

## 1. Inclusion–exclusion principle for 4 events:

$$\begin{aligned}
 P(A_1 \cup A_2 \cup A_3 \cup A_4) = & P(A_1) + P(A_2) + P(A_3) + P(A_4) \\
 & - P(A_1 \cap A_2) - P(A_1 \cap A_3) - P(A_1 \cap A_4) - P(A_2 \cap A_3) - P(A_2 \cap A_4) - P(A_3 \cap A_4) \\
 & + P(A_1 \cap A_2 \cap A_3) + P(A_1 \cap A_2 \cap A_4) + P(A_1 \cap A_3 \cap A_4) + P(A_2 \cap A_3 \cap A_4) \\
 & - P(A_1 \cap A_2 \cap A_3 \cap A_4).
 \end{aligned}$$

## 2. Conditional probability:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \Leftrightarrow P(A \cap B) = P(A|B) \times P(B).$$

## 3. Law of total probability:

For event  $A$  and the mutually exclusive & collectively exhaustive set of events  $\{B_1, B_2, \dots, B_k\}$  for the same sample space,

$$\begin{aligned}
 P\left(\underbrace{A}_{\text{e.g., has Cancer}}\right) &= P\left(\underbrace{A \cap B_1}_{\text{has Cancer AND from State-1}}\right) + P\left(\underbrace{A \cap B_2}_{\text{has Cancer AND from State-2}}\right) + \dots + P\left(\underbrace{A \cap B_k}_{\text{has Cancer AND from State-k}}\right) \\
 &= P(A|B_1) \times P(B_1) + P(A|B_2) \times P(B_2) + \dots + P(A|B_k) \times P(B_k).
 \end{aligned}$$

Additional conditioning form:

$$\begin{aligned}
 P\left(\underbrace{A}_{\text{e.g., has Cancer}} \mid \text{male}\right) &= P\left(\underbrace{A \cap B_1}_{\text{has Cancer AND from State-1}} \mid \text{male}\right) + P\left(\underbrace{A \cap B_2}_{\text{has Cancer AND from State-2}} \mid \text{male}\right) + \dots + P\left(\underbrace{A \cap B_k}_{\text{has Cancer AND from State-k}} \mid \text{male}\right) \\
 &= P(A|B_1, \text{male}) \times P(B_1 | \text{male}) + P(A|B_2, \text{male}) \times P(B_2 | \text{male}) + \dots + P(A|B_k, \text{male}) \times P(B_k | \text{male}).
 \end{aligned}$$

## 4. Bayes' theorem:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B \cap A)}{P(B)} = \frac{P(B|A) \times P(A)}{P(B)} = \frac{P(B|A) \times P(A)}{P(B|A) \times P(A) + P(B|A^c) \times P(A^c)}$$

Additional conditioning form:

$$P(A|B, C) = \frac{P(B|A, C) \times P(A|C)}{P(B|C)} = \frac{P(B|A, C) \times P(A|C)}{P(B|A, C) \times P(A|C) + P(B|A^c, C) \times P(A^c|C)}.$$

## 5. Discrete random variables:

Random Variable $X$	Parameters	Values Taken $j$ or $x$	PMF $P_X(j)$ $= P(X = j)$	Expected Value $E[X]$ $= \sum_j j P_X(j)$	Variance $Var[X]$ $= \sum_j (j - E[X])^2 P_X(j)$
Bernoulli	$p$	$j = 0, 1$	$p^j(1-p)^{1-j}$	$p$	$p(1-p)$
Multinoulli	$p_1, p_2, \dots, p_k$	$x = \underbrace{\begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}}_{\text{assuming } k=4}$	$\prod_{i=1}^k p_i^{I(x_i=1)}$	$\underbrace{\begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix}}_{\text{assuming } k=4}$	$\underbrace{\begin{bmatrix} p_1(1-p_1) \\ p_2(1-p_2) \\ p_3(1-p_3) \\ p_4(1-p_4) \end{bmatrix}}_{\text{assuming } k=4}$
Binomial	$n, p$	$j = 0, 1, \dots, n$	$\binom{n}{j} p^j (1-p)^{n-j}$	$np$	$np(1-p)$
Multinomial	$n, p_1, p_2, \dots, p_k$	$x = \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}}_{\text{assuming } k=4}, \text{ where } \sum_{i=1}^4 x_i = n$	$\underbrace{\binom{n}{x_1, x_2, x_3, x_4} \prod_{i=1}^4 p_i^{x_i}}_{\text{assuming } k=4}$	$\underbrace{\begin{bmatrix} np_1 \\ np_2 \\ np_3 \\ np_4 \end{bmatrix}}_{\text{assuming } k=4}$	$\underbrace{\begin{bmatrix} np_1(1-p_1) \\ np_2(1-p_2) \\ np_3(1-p_3) \\ np_4(1-p_4) \end{bmatrix}}_{\text{assuming } k=4}$
Negative Binomial	$r, p$	$j = r, r+1, \dots$	$\binom{j-1}{r-1} p^r (1-p)^{j-r}$	$\frac{r}{p}$	$\frac{r(1-p)}{p^2}$
Geometric	$p$	$j = 1, 2, \dots$	$(1-p)^{j-1} p$	$\frac{1}{p}$	$\frac{1-p}{p^2}$
Poisson	$\lambda$	$j = 0, 1, \dots$	$\frac{e^{-\lambda} \lambda^j}{j!}$	$\lambda$	$\lambda$
Hypergeometric	$n_{success}, n_{failure}, n$	$j = 0, 1, \dots, n$	$\frac{\binom{n_{success}}{j} \binom{n_{failure}}{n-j}}{\binom{n_{success}+n_{failure}}{n}}$	where $p = \frac{n_{success}}{n_{success}+n_{failure}}$	where $N = n_{success} + n_{failure}$ $\frac{np(1-p)(N-n)}{N-1}$

## 6. Continuous random variables:

Random Variable	Parameters	PDF	Expected Value	Variance
Normal	$\mu, \sigma$	$f_X(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	$\mu$	$\sigma^2$
Exponential	$\lambda$	$f_T(t) = \begin{cases} \lambda e^{-\lambda t} & \text{if } t \geq 0, \\ 0 & \text{if } t < 0. \end{cases}$	$\frac{1}{\lambda}$	$\frac{1}{\lambda^2}$
Uniform	$a, b$	$f_X(x) = \begin{cases} \frac{1}{b-a}, & \text{if } a \leq x \leq b, \\ 0 & \text{otherwise.} \end{cases}$	$\frac{a+b}{2}$	$\frac{(b-a)^2}{12}$