

Conditioning Probabilistic Databases

Dan Olteanu (Oxford University Computing Laboratory)

Joint work with Christoph Koch (Cornell University Database Systems Group)

Main goals of the MayBMS project

Create a scalable DBMS for uncertain/probabilistic data

- Representation and storage mechanisms
- Uncertainty-aware query and data manipulation language
- Efficient processing techniques for queries and constraints

This talk covers aspects of (3).

MayBMS available at sourceforge.net !

Conditioning c-table-like Probabilistic Databases

Transform a probabilistic database of priors into a posterior probabilistic database.

Example: Probabilistic database representing four *weighted* instances of relation R defining social security numbers and names:

R^1	SSN	NAME	R^2	SSN	NAME	
	1	John		7	John	
	4	Bill		4	Bill	
P = .06			P = .24			
R^3	SSN	NAME	R^4	SSN	NAME	
R ³	SSN 1	NAME John	R^4	SSN 7	NAME John	
<i>R</i> ³	SSN 1 7		R^4	SSN 7 7		

Events: A_x = Bill has SSN x; B = SSN is unique in R.

 $Q_1 = \text{select SSN}$, **conf()** from R where NAME = 'Bill' group by SSN; assert SSN \rightarrow NAME on R; Q_1

$$P(A_4) = .3$$
 $P(A_4 \mid B) = \frac{P(A_4 \land B)}{P(B)} = \frac{.3}{.06 + .24 + .14} \approx .68$

Challenges

Conditioning/confidence computation is NP-hard on *succinct* representations.

- No prior work on conditioning probabilistic databases (i.e., on using assert)
- Some prior work on confidence computation (MystiQ, Trio, MayBMS, ...)

Exact versus approximate computation.

- Approximation problematic for compositional query languages for probabilistic databases.
 - Introduced errors aggregate and grow.
 - conf() used in comparison predicates.

Materialize the (succinct) probabilistic database result of conditioning.

• assert is natural for data cleaning under possible worlds semantics.

- Discrete independent (random) variables.
- Representation: U-relations + table W representing distributions.
- The schema of each U-relation consists of
 - ▶ a set of column pairs $WSD = (Var \rightarrow Dom)$ representing variable assignments,
 - a set of value columns,
 - (a tuple id column).

W	Var	Dom	Р	U_R	WSD	SSN	NAME
	j	1	.2		$\{j\mapsto 1\}$	1	John
	j	7	.8		$\{j \mapsto 7\}$	7	John
	Ь	4	.3		$\{b \mapsto 4\}$	4	Bill
	Ь	7	.7		$\{b \mapsto 7\}$	7	Bill

Properties of U-relational databases

- Complete representation system for finite sets of possible worlds.
- Purely relational representation of uncertainty at attribute-level.
- Efficient relational evaluation of SPJ queries (without conf()).

W	Var	Dom	Ρ	U_R			NAME
	j	1	.2		$\{j\mapsto 1\}$	1	John
	j	7	.8		$\{j \mapsto 7\}$	7	John
	Ь	4	.3		$\{b \mapsto 4\}$	4	Bill
	Ь	7	.7		$\{b \mapsto 7\}$	7	Bill

W	Var	Dom	Ρ
	j	1	.2
	j	7	.8
	Ь	4	.3
	Ь	7	.7

U_R	WSD	SSN	NAME
	$\{j\mapsto 1\}$	1	John
	$\{j \mapsto 7\}$	7	John
	$\{b \mapsto 4\}$	4	Bill
	$\{b \mapsto 7\}$	7	Bill

R^1	SSN	NAME	R^2	SSN	NAME
	1	John		7	John
	4	Bill		4	Bill
P =	= .2 · .3	= .06	P :	= .8 · .3	8 = .24
R^3	SSN	NAME	R^4	SSN	NAME
	1	John		7	John
	7	Bill		7	Bill
$P = .2 \cdot .7 = .14$				= .8 · .7	

W	Var	Dom	Р
	j	1	.2
	j	7	.8
	Ь	4	.3
	b	7	.7

U_R	WSD	SSN	NAME
	$\{j\mapsto 1\}$	1	John
	$\{j \mapsto 7\}$	7	John
	$\{b \mapsto 4\}$	4	Bill
	$\{b \mapsto 7\}$	7	Bill

R^1	SSN	NAME		R^2	SSN	NAME
	1	John			7	John
	4	Bill			4	Bill
P :	$P = .2 \cdot .3 = .06$			P :	= .8 · .3	.24
R^3	SSN	NAME		R^4	SSN	NAME
	1	John			7	John
	7	Bill			7	Bill
$P = .2 \cdot .7 = .14$			P -	= .8 · .7	- 56	

W	Var	Dom	Р
	j	1	.2
	j	7	.8
	Ь	4	.3
	Ь	7	.7

U_R	WSD	SSN	NAME
	$\{j\mapsto 1\}$	1	John
	$\{j \mapsto 7\}$	7	John
	$\{b \mapsto 4\}$	4	Bill
	$\{b \mapsto 7\}$	7	Bill

_	R^1	SSN	NAME	R^2	SSN	NAME
		1	John		7	John
_		4	Bill		4	Bill
	P =	= .2 · .3	.06	P =	= .8 · .3	8 = .24
	R^3	SSN	NAME	R^4	SSN	NAME
		1	John		7	John
		7	Bill		7	Bill
	P =	= .2 · .7	′ = .14	P =	= .8 · .7	′ = .56

W	Var	Dom	Ρ
	j	1	.2
	j	7	.8
	Ь	4	.3
	Ь	7	.7

U_R	WSD	SSN	NAME
	$\{j\mapsto 1\}$	1	John
	$\{j \mapsto 7\}$	7	John
	$\{b \mapsto 4\}$	4	Bill
	$\{b \mapsto 7\}$	7	Bill

R^1	SSN	NAME		R^2	SSN	NAME
	1	John			7	John
	4	Bill			4	Bill
Р	$P = .2 \cdot .3 = .06$				= .8 · .3	3 = .24

R^3	SSN	NAME		R^4	SSN	NAME
	1	John			7	John
	7	Bill			7	Bill
Р	= .2 · .7	7 = .14	1	P =	= .8 · .7	= .56

Queries on U-Relational Databases

W	Var	Dom	Ρ	U_R	WSD	SSN	NAME
	j	1	.2		$\{j\mapsto 1\}$	1	John
	j	7	.8		$\{j \mapsto 7\}$	7	John
	Ь	4	.3		$\{b \mapsto 4\}$	4	Bill
	Ь	7	.7		$\{b \mapsto 7\}$	7	Bill

 Q_1 = select SSN, **conf()** as P from R where NAME = 'Bill' group by SSN;

_	Q_1	SSN	Р
		4	$P(\{b \mapsto 4\})$
		7	$P(\{b \mapsto 7\})$

What makes confidence computation hard?

Succinct representation of uncertainty.

- Each tuple in a probabilistic database is associated with a *world-set descriptor* that succinctly encodes the set of worlds containing that tuple.
 World-set descriptor = Conjunction of variable assignments.
 Examples: {j → 1}, {j → 1, b → 4}.
- Arbitrary combinations of input world-set descriptors produced by query joins.

Queries with projections can create duplicate answer tuples.

▶ Distinct tuples can be associated with sets of world-set descriptors. Set of world-set descriptors = DNF expression over variable assignments. Examples: {{j → 1}} and {{j → 1}, {j → 1, b → 4}, {b → 7}}.

SAT (Model counting) is #P-hard for arbitrary DNF expressions.

- Model counting is a special case of confidence computation.
- Arbitrary sets of world-set descriptors can be created by queries.
- The sets of models of different conjunctions in a DNF expression can overlap and have exponential size.

Knowledge Compilation Techniques to the Rescue

- Useful for compiling formulas into propositional theories with tractable properties, e.g., (#)SAT.
 ROBDDs (Bryant), d-NNFs (Darwiche), and variations thereof.
- Successfully applied to system modelling and verification.

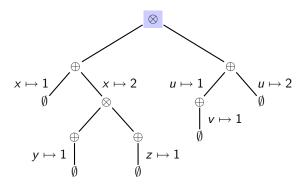
In this paper: ws-sets compiled into ws-trees.

- more succinct than OBDDs and similar to d-NNFs
- structurally limited (trees) and with multistate variables
- ws-sets can be compiled into ws-trees of exponential size but like OBDDs tend to behave well in practice

Idea behind ws-tree construction: Given a tuple t with a ws-set S, partition S

- into independent subsets (*exploit contextual independence*)
- by variable elimination (Davis-Putnam procedure)

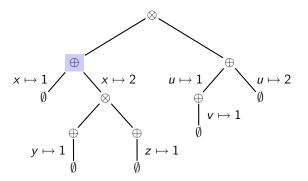
 $S = \{\{x \mapsto 1\}, \{x \mapsto 2, y \mapsto 1\}, \{x \mapsto 2, z \mapsto 1\}, \{u \mapsto 1, v \mapsto 1\}, \{u \mapsto 2\}\}$ Assume dom_x = {1, 2, 3} and dom_y = dom_z = dom_u = dom_v = {1, 2}.



Apply independence partitioning to S:

- left: $\{\{x \mapsto 1\}, \{x \mapsto 2, y \mapsto 1\}, \{x \mapsto 2, z \mapsto 1\}\}$
- right: $\{\{u \mapsto 1, v \mapsto 1\}, \{u \mapsto 2\}\}.$

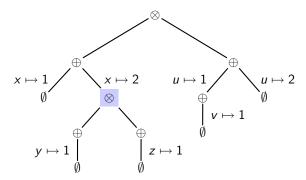
 $S = \{\{x \mapsto 1\}, \{x \mapsto 2, y \mapsto 1\}, \{x \mapsto 2, z \mapsto 1\}, \{u \mapsto 1, v \mapsto 1\}, \{u \mapsto 2\}\}$ Assume dom_x = {1, 2, 3} and dom_y = dom_z = dom_u = dom_v = {1, 2}.



Apply variable elimination to $\{\{x \mapsto 1\}, \{x \mapsto 2, y \mapsto 1\}, \{x \mapsto 2, z \mapsto 1\}\}.$

- left: $x \mapsto 1 : \emptyset$
- right: $x \mapsto 2 : \{\{y \mapsto 1\}, \{z \mapsto 1\}\}$.

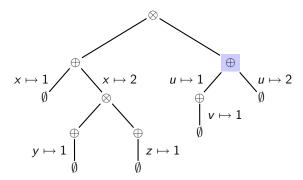
 $S = \{\{x \mapsto 1\}, \{x \mapsto 2, y \mapsto 1\}, \{x \mapsto 2, z \mapsto 1\}, \{u \mapsto 1, v \mapsto 1\}, \{u \mapsto 2\}\}$ Assume dom_x = {1, 2, 3} and dom_y = dom_z = dom_u = dom_v = {1, 2}.



Apply independence partitioning to $\{\{y \mapsto 1\}, \{z \mapsto 1\}\}$.

- left: $\{\{y \mapsto 1\}\}$
- right: $\{\{z \mapsto 1\}\}$

 $S = \{\{x \mapsto 1\}, \{x \mapsto 2, y \mapsto 1\}, \{x \mapsto 2, z \mapsto 1\}, \{u \mapsto 1, v \mapsto 1\}, \{u \mapsto 2\}\}$ Assume dom_x = {1, 2, 3} and dom_y = dom_z = dom_u = dom_v = {1, 2}.



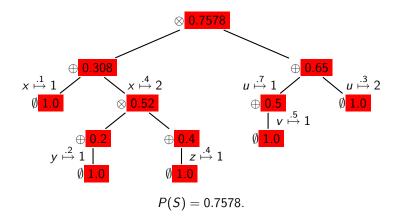
Apply variable elimination to $\{\{u \mapsto 1, v \mapsto 1\}, \{u \mapsto 2\}\}.$

- left: $u \mapsto 1 : \{\{v \mapsto 1\}\}$
- right: $u \mapsto 2 : \emptyset$

Confidence computation using ws-trees

$$S = \{\{x \mapsto 1\}, \{x \mapsto 2, y \mapsto 1\}, \{x \mapsto 2, z \mapsto 1\}, \{u \mapsto 1, v \mapsto 1\}, \{u \mapsto 2\}\}$$

Assume: dom_x = {1, 2, 3} and dom_y = dom_z = dom_u = dom_v = {1, 2}.
$$x \stackrel{.1}{\mapsto} 1, x \stackrel{.4}{\mapsto} 2, y \stackrel{.2}{\mapsto} 1, z \stackrel{.4}{\mapsto} 1, u \stackrel{.7}{\mapsto} 1, u \stackrel{.3}{\mapsto} 2, v \stackrel{.5}{\mapsto} 1.$$



Conditioning using ws-trees

Assert constraint ϕ on U-relational database U.

- Compute the ws-set S that describes the worlds in which φ holds. Evaluation of Boolean query for φ followed by complement with W.
- **2** Compile S into a ws-tree T.
- Renormalize T such that the probabilities of all remaining worlds sum up to 1. Introduce new variables to reflect renormalization.
- Update the ws-descriptors WSD in U according to renormalized T.
 While traversing T, remove from WSD the encountered variables and add the newly created ones.

The last three steps can be done together and T need not be materialized.

Data cleaning example: Evaluate

W	Var	Dom	Р	U_R	WSD	SSN	NAME
	j	1	.2		$\{j\mapsto 1\}$	1	John
	j	7	.8		$\{j \mapsto 7\}$	7	John
	Ь	4	.3		$\{b \mapsto 4\}$	4	Bill
	Ь	7	.7		$\{b \mapsto 7\}$	7	Bill

Keep only those worlds that satisfy the key constraint on R:

assert SSN \rightarrow NAME on R;

Expressed as a Boolean query as a complement of $\pi_{\emptyset}(R \bowtie_{\phi} R)$ where $\phi := (1.SSN = 2.SSN \land 1.NAME \neq 2.NAME)$. On U-relation U_R ,

 $\pi_{WSD}(U_R \bowtie_{\phi \land 1.WSD \text{ consistent with } 2.WSD} U_R).$

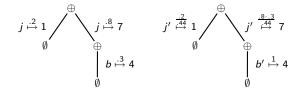
Result consists of WSD $\{j \mapsto 7, b \mapsto 7\}$. Its complement with the (entire) world-set given by W is:

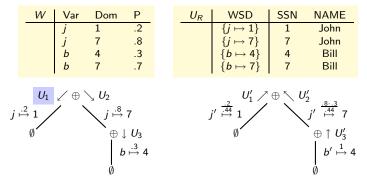
- $\{\{j \mapsto 1\}, \{j \mapsto 7, b \mapsto 4\}\}$, or (equivalently)
- {{ $b \mapsto 4$ }, { $b \mapsto 7, j \mapsto 1$ }}.

Data cleaning example: Compile and Renormalize

W	Var	Dom	Ρ	U_R	WSD	SSN	NAME
	j	1	.2		$\{j\mapsto 1\}$		John
	j	7	.8		$\{j \mapsto 7\}$	7	John
	Ь	4	.3		$\{b \mapsto 4\}$	4	Bill
	Ь	7	.7		$\{b \mapsto 7\}$	7	Bill

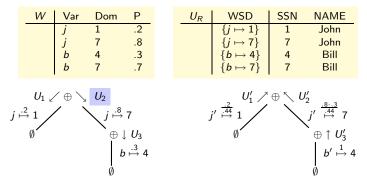
SSN \rightarrow NAME holds in the worlds defined by $S = \{\{j \mapsto 1\}, \{j \mapsto 7, b \mapsto 4\}\}$. Compile S into a ws-tree and renormalize the latter.





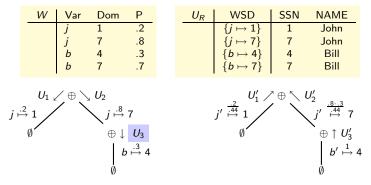
The U-relation tuples to be conditioned are passed down the ws-tree:

$U_1 = j \mapsto 1 : U_R$		SSN	NAME
	$\{j\mapsto 1\}$	1	John
	$\{j\mapsto 1,b\mapsto 4\}$	4	Bill
	$egin{array}{l} \{j\mapsto1\}\ \{j\mapsto1,b\mapsto4\}\ \{j\mapsto1,b\mapsto7\} \end{array}$	7	Bill



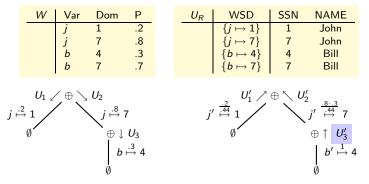
The U-relation tuples to be conditioned are passed down the ws-tree:

$U_2 = j \mapsto 7 : U_R$		SSN	NAME
	$\{j \mapsto 7\}$	1	John
	$\{j \mapsto 7, b \mapsto 4\}$	4	Bill
	$ \begin{cases} j \mapsto 7 \\ \{ j \mapsto 7, b \mapsto 4 \\ \{ j \mapsto 7, b \mapsto 7 \end{cases} $	7	Bill



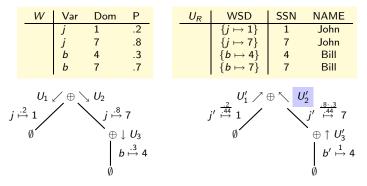
The U-relation tuples to be conditioned are passed down the ws-tree:

$U_3 = b \mapsto 4 : U_2$		SSN	NAME
	$\{j \mapsto 7, b \to 4\}$	1	John
	$\{j \mapsto 7, b \to 4\}$ $\{j \mapsto 7, b \mapsto 4\}$	4	Bill



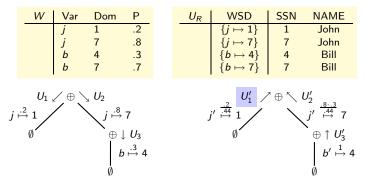
Replace old variables by new variables in the U-relations to be pushed up the normalized ws-tree:

$U'_3 = Replace \ b \ by \ b' \ in \ U_3$		SSN	NAME
	$\{j \mapsto 7, b' \mapsto 4\}$ $\{j \mapsto 7, b' \mapsto 4\}$	1	John
	$\{j \mapsto 7, b' \mapsto 4\}$	4	Bill



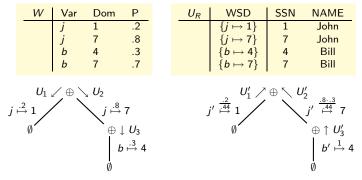
Replace old by new variables in the U-relation tuples to be pushed up the normalized ws-tree:

$U_2' = Replace\; j\; by\; j'\; in\; U_3'$	WSD		NAME
	$ \begin{array}{l} \{j' \mapsto 7, b' \mapsto 4\} \\ \{j' \mapsto 7, b' \mapsto 4\} \end{array} $	1	John
	$\{j'\mapsto 7, b'\mapsto 4\}$	4	Bill



Replace old by new variables in the U-relation tuples to be pushed up the normalized ws-tree:

$U_1^\prime = Replace\; j\; by\; j^\prime\; in\; U_1$		SSN	NAME
	$\{j'\mapsto 1\}$	1	John
	$\{j'\mapsto 1,b\mapsto 4\}$	4	Bill
	$egin{array}{l} \{j'\mapsto 1\} \ \{j'\mapsto 1,b\mapsto 4\} \ \{j'\mapsto 1,b\mapsto 7\} \end{array}$	7	Bill



The U-relational database after conditioning (b' and j are useless and removed):

W' Var Dom P	$U_R' = U_1' \cup U_2'$ WSD	SSN	NAME
	$\{j'\mapsto 1\}$	1	John
b 4 .3	$\{j'\mapsto 7,b'\mapsto 4\}$	1	John
b 7 .7	$\{j'\mapsto 1,b\mapsto 4\}$	4	Bill
j' 1 .2/.44	$\{j' \mapsto 1, b \mapsto 7\}$	7	Bill
j' 7 .8 · .3/.44	$\{j'\mapsto 7,b'\mapsto 4\}$	4	Bill

Experiments

Tuple-independent TPC-H Data

Queries

- select distinct true from customer c, orders o, lineitem I where c.mktsegment = 'BUILDING' and c.custkey = o.custkey and o.orderkey = l.orderkey and o.orderdate > '1995-03-15'
- select distinct true from lineitem where shipdate between '1994-01-01' and '1996-01-01' and discount between '0.05' and '0.08' and quantity < 24</p>

Query	Size of	TPC-H	#Input	Size of	User
	ws-desc.	Scale	Vars	ws-set	Time(s)
		0.01	77215	9836	5.10
Q_1	3	0.05	382314	43498	99.76
		0.10	765572	63886	356.56
		0.01	60175	3029	0.20
Q_2	1	0.05	299814	15545	8.24
		0.10	600572	30948	33.68

Tractable cases of query evaluation on probabilistic databases beyond safe plans:

- Using OBDDs for Efficient Query Evaluation on Probabilistic Databases.
 O. and Huang. In Proc. SUM 2008.
- Lazy versus Eager Query Plans for Tuple-Independent Probabilistic Databases.
 O., Huang, and Koch. 2008.

#P-hard cases

Input: ws-sets similar to those associated with the answers of non-safe Boolean queries on probabilistic databases.

Compared agorithms for confidence computation

- INDVE: independence partitioning and variable elimination
- VE: only variable elimination
- KL: (adapted) optimal Monte Carlo simulation based on Karp-Luby FPRAS for DNF counting

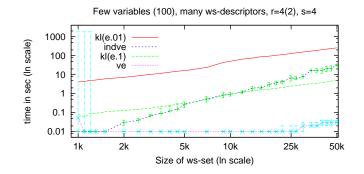
Given a DNF formula with *m* clauses, compute an (ϵ, δ) -approximation \hat{c} of the number of solutions *c* of the DNF formula such that

$$\Pr[|\boldsymbol{c} - \hat{\boldsymbol{c}}| \leq \epsilon \cdot \boldsymbol{c}] \geq 1 - \delta$$

for any given $0 < \epsilon < 1$, $0 < \delta < 1$. It does so within $\lceil 4 \cdot m \cdot \log(2/\delta)/\epsilon^2 \rceil$ iterations of an efficiently computable estimator.

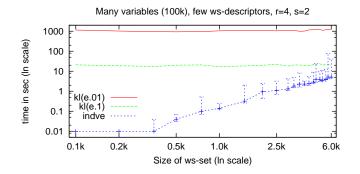
INDVE is now part of the MayBMS engine!

#variables and #wsds differ by orders of magnitude



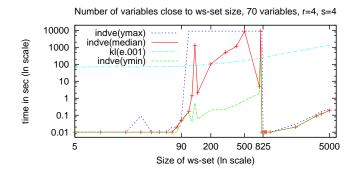
r = domain size of variables; s = size of wsds = #joins used to produce them.

#variables and #wsds differ by orders of magnitude



r = domain size of variables; s = size of wsds = #joins used to produce them.

#variables and #wsds are close: Easy-hard-easy pattern

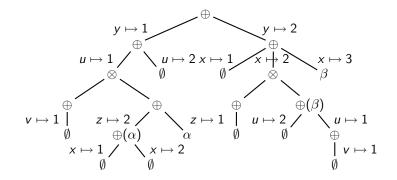


Known that the computation becomes harder in this case. The hard area is smaller for SAT than for #SAT.

Thanks!

Order of Variable Elimination Matters!

 $S = \{\{x \mapsto 1\}, \{x \mapsto 2, y \mapsto 1\}, \{x \mapsto 2, z \mapsto 1\}, \{u \mapsto 1, v \mapsto 1\}, \{u \mapsto 2\}\}$ Assume dom_x = {1, 2, 3} and dom_y = dom_z = dom_u = dom_v = {1, 2}.



Different ws-tree for the same ws-set S!