ESMA 5015: Accept Reject

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1 notes for 2025-03-06

$$E(w) = \alpha \beta$$

$$w \sim gamma(\alpha, \beta) \quad var(w) = \alpha \beta^2$$

$$F_{y}(g) = \frac{1}{2}e^{-y} + \frac{1}{2}ye^{-y}$$

$$E[y] = \int_{0}^{\infty} yf_{y}(y)dy$$

$$= \frac{1}{2}E[y_{1}] + \frac{1}{2}E[y_{2}]$$

$$y_{1} \sim gamma(1, 1)$$

$$y_{2} \sim gamma(2, 1)$$

$$= \frac{1}{2}1 + \frac{1}{2}2$$

$$= \frac{3}{2}$$

$$var(y) = E[y^{2}] - E[y]^{2}$$

$$E[y^{2}] = \int_{0}^{\infty} y^{2} f_{y}(y) dy$$

$$= .5E[y_{1}^{2}] + .5E[y_{2}^{2}]$$

$$= \frac{1}{2}2 + \frac{1}{2}6$$

$$= 4$$

$$E[y_1^2] = var(y_1) + E[y_1]^2$$
= 1 + 1²
= 2

$$E[y_2^2] = var(y_2) + E[y_2]^2$$

= 2 + 2²
= 6

$$= 4 - \frac{3}{2}^{2}$$

$$= 4 - \frac{9}{4}$$

$$= \frac{7}{4}$$

2 Consideren un algoritmo Accept-Reject para simular $X \sim N(0,1)$

1. usando $Y \sim cauchy(0,1)$

$$F_Y(y) = \frac{1}{\pi} \frac{1}{1 + y^2} \quad y \in \mathbb{R}$$

2. usando $Y \sim double - exponential(0, 1)$

$$f_Y(y) = \frac{1}{2}e^{-|y|} \quad y \in \mathbb{R}$$

2.1 theory

1. calculate $M = \sup_{x} \frac{f_X(x)}{f_Y(y)}$

$$= \sup_{x} \frac{\frac{1}{\sqrt{2\pi}} e^{-x^{2}/2}}{\frac{1}{\pi} \frac{1}{1+x^{2}}}$$
$$= \sup_{x} \frac{\pi}{\sqrt{2}} e^{-x^{2}/2} (1+x^{2})$$

sea $h(x) = e^{-x^2/2}(1+x^2)$

$$\frac{dh(x)}{dx} = -xe^{-x^2/2}(1+x^2) + e^{-x^2/2}2x$$

$$= \vdots$$

$$= -xe^{-x^2/2}(x^2 - 1)$$

$$\frac{dh(x)}{dx}=0 \Rightarrow x=0,\pm 1$$
 puede demostra maxiomo occurra en $x=\pm 1 \implies M=\frac{w\sqrt{\pi}}{\sqrt{2}}e^{-1/2}=1.52$

2.2 algorithm

- 1. simular $Y \sim cauchy(0,1)$ y $U \sim U(0,1)$ independientes.
- 2. si

$$U < \frac{f_X(Y)}{Mf_Y(Y)}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-1/2} \frac{\sqrt{\pi}}{\sqrt{\pi}} (1 + Y^2)$$

$$= \frac{1}{2} (1 + Y^2) e^{\frac{-Y^2 + 1}{2}}$$

aceptar X = Y

3. si no, regresar a paso 1.

2.3 steps

1.

$$M = \sup_{x} \frac{f_X(x)}{f_Y(y)} = \sup_{x} \frac{\int \frac{1}{\sqrt{2\pi}} e^{-x^2/2}}{\frac{1}{2}e^{-|x|}}$$

$$= \sup_{x} \frac{\sqrt{2}}{\sqrt{\pi}} e^{-x^2/2 + |x|}$$

$$h(x) = \ln\left(e^{-x^2/2 + |x|}\right)$$

$$\frac{dh(x)}{dx} = \frac{d}{dx} \left(-\frac{x^2}{2} + |x|\right) = \begin{cases} -x - 1 & x < 0\\ -x + 1 & x > 0 \end{cases}$$

$$\frac{dh(x)}{dx} = 0 \Rightarrow x = \pm 1$$

debe demostrar que el supremo ocure en $x=\pm 1$

2.4 algorithm

- 1. $M = \frac{\sqrt{2}}{\sqrt{\pi}}e^{-1/2+1} = 1.31$
- 2. simular $Y \sim double exponential(0,1)$ y $U \sim U(0,1)$ independientes.
- 3. si

$$U < \frac{f_X(Y)}{Mf_Y(Y)} = e^{\frac{-y^2}{2} + |y| - 1/2}$$

entonces aceptar X = Y

4. si no, regresar a paso 2.

3 Generar una $X \sim Beta(\alpha, \beta)$

Donte 0 < x < 1 y $\alpha, \beta > 0$ Utilizar $y \sim U(0, 1)$.

$$M = \sup_{x} \frac{f_X(x)}{f_Y(y)} = \frac{\frac{\gamma(\alpha+\beta)}{\gamma(\alpha)\gamma(\beta)}x^{\alpha-1}(1-x)^{\beta-1}}{1}$$
$$h(x) = \ln\left(X^{\alpha-1}(1-x)^{\beta-1}\right)$$
$$\frac{dh(x)}{dx} = \frac{\alpha-1}{x} - \frac{\beta-1}{1-x}$$
$$\frac{dh(x)}{dx} = 0 \Rightarrow x = \frac{\alpha-1}{\alpha+\beta-2} \text{ y } \beta! = 1, \alpha! = 1$$

puede demostrar que en esta X OCURRE UN maxiomo

3.1 algorithm

- 1. Generar $y \sim U(0,1)$ y $U \sim U(0,1)$ independientes.
- 2. Si

$$u < \frac{f_X(y)}{Mf_Y(y)} = \frac{\frac{\gamma(\alpha+\beta)}{\gamma(\alpha)\gamma(\beta)}y^{\alpha-1}(1-y)^{\beta-1}}{\frac{\gamma(\alpha+\beta)}{\gamma(\alpha)\gamma(\beta)}\frac{\alpha-1}{\alpha+\beta-2}\alpha^{-1}(1-\frac{\alpha-1}{\alpha+\beta-2})^{\beta-1}}$$

define X = y

3. si no, regresar a paso 1.

4 Ejemplo generar $X \sim Beta(\alpha = 2.7, \beta = 6.3)$

M = 2.6667444 que ocurre en $x = \frac{2.7 - 1}{2.7 + 6.3 - 2} = 0.2428$

4.1 algorithm

- 1. Generar $y \sim U(0,1)$ y $U \sim U(0,1)$ independientes.
- 2. Si

$$u < \frac{f_X(y)}{Mf_Y(y)} = \frac{\frac{\gamma(\alpha+\beta)}{\gamma(\alpha)\gamma(\beta)}y^{\alpha-1}(1-y)^{\beta-1}}{2.666744}$$

Define X = y

3. si no, regresar a paso 1.

5 Bayesian Inference

Accept y Metropolis Hasting (topico de la proxima clase) surgen naturlament en estadisticas Bayesiana. En el Analisis Bayesiano ademas de espexifixar el modelo de los datos observadoss $X = x_1, x_2, \dots, x_n$ dado un vector de parametros desxonoxidos θ definido por $f(x|\theta)$, se define θ como una variable aleatoria que tiene una distribucion priori $\pi(\theta)$. El Conocimiento de θ se axtualiza con cm el conocimiento que se obtiene de los datos basadosk la inferencia conxerniente a θ , en la distribucion posterior definida por

$$\pi(\theta|x) = \frac{f(x|\theta)\pi(\theta)}{\int_{\Theta}f(x|\theta)\pi(\theta)d\theta}$$
 Teorema de Bayes

$$\pi(\theta|x)\alpha f(x|\theta)\pi(\theta)$$

5.1 Ejemplo

 x_1, x_2, \ldots, x_n iid $Bernulli(\theta)$

5.1.1 Frecuentista

IC de $(1-\alpha)100\%$ para θ

$$\hat{\theta} \pm z_{\alpha/2} \sqrt{\frac{\hat{\theta}(1-\hat{\theta})}{n}}$$

5.1.2 Bayesiana

$$f(x_1, x_2, \dots, x_n | \theta) = \prod_{i=1}^n \theta^{x_i} (1 - \theta)^{1 - x_i} = \theta^{\sum x_i} (1 - \theta)^{n - \sum x_i}$$
$$\frac{\pi(\theta | x_1, x_2, \dots, x_n) = \theta^{\sum x_i} (1 - \theta)^{n - \sum x_i} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha - 1} (1 - \theta)^{\beta - 1}}{\int_0 \theta^{\sum x_i} (1 - \theta)^{n - \sum x_i} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha - 1} (1 - \theta)^{\beta - 1} d\theta}$$