

Lecture 2 - scribbles

Friday, September 6, 2019 13:34

key themes:

representation: how to represent structured prob. distributions?

→ parameterization
full table param.
vs.
"exponential family"

estimation: given data, how do learn/estimate
the parameters of dist.?

→ learning e.g. maximum likelihood
maximum entropy

inference: answer questions about data

e.g. compute $p(y|x)$ or $p(x)$
query observation
conditional marginal

→ computation e.g. message passing

- approximate inference
 - Sampling
 - variational methods

today: probability review

why? → principled framework to model uncertainty

Sources of uncertainty

1) intrinsic uncertainty → quantum mechanics

2) partial information/observation:

- card games
- rolling a dice
→ don't know the initial conditions

3) incomplete modeling of a complex phenomenon

(computational issues are also important)

Example: • "most birds can fly"
→ simple rule can be advantageous but then yields uncertainty

• "AI"

Notation:

X_1, X_2, X_3

↑
random variables

X, Y, Z

(usually real-valued)

x_1, x_2, x_3

$\underbrace{\quad}_{\text{their "realizations"}}$

x, y, z

X a random variable \rightarrow represents an uncertain quantity

$X=x$ represents the "event" that X takes the value x

$\Omega \rightarrow$ the sample space of "elementary events"

possible values for my. R.V.

e.g. X is result of a die throw

$$\Omega = \{1, 2, 3, 4, 5, 6\}$$

two types of R.V. $\xrightarrow{\text{discrete}}$ where Ω is countable

$\xrightarrow{\text{continuous}}$ (Ω is uncountable)

I) [assume Ω is countable \rightarrow discrete case]

(discrete) R.V. X is characterized by a probability mass function (pmf)

"lower case"

$$\rightarrow p(x) \text{ for } x \in \Omega$$

$$p(x) \stackrel{!}{=}$$

"closed case"

$$p(x) \text{ for } x \in \Omega$$

pmf p is s.t. $\begin{cases} p(x) > 0 \quad \forall x \in \Omega \\ \sum_{x \in \Omega} p(x) = 1 \end{cases}$

probability distribution P

is a mapping $P: \mathcal{E} \rightarrow [0, 1]$

that satisfy the
Kolmogorov
axioms

$$\begin{aligned} P(E) &\geq 0 \quad \forall E \in \mathcal{E} \\ P(\Omega) &= 1 \\ P\left(\bigcup_{i=1}^{\infty} E_i\right) &= \sum_{i=1}^{\infty} P(E_i) \quad \text{when } E_i \text{ are disjoint} \end{aligned}$$

notation: $P\{X=x\}$

$$P\{X=x \text{ or } X=y\} = p(x) + p(y) \quad \text{if } x \neq y$$

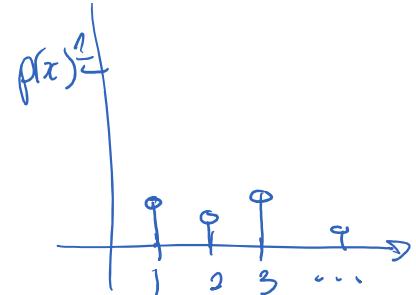
$E = \{x, y\}$

pmf

14n23

for discrete R.V., $P(E) = \sum_{x \in E} p(x)$

continuous R.V. is characterized by a probability density function (pdf)



$\mathcal{E} = 2^{\Omega} \stackrel{?}{=} \text{set of all subsets of } \Omega$
 set of "events"
 ("sigma-field" in measure theory
 needed when Ω is uncountable)

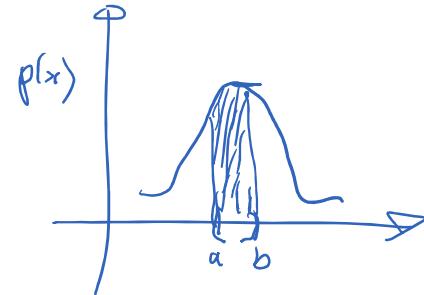
$$\begin{aligned} P\{X=x\} &= P\{\{x\}\} \\ &= p(x) \end{aligned}$$

Continuous R.V. is characterized by a probability density function p (pdf)

$$p: \Omega \rightarrow \mathbb{R}$$

$$p(x) \geq 0 \quad \forall x \in \Omega$$

$$p \text{ is integrable and } \int_{\Omega} p(x) dx = 1$$



prob. of events:

$$\Omega = \mathbb{R} : P([a, b]) = \int_a^b p(x) dx$$

$$p(x) = \lim_{n \rightarrow \infty} \frac{P(B_n)}{\text{volume}(B_n)}$$

where B_n are balls enclosing x and decreasing in radius



Recaps

discrete R.V. X ; pmf $p(x) \Leftrightarrow P\{X=x\} = p(x)$

cts. R.V. X ; pdf $p(x) \Leftrightarrow P\{X=x\} = 0$

$$\left| P\{X \in [x - \frac{\Delta x}{2}, x + \frac{\Delta x}{2}]\} \approx p(x) \Delta x \right|$$

$$P\{X \in [x - \frac{\Delta x}{2}, x + \frac{\Delta x}{2}]\} = \int_{x - \frac{\Delta x}{2}}^{x + \frac{\Delta x}{2}} p(x) dx$$

[Sidenote: can change pdf p on countable # of pts. according to Lebesgue has measure zero]

[Sidenote: can change pdf p on countable # of pts. according to Lebesgue measure without changing "anything"]

joint, marginal, etc. (multivariate R.V.)

$$Z = (X, Y) \quad \Omega_Z \triangleq \Omega_X \times \Omega_Y$$

(discrete) pmf of Z "joint pmf" on Ω_Z

$$p(x, y) = P\{X=x, Y=y\}$$

↑
joint distribution

can represent elementary events of $\Omega_{(X,Y)}$ as table

	X=0	X=1
Y=0	○	Y ₂
Y=1	Y ₂	○

$p(1,1)$

Say X is whether die result is even
 Y " " " " " is odd

cts. case: if $X \in Y$ are cts "and"
 $\int_{\text{box region}} p(x, y) dx dy$

Marginal distribution (in the context of a joint)

↳ dist. of a component of a random vector

$$P\{X=x\} = \sum_{y \in \Omega_Y} P\{\underbrace{X=x, Y=y}_{p(x,y)}\} \quad \text{"sum rule"} \\ \text{"marginalizing out } Y\text{"}$$

independence:

- X is independent of $Y \Leftrightarrow p(x,y) = p(x)p(y) \quad \forall (x,y) \in \Omega_X \times \Omega_Y$

notation: $X \perp\!\!\!\perp Y$

- R.V. X_1, \dots, X_n are "mutually independent" $\Leftrightarrow p(x_1, \dots, x_n) = \prod_{i=1}^n p(x_i) \quad \forall x_{1:n} \in \prod_{i=1}^n \Omega_{X_i}$

conditioning:

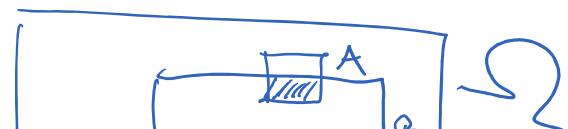
- for events $A \subseteq B$, suppose $P(B) \neq 0$

then define $P(A|B) \triangleq \frac{P(A \cap B)}{P(B)}$

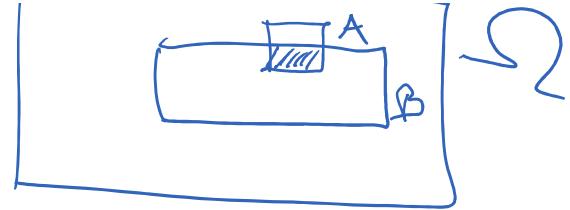
↑
normalize

illustration:

$$P(B) = \sum_{A \in \text{partition of } \Omega} P(A \cap B)$$



normalize



- for discrete R.V.
define "conditional pmf"

$$p(x|y) \triangleq P(X=x | Y=y) \triangleq \frac{P(\{X=x, Y=y\})}{P(\{Y=y\})} \quad \begin{array}{l} \text{\{joint pmf}} \\ \text{\{marginal pmf}} \end{array}$$
$$= \frac{p(x,y)}{p(y)}$$

$p(x|y)$ or $p(x,y)$

(normalization const.: $\sum_x p(x|y) = p(y)$)

- for cts. R.V.

"conditional pdf" $p(x|y) \triangleq \frac{p(x,y)}{p(y)}$ density

Subtle point: $p(x|y)$ is undefined when $p(y)=0$

independent: if $X \perp\!\!\!\perp Y$

$$p(x|y) = \frac{p(x,y)}{p(y)} \stackrel{\text{indep.}}{=} \frac{p(x)p(y)}{p(y)} = p(x)$$

Example of conditioning : " $P(\text{having cancer} \mid \text{tumor measurement} = a)$ "