# Introduction

## What is Slice Sampling?

A "black-box" auxiliary variable Markov Chain Monte Carlo (MCMC) method that avoids the need to tune hyperparameters. Introduced by Neal (2003).

The idea of slice sampling. Suppose we wish to sample from a distribution for a variable, $x$, taking values in some subset of $R^n$ , whose density is proportional to some function $f(x)$. We can do this by sampling uniformly from the (n + 1)-dimensional region that lies under the plot of $f(x)$. This idea can be formalized by introducing an auxiliary real variable, $y$, and defining a joint distribution over $x$ and $y$ that is uniform over the region $U = \{(x, y) : 0 < y < f(x)\}$ below the curve or surface defined by $f(x)$. That is, the joint density for $(x, y)$ is

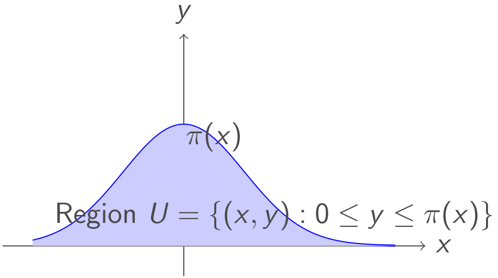
$$p(x, y) = \frac{1}{Z} \begin{cases} 1, & \text{if } 0 < y < f(x) \\ 0, & \text{otherwise} \end{cases}$$

where $Z = \int f(x)dx$. The marginal density for $x$ is then

# Intuition Behind Slice Sampling

**The Fundamental Idea**

To sample from $\pi(x)$, we can sample uniformly from the region under the curve of $\pi(x)$




**Step 1: Vertical Slice**

- Given current position $x$
- Sample height $y \sim \text{Uniform}(0, \pi(x))$

**Step 2: Horizontal Slice**

- Sample new $x$ uniformly from slice
- $S = \{x : \pi(x) \geq y\}$

# The Slice Sampling Algorithm

## Basic Algorithm

**Given:** Current state $x_t$, target distribution $\pi(x)$

## Algorithm

1. **Sample auxiliary variable:** Draw $y \sim \text{Uniform}(0, \pi(x_t))$
2. **Find the slice:** Identify $S = \{x : \pi(x) \geq y\}$
3. **Sample from the slice:** Draw $x_{t+1} \sim \text{Uniform}(S)$

**The Challenge: Finding and Sampling from $S$**
In practice, finding $S = \{x : \pi(x) \geq y\}$ can be difficult!
**Key Idea: Leave Distribution Invariant**

# How to sample from $S$

**The Stepping Out Procedure**

1. **Create initial interval:**
2. $L = x_t - w \cdot U$, $R = L + w$, where $U \sim \text{Uniform}(0, 1)$
3. **Step out left:**
4. While $\pi(L) \geq y$: $L = L - w$
5. **Step out right:**
6. While $\pi(R) \geq y$: $R = R + w$

**The Shrinking Procedure**

1. **Sample and shrink:**
2. Loop: $x' \sim \text{Uniform}(L, R)$
3. If $\pi(x') \geq y$: accept $x_{t+1} = x'$
4. Else: shrink $[L, R]$ by setting $L = x'$ or $R = x'$

**Adaptive Nature**

The algorithm automatically adapts to the local scale of $\pi(x)$. Wide regions are explored with large steps, narrow regions with small steps.

Alternative procedures exist for sampling from $S$ (e.g., doubling, multi-dimensional

# Why $w$ is Not a Critical Tuning Parameter

**The Width Parameter $w$: Efficiency vs. Correctness**

Yes, $w$ IS technically a tuning parameter, BUT...

**Traditional MCMC (e.g., RW-Metropolis)**

- **Poor tuning $\rightarrow$ Poor mixing**
- $\sigma$ too small $\rightarrow$ Tiny steps, stuck
- $\sigma$ too large $\rightarrow$ High rejection
- Can take exponentially long
- Affects correctness in finite time

**Slice Sampling with $w$**

- **Poor $w$ $\rightarrow$ More computation**
- $w$ too small $\rightarrow$ Many step-outs
- $w$ too large $\rightarrow$ More shrinking
- Always finds correct slice
- Only affects efficiency

**Why $w$ is Robust: The Self-Correcting Mechanism**

**Case 1: $w \ll$ typical slice width**

**Case 2: $w \gg$ typical slice width**

# Why Slice Sampling Converges

## Formal Convergence Properties

### 1. Detailed Balance

Let $T(x'|x)$ be the transition kernel. We need: $\pi(x) \cdot T(x'|x) = \pi(x') \cdot T(x|x')$

**Proof sketch:**

- Given $x$, sample $y \sim \text{Uniform}(0, \pi(x))$
- Probability density of moving from $x$ to $x'$:

$$T(x'|x) = \int_0^{\min(\pi(x),\pi(x'))} \frac{1}{\pi(x)} \cdot \frac{1}{|S_y|} dy$$

  where $|S_y|$ is the length of slice $\{z : \pi(z) \geq y\}$
- This is symmetric: $T(x'|x) = T(x|x') \Rightarrow$ detailed balance holds

### 2. Irreducibility

For any $x, x'$ where $\pi(x) > 0$ and $\pi(x') > 0$:

# Convergence: Additional Mathematical Details

## Detailed Balance - Complete Argument

Consider augmented state space $(x, y)$ with invariant distribution:

$$\pi^*(x, y) = \frac{1}{Z} \cdot \mathbf{1}\{0 \leq y \leq \pi(x)\}$$

where $Z = \int \pi(x) dx$ is the normalization constant.

**The Gibbs Sampler View**

Slice sampling is a Gibbs sampler on the augmented space:

- **Step 1:** Sample $y|x \sim \text{Uniform}(0, \pi(x))$
- **Step 2:** Sample $x|y \sim \text{Uniform}(\{x : \pi(x) \geq y\})$

Each conditional distribution is correct:

$$p(y|x) = \frac{1}{\pi(x)} \cdot \mathbf{1}\{0 \leq y \leq \pi(x)\} \qquad (1)$$

# Extensions

- elliptic slice sampling (Murray et al., 2010) for Gaussian priors

# Summary

## Advantages of Slice Sampling

- ✓ No rejection step (unlike MH)
- ✓ Self-adapting to different scales
- ✓ Only requires $\pi(x)$ evaluation
- ✓ Minimal tuning (only $w$)
- ✓ Guaranteed convergence

## Common Uses

- Bayesian inference
- Hierarchical models
- Within Gibbs samplers

## Disadvantages

- × Computationally expensive
- × Difficult in high dimensions
- × Slow for multimodal distributions

## Best For

- Univariate sampling
- Unusual distributions
- Avoiding tuning phase