Knowledge Compilation for Queries on Probabilistic Graphs

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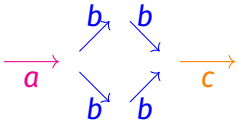
Queries on graphs

- Fix: a signature Σ of edge labels, e.g., $\Sigma = \{a, b, c\}$
- Graph: a directed graph with edges labeled in Σ



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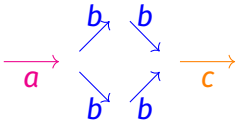

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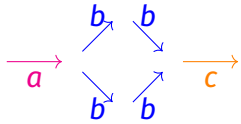

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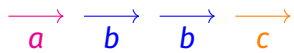
- **Conjunctive query:** existence of explicit pattern, *e.g.*, 

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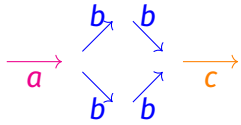

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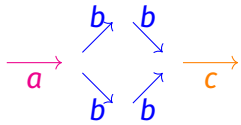

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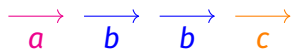

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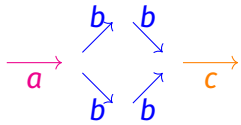

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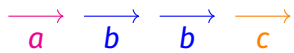
- **Conjunctive query:** existence of explicit pattern, *e.g.,* 

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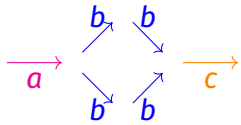

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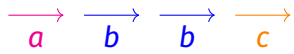
- Conjunctive query: existence of explicit pattern, *e.g.,* 

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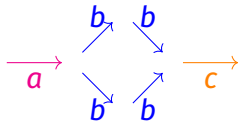

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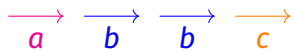
- **Conjunctive query:** existence of explicit pattern, *e.g.,* 

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- **Combined complexity:** as a function of Q and G
- **Data complexity** for fixed Q: as a function of G only

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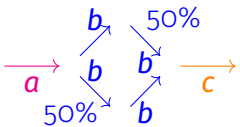
- Probabilistic graph: edges carry a probability along with their label in Σ
- Each edge is present with the indicated probability, assuming independence
- Concise representation of a probability distribution on the subgraphs



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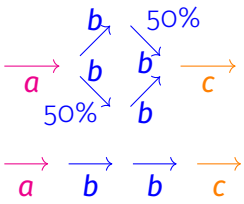

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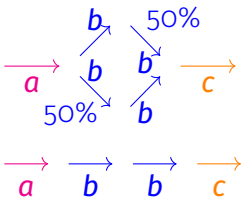

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We can always **consider all subgraphs** (exponential), but can we do **better**?

$\rightarrow$ **Exact computation**, or **approximate computation** (FPRAS):

- $\rightarrow$ Randomized algorithm with probability $> 3/4$ that computes a probability p such that the true probability p^* satisfies $(1-\epsilon)p^* \leq p \leq (1+\epsilon)p^*$, in PTIME in the input and in ϵ^{-1}

Provenance for queries on graphs

The (Boolean) provenance of a query Q on a graph G with edge set E is the Boolean function $\mathrm{Prov}(Q, G)$ on variable set E that evaluates to true on E' precisely when $G_{|E'}$ satisfies Q

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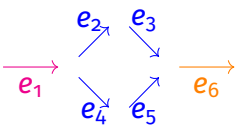
$G =$ 

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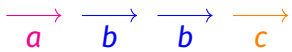
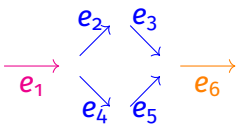
$Q =$ 

$G =$ 

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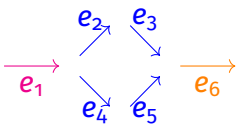
$G =$ 

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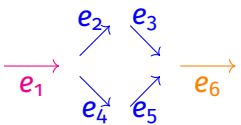
$G =$ 

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- Use tractable (approximate) model counting on the circuit

Data complexity

CQs and UCQs

For exact probabilistic query evaluation, remember Mikaël's talk:

- Dalvi-Suciu dichotomy between safe UCQs (in FP) and unsafe UCQs (#P-hard)
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- Compute all matches of the UCQ Q on the graph G
  → Each match has size $\leq |Q|$ so at most $|G|^{|Q|}$ matches: poly in data complexity
- Write this as a DNF representation of the provenance
  → DNF = disjunctive normal form
- Use the Karp-Luby-Madras algorithm to approximate #SAT on the DNF

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Open: what about lineage lower bounds?

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Combined complexity

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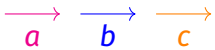
A CQ is self-join-free if it has no repeated labels, *e.g.*, 

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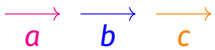
A CQ is **self-join-free** if it has no repeated labels, *e.g.*, 

For **exact** probabilistic query evaluation, recall what Mikaël presented:

- For **non-hierarchical** self-join-free CQs, the task is **#P-hard** (already in data)
- For **hierarchical** self-join-free CQs, tractable **also in combined complexity**
  → We can compute an **OBDD** for the provenance (or a d-D, cf Mikaël's proof)

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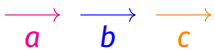
A CQ is self-join-free if it has no repeated labels, *e.g.*, 

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- For non-hierarchical self-join-free CQs, the task is #P-hard (already in data)
- For hierarchical self-join-free CQs, tractable also in combined complexity
  → We can compute an OBDD for the provenance (or a d-D, cf Mikaël's proof)

For approximate probabilistic query evaluation, result by Kuldeep and Tim:
There is a combined FPRAS for self-join-free CQs of bounded hypertreewidth

→ Amounts to computing a SDNNF of the query provenance

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For approximate probabilistic query evaluation:

- One-way path CQs with self-joins have no FPRAS assuming RP $\neq$ NP
- Open: what about one-way path CQs on a unary alphabet ($\Sigma = \{a\}$)

Restricting the data

Can we make combined probabilistic query evaluation more tractable?

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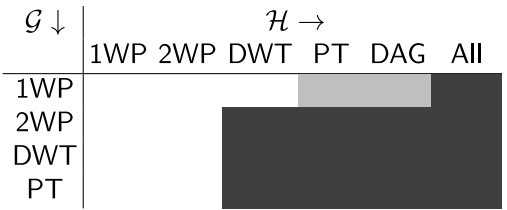

(A) Complexity of $\mathsf{PHom}_{\mathsf{L}}(\mathcal{G},\mathcal{H})$.

(B) Complexity of $\mathsf{PHom}_{\not\mathsf{L}}(\mathcal{G},\mathcal{H})$.

1WP = one-way path; 2WP = two-way path; DWT = downward tree; PT = polytree

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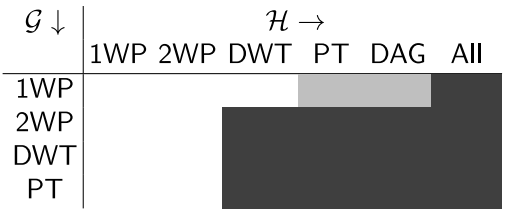

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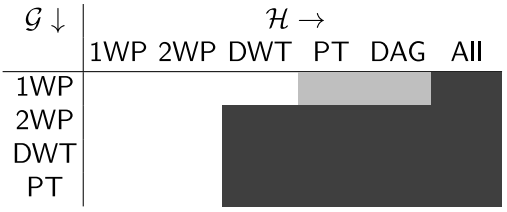

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Inapproximable cases come with DNNF lower bounds

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Thanks for your attention!

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