

# Sampling up to the *Uniqueness* Threshold

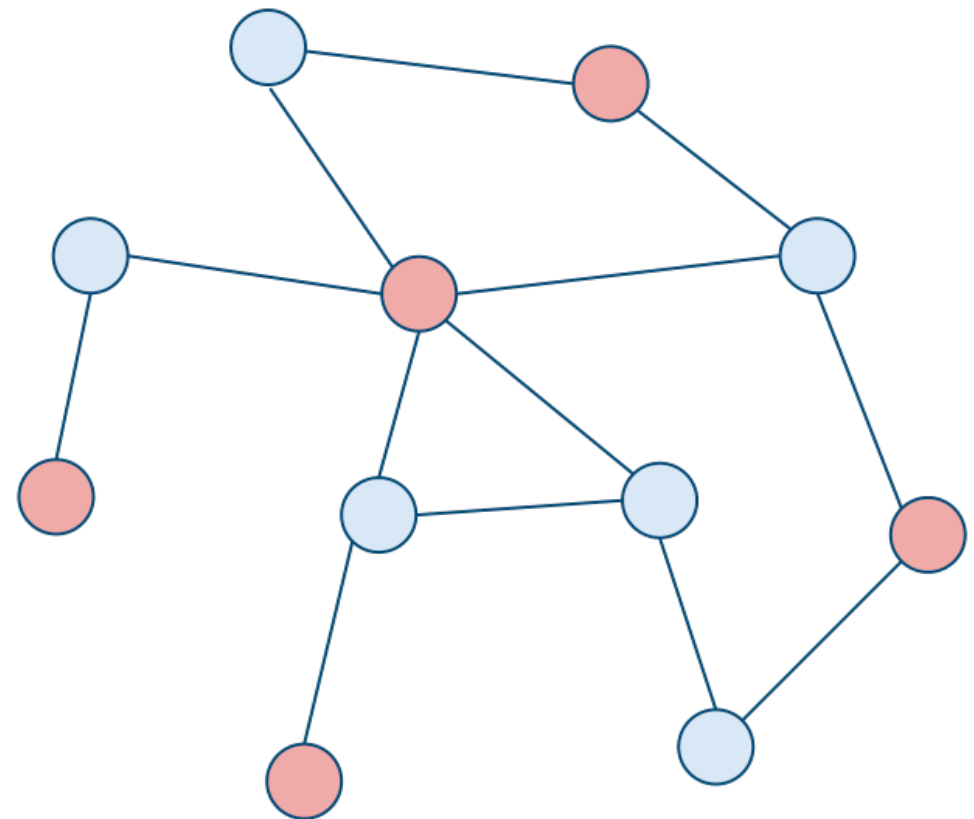
Yitong Yin  
Nanjing University

Joint work with: Charis Efthymiou (Goethe-Universität Frankfurt)  
Thomas P. Hayes (UNM)  
Daniel Štefankovič (Rochester)  
Eric Vigoda (Georgia Tech)

# Sampling Independent Set

undirected graph  $G(V, E)$  of max-degree  $\Delta$

- Sample (*nearly*) uniform random **independent set**.



# Sampling Independent Set

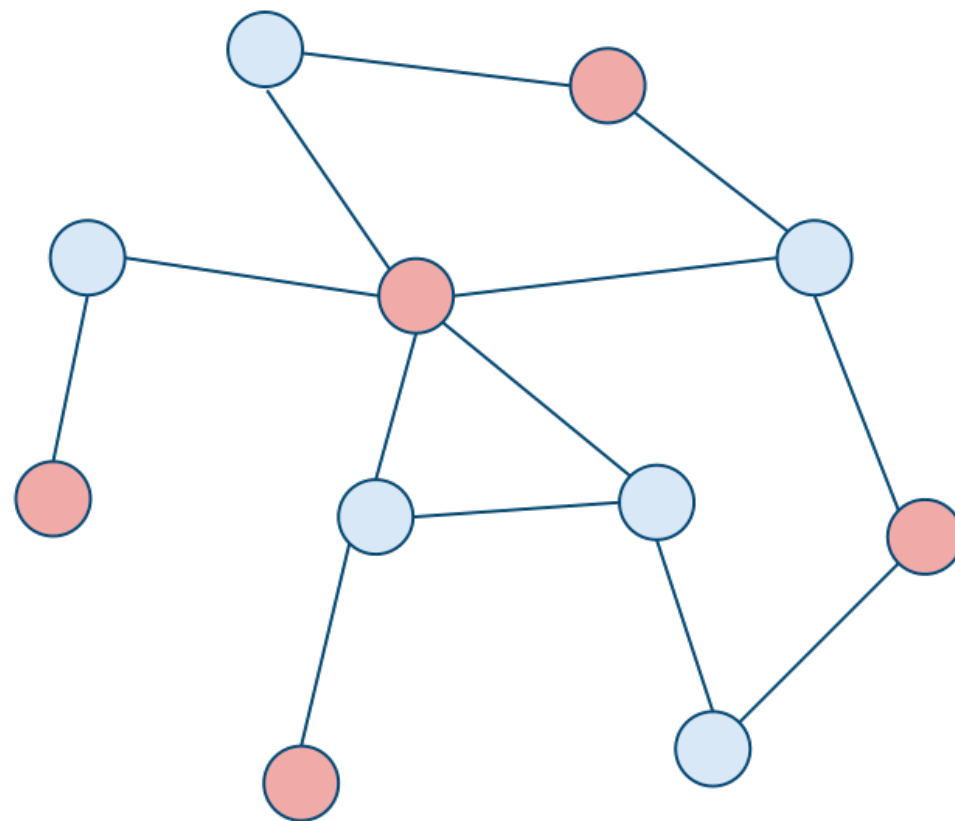
undirected graph  $G(V, E)$  of max-degree  $\Delta$

- Sample (*nearly*) uniform random **independent set**.

- $\Delta \leq 5 \Rightarrow$  poly-time

**Conjecture:**  $O(n \log n)$  time

- $\Delta \geq 6 \Rightarrow$  NP-hard



# Hardcore Model

undirected graph  $G(V, E)$  of max-degree  $\Delta$

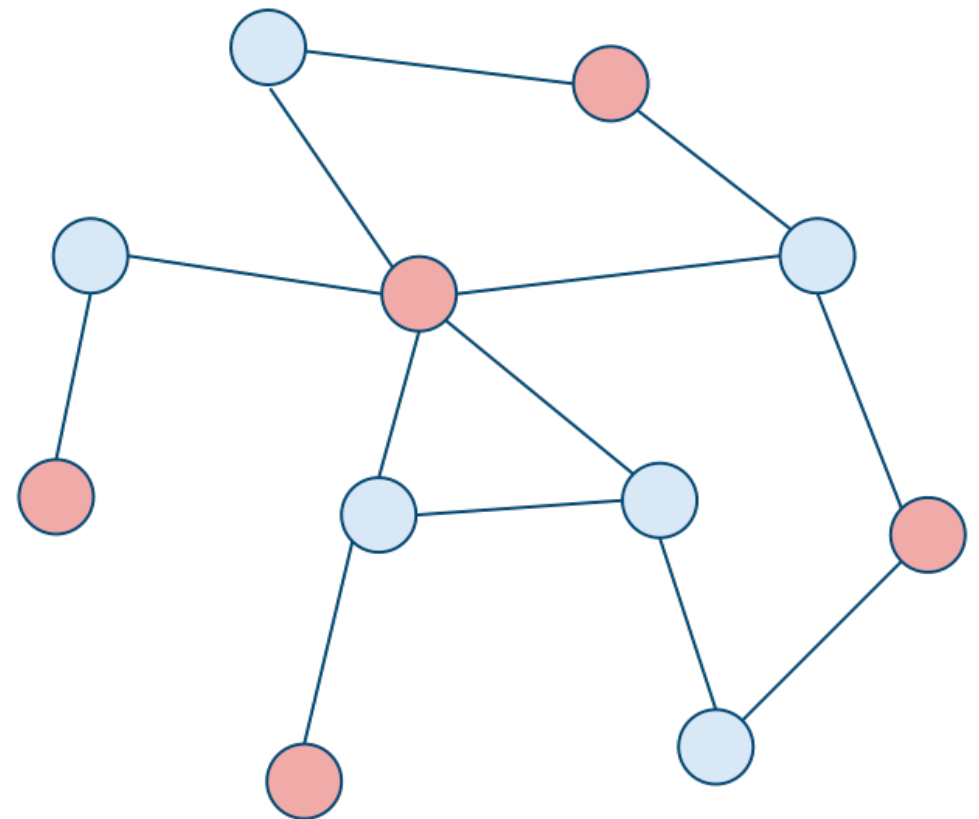
- fugacity parameter  $\lambda > 0$
- each independent set  $I$  in  $G$  is assigned a weight:

$$w(I) = \lambda^{|I|}$$

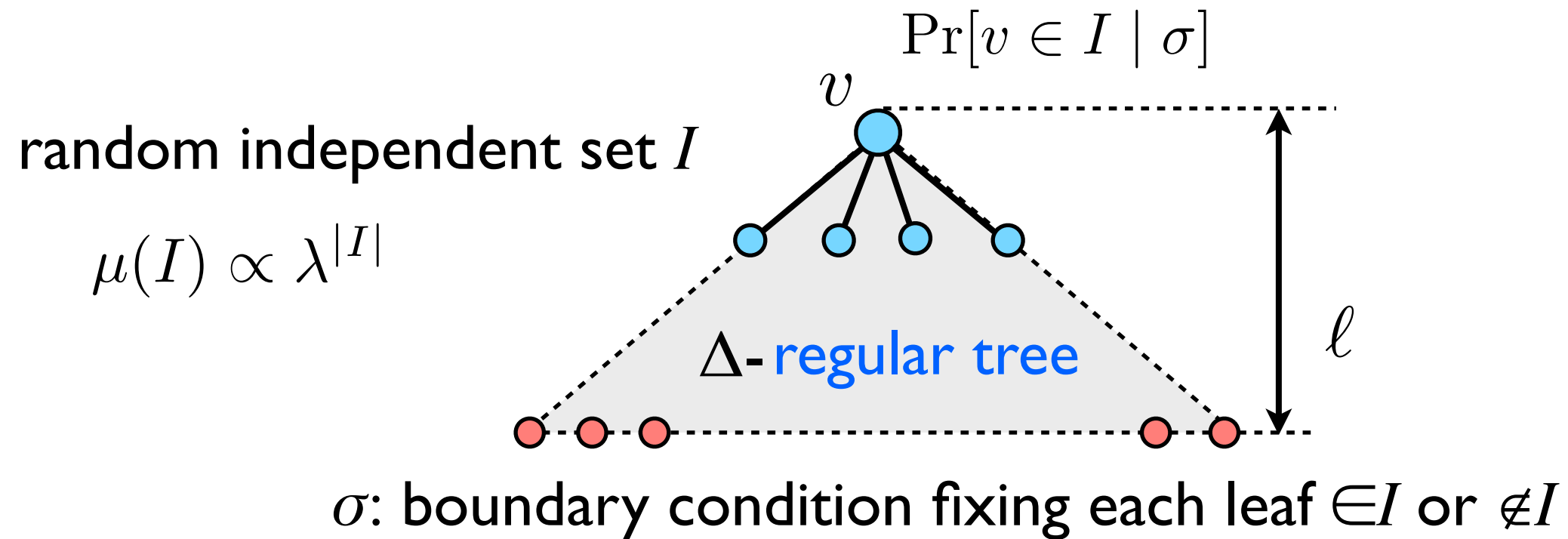
- distribution  $\mu$  over all independent sets in  $G$ :

$$\mu(I) = \frac{w(I)}{\sum_I w(I)}$$

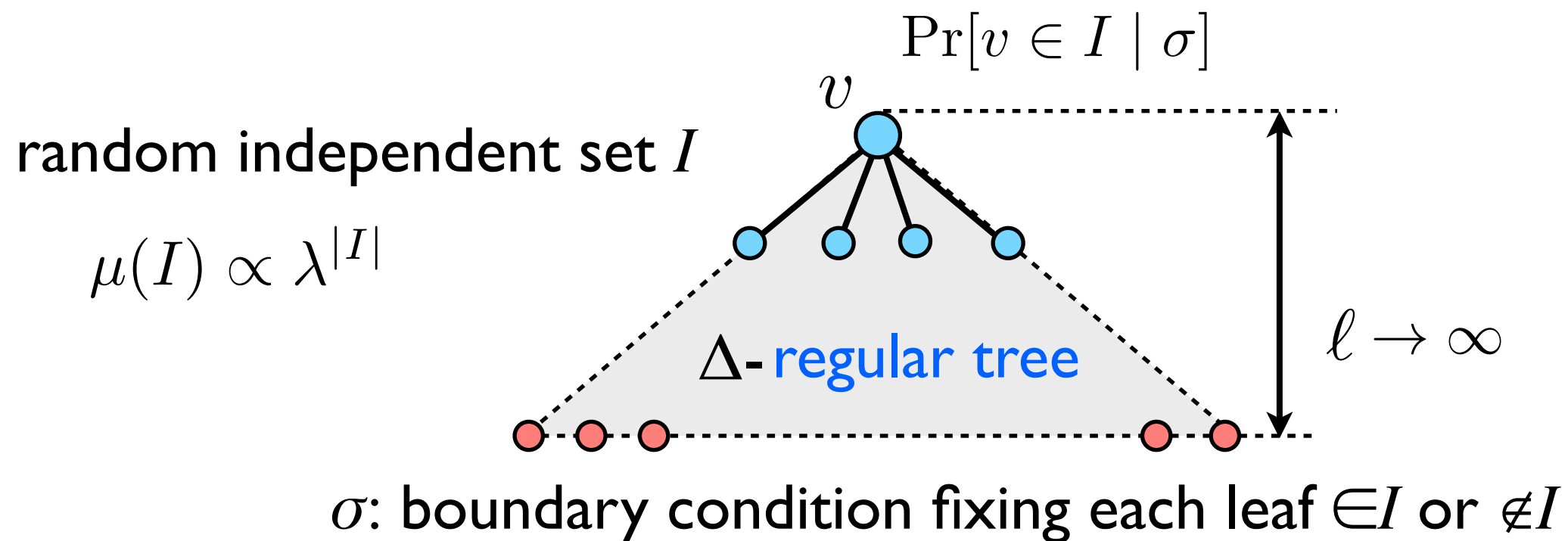
- $\lambda=1$ : uniform distribution over independent sets



# Uniqueness Threshold



# Uniqueness Threshold

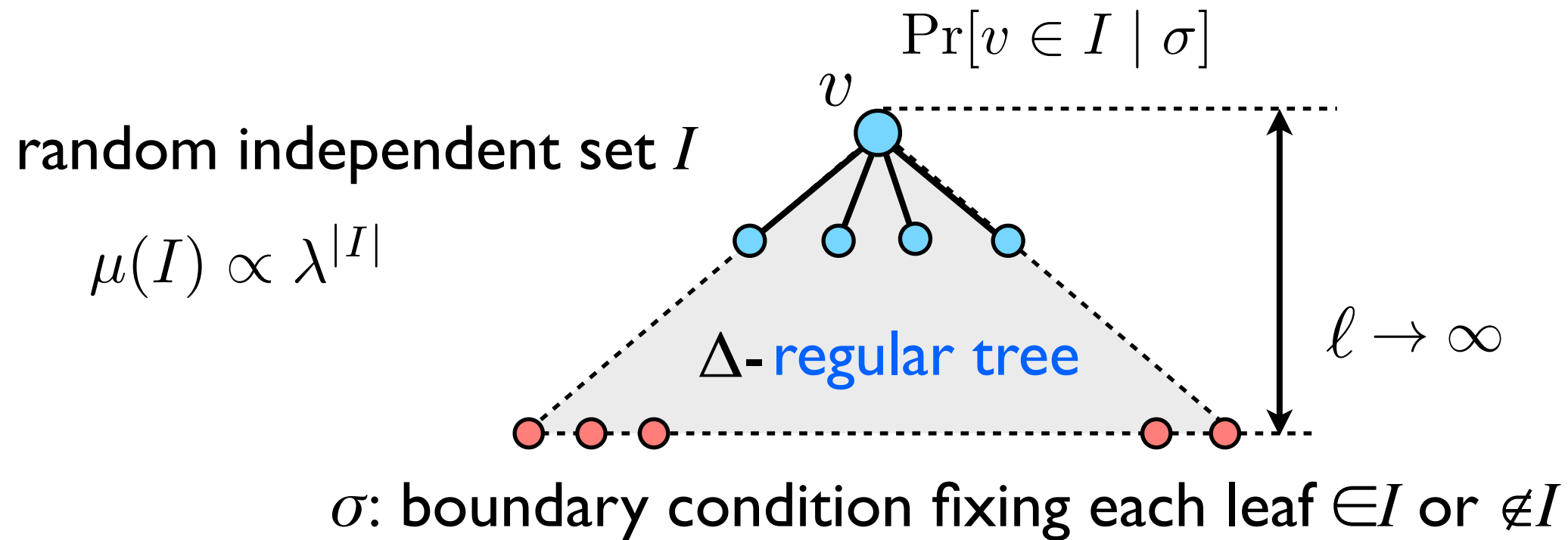


**Critical phenomenon:**

$\Pr[v \in I \mid \sigma]$  is independent of  $\sigma$  when  $\ell \rightarrow \infty$

$$\text{iff } \lambda \leq \lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta}$$

# Uniqueness Threshold



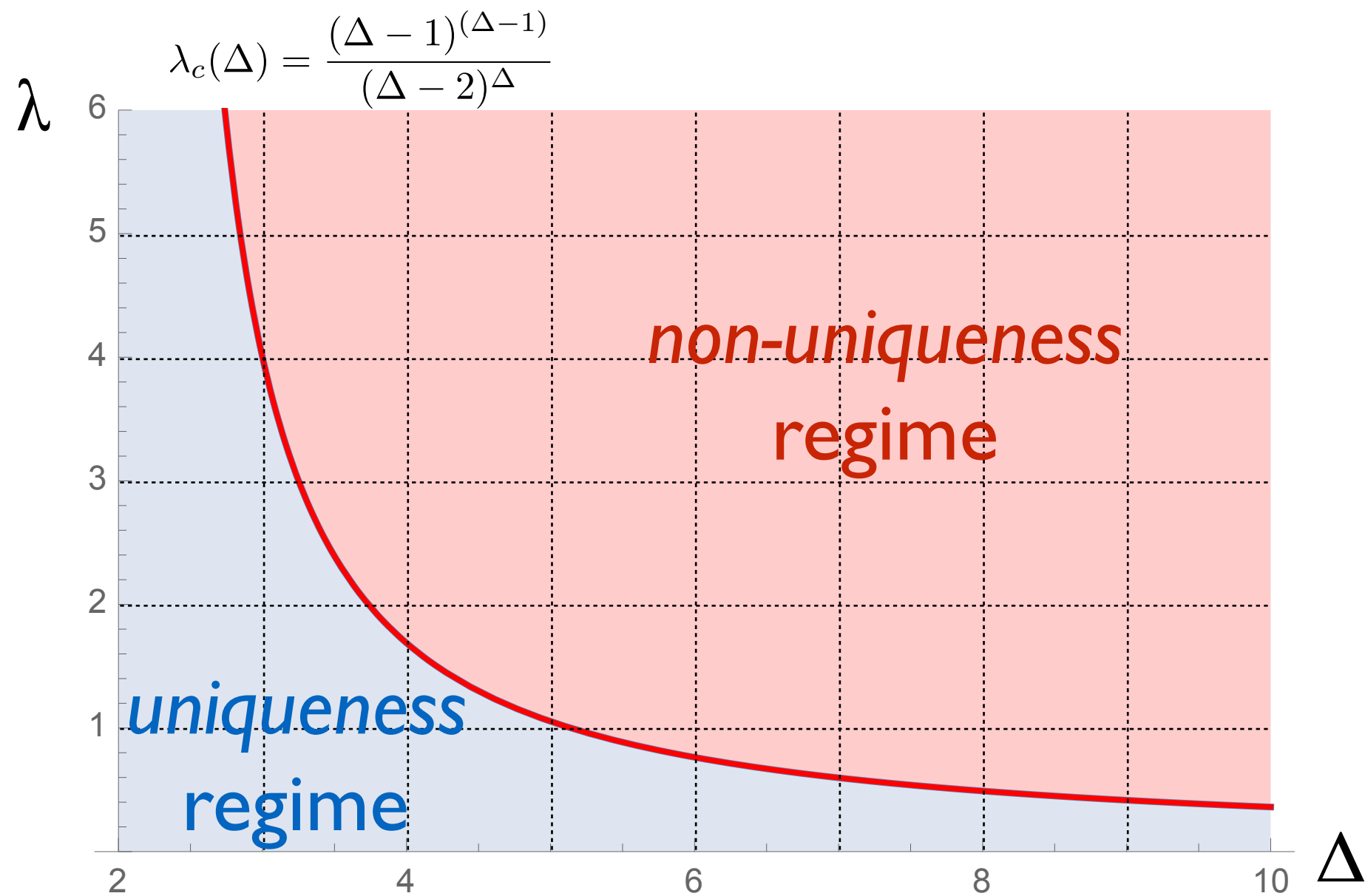
Critical phenomenon:

$\Pr[v \in I \mid \sigma]$  is independent of  $\sigma$  when  $\ell \rightarrow \infty$

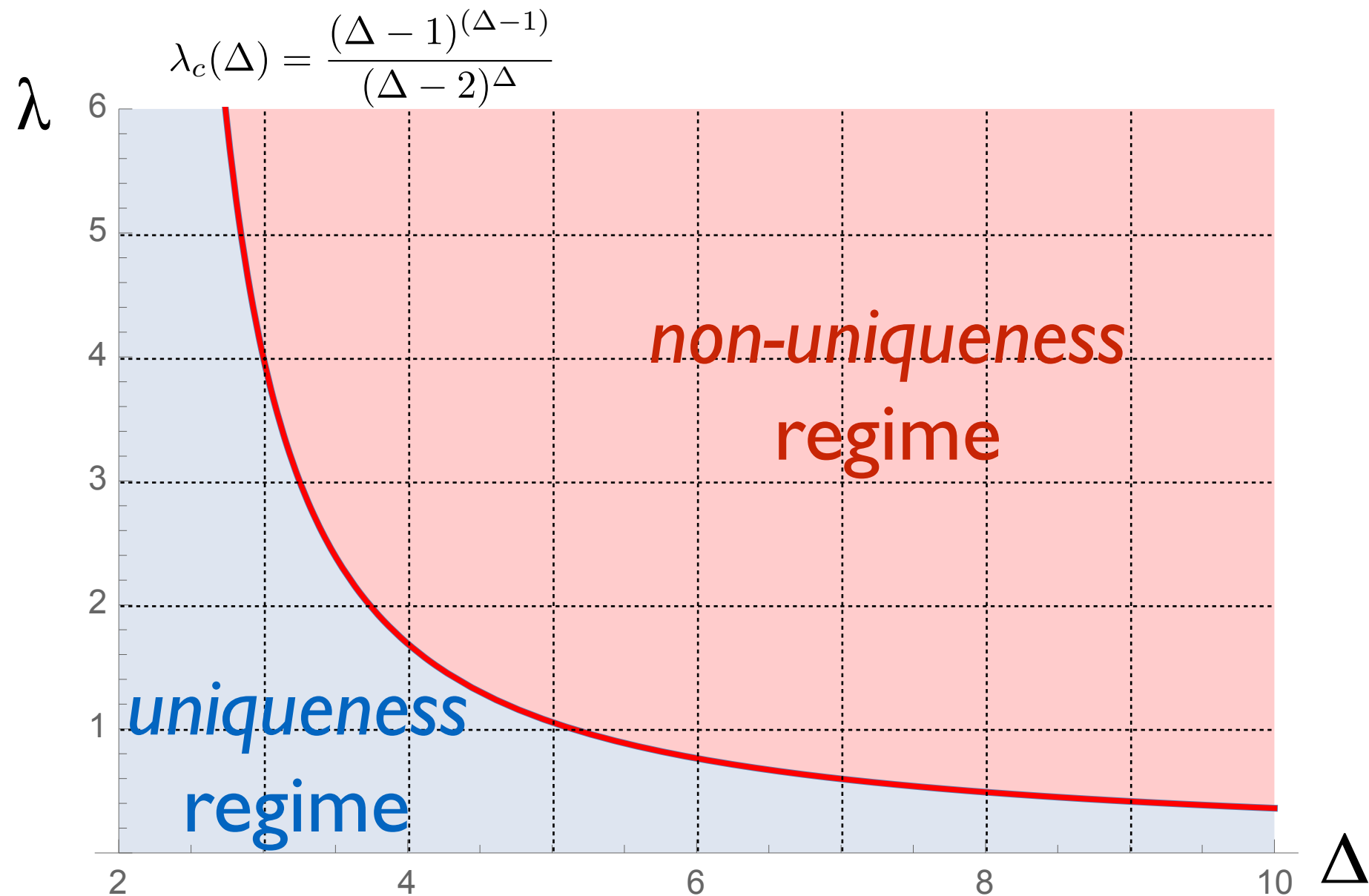
iff  $\lambda \leq \lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

Uniqueness threshold

# Phase Transition



# Phase Transition



sampling (**with bounded error**) from the hardcore model  
on graphs of **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

# Glauber Dynamics

[Glauber'63]

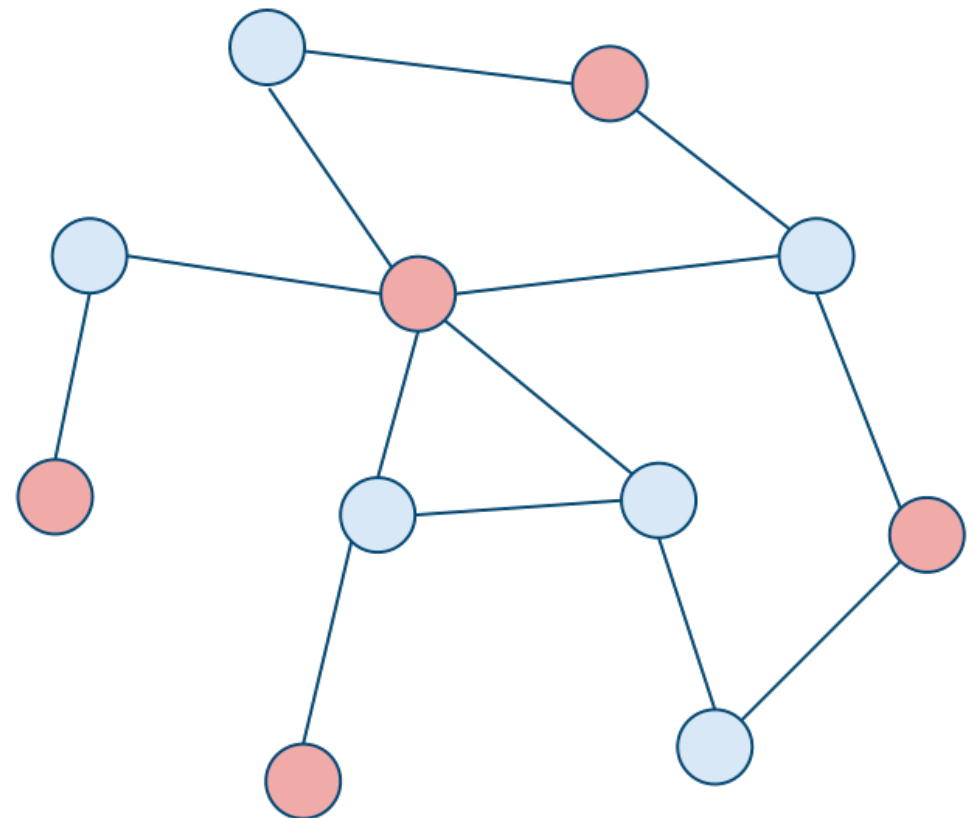
**Markov chain**  $\{X_t\}_{t=0,1,2,\dots}$  over independent sets in  $G(V,E)$

transition  $X_t \rightarrow X_{t+1}$  :

pick a **uniform random** vertex  $v$ ;  
if  $u \notin X_t$  for all  $v$ 's neighbors  $u$ :

$$X_{t+1} = \begin{cases} X_t \cup \{v\} & \text{with prob. } \frac{\lambda}{1+\lambda} \\ X_t \setminus \{v\} & \text{with prob. } \frac{1}{1+\lambda} \end{cases}$$

else  $X_{t+1} = X_t$ ;



# Glauber Dynamics

[Glauber'63]

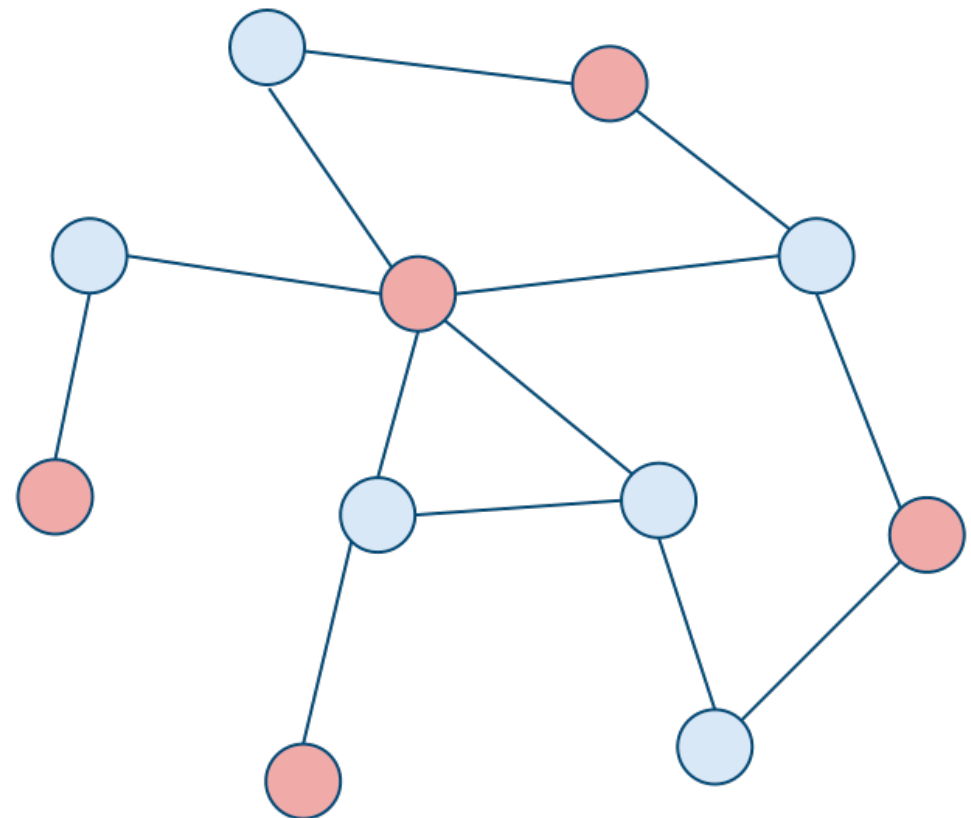
**Markov chain**  $\{X_t\}_{t=0,1,2,\dots}$  over independent sets in  $G(V,E)$

transition  $X_t \rightarrow X_{t+1}$ :

pick a **uniform random** vertex  $v$ ;  
if  $u \notin X_t$  for all  $v$ 's neighbors  $u$ :

$$X_{t+1} = \begin{cases} X_t \cup \{v\} & \text{with prob. } \frac{\lambda}{1+\lambda} \\ X_t \setminus \{v\} & \text{with prob. } \frac{1}{1+\lambda} \end{cases}$$

else  $X_{t+1} = X_t$ ;



**ergodic, irreducible**  
**time-reversible** w.r.t.  $\mu$

Markov chain  
convergence Thm

$$X_t \rightarrow \mu \text{ as } t \rightarrow \infty$$

# Glauber Dynamics

[Glauber'63]

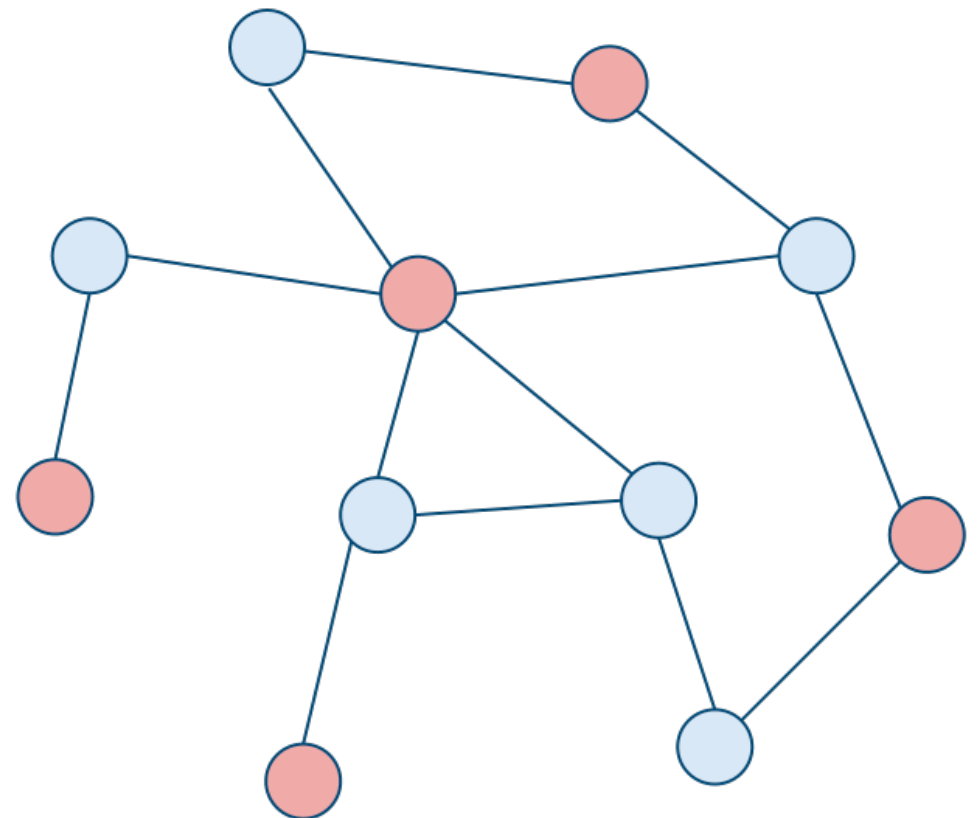
**Markov chain**  $\{X_t\}_{t=0,1,2,\dots}$  over independent sets in  $G(V,E)$

transition  $X_t \rightarrow X_{t+1}$ :

pick a **uniform random** vertex  $v$ ;  
if  $u \notin X_t$  for all  $v$ 's neighbors  $u$ :

$$X_{t+1} = \begin{cases} X_t \cup \{v\} & \text{with prob. } \frac{\lambda}{1+\lambda} \\ X_t \setminus \{v\} & \text{with prob. } \frac{1}{1+\lambda} \end{cases}$$

else  $X_{t+1} = X_t$ ;



**ergodic, irreducible**  
**time-reversible** w.r.t.  $\mu$

Markov chain  
convergence Thm

$$X_t \rightarrow \mu \text{ as } t \rightarrow \infty$$

**mixing time:**  $\tau_{\text{mix}} = \max_{X_0} \min\{t \mid d_{\text{TV}}(X_t, \mu) < 0.1\}$

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

- [Glauber'63] discovery of Glauber dynamic

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

- [Glauber'63] discovery of Glauber dynamic
- [Luby-Vigoda'99][Dyer-Greenhill'00][Vigoda'01]  
 $\tau_{\text{mix}} = O(n \log n)$  for Glauber dynamics when  $\lambda < 2/(\Delta - 2)$

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

- [Glauber'63] discovery of Glauber dynamic
- [Luby-Vigoda'99][Dyer-Greenhill'00][Vigoda'01]  
 $\tau_{\text{mix}} = O(n \log n)$  for Glauber dynamics when  $\lambda < 2/(\Delta - 2)$
- [Weitz'06] poly-time sampler when  $\lambda < \lambda_c(\Delta)$  for  $\Delta = O(1)$

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

- [Glauber'63] discovery of Glauber dynamic
- [Luby-Vigoda'99][Dyer-Greenhill'00][Vigoda'01]  
 $\tau_{\text{mix}} = O(n \log n)$  for Glauber dynamics when  $\lambda < 2/(\Delta - 2)$
- [Weitz'06]  $n^{O(\log \Delta)}$ -time poly-time sampler when  $\lambda < \lambda_c(\Delta)$  for  $\Delta = O(1)$

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

- [Glauber'63] discovery of Glauber dynamic
- [Luby-Vigoda'99][Dyer-Greenhill'00][Vigoda'01]  
 $\tau_{\text{mix}} = O(n \log n)$  for Glauber dynamics when  $\lambda < 2/(\Delta - 2)$
- [Weitz'06]  $n^{O(\log \Delta)}$ -time poly-time sampler when  $\lambda < \lambda_c(\Delta)$  for  $\Delta = O(1)$
- [Mossel-Weitz-Wormald'09] slow mixing of Glauber dynamics when  $\lambda > \lambda_c(\Delta)$

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

- [Glauber'63] discovery of Glauber dynamic
- [Luby-Vigoda'99][Dyer-Greenhill'00][Vigoda'01]  
 $\tau_{\text{mix}} = O(n \log n)$  for Glauber dynamics when  $\lambda < 2/(\Delta - 2)$
- [Weitz'06]  $n^{O(\log \Delta)}$ -time poly-time sampler when  $\lambda < \lambda_c(\Delta)$  for  $\Delta = O(1)$
- [Mossel-Weitz-Wormald'09] slow mixing of Glauber dynamics when  $\lambda > \lambda_c(\Delta)$
- [Sly'10] NP-hardness of sampling when  $\lambda > \lambda_c(\Delta)$

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

- [Glauber'63] discovery of Glauber dynamic
- [Luby-Vigoda'99][Dyer-Greenhill'00][Vigoda'01]  
 $\tau_{\text{mix}} = O(n \log n)$  for Glauber dynamics when  $\lambda < 2/(\Delta - 2)$
- [Weitz'06]  $n^{O(\log \Delta)}$ -time poly-time sampler when  $\lambda < \lambda_c(\Delta)$  for  $\Delta = O(1)$
- [Mossel-Weitz-Wormald'09] slow mixing of Glauber dynamics when  $\lambda > \lambda_c(\Delta)$
- [Sly'10] NP-hardness of sampling when  $\lambda > \lambda_c(\Delta)$

**Theorem** (Efthymiou-Hayes-Štefankovič-Vigoda-Y.'16):

$\tau_{\text{mix}} = O(n \log n)$  for Glauber dynamics when  $\lambda < \lambda_c(\Delta)$ ,  
if  $\Delta$  is sufficiently large, and there is no small cycles.

sampling (**with bounded error**) from the hardcore model  
on graphs with **max-degree**  $\Delta$  and **fugacity**  $\lambda > 0$

**uniqueness threshold:**  $\lambda_c(\Delta) = \frac{(\Delta - 1)^{(\Delta - 1)}}{(\Delta - 2)^\Delta} \approx \frac{e}{\Delta - 2}$

- [Glauber'63] discovery of Glauber dynamic
- [Luby-Vigoda'99][Dyer-Greenhill'00][Vigoda'01]  
 $\tau_{\text{mix}} = O(n \log n)$  for Glauber dynamics when  $\lambda < 2/(\Delta - 2)$
- [Weitz'06]  $n^{O(\log \Delta)}$ -time poly-time sampler when  $\lambda < \lambda_c(\Delta)$  for  $\Delta = O(1)$
- [Mossel-Weitz-Wormald'09] slow mixing of Glauber dynamics when  $\lambda > \lambda_c(\Delta)$
- [Sly'10] NP-hardness of sampling when  $\lambda > \lambda_c(\Delta)$

**Theorem** (Efthymiou-Hayes-Štefankovič-Vigoda-Y.'16):

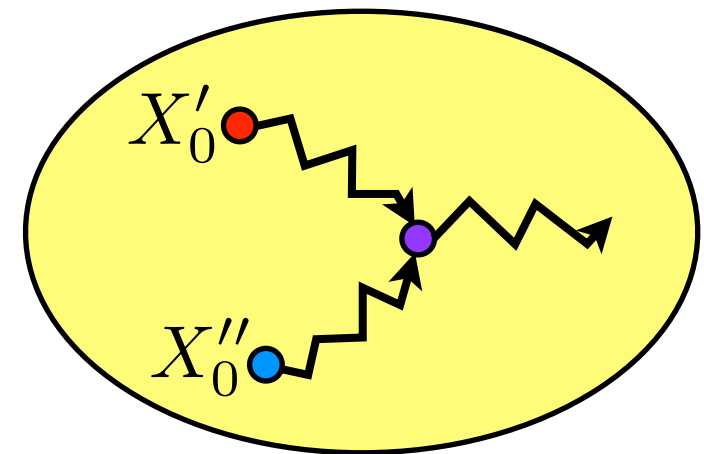
$\forall \delta > 0, \exists \Delta_0$  s.t.  $\tau_{\text{mix}} = O(n \log n)$  for all graphs of max-degree  $\Delta \geq \Delta_0$  and girth  $\geq 7$  when  $\lambda \leq (1 - \delta)\lambda_c(\Delta)$ .

# Coupling

a **coupling** of a Markov chain  $X_t$  is a joint Markov chain  $(X'_t, X''_t)$ :

- both  $X'_t$  and  $X''_t$  follow the same transition rule as  $X_t$
- once collides, makes identical moves thereafter

$$X'_t = X''_t \quad \longrightarrow \quad X'_{t+1} = X''_{t+1}$$



# Coupling

a **coupling** of a Markov chain  $X_t$  is a joint Markov chain  $(X'_t, X''_t)$ :

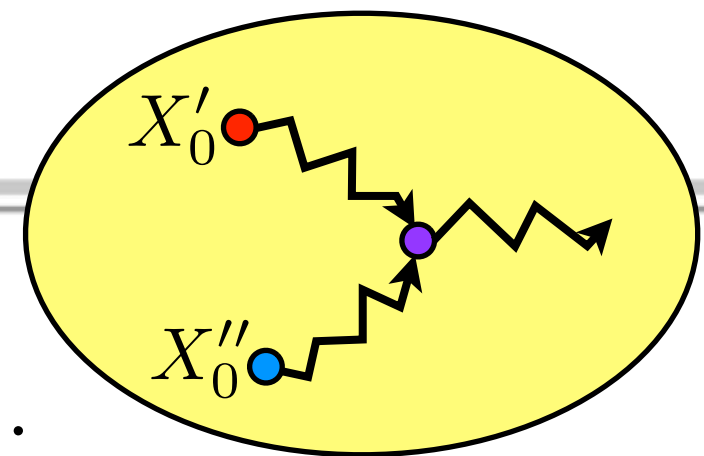
- both  $X'_t$  and  $X''_t$  follow the same transition rule as  $X_t$
- once collides, makes identical moves thereafter

$$X'_t = X''_t \quad \longrightarrow \quad X'_{t+1} = X''_{t+1}$$

**Theorem** (Griffeath'78, Aldous'83):

$\forall$  coupling  $(X'_t, X''_t)$  of Markov chain  $X_t$ :

$$\tau_{\text{mix}} \leq \max_{X'_0, X''_0} \min\{t \mid \Pr[X'_t \neq X''_t] < 0.1\}$$



# Path Coupling

**Theorem** (Bubley-Dyer'97):

If there is a **metric**  $\Phi(\cdot, \cdot)$  over all states for the chain and a coupling  $(X_t, Y_t) \rightarrow (X_{t+1}, Y_{t+1})$  for **adjacent**  $(X_t, Y_t)$

$$\text{s.t.: } \mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$$

$$\Rightarrow \tau_{\text{mix}} = O\left(\frac{n}{\alpha} \log n\right)$$

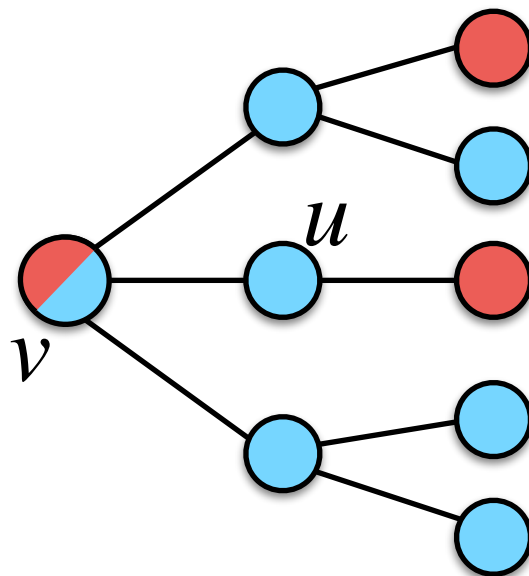
# Path Coupling

**Theorem** (Bubley-Dyer'97):

If there is a **metric**  $\Phi(\cdot, \cdot)$  over all states for the chain and a coupling  $(X_t, Y_t) \rightarrow (X_{t+1}, Y_{t+1})$  for **adjacent**  $(X_t, Y_t)$

$$\text{s.t.: } \mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$$

➡  $\tau_{\text{mix}} = O\left(\frac{n}{\alpha} \log n\right)$



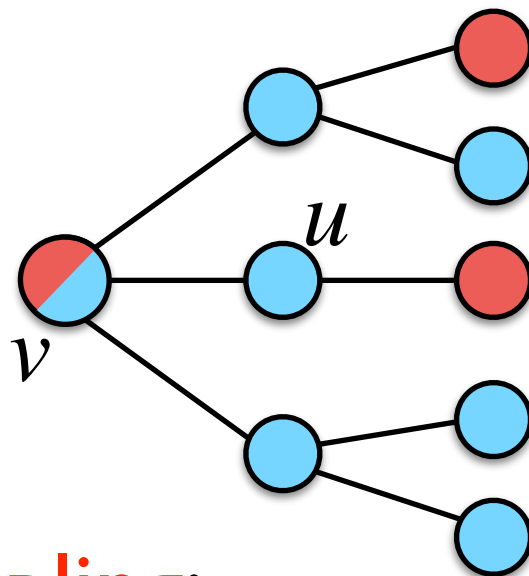
# Path Coupling

**Theorem** (Bubley-Dyer'97):

If there is a **metric**  $\Phi(\cdot, \cdot)$  over all states for the chain and a coupling  $(X_t, Y_t) \rightarrow (X_{t+1}, Y_{t+1})$  for **adjacent**  $(X_t, Y_t)$

$$\text{s.t.: } \mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$$

➡  $\tau_{\text{mix}} = O\left(\frac{n}{\alpha} \log n\right)$

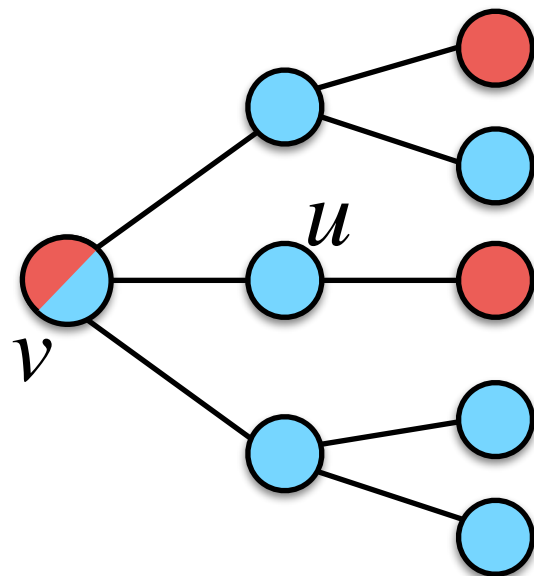


**one-step optimal coupling:**

$\Pr[X_{t+1}(u) \neq Y_{t+1}(u) \mid u \text{ is picked in step } t]$  is minimized

one-step optimal coupling for  $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

**Goal:**  $\mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$

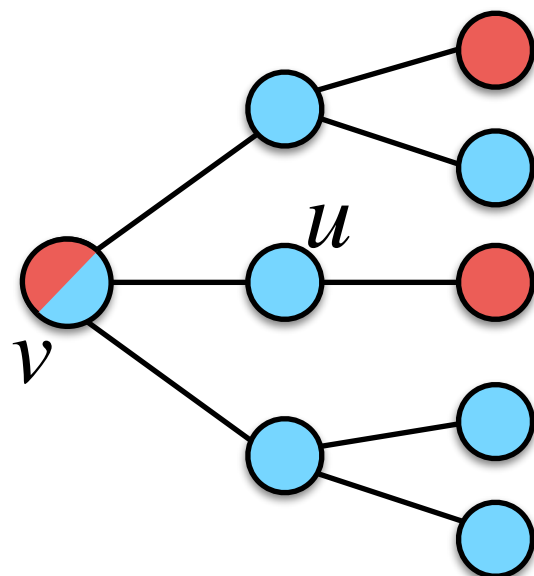


metric  $\Phi(\cdot, \cdot)$  is a **weighted Hamming distance**:

$$\Phi(X, Y) = \sum_{v \in X \oplus Y} \Phi_v \text{ where } \Phi_v \geq 1 \text{ is } v\text{'s weight}$$

**one-step optimal coupling** for  $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

**Goal:**  $\mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$

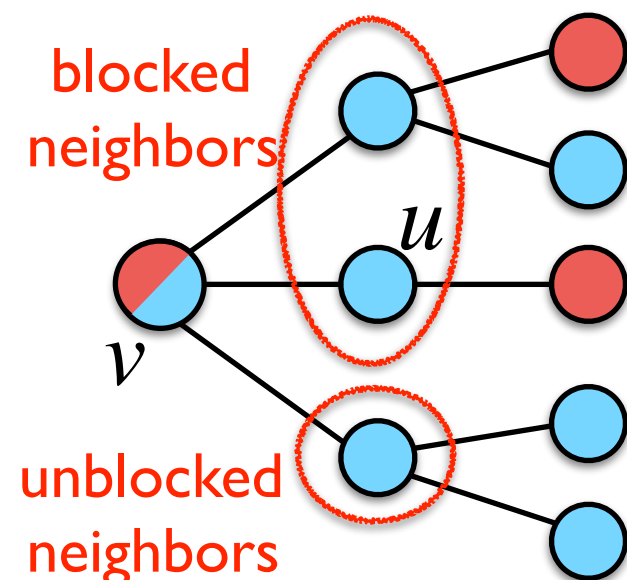


metric  $\Phi(\cdot, \cdot)$  is a **weighted Hamming distance**:

$$\Phi(X, Y) = \sum_{v \in X \oplus Y} \Phi_v \text{ where } \Phi_v \geq 1 \text{ is } v\text{'s weight}$$

**one-step optimal coupling** for  $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

**Goal:**  $\mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$



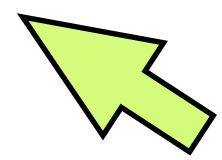
$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

metric  $\Phi(\cdot, \cdot)$  is a **weighted Hamming distance**:

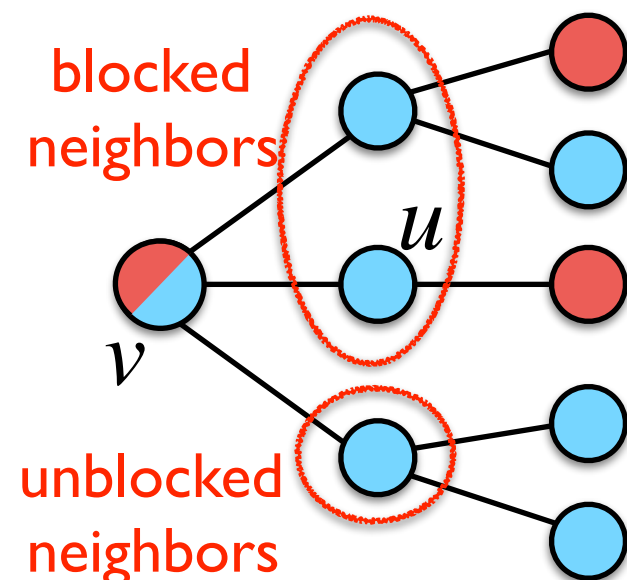
$$\Phi(X, Y) = \sum_{v \in X \oplus Y} \Phi_v \text{ where } \Phi_v \geq 1 \text{ is } v\text{'s weight}$$

**one-step optimal coupling** for  $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

**Goal:**  $\mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$



$$\sum_{u \in N(v)} \frac{\lambda}{1 + \lambda} W_u^{(t)} \Phi_u \leq (1 - \alpha)\Phi_v$$



$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

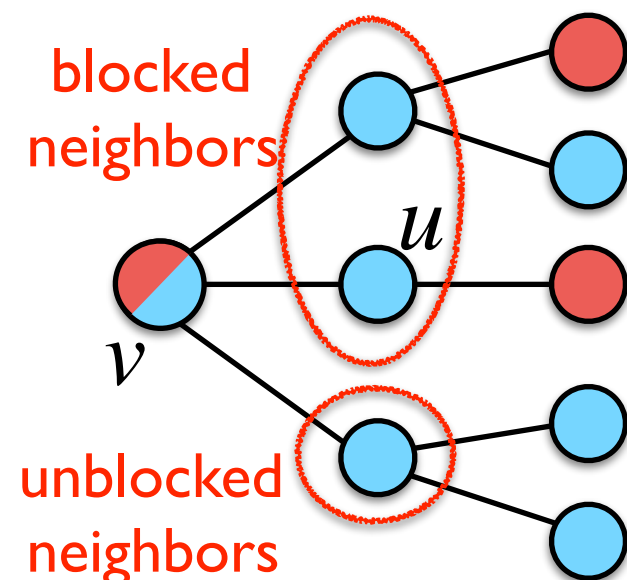
metric  $\Phi(\cdot, \cdot)$  is a **weighted Hamming distance**:

$$\Phi(X, Y) = \sum_{v \in X \oplus Y} \Phi_v \text{ where } \Phi_v \geq 1 \text{ is } v\text{'s weight}$$

**one-step optimal coupling** for  $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

**Goal:**  $\mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$

$$\sum_{u \in N(v)} \frac{\lambda}{1 + \lambda} W_u^{(t)} \Phi_u \leq \sum_{u \in N(v)} \frac{\lambda W_u^{(t)}}{1 + \lambda W_u^{(t)}} \Phi_u \leq (1 - \alpha) \Phi_v$$



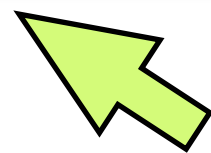
$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

metric  $\Phi(\cdot, \cdot)$  is a **weighted Hamming distance**:

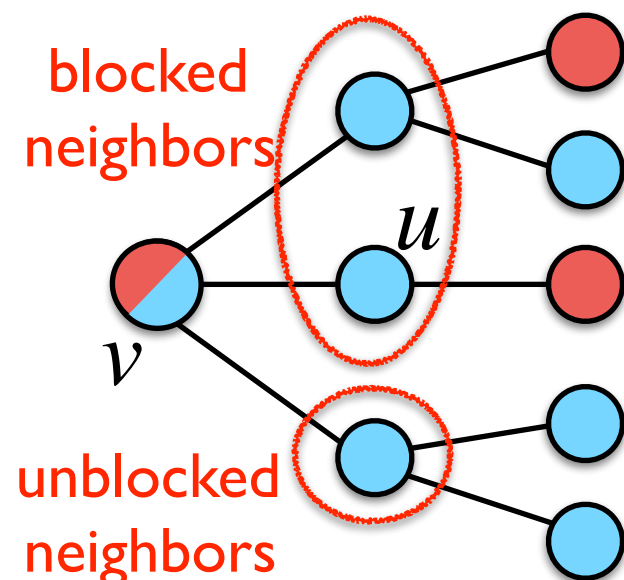
$$\Phi(X, Y) = \sum_{v \in X \oplus Y} \Phi_v \text{ where } \Phi_v \geq 1 \text{ is } v\text{'s weight}$$

**one-step optimal coupling** for  $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

**Goal:**  $\mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$



$$\sum_{u \in N(v)} \frac{\lambda W_u^{(t)}}{1 + \lambda W_u^{(t)}} \Phi_u \leq (1 - \alpha)\Phi_v$$



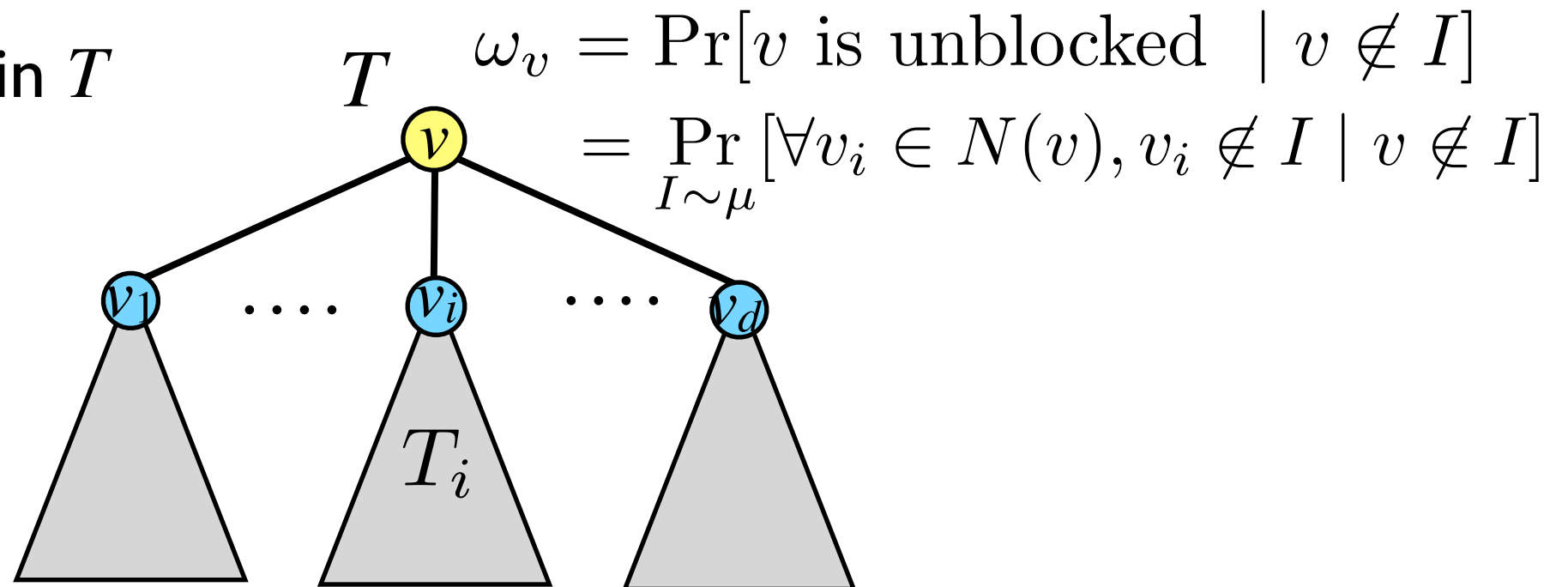
$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

# Belief Propagation

[Pearl'82]

independent set  $I$  in  $T$

$$\mu(I) \propto \lambda^{|I|}$$

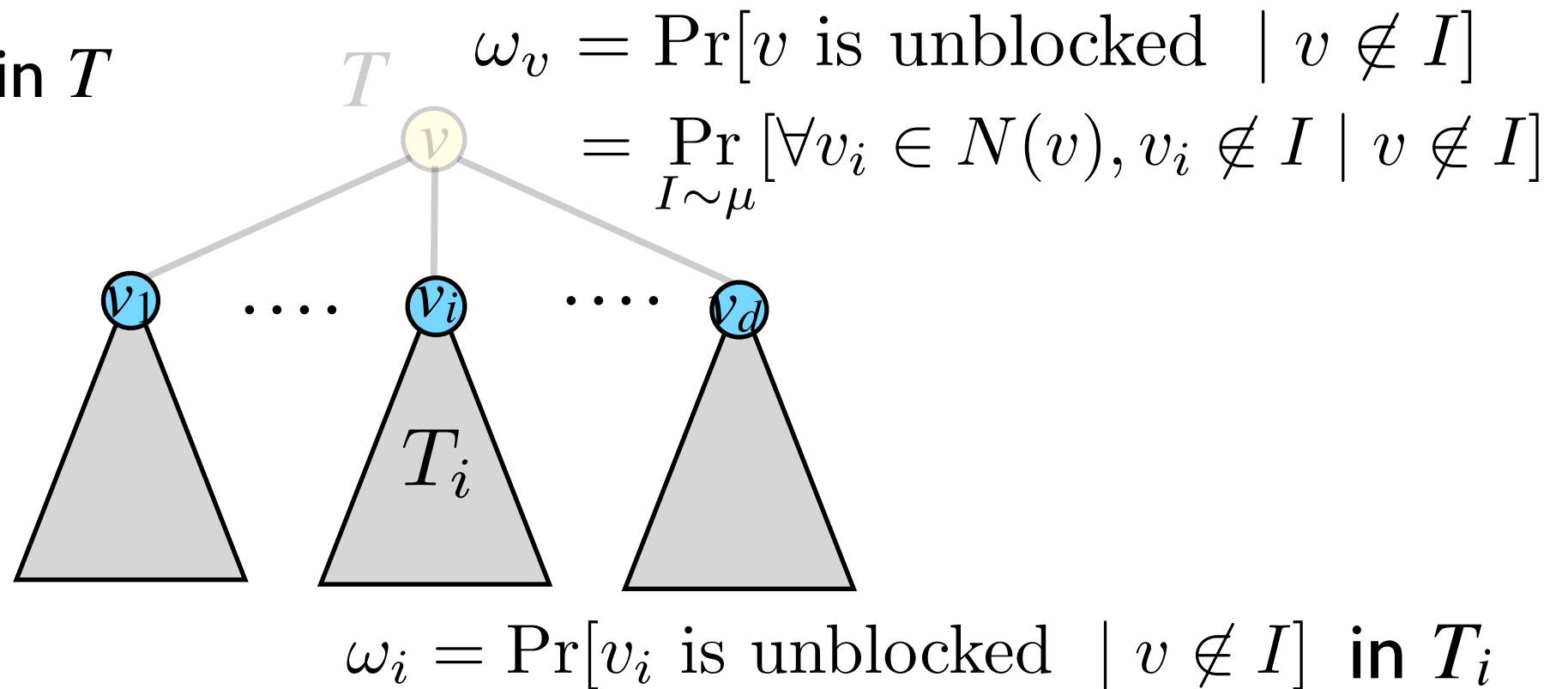


# Belief Propagation

[Pearl'82]

independent set  $I$  in  $T$

$$\mu(I) \propto \lambda^{|I|}$$

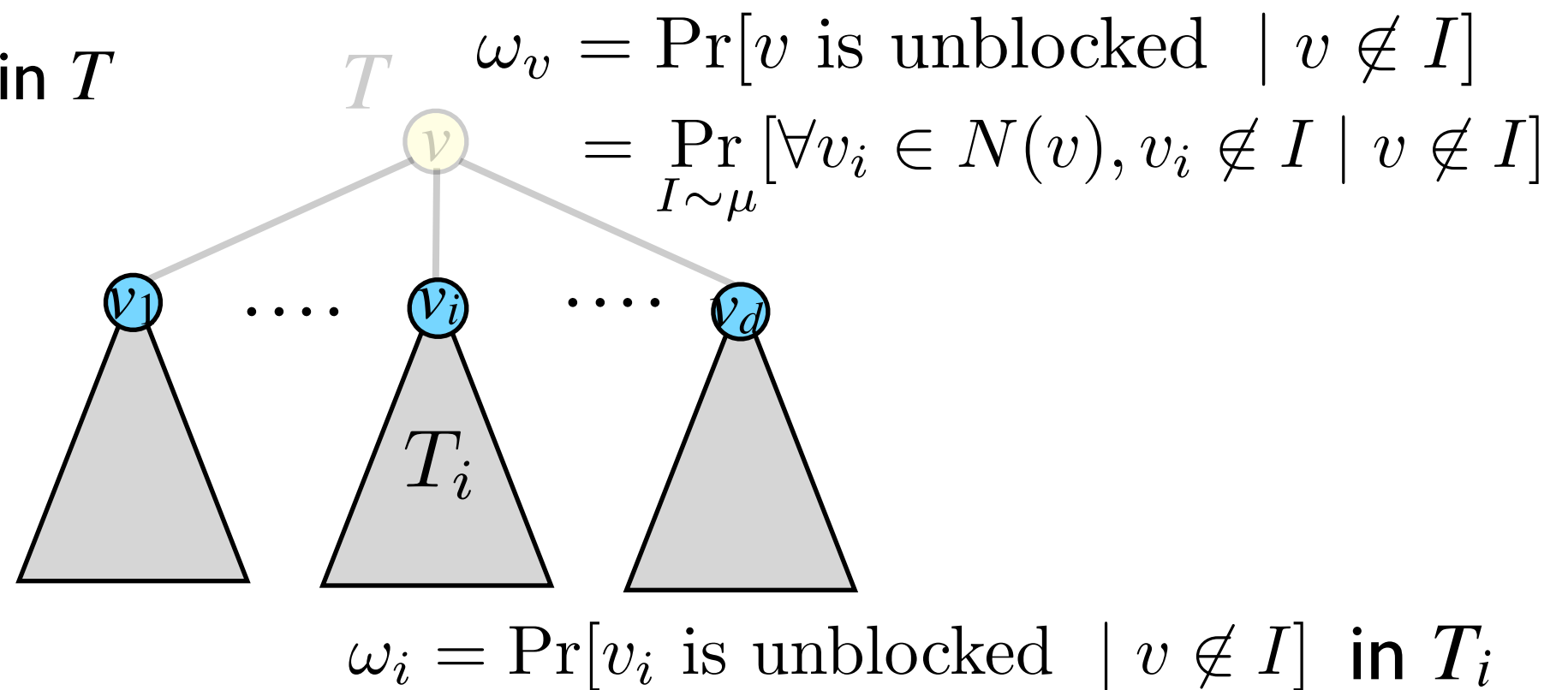


# Belief Propagation

[Pearl'82]

independent set  $I$  in  $T$

$$\mu(I) \propto \lambda^{|I|}$$



**Belief propagation (BP):**

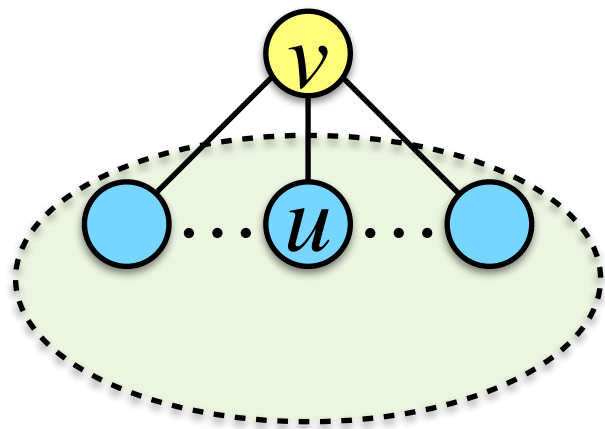
$$\omega_v = \prod_{i=1}^d \frac{1}{1 + \lambda \omega_i}$$

# Loopy Belief Propagation

graph  $G(V, E)$  with max-degree  $\leq \Delta$        $\vec{\omega} \in [0, 1]^V$

**loopy BP:**       $\vec{\omega}^{(t+1)} = F(\vec{\omega}^{(t)})$

where  $\forall v$ :       $\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$

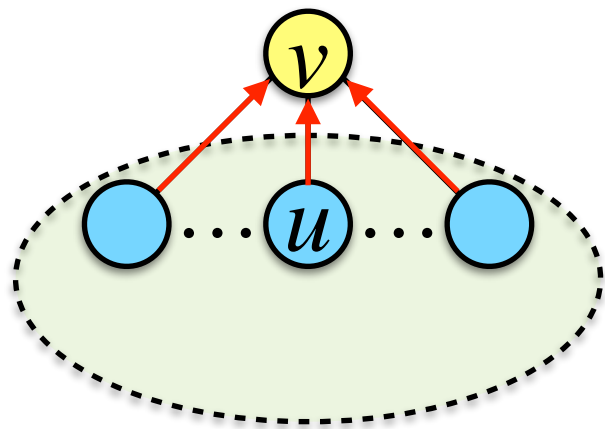


# Loopy Belief Propagation

graph  $G(V, E)$  with  $\text{max-degree} \leq \Delta$        $\vec{\omega} \in [0, 1]^V$

**loopy BP:**       $\vec{\omega}^{(t+1)} = F(\vec{\omega}^{(t)})$

where  $\forall v$ :       $\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$

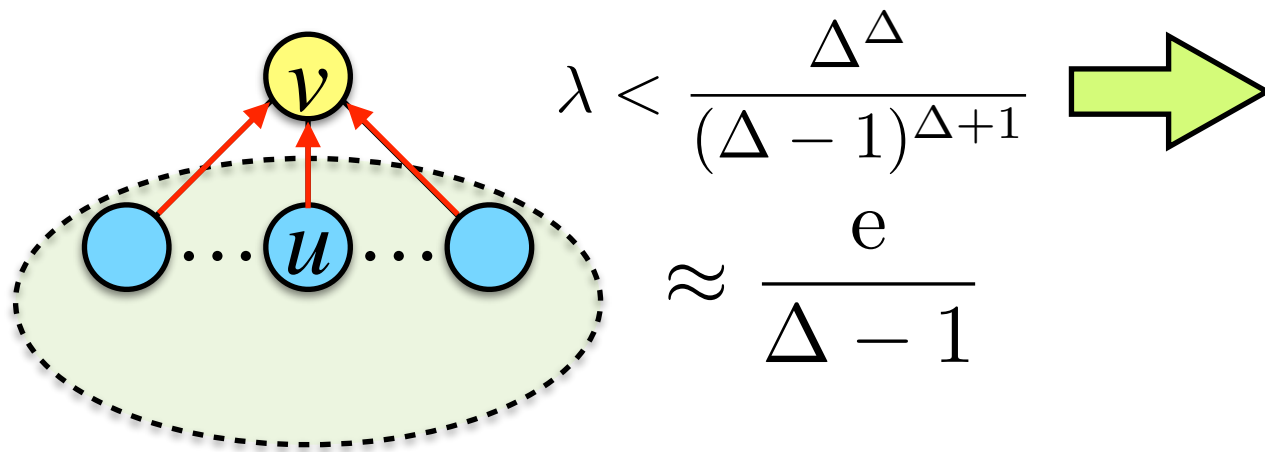


# Loopy Belief Propagation

graph  $G(V, E)$  with  $\text{max-degree} \leq \Delta$        $\vec{\omega} \in [0, 1]^V$

**loopy BP:**  $\vec{\omega}^{(t+1)} = F(\vec{\omega}^{(t)})$

where  $\forall v$ :  $\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$



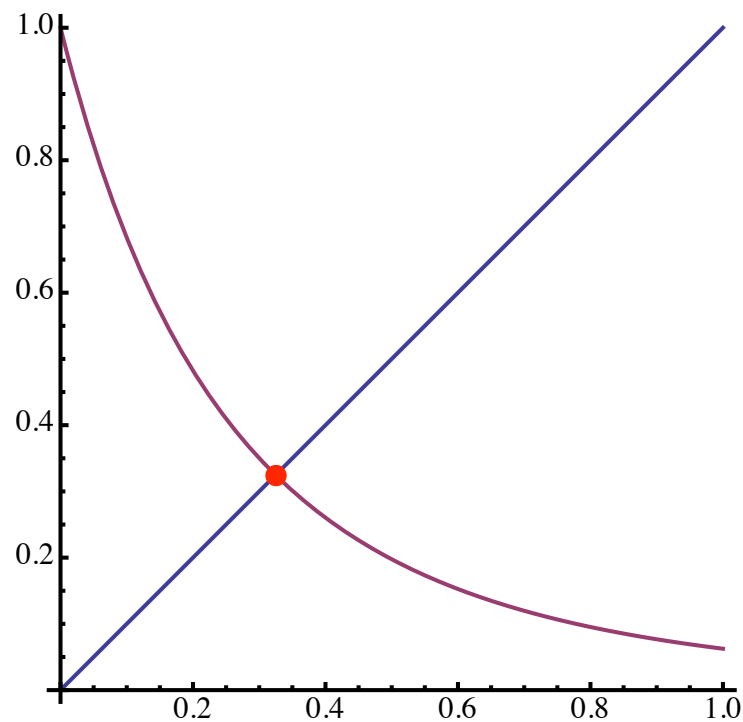
$\forall$  initial values  $\vec{\omega}^{(0)} \in [0, 1]^V$   
 $\vec{\omega}^{(t)}$  **converges** to a **unique**  
**fixpoint**  $\omega^* = F(\omega^*)$   
at an **exponential rate**.

# BP Convergence

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

univariate dynamical system:

$$f(x) = (1 + \lambda x)^{-\Delta}$$

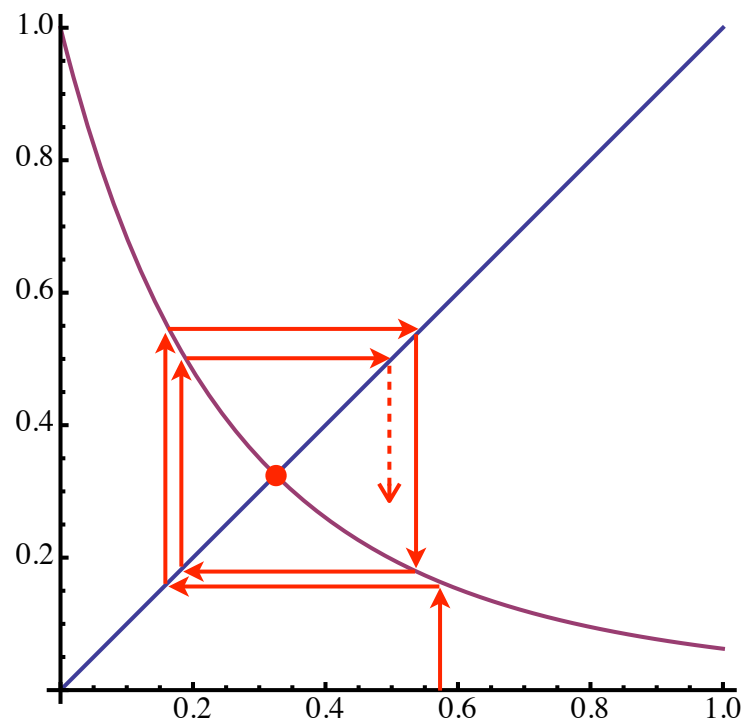


# BP Convergence

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

univariate dynamical system:

$$f(x) = (1 + \lambda x)^{-\Delta}$$



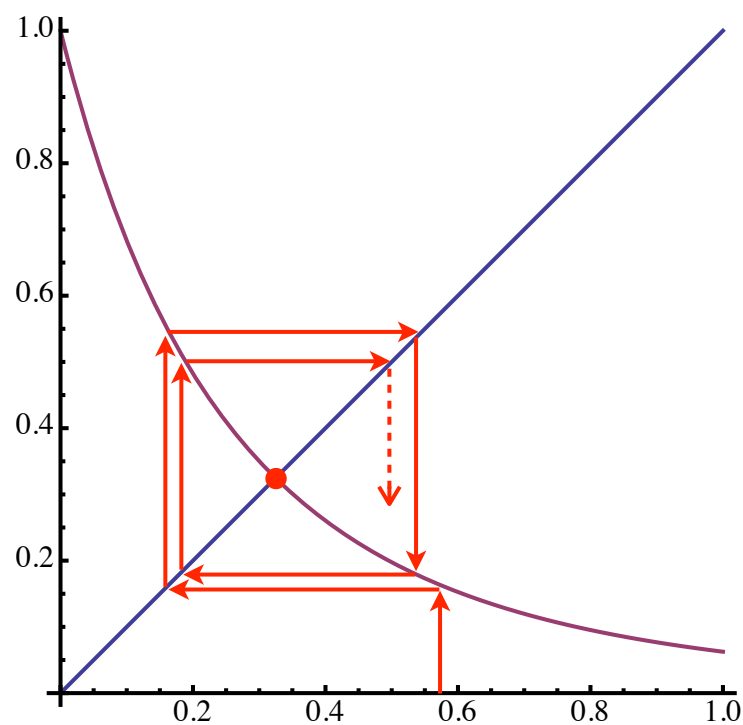
$$\lambda < \frac{\Delta^\Delta}{(\Delta - 1)^{\Delta+1}}$$

# BP Convergence

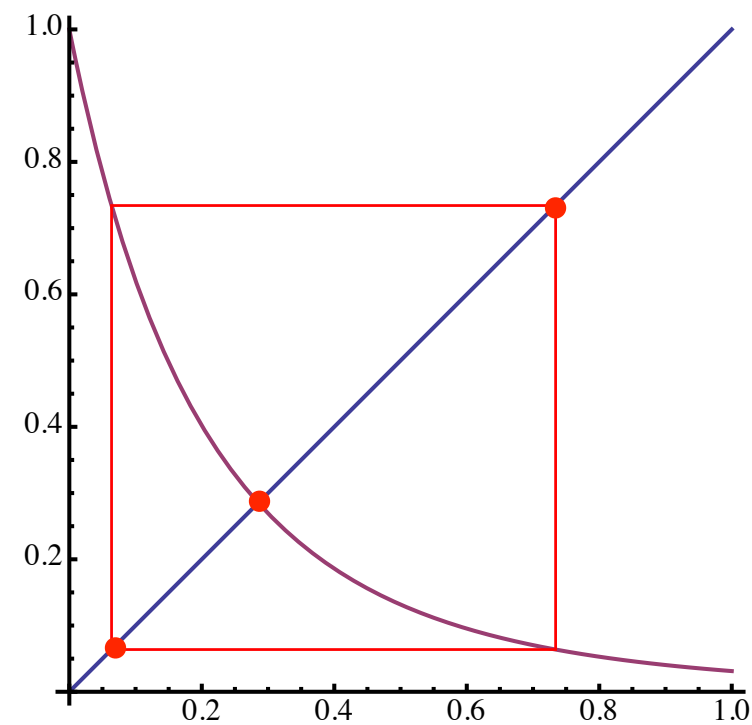
$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

univariate dynamical system:

$$f(x) = (1 + \lambda x)^{-\Delta}$$



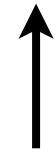
$$\lambda < \frac{\Delta^\Delta}{(\Delta - 1)^{\Delta+1}}$$



$$\lambda > \frac{\Delta^\Delta}{(\Delta - 1)^{\Delta+1}}$$

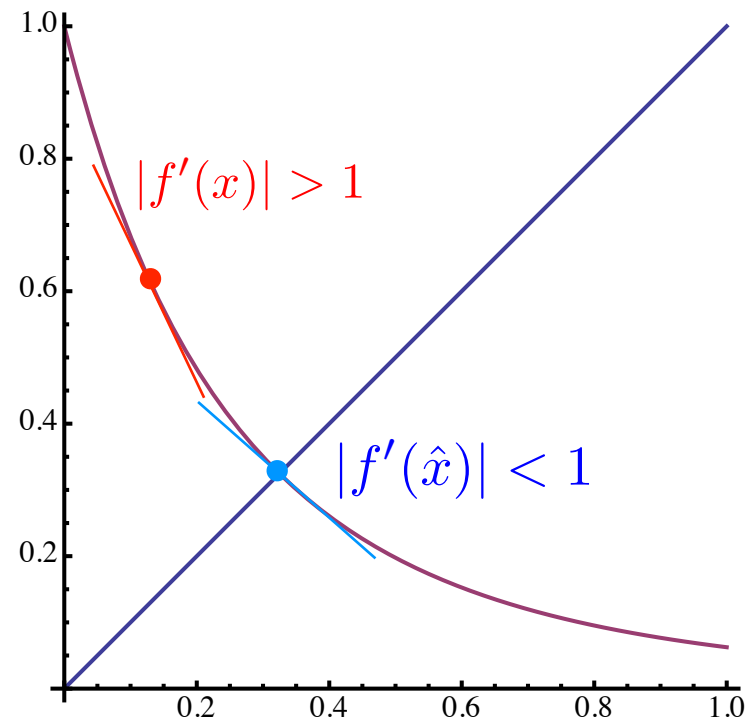
# Potential Method

$$f(x) = (1 + \lambda x)^{-\Delta}$$



$x$

$$f(x) = (1 + \lambda x)^{-\Delta}$$



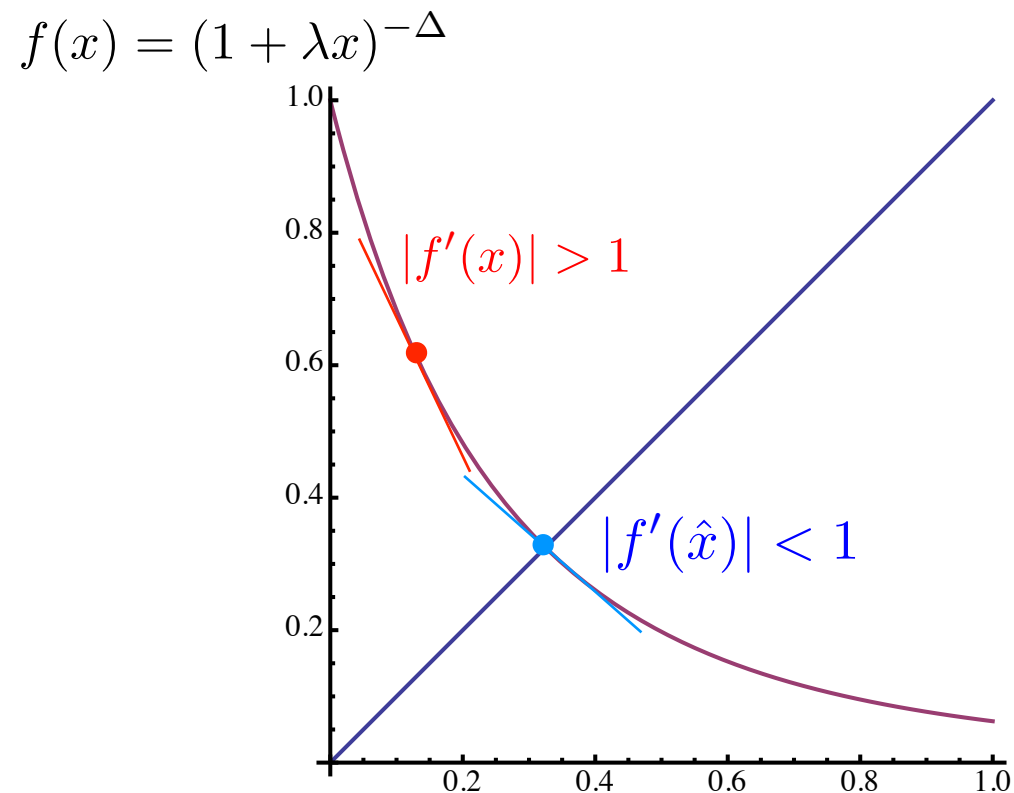
# Potential Method

$$f(x) = (1 + \lambda x)^{-\Delta} \xrightarrow{\psi} g(y)$$

$$\begin{array}{ccc} & \uparrow & \\ x & \xrightarrow{\psi(x) = \operatorname{arcsinh}(\sqrt{\lambda x})} & y \end{array}$$

used in

[Li-Lu-Y.'13] [Sinclair-Srivastava-Y.'13] [Sinclair-Srivastava-Štefankovič-Y.'15]



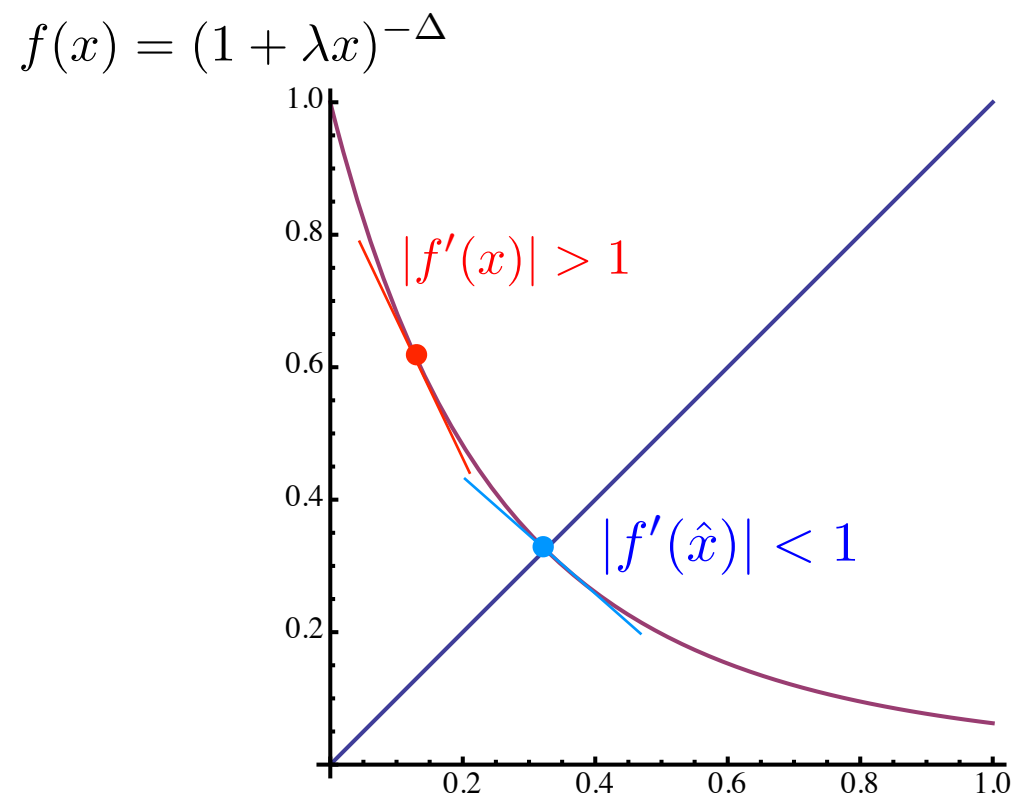
# Potential Method

$$f(x) = (1 + \lambda x)^{-\Delta} \xrightarrow{\psi} g(y) = \psi(f(\psi^{-1}(y)))$$

$\uparrow$   $\psi(x) = \operatorname{arcsinh}(\sqrt{\lambda x})$   $\uparrow$   
 $x$   $y$

used in

[Li-Lu-Y.'13] [Sinclair-Srivastava-Y.'13] [Sinclair-Srivastava-Štefankovič-Y.'15]



# Potential Method

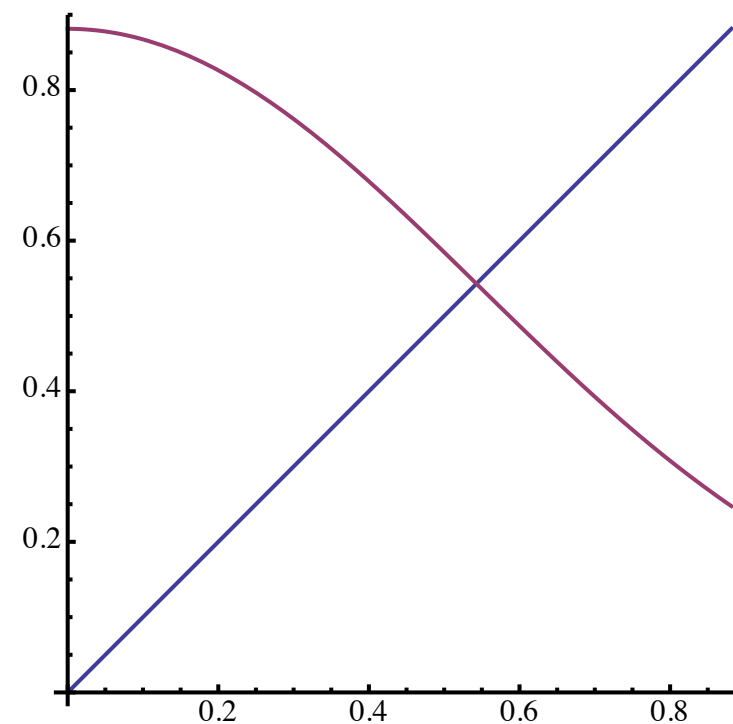
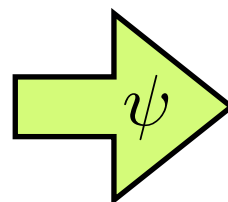
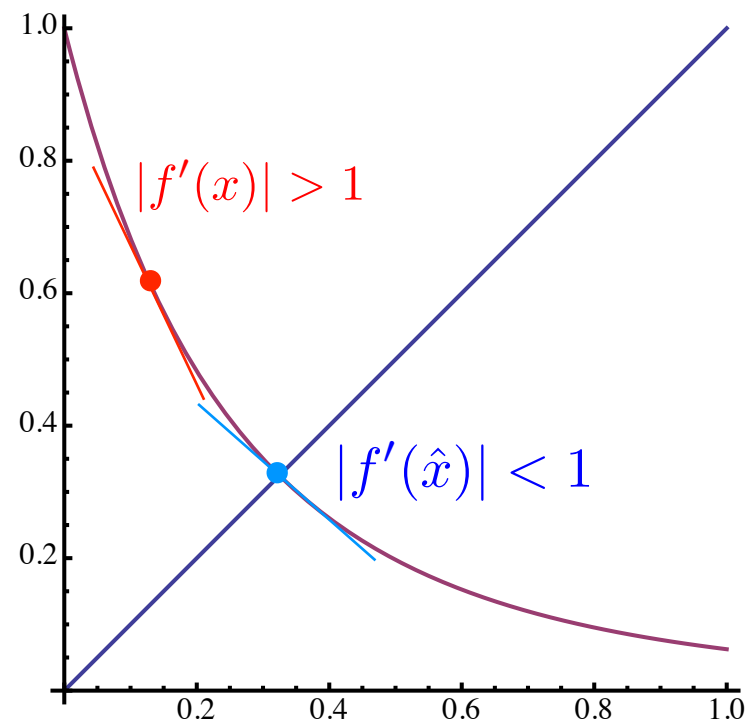
$$f(x) = (1 + \lambda x)^{-\Delta} \xrightarrow{\psi} g(y) = \psi(f(\psi^{-1}(y)))$$

$\uparrow$   $\psi(x) = \operatorname{arcsinh}(\sqrt{\lambda x})$   $\uparrow$   
 $x$   $y$

used in

[Li-Lu-Y.'13] [Sinclair-Srivastava-Y.'13] [Sinclair-Srivastava-Štefankovič-Y.'15]

$$f(x) = (1 + \lambda x)^{-\Delta}$$



# Potential Method

$$f(x) = (1 + \lambda x)^{-\Delta} \xrightarrow{\psi} g(y) = \psi(f(\psi^{-1}(y)))$$

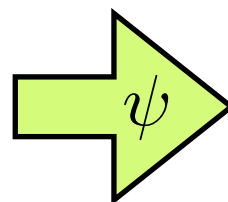
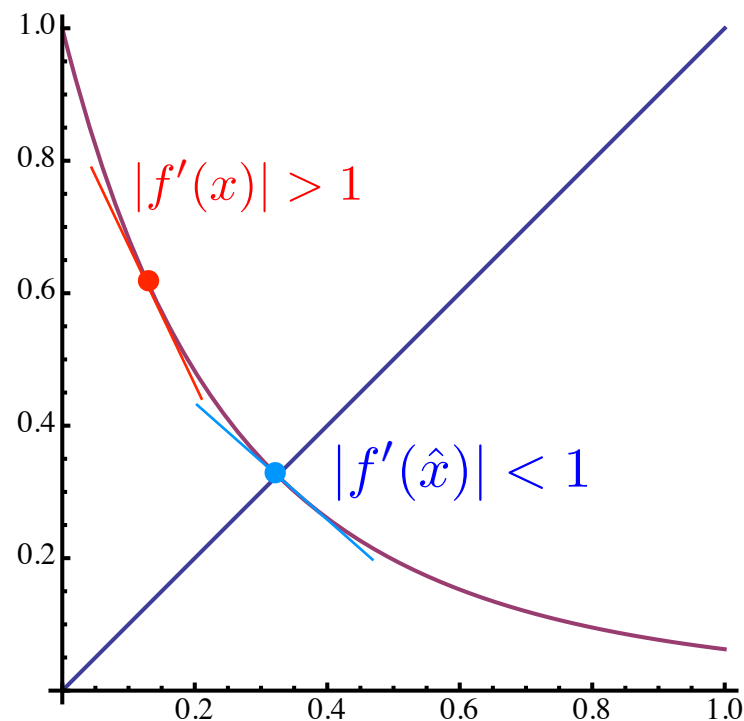
$\psi(x) = \operatorname{arcsinh}(\sqrt{\lambda x})$

Always contract!

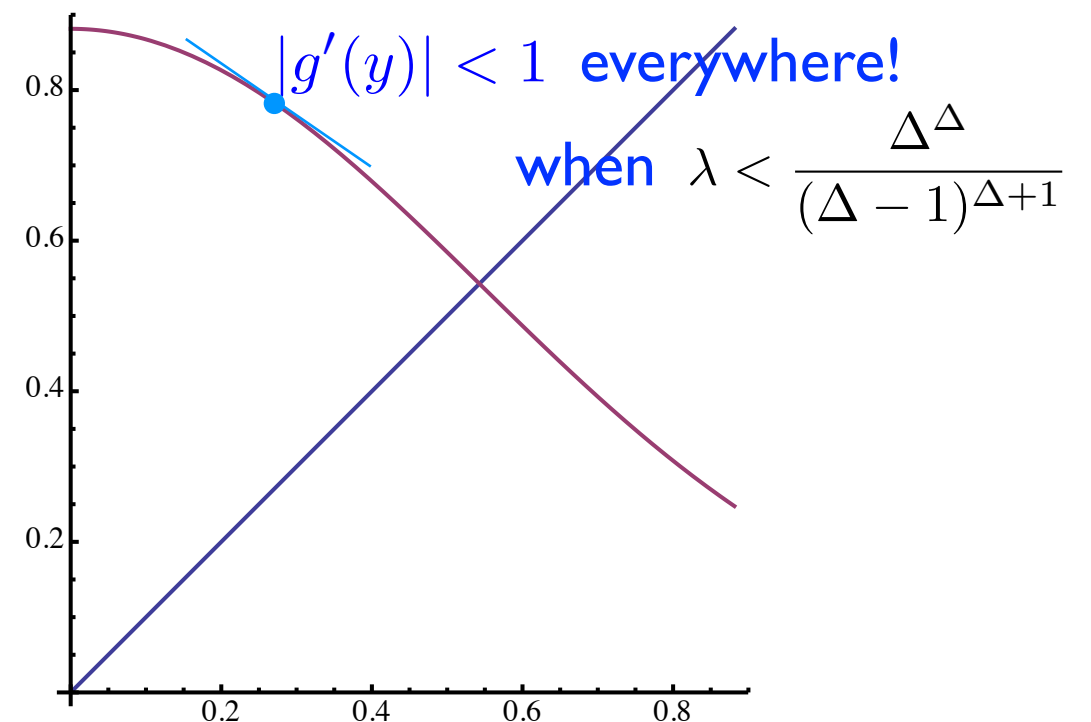
used in

[Li-Lu-Y.'13] [Sinclair-Srivastava-Y.'13] [Sinclair-Srivastava-Štefankovič-Y.'15]

$$f(x) = (1 + \lambda x)^{-\Delta}$$



$$g(y) = \psi(f(\psi^{-1}(y)))$$



original BP:

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

**potentials:**  $\chi_v = \psi(\omega_v) = \operatorname{arcsinh}(\sqrt{\lambda \omega})$

original BP:

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

BP for potentials:

$$\chi_v^{(t+1)} = \psi \left( \prod_{u \in N(v)} \frac{1}{1 + \lambda \cdot \psi^{-1}(\chi_u^{(t)})} \right)$$

**potentials:**  $\chi_v = \psi(\omega_v) = \operatorname{arcsinh}(\sqrt{\lambda \omega})$

original BP:

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

BP for potentials:

$$\chi_v^{(t+1)} = \psi \left( \prod_{u \in N(v)} \frac{1}{1 + \lambda \cdot \psi^{-1}(\chi_u^{(t)})} \right)$$

potentials:  $\chi_v = \psi(\omega_v) = \operatorname{arcsinh}(\sqrt{\lambda \omega})$

Jacobian for potentials :  $J_{vu} = \frac{\partial \chi_v^{(t+1)}}{\partial \chi_u^{(t)}} = \frac{\partial \omega_v^{(t+1)}}{\partial \omega_u^{(t)}} \frac{\psi'(\omega_v^{(t+1)})}{\psi'(\omega_u^{(t)})}$

original BP:

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

BP for potentials:

$$\chi_v^{(t+1)} = \psi \left( \prod_{u \in N(v)} \frac{1}{1 + \lambda \cdot \psi^{-1}(\chi_u^{(t)})} \right)$$

potentials:  $\chi_v = \psi(\omega_v) = \operatorname{arcsinh}(\sqrt{\lambda \omega})$

Jacobian for potentials :  $J_{vu} = \frac{\partial \chi_v^{(t+1)}}{\partial \chi_u^{(t)}} = \frac{\partial \omega_v^{(t+1)}}{\partial \omega_u^{(t)}} \frac{\psi'(\omega_v^{(t+1)})}{\psi'(\omega_u^{(t)})}$

**Theorem** (Sinclair-Srivastava-Štefankovič-Y.'15):

$$\lambda < \frac{\Delta^\Delta}{(\Delta - 1)^{\Delta+1}} \implies \forall \vec{\omega}^{(t)} \in [0, 1]^V, \quad \|J\|_\infty = \max_v \sum_{u \in N(v)} \frac{\lambda \omega_v^{(t+1)}}{1 + \lambda \omega_u^{(t)}} \frac{\psi'(\omega_v^{(t+1)})}{\psi'(\omega_u^{(t)})} < 1$$

original BP:

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

BP for potentials:

$$\chi_v^{(t+1)} = \psi \left( \prod_{u \in N(v)} \frac{1}{1 + \lambda \cdot \psi^{-1}(\chi_u^{(t)})} \right)$$

potentials:  $\chi_v = \psi(\omega_v) = \operatorname{arcsinh}(\sqrt{\lambda \omega})$

Jacobian for potentials :  $J_{vu} = \frac{\partial \chi_v^{(t+1)}}{\partial \chi_u^{(t)}} = \frac{\partial \omega_v^{(t+1)}}{\partial \omega_u^{(t)}} \frac{\psi'(\omega_v^{(t+1)})}{\psi'(\omega_u^{(t)})}$

**Theorem** (Sinclair-Srivastava-Štefankovič-Y.'15):

$$\lambda < \frac{\Delta^\Delta}{(\Delta - 1)^{\Delta+1}} \implies \forall \vec{\omega}^{(t)} \in [0, 1]^V, \quad \|J\|_\infty = \max_v \sum_{u \in N(v)} \frac{\lambda \omega_v^{(t+1)}}{1 + \lambda \omega_u^{(t)}} \frac{\psi'(\omega_v^{(t+1)})}{\psi'(\omega_u^{(t)})} < 1$$

$\vec{\omega}^{(t)}$  converges to a unique fixpoint  $\omega^* = F(\omega^*)$

original BP:

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

potentials:

$$\chi_v = \psi(\omega_v) = \operatorname{arcsinh}(\sqrt{\lambda \omega})$$

**Theorem** (Sinclair-Srivastava-Štefankovič-Y.'15):

$$\lambda < \frac{\Delta^\Delta}{(\Delta - 1)^{\Delta+1}} \quad \Rightarrow \quad \forall \vec{\omega}^{(t)} \in [0, 1]^V, \quad \|J\|_\infty = \max_v \sum_{u \in N(v)} \frac{\lambda \omega_v^{(t+1)}}{1 + \lambda \omega_u^{(t)}} \frac{\psi'(\omega_v^{(t+1)})}{\psi'(\omega_u^{(t)})} < 1$$

$\vec{\omega}^{(t)}$  converges to a unique fixpoint  $\omega^* = F(\omega^*)$

$$\sum_{u \in N(v)} \frac{\lambda \omega_u^*}{1 + \lambda \omega_u^*} \frac{1}{\omega_u^* \psi'(\omega_u^*)} < \frac{1}{\omega_v^* \psi'(\omega_v^*)}$$

original BP:

$$\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$$

potentials:

$$\chi_v = \psi(\omega_v) = \operatorname{arcsinh}(\sqrt{\lambda \omega_v})$$

**Theorem** (Sinclair-Srivastava-Štefankovič-Y.'15):

$$\lambda < \frac{\Delta^\Delta}{(\Delta - 1)^{\Delta+1}} \implies \forall \vec{\omega}^{(t)} \in [0, 1]^V, \quad \|J\|_\infty = \max_v \sum_{u \in N(v)} \frac{\lambda \omega_v^{(t+1)}}{1 + \lambda \omega_u^{(t)}} \frac{\psi'(\omega_v^{(t+1)})}{\psi'(\omega_u^{(t)})} < 1$$

$\vec{\omega}^{(t)}$  converges to a unique fixpoint  $\omega^* = F(\omega^*)$

$$\sum_{u \in N(v)} \frac{\lambda \omega_u^*}{1 + \lambda \omega_u^*} \underbrace{\frac{1}{\omega_u^* \psi'(\omega_u^*)}}_{\Phi_u} < \underbrace{\frac{1}{\omega_v^* \psi'(\omega_v^*)}}_{\Phi_v}$$

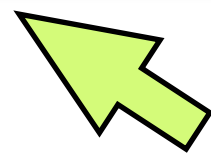
define  $\Phi_v \triangleq \frac{1}{\omega_v^* \cdot \psi'(\omega_v^*)} = 2 \sqrt{\frac{1 + \lambda \omega_v^*}{\lambda \omega_v^*}}$

metric  $\Phi(\cdot, \cdot)$  is a **weighted Hamming distance**:

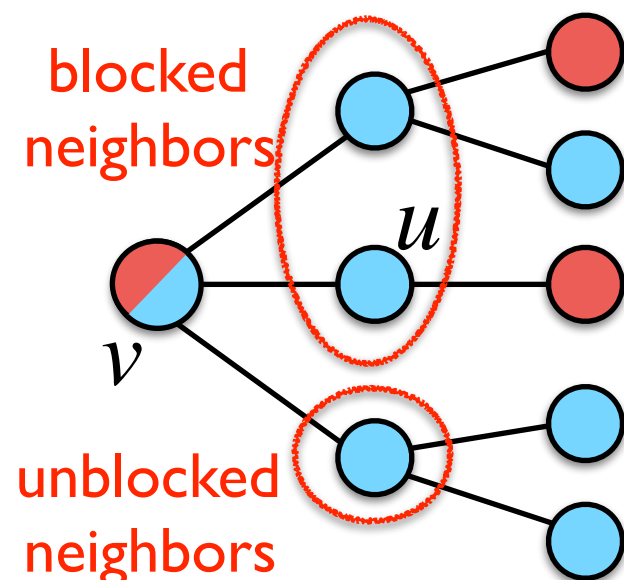
$$\Phi(X, Y) = \sum_{v \in X \oplus Y} \Phi_v \text{ where } \Phi_v \geq 1 \text{ is } v\text{'s weight}$$

**one-step optimal coupling** for  $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

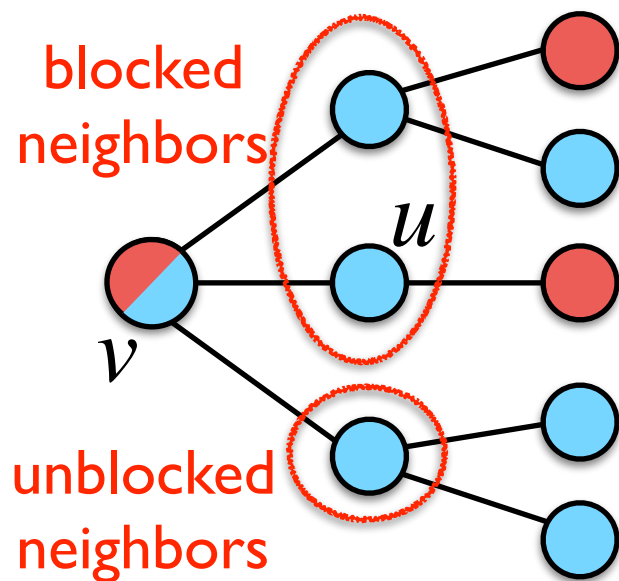
**Goal:**  $\mathbb{E}[\Phi(X_{t+1}, Y_{t+1}) \mid X_t, Y_t] \leq (1 - \frac{\alpha}{n})\Phi(X_t, Y_t)$



$$\sum_{u \in N(v)} \frac{\lambda W_u^{(t)}}{1 + \lambda W_u^{(t)}} \Phi_u \leq (1 - \alpha)\Phi_v$$



$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

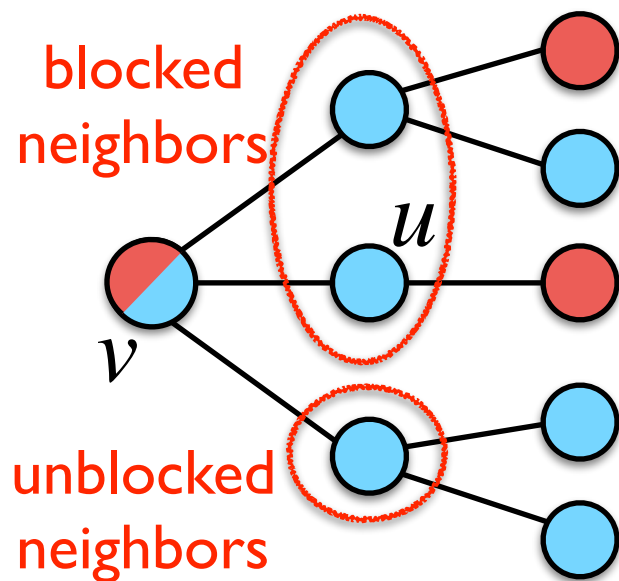


for coupling of Glauber dynamics  
 $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

$\exists$  vertex weights  $\Phi_v$ :

$$\sum_{u \in N(v)} \frac{\lambda W_u^{(t)}}{1 + \lambda W_u^{(t)}} \Phi_u < \Phi_v$$

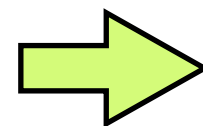


for coupling of Glauber dynamics  
 $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

$\exists$  vertex weights  $\Phi_v$ :

$$\sum_{u \in N(v)} \frac{\lambda W_u^{(t)}}{1 + \lambda W_u^{(t)}} \Phi_u < \Phi_v$$

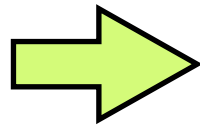


$$\tau_{\text{mix}} = O(n \log n)$$

**loopy BP:**  $\omega_v^{(t+1)} = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^{(t)}}$

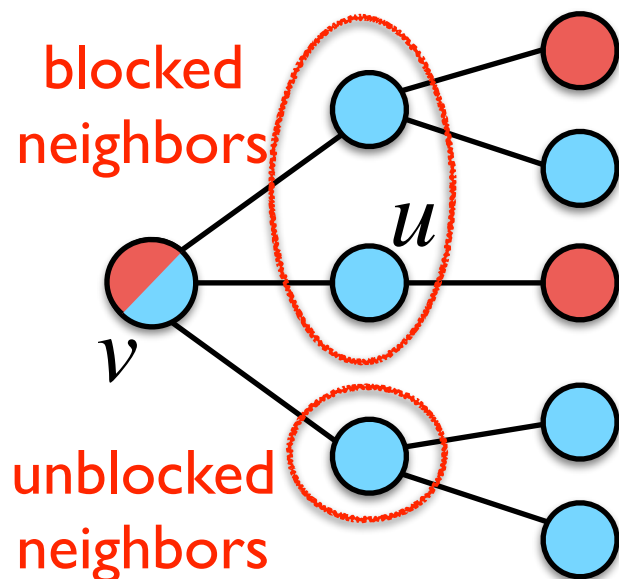
**fixpoint:**  $\omega_v^* = \prod_{u \in N(v)} \frac{1}{1 + \lambda \omega_u^*}$

$$\lambda < \frac{\Delta^\Delta}{(\Delta - 1)^{\Delta+1}}$$



$$\sum_{u \in N(v)} \frac{\lambda \omega_u^*}{1 + \lambda \omega_u^*} \Phi_u < \Phi_v$$

where  $\Phi_v = 2 \sqrt{\frac{1 + \lambda \omega_v^*}{\lambda \omega_v^*}}$

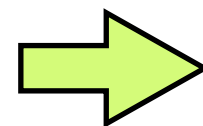


for coupling of Glauber dynamics  
 $(X_t, Y_t)$  that  $X_t \oplus Y_t = \{v\}$

$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

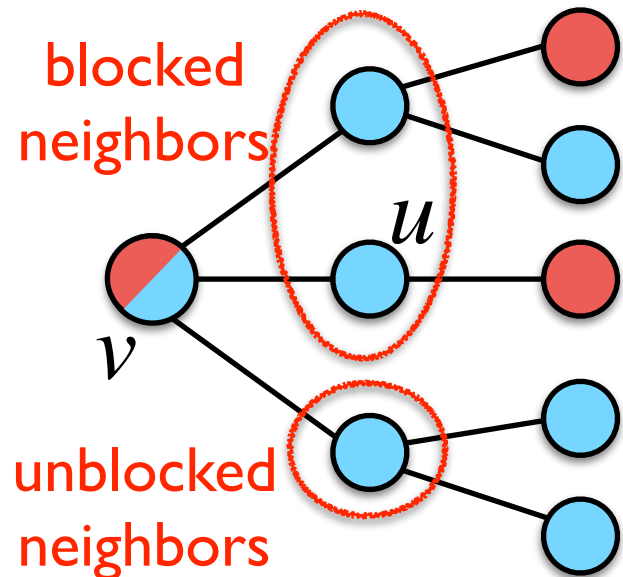
$\exists$  vertex weights  $\Phi_v$ :

$$\sum_{u \in N(v)} \frac{\lambda W_u^{(t)}}{1 + \lambda W_u^{(t)}} \Phi_u < \Phi_v$$



$$\tau_{\text{mix}} = O(n \log n)$$

# Local Uniformity



Glauber dynamics  $X_t$

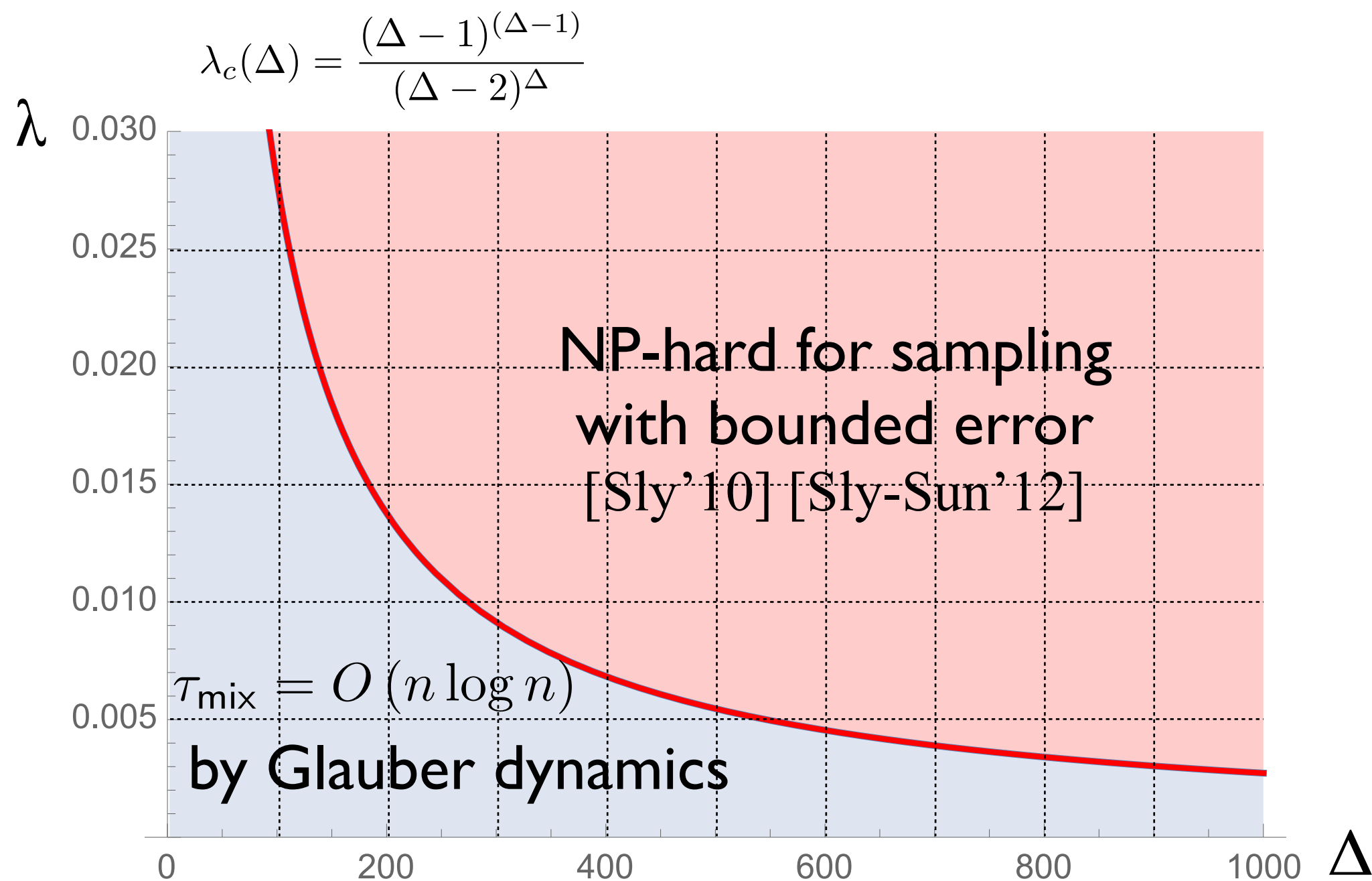
$$W_u^{(t)} = I[u \text{ is unblocked in } X_t]$$

$\forall \epsilon, \delta > 0, \exists \Delta_0$  and  $\mathcal{I} = [O(n \log \Delta), n \exp(\Omega(\Delta))]$  s.t.  
for all graphs of max-degree  $\Delta \geq \Delta_0$  and girth  $\geq 7$ :  
 $\lambda \leq (1 - \delta) \lambda_c(\Delta) \implies \forall$  vertex  $v$ :

$$\Pr \left[ \forall t \in \mathcal{I} : \sum_{u \in N(v)} \frac{\lambda W_u^{(t)}}{1 + \lambda W_u^{(t)}} \Phi_u < \sum_{u \in N(v)} \frac{\lambda \omega_u^*}{1 + \lambda \omega_u^*} \Phi_u + \epsilon \right] \geq 1 - \exp(-\Omega(\Delta))$$

proved by **concentration** using the arguments in:

[Dyer-Frieze-Hayes-Vigoda'04] [Hayes-Vigoda'05] [Hayes'13]



# Summary

- Optimal mixing time for Glauber dynamics for the hardcore model in the *uniqueness* regime (when degree is big enough and there is no small cycle).
- Connecting *rapid mixing of MCMC sampling* with *BP convergence*:
  - If BP converges, there probably is contraction for Markovian coupling.
  - Path coupling “*from art to science*”.
- Open problem: get rid of the degree and girth requirements.

Charis Efthymiou, Thomas P. Hayes, Daniel Štefankovič, Eric Vigoda, Yitong Yin.  
*Convergence of MCMC and Loopy BP in the Tree Uniqueness Region for the Hard-Core Model*. **FOCS'16**. arxiv: 1604.01422.

# Thank you!

*Any questions?*