

# Summary of Lecture 1

- An **experiment** can have a number of possible **outcomes**, but which outcome will occur is not known in advance
- **Events** are combinations of outcomes which behave as **sets**, and can be combined or modified using the operations **not** ( $^c$ ), **or** ( $\cup$ ) and **and** ( $\cap$ ).
- Different outcomes may be more (or less) **likely** than others to be the result of the experiment.
- We quantify how likely each outcome is by defining a **probability** for each outcome (and by implication, each event)
- Probability must obey the **Axioms of Probability** (and their consequences), ie probability is defined to be a real number in  $[0, 1]$  with larger values indicating more likely events.
- There are simple formulæ for the probabilities of the compound events  $A^c$  and  $A \cup B$

# Summary of Lecture 2

- When learning that event  $B$  has occurred changes the probability that event  $A$  will occur, then we call this *updated* probability the **conditional probability** of  $A$  given  $B$  —  $P[A|B]$
- If learning that event  $B$  has occurred does *not* change the probability that event  $A$  will occur, then we say  $A$  and  $B$  are **independent**
- In some problems, it is natural to divide the sample space into a collection of disjoint events - a **partition** - which can be used to simplify more complex probabilities via the **Partition Theorem**
- We can express the conditional probability  $P[A|B]$  in terms of  $P[B|A]$  via **Bayes Theorem**
- When the results of our experiment give numerical outcomes, we call the uncertain outcome a **random variable**

# Summary of Lecture 3

- A **discrete random variable**  $X$  can only take a finite number of possible values, and we describe its probabilistic behaviour by a table of probabilities – its **probability distribution**
- A **continuous random variable**  $Y$  takes possible values from the real line, and we describe its probabilistic behaviour by a **probability density function**  $f(x)$  over the possible values
- We must **integrate** the pdf to get probabilities, or we use the **cumulative distribution function**  $F(x) = \int_{-\infty}^x f(x) dx$
- When we have more than one random variable, we describe the behaviour of the pair via a **joint distribution** (picture!)
- We can summarise distributions, one such summary is the **expectation** (or mean, or average)
- Expectation has a number of handy properties

# Summary of Lecture 4

- Expectation summarises the **location** of a distribution, it is the “centre of probability”
- Variance summarises the **spread** of a distribution, and is a measure of how far on average we would expect values to be from the expectation
- We calculate expectations differently depending on whether the random variable is discrete or continuous
- There are two ways to express variance as an expectation
- Expectations and variances of linear combinations of random variables can be simplified

# Summary of Lecture 5

- A common example of a discrete random variable occurs when we are interested in the **counts** of things
- Under certain circumstances, such variables may follow the Binomial or the Poisson distributions
- We have a Binomial situation when the problem can be thought of as equivalent to counting the number of successes in  $n$  independent trials, each with constant probability  $p$  of success
- The Poisson applies when we count the number of random events which occur in a time period  $s$  where the random events occur with a rate of  $\lambda$  per unit time and their times of occurrence are independent of each other.
- We can use the Poisson distribution to approximate Binomial probabilities when  $n$  is large and  $p$  is small

# Summary of Lecture 6

- The Normal distribution is a useful continuous distribution which is parametrised by its mean  $\mu$  and its variance  $\sigma^2$
- The standard normal random variable  $Z \sim N(0, 1)$  is one example, and has a cumulative distribution function  $\Phi(z)$
- The cumulative probabilities for the  $Z$  (ie the values of  $\Phi(z)$ ) are given in standard normal tables for certain values of  $z$
- Any  $X \sim N(\mu, \sigma^2)$  can be transformed into an equivalent  $Z \sim N(0, 1)$  allowing us to use standard Normal probabilities to answer questions about  $X$
- We can exploit properties of the Normal distribution (such as symmetry) to determine probabilities which are not tabulated
- A Binomial rv  $X \sim \text{Bin}(n, p)$  with  $n$  large and  $p \simeq 0.5$  can be well approximated by  $X' \sim N(np, np(1 - p))$ .