Open-World Probabilistic Databases

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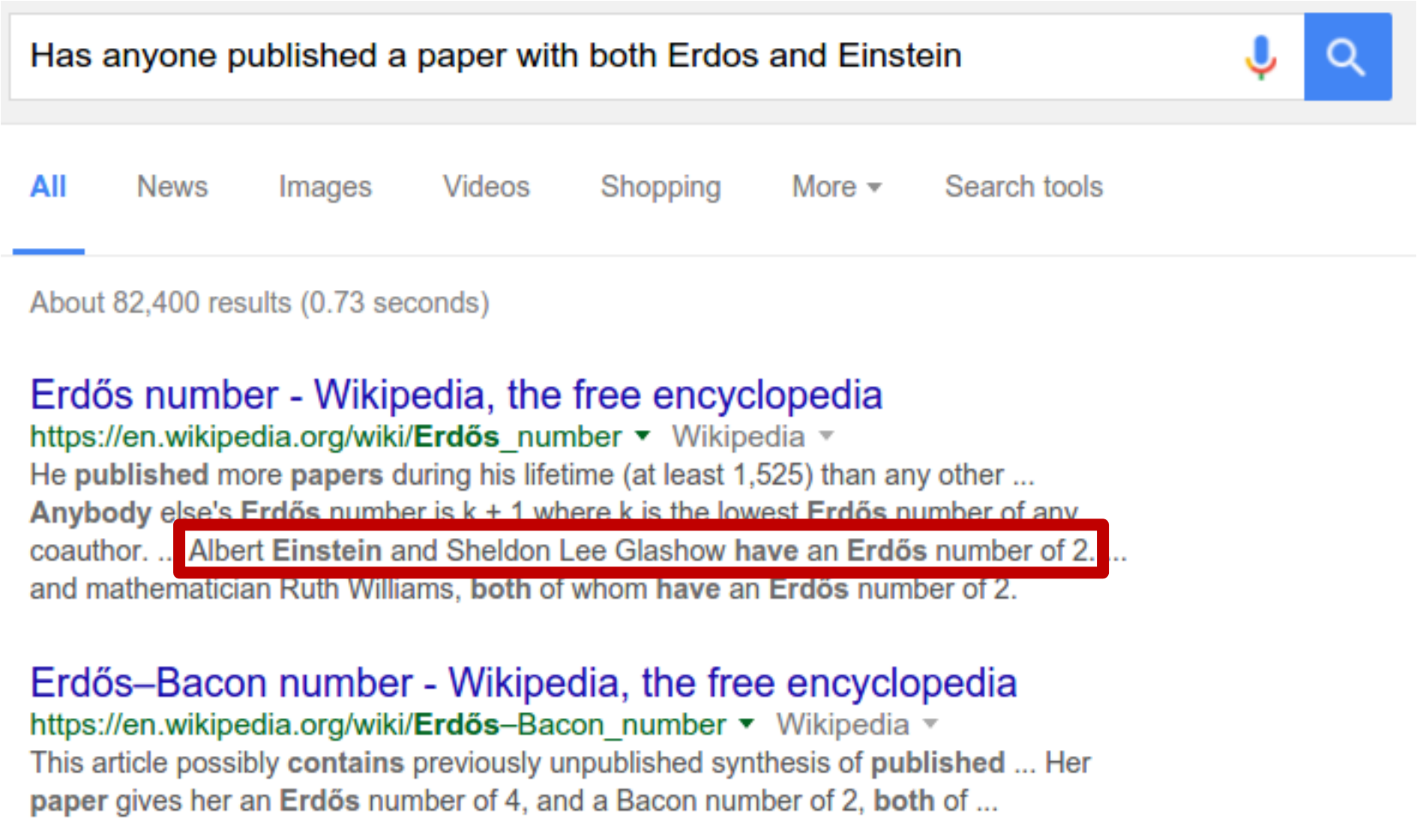
FLAIRS
May 23, 2017

Overview

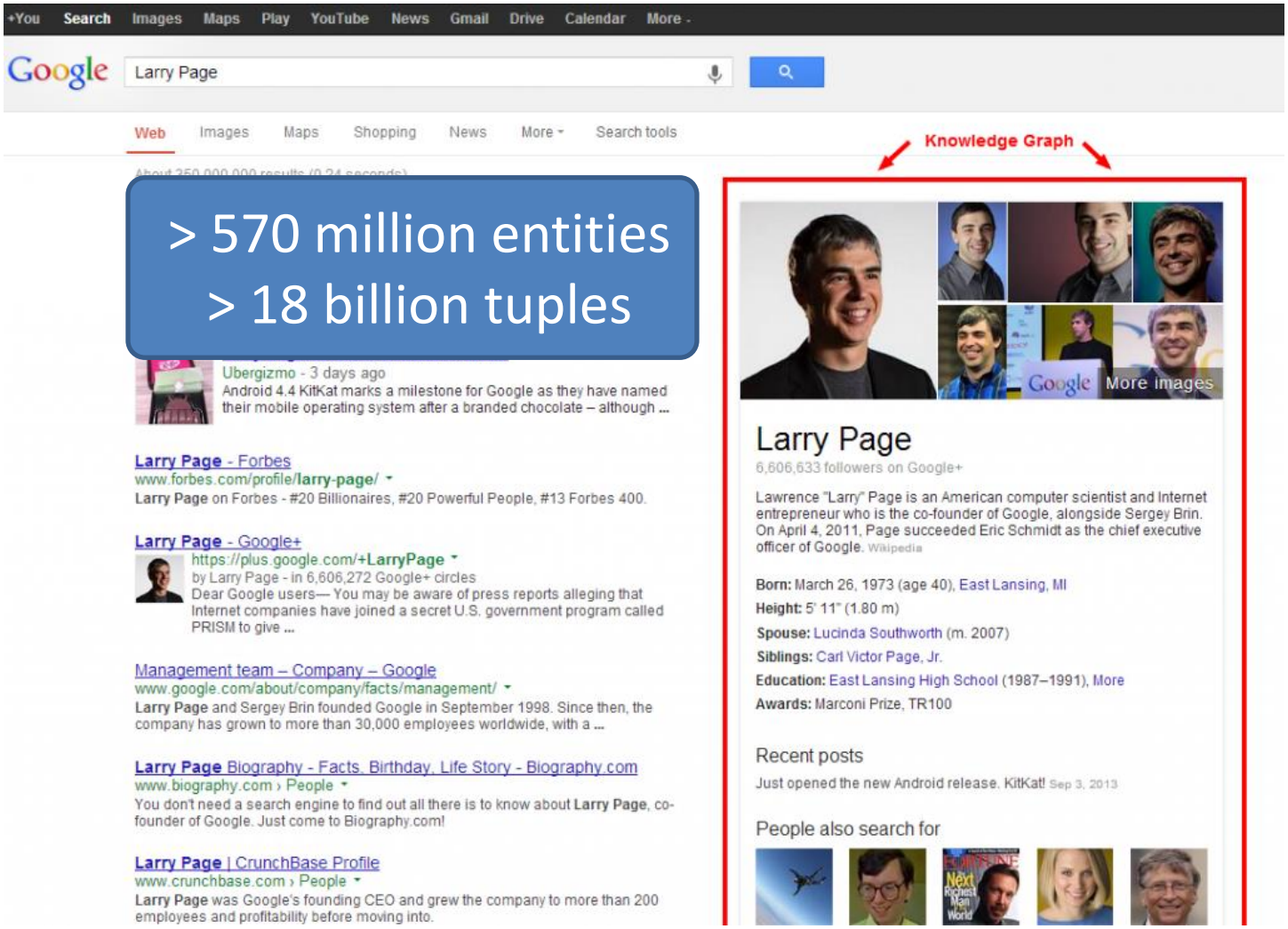
1. ***Why*** *probabilistic databases?*
2. ***How*** *probabilistic query evaluation?*
3. ***Why*** *open world?*
4. ***How*** *open-world query evaluation?*
5. ***What*** *is the broader picture?*

Why *probabilistic databases?*

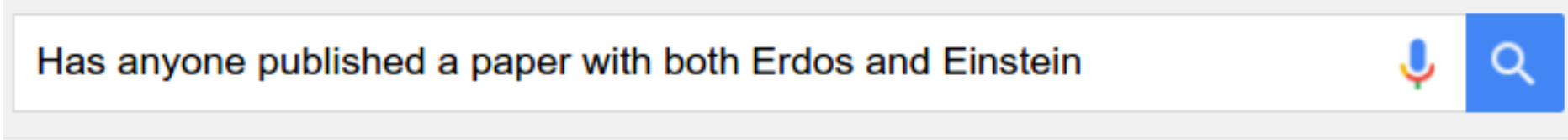
What we'd like to do…



Google Knowledge Graph



Probabilistic Databases



- Tuple-independent probabilistic database

Scientist

x	P
Erdos	0.9
Einstein	0.8
Pauli	0.6

Coauthor

x	y	P
Erdos	Renyi	0.6
Einstein	Pauli	0.7
Obama	Erdos	0.1

- Learned from the web, large text corpora, ontologies, etc., using **statistical** machine learning.

[Suciu'11]

Information Extraction is Noisy!

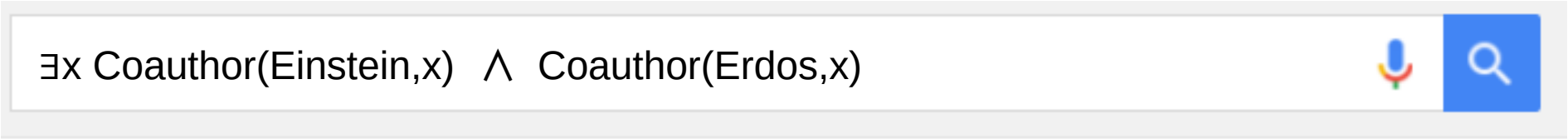
PhD Students Luc De Raedt

- Laura-Andrea Antanas(co-promotor Tinne Tuytelaars)
- Dries Van Daele (co-promotor Kathleen Marchal)
- Thanh Le Van (co-promotor Kathleen Marchal)
- Bogdan Moldovan
- Davide Nitti (co-promotor Tinne De Laet)
- José Antonio Oramas Mogrovejo (key supervisor Tinne Tuytelaars)
- Francesco Orsini (co-supervisor Paol Frasconi)
- Sergey Paramonov
- Joris Renkens
- Mathias Verbeke (with Bettina Berendt)
- Jonas Vlasselaer

Coauthor

x	y	P
Luc	Laura	0.7
Luc	Hendrik	0.6
Luc	Kathleen	0.3
Luc	Paol	0.3
Luc	Paolo	0.1

What we'd like to do…



Einstein is in the Knowledge Graph

Albert Einstein

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Albert Einstein - Wikipedia, the free encyclopedia
https://en.wikipedia.org/wiki/**Albert_Einstein** Wikipedia
Albert Einstein (/ˈaɪnstaɪn/; German: ['albɛɐ̯t 'aɪnʃtaɪn] (listen); 14 March 1879 – 18 April 1955) was a German-born theoretical physicist.
Hans Albert Einstein - Mass–energy equivalence - Eduard Einstein - Elsa Einstein

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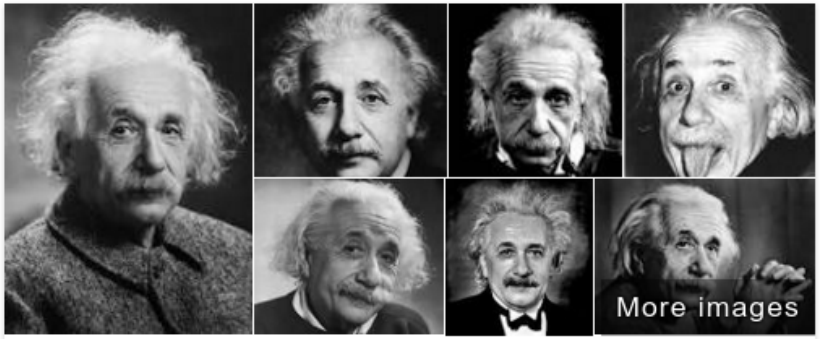
Albert Einstein - Biographical - Nobelprize.org
www.nobelprize.org/nobel_prizes/physics/.../**einstein**-bio.htm... Nobel Prize
Albert Einstein was born at Ulm, in Württemberg, Germany, on March 14, 1879. ...
Later, they moved to Italy and Albert continued his education at Aarau



Albert Einstein

Theoretical Physicist

Albert Einstein was a German-born theoretical physicist. He developed the general theory of relativity, one of the two pillars of modern physics. Einstein's work is also known for its influence on the philosophy of science. Wikipedia

Born: March 14, 1879, Ulm, Germany
Died: April 18, 1955, Princeton, NJ
Influenced by: Isaac Newton, Mahatma Gandhi, More
Children: Eduard Einstein, Lieserl Einstein, Hans Albert Einstein
Spouse: Elsa Einstein (m. 1919–1936), Mileva Marić (m. 1903–1919)

Erdős is in the Knowledge Graph

Paul Erdos

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Paul Erdős - Wikipedia, the free encyclopedia
https://en.wikipedia.org/wiki/**Paul_Erdős** Wikipedia
Paul Erdős was a Hungarian Jewish mathematician. He was one of the most prolific mathematicians of the 20th century. He was known both for his social ...
Fan Chung - Ronald Graham - Béla Bollobás - Category:Paul Erdős

The Man Who Loved Only Numbers - The New York Times
https://www.nytimes.com/books/.../hoffman-man.ht... The New York Times
Paul Erdős was one of those very special geniuses, the kind who comes along only once in a very long while yet he chose, quite consciously I am sure, to share ...

Paul Erdos | Hungarian mathematician | Britannica.com
www.britannica.com/biography/**Paul-Erdos** Encyclopaedia Britannica
Paul Erdős, (born March 26, 1913, Budapest, Hungary—died September 20, 1996, Warsaw, Poland), Hungarian "freelance" mathematician (known for his work ...

Paul Erdős - University of St Andrews
www-groups.dcs.st-and.ac.uk/~history/Biographies/**Erdos**.html
Paul Erdős came from a Jewish family (the original family name being Engländer) although neither of his parents observed the Jewish religion. Paul's father ...

[PDF] **Paul Erdős Mathematical Genius, Human - UnTruth.org**
www.untruth.org/~josh/math/**Paul**%20**Erdös**%20bio-rev2.pdf
by J Hill - 2004 - Related articles

Paul Erdős

Mathematician

Paul Erdős was a Hungarian Jewish mathematician. He was one of the most prolific mathematicians of the 20th century. He was known both for his social practice of mathematics and for his eccentric lifestyle.
Wikipedia

Born: March 26, 1913, Budapest, Hungary

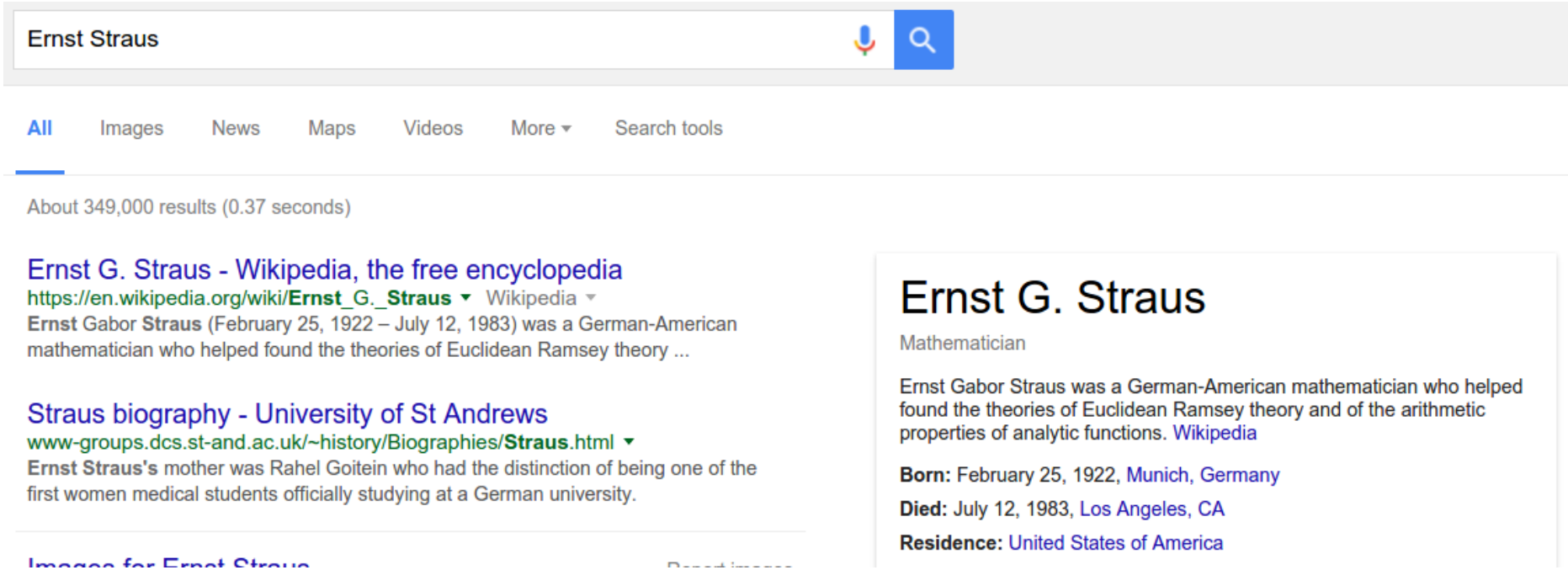
Died: September 20, 1996, Warsaw, Poland

Education: Eötvös Loránd University (1934)

Books: Probabilistic Methods in Combinatorics, More

Notable students: Béla Bollobás, Alexander Soifer, George B. Purdy, Joseph Kruskal

This guy is in the Knowledge Graph



… and he published with both Einstein and Erdos!

Desired Query Answer

Has anyone published a paper with both Erdos and Einstein

Ernst Straus

Barack Obama, …

Justin Bieber, …

1. Fuse uncertain information from web

⇒ **Embrace probability!**

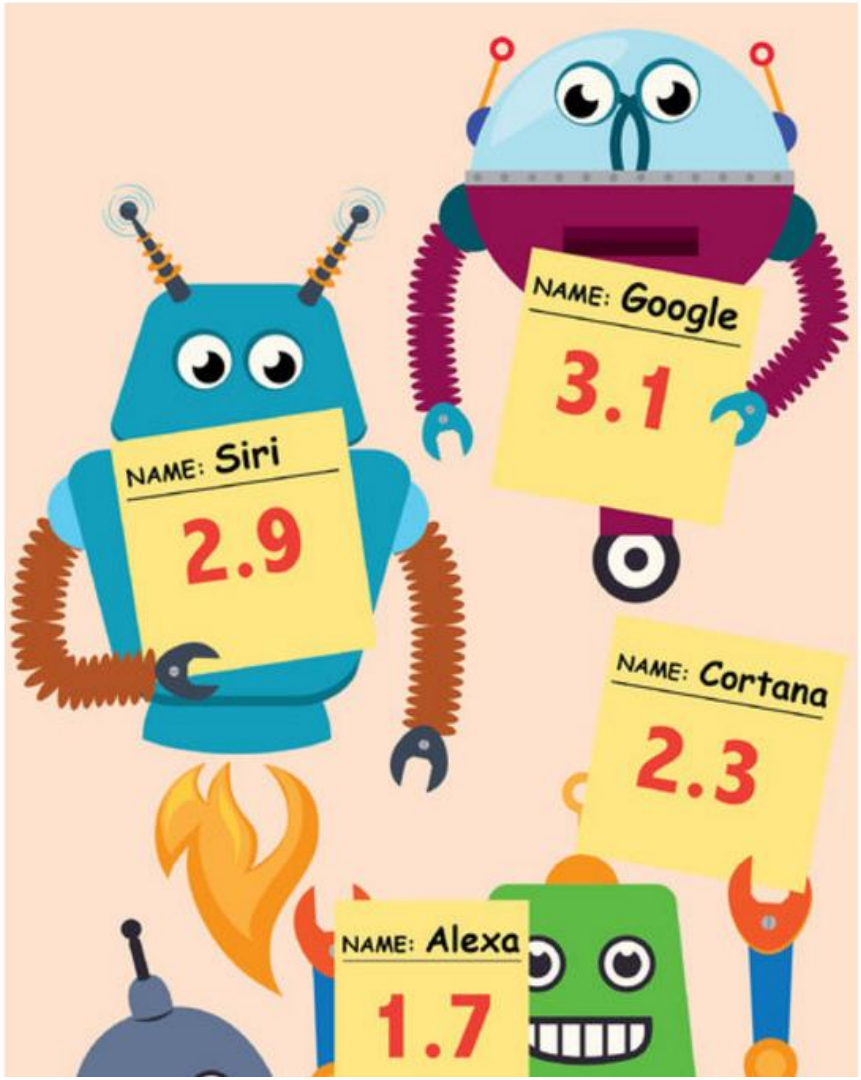
2. Cannot come from labeled data

⇒ **Embrace query eval!**

Siri, Alexa and Other Virtual Assistants Put to the Test

Tech Fix

By BRIAN X. CHEN JAN. 27, 2016



WHEN I asked Alexa earlier this week who was playing in the Super Bowl, she responded, somewhat monotonously, "Super Bowl 49's winner is New England Patriots."

"Come on, that's last year's Super Bowl," I said. "Even I can do better than that."

At the time, I was actually alone in my living room. I was talking to the virtual companion inside Amazon's wireless speaker, Echo, which was released last June. Known as Alexa, she has gained raves from Silicon Valley's tech-obsessed digerati and has become one of the newest members of the virtual assistants club.

All the so-called Frightful Five tech

[Chen'16] (NYTimes)

***How** probabilistic query evaluation?*

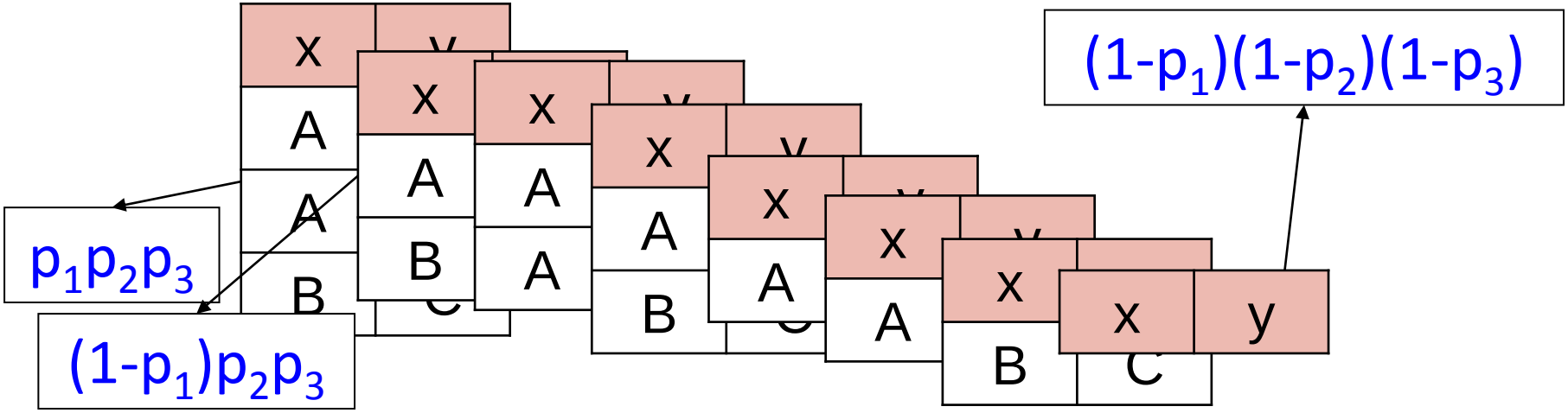
Tuple-Independent Probabilistic DB

Probabilistic database D:

Coauthor

x	y	P
A	B	p_1
A	C	p_2
B	C	p_3

Possible worlds semantics:



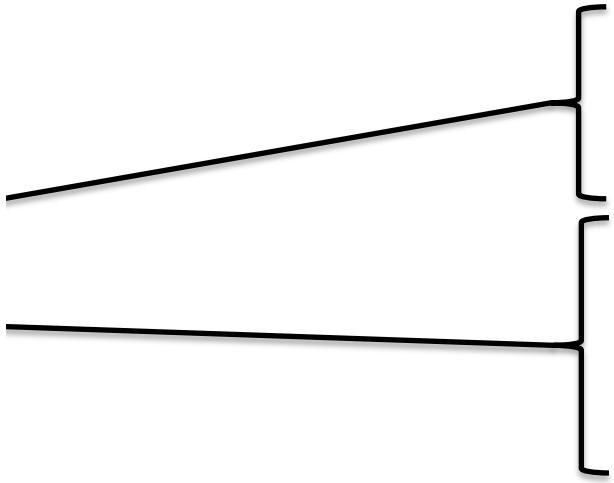
Probabilistic Query Evaluation

$Q = \exists x \exists y\ Scientist(x) \wedge Coauthor(x,y)$

$$P(Q) = 1 - \{1 - p_1 * [\ 1-(1-q_1)*(1-q_2)\ ]\} * \{1 - p_2 * [\ 1-(1-q_3)*(1-q_4)*(1-q_5)\ ]\}$$

Scientist

x	P
A	p_1
B	p_2
C	p_3



Coauthor

x	y	P
A	D	q_1
A	E	q_2
B	F	q_3
B	G	q_4
B	H	q_5

Lifted Inference Rules

Preprocess Q (omitted),
Then apply rules (some have preconditions)

$P(\neg Q) = 1 - P(Q)$ — Negation

$P(Q1 \wedge Q2) = P(Q1)\,P(Q2)$
$P(Q1 \vee Q2) = 1 - (1 - P(Q1))\,(1 - P(Q2))$ — Decomposable ∧,∨

$P(\exists z\, Q) = 1 - \prod_{A \in Domain} (1 - P(Q[A/z]))$
$P(\forall z\, Q) = \prod_{A \in Domain} P(Q[A/z])$ — Decomposable ∃,∀

$P(Q1 \wedge Q2) = P(Q1) + P(Q2) - P(Q1 \vee Q2)$
$P(Q1 \vee Q2) = P(Q1) + P(Q2) - P(Q1 \wedge Q2)$ — Inclusion/exclusion

[Suciu'11]

Closed-World Lifted Query Eval

$Q = \exists x\, \exists y\, \text{Scientist}(x) \wedge \text{Coauthor}(x,y)$

Decomposable ∀-Rule

$$P(Q) = 1 - \prod_{A \in \text{Domain}} (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y)))$$

Check independence:

$\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y)$

$\text{Scientist}(B) \wedge \exists y\, \text{Coauthor}(B,y)$

$$\begin{aligned} = 1 - (1 - P(&\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y)) \\ &\times (1 - P(\text{Scientist}(B) \wedge \exists y\, \text{Coauthor}(B,y)) \\ &\times (1 - P(\text{Scientist}(C) \wedge \exists y\, \text{Coauthor}(C,y)) \\ &\times (1 - P(\text{Scientist}(D) \wedge \exists y\, \text{Coauthor}(D,y)) \\ &\times (1 - P(\text{Scientist}(E) \wedge \exists y\, \text{Coauthor}(E,y)) \\ &\times (1 - P(\text{Scientist}(F) \wedge \exists y\, \text{Coauthor}(F,y)) \\ &\quad \ldots \end{aligned}$$

Complexity PTIME

Limitations

$H_0 = \forall x \forall y\ \text{Smoker}(x) \vee \text{Friend}(x,y) \vee \text{Jogger}(y)$

The decomposable ∀-rule: $P(\forall z\ Q) = \Pi_{A \in \text{Domain}}\ P(Q[A/z])$

… does not apply:

$H_0[\text{Alice}/x]$ and $H_0[\text{Bob}/x]$ are dependent:

Dependent

$\forall y\ (\text{Smoker}(\text{Alice}) \vee \text{Friend}(\text{Alice},y) \vee \text{Jogger}(y))$

$\forall y\ (\text{Smoker}(\text{Bob}) \vee \text{Friend}(\text{Bob},y) \vee \text{Jogger}(y))$

Lifted inference sometimes fails.
Computing $P(H_0)$ is #P-hard in size database

[Suciu'11]

Are the Lifted Rules Complete?

You already know:

- Inference rules: PTIME data complexity
- Some queries: #P-hard data complexity

Dichotomy Theorem for UCQ / Mon. CNF

- If lifted rules succeed, then PTIME query
- If lifted rules fail, then query is #P-hard

Lifted rules are complete for UCQ!

[Dalvi and Suciu;JACM'11]

Why *open world?*

Knowledge Base Completion

Given:

Coauthor

x	y	P
Einstein	Straus	0.7
Erdos	Straus	0.6
Einstein	Pauli	0.9
…	…	…

Learn:

0.8::Coauthor(x,y) :- Coauthor(z,x) ∧ Coauthor(z,y).

Complete:

x	y	P
Straus	Pauli	0.504
…	…	…

Bayesian Learning Loop

Bayesian view on learning:

1. Prior belief:

   P(Coauthor(Straus,Pauli)) = 0.01

2. Observe page

   P(Coauthor(Straus,Pauli)|) = 0.2

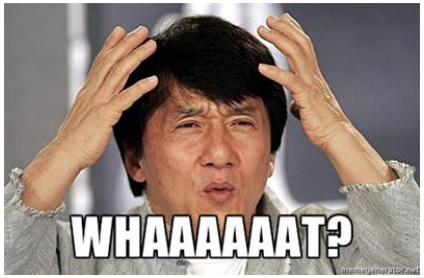
3. Observe page

   P(Coauthor(Straus,Pauli)| ,) = 0.3

Principled and sound reasoning!

Problem: Broken Learning Loop

Bayesian view on learning:



1. Prior belief:

   P(Coauthor(Straus,Pauli)) = 0

2. Observe page

   P(Coauthor(Straus,Pauli|) = 0.2

3. Observe page

   P(Coauthor(Straus,Pauli)| ,) = 0.3

This is mathematical nonsense!

[Ceylan, Darwiche, Van den Broeck; KR'16]

What we'd like to do…

∃x Coauthor(Einstein,x) ∧ Coauthor(Erdos,x)

Ernst Straus

Kristian Kersting, …

Justin Bieber, …

Open World DB

- What if fact missing?
- Probability 0 for:

Coauthor

X	Y	P
Einstein	Straus	0.7
~~**Erdos**~~	~~**Straus**~~	~~**0.6**~~
Einstein	Pauli	0.9
Erdos	Renyi	0.7
Kersting	Natarajan	0.8
Luc	Paol	0.1
…	…	…

Q1 = ∃x Coauthor(Einstein,**x**) ∧ Coauthor(Erdos,**x**)

Q2 = ∃x Coauthor(Bieber,**x**) ∧ Coauthor(Erdos,**x**)

Q3 = Coauthor(Einstein,**Straus**) ∧ Coauthor(Erdos,**Straus**)

Q4 = Coauthor(Einstein,**Bieber**) ∧ Coauthor(Erdos,**Bieber**)

Q5 = Coauthor(Einstein,**Bieber**) ∧ ¬Coauthor(**Einstein**,**Bieber**)

Intuition

X	Y	P
Einstein	Straus	0.7
~~Erdos~~	~~Straus~~	~~0.6~~
Einstein	Pauli	0.9
Erdos	Renyi	0.7
Kersting	Natarajan	0.8
Luc	Paol	0.1
…	…	…

Q1 = ∃x Coauthor(Einstein,**x**) ∧ Coauthor(Erdos,**x**)

Q2 = ∃x Coauthor(Bieber,**x**) ∧ Coauthor(Erdos,**x**)

Q3 = Coauthor(Einstein,**Straus**) ∧ Coauthor(Erdos,**Straus**)

Q4 = Coauthor(Einstein,**Bieber**) ∧ Coauthor(Erdos,**Bieber**)

Q5 = Coauthor(Einstein,**Bieber**) ∧ ¬Coauthor(**Einstein**,**Bieber**)

We know for sure that P(Q1) ≥ P(Q3), P(Q1) ≥ P(Q4)

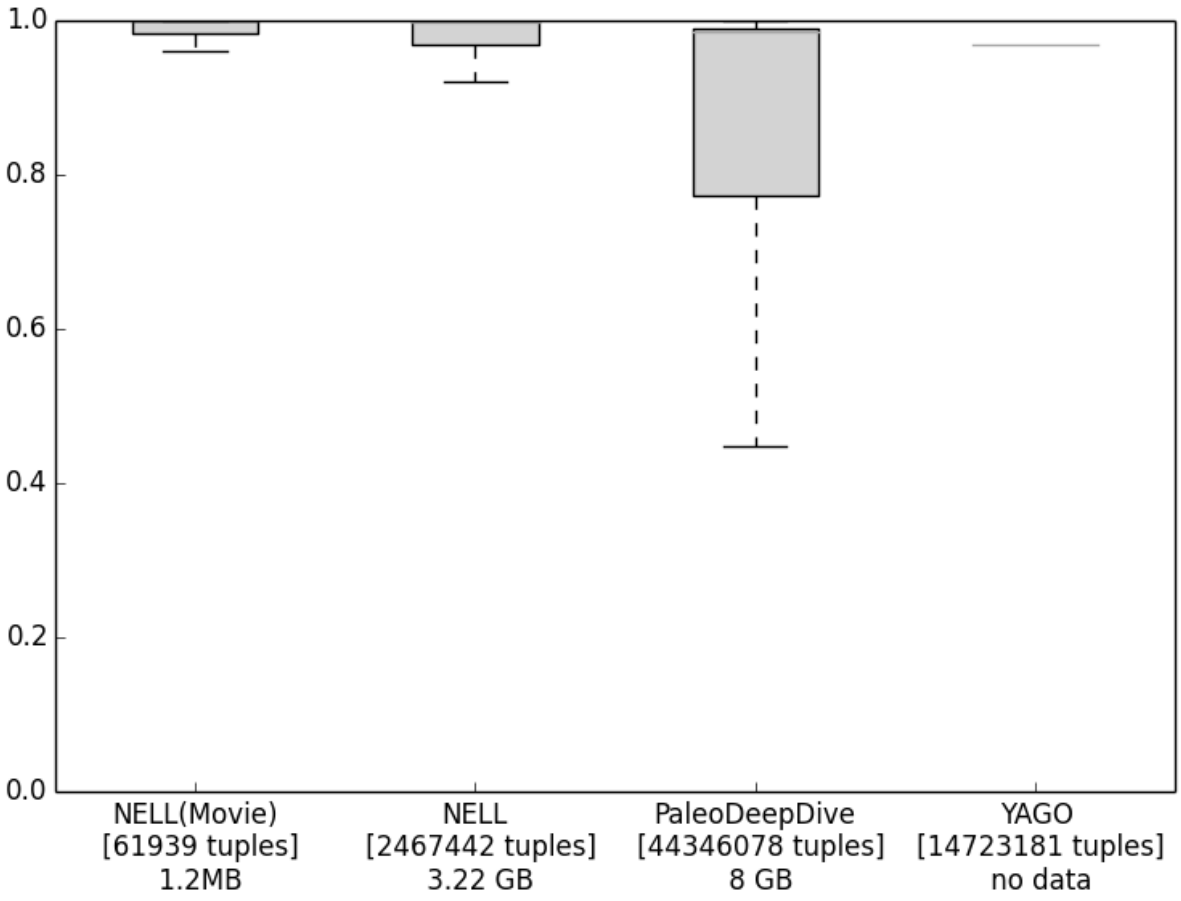
and P(Q3) ≥ P(Q5), P(Q4) ≥ P(Q5) because P(Q5) = 0.

We have strong evidence that P(Q1) ≥ P(Q2).

[Ceylan, Darwiche, Van den Broeck; KR'16]

Problem: Curse of Superlinearity

- Reality is worse!
- Tuples are **intentionally** missing!



Problem: Curse of Superlinearity

Sibling

x	y	P
…	…	…

Facebook scale
⇒ 200 Exabytes of data”

All Google storage is 2 exabytes…

Randall Munroe. Google’s datacenters on punch cards, 2015.

[Ceylan, Darwiche, Van den Broeck; KR’16]

Problem: Model Evaluation

Given:

Coauthor

x	y	P
Einstein	Straus	0.7
Erdos	Straus	0.6
Einstein	Pauli	0.9
…	…	…

Learn:

0.8::Coauthor(x,y) :- Coauthor(z,x) ∧ Coauthor(z,y).

OR

0.6::Coauthor(x,y) :- Affiliation(x,z) ∧ Affiliation(y,z).

What is the likelihood, precision, accuracy, …?

[De Raedt et al; IJCAI'15]

Open-World Prob. Databases

Intuition: tuples can be added with P < λ

Q2 = Coauthor(Einstein,**Straus**) ∧ Coauthor(Erdos,**Straus**)

$0.7 * \lambda \geq P(Q2) \geq 0$

Coauthor

X	Y	P
Einstein	Straus	0.7
Einstein	Pauli	0.9
Erdos	Renyi	0.7
Kersting	Natarajan	0.8
Luc	Paol	0.1
…	…	…

Coauthor

X	Y	P
Einstein	Straus	0.7
Einstein	Pauli	0.9
Erdos	Renyi	0.7
Kersting	Natarajan	0.8
Luc	Paol	0.1
…	…	…
Erdos	**Straus**	**λ**

How *open-world query evaluation?*

UCQ / Monotone CNF

- Lower bound = closed-world probability
- Upper bound = probability after **adding all tuples** with probability λ

- Polynomial time ☺
- Quadratic blow-up ☹
- 200 exabytes … again ☹

Closed-World Lifted Query Eval

$Q = \exists x\, \exists y\, Scientist(x) \wedge Coauthor(x,y)$

Decomposable ∀-Rule

$$P(Q) = 1 - \Pi_{A \in Domain} (1 - P(Scientist(A) \wedge \exists y\, Coauthor(A,y))$$

Check independence:

$Scientist(A) \wedge \exists y\, Coauthor(A,y)$

$Scientist(B) \wedge \exists y\, Coauthor(B,y)$

$$= 1 - (1 - P(Scientist(A) \wedge \exists y\, Coauthor(A,y))$$
$$\times (1 - P(Scientist(B) \wedge \exists y\, Coauthor(B,y))$$
$$\times (1 - P(Scientist(C) \wedge \exists y\, Coauthor(C,y))$$
$$\times (1 - P(Scientist(D) \wedge \exists y\, Coauthor(D,y))$$
$$\times (1 - P(Scientist(E) \wedge \exists y\, Coauthor(E,y))$$
$$\times (1 - P(Scientist(F) \wedge \exists y\, Coauthor(F,y))$$
$$\ldots$$

Complexity PTIME

Closed-World Lifted Query Eval

$Q = \exists x\, \exists y\, \text{Scientist}(x) \wedge \text{Coauthor}(x,y)$

$P(Q) = 1 - \prod_{A \in \text{Domain}} (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y)))$

$= 1 - (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y))$
$\times (1 - P(\text{Scientist}(B) \wedge \exists y\, \text{Coauthor}(B,y))$
$\times (1 - P(\text{Scientist}(C) \wedge \exists y\, \text{Coauthor}(C,y))$
$\times (1 - P(\text{Scientist}(D) \wedge \exists y\, \text{Coauthor}(D,y))$
$\times (1 - P(\text{Scientist}(E) \wedge \exists y\, \text{Coauthor}(E,y))$
$\times (1 - P(\text{Scientist}(F) \wedge \exists y\, \text{Coauthor}(F,y))$
$\times \ldots$

⇨ No supporting facts in database!

⇨ Probability 0 in closed world

⇨ Ignore these queries!

Complexity linear time!

Open-World Lifted Query Eval

$Q = \exists x\, \exists y\, \text{Scientist}(x) \wedge \text{Coauthor}(x,y)$

$$P(Q) = 1 - \Pi_{A \in \text{Domain}} (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y)))$$

$$\begin{aligned}
&= 1 - (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y)) \\
&\quad \times (1 - P(\text{Scientist}(B) \wedge \exists y\, \text{Coauthor}(B,y)) \\
&\quad \times (1 - P(\text{Scientist}(C) \wedge \exists y\, \text{Coauthor}(C,y)) \\
&\quad \times (1 - P(\text{Scientist}(D) \wedge \exists y\, \text{Coauthor}(D,y)) \\
&\quad \times (1 - P(\text{Scientist}(E) \wedge \exists y\, \text{Coauthor}(E,y)) \\
&\quad \times (1 - P(\text{Scientist}(F) \wedge \exists y\, \text{Coauthor}(F,y)) \\
&\quad \ldots
\end{aligned}$$

⇨ No supporting facts in database!

⇨ Probability p in closed world

Complexity PTIME!

Open-World Lifted Query Eval

$Q = \exists x\, \exists y\, \text{Scientist}(x) \wedge \text{Coauthor}(x,y)$

$P(Q) = 1 - \prod_{A \in \text{Domain}} (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y)))$

$= 1 - (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y))$
$\times (1 - P(\text{Scientist}(B) \wedge \exists y\, \text{Coauthor}(B,y))$
$\times (1 - P(\text{Scientist}(C) \wedge \exists y\, \text{Coauthor}(C,y))$
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$\times (1 - P(\text{Scientist}(E) \wedge \exists y\, \text{Coauthor}(E,y))$
$\times (1 - P(\text{Scientist}(F) \wedge \exists y\, \text{Coauthor}(F,y))$
$\ldots$

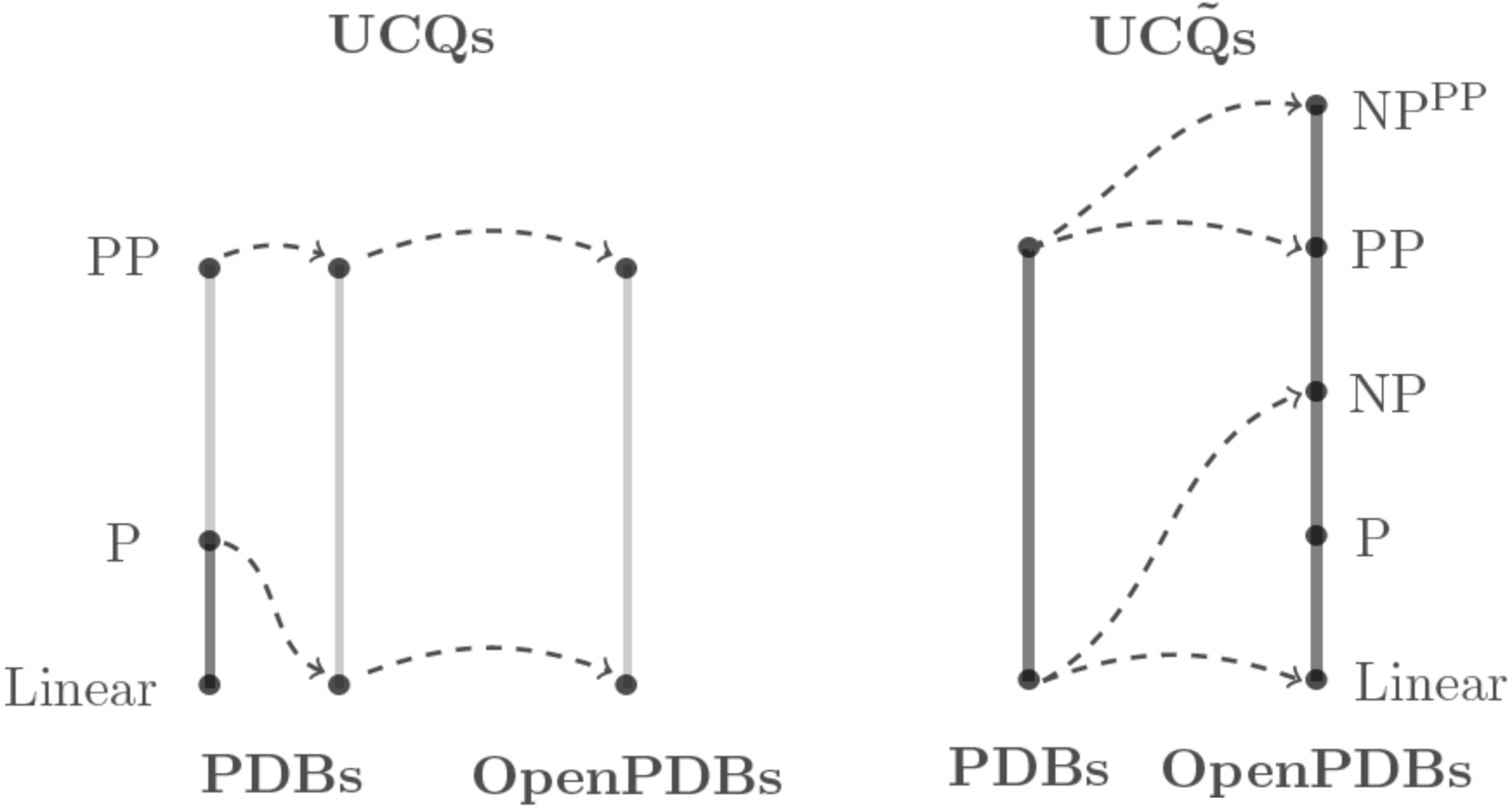
⇒ No supporting facts in database!

⇒ Probability p in closed world

⇒ All together, probability $(1-p)^k$
Do symmetric lifted inference

Complexity linear time!

Complexity Results



$$\text{Linear} \subseteq \text{P} \subseteq \text{NP} \subseteq \text{PP} \subseteq \text{P}^{\text{PP}} \subseteq \text{NP}^{\text{PP}} \subseteq \text{PSpace} \subseteq \text{ExpTime}$$

[Ceylan'16]

Implement PDB Query in SQL

- Convert to nested SQL recursively
- Open-world existential quantification

$Q = \exists x\, P(x) \wedge Q(x)$

```
SELECT (1.0-(1.0-pUse)*power(1.0-0.0001,(4-ct))) AS pUse
FROM
  (SELECT ior(COALESCE(pUse,0)) AS pUse,
          count(*) AS ct
   FROM SQL(conjunction)
```

`0.0001` = open-world probability; `4` = # open-world query instances

`ior` = Independent OR aggregate function

- Conjunction

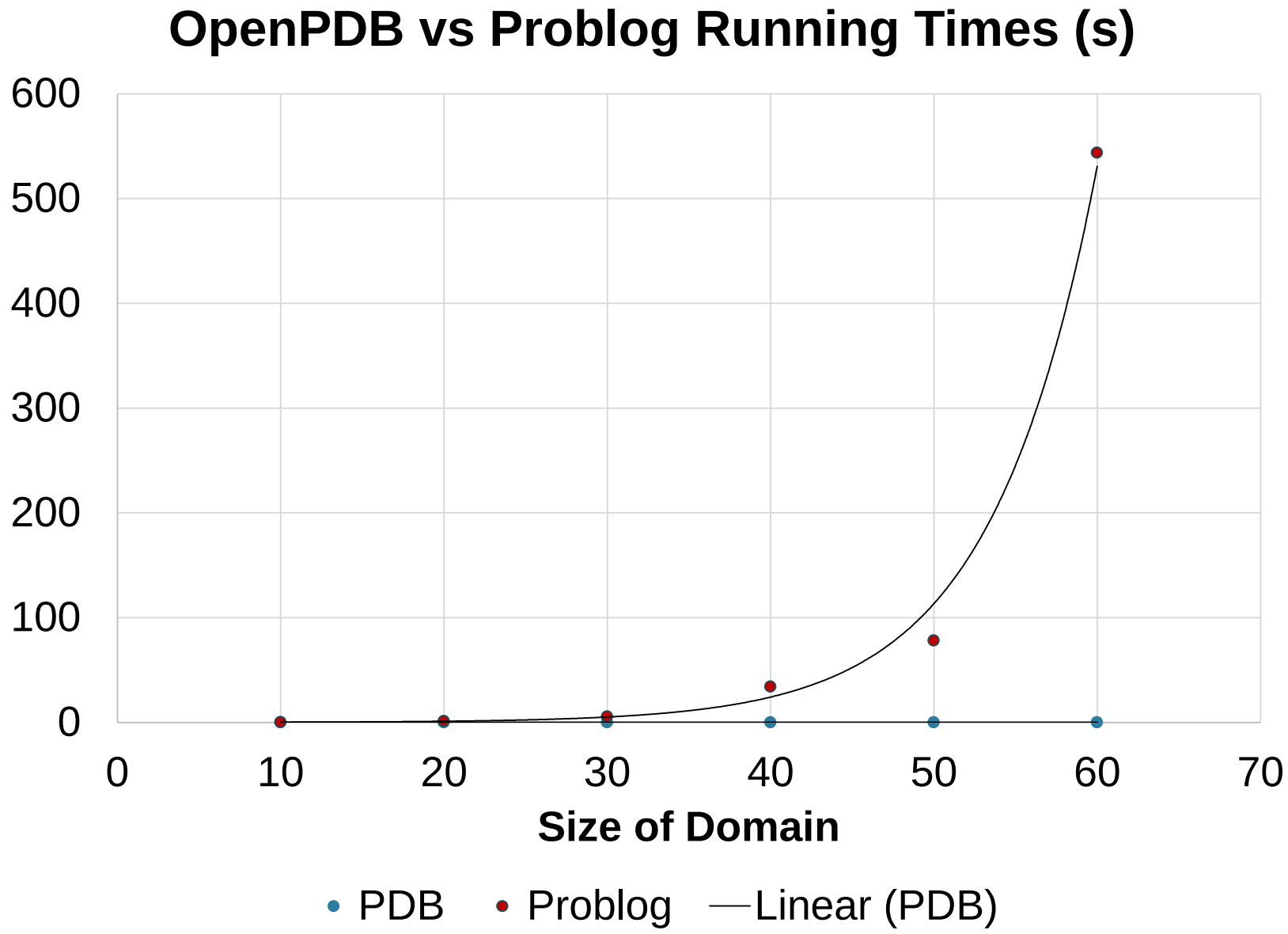
```
SELECT q9.c5,
  COALESCE(q9.pUse,λ)*COALESCE(q10.pUse,λ) AS pUse
FROM
  SQL(Q(X)) OUTER JOIN SQL(P(X))
```

```
SELECT Q.v0 AS c5,
       p AS pUse
         FROM Q
```

- Run as single query!

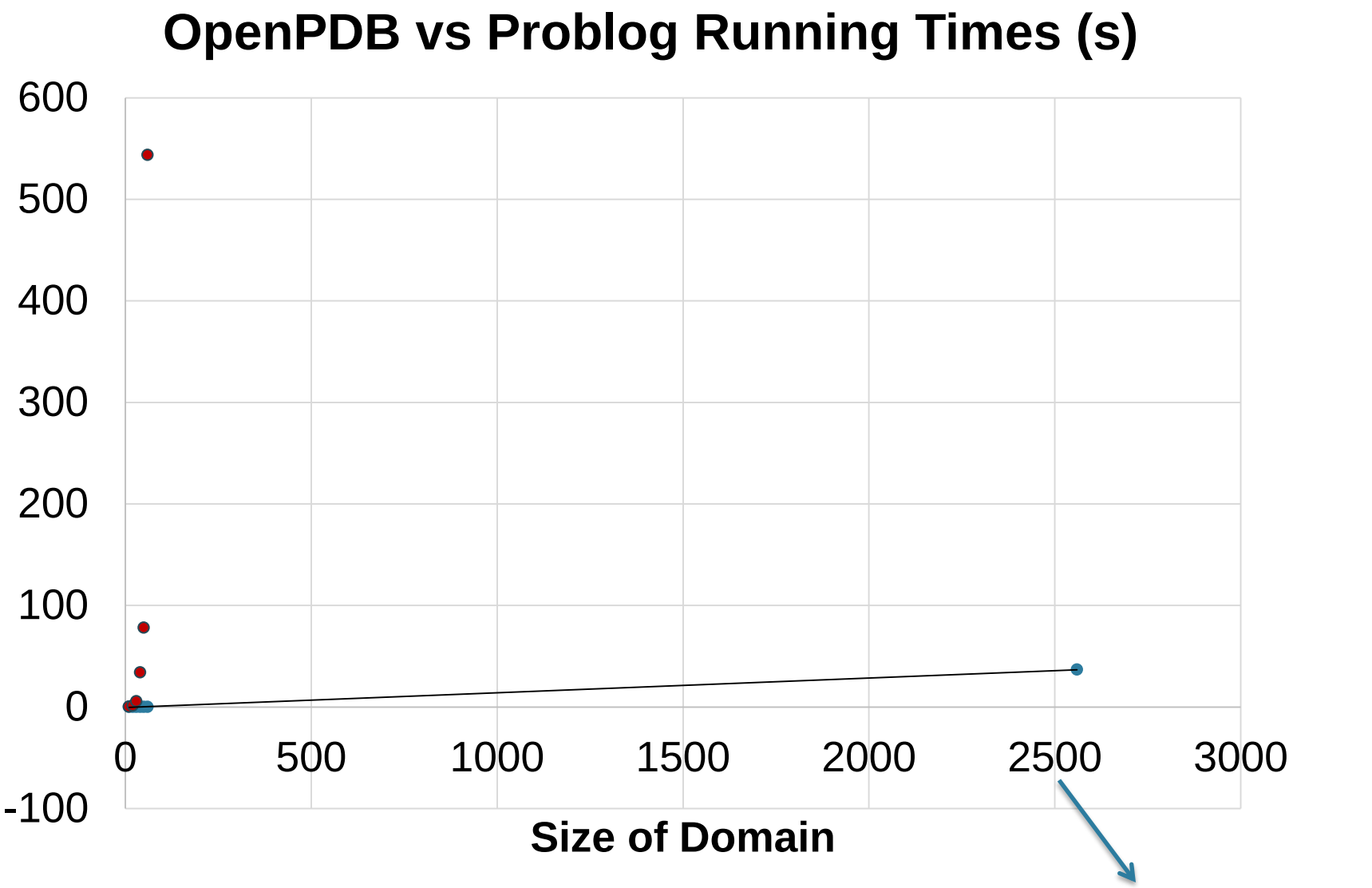
[Tal Friedman, Eric Gribkoff]

[Tal Friedman]



Out of memory trying to run the ProbLog query with 70 constants in domain

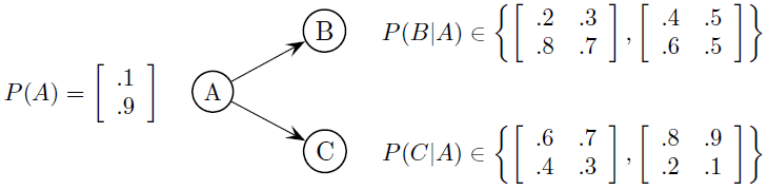
[Tal Friedman]



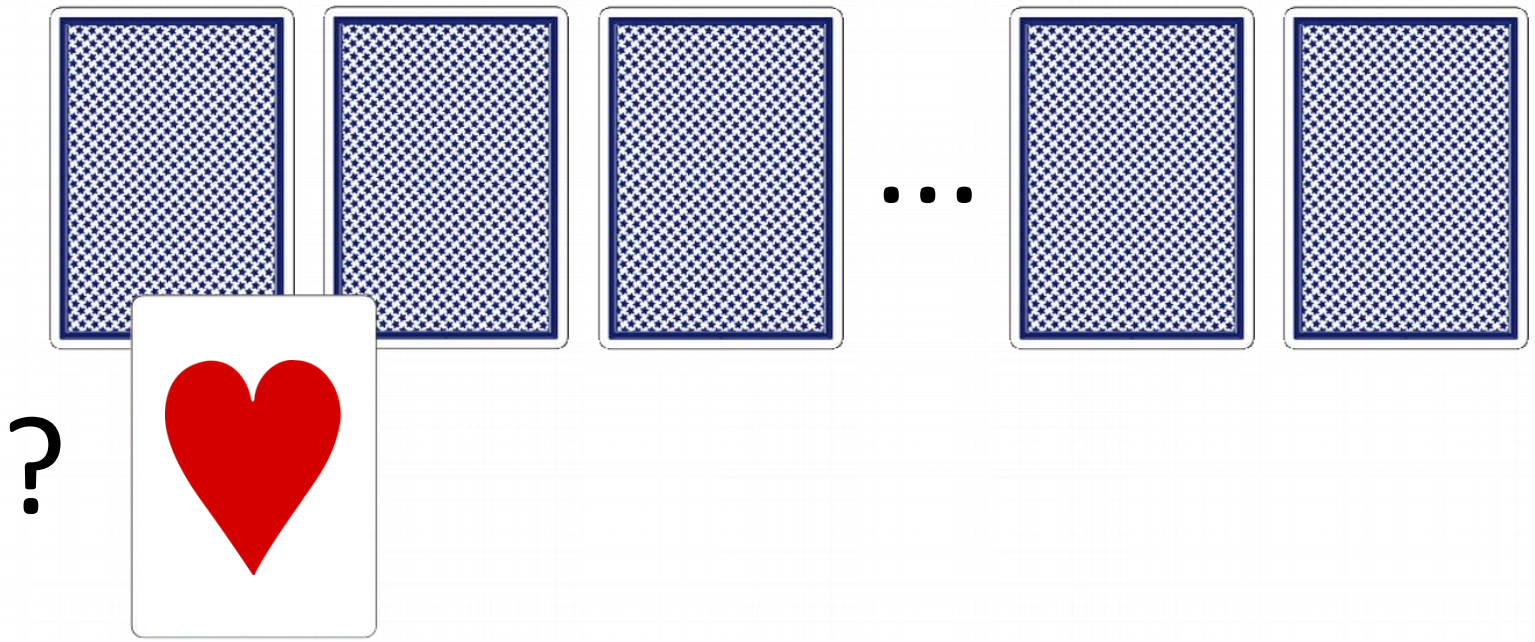
***What** is the broader picture?*

The Broader Picture

- Statistical relational learning (e.g., Markov logic)
  - Open-domain models (BLOG)
- Probabilistic description logics
- Certain query answers in databases
- Open information extraction
- Learning from positive-only examples
- Imprecise probabilities
  - Credal sets, interval probability, qualitative uncertainty
- Credal Bayesian networks



Related Work: Lifted Probabilistic Inference



Probability that Card1 is Hearts? 1/4

[Van den Broeck; AAAI-KRR'15]

Open-World Lifted Query Eval

$Q = \exists x\, \exists y\, \text{Smoker}(x) \wedge \text{Friend}(x,y)$

$$P(Q) = 1 - \prod_{A \in \text{Domain}} (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y)))$$

$$= 1 - (1 - P(\text{Scientist}(A) \wedge \exists y\, \text{Coauthor}(A,y))$$
$$\times (1 - P(\text{Scientist}(B) \wedge \exists y\, \text{Coauthor}(B,y))$$
$$\times (1 - P(\text{Scientist}(C) \wedge \exists y\, \text{Coauthor}(C,y))$$
$$\times (1 - P(\text{Scientist}(D) \wedge \exists y\, \text{Coauthor}(D,y))$$
$$\times (1 - P(\text{Scientist}(E) \wedge \exists y\, \text{Coauthor}(E,y))$$
$$\times (1 - P(\text{Scientist}(F) \wedge \exists y\, \text{Coauthor}(F,y))$$
$$\ldots$$

⇨ All together, probability $(1-p)^k$

Open-world query evaluation on empty db
= Lifted inference in AI

Conclusions

- Relational probabilistic reasoning is **frontier** and **integration** of AI, KR, ML, DB, TH, etc.
- We need
  - relational models and logic
  - probabilistic models and statistical learning
  - algorithms that scale
- Open-world data model
  - semantics makes sense
  - FREE for UCQs
  - expensive otherwise

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