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## Chapter 1

### Introduction

#### 1.1 Motivation

Suppose we are modelling COVID. Let

- S be he number of the susceptible;
- I be the number of the infected;
- R be the number of the removed (those who have either recovered or died).

#### 1.1.1 A Deterministic Model

A deterministic model might be

$$\begin{split} \dot{S} &= - \, \beta I S, \\ \dot{I} &= \! \beta I S - \gamma I, \\ \dot{R} &= \! \gamma I. \end{split}$$

But there are some problems in this model:

- S, I and R are integers, so it does not make sense to talk about  $\dot{S}$ ,  $\dot{I}$  and  $\dot{R}$ .
- There is variability in when contacts are made and lead to infection.

#### 1.1.2 A Stochastic Model

A better model might be stochastic

$$\mathbb{P}(S \to S - 1 \& I \to I - 1 \text{ in } \Delta t) = \beta I S \Delta t + o(\Delta t)$$

$$\mathbb{P}(I \to I - 1 \& R \to R + 1 \text{ in } \Delta t) = \gamma I \Delta t + o(\Delta t).$$

The problem of this model is that contacts are usually not made uniformally in the whole population.

#### 1.1.3 A Network Model

We can use a network model, in which nodes represent individuals and edge weights represent contact rates, to avoid uniform contacts. But tis is unrealistic: the network is too big to represent 60 million people in the UK.

### 1.1.4 A Random Network Model

Based on the network model, we can make probability distributions on networks and derive probabilistic conclusions over the combination of stochastic dynamics and randomness of networks.

## Chapter 2

## Probability and Random Variables

### 2.1 Probability Theory

Suppose we are doing an experiment which have different random outcomes.

**Definition 2.1.1** (Sample Spaces). The **sample space** of the experiment is the set of all possible outcomes, denoted as  $\Omega$ .

**Definition 2.1.2** (Sigma Algebra). The  $\sigma$ -algebra of subsets of  $\Omega$ , denoted as  $\mathcal{F}$ , is a set of subsets of  $\Omega$  which satisfies:

- $\Omega \in \mathcal{F}$ ;
- $A \in \mathcal{F} \implies A^c \in \mathcal{F}$ ;
- $\{A_i|i\in\mathcal{I}\}\subset\mathcal{F} \text{ with }\mathcal{I} \text{ being countable }\Longrightarrow\bigcup_{i\in\mathcal{I}}A_i\in\mathcal{F}.$

**Remark.** We say  $\mathcal{I}$  is countable if there exists a one-to-one map from  $\mathcal{I}$  into  $\mathbb{Z}$ , so "countable" includes "finite".

**Example 2.1.1.** If  $\Omega$  is countable, we usually take  $\mathcal{F} = 2^{\Omega}$ , which is the power set of  $\Omega$ .

**Example 2.1.2.** When  $\Omega$  is not countable, e.g. [0,1], if you allow Axiom of Choice, then there exist unmeasurable subsets, and