

## lecture 13: Markov chain Monte Carlo

learning goals

- apply MCMC to sample from probability distributions

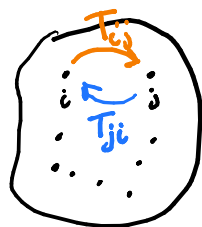
equilibrium properties determined by average over  $P(\underline{s})$ , but this is impossible to do when variables are coupled and  $N$  is large

we can solve this problem by randomly sampling from  $P(\underline{s})$ , but this is also hard because

$$P(\underline{s}) = \frac{e^{-\beta E(\underline{s})}}{Z} \quad \leftarrow \text{normalization also requires sum over } \underline{s}!$$

arbitrary!

solution: start with a probability distribution  $P_0(\underline{s})$  and write down dynamics to evolve it towards  $P(\underline{s})$



call the transition probability from the configuration labeled  $i$  to the one labeled  $j$   $T_{ij}$ , then we want

$$\frac{dP_i}{dt} = \underbrace{\sum_j T_{ji} P_j}_{\text{flux in}} - \underbrace{\sum_j T_{ij} P_i}_{\text{flux out}}$$

Gibbs distribution  
↓

to be 0 for all configurations  $i$  if  $P = P(\underline{s})$

detailed balance ensures that this is true, set

$$P_i T_{ij} = P_j T_{ji} \quad \text{so that all probability fluxes balance exactly}$$

$$\text{this is satisfied if we choose } \frac{T_{ji}}{T_{ij}} = \frac{P_j}{P_i} = \frac{e^{-\beta E_j/Z}}{e^{-\beta E_i/Z}} = e^{\beta(E_i - E_j)}$$

tricky normalization  $Z$  cancels!

detailed balance only sets the ratio of transition probabilities, so we can choose

$$\text{common choice is the Metropolis rule: } T_{ij} = \begin{cases} 1 & \text{if } E_j < E_i \\ e^{-\beta(E_j - E_i)} & \text{if } E_j > E_i \end{cases}$$

note:  $T_{ij} = T_{ji} = 0$  also ok, all possible transitions need not have  $T_{ij}$  nonzero

\*notebook example, two spin system