

Markov property for Continuous time Processes

$\{ P(X(t) = j \mid X(0) = i, X(t_{n-1}) = i_{n-1}, \dots, X(t_1) = i_1) \}$
 $= P(X(t) = j \mid X(0) = i)$; where $0 \leq t_1 \leq t_2 \leq \dots \leq t_{n-1} \leq s \leq t$; and
 $i_1, i_2, \dots, i_{n-1}, i, j \in S$ are $(n+1)$ states in the state space; $t, n \geq 1, n \in \mathbb{N}$.

This is called Markov Property (in continuous time).

Defⁿ (Continuous Time Markov Chain or CTMC).

A continuous-time stochastic process $\{X(u) | u \geq 0\}$ is called a continuous-time markov chain (CTMC) if it has the Markov property.

→ Memorylessness (Markov property).

→ time-homogeneity.

Defⁿ (Time Homogeneity).

We say that a CTMC is time-homogeneous if for any $s \leq t$ and any states $i, j \in S$

$$\begin{aligned}
 P(X(s) = j \mid X(0) = i) &= P(X(t-s) = j \mid X(0) = i) \\
 &= P(X(t_1) = j \mid X(t+s-t_1) = i)
 \end{aligned}$$

The key thing to note & so on.
is that the difference in the time argument is $(t-s)$.

Not all CTMC need be time-homogeneous
but in this course we will only consider
time-homogeneous CTMC!

Meaning of time-homogeneity.

Whenever the process enters state i ; the way it evolves probabilistically from that pt is the same as if the process started in State i at time 0.

Defⁿ (Holding time) :- When the process enters state i , the time it spends there before it leaves state i is called the holding time.

T_i := holding time in state i
(just like in our motivating example of the n-server system).

Proposition :- $T_i \sim \text{exponential } D^n$.

Recall ; $P_{i,j}$ = probability of going from State i to j

Similar to
Discrete
time
Markov
chain
generated by CamScanner

$q_{i,j}$ = rate at which the system goes from state i to j
(rate at which the exponential alarm clocks go off).

Here, in CTMC, both $p_{i,j}$ & $q_{i,j}$
are fⁿ of time:- $p_{i,j}(t)$ & $q_{i,j}(t)$

$$p_{i,j} = \frac{q_{i,j}}{v_i} ; v_i = \sum_{j \in S} q_{i,j} < \infty$$

By def, $[q_{ii} = 0]$

$$\Rightarrow q_{i,j} = v_i p_{i,j}$$

$(v_i = 0 \Rightarrow \text{state } i \text{ is absorbing state})$

The entries $p_{i,j}$ form a matrix
 $P = P(t)$ known as the Stochastic Matrix.

Note :- $q_{i,j}$ has more information about-
CTMC (continuous stochastic process)

than $p_{i,j}$ b/c if we know all

the $q_{i,j}$'s then we can find

v_i & $p_{i,j}$. But if we know

the $p_{i,j}$'s we cannot find $q_{i,j}$!

Later we will see that-
the $q_{i,j}$'s from a matrix
that is called matrix
generates the $p_{i,j}$.

- In many ways, $q_{i,j}$ are to CTMC
What the $p_{i,j}$ are to DTMC.

$q_{i,j} > 0$ but $q_{i,j}$ need not be ≤ 1 like
the $p_{i,j}$'s.

Stochastic Matrix

$P(t)$ comprise of $P_{ij}(t) = P(X(t) = j | X(0) = i)$

Note there is no "time step" in CTMC, instead we have $\phi_{ij}(t)$ which is a continuous f^{nq} time.

Often for CTMC; instead of writing $\phi_{ij}(t)$ we use uppercase $P_{i,j}(t) \triangleq \phi_{ij}(t)$

e.g if the CTMC is a poisson process; then

$$\begin{aligned} \phi_{ij}(t) &= P(\text{there are } j-i \text{ events (arrivals) in } t \text{ interval of time}) \\ &= \frac{(\lambda t)^{j-i} e^{-\lambda t}}{(j-i)!} \end{aligned}$$

Chapman - Kolmogorov eqn for CTMC.

$$\begin{aligned} P_{ij}(t+s) &= \sum_{k \in S} P_{kj}(s) P_{ik}(t) \\ &\equiv \sum_{k \in S} \phi_{ik}(t) \phi_{kj}(s) \end{aligned}$$

The above is the $(ij)^{\text{th}}$ entry of $P(t+s)$

$$P(t+s) = P(t) P(s)$$

Recall $T_i \sim \exp(\nu_i)$; $\nu_i = \sum q_{ij}$

$$\therefore f_{T_i}(h) = \nu_i e^{-\nu_i h}$$

$$\therefore P(T_i \leq h) = 1 - e^{-\nu_i h}$$

$$\Rightarrow P(T_i > h) = e^{-\nu_i h}$$

$$\begin{aligned} &\text{Taylor} \\ &\text{expand} \\ &\text{at } h=0 \end{aligned} \quad 1 - \nu_i h + \frac{(\nu_i h)^2}{2!} - \dots$$

$$= 1 - \nu_i h + \underbrace{\mathcal{O}(h)}_{\hookrightarrow \mathcal{O}(h^2)}$$

$$\Rightarrow P(T_i \leq h) = 1 - (1 - \nu_i h + \mathcal{O}(h)) \\ = \nu_i h + \mathcal{O}(h)$$

$$\therefore P(0 \text{ transitions by time } h | X(0) = i)$$

$$= P(T_i > h) = 1 - \nu_i h + \mathcal{O}(h)$$

$$P(\text{Exactly 1 transition by time } h | X(0) = i)$$

$$= 1 - P(0 \text{ transitions by time } h | X(0) = i)$$

$$= 1 - (1 - \nu_i h + \mathcal{O}(h)) = \nu_i h + \mathcal{O}(h)$$

& likewise, it can be shown that - Try it out yourself

$$P(2 \text{ or more transitions by time } h | X_0 = i)$$

$$= \mathcal{O}(h)$$

Now

$$P(X(h) = j | X(0) = i) = (\text{with } f_0(h)) p_{ij} + P(\text{exactly one event occurred})$$

or more events).
 p_{ij}

$$= v_i p_{ij} h + O(h) + O(h)$$

$$= v_i p_{ij} h + O(h) \quad \text{--- (I)}$$

Similarly.

$$P(X(h) = i | X(0) = i) = 1 - v_i h + O(h) + O(h)$$

$$= 1 - v_i h + O(h) \quad \text{--- (II)}$$

Further

$$p_{ij}(t+h) = P(X(t+h) = j | X(0) = i)$$

$\xrightarrow{\substack{\text{law of} \\ \text{total} \\ \text{prob.}}}$ $\sum_{k \in S} P(X(t+h) = j | X(h) = k, X(0) = i) \cdot P(X(h) = k | X(0) = i)$

$\xrightarrow{\substack{\text{Markov} \\ \text{prop.}}}$ $\sum_{k \in S} P(X(t+h) = j | X(h) = k) \cdot P(X(h) = k | X(0) = i)$

$\xrightarrow{\substack{\text{reset} \\ \text{on} \\ \text{time} \\ \text{homogeneity}}}$ $\sum_{k \in S} P(X(t+h) = j | X(0) = k) p_{ik}(h)$

$$= \sum_{k \in S} p_{kj}(t) f_{ik}(h)$$

Basically
Chapman
Kolmogorov

Using (I) & (II) above.

$$p_{ij}(t+h) = p_{ij}(t) (1 - v_i h + O(h)) + \sum_{k \neq i} p_{kj}(t) (v_i f_{ik} h + O(h))$$

or equivalently

$$P_{ij}(t+h) - P_{ij}(t) = -\nu_i P_{ij}(t)h + \sum_{k \neq i} p_{kj}(t) \nu_k P_{ik}^h + o(h)$$

Dividing by h ; taking limit $h \rightarrow 0$ & using $\nu_i P_{ik}^h = q_{ik}$

$$\boxed{P'_{ij}(t) = \sum_{k \neq i} q_{ik} p_{kj}(t) - \nu_i P_{ij}(t)} \quad (A.1)$$

or equivalently

$$\boxed{(P'(t))_{ij} = (G P(t))_{ij}} \quad (A.2)$$

or

$$\boxed{P'(t) = G P(t)} \quad (A.3)$$

(A.1), (A.2) & (A.3) are called Kolmogorov's

Backward Eqns.

w) the infinitesimal generator matrix G given by

$$\boxed{\begin{aligned} g_{ij} &= q_{ij} & i \neq j \\ g_{ii} &= -\nu_i \end{aligned}}$$

With bdy condⁿ $P(0) = I$

Identity matrix

Likewise, we have Kolmogorov's Fwd eqns

$$P'(t) = P(t) G \quad (B.1)$$

Kolmogorov's Bkwd & Fwd eqns, w/ the
bdy condn $P(0) = \mathbb{I}$, both have the
same soln

$$P(t) = e^{tG} := \mathbb{I} + tG + \frac{(tG)^2}{2!} + \dots \quad (C)$$

Even though we cannot normally obtain $P(t)$ in a simple closed form

We can use eqn(C) to obtain a numerical approx" to $P(t)$ if $|s|$ is finite by truncating the ∞ sum to a finite sum.

* the solution $P(t) = e^{tG}$ shows how basic the generator matrix G is to the properties of CTMC.

We will find, in the subsequent lectures, that G is also a key element for determining steady state Dⁿ of CTMC.

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Stny Distributions

pg(5)

Defn:- Let $\{X(t) | t \geq 0\}$ be a CTMC w/ state space S , generator G & matrix^Q transition probability $f^n P(t)$

An $|S|$ -dimensional (row) vector

$\vec{\pi} = (\pi_i)_{i \in S}$ w/ $\pi_i \geq 0 \forall i$ and

$\sum_{i \in S} \pi_i = 1$ is said to be a

Stationary Distribution if

$$\vec{\pi} = \vec{\pi} P(t) \quad \forall t \geq 0.$$

Question :- How does the generator G relate to the definition of Stny.

Ans:- $\vec{\pi}$ is a Stny distribution $\Leftrightarrow \vec{\pi} = \vec{\pi} P(t), \forall t \geq 0$

$$P = e^{tG} \quad \vec{\pi} = \sum_{n=0}^{\infty} \frac{(tG)^n}{n!}, \forall t \geq 0$$

from prov.
lecture on
Kolmogorov
eqns for
CTMC

$$\Leftrightarrow \vec{\pi} - \vec{\pi} = \sum_{n=1}^{\infty} \frac{t^n}{n!} \vec{\pi} G^n, \forall t \geq 0$$

$$\Leftrightarrow 0 = \vec{\pi} G^n \quad \forall n \geq 1$$

$$\Leftrightarrow \boxed{\vec{\pi} G = 0}$$

sum of
the terms
is zero if
and only
if each summand
is zero.

therefore the condition $\frac{d}{dt} \pi = \pi P(t) + t \geq 0$,
 that will be quite difficult to check,
 reduces to the much simpler condition

$$\boxed{\pi G = 0}$$

Always note $\sum_{i \in S} \pi_i = 0$.

\uparrow
 a set of $|S|$
 linear eqns.

i.e. $\pi_j v_j = \sum_{i \neq j} \pi_i q_{ij}$; $v_j = \sum_{i \in S} q_{ji}$

Physical interpretation:

long run
 proportion of time
 the process is in
 state j

rate of leaving
 state j when
 the process is
 in state j

long run rate of
 going from state
 i to state j

$$\Rightarrow \pi_j v_j = \text{long run rate of leaving state } j$$

$\Rightarrow \sum_{i \neq j} \pi_i q_{ij} = \text{long run rate of going to state } j$

$$\Rightarrow \text{"the long run rate out of state } j" = \text{"long run rate into state } j"$$

i.e. ~~that~~ it is a statement of dynamic equilibrium

& the eqn. $\pi G = 0$ is also called
 the Global Balance eqn / Balance eqn

Detailed Balance eqns. (Also known as Local Balance)

For a continuous time Markov Ch(CTMC) w/ transition matrix Q ; if π_i can be found s.t. for every pair of states i & j

$$\pi_i q_{ij} = \pi_j q_{ji} \quad \text{— (Detailed Balance condition)}$$

holds; then by summing over j ; the global balance eqns are satisfied & π is stny. Dⁿ of the process.

* If such a solution can be found the resulting eqns are usually much easier than directly solving the global balance eqns.

* A CTMC is reversible \Leftrightarrow detailed balance holds for every (i,j)

Note :- The equivalent detailed balance for DTMC is

$$\pi_i p_{ij} = \pi_j p_{ji} \quad \forall i,j \text{ pairs}$$

Limiting Probabilities -

for a CTMC $\{X(t) \mid t \geq 0\}$,

$$\lim_{t \rightarrow \infty} P_{ij}(t) = \lim_{t \rightarrow \infty} P(X(t) = j \mid X(0) = i)$$

$$\equiv \pi_j$$

i.e. limiting probability $\underset{(t \rightarrow \infty)}{\approx}$ stay prob. D^n .

Application of Local (detailed) Balance Equations

Local balance :- $\pi_i q_{ij} = \pi_j q_{ji}$ $\forall i, j \in S$
 if j

There are $|S| C_2$ such eqns.

but typically most of the eqns are trivially satisfied b/c

$$q_{ij} = q_{ji} = 0$$

* Recall thae for global balance (s.t. stay cond.) to exist; it is not necessary that local balance condn. ^{always} holds but if local balance does hold then surely global balance (& stay) do hold.

* One quick way to check if local balance does NOT hold for stationarity is to check if there are any rates

q_{ij} and q_{ji} s.t. $q_{ij} > 0$ and pg(7)

$q_{ji} = 0$ or $q_{ij} = 0$ & $q_{ji} > 0$.

(In these cases, the local balance route to investigating stationarity will be futile).

JK