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TAM 598

Lecture 8 :

THE MONTE CARLO METHOD

FOR ESTIMATING EXPECTATIONS

Announcements:

- HW 2 covers lectures 4-8 ; due on Feb 26

Our problem today: high dimensional integrals

say we have a random vector $\underline{x} = \{x_1, x_2, \dots, x_d\} \in \mathbb{R}^d$
and some function $g(\underline{x})$.

things we want to compute:

expectation $\mathbb{E}[g(\underline{x})] = \int \dots \int g(x_1, \dots, x_d) p(x_1, \dots, x_d) dx_1 \dots dx_d$

$= \underline{\int \dots \int g(\underline{x}) p(\underline{x}) d\underline{x}}$

variance $\mathbb{V}[g(\underline{x})] = \mathbb{E}[(g(\underline{x}) - \mathbb{E}[g(\underline{x})])^2]$

$$= \int \dots \int (g(\underline{x}) - \mathbb{E}[g(\underline{x})])^2 p(\underline{x}) d\underline{x}$$

$1_A(x)$
 $= \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{else} \end{cases}$
CDF

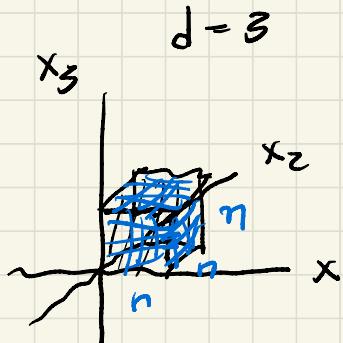
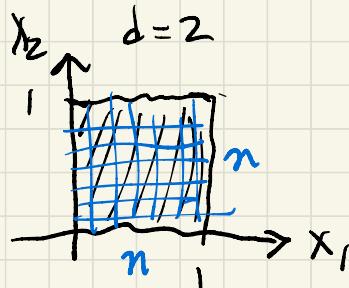
$$F(\underline{x}) = P[g(\underline{Y}) \leq \underline{x}] = \int \dots \int \frac{1}{(-\infty, \underline{x})} g(\underline{Y}) p(\underline{Y}) d\underline{Y}$$

(2)

CURSE OF DIMENSIONALITY

- why high dim. integrals are hard

let $\tilde{X} = \{x_1, \dots, x_d\}$ be uniform in $[0, 1]^d$ $d = \text{dimension}$



want to evaluate

$$\mathbb{E}[g(\tilde{x})] = \int_{\text{inside cube}} g(x_1, \dots, x_d) dx_1 \dots dx_d$$

use quadrature

$$\int_{\text{cube}} g(\tilde{x}) d\tilde{x} \approx \frac{1}{n^d} \left(\sum_{i_1=1}^n \dots \sum_{i_d=1}^n g\left(\frac{i_1}{n}, \dots, \frac{i_d}{n}\right) \right)$$

terms in sum = n^d
 gives exponential w/ d

say
 $n=10$

$d=2$
 $10^2 = 100$
 terms

$d=3$
 1000

$d=5$
 $100,000$

$d=10$
 10^{10}

$d=20$
 10^{20}

If each term requires 0.1 ms

0.1 s 1 s

100 s

115 days

3.1 billion years

LAW OF LARGE NUMBERS

Say we have an infinite series of independent random variables x_1, x_2, \dots all with the same distribution.

we call this an **independent, identically distributed (i.i.d)** sequence

Let $\mu = \mathbb{E}[x_i]$ be the common mean of the random variables

Then

$$\tilde{x}_N = \frac{x_1 + x_2 + \dots + x_N}{N} = \frac{1}{N} \sum_{i=1}^N x_i \text{ converges}$$

to μ as $N \rightarrow \infty$

MONTE CARLO KI 4Ú44

Ulam, von Neumann (1940s)

want to compute expectation

$$\underbrace{\int g(\underline{x}) p(\underline{x}) d\underline{x}}_{\text{or}} = \mathbb{E}_{p(\underline{x})} [g(\underline{x})]$$

$p(\underline{x})$ = "target distribution"

$$\text{or } \sum_{\substack{\underline{x} \\ \sim}} g(\underline{x}) p(\underline{x}) = \mathbb{E}_{p(\underline{x})} [g(\underline{x})] \text{ for discrete}$$

Say we can draw independent samples $\underline{x}_1, \underline{x}_2, \dots, \underline{x}_N \sim p(\underline{x})$

Then

$$\boxed{\int g(\underline{x}) p(\underline{x}) d\underline{x}} \approx \boxed{\frac{1}{N} \sum_{n=1}^N g(\underline{x}_n)} = \overline{I}_N$$

Monte Carlo estimator of E

from the law of large numbers, the sum converges to $\mathbb{E}_{p(\underline{x})} [g(\underline{x})]$ for large N

say we want to estimate not only the expectation of a distribution by sampling, but also the variance. We can do this by deriving an expression for a variance estimator.

$$\text{Var}_{P(\underline{x})} [g(\underline{x})] = \mathbb{E}_{P(\underline{x})} [g^2(\underline{x})] - \mathbb{E}_{P(\underline{x})} [g(\underline{x})]^2$$

↓ ↓

consider the random variables
 $\underline{Y}_1 = g^2(\underline{x}_1), \underline{Y}_2 = g^2(\underline{x}_2) \dots \underline{Y}_N = g^2(\underline{x}_N)$

$\left(\frac{1}{N} \sum_{n=1}^N g(\underline{x}_n) \right)^2$

these are iid so

$$\frac{1}{N} \sum_{n=1}^N g^2(\underline{x}_n)$$

$$\text{Var}_{P(\underline{x})} [g(\underline{x})] =$$

$$\frac{1}{N} \sum_{n=1}^N g^2(\underline{x}_n) - \bar{Y}_N^2$$

variance estimator

Show that the average of the estimator converges to the expectation.

$$\mathbb{E}_{\{\tilde{x}_n\}} \left[\underbrace{\frac{1}{N} \sum_{n=1}^N g(\tilde{x}_n)}_{\text{estimator}} \right] = \frac{1}{N} \sum_{n=1}^N \mathbb{E}_{\{\tilde{x}_n\}} \left[\underline{g(\tilde{x}_n)} \right]$$

$$= \frac{1}{N} \sum_{n=1}^N \int \dots \int \underbrace{p(\tilde{x}'_1) \dots p(\tilde{x}'_n) \dots p(\tilde{x}'_N)}_{\text{because samples are independent}} g(\tilde{x}'_n) d\tilde{x}'_1 \dots d\tilde{x}'_N$$

$\begin{array}{l} \text{samples} \\ \text{independent} \\ \text{of each other} \end{array}$

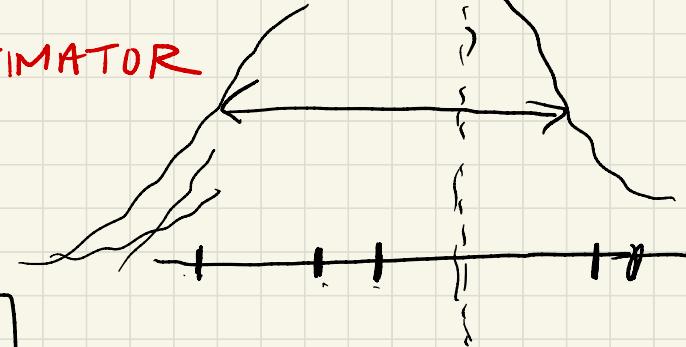
$$\begin{aligned} n=1 &: \text{HTHT} \\ n=2 &: \text{THHT} \\ n=3 &: \text{HTHT} \\ \vdots & \\ n=5 &: \text{HTHTHT} \end{aligned}$$

$$\frac{1}{N} \sum_{n=1}^N \int \underbrace{p(\tilde{x}'_n)}_{\mathbb{E}_{p(x)} [g(x)]} g(\tilde{x}'_n) d\tilde{x}'_n$$

$$= \mathbb{E}_{p(x)} [g(x)]$$

VARIANCE OF A MONTE CARLO ESTIMATOR

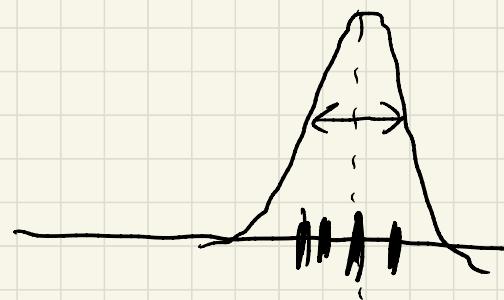
$$\mathbb{V}_{\{\tilde{x}_n\}} \left[\frac{1}{N} \sum_{n=1}^N g(\tilde{x}_n) \right]$$



$$= \frac{1}{N^2} \sum_{n=1}^N \mathbb{V}_{\{\tilde{x}_n\}} [g(\tilde{x}_n)]$$

$$= \frac{1}{N^2} \sum_{n=1}^N \underbrace{\mathbb{V}_{p(x)} [g(x)]}_{}$$

$$= \frac{1}{N} \mathbb{V}_{p(x)} [g(x)]$$



our error $\sim \frac{1}{\sqrt{N}}$