Note 8

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From last time:

$$f(\theta) = \int_0^\infty f(r, \theta) dr$$

$$f_R(r) = \int_0^{2\pi} f(r, \theta) d\theta$$

Monte Carlo Integration

If we have

$$\int g(x)dx = \theta$$

Sampling approach

$$x_1,...,x_m \sim f(x)$$

use this kind of method to estimate θ

$$\theta = E(x) = \int_{-\infty}^{\infty} x f(x) dx$$

$$E(x^2) = \int_{-\infty}^{\infty} x^2 f(x) dx$$

$$\theta = E(g(x)) = \int_{-\infty}^{\infty} g(x) f(x) dx = \mu$$

By LLN

$$\lim_{n \to \infty} P(|\bar{x} - \mu| < \epsilon) = 1$$
$$\bar{g}(x) = \frac{\sum g(x_i)}{m} = \hat{\theta}$$
$$\lim_{m \to \infty} P(|\hat{\theta} - \theta| < \epsilon) = 1$$

Simple Monte Carlo Integration

$$\theta = \int_0^1 g(x)dx = \int_0^1 g(x)1dx$$

Then Generate X by Unif(0,1)

$$\hat{\theta} = \frac{\Sigma g(x_i)}{m}$$

Ex:

$$\theta = \int_0^1 e^{-x^2} dx$$

$$\hat{\theta} = \frac{\sum e^{-x^2}}{m}$$

$$\theta = \int_{a}^{b} g(x)dx = \int_{a}^{b} g(x)\frac{b-a}{b-a}dx = b-a\int_{a}^{b} g(x)\frac{1}{b-a}dx = (b-a)E_{U}[g(x)]$$
$$\hat{\theta} = (b-a)\frac{\sum g(x_{i})}{m}$$

Is $\hat{\theta}$ a consistent estimator?

$$\begin{split} MSE(\hat{\theta}) &= Var(\hat{\theta}) + bias^2 = Var(\hat{\theta}) + [E(\hat{\theta}) - \theta]^2 \\ E[\bar{g}(x)] &= E[\frac{\Sigma g(x_i)}{m}] = E[g(x)] = \theta \\ \theta - \theta &= 0: \ Unbiased \\ Var(\hat{\theta}) &= Var[\frac{\Sigma g(x_i)}{m}] = \frac{1}{m^2} Var[g(x)] = \frac{1}{m^2} \{E[g^2(x) - E[g(x)]^2]\} \\ &= \frac{1}{m} \{\int g^2(x) f(x) dx - \theta^2 \} \end{split}$$

To make the Variance small, we have many ways:

- 1. $m \to \infty$
- 2. find f(x) such that $\int g^2(x)f(x)dx \simeq \theta^2$

 $\mathbf{E}\mathbf{x}$:

$$F_X(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt = \theta$$

If x > 0

$$F_X(x) = 0.5 + \int_0^x \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$$

$$F_X(x) = 0.5 + x \int_0^x \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} \frac{1}{x} dt$$

$$F_X(x) = 0.5 + x \frac{\sum \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}}}{m}$$

If x < 0

$$F_X(x) = \int_{-\infty}^x f(t)dt$$

$$F_X(x) = 1 - [0.5 + |x| \int_0^{|x|} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} \frac{1}{x} dt]$$

Change of Variable

Let x/x, set $y = \frac{t}{x}$ and dt = xdy

$$\int_{0}^{1} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(xy)^{2}} x dy$$
$$\frac{x}{\sqrt{2\pi}} \int_{0}^{1} e^{-\frac{1}{2}(xy)^{2}} 1 dy$$
$$\theta = \sum_{i=1}^{\infty} \frac{e^{-\frac{1}{2}(xy_{i})^{2}}}{m}$$

Hit-or-Miss Apporach

$$X_1, X_2..., X_n \sim N(0, 1)$$
$$\hat{F}_X(x) = \frac{\sum I(X_i \leq x)}{n}$$

To conclude the both method:

$$Var(\hat{F}_X(x)) = \hat{F}_X(x)[1 - \hat{F}_X(x)]\frac{1}{n}$$

$$\sqrt{Var(\hat{F}_X(x))} = SE[\hat{F}_X(x)]$$

$$SE(\hat{\theta}) = \sqrt{Var(\hat{\theta})} = \sqrt{\frac{1}{m}}\sigma^2$$

$$\hat{\sigma}_{MLE}^2 \to \sigma^2$$

$$\hat{\sigma}_{MLE}^2 = \frac{\Sigma[g(x_i) - \bar{g}(x)]^2}{m}$$

$$SE(\hat{\theta}) = \sqrt{\frac{\Sigma[g(x_i) - \bar{g}(x)]^2}{m^2}} = \frac{\hat{\sigma}_{MLE}}{\sqrt{m}}$$