

Outline

1 Discrete-Time Continuous-State Markov Process

Stochastic Difference Equations

Gauss-Markov process

Difference equations of Gauss-Markov process

Gaussian process - Mean

Gaussian process - Covariance

2 Monte Carlo simulation of a discrete-time continuous-state Markov process

Simulation

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Learning Goals

At the end of this lecture, you will be able to:

- 1 Define a discrete-state continuous-time Gauss- Markov process.
- 2 Define a stochastic difference equation.
- 3 Check if a stochastic process is Gauss-Markov.
- 4 Monte Carlo simulate a discrete-state continuous-time Markov process.





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Discrete-Time Continuous-State Markov Process

- Discrete time: $T \in \{1, 2, \ldots\}$.
- State space \mathbb{R}^n , $n \in \mathbb{N}^+$ (continuous state space!).
- Similar to the finite state case, $p_{X_{t+1}|X_t}(x|y)$ is to be understood as the transition probability density function at $X_{t+1} = x$ given $X_t = y$, with

$$\rho_{X_{t+1}|X_t}(x|y) \ge 0, \forall i, j \in \mathbb{R}^n$$

$$\int \rho_{X_{t+1}|X_t}(x|y)dx = 1.$$

Markov property is satisfied.





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Stochastic Difference Equations

A general stochastic difference equation has the form

$$X_t = f(t, X_{t-1}, \omega_t), t \geq 1,$$

where $\{X_t\}$ takes values from \mathbb{R}^n and $\omega_0, \omega_1, \ldots, \omega_t$ i.i.d. drawings from [0, 1].

Example:

$$X_t = 2X_{t-1} + 3W_t,$$

 $\{X_t\}$ an \mathbb{R} -valued stochastic process, X_0 is Gaussian and independent of W_t , with W_t Gaussian.





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Application - an example

Flight path under wind uncertainty, where the wind is normally distributed.

Example*: s_t is the 3D position of an aircraft at time t, having velocity v_t at time t, heading angle ψ , flight path angle γ , bank angle ϕ and i.i.d. normally distributed W_t^x , W_t^y , W_t^z variation in the position, $\Delta \to 0$.

$$\begin{split} s_{t+\Delta}^{x} &= s_{t}^{x} + \Delta v_{t} \cos \psi \cos \gamma + \Delta W_{t}^{x}, \\ s_{t+\Delta}^{y} &= s_{t}^{y} + \Delta v_{t} \sin \psi \cos \gamma + \Delta W_{t}^{y}, \\ s_{t+\Delta}^{z} &= s_{t}^{z} + \Delta v_{t} \sin \gamma + \Delta W_{t}^{z}, \\ v_{t+\Delta} &= v_{t} + \Delta \frac{g \tan \phi}{v_{t}}. \end{split}$$

*A multi-Aircraft model for conflict detection and resolution algorithm evaluation", W. Glover and J. Lygeros, 2004, Section 3: Aircraft dynamics

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Gauss-Markov process

Gauss-Markov process: an example of a discrete-time continuous-state Markov process.

- **1** A Gaussian process is a process with the property that for any t_1, \ldots, t_n , $(X_{t_1}, \ldots, X_{t_n})$ have a joint Gaussian distribution.
- 2 A Markov process is said to satisfy the Markov property when its future and past states are conditionally independent given its present state, i.e.,

$$p_{X_t|X_{t-1},X_{t-2},...,X_0}(x|x',x'',...,x^*)=p_{X_t|X_{t-1}}(x|x').$$





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Difference equations of Gauss-Markov process

$$X_0 = C_0 V_0 \tag{1}$$

$$X_t = X_{t-1} + BU(t) + CV_t, t \ge 1,$$
 (2)

 $X_t \in \mathbb{R}^n$, U(t) a deterministic, scalar-valued sequence, $\{V_t\}$ a sequence of i.i.d. standard Gaussian random variables, i.e., $V_t \sim N(0,1)$, B and C are n-size vectors.

• Gaussian process

$$X_{t+1} = (X_{t+1} - X_t) + (X_t - X_{t-1}) + \ldots + X_1.$$

 X_{t+1} is a linear combination of X_{t+1}, X_t, \dots, X_1 , which is Gaussian. Thus, X_{t+1}, X_t, \dots, X_1 are themselves jointly normal.

Markov property

The sequence generated by (2) is Markov since, given X_{t-1} , X_t depends only on ω_t , which is independent of X_{t-2}, \ldots, X_0 .



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Gaussian process - Mean

 Reminder: Linear functions of Gaussian random variables are also Gaussian.

From (1), X_0 follows a normal distribution with mean $\bar{X}_0 = 0$ and covariance $\bar{R}_0 = C_0 C_0^T$, where C_0^T is the transpose of C_0 . Then, from (1) and (2), X_t follows a normal distribution with mean \bar{X}_t and covariance \bar{R}_t .

$$\begin{split} \bar{X}_{t+1} &= \mathbb{E}[X_{t+1}] \\ &= \mathbb{E}[X_t + BU_{t+1} + CV_{t+1}] \\ &= \mathbb{E}[X_t] + B\mathbb{E}[U(t+1)] + C\mathbb{E}[V_{t+1}] \\ &= \mathbb{E}[X_t] + BU(t+1) \\ &= \bar{X}_t + BU(t+1). \end{split}$$



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Gaussian process - Covariance

$$\begin{split} \bar{R}_{t+1} &= \mathbb{E}[(X_{t+1} - \bar{X}_{t+1})(X_{t+1} - \bar{X}_{t+1})^T] \\ &= \mathbb{E}[(X_t + BU_{t+1} + CV_{t+1} - \bar{X}_t - BU_{t+1}) \\ &\cdot (X_t + BU_{t+1} + CV_{t+1} - \bar{X}_t - BU_{t+1})^T] \\ &= \mathbb{E}[(X_t - \bar{X}_t)(X_t - \bar{X}_t)^T] + \mathbb{E}[(X_t - \bar{X}_t)(CV_{t+1})^T] \\ &+ \mathbb{E}[(CV_{t+1})(X_t - \bar{X}_t)^T] + \mathbb{E}[CV_{t+1}(CV_{t+1})^T] \\ &= \mathbb{E}[(X_t - \bar{X}_t)(X_t - \bar{X}_t)^T] + C\mathbb{E}[V_{t+1}(V_{t+1})^T]C^T \\ &= \bar{R}_t + CC^T. \end{split}$$

Note: $\bar{R}_0 = C_0 C_0^T$.



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Monte Carlo simulation of a discrete-time continuous-state Markov process

Initial condition:

$$X_0 = f(\omega_0)$$
, where $\omega_0 \sim N(\mu, \sigma^2)$

2 The outcome of X_t is defined by X_{t-1} and ω_t , where $\omega_0, \omega_1, \ldots, \omega_t$ are independent drawings from Uniform(0,1). Thus,

$$X_t = f(t, X_{t-1}, \omega_t).$$

Note: In Matlab, the function randn generates a random variable $\sim N(0,1)$, while the function rand generates a random variable $\sim U(0,1)$.



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Simulating $Y \sim N(\mu_Y, \sigma_Y^2)$

Let $Y \sim N(\mu_Y, \sigma_Y^2)$ and $X \sim N(0, 1)$. Question: How to simulate Y using N(0, 1)?

Reminder: A linear combination of normally distributed random variable is again a normally distributed random variable.

 $Y = \alpha X + \beta$ is normally distributed. But what are the values for α and β such that $Y \sim N(\mu_Y, \sigma_Y^2)$?

$$\mathbb{E}[Y] = \mathbb{E}[\alpha X + \beta] = \beta$$

$$Var[Y] = Var[\alpha X + \beta] = \alpha^{2} Var[X] = \alpha^{2}$$

So, to generate $Y \sim N(\mu_Y, \sigma_Y^2)$, we use $\sigma_Y \cdot randn + \mu_Y$.



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