Probability for Machine Learning

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1. Random Variable (= r.v.)

- · (Rough) Definition: Variable with a probability
- Probability that x = a

$$riangleq P_X(x=a) \;=\; P(x=a) \;\implies\; egin{cases} 1)\; P(x=a) \geq 0 \ 2)\; \sum_{ ext{all}} P(x) = 1 \end{cases}$$

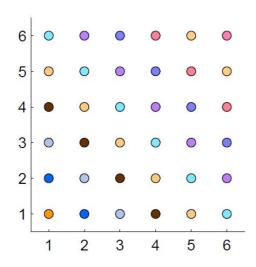
• $\begin{cases} \text{continuous r.v.} & \text{if } x \text{ is continuous} \\ \text{discrete r.v.} & \text{if } x \text{ is discrete} \end{cases}$

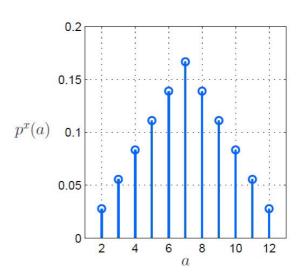
• x: die outcome

$$P(X=1) = P(X=2) = \cdots = P(X=6) = \frac{1}{6}$$

Question

$$y=x_1+x_2: \quad ext{sum of two dice} \ P_Y(y=5)=?$$





Expectation = mean

$$E[x] = \left\{ egin{array}{ll} \sum\limits_{x} x P(x) & ext{discrete} \ \int_{x} x P(x) dx & ext{continuous} \end{array}
ight.$$

Example

Sample mean $E[x] = \sum_{x} x \cdot \frac{1}{m}$ (: uniform distribution assumed)

Variance $var[x] = E\left[(x - E[x])^2\right]$: mean square deviation from mean

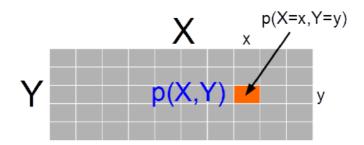
2. Random Vectors (multivariate R.V.)

$$x = egin{bmatrix} x_1 \ x_2 \ dots \ x_n \end{bmatrix}, \;\; n \; ext{random variables}$$

2.1. Joint density probability

• Joint density probability models probability of co-occurrence of many r.v.

$$P_{X_1,\cdots,X_n}(X_1=x_1,\cdots,X_n=x_n)$$

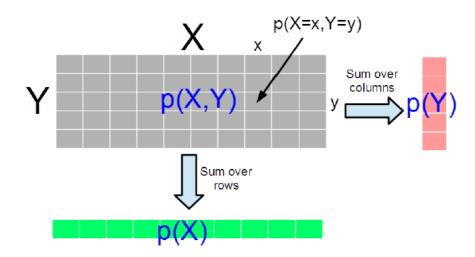


2.2. Marginal density probability

$$egin{aligned} P_{X_1}(X_1=x_1)\ dots\ P_{X_n}(X_n=x_n) \end{aligned}$$

· For two r.v.

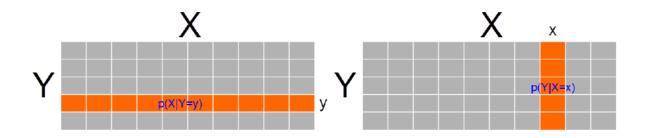
$$P(X) = \sum_{y} P(X, Y = y)$$
 $P(Y) = \sum_{x} P(X = x, Y)$



2.3. Conditional probability

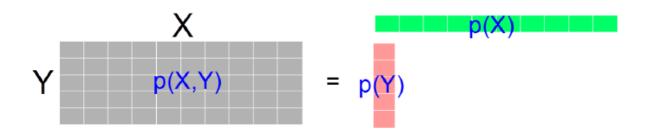
• Probability of one event when we know the outcome of the other

$$P_{X_1|X_2}(X_1=x_1\mid X_2=x_2)=rac{P(X_1=x_1,X_2=x_2)}{P(X_2=x_2)}:$$
 Conditional prob. of x_1 given x_2



- · Independent random variables
 - when one tells nothing about the other

$$egin{aligned} P(X_1 = x_1 \mid X_2 = x_2) &= P(X_1 = x_1) \ &\updownarrow \ P(X_2 = x_2 \mid X_1 = x_1) &= P(X_2 = x_2) \ &\updownarrow \ P(X_1 = x_1, X_2 = x_2) &= P(X_1 = x_1) P(X_2 = x_2) \end{aligned}$$

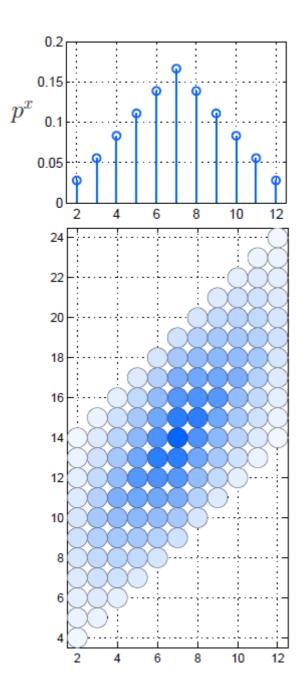


• four dice $\,\omega_1\,,\;\omega_2\,,\;\omega_3\,,\;\omega_4\,$

$$x=\omega_1+\omega_2$$
 : sum of the first two dice $y=\omega_1+\omega_2+\omega_3+\omega_4$: sum of all four dice probability of $\begin{bmatrix} x \\ y \end{bmatrix}=?$

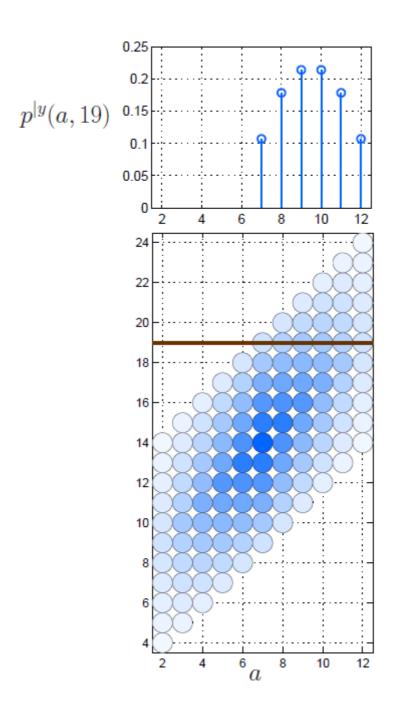
• marginal probability

$$P_X(x) = \sum_y P_{XY}(x,y)$$

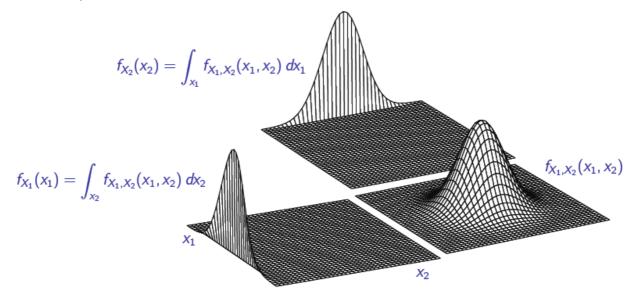


- conditional probability
 - ullet suppose we measured $\,y=19\,$

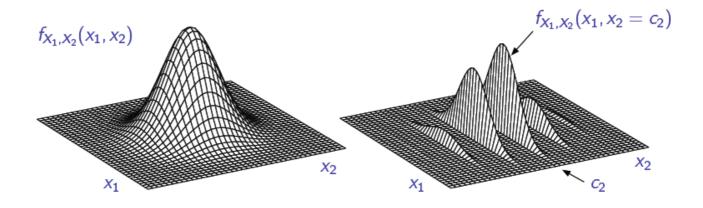
$$P_{X\mid Y}(x\mid y=19)=?$$



Pictorial Explanation



Marginal densities: integrate a continuous joint density (or sum a discrete mass function) over the other variable (by the Law of total probability).



► Conditional density: a "slice" of the joint density, renormalized to integrate to one.

$$f_{X_1|X_2}(x_1|x_2=c_2)=\frac{f_{X_1,X_2}(x_1,x_2=c_2)}{\int_{X_1}f_{X_1,X_2}(x_1,x_2=c_2)\,dx_1}.$$

- Suppose we have three bins, labeled A, B, and C.
- Two of the bins have only white balls, and one bin has only black balls.
- 1) We take one ball, what is the probability that it is white? (white = 1)

$$P(X_1=1)=\frac{2}{3}$$

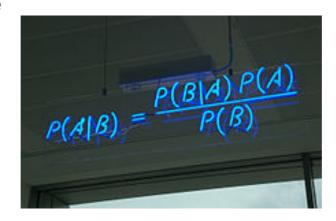
2) When a white ball has been drawn from bin C, what is the probability of drawing a white ball from bin B?

$$P(X_2 = 1 \mid X_1 = 1) = \frac{1}{2}$$

3) When two balls have been drawn from two different bins, what is the probability of drawing two white balls?

$$P(X_1=1,X_2=1)=P(X_2=1\mid X_1=1)P(X_1=1)=rac{1}{2}\cdotrac{2}{3}=rac{1}{3}$$

3. Bayes Rule



ullet enables us to swap A and B in conditional probability

$$P(X_2, X_1) = P(X_2 \mid X_1)P(X_1) = P(X_1 \mid X_2)P(X_2)$$

$$\therefore P(X_2 \mid X_1) = \frac{P(X_1 \mid X_2)P(X_2)}{P(X_1)}$$

- Suppose that in a group of people, 40% are male and 60% are female.
- 50% of the males are smokers, 30% of the females are smokers.
- · Find the probability that a smoker is male

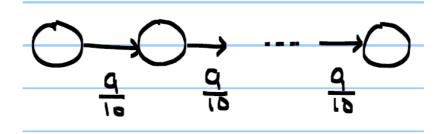
$$P(x = M) = 0.4$$
 $x = M \text{ or F}$ $P(x = F) = 0.6$
 $y = S \text{ or N}$ $P(y = S \mid x = M) = 0.5$
 $P(y = S \mid x = F) = 0.3$
 $P(x = M \mid y = S) = ?$

· Baye's Rule + conditional probability

$$P(x = M \mid y = S) = \frac{P(y = S \mid x = M)P(x = M)}{P(y = S)} = \frac{0.20}{0.38} \approx 0.53$$
 $P(y = S) = P(y = S \mid x = M)P(x = M) + P(y = S \mid x = F)P(x = F)$
 $= 0.5 \times 0.4 + 0.3 \times 0.6 = 0.38$

Example

History



$$\left(rac{9}{10}
ight)^{20}pprox 0.1216$$

4. Linear Transformation of Random Variables

4.1. For single random variable

$$X\mapsto Y=aX$$
 $E[aX]=aE[X] \ {
m var}(aX)=a^2{
m var}(X)$

$$ext{var}(X) = E[(X - E[X])^2] = E[(X - \bar{X})^2] = E[X^2 - 2X\bar{X} + \bar{X}^2]$$

 $= E[X^2] - 2E[X\bar{X}] + \bar{X}^2 = E[X^2] - 2E[X]\bar{X} + \bar{X}^2$
 $= E[X^2] - E[X]^2$

4.2. Sum of two random variables \boldsymbol{X} and \boldsymbol{Y}

$$Z = X + Y$$
 (still univariate)

$$egin{aligned} E[X+Y] &= E[X] + E[Y] \ \mathrm{var}(X+Y) &= E[(X+Y-E[X+Y])^2] = E[((X-ar{X})+(Y-ar{Y}))^2] \ &= E[(X-ar{X})^2] + E[(Y-ar{Y})^2] + 2E[(X-ar{X}(Y-ar{Y})] \ &= \mathrm{var}(X) + \mathrm{var}(Y) + 2\mathrm{cov}(X,Y) \end{aligned}$$

$$cov(X,Y) = E[(X - \bar{X})(Y - \bar{Y})] = E[XY - X\bar{Y} - \bar{X}Y + \bar{X}\bar{Y}]$$

$$= E[XY] - E[X]\bar{Y} - \bar{X}E[Y] - \bar{X}\bar{Y} = E[XY] - E[X]E[Y]$$

· Note: quality control in manufacturing process

$$var(X + Y) = var(X) + var(Y) + 2cov(X, Y)$$

Remark

- · variance for univariable
- · covariance for bivariable
- · Covariance two r.v.

$$\mathrm{cov}(x,y) = E[(x-\mu_x)(y-\mu_y)]$$

Covariance matrix for random vectors

$$egin{aligned} \operatorname{cov}(X) &= E[(X-\mu)(X-\mu)^T] = egin{bmatrix} \operatorname{cov}(X_1,X_1) & \operatorname{cov}(X_1,X_2) \ \operatorname{cov}(X_2,X_1) & \operatorname{cov}(X_2,X_2) \end{bmatrix} \ &= egin{bmatrix} \operatorname{var}(X_1) & \operatorname{cov}(X_1,X_2) \ \operatorname{cov}(X_2,X_1) & \operatorname{var}(X_2) \end{bmatrix} \end{aligned}$$

· Moments: provide rough clues on probability distribution

$$\int x^k P_x(x) dx$$
 or $\sum x^k P_x(x) dx$

4.3. Affine transformation of random vectors

$$y = Ax + b$$

1.
$$E[y] = AE[x] + b$$

$$2. \ \operatorname{cov}(y) = A\operatorname{cov}(x) A^T$$

- IID random variables $\begin{cases} identically \ distributed \\ independent \end{cases}$
- Suppose x_1, x_2, \cdots, x_m are IID with mean μ and variance σ^2

$$\operatorname{Let} x = egin{bmatrix} x_1 \ dots \ x_m \end{bmatrix}, & \operatorname{then} E[x] = egin{bmatrix} \mu \ dots \ \mu \end{bmatrix}, & \operatorname{cov}(x) = egin{bmatrix} \sigma^2 & & & \ & \sigma^2 & & \ & & \ddots & \ & & & \sigma^2 \end{bmatrix}$$

Sum of IID random variables (→ single r.v.)

$$S_m = rac{1}{m} \sum_{i=1}^m x_i \;\; \Longrightarrow \; S_m = Ax \;\; ext{where} \; A = rac{1}{m} [\, 1 \;\; \cdots \;\; 1\,]$$

$$egin{aligned} E[S_m] &= AE[x] = rac{1}{m} [\ 1 \ \cdots \ 1] egin{bmatrix} \mu \ dots \ \mu \end{bmatrix} = rac{1}{m} m \mu = \mu \ & ext{var}(S_m) = A \operatorname{cov}(x) \, A^T = A egin{bmatrix} \sigma^2 \ & \ddots \ & \sigma^2 \end{bmatrix} A^T = rac{\sigma^2}{m} \end{aligned}$$

ullet Reduce the variance by a factor of $m \implies {\sf Law}$ of large numbers or Central limit theorem

$$ar{x} \longrightarrow N\left(\mu, \left(\frac{\sigma}{\sqrt{m}}\right)^2\right)$$

In [1]:

%%javascript

\$.getScript('https://kmahelona.github.io/ipython_notebook_goodies/ipython_notebook_toc.
js')