

ISyE 6416: Computational Statistics
Spring 2017

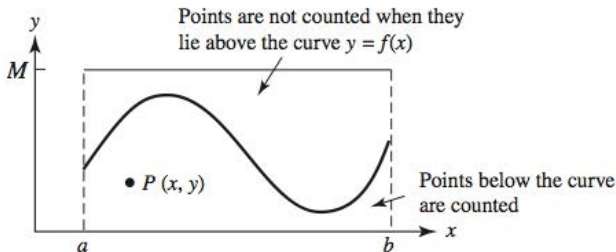
Lecture 13: Monte Carlo Methods

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Determine area under a curve

- ▶ determine area under a curve $y = h(x)$, continuous function with $0 \leq h(x) \leq M$ over the closed interval $a \leq x \leq b$
- ▶ select points at random from within the rectangular region
- ▶ area under the curve / area of rectangle \approx number of points counted below curve / total number of random points



Monte Carlo integration

- ▶ To compute $\mathbb{E}[h(X)] = \int h(x)f(x)dx$
 $h(x)$: integrand, $f(x)$: probability density function
- ▶ Monte Carlo approach to approximate the integration:
Take i.i.d. samples X_1, \dots, X_n from pdf $f(x)$.
Then take sample average

$$\hat{I}_1 = \frac{1}{n} \sum_{i=1}^n h(X_i)$$

- ▶ Convergence: law of large numbers, as $n \rightarrow \infty$

$$\frac{1}{n} \sum_{i=1}^n h(X_i) \rightarrow \mathbb{E}[h(X)]$$

Monte Carlo methods

- ▶ Monte Carlo methods (or Monte Carlo experiments) are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results.
- ▶ most useful when it is difficult or impossible to use other approaches.
- ▶ Monte Carlo methods are mainly used in three distinct problem classes: optimization, numerical integration, and generating draws from a probability distribution.

Estimating probabilities

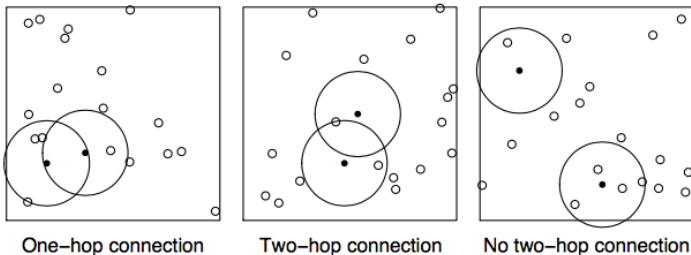
- ▶ Evaluating probability can be rewritten using indicator function as

$$\mathbb{P}(X \in \mathcal{A}) = \mathbb{I}_{\mathcal{A}}(x)$$

- ▶ Widely used in engineering: example, wireless multi-hop networks
- ▶ There are $m \geq 3$ nodes randomly distributed in the unit square
- ▶ Each node can communicate directly with any other node that is within a distance r of it
- ▶ A two-hop connection arises between nodes 1 and 2 when nodes 1 and 2 are farther than r but are both within distance r of node j for one or more $j \in \{3, \dots, m\}$

Source: A. Owen, Monte Carlo theory, methods and examples.

Multi-hop network illustration



$$m = 40$$

- ▶ Question: What is the probability of forming a two-way connection?
- ▶ This probability is an integral over $2m = 40$ dimensional space
- ▶ Run 10,000 independent replications of this problem
- ▶ Among them, 650 cases have two-hop connection
- ▶ The probability is estimated to be

$$\hat{p} = 650/10000 = 0.065.$$

- ▶ How good is the estimation?
CLT-based 99% confidence interval for p

$$\hat{p} \pm \underbrace{z_{0.005}}_{2.58} \sqrt{\frac{\hat{p}(1 - \hat{p})}{n}}$$

leading to

$$0.065 \pm 2.58 \sqrt{\frac{0.065 \times 0.945}{10000}} = 0.065 \pm 0.0064$$

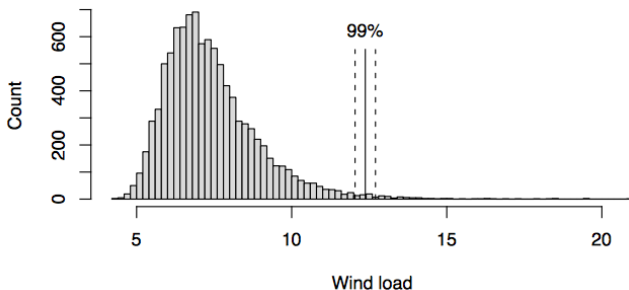
	Lower	Upper
CLT	0.05865	0.07135
Exact	0.05881	0.07161

Estimating tail probability

- How strong a wind should we construct a building to be resistant to?

$$\mathbb{P}(W \leq w) = \exp(-\exp((w - 52)/4))$$

50 year maximum wind load



Estimating tail probability

- ▶ Suppose the random variable X is binomially distributed with m trials and success probability p . We want to evaluate the right-tail probability $\alpha = \mathbb{P}\{X \geq z\}$
- ▶ evaluating tail probability is important in hypothesis testing: finding the significance level of the test, we need to evaluate the tail probability of the test statistics under the null distribution
- ▶ tail probability also used for risk management in insurance, and portfolio investment
- ▶ For z much larger than mp , α is very small, and estimating this small probability accurately is not easy

Convergence property

- ▶ If X is square integrable, we have

$$\frac{1}{n} \sum_{i=1}^n h(X_i) \Rightarrow \mathcal{N} \left(\mathbb{E}[h(X)], \frac{1}{n} \text{Var}[h(X)] \right)$$

- ▶ Estimate the order of the rate of convergence by

$$\sqrt{v/n}, \quad v = \frac{1}{n-1} \sum_{i=1}^n \left[h(X_i) - \frac{1}{n} \sum_{j=1}^n h(X_j) \right]^2$$

- ▶ disadvantage: slow convergence rate $n^{-1/2}$
- ▶ can we reduce v by generating samples smartly?

Important Sampling

- ▶ variance reduction method in Monte Carlo integration
- ▶ main idea: using samples generated from a different distribution rather than the distribution given
- ▶ suppose $g(x)$ is another pdf

$$\int h(x) \textcolor{red}{f}(\textcolor{red}{x}) dx = \int h(x) \underbrace{\frac{f(x)}{g(x)}}_{\text{likelihood ratio}} \textcolor{blue}{g}(\textcolor{blue}{x}) dx$$

change the function to be integrated from

$$h(x) \rightarrow h(x) \frac{f(x)}{g(x)}$$

change the pdf from $\textcolor{red}{f}(\textcolor{red}{x})$ to $\textcolor{blue}{g}(\textcolor{blue}{x})$

- ▶ based on this, now we can sample Y_1, Y_2, \dots, Y_n i.i.d. from $g(x)$
- ▶ estimate the integration as

$$\hat{I}_2 = \frac{1}{n} \sum_{i=1}^n h(Y_i) \underbrace{\frac{f(Y_i)}{g(Y_i)}}_{\text{weighted by likelihood ratio}}$$

- ▶ we can choose $g(x)$ smartly so this estimator \hat{I}_2 has smaller variance than the one based on direct sampling \hat{I}_1
- ▶ choose a distribution to encourage “important” values

How to choose a pdf to sample from

- ▶ we want to show that $\text{var}\{\hat{I}_2\} \leq \text{var}\{\hat{I}_1\}$, since both methods are unbiased: $\mathbb{E}\{\hat{I}_1\} = \mathbb{E}\{\hat{I}_2\}$, or equivalently $\mathbb{E}\{\hat{I}_2^2\} \leq \mathbb{E}\{\hat{I}_1^2\}$:

$$\int \left[h(x) \frac{f(x)}{g(x)} \right]^2 g(x) dx \leq \int h(x)^2 f(x) dx, (*)$$

- ▶ choose $g(x) = \frac{|h(x)|f(x)}{\int |h(v)|f(v)dv}$, we can show (*) is true
- ▶ main idea: choose $g(x)$ to resemble $|h(x)|f(x)$, the standard error tends to be reduced
- ▶ difficulty: if $|h(x)|f(x)$ is unknown, we have to approximate it

Proof.

$$\begin{aligned}& \int \left[\frac{h(x)f(x)}{g(x)} \right]^2 g(x) dx \\&= \int [h(x)f(x)]^2 / g(x) dx \\&= \int [h(x)f(x)]^2 / (|h(x)|f(x)) dx \cdot \left[\int |h(v)|f(v) dv \right] \\&= \left(\int |h(x)|f(x) dx \right)^2 \text{ Cauchy Schwartz} \\&\leq \int |h(x)|^2 f(x) dx \underbrace{\int f(x) dx}_{=1} \\&= \int h^2(x) f(x) dx\end{aligned}$$

