

Sampling Based Inference

Il-Chul Moon
Dept. of Industrial and Systems Engineering
KAIST

icmoon@kaist.ac.kr

Weekly Objectives

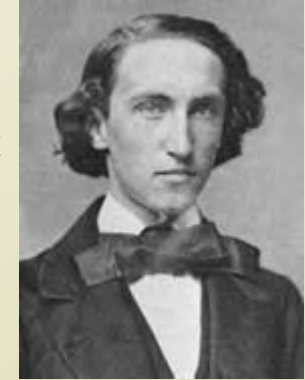
- Learn basic sampling methods
 - Understand the concept of Markov chain Monte Carlo
 - Able to apply MCMC to the parameter inference of Bayesian networks
 - Know the mechanism of rejection sampling
 - Know the mechanism of importance sampling
- Learn sampling based inference
 - Understand the concept of Metropolis-Hastings Algorithm
 - Know the mechanism of Gibbs sampling
- Know a case study of sampling based inference
 - Understand the latent Dirichlet allocation model
 - Know the collapsed Gibbs sampling
 - Know how to derive Gibbs sampling formula for LDA

Gibbs Sampling

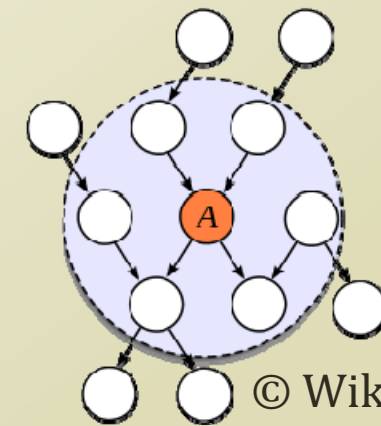
Josiah Willard Gibbs
(1839 - 1903)

- physicist

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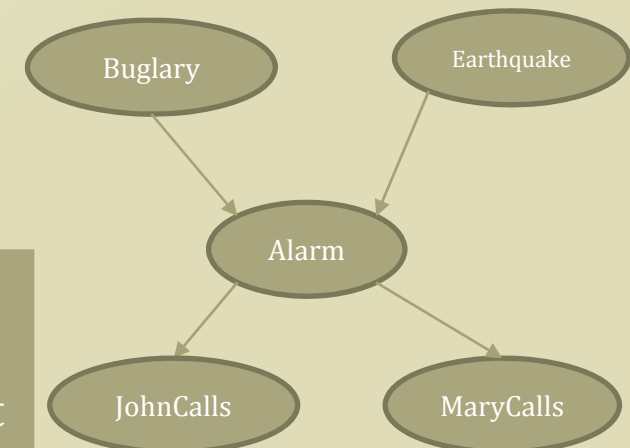


- Gibbs Sampling: A special case of M-H algorithm
 - Let's suppose $z^t = (z_k^t, z_{-k}^t) \rightarrow z^* = (z_k^*, z_{-k}^*)$
 - $T_{t,*}^{MH} = q(z^*|z^t)\alpha(z^*|z^t)$
 - $q(z^*|z^t) = P(z_k^*, z_{-k}^t | z_{-k}^t) = P(z_k^* | z_{-k}^t)$
 - Let's observe the balance equation
 - Should hold $P(z^t)q(z^*|z^t) = P(z^*)q(z^t|z^*)$
 - $P(z^t)q(z^*|z^t) = P(z_k^t, z_{-k}^t)P(z_k^* | z_{-k}^t) = P(z_k^t | z_{-k}^t)P(z_{-k}^t)P(z_k^* | z_{-k}^t) = P(z_k^t | z_{-k}^t)P(z_k^*, z_{-k}^t) = q(z^t|z^*)P(z^*)$
 - Always hold the balance equation!
 - Then, the acceptance probability becomes $\alpha(z^*|z^t) = 1$
- Example of Gibbs sampling
 - When the joint distribution is not known explicitly or is difficult to sample from directly, but the conditional distribution of each variable is known and is easy
 - $P(E, JC, B | A=F, MC=T) = ?$
 - Hard to sample directly. Why?
 - Consider a conditional distribution $p(z_i | z_{-i}, e)$
 - $P(E | B, A, JC, MC) = P(E | A, B)$
 - $P(JC | B, E, A, MC) = P(JC | A)$
 - $P(B | E, A, JC, MC) = P(B | A, E)$
 - Update one random variable at a time



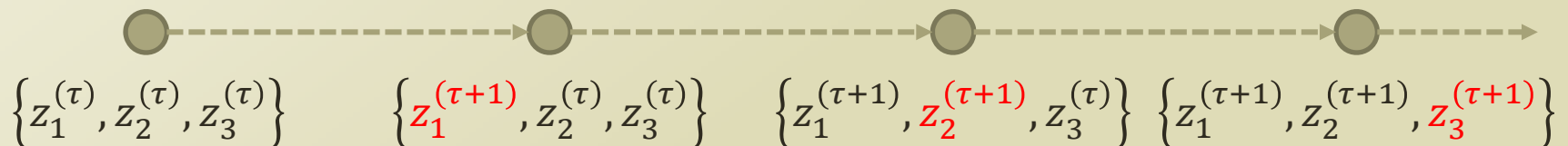
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Can simplify
using the
Markov blanket



Concept of Gibbs Sampling

- Each step involves **replacing** the value of one of the variables by a value drawn from the distribution of that variable conditioned on the values of the remaining variables
- Repeated either by cycling through the variables in some particular order or by choosing the variable to be updated at each step at random from some distribution
- Example
 1. Full joint probability : $p(z_1, z_2, z_3)$
 2. Sample $z_1 \sim p(z_1 | z_2^{(\tau)}, z_3^{(\tau)}) \rightarrow$ Obtain a value $z_1^{(\tau+1)}$
 3. Sample $z_2 \sim p(z_2 | z_1^{(\tau+1)}, z_3^{(\tau)}) \rightarrow$ Obtain a value $z_2^{(\tau+1)}$
 4. Sample $z_3 \sim p(z_3 | z_1^{(\tau+1)}, z_2^{(\tau+1)}) \rightarrow$ Obtain a value $z_3^{(\tau+1)}$



Gibbs Sampling Algorithm

- Full joint distribution, $p(\mathbf{z}) = p(z_1, \dots, z_M)$
- State = $\{z_i: i = 1, \dots, M\}$
- Algorithm
 1. Initialize $\{z_i: i = 1, \dots, M\}$
 2. For step $\tau = 1, \dots, T$:
 - Sample $z_1^{(\tau+1)} \sim p(z_1 | z_2^{(\tau)}, z_3^{(\tau)}, \dots, z_M^{(\tau)})$
 - Sample $z_2^{(\tau+1)} \sim p(z_2 | z_1^{(\tau+1)}, z_3^{(\tau)}, \dots, z_M^{(\tau)})$
 - \vdots
 - Sample $z_j^{(\tau+1)} \sim p(z_j | z_1^{(\tau+1)}, \dots, z_{j-1}^{(\tau+1)}, z_{j+1}^{(\tau)}, \dots, z_M^{(\tau)})$
 - \vdots
 - Sample $z_M^{(\tau+1)} \sim p(z_M | z_1^{(\tau+1)}, z_2^{(\tau+1)}, \dots, z_{M-1}^{(\tau+1)})$

Gibbs Sampling based GMM

- Hard to tell the performance with the simple GMM
 - Sampling based inference
 - Simulation based
 - EM based inference
 - Optimization based
- Real power of Gibbs sampler comes from collapsing! → Collapsed Gibbs Sampler
 - Let's look at more sophisticated model for collapsing technique

