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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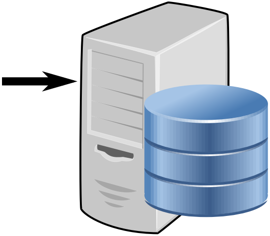
Data

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...

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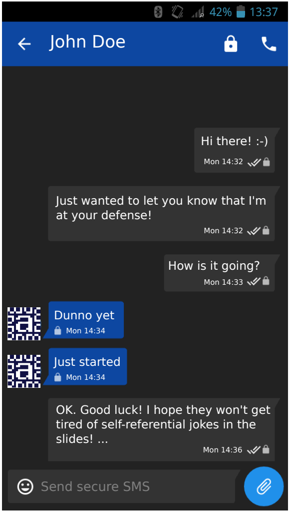
→ Let's see a few examples...

Database example: SMS on Android



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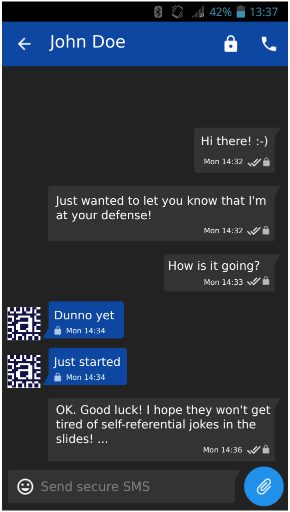

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In reality...

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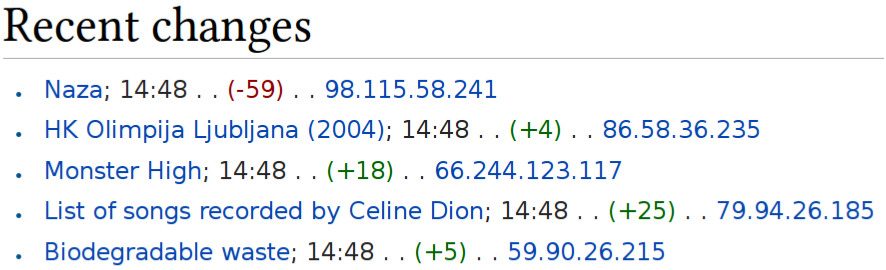
  mismatched_identities TEXT, service_center TEXT,
  date_delivery_received INTEGER);
INSERT INTO sms VALUES(
  14041,224,'+33611210549',1,NULL,1451921855098,
  1451921849000,0,1,-1,-2147483628,0,0,NULL,
  'Hi there!',NULL,'+33609002960',0);
INSERT INTO sms VALUES(
  14042,224,'+33611210549',1,NULL,1451921945081,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

Database example: Wikipedia



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

title	time	size	user
Naza	14:48	-59	92.115.58.241
HK Olimpija Ljubljana (2004)	14:48	+4	86.58.36.235
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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, '');
```

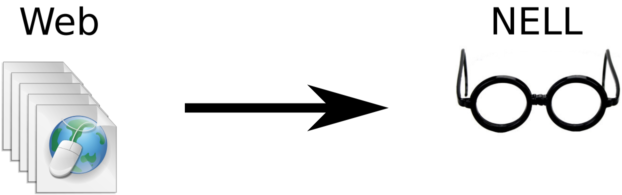
Uncertainty

- 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



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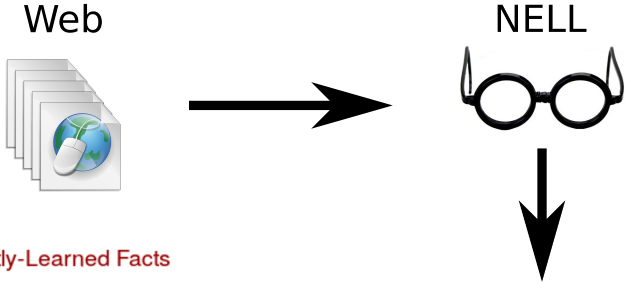

Recently-Learned Facts

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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- Entity disambiguation:
  "The place and function of Venus in Ovid..."
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  "Obama told Hollande that he was not a spying target"

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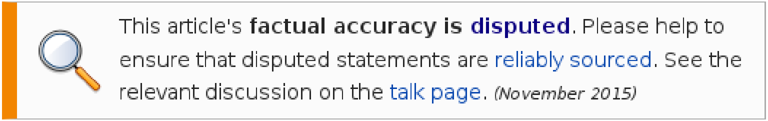
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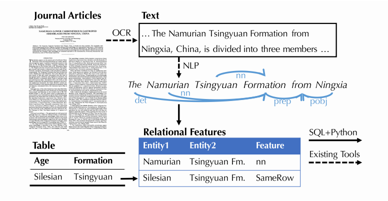
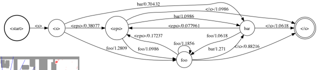
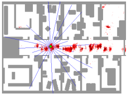
- Entity disambiguation:
  "The place and function of Venus in Ovid..."
  "Computed backscattering function of Venus and the moon..."
- Anaphora resolution:
  "Obama told Hollande that he was not a spying target"
- Incompleteness

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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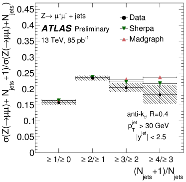

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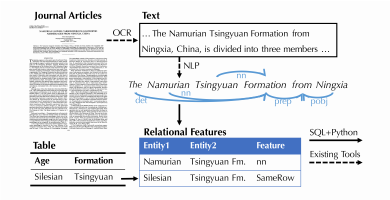
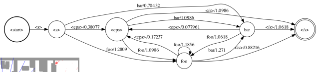
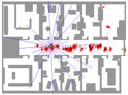
- PhD defense scheduling







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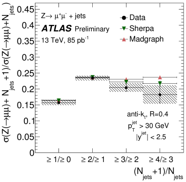

Uncertainty applied to PhD defenses

Who will attend this PhD defense?

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Statistics
Number of people invited

Uncertainty applied to PhD defenses

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Number of additional people showing up	

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- Data is uncertain if we don't know its exact state
- A possible world is an actual outcome

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- Dave
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- Tat
- ...
- more?

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- more?

→ 27 uncertain people

→ 134 217 728 possibilities

→ 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

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Guy	0.3
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→ Logical constraints

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

Summary of uncertainty goals

→ End goal: A database system with first-class uncertainty

- Feed uncertain data to the system
- Get uncertain query results

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How many people
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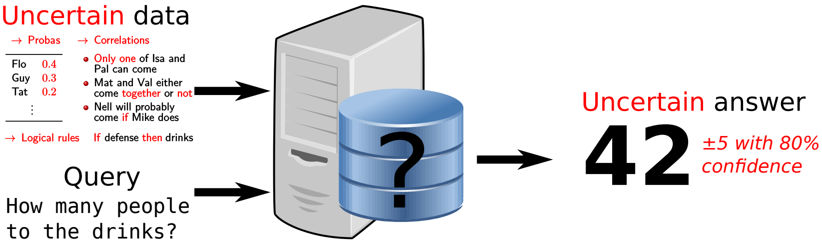

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42 ±5 with 80% confidence

- Representing our knowledge about the data
- Computing numerical probabilities
- Reasoning with logical constraints

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Why are uncertainty and probabilities challenging?

Uncertain attendees

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

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People who should meet

Dave	Guy
Ell	Tat
Ell	Guy

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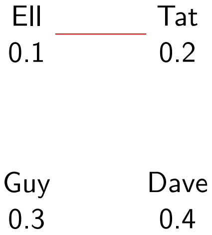
⋮	

People who should meet

Dave	Guy
Ell	Tat
Ell	Guy

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

Computing probabilities



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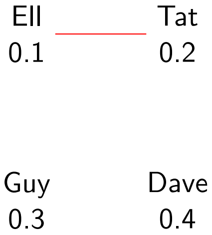


$$0.1 \times 0.2$$

Computing probabilities

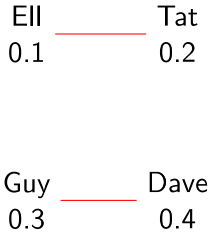
Ell 0.1 — Tat 0.2

Guy 0.3

Dave 0.4

$$0.1 \times 0.2 = 0.02$$

Computing probabilities



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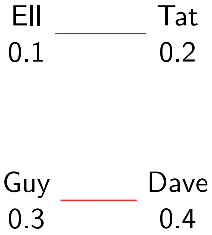

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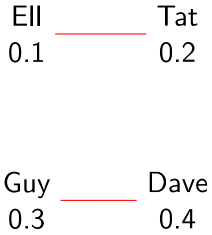

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Computing probabilities

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0.1 0.2

Guy ——— Dave
0.3 0.4

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

Computing probabilities

Ell — Tat
0.1 0.2

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

Guy — Dave
0.3 0.4

Computing probabilities

Ell —— Tat
0.1 0.2

Guy —— Dave
0.3 0.4

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

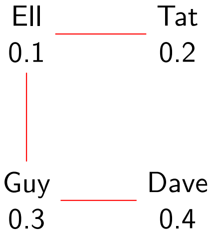
Computing probabilities

Ell ______ Tat
0.1 0.2

Guy ______ Dave
0.3 0.4

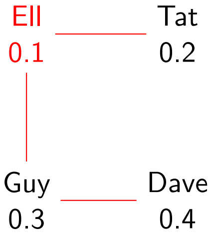
$$0.1 \times 0.2 = 0.02$$
$$0.3 \times 0.4 = 0.12$$
$$1 - (1 - 0.02) \times (1 - 0.12) = 0.1376$$

Computing probabilities

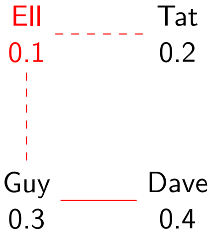


Computing probabilities

If Ell is missing:

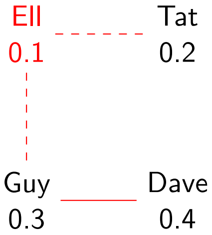


Computing probabilities



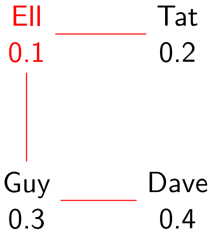
If Ell is missing:
0.3×0.4

Computing probabilities



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

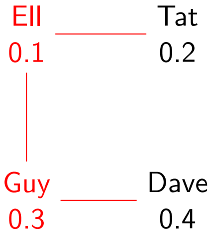
Computing probabilities



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

If Ell is here:

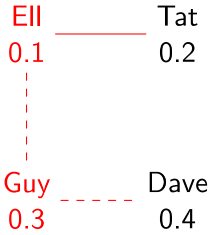
Computing probabilities



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

If Ell is here:
If Guy is missing:

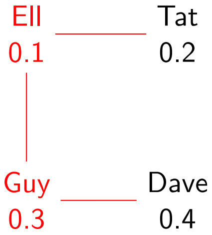
Computing probabilities



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

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

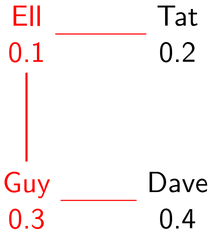
Computing probabilities



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:

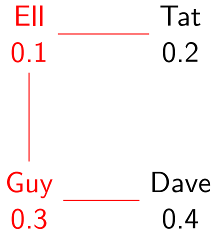
Computing probabilities



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:
$0.3 \times 0.4 = 0.12$

If Ell is here:
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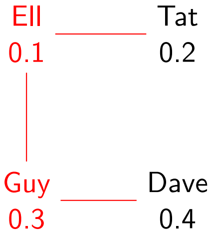
Total:

Computing probabilities

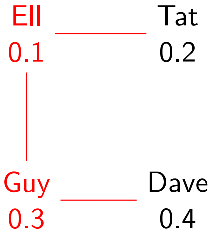


If Ell is missing:
$0.3 \times 0.4 = 0.12$

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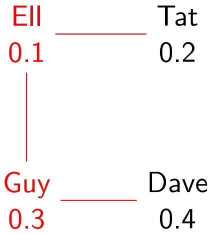
Total: $(1 - 0.1) \times 0.12$

$+ 0.1 \times$

Computing probabilities



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

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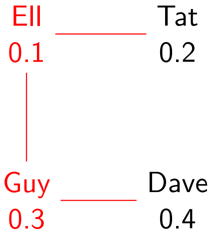
- If Guy is here: success!

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

Computing probabilities

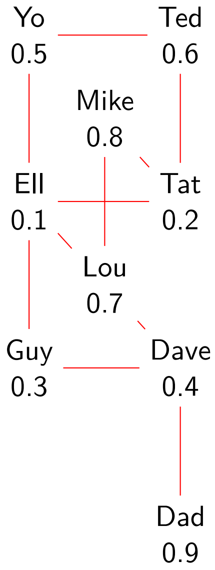


If Ell is missing:
$0.3 \times 0.4 = 0.12$

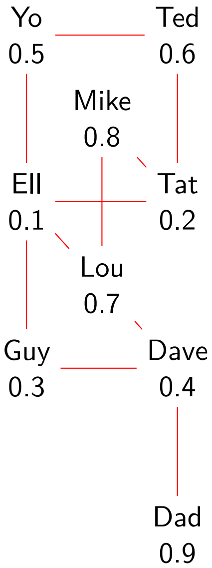
If Ell is here:
- If Guy is missing:
  - We need Tat: 0.2
- If Guy is here: success!

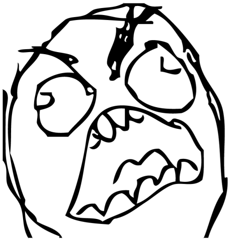
Total: $(1 - 0.1) \times 0.12$
$+ 0.1 \times \big(0.3 + (1 - 0.3) \times 0.2\big)$
$= 0.152$

Computing probabilities

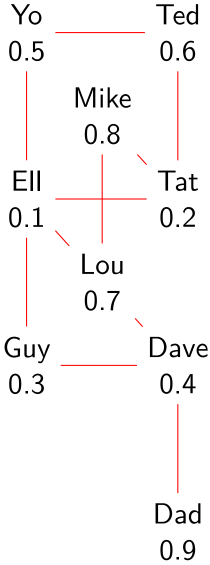


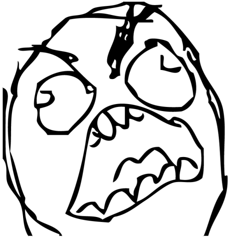
Computing probabilities





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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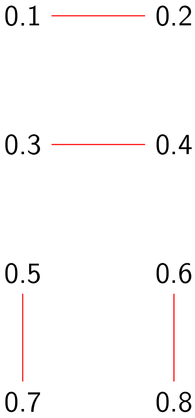

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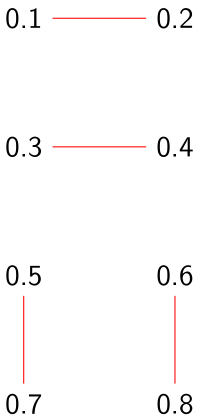

- $0.1 \times 0.2 = 0.02$

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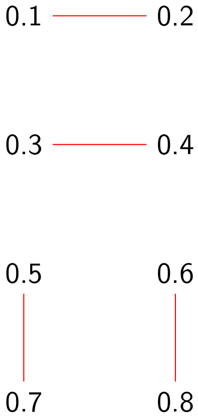

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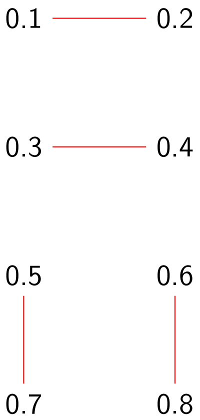

- $0.1 \times 0.2 = 0.02$
- $0.3 \times 0.4 = 0.12$
- $0.5 \times 0.7 = 0.35$

My PhD topic

→ Make it easier to use uncertain data
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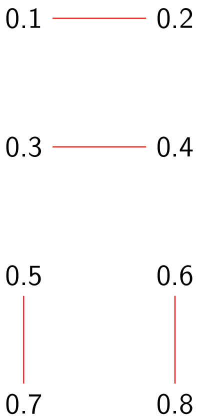

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- $0.6 \times 0.8 = 0.48$

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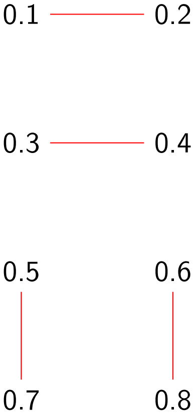

- $0.1 \times 0.2 = 0.02$
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- $0.6 \times 0.8 = 0.48$

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

My PhD topic

→ Make it easier to use uncertain data
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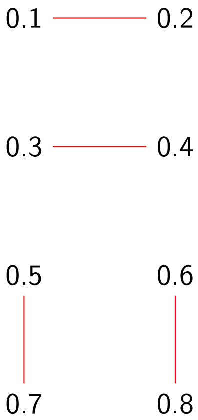

- $0.1 \times 0.2 = 0.02$
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→ $1 - (1 - 0.02) \times \cdots \times (1 - 0.48)$
$= 0.7085088$

My PhD topic

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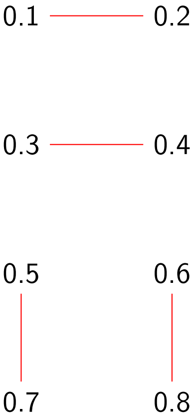

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→ $1 - (1 - 0.02) \times \cdots \times (1 - 0.48)$
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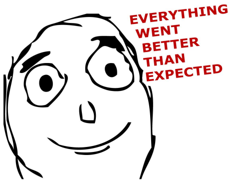

Table of contents

Roadmap

I investigated various kinds of uncertain data:

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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

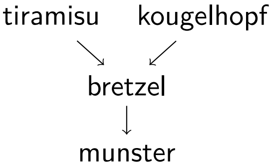
champagne

riesling

- I partially know guest preferences

Uncertain ordered relations

Food



Drinks

- I partially know guest preferences

Uncertain ordered relations

Food

tiramisu → bretzel ← kougelhopf

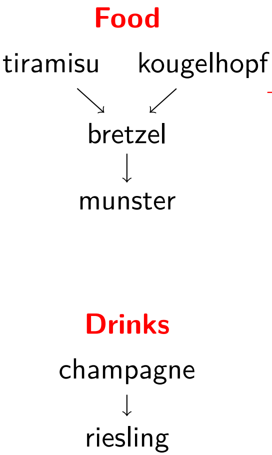
bretzel → munster

Drinks

champagne → riesling

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

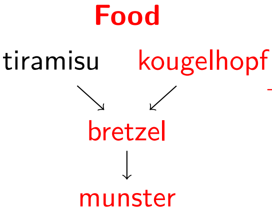
Uncertain ordered relations



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

→ What are the top two Alsatian products?

Uncertain ordered relations



- I partially know guest preferences
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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

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

Uncertain ordered relations

Food

tiramisu ↘ bretzel ↙ kougelhopf

bretzel ↓ munster

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

→ What are the top two Alsatian products?

Possible: riesling ↓ kougelhopf

Not possible: kougelhopf ↓ munster

Drinks

champagne ↓ riesling

→ I extended relational algebra (bag semantics, including aggregation) to uncertain ordered data

→ I showed complexity results for possible and certain answers depending on the query and data

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	

- 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
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large
sweet

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both

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salty

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- How much food do people eat?
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Uncertain numerical values

small sweet

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small salty

medium sweet

small both

medium salty

large sweet

medium both

large salty

large both

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

Uncertain numerical values

small sweet

tiny both

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medium sweet

small both

medium salty

large sweet

medium both

large salty

large both

- How much food do people eat?
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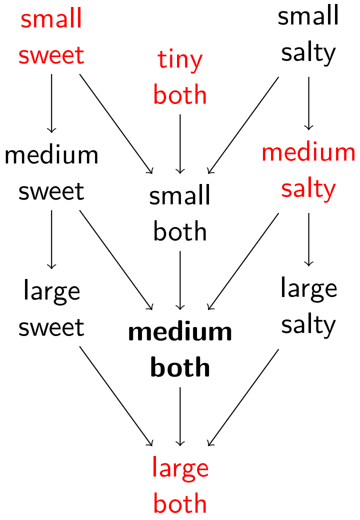
Uncertain numerical values

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

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

Uncertain numerical values



- How much food do people eat?
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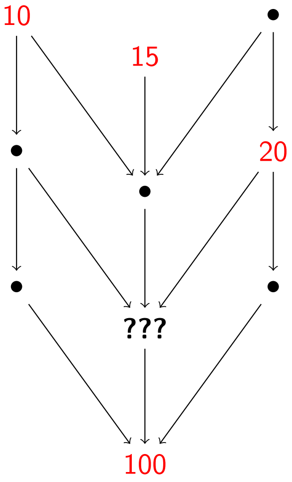
Uncertain numerical values



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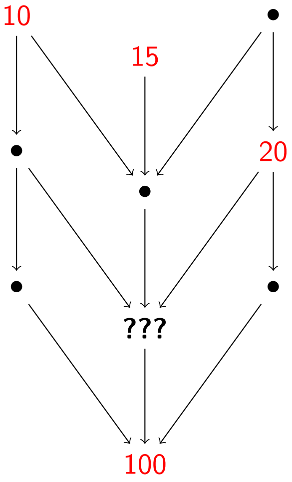
Uncertain numerical values



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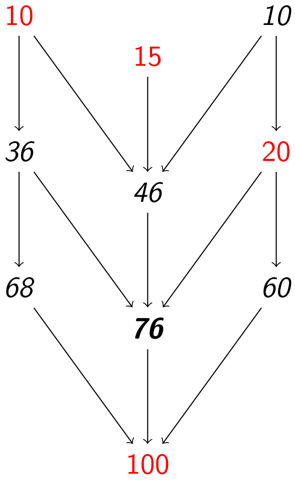
→ I extended interpolation to posets based on integration on polytopes

Uncertain numerical values



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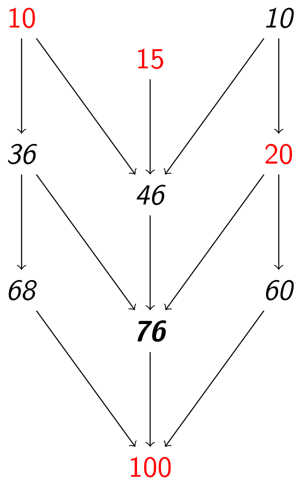

- How much food do people eat?
- Let's ask friends who defended recently
- How to estimate for my own defense?
- Some order relations are implied

→ I extended interpolation to posets based on integration on polytopes

→ I showed hardness of the problem and identified tractable cases

Open-world query answering

Incomplete data:

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

Open-world query answering

Incomplete data:

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

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

Open-world query answering

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Logical constraints:

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

Logical constraints:

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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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Open-world query answering

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

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- 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:

- Fabian advises Luis
- Fabian is at the defense
- Fabian is in DBWeb
- Fabian comes to the drinks
- Luis is a DBWeb student
- Luis comes to the drinks

Logical constraints:

- People at the defense will have drinks
- All DBWeb students will have drinks
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→ Yes!

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→ For which constraint 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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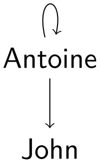
→ I proposed a language that combines these features (with some restrictions on the higher-arity rules)

→ I showed that query answering for the language is decidable

Query answering assuming finiteness

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

Data:



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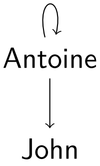

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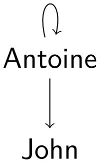

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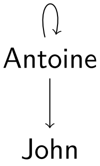

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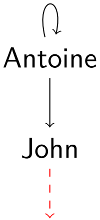

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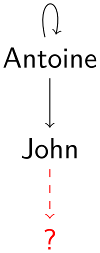

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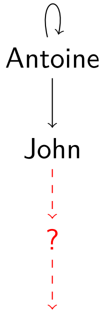

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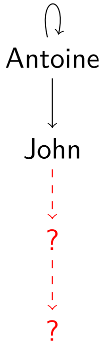

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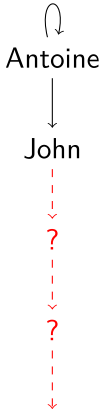

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→ Is this sensible? **No!**

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→ Can we do reasoning assuming finiteness?

Query answering assuming finiteness

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→ Can we do reasoning assuming finiteness?

→ What difference does it make?

Finite open-world query answering

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→ 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 (TID)

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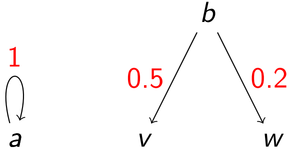

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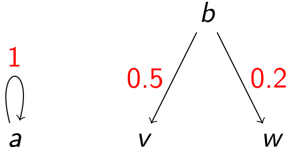

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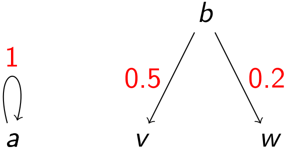

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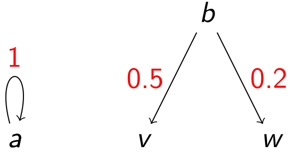

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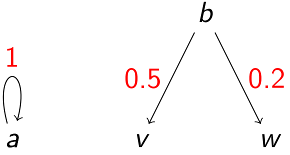

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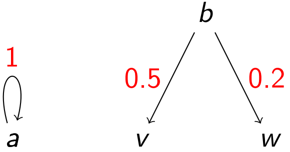

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Is there a smaller class $\mathcal{I}$ such that PQE is tractable for a larger $\mathcal{Q}$?

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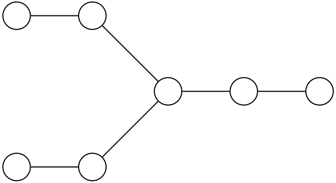

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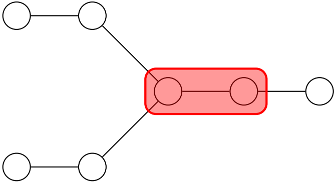

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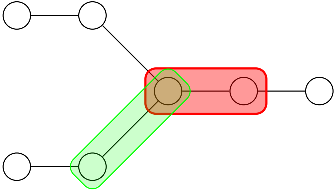

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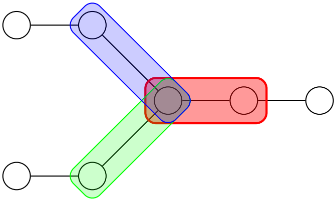

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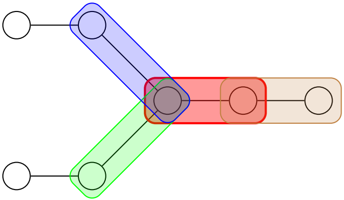

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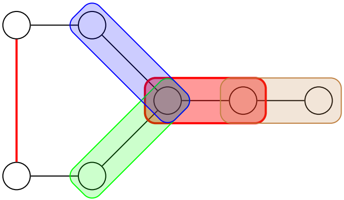

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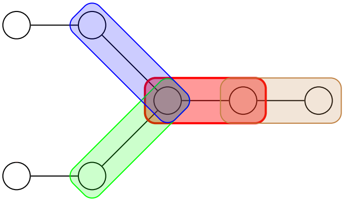

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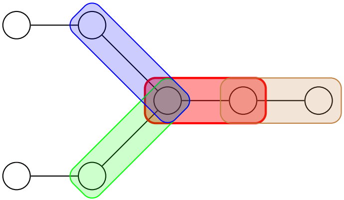

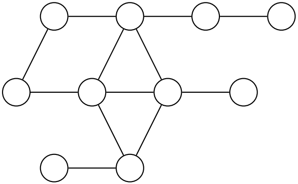

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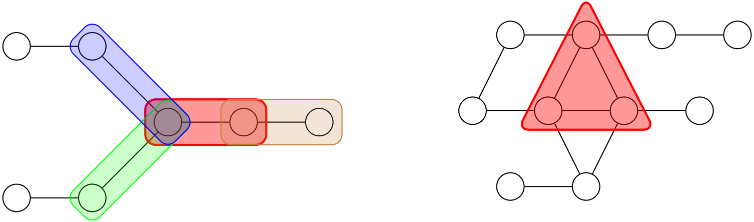

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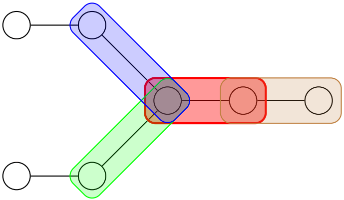

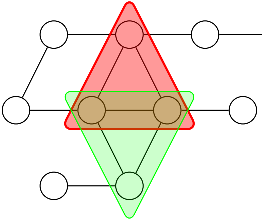

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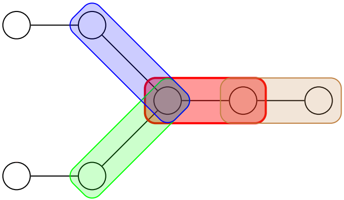

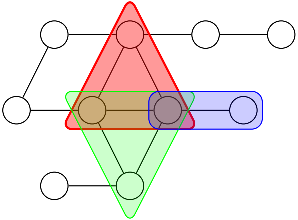

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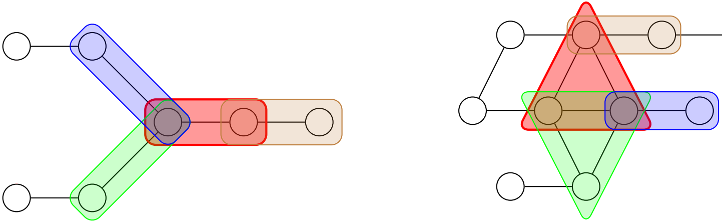

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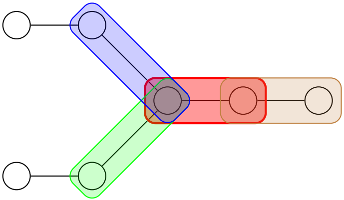

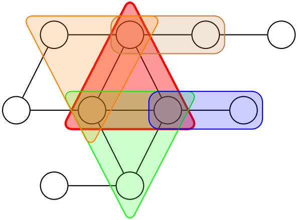

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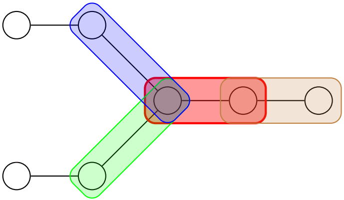

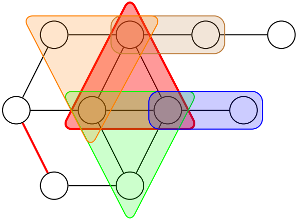

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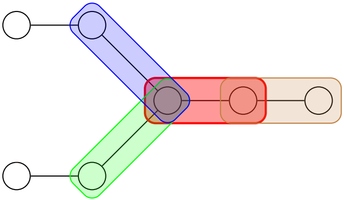

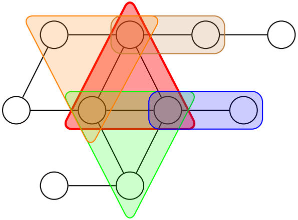

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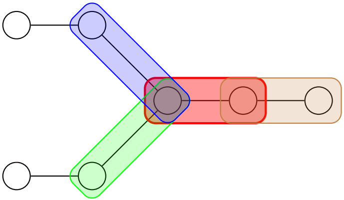

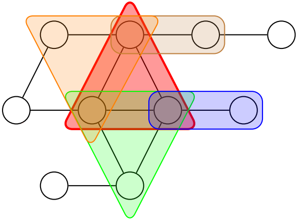

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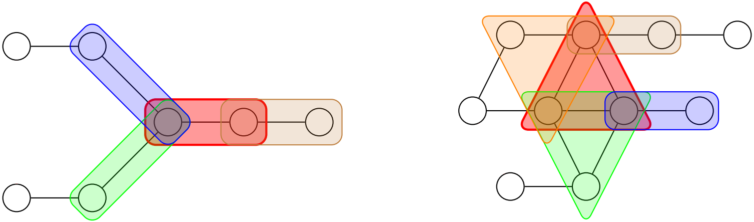

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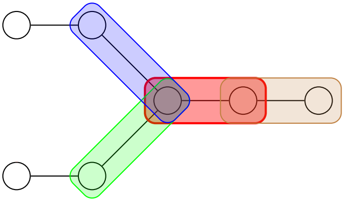

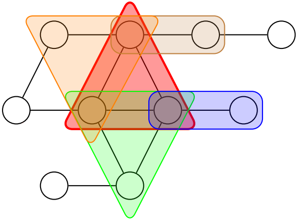

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$\rightarrow$ Does this extend to probabilistic QE?

Our main result

An instance-based dichotomy result:

Upper bound.

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

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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

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- Boolean function ϕ whose variables are the facts of I
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$\rightarrow$ Lineage: $f_2 \wedge \big((g_2 \wedge h_1) \vee (g_3 \wedge h_2)\big)$

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

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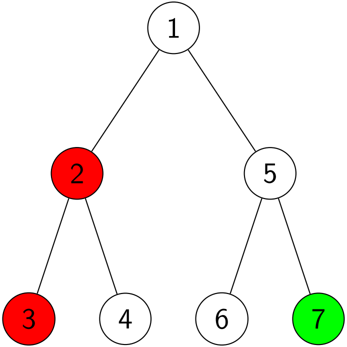
Uncertain trees



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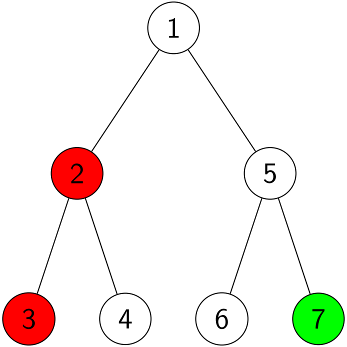

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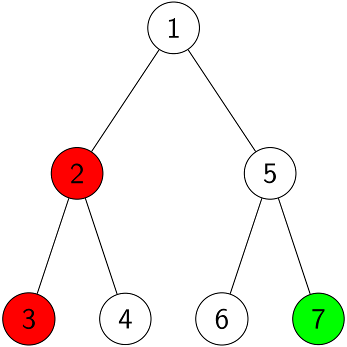

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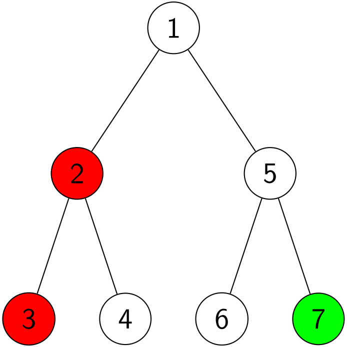

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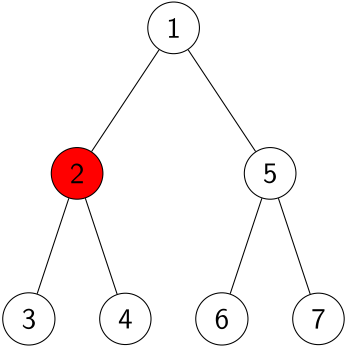

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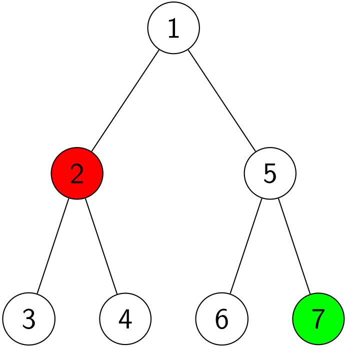

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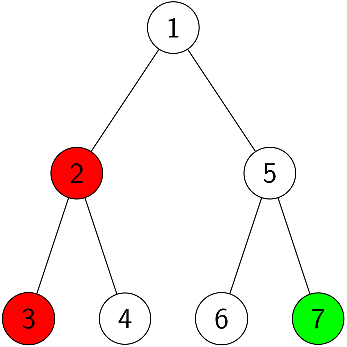

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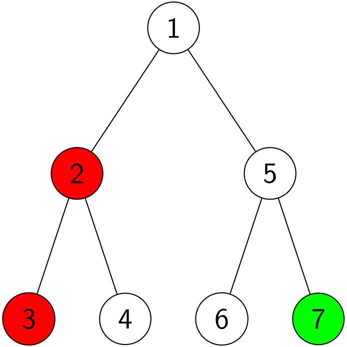

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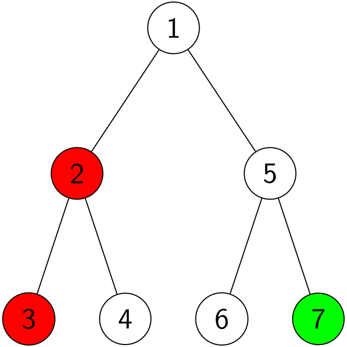

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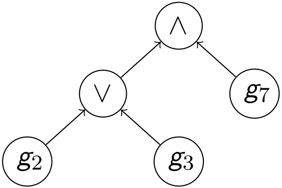

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Corollary

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

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→ We have a linear-size (and treelike) arithmetic circuit instead of a polynomial-size $\mathbb{N}[X]$-formula

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

Extension 2: correlations

- Our probabilistic instances assume independence on all facts
- More expressive: Block-Independent Disjoint instances:

name	favorite	p
john	kougelhopf	0.8
john	bretzel	0.2
jane	kougelhopf	0.1
jane	bretzel	0.9

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

Generalises to pc-tables with treelike correlations

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- Class $\mathcal{I}$ of unbounded-treewidth instances, query q in class $\mathcal{Q}$
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There is a first-order query q such that for any unbounded-tw, tw-constructible, arity-2 instance family $\mathcal{I}$, probabilistic query eval for q on $\mathcal{I}$ is #P-hard under RP reductions.

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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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- I proved that reasoning is decidable for new constraint languages on incomplete data, in particular assuming finiteness
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- I showed an instance-based dichotomy for probabilistic data including extensions to semiring provenance and correlations

Ongoing and future work

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  - Hybrid tractability criteria based on instance and query
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Thanks for your attention!

Main publications:

(A., Amsterdamer, Milo 2014a) ICDT'14
(A., Benedikt 2015a) IJCAI'15
(A., Benedikt 2015b) LICS'15
(A. 2014) AMW'14
(A., Bourhis, Senellart 2015) ICALP'15
(A., Bourhis, Senellart 2016) PODS'16

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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Our main result on trees

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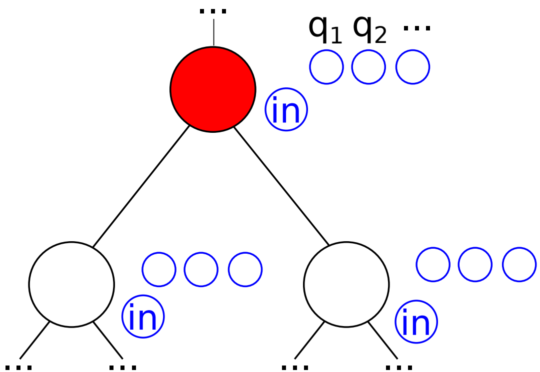

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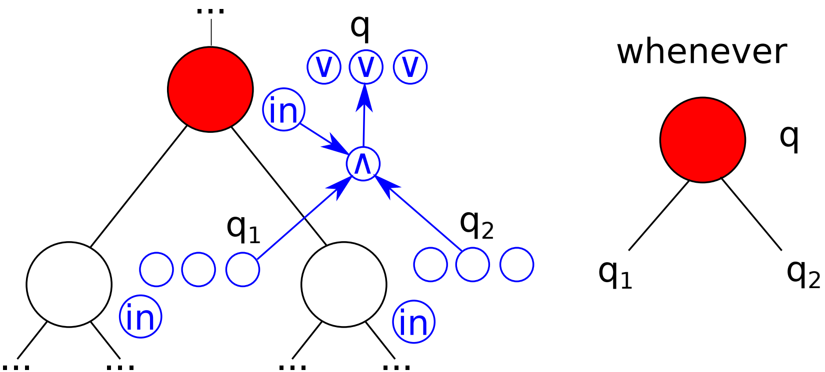

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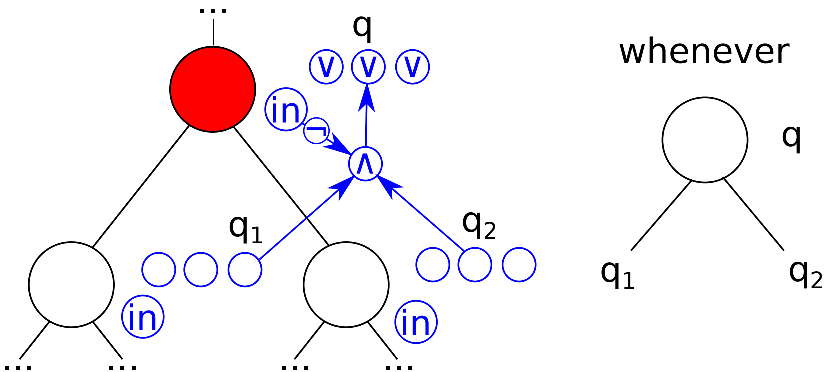

Treelike instances

- Treelike instance I
- Tree encoding: tree E on fixed alphabet, represents I
- MSO query on I translates to
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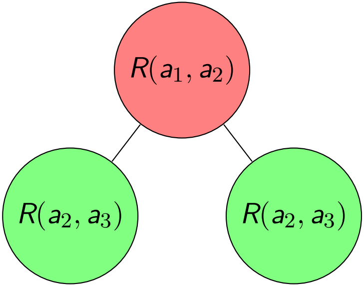
R	
a	b
b	c
b	d



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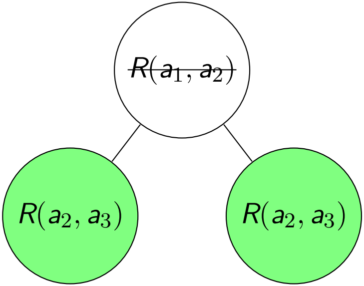

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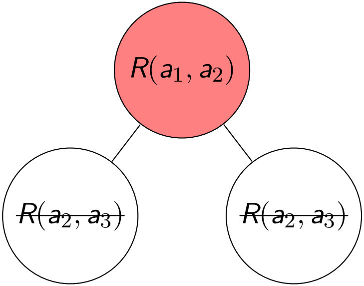

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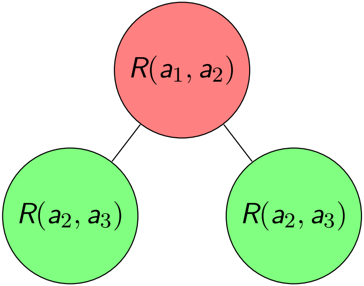

Our main result on treelike instances

Theorem

For any fixed MSO query q and $k \in \mathbb{N}$,
for any input instance I of treewidth $\leq k$,
we can build in linear time in I a provenance circuit of q on I.

Probability evaluation

Two alternate ways to see why probability evaluation is tractable on our provenance circuits:

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- They have bounded treewidth themselves
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Corollary

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

Encoding treelike instances (Chaudhuri, Vardi 1992)

Instance:

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c	d
d	e
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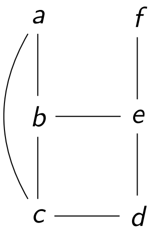
Gaifman graph:



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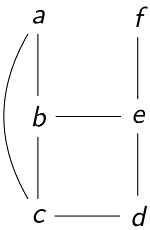

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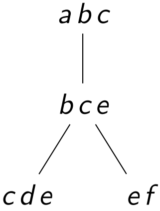

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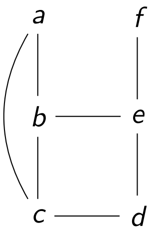

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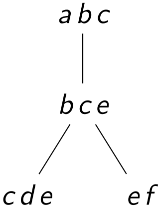

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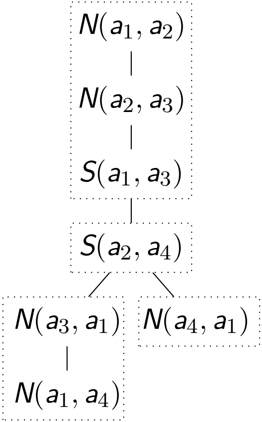

Provenance semirings

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

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$\rightarrow$ Our circuits capture $\mathrm{PosBool}[X]$-provenance in this sense

  - The definitions match: all subinstances that satisfy the query
  - For monotone queries, we can construct positive circuits

Universal provenance

- Universal semiring of polynomials $(\mathbb{N}[X], +, \times, 0, 1)$

  $\rightarrow$ The provenance for $\mathbb{N}[X]$ can be specialized to any $K[X]$

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  $\rightarrow$ The provenance for $\mathbb{N}[X]$ can be specialized to any $K[X]$
- Captures many useful semirings:
  - counting the number of matches of a query
  - computing the security level of a query result
  - computing the cost of a query result

$\mathbb{N}[X]$-provenance example

R		
a	b	x_1
b	c	x_2
d	e	x_3
e	d	x_4
f	f	x_5

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R		
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$$\exists x\, y\, z\; R(x, y) \wedge R(y, z)$$

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  - Sum over query matches
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$\rightarrow$ $\mathrm{PosBool}[X]$-provenance:

$$(x_1 \wedge x_2) \vee (x_3 \wedge x_4)$$

$\rightarrow$ $\mathbb{N}[X]$-provenance:

$$(x_1 \times x_2) + (x_3 \times x_4)$$

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$\mathbb{N}[X]$-provenance example

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How is $\mathbb{N}[X]$ more expressive than $\text{PosBool}[X]$?

→ Coefficients: counting multiple matches

→ Exponents: using facts multiple times

Capturing $\mathbb{N}[X]$-provenance

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→ What fails for MSO and Datalog?

- Unbounded maximal multiplicity of fact uses

Correlations

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More expressive formalism: Block-Independent Disjoint instances:

name	city	iso	p
pods	san francisco	us	0.8
pods	los angeles	us	0.2
icalp	rome	it	0.1
icalp	florence	it	0.9

pc-tables

More generally, pc-tables to represent arbitrary correlations

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date	teacher	room	
04	John	C42	$\neg x_1$
04	Jane	C42	x_1
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11	Jane	C017	$x_2 \wedge x_1$
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x_1 John gets sick

$\rightarrow$ Probability 0.1

x_2 Room C017 is available

$\rightarrow$ Probability 0.2

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"Tree-like" refers to the underlying instance, adding facts
to represent variable occurrences and co-occurrences

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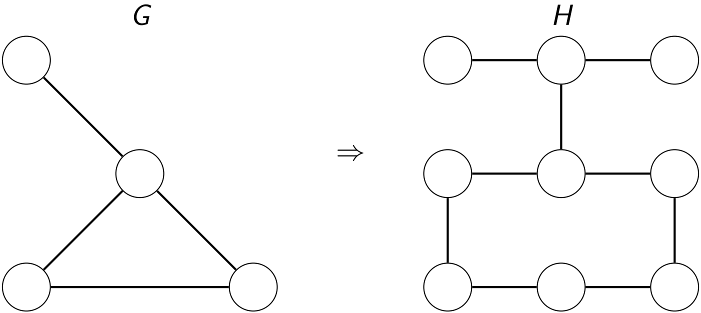

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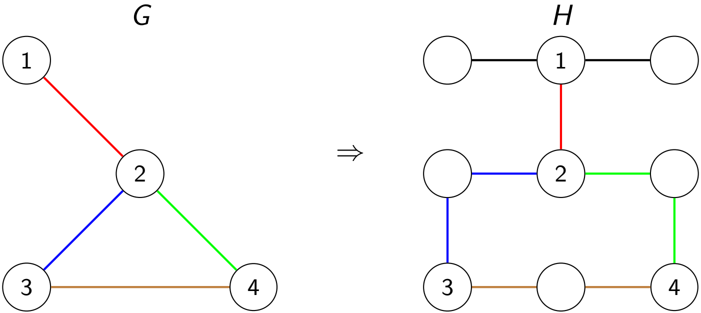

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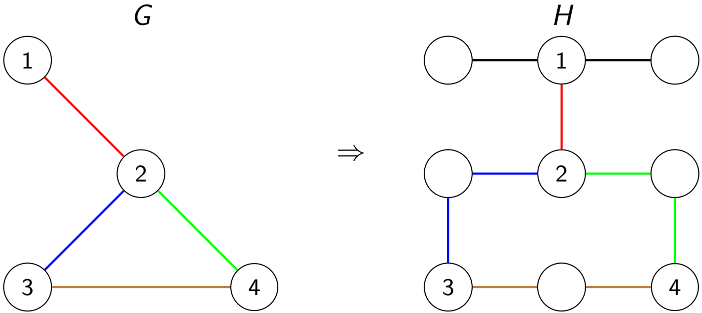

- Map vertices to vertices
- Map edges to vertex-disjoint paths

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More recently:

Theorem ((Chekuri, Chuzhoy 2014))

There is a certain constant $c \in \mathbb{N}$ such that
for any planar graph G of degree ≤ 3,
for any graph H of treewidth $\geq |G|^c$,
G is a topological minor of H and
we can embed G in H (with high probability) in PTIME in $|H|$.

Intuition for our result: reduction

- Choose a problem from which to reduce:
  - Must be #P-hard on planar degree-3 graphs
  - Must be encodable to an FO query q (more later)
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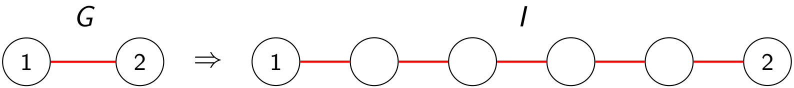
- Construct a probability valuation π of I such that:
  - Unneccessary edges of I are removed
  - Probability eval for q gives the answer to the hard problem

Technical issue



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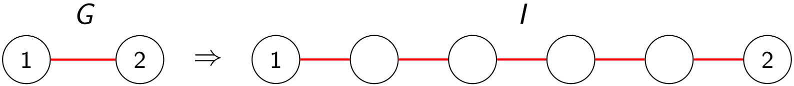

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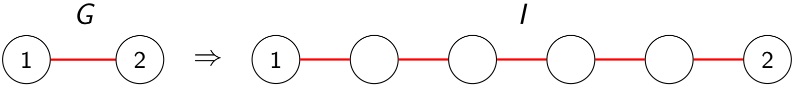

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→ For non-probabilistic evaluation, using FO does not work (Frick, Grohe 2001)

→ Lower bounds for non-probabilistic evaluation are for MSO (Ganian et al. 2014)

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→ This UCQ with inequalities is hard in a weaker sense
(no polynomial-size OBDD representations of provenance)

→ We don't know whether it's #P-hard (because of subdivisions)