How Robust are Thresholds for Community Detection?

Alex Wein (MIT)

Joint with Ankur Moitra (MIT) and Will Perry (MIT)

Two Worldviews

Convex Optimization

Statistical Physics

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- Algorithm: semidefinite programming (SDP)
  - Most powerful known algorithm for various worst-case and average-case problems

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  - Integrality gaps
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And if they don’t agree, which one is correct?

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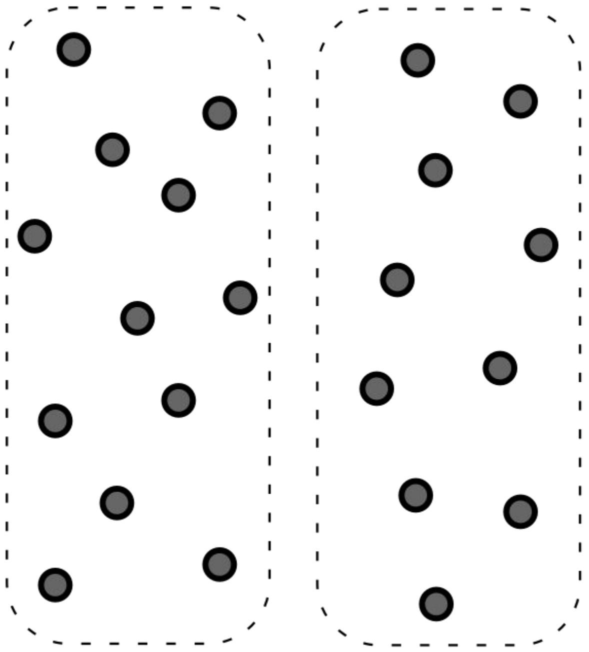

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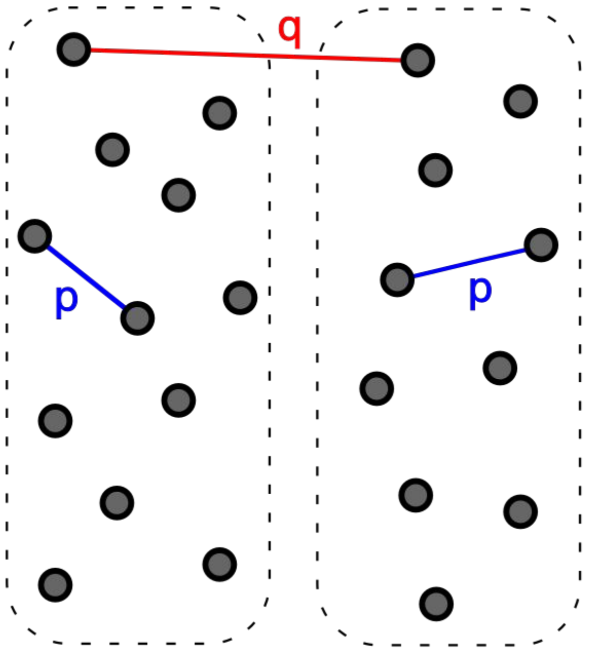

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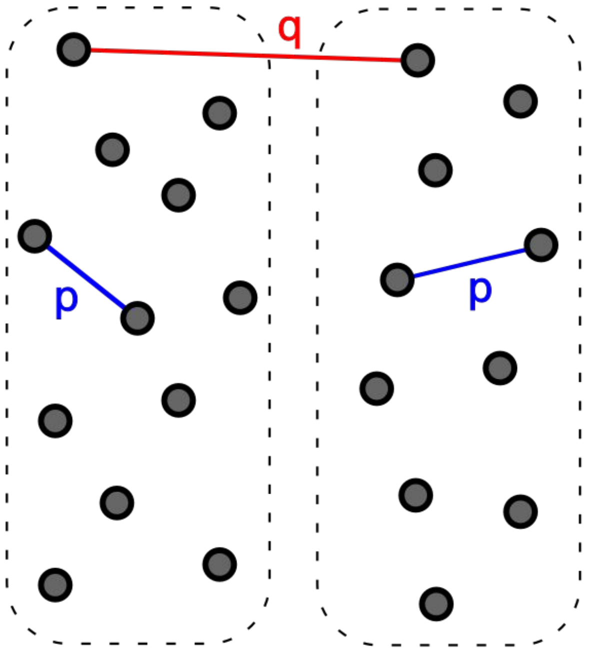

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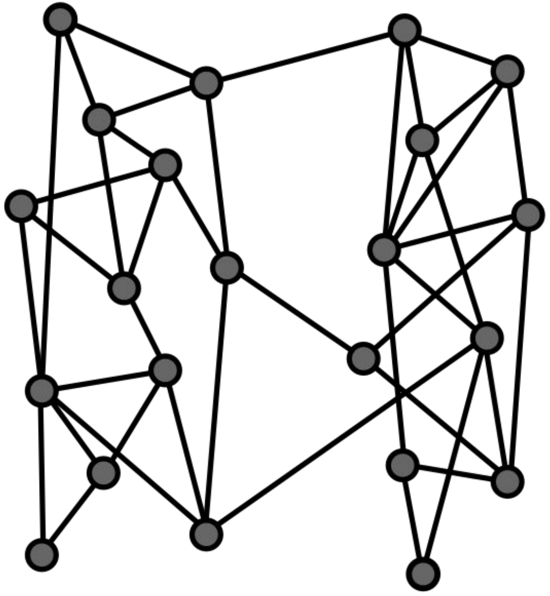

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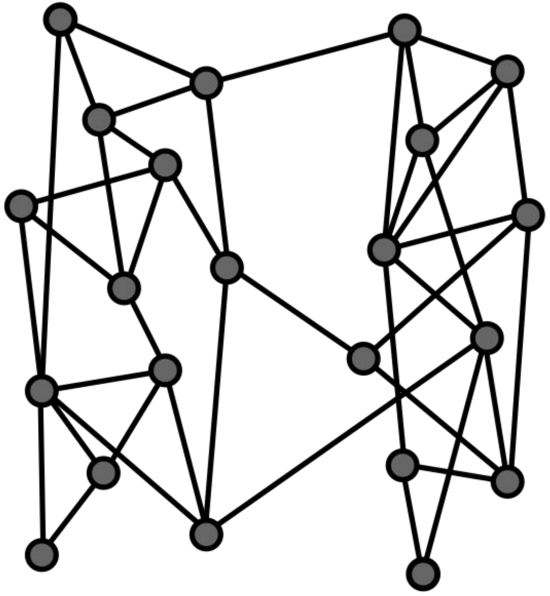
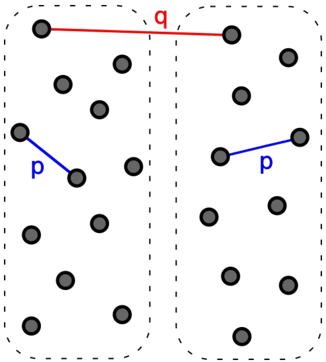


Studied in statistics, information theory, computer science, statistical physics, ...

Sharp Threshold Behavior



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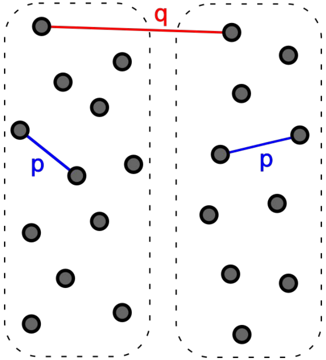

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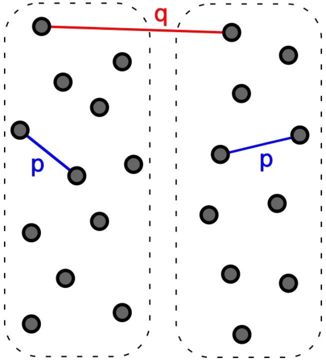

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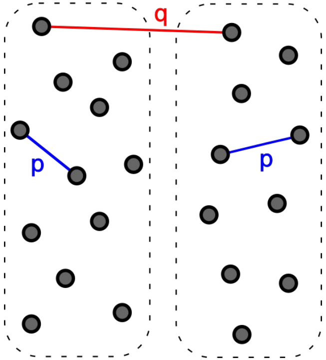

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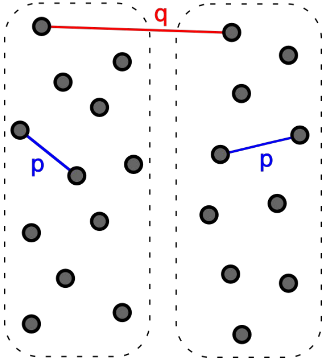

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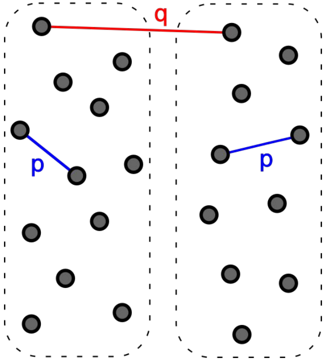

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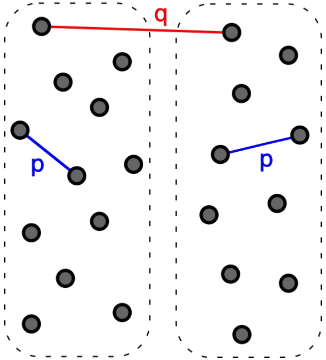

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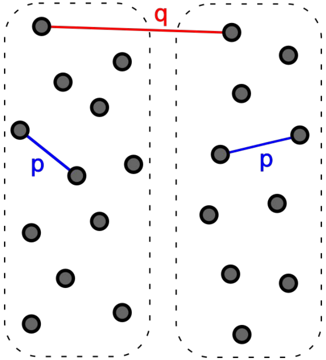

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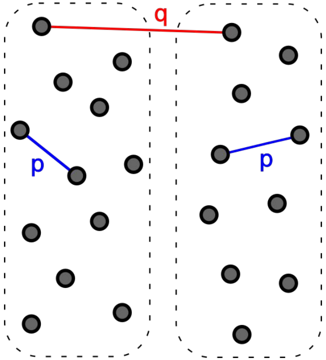

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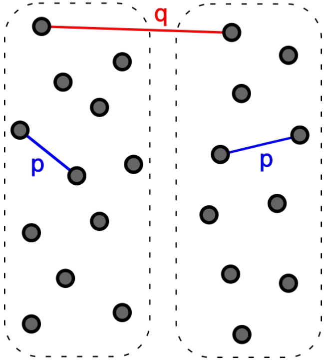

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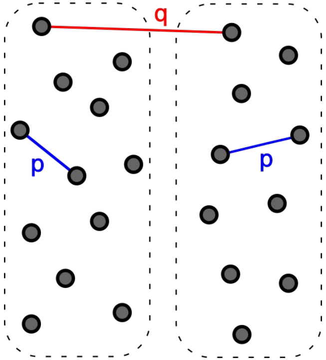

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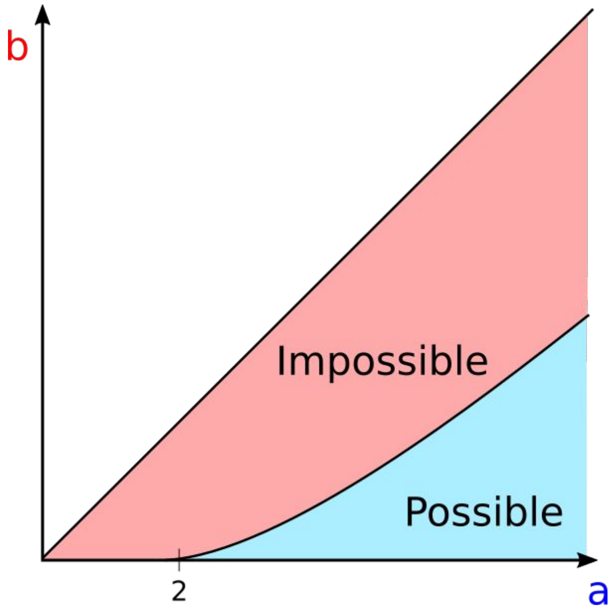

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Answer: We will give evidence that SDPs cannot reach the threshold! — but only because they are actually solving a harder problem.

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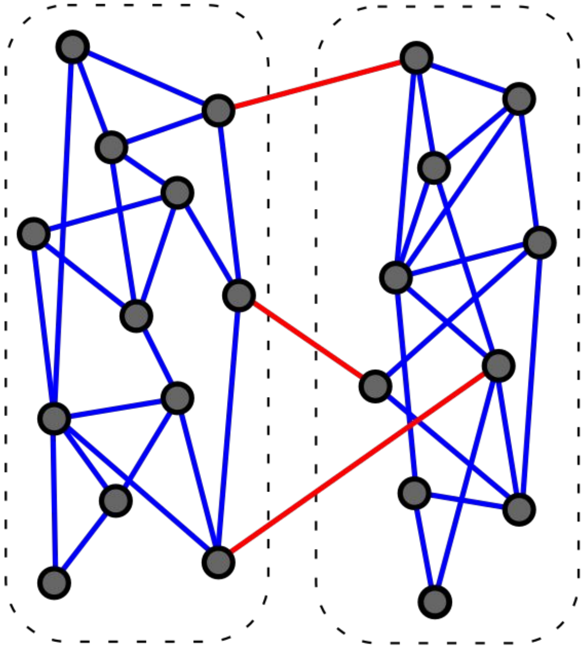

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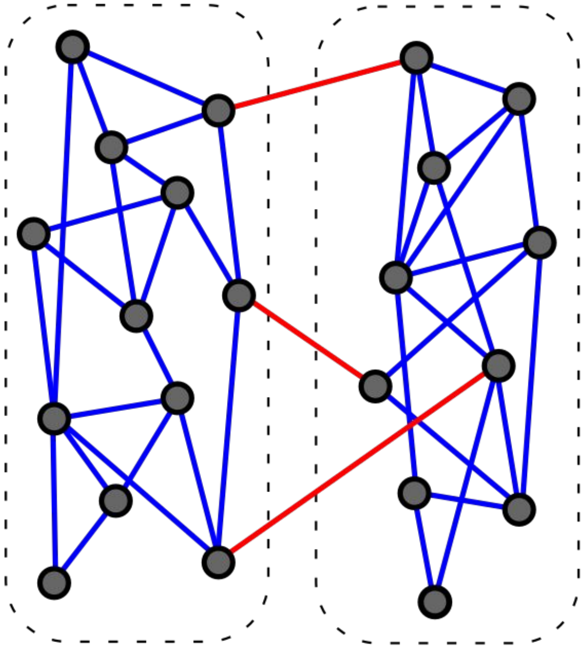

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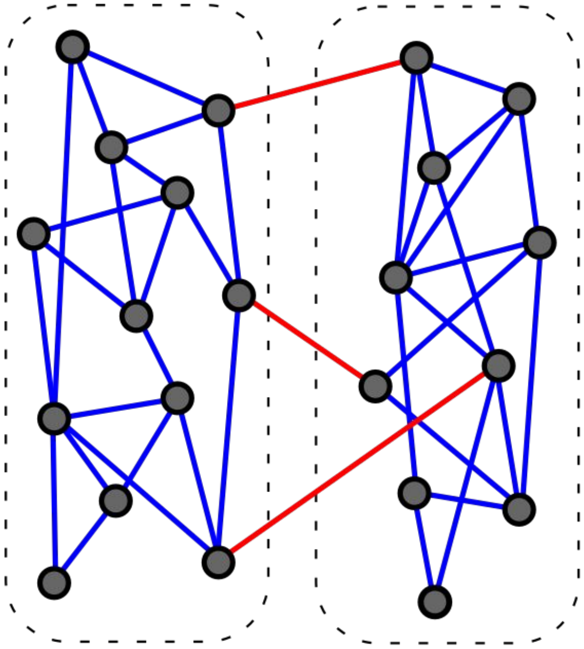

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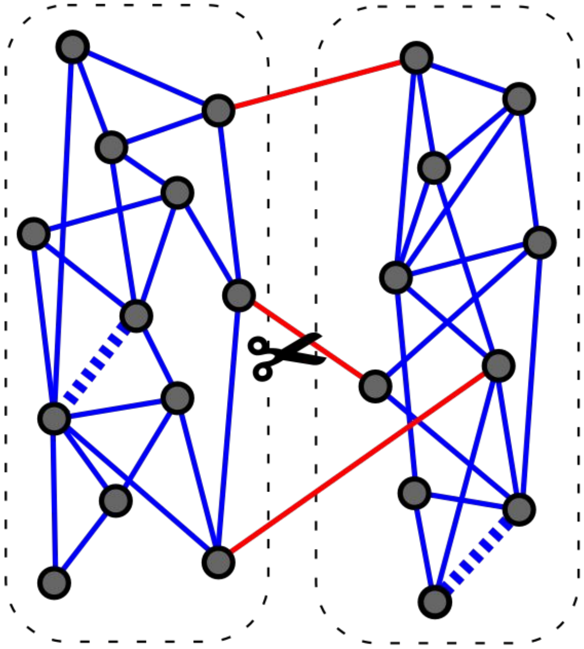

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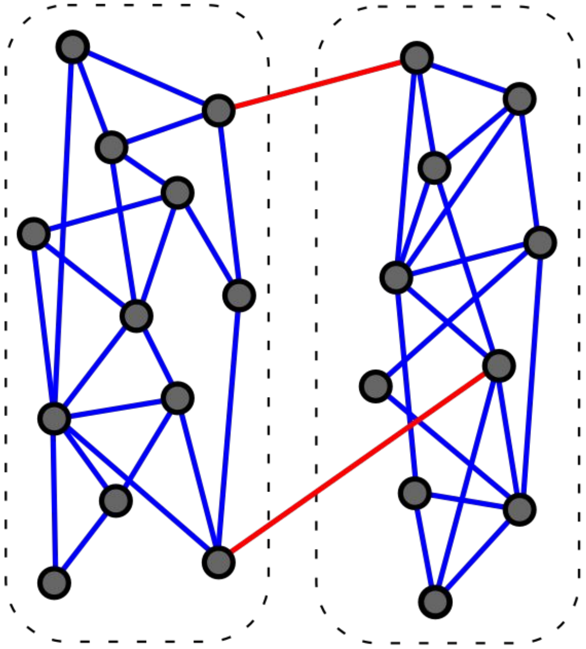

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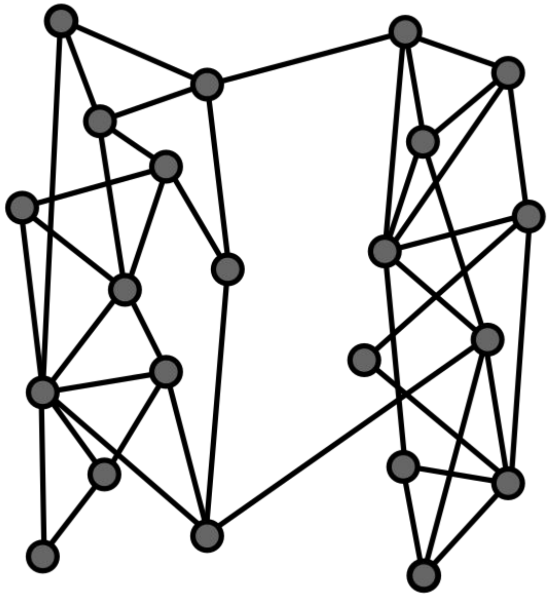

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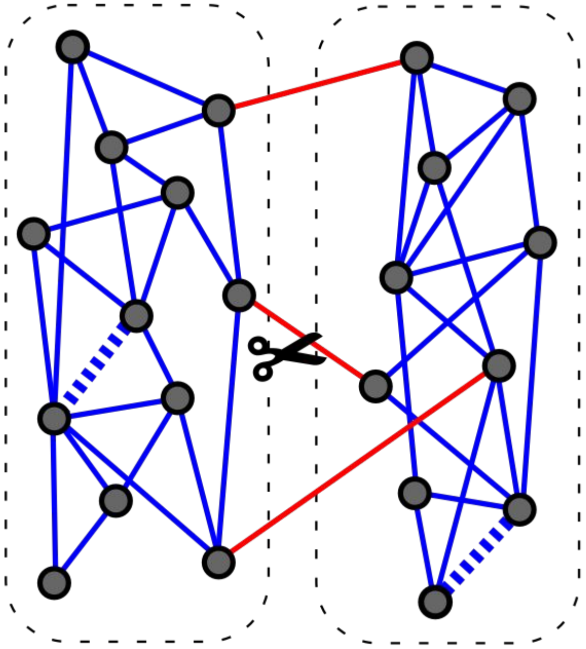

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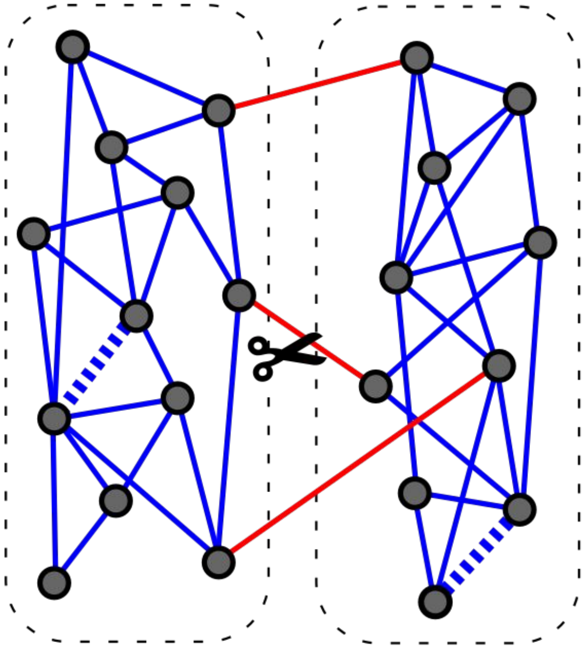

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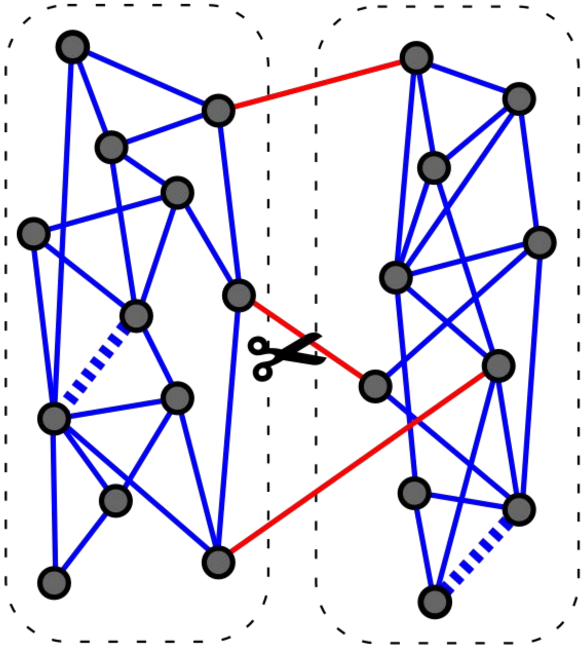

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Captures some notion of 'robustness'

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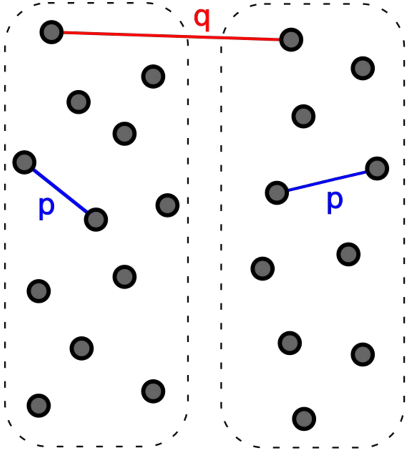

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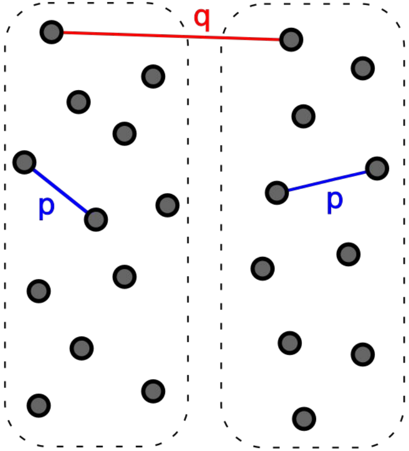

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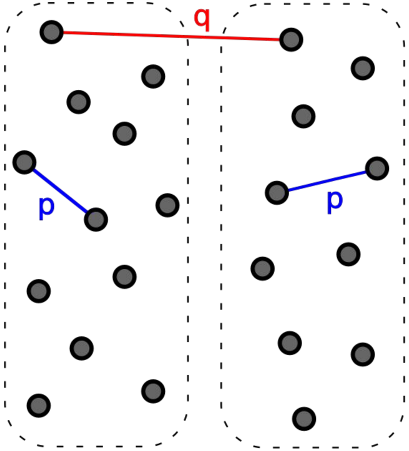

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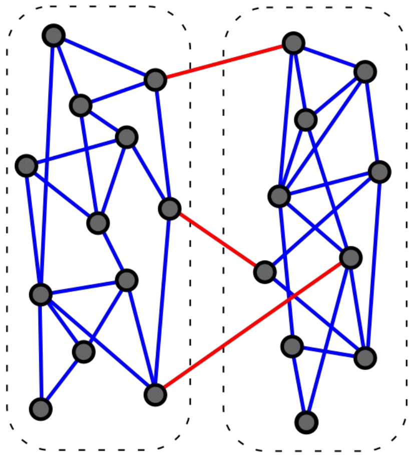

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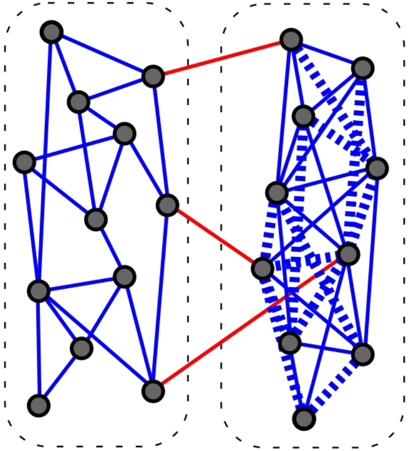
Semirandom model: adversary can break this — add a clique on one community



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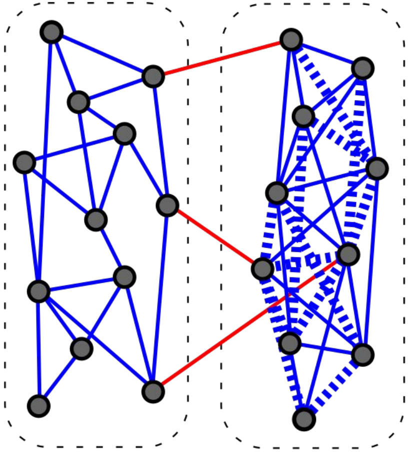

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- Open: Can [Montanari–Sen '15] analysis be made robust?

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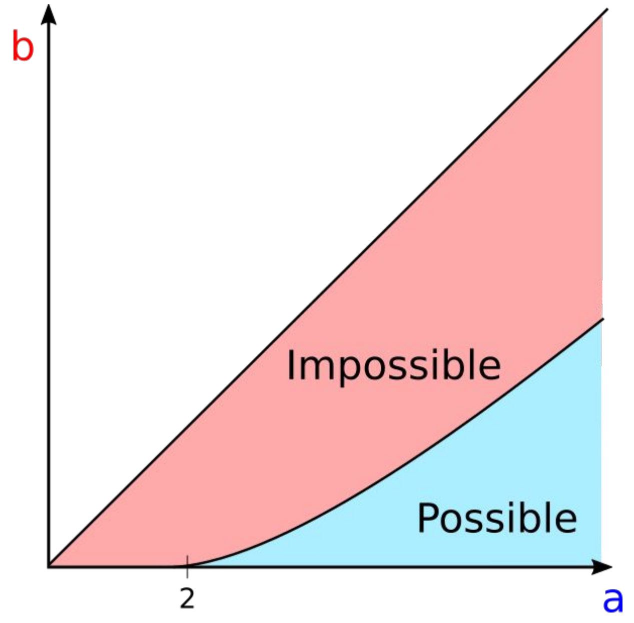

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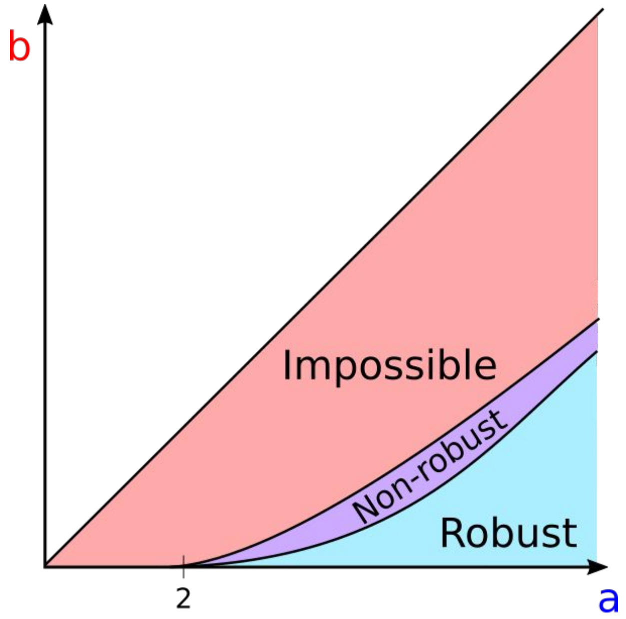

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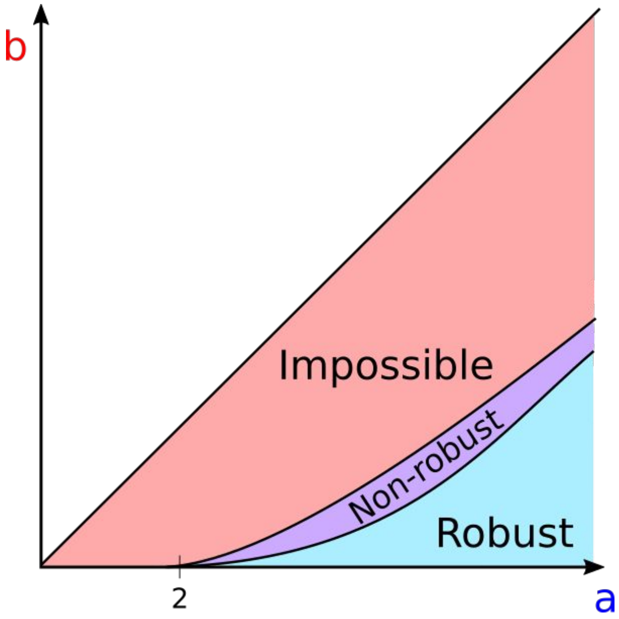

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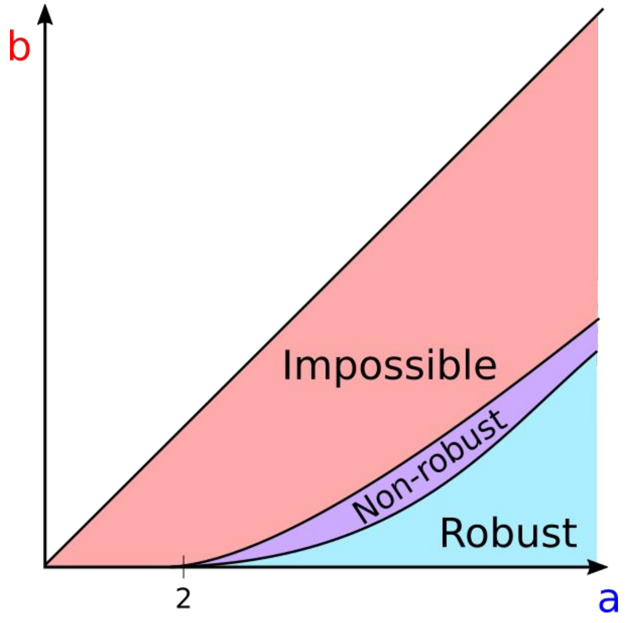

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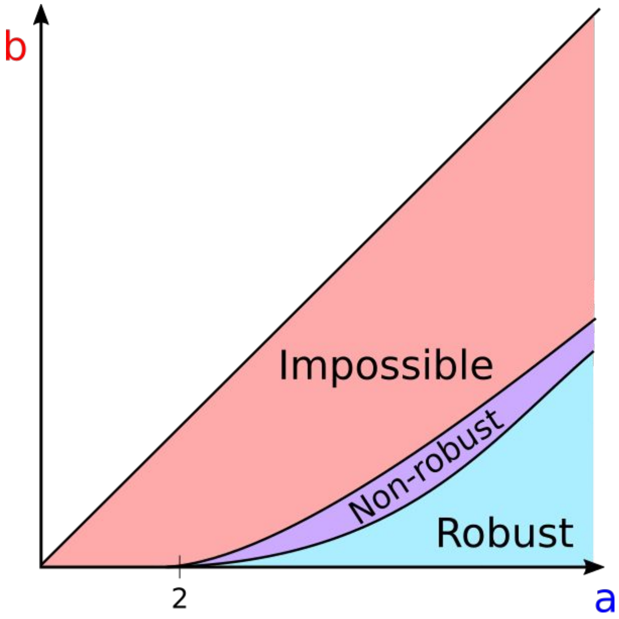

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Additional evidence: statistical physics predicts (non-rigorous) that SDP misses the threshold [JMR'15]

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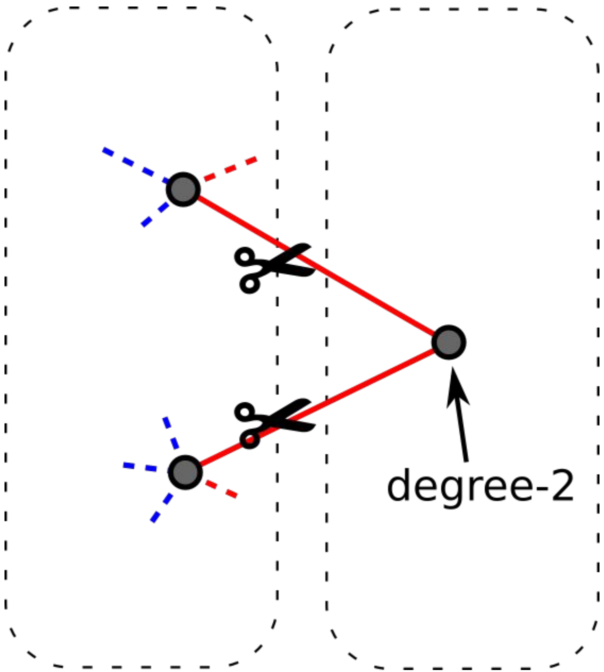

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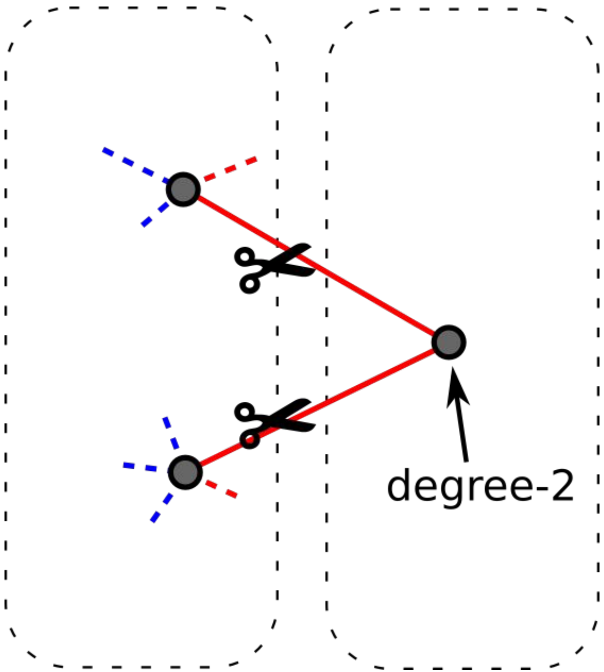

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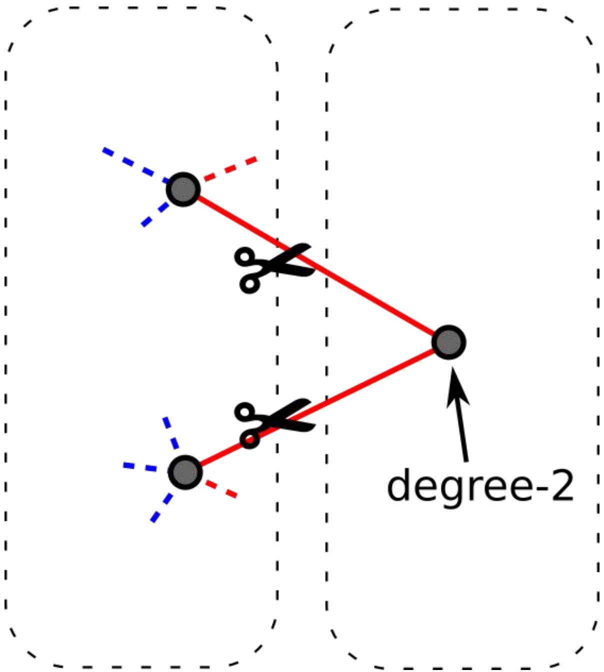

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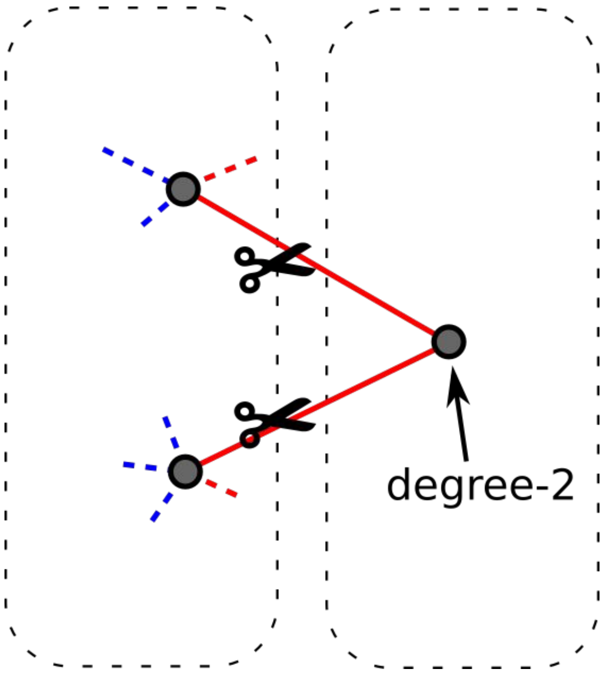

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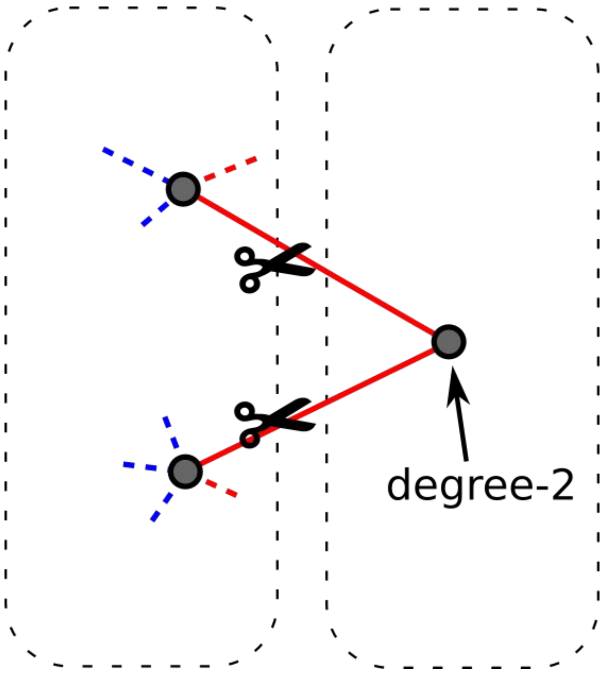
Interpretation: algorithms reaching the threshold (e.g. linearized belief propagation) rely on the distribution of these structures in the noise



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Use connection to ***broadcast tree model***

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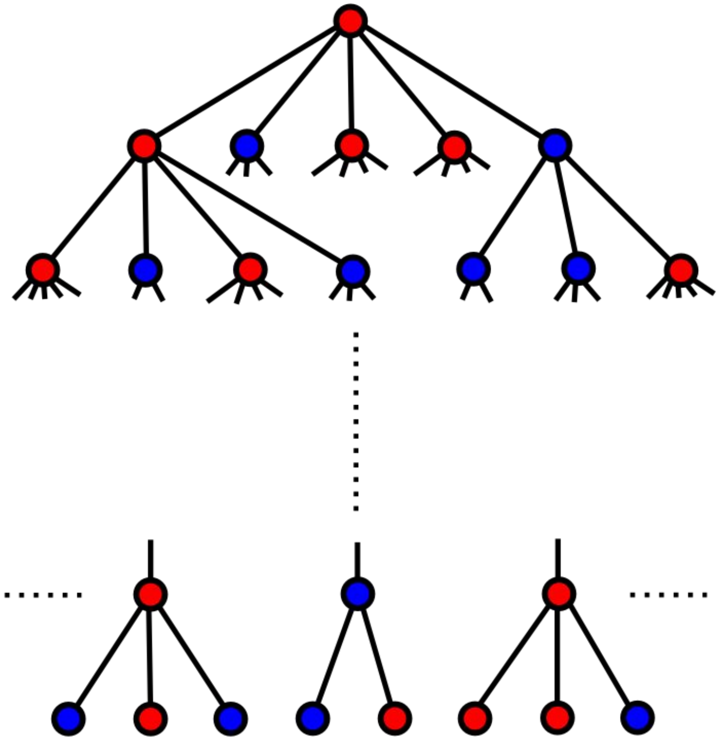

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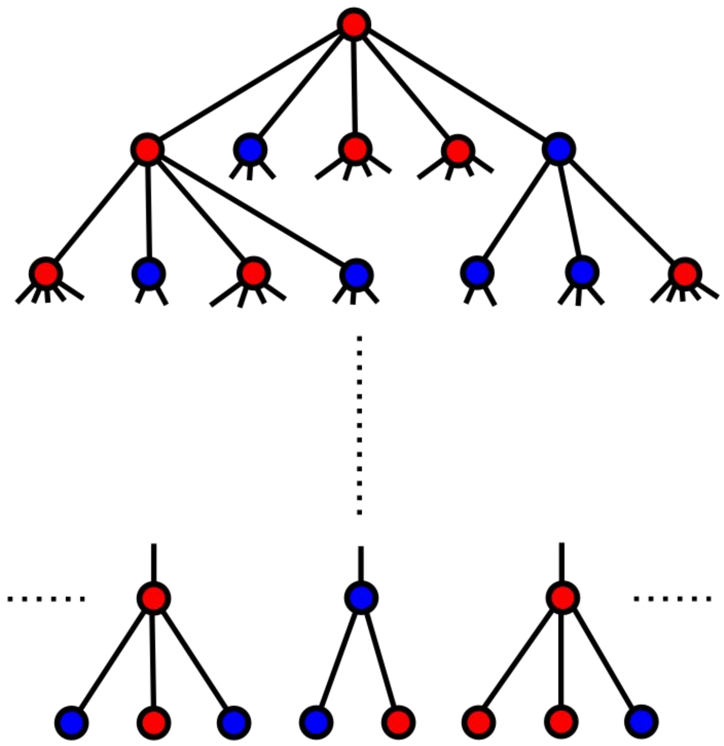
2 colors: red, blue (corresponding to 2 communities)



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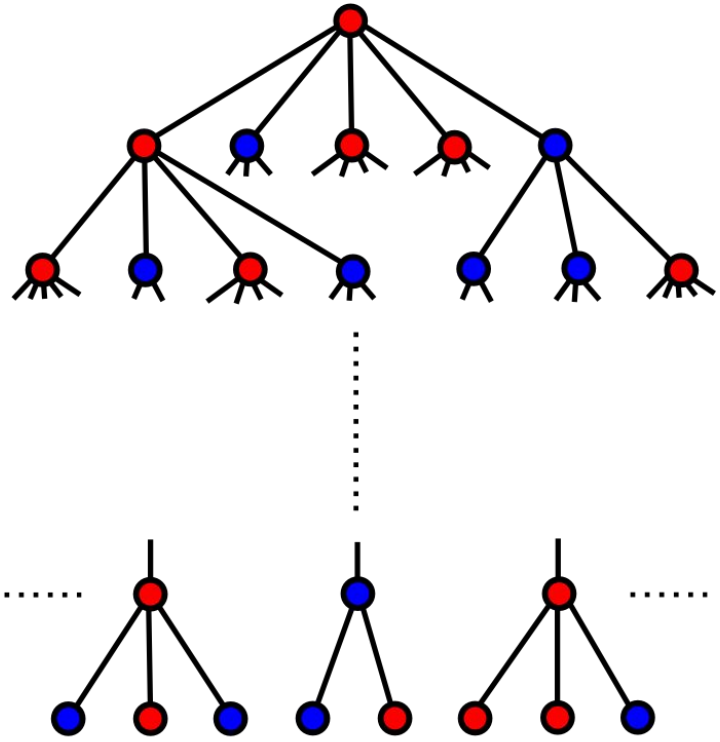

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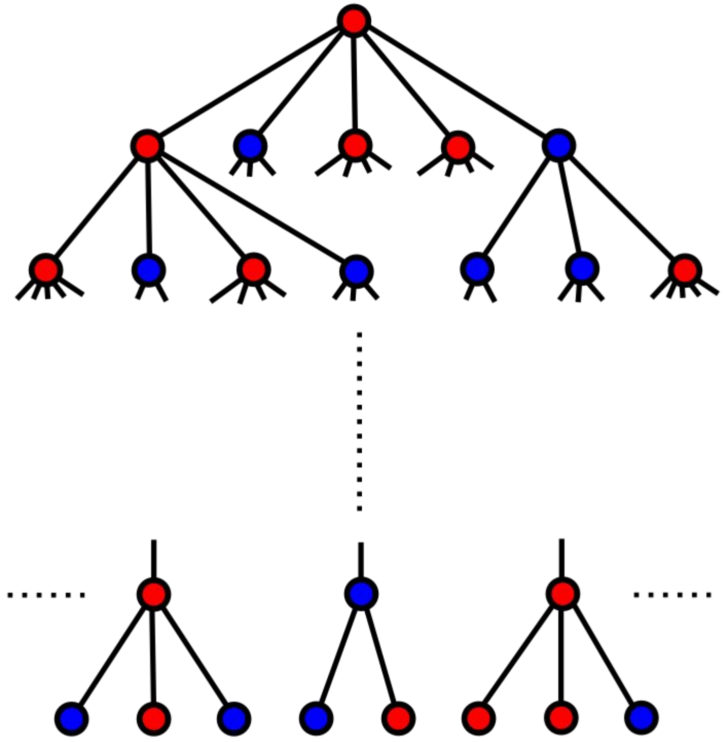

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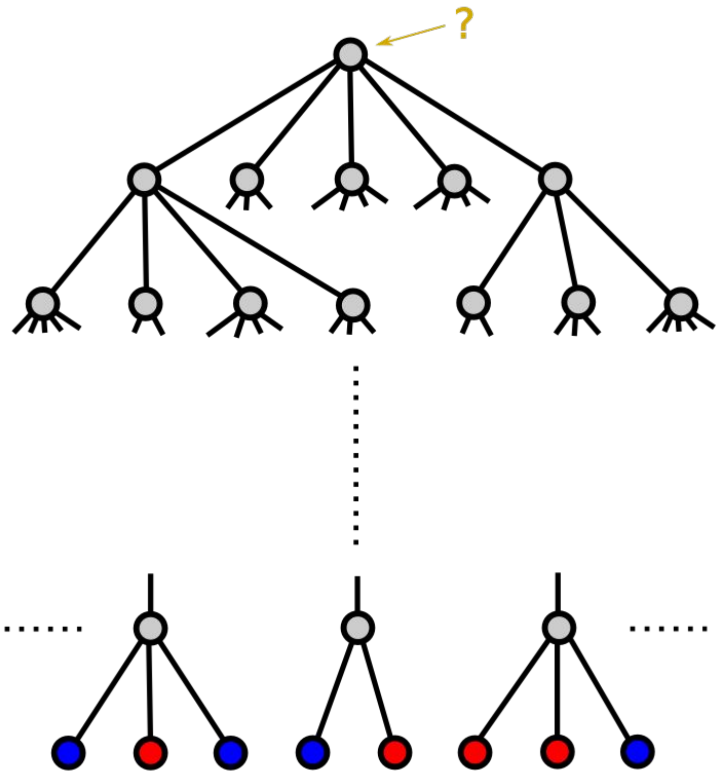

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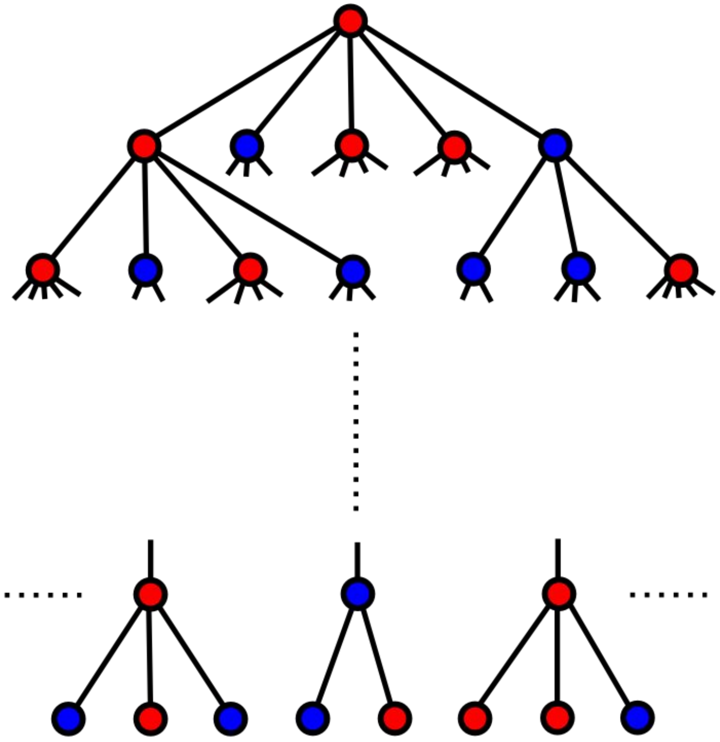
[Kesten-Stigum '66, Evans-Kenyon-Peres-Schulman '00]



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