

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 $x_{n+1} = f_n(x_n)$ as before, but this time with the function changing randomly as well. $f_n: S \rightarrow S$ random function.

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

Here's a more precise model:

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

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

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

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

Dynamical System:

$$x_{n+1} = f(x_n, \zeta_{n+1}) \quad \text{with } X_0: (\Omega, \mathcal{F}) \rightarrow (S, \mathcal{B}) \text{ measurable}$$

That is: our random function has the form $f_n = f(\cdot, \{\zeta_n\}_{n=1}^{\infty})$ indep. from $\{\zeta_n\}_{n=1}^{\infty}$

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

$$= F_n(X_0, \{\zeta_1\}, \{\zeta_2\}, \dots, \{\zeta_n\})$$

$$F_n : S \times \mathbb{R}^n \rightarrow S \quad F_n(x, y_1, \dots, y_n)$$

$$= f(f(\dots f(f(x, y_1), y_2), \dots), y_{n-1}), y_n)$$

measurable $\mathcal{B} \otimes \mathcal{H}^{\otimes n} / \mathcal{B}$.

$$\text{Set } \mathcal{F}_n = \sigma(X_0, X_1, \dots, X_n), \quad n \geq 0 \quad \mathcal{F}_0 = \sigma(X_0)$$

$$= \sigma(X_0, \{\zeta_1\}, \dots, \{\zeta_n\})$$

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

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

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

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

$$\begin{aligned} &= \int g(y) Q_{n+1}(x dy) |_{x=X_n} \\ &= (L_{n+1} g)(X_n) \end{aligned}$$

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

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

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

$$\mathbb{E}_{\sigma(X_n)}(\mathbb{E}[g(X_{n+1}) | \mathcal{F}_n]) = \mathbb{E}[g(X_{n+1}) | X_n] \text{ a.s. b/c } \sigma(X_n) \subseteq \mathcal{F}_n.$$

$$\mathbb{E}_{\sigma(X_n)}[(L_{n+1}g)(X_n) | \sigma(X_n)] = L_{n+1}g(X_n) = \mathbb{E}[g(X_{n+1}) | \mathcal{F}_n] \text{ a.s.}$$

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

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

$\rightarrow \mathbb{E}[g(X_n) | \mathcal{F}_k] = (L_n L_{n-1} \dots L_{k+1} g)(X_k).$