

CMSC 724: Uncertainty in Databases

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Outline

1 Overview

2 Probabilistic Databases

Uncertainty

- Relational databases assume “exact” data
- Increasingly breaking down
 - “Sensor” data
 - Physical/hardware sensors
 - Also data observed by people (called “persono-scopes”)
 - Data integration type of applications
 - Confidence/trust/“quality” issues
 - Machine generated schema mappings
 - Automatically extracted information/knowledge
 - Reasoning using Machine Learning techniques
 - Many classifiers provide probabilities of belonging to different classes
 - Data may be exact, but queries may not be
 - inst-name like “UMD” (does this match “Univ of MD” ?)
 - Common in Information Retrieval

Types of uncertainty

- “Nulls” (very interesting early work on this)
- More generally, missing values/incomplete databases
- Existence uncertainty: Tuples may or may not exist
 - Can be modeled logically, probabilities, fuzzy logic etc. . .
- Attribute values are uncertain
 - I saw a car, but not sure of the color
 - Sensor values have “noise” in them
- Approximations/Summarization
- Confidence/Trust/Quality
- “Correlations”
 - Either this tuple exists or that
 - If this attribute is 1, then that attribute is 2

Lineage/Data Provenance

- Another thing databases don't do well
- Goal: Trace back a query result to original data
- Provenance/Lineage
 - Carry around enough information during query processing to trace back

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- Another thing databases don't do well
- Goal: Trace back a query result to original data
- Provenance/Lineage
 - Carry around enough information during query processing to trace back
- Very important in sensor applications
 - Vision: Highly automated systems that process vast amounts of data to decide what to do next
 - Large amounts of aggregation, distributed processing
 - A small mistake/noise can cause large errors later on
 - Custom-build sensor processing code makes it harder

Uncertainty Management

- Approach
 - Lets assume relational database for now
 - Attach numbers with the tuples or attribute values
 - Propagate numbers through the operations
- Key questions:
 - How to operate on the numbers ?
 - Probability Theory is a natural choice, but not the only one
 - Rich literature on other types of operations
 - How to do query processing ?
 - Actually very challenging...
 - Concrete results known only under simplifying assumptions

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Probabilistic Databases

- Use probabilities to model the uncertainty
- Use laws of probability to process the data
- Tuple-level uncertainty
 - All attributes in a tuple are known precisely
 - Existence of the tuple is uncertain
- Attribute-level uncertainty
 - Tuples (identified by “keys”) exist for certain
 - Exact value of an attribute is uncertain

A Tuple-level Uncertainty Model

- Proposed by Fuhr et al. in Information Retrieval Context
 - Later work by Dalvi and Suciu, by us here at UMD (Prithviraj Sen)
 - Examples from Dalvi and Suciu, VLDB 2004
- A simple probabilistic database

$$S^p =$$

	A	B	
s_1	'm'	1	0.8
s_2	'n'	1	0.5

$$T^p =$$

	C	D	
t_1	1	'p'	0.6

Possible Worlds

- The best way to think of probabilistic databases
- A world is a fixed set of tuples – no uncertainty
- Assuming “independence”:

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$$S^p = \begin{array}{c} \begin{array}{|c|c|} \hline \mathbf{A} & \mathbf{B} \\ \hline \end{array} \\ \begin{array}{l} s_1 \\ s_2 \end{array} \end{array} \begin{array}{|c|c|} \hline \mathbf{A} & \mathbf{B} \\ \hline \end{array} \begin{array}{l} 0.8 \\ 0.5 \end{array}$$

$$T^p = \begin{array}{c} \begin{array}{|c|c|} \hline \mathbf{C} & \mathbf{D} \\ \hline \end{array} \\ t_1 \end{array} \begin{array}{|c|c|} \hline \mathbf{C} & \mathbf{D} \\ \hline \end{array} 0.6$$

	database instance	probability
$pwd(D^p) =$	$D_1 = \{s_1, s_2, t_1\}$	0.24
	$D_2 = \{s_1, t_1\}$	0.24
	$D_3 = \{s_2, t_1\}$	0.06
	$D_4 = \{t_1\}$	0.06
	$D_5 = \{s_1, s_2\}$	0.16
	$D_6 = \{s_1\}$	0.16
	$D_7 = \{s_2\}$	0.04
	$D_8 = \phi$	0.04

Query Evaluation

- Evaluate on each possible world
- Combine the results together somehow
 - Semantics of this can be tricky
- Example: $\pi_D(S \bowtie_{B=C} T)$

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	A	B	
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$pwd(D^p) =$

database instance	probability	Result
$D_1 = \{s_1, s_2, t_1\}$	0.24	{p}
$D_2 = \{s_1, t_1\}$	0.24	{p}
$D_3 = \{s_2, t_1\}$	0.06	{p}
$D_4 = \{t_1\}$	0.06	$\emptyset$
$D_5 = \{s_1, s_2\}$	0.16	$\emptyset$
$D_6 = \{s_1\}$	0.16	$\emptyset$
$D_7 = \{s_2\}$	0.04	$\emptyset$
$D_8 = \emptyset$	0.04	$\emptyset$

answer	probability
{p}	0.54
$\emptyset$	0.46

Query Evaluation

- Another Example: $\pi_A(S \bowtie_{B=C} T)$

$S^p =$			$T^p =$		
	A	B		C	D
s_1	'm'	1	0.8	t_1	1
s_2	'n'	1	0.5		'p'

database instance		probability	Result											
$pwd(D^p) =$	$D_1 = \{s_1, s_2, t_1\}$	0.24	$\{\text{'m'}, \text{'n'}\}$	$=$ <table><tr><th>answer</th><th>probability</th></tr><tr><td>$\{\text{'m'}, \text{'n'}\}$</td><td>0.24</td></tr><tr><td>$\{\text{'m'}\}$</td><td>0.24</td></tr><tr><td>$\{\text{'n'}\}$</td><td>0.06</td></tr><tr><td>$\emptyset$</td><td>0.46</td></tr></table>	answer	probability	$\{\text{'m'}, \text{'n'}\}$	0.24	$\{\text{'m'}\}$	0.24	$\{\text{'n'}\}$	0.06	$\emptyset$	0.46
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- Can't convert to possible worlds and evaluate the query
 - Too many possible worlds
 - With just 20 uncertain tuples, number of worlds is at least $2^{20} = 1$ million.

Query Evaluation

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 - With just 20 uncertain tuples, number of worlds is at least $2^{20} = 1$ million.
- Extensional semantics
 - Combine probabilities when tuples are put together
 - Issues with correlations
- Intensional semantics
 - Represent each result as a boolean formula
 - Evaluate it at end
 - #P-Complete

Extensional: Example 1

- $\pi_D(S \bowtie_{B=C} T) \rightarrow$ Do Join first, then Projection

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Joins: assume independence

A	B	C	D	<i>prob</i>
'm'	1	1	'p'	$0.8 * 0.6 = 0.48$
'n'	1	1	'p'	$0.5 * 0.6 = 0.30$

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Projection: union probability; assume independence

$$\begin{array}{|c|} \hline \mathbf{D} \\ \hline \text{'p'} \\ \hline \end{array} \quad (1 - (1 - 0.48)(1 - 0.3)) = 0.636$$

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D	prob
'p'	$(1 - (1 - 0.48)(1 - 0.3)) = 0.636$

Umm..This is wrong !!

Why ? The two tuples above are not independent.

Extensional: Example 2

- $\pi_D(S \bowtie_{B=C} T) \rightarrow$ Do Projection first, then Join

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$$T^p =$$

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Projection: union probability; assume independence

B	<i>prob</i>
1	$(1 - (1 - 0.8)(1 - 0.5)) = 0.9$

Join: assume independence

B	C	D	<i>prob</i>
1	1	'p'	$0.9 * 0.6 = 0.54$

This is correct.

The correctness unfortunately depends on the plan used.
Called “safe plans” [Dalvi, Suciu 2004]

Extensional Evaluation: Safe Plans

- “Efficient Query Evaluation..”; Dalvi et al.
- Safe Plans:
 - Plans for which extensional evaluation returns correct probabilities
 - Carefully manage the operations (especially “project”s) to ensure safe-ness
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 - A query either has a safe plan, or is #P-Hard

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 - Only works if the base tuples are independent
- Dichotomy (Dalvi et al., PODS 2007):
 - A query either has a safe plan, or is #P-Hard
 - Nothing about the actual instance though
 - A specific relation instance may still have a safe plan
 - This is a pessimistic, worst-case bound

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Join (intersection):

A	B	C	D	E
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'n'	1	1	'p'	$s_2 \wedge t_1$

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- Evaluate the expression at the end (this can be #P-Hard)
- Can handle correlations (between tuples)

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- Sen and Deshpande, ICDE 2007
 - Using Graphical Models to represent the correlations between tuples
 - “Closed”

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 - Always correct (which means still #P-Hard in general)
 - Can achieve the best of both worlds
 - If data doesn't have correlations, as fast as extensional

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 - Always correct (which means still #P-Hard in general)
 - Can achieve the best of both worlds
 - If data doesn't have correlations, as fast as extensional
- Still many unanswered questions
 - Can we do better if approximations are allowed ?
 - Probabilities are rarely required exactly
 - “Ranking” is all that's needed

Attribute-level Uncertainty

- In some cases easier, in some cases harder to deal with
- Continuous distributions common (e.g. in sensor applications)
- Hard to do exact querying over continuous attributes
- What about correlations ?
 - Temperatures at nearby locations are usually correlated
- Much work on this topic; some we are doing here

Lineage

- Given a tuple t , we would like to know:
 - When t was derived ?
 - How t was derived ?
 - What data was used to derive t ?
 - Who (which user) cause t to be derived ?
- Can keep the information along with the t
 - Propagate it as the new result tuples are generated
 - Clearly not feasible
 - Try storing with relations instead of each tuple
 - Annotate the tuples somehow
 - ...
- A lot of open questions, few answers

Discussion

- Very interesting “hot” area
- Lot of work by many groups
 - On defining models, efficient query processing, building systems etc. . .
 - We are doing a bunch of work here
- No real consensus yet emerging
- “Killer Application” ??
- Key is keeping it simple, otherwise no one will use it