Lecture 8: Rejection Sampling and Markov chain review

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Last Time

- Latent variable models
  - Bayesian hierarchical model (COVID meta-analysis)
  - Hidden Markov model (ice cores)
  - Election forecasting model

This time: approximate inference via sampling algorithms

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- How many samples to get error ε?

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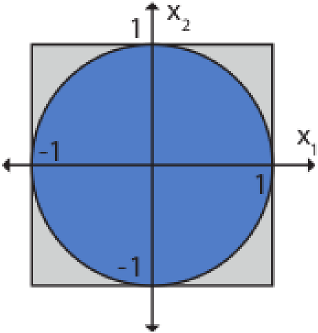
First, need some build-up:

- Rejection sampling
- Markov chains

Warm-up: Sampling from unit circle



How to sample uniformly from the blue region?

Rejection sampling

[Jupyter demos]

Rejection sampling

[on board: general algorithm and normalization constant]

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Pros: simple, can use with many pairs of densities, provides exact samples
Cons: can be slow (curse of dimensionality)

Markov chains

Markov Chains

Markov chain: sequence $x_1, x_2, \ldots, x_T$ where distribution of x_t depends only on x_{t-1}

Defined by *transition distribution* $A(x^{\text{new}} \mid x^{\text{old}})$, together with initial state x_1

Examples:

- Random walk on a graph
- Repeatedly shuffling a deck of cards
- Process defined by

$$x_1 = 0, \quad x_t \mid x_{t-1} \sim N(0.9x_{t-1}, 1)$$

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The distribution $\bar{p}(x)$ is also what we get if we count how many times x_t visits each state, as $T \to \infty$.

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Other examples:

- Random walk on complete graph with n vertices
- Random walk on path of length n

The Annals of Applied Probability
1992, Vol. 2, No. 2, 294–313

TRAILING THE DOVETAIL SHUFFLE TO ITS LAIR

BY DAVE BAYER[1] AND PERSI DIACONIS[2]

Columbia University and Harvard University

We analyze the most commonly used method for shuffling cards. The main result is a simple expression for the chance of any arrangement after any number of shuffles. This is used to give sharp bounds on the approach to randomness: $\frac{3}{2}\log_2 n + \theta$ shuffles are necessary and sufficient to mix up n cards.

Key ingredients are the analysis of a card trick and the determination of the idempotents of a natural commutative subalgebra in the symmetric group algebra.

1. Introduction. The dovetail, or riffle shuffle is the most commonly used method of shuffling cards. Roughly, a deck of cards is cut about in half and then the two halves are riffled together. Figure 1 gives an example of a riffle shuffle for a deck of 13 cards.

A mathematically precise model of shuffling was introduced by Gilbert and Shannon [see Gilbert (1955)] and independently by Reeds (1981). A deck of n cards is cut into two portions according to a binomial distribution; thus, the chance that k cards are cut off is $\binom{n}{k}/2^n$ for $0 \le k \le n$. The two packets are then riffled together in such a way that cards drop from the left or right heaps

Markov chains: recap

- Governed by proposal distribution $A(x^{\text{new}} \mid x^{\text{old}})$
- Stationary distribution: limiting distribution of x_T
- Mixing time: how long it takes to get to stationary distribution