

**Lecture 11. The Poisson process. Markov processes in queueing theory. Kolmogorov equations.**

We are considering an example started in Lecture 10, with  $v_x = a_{x,x+1} = \lambda$ .

We know that the distribution of the sum of  $n$  independent random variables having the same exponential distribution with parameter  $\lambda$  is the  $\Gamma$ -distribution with parameters  $n, \lambda$ . This means that the distribution of the random variable  $\tau_n$  has the probability density

$$p_{\tau_n}(t) = \begin{cases} 0, & t \leq 0, \\ \frac{\lambda^n t^{n-1}}{(n-1)!} e^{-\lambda t}, & t > 0 \end{cases} \quad (11.1)$$

(the distribution is the same independently with respect to which probability  $P_x$  we take it). So we have for  $n > 0$ :

$$p(t, x, x+n) = \int_0^t \frac{\lambda^n s^{n-1}}{(n-1)!} e^{-\lambda s} ds - \int_0^t \frac{\lambda^{n+1} s^n}{n!} e^{-\lambda s} ds = \frac{\lambda^n}{n!} \int_0^t (n s^{n-1} - \lambda s^n) e^{-\lambda s} ds. \quad (11.2)$$

The integrand is equal to  $\frac{d}{ds}(s^n e^{-\lambda s})$ , so

$$p(t, x, x+n) = \frac{\lambda^n t^n e^{-\lambda t}}{n!}. \quad (11.3)$$

For  $n = 0$  (taking into account that  $\tau_0 = 0$ ,  $P_x\{\tau_0 \leq t\} = 1$  for  $t \geq 0$ ):

$$p(t, x, x) = 1 - P_x\{\tau_1 \leq t\} = 1 - \int_0^t \lambda e^{-\lambda s} ds = e^{-\lambda t}; \quad (11.4)$$

i. e., formula (11.3) is true also for  $n = 0$ .

The entries of the transition matrix  $P^t$  are given by formula (11.3) for  $n \geq 0$ , and  $p(t, x, y) = 0$  for  $y < x$ . It is easy to check that for every  $t \geq 0$  this is a stochastic matrix,  $P^0 = 0$ , and  $P^s \cdot P^t = P^{s+t}$  (the last equality is equivalent to the statement that the sum of two independent random variables having Poisson distributions with parameters  $\lambda s$  and  $\lambda t$  has the Poisson distribution with parameter  $\lambda(s+t)$ ).

It is easy to check that the matrix  $A = \frac{d^+}{dt} P^t \Big|_{t=0}$  is the one that we started with:  $-\lambda$ 's on the main diagonal, and  $\lambda$ 's on the first diagonal above it.

Equality (11.3) means that the difference  $\xi_t - \xi_0$  (and also every difference  $\xi_{s+t} - \xi_s$ ) has the Poisson distribution with parameter  $\lambda t$ . This is why the Markov process  $\xi_t$  is called *the Poisson process*.

At this time I would like to introduce the terms for the quantities  $a_{xy}$  and  $v_x = -a_{xx}$ . They are (right-hand) *derivatives*, i. e. rates of change; so I'll call  $v_x$  the *exit rate* (from the state  $x$ ), and  $a_{xy}$ ,  $y \neq x$ , the *transition rates*.

One more example.

Continuous-time Markov chains have applications in what is called *Queueing Theory* (*queue* is the French-British word for a *line*, used traditionally in the Queueing Theory).

Let us consider a serving system (say, a gas station). The state of the system at a time  $t$  can be characterized by the number  $\xi_t$  of customers in the system at this time.

To be concrete, let us suppose that it is a gas station with two pumps (in the lecture it was *one* pump), and the cars that arrive while both pumps are busy form a queue of length not more than 2 (if a car drives up and finds both pumps busy and both places in the queue occupied, it drives away). The state space (the set of all possible states) here is  $X = \{0, 1, 2, 3, 4\}$ .

Suppose the process starts at time  $t = 0$ . Let  $U_1 > 0$  be the time before the first new customer comes (*new* means that it is possible that there was some number of customers in the system at time  $t = 0$ ; so we are speaking of the next customer to come);  $U_2$  the time between the coming of the first new customer and the next one;  $U_3$ , between the second customer and the third; etc. (these  $U_k$  can be described as *interarrival times*; I seem to run out of Greek letters for denoting random variables, so I am using capital Roman ones). Of course, if we don't suppose that the distribution of these random variables is exponential, we'll never get a Markov process. Suppose that the random variables  $U_k$  have an exponential distribution with parameter  $\lambda$ .

Now, there are *service times*: for the first pump, the first service time  $S_{11}$  (from the time point 0 if the system was busy at this time, or from the time when it starts to be busy if  $\xi_0$  was equal to 0, to the time at which the service of the first customer is finished); the second service time  $S_{12}$ , etc.; and  $S_{21}, S_{22}, S_{23}, \dots$  for the second pump. Again, we have no chance of obtaining a continuous-time Markov chain unless we suppose that the service times  $S_{ik}$  are exponential. Let them be exponential with parameter  $\mu$ .

And let all random variables  $U_1, U_2, \dots, U_n, \dots, S_{11}, S_{12}, \dots, S_{1n}, \dots, S_{21}, S_{22}, \dots, S_{2n}, \dots$ , be independent.

What are the exit rates  $v_x$  and the transition rates  $a_{xy}$  for the Markov chain  $X_t$  describing the number of customers in this system?

Note that the problem of finding the *transition probabilities*  $p(t, x, y), 0 \leq t < \infty, x, y = 0, 1, 2, 3, 4$ , is much more complicated than that of finding the infinitesimal (differential) characteristics  $a_{xy}$ .

First of all, transitions from one state to another occur at the times at which either a new customer comes (and then we move from the state  $x$ , which is equal to 0, 1, 2, or 3, to  $x + 1$ ); or at times at which serving a customer is finished (and at such times we go from a state  $x$  to  $x - 1$ ; note that there is no transition to the left from the point  $x = 0$  – because no customer is being served if there are no customers in the system). The possible transitions can be shown as follows:

$$0 \rightleftharpoons 1 \rightleftharpoons 2 \rightleftharpoons 3 \rightleftharpoons 4. \quad (11.5)$$

So we have  $a_{xy} = 0$  if  $|y - x| > 1$ .

Transitions from the point  $x = 0$  are possible only to the state  $y = 1$ ; the time before this happens is equal to the random variable  $U_1$ , whose distribution is exponential with parameter  $\lambda$ : so the first state change time  $\tau_1 = U_1$  if  $\xi_0 = 0$ ; so

$$v_0 = a_{01} = \lambda. \quad (11.6)$$

If we are at a state  $x > 0$  at time  $t = 0$ , the situation is more complicated: if a new customer comes – at the time  $U_1$  – *before* the service of the customer(s) currently being served is finished – at time  $S_{11}$  or  $S_{21}$  – then the system jumps to the state  $x + 1$ ; and if  $S_{11}$  or  $S_{21}$  is less than  $U_1$ , the customer that has been served leaves the system, and we go to the state  $x - 1$ .

If  $\xi_0 = x = 1$ , only one customer is being served at time  $t = 0$ ; suppose it (the customer = a car) is being served at pump number 1. Then we have:

$$\begin{cases} \tau_1 = U_1, & \xi_{\tau_1} = x + 1 & \text{if } U_1 < S_{11}, \\ \tau_1 = S_{11}, & \xi_{\tau_1} = x - 1 & \text{if } S_{11} < U_1. \end{cases} \quad (11.7)$$

We may think also of the case of  $U_1 = S_{11}$ , when the first service is ended *exactly* at the time that the first new customer comes (so the system remains in the same state at this time); but we have a feeling that it is practically impossible, and we'll see that it can be *proved* that  $P\{U_1 = S_{11}\} = 0$ .

So if  $U_1 \neq S_{11}$ , we have:

$$\tau_1 = \min(U_1, S_{11}). \quad (11.8)$$

We want to find the distribution of this random variable (if we discover that it is an exponential distribution, its parameter will be the value of  $v_x$ ); and find also the probabilities of the two alternatives in (11.7) (and these will be  $a_{x, x+1}/v_x$  and  $a_{x, x-1}/v_x$ ). To do this, let us write the joint density of the random variables  $U_1, S_{11}$ : since they are independent, we have

$$f_{U_1, S_{11}}(u, s) = f_{U_1}(u) \cdot f_{S_{11}}(s) = \begin{cases} 0 & \text{if } u \leq 0 \text{ or } s \leq 0, \\ \lambda\mu e^{-\lambda u - \mu s} & \text{if } u, s > 0. \end{cases} \quad (11.9)$$

First of all, the distribution of the random variable (11.8) is clearly continuous. To find its density, the standard way is to find the cumulative distribution function  $F_{\min(U_1, S_{11})}$  first:

$$F_{\min(U_1, S_{11})}(b) = P\{\min(U_1, S_{11}) \leq b\} = \begin{cases} 0 & \text{for } b < 0, \\ \iint_{\min(u, s) \leq b} f_{U_1, S_{11}}(u, s) \, du \, ds & \text{for } b \geq 0. \end{cases} \quad (11.10)$$

Since the integrand here is equal to 0 except for  $u$  and  $s$  positive, and given by the second formula (11.9) if they are positive, the integral in (11.10) is equal to

$$\iint_{0 < \min(u, s) \leq b} \lambda\mu e^{-\lambda u - \mu s} \, du \, ds. \quad (11.11)$$

Make a picture and show in it the angular-shaped range of integration  $\{(u, s) : 0 < \min(u, s) \leq b\}$ .

It is easier to find this probability through the probability of the opposite event: the integral (11.11) is equal to

$$\begin{aligned} 1 - \iint_{\min(u, s) > b} \lambda \mu e^{-\lambda u - \mu s} du ds &= 1 - \int_b^\infty \left[ \int_b^\infty \lambda \mu e^{-\lambda u - \mu s} ds \right] du \\ &= 1 - \int_b^\infty \lambda e^{-\lambda u} \cdot e^{-\mu b} du = 1 - e^{-(\lambda + \mu)b}. \end{aligned} \quad (11.12)$$

Differentiating the cumulative distribution function given by formulas (11.10),(11.12), we obtain:

$$f_{\min(U_1, S_{11})}(t) = \begin{cases} 0, & t \leq 0, \\ (\lambda + \mu) e^{-(\lambda + \mu)t}, & t > 0; \end{cases} \quad (11.13)$$

so the distribution is exponential with parameter  $\lambda + \mu$ , and we have:

$$v_1 = \lambda + \mu, \quad a_{11} = -\lambda - \mu. \quad (11.14)$$

As for the probabilities of the two alternatives in (11.7), we have:

$$\begin{aligned} P\{U_1 < S_{11}\} &= \iint_{u < s} f_{U_1, S_{11}}(u, s) du ds = \iint_{0 < u < s} \lambda \mu e^{-\lambda u - \mu s} du ds \\ &= \int_0^\infty \left[ \int_u^\infty \lambda \mu e^{-\lambda u - \mu s} ds \right] du = \int_0^\infty \lambda e^{-(\lambda + \mu)u} du = \frac{\lambda}{\lambda + \mu}, \end{aligned} \quad (11.15)$$

$$\begin{aligned} P\{S_{11} < U_1\} &= \iint_{0 < s < u} \lambda \mu e^{-\lambda u - \mu s} du ds \\ &= \int_0^\infty \left[ \int_s^\infty \lambda \mu e^{-\lambda u - \mu s} du \right] ds = \int_0^\infty \mu e^{-(\lambda + \mu)s} ds = \frac{\mu}{\lambda + \mu}; \end{aligned} \quad (11.16)$$

so

$$\frac{a_{12}}{v_1} = \frac{\lambda}{\lambda + \mu}, \quad \frac{a_{10}}{v_1} = \frac{\mu}{\lambda + \mu}, \quad (11.17)$$

and

$$a_{12} = \lambda, \quad a_{10} = \mu. \quad (11.18)$$

As for the promised equality  $P\{U_1 = S_{11}\} = 0$ , here is its proof:

$$P\{U_1 = S_{11}\} = \iint_{u=s} f_{U_1, S_{11}}(u, s) du ds = 0, \quad (11.19)$$

because this is an two-dimensional integral over a *line*, which has two-dimensional area equal to 0.

If the initial point  $\xi_0 = x > 2$  or  $3$ , then both pumps are serving their cars at time  $t = 0$ , and we have to consider the minimum

$$\tau_1 = \min(U_1, S_{11}, S_{12}); \quad (11.20)$$

the same kind of calculations, with a triple integral instead of double, leads us to

$$v_x = \lambda + 2\mu, \quad \pi_{x, x+1} = \frac{\lambda}{\lambda + 2\mu}, \quad \pi_{x, x-1} = \frac{2\mu}{\lambda + 2\mu}, \quad (11.21)$$

$$a_{x, x+1} = \lambda, \quad a_{x, x-1} = 2\mu. \quad (11.22)$$

Finally, if  $\xi_0 = x = 4$ , the number of customers in the system cannot increase,  $\tau_1 = \min(S_{11}, S_{21})$ , and

$$v_4 = -a_{44} = a_{43} = 3\mu. \quad (11.23)$$

So we can write the matrix  $A$  of rates:

$$A = \begin{pmatrix} -\lambda & \lambda & 0 & 0 & 0 \\ \mu & -\lambda - \mu & \lambda & 0 & 0 \\ 0 & 2\mu & -\lambda - 2\mu & \lambda & 0 \\ 0 & 0 & 2\mu & -\lambda - 2\mu & \lambda \\ 0 & 0 & 0 & 2\mu & -2\mu \end{pmatrix}. \quad (11.24)$$

This can be shown in the following scheme:

$$0 \begin{array}{c} \xrightarrow{\lambda} \\ \xleftarrow{\mu} \end{array} 1 \begin{array}{c} \xrightarrow{\lambda} \\ \xleftarrow{2\mu} \end{array} 2 \begin{array}{c} \xrightarrow{\lambda} \\ \xleftarrow{2\mu} \end{array} 3 \begin{array}{c} \xrightarrow{\lambda} \\ \xleftarrow{2\mu} \end{array} 4. \quad (11.25)$$

Let me start (only start) a new thing.

In the discrete-time case the whole family of  $n$ -step transition matrices  $P^n$  can be produced if we know only the one-step transition matrix  $P$ . Can all information about the family of transition matrices  $P^t$  in the continuous-time case be obtained from one matrix only? We suspect that this should be the rate matrix  $A$ .

It turns out that we can write some differential equations for the transition probabilities  $p(t, x, y)$  (or, which is the same: for the transition matrices  $P^t$ ). These equations were derived by A.N.Kolmogorov, and they are called *Kolmogorov equations*.

Let us start with the equalities

$$P^{t+h} = P^h \cdot P^t = P^t \cdot P^h, \quad (11.26)$$

or, for the entries of these matrices:

$$p(t+h, x, z) = \sum_y p(h, x, y) \cdot p(t, y, z) = \sum_y p(t, x, y) \cdot p(h, y, z). \quad (11.27)$$

Let us write the expression for the derivative  $\frac{d}{dt} p(t, x, z)$ :

$$\begin{aligned} \frac{d}{dt} p(t, x, z) &= \lim_{h \rightarrow 0} \frac{p(t+h, x, z) - p(t, x, z)}{h} = \lim_{h \rightarrow 0} \frac{\sum_y p(h, x, y) \cdot p(t, y, z) - p(t, x, z)}{h} \\ &= \lim_{h \rightarrow 0} \frac{\sum_y p(t, x, y) \cdot p(h, y, z) - p(t, x, z)}{h}. \end{aligned} \quad (11.28)$$

In the first representation, let us replace  $p(t, x, z)$  with  $\sum_y \delta_{xy} \cdot p(t, y, z)$ , in the second, with  $\sum_y p(t, x, y) \cdot \delta_{yz}$ . The limit (11.28) is equal to each of the two limits:

$$\lim_{h \rightarrow 0} \frac{\sum_y [p(h, x, y) - \delta_{xy}] \cdot p(t, y, z)}{h}, \quad \lim_{h \rightarrow 0} \frac{\sum_y p(t, x, y) \cdot [p(h, y, z) - \delta_{yz}]}{h}. \quad (11.29)$$

We know that  $\lim_{h \rightarrow 0^+} \frac{p(h, x, y) - \delta_{xy}}{h} = a_{xy}$  (same in the second limit, with  $a_{yz}$  instead of  $a_{xy}$ ); so it would seem that

$$\frac{d}{dt} p(t, x, z) = \sum_y a_{xy} \cdot p(t, y, z) = \sum_y p(t, x, y) \cdot a_{yz}. \quad (11.30)$$

In the matrix form it is

$$\frac{d}{dt} P^t = A P^t = P^t A. \quad (11.31)$$

However, I have to admit that it only *seems* so to us: we see only the direction in which we have to move. But there are awful gaps in our reasoning (which was no real reasoning, but only writing formulas). First of all,  $a_{xy}$  are only *right-hand* derivatives of  $p(t, x, y)$  at  $t = 0$ ; so what we have now is, at most, the statement about the right-hand derivative:  $\frac{d^+}{dt} P^t = A P^t = P^t A$ . And secondly, we can replace the limit of the sums by the sum of the limits in the case of *finite* sums (i. e., for the space  $X$ , over which  $y$  changes, being finite); for infinite sums we need some extra conditions.

We see that there is something to think about.

But with this to the next lecture.