# Conjunctive Queries on Probabilistic Graphs: The Limits of Approximability 

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## Motivating Question 1: Operations Research



The two-terminal network reliability problem asks the following:
Given a directed graph with independent edge failure probabilities, and two vertices $s$ and $t$, determine the probability that $s$ and $t$ are connected.
Applications to verifying reliability of power transmission networks, computer networks, etc.

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Today: When the graph is a DAG, we can!

## Motivating Question 2: Probabilistic Databases

Add probability labelling $\pi$ to database $D$ to get a tuple-independent probabilistic database (TID) $H=(D, \pi)$.

Classes

|  | Lec | Rm | Time |
| :---: | :---: | :---: | :---: |
| 0.5 | alice | 02.10 | 10 |
| 0.1 | bob | 01.5 | 9 |
| 0.5 | charlie | 01.6 | 10 |

Mentors

|  | Lec | Student |
| :---: | :---: | :---: |
| 0.2 | alice | david |
| 0.5 | bob | emma |

Query: is there someone who teaches a class at 10 and mentors David?

$$
q=\exists x \exists y \cdot \operatorname{Classes}(x, y, 10) \wedge \text { Mentors }(x, \text { david })
$$

Returns: $q(D)=$ true $\operatorname{Pr}_{H}(q)=$ ?

## Motivating Question 2: Probabilistic Databases

## Theorem

Let $q$ be a Boolean conjunctive query that:

- has bounded hypertree width
- is self-join-free
- e.g., $\exists x y \cdot R(x) \wedge S(x, y) \checkmark \quad \exists x y \cdot R(x, y) \wedge R(y, z) x$

Then $q$ can be tractably approximated (FPRAS) in combined complexity on any TID.

Can we relax either of the two conditions on the query above and still always get an FPRAS?

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Can we relax either of the two conditions on the query above and still always get an FPRAS?

Today: No! (assuming RP $\neq \mathrm{NP}$ )

## Data as Graphs

To answer these motivating questions (among others), we consider the restricted setting of binary signatures-i.e., data represented as a labelled graph.

| WorkedAt |  | HasSubsidiary |  |
| :---: | :---: | :---: | :---: |
|  |  |  | BigCorp |
| Alice | BigCorp | TinyCo |  |
| Bob | MegaCo |  | AmaSoft |
| Charlie | AmaSoft |  |  |
| Charlie | BigCorp |  |  |



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- More formally: matches are homomorphisms from a query graph
- these homomorphisms need not be injective!
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- Yes
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- Denote that $G$ has a match in $H$ by $G \rightsquigarrow H$


## Uncertain Data

- Probabilistic labelled graphs



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- Vertices always stay fixed
- Probability distribution on $2^{|H|}$ subgraphs
- Special case when all probabilities are $50 \% \rightarrow$ every subgraph is equally likely


## Probabilistic Graph Homomorphism

## $\operatorname{PHom}_{\mathrm{L}}(\mathcal{G}, \mathcal{H})$

## Given:

- labelled (non-probabilistic) "query" graph $G \in \mathcal{G}$
- probabilistic labelled "instance" graph $H \in \mathcal{H}$

Compute: probability that a randomly sampled subgraph $H^{\prime} \subseteq H$ admits a homomorphism from $G$ :

$$
\operatorname{Pr}(G \rightsquigarrow H)=\sum_{H^{\prime} \subseteq H \text { s.t. } G \rightsquigarrow H^{\prime}} \prod_{e \in H^{\prime}} \operatorname{Pr}(e) \prod_{e \in H \backslash H^{\prime}}(1-\operatorname{Pr}(e))
$$

Observe that the problem is stated in terms of combined complexity (both query and instance as input).

## Probabilistic Graph Homomorphism

## $\operatorname{PHom}_{\nless}(\mathcal{G}, \mathcal{H})$

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## Graph Classes

Many possible choices for graph classes $\mathcal{G}$ and $\mathcal{H}$ :

- The class 1WP of one-way paths:

$$
a_{1} \xrightarrow{R_{1}} \ldots \xrightarrow{R_{m-1}} a_{m}
$$

- The class of two-way paths (2WP) of the form:

$$
a_{1}-\ldots-a_{m}
$$

with each - being $\xrightarrow{R_{i}}$ or $\stackrel{R_{i}}{\leftarrow}$

- $\ldots$


## Previous Work

The complexity of probabilistic graph homomorphism has been studied before for various combinations of graph classes $\mathcal{G}$ (query) and $\mathcal{H}$ (instance).
[Amarilli, Monet, and Senellart, PODS 2017]

Existing results imply the tables below.
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| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1WP 2WP | DWT | PT | DAG All |  | 1WP | 2WP | DWT | PT | DAG All |
| 1WP |  |  |  |  | 1WP |  |  |  |  |  |
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What about for approximations?

## FPRAS for Probabilistic Graph Homomorphism

## FPRAS for $\operatorname{PHom}_{\mathrm{L}}(\mathcal{G}, \mathcal{H}) / \operatorname{PHom}_{\nless}(\mathcal{G}, \mathcal{H})$

## Given:

- (non-probabilistic) "query" graph $G \in \mathcal{G}$
- probabilistic "instance" graph $H \in \mathcal{H}$
- $\epsilon, \delta>0$

Compute: a quantity $t$ such that

$$
\operatorname{Pr}[(1-\epsilon) \operatorname{Pr}(G \rightsquigarrow H) \leq t \leq(1+\epsilon) \operatorname{Pr}(G \rightsquigarrow H)] \geq 1-\delta
$$

in time polynomial in $|G|,|H|, \epsilon^{-1}$, and $\delta^{-1}$

## FPRAS for Probabilistic Graph Homomorphism

## Query G:

$$
x \xrightarrow{\text { WorkedAt }} y \xrightarrow{\text { HasSubsidiary }} \boldsymbol{z}
$$

Instance $H$ :


- Transform the instance graph to one in which all probabilities are $50 \%$-the problem now is equivalent to counting subgraphs that admit a homomorphism from $G$
- The key idea: intensional query evaluation. We build a non-deterministic ordered binary decision diagram (nOBDD) $\Delta$ that represents the Boolean provenance of $G$ on $H$. Satisfying assignments of $\Delta$ are in bijection with the subgraphs of $H$ admitting a homomorphism from $G$
- We can then apply an off-the-shelf FPRAS for counting the satisfying assignments of $\Delta$
[Arenas, Croquevielle, Jayaram, and Riveros, J. ACM 2021]


## Crash course: (n)OBDDs

Ordered binary decision diagrams (OBDDs): compact representations of Boolean functions.

$$
(x \wedge y) \vee(z \wedge w)
$$



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Non-deterministic ordered binary decision diagrams (nOBDDs): even more compact representations of Boolean functions.

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## Theorem

Every nOBDD admits an FPRAS for counting its satisfying assignments.

## Probabilistic Graph Homomorphism via nOBDDs



## Probabilistic Graph Homomorphism via nOBDDs



## Theorem

PHom ${ }_{\mathrm{L}}$ (1WP, DAG) admits an FPRAS.

## Refined Perspective

We can also show a number of inapproximability results (not discussed today), conditional on RP $\neq \mathrm{NP}$.

Taken together with our approximability results, we may refine the table earlier:

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We also get unconditional circuit lower bounds on the size of Boolean provenance representations in a mildly tractable form (DNNF), for all of the inapproximable pairs.

## Application to Operations Research



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## Theorem

The two-terminal network reliability problem on DAGs admits an FPRAS.

Was an open problem specifically posed for DAGs.

## Network Reliability: Example 1

Consider computing the probability that nodes 1 and 6 are connected, where each link fails independently with a given probability.

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\operatorname{Pr}(\text { node } 1 \text { and } 6 \text { connected })=\operatorname{Pr}(G \rightsquigarrow H)
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## Network Reliability: Example 2

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$$
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$$

$\operatorname{Pr}($ node 1 and 6 connected $) \neq \operatorname{Pr}(G \rightsquigarrow H)$

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Queries $G_{1}=\longrightarrow \longrightarrow \longrightarrow$ and $G_{2}=\longrightarrow \longrightarrow$
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## Conclusion and Future Work

## Recap

- Studied the (in)approximability of probabilistic graph homomorphism in combined complexity, and also showed lower bounds on tractable (DNNF) provenance circuit sizes
- Results show that \#P-hardness usually implies hardness of approximation, with important exception of one-way path queries on DAGs


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## Future work

- Figuring out missing gaps (approximability status of $\mathrm{PHom}_{火}(1 \mathrm{WP}$, All) and PHom $_{k}$ (DWT, All))
- Extensions to richer queries and graph classes (e.g., bounded DAG-width, disconnected queries, recursion)
- Lifting to general prob. database setting, i.e., signatures of arbitrary arity


## Thank you! Questions?

