

Phase Transitions via Complex Extensions of Markov Chains

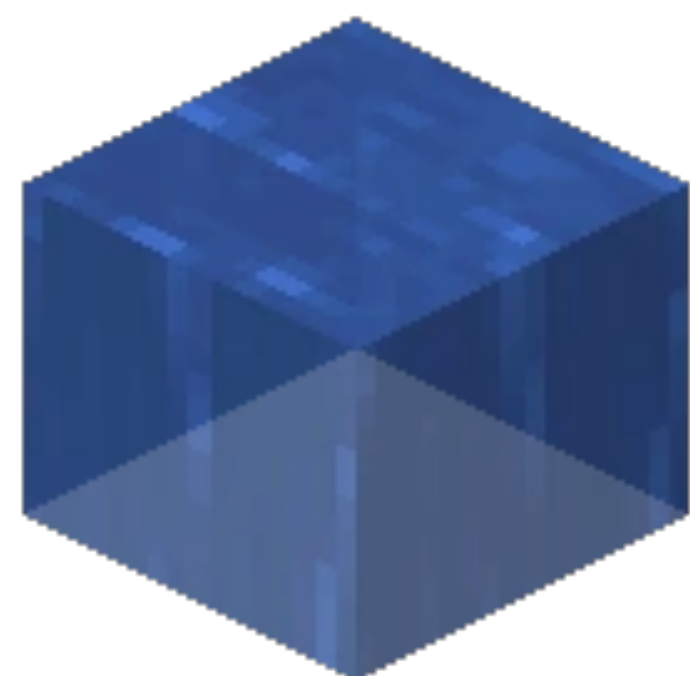
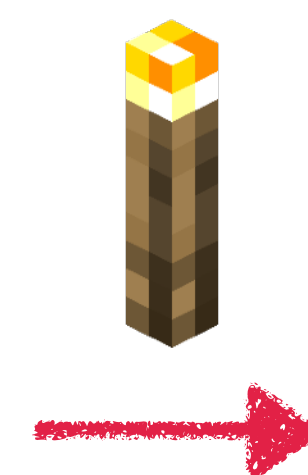
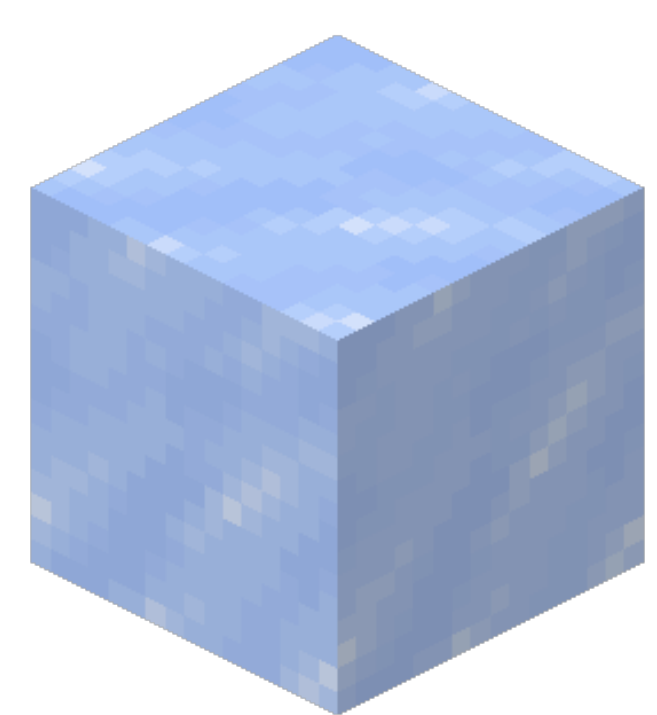
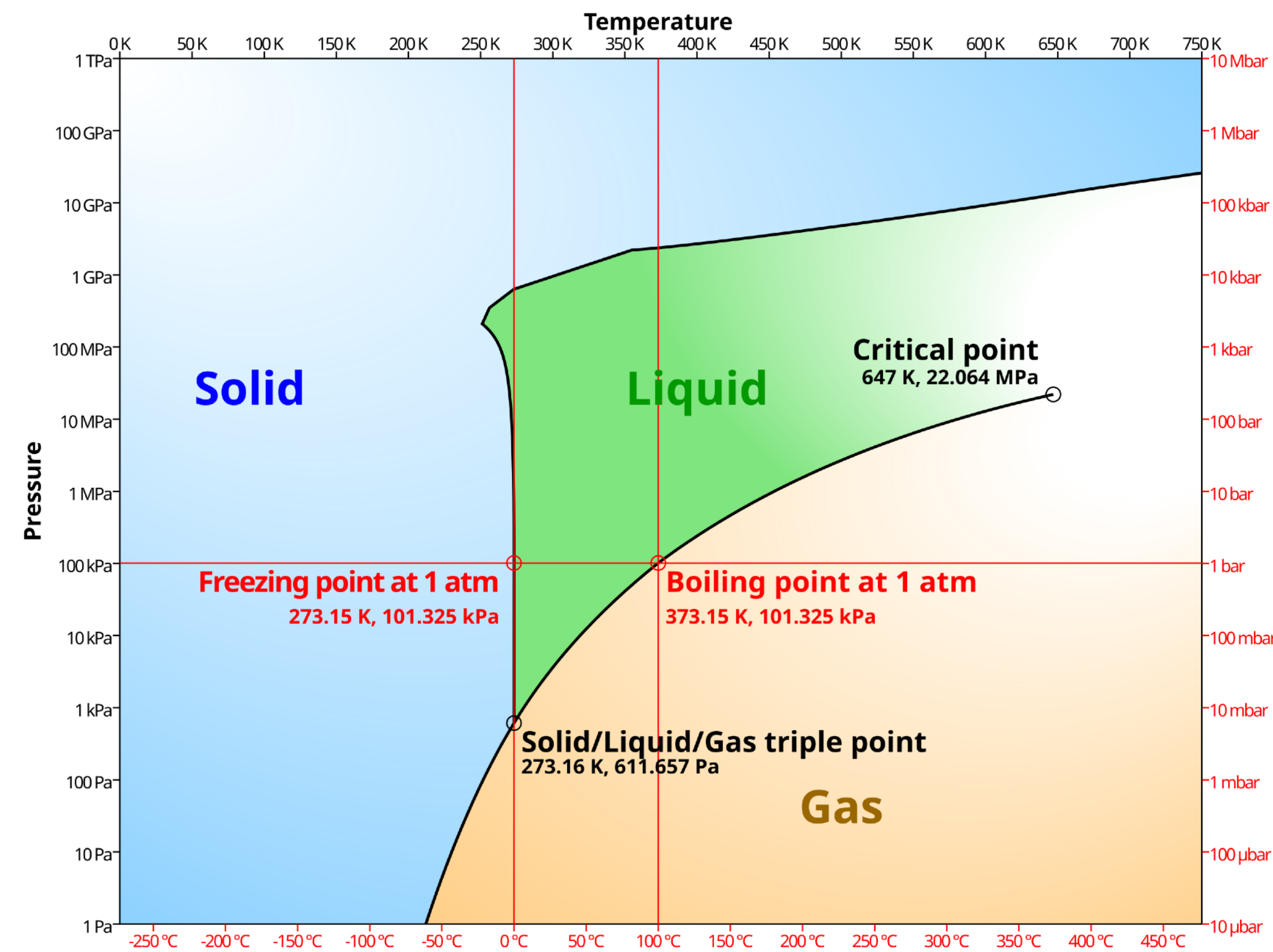
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Nanjing University

Joint work with Jingcheng Liu, Chunyang Wang and Yitong Yin

STOC 2025

Phase transition



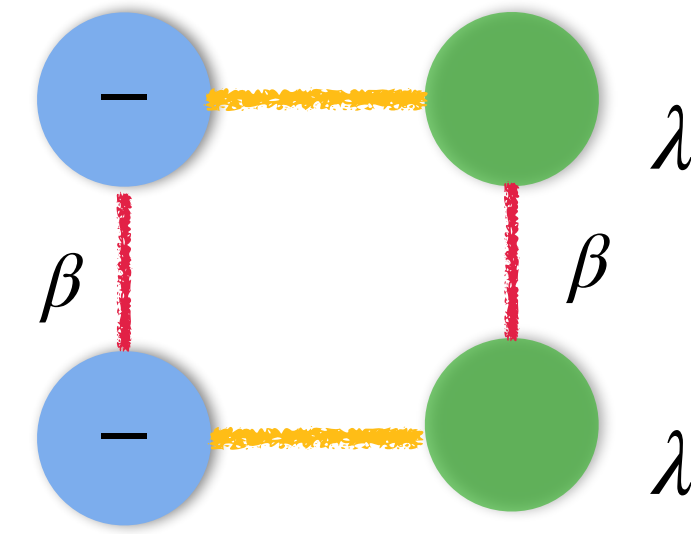
water's phase transition

Phase transition and zero-freeness

Lee-Yang theory: phase transition \approx complex zeros of partition function.



Example of zero-free region



Example of spin system

Computational phase transition - an example

Hardcore model

A graph $G = (V, E)$, a vertex weight $\lambda > 0$.

Ω : set of independent set.

Partition function $Z = \sum_{X \in \Omega} \lambda^{|X|}$. Gibbs distribution: $\forall X \in \Omega, \mu(X) = \frac{\lambda^{|X|}}{Z}$.

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Approximately sample an independent set in μ .

Approximately compute the partition function Z .

(They are equivalent by [Jerrum, Valiant, Vazirani'86]).

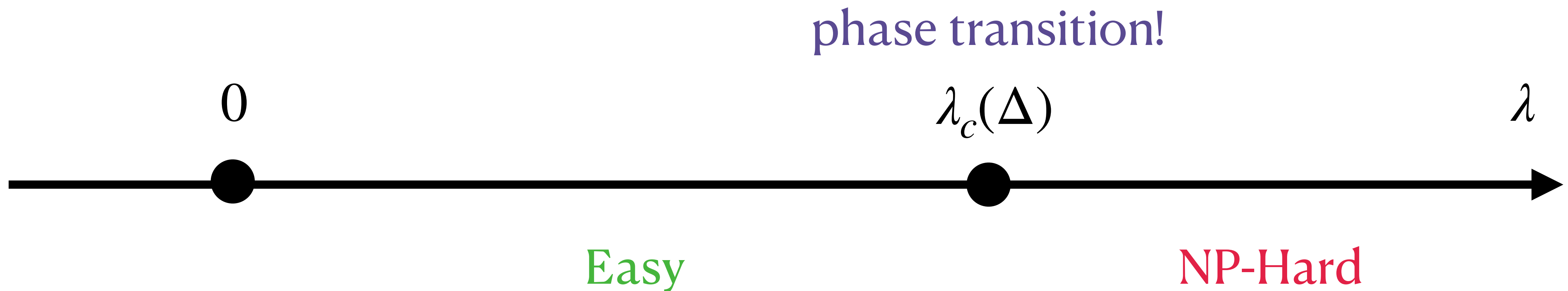
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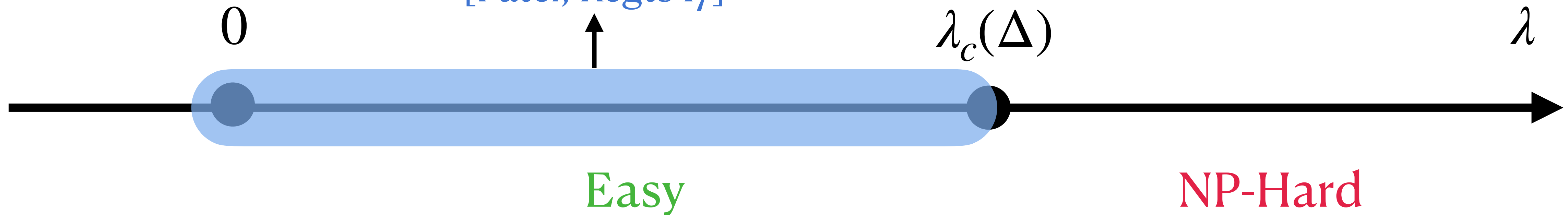
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Zero-freeness, $Z(\lambda) \neq 0$
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Computational phase transition - an example

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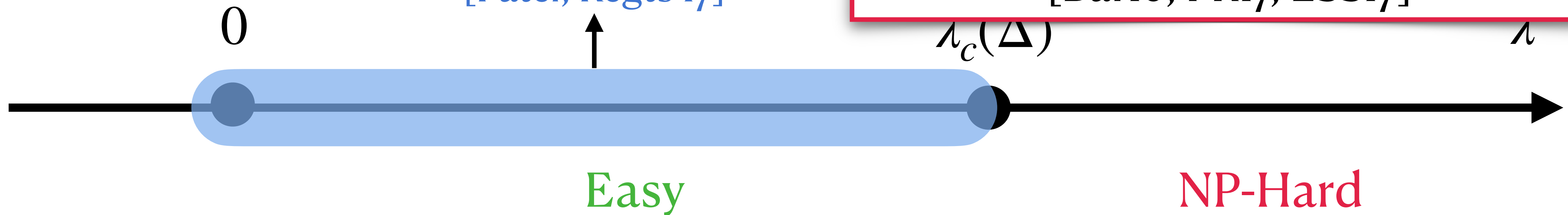
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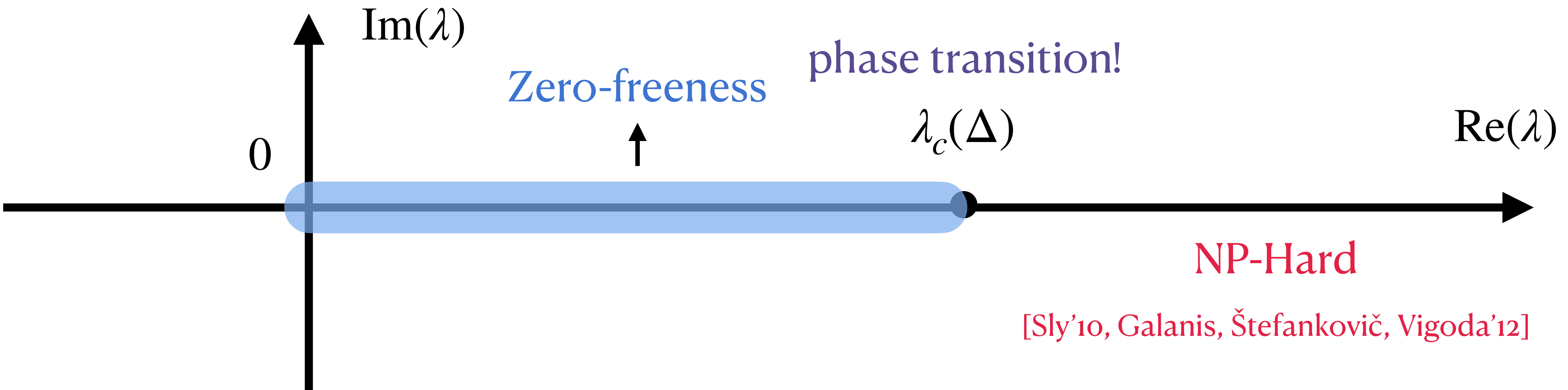
This implies an FPTAS by the polynomial interpolation method.

[Bar16, PR17, LSS17]

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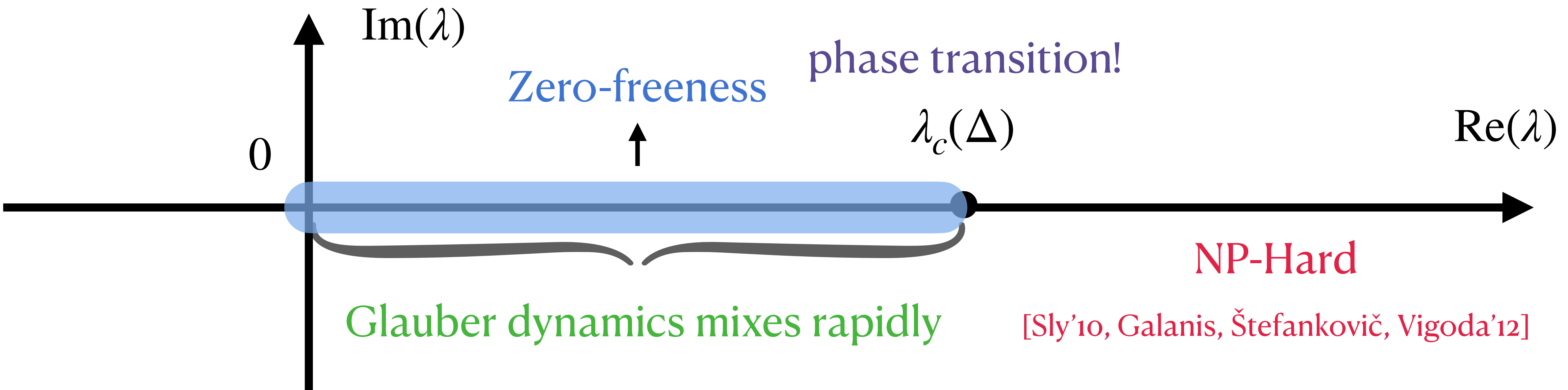
Computational phase transition - an example



Different notions of phase transition matching $\lambda_c(\Delta)$:

Zero-freeness: [Patel, Regts'17]

Computational phase transition - an example

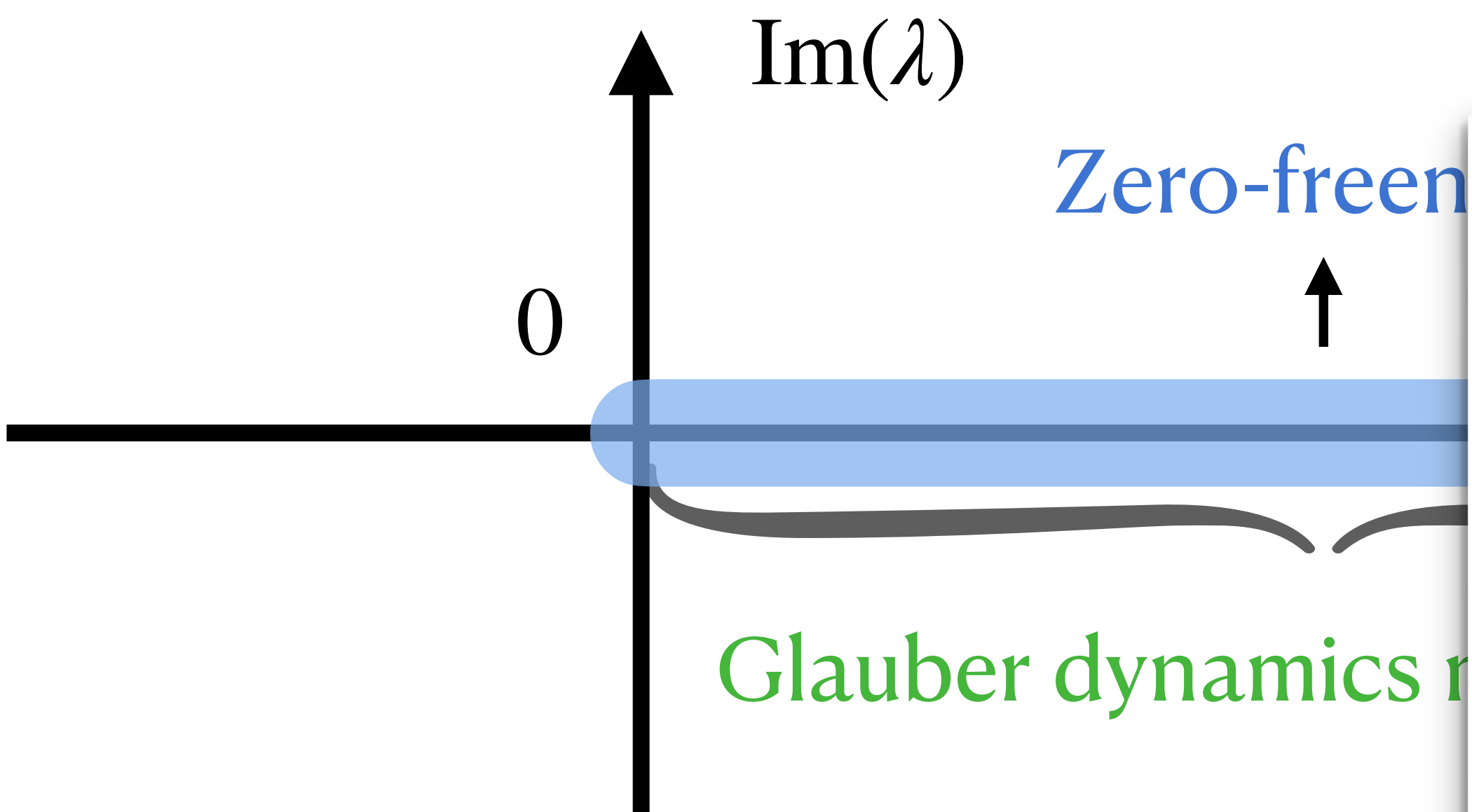


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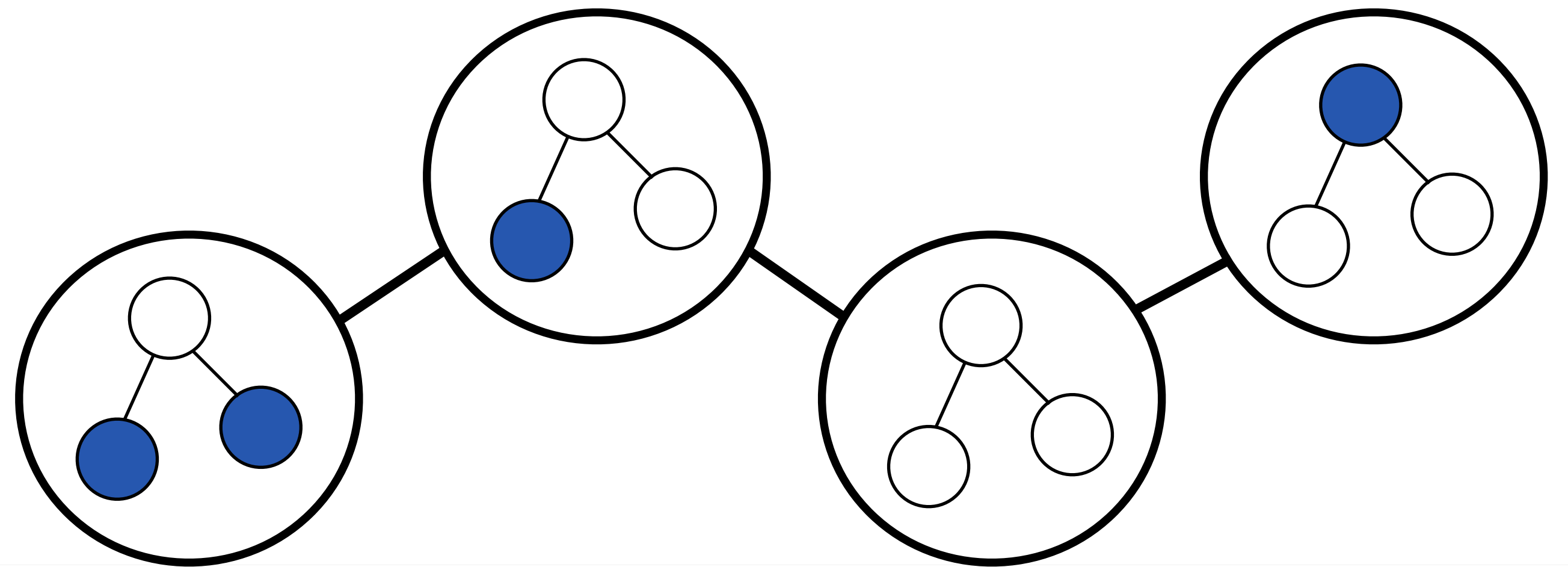
Zero-freeness: [Patel, Regts'17]

Rapid mixing: [Chen, Liu, Vigoda'20, Chen, Liu, Vigoda'21, Chen, Feng, Yin, Zhang'22, Chen, Elden'22]

Computational phase transition - an example



Rapid mixing: Glauber dynamics mixes rapidly

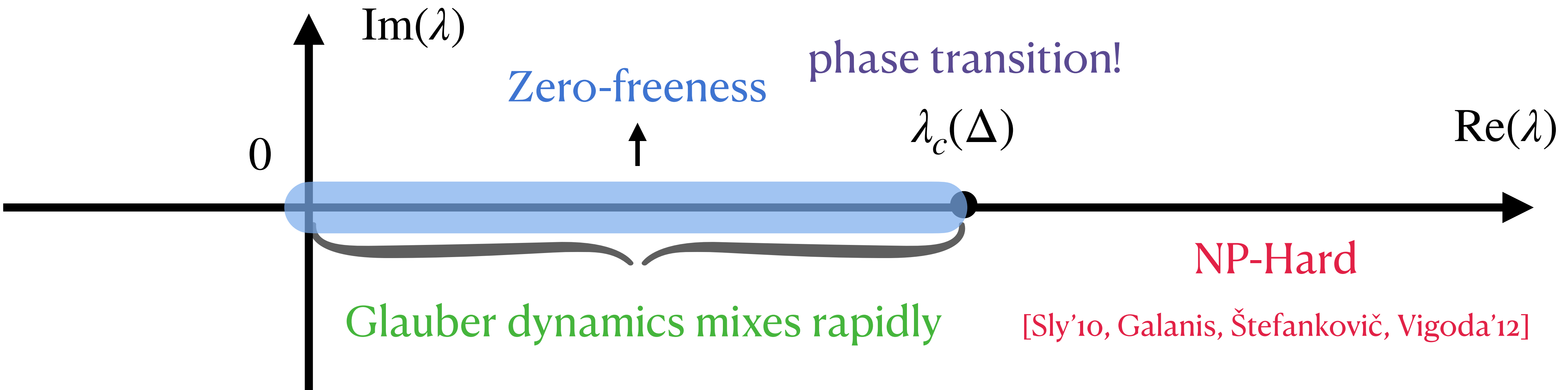


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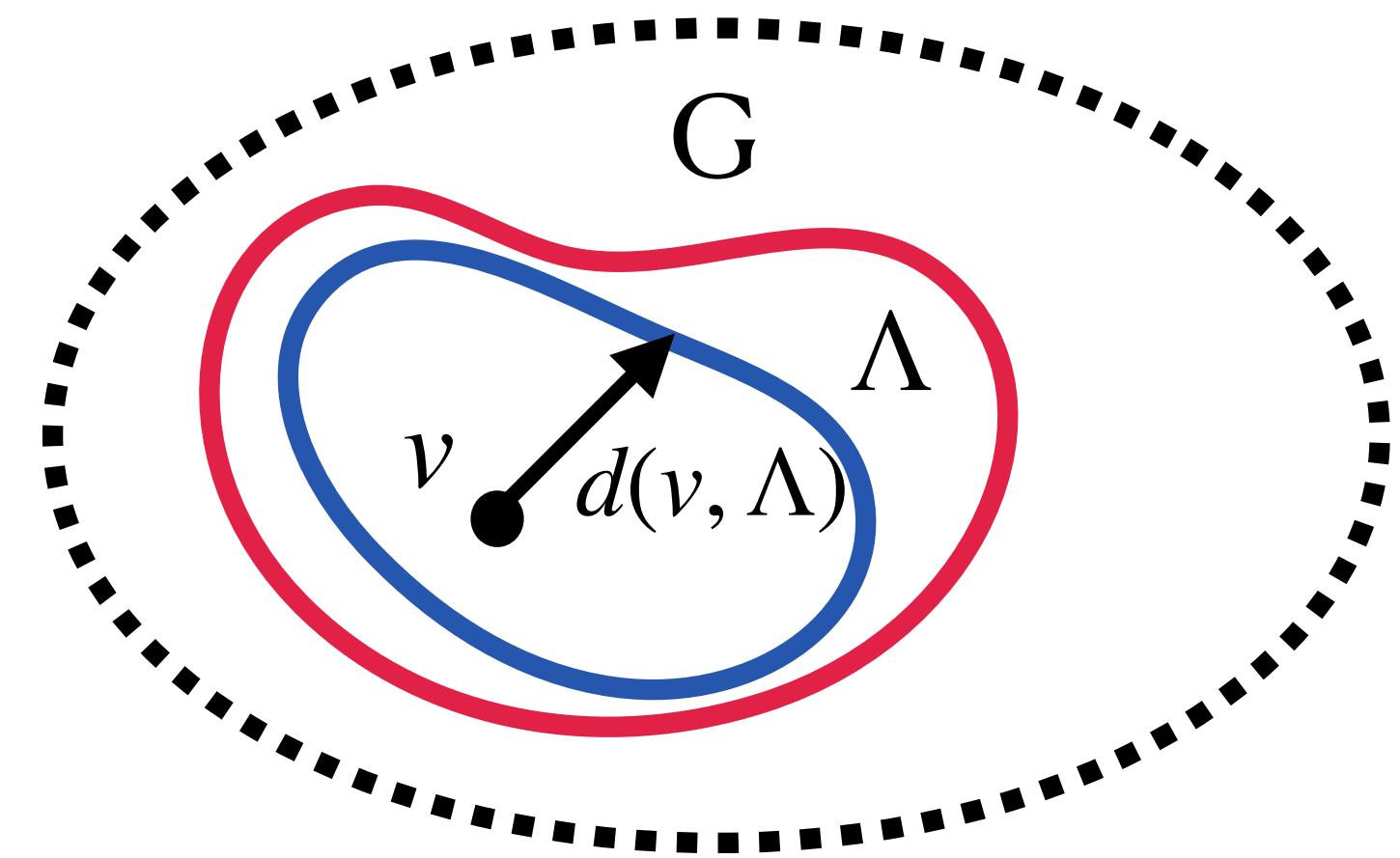
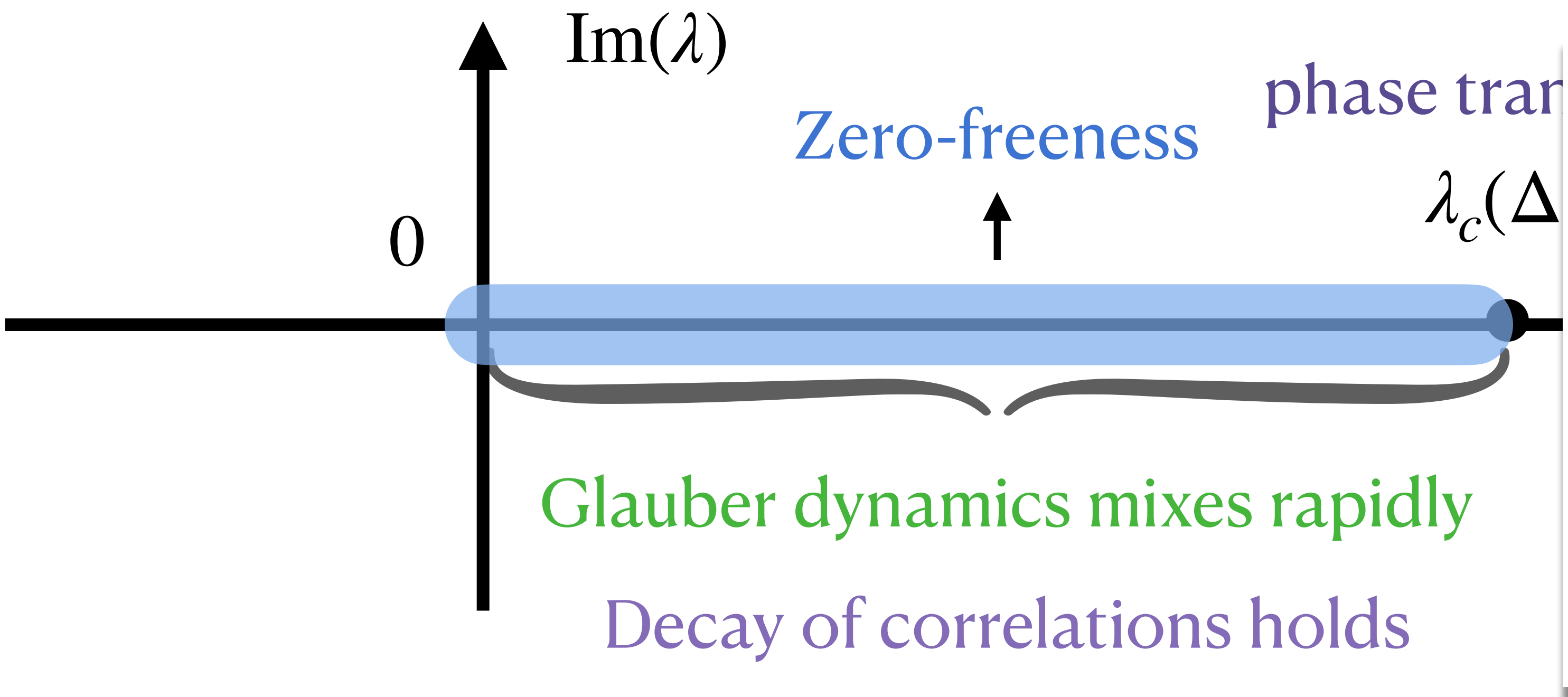


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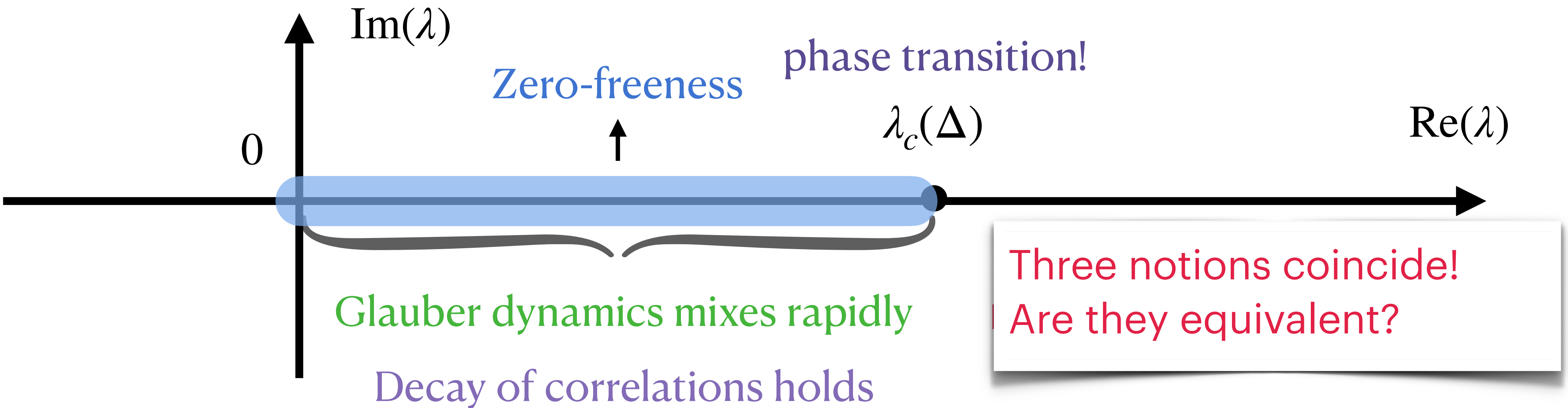
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Decay of correlations: [Weitz'o6]

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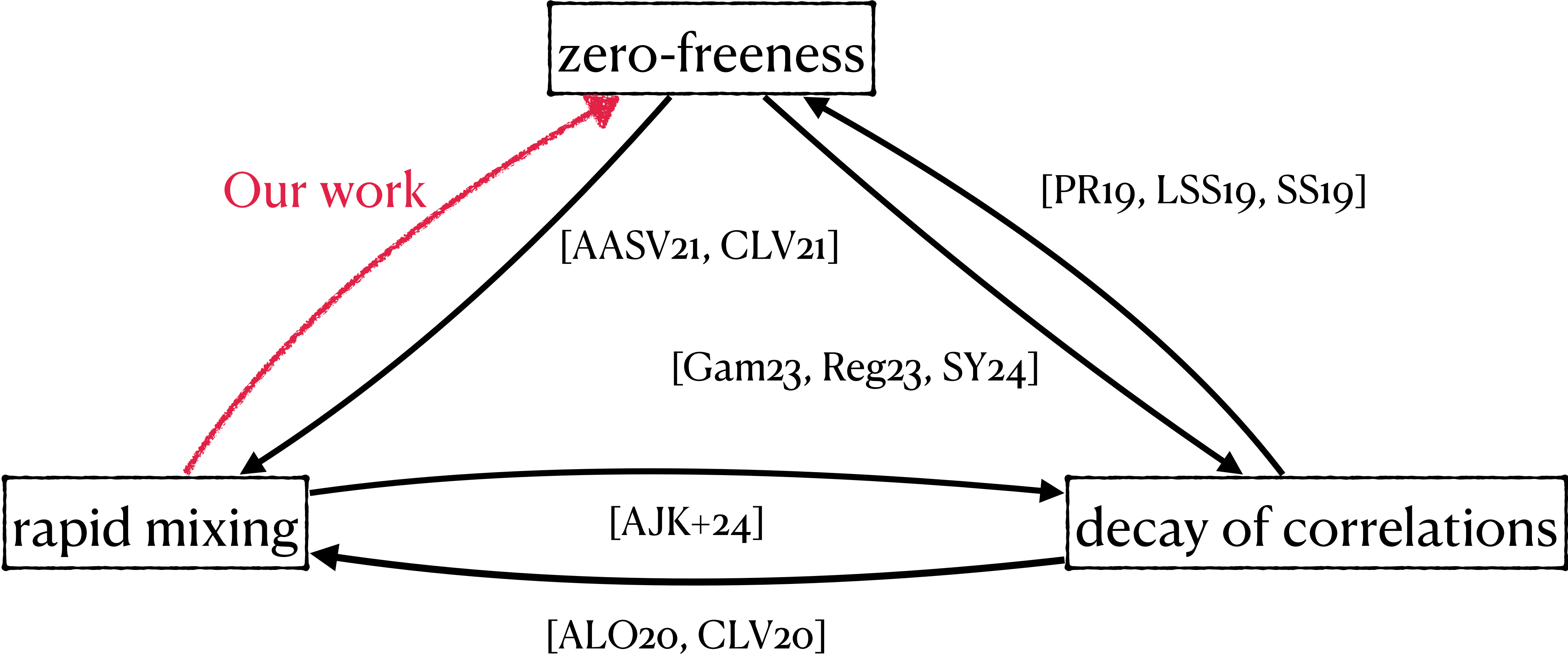
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Connections among three notions



Hypergraph independent set

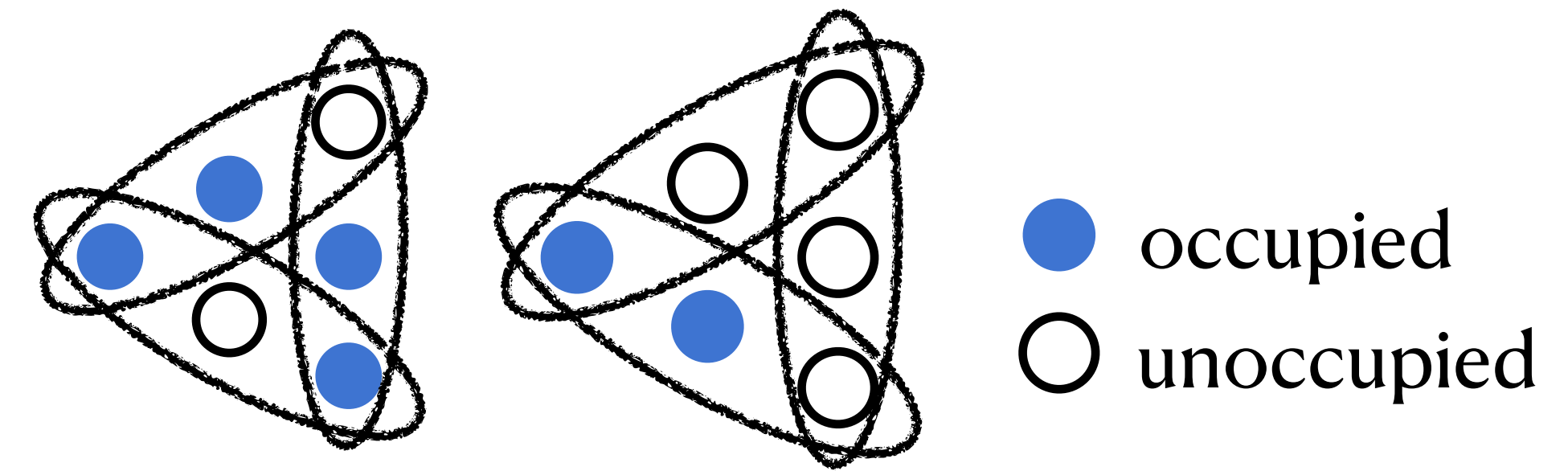
Hardcore model on **hypergraph**

A **hypergraph** $H = (V, \mathcal{E})$, a vertex weight $\lambda > 0$.

Ω set of **hypergraph independent set**.

Partition function $Z = \sum_{X \in \Omega} \lambda^{|X|}$.

Gibbs distribution: $\forall X \in \Omega, \mu(X) = \frac{\lambda^{|X|}}{Z}$.



Examples of hypergraph independent set

We consider the **k -uniform** hypergraph with **maximum degree Δ** .

Hypergraph independent set

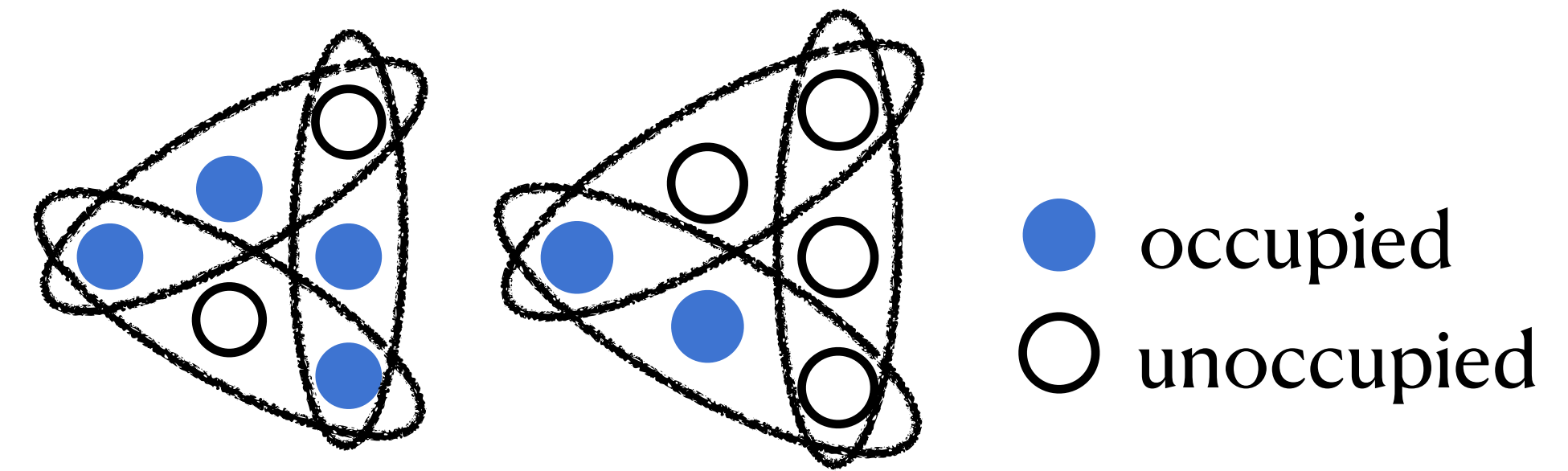
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Examples of hypergraph independent set

We consider the **k -uniform** hypergraph with **maximum degree Δ** .

For $\lambda = 1$, Z is the number of HIS, μ is the uniform distribution of HIS.

Easy for $\Delta \lesssim 2^{k/2}$ (“sampling LLL condition”) [HSZ19, HSW21, QWZ22, FGW+23].

NP-hard for $\Delta \geq 5 \cdot 2^{k/2}$ [BGG+19].

Rapid mixing of Markov chains

Approximate counting/sampling hypergraph independent sets under “sampling LLL conditions”.

[Hermon, Sly, Zhang’19]: rapid mixing of Glauber dynamics.

[He, Sun, Wu’21, Qiu, Wang, Zhang’22]: perfect sampler.

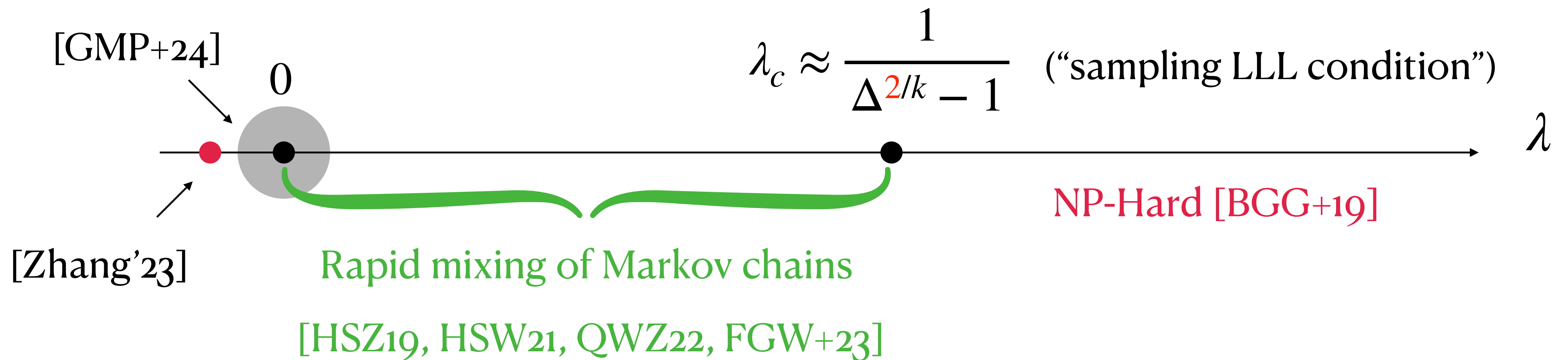
[Feng, Guo, Wang, Wang, Yin’23]: local sampler.

They are all based on **Markov chains** through the lens of **percolation**.

Zero-freeness

[Galvin, McKinley, Perkins, Sarantis, Tetali'24] shows a zero-free disk centered at origin with radius $\approx \frac{1}{e\Delta}$.

[Zhang'23] shows that for k-uniform linear hypergraph, there is a zero at $\lambda \approx -\frac{\log \Delta}{\Delta}$.



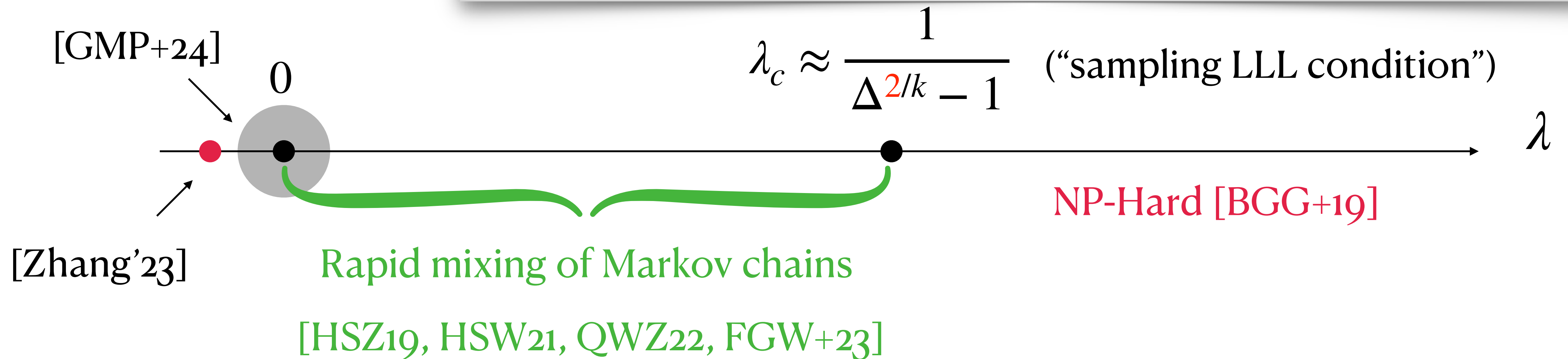
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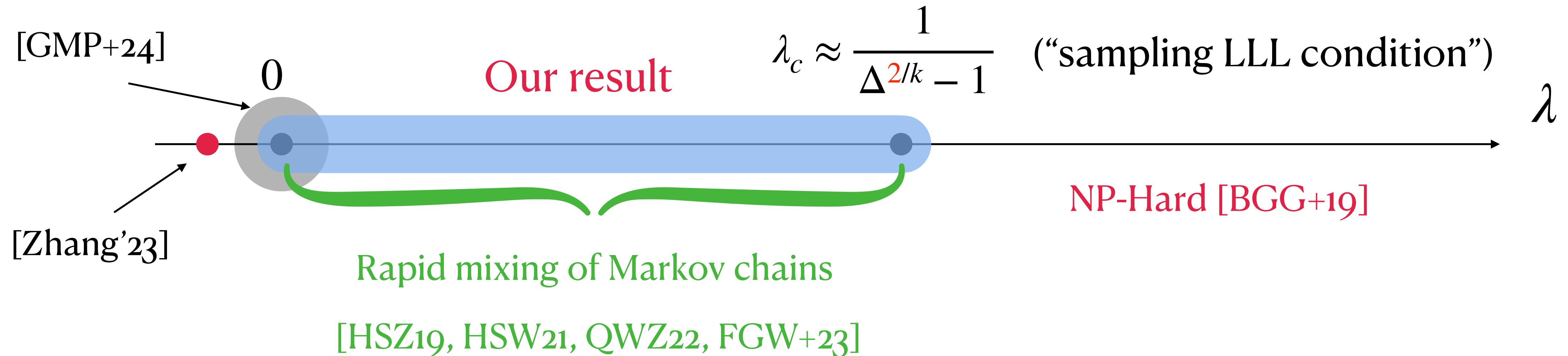
Zero-free region is lagging behind.

Existing tools for zero-free region can not capture the uniformity.



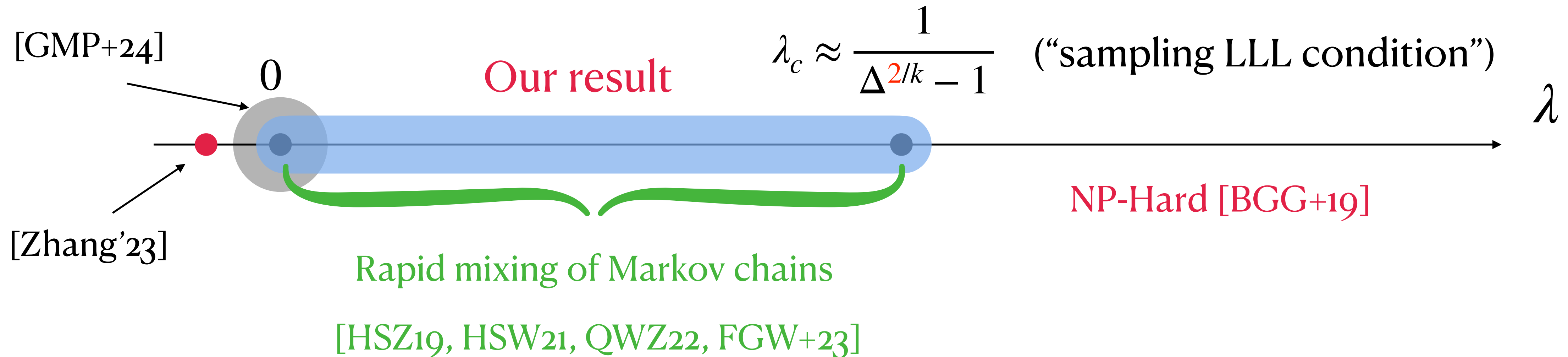
Our result - improved zero-free region from Markov chains

For k -uniform hypergraph with maximum degree Δ :



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For k -uniform hypergraph with maximum degree Δ :



Corollaries of zero-freeness (in the same regime, informal):

1. FPTAS for approximating the partition function based on [Barvinok'16, Patel, Regts'17, Liu, Sinclair, Srivastava'17].
2. Central limit theorem and local central limit theorem based on [Michelen, Sahasrabudhe'19, Jain, Perkins, Sah, Sawhney'22].
3. FPTAS for approximating the number of t -size independent sets based on [Jain, Perkins, Sah, Sawhney'22].

Technical contribution - complex measure

A vertex weight $\lambda \in \mathbb{C} \setminus \{-1\}$.

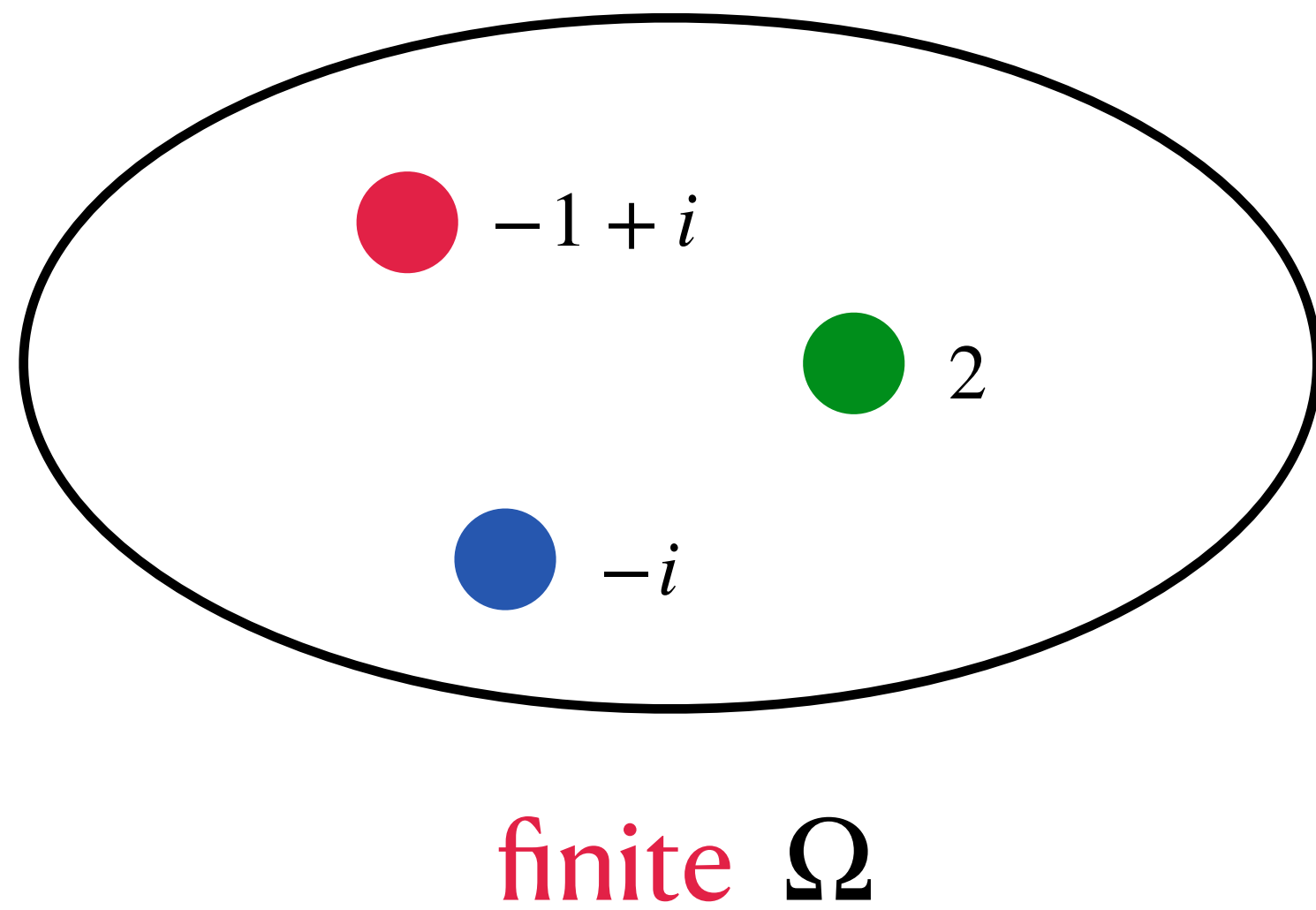
Ω = set of hypergraph independent sets.

Partition function $Z = \sum_{X \in \Omega} \lambda^{|X|}$.

Complex Gibbs measure: $\forall X \in \Omega, \mu(X) = \frac{\lambda^{|X|}}{Z}$.

We analyze complex Gibbs measure in a manner of distributions.

Technical contribution - complex measure



Normalized measure: $\mu(\Omega) = 1$.

Conditional measure: $\mu(\cdot | A) = \frac{\mu(\cdot \wedge A)}{\mu(A)}$ ($\mu(A) \neq 0$).

Independence: $\mu(A_1 \cap A_2) = \mu(A_1) \cdot \mu(A_2)$.

Law of total measure: $\mu(B) = \sum_{i=1}^m \mu(B \cap A_i)$

(A_i s are disjoint and $\bigcup_i A_i = \Omega$)

Complex measure μ over measurable space (Ω, \mathcal{F})

Technical contribution - complex measure

For distributions, we have **monotonicity**:

For two events $B \subseteq A$, it holds that $\mathbb{P}[B] \leq \mathbb{P}[A]$.



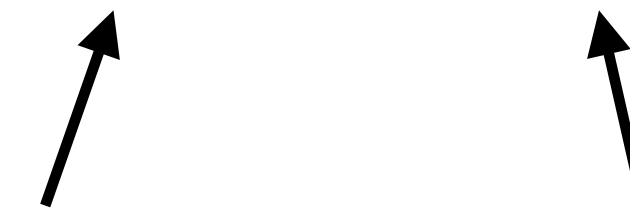
Hard to bound **Easy to bound**

For complex measure, monotonicity does not hold anymore!

Technical contribution - complex measure

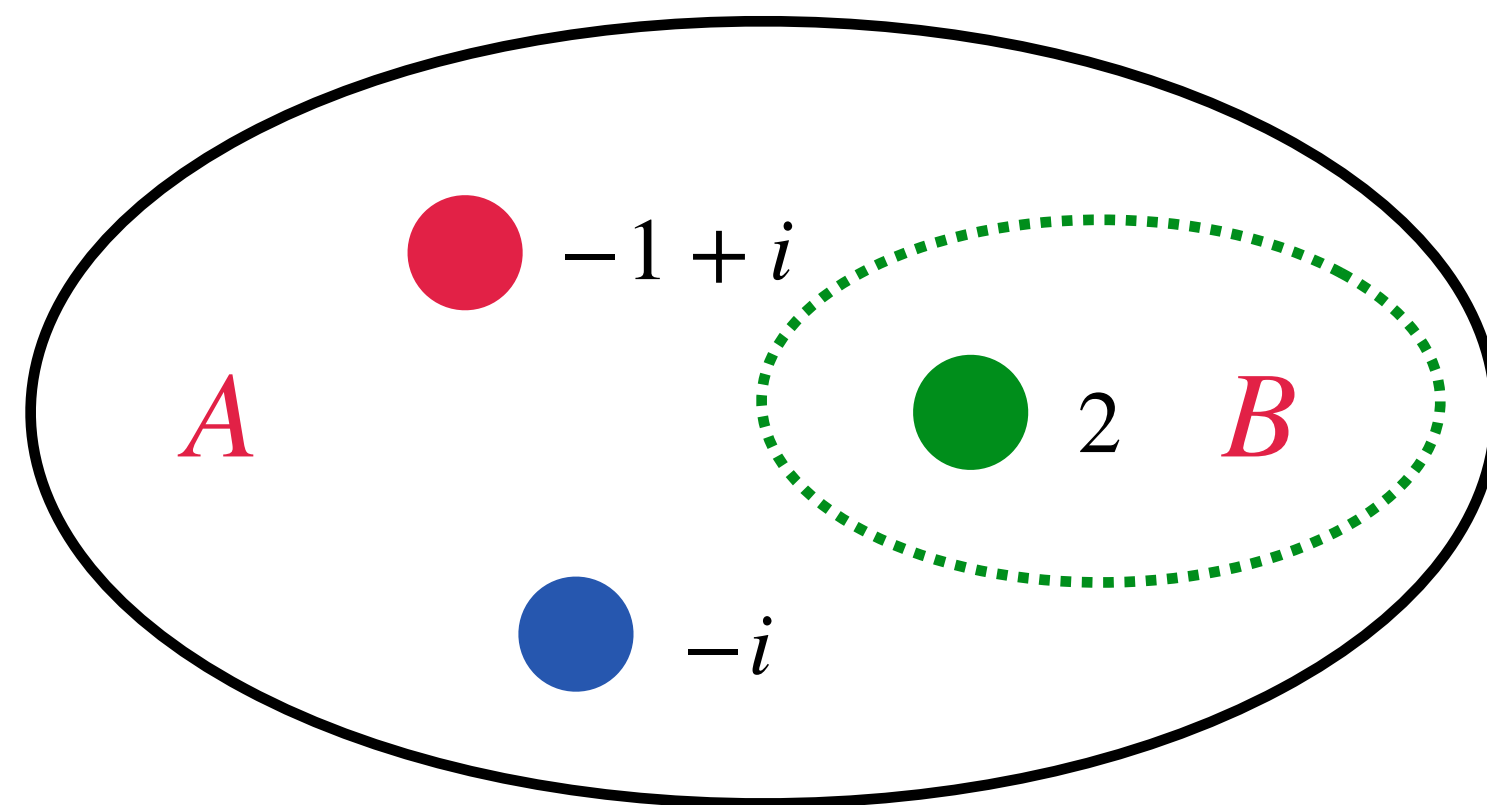
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For complex measure, monotonicity does not hold anymore!



$$B \subseteq A, \text{ but } |\mu(B)| > |\mu(A)|$$

Technical contribution - complex measure

For complex measure, we use “zero-one law” to recover monotonicity.

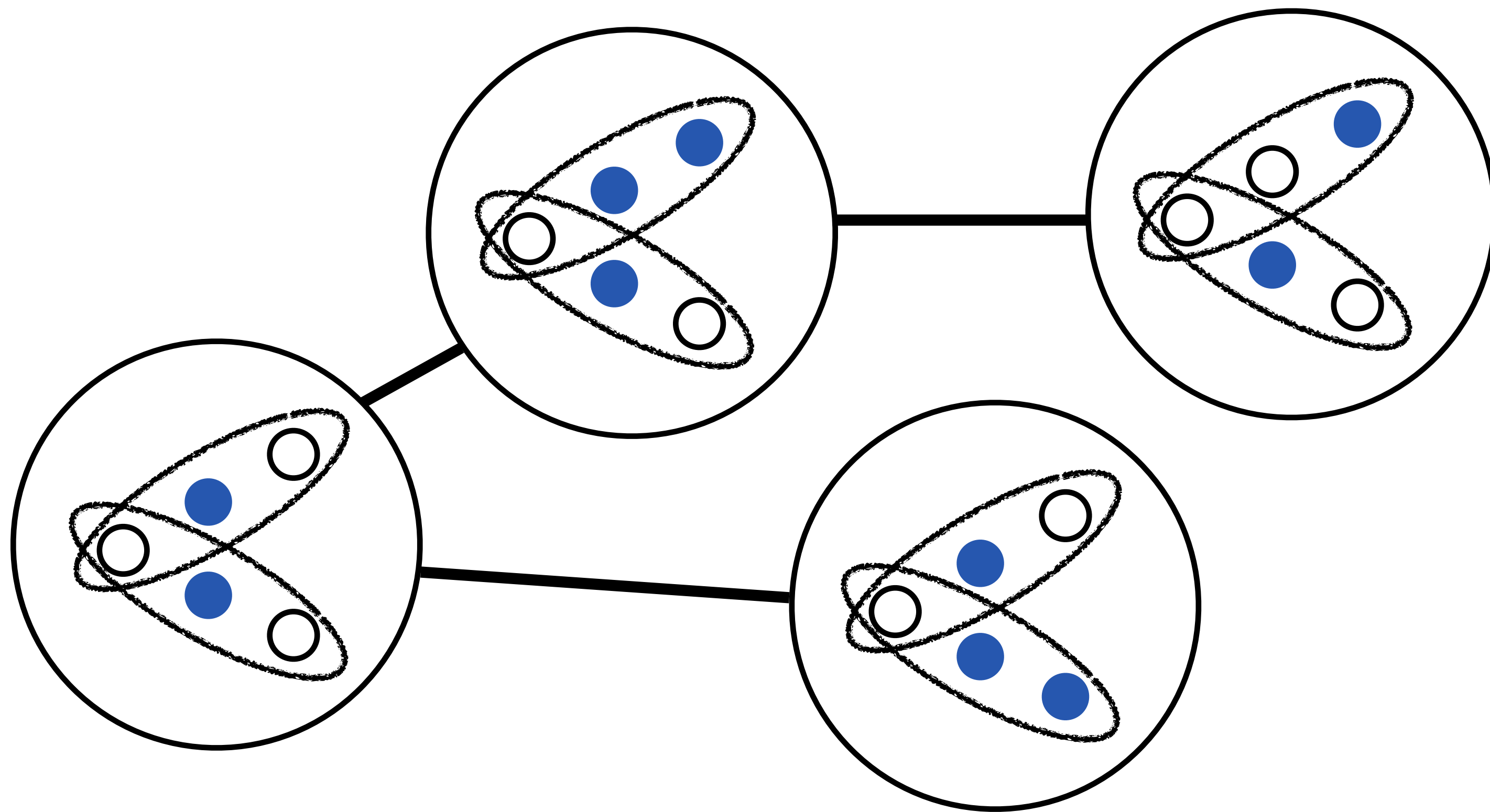
For two events $B \subseteq A$, it holds that

$$\left| \mu(B) \right| = \left| \mu(A \wedge B) \right| = \left| \mu(A) \right| \cdot \left| \mu(B \mid A) \right| \leq \left| \mu(A) \right|.$$

A is a witness of B .

The key is to design a **witness** A , such that $\mu(B \mid A) \in \{0,1\}$ and $\left| \mu(A) \right|$ is easy to deal with.

Technical contribution - complex extensions of Markov chains



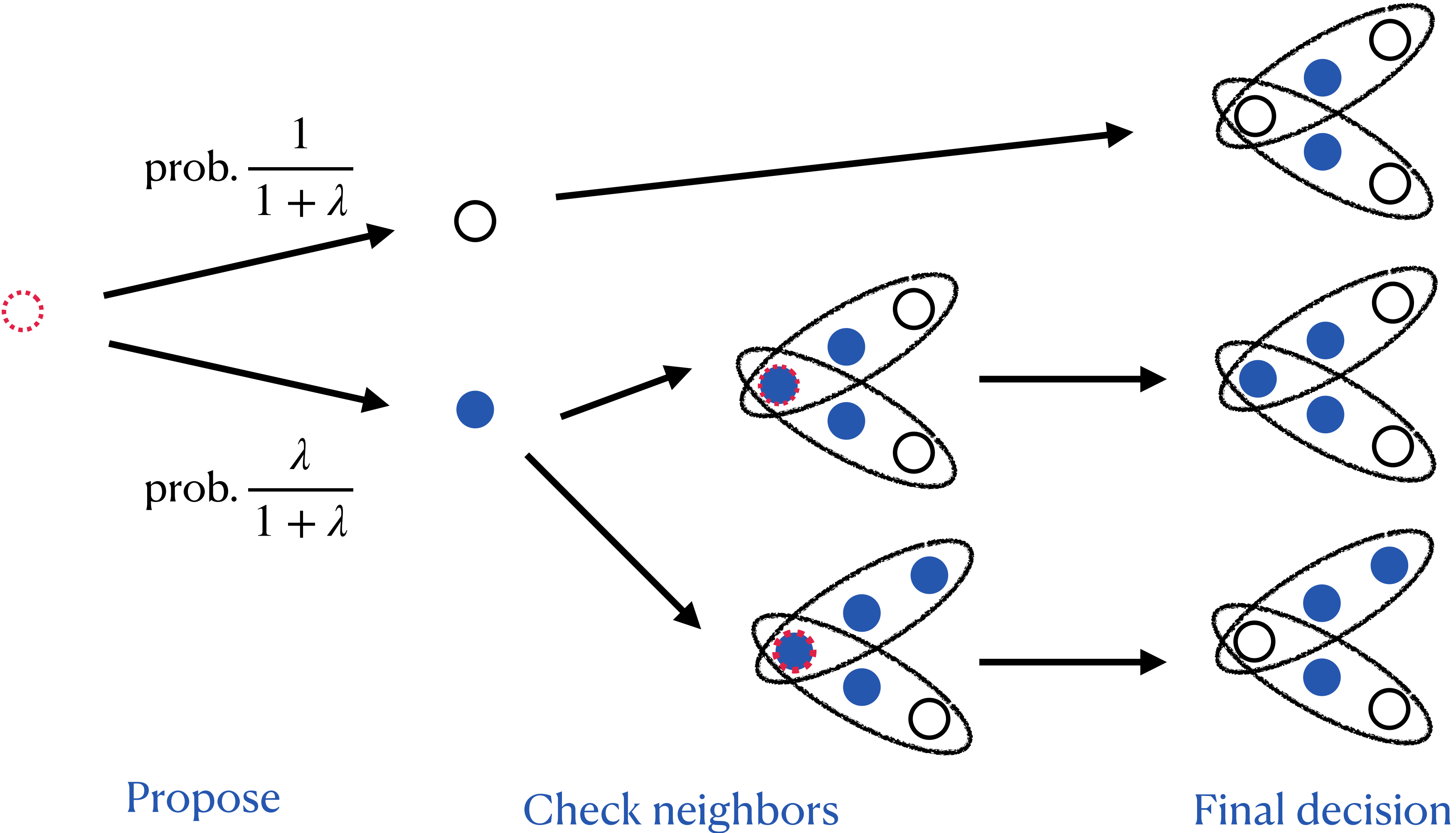
Start with an independent set.

In each update:

1. Choose a vertex v u.a.r.;
2. Update v .

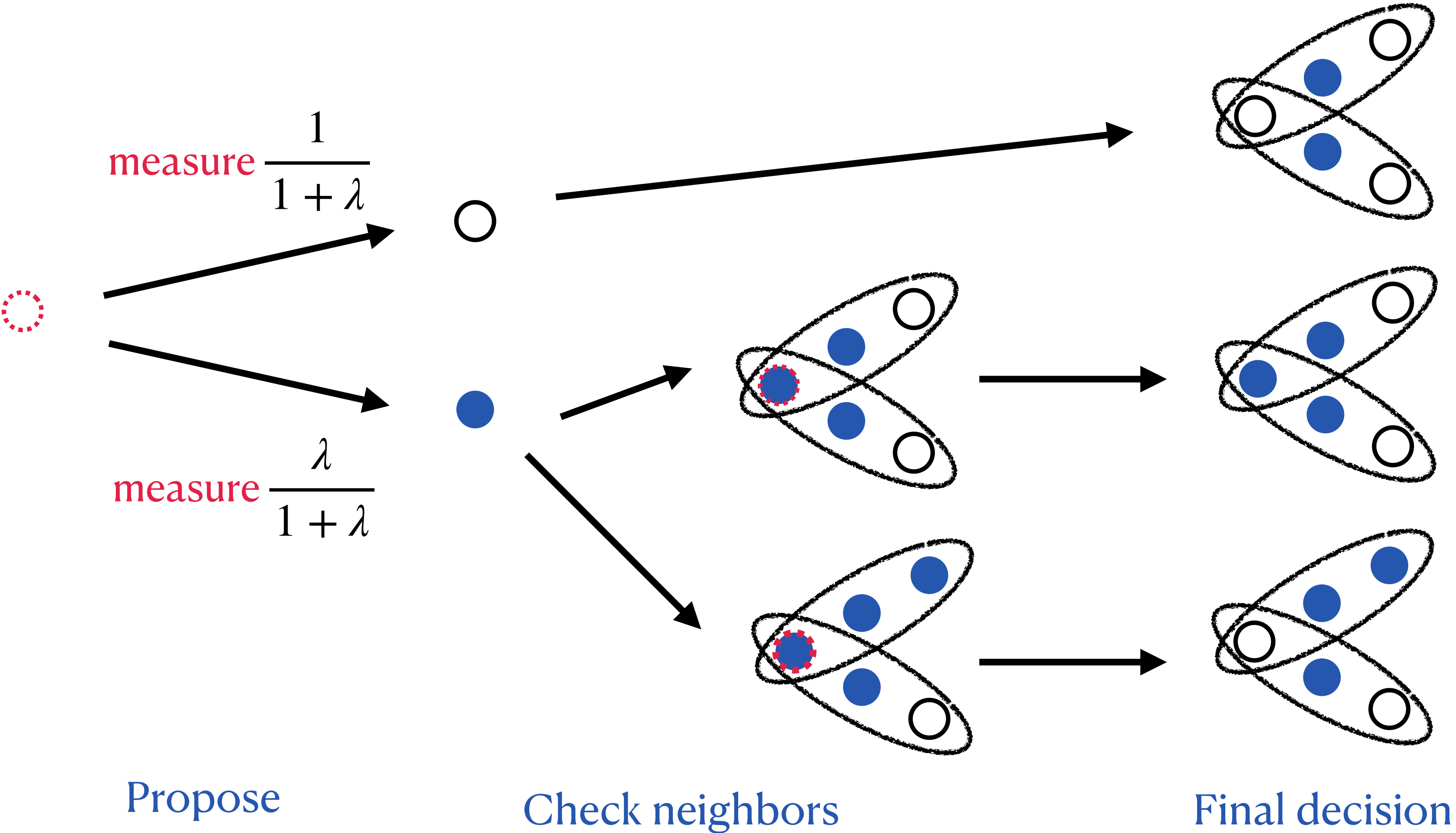
Classical Glauber dynamics

Technical contribution - complex extensions of Markov chains



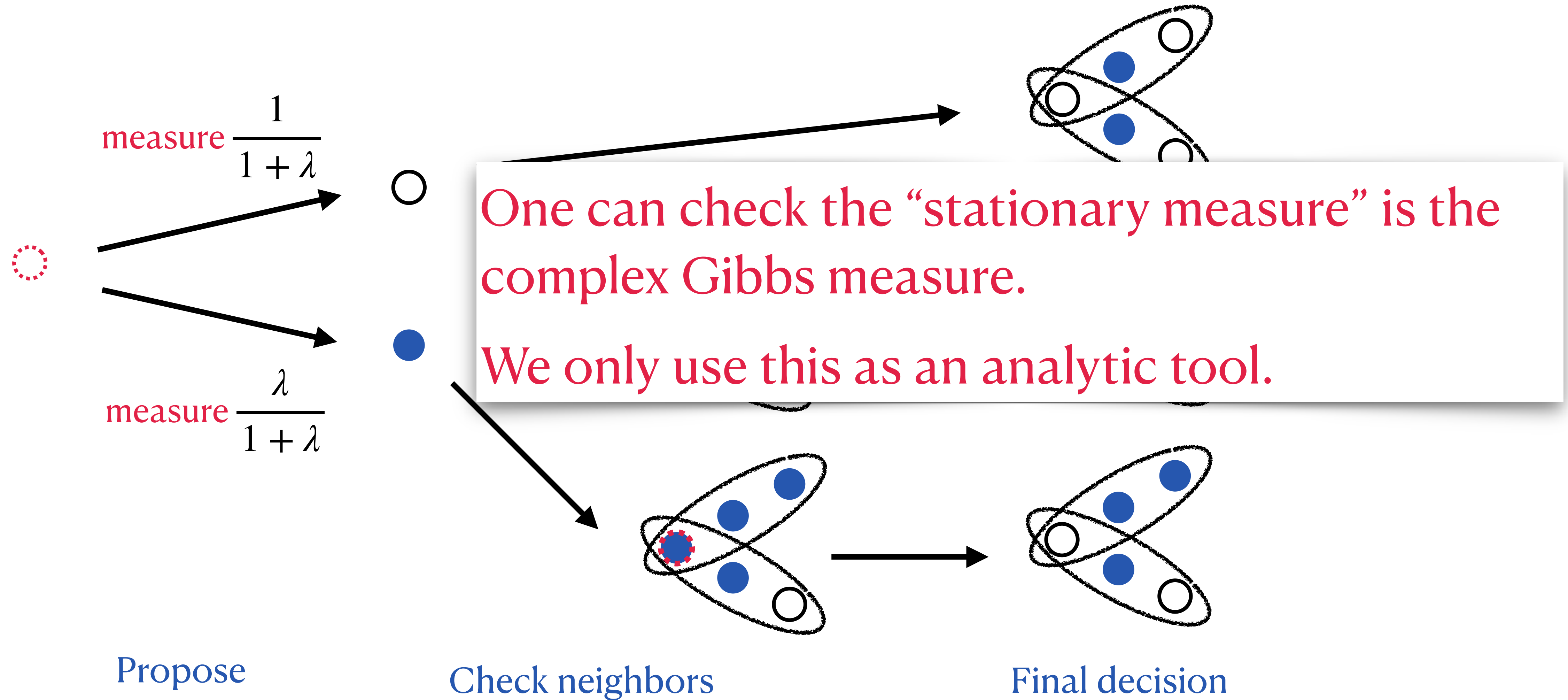
Update rule of classical Glauber dynamics

Technical contribution - complex extensions of Markov chains



Update rule of **complex Glauber dynamics**

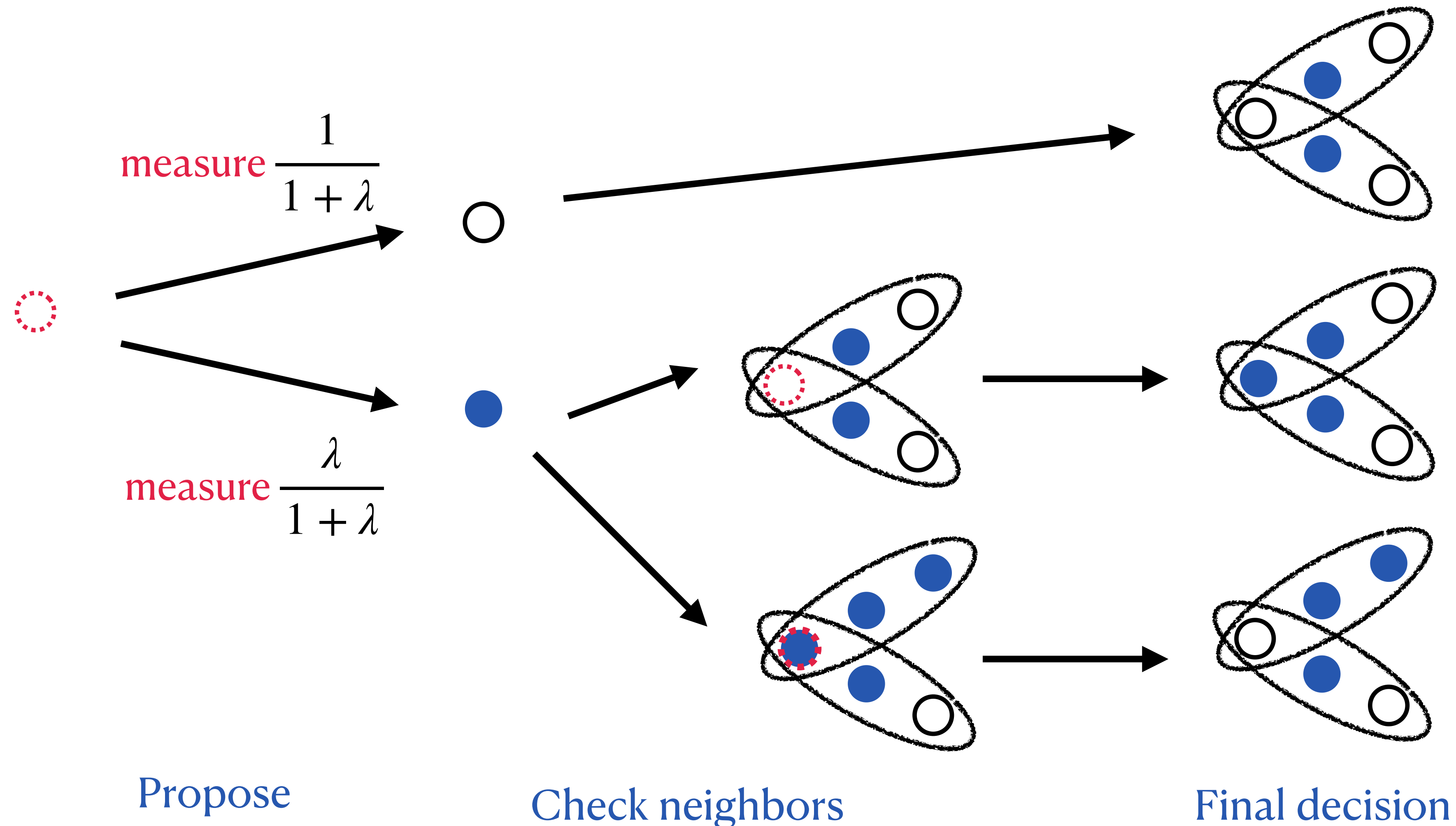
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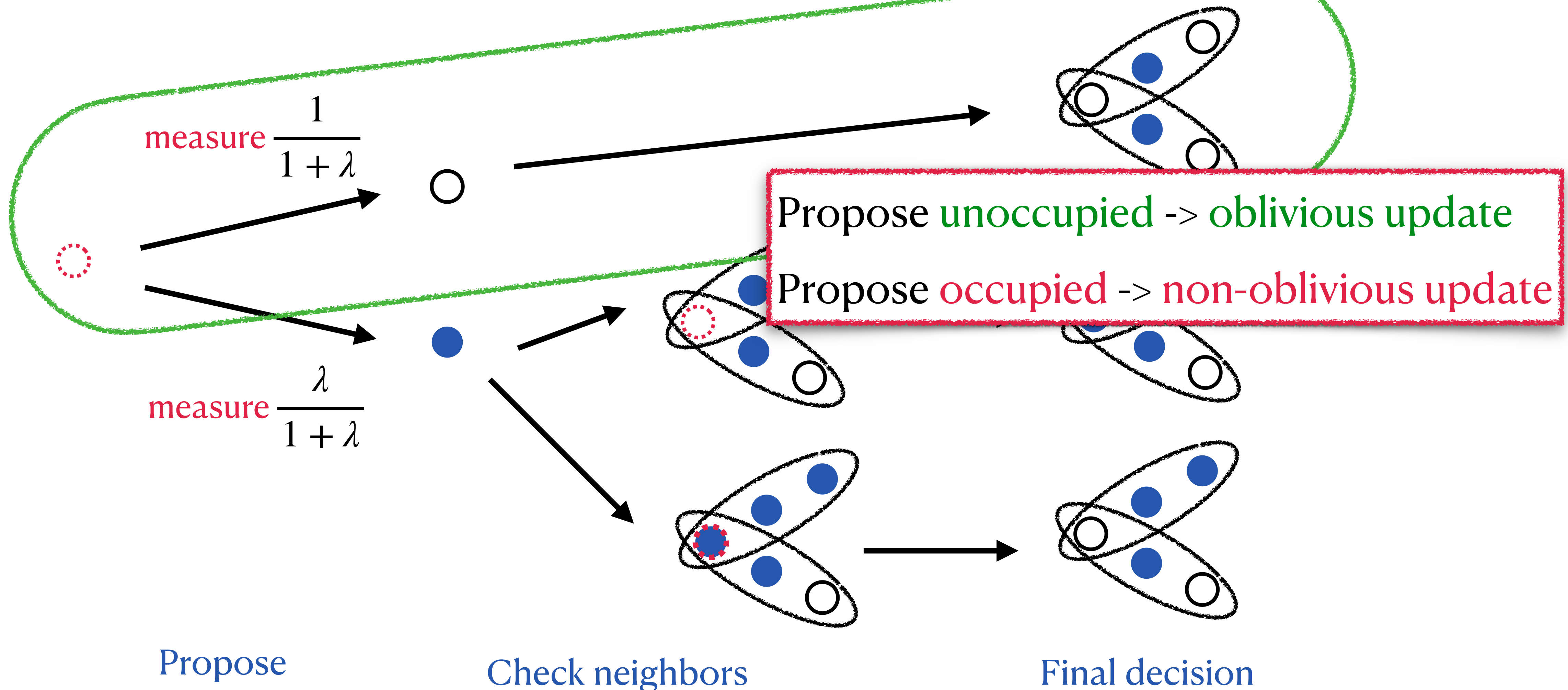
Technical contribution - complex percolation

Decomposition: decompose each transition into **oblivious part** and **non-oblivious part**.



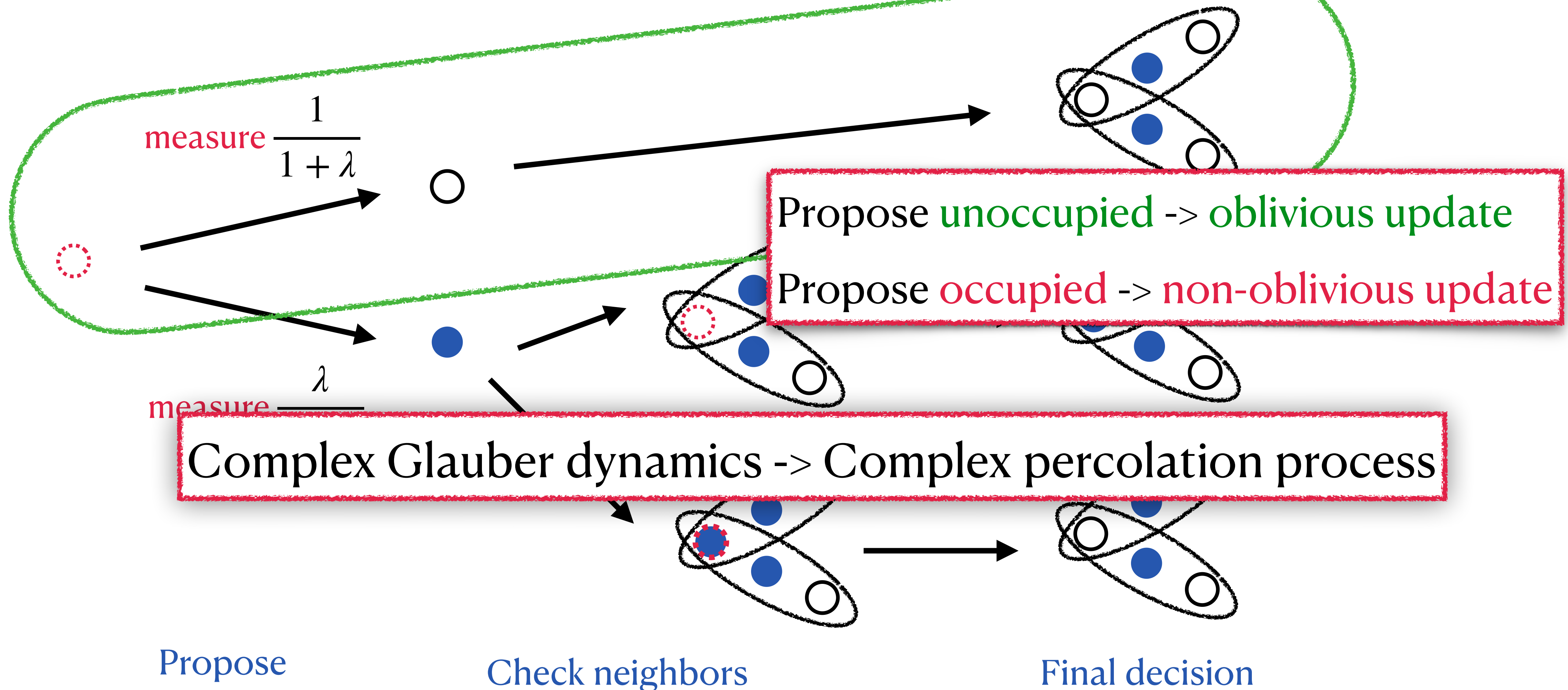
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Complex Glauber dynamics \rightarrow Complex percolation process



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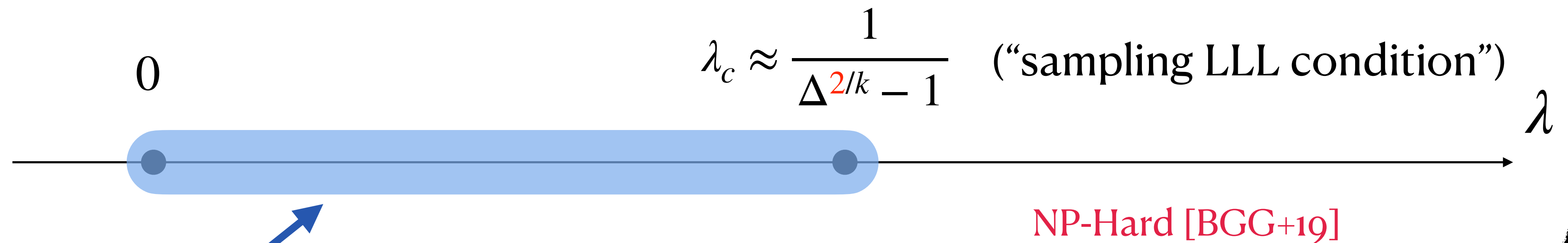


We use our zero-one law to bound these norms.

Technical contribution - complex percolation

We use **complex percolation** to analyze the **complex systematic scan Glauber dynamics**.

For k -uniform hypergraph with maximum degree Δ :



We show in this **strip**, **complex systematic scan Glauber dynamics converges and $Z(\lambda) \neq 0$** .

Proof overview

Zero-freeness



Complex Gibbs measure

$$\left| \mu_H(\sigma_e = 1^{|e|}) \right| < 1$$

By **standard edge-wise self-reducibility**, it suffices to bound the norm of a complex marginal measure.

Proof overview

Zero-freeness



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T-step complex Glauber
dynamics $\sigma_e = 1^{|e|}$

+

Expressing the complex Gibbs measure
via the complex Glauber dynamics.

Proof overview

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T-step complex Glauber
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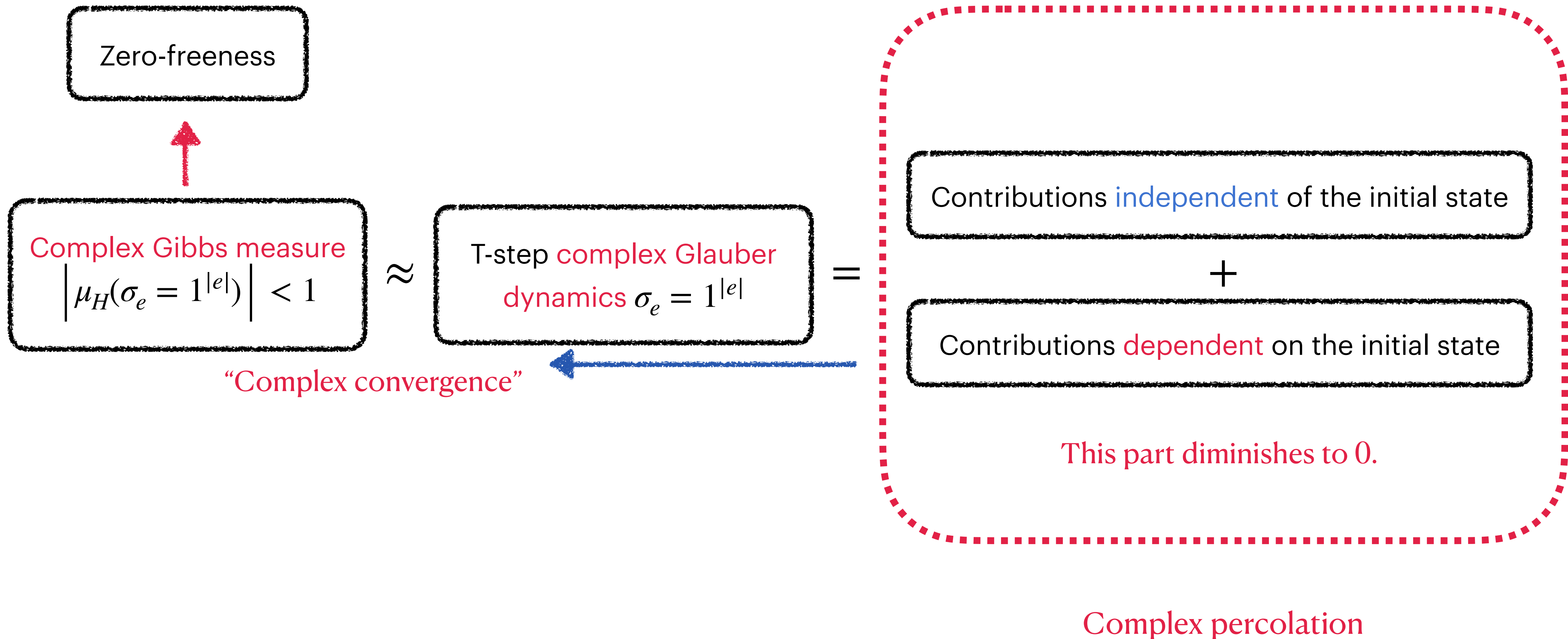
Contributions **independent** of the initial state

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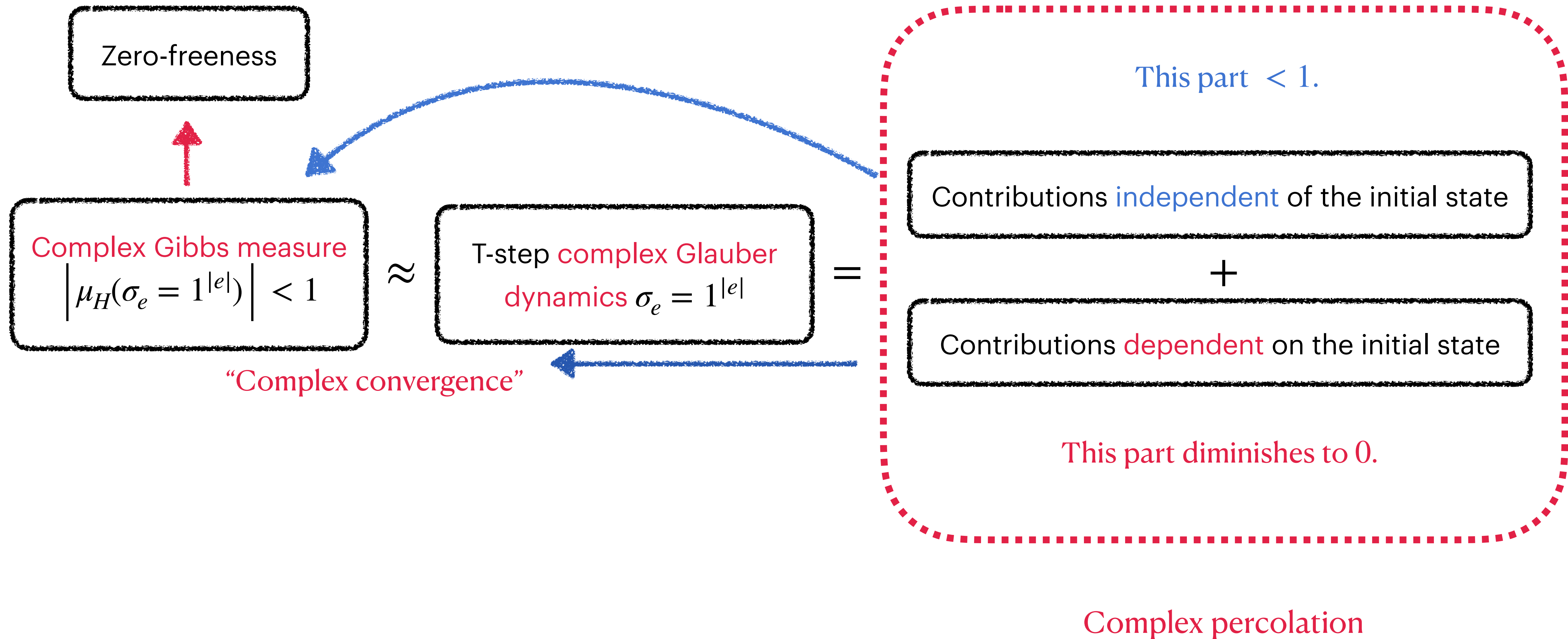
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Complex percolation

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Summary

We define the **complex extensions of Markov chains** and use it to improve the **zero-free region** of hardcore model on hypergraph.

As corollaries, we obtain efficient algorithms for:

1. approximating the partition function under the “sampling LLL condition”,
2. approximating the number of t -size hypergraph independent sets.

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Open problems

1. Zero-freeness for general CSPs.
2. Does complex convergence imply zero-freeness?

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Thanks! Any questions?

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