

Stochastic Modelling and Random Processes

Yiming MA

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Chapter 1

Introduction

1.1 Motivation

Suppose we are modelling COVID. Let

- S be the 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

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

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

$$\begin{aligned}\mathbb{P}S \rightarrow S-1 \ \& \ I \rightarrow I-1 \text{ in } \Delta t = \beta IS\Delta t + o(\Delta t) \\ \mathbb{P}I \rightarrow I-1 \ \& \ R \rightarrow R+1 \text{ in } \Delta t = \gamma I\Delta t + o(\Delta t).\end{aligned}$$

The problem of this model is that contacts are usually not made uniformly 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 this 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 Ω .

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

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

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

Example 2.1.2. When Ω is not countable, e.g. $[0, 1]$, if you allow [Axiom of Choice](#)¹, then there exist unmeasurable subsets, and we exclude them from \mathcal{F} , i.e. \mathcal{F} is the set of all Lebesgue-measurable subsets on $[0, 1]$.

Definition 2.1.3 (Events). The members of \mathcal{F} are called *events*.

Definition 2.1.4 (Probability). $\mathbb{P}[\cdot] : \mathcal{F} \mapsto \mathbb{R}$ is called a probability if

- $\mathbb{P}[A] \in [0, 1], \forall A \in \mathcal{F}$;
- $\mathbb{P}[\Omega] = 1$;
- $\mathbb{P}[\cdot]$ satisfies the *countable additivity*: $\forall \{A_i | i \in \mathcal{I}\} \subset \mathcal{F}$, where \mathcal{I} is a countable set, if A_i 's are disjoint, then

$$\mathbb{P}\left[\bigcup_{i \in \mathcal{I}} A_i\right] = \sum_{i \in \mathcal{I}} \mathbb{P}[A_i].$$

¹A Cartesian product of a collection of nonempty sets is nonempty.

Definition 2.1.5 (Independence). Say $A, B \in \mathcal{F}$ are *independent* if

$$\mathbb{P}[A \cap B] = \mathbb{P}[A]\mathbb{P}[B].$$

Definition 2.1.6 (Conditional Probabilities). If $\mathbb{P}[B] > 0$, then the *conditional probability* $\mathbb{P}[A|B]$ is defined by

$$\mathbb{P}[A|B] = \frac{\mathbb{P}[A \cap B]}{\mathbb{P}[B]}, \quad \forall A \in \mathcal{F}.$$

Definition 2.1.7 (Partitions). $\{B_i | i \in \mathcal{I}\}$ is called a *partition* of the sample space Ω if:

- B_i 's are *pairwise disjoint*: $B_i \cap B_j = \emptyset, \forall i, j \in \mathcal{I}, i \neq j$;
- $B_i \neq \emptyset, \forall i \in \mathcal{I}$;
- $\{B_i | i \in \mathcal{I}\}$ *covers* Ω : $\bigcup_{i \in \mathcal{I}} B_i = \Omega$.

Theorem 2.1.1 (The Law of Total Probability). Let $\{B_i | i \in \mathcal{I}\}$ be a countable partition of Ω , with $B_i \in \mathcal{F}$ and $\mathbb{P}[B_i] > 0, \forall i \in \mathcal{I}$. Then $\forall A \in \mathcal{F}$, we have

$$\mathbb{P}[A] = \sum_{i \in \mathcal{I}} \mathbb{P}[A|B_i] \mathbb{P}[B_i].$$

Chapter 3

Discrete-Time Markov Chain

Chapter 4

Continuous-Time Markov Chain

Chapter 5

Continuous State Space Markov Processes

Chapter 6

Stochastic Particle Systems

Chapter 7

Networks

Chapter 8

Random Networks