

# Introduction to Stochastic Processes

$(\Omega, \mathcal{F}, P)$        $(S, \mathcal{B})$

$T \leftarrow$  ordered set (with minimal element)     $T = \mathbb{N}$ ,  $T = [0, \infty)$ ,  $[a, b]$

A **stochastic process** is a collection  $\{X_t\}_{t \in T}$  of random variables  $X_t: (\Omega, \mathcal{F}) \rightarrow (S, \mathcal{B})$ .

The minimal information we'd like to have about a stochastic process is its **finite-dimensional distributions**:

For each finite set  $\Lambda \subseteq T$ , the measures  $\text{Law}_P(X_t)_{t \in \Lambda} \in \text{Prob}(S^\Lambda, \mathcal{B}^{\otimes \Lambda})$   
↑ usually inadequate to characterize  $(X_t)_{t \in T}$ .

Eg.  $T = \mathbb{N}$ ,  $\{\xi_k\}_{k=1}^\infty$  iid in  $\mathbb{R}^d$ . Set  $X_n = \sum_{k=1}^n \xi_k$ .     $\xi_k \stackrel{d}{=} \mu$

Can explicitly describe the f.d. distributions.

$\hookrightarrow (X_1, X_3, X_4) = F(X_1, X_3 - X_1, X_4 - X_3) = F(\xi_1, \xi_2 + \xi_3, \xi_4) \leftarrow \mu \otimes \mu + \mu \otimes \mu$   
 $F(x, y, z) = (x, x+y, x+y+z)$

As we saw in [Lecture 34.2], it is often important to understand  $\sigma(X_1, X_2, \dots, X_n)$  as  $n$  varies.

**Def:** A collection  $(\mathcal{F}_t)_{t \in T}$  of  $\sigma$ -fields is called a **filtration** if  $\mathcal{F}_s \subseteq \mathcal{F}_t$  when  $s \leq t$  in  $T$ .

E.g. If  $\{X_n\}_{n=1}^{\infty}$  is a seq. of rvs,  $\mathcal{F}_n = \sigma(X_1, \dots, X_n)$  is a filtration.

If  $(\Omega, \mathcal{F}, \mathbb{P})$  is a probability space, and  $\mathcal{F}_t \subseteq \mathcal{F} \quad \forall t \in T$ , then  $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \in T}, \mathbb{P})$  is called a **filtered probability space**.

A stochastic process  $(X_t)_{t \in T}$  (with  $X_t: (\Omega, \mathcal{F}) \rightarrow (S, \mathcal{B})$ ) is called **adapted** if  $X_t$  is  $\mathcal{F}_t / \mathcal{B}$ -measurable  $\forall t \in T$ .

E.g. If we set  $\mathcal{F}_t = \sigma(X_s)$  then  $X_t$  is clearly adapted.

↑ typically not a filtration =  $\sigma(X_s) \not\subseteq \sigma(X_t)$

$$\mathcal{F}_t = \sigma(\{X_s : s \leq t\})$$

Usually we can safely take this as the filtration. But if we have more than one process around, we may need a more general filtration.

Ex.  $\{\xi_k\}_{k=1}^{\infty}$  iid,  $X_n = \xi_1 + \dots + \xi_n$ ,  $\mathcal{F}_n = \sigma(X_1, \dots, X_n)$ .  
 $= \sigma(\xi_1, \dots, \xi_n)$

$$\mathbb{E}[g(X_n) | \mathcal{F}_k] = \mathbb{E}[g(X_k + \underbrace{\xi_{k+1} + \dots + \xi_n}_{\text{indep.}}) | \sigma(X_1, \dots, X_k)]$$

$$= \mathbb{E}[g(x + \xi_{k+1} + \dots + \xi_n) | x = X_k]$$

$$= \mathbb{E}[g(X_k + \xi_{k+1} + \dots + \xi_n) | X_k] = \mathbb{E}[g(X_n) | X_k]$$

This process satisfies the Markov property.

(Indeed, it fits the "random dynamics" model:  $X_{n+1} = f(X_n, \xi_{n+1})$ ,  $X_0 = 0$ .)  
 $f(x, y) = x + y$ .

In the special case (on  $\mathbb{R}^d$ ) that the law of  $\xi_1$  is

$$\mathbb{P}(\xi_1 = \pm e_j) = \frac{1}{2d} \quad 1 \leq j \leq d$$

$$\mathbb{R}^1: \xi_1 \stackrel{d}{=} \frac{1}{2}\delta_{-1} + \frac{1}{2}\delta_1$$

we call this stochastic process **simple random walk**.

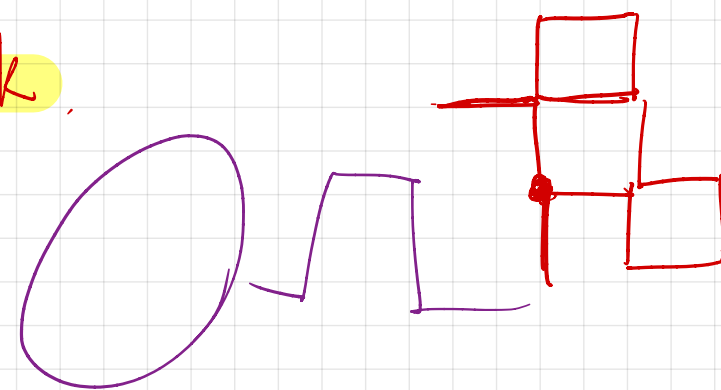
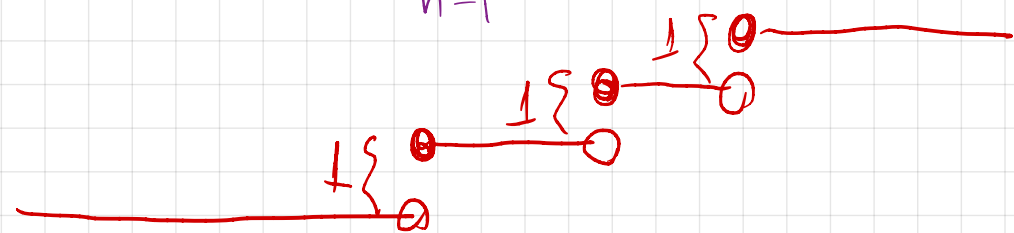


Fig. Suppose  $(X_n)_{n \geq 0}$  is a non-decreasing process

$$X_n = \sum_{k=1}^n \xi_k \quad \xi_k \in [0, \infty)$$

Define  $N_t = \sum_{n=1}^{\infty} \mathbb{1}_{\{0, t\}}(X_n) = \sup \{n : X_n \leq t\}$



Any such  $(X_n)_{n \geq 0} \uparrow$  is called an **arrival process**.

The process  $(N_t)_{t \geq 0}$  is the associated **counting process**.

If we set  $\xi_n := X_n - X_{n-1}$ , the  $\{\xi_n\}_{n=1}^{\infty}$  are the **inter-arrival times**.

If the inter-arrival times are iid,  $(X_n)_{n \geq 0}$  is a **renewal process**.

The most important example of (the counting process associated to) a renewal process is the **Poisson process**, which we'll study next time.