

# Monte Carlo Methods

732A90

Computational Statistics

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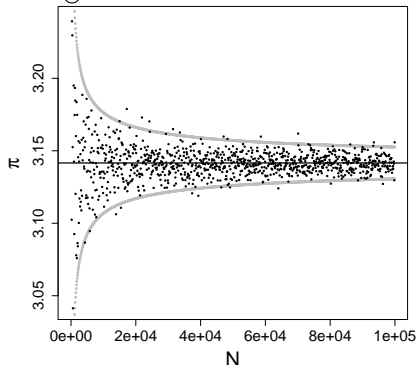
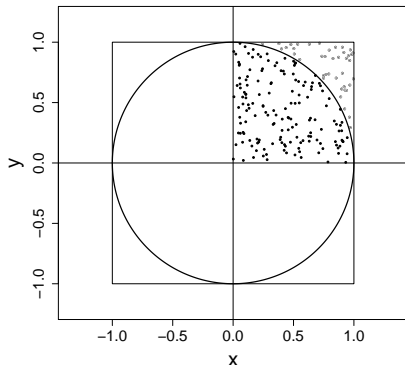
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# What is the area of the unit circle?

```
f.circArea<-function(N){  
  m.xy<-cbind(runif(N),runif(N))  
  4*sum(apply(m.xy,1,function(xy){xy[1]^2+xy  
    [2]^2<1}))/N  
}
```

$$3.141 \approx \pi = \int 1dx$$



# Monte Carlo methods: outline

- **Monte Carlo methods** are a class of computational algorithms that use repeated random sampling to compute their results.
- Monte Carlo methods for random number generation
  - Metropolis–Hastings algorithm
  - Gibbs sampler
- Monte Carlo methods for statistical inference
  - Estimate integrals (we already did!)
  - Variance estimation
  - Variance reduction: importance sampling, control variates

**Previous lecture:** Generate

- univariate distributions (inverse CDF, acceptance/rejection)
- multivariate normal

but general multivariate distribution?

## MCMC

# Bayesian inference: Recap

A dataset  $D$  is obtained by sampling from a distribution  $f(\cdot|\theta)$ .  
How to estimate  $\theta$ ?

- *Frequentists*:  $\theta$  is an unknown but fixed parameter, compose likelihood  $\mathcal{L}(D|\theta)$  and find  $\theta$  that maximizes it.
- *Bayesians*:  $\theta$  is a random variable with **prior** probability law  $p(\theta)$  before observing  $D$
- After observing  $D$ , Bayes' theorem gives

$$p(\theta|D) = \frac{p(D|\theta)p(\theta)}{p(D)} = \frac{p(D|\theta)p(\theta)}{\int p(D|\theta)p(\theta)d\theta}$$

# Bayesian inference: Recap

$$p(\theta|D) = \frac{p(D|\theta)p(\theta)}{p(D)} = \frac{p(D|\theta)p(\theta)}{\int p(D|\theta)p(\theta)d\theta}$$

We know:  $p(D|\theta)$  (the model),  $p(\theta)$  (the prior)

We need: simulate from  $p(\theta|D)$  (the posterior)

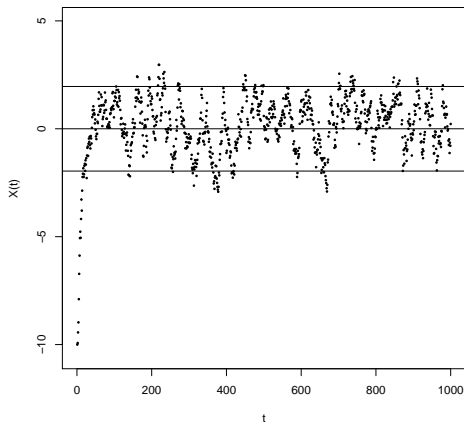
- ❶ General (multivariate) type distribution
  - ❷ Integral can be impossible to compute
- 
- ❶ MCMC solves this
  - ❷ Not needed (given  $D$  it is constant)

# Markov Chains: Recap

- A Markov chain is a sequence  $X_0, X_1, \dots$  of random variables such that the distribution of the next value depends only on the current one (and parameters).
- $P(X_{t+1}|X_t)$  is called a **transition kernel**. Assume it does not depend on  $t$  (**time homogeneous**).
- A Markov chain is **stationary**, with stationary distribution  $\Phi$ , if  $\forall_k X_k \sim \Phi$
- One shows (not trivial in general) that under *certain* conditions a Markov chain will converge to the stationary distribution in the limit.

# Markov Chains: Example

$$X(t+1) = e^{-1}X(t) + \epsilon, \epsilon \sim \mathcal{N}(0, \frac{5}{2} \cdot (1 - e^{-2}))$$



Discard first  $K - 1$  samples: **burn-in period**



# MCMC: Example

**Linear regression** with residual normally/student/etc. distributed

$$Y = \beta X + \epsilon$$

How to find credible interval for  $\beta$  if we know  $\text{Var}[\epsilon] = \sigma^2$ ?

❶

$$P(Y|X, \beta) = \prod_{i=1}^N f(Y_i | \text{mean} = \beta X_i, \text{var} = \sigma^2)$$

- ❷ Obtain  $P(\beta|Y, X)$  by drawing from  $P(Y|X, \beta)P(\beta)$  **in a clever way.**
- ❸ The prior ?
- ❹ Use the MCMC sample to obtain quantiles.

Normal residual: analytical solution

We have

- A PDF  $\pi(x)$  that we want to sample from.
- A **proposal distribution**  $q(\cdot|X_t)$  that has a **regular** form w.r.t. to  $\pi(\cdot)$   
E.g.  $q(\cdot|X_t)$  is normal with mean  $X_t$  and given variance
- *Regular* form: suffices that the proposal has the same support as  $\pi$ .

# Metropolis–Hastings Sampler

$$\alpha(X_t, Y) = \min \left\{ 1, \frac{\pi(Y)q(X_t|Y)}{\pi(X_t)q(Y|X_t)} \right\}$$

```
1: Initialize chain to  $X_0$ ,  $t = 0$ 
2: while  $t < t_{\max}$  do
3:   Generate a candidate point  $Y \sim q(\cdot|X_t)$ 
4:   Generate  $U \sim Unif(0, 1)$ 
5:   if  $U < \alpha(X_t, Y)$  then
6:      $X_{t+1} = Y$ 
7:   else
8:      $X_{t+1} = X_t$ 
9:   end if
10:   $t = t + 1$ 
11: end while
```

# Metropolis–Hastings Sampler: Properties

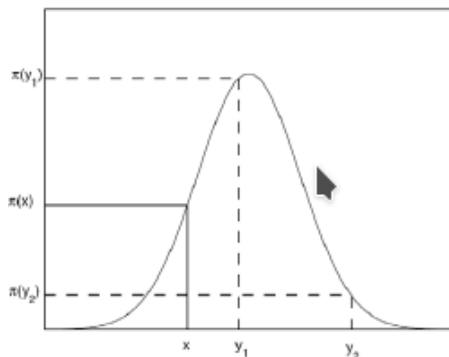
- Informally: “The chain  $(X_t)_{t=0}^{\infty}$  will converge to  $\pi(\cdot)$ .”
- The chain might not move sometimes.
- The values of the chain are dependent.
- If  $q(X_t|Y) = q(Y|X_t)$  (i.e. symmetric proposal) we get **Random–walk Monte Carlo**:

$$\alpha(X_t, Y) = \min \left\{ 1, \frac{\pi(Y)}{\pi(X_t)} \right\}$$

# Choice of proposal distribution

- In Random-Walk Monte Carlo

If  $\pi(Y) \geq \pi(X)$ , the chain moves to the next point, otherwise only with some probability.

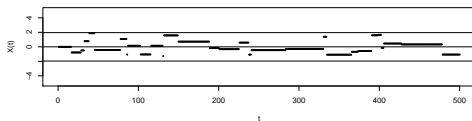
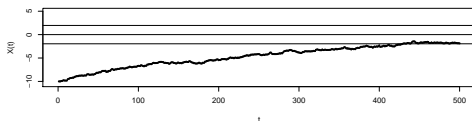
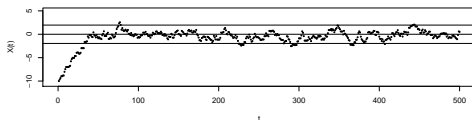


Choice of proposal dist.: **target:**  $\pi(\cdot) = \mathcal{N}(0, 1)$

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# Choice of proposal distribution

$q$  normal with sd: props= 0.5, 0.1 and 20



# Gibbs sampler: alternative to Metropolis–Hastings

We want to generate from a distribution on  $\mathbb{R}^d$ .

- 1: Initialize chain to  $X_0 = (X_{0,1}, \dots, X_{0,d})$ ,  $t = 0$
- 2: **while**  $t < t_{\max}$  **do**
- 3:   **for**  $i = 1, \dots, d$  **do**
- 4:     Generate

$$X_{t+1,i} \sim f(\cdot | X_{t+1,1}, \dots, \mathbf{X}_{\mathbf{t}+1, \mathbf{i}-1}, \mathbf{X}_{\mathbf{t}, \mathbf{i}+1}, \dots, X_{t,d})$$

- 5:   **end for**
- 6:    $t = t + 1$
- 7: **end while**



# Gibbs sampler

- At each iteration inside the `for` loop univariate random numbers are generated.
- Only one element is updated.
- **WE NEED TO KNOW THE CONDITIONAL MARGINAL DISTRIBUTIONS.**
- Convergence may be slow.
- Can be useful in high dimensions (i.e. proposal density may be difficult to find in another way).

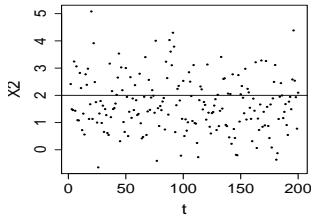
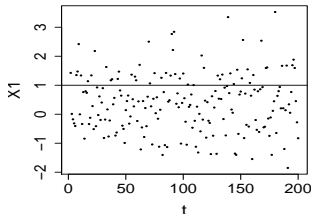
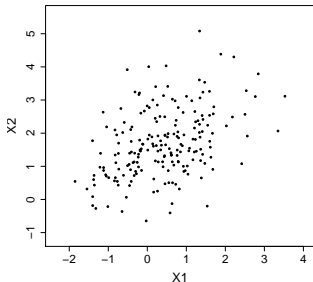
Gibbs sampler: target:  $d$ -dim  $\mathcal{N}(\mu, \Sigma)$

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# Gibbs sampler: Example (code: see R scripts)

Generate from

$$\mathcal{N}([1 \ 2]^T, \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix})$$



- When should we stop the chain? When are we (nearly) at the stationary distribution?
- Typically such a sample is generated to make further inference.

# Convergence monitoring: Gelman–Rubin method

We want to estimate  $v(\theta)$ .

- 1 Generate  $k$  sequences of length  $n$  with different starting points.
- 2 Compute between- and within- sequence variances:

$$B = \frac{n}{k-1} \sum_{i=1}^k (\bar{v}_{i\cdot} - \bar{v}_{..})^2 \quad W = \sum_{i=1}^k \frac{s_i^2}{k} \quad s_i^2 = \sum_{j=1}^n \frac{(\bar{v}_{ij} - \bar{v}_{i\cdot})^2}{n-1}$$

- 3 Overall variance estimate:  $\hat{\text{Var}}[v] = \frac{n-1}{n}W + \frac{1}{n}B$
- 4 Gelman–Rubin factor:

$$\sqrt{R} = \sqrt{\frac{\hat{\text{Var}}[v]}{W}}$$

- 5 Values much larger than 1 indicate lack of convergence
- 6 See `?coda::gelman.diag`

# Gibbs sampler

```
library(coda)
f1<-mcmc.list(); f2<-mcmc.list(); n<-100; k<-20
X1<-matrix(rnorm(n*k), ncol=k, nrow=n)
X2<-X1+(apply(X1, 2, cumsum)*(matrix(rep(1:n, k), ncol=
    k)^2))
for (i in 1:k){f1[[i]]<-as.mcmc(X1[, i]); f2[[i]]<-as
    .mcmc(X2[, i])}
print(gelman.diag(f1))
# Potential scale reduction factors:
#      Point est. Upper C.I.
#[1,]      0.999      1.01

print(gelman.diag(f2))
# Potential scale reduction factors:
#      Point est. Upper C.I.
#[1,]      1.82      2.38
```

# MC for inference

- Estimation of a definite integral

$$\theta = \int_D f(x)dx \quad \left( \text{recall } \pi = \int_{\mathcal{O}} 1dx \right)$$

- Decompose into:

$$f(x) = g(x)p(x) \quad \text{where} \quad \int_D p(x)dx = 1$$

- Then, if  $X \sim p(\cdot)$

$$\theta = \mathbb{E}[g(X)] = \int_D g(x)p(x)dx$$

- 

$$\hat{\theta} = \frac{1}{n} \sum_{i=1}^n g(x_i), \quad \forall_i x_i \sim p(\cdot)$$

# MC for inference

- Decomposition is not unique, some will be better (lower variance) others worse.  $p(x) \propto |f(x)|$ : minimal
- Can we easily generate from  $p(\cdot)$ ?
- Bayesian inference: use MCMC samples from  $p(\theta|D)$  to obtain a point estimator

$$\theta^* = \int \theta p(\theta|D) \approx \frac{1}{n} \sum_{i=1}^m \theta_i$$

- $\hat{\theta}$  depends on  $n$  and  $g(X)$ , how variable will it be?

$$\widehat{\text{Var}} \left[ \hat{\theta} \right] = \frac{1}{n(n-1)} \sum_{i=1}^n \left( g(x_i) - \overline{g(x)} \right)^2$$

- MCMC: estimator biases as chain correlated, use longer chain and batch mean instead of  $x_i$ .



- ① Generating data from a general multivariate distribution
- ② Markov Chain Monte Carlo:  
Metropolis–Hastings algorithm, Gibbs sampling
- ③ Convergence: Gelman–Rubin method
- ④ Estimation of integral