

CSE 107 3-8-24

## Supplemental Lecture

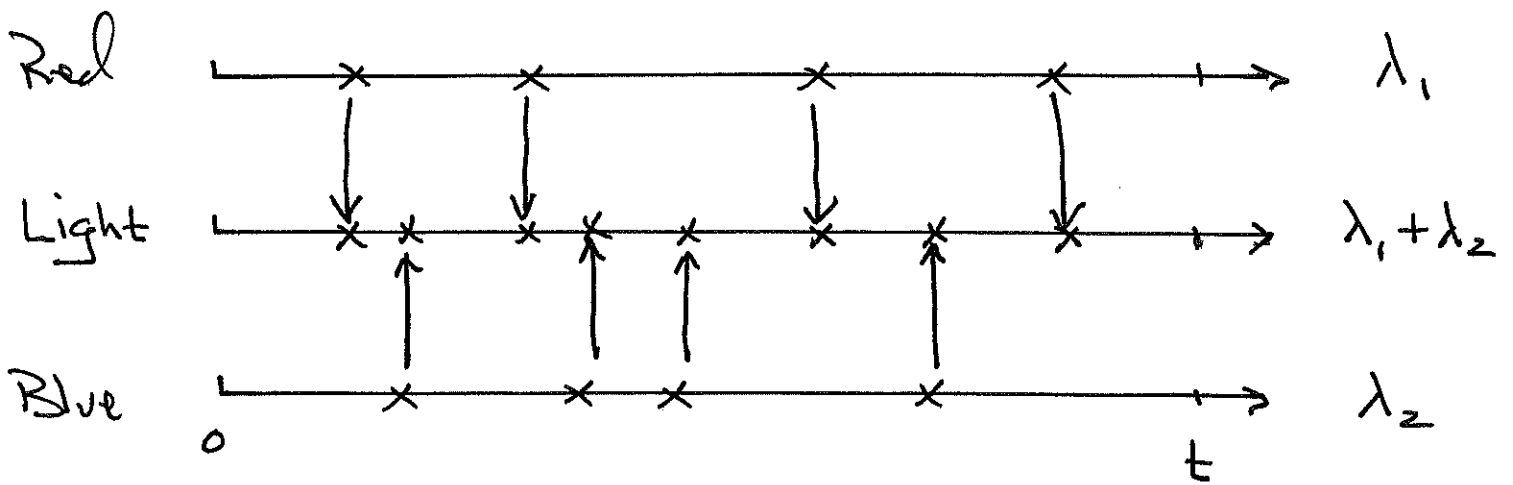
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### Merging Poisson Processes

Ex.

An observer sees 2 lights that flash at random times, one Red one Blue. The Red is a Poisson Process with rate  $\lambda_1$ , the Blue is Poisson with rate  $\lambda_2$ . The observer is colourblind and sees just flashing lights.

What kind of Process is the observer seeing?



Let

$$X = \# \text{ Red lights in } [0, t]$$

$$Y = \# \text{ Blue " " "}$$

$$M = \# \text{ lights " "}$$

we know  $X$  is a Poisson r.v. with parameter  $\lambda_1 t$ , and same for  $Y$  but with parameter  $\lambda_2 t$

we have  $M = X + Y$ , hence  $M$  is a Poisson r.v. with

Parameter

$$\lambda_1 t + \lambda_2 t = (\lambda_1 + \lambda_2) t$$

∴ the Process seen by the observer is Poisson with rate  $\lambda_1 + \lambda_2$ .

Ex.

Suppose observer sees a single flash. what is the Probability that it was Red?

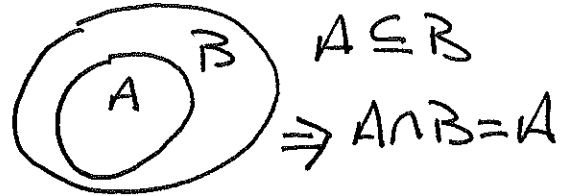
Solution 1

use small interval Probabilities.

Let  $\delta$  be the width of a small time interval containing the flash.

We seek

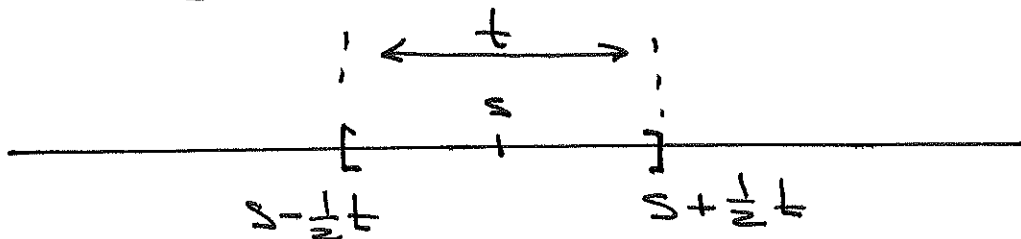
$$\begin{aligned}
 & P(1 \text{ Red} | 1 \text{ light}) \\
 &= \frac{P(1 \text{ Red}, 1 \text{ light})}{P(1 \text{ light})} \\
 &= \frac{P(1 \text{ Red})}{P(1 \text{ Light})} \\
 &= \frac{\lambda_1 s}{(\lambda_1 + \lambda_2) s} = \frac{\lambda_1}{\lambda_1 + \lambda_2}
 \end{aligned}$$



Solution 2

without small interval probabilities

⇒ suppose light flashes at time  $s$



consider an interval of width  $t$  centered at  $s$ .  $[s - \frac{1}{2}t, s + \frac{1}{2}t] = I_t$

We seek

$$P(1 \text{ Red in } I_t \mid 1 \text{ light in } I_t)$$

$$= \frac{P(1 \text{ Red in } I_t, 1 \text{ light in } I_t)}{P(1 \text{ light in } I_t)}$$

$$= \frac{P(1 \text{ Red in } I_t)}{P(1 \text{ light in } I_t)}$$

$$= \frac{e^{-\lambda_1 t} \cdot \frac{(\lambda_1 t)^1}{1!}}{e^{-(\lambda_1 + \lambda_2)t} \cdot \frac{(\lambda_1 + \lambda_2)t}{1!}}$$

$$= e^{\lambda_2 t} \cdot \frac{\lambda_1}{\lambda_1 + \lambda_2} \xrightarrow[t \rightarrow 0]{\text{as}} \frac{\lambda_1}{\lambda_1 + \lambda_2}$$



## 7.1 Discrete Markov Chains

we consider now Processes in which future does depend on the Past. That dependence is embodied by a state which changes over time. We always take set of states  $\mathcal{S}$  to be

$$\mathcal{S} = \{1, 2, 3, \dots, m\}.$$

Let  $X_0, X_1, X_2, \dots, X_n, \dots$  be a sequence of r.v.s taking values in  $\mathcal{S}$ . We consider

$X_n =$  the state at time  $n$ .

we define transition probabilities

$P_{ij}$  to be

$$P_{ij} = P(X_{n+1} = j | X_n = i)$$

for any  $i, j \in S$  and  $n \geq 0$ . This process satisfies the Markov Property

iff

$$\begin{aligned} &P(X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, \dots, X_1 = i_1, X_0 = i_0) \\ &= P(X_{n+1} = j | X_n = i) = P_{ij} \end{aligned}$$

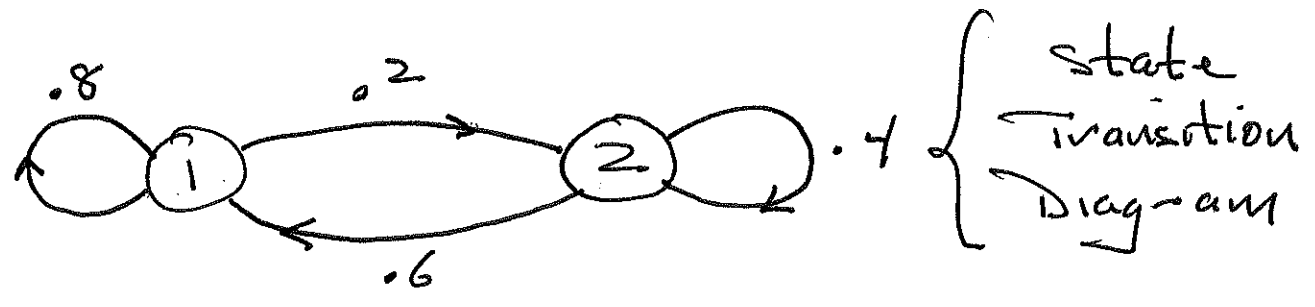
i.e. the next state depends on the past only through the immediately preceding state, not the entire history.

Defn

A Markov Chain Model is a random Process on state space  $\Omega$  and satisfying Markov Property.

Ex.  $M=2$ ,  $S=\{1, 2\}$  and

$P_{11} = .8, P_{12} = .2, P_{21} = .6, P_{22} = .4$



Suppose  $X_0 = 1$ . Find  $P(X_2 = 2)$

$$P(X_2 = 2) = P(X_2 = 2 | X_1 = 1) \cdot P(X_1 = 1) + P(X_2 = 2 | X_1 = 2) \cdot P(X_1 = 2)$$

By total Prob. thm.

$$= P_{12} \cdot \underbrace{P(X_1=1)}_{P_{11}} + P_{22} \cdot \underbrace{P(X_1=2)}_{P_{12}}$$

note:

$$\begin{aligned} P(X_1=1) &= P(X_1=1|X_0=1) \cdot \underbrace{P(X_0=1)}_1 \\ &\quad + P(X_1=1|X_0=2) \cdot \underbrace{P(X_0=2)}_0 \\ &= P_{11} \end{aligned}$$

Also  $P(X_1=2) = P(X_1=2|X_0=1) = P_{12}$

Thus

$$\begin{aligned} P(X_2=2) &= P_{12} \cdot P_{11} + P_{22} \cdot P_{12} = P_{11}P_{12} + P_{12}P_{22} \\ &= (.8)(.2) + (.2)(.4) \\ &= .16 + .08 = \boxed{.24} \end{aligned}$$

Similarly

$$P(X_2=1) = P_{11} \cdot P_{11} + P_{12}P_{21} = (.8)^2 + (.2)(.6) = \boxed{.76}$$

In the same manner, if  $X_0 = 2$ ,

then

$$P(X_2 = 1) = P_{21}P_{11} + P_{22}P_{21} = \boxed{.72}$$

and

$$P(X_2 = 2) = P_{21}P_{12} + P_{22}P_{22} = \boxed{.28}$$

We can summarize all these calculations using transition probability matrix.

$$R = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} = \begin{pmatrix} .8 & .2 \\ .6 & .4 \end{pmatrix}$$

↑ called a probability matrix.

observe

$$R^2 = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix}$$

$$= \begin{pmatrix} P_{11}^2 + P_{12}P_{21} & P_{11}P_{12} + P_{12}P_{22} \\ P_{21}P_{11} + P_{22}P_{21} & P_{21}P_{12} + P_{22}^2 \end{pmatrix}$$

$$= \begin{pmatrix} .76 & .24 \\ .72 & .28 \end{pmatrix}$$

Thus the  $ij^{\text{th}}$  element of  $R^2$  is the probability of going from state  $i$  to state  $j$  in exactly 2 steps.

Defn

The  $n$ -step transition probabilities are

$$r_{ij}(n) = P(X_n = j \mid X_0 = i)$$

for any  $i, j \in S$  and  $n \geq 0$ . Note  $P_{ij} = r_{ij}(1)$ . Thus  $r_{ij}(n)$  is Prob. of going from state  $i$  to state  $j$  in  $n$  steps.

Theorem Chapman-Kolmogorov equations.

$$r_{ij}(n) = \sum_{k=1}^n r_{ik}(n-1) \cdot P_{kj} \quad (i, j \in S, n \geq 2)$$