

Gibbs Sampler

- Gibbs sampler is used when samples consist of multiple components, e.g. (x_1, x_2, \dots, x_n) .
- The joint density $f(x_1, \dots, x_n)$ is not known (or complicated to obtain).
- But $f(x_i | x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$ are given.

Assume (x_1^t, \dots, x_n^t) is a sample at time t . Then

$$x_1^{t+1} \sim f(x_1 | x_2^t, \dots, x_n^t)$$

$$x_2^{t+1} \sim f(x_2 | x_1^{t+1}, x_3^t, \dots, x_n^t)$$

$$x_3^{t+1} \sim f(x_3 | x_1^{t+1}, x_2^{t+1}, x_4^t, \dots, x_n^t)$$

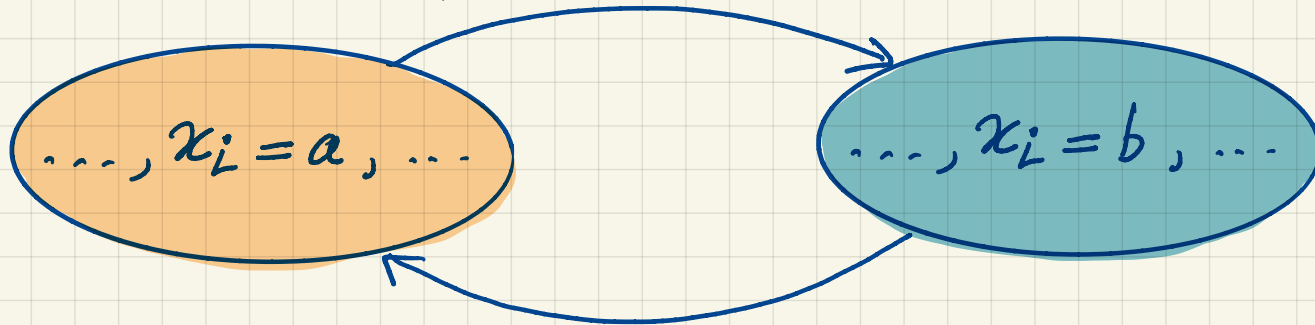
⋮

$$x_n^{t+1} \sim f(x_n | x_1^{t+1}, \dots, x_{n-1}^{t+1})$$

claim: $(x_1^t, x_2^t, \dots, x_n^t) \sim f(x_1, x_2, \dots, x_n)$

f satisfies detailed balance "component-wise"

$$f(x_i = b \mid x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$$



$$f(x_i = a \mid x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$$

$$f(x_1, \dots, x_i = a, \dots, x_n) f(x_i = b \mid x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$$

$$= \frac{f(x_1, \dots, x_i = a, \dots, x_n) f(x_1, \dots, x_{i-1}, x_i = b, x_{i+1}, \dots, x_n)}{f(x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)}$$

$$= f(x_i = a \mid x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) f(x_1, \dots, x_{i-1}, x_i = b, x_{i+1}, \dots, x_n)$$

Gibbs can be viewed as an instance of Metropolis-Hastings

- * α , the prob. of accept is always 1
- * the proposal distribution alternates among n distributions, one for each component.

For component i , we propose $x_i^{\delta+1} \sim f(x_i | x_1^{\delta+1}, \dots, x_{i-1}^{\delta+1}, x_{i+1}^{\delta}, \dots, x_n^{\delta})$

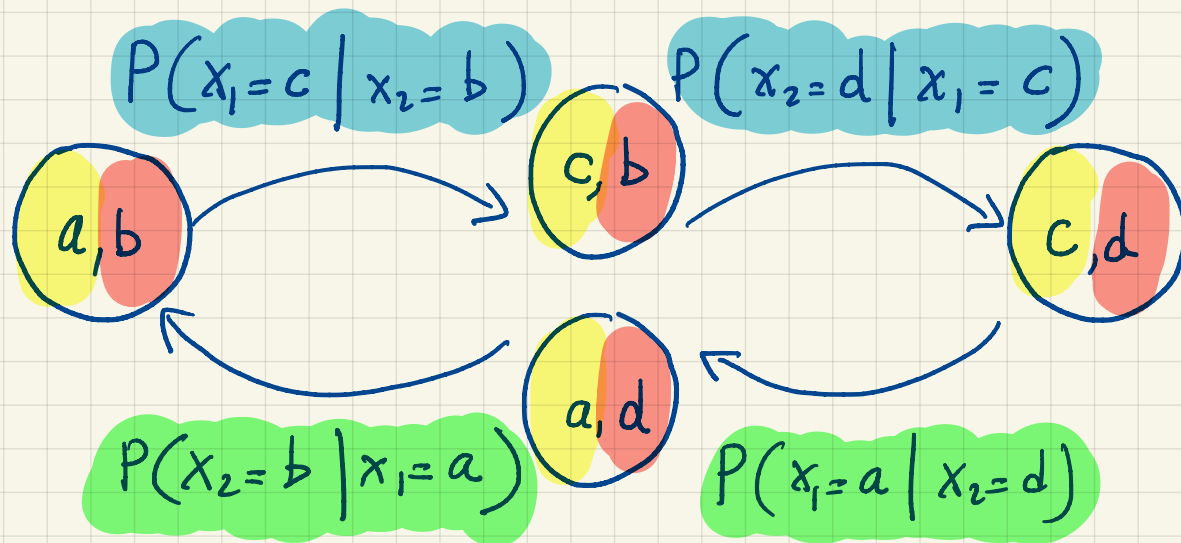
and $x_j^{\delta+1} = x_j^{\delta}$ with prob. 1 for $j \neq i$

we have $n\delta$ steps within one t step

Remark: Gibbs does NOT satisfy detailed balance for entire sample. (one big step)

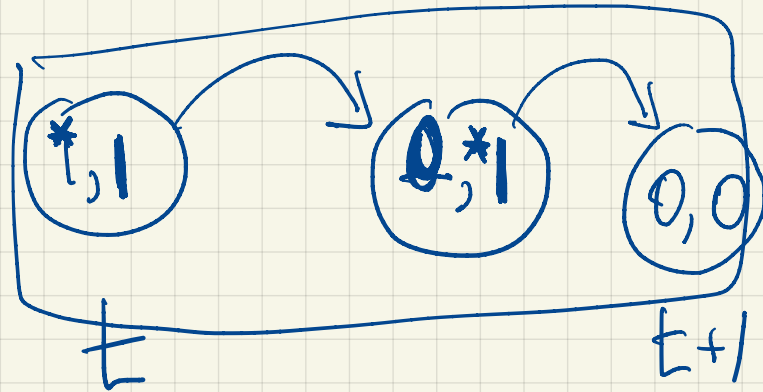
$$\text{e.g. } P(x_1=a, x_2=b) P(x_1=c, x_2=d \mid x_1=a, x_2=b)$$

$$\neq P(x_1=c, x_2=d) P(x_1=a, x_2=b \mid x_1=c, x_2=d)$$



Example:

		x_2	
		0	1
x_1	0	$\frac{1}{3}$	$\frac{1}{3}$
	1	0	$\frac{1}{3}$

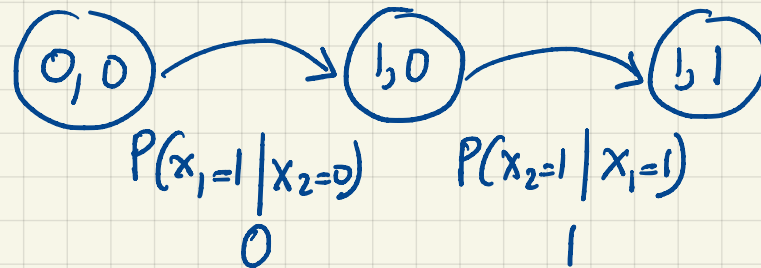


$$P(0,0) = \frac{1}{3}$$

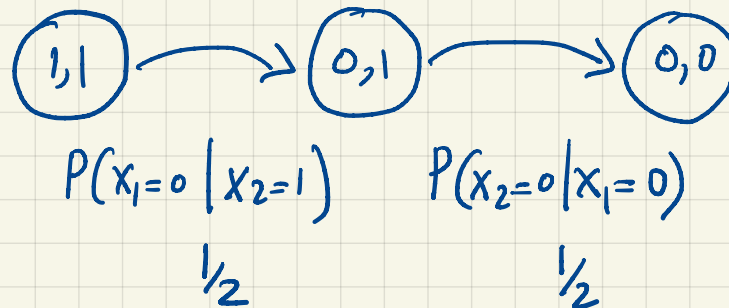
$$P(1,1) = \frac{1}{3}$$

$$P(0,0) P(1,1 | 0,0) = P(1,1) P(0,0 | 1,1)$$

$$P(1,1 | 0,0) = 0$$



$$P(0,0 | 1,1) = \frac{1}{4}$$

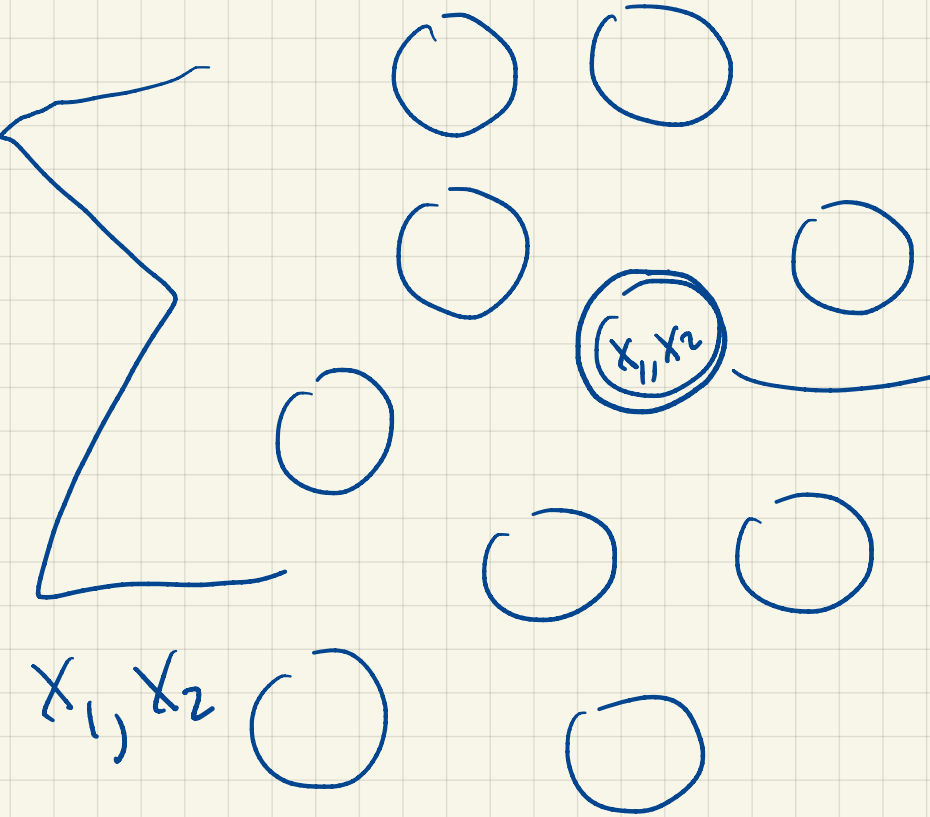
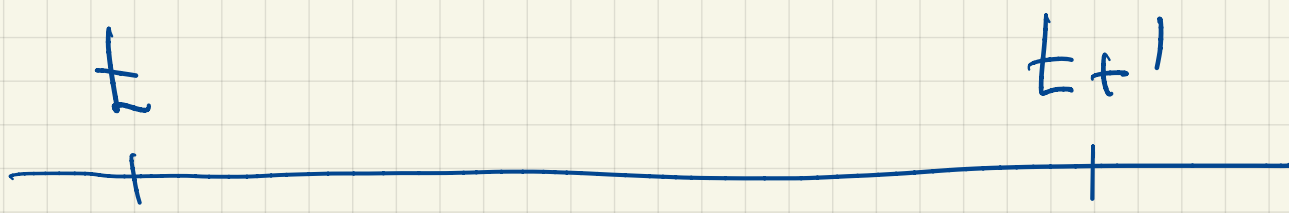


$$\frac{1}{3} \times \frac{1}{4} \neq \frac{1}{3} \times 0$$

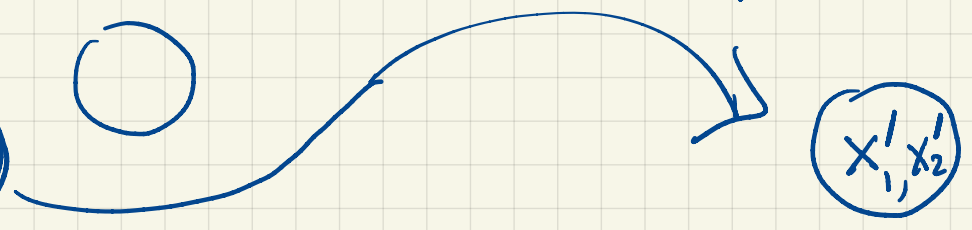
Showing that $P(x_1, x_2)$ is stationary

What's the prob.
that our next sample
is (x'_1, x'_2)

$$\begin{aligned} & \sum_{x_1, x_2} P(x_1, x_2) \cdot P(x'_1 | x_2) P(x'_2 | x'_1) \\ &= P(x'_2 | x'_1) \sum_{x_2} \left(P(x'_1 | x_2) \underbrace{\sum_{x_1} P(x_1, x_2)}_{P(x_2)} \right) \\ & \quad \underbrace{\hspace{10em}}_{P(x'_1, x_2)} \\ & \quad \underbrace{\hspace{15em}}_{P(x'_1)} \\ & P(x'_1, x'_2) \end{aligned}$$



$$P(x_1 = x'_1 | x_2) P(x_2 = x'_2 | x'_1)$$



$P(x_1, x_2)$

Application to Bayes

$$x_i | \mu, \sigma^2 \sim N(\mu, \sigma^2)$$

priors: $\mu \sim N(\beta, \tau^2)$

$$\frac{S_0}{\sigma^2} \sim \chi^2_k$$

[semi-conjugate prior]

Conditional posteriors: $\mu | \sigma^2, \bar{x} \sim N\left(\frac{\sigma^2 \beta/n + \tau^2 \bar{x}}{\sigma^2/n + \tau^2}, \frac{\sigma^2 \tau^2/n}{\sigma^2/n + \tau^2}\right)$

posteriors: $\frac{S+S_0}{\sigma^2} | \mu, \bar{x} \sim \chi^2_{k+n}$ where $S = \sum (x_i - \mu)^2$

Gibbs: start with some (μ^0, σ^0)

repeat $t = 0, 1, 2, 3, \dots$

sample $\mu^{t+1} \sim N(\text{---}, \text{---})$ given σ^t

sample σ^{t+1} using $\left(\frac{S+S_0}{\sigma^2}\right)^{t+1} \sim \chi^2_{k+n}$ given μ^{t+1}

$f(\mu, \sigma | \bar{x})$ is stationary for this Gibbs.