Tractability and Optimization of Shap-Score Computation for Explainable AI

Leopoldo Bertossi

Explanations in Machine Learning

- Bank client $\mathbf{e} = \langle \text{john}, 18, \text{plumber}, 70\text{K}, \text{harlem}, \ldots \rangle$

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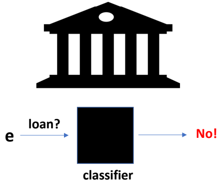

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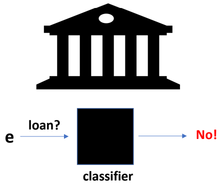
- The client asks *Why?*



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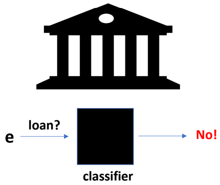

- The client asks *Why?*

- What kind of *explanation?*

  How?

  From what?

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  In data management and machine learning
- Some of them (in data management or ML)
  - Responsibility (in its original and generalized versions)
  - The Causal Effect score
  - The Shapley value (as Shap in ML)

Shap Scores

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- For $S \subseteq \mathcal{F}$, and $\mathbf{e}_S$ the projection of $\mathbf{e}$ on S:

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- Assumes a probability distribution on entity population

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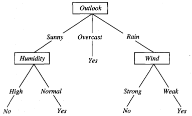

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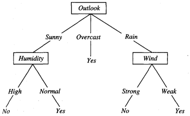

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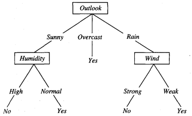

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- Can we compute *Shap* in polynomial time?

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- We investigated this problem in detail[1]

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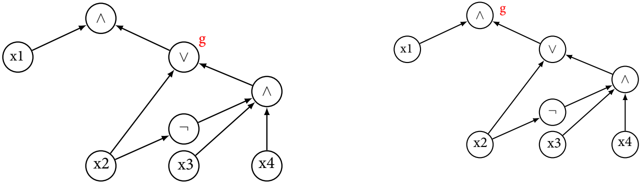
- Theorem: *Shap* can be computed in polynomial time for dDBCs under the uniform distribution
- Can be extended to a product distribution on $\mathcal{E} = \{0,1\}^N$



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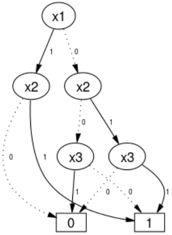
Compatible variable orders along full paths

Compact representation of Boolean formulas



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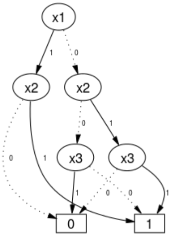

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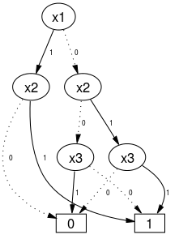

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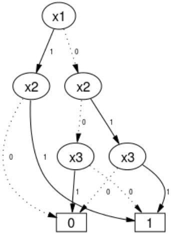

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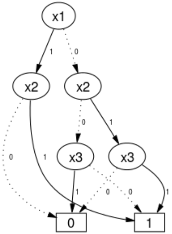

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- An optimized efficient algorithm for *Shap* computation can be applied to any of these

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- Particularly if the target dDBC will be used multiple times, as is the case for explanations
- We illustrate the approach by means of an example

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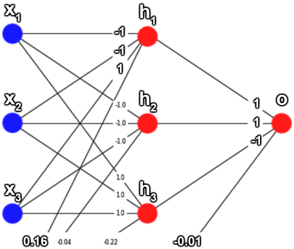

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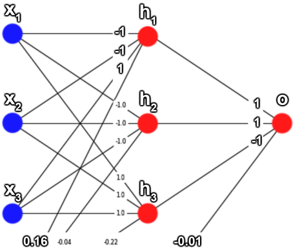

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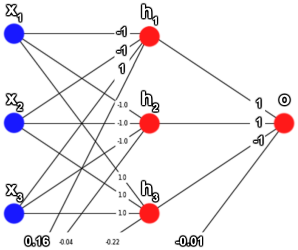

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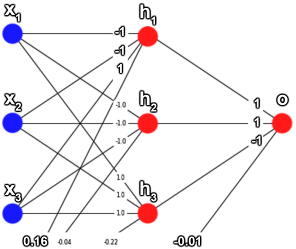

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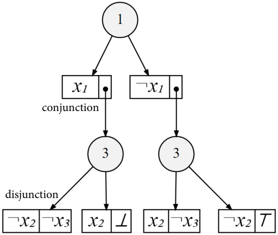

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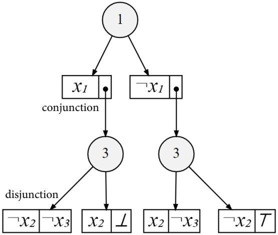

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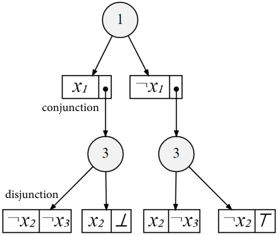

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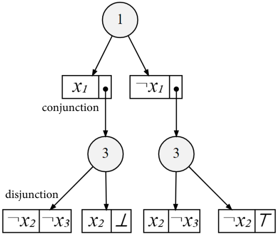
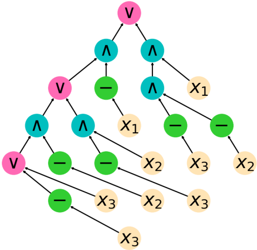
- The SDD is easily transformed into a dDBC





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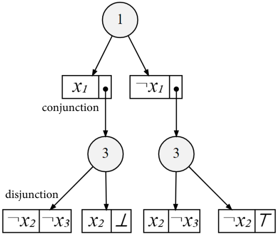

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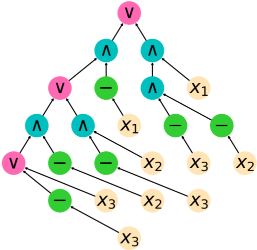
  A measure of how close it is to a tree
  (In example, graph is clique, TW is #vars -1 =2)



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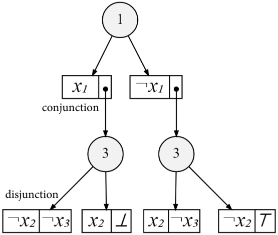

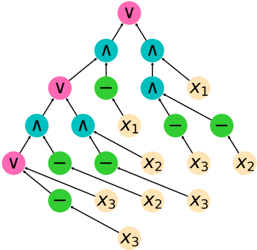

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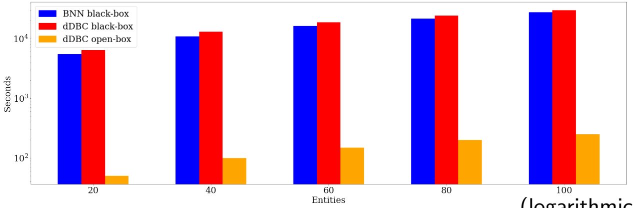

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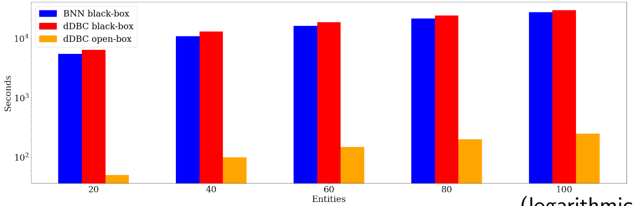

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  How far can we go with other distributions?

  Do we still have an efficient algorithm?

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  Specific general and expected properties for Explanations Scores (in AI)?