

Towards Querying Probabilistic Knowledge Bases

Guy Van den Broeck

First Conference on
Automated Knowledge Base Construction

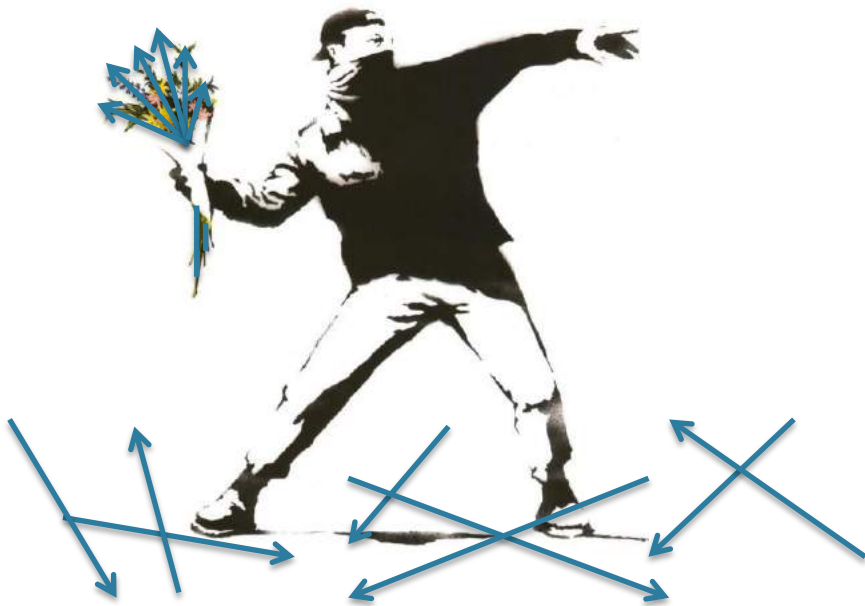
May 20, 2019

UCLA

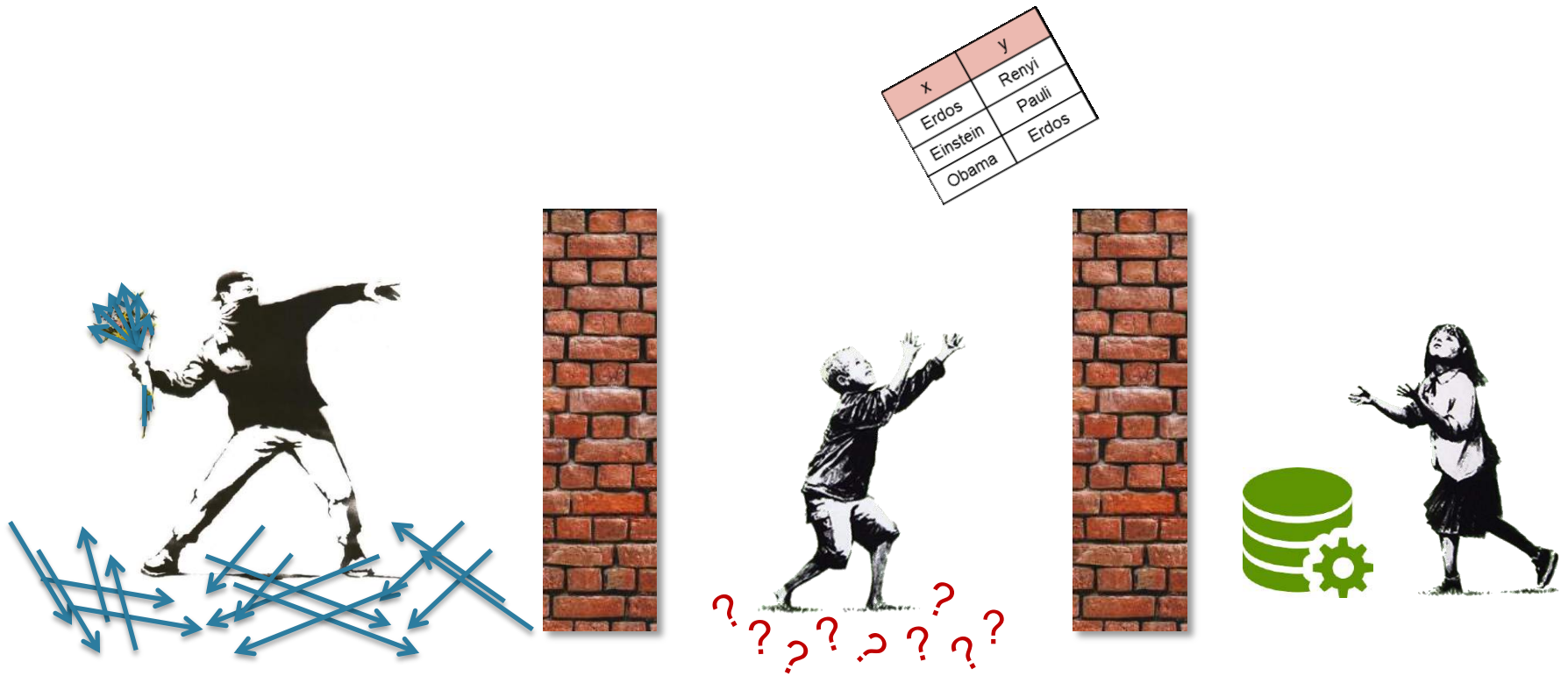


Cartoon Motivation

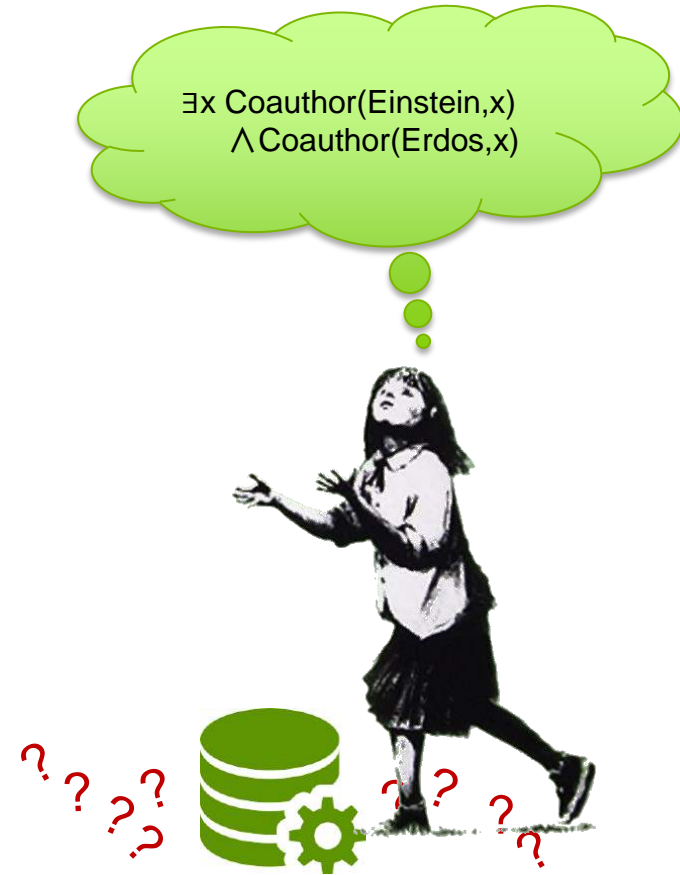
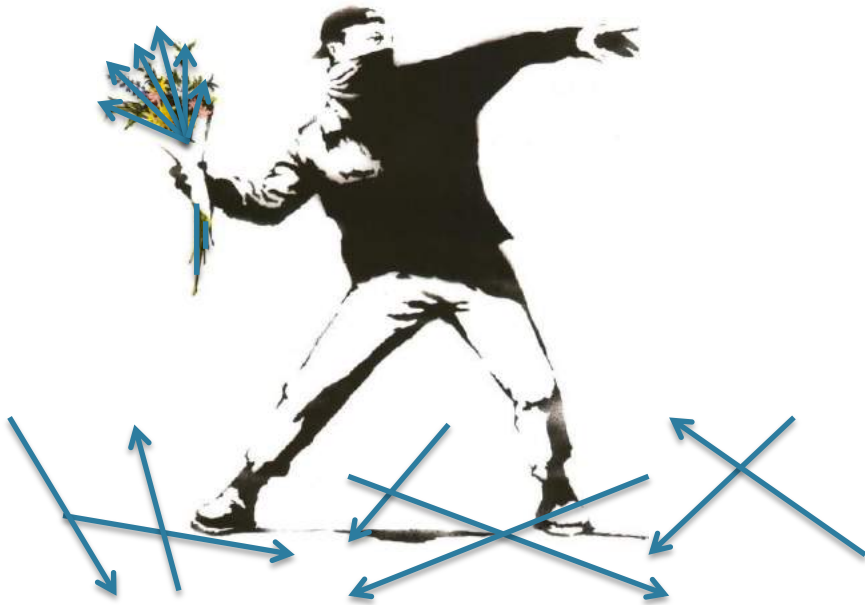
Cartoon Motivation: Relational Embedding Models



Cartoon Motivation 2: Relational Embedding Models

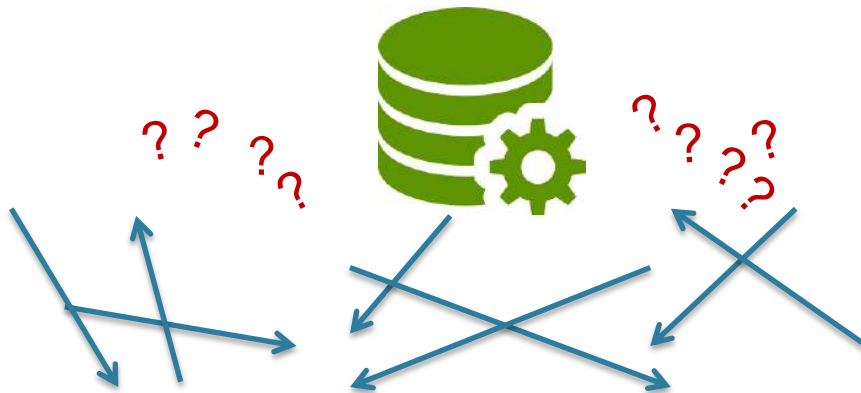


Goal 1: Probabilistic Query Evaluation

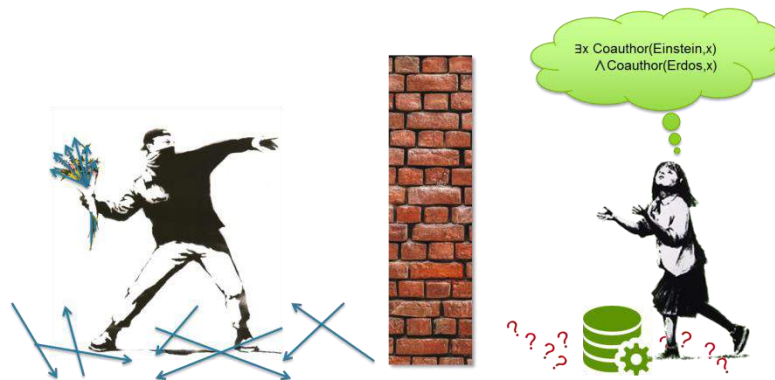


Goal 2: Querying Relational Embedding Models

$\exists x \text{ Coauthor}(\text{Einstein}, x)$
 $\wedge \text{ Coauthor}(\text{Erdos}, x)$



Probabilistic Query Evaluation



What we'd like to do...

Has anyone published a paper with both Erdos and Einstein



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Erdős number - Wikipedia, the free encyclopedia

https://en.wikipedia.org/wiki/Erdős_number ▾ Wikipedia ▾

He **published** more **papers** during his lifetime (at least 1,525) than any other ...

Anybody else's Erdős number is $k + 1$ where k is the lowest Erdős number of any coauthor. ... **Albert Einstein and Sheldon Lee Glashow have an Erdős number of 2.** ...

and mathematician Ruth Williams, **both** of whom **have** an Erdős number of 2.

Erdős–Bacon number - Wikipedia, the free encyclopedia

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This article possibly **contains** previously unpublished synthesis of **published** ... Her **paper** gives her an Erdős number of 4, and a Bacon number of 2, **both** of ...

What we'd like to do...

$\exists x \text{ Coauthor}(\text{Einstein}, x) \wedge \text{ Coauthor}(\text{Erdos}, x)$



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Erdős–Bacon number - Wikipedia, the free encyclopedia

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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: [ˈalbɛʁt ˈaɪnʃtaɪn] (listen); 14 March 1879 – 18 April 1955) was a German-born theoretical physicist.

[Hans Albert Einstein](#) - [Mass–energy equivalence](#) - [Eduard Einstein](#) - [Elsa Einstein](#)

Albert Einstein (@AlbertEinstein) | Twitter

<https://twitter.com/AlbertEinstein>

16 hours ago - [View on Twitter](#)

ICYMI, Albert Einstein knew a thing or two about being romantic. Learn about the love letters he wrote. guff.com/didnt-know-einst...

20 hours ago - [View on Twitter](#)

An interesting read on Einstein's superstar status. What are your thoughts? twitter.com/aeonmag/status...

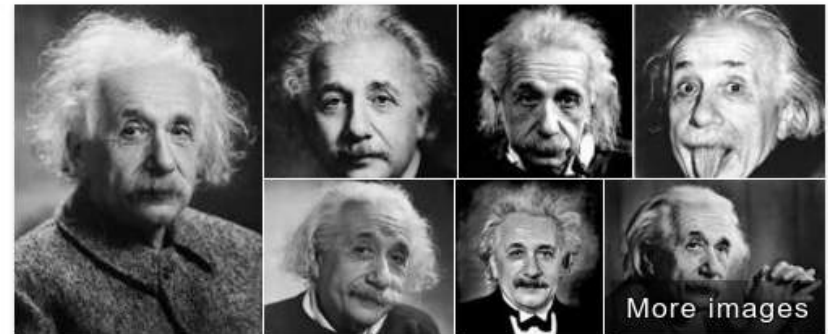


Albert Einstein - Biographical - Nobelprize.org

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%20Erdős%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

Ernst Straus

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Ernst G. Straus - Wikipedia, the free encyclopedia
https://en.wikipedia.org/wiki/Ernst_G._Straus Wikipedia
Ernst Gabor Straus (February 25, 1922 – July 12, 1983) was a German-American mathematician who helped found the theories of Euclidean Ramsey theory ...

Straus biography - University of St Andrews
www-groups.dcs.st-and.ac.uk/~history/Biographies/Straus.html
Ernst Straus's mother was Rahel Goitein who had the distinction of being one of the first women medical students officially studying at a German university.

Ernst G. Straus
Mathematician
Ernst Gabor Straus was a German-American mathematician who helped found the theories of Euclidean Ramsey theory and of the arithmetic properties of analytic functions. [Wikipedia](#)
Born: February 25, 1922, Munich, Germany
Died: July 12, 1983, Los Angeles, CA
Residence: United States of America

... 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!**

Probabilistic Databases

Has anyone published a paper with both Erdos and Einstein



- 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

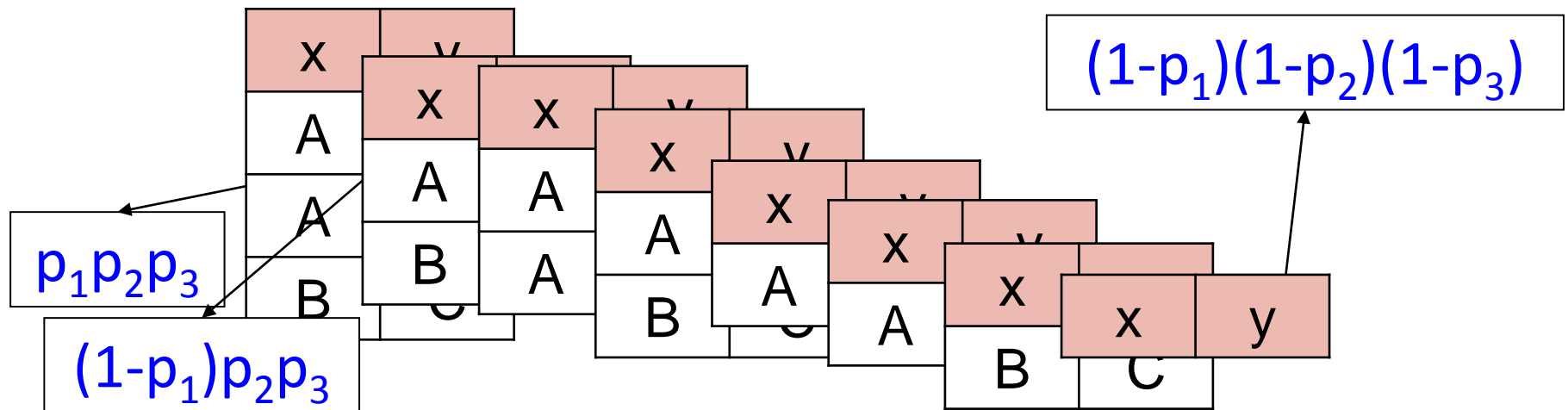
- Learned from the web, large text corpora, ontologies, etc., using **statistical** machine learning.

Tuple-Independent Probabilistic DB

Probabilistic database D:

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

Possible worlds semantics:



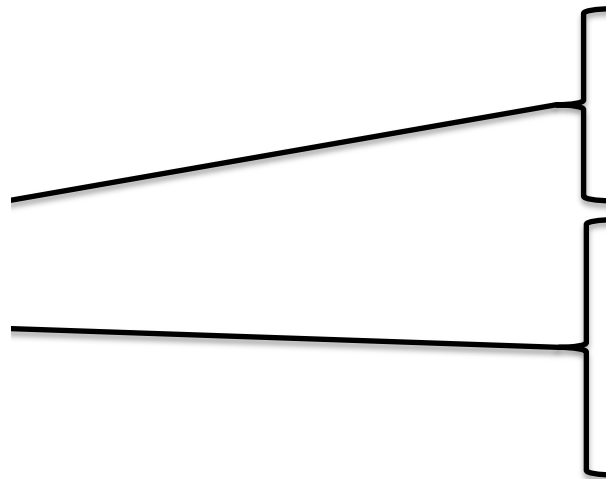
Probabilistic Query Evaluation

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

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

Scientist

x	P
A	p_1
B	p_2
C	p_3



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

Coauthor

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 \wedge, \vee

$$P(\forall z Q) = \prod_{A \in \text{Domain}} P(Q[A/z])$$
$$P(\exists z Q) = 1 - \prod_{A \in \text{Domain}} (1 - P(Q[A/z]))$$

Decomposable \exists, \forall

$$P(Q1 \wedge Q2) = P(Q1) + P(Q2) - P(Q1 \vee Q2)$$
$$P(Q1 \vee Q2) = P(Q1) + P(Q2) - P(Q1 \wedge Q2)$$

Inclusion/
exclusion

Example Query Evaluation

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

Decomposable \exists -Rule

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

Check independence:

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

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

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

...

Complexity PTIME


Limitations

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

The decomposable \forall -rule:
... does not apply:

$$P(\forall z Q) = \prod_{A \in \text{Domain}} P(Q[A/z])$$

$H_0[\text{Alice}/x]$ 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.

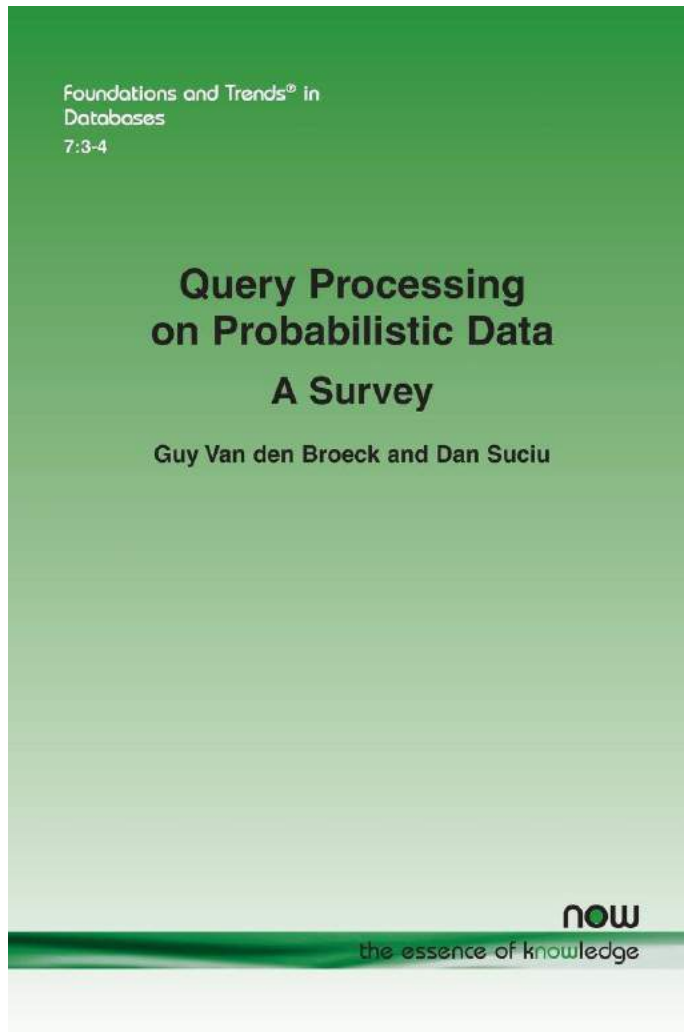
Are the Lifted Rules Complete?

Dichotomy Theorem for Unions of Conjunction Queries / Monotone CNF

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

Lifted rules are complete for UCQ!

Commercial Break



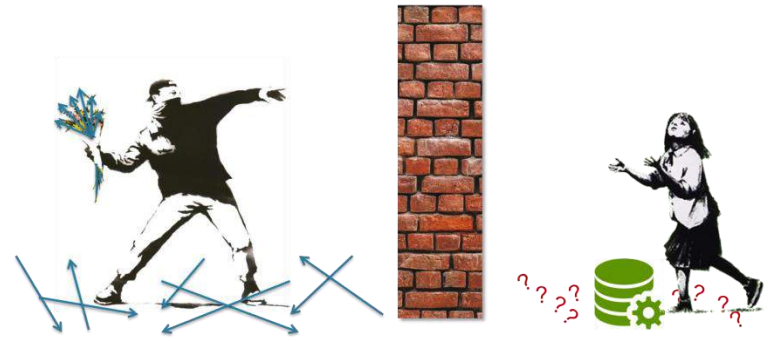
- **Survey book**

<http://www.nowpublishers.com/article/Details/DBS-052>

- **IJCAI 2016 tutorial**

<http://web.cs.ucla.edu/~guyvdb/talks/IJCAI16-tutorial/>

Throwing Relational Embedding Models Over the Wall



- Notion of distance $d(h, r, t)$ in vector space (Euclidian, 1-cosine, ...)
- Probabilistic semantics:
 - Distance $d(h, r, t) = 0$ is certainty
 - Distance $d(h, r, t) > 0$ is uncertainty

$$P(r(h,t)) \approx e^{-\alpha \cdot d(h,r,t)}$$

What About Tuple-Independence?

- Deterministic databases
= tuple-independent
- Relational embedding models
= tuple-independent

*At no point do we model
joint uncertainty between tuples*

- We can capture correlations, but query evaluation becomes much harder!
 - See probabilistic database literature
 - See statistical relational learning literature

So everything is solved?

What we'd like to do...

$\exists x \text{ Coauthor}(\text{Einstein}, x) \wedge \text{ Coauthor}(\text{Erdos}, x)$



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
...

$$Q1 = \exists x \text{ Coauthor}(\text{Einstein}, x) \wedge \text{Coauthor}(\text{Erdos}, x)$$

$$Q2 = \exists x \text{ Coauthor}(\text{Bieber}, x) \wedge \text{Coauthor}(\text{Erdos}, x)$$

$$Q3 = \text{Coauthor}(\text{Einstein}, \text{Straus}) \wedge \text{Coauthor}(\text{Erdos}, \text{Straus})$$

$$Q4 = \text{Coauthor}(\text{Einstein}, \text{Bieber}) \wedge \text{Coauthor}(\text{Erdos}, \text{Bieber})$$

$$Q5 = \text{Coauthor}(\text{Einstein}, \text{Bieber}) \wedge \neg \text{Coauthor}(\text{Einstein}, \text{Bieber})$$

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
...

$$Q1 = \exists x \text{ Coauthor}(\text{Einstein}, x) \wedge \text{Coauthor}(\text{Erdos}, x)$$

$$Q2 = \exists x \text{ Coauthor}(\text{Bieber}, x) \wedge \text{Coauthor}(\text{Erdos}, x)$$

$$Q3 = \text{Coauthor}(\text{Einstein}, \mathbf{\text{Straus}}) \wedge \text{Coauthor}(\text{Erdos}, \mathbf{\text{Straus}})$$

$$Q4 = \text{Coauthor}(\text{Einstein}, \mathbf{\text{Bieber}}) \wedge \text{Coauthor}(\text{Erdos}, \mathbf{\text{Bieber}})$$

$$Q5 = \text{Coauthor}(\text{Einstein}, \mathbf{\text{Bieber}}) \wedge \neg \text{Coauthor}(\mathbf{\text{Einstein}}, \mathbf{\text{Bieber}})$$

We know for sure that $P(Q1) \geq P(Q3)$, $P(Q1) \geq P(Q4)$

and $P(Q3) \geq P(Q5)$, $P(Q4) \geq P(Q5)$ because $P(Q5) = 0$.

We have strong evidence that $P(Q1) \geq P(Q2)$.

Problem: Curse of Superlinearity

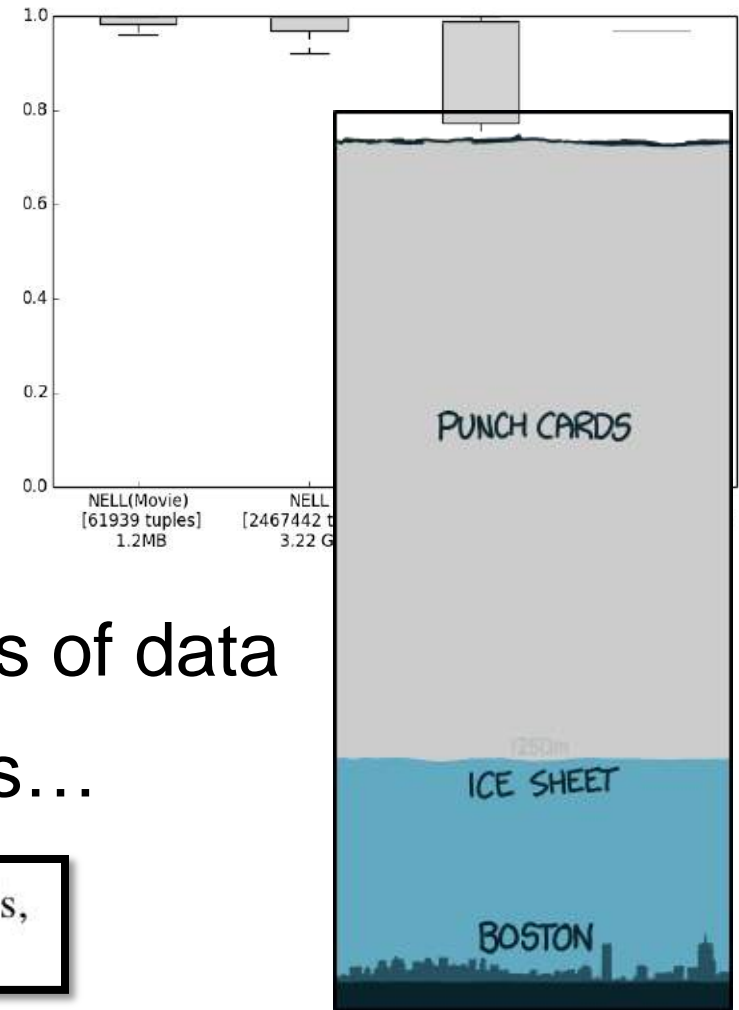
Reality is worse: tuples **intentionally** missing!

Sibling

x	y	P
...

Facebook scale \Rightarrow 200 Exabytes of data
All Google storage is 2 exabytes...

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



Bayesian Learning Loop

Bayesian view on learning:

1. Prior belief:

$$P(\text{Coauthor}(\text{Straus}, \text{Pauli})) = 0.01$$

2. Observe page

$$P(\text{Coauthor}(\text{Straus}, \text{Pauli}) \mid \text{Screenshot of a page}) = 0.2$$

3. Observe page

$$P(\text{Coauthor}(\text{Straus}, \text{Pauli}) \mid \text{Screenshot of a page}, \text{Screenshot of a page}) = 0.3$$

Principled and sound reasoning!

Problem: Broken Learning Loop

Bayesian view on learning:

1. Prior belief:

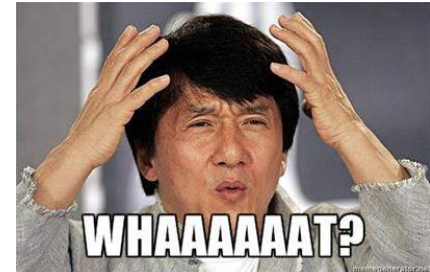
$$P(\text{Coauthor}(\text{Straus}, \text{Pauli})) = 0$$

2. Observe page

$$P(\text{Coauthor}(\text{Straus}, \text{Pauli} \mid \text{Screenshot 1})) = 0.2$$

3. Observe page

$$P(\text{Coauthor}(\text{Straus}, \text{Pauli} \mid \text{Screenshot 1}, \text{Screenshot 2})) = 0.3$$



This is mathematical nonsense!

Problem: Model Evaluation

Given:

Coauthor	x	y	P
	Einstein	Straus	0.7
	Erdoes	Straus	0.6
	Einstein	Pauli	0.9

Learn:

0.8::Coauthor(x,y) :- Coauthor(z,x) \wedge Coauthor(z,y).

OR

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

What is the likelihood, precision, accuracy, ...?

Open-World Prob. Databases

Intuition: tuples can be added with $P < \lambda$

$Q2 = \text{Coauthor}(\text{Einstein}, \mathbf{\text{Straus}}) \wedge \text{Coauthor}(\text{Erdos}, \mathbf{\text{Straus}})$

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

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

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

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

Decomposable \exists -Rule

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

Check independence:

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

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

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

...

Complexity PTIME

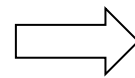
Closed-World Lifted Query Eval

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

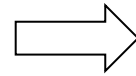
$$P(Q) = 1 - \prod_{A \in \text{Domain}} (1 - P(\text{Scientist}(A) \wedge \exists y \text{Coauthor}(A,y)))$$

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

...



No supporting facts
in database!



Probability 0 in closed world



Ignore these sub-queries!

Complexity linear time!

Open-World Lifted Query Eval

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

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

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

$$\times (1 - P(\text{Scientist}(B) \wedge \exists y \text{Coauthor}(B,y)))$$

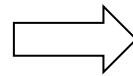
$$\times (1 - P(\text{Scientist}(C) \wedge \exists y \text{Coauthor}(C,y)))$$

$$\times (1 - P(\text{Scientist}(D) \wedge \exists y \text{Coauthor}(D,y)))$$

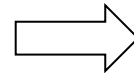
$$\times (1 - P(\text{Scientist}(E) \wedge \exists y \text{Coauthor}(E,y)))$$

$$\times (1 - P(\text{Scientist}(F) \wedge \exists y \text{Coauthor}(F,y)))$$

...



No supporting facts
in database!



Probability λ in open world

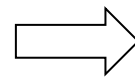
Complexity PTIME!

Open-World Lifted Query Eval

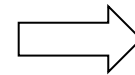
$$Q = \exists x \exists y \text{Scientist}(x) \wedge \text{Coauthor}(x,y)$$

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

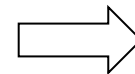
$$\begin{aligned} &= 1 - (1 - P(\text{Scientist}(A) \wedge \exists y \text{Coauthor}(A,y)) \\ &\quad \times (1 - P(\text{Scientist}(B) \wedge \exists y \text{Coauthor}(B,y)) \\ &\quad \times (1 - P(\text{Scientist}(C) \wedge \exists y \text{Coauthor}(C,y)) \\ &\quad \times (1 - P(\text{Scientist}(D)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



No supporting facts
in database!



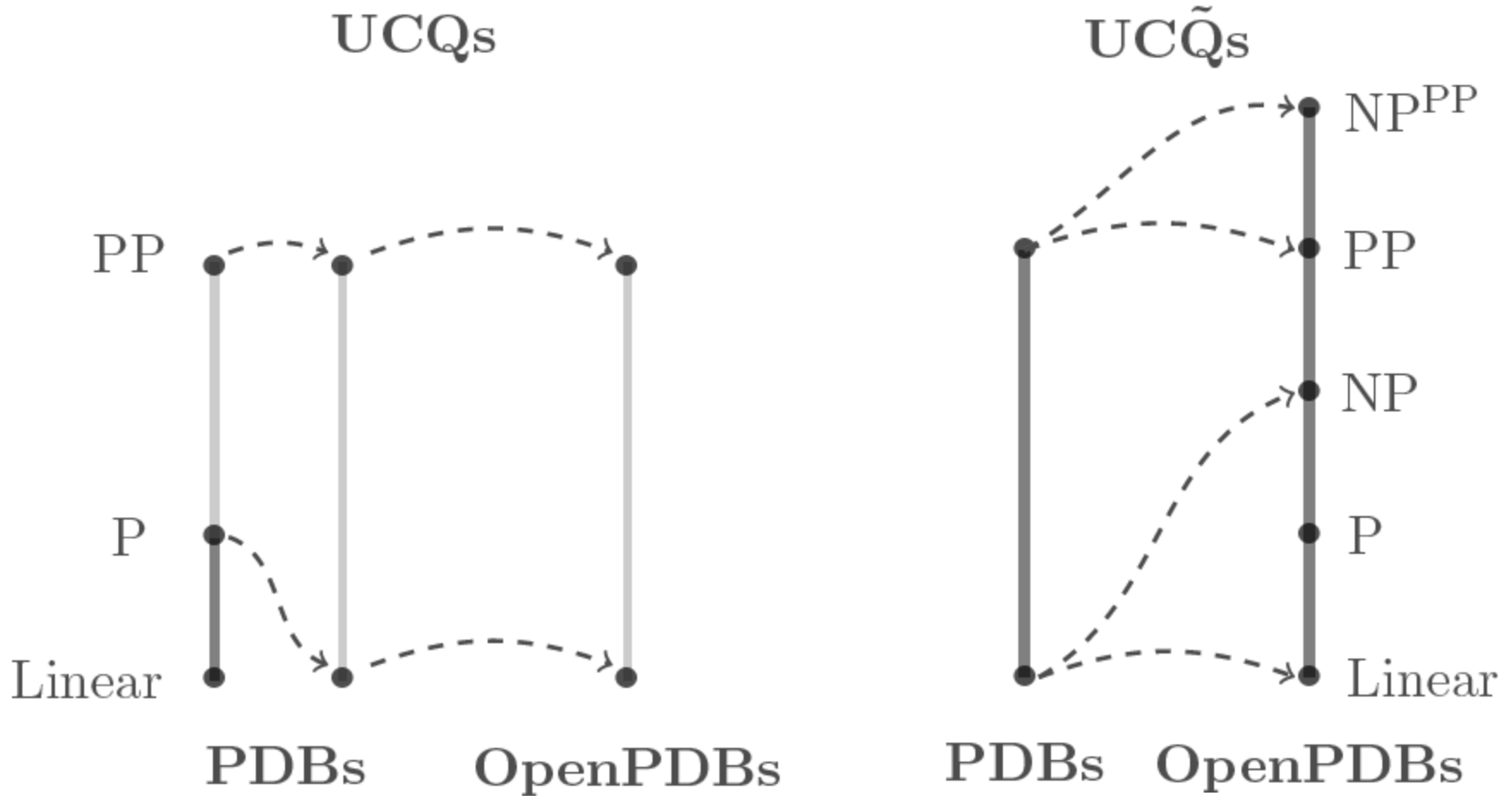
Probability p in closed world



All together, probability $(1-p)^k$
Exploit symmetry
Lifted inference

Complexity linear time!

Complexity Results



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

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

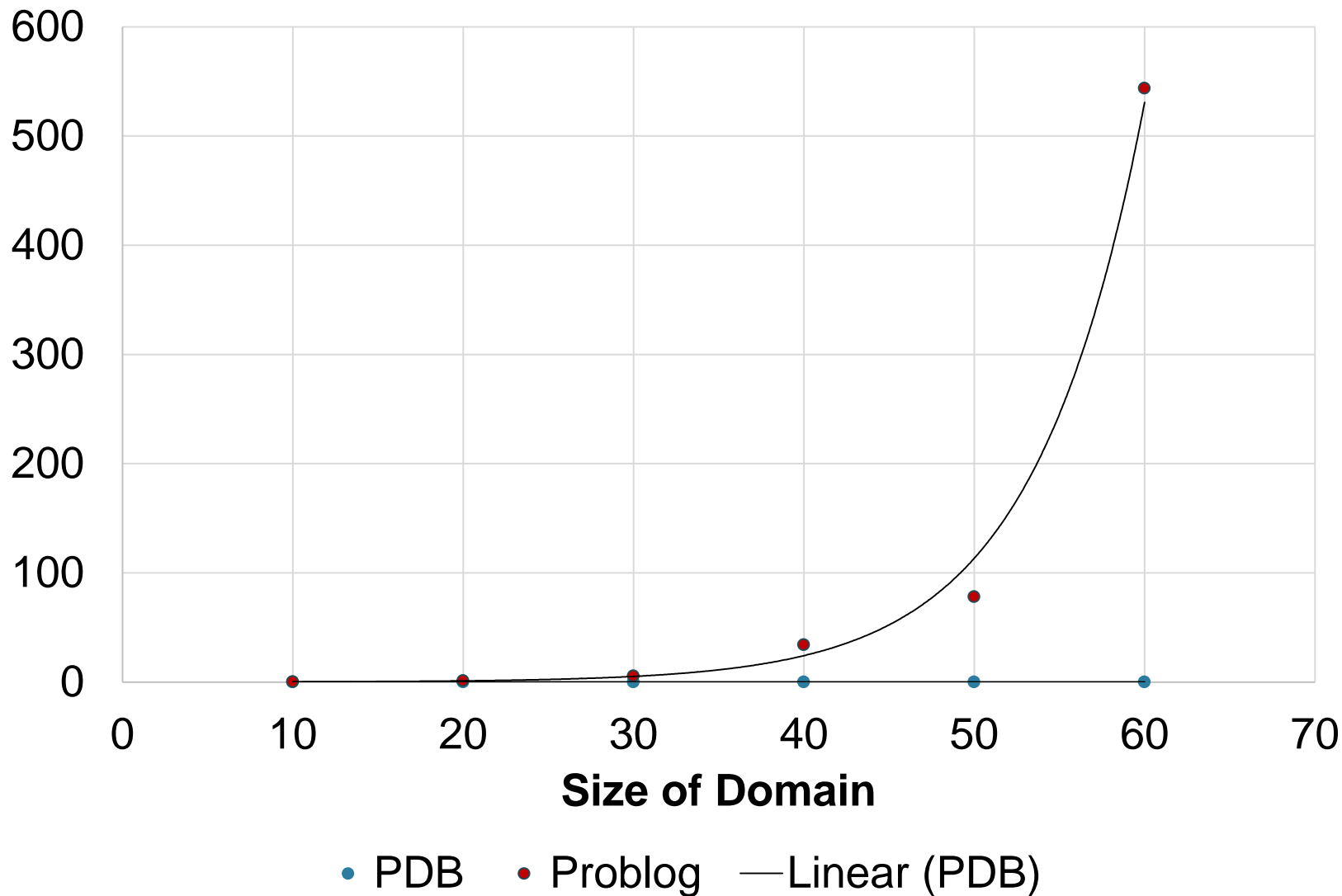
- Conjunction

```
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
```

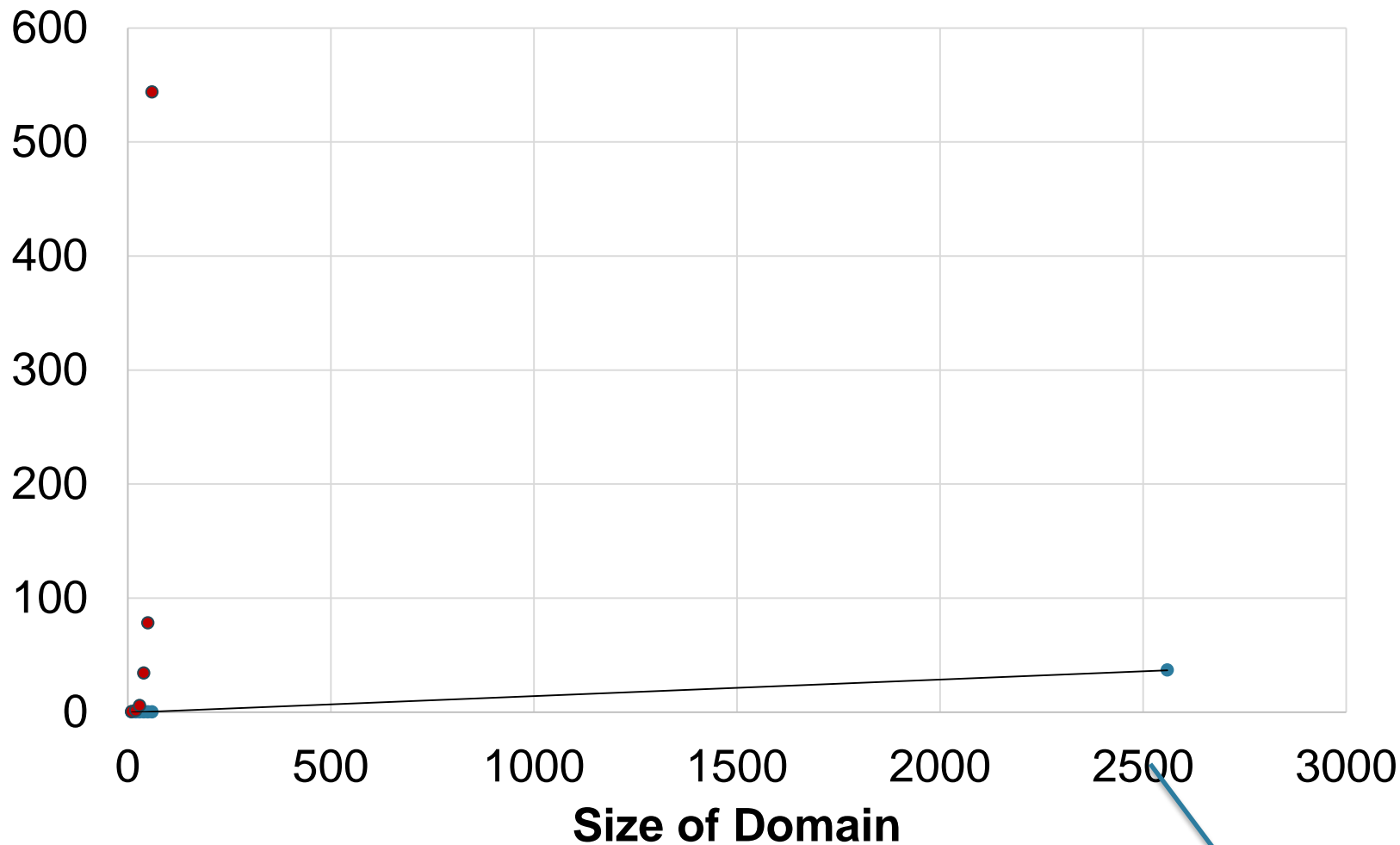
- Run as single  PostgreSQL query!

OpenPDB vs Problog Running Times (s)



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

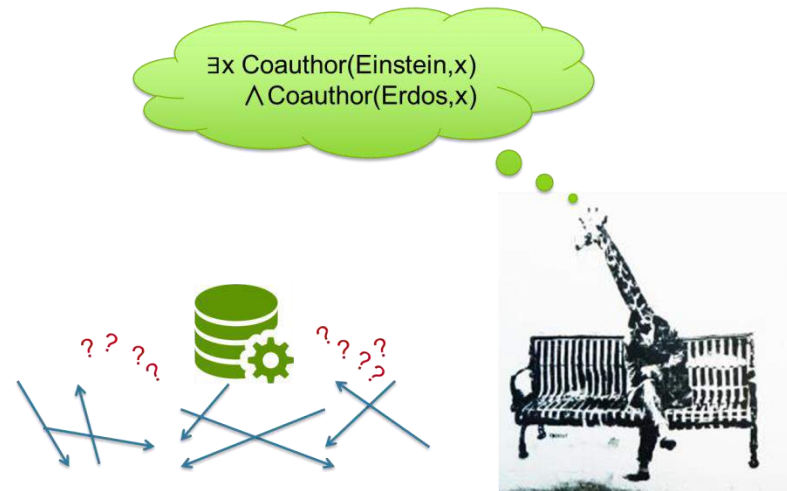
OpenPDB vs Problog Running Times (s)



• PDB • Problog — Linear (PDB)

12.5 million
random variables!

Querying *Relational Embedding Models*



Ongoing Work

- Run query evaluation *in vector space*?
 - DistMult model on Wordnet18RR
 - Query most likely answers to:

$$Q(h) = R(h, 'c')$$

$$Q(t) = R('c', t)$$

- Solver: gradient descent on query probability

Prediction Method	MRR	hits@5	hits@1
Ranking Entities	0.305	0.383	0.234
Vector Search	0.301	0.377	0.232

- Fast approximate query answering

Ongoing Work

- Join algorithms *in vector space*?
 - DistMult model on Wordnet18RR
 - Query most likely answers to:

$Q(x) = \text{Hypernym}(\text{'OliveTree'}, x) \wedge \text{Hypernym}(x, \text{'FloweringTree'})$

- Answer: $x = \text{'SpiceTree'}$
- Projection ($\exists x$)?
 - Skolemization in vector space
- More to come!

Conclusions

- You can do much more with knowledge bases/graphs than just completing missing tuples
- Let's tear down the wall(s) between
 - statistical models for knowledge base completion and
 - query evaluation systems
- Relational probabilistic reasoning is **frontier** and **integration** of AI, KR, ML, DB, TH, etc.
- Forward pointers @AKBC:
 - Arcchit Jain, Tal Friedman, Ondrej Kuzelka, Guy Van den Broeck and Luc De Raedt. [Scalable Rule Learning in Probabilistic Knowledge Bases](#)
 - Tal Friedman and Guy Van den Broeck. [On Constrained Open-World Probabilistic Databases](#)

QUESTIONS?



**THE
FIRST ORDER
NEEDS YOU**