

## Stochastic processes in continuous time

A stochastic process is a collection  $X_t$ ,  $t \in T$  of random variables having common state space  $S$ .

For Markov chains,  $T = \{0, 1, 2, \dots\}$ , which is infinite, but countable.

Now we will consider  $T = [0, \infty)$ .

For many reasons, this is more natural.

### Examples

1.  $X_t$  is the number of people on hold on the telephone to some company at time  $t$
2.  $X_t$  is the number of cars in Lot A at time  $t$
3.  $X_t$  is the temperature, wind speed, whatever, at time  $t$
4.  $X_t$  is the number of individuals in a biological population at time  $t$ .

In three of these examples, the state space  $S$  is  $\{0, 1, 2, \dots\}$ ; in the other,  $S = \mathbb{R}$ .

It turns out that this sort of situation is the easiest to begin with.

Also, there are so many random variables in the collection  $X_t$ ,  $t \geq 0$  that it doesn't make sense to begin with the iid case.

Perhaps the simplest place to begin is with processes satisfying the Markov property.

Markov processes (Continuous time Markov chains - Chapter VI)

Let  $X_t, t \geq 0$  be a collection of random variables taking values in a countable set  $S$ .

Suppose that for all  $s, t \geq 0$  and  $i, j$  in  $S$ ,

$$P(X_{t+s} = j \mid X_r, r \leq t, X_t = i) = P(X_{t+s} = j \mid X_t = i)$$

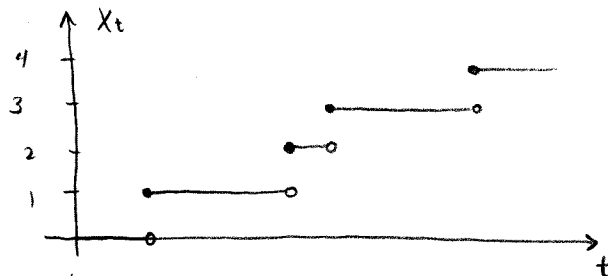


Then  $X$  is said to be a Markov process.

(Some people call it a continuous time chain, but to me "chain" refers to the discreteness of time, not space)

Example Let  $X$  be a Poisson arrival process with constant rate  $\lambda$ .

$X_t = \#$  arrivals in  $(0, t]$ .



Then  $X_t, t \geq 0$  is a collection of random variables taking values in  $S = \{0, 1, 2, \dots\}$ .

Let  $i \leq j$ .

$$\begin{aligned} &P(X_{t+s} = j \mid X_r, r \leq t, X_t = i) \\ &= P(X_{t+s} - X_t = j - i \mid X_r, r \leq t, X_t = i) \\ &= P(X_{t+s} - X_t = j - i) \quad \text{independence} \\ &= P(X_{t+s} - X_t = j - i \mid X_t = i) \quad \text{independence} \\ &= P(X_{t+s} = j \mid X_t = i), \end{aligned}$$

which shows that  $X$  satisfies the Markov property.

Moreover,

$$P(X_{t+s} = j \mid X_t = i) = \begin{cases} \frac{e^{-\lambda s} (\lambda s)^{j-i}}{(j-i)!} & \text{if } j \geq i \\ 0 & \text{if } j < i. \end{cases}$$

If it happens that  $\mathbb{P}(X_{t+s} = j \mid X_t = i)$  does not depend on  $t$  (as in the previous example), then we say  $X$  is time homogeneous.

Then we write

$$P_{ij}(s) = \mathbb{P}(X_{t+s} = j \mid X_t = i).$$

Whereas for Markov chains we had  $P, P^2, P^3, P^4, \dots, P^s$  to describe transition probabilities over  $1, 2, 3, 4, \dots, s$  time steps, now we have a matrix  $P(s)$  for every  $s \geq 0$  to tell the probabilities of transitions over time  $s$ . These are matrices parameterized by  $s$ .

We can still think of this as matrix multiplication:

### Chapman - Kolmogorov equation

For  $s, t \geq 0$ ,  $P(t+s) = P(t)P(s)$ , a matrix product

Proof

$$\begin{aligned}
 P_{ij}(t+s) &= \mathbb{P}(X_{t+s} = j \mid X_0 = i) \quad \begin{array}{c} \longleftarrow \\ 0 \quad t \quad t+s \end{array} \\
 &= \sum_{k \in S} \mathbb{P}(X_{t+s} = j, X_t = k \mid X_0 = i) \\
 &= \sum_{k \in S} \mathbb{P}(X_{t+s} = j \mid X_t = k, X_0 = i) \cdot \mathbb{P}(X_t = k \mid X_0 = i) \\
 &= \sum_{k \in S} \mathbb{P}(X_{t+s} = j \mid X_t = k) \cdot \mathbb{P}(X_t = k \mid X_0 = i) \\
 & \hspace{15em} \text{(Markov property)} \\
 &= \sum_{k \in S} P_{kj}(s) P_{ik}(t) \\
 &= (P(t)P(s))_{ij}
 \end{aligned}$$

Example For a Poisson process,

$$P(s) = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & \dots \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ \vdots \end{matrix} & \begin{bmatrix} e^{-\lambda s} & \frac{e^{-\lambda s} (\lambda s)^1}{1!} & \frac{e^{-\lambda s} (\lambda s)^2}{2!} & \dots & \\ 0 & e^{-\lambda s} & \frac{e^{-\lambda s} (\lambda s)^1}{1!} & \dots & \\ 0 & 0 & e^{-\lambda s} & \dots & \\ 0 & 0 & 0 & e^{-\lambda s} & \dots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \end{matrix}$$

For small  $s$ ,  $P(s) \approx I$

For large  $s$ ,  $P(s) \approx \begin{bmatrix} 0 & 0 & \dots \\ \vdots & \vdots & \dots \\ c & 0 & \dots \end{bmatrix}$

Markov property  $\mathbb{P}(X_{t+s} = j \mid X_t = i, X_r, r \leq t) = \mathbb{P}(X_{t+s} = j \mid X_t = i)$   
 Time homogeneity  $= P_{ij}(s)$

Regularity assumption  $\lim_{s \rightarrow 0^+} P_{ij}(s) = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases}$

Then  $P(t)$  is <sup>right</sup> continuous in  $t$ , for  $\lim_{s \rightarrow 0^+} P(t+s) = \lim_{s \rightarrow 0^+} P(t)P(s) = P(t) \lim_{s \rightarrow 0^+} P(s) = P(t) \cdot \mathbf{I} = P(t)$ .

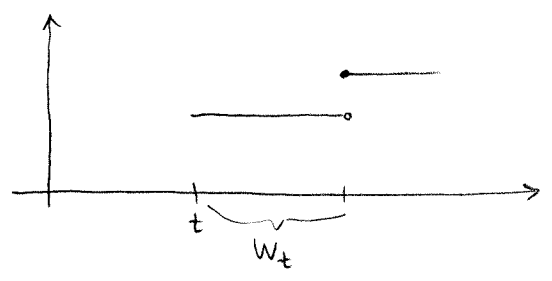
Extension of Markov property. Let  $A = "X_{t+s}, s \geq 0 \text{ does some particular thing}"$ .

$$\begin{aligned} \mathbb{P}(A \mid X_t = i, X_r, r \leq t) &= \mathbb{P}(A \mid X_t = i) \\ &= \mathbb{P}(A \text{ relative to } 0 \mid X_0 = i) \end{aligned}$$

Time spent in each state

Starting at time  $t$ , let  $W_t$  be the amount of time the chain remains in its current state before jumping.

$$W_t = \inf (s > 0 : X_{t+s} \neq X_t)$$



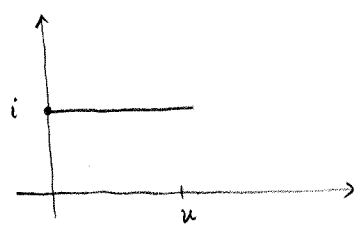
Theorem For each  $i$  in  $S$ , there exists  $\lambda(i)$  in  $[0, \infty]$  such that, for all  $t \geq 0$ ,  
 $\mathbb{P}(W_t > u \mid X_t = i) = e^{-\lambda(i)u}$  for all  $u \geq 0$ .

Proof

The event  $A$  is that  $X_{t+s}, s \geq 0$  remains in the current state at least  $u$  units of time.

By time homogeneity this probability is equal to

$$\begin{aligned} \mathbb{P}(W_0 > u \mid X_0 = i) \\ = \mathbb{P}(X_s = i \text{ for } s \text{ in } [0, u] \mid X_0 = i) \end{aligned}$$



Let  $f(u)$  denote this probability.

$$\begin{aligned} \text{Then } f(u+v) &= \mathbb{P}(X_s = i \text{ for } s \text{ in } [0, u+v] \mid X_0 = i) \\ &= \mathbb{P}(X_s = i \text{ for } s \text{ in } [0, u] \text{ and } X_s = i \text{ for } s \text{ in } [u, u+v] \mid X_0 = i) \\ &= \mathbb{P}(X_s = i \text{ for } s \text{ in } [u, u+v] \mid X_s = i \text{ for } s \text{ in } [0, u], X_0 = i) \cdot \\ &\quad \mathbb{P}(X_s = i \text{ for } s \text{ in } [0, u] \mid X_0 = i) \\ &= \mathbb{P}(X_s = i \text{ for } s \text{ in } [u, u+v] \mid X_u = i) \cdot \mathbb{P}(X_s = i \text{ for } s \text{ in } [0, u] \mid X_0 = i) \\ &= f(v) \cdot f(u), \end{aligned}$$

so  $f(u) = e^{-\lambda(i)u}$  for some number  $\lambda(i)$ . □

Thus, the time spent in each state is exponentially distributed.

If  $\lambda(i) = 0$ , then  $P(W_t > u \mid X_t = i) = 1$  for all  $u$ ,  
so  $X$  never leaves state  $i$ , and  $i$  is  
called absorbing.

If  $0 < \lambda(i) < \infty$ , then  $i$  is called stable.

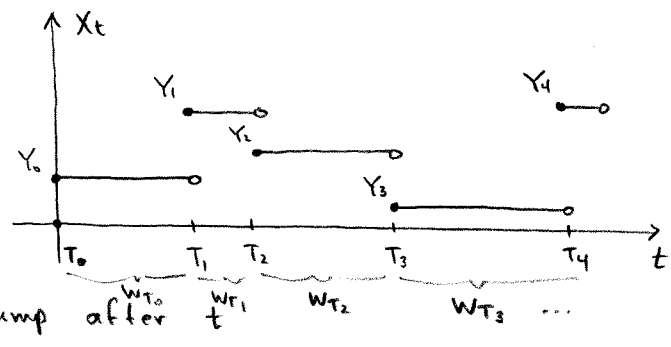
If  $\lambda(i) = \infty$ , then  $P(W_t > u \mid X_t = i) = 0$  for all  $u$ ,  
so that  $X$  leaves state  $i$  as soon as it  
enters it.  $i$  is called instantaneous.

Instantaneous states are really new, particular to continuous time.

For now on, we assume there are no instantaneous states.

In fact, we must assume that the process is regular enough.

There are many details, all of which will be skipped, more or less.

Jump times

Recall that

$W_t$  = length of time until next jump after  $t$

Then

$$T_1 = W_0$$

$$T_2 = T_1 + W_{T_1}$$

$$T_3 = T_2 + W_{T_2}$$

$\vdots$

$$T_{n+1} = T_n + W_{T_n}$$

States visited

Let  $Y_n = X_{T_n}$  for  $n = 0, 1, 2, \dots$

Then  $Y_n, n = 0, 1, 2, \dots$  is a sequence of random variables taking values in  $S$ .

Strong Markov property

Let  $A = "X_{T_n+s}, s \geq 0$  does some particular thing".

$$\begin{aligned} \text{Then } P(A \mid X_{T_n} = i, X_r \text{ for } r \leq T_n) &= P(A \mid X_{T_n} = i) \\ &= P(A \text{ relative to } 0 \mid X_0 = i) \\ &= P(X_s, s \geq 0 \text{ does that thing} \mid X_0 = i) \end{aligned}$$

Theorem (Structure of a Markov process) (similar thm 8.3.3)

Suppose  $X$  is Markov, time homogeneous, and satisfies the regularity condition.  
Suppose also that  $X$  has no instantaneous or absorbing states.

① Below

Then for all  $i, j$  in  $S$ ,  $n \geq 0$  and  $u \geq 0$ ,

$$\mathbb{P}(Y_{n+1} = j, T_{n+1} - T_n > u \mid Y_n = i, Y_0, \dots, Y_{n-1}, T_0, \dots, T_n) = Q(i, j) e^{-\lambda(i)u},$$

where

$$Q(i, j) = \mathbb{P}(Y_1 = j \mid Y_0 = i) = \mathbb{P}(X_{W_0} = j \mid X_0 = i).$$

Proof

$$\begin{aligned} & \mathbb{P}(Y_{n+1} = j, T_{n+1} - T_n > u \mid Y_n = i, Y_0, \dots, Y_{n-1}, T_0, \dots, T_n) \\ &= \mathbb{P}(X_{T_n + W_{T_n}} = j, W_{T_n} > u \mid X_{T_n} = i, X_r \text{ for } r \leq T_n) \end{aligned}$$

$$\left[ \begin{array}{l} \text{Recall } Y_{n+1} = X_{T_{n+1}}, \quad T_{n+1} = T_n + W_{T_n} \\ \text{Also, knowing } Y_n = i, Y_0, \dots, Y_{n-1}, T_0, \dots, T_n \text{ is equivalent to knowing} \\ X_{T_n} = i \text{ and } X_r \text{ for } r \leq T_n. \end{array} \right.$$

$$= \mathbb{P}(X_{T_n + W_{T_n}} = j, W_{T_n} > u \mid X_{T_n} = i) \quad \text{strong Markov property,}$$

$$= \mathbb{P}(X_{W_0} = j, W_0 > u \mid X_0 = i) \quad \text{time homogeneity}$$

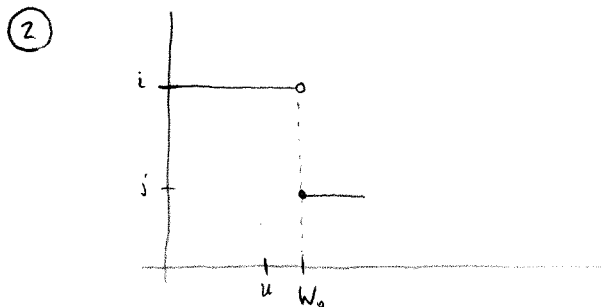
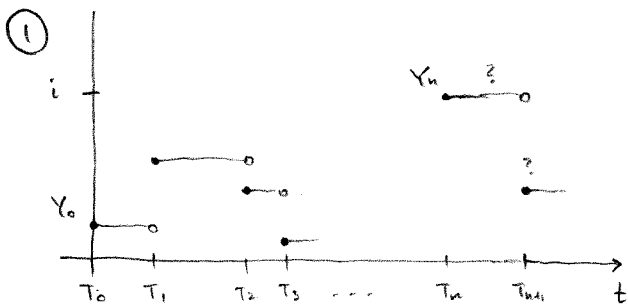
$$= \mathbb{P}(X_{W_0} = j \mid W_0 > u, X_0 = i) \cdot \mathbb{P}(W_0 > u \mid X_0 = i)$$

$$= \mathbb{P}(X_{W_0} = j \mid X_s = i, s \in [0, u]) \cdot e^{-\lambda(i)u} \quad \text{earlier result}$$

$$= \mathbb{P}(X_{u+W_0} = j \mid X_u = i) \cdot e^{-\lambda(i)u} \quad \text{Markov property}$$

$$= \mathbb{P}(X_{W_0} = j \mid X_0 = i) \cdot e^{-\lambda(i)u} \quad \text{time homogeneity}$$

$$= Q(i, j) \cdot e^{-\lambda(i)u}.$$



Some corollaries:

- The sequence  $Y_n, n=0,1,\dots$  is a Markov chain with transition matrix  $Q$ , for with  $u=0$ , and imagining the proof without conditioning on  $T_0, \dots, T_n$ ,
 
$$\begin{aligned} P(Y_{n+1} = j \mid Y_n = i, Y_0, \dots, Y_{n-1}) \\ &= P(Y_{n+1} = j, T_{n+1} - T_n > 0 \mid Y_n = i, Y_0, \dots, Y_{n-1}) \\ &= Q(i, j) e^{-\lambda(i) \cdot 0} \\ &= Q(i, j) \\ &= P(Y_{n+1} = j \mid Y_n = i). \end{aligned}$$

Thus successive states visited forms a Markov chain.

- $Q(i, i) = 0$ , for

$$Q(i, i) = P(X_{T_1} = i \mid X_0 = i)$$

But for there to be a jump, the state must change, so this probability is 0.

- Time spent in state  $i$  does not depend on previous states

$$P(T_{n+1} - T_n > u \mid Y_n = i, Y_0, \dots, Y_{n-1}) = e^{-\lambda(i)u},$$

by summing over  $j$ .

- Time spent in state  $i$  does not depend on next state to be visited.

$$P(Y_{n+1} = j, T_{n+1} - T_n > u \mid Y_n = i) = Q(i, j) e^{-\lambda(i)u}$$

and also equals

$$\begin{aligned} &P(T_{n+1} - T_n > u \mid Y_{n+1} = j, Y_n = i) \cdot P(Y_{n+1} = j \mid Y_n = i) \\ &= P(T_{n+1} - T_n > u \mid Y_{n+1} = j, Y_n = i) \cdot Q(i, j), \end{aligned}$$

so that

$$P(T_{n+1} - T_n > u \mid Y_{n+1} = j, Y_n = i) = e^{-\lambda(i)u},$$

independent of  $j$ .