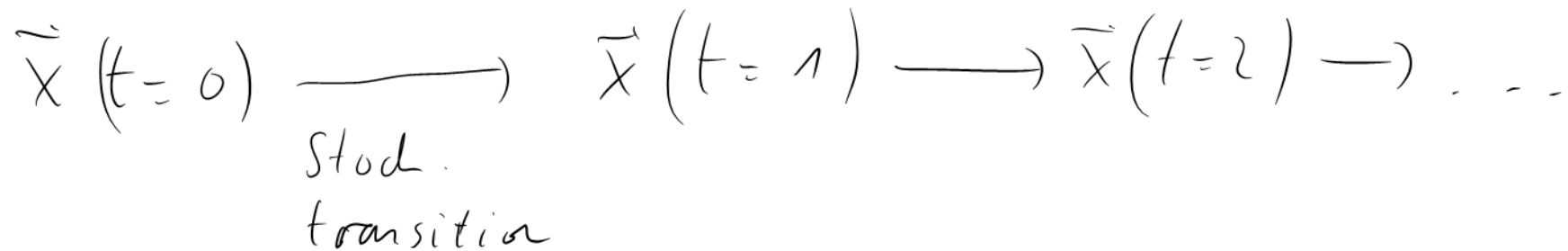


# Markov Chains

$\vec{x}$  : states of a system, discrete, finite in number

$t$  : discrete "time"



Markov property: Transition probability depends only on the initial state, but not on the past.

homogeneous Markov chain:

transition probabilities do not explicitly depend on time.

$w(\bar{x} \rightarrow \bar{y})$ : probability to go from  $\bar{x}$  to  $\bar{y}$

$$0 \leq w(\bar{x} \rightarrow \bar{y}) \leq 1$$

$$\sum_{\bar{y}} w(\bar{x} \rightarrow \bar{y}) = 1$$

$P(\bar{x}, t)$ : probability for the system to be at  $\bar{x}$   
at time  $t$

Master equation:

$$P(\vec{x}, t+1) = \underbrace{P(\vec{x}, t)} + \sum_{\vec{y}(\neq \vec{x})} w(\vec{y} \rightarrow \vec{x}) P(\vec{y}, t) - \sum_{\vec{y}(\neq \vec{x})} w(\vec{x} \rightarrow \vec{y}) P(\vec{x}, t)$$

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Now  $P(\vec{x}, t) \left[ 1 - \sum_{\vec{y}(\neq \vec{x})} w(\vec{x} \rightarrow \vec{y}) \right]$

$$= P(\vec{x}, t) \left[ \sum_{\vec{y}} w(\vec{x} \rightarrow \vec{y}) - \sum_{\vec{y}(\neq \vec{x})} w(\vec{x} \rightarrow \vec{y}) \right]$$

$$= P(\vec{x}, t) w(\vec{x} \rightarrow \vec{x})$$

$$P(\vec{x}, t+1) = \sum_{\vec{y}} w(\vec{y} \rightarrow \vec{x}) P(\vec{y}, t)$$

new notation:  $w(\vec{x} \rightarrow \vec{y}) = : w_{ij}$   $i \hat{=} \vec{x}$   
 $j \hat{=} \vec{y}$   
↑ initial ↑ final

$$P_i(t+1) = \sum_j w_{ji} P_j(t)$$

$$\vec{P}(t+1) = \vec{W}^T \vec{P}(t)$$

↑ transposed matrix

$$\vec{P}(t) = (\vec{W}^t)^T \vec{P}(0)$$

Stationary distribution:

$$P(\vec{x}, t+n) = P(\vec{x}, t) = P_{\text{Stat}}(\vec{x})$$

$$\vec{P}_{\text{Stat}} = W^{-T} \vec{P}_{\text{Stat}} \Rightarrow \vec{P}_{\text{Stat}} \text{ is an eigenvector of } W^{-T}, \text{ eigenvalue is ONE.}$$

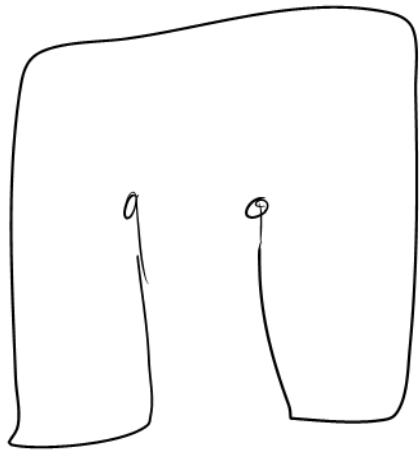
Questions:

$$(i) \vec{P}(t) \xrightarrow[\text{??}]{t \rightarrow \infty} \vec{P}_{\text{Stat}}$$

$$(ii) W^{-t} \xrightarrow{t \rightarrow \infty} \text{??}$$

Definition: A Markov chain is called ERGODIC

if each state can be reached from each other state, in a finite number of steps, with a finite probability.



In other words: There is an  $L \geq 1$  and  
there is a  $\delta > 0$ :  $(W^L)_{ij} \geq \delta$   
for all pairs  $(ij)$

Ergodic Theorem by Markov: If the chain is  
ergodic, then:

(i) There is ONE UNIQUE stationary distribution  
 $\vec{P}_{stat}$ , and  $\vec{P}(t) \xrightarrow{t \rightarrow \infty} \vec{P}_{stat}$  regardless  
of the initial conditions,

$$(ii) \quad (w^t)_{ij} \xrightarrow{t \rightarrow \infty} P_{j \text{ stat}}$$

↑ initial
↑ final

Remark:

$$P_i(t) = \sum_j (w^t)_{ji} P_j(0) \xrightarrow[t \rightarrow \infty]{\text{assume (ii)}}$$

$$\longrightarrow \underbrace{\sum_j P_j(0)}_{\uparrow} P_{i \text{ stat}} = P_{i \text{ stat}} \quad \Rightarrow$$

(ii) implies (i)

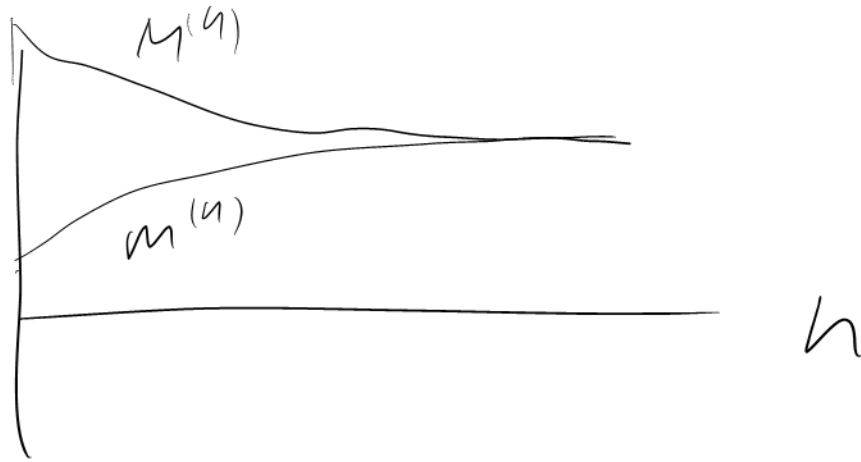


Proof: Let  $w_{ij}^{(k)} = (\bar{W}^k)_{ij}$

and  $m_j^{(k)} = \min_i w_{ij}^{(k)}$        $M_j^{(k)} = \max_i w_{ij}^{(k)}$

Study  $m_j^{(k)}$ ,  $M_j^{(k)}$  as a function of  $k$

Show:



$$\underline{m_j^{(n+1)}} = \min_i w_{ij}^{(n+1)} = \min_i \sum_k w_{ik} w_{kj}^{(n)} \geq$$

$$\geq \min_i \underbrace{\sum_k w_{ik}}_1 m_j^{(n)} = \underline{m_j^{(n)}}$$

$0 \leq m_j^{(n)} \leq 1 \rightarrow m_j^{(n)}$  converges

Similar:  $M_j^{(n)}$  decreases, converges.

Now study  $M_j^{(n)} - m_j^{(n)} (\geq 0)$

slow:  $M_j^{(n)} - m_j^{(n)} \rightarrow 0$  for  $n \rightarrow \infty$

then we are DONE!


$$\text{Now } M_j^{(n+L)} - m_j^{(n+L)} = w_{ij}^{(n+L)} - w_{kj}^{(n+L)}$$

for some suitable  $i, k$

$$\text{Factorize this: } M_j^{(n+L)} - m_j^{(n+L)} =$$

$$= \sum_l \left( w_{il}^{(L)} w_{lj}^{(n)} - w_{kl}^{(L)} w_{lj}^{(n)} \right) =$$

$$= \sum_l \left( w_{il}^{(L)} - w_{kl}^{(L)} \right) w_{lj}^{(n)}$$


 this is  $\begin{cases} \geq 0 & \text{for } l \in I_+ \\ < 0 & \text{for } l \in I_- \end{cases}$

$$= \sum_{l \in \bar{I}_+} (w_{ix}^{(l)} - w_{kx}^{(l)}) \underbrace{w_{lj}^{(n)}}_{\leq M_j^{(n)}} - \sum_{l \in \bar{I}_-} \underbrace{(w_{kx}^{(l)} - w_{ix}^{(l)})}_{\geq 0} \underbrace{w_{lj}^{(n)}}_{\geq m_j^{(n)}} \leq$$

$$\leq \sum_{l \in \bar{I}_+} (w_{ix}^{(l)} - w_{kx}^{(l)}) M_j^{(n)} - \sum_{l \in \bar{I}_-} (w_{kx}^{(l)} - w_{ix}^{(l)}) m_j^{(n)}$$

$$= \sum_{l \in \bar{I}_+} (w_{ix}^{(l)} - w_{kx}^{(l)}) (M_j^{(n)} - m_j^{(n)})$$

$$+ \sum_{l \in \bar{I}_+} (w_{ix}^{(l)} - w_{kx}^{(l)}) m_j^{(n)} + \sum_{l \in \bar{I}_-} (w_{ix}^{(l)} - w_{kx}^{(l)}) m_j^{(n)} =$$

$$= \sum_{l \in I_+} \underbrace{\left( w_{i_l}^{(l)} - w_{k_l}^{(l)} \right)}_{\text{some factor}} \underbrace{\left( M_j^{(n)} - m_j^{(n)} \right)}_{\geq} M_j^{(n+l)} - m_j^{(n+l)}$$

some factor

if we can show that

$$0 \leq \sum_{l \in I_+} \left( w_{i_l}^{(l)} - w_{k_l}^{(l)} \right) \leq 1$$

then  $M_j^{(n)} - m_j^{(n)} \xrightarrow{n \rightarrow \infty} 0$  and we are done!

Study  $\sum_{l \in I_+} (w_{ix}^{(l)} - w_{kx}^{(l)})$

We know:  $\sum_{l \in I_+} (w_{ix}^{(l)} - w_{kx}^{(l)}) \geq 0$

$$\sum_{l \in I_+} w_{ix}^{(l)} \leq \sum_l w_{ix}^{(l)} = 1$$

$$\sum_{l \in I_+} w_{kx}^{(l)} \geq \delta \quad \left\{ \begin{array}{l} I_+ \text{ cannot be empty, since} \\ \text{otherwise} \end{array} \right.$$

$$0 = \sum_{l \in I_-} (w_{ix}^{(l)} - w_{kx}^{(l)}) < 0 \quad \{ \}$$

$$\Rightarrow 0 \leq \sum_{l \in I_{\neq}} (w_{ik}^{(l)} - w_{kl}^{(l)}) \leq 1 - \delta$$

theorem proven

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application: construct  $w(\bar{x} \rightarrow \bar{y})$  in such a way

that  $P_{\text{stat}}(\bar{x})$  is some desired distribution

(and the chain is ergodic)

$\searrow$   
Boltzmann

Master equation:

$$P_{\text{stat}}(\vec{x}') = P_{\text{stat}}(\vec{x}) + \sum_{\vec{y}(\neq \vec{x})} w(\vec{y} \rightarrow \vec{x}) P_{\text{stat}}(\vec{y})$$

$$- \sum_{\vec{y}(\neq \vec{x})} w(\vec{x} \rightarrow \vec{y}) P_{\text{stat}}(\vec{x})$$

$$+ w(\vec{x} \rightarrow \vec{x}) P_{\text{stat}}(\vec{x})$$

$$\sum_{\vec{y}} w(\vec{y} \rightarrow \vec{x}) P_{\text{stat}}(\vec{y}) = \sum_{\vec{y}} w(\vec{x} \rightarrow \vec{y}) P_{\text{stat}}(\vec{x})$$

stronger condition: detailed balance:



$$w(\vec{y} \rightarrow \vec{x}) \underline{\underline{P_{stat}(\vec{y})}} = w(\vec{x} \rightarrow \vec{y}) \underline{\underline{P_{stat}(\vec{x})}}$$



























