Just another Gibbs sampling presentation

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Recap: Markov Chain Monte Carlo (MCMC)

Markov Chain Monte Carlo

Goal: Bayesian posterior distribution

Monte Carlo Casino (Fruitpunchline, Wikipedia, CC BY-SA 4.0)

Problem: Analytical solution difficult! :(

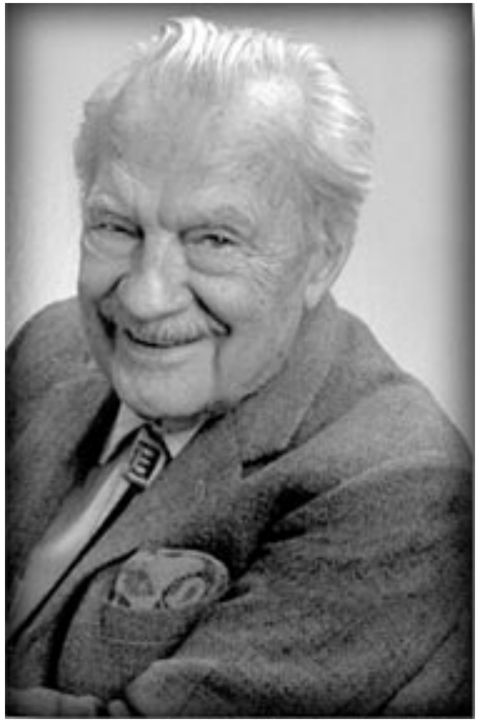
Approach: Sampling of representative values from Bayesian posterior distribution and application of law of large numbers

Kruschke, J. (2014)

Course notes: Azim Ansari (2019)

Recap: Metropolis algorithm

Metropolis algorithm



Nicholas Metropolis (Public Domain)

Random walk:

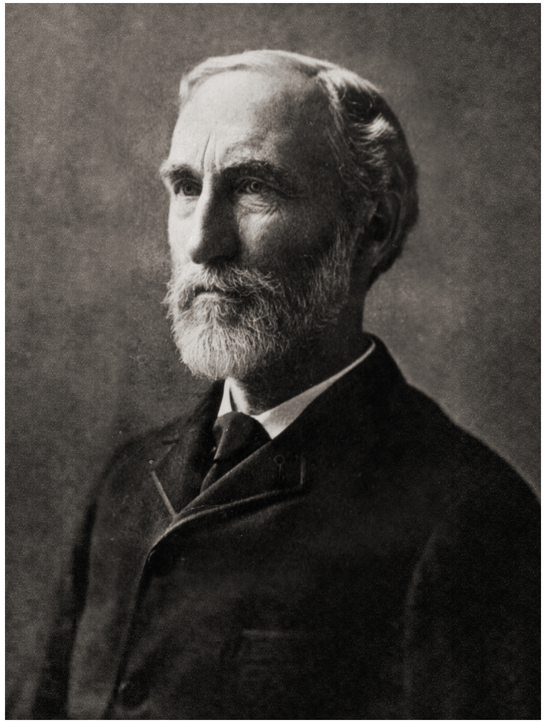
1. Proposal distribution (e.g. $N(x,\sigma^2)$): θ_{prop}
2. Ratio: $p(\theta_{prop})/p(\theta_{t-1})$
3. $p_{accept} = \min(p(\theta_{prop})/p(\theta_{t-1}), 1)$
4. Uniform distribution over $[0,1]$: u
4. If $u < p_{accept}$: $\theta_{prop} = \theta_t$

Kruschke, J. (2014)

Course notes: Azim Ansari (2019)

Gibbs sampling

Gibbs sampling



Josiah Willard Gibbs (Public Domain)

Introduced in 1984 by Geman & Geman

(Very) efficient for multivariate models

Key idea: In each step, a value for one variable is sampled conditional on the current values of all other variables ("orthogonal" exploration of distribution)

Kruschke, J. (2014)

Craiu & Rosenthal (2014)

Gibbs sampling

[The Markov-chain Monte Carlo Interactive Gallery](github.com/chi-feng/mcmc-demo)

Chi Feng (2019), URL: github.com/chi-feng/mcmc-demo

(Dis-)advantages of Gibbs sampling

- (Very) efficient for models with multiple parameters
- Effective size ≤ number of proposed steps

- Conditional distributions must be known and sampleable
- Inefficient in case of highly correlated parameters

Kruschke, J. (2014)

References

Kruschke, J. (2014). Doing Bayesian Data Analysis, 2nd Edition. Academic Press. Accessed online: https://learning.oreilly.com/library/view/doing-bayesian-data/9780124058880 (December 2019).

Craiu, R. V. & Rosenthal, J. S. (2014). Bayesian Computation Via Markov Chain Monte Carlo. *Annu. Rev. Stat. Appl.*, 1:179–201.