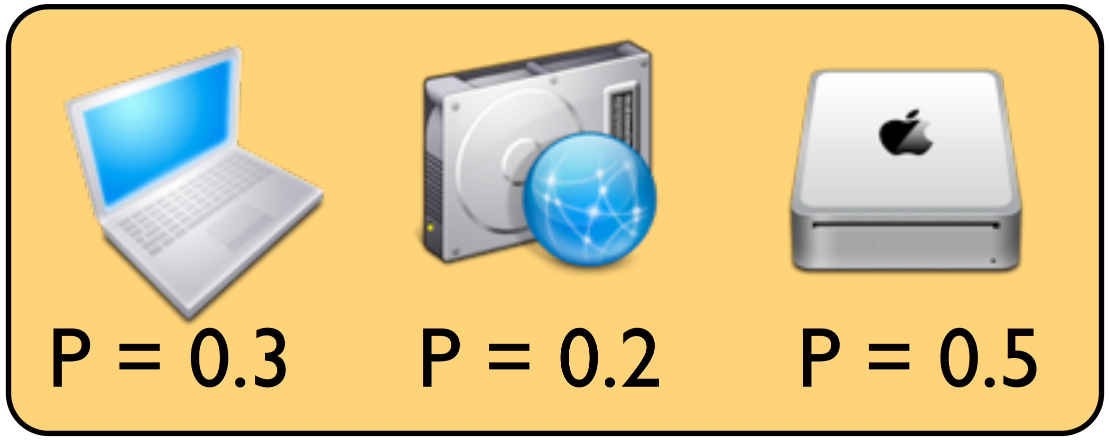
{a} {a,b}

Answer: ({a}, 0.3); ({a,b}, 0.5)

Probability distribution on sets of tuples

Possible Tuples Semantics

Probabilistic DB:



Q Q Q

{a} {a,b}

Answer: (a, 0.8), (b, 0.5)

Probability distribution on tuples

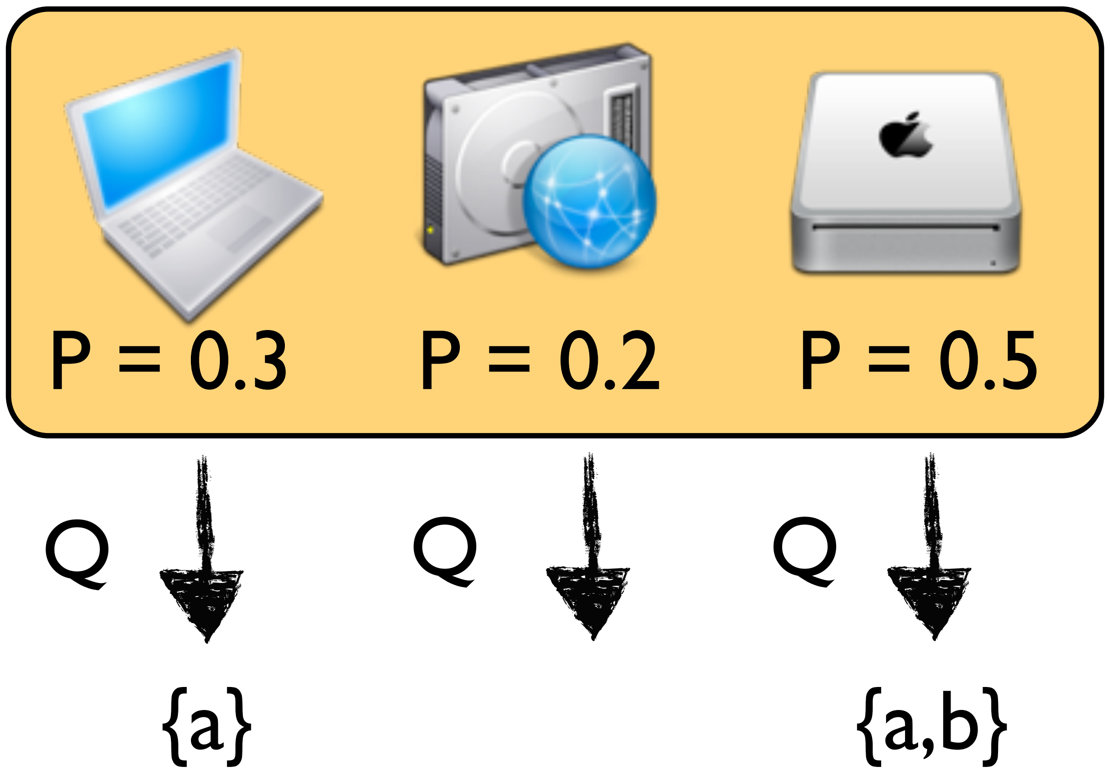
Possible Answer vs Possible Tuple Semantics

[Dalvi,Suciu'09]

- Possible answers semantics:
  - Precise
  - Can be used to compose queries
  - Difficult user interface
- Possible tuples semantics:
  - Less precise, but simple; sufficient for most apps
  - Cannot be used to compose queries
  - Simple user interface

Goals of Query Answering

Probabilistic DB:



Answer: (a, 0.8), (b, 0.5)

Goals of Query Answering

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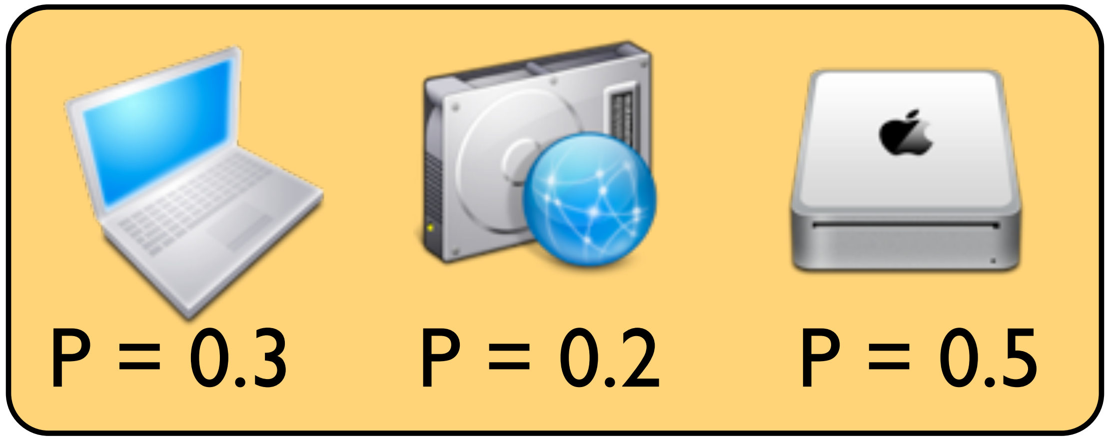


Q ↓ {a} Q ↓ Q ↓ {a,b}

Answer: (a, 0.8), (b, 0.5)

theory | practice

- There may be EXP many worlds ➜ naive evaluation is exponential
- Can we do better?

Goals of Query Answering

Probabilistic DB:

P = 0.3   P = 0.2   P = 0.5

Q   Q   Q

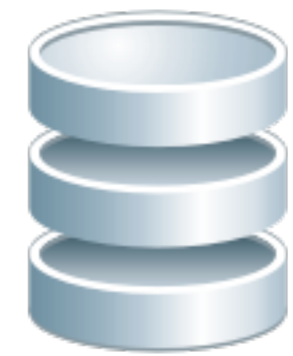
{a}   {a,b}

Answer: (a, 0.8), (b, 0.5)

semantics

theory | practice

Representation of Prob DB:



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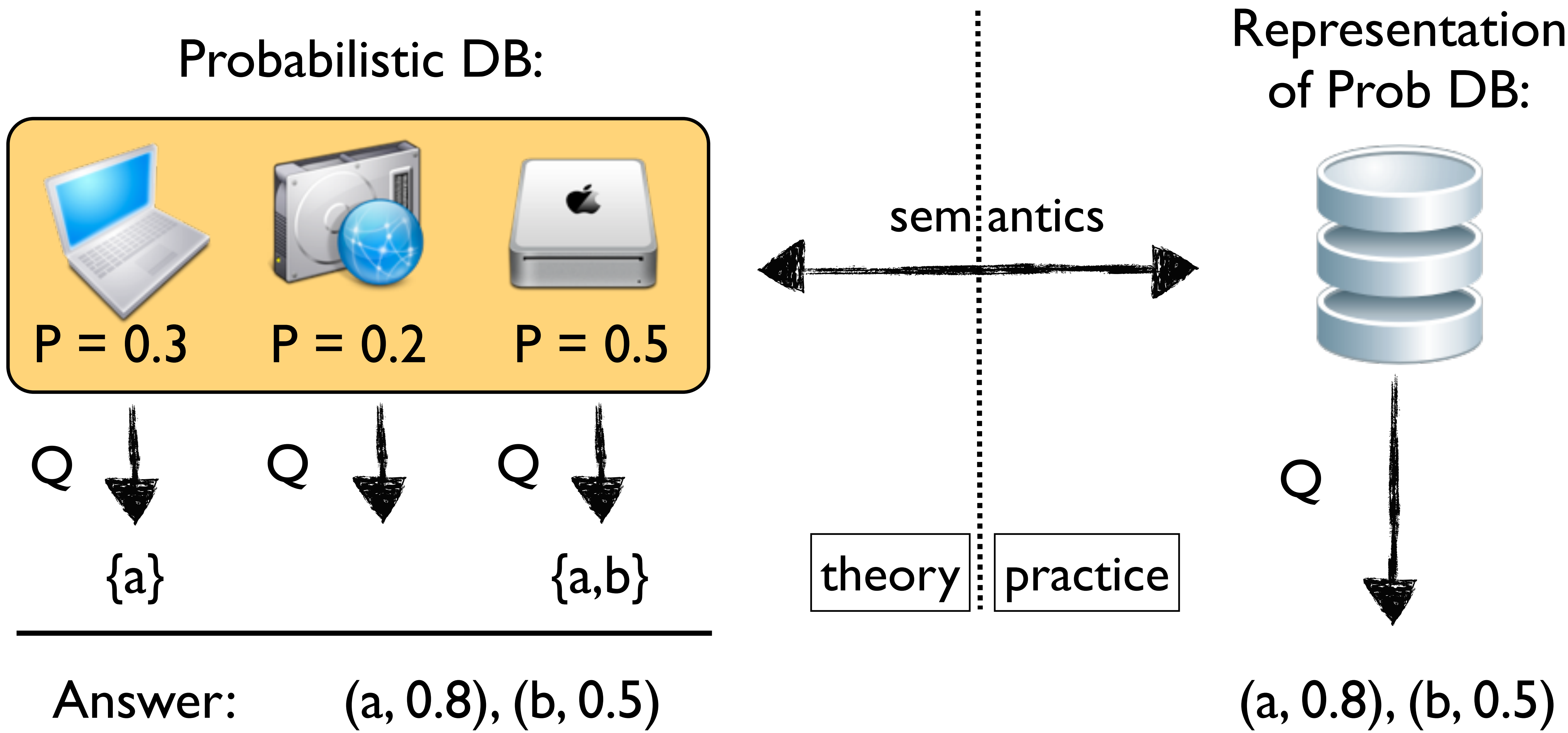

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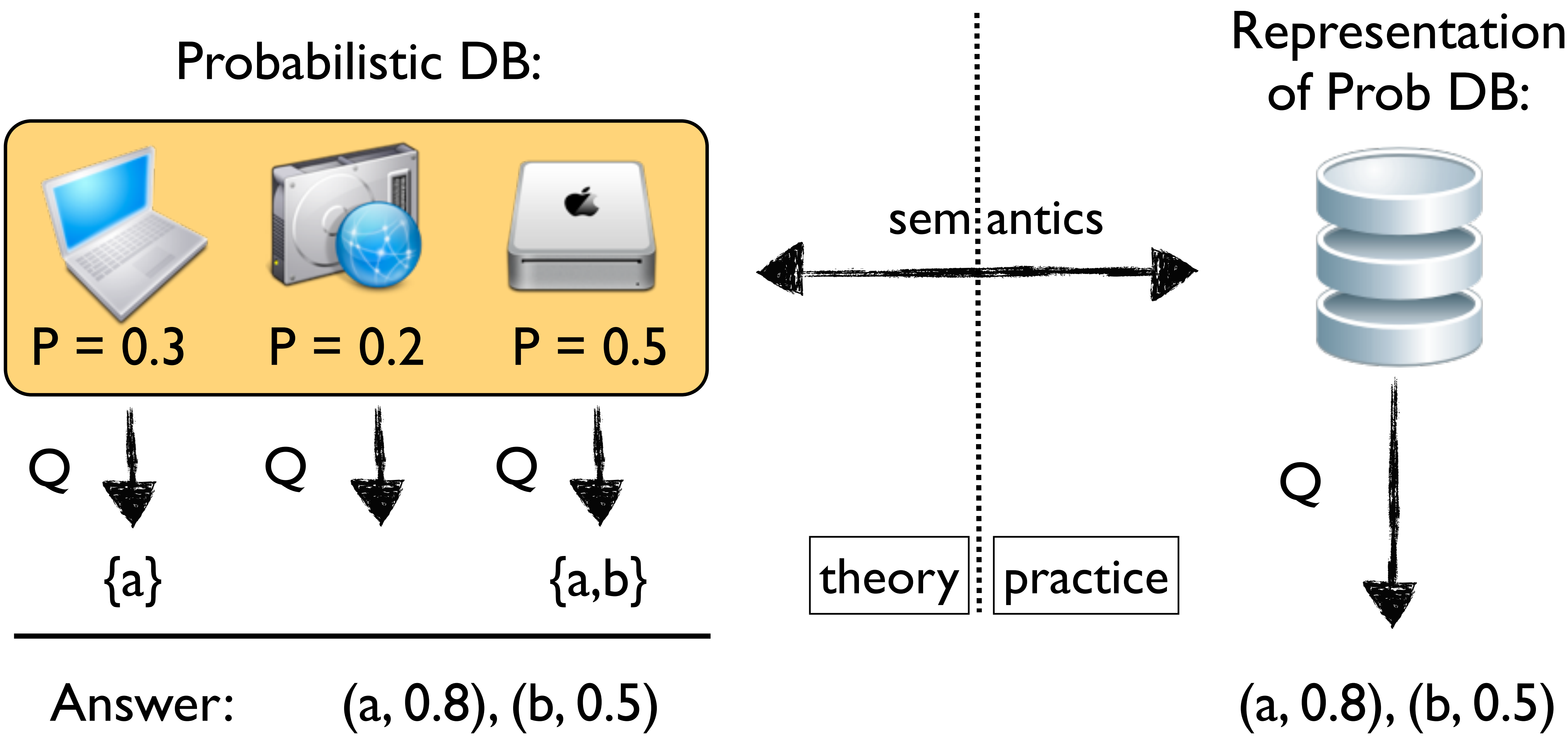

- There may be EXP many worlds ➜ naive evaluation is exponential
- Can we do better?
- Goal: to find out how to query representation system directly

Part III: Querying Probabilistic Databases

- Semantics
- Lineage computation and #P-Hardness
- Special tractable case within Probabilistic XML

General Lineage: Examples of Operators (1)

Drivers

ID	person	car	Lineage
31	Jimmy	Toyota	$x \wedge y$
32	Jimmy	Honda	y
33	Hank	Honda	$x \vee z$

Saw

ID	witness	car	Lineage
21	Cathy	Honda	w

$Pr(x \text{ is true}) = 0.2$ $Pr(z \text{ is true}) = 0.8$
$Pr(y \text{ is true}) = 0.4$ $Pr(w \text{ is true}) = 0.5$

Project = π_{person} (Drives)

Select = $\sigma_{car=\text{"honda"}}$ (Drives)

Project

person	Lineage
Jimmy	$(x \wedge y) \vee y$
Hank	$x \vee z$

Select

person	car	Lineage
Jimmy	Honda	y
Hank	Honda	$x \vee z$

General Lineage: Examples of Operators (1)

Drivers

ID	person	car	Lineage
31	Jimmy	Toyota	$x \wedge y$
32	Jimmy	Honda	y
33	Hank	Honda	$x \vee z$

Saw

ID	witness	car	Lineage
21	Cathy	Honda	w

Pr(x is true) = 0.2 Pr(z is true) = 0.8
Pr(y is true) = 0.4 Pr(w is true) = 0.5

Project = π_{person} (Drives)

Select = $\sigma_{car=\text{"honda"}}$ (Drives)

Project

person	Lineage
Jimmy	$(x \wedge y) \vee y$
Hank	$x \vee z$

Select

person	car	Lineage
Jimmy	Honda	y
Hank	Honda	$x \vee z$

General Lineage: Examples of Operators (2)

Drivers

ID	person	car	Lineage
31	Jimmy	Toyota	$x \wedge y$
32	Jimmy	Honda	y
33	Hank	Honda	$x \vee z$

Saw

ID	witness	car	Lineage
21	Cathy	Honda	w

Pr(x is true) = 0.2 Pr(z is true) = 0.8
Pr(y is true) = 0.4 Pr(w is true) = 0.5

Join = Saw $\bowtie_{car}$ Drives

Several = $\pi_{person}(\sigma_{person=\text{"Hank"}}$ (Saw $\bowtie_{car}$ Drives)

Join

person	car	witness	Lineage
Jimmy	Honda	Cathy	$y \wedge w$
Hank	Honda	Cathy	$(x \vee z) \wedge w$

Several

person	Lineage
Hank	$(x \vee z) \wedge w$

General Lineage: Examples of Operators (2)

Drivers

ID	person	car	Lineage
31	Jimmy	Toyota	$x \wedge y$
32	Jimmy	Honda	y
33	Hank	Honda	$x \vee z$

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Several = $\pi_{person}(\sigma_{person=\text{"Hank"}}$ (Saw $\bowtie_{car}$ Drives)

Join

person	car	witness	Lineage
Jimmy	Honda	Cathy	$y \wedge w$
Hank	Honda	Cathy	$(x \vee z) \wedge w$

Several

person	Lineage
Hank	$(x \vee z) \wedge w$

General Lineage: Examples of Operators (3)

Saw-day

ID	witness	car	Lineage
31	Cathy	Honda	z
32	Bob	BMW	$y \wedge w$

Saw-night

ID	witness	car	Lineage
21	Cathy	Honda	w

Pr(x is true) = 0.2 Pr(z is true) = 0.8
Pr(y is true) = 0.4 Pr(w is true) = 0.5

Union = Saw-day ∪ Saw-night

Difference = Saw-day \ Saw-night

Union

witness	car	Lineage
Cathy	Honda	$z \vee w$
Bob	BMW	$y \wedge w$

Difference

witness	car	Lineage
Cathy	Honda	$z \wedge (\neg w)$
Bob	BMW	$y \wedge w$

General Lineage: Examples of Operators (3)

Saw-day

ID	witness	car	Lineage
31	Cathy	Honda	z
32	Bob	BMW	$y \wedge w$

Saw-night

ID	witness	car	Lineage
21	Cathy	Honda	w

Pr(x is true) = 0.2 Pr(z is true) = 0.8
Pr(y is true) = 0.4 Pr(w is true) = 0.5

Union = Saw-day ∪ Saw-night

Difference = Saw-day \ Saw-night

Union

witness	car	Lineage
Cathy	Honda	$z \vee w$
Bob	BMW	$y \wedge w$

Difference

witness	car	Lineage
Cathy	Honda	$z \wedge (\neg w)$
Bob	BMW	$y \wedge w$

Query Probabilities from Lineage

Join = Saw $\bowtie_{car}$ Drives

Pr(x is true) = 0.2   Pr(z is true) = 0.8
Pr(y is true) = 0.4   Pr(w is true) = 0.5

Join

person	car	witness	Lineage
Jimmy	Honda	Cathy	$y \wedge w$
Hank	Honda	Cathy	$(x \vee z) \wedge w$

Theorem: SPJUD-query evaluation over PrRBDs with boolean-formulas lineage is #P-hard, i.e. intractable

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Join

person	car	witness	Lineage
Jimmy	Honda	Cathy	$y \wedge w$
Hank	Honda	Cathy	$(x \vee z) \wedge w$

- Pr(Jimmy $\in$ (Saw $\bowtie_{car}$ Drives)) = $Pr(y \wedge w) = Pr(y) \times Pr(w) = 0.4 \times 0.5 = 0.2$

Theorem: SPJUD-query evaluation over PrRBDs with boolean-formulas lineage is #P-hard, i.e. intractable

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Join

person	car	witness	Lineage
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- Pr(Jimmy $\in$ (Saw $\bowtie_{car}$ Drives)) = $Pr(y \wedge w) = Pr(y) \times Pr(w) = 0.4 \times 0.5 = 0.2$
- Pr(Hank $\in$ (Saw $\bowtie_{car}$ Drives)) = $Pr((x \vee z) \wedge w))$

$$= Pr(x \vee z) \times Pr(w)$$
$$= [\, Pr(x) + Pr(z) - Pr(x \wedge z) \,] \times 0.5$$
$$= [\, Pr(x) + Pr(z) - Pr(x) \times Pr(z) \,] \times 0.5$$
$$= [\, 0.2 + 0.8 - 0.2 \times 0.8 \,] \times 0.5 = 0.42$$

Theorem: SPJUD-query evaluation over PrRBDs with boolean-formulas lineage is #P-hard, i.e. intractable

Query Probabilities from Lineage

Join = Saw $\Join_{car}$ Drives

Pr(x is true) = 0.2 Pr(z is true) = 0.8
Pr(y is true) = 0.4 Pr(w is true) = 0.5

Join

person	car	witness	Lineage
Jimmy	Honda	Cathy	$y \wedge w$
Hank	Honda	Cathy	$(x \vee z) \wedge w$

- Pr(Jimmy $\in$ (Saw $\Join_{car}$ Drives)) = $Pr(y \wedge w) = Pr(y) \times Pr(w) = 0.4 \times 0.5 = 0.2$
- Pr(Hank $\in$ (Saw $\Join_{car}$ Drives)) = $Pr((x \vee z) \wedge w))$

$$= Pr(x \vee z) \times Pr(w)$$
$$= [\, Pr(x) + Pr(z) - Pr(x \wedge z) \,] \times 0.5$$
$$= [\, Pr(x) + Pr(z) - Pr(x) \times Pr(z) \,] \times 0.5$$
$$= [\, 0.2 + 0.8 - 0.2 \times 0.8 \,] \times 0.5 = 0.42$$

In general:
Pr(lineage) = Pr(φ)
where φ is a prop. formula

Theorem: SPJUD-query evaluation over PrRBDs with boolean-formulas lineage is #P-hard, i.e. intractable

#P Functions

- Probability computation is a function and not a decision problem
- Usually complexity is studied for decision problems: P(x) = yes/no
- Complexity classes for probability computation are for classes of functions
- #P functions: f(x) = n
  - there is a PTIME non-deterministic Turing machine M_f
  - n = the number of accepting runs of M_f on x, i.e., of $M_f(x)$
- #P functions are counting counterparts of NP decision problems
- Example of #P-complete function:
  #2DNF: count number of evaluations for 2DNF propositional formulas
- #P-comp. functions are counter counterparts of NP-comp. problems

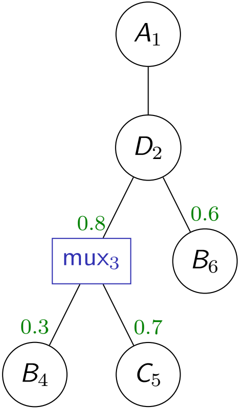
Part III: Querying Probabilistic Databases

- Semantics
- Lineage computation and #P-Hardness
- Special tractable case within Probabilistic XML

Algorithm for TP over 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

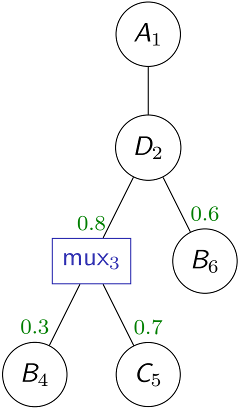
mux convex sum

ordinary inclusion-exclusion

Algorithm for TP over local dependencies

[Kimelfeld and Sagiv, 2007]

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



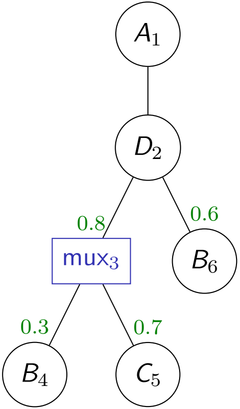
	A_1	D_2	mux_3	B_4	C_5	B_6
/B			0.3	1	0	1
//B			0.3	1	0	1
/A//B			0	0	0	0

mux	convex sum
ordinary	inclusion-exclusion

Algorithm for TP over 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

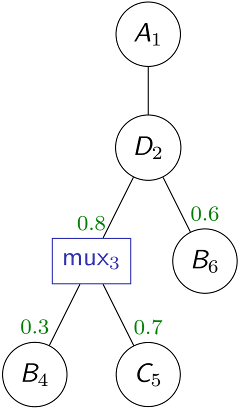
ordinary — inclusion-exclusion

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

Algorithm for TP over 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

Part IV: To go further

Systems

Trio `http://infolab.stanford.edu/trio/`, useful to see lineage computation

MayBMS `http://maybms.sourceforge.net/`, full-fledged probabilistic relational DBMS, on top of PostgreSQL, usable for actual applications.

ProApproX `http://www.infres.enst.fr/~souihli/Publications.html` to play with various approximation and exact query evaluation methods for probabilistic XML.

Reading material

- An influential paper on incomplete databases [Imielinski and Lipski, 1984]
- A book on probabilistic relational databases, focused around TIDs/BIDs and MayBMS [Suciu et al., 2011]
- An in-depth presentation of MayBMS [Koch, 2009]
- A gentle presentation of relational and XML probabilistic models [Kharlamov and Senellart, 2011]
- A survey of probabilistic XML [Kimelfeld and Senellart, 2013]

Merci.

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