

**Probability and statistics, 2022, Computer Science
Algorithmics, Undergraduate Course, Part II, lecturer:
Mirosław Kutylowski**

3- Stochastic Processes

Stochastic process

- Time dependent random variables : time+space
 - time: $1, 2, 3, 4, \dots$
 $t \in (0, +\infty)$
 - space: Ω
 - state: $X(t, \omega)$ where $t \in \text{Time}, \omega \in \Omega$

Examples:

- Trajectory of a particle



- Noise

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- Rain

- Messages in a communication bus

Examples:

- CPU usage

- microcontrollers power consumption

1) **Discrete time process**

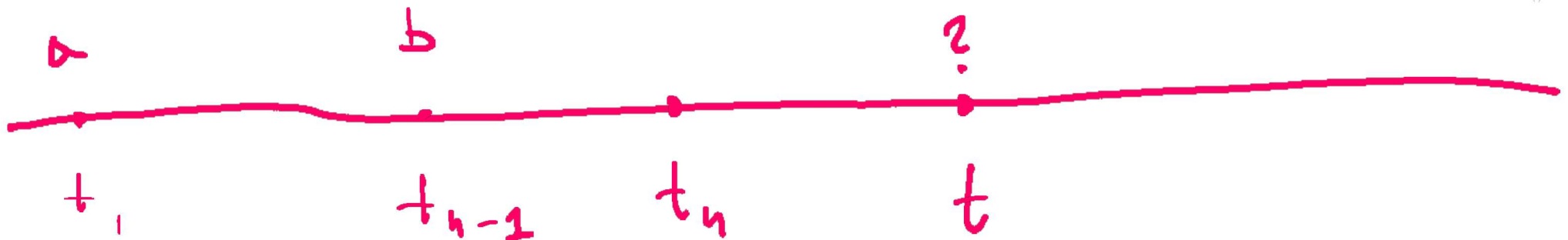
2) **Continuous time process**

Markov process

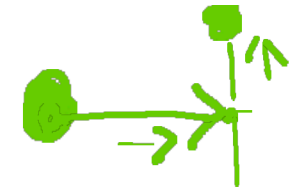
only the most recent state counts

Stochastic process $X(t)$ is Markov if for any $t_1 < \dots < t_n < t$ and any sets $A; A_1, \dots, A_n$

$$\begin{aligned} P \{X(t) \in A \mid X(t_1) \in A_1, \dots, X(t_n) \in A_n\} \\ = P \{X(t) \in A \mid X(t_n) \in A_n\}. \end{aligned} \quad (6.1)$$



Markov chain



- discrete Markov process
- **the state at time t+1 depends only on the state at time t**

$$\begin{aligned} p_{ij}(t) &= P \{X(t+1) = j \mid X(t) = i\} \\ &= P \{X(t+1) = j \mid X(t) = i, X(t-1) = h, X(t-2) = g, \dots\} \end{aligned}$$

Transition probability:

$$p_{ij}^{(t)}(t) = P \{X(t+1) = j \mid X(t) = i\}$$

Homogenous Markov chain

- Transition pbb does not depend on the time

$P_{ij}(t)$ is constant, notation: P_{ij}

P_{ij} = pbb pnajsia ze stanu i do j

- Transition matrix

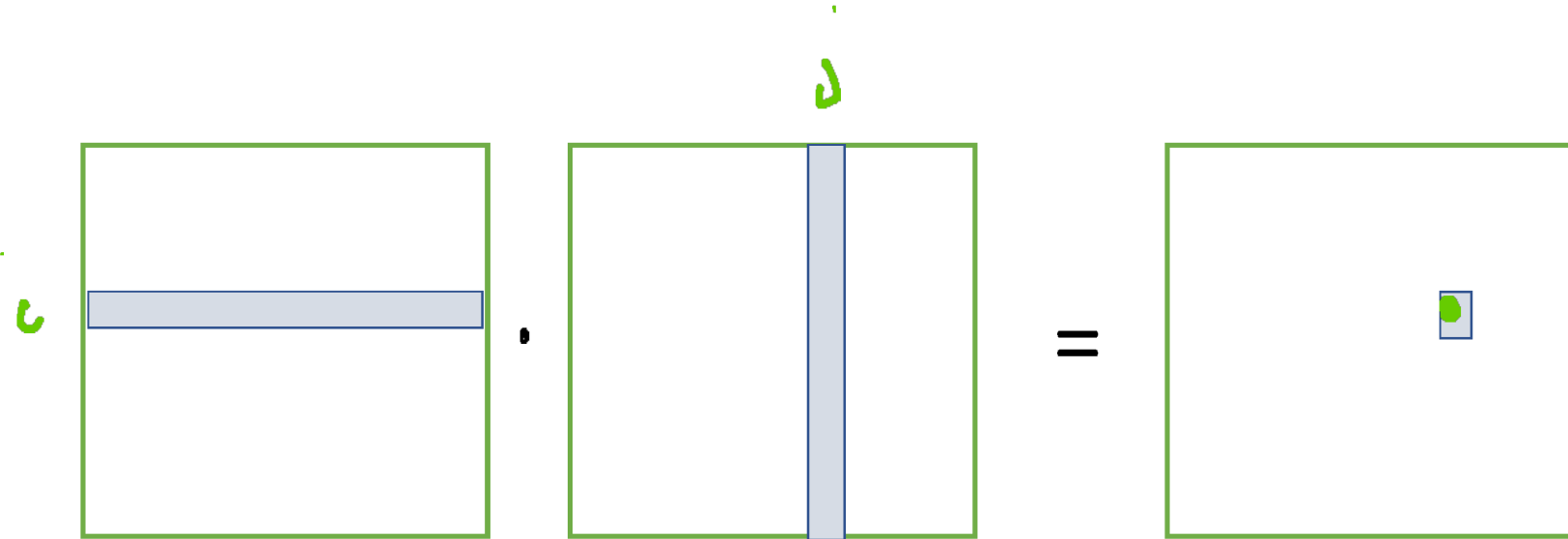
$$\begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix}$$

Transition in 2 steps



$$\begin{aligned} p_{ij}^{(2)} &= P\{X(2) = j \mid X(0) = i\} \\ &= \sum_{k=1}^n P\{X(1) = k \mid X(0) = i\} \cdot P\{X(2) = j \mid X(1) = k\} \\ &= \sum_{k=1}^n \underline{p_{ik}} p_{kj} = (p_{i1}, \dots, p_{in}) \begin{pmatrix} p_{1j} \\ \vdots \\ p_{nj} \end{pmatrix}. \end{aligned}$$

Transition pbb in two steps

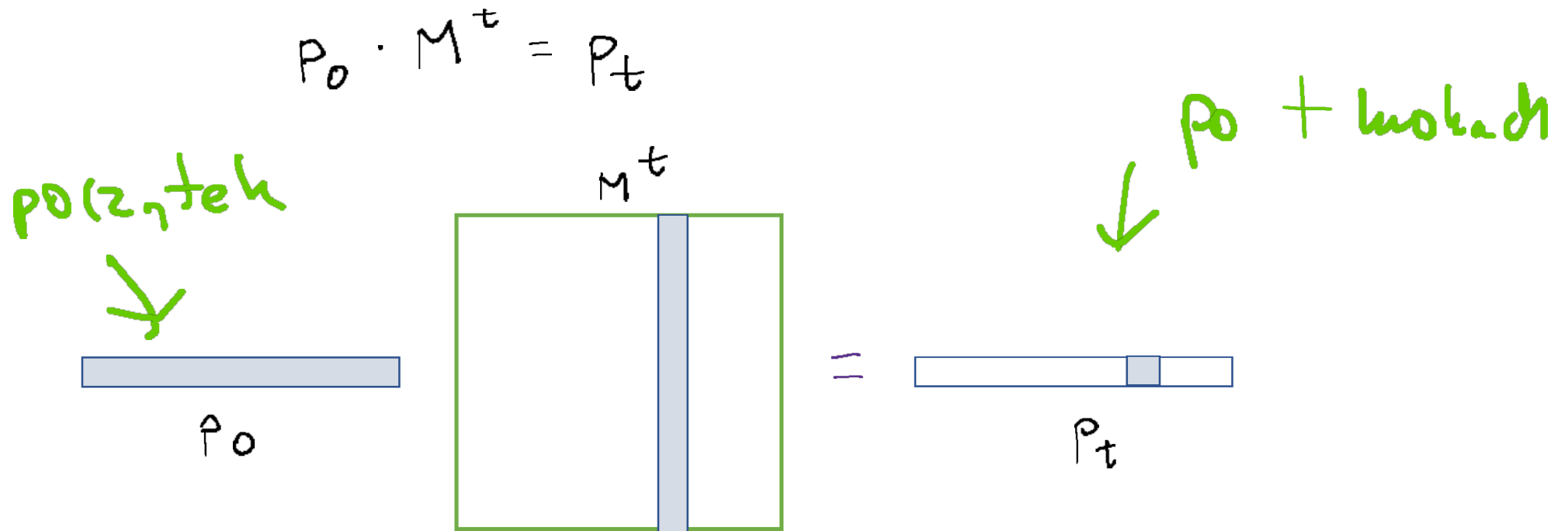


macierz przejścia T
dla 2 kroków T^2
 n kroków T^n

3-stochastic processes

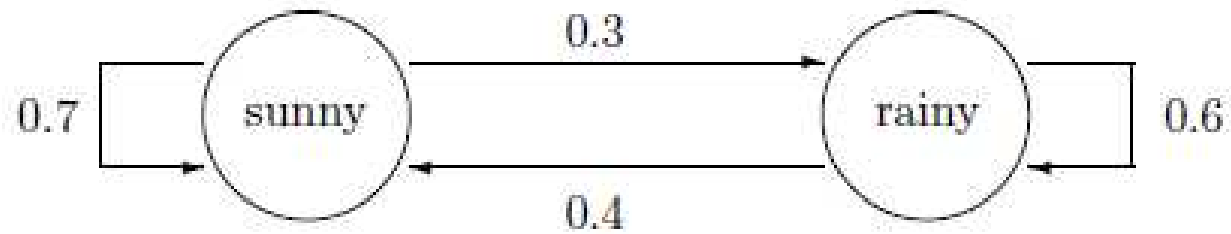
Probabilities at time t

- Transition matrix M of a homogenous chain



3-stochastic processes

Description via a Transition diagram



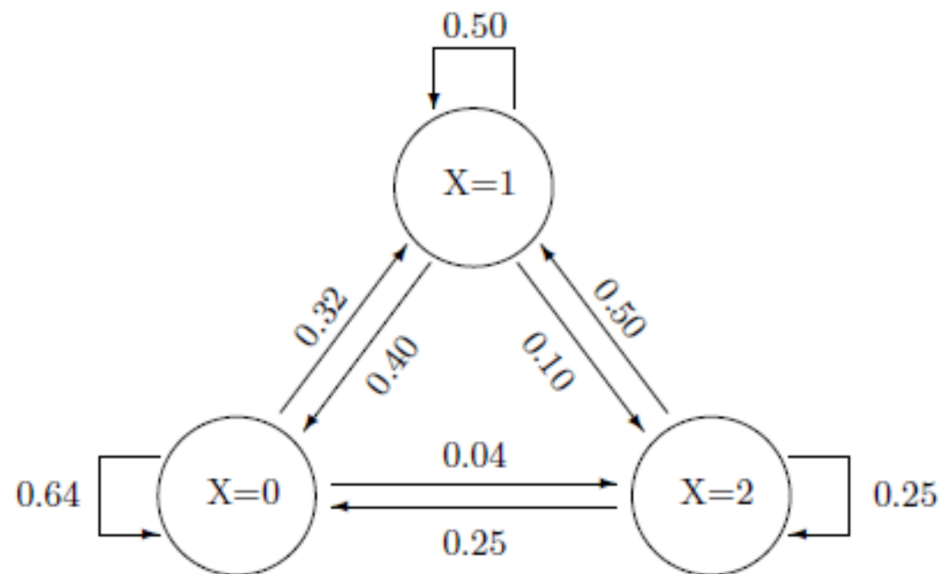
3-stochastic processes

Transition diagram

2 users: active user disconnects with pbb 0.5

inactive user connects with ppb 0.2

X = number of active users



3-stochastic processes

Steady state distribution

„eventually it does not depend on the initial state”

A collection of limiting probabilities

$$\pi_x = \lim_{h \rightarrow \infty} P_h(x)$$

is called a steady-state distribution of a Markov chain $X(t)$.

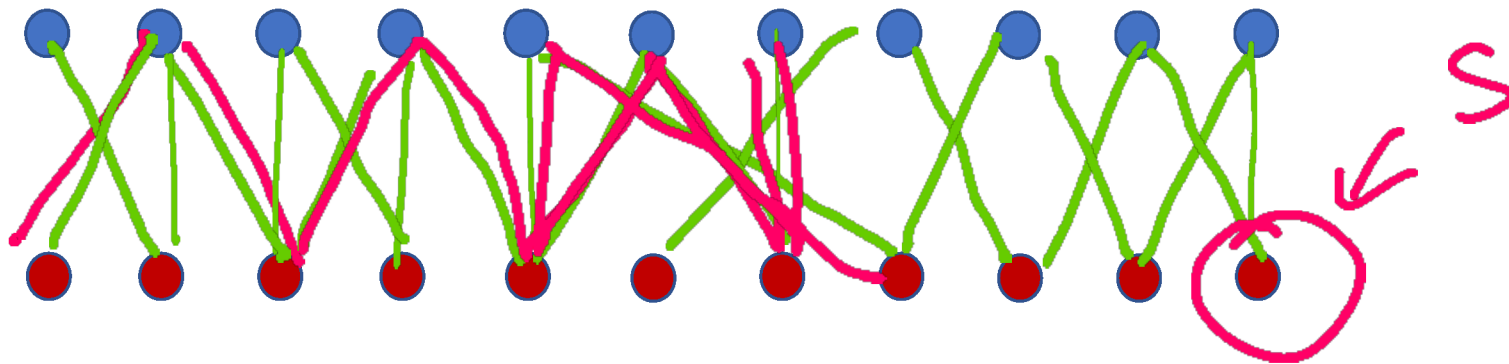
It is **not clear** in advance that a steady-state distribution **exists**

Another name used: ***stationary distribution***

Example: no steady state distribution

random walk in a bipartite graph

process
periodicity



parzyste kroki: na dale
nieparzyste: na górze

$$P_{17}(s) = 0$$
$$P_{18}(s) = ?$$
$$P_{19}(s) = 0$$

Computing steady state distribution

$$\underline{P_h P = P_0 P^h P = P_0 P^{h+1} = P_{h+1}.}$$

$$\pi P = \pi.$$

this is a system of linear equations. Moreover:

$$\underline{\sum \pi_i = 1}$$

(the probabilities must sum up to 1)

$$\begin{pmatrix} \pi_0 & \pi_1 \end{pmatrix} \begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{pmatrix} \pi_0 & \pi_1 \end{pmatrix}$$
$$\left\{ \begin{array}{l} \pi_0 \cdot a + \pi_1 \cdot b = \pi_0 \\ \pi_0 \cdot c + \pi_1 \cdot d = \pi_1 \end{array} \right.$$

Weather example cnt

$$(\pi_1, \pi_2) = (\pi_1, \pi_2) \begin{pmatrix} 0.7 & 0.3 \\ 0.4 & 0.6 \end{pmatrix} = (0.7\pi_1 + 0.4\pi_2, 0.3\pi_1 + 0.6\pi_2).$$

$$\begin{cases} 0.7\pi_1 + 0.4\pi_2 = \pi_1 \\ 0.3\pi_1 + 0.6\pi_2 = \pi_2 \end{cases} \Leftrightarrow \begin{cases} 0.4\pi_2 = 0.3\pi_1 \\ 0.3\pi_1 = 0.4\pi_2 \end{cases} \Leftrightarrow \pi_2 = \frac{3}{4}\pi_1.$$

$$\pi_1 + \pi_2 = \pi_1 + \frac{3}{4}\pi_1 = \frac{7}{4}\pi_1 = 1,$$

$$\underline{\pi_1 = 4/7} \text{ and } \underline{\pi_2 = 3/7}.$$

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