Leveraging the Structure of Uncertain Data
Tirer parti de la structure des données incertaines

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Databases

Computers often use databases to store data and query it

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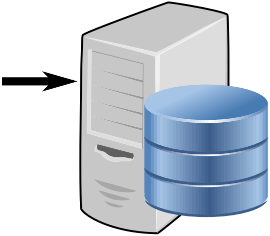
Data

time	from	to	message
14:42	Spam	John	Cheap Watch...
14:34	A.	John	Just started
18:20	Mom	John	Hi John!...
14:49	John	Spam	STOP
14:36	John	A.	OK. Good...
⋮	⋮	⋮	⋮



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Query

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SELECT * FROM Data
WHERE from='A.' OR to='A.'
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Query

```
SELECT * FROM Data
WHERE from='A.' OR to='A.'
```

Answer

time	from	to	message
14:32	John	A.	Hi there! :)
14:32	John	A.	Just wanted...
14:33	John	A.	How is it...
14:34	A.	John.	Dunno yet
14:34	A.	John.	Just started
14:36	John	A.	OK. Good...

Databases

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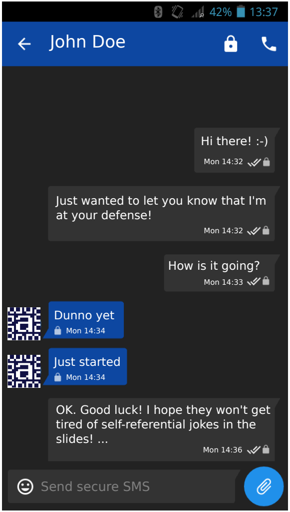
→ Let's see a few examples...

Database example: SMS on Android



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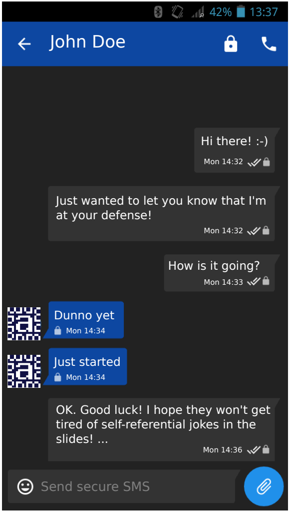

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14:34	A.	John	Just started
14:36	John	A.	OK. Good...

In reality...

```
CREATE TABLE sms (_id INTEGER, thread_id INTEGER,
  address TEXT, address_device_id INTEGER, person INTEGER,
  date INTEGER, date_sent INTEGER, protocol INTEGER,
  read INTEGER, status INTEGER, type INTEGER,
  reply_path_present INTEGER,
  delivery_receipt_count INTEGER, subject TEXT, body TEXT,
  mismatched_identities TEXT, service_center TEXT,
  date_delivery_received INTEGER);
```

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  reply_path_present INTEGER,
  delivery_receipt_count INTEGER, subject TEXT, body TEXT,
  mismatched_identities TEXT, service_center TEXT,
  date_delivery_received INTEGER);
INSERT INTO sms VALUES(
  14041,224,'+33611210549',1,NULL,1451921855098,
  1451921849000,0,1,-1,-2147483628,0,0,NULL,
  'Hi there!',NULL,'+33609002960',0);
INSERT INTO sms VALUES(
  14042,224,'+33611210549',1,NULL,1451921945081,
  1451921945081,NULL,1,-1,-2147483561,NULL,0,NULL,
  'Just wanted...',NULL,NULL,0);
```

Database example: Wikipedia

Recent changes

- Naza; 14:48 . . (-59) . . 98.115.58.241
- HK Olimpija Ljubljana (2004); 14:48 . . (+4) . . 86.58.36.235
- Monster High; 14:48 . . (+18) . . 66.244.123.117
- List of songs recorded by Celine Dion; 14:48 . . (+25) . . 79.94.26.185
- Biodegradable waste; 14:48 . . (+5) . . 59.90.26.215

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title	**time**	**size**	**user**
Naza	14:48	-59	92.115.58.241
HK Olimpija Ljubljana (2004)	14:48	+4	86.58.36.235
Monster High	14:48	+18	66.244.123.117
List of songs recorded by Celine Dion	14:48	+25	79.94.26.185
Biodegradable waste	14:48	+5	59.90.26.215

In reality...

```
CREATE TABLE mw_recentchanges (rc_id INT(8),
  rc_timestamp VARCHAR(14), rc_cur_time VARCHAR(14),
  rc_user INT(10), rc_user_text VARCHAR(255),
  rc_namespace INT(11), rc_title VARCHAR(255),
  rc_comment VARCHAR(255), rc_minor TINYINT(3),
  rc_bot TINYINT(3), rc_new TINYINT(3),
  rc_cur_id INT(10), rc_this_oldid INT(10),
  rc_last_oldid INT(10), rc_type TINYINT(3),
  rc_moved_to_ns TINYINT(3), rc_moved_to_title VARCHAR(255),
  rc_patrolled TINYINT(3), rc_ip CHAR(15),
  rc_old_len INT(10), rc_new_len INT(10),
  rc_deleted TINYINT(1), rc_logid INT(10),
  rc_log_type VARCHAR(255), rc_log_action VARCHAR(255),
  rc_params BLOB,
);
```

In reality...

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  rc_old_len INT(10), rc_new_len INT(10),
  rc_deleted TINYINT(1), rc_logid INT(10),
  rc_log_type VARCHAR(255), rc_log_action VARCHAR(255),
  rc_params BLOB,
);
INSERT INTO mw_recentchanges VALUES
  (1, '20160314144837', '20160314144827', 1, '92.115.58.241', 0,
  'Naza', '', 0, 0, 0, 1, 2, 1, 0, 0, '', 1, '92.115.58.241',
  559, 500, 0, 0, NULL, NULL, ''),
INSERT INTO mw_recentchanges VALUES
  (2, '20160314144842', '20160314144842', 1, '66.244.123.117', 2,
  'Monster High', '', 0, 0, 1, 2, 3, 0, 1, 0, '', 1, '66.244.123.117',
  102, 120, 0, 0, NULL, NULL, '');
```

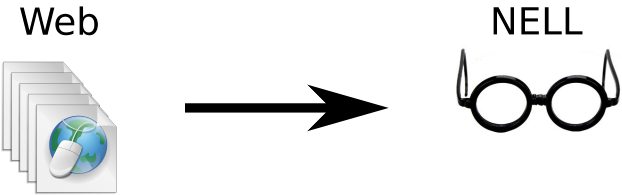
Uncertainty

- Databases usually assume that data is
  - → complete
  - → crisp
  - → certain
  - → correct
- In many situations, this is not the case...

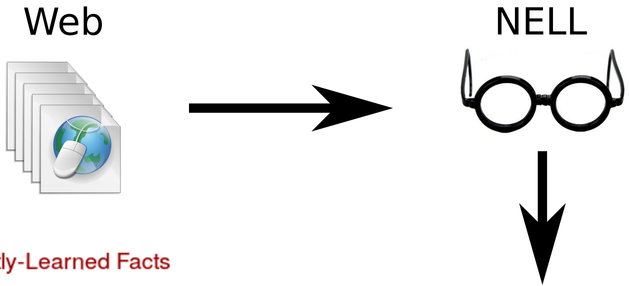
Example: Never-Ending Language Learning

Web

Example: Never-Ending Language Learning



Example: Never-Ending Language Learning



Recently-Learned Facts

Refresh

instance	iteration	date learned	confidence
kampioenschap van zwitserland is a sports race	955	20-oct-2015	95.0
cochran mill nature center is an aquarium	955	20-oct-2015	96.9
kozy shack chocolate pudding is a kind of candy	956	23-oct-2015	90.3
red delicious apple tree is a plant	955	20-oct-2015	92.8
sale miami dade county is a sport	955	20-oct-2015	99.1
chicken001 eat black beans	955	20-oct-2015	100.0
wrigley field is the home venue for the sports team chicago cubs	959	07-nov-2015	100.0
lorena ochoa is a person who has residence in the geopolitical location mexico	958	03-nov-2015	100.0
umass lowell river hawks hired john calipari	955	20-oct-2015	98.4
nuggets participated in the event games	955	20-oct-2015	100.0

Many sources of uncertainty

- Errors in sources:

> This article's **factual accuracy is disputed**. Please help to ensure that disputed statements are reliably sourced. See the relevant discussion on the talk page. *(November 2015)*

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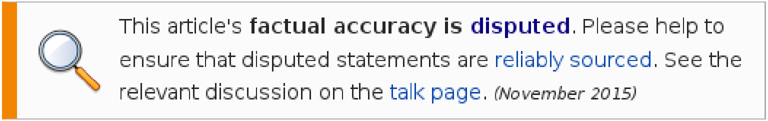

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  "The place and function of Venus in Ovid..."
  "Computed backscattering function of Venus and the moon..."

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- Anaphora resolution:
  "Obama told Hollande that he was not a spying target"

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- Entity disambiguation:
  "The place and function of Venus in Ovid..."
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- Anaphora resolution:
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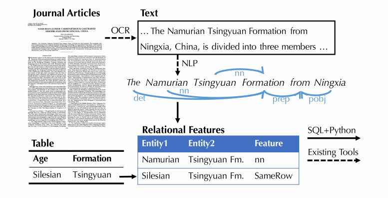
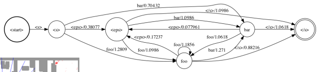
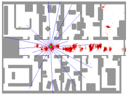
- Incompleteness

Many uncertain data applications

- Information extraction
- Machine learning
- Speech recognition
- Data integration
- Crowdsourcing
- …







	Possible Mapping	Prob
$m_1 =$	{(pname, name), (email-addr, email), (current-addr, mailing-addr), (permanent-addr, home-addr)}	0.5
$m_2 =$	{(pname, name), (email-addr, email), (permanent-addr, mailing-addr), (current-addr, home-addr)}	0.4
$m_3 =$	{(pname, name), (email-addr, mailing-addr), (current-addr, home-addr)}	0.1

(a)

pname	email-addr	current-addr	permanent-addr
Alice	alice@	Mountain View	Sunnyvale
Bob	bob@	Sunnyvale	Sunnyvale

(b)

Tuple (mailing-addr)	Prob
('Sunnyvale')	0.9
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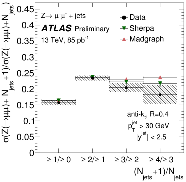

Many uncertain data applications

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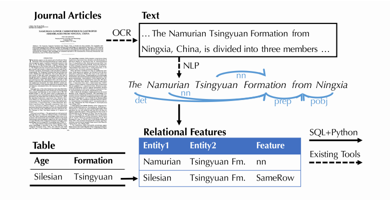
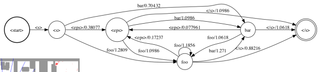
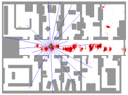
- PhD defense scheduling







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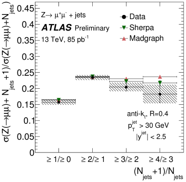

Uncertainty applied to PhD defenses

Who will attend this PhD defense?

Statistics
Number of people invited

Uncertainty applied to PhD defenses

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Statistics	
Number of people invited	79

Uncertainty applied to PhD defenses

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Uncertainty applied to PhD defenses

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Uncertainty applied to PhD defenses

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$\rightarrow$ If the list of people is incomplete, infinitely many possible completions

Uncertainty representation and semantics

Uncertain databases represent implicitly the possible worlds

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→ Probabilities

Flo	0.4
Guy	0.3
Tat	0.2
⋮	

Uncertainty representation and semantics

Uncertain databases represent implicitly the possible worlds

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$\rightarrow$ Correlations

- Only one of Isa and Pal can come
- Mat and Val either come together or not
- Nell will probably come if Mike does

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→ Logical rules

If someone comes to the defense then they will also come to the drinks

Summary of uncertainty goals

- Representing our knowledge about the data
- Computing numerical probabilities
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Query

How many people to the drinks?

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Query

```
How many people
to the drinks?
```

Uncertain answer

42 ±5 with 80% confidence

Why are uncertainty and probabilities challenging?

Uncertain attendees

Flo	0.4
Guy	0.3
Tat	0.2
Ell	0.1
$\vdots$	

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Uncertain attendees

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Guy	0.3
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Ell	0.1
$\vdots$	

People who should meet

Flo	Guy
Ell	Tat
Ell	Guy

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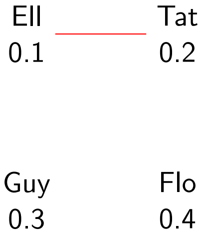
⋮	

People who should meet

Flo	Guy
Ell	Tat
Ell	Guy

What is the probability that one of the pairs can meet?

Computing probabilities



Computing probabilities

Ell	Tat
0.1	0.2

$$0.1 \times 0.2$$

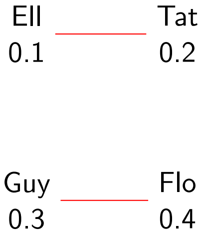
Guy	Flo
0.3	0.4

Computing probabilities

Ell		Tat
0.1		0.2
Guy		Flo
0.3		0.4

$$0.1 \times 0.2 = 0.02$$

Computing probabilities



Computing probabilities

Ell		Tat
0.1		0.2
Guy		Flo
0.3		0.4

$$0.1 \times 0.2$$

Computing probabilities

Ell — Tat
0.1 0.2

$$0.1 \times 0.2 = 0.02$$

Guy — Flo
0.3 0.4

Computing probabilities

Ell ——— Tat
0.1 0.2

Guy ——— Flo
0.3 0.4

$$0.1 \times 0.2 = 0.02$$
$$0.3 \times 0.4$$

Computing probabilities

Ell ——— Tat

0.1 0.2

Guy ——— Flo

0.3 0.4

$$0.1 \times 0.2 = 0.02$$
$$0.3 \times 0.4 = 0.12$$

Computing probabilities

Ell —— Tat
0.1 0.2

Guy —— Flo
0.3 0.4

$$0.1 \times 0.2 = 0.02$$
$$0.3 \times 0.4 = 0.12$$
$$1 - (1 - 0.02) \times (1 - 0.12)$$

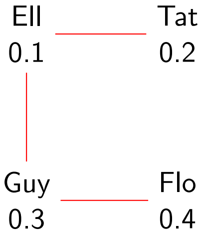
Computing probabilities

Ell — Tat
0.1 0.2

Guy — Flo
0.3 0.4

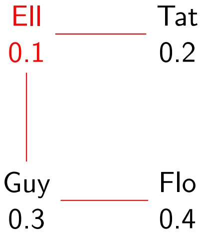
$$0.1 \times 0.2 = 0.02$$
$$0.3 \times 0.4 = 0.12$$
$$1 - (1 - 0.02) \times (1 - 0.12) = 0.1376$$

Computing probabilities

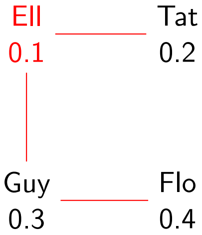


Computing probabilities

If Ell is missing:

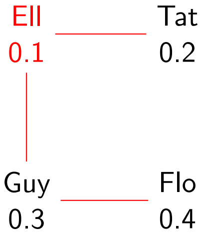


Computing probabilities



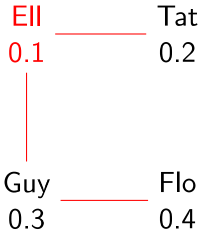
If Ell is missing:
0.3×0.4

Computing probabilities



If Ell is missing:
$0.3 \times 0.4 = 0.12$

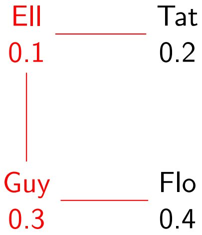
Computing probabilities



If Ell is missing:
$0.3 \times 0.4 = 0.12$

If Ell is here:

Computing probabilities

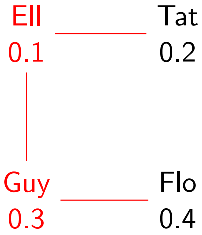


If Ell is missing:
$0.3 \times 0.4 = 0.12$

If Ell is here:

  If Guy is missing:

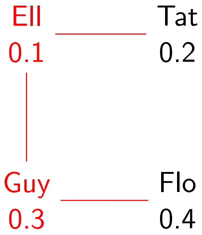
Computing probabilities



If Ell is missing:
$0.3 \times 0.4 = 0.12$

If Ell is here:
- If Guy is missing:
  - We need Tat: 0.2

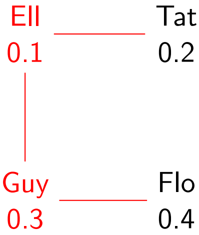
Computing probabilities



If Ell is missing:
$0.3 \times 0.4 = 0.12$

If Ell is here:
- If Guy is missing:
  - We need Tat: 0.2
- If Guy is here:

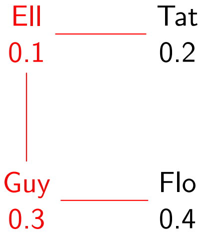
Computing probabilities



If Ell is missing:
$0.3 \times 0.4 = 0.12$

If Ell is here:
- If Guy is missing:
  - We need Tat: 0.2
- If Guy is here: success!

Computing probabilities



If Ell is missing:
$0.3 \times 0.4 = 0.12$

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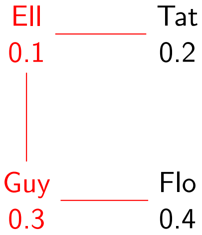
Total:

Computing probabilities

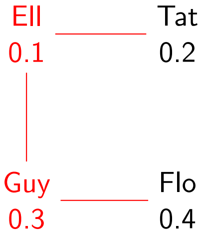


If Ell is missing:
$0.3 \times 0.4 = 0.12$

If Ell is here:
  If Guy is missing:
    We need Tat: 0.2
  If Guy is here: success!

Total: $(1 - 0.1) \times 0.12$

Computing probabilities



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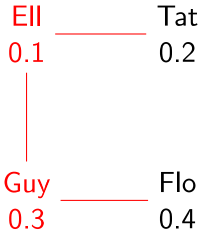
Total: $(1 - 0.1) \times 0.12$
$+ 0.1 \times$

Computing probabilities



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If Ell is here:
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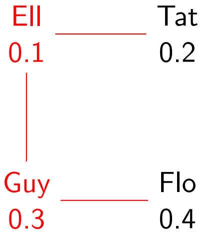
If Guy is here: success!

Total: $(1 - 0.1) \times 0.12$
$+ 0.1 \times \big(0.3 + (1 - 0.3) \times 0.2\big)$

Computing probabilities

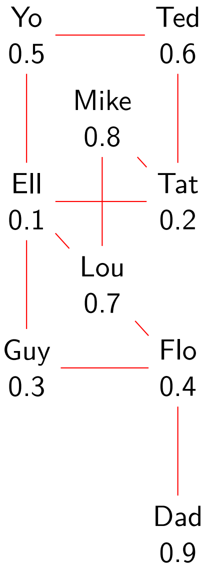


If Ell is missing:
$0.3 \times 0.4 = 0.12$

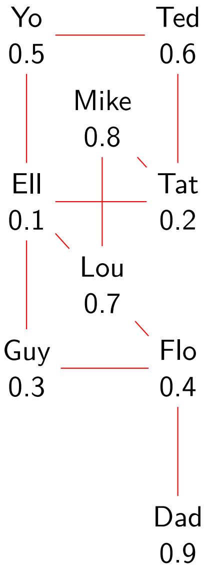
If Ell is here:
- If Guy is missing:
  - We need Tat: 0.2
- If Guy is here: success!

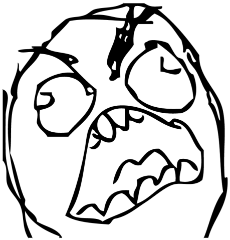
Total: $(1 - 0.1) \times 0.12$
$+ 0.1 \times \big(0.3 + (1 - 0.3) \times 0.2\big)$
$= 0.152$

Computing probabilities

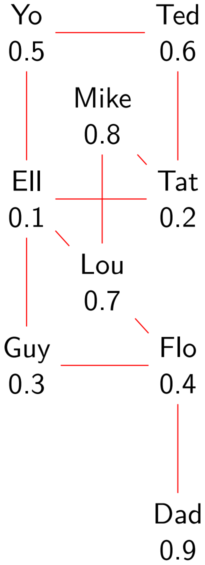


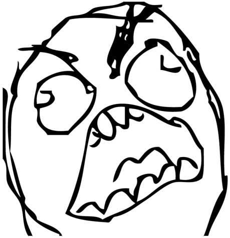
Computing probabilities





Computing probabilities





- This task is intractable (#P-hard)
- Many other tasks on uncertain data are intractable or even undecidable

My PhD topic

→ Make it easier to use uncertain data
by making assumptions on the structure of data

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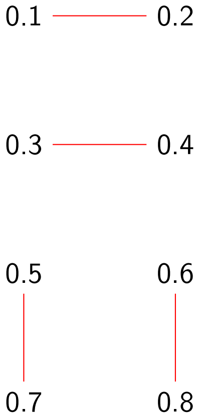

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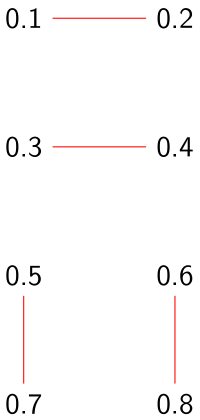

- $0.1 \times 0.2 = 0.02$

My PhD topic

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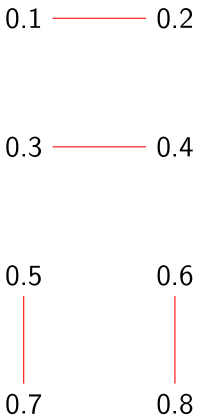

- $0.1 \times 0.2 = 0.02$
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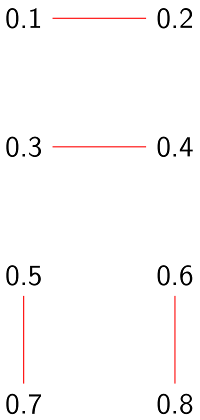

- $0.1 \times 0.2 = 0.02$
- $0.3 \times 0.4 = 0.12$
- $0.5 \times 0.7 = 0.35$

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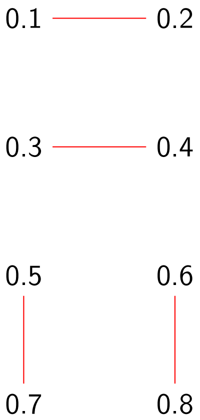

- $0.1 \times 0.2 = 0.02$
- $0.3 \times 0.4 = 0.12$
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- $0.6 \times 0.8 = 0.48$

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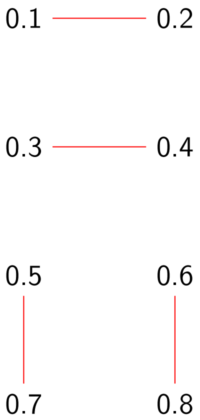

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→ $1 - (1 - 0.02) \times \cdots \times (1 - 0.48)$

My PhD topic

→ Make it easier to use uncertain data
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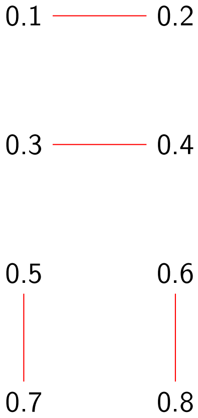

- $0.1 \times 0.2 = 0.02$
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→ $1 - (1 - 0.02) \times \cdots \times (1 - 0.48)$
$= 0.7085088$

My PhD topic

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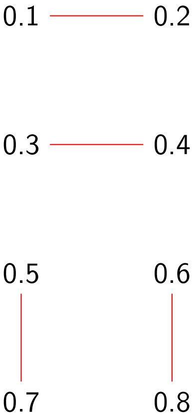

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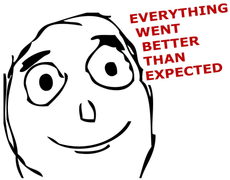

Table of contents

Roadmap

I studied different questions related to uncertainty:

Roadmap

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Other work: (A. 2014, 2015a,b; A., Allauzen, Mohri 2015; A., Amsterdamer, Milo 2014a,b; A., Maniu, Senellart 2015; A., Galárraga, Preda, Suchanek 2014; Talaika, Biega, A., Suchanek 2015; Tang, A., Senellart, Bressan 2014a,b)

Uncertain ordered relations

Food

tiramisu kougelhopf

bretzel

munster

Drinks

champagne

riesling

Uncertain ordered relations

Food

tiramisu kougelhopf

bretzel

munster

Drinks

champagne

riesling

- I partially know guest preferences

Uncertain ordered relations

Food

$$\begin{tikzcd}
\text{tiramisu} \arrow[dr] & & \text{kougelhopf} \arrow[dl] \\
& \text{bretzel} \arrow[d] & \\
& \text{munster} &
\end{tikzcd}$$

Drinks

$$\begin{tikzcd}
\text{champagne} \arrow[d] \\
\text{riesling}
\end{tikzcd}$$

- I partially know guest preferences

Uncertain ordered relations

Food

$$\begin{array}{ccc} \text{tiramisu} & & \text{kougelhopf} \\ & \searrow \;\; \swarrow & \\ & \text{bretzel} & \\ & \downarrow & \\ & \text{munster} & \end{array}$$

Drinks

$$\begin{array}{c} \text{champagne} \\ \downarrow \\ \text{riesling} \end{array}$$

- I partially know guest preferences
- What should my parents bring?

Uncertain ordered relations

Food

$$\begin{tikzcd} \text{tiramisu} \arrow[dr] & & \text{kougelhopf} \arrow[dl] \\ & \text{bretzel} \arrow[d] & \\ & \text{munster} & \end{tikzcd}$$

Drinks

$$\begin{tikzcd} \text{champagne} \arrow[d] \\ \text{riesling} \end{tikzcd}$$

- I partially know guest preferences
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→ What are the top two Alsatian products?

Uncertain ordered relations

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$$\begin{tikzcd} \text{tiramisu} \arrow[dr] & & \text{kougelhopf} \arrow[dl] \\ & \text{bretzel} \arrow[d] & \\ & \text{munster} & \end{tikzcd}$$

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Uncertain ordered relations

Food

$$\begin{array}{ccc} \text{tiramisu} & & \text{kougelhopf} \\ & \searrow \quad \swarrow & \\ & \text{bretzel} & \\ & \downarrow & \\ & \text{munster} & \end{array}$$

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- I partially know guest preferences
- What should my parents bring?

→ What are the top two Alsatian products?

Possible:

$$\begin{array}{c} \text{riesling} \\ \downarrow \\ \text{kougelhopf} \end{array}$$

Uncertain ordered relations

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$$\begin{array}{ccc} \text{tiramisu} & & \text{kougelhopf} \\ & \searrow \quad \swarrow & \\ & \text{bretzel} & \\ & \downarrow & \\ & \text{munster} & \end{array}$$

Drinks

$$\begin{array}{c} \text{champagne} \\ \downarrow \\ \text{riesling} \end{array}$$

- I partially know guest preferences
- What should my parents bring?

→ What are the top two Alsatian products?

Possible:

$$\begin{array}{c} \text{riesling} \\ \downarrow \\ \text{kougelhopf} \end{array}$$

Not possible:

$$\begin{array}{c} \text{kougelhopf} \\ \downarrow \\ \text{munster} \end{array}$$

Uncertain ordered relations

Food

tiramisu → bretzel ← kougelhopf

bretzel → munster

Drinks

champagne → riesling

- I partially know guest preferences
- What should my parents bring?

→ What are the top two Alsatian products?

Possible:

riesling → kougelhopf

Not possible:

kougelhopf → munster

→ On which queries and data can we efficiently find possible and certain answers?

Uncertain numerical values

- How much food do people eat?

Uncertain numerical values

- How much food do people eat?
- Let's ask friends who defended recently

Uncertain numerical values

small sweet	tiny both	small salty
medium sweet	small both	medium salty
large sweet	medium both	large salty
	large both	

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Uncertain numerical values

small sweet	tiny both	small salty
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	large both	

- How much food do people eat?
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Uncertain numerical values

small sweet

small salty

tiny both

medium sweet

medium salty

small both

large sweet

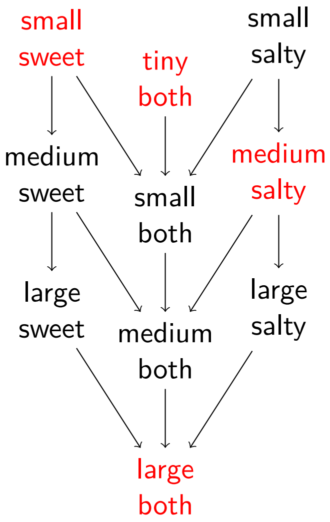
large salty

medium both

large both

- How much food do people eat?
- Let's ask friends who defended recently
- Some order relations are implied

Uncertain numerical values



- How much food do people eat?
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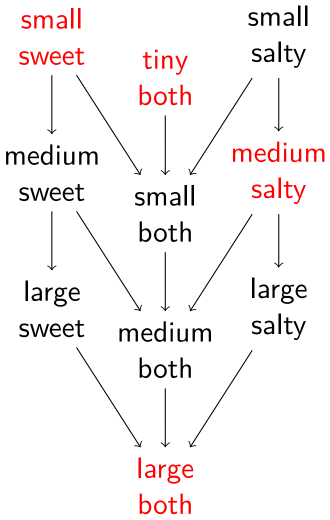
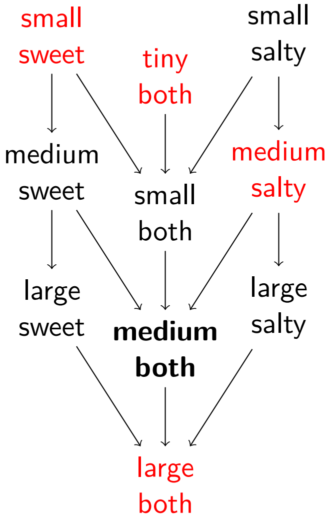


- How much food do people eat?
- Let's ask friends who defended recently
- Some order relations are implied
- How to estimate for my own defense?

Uncertain numerical values



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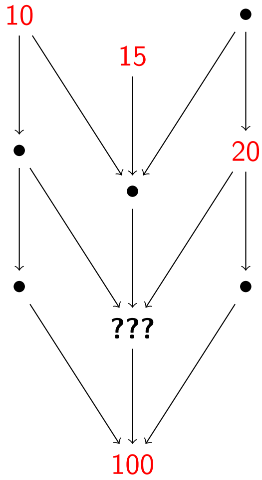

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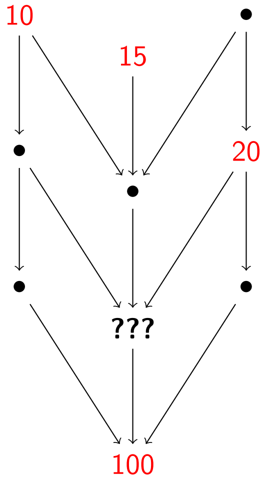

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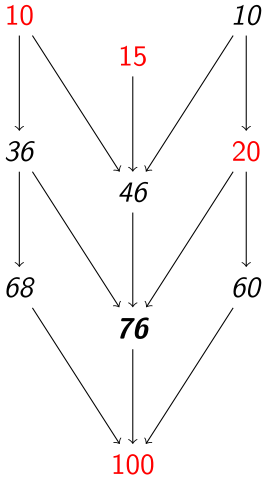
→ Interpolation scheme for posets based on integration on polytopes

Uncertain numerical values



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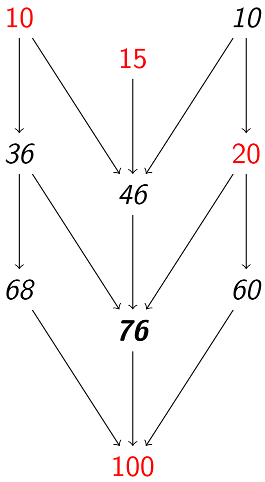

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→ Interpolation scheme for posets based on integration on polytopes

→ Complexity study and tractable cases

Open-world query answering

Incomplete data:

- Fabian supervises Luis
- Fabian is at the defense
- Fabian is in DBWeb

Open-world query answering

Incomplete data:

- Fabian supervises Luis
- Fabian is at the defense
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Logical constraints:

- People at the defense will have drinks
- All DBWeb students will have drinks
- If your advisor is in DBWeb
  then you are a DBWeb student

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Is the following query certain?

→ Will a DBWeb student meet their advisor at the drinks?

Open-world query answering

Incomplete data:

- Fabian supervises Luis
- Fabian is at the defense
- Fabian is in DBWeb
- Fabian comes to the drinks

Logical constraints:

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- All DBWeb students will have drinks
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Is the following query certain?

→ Will a DBWeb student meet their advisor at the drinks?

Open-world query answering

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- Fabian is in DBWeb
- Fabian comes to the drinks
- Luis is a DBWeb student
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Logical constraints:

- People at the defense will have drinks
- All DBWeb students will have drinks
- If your advisor is in DBWeb then you are a DBWeb student

Is the following query certain?

→ Will a DBWeb student meet their advisor at the drinks?

Open-world query answering

Incomplete data:

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→ For which rule languages is this task decidable?

Expressive open-world query answering

Different communities use different kinds of constraints:

- Constraints with facts of arity > 2

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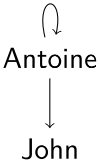
$\rightarrow$ I show that those can be combined under some restrictions to obtain decidable query answering

Query answering assuming finiteness

Consider the guests to the defense, $\longrightarrow$ shows who invites whom

Data:



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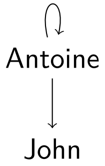

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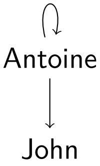

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$$\begin{tikzcd} \text{Antoine} \arrow[loop above] \arrow[d] \\ \text{John} \end{tikzcd}$$

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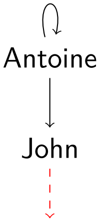

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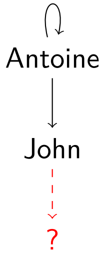

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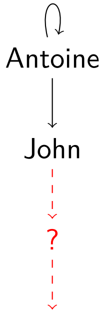

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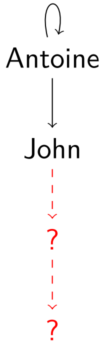

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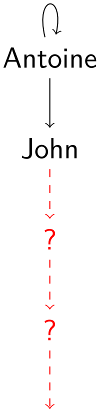

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$\rightarrow$ Is this sensible? **No!**

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Rules:

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Query answering assuming finiteness

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→ Can we do reasoning assuming finiteness?

→ What difference does it make?

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$\rightarrow$ First techniques for open-world query answering with arbitrary arity signatures and functional dependencies where assuming finiteness makes a difference

Table of contents

Tuple-independent databases

We fix a relational signature σ (here: S, arity 2).

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a	a	1
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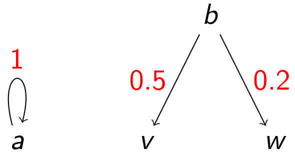

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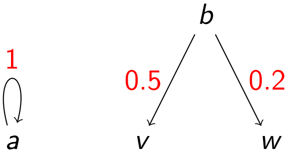

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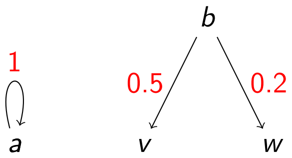

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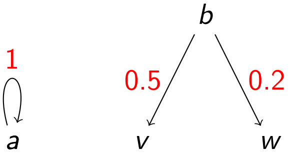

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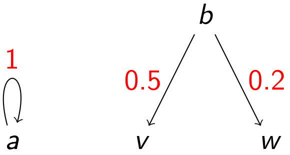

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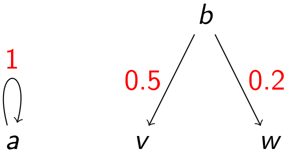

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Is there a smaller class $\mathcal{I}$ such that PQE is tractable for a larger $\mathcal{Q}$?

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$\rightarrow$ Does this extend to probabilistic QE?

Our main result

An instance-based dichotomy result:

Upper bound.

For $\mathcal{I}$ the treelike instances and $\mathcal{Q}$ the MSO queries

$\rightarrow$ PQE is in linear time modulo arithmetic costs

Our main result

An instance-based dichotomy result:

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For $\mathcal{I}$ the treelike instances and $\mathcal{Q}$ the MSO queries

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- Also for expressive provenance representations
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Lower bound.

For any unbounded-tw family $\mathcal{I}$ and $\mathcal{Q}$ the FO queries

$\rightarrow$ PQE is #P-hard under RP reductions assuming:

- Signature arity is 2 (graphs)
- High-tw instances in $\mathcal{I}$ are easily constructible

Technical tool: lineages

The lineage of a query q on an instance I:

- Boolean function ϕ whose variables are the facts of I
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R		
a	b	f_1
b	c	f_2
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$\rightarrow$ Lineage: $(f_1 \land f_2) \lor (f_3 \land f_4) \lor f_5$

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→ Lineage: $(f_1 \wedge f_2) \vee (f_3 \wedge f_4) \vee f_5$

→ For all $\nu : I \to \{0, 1\}$ we have $\nu(\phi) = 1$ iff $\{F \in I \mid \nu(F) = 1\} \models q$

Using lineages

- To solve the PQE problem on treelike instances for MSO

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  - First solve the problem on trees

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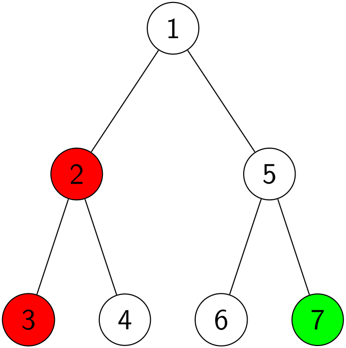
  - $\rightarrow$ Probability of the lineage = probability of the query
  - Compute the lineage probability efficiently (show it is not #P-hard as in the general case)

Uncertain trees



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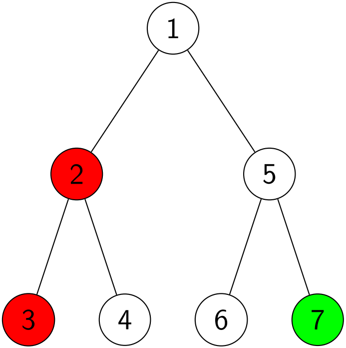

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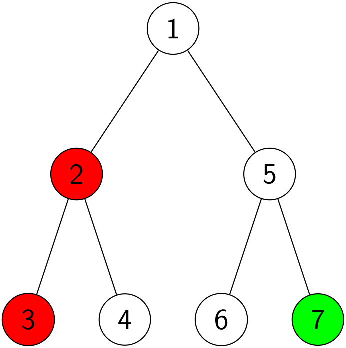

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Example query:
"Is there both a red and a green node?"

Valuation: $\{2, 3, 7\}$

The query is true

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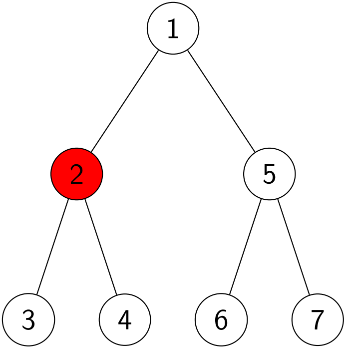

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Valuation: $\{2\}$

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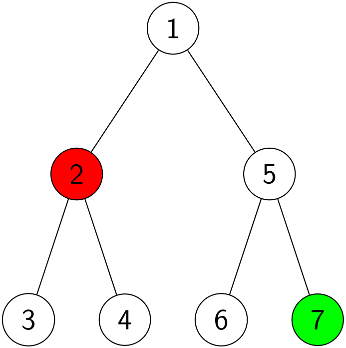

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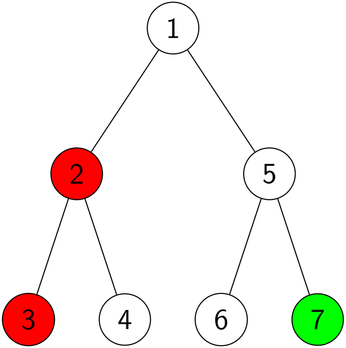
Lineage circuits on trees



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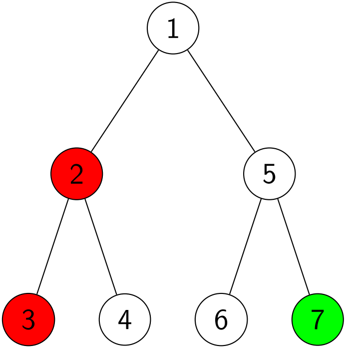

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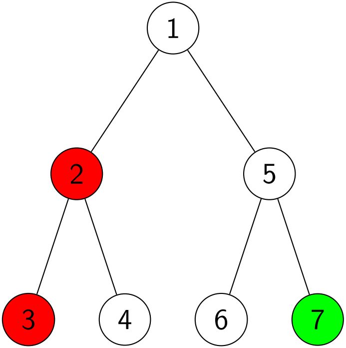

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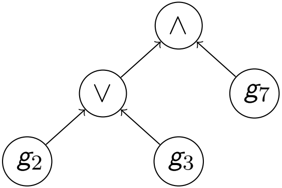

Our main results

Theorem

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Corollary

Probabilistic query evaluation of MSO queries on treelike instances is in linear time up to arithmetic operations.

Extension 1: general semirings

- Semiring of positive Boolean functions $(\mathrm{PosBool}[X], \vee, \wedge, \mathfrak{f}, \mathfrak{t})$

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Our construction can be extended to $\mathbb{N}[X]$-provenance
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For any fixed UCQ q and $k \in \mathbb{N}$,
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we can build in linear time a $\mathbb{N}[X]$-provenance circuit of q on I.

Extension 2: correlations

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Generalises to pc-tables with treelike correlations

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Theorem

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Proven by extracting arbitrary graphs as minors of high-treewidth families using (Chekuri, Chuzhoy 2014)

Table of contents

Conclusion

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    - Lower bound for FO on any non-treelike family *(assuming arity-two and treewidth-constructibility)*

Ongoing and future work

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Thanks for your attention!

Image sources

- Slides 2 and 14: https://openclipart.org/download/163711/database-server.svg
- Slide 3: SMSSecure https://smssecure.org/ and AOSP https://source.android.com/
- Slide 7: https://openclipart.org/download/36529/interrogation.svg
- Slide 8: http://rtw.ml.cmu.edu/, https://openclipart.org/download/25537/HMTL.svg, and https://twitter.com/cmunell
- Slide 9: https://en.wikipedia.org/wiki/Template:Disputed
- Slide 10: Zhang 2015, p. 9, Dong, Halevy, Yu 2009, p. 4, https://atlas.web.cern.ch/Atlas/GROUPS/PHYSICS/CONFNOTES/ATLAS-CONF-2015-041/fig_06b.png, https://code.google.com/p/transducersaurus/wiki/CascadeTutorial, https://www.cs.washington.edu/robotics/mcl/
- Slide 16: https://diaryofawhinyguy.files.wordpress.com/2013/01/rage-guy.png
- Slide 17: http://mylolface.com/assets/faces/happy-everything-went-better-than-expected.jpg

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