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Highly-Efficient Reasoning via Trigger Graphs

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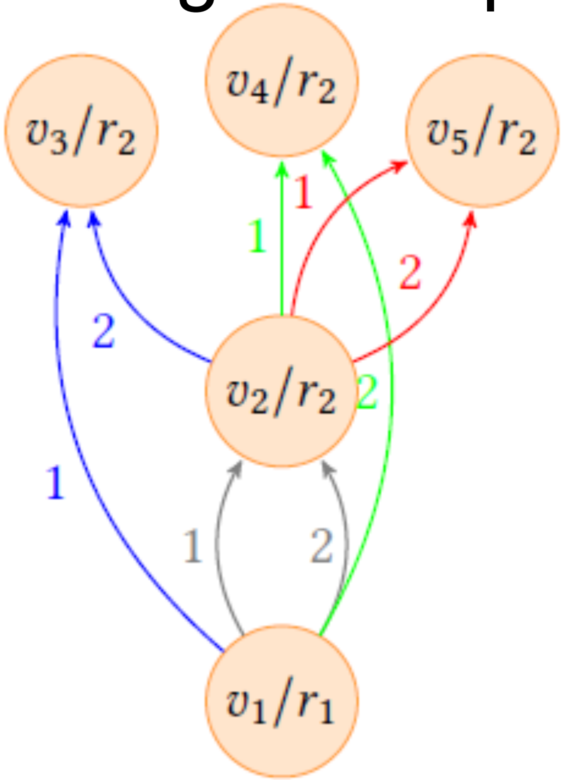
Disclaimer

This talk is **not** about stream reasoning…

…however, it presents a reasoning technique that can be naturally extended to reasoning in an incremental fashion.

The reasoning technique is based on a notion called **Trigger Graphs (TGs)**.



$$p(X,Y) \leftarrow e(X,Y) \qquad (r_1)$$
$$p(X,Y) \leftarrow p(X,Z) \wedge p(Z,Y) \qquad (r_2)$$

"Materializing Knowledge Bases via Trigger Graphs", **VLDB 2021**

"Probabilistic Reasoning at Scale: Trigger Graphs to the Rescue", **SIGMOD 2023**

Performance benefits of Trigger Graphs: non-probabilistic reasoning

Table 4: Datalog scenarios. Runtime is in sec and memory in MB. $*$ denotes timeout after 1h.

	VLog		RDFox		COM		GLog Runtime			GLog Memory		
Scenario	Runtime	Memory	Runtime	Memory	Runtime	Memory	No opt	m	m+r	No opt	m	m+r
LUBM-L	1.5	324	23	2301	20.4	4479	2.4	2.2	1.0	446	424	264
LUBM-LE	170.5	2725	116.6	3140	115.9	3610	17.3	17.2	16.1	1340	1310	1338
UOBM-L	7.3	1021	10	784	10	4215	2.6	2.4	2.6	335	335	342
DBpedia-L	41.6	827	64.4	3290	198.4	3878	20	19	19	1341	1352	1339
Claros-L	431	3170	2512	5491	2373.0	6453	122	118.3	119	6076	6077	6078
Claros-LE	2771.8	11 895	*	*	*	*	1040.8	1012.2	1053.9	48 464	48 474	48 455

Performance benefits of Trigger Graphs: probabilistic reasoning

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Table 3: Total time (default is ms) to answer the queries in LUBM010 and LUBM100 with ProbLog2 **(P),** Scallop **(S),** vProbLog **(vP) and LTGs (L). Probabilities are computed via PySDD (SDD), d-tree and c2d. Shaded cells contain the best times.**

	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_{10}	Q_{11}	Q_{12}	Q_{13}	Q_{14}
P+SDD	59	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	78	NA	150
S(30)+SDD	1.3s	NA	729	NA	4.5s	817s	6s	NA	NA	NA	63	165s	30s	326
vP+SDD	587	7.2s	306	5.6s	13.6s	NA	6.3s	NA	NA	1.3s	2s	17.3s	12.4s	3.1s
L w/o+SDD	57	420	38	1.1s	1.3s	NA	353	35.1s	348s	187	7	10.6s	541	337
L w/+SDD	49	383	38	175	365	NA	315	21.8s	174s	162	5	387	176	273
L w/+d-tree	49	676	40	461	595	NA	4.9s	668s	108s	1.5s	6	1s	206	273
L w/+c2d	49	41s	316	3.9s	62s	NA	27s	NA	NA	2.4s	6	13s	6.2s	273

	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_{10}	Q_{11}	Q_{12}	Q_{13}	Q_{14}
P+SDD	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
S(30)+SDD	15.5	NA	8.9s	NA	NA	NA	NA	NA	NA	NA	372	NA	NA	3.3s
vP+SDD	7.3s	NA	2.5s	NA	NA	NA	NA	NA	NA	NA	2s	NA	NA	38.7s
L w/o+SDD	647	52s	455	2.4s	4.7s	NA	2s	51.8s	NA	1.7s	31	12.7s	6.1s	4.9s
L w/+SDD	617	46.1s	444	1.5s	3.7s	NA	1.9s	71.4s	NA	1.6s	21	1.6s	2.8s	6s
L w/+d-tree	617	42s	411	1.7s	2.7s	NA	6.3s	658s	NA	2.9s	21	2s	2.4s	6s
L w/+c2d	617	NA	1s	7.4s	113s	NA	32s	NA	NA	4.2s	21	16s	16s	6s

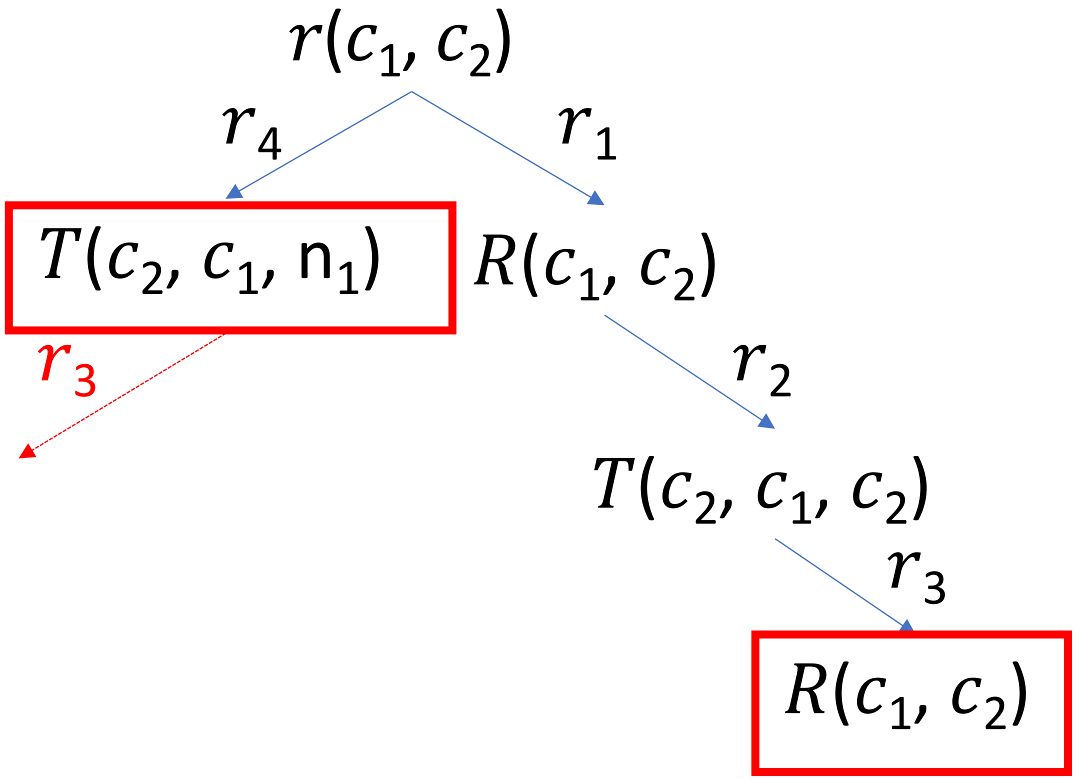
	Query ID	2343894_40	2327997_45	2322829_40	2416754_49	2346575_46
Runtime	S(1)	1.5s	800ms	721ms	793ms	1.1s
	S(20)	1311s	148s	88s	45s	40s
	S(30)	TO	1415s	89s	42s	41s
	LTGs w/	353s	7.3s	6.1s	20s	17.6s
Probability	S(1)	0.03	0.003	0.04	0.006	0.68
	S(20)	0.12	0.02	0.05	0.007	0.97
	S(30)	TO	0.02	0.05	0.007	0.97
	LTGs w/	0.13	0.02	0.11	0.015	0.97

Table. Results over the VQAR benchmark (NeurIPS 2021).

Overview

- TGs: non-probabilistic case
- TGs: probabilistic case

Motivation

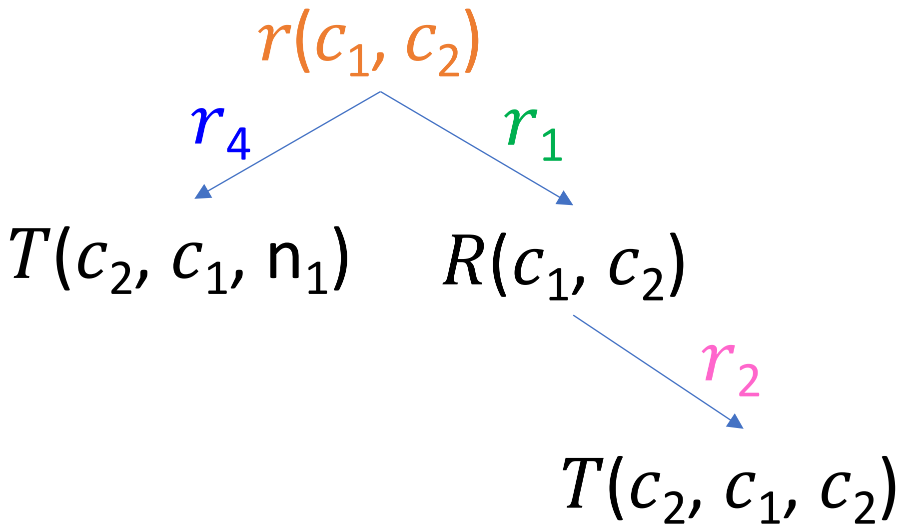


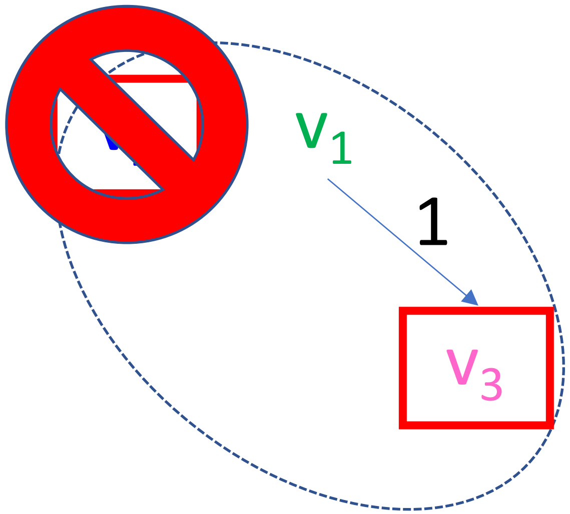
$$r(X,Y) \rightarrow R(X,Y) \quad (r_1)$$
$$R(X,Y) \rightarrow T(Y,X,Y) \quad (r_2)$$
$$T(Y,X,Y) \rightarrow R(X,Y) \quad (r_3)$$
$$r(X,Y) \rightarrow \exists Z.\, T(Y,X,Z) \quad (r_4)$$
$$B = \{r(c_1, c_2)\}$$

Standard bottom-up seminaive evaluation

- ❑ **cannot** prevent the derivation of logically redundant facts
- ❑ **cannot** prevent redundant homomorphism checks

TG Construction for Linear Rules: Intuition





$$r(X,Y) \rightarrow R(X,Y) \quad (r_1)$$
$$R(X,Y) \rightarrow T(Y,X,Y) \quad (r_2)$$
$$T(Y,X,Y) \rightarrow R(X,Y) \quad (r_3)$$
$$r(X,Y) \rightarrow \exists Z.\, T(Y,X,Z) \quad (r_4)$$

- Reason over an instance **B*** that captures *all* possible rule execution patterns.
- Build a TG that captures the derivations over **B***.
- Eliminate nodes producing logically redundant facts:
  - preserving homomorphisms

TG-Based Reasoning: Datalog Rules

- No time to cover. Read our VLDB 2021 paper!

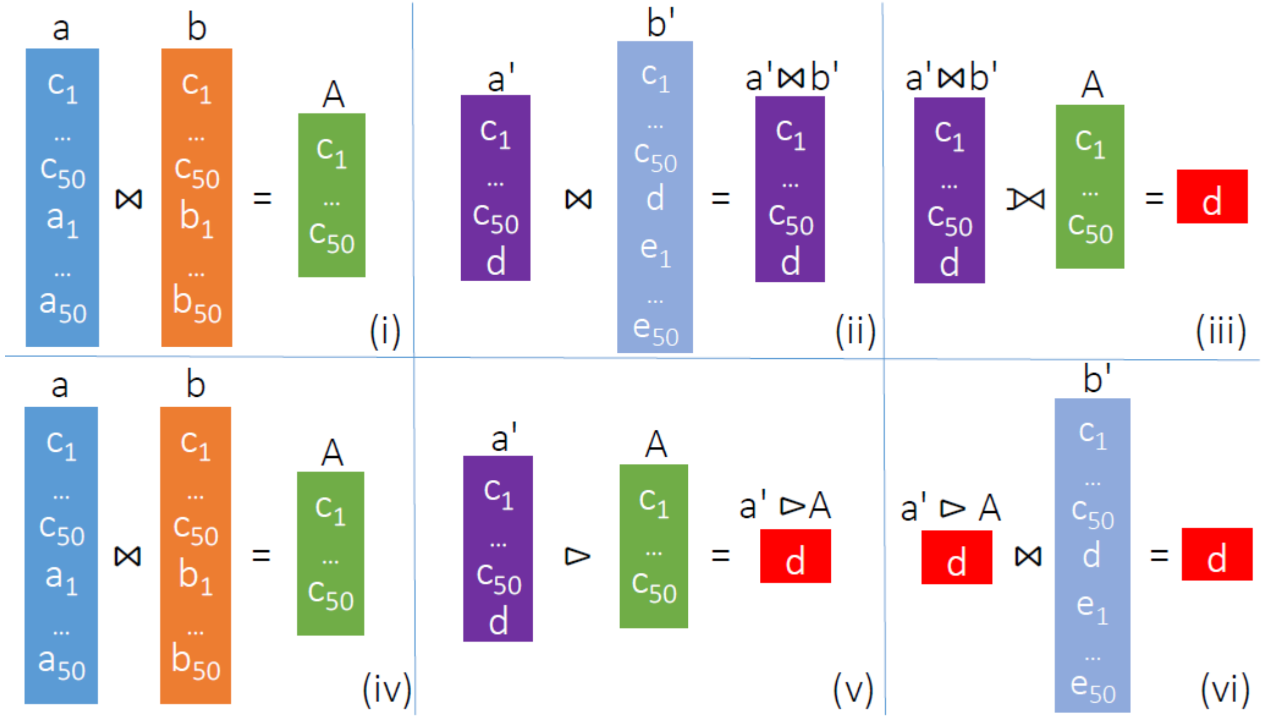
TG minimization

- ❑Computing rewritings over the TG.
- ❑Reduce to query containment (de cidable as the check does not con sider the rules).

Theoretical results:

- ❑Produce a minimal (all instance g uarantees) TG.
- ❑Decision problem is co-NP-compl ete.

TG-based rule execution strategy



Overview

- TGs: non-probabilistic case
- TGs: probabilistic case (actually Datalog reasoning over tuple-independent PDBs)

Probabilities into the game

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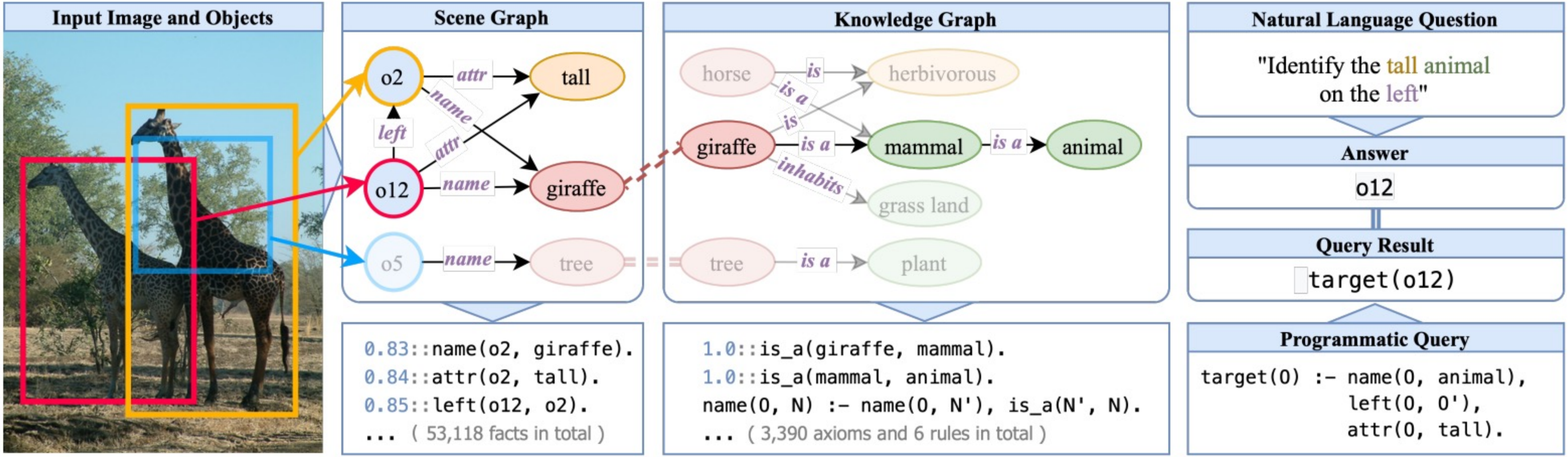
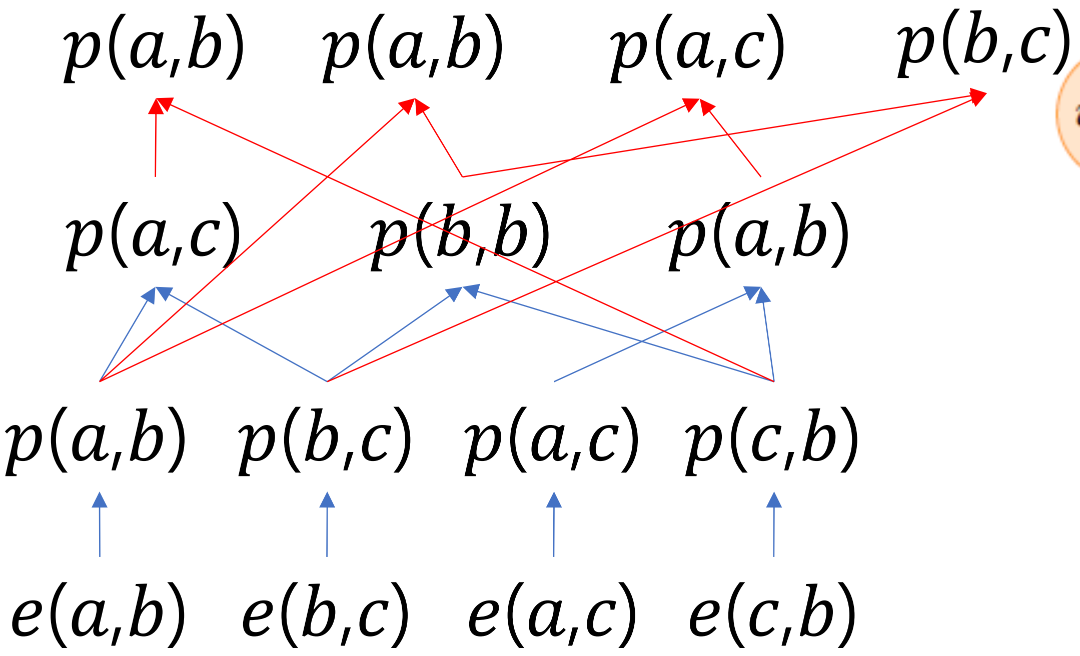
- Auto-mined KGs
  - Google's Knowledge Vault
  - Microsoft's Concept Graph
- Visual Question Answering

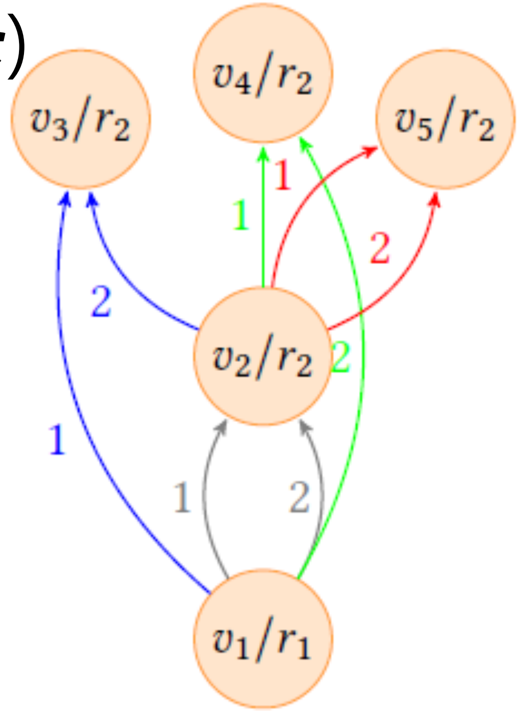


TG extensions to account for probabilities

- Why TGs should be extended?
  - We need to account for **all** possible non-redundant ways to derive each fact
  - Then, the derivations are compiled in a formula to compute the probability a derived fact is true.

TG-Based Probabilistic Reasoning: Intuition





- Keep the provenance at reasoning-time within the nodes of the TG (this can be done efficiently).
- Stop when the derivation of a fact depends on itself.

$$p(X,Y) \leftarrow e(X,Y) \qquad (r_1)$$

$$p(X,Y) \leftarrow p(X,Z) \wedge p(Z,Y) \qquad (r_2)$$

$$e(a,b),\ e(b,c),\ e(a,c),\ e(c,b)$$

TG-Based Probabilistic Reasoning: Collapsing

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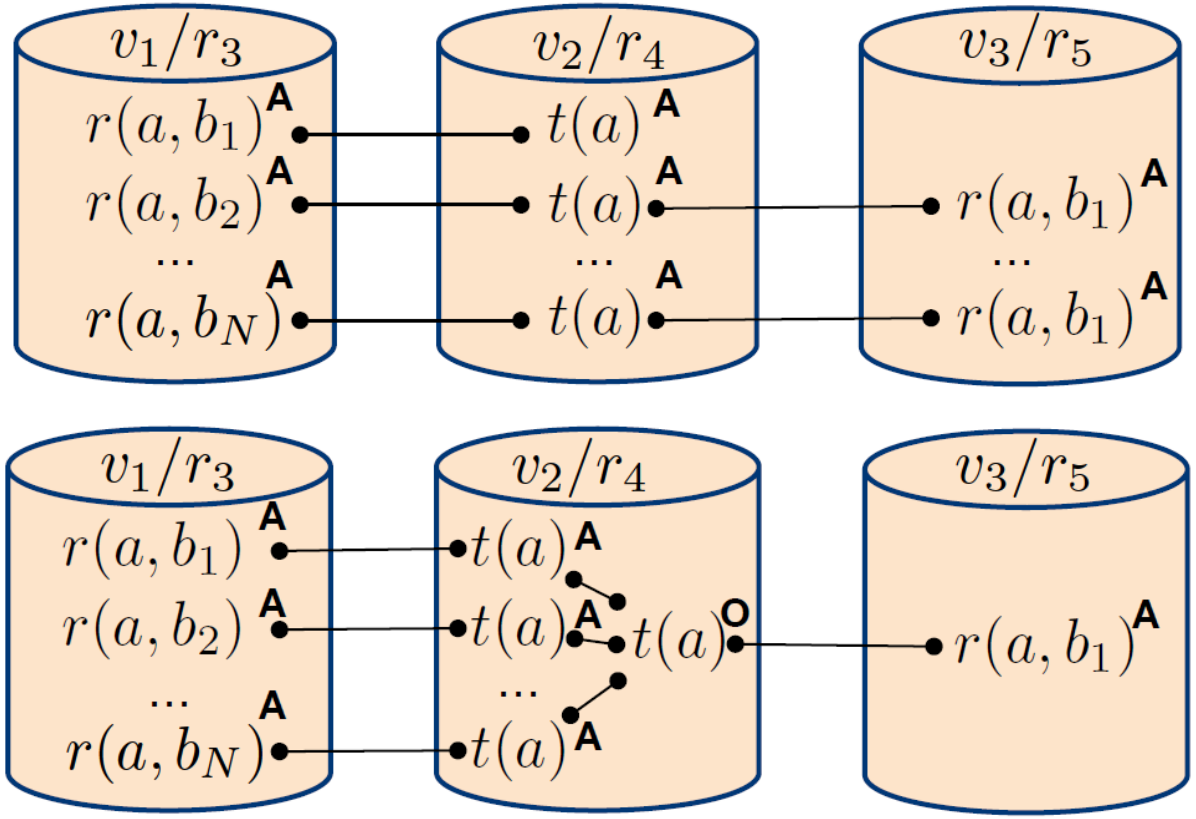

$$r(X,Y) \leftarrow q(X,Y) \qquad (r_3)$$

$$t(X) \leftarrow r(X,Y) \qquad (r_4)$$

$$r(X,Y) \leftarrow t(X) \wedge s(X,Y) \qquad (r_5)$$

$q(a,b_i)$, for $1 \leq i \leq N$, and $s(a,b_1)$

- The previous technique is sound… however, it can explode space-wise.
- Keep only one derivation per fact within each node.
- Extends the notion of absorptive provenance circuits [D. Deutch, ICDT 2014], but we decide when to collapse or not.

Probabilistic reasoning: prior art

- How prior art [Tsamoura et al., AAAI 2020] works? Read our SIGMOD 2023 where we explain via an example!
  - They are based on **provenance semirings** [T.J. Green, PODS 2007] and have **exponential space complexity** [D. Deutch, ICDT 2014].

Connections to incremental reasoning

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- ???

A few last things about my research

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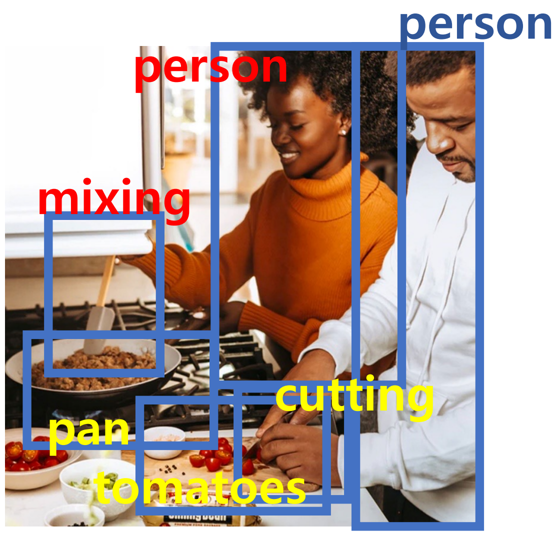
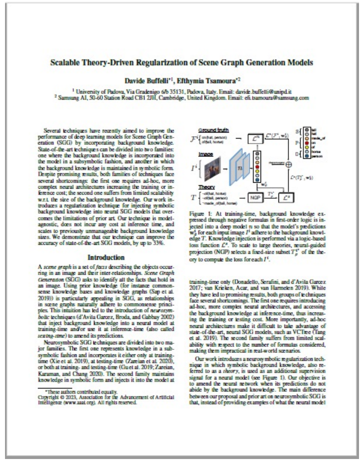
Scene graph generation



AAAI 2023


Scalable Theory-Driven Regularization of Scene Graph Generation Models

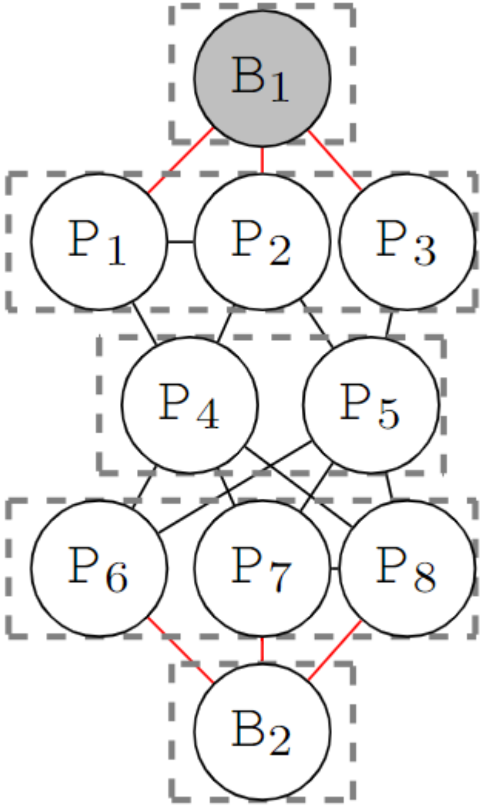
Davide Buffelli, Efthymia Tsamoura

AAAI 2023


Principled and Efficient Motif Finding for Structure Learning in Lifted Graphical Models

Jonathan Feldstein, Efthymia Tsamoura

Structural motifs mining for lifted graphical models under (ε,α)-guarantees ...and some nice complexity results.



Thanks!

- Please feel free to reach out if
  - ❑you want to visit me in Cambridge, UK, or
  - ❑you have a nice idea to work on, or
  - ❑you want to learn more about my projects including TGs!