## Probabilistic Databases: Introduction

EDBT-Intended Summer School

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Paris
E

## Uncertain data: Practical motivations

Numerous sources of uncertain data:

- Measurement errors
- Data integration from contradicting sources
- Imprecise mappings between heterogeneous schemata
- Imprecise automated processes (information extraction, NLP, etc.)
- Imperfect human judgment
- Lies, opinions, rumors


## Use case：Web information extraction

## Recently－Learned Facts twitter

| instance | iteration date learned confidence |  |  |
| :---: | :---: | :---: | :---: |
| oliguric＿phase is a non－disease physiological condition | 1111 | 06－jul－2018 | 97.5 ת\％\％ |
| alaska＿airlines is an organization | 1114 | 25－aug－2018 | 100.0 \％\％\％ |
| heating＿insurance＿policies is a physical action | 1111 | 06－jul－2018 | 90.4 ת \％\％ |
| n98＿12 is a term used by physicists | 1111 | 06－jul－2018 | 94.2 ת\％\％\％ |
| dragonball＿z super butoden＿2 is software | 1111 | 06－jul－2018 | 100.0 多 雨 |
| general motors corp is a company headquartered in the city detroit | 1116 | 12－sep－2018 | 100.0 令 |
| the companies herald and la compete with eachother | 1111 | 06－jul－2018 | 99.6 ת\％ |
| stanford hired montgomery | 1111 | 06－jul－2018 | 98.4 ת \％\％ |
| kimn is a radio station in the city denver | 1116 | 12－sep－2018 | 100.0 为 |
| radisson＿sas＿portman hotel is a park in the city central london | 1116 | 12－sep－2018 | 100.0 多 |

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

## 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, https://www. yago-knowledge.org/

## Other use case: Information extraction from scientific articles



## Other use case: Crowdsourcing

## All HITs

1-10 of 2751 Results

```
Sort by: HITs Available (most first) v (\sigma0) Show all details | Hide all details 1\underline{2}\underline{4}\underline{5}>\underline{Next > Last}
```

| Transcribe data |  | View a HIT in this group |  |
| :--- | :--- | :--- | :--- | :--- |
| Requester: p9r | HIT Expiration Date: | Nov 18, 2015 (23 hours 59 minutes) Reward: $\$ 0.03$ |  |
|  |  |  |  |
|  | Time Allotted: | 45 minutes |  |

Description: Please transcribe the data from the following images
Keywords: transcribe, handwriting, data entry
Qualifications Required:
HIT approval rate (\%) is greater than 90

## Classify Receipt

View a HIT in this group

| Requester: Jon Brelig | HIT Expiration Date: | Nov 24, 2015 (6 days 23 hours) Reward: $\$ 0.02$ |
| :--- | :--- | :--- | :--- |
|  | Time Allotted: | 20 minutes |

Description: Looking at a receipt image, identify the business of the receipt
Keywords: image, receipt, categorize, transcribe, extract, data, entry, transcription, text, easy, qualification, jon, breliq, prod

## Other use case: Speech recognition and OCR



## Different types of uncertainty

- The uncertainty can be qualitative (e.g., NULL)...
- ... or quantitative (e.g., 95\%)

Further, there are 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
- Missing data: we know that some data is missing (open-world semantics)


## What happens to this uncertainty?

Naive solution<br>Forget about uncertainty, or apply a threshold after each computation step

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Instead of neglecting uncertainty, let's manage it rigorously throughout the whole process of answering a query

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## Ideal solution

Instead of neglecting uncertainty, let's manage it rigorously throughout the whole process of answering a query

Also: it leads to interesting theoretical questions! :)

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Idea: use a representation system
Possible world: A regular (deterministic) relational database

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Possible world: A regular (deterministic) relational database
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| date | teacher |  |
| :--- | :--- | :--- |
| 08 | Diego | 0.9 |
| 09 | Paolo | 0.8 |
| 09 | Floris | 0.7 |

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- Present treewidth-based approaches to efficient PQE
- Give an overview of other topics on probabilistic databases


## Probabilistic Databases: Models and PQE

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Paris


## Relational model by example

Guest

|  |  | email |
| :--- | :--- | :--- |
| id | name | John Smith |
| 1 | john.smith@gmail.com |  |
| 2 | Alice Black | alice@black.name |
| 3 | John Smith | john.smith@ens.fr |

Reservation

| id | guest | room | arrival | nights |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 1 | 504 | $2022-01-01$ | 5 |
| 2 | 2 | 107 | $2022-01-10$ | 3 |
| 3 | 3 | 302 | $2022-01-15$ | 6 |
| 4 | 2 | 504 | $2022-01-15$ | 2 |
| 5 | 2 | 107 | $2022-01-30$ | 1 |

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## Formally:

- A database schema $\mathcal{D}$ maps each relation name to an arity (we add attribute names in our examples)


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We can write tuples as table rows or as ground facts:

Guest

|  |  | email |
| :--- | :--- | :--- |
| id | name | John Smith |
| john.smith@gmail.com |  |  |
| 2 | Alice Black | alice@black.name |
| 3 | John Smith | john.smith@ens.fr |

Guest(1, John Smith, john.smith@gmail.com), Guest(2, Alice Black, alice@black.name),
Guest(3, John Smith, john.smith@ens.fr)

## Queries

- A query is an arbitrary function over database instances over a fixed schema $\mathcal{D}$
- We only study Boolean queries, i.e., queries returning only true or false


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- Example of query languages:
- Conjunctive queries (CQ)
- $\exists \wedge \cdots$ existentially quantified conjunctions of atoms
- $Q$ : $\exists x y z x^{\prime} y^{\prime}$ Guest $(x, y, z) \wedge G u e s t\left(x^{\prime}, y^{\prime}, z\right)$


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- $\cup \exists \wedge \cdots$ : unions of CQs
- First-Order logic (FO)
- Monadic-Second Order logic (MSO)

TID

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$\rightarrow$ Assume independence between facts

## Semantics of TID

- Each fact is kept or discarded with the indicated probability
- Probabilistic choices are independent across facts


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date teacher

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90\%

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$$
90 \% \times
$$

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What's the probability of this possible world?

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Formally, for a TID I, the probability of $J \subseteq I$ is:

- product of $\operatorname{Pr}(F)$ for each fact $F$ kept in J
- product of $1-\operatorname{Pr}(F)$ for each fact $F$ not kept in J


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Do the probabilities of the possible words always sum to 1 ?

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$\rightarrow$ The sum of these probabilities is the result of expanding the expression:

$$
\left(\operatorname{Pr}\left(\mathrm{F}_{1}\right)+\left(1-\operatorname{Pr}\left(\mathrm{F}_{1}\right)\right)\right) \times \cdots \times\left(\operatorname{Pr}\left(\mathrm{F}_{\mathrm{N}}\right)+\left(1-\operatorname{Pr}\left(\mathrm{F}_{\mathrm{N}}\right)\right)\right)
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- All factors are equal to 1 , so the probabilities sum to 1


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$$
\begin{aligned}
& \frac{U_{1}}{\text { teacher }} \\
& \hline \text { Jane } \\
& \hline \pi\left(U_{1}\right)=80 \%
\end{aligned}
$$

## Expressiveness of TID

Can we represent all probabilistic instances with TID?
"The class is taught by Jane or Joe or no one but not both"

| $\frac{U_{1}}{\text { teacher }}$ |  | $U_{2}$ |
| :--- | :--- | :--- |
|  |  | teacher |
|  |  | Joe |
| $\pi\left(U_{1}\right)=80 \%$ |  | $\pi\left(U_{2}\right)=10 \%$ |

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Can we represent all probabilistic instances with TID?
"The class is taught by Jane or Joe or no one but not both"

| $\frac{U_{1}}{\text { teacher }}$ |
| :--- |
| Jane |
| $\pi\left(U_{1}\right)=80 \%$ |


| $\frac{U_{2}}{\text { teacher }}$ |
| :--- |
| Joe |
| $\pi\left(U_{2}\right)=10 \%$ |


| $\frac{U_{3}}{\text { teacher }}$ |
| :---: |
| $\pi\left(U_{3}\right)=10 \%$ |

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Can we represent all probabilistic instances with TID?
"The class is taught by Jane or Joe or no one but not both"

| $U_{1}$ | $U_{2}$ | $\mathrm{U}_{3}$ |
| :---: | :---: | :---: |
| teacher | teacher | teacher |
| Jane | Joe |  |
| $\pi\left(U_{1}\right)=80 \%$ | $\pi\left(U_{2}\right)=10 \%$ | $\pi\left(U_{3}\right)=10 \%$ |
|  |  | teacher |
|  |  | Jane |
|  |  | Joe |

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| teacher | teacher | teacher |
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|  |  | Joe | 80\% |

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"The class is taught by Jane or Joe or no one but not both"

| $\frac{U_{1}}{\text { teacher }}$ |
| :--- |
| Jane |
| $\pi\left(U_{1}\right)=80 \%$ |


| $\frac{U_{2}}{\text { teacher }}$ |  | $\frac{U_{3}}{\text { teacher }}$ |
| :--- | :--- | :--- |
| Joe   <br> $\pi\left(U_{2}\right)=10 \%$   <br>   teacher <br>  Jane $10 \%$  <br>  Joe $\quad 80 \%$  |  |  |

$\rightarrow$ We cannot forbid that both teach the class!

BID

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|  |  | $U$ |
| :--- | :--- | :--- |
| day | time | teacher |
| 09 | AM | Paolo |
| 09 | AM | Floris |
| 09 | PM | Floris |
| 09 | PM | Paolo |

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| day | time | teacher |  |
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| 09 | AM | Floris | $10 \%$ |
| 09 | PM | Floris | $70 \%$ |
| 09 | PM | Paolo | $1 \%$ |

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- Each tuple has a probability
- Probabilities must sum up to $\leq 1$ in each block


## BID semantics

|  | $U$ |  |  |
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| 09 | AM | Floris | $10 \%$ |
| 09 | PM | Floris | $70 \%$ |
| 09 | PM | Paolo | $1 \%$ |

- For each block:


## BID semantics

|  | $U$ |  |  |
| :--- | :--- | :--- | :--- |
| day | time | teacher |  |
| O9 | AM | Paolo | $80 \%$ |
| O9 | AM | Floris | $10 \%$ |
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- For each block:
- Pick one fact according to probabilities


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| :---: | :---: | :---: | :---: | :---: |
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| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| day | time | teacher |  | day | time | teacher |
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| $U_{1}$ |
| :--- |
| teacher |
| Diego |
| Paolo |
| $\pi\left(U_{1}\right)=80 \%$ |

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| $\frac{U_{1}}{\text { teacher }}$ |  | $U_{2}$ |
| :--- | :--- | :--- |
|  |  | teacher <br> Diego <br> Paolo |
| $\pi\left(U_{1}\right)=80 \%$ Floris <br>   <br> $\pi\left(U_{2}\right)=10 \%$  |  |  |

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Can we represent all probabilistic instances with BID?
"The class is taught by exactly two among Diego, Paolo, Floris."

| $U_{1}$ | $U_{2}$ | $U_{3}$ |
| :---: | :---: | :---: |
| teacher | teacher | teacher |
| Diego | Diego | Paolo |
| Paolo | Floris | Floris |
| $\pi\left(U_{1}\right)=80 \%$ | $\pi\left(U_{2}\right)=10 \%$ | $\pi\left(U_{3}\right)=10 \%$ |

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$\rightarrow$ If teacher is a key teacher, then TID
$\rightarrow$ If teacher is not a key, then only one fact
$\rightarrow$ We cannot represent this probabilistic instance as a BID
pc-tables

## Boolean c-tables

- Set of Boolean variables $x_{1}, x_{2}, \ldots$
- Each fact has a condition: Variables, Boolean operators


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$x_{1}$ Jane is sick
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A (Boolean) pc-table is:

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- Product of the $1-p_{i}$ for the $x_{i}$ with $\nu\left(x_{i}\right)=0$
$\rightarrow$ This is like TIDs
- The probability of a possible world $J \subseteq I$ is the total probability of the valuations $\nu$ such that $I_{\nu}=J$


## pc-table example

| date | teacher | room |  |
| :--- | :--- | :--- | :--- |
| 04 | Jane | Amphi $A$ | $\neg x_{1}$ |
| 04 | Joe | Amphi $A$ | $x_{1}$ |
| 11 | Jane | Amphi B | $x_{2} \wedge \neg x_{1}$ |
| 11 | Joe | Amphi B | $x_{2} \wedge x_{1}$ |
| 11 | Jane | Amphi $C$ | $\neg x_{2} \wedge \neg x_{1}$ |
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$x_{1}$ Jane is sick
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| 11 | Joe | Amphi $C$ | $\neg x_{2} \wedge x_{1}$ |

$x_{1}$ Jane is sick
$\rightarrow$ Probability $10 \%$
$x_{2}$ Amphi $B$ is available
$\rightarrow$ Probability 20\%

## pc-table semantics example

| date | teacher | room | $x_{1}: 10 \%, x_{2}: 20 \%$ |
| :--- | :--- | :--- | :--- |
| 04 | Jane | Amphi $A$ | $\neg x_{1}$ |
| 04 | Joe | Amphi $A$ | $x_{1}$ |
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| 11 | Joe | Amphi B | $x_{2} \wedge x_{1}$ |
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$\rightarrow$ Here: only this valuation, 18\%


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Yet, in the rest of the talk, we focus on TIDs $\rightarrow$ easier to characterize tractable queries

PQE

## Query evaluation on probabilistic databases (PQE)

How can we evaluate a query $Q$ over a probabilistic database $D$ ?

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- Intuitively: the probability that $Q$ holds is the probability of drawing a possible world $D^{\prime} \subseteq D$ which satisfies $Q$


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Probabilistic query evaluation (PQE) problem for a query $Q$ over TIDs: given a TID, compute the probability that $Q$ holds

## Example of PQE on TID

| name | position | city | classification | prob |
| :--- | :--- | :--- | :--- | :---: |
| John | Director | New York | unclassified | 0.5 |
| Paul | Janitor | New York | restricted | 0.7 |
| Dave | Analyst | Paris | confidential | 0.3 |
| Ellen | Field agent | Berlin | secret | 0.2 |
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What is the probability to have a tuple with value New York?

- It is one minus the probability of not having such a tuple
- Not having such a tuple is the independent AND of not having each tuple
- So the result is $1-(1-0.5) \times(1-0.7)=0.85$


## Complexity of PQE

## Formal question:

- We fix a Boolean query, e.g., $\exists x y R(x), S(x, y), T(y)$


## Complexity of PQE

Formal question:

- We fix a Boolean query, e.g., $\exists x y R(x), S(x, y), T(y)$
- We are given a tuple-independent database D, i.e., a relational database where facts are independent and have probabilities


## Complexity of PQE

Formal question:

- We fix a Boolean query, e.g., $\exists x y R(x), S(x, y), T(y)$
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- Sum the probabilities of all worlds that satisfy the query


## Naive probabilistic query evaluation example

| TID D |  |  | Query Q$R(x, y) \wedge R(y, z)$ |
| :---: | :---: | :---: | :---: |
| in | Ou |  |  |
| A | B | 0.8 |  |
| B | C | 0.2 |  |

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Possible worlds and probabilities:


Total probability that $Q$ holds: $0.8 \times 0.2=0.16$.

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$\rightarrow$ But some queries admit an efficient algorithm!


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## Probabilistic Databases: The Dichotomy of PQE

EDBT-Intended Summer School

Antoine Amarilli

Paris


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Result of the form:
if $Q$ has a certain form then $\operatorname{PQE}(Q)$ is in PTIME, otherwise it is \#P-hard

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## Theorem ([Dalvi and Suciu, 2007])

Let $Q$ be an arity-two self-join-free CQ:

- If $Q$ is a conjunction of stars, then $\operatorname{PQE}(Q)$ is in PTIME
- Otherwise, $\mathrm{PQE}(Q)$ is \#P-hard


## Conjunction of stars

- A star is a CQ with a separator variable that occurs in all edges
- A conjunction of stars is a conjunction of one or several stars


The following is not a star: $x \longrightarrow y \longrightarrow z \longrightarrow w$

## Proving the small dichotomy (upper bound, 1)

$x \rightleftarrows y \longleftrightarrow_{z}^{w} \quad u \longrightarrow v \quad$ How to solve $\operatorname{PQE}(Q)$ for $Q$ a conjunction of stars?

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\begin{aligned}
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$$

$$
x \rightleftarrows y \longleftrightarrow z
$$

- We consider each connected component separately
$\rightarrow$ Independent conjunction over the connected components
How to solve $\operatorname{PQE}(Q)$ for $Q$ a conjunction of stars?
- We can test all possible values of the separator variable
$\rightarrow$ Independent disjunction over the values of the separator

$$
\begin{aligned}
& x \longleftrightarrow a_{1} \longrightarrow{ }_{z} \\
& x \longrightarrow a_{2} \longrightarrow Z \\
& x \longleftrightarrow a_{3} \longrightarrow{ }_{z}^{w}
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$$

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- We consider every fact
$b \longrightarrow a$
$\rightarrow$ Independent conjunction over the facts
$\rightarrow$ Just read the probability of the ground fact $R(b, a)$.


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Every arity-two self-join-free CQ which is not a conjunction of stars contains a pattern essentially like:

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We can add facts with probability 1 to instances so the other facts are always satisfied, and focus on only these three facts
$\rightarrow$ Let us show \#P-hardness of this query

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- e.g., given $(x \vee y) \wedge z$, compute that it has 3 satisfying valuations


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Reduce from \#PP2DNF to PQE(Q) for CQ $Q: x \longrightarrow y \longrightarrow z \longrightarrow w$ Example: $\phi:\left(X_{1} \wedge Y_{1}\right) \vee\left(X_{1} \wedge Y_{2}\right) \vee\left(X_{2} \wedge Y_{2}\right) \vee\left(X_{3} \wedge Y_{1}\right) \vee\left(X_{3} \wedge Y_{2}\right)$

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$\rightarrow$ The probability of $Q$ on $I_{\phi}$ is the number of accepting valuations of $\phi$, divided by the number of valuations ( $2^{-\mid \text {Vars } \mid}$ )


## Extending beyond arity-two (1)

How can we extend beyond arity-two queries?
Theorem ([Dalvi and Suciu, 2007])
Let $Q$ be a arity-two self-join-free CQ:

- If $Q$ is a conjunction of stars hierarchical, then $\operatorname{PQE}(Q)$ is in PTIME
- Otherwise, $\mathrm{PQE}(Q)$ is \#P-hard


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Class of Hierarchical CQs defined inductively:

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$\exists x\left(\exists y\left(\exists z R_{1}(x, y, z)\right) \wedge\left(\exists z^{\prime} R_{2}\left(x, y, z^{\prime}\right)\right)\right) \wedge\left(\exists y^{\prime} \exists z^{\prime \prime} R_{3}\left(x, y^{\prime}, z^{\prime \prime}\right)\right)$

$$
\wedge\left(\exists u\left(\exists v R_{4}(u, v)\right) \wedge\left(\exists w R_{5}(u, v, w)\right)\right)
$$



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Via equivalent characterization: a non-hierarchical query has two variables $x$ and $y$ and:

- One atom containing $x$ and $y$
- One atom containing $x$ but not $y$
- One atom containing $y$ but not $x$


## The "big" Dalvi and Suciu dichotomy

Full dichotomy on the unions of conjunctive queries (UCQs):
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- Lower bound: hardness proof on minimal cases where the algorithm does not work (very challenging)


## References i

(in Dalvi, N. and Suciu, D. (2007).
The dichotomy of conjunctive queries on probabilistic structures.
In Proc. PODS.
图 Dalvi, N. and Suciu, D. (2012).
The dichotomy of probabilistic inference for unions of conjunctive queries. J. $A C M, 59(6)$.

## Probabilistic Databases: Provenance Circuits and Knowledge

 CompilationEDBT-Intended Summer School

Antoine Amarilli

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## Related work: Semiring provenance

Semiring provenance ([Green et al., 2007], on Tuesday): annotate results of a relational algebra query with a semiring expression

(a)

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| A C |  |
| :--- | :--- |
| $a c$ | $2 p^{2}$ |
| $a e$ | $p r$ |
| $d c$ | $p r$ |
| $d e$ | $2 r^{2}+r s$ |
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Figure 5: Why-prov. and provenance polynomials

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| $a c$ | $\{p\}$ |
| $a e$ | $\{p, r\}$ |
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## What is the difference?

- We only care about Boolean provenance
$\rightarrow$ No multiplicity of facts or derivations
- Circuit representation: more concise


## The intensional approach to PQE

- Previously, for a tractable query $Q$ : we can solve $\operatorname{PQE}(Q)$
- Now, let's see the intensional approach
- Compute a circuit representing the Boolean provenance of $Q$
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Setting $A \longrightarrow$ Task 1
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## Boolean circuit representations

Circuits are just a way to represent Boolean formulas while factoring common subexpressions (more concise)


- Directed acyclic graph of gates
- Output gate:
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- Regular path queries (RPQ), Datalog, etc.

Theorem [Deutch et al., 2014]
For any Datalog query, given an instance, we can get its Boolean provenance in PTIME

## Computing Boolean provenance: practice

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```
a3nm=# SELECT id, name, city FROM personnel;
id I name | city
    1 | John | New York
    2 I Paul I New York
    3 | Dave | Paris
    4 Ellen | Berlin
    5 | Magdalen | Paris
    | Nancy | Paris
    7 S Susan | Berlin
(7 rows)
a3nm=# SELECT *,formula(provenance(), 'personnel_id') FROM
(SELECT DISTINCT city FROM personnel) t;
    city | formula
    Paris | (3 \oplus5 ¢ 6)
    Berlin | (4 @ 7)
    New York I (1 \oplus 2)
(3 rous)
```


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$\rightarrow$ The circuit that we constructed falls in a restricted class satisfying such conditions


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$$
P(g):=1-P\left(g^{\prime}\right)
$$

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( $\quad P(g):=1-P\left(g^{\prime}\right)$
$\rightarrow d$-DNNFs are one of many tractable circuit classes in knowledge compilation


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## Corollary

For any hierarchical self-join-free $C Q Q$, the problem $\operatorname{PQE}(Q)$ is in linear time up to the cost of arithmetic operations

## Other results for the intensional approach

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- Crux of the problem: capture arithmetic operations on probabilities with a d-D circuit, specifically inclusion-exclusion; see [Monet, 2020]

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| $\mathbf{S}$ |  |  |
| :--- | :--- | :--- |
| $a$ | $a$ | $s_{1}$ |
| $b$ | $v$ | $s_{2}$ |
| $b$ | $w$ | $s_{3}$ |


$\rightarrow$ We can compute the probability of an OBDD bottom-up

## Probabilistic Databases: Width-Based Approaches

EDBT-Intended Summer School

Antoine Amarilli

Paris


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Fix a bound $k \in \mathbb{N}$ and fix a Boolean monadic second-order query $Q$. Then PQE(Q) is in PTIME on input TID instances of treewidth $\leq k$


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Conversely, there is a query $Q$ for which $\mathrm{PQE}(Q)$ is intractable on any input instance family of unbounded treewidth (under some technical assumptions)


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Computational complexity as a function of $w$
(the query $Q$ is fixed)

## Monadic second-order logic (MSO)



- $P_{\bigcirc}(x)$ means " $x$ is blue"; also $P_{\bigcirc}(x), P_{\bigcirc}(x)$
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- Monadic second-order logic (MSO): adds quantifiers over sets
- $\exists S \forall x S(x)$ means "there is a set $S$ containing every element $x$ "
- Can express transitive closure $x \rightarrow^{*} y$, i.e., " $x$ is before $y$ "
- $\forall x P_{\bigcirc}(x) \Rightarrow \exists y P_{\bigcirc}(y) \wedge x \rightarrow^{*} y$


## Word automata

Translate the query $Q$ to a deterministic word automaton Alphabet: $\bigcirc \bigcirc \bigcirc$ w: ○-○-○-○
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## Corollary

Query evaluation of MSO on words is in linear time (in data complexity)

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## Theorem

For any fixed MSO query $Q$, the problem $\operatorname{PQE}(Q)$ on trees is in linear time assuming constant-time arithmetics

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Q: "Is there both a pink and a blue node?"
$\rightarrow$ This is just a Boolean provenance circuit on the "color facts" of the tree nodes!

## Example: Provenance circuit



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Formal definition of provenance circuits:

- Boolean query $Q$, uncertain tree $T$, circuit $C$
- Variable gates of $C$ : nodes of $T$
- Condition: Let $\nu$ be a valuation of $T$, then $\nu(C)$ iff $\nu(T)$ satisfies $Q$


## Provenance circuits on trees

| Theorem |  |
| :--- | :--- |
| For any bottom-up | tree automaton $A$ and input tree $T$, |
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## Provenance circuits on trees

## Theorem

For any bottom-up unambiguous tree automaton $A$ and input tree $T$, we can build a Boolean d-SDNNF provenance circuit of $A$ on $T$ in $O(|A| \times|T|)$

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## Corollary

For any MSO query $Q$, the problem $\mathrm{PQE}(Q)$ on probabilistic trees is in linear time assuming constant-time arithmetics

## Treewidth

We have shown tractability of PQE on trees; let us extend to bounded treewidth

## Treewidth by example:



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$\rightarrow$ Treelike: the treewidth is bounded by a constant


## Courcelle's theorem and extension to PQE

[^0]
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Treelike data

MSO query

## Courcelle's theorem and extension to PQE

Treelike data Tree encoding



## Courcelle's theorem and extension to PQE



## Courcelle's theorem and extension to PQE



## Theorem ([Courcelle, 1990])

For any fixed Boolean MSO query $Q$ and $k \in \mathbb{N}$, given a database $D$ of treewidth $\leq k$, we can compute in linear time in $D$ whether $D$ satisfies $Q$

## Courcelle's theorem and extension to PQE



MSO query

$$
\begin{gathered}
\exists x y \\
P_{\bigcirc}(x) \wedge P_{\bigcirc}(y)
\end{gathered}
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## Probabilistic

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MSO query
Tree automaton
$\underset{P_{O}(x) \wedge P_{O}(y)}{\exists x y} \rightarrow$

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## Theorem (A., Bourhis, Senellart, 2015, 2016)

For any fixed Boolean MSO query $Q$ and $k \in \mathbb{N}$, given a database $D$ of treewidth $\leq k$, we can solve the PQE problem in linear time (assuming constant-time arithmetics)

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$\rightarrow$ Proof idea: extract wall graphs as topological minors ([Chekuri and Chuzhoy, 2014]) and use them for a lower bound


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## Probabilistic Databases: Other Topics and Conclusion

EDBT-Intended Summer School

Antoine Amarilli

Paris


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Summary and directions

Recursive and
homomorphism-closed queries

## Going to more general queries

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We study the case of queries closed under homomorphisms
$\rightarrow$ We restrict to arity-two signatures (work in progress...)

## Homomorphism-closed queries

- A homomorphism from a graph $G$ to a graph $G^{\prime}$ maps the vertices of $G$ to those of $G^{\prime}$ while preserving the edges

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- Queries with negations or inequalities are not homomorphism-closed
- Homomorphism-closed queries can equivalently be seen as infinite unions of CQs (corresponding to their models)


## Our result

We show:

## Theorem (A., Ceylan, 2020)

For any query Q closed under homomorphisms on an arity-two signature:

- Either $Q$ is equivalent to a tractable UCQ and $\operatorname{PQE}(Q)$ is in PTIME
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- Hence, $\mathrm{PQE}(Q)$ is \#P-hard


## Uniform probabilities

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We limit to self-join-free CQs and extend the "small" Dalvi and Suciu dichotomy to UR:
Theorem (A., Kimelfeld, 2022)
Let $Q$ be a self-join-free CQ:

- If $Q$ is hierarchical, then $\operatorname{PQE}(Q)$ is in PTIME
- Otherwise, even UR(Q) is \#P-hard



## Approximate evaluation

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- One possibility is to compute a lower bound and upper bound:
- $\max (\operatorname{Pr}(\phi), \operatorname{Pr}(\psi)) \leq \operatorname{Pr}(\phi \vee \psi) \leq \min (\operatorname{Pr}(\phi)+\operatorname{Pr}(\psi), 1)$
- $\max (0, \operatorname{Pr}(\phi)+\operatorname{Pr}(\psi)-1) \leq \operatorname{Pr}(\phi \wedge \psi) \leq \min (\operatorname{Pr}(\phi), \operatorname{Pr}(\psi))$ (by duality)
- $\operatorname{Pr}(\neg \phi)=1-\operatorname{Pr}(\phi)$ (reminder)


## Approximation by sampling

Another possibility is to approximate via Monte-Carlo sampling:

- Pick a random possible world according to the fact probabilities:
$\rightarrow$ Keep $F$ with probability $\operatorname{Pr}(F)$ and discard it otherwise
$\rightarrow$ Repeat for the other variables


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- Evaluate the lineage formula $\phi$ under this valuation
- Approximate the probability of the formula $\phi$ as the proportion of times when it was true
- Theoretical guarantees: on how many samples suffice so that, with high probability, the estimated probability is almost correct

Other method for a multiplicative approximation: Karp-Luby algorithm

## Using external tools

- Specialized software to compute the probability of a formula: weighted model counters
- Examples (ongoing research):
- c2d: http://reasoning.cs.ucla.edu/c2d/download.php
- d4: https://www.cril.univ-artois.fr/KC/d4.html
- dsharp: https://bitbucket.org/haz/dsharp


## Repairs

## Repairs

- Another kind of uncertainty: we know that the database must satisfy some constraints (e.g., functionality)
- The data that we have does not satisfy it
- Reason about the ways to repair the data, e.g., removing a minimal subset of tuples
- Can we evaluate queries on this representation? E.g., is a query true on every maximal repair? See, e.g., [Koutris and Wijsen, 2015].
$\rightarrow$ Tutorial by Jef Wijsen


# Incompleteness: Open-World Query Answering 

## Open-world query answering

- Most data sources are incomplete, e.g., Wikidata
- Idea: see an incomplete data source as representing all possible completions
- A query result is certain if it is true on every possible completion
- We also assume constraints to restrict the possible completions (e.g., IDs and FDs, see Andreas's talk)


## Open-world query answering problem

Definition of the open-world query answering problem (OWQA):

- Given:
- An incomplete database D
- Logical constraints $\Sigma$ on the true state of the world
- A query Q
- Determine if $Q$ is true in every completion of $D$ that satisfies $\Sigma$


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- Equivalently: satisfiability of $D \wedge \Sigma \wedge \neg Q$

Note: We assume that the incomplete database $D$ satisfies the constraints. (Otherwise we need to repair it.)

## Results on OWQA

- The OWQA problem can be undecidable if we allow arbitrary first-order logic for $\Sigma$
- It is also undecidable for common database constraint languages, e.g., tuple-generating dependencies
- It is decidable for better-behaved logical fragments, e.g., the guarded fragment


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## Results on OWQA

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- Backward chaining, aka "query rewriting": change the query to reflect the constraints


## Incompleteness: NULLs

## Codd tables, a.k.a. SQL NULLs

| Patient | Examin. 1 | Examin. 2 | Diagnosis |
| :---: | :---: | :---: | :---: |
| A | 23 | 12 | $\alpha$ |
| B | 10 | 23 | $\perp_{1}$ |
| C | 2 | 4 | $\gamma$ |
| D | 15 | 15 | $\perp_{2}$ |
| E | $\perp_{3}$ | 17 | $\beta$ |

- 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 possible completions of the table (infinitely many)
- In SQL, three-valued logic, weird semantics:

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

## Problem: Codd tables and query evaluation

| Appointment |  |  | Illness |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |
|  | Doctor | Patient |  |  |
| D1 | A |  | Diagnosis |  |
| D2 | A |  |  |  |

Let's join the two tables...

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- We know that $\perp_{1}=\perp_{2}$, but we cannot represent it
- Simple solution: named nulls aka v-tables
- More expressive solution: c-tables

Summary and directions

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- Extensions: homomorphism-closed queries, uniform reliability...


## Other topics of research

- Queries with negation [Fink and Olteanu, 2016]
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- A summary: Dan Suciu, Probabilistic Databases for All [Suciu, 2020]


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- This contradicts the minimality of the large $D$


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$\rightarrow$ Call this an iterable pattern

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## Proof technique

Hard part: show hardness for (variants of) the query $Q: x \longrightarrow y \longrightarrow z \longrightarrow w$ We reduce from $\operatorname{PQE}(Q)$, on probabilistic graphs $G$ of the following form:


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- Show that each $N_{i}$ is a linear function of $X_{1}, \ldots, X_{k}$, so:

$$
\left(\begin{array}{c}
N_{1} \\
\vdots \\
N_{k}
\end{array}\right)=\left(\begin{array}{ccc}
\alpha_{1,1} & \cdots & \alpha_{1, k} \\
\vdots & \ddots & \vdots \\
\alpha_{k, 1} & \cdots & \alpha_{k, k}
\end{array}\right) \cdot\left(\begin{array}{c}
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\vdots \\
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\end{array}\right)
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- Split the subsets on some parameter e.g., the number of nodes: $X=X_{1}+\cdots+X_{k}$
- Create unweighted copies of $G$ modified with some parameterized gadgets
$\rightarrow$ Call the oracle for $\operatorname{SC}(\mathrm{Q})$ on each to get answers $N_{1}, \ldots, N_{k}$
- Show that each $N_{i}$ is a linear function of $X_{1}, \ldots, X_{k}$, so:

$$
\left(\begin{array}{c}
N_{1} \\
\vdots \\
N_{k}
\end{array}\right)=\left(\begin{array}{ccc}
\alpha_{1,1} & \cdots & \alpha_{1, k} \\
\vdots & \ddots & \vdots \\
\alpha_{k, 1} & \cdots & \alpha_{k, k}
\end{array}\right) \cdot\left(\begin{array}{c}
X_{1} \\
\vdots \\
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$$

- Show invertibility of this matrix to recover the $X_{i}$ from the $N_{i}$


## Using the equation system

We have obtained the system:

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$\rightarrow$ If the matrix is invertible, then we have succeeded
We can choose gadgets and parameters to get a Vandermonde matrix, and show invertibility via several arithmetical tricks


## The semistructured model and XML



- 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
$\cdot \Rightarrow$ some sets of possible worlds are not expressible this way!


## Annotations with event variables

| Event | Prob. |
| :---: | :---: |
| $w_{1}$ | 0.8 |
| $w_{2}$ | 0.7 |



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| Event | Prob. |
| :---: | :---: |
| $w_{1}$ | 0.8 |
| $w_{2}$ | 0.7 |
|  | $p_{1}=0.06 \quad p_{2}=0.70 \quad p_{3}=0.24$ |



- Expresses arbitrarily complex dependencies


## Query evaluation on probabilistic XML

- Query evaluation for probabilistic XML: what is the probability that a (fixed) tree automaton accepts?


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- \#P-hard in the general model
- This generalizes to PQE for MSO on relational databases (TID) when assuming that the treewidth is bounded [Amarilli et al., 2015]
- Bounding the treewidth is necessary for tractability in a certain sense [Amarilli et al., 2016]


## 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


$$
P: \text { person }
$$



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


## C-tables [Imielinski and Lipski, 1984]

| Patient | Examin. 1 | Examin. 2 | Diagnosis | Condition |
| :---: | :---: | :---: | :---: | :---: |
| A | 23 | 12 | $\alpha$ |  |
| B | 10 | 23 | $\perp_{1}$ |  |
| C | 2 | 4 | $\gamma$ |  |
| D | $\perp_{2}$ | 15 | $\perp_{1}$ |  |
| E | $\perp_{3}$ | 17 | $\beta$ | $18<\perp_{3}<\perp_{2}$ |

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


[^0]:    Treelike data
    

    MSO query

    $$
    \begin{gathered}
    \exists x y \\
    P_{\bigcirc}(x) \wedge P_{\bigcirc}(y)
    \end{gathered}
    $$

