

this conditional
time: probability
next discrete
time: continuous
random variables

read for next
fine: IS pp.
55-166
free ①
app: Kanscamer

AMS13,
4 Aug 17

simulation
(Monte Carlo)
approach to
approximating
probabilities

if $p = P(A)$ then
the odds in favor of
A are $o = \frac{p}{1-p}$

$$\Leftrightarrow p = \frac{o}{1+o}$$

Buffon
(1720)

William Gosset (1905)

Metropolis & Ulam
(1942)
(1949)

pseudo-
random
numbers

van Neumann
(1942)

Feynman

Alan Turing
(1940)

$n = \#$ of simulation replications
as $n \rightarrow \infty$ \hat{p} (Monte Carlo estimate) $\rightarrow p$

graph theory

nodes

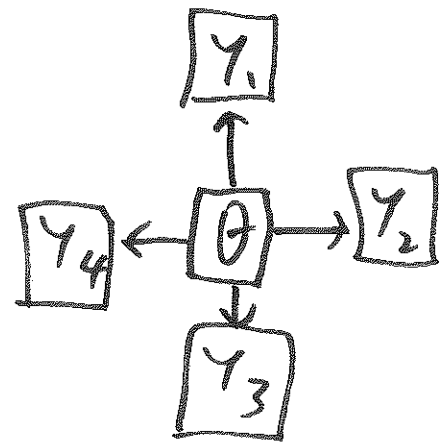
edge

\mathcal{Y}_i : dependent

4 nodes

6 edges

$x \rightarrow y$
 $x \perp y$
 are dependent



(2)

$x \rightarrow y$
 x causes y

5 nodes

4 edges

n nodes \leftrightarrow # data points

$$\binom{n}{2} \text{ edges} = \frac{n(n-1)}{2}$$

$(n+1)$ nodes
 n edges $= O(n)$

$= O(n^2)$
 this is of order n^2
 = Big Oh of n^2

now
 \mathcal{Y}_i are conditionally independent given θ

$O(n^2)$ in this model, the past and the future are conditionally independent given the truth (θ)

$$P(B_i | A) \stackrel{\text{(def)}}{=} \frac{P(B_i \text{ and } A)}{P(A)} \quad (3)$$

$$P(A | B_i) \stackrel{\text{(def)}}{=} \frac{P(A \text{ and } B_i)}{P(B_i)}$$

$$P(B_i \text{ and } A) = P(A) P(B_i | A) \quad \leftarrow \begin{array}{l} \text{mult} \\ \text{by } P(A) \end{array}$$

$$\begin{array}{l} \text{mult.} \\ \text{by} \\ P(B_i) \end{array} \quad P(A \text{ and } B_i) = P(B_i) P(A | B_i)$$

$$\therefore P(A) P(B_i | A) = P(B_i) P(A | B_i)$$

$$\therefore P(B_i | A) = \frac{P(B_i) P(A | B_i)}{P(A)}$$