# ENGSCI 213: MATHEMATICAL MODELLING 2SE

Oliver Maclaren oliver.maclaren@auckland.ac.nz

## MODULE OVERVIEW

Introduction to Probability (Oliver Maclaren) [9 lectures]

#### 1. Basic concepts [3 lectures]

Basic concepts of probability. Sets and subsets, sample spaces and events. Probability and counting, conditional probability, independence, Bayes' theorem. Random variables. Simple data structures for probability calculations.

#### 2. Discrete probability models [3 lectures]

Discrete random variables and discrete probability distributions. Probability mass functions and cumulative distribution functions. Binomial and Poisson distributions.

#### 3. Continuous probability models [3 lectures]

Continuous random variables and continuous probability distributions. Probability density functions and cumulative distribution functions. Exponential and Normal distributions.

#### **RECAP: KOLMOGOROV**

Formal probability theory consists of three ingredients

- 1. A sample space S for the set of all possible outcomes of an uncertain experiment
- 2. A collection  $\Sigma$  of events E each event is a subset of the sample space S, i.e.  $E \subseteq S$ , and an element of the collection of events  $\Sigma$ , i.e.  $E \in \Sigma$
- 3. A probability function P (or 'measure') this assigns a probability P(E) to each event E (subset of the sample space)

# RECAP: EVENTS AS DEFINED BY PARTIAL INFORMATION

outcome ↔ the 'individual' defined by the most-detailed description

event ↔ the set (of individuals) determined by a partial description

sample space ↔ the set (of individuals)

determined by the least-detailed

description

## NOTE: PROBABILITY AS AN INTERMEDIATE-LEVEL DESCRIPTION

What should I include in the sample space? Err on the side of noting down as much as you think is relevant at first.

We can always drop some - and/or include more - 'background' information!

i.e. we work at an *intermediate* level of description. Everything we don't note down is effectively set to an arbitrary value and *assumed irrelevant* (for now).

#### **LECTURE 2**

The third model ingredient: probability functions
Conditional probability
Applications and interpretations

# FORMAL MODEL INGREDIENT THREE: PROBABILITY FUNCTIONS

Our model is

$$(S, \Sigma, P)$$

- *S* is our underlying set of outcomes
- $\Sigma$  is our set of events
- *P* is our 'probability function'

We want to talk about this last object today.

#### **BASIC REQUIREMENTS**

'Within' a probability *model* we have a probability *function* which assigns probability *numbers* (to events):

- Any probability is a number between 0 and 1.
- All possible outcomes together must have probability 1.
- If two events have no outcomes in common, the probability that one or the other occurs is the sum of their individual probabilities.

#### PROBABILITY AXIOMS (KOLMOGOROV)

This leads to

The probability P(A) of any event A satisfies  $0 \le P(A) \le 1$ 

If S is the sample space in a probability model, then P(S) = 1

If A and B are mutually exclusive then  $P(A \cup B) = P(A) + P(B)$ 

### **CONDITIONAL PROBABILITY (KOLMOGOROV)**

Conditional probability is then defined by

$$P(A|B) = \frac{P(A \cap B)}{P(B)}, P(B) > 0$$

But isn't all probability 'conditional on something'??

# CONDITIONAL PROBABILITY AS THE BASIC CONCEPT

Jaynes (for example) starts from conditional probability and emphasises that the sum and product rules (for any events A, B, C) are fundamental

$$P(A|C) + P(\overline{A}|C) = 1$$

$$P(A \cap B|C) = P(A|B \cap C)P(B|C)$$
$$= P(B|A \cap C)P(A|C)$$

Some useful consequences of the sum and product rules include the *extended sum rule*:

If A and B are mutually exclusive events then  $P(A \cup B|C) = P(A|C) + P(B|C)$ 

(or

$$P(A \cup B|C) = P(A|C) + P(B|C) - P(A \cap B|C)$$

for arbitrary events) as well as...

...the *partition theorem*:

If 
$$B_1, \ldots, B_k$$
 form a partition of  $C$  then 
$$P(A|C) = \sum_{i=1}^k P(A \cap B_i|C) \text{ i.e.}$$

$$P(A|C) = \sum_{i=1}^k P(A|B_i \cap C)P(B_i|C)$$

$$i=1$$

Bayes' theorem is a simple consequence of conditional probability but is conceptually important as it allows us to 'invert' a given conditioning

$$P(B|A \cap C) = \frac{P(A|B \cap C)P(B|C)}{P(A|C)}$$

or, if  $B_1, \ldots, B_k$  form a *partition* of C then

$$P(B_j|A \cap C) = \frac{P(A|B_j \cap C)P(B_j|C)}{\sum_{i=1}^k P(A|B_i \cap C)P(B_i|C)}$$

$$P(\varnothing) = 0$$
$$P(\overline{A}) = 1 - P(A)$$

#### STATISTICAL INDEPENDENCE

We can define statistical independence of A relative to B (given C) using either

$$P(A|B \cap C) = P(A|C)$$

or (equivalently)

$$P(A \cap B|C) = P(A|C)P(B|C)$$

#### **DAILY REMINDER**

We always operate 'within' a probability model with boundaries given by the 'background assumptions' or 'context'.

#### RELATION TO KOLMOGOROV APPROACH

- We can think of our 'unconditional' Kolmogorov axioms for a probability *function* as *implicitly conditioned* on C=S
- Or we can note that Kolmogorov defines a probability *model* as consisting of three parts  $(S, \Sigma, P)$ . Changing one part e.g. S or  $\Sigma$  changes our model!
- In particular, Kolmogorov's definition of *conditional* probability P(A|B) is a way of *changing context* from the original sample space S to the new sample space B and then assuming everything works as usual *within the new context*.

Example: discrete probability distribution on a discrete sample space

Example: equally likely outcomes and counting

Example: tables of survery counts, conditional probability and 'conditional counting' with probability trees.

**TABLE** 

Results from survey asking respondents which they value more in a car: ease of parking or style/prestige

	Younger than 40	Older than 40	Total
Prestige more important than parking	79	51	130
Prestige less important than parking	71	99	170
Total	150	150	300

Example: Bayes' theorem and solving 'inverse problems'

## HOMEWORK/CHALLENGES

Finish the example problems
The Monty Hall problem!