

## Motivation: Dynamical Systems

There are two broad (and interwoven) kinds of dynamical systems: discrete and continuous.

**Discrete dynamics:** State space  $S$ ,  $x_0 \in S$   
Function  $f: S \rightarrow S$

Study the behaviour of the sequence

$$x_{n+1} = f(x_n)$$

**Continuous dynamics:** State space  $S$  ( $= \mathbb{R}^d$  or a manifold),  $x_0 \in S$   
Function ("vector field")  $f: S \rightarrow S$  (or maybe  $T(S)$ )

Study the behaviour of the curve

$$\frac{dx(t)}{dt} = f(x(t)), \quad x(0) = x_0.$$

In both settings, the dynamics is **deterministic**: if you know  $f$  and  $x_0$  with perfect precision, you know the full dynamics (in principle).

But what if there's noise / measurement error?

## A Model for Noisy (Discrete) Dynamics

State space  $S$ . We want to iterate  $x_{n+1} = f(x_n)$  as before, but this time with the function changing randomly as well.

That's too vague/broad to do any consistent analysis.

Here's a more precise model:

Probability space  $(\Omega, \mathcal{F}, P)$ , measurable space  $(R, \mathcal{G})$

iid. sequence  $\{z_n : (\Omega, \mathcal{F}, P) \rightarrow (R, \mathcal{G})\}$

State (measurable) space  $(S, \mathcal{B})$

Function:  $f : S \times R \rightarrow S$

Dynamical System:

$$x_{n+1} =$$

That is: our random function has the form

$$X_n = f(X_{n-1}, \zeta_n) = f(f(X_{n-2}, \zeta_{n-1}), \zeta_n)$$

Set  $\mathcal{F}_n = \sigma(X_0, X_1, \dots, X_n), n \geq 0$   
 $= \sigma(X_0, \zeta_1, \dots, \zeta_n)$

$\therefore \zeta_{n+1}$  is independent from  $\mathcal{F}_n$

Thus, if  $g \in \mathcal{B}(S, \mathcal{B})$ ,

$$\mathbb{E}[g(X_{n+1}) | \mathcal{F}_n] = \mathbb{E}[g(f(X_n, \zeta_{n+1})) | \mathcal{F}_n]$$

Set  $Q_n(x, \cdot) := \text{Law}(f(x, \zeta_n)), L_n$  its Markov generator.

Thus  $\mathbb{E}[g(X_{n+1}) | \mathcal{F}_n]$

$$= \mathbb{E}[g(X_{n+1}) | X_0, X_1, \dots, X_n] = (\mathbb{L}_{n+1}g)(X_n)$$

Take  $\mathbb{E}_{\sigma(X_n)}$  of both sides.

$$\mathbb{E}_{\sigma(X_n)} [\mathbb{E}[g(X_n) | \mathcal{F}_n]]$$

$$\mathbb{E}_{\sigma(X_n)} [(\mathbb{L}_{n+1}g)(X_n) | \sigma(X_n)]$$

We've arrived at the **Markov Property**:

$$\mathbb{E}[g(X_{n+1}) | X_0, \dots, X_n] = \mathbb{E}[g(X_{n+1}) | X_n] \text{ a.s. } \forall g \in \mathbb{B}(S, \mathcal{B})$$

Iterating the above argument yields the nominally stronger

$$\boxed{\mathbb{E}[g(X_n) | \mathcal{F}_k] = \mathbb{E}[g(X_n) | X_k] \text{ a.s. } \forall k < n}$$