## **Continious-Time Markov Chains** (CTMC)

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### **Definition of a CTMC**

- For the continuous-time Markov chain {X(t) : t
   ≥ 0} with N states, the Markov property can be written as
- $P[X(s + t) = j | X(s) = i, X(u) = x(u), 0 \le u < s] = P[X(s + t) = j | X(s) = i], i, j \in S, 0 \le t < \infty,$
- and reflects the fact that the future state at time s+t only depends on the current state at time s.

### transition probabilities functions

 We consider the special case of stationary transition probabilities functions (sometimes referred to as homogeneous transition probabilities functions), occurring when

 $P[X(s + t) = j | X(s) = i] = P[X(t) = j | X(0) = i] = P_{ij}(t)$ for all states i and j and for all times s > 0 and t > 0;

*P<sub>ij</sub>(t)* is called stationary transition probabilities
 i.e. the independence of s characterizes the stationarity.
 *and*

 $\boldsymbol{P}(t) = [P_{ij}(t)]$ 

*is called the transition probability matrix function* (*TPMF*).( a function of time compared to TPM)

#### **Behavior of a CTMC**



- $T_i$  = sojourn time in state i (random variable)
- $p_{ij}$  = probability of moving to state j when leaving state i

- **Proposition:** T<sub>i</sub> is exponentially distributed
- **Proof:** By time homogeneity, we assume that the process starts out in state *i*. For  $s \ge 0$  the event  $\{T_i > s\}$  is equivalent to the event  $\{X(u) = i \text{ for } 0 \le u \le s\}$ .
- Similarly, for s,  $t \ge 0$  the event  $\{T_i > s+t\}$  is equivalent to the event  $\{X(u) = i \text{ for } 0 \le u \le s + t\}$ .

- Therefore,
  - $P(T_i > s + t | T_i > s)$
  - $= P(X(u) = i \text{ for } 0 \le u \le s + t | X(u) = i \text{ for } 0 \le u \le s)$
  - $= P(X(u) = i \text{ for } s < u \le s + t | X(u) = i \text{ for } 0 \le u \le s)$
  - $= P(X(u) = i \text{ for } s < u \le s + t | X(s) = i)$
  - $= P(X(u) = i \text{ for } 0 < u \leq t | X(0) = i)$

 $= P(T_i > t),$ 

#### • where

- the second equality follows from the simple fact that  $P(A \cap B|A) = P(B|A)$ , where we let  $A = \{X(u) = i \text{ for } 0 \le u \le s\}$  and  $B = \{X(u) = i \text{ for } s < u \le s + t\}$ .

- the third equality follows from the Markov property.
- the fourth equality follows from time homogeneity.

Therefore, the distribution of  $T_i$  has the memoryless property, which implies that it is exponential.

• Papoulis (4<sup>th</sup> ed) pages 775-776

 $T_i \sim$  the waiting time for a change of state for a Markov process X(t), given that it is in state i at time 0. if  $T_i >$ s, then the process will be in the same state i at time t<sub>0</sub>+s as at t<sub>0</sub> and (being a Markov process) its subsequent behavior is independent of s. Hence,

 $P\{T_i > s + t \mid T_i > s\} = P\{T_i > t\} \triangleq \varphi_i(t)$ 

represents the probability that the event  $\{P(T_i > s + t\}$  given that  $P\{T_i > s\}$ . But

$$\varphi_i(t + s) = P\{T_i > s + t\} = P\{T_i > s + t, T_i > s\} = P\{T_i > s + t | T_i > s\} P\{T_i > s\} = \varphi_i(t)\varphi_i(s)$$

Or

$$log\varphi_i(t+s) = log\varphi_i(t) + log\varphi_i(s)$$

The only function satisfies above is either of the form ct (c=cte) or unbounded form above. Thus

$$log\varphi_i(t) = -\lambda_i(t) \qquad \varphi_i(t) = P\{T_i > t\} = e^{-\lambda_i(t)} \quad t \ge 0$$

Thus sojourn time has an exponential distribution for all Markov processes

### **Chapman-Kolmogorov equations**

- Lemma 1. (Chapman-Kolmogorov equations) For all  $s \ge 0$  and  $t \ge 0, P_{i,j}(s + t) = \sum_k P_{i,k}(s)P_{k,j}(t)$
- Or in matrix notation P(s + t) = P(s)P(t)
- Proof
- We can compute P<sub>i,j</sub>(s + t) by considering all possible places the chain could be at time s.
- We then condition and and uncondition, invoking the Markov property to simplify the conditioning; i.e.,

$$P_{i,j}(s + t) = P(X(s + t) = j | X(0) = i)$$

### **Chapman-Kolmogorov equations**

- Proof (cntd.)
- $=\sum_{k} P(X(s + t) = j,X(s) = k | X(0) = i)$
- $\sum_{k} P(X(s) = k | X(0) = i)P(X(s + t) = j | X(s) = k,X(0) = i)$ (conditioning on X(s)=k)
- $= \sum_{k} P(X(s) = k | X(0) = i) P(X(s + t) = j | X(s) = k)$

(Markov property) (uncondition)

=  $\sum_{k} P_{i,k}(s) P_{k,j}(t)$  (stationary transition probabilities)

## **Describing a CTMC**

- A CTMC is well specified if we specify:
- (1) its initial probability distribution –
   p(X(0) = i) for all states i
- (2) its transition probabilities P<sub>i,j</sub>(t) for all states i and j and positive times t.
- Thus we use these two elements to compute the distribution of X(t) for each t,
- $P(X(t) = j) = \sum_{i} P(X(0) = i) P_{i,j}(t)$

### **Describing a CTMC**

 Since the CTMC must be at any time in one of the N states, the analogous of DTMC is, for any state i

$$\sum_{j=1}^{N} P_{i,j}(t) = 1$$

# constructing a CTMC model- four approaches(models)

- for all four models:
- the initial distribution are required and thus we focus on specifying the model beyond the initial distribution.
- The four models are equivalent: you can get to each from any of the others.
- Even though these four approaches are redundant, they are useful because they together give a different more comprehensive view of a CTMC.

 For the DTMC with transition matrix P (looking at the transition epochs of the CTMC thus p<sub>ii</sub>=0), the transition probabilities of the embedded chain

$$p_{i,j} = \lim_{\Delta t \to 0} P\{X_{t+\Delta t} = j | X_{t+\Delta t} \neq i, X_t = i\}$$

$$= \lim_{\Delta t \to 0} \frac{P\{X_{t+\Delta t} = j, X_{t+\Delta t} \neq i | X_t = i\}}{P\{X_{t+\Delta t} \neq i | X_t = i\}}$$

$$= \begin{cases} \frac{q_{i,j}}{\sum_j q_{i,j}} & i \neq j & \text{cf. } P\{\min(X_1, \dots, X_n) = X_i\} = \frac{\lambda_i}{\lambda_1 + \dots + \lambda_n}, \text{ when } X_i \sim Exp(\lambda_i) \\ 0 & i = j \end{cases}$$

the second line numerator and denominator are divided by  $\Delta t$ , and defining

$$q_{i,j} = \lim_{\Delta t \to 0} \frac{P[X_{t+\Delta t} = j, X_{t+\Delta t} \neq i | X_{t+\Delta t} = i]}{\Delta t} \qquad i \neq j$$

- Markov process, transition rates q<sub>i,i</sub>
- equilibrium probabilities  $\tilde{\pi}_{i}$



- Embedded Markov chain(EMC), transition probabilities p<sub>i,i</sub>
- equilibrium probabilities  $\pi_i$



 For this DTMC (EMC) the steady state probability vector is π, the unique probability vector satisfying the equation

 $\pi = \pi P \qquad (1)$ 

 Instead of having each transition take unit time, now we assume that the time required to make a transition from state *i* has an exponential distribution with rate q<sub>i</sub>, and thus mean 1/q<sub>i</sub>, independent of the history before reaching state i.

- Relating the steady-state (stationary) probability vector  $\tilde{\pi}$  of the CTMC to steady state probability vector of DTMC (EMC)  $\pi$
- $\tilde{\pi}_{j} = \frac{(\pi_{j}/q_{j})}{\sum_{k} (\pi_{k}/q_{k})} \quad (2) (1/q_{j} \text{ is life time in state } i \text{ slide 18})$
- Indeed, this first modelling approach corresponds to treating the CTMC as a special case of a semi-Markov process (SMP)
- We assume that there are no one-step transitions from any state to itself in the DTMC (no self-loop); i.e., we assume that P<sub>i,i</sub> = 0 for all i (we look at the chain at transitions)
- this assumption is not critical, (see the third modelling)

Markov processes have no self-loops and their state transitions are characterized by a *generator matrix*, which is analogous to a probability transition matrix. The classification of states have analogous statements for Markov processes where the probability transition matrix is replaced by a generator matrix.

The generator matrix of a Markov process, denoted by *Q*, has entries that are the rates at which the process jumps from state to state. These entries are defined by

$$q_{i,j} = \lim_{\tau \to 0} \frac{P[X(t+\tau)=j|X(t)=i]}{\tau} \qquad i \neq j \quad (3')$$

(We assume that the Markov process is time homogeneous and thus that (3')  $\{q_{i,j} = \lim_{\tau \to 0} \frac{P[X(t+\tau)=j|X(t)=i]}{\tau} | i \neq j\}$  is independent of *t*.)

The total rate out of state i is denoted by  $q_i$  and equals  $q_i = \sum_{j \neq i}^{\infty} q_{i,j}$  (4')

The holding time of state i is exponentially distributed with rate  $q_i$ .

By definition, we set the diagonal entries of Q equal to minus the total rate,

$$q_{i,i} = -q_i$$
 (5')

This implies that the row sums of matrix *Q* equal 0.

• **stationary probabilities** in terms of the generator matrix. Using the results of EMC in SMP (i.e.  $\tilde{\pi}_j = \frac{\pi^{e_j} E[S_j]}{\sum_{k \in S} \pi^{e_k} E[S_k]}$ ,  $i \in S$ , ) and multiplying (2) by  $q_{ji}$  and summing yields [and using (5')  $q_{i,i} = -q_i$  and  $\pi_i = \sum_{j \neq i} \pi_j p_{j,i} = \sum_{j \neq i} \pi_j \frac{q_{j,i}}{q_j}$ slide 12]

$$\sum_{j=0}^{\infty} \tilde{\pi}_{j} q_{ji} = \frac{\sum_{j=0}^{\infty} (\pi_{j} q_{ji}/q_{j})}{\sum_{k} (\pi_{k}/q_{k})} = \frac{\sum_{j\neq i} (\pi_{j} q_{ji}/q_{j}) + \pi_{i} q_{ii}/q_{i}}{\sum_{k} (\pi_{k}/q_{k})}$$
$$= \frac{\pi_{i} - \pi_{i}}{\sum_{k} (\pi_{k}/q_{k})} = \mathbf{0} \quad [\text{nel (8.65)}]$$

Rewriting in matrix form, shows that the stationary probabilities of a Markov process satisfy π Q = 0, with the additional normalization requirement that ||π|| = 1.

- We look at the chain at any time (so we need to define zero-time transition probabilities, P<sub>i,i</sub>(0) = 1 since there is no instant jump from a state)
- let P(0) = I, where I is the identity matrix; i.e., we set P<sub>i,i</sub>(0) = 1 for all i and we set P<sub>i,j</sub>(0) = 0 whenever i ≠ j.
- We define  $Q \equiv \lim_{h \downarrow 0} \frac{P(h) I}{h} = \lim_{h \downarrow 0} \frac{P(h) P(0)}{h}$
- = P'(0+) (it is rate)

See Ross prob. Models 9<sup>th</sup> ed. ch 6 page 378

• Thus the transition rate from state i to state j be defined in terms of the derivatives:

$$Q_{i,j} \equiv \lim_{h \downarrow 0} \frac{P_{i,j}(h) - P_{i,j}(0)}{h} = P'_{i,j}(0+) = \frac{dP_{i,j}(t)}{dt} |_{t=0+}$$
(3)  
$$Q_{i,i} \equiv \lim_{h \downarrow 0} \frac{P_{i,i}(h) - P_{i,i}(0)}{h} = \frac{P_{i,i}(h) - 1}{h} = P'_{i,i}(0+) = \frac{dP_{i,i}(t)}{dt} |_{t=0+}$$

 in most treatments of CTMC's instead of above, it is common to assume that

$$P_{i,j}(h) = Q_{i,j}h + o(h) as h↓0 if j ≠ i (4) and
 $P_{i,i}(h) - 1 = Q_{i,i}h + o(h) as h↓0,$  (5)$$

- For finite state space, (for infinite state spaces under extra regularity conditions ), we have
- $Q_{i,i} = \sum_{j,j \neq i} Q_{i,j}(t)$  (6)

**Proof:** since  $P_{i,j}(t)$  sum over j to 1  $\sum_{i=1}^{N} P_{i,i}(t) = 1$  so  $P_{i,i}(t) + \sum_{i=1, i \neq i}^{N} P_{i,i}(t) = 1$ 

 $\sum_{j=1, j \neq i}^{N} P_{i,j}(t) = 1 - P_{i,i}(t)$ 

Dividing by t and let  $t \rightarrow 0$  we obtain (6)

And let

$$-Q_{i,i} = q_i$$
 (7) for all i,

- Same as DTMC model that is specified via a transition probability matrix P, we can specify a CTMC model via the transition-rate matrix Q.
- In specifying the transition-rate matrix Q, it suffices to specify the off-diagonal elements

 $Q_{i,j}$  for  $i \neq j$ , because the diagonal elements  $Q_{i,i}$  are always defined by (6).

- The off-diagonal elements are always nonnegative, whereas the diagonal elements are always negative.
- Each row sum of Q is zero.

- In fact, this approach to CTMC modelling is perhaps best related to modelling with ordinary differential equations,
- We may use Chapman-Kolmogorov equations to find the transition probabilities P<sub>i,j</sub>(t) from the transition rates Q<sub>i,j</sub> ≡ P'<sub>i,j</sub>(0+)
- To do this we use the two systems of ordinary differential equations (ODE's) generated by the transition rates namely, Kolmogorov forward and backward ODE's (defined next).

**Theorem 1.** (Kolmogorov forward and backward ODE's) The transition probabilities satisfy both the Kolmogorov forward differential equations  $P'_{i,j}(t + h) = \sum_k P_{i,k}(t)Q_{k,j}(h)$  for all i, j (9) in matrix notation is the matrix ODE

 $P'(t) = P(t)Q \quad (10)$ 

and the Kolmogorov backward differential equations

 $P'_{i,j}(h + t) = \sum_{k} Q_{i,k}(h) P_{k,j}(t) \quad for \ all \ i, j \quad (11)$ in matrix notation is the matrix ODE  $P'(t) = QP(t) \quad (12)$ 

Proof: We apply the Chapman-Kolmogorov equations to write

P(t + h) = P(t)P(h) ,

and then do an asymptotic analysis as h  $\downarrow$  0.

We subtract P(t) from both sides and divide by
 h, to get

$$\frac{P(t+h) - P(t)}{h} = P(t) \frac{P(h) - I}{h}$$

where *I* is the identity matrix

- Recalling that I = P(0), we can let  $h \downarrow 0$  to get the desired result (10).
- To get the backward equation (12), we start with

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P(t + h) = P(h + t) = P(h)P(t)
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and reason in the same way

- Example (Transient Probabilities for the M/M/1 Queue)
- Note that given that the initial state at time 0 was state i,

$$P_{i,j}(t + \Delta t) = \sum_{k=0}^{\infty} P_{i,k}(\Delta t) P_{k,j}(t)$$
  
=  $\sum_{k \neq i} P_{i,k}(\Delta t) P_{k,j}(t) + P_{i,i}(\Delta t) P_{i,j}(t).$  (8.118)

$$\frac{P_{i,j}(t+\Delta t)-P_{i,j}(t)}{\Delta t} = \sum_{k\neq i} \frac{P_{i,k}(\Delta t)}{\Delta t} P_{k,j}(t) - \frac{1-P_{i,i}(\Delta t)}{\Delta t} P_{i,j}(t).$$

Thus we find chapman-Kolmogorov backward equation. Nel page 379

$$\frac{dP_{i,j}(t)}{dt} = \sum_{k \neq i} q_{i,k} P_{k,j}(t) - q_i P_{i,j}(t).$$

- Example (Transient Probabilities for the M/M/1 Queue)
- Note that given that the initial state at time 0 was state i,
- Writing the forward equation for the *MIMI1* queue yields

• 
$$\frac{dP_{i,0}(t)}{dt} = \mu P_{i,1}(t) - \lambda P_{i,0}(t),$$

• 
$$\frac{dP_{i,j}(t)}{dt} = \mu P_{i,j+1}(t) + \lambda P_{i,j-1}(t) - (\lambda + \mu) P_{i,j}(t).$$

• **Example (Cntd.)** The solution to these equations for this case is then given by

$$P_{i,j}(t) = e^{-(\lambda + \mu)} \begin{bmatrix} \rho^{(j-i)/2} I_{j-i}(\alpha t) + \rho^{(j-i-1)/2} I_{j+i+1}(\alpha t) \\ + (1-\rho)\rho^{j} \sum_{k=j+i+2} \rho^{-k/2} I_{k}(\alpha t) \end{bmatrix}$$

• where  $\rho = \frac{\lambda}{\mu}$  and  $\alpha = 2 \mu \sqrt{\rho}$  and

• 
$$I_k(x) = \sum_{m=0}^{\infty} \frac{\left(\frac{x}{2}\right)^{k+2m}}{(k+m)!m!} \qquad k \ge -1$$

is the series expansion for the modified Bessel function of the first kind.

- **Example (Cntd.)** It is difficult to have any intuition regarding the solution except for its limiting, and thus stationary, values.
- (no need for normalization eq. since initial condition P(0) =(0,...0, 1,0,,...) being in state i at t=0 (p<sub>ii</sub>(0)=1) is an extra equation)
- In the third term (i.e. coefficient  $(1 \rho)\rho^{j}$ ) we see factors corresponding to the stationary distribution.
- it must be  $\lim_{t\to\infty} P_{i,j}(t) = (1-\rho)\rho^j$  independent of i.
- The solution of transient probabilities suggests that :
- $\lim_{t\to\infty} e^{-(\lambda+\mu)} \rho^{(j-i)/2} I_{j-i}(\alpha t) = 0$
- $\lim_{t\to\infty} e^{-(\lambda + \mu)} \rho^{(j-i-1)/2} I_{j+i+1}(\alpha t) = 0$
- $\lim_{t \to \infty} e^{-(\lambda + \mu)} \sum_{k=j+i+2} \rho^{-k/2} I_k(\alpha t) = 1$

- Equations (10 &12) are matrix ODE's in t that can be similarly solved as the scalar ODE f'(t)=qf(t) and have matrix exponential solution.
- (P(0) = I, the initial condition plays no role) In particular, as a consequence of Theorem 1, and If all entries of *Q* are bounded, (*Q* is said to be uniform: the name comes from uniformization of CTMC in model 4) we have the following Theorem2.
- Q<sub>i,j</sub>=∞ means instantaneous jump from state *I* upon entering this state

• **Theorem 2**. (matrix exponential representation) The transition function can be expressed as a matrix-exponential function of the rate matrix Q, i.e.,

$$P(t) = e^{Qt} = \sum_{n=0}^{\infty} \frac{Q^n t^n}{n!}$$
 (13)

This matrix exponential is the unique solution to the two ODE's with initial condition P(0) = I.

 Proof: If we verify or assume that we can interchange summation and differentiation in (13), we can check that the displayed matrix exponential satisfies the two ODE's

$$P'(t) = \frac{d}{dt} \sum_{n=0}^{\infty} \frac{Q^n t^n}{n!} = \sum_{n=0}^{\infty} \frac{d}{dt} \frac{Q^n t^n}{n!}$$
$$= \sum_{n=0}^{\infty} \frac{nQ^n t^{n-1}}{n!} = Q \sum_{n=0}^{\infty} \frac{Q^n t^n}{n!} = Qe^{Qt}$$
  
Note: limiting prob of ctmc(ross, 9<sup>th</sup>, page 384)

#### Summary of some Models of Markov Processes

Type of Process		Self-Loops	Holding Time
Semi-Markov Processes		No	Arbitrary
Markov chains	Model 1	Yes	$H_i = 1$
	Model 2	No	Geometric, $E[H_i] = (1 - p_{i,i})^{-1}$
Markov processes	Continuous time	No	Exponential, $E[H_i] = q_i^{-1}$
	Uniformized–Model 1	Yes	$H_i = 1$
	Uniformized–Model 2	No	Geometric, $E[H_i] = q_{\max}/q_i$