Selected Research Topics

Mikaël Monet

Simons Institute's *Meet the Fellows* day

Berkeley, Friday September 8th, 2023

Academic career

2012–2015: Engineering school

2014–2015: Parisian master of research in computer science

2015–2018: PhD at Télécom Paris with **Pierre Senellart** and **Antoine Amarilli**, on "Combined Complexity of Probabilistic Query Evaluation"

2019–2020: Postdoc at Millennium Institute for Foundational Research on Data (Santiago, Chili) with **Pablo Barceló**

Octobre 2020–: Research position at Inria Lille

Uncertain data, provenance and knowledge compilation

Uncertain data

- Real-world data can be uncertain
    - missing values
    - inconsistent data sources
    - information extraction from the Web
    - machine learning techniques (NLP, etc.)
    - imprecise sensors in experimental sciences
    - ...

→ We need methods to manage this uncertainty

- Main models for relational data: probabilistic or incomplete databases

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Applies		π
Alice	Inria	0.9
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Bob	Inria	0.2
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$\Pr((D,\pi) \models q) = \sum_{\substack{D' \subseteq D \\ D' \models q}} \Pr(D')$ **exhaustive computation is too costly!**

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we can use it for probabilistic computation!

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→ Knowledge compilation: studies Boolean function representations with "good properties"
  - → propositional formulas (DNF, CNF)
  - → Binary Decision Diagrams (OBDDs, FBDDs)
  - → restricted classes of Boolean circuits (NNF, d-DNNF, dec-DNNF, SDDs, d-D, d-SDNNFs etc.)

Relevance score of tuples for query answering

Provenance can also be used to compute so-called Shapley values

Definition: problem $\mathsf{Shapley}(q)$

Input: A database D and a tuple $f \in D$

Output: The value $\mathsf{Shapley}(q, D, f)$

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Similar results for the **SHAP-score** from ML (With Marcelo Arenas, Pablo Barceló and Leopoldo Bertossi).

A hardness result on counting weighted matchings for unbounded-treewidth graph families

Counting weighted matchings and treewidth

Let $\mathcal{G}$ be a family of (undirected) graphs.

Definition: problem ProbMatch($\mathcal{G}$)

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Theorem [With Antoine Amarilli]

Let $\mathcal{G}$ be an arbitrary family of graphs having unbounded treewidth which is *treewidth constructible*. Then ProbMatch($\mathcal{G}$) is intractable.

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Result [With Antoine Amarilli]

We characterize exactly what are the regular languages that are enumerable. When it is the case we provide an algorithm that enumerates the words with a constant delay (the delay depends on the language but not on the length of the current word).

An open problem about perfect matchings in the Boolean lattice

An open problem (1/3)

- A matching of an undirected graph $G = (V, E)$ is a subset $M \subseteq E$ of edges such that $e \cap e'$ for all $e, e' \in M$.
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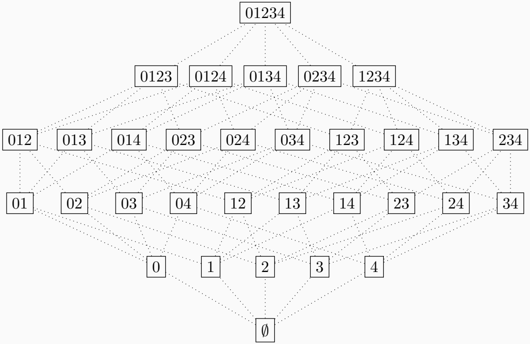
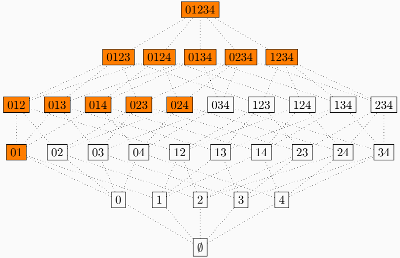
Let's consider the Boolean lattice over k elements. Example for $k = 5$:



An open problem (2/3)

Let O be a set of nodes that is upward-closed and such that O has as many nodes of even size as nodes of odd size. Example: $O =$ the orange nodes



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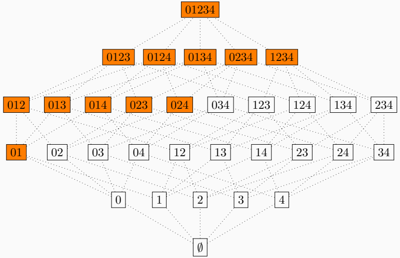

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For any k and O satisfying this property, then: either the graph induced by O has a perfect matching, or the complement graph has a perfect matching.

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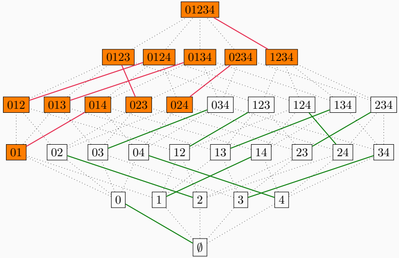

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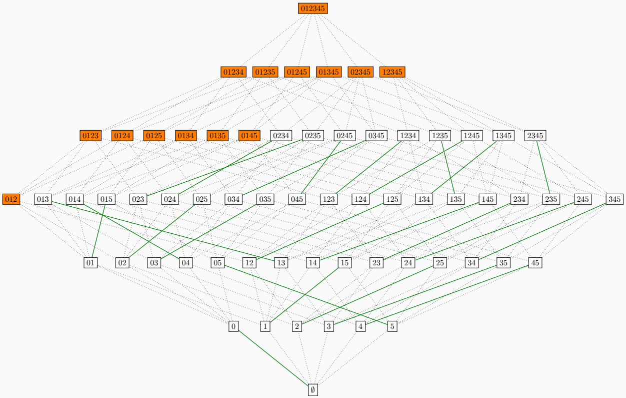
An open problem (3/3)

In some cases, one the top or the bottom graph (but not both) has a perfect matching. Example:



Computer search for counterexample: none so far.

Thanks for your attention!