## 1 Outcomes, events, and Probability

Definition 1.1. (Random) Experiment is a mechanism that results in random outcomes

**Definition 1.2. Sample Space**  $(\Omega)$  is the set of all possible outcomes from and experiment

**Definition 1.3. Event** is a subset of  $\Omega$ 

**Definition 1.4.** Mutually Exclusive (Disjoint):  $A \cup B = \{\} = \emptyset$ 

**Definition 1.5. Commutative:**  $A \cup B = B \cup A \mid \mathbf{Associative:} \ (A \cup B) \cup C = A \cup (B \cup C) \mid$ 

**Distributive**  $A \cup (B \cap C) = (A \cup B) \cap (A \cup C), A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$ 

**Definition 1.6.** A implies B  $A \cap B = A$ ,  $A \subset B$ 

**Definition 1.7. Probability Function** P on finite  $\Omega$  assigns each event A a P(A) s.t. (Axioms)

i)  $P(A) \ge 0$  ii)  $P(\Omega) = 1$  iii)  $P(A \cup B) = P(A) + P(B)$  if disjoint.

**Definition 1.8. Useful Probabilities**: Union:  $P(A \cup B) = P(A \cap B^c) + P(A \cap B) + P(A^c \cap B)$ ,  $P(A \cup B) = P(A) + P(B) - P(A \cap B)$ Complement  $P(\Omega) = P(A) + P(A^c)$ ,  $P(A^c) = 1 - P(A)$ 

**Definition 1.9. Calculating by counting** applies only when i) all outcomes are equally likely ii)  $\Omega$  is finite then  $P(A) = \frac{\text{number of outcomes belonging to } A}{\text{total number of outcomes in } \Omega}$ 

**Definition 1.10. Product of Sample Space** in general is  $\Omega = \Omega_1 \times \Omega_2 = \{(\omega_1, \omega_2) : \omega_1 \in \Omega_1, \omega_2 \in \Omega_2\}$ 

**Definition 1.11. Permutation** of a set N of size n is  ${}_{N}P_{n} = \frac{N!}{(N-n)!}$ .

**Definition 1.12. Combination** of a set N of size n is  $\binom{N}{n} = \frac{N!}{(N-n)! \cdot N!}$ 

**Definition 1.13. De Morgan's Law** for A, B, we have  $(A \cup B)^c = A^c \cap B^c$  and  $(A \cap B)^c = A^c \cup B^c$ 

# 2 Conditional Probability

**Definition 2.1. Conditional Probability** of A given C is, in general,  $P(A|C) = \frac{P(A \cap C)}{C}$  for any P(C) > 0

**Definition 2.2. Law of Total Probability** states, for disjoint  $C_1, \ldots, C_m, C_1 \cup \cdots \cup C_m = \Omega, P(A) = \sum_{i=1}^m [P(A|C_i)P(C_i)]$ 

**Definition 2.3. Bayes' Rule** states, for disjoint  $C_1, \ldots, C_m, C_1 \cup \cdots \cup C_m = \Omega, P(C_i|A) = \frac{P(A|C_i) \cdot P(C_i)}{\sum_{i=1}^m |P(A|C_i)P(C_i)|}$ 

**Definition 2.4. Independence** between A and B implies P(A|B) = P(A)

**Definition 2.5. Relation between Independent Probabilities**: i) A independent of  $B \iff A^c$  independent of B and ii) A independent of  $B \iff B$  independent of A

**Definition 2.6.** Independence of Two or More Events:  $P(A_1 \cap A_2 \cap \cdots \cap A_n) = \prod_{i=1}^n A_i$ 

## 3 Random Variables

**Definition 3.1.** The **probability mass function** of drv **X** is  $p : \mathbb{R} \to [0,1]$  defined by p(k) = P(x = k) for  $-\infty < k < \infty$ .

**Definition 3.2. Discrete Random Variable** *X* takes a countable number of values.

**Definition 3.3. Continuous Random Variable** X has  $P(A \le X \le B) = \int_a^b f(x)dx$  with i)  $\forall x, f(x) \ge 0$  ii)  $\int_{-\infty}^{\infty} f(x)dx = 1$ . f is the **probability density function** of X and f(x) is the **probability density** of X at x. Note: a random variable is *continuous* if its cdf is continuous everywhere

**Definition 3.4.** The cumulative distribution function F of a drv or crv  $\mathbf{X}$  is the function  $F: \mathbb{R} \to [0,1]$  defined by  $F(a) = P(X \le a)$  for  $-\infty < a < \infty$ 

### 4 Common Distributions

#### 4.1 Discrete

**Definition 4.1. Bernoulli**  $X \sim \mathbf{Ber}(\theta)$ : Parameter  $\theta$ ,  $0 \le \theta \le 1$  and **pmf** given by  $p_X(X) = \begin{cases} \theta & x = 1 \\ 1 - \theta & x = 0 \end{cases}$ 

Useful for modelling experiments with exactly two possible outcomes

**Definition 4.2. Binomial** Bin $(n, \theta)$ : Parameters n and  $\theta$  with  $n \in \mathbb{N}$  and  $0 \le \theta \le 1$  and **pmf** given by  $p_X(x) = \binom{n}{x} \theta^x (1 - \theta)^{n-x}$  This distribution describes a sum of n independent and identical Bernoulli trials

**Definition 4.3. Geometric** Geo( $\theta$ ): Parameters  $\theta$  with  $0 \le \theta \le 1$  and **pmf** given by  $p_X(x) = (1 - \theta)^{x-1}\theta$  for  $x \in \mathbb{N}$ .

The number of identical Bernoulli trials until the first success

**Definition 4.4. Poisson** Pois( $\lambda$ ): Parameters  $\lambda$  with  $\lambda > 0$  and **pmf** given by  $p_X(x) = \frac{e^{-\lambda} \lambda^x}{x!}$  for  $x \in \mathbb{Z}^+$ 

Captures the count of events in a fixed interval of Poisson Process. Assumptions: i) the expected rate  $\lambda$  is constant ii) all events are independent of each other iii) events cannot occur simultaneously

### 4.2 Continuous

**Definition 4.5. Uniform** 
$$U(\alpha, \beta)$$
: on interval  $[\alpha, \beta]$  and **pdf** given by  $f(x) = \begin{cases} \frac{1}{\beta - \alpha} & \alpha \leq x \leq \beta \\ 0 & \text{otherwise} \end{cases}$ 

Uniform distribution assigns equal probabilities across a fixed interval, useful for modelling  $completely\ arbitrary$  experiments/ $complete\ ignorance$  about probabilities

**Definition 4.6. Exponential Exp**(
$$\lambda$$
): Parameter  $\lambda$  with  $\lambda > 0$  and **pdf**  $f(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & otherise \end{cases}$ 

Useful for modelling time until next event in a Poisson process.  $\lambda$  is the expected rate of events. Note:  $F_Y$  is continuous everywhere,  $f_Y$  is discontinuous at 0.

**CDF** given by  $1 - e^{-\lambda x}$ 

**Definition 4.7. Gamma**  $G \sim \text{Gamma}(\alpha, \beta)$ : Parameters  $\alpha, \beta$  with  $\beta, \alpha > 0$  with **pdf** given by  $f(x) = \frac{1}{\Gamma(a)} \beta^{\alpha} x^{\alpha - 1} e^{-\beta x}$  for x > 0

**Definition 4.8. Normal**  $N(\mu, \sigma^2)$ : Parameters  $\mu, \sigma^2$  with  $\sigma^0 > 0$  with  $\mathbf{pdf}$   $f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{1}{2}(\frac{x-\mu^2}{\sigma})\right\}$  **Standard Normal Distribution** is when  $\mu = 0$  and  $\sigma^2 = 1$  with  $\mathbf{pdf}$   $\phi(z) = \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2}$  and  $\mathbf{cdf}$   $\Phi(a) = \int_{-\infty}^a \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}z^2}dz$ Often used to model observational errors. Note: Normal distributions have symmetry along its centre,  $\mu$  and  $\sigma$  controls the spread of distribution. Note:  $\Phi(-a) = 1 - \Phi(a)$ 

Note: transform  $X \sim N(\mu, \sigma^2)$  to  $Z = \frac{X - \mu}{\sigma}$  to use with LUT.  $1 - \Phi(a) = P(Z \ge a)$  for N(0, 1)

## 5 Quantile, Percent, and Median

**Definition 5.1. Quantile Function** of random variable X with cdf F is  $F^{-1} = \min\{x : F(x) \ge T\}$  for  $0 \le T \le 1$ 

### 6 Useful Stuff

$$\binom{n}{k} = \frac{n!}{k!(n-k)!} \tag{1}$$

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \tag{2}$$