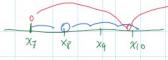
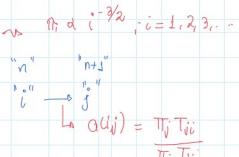


Example 5.2 Power-law distributions are positive probability distributions of the form $\pi_i \propto i^s$, for some constant S. Unlike distributions with exponentially decaying tails (e.g., Poisson, geometric, exponential, normal), power-law distributions have fat tails, and thus are often used to model skewed data. Let



$$\pi_{i} = \frac{i^{-3/2}}{\sum_{k=1}^{\infty} k^{-3/2}}, \text{ for } i = 1, 2, \dots$$

$$\begin{array}{c} \chi_{0/1} \chi_{1/2} \chi_{2/2} \chi_{1/2} \chi_{1$$



Implement a Metropolis-Hastings algorithm to simulate from π .

- 1. Choose a new state according to T. That is, choose j with probability T_{ij} . State j is called the proposal state.
- 2. Decide whether to accept j or not. Let

$$a(i,j) = \frac{\pi_j T_{ji}}{\pi_i T_{ii}}.$$

The function a is called the acceptance function. If $a(i,j) \ge 1$, then j is accepted

as the next state of the chain. If a(i,j) < 1, then j is accepted with probability a(i,j). If j is not accepted, then i is kept as the next step of the chain.

In other words, assume that $X_n = i$. Let U be uniformly distributed on (0, 1). Set

 $X_{n+1} = \begin{cases} j, & \text{if } U \le a(i,j), \\ i, & \text{if } U > a(i,j). \end{cases} \bigcup \Diamond \bigcup (0,1)$

$$T_{ij} = \begin{cases} 1/2, & \text{if } j = i \pm 1 \text{ for } i > 1, \\ 1, & \text{if } i = 1 \text{ and } j = 2, \end{cases}$$

$$X_{n+1} = \begin{cases} J, & \text{if } U \leq a(i,j), \\ i, & \text{if } U > a(i,j). \end{cases}$$

$$I_{ij} = \begin{cases} 1/2, & \text{if } j = i \pm 1 \text{ for } i > 1, \\ 1, & \text{if } i = 1 \text{ and } j = 2, \\ 0 & \text{otherwise.} \end{cases}$$

$$O(\frac{1}{2}, \frac{1}{2}) = O(\frac{1}{2}, \frac{1}{2})$$

$$a(i, i+1) = \left(\frac{i}{i+1}\right)^{3/2}$$
, and $a(i+1, i) = \left(\frac{i+1}{i}\right)^{3/2}$, for $i \ge 2$,

with

$$a(1,2) = \frac{\pi_2 T_{21}}{\pi_1 T_{12}} = \left(\frac{1}{2}\right)^{3/2} \frac{1}{2} = \left(\frac{1}{2}\right)^{5/2}$$
 and $a(2,1) = 2^{5/2}$.

ALGORITMO METROPOLIS HASTINGS: ESPACIO DE ESTADOS CONTINUO

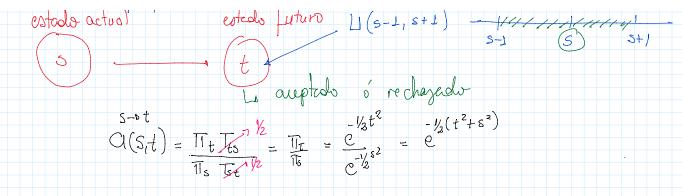
Example 5.5 Using only a uniform random number generator, simulate a standard normal random variable using MCMC.

$$f(z) = \frac{1}{\sqrt{2\pi}} \cdot e^{\frac{1}{2}z^2}$$
; $z \sim N(0, 1)$ espacio de estades continues $z \in (-\infty, +\infty)$

T-o función de deusidad e purponer caudidates para las variables electoria

Propuesta: $1 \times 11(i-1, i+1)$ po longitud es 2 (i+1) - (i-1) = 2

 $T = \int \frac{1}{2} i \, i \, \tilde{\epsilon}(i+1, i-1)$ estado actual 0, c. (estado futuro $\coprod (s-1, s+1)$ $\xrightarrow{s-1}$ (S)



MUESTREADOR DE GIBBS (GIBBS SAMPLER OR GIBBS SAMPLING)

In the Gibbs sampler, the target distribution π is an m-dimensional joint density

$$\pi(x) = \pi(x_1, \dots, x_m).$$

A multivariate Markov chain is constructed whose limiting distribution is π , and which takes values in an m-dimensional space. The algorithm generates elements of the form

$$X^{(0)}, X^{(1)}, X^{(2)}, \dots$$

= $(X_1^{(0)}, \dots, X_m^{(0)}), (X_1^{(1)}, \dots, X_m^{(1)}), (X_1^{(2)}, \dots, X_m^{(2)}), \dots$

by iteratively updating each component of an m-dimensional vector conditional on the other m-1 components. We show that the Gibbs sampler is a special case of the Metropolis–Hastings algorithm, with a particular choice of proposal distribution.

The Gibbs sampler is a special case of the Metropolis–Hastings algorithm. To see this, assume that π is an m-dimensional joint distribution. To avoid excessive notation and simplify the presentation, we just consider one step of the Gibbs sampler when the first component is being updated.

Assume that $i = (x_1, x_2, ..., x_m)$ is the current state, and $j = (x'_1, x_2, ..., x_m)$ is the proposed state. The proposal distribution T is the conditional distribution of X_1 given $X_2, ..., X_m$. The acceptance function is $a(i,j) = \pi_i T_{ii} / \pi_i T_{ii}$.

We have that

$$\begin{split} \pi_{j}T_{ji} &= \pi(x'_{1}, x_{2}, \dots, x_{m}) f_{X_{1}|X_{2},\dots,X_{m}}(x_{1}|x_{2},\dots,x_{m}) \\ &= \pi(x'_{1}, x_{2},\dots,x_{m}) \left(\frac{\pi(x_{1}, x_{2},\dots,x_{m})}{\int \pi(x_{1}, x_{2},\dots,x_{m}) \ dx} \right) \\ &= \pi(x_{1}, x_{2},\dots,x_{m}) \left(\frac{\pi(x'_{1}, x_{2},\dots,x_{m})}{\int \pi(x_{1}, x_{2},\dots,x_{m}) \ dx} \right) \\ &= \pi(x_{1}, x_{2},\dots,x_{m}) f_{X_{1}|X_{2},\dots,X_{m}}(x'_{1}|x_{2},\dots,x_{m}) \\ &= \pi_{i}T_{ij}. \end{split}$$

EJEMPLO: Condicional de la normal bivariada

DISTRIBUCIÓN NORMAL BIVARIADA. Se dice que las variables aleatorias continuas X y Y tienen una distribución normal bivariada si su función de densidad conjunta es

$$\begin{split} f(x,y) &= \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \\ &\exp\left(-\frac{1}{2(1-\rho^2)}\left[(\frac{x-\mu_1}{\sigma_2})^2 - 2\rho(\frac{x-\mu_1}{\sigma_1})(\frac{y-\mu_2}{\sigma_2}) + (\frac{y-\mu_2}{\sigma_2})^2\right]\right), \end{split}$$

para cualesquiera valores reales de x y y, y en donde $-1 < \rho < 1$, $\sigma_1 > 0$, $\sigma_2 > 0$, y μ_1 , μ_2 son dos constantes reales sin restricción. Se escribe entonces $(X,Y) \sim \mathcal{N}(\mu_1,\sigma_1^2,\mu_2,\sigma_2^2,\rho)$. Cuando $\mu_1 = \mu_2 = 0$, y $\sigma_1 = \sigma_2 = 1$, la distribución se llama normal bivariada *estándar*, y su gráfica se muestra en la Figura 3.11 cuando $\rho = 0$. En el siguiente ejercicio se enuncian algunas propiedades de esta distribución.

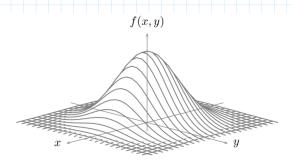


Figura 3.11: Función de densidad normal bivariada estándar.

Sea (X,Y) un vector con distribución normal $\mathrm{N}(\mu_1,\sigma_1^2,\mu_2,\sigma_2^2,\rho)$. Demuestre que la distribución condicional de Y dado que X=x es normal con media $\mu_2+\rho(x-\mu_1)\sigma_2/\sigma_1$ y varianza $\sigma_2^2(1-\rho^2)$, y que la distribución condicional de X dado que Y=y es normal con media $\mu_1+\rho(y-\mu_2)\sigma_1/\sigma_2$ y varianza $\sigma_1^2(1-\rho^2)$.