ORIE 4580/5580: Simulation Modeling and Analysis

ORIE 5581: Monte Carlo Simulation

Unit 1: Probability Review

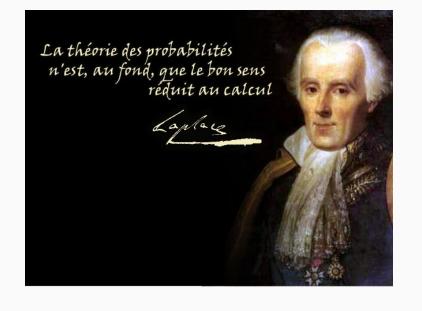
Sid Banerjee School of ORIE, Cornell University

clicker question: random chords

Given the circle $x^2 + y^2 = 1$, we want to sample a uniform random chord. How can we do this?

- (a) Pick 2 endpoints u.a.r on the circumference of the circle
- (b) Pick circumference $C(\theta)$ at uniform random angle $\theta \in [0,2\pi]$, and pick chord-center u.a.r. on $C(\theta)$
- (c) Pick the chord-center u.a.r. inside the circle (draw radius to point, and chord perpendicular)
- (d) All of these are the same

Given the circle $x^2+y^2=1$, we want to sample a uniform random chord. How can we do this?



"probability theory is common sense reduced to calculation"

not quite...

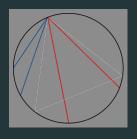
Bertrand's problem

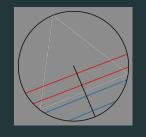
given equilateral triangle inscribed in a circle and a random chord, what is the $\mathbb{P}[\mathsf{chord}]$ is longer than side of the triangle]?

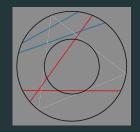
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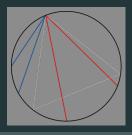


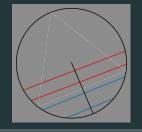


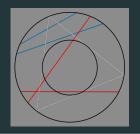
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Bertrand's problem

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the moral (for this course...and for life)

be very precise about defining experiments/random variables/distributions

also see Wikipedia article on Bertrand's paradox

the essentials

These are the things you must know and understand

- Random variables (rv) + Cumulative Distribution Fn (cdf)
- Expectation and Variance of random variables
- Independence (and also dependence mutually exclusive events, conditioning, Bayes rule)
- Common rvs (Bernoulli, Binomial, Geometric, Gaussian, Exponential, Poisson)



random variables

sample space Ω : set of all possible outcomes of random expmt

random variable: any function from $\Omega \to \mathbb{R}$

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example: Youtube's ad algo (I think!) – pick a random number of ads between 0 and 2 (inclusive), and a random length between 0 and 30s for each ad. Let T= Total length of ads on video

probabilities

Probability $\mathbb{P}(E)$: 'number' for 'every' subset $E \subseteq \Omega$, such that:

- $\mathbb{P}(E) \geq 0$ for all $E \subset \Omega$
- $lackbox{\mathbb{P}}(\Omega)=1$ (i.e., probs 'summed over all outcomes' adds to 1)
- $\mathbb{P}(E_1 \cup E_2) = \mathbb{P}(E_1) + \mathbb{P}(E_2)$ (i.e., probs add for mutually exclusive events $E_1 \cap E_2 = \varphi$)

cumulative distribution function

ALERT!!

always try to think of probability and rvs through the cdf

 for any rv X (discrete or continuous), its probability distribution is defined by its cumulative distribution function (cdf)

$$F(x) =$$

using the cdf we can compute probabilities

$$\mathbb{P}[a < X \le b] =$$

visualizing a cdf

The plot of a cdf obeys 3 essential rules + one convention

Example: consider an $rv \in [-2, 5]$ with a **jumps** at 1 and 2

discrete rv

• for a discrete random variable, another characterization is its probability mass function (pmf) $p(\cdot)$

$$p(x) = \mathbb{P}[X = x]$$

• The pmf $p(\cdot)$ is related to the cdf $F(\cdot)$ as

$$F(x) =$$

$$p(x) =$$

• further, any pmf p(x) obeys 2 properties:

continuous random variables

• for a continuous random variable taking values in \mathbb{R} , another characterization is its probability density function (pdf) $f(\cdot)$

$$\mathbb{P}[a < X \le b] =$$

• any pdf f(x) obeys 2 properties:

• ALERTII not true that $f(x) = \mathbb{P}[X = x]$. In fact, for any x,

$$\mathbb{P}[X=x]=$$

continuous random variables

• for continuous rv X with pdf $f(\cdot)$ and cdf $F(\cdot)$, we have

$$\mathbb{P}[a < X \le b] = F(b) - F(a) = \int_a^b f(x) dx$$

now we can go from one function to the other as

$$F(x) =$$

$$f(x) =$$

note on end-points

we wrote: $\mathbb{P}[a < X \le b] = F(b) - F(a)$: is $< vs \le important$?

clicker question: practice with cdfs

The probability density function of the rv X is given by:

$$f(x) = \begin{cases} x/4 & \text{if } 1 \le x \le 3\\ 0 & \text{otherwise.} \end{cases}$$

(a)
$$F(x) = \frac{1}{4}$$
 for $x \ge 0$

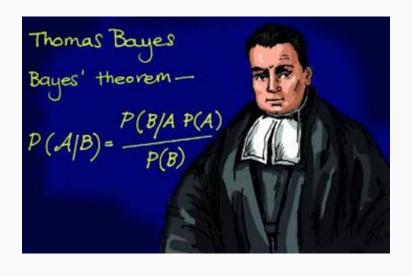
(b)
$$F(x) = \frac{x^2}{8}$$
 for $x \ge 0$

(c)
$$F(x) = \frac{x^2 - 1}{8}$$
 for $x \ge 0$

clicker question: solution

The probability density function of the rv X is given by:

$$f(x) = \begin{cases} x/4 & \text{if } 1 \le x \le 3\\ 0 & \text{otherwise.} \end{cases}$$



conditioning and Bayes' rule

marginals and conditionals

let X, Y be discrete rvs taking values in \mathbb{N} . denote the joint pmf:

$$p_{XY}(x,y) = \mathbb{P}[X = x, Y = y]$$

marginalization: computing individual pmfs from joint pmfs as

$$p_X(x) = \sum_{y \in \mathbb{N}} p_{XY}(x, y) \qquad p_Y(y) = \sum_{x \in \mathbb{N}} p_{XY}(x, y)$$

conditioning: pmf of X given Y = y (with $p_Y(y) > 0$) defined as:

$$\mathbb{P}[X = x | Y = y] \triangleq p_{X|Y}(x|y) = \frac{p_{XY}(x,y)}{p_{Y}(y)}$$

more generally, can define $\mathbb{P}[X \in \mathcal{A}|Y \in \mathcal{B}]$ for sets $\mathcal{A}, \mathcal{B} \in \mathbb{N}$ see also this visual demonstration

Bayesian inference

let X, Y be discrete rvs taking values in \mathbb{N} , with joint pmf p(x, y)

product rule

for $x, y \in \mathbb{N}$, we have: $p_{XY}(x, y) = p_X(x)p_{Y|X}(y|x) = p_Y(y)p_{X|Y}(x|y)$

sum rule

for $x \in \mathbb{N}$, we have: $p_X(x) = \sum_{y \in \mathbb{N}} p_{X|Y}(x|y) p_Y(y)$

Bayes rule

for any $x, y \in \mathbb{N}$, we have:

$$p_{X|Y}(x|y) = rac{p_X(x)p_{Y|X}(y|x)}{\sum_{x \in \mathbb{N}} p_{Y|X}(y|x)p_X(x)}$$

see also this video for an intuitive take on Bayes rule

clicker question: Bayesian inference

Mackay's three cards

We have 3 cards C1, C2, C3, with C1 having faces Red-Green, C2 having faces Green-Green; and C3 having faces Red-Red.

A card is randomly drawn and placed on a table – its upper face is Red. What is $\mathbb{P}[\text{lower face is Red}]$?

- (a) 0
- (b) 1/3
- (c) 1/2
- (d) 2/3
- (e) None of these

clicker question: Bayesian inference

Bayesian inference: example

Eddy's mammogram problem

- $\mathbb{P}[\mathsf{women} \ \mathsf{at} \ \mathsf{age} \ \mathsf{40} \ \mathsf{have} \ \mathsf{breast} \ \mathsf{cancer}] = 0.01$
- A mammogram detects the disease 80% of the time, but also mis-classifies healthy patients 9.6% of the time.

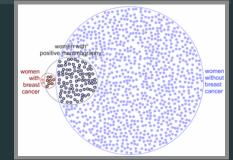
If a 40-year old woman has a positive mammogram test, what is the probability she has breast cancer?

Bayesian inference: example

Eddy's mammogram problem

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- A mammogram detects the disease 80% of the time, but also mis-classifies healthy patients 9.6% of the time.

If a 40-year old woman has a positive mammogram test, what is the probability she has breast cancer?



credit: Micallef et al.



expectations and independence

expected value (mean, average)

let X be a random variable, and $g(\cdot)$ be any real-valued function

• If X is a discrete rv with $\Omega = \mathbb{Z}$ and $\operatorname{pmf} p(\cdot)$, then

$$\mathbb{E}[X] =$$

$$\mathbb{E}[g(X)] =$$

• If X is a continuous rv with $\Omega = \mathbb{R}$ and $\mathsf{pdf}\ f(\cdot)$, then

$$\mathbb{E}[X] =$$

$$\mathbb{E}[g(X)] =$$

variance and standard deviation

• Definition:
$$Var(X) = \sigma(X) =$$

• (More useful formula for computing variance)

$$Var(X) =$$

independence

what do we mean by "random variables X and Y are independent"? (denoted as $X \perp \!\!\! \perp Y$; similarly, $X \not \!\! \perp Y$ for 'not independent')

intuitive definition: knowing X gives no information about Y

formal definition:

• One measure of independence between rv is their covariance

$$Cov(X, Y) =$$
 (formal definition)

independence and covariance

how are independence and covariance related?

- X and Y are independent, then they are uncorrelated in notation: X ⊥ Y ⇒ Cov(X, Y) = 0
- however, uncorrelated rvs can be dependent in notation: $Cov(X, Y) = 0 \implies X \perp\!\!\!\perp Y$
- $Cov(X, Y) = 0 \Rightarrow X \perp \!\!\!\perp Y$ only for multivariate Gaussian rv (this though is confusing; see this Wikipedia article)

linearity of expectation

for any rvs X and Y, and any constants $a,b\in\mathbb{R}$

$$\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y]$$

note 1: no assumptions! (in particular, does not need independence)

linearity of expectation

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$$\mathbb{E}[aX + bY] = a\mathbb{E}[X] + b\mathbb{E}[Y]$$

note 1: no assumptions! (in particular, does not need independence) note 2: does not hold for variance in general

ullet for general X,Y

$$Var(aX + bY) =$$

when X and Y are independent

$$Var(aX + bY) =$$

using linearity of expectation

the TAs get lazy and distribute graded assignments among n students uniformly at random. On average, how many students get their own hw?

using linearity of expectation

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Let
$$X_i = 1$$
 [student i gets her hw] (indicator rv)

N = number of students who get their own hw $= \sum_{i=1}^{10} X_i$ then we have:

$$\mathbb{E}[N] = \mathbb{E}\left[\sum_{i=1}^{n} X_{i}\right]$$

$$= \sum_{i=1}^{n} \mathbb{E}[X_{i}]$$

$$= \sum_{i=1}^{n} \mathbb{P}[X_{i} = 1] = \sum_{i=1}^{n} \frac{1}{n} = 1$$



sums and averages of independent rv

- X_1, X_2, \ldots are independent random variables that are uniformly distributed over the interval [0, 1].
- $\mathbb{E}[X_1] = 1/2$, $Var(X_1) = 1/12$.
- ullet The probability density function of X_1 looks like

• What about the pdf of $X_1 + X_2$ and $(X_1 + X_2)/2$?

sums and averages of independent rv

$$S_n = X_1 + \ldots + X_n$$

$$\bar{X}_n = \frac{1}{n} \left[X_1 + \ldots + X_n \right]$$

• $\mathbb{E}[S_n] =$

$$\mathbb{E}[\bar{X}_n] =$$

$$Var(S_n) =$$

$$Var(\bar{X}_n) =$$

- (roughly) sum of n i.i.d. random variables is \sqrt{n} times as variable as any one of the random variables
- average of n i.i.d. random variables is $1/\sqrt{n}$ times as variable as any one of the random variables