Continuous Time Markov Chains (CTMC)

Definition of a CTMC

Transient Solution

Embedded MC of a CTMC

Classification of States

Steady State

Semi-Markov Process

Finite Absorbing Chains

Stochastic Network Modeling (SNM)

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II. Discrete Time Markov Chains (DTMC)
III. Continuous Time Markov Chains (CTMC)
IV. Queuing Theory

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Properties of a continuous time MC

- The states must be a numerable set.
- Let $X(t)$ be the event {at time t the system is in state i}, then it must hold the memoryless property:

$$\boxed{\begin{aligned} &P\big(X(t_n) = i \mid X(t_1) = j, X(t_2) = k, \ldots\big) = \\ &\qquad P\big(X(t_n) = i \mid X(t_1) = j\big) \text{ for any } t_n > t_1 > t_2 > t_3 \ldots \end{aligned}}$$

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Transition Matrix

- Transition probabilities:

$$p_{ij}(t_1, t_2) = P\big(X(t_2) = j \mid X(t_1) = i\big)$$

- For an homogeneous chain:

$$p_{ij}(t) = P\big(X(t_1 + t) = j \mid X(t_1) = i\big) =$$
$$= P\big(X(t) = j \mid X(0) = i\big),\ \forall t_1$$

- In matrix form (transition probability matrix):

$$\mathbf{P}(t) = \begin{bmatrix} p_{11}(t) & p_{12}(t) & \cdots \\ p_{21}(t) & p_{22}(t) & \cdots \\ \cdots & \cdots & \cdots \end{bmatrix},\ t \geq 0$$

- Notes:
  - Compare with the n-step prob. matrix of a DTMC: $\mathbf{P}(n)$.
  - $\mathbf{P}(t)$ must be a stochastic matrix (all rows add to 1).

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Definition of a CTMC

Transition Matrix

$$p_{ij}(t) = P\big(X(t) = j \mid X(0) = i\big),\ t \geq 0$$

- We look for an equivalent 1-step prob. matrix **P** of DTMCs.
- For consistency: $\lim_{t\to 0} p_{ij}(t) = \delta_{ij}$. In matrix form:

$$\lim_{t\to 0} \mathbf{P}(t) = \mathbf{I}.$$

- And assume that the following transition rates exist:

$$q_{ij} = \lim_{t\to 0} \frac{p_{ij}(t)}{t},\ i \neq j; \quad q_{ii} = \lim_{t\to 0} \frac{p_{ii}(t) - 1}{t}$$

- In matrix form: $\mathbf{Q} = \lim_{t\to 0} \frac{\mathbf{P}(t) - \mathbf{I}}{t}$
- Note that $\sum_j p_{ij}(t) = 1 \Rightarrow p_{ii}(t) = 1 - \sum_{j\neq i} p_{ij}(t)$, thus:

$$q_{ii} = \lim_{t\to 0} \frac{p_{ii}(t) - 1}{t} = \lim_{t\to 0} \frac{-\sum_{j\neq i} p_{ij}(t)}{t} = -\sum_{j\neq i} q_{ij}$$

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Transition Matrix

- The matrix $\mathbf{Q}$ is called the transition rate or infinitesimal generator of the chain.
- Since $q_{ii} = -\sum_{j \neq i} q_{ij}$, all the rows of $\mathbf{Q}$ add to 0.
- The rate q_{ij}, $i \neq j$ measures "how fast" the chain moves from state i to j: the higher is q_{ij}, the faster it moves from i to j.
- For $q_{ii} = -\sum_{j \neq i} q_{ij}$, the higher $-q_{ii}$ is, the faster the chain leaves state i.
- If $q_{ij} = 0, \forall j \Rightarrow q_{ii} = 0$, then i is an absorbing state: the chain "moves with rate 0 from i to other states", i.e. never leaves i.

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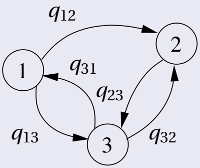
State Transition Diagram

- A continuous MC is characterized by the transition rate or infinitesimal generator: the Q-matrix.
- The state transition diagram is now represented as:



$$\Rightarrow \mathbf{Q} = \begin{bmatrix} -(q_{12}+q_{13}) & q_{12} & q_{13} \\ 0 & -q_{23} & q_{23} \\ q_{31} & q_{32} & -(q_{31}+q_{32}) \end{bmatrix}$$

- Note that now we have transition rates ($0 \le q_{ij} < \infty$, $i \ne j$) and not probabilities.
- The rates q_{ii} are not written in the diagram, no self transitions.

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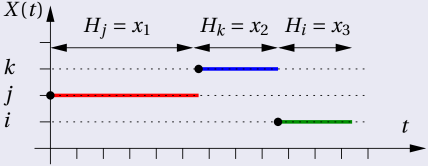
Sojourn Time

- Sojourn or holding time: Is the RV H_k equal to the sojourn time in state k:

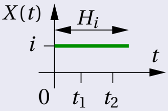


- The Markov property implies that the sojourn time is exponentially distributed with parameter q_{ii}:

$$\boxed{P(H_i \le x) = 1 - e^{q_{ii}x} \Rightarrow P(H_i > x) = e^{q_{ii}x},\ q_{ii} = -\sum_{j \ne i} q_{ij},\ x \ge 0}$$

Definition of a CTMC

The exponential distribution satisfies the Markov property



- Markov property (memoryless):

$$P\big(X(t_2) = i \mid X(t_1) = i, X(0) = i\big) =$$
$$P\big(X(t_2) = i \mid X(t_1) = i\big),\ t_2 > t_1 > 0$$

- In terms of the sojourn time:

$$P\big(H_i > t_2 \mid H_i > t_1\big) = P(H_i > t_2 - t_1)$$

- But:

$$P\big(H_i > t_2 \mid H_i > t_1\big) =$$
$$\frac{P(H_i > t_2, H_i > t_1)}{P(H_i > t_1)} = \frac{P(H_i > t_2)}{P(H_i > t_1)} = \frac{e^{q_{ii}\,t_2}}{e^{q_{ii}\,t_1}} = e^{q_{ii}\,(t_2 - t_1)} =$$
$$P(H_i > t_2 - t_1) \quad \square$$

- The exponential distribution is the only one satisfying the memoryless property.

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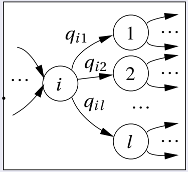
Exponential Jumps Description of a CTMC

Assume a process built as follows:



- Upon reaching a state i
  1. the process can jump to a state $j \in \{1, 2, \cdots l\}$.
  2. A set of independent exponential RVs, $\{H_{i1}, H_{i2}, \cdots H_{il}\}$, with parameters $\{q_{i1}, q_{i1}, \cdots q_{il}\}$ are triggered. That is, $P(H_{ij} \le t) = 1 - e^{-q_{ij} t}$, $t \ge 0$.
- If $\min\{H_{i1}, H_{i2}, \cdots H_{il}\} = H_{ij} \Rightarrow$ the process jumps to the state j. In other words, a transition occurs to state j if the RV H_{ij} is the minimum of $\{H_{i1}, H_{i2}, \cdots H_{il}\}$.

Theorem: This process is a CTMC with transition rates q_{ij}.

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Exponential Jumps Description of a CTMC

$$P(H_{ij} \le t) = 1 - \mathrm{e}^{-q_{ij}\,t}.$$

Theorem: This process is a CTMC with transition rates q_{ij}.

Proof:

- The RV $H_i = \min\{H_{i1}, H_{i2}, \cdots H_{il}\}$ (sojourn time in state i) is exponentially distributed with parameter $q_i = \sum_j q_{ij}$: $P(H_i \le t) = 1 - \mathrm{e}^{-q_i\,t}$.
- $P(\min\{H_{i1}, H_{i2}, \cdots H_{il}\} = H_{ij}) = q_{ij}/\sum_j q_{ij}$. Thus, the transition rate to state j is:

$$\lim_{t\to 0} \frac{p_{ij}(t)}{t} = \lim_{t\to 0} \frac{P(\min\{H_{i1}, H_{i2}, \cdots H_{il}\} = H_{ij}) \times P(H_i \le t)}{t} =$$

$$\frac{q_{ij}}{\sum_j q_{ij}} \left.\frac{\partial P(H_i \le t)}{\partial t}\right|_{t=0} = \frac{q_{ij}}{\sum_j q_{ij}} \sum_j q_{ij} = q_{ij} \quad \square$$

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Example: Pure Aloha System

- Consider a Pure Aloha System with 2 nodes:
  - Nodes in thinking state Tx a packet in a time exponentially distributed with rate λ.
  - Transmission time is exponentially distributed with rate μ.
  - If two transmissions overlap, the packet is lost and stations become backlogged (after the packet transmission) until the packet is successfully transmitted.
  - Nodes in backlogged state Tx a packet in a time exponentially distributed with rate α.

Questions

- Build the state transition diagram.

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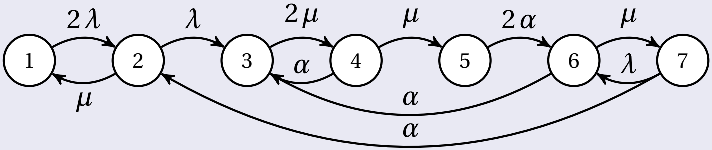
Example: Pure Aloha System



State	Condition
1	T,T
2	X,T
3	C,C
4	B,C
5	B,B
6	X,B
7	T,B

Legend	
T	Thinking
X	Transmitting
C	Collided transmission
B	Backlogged

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Chapman-Kolmogorov Equations

- Chapman-Kolmogorov: $p_{ij}(t) = \sum_k p_{ik}(t-\alpha) p_{kj}(\alpha), 0 \le \alpha \le t$
- Thus:
$$\frac{p_{ij}(t+\Delta t) - p_{ij}(t)}{\Delta t} = \sum_k \left\{ \frac{p_{ik}(t+\Delta t-\alpha) - p_{ik}(t-\alpha)}{\Delta t} p_{kj}(\alpha) \right\}$$
- Taking the limit
$$\alpha \to t, \Delta t \to 0 \Rightarrow \begin{cases} p_{ik}(t-\alpha) \to 0, & i \ne k \\ p_{ik}(t-\alpha) \to 1, & i = k \end{cases}$$

and using:

$$\begin{cases} q_{ij} = \lim_{t \to 0} \dfrac{p_{ij}(t)}{t}, & i \ne j \\ q_{ij} = \lim_{t \to 0} \dfrac{p_{ij}(t)-1}{t}, & i = j \end{cases}$$

we have:

$$\boxed{\frac{\partial p_{ij}(t)}{\partial t} = \sum_k q_{ik}\, p_{kj}(t), \quad t \ge 0, \forall i,j}$$

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Chapman-Kolmogorov Equations (cont)

- we have: $\dfrac{\partial p_{ij}(t)}{\partial t} = \sum_k q_{ik}\, p_{kj}(t),\ t \geq 0,\ \forall i,j$
- In matrix form: $\boxed{\dfrac{\partial \mathbf{P}(t)}{\partial t} = \mathbf{Q}\,\mathbf{P}(t),\ t \geq 0}$ known as the master equations of a CTMC.
- The solution of the previous matrix differential equation is the exponential matrix:

$$\boxed{\mathbf{P}(t) = e^{\mathbf{Q}\,t} = \sum_{i=0}^{\infty} \frac{(\mathbf{Q}\,t)^i}{i!} = \mathbf{I} + \mathbf{Q}\,t + \frac{\mathbf{Q}^2\,t^2}{2!} + \frac{\mathbf{Q}^3\,t^3}{3!} + \cdots,\ t \geq 0}$$

- Due to rounding errors, the previous series is difficult to compute numerically (the powers of $\mathbf{Q}$ have positive and negative entries).

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State Probabilities

- Define the probability of being in state i at time t:

$$\boxed{\pi_i(t) = P(X(t) = i)}$$

- In vector form (row vector)

$$\boldsymbol{\pi}(t) = (\pi_1(t), \pi_2(t), \cdots).$$

- Clearly:

$$\pi_i(t) = \sum_k P(X(0) = k)\, P\big(X(t) = i \mid X(0) = k\big) = \sum_k \pi_k(0)\, p_{ki}(t)$$

- In matrix form:

$$\boxed{\boldsymbol{\pi}(t) = \boldsymbol{\pi}(0)\, \mathbf{P}(t) = \boldsymbol{\pi}(0)\, e^{\mathbf{Q}\, t},\ t \geq 0}$$

where $\boldsymbol{\pi}(0)$ is the initial distribution.

- NOTE: Compare with DTMC

$$\boldsymbol{\pi}(n) = \boldsymbol{\pi}(0)\, \mathbf{P}^n,\ n \geq 0$$

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Transient Solution

- If we are interested in the transient evolution we shall study $\boldsymbol{\pi}(t) = \boldsymbol{\pi}(0)\,\mathbf{P}(t) = \boldsymbol{\pi}(0)\,\mathrm{e}^{\mathbf{Q}\,t}$, $t \geq 0$.
- Assume a finite CTMC with N states (infinitesimal generator $\mathbf{Q}^{N\times N}$).
- Assume that $\mathbf{Q}$ can be diagonalized: $\mathbf{Q} = \mathbf{L}^{-1}\,\Lambda\,\mathbf{L}$, where Λ is the diagonal matrix $\Lambda = \mathrm{diag}(\lambda_1, \cdots \lambda_N)$, with λ_l, $l = 1, \cdots N$ the eigenvalues of $\mathbf{Q}$.
- NOTE: the eigenvalues λ_l of a matrix $\mathbf{A}$ are scalars that satisfy: $\boldsymbol{l}\mathbf{A} = \lambda_l\,\boldsymbol{l}$ (or $\mathbf{A}\,\boldsymbol{r} = \lambda_l\,\boldsymbol{r}$) for some row vectors $\boldsymbol{l}$ (column vectors $\boldsymbol{r}$), referred to as *left* and *right* eigenvectors, respectively. Thus, solve the characteristic polynomial $\det(\lambda\,\mathbf{I} - \mathbf{A}) = 0$.

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Transient Solution

... assume that $\mathbf{Q}$ can be diagonalized: $\mathbf{Q} = \mathbf{L}^{-1}\,\Lambda\,\mathbf{L}$

- Since

$$\mathbf{P}(t) = e^{\mathbf{Q}\,t} = \sum_{i=0}^{\infty} \frac{(\mathbf{Q}\,t)^i}{i!} = \sum_{i=0}^{\infty} \frac{(\mathbf{L}^{-1}\,\Lambda\,\mathbf{L}\,t)^i}{i!} =$$

$$\mathbf{L}^{-1}\,\mathrm{diag}\left(\sum_{i=0}^{\infty} \frac{(\lambda_1\,t)^i}{i!}, \cdots\right)\mathbf{L} = \mathbf{L}^{-1}\,\mathrm{diag}(e^{\lambda_1\,t}, \cdots)\,\mathbf{L}$$

we have that

$$\boxed{\begin{aligned}&\boldsymbol{\pi}(t) = \boldsymbol{\pi}(0)\,e^{\mathbf{Q}\,t} = \\ &\quad \boldsymbol{\pi}(0)\,\mathbf{L}^{-1}\,\mathrm{diag}(e^{\lambda_1\,t}, e^{\lambda_2\,t}, \cdots e^{\lambda_L\,t})\,\mathbf{L}\end{aligned}}$$

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Transient Solution

... we have that $\boldsymbol{\pi}(t) = \boldsymbol{\pi}(0)\, \mathbf{L}^{-1}\, \mathrm{diag}(e^{\lambda_1 t}, e^{\lambda_2 t}, \cdots e^{\lambda_L t})\, \mathbf{L}$

- Thus, the probability of being in state i is given by:

$$\boxed{\pi_i(t) = (\boldsymbol{\pi}(t))_i = \sum_{l=1}^{N} a_i^{(l)}\, e^{\lambda_l t},\ t \geq 0}$$

where the unknown coefficients $a_i^{(l)}$ can be obtained solving the system of equations:

$$\boxed{\left.\frac{\partial^n \pi_i(t)}{\partial t^n}\right|_{t=0} = (\boldsymbol{\pi}(0)\, \mathbf{Q}^n)_i,\ n = 0, \cdots N-1}$$

NOTE: Compare with $(\boldsymbol{\pi}(n))_i = (\boldsymbol{\pi}(0)\, \mathbf{P}^n)_i,\ n = 0, \cdots N-1$

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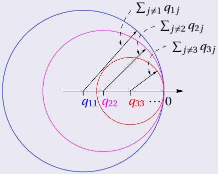
Eigenvalues of an Infinitesimal Generator

- $\mathbf{Q}$ has an eigenvalue equal to 0 ($\mathbf{Q}\,\boldsymbol{x} = \lambda\,\boldsymbol{x}$, for $\lambda = 0$, $\boldsymbol{x} \neq \mathbf{0}$).
  Proof: $\mathbf{Q}\,\mathbf{e} = \mathbf{0}$, where $\mathbf{e} = (1, 1, \cdots)^{\mathrm{T}}$ is a column vector of 1 (all rows of $\mathbf{Q}$ add to 0). $\square$
- The eigenvalue $\lambda = 0$ is single if $\mathbf{Q}$ is irreducible (Perron-Frobenius theorem). $\mathbf{Q}$ is irreducible if all states communicate: for $t > 0$, $p_{ij}(t) > 0$, $\forall i, j$.
- All eigenvalues of $\mathbf{Q}$ are $\lambda_l \leq 0$.

Proof: Using Gerschgorin's theorem and the fact that the rows of $\mathbf{Q}$ add to 0. $\square$



Gershgorin discs of a rate matrix

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Example

- Assume a CTMC with

$$\mathbf{Q} = \begin{bmatrix} -1 & 1 \\ 1/2 & -1/2 \end{bmatrix}$$

- We want the probability of being in state 2 at time t starting from state 1: $\pi_2(t)$ with $\boldsymbol{\pi}(0) = \begin{bmatrix} 1 & 0 \end{bmatrix}$.

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Solution

- It can be easily found that the eigenvalues of $\mathbf{Q}$ are $\lambda_1 = 0$ and $\lambda_2 = -3/2$.

$$\pi_2(t) = a\mathrm{e}^{\lambda_1 t} + b\mathrm{e}^{\lambda_2 t} = a + b\mathrm{e}^{-(3/2)\,t}$$

- Imposing the boundary conditions:

$$\pi_2(0) = a + b = (\boldsymbol{\pi}(0)\,\mathbf{Q}^0)_2 = (\boldsymbol{\pi}(0)\,\mathbf{I})_2 = (\boldsymbol{\pi}(0))_2 = 0$$

$$\left.\frac{\partial \pi_2(t)}{\partial t}\right|_{t=0} = b(-3/2) = (\boldsymbol{\pi}(0)\,\mathbf{Q})_2 = \mathbf{Q}_{12} = 1$$

we have that $a = 2/3$, $b = -2/3$, thus:

$$\pi_2(t) = 2/3\,(1 - \mathrm{e}^{-(3/2)\,t}), \quad t \geq 0$$

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Chain with a Defective Matrix

- What if $\mathbf{Q}$ cannot be diagonalized? (defective matrix).
- Let λ_l, $l = 1, \cdots L$ be the eigenvalues of $\mathbf{Q}^{N\times N}$, each with multiplicity k_l ($k_l \geq 1$, $\sum_l k_l = N$). Then [1]:

$$\boxed{\pi_j(t) = \sum_{l=1}^{L} \mathrm{e}^{\lambda_l t} \sum_{m=0}^{k_l-1} a_j^{(l,m)}\, t^m}$$

where $a_j^{(l,m)}$ are constants. So, exponentials associated with eigenvalues λ_l of multiplicity $k_l > 1$ are multiplied by polynomials in t of degree $k_l - 1$.

[1] Llorenç Cerdà-Alabern. *Transient Solution of Markov Chains Using the Uniformized Vandermonde Method*. Tech. rep. UPC-DAC-RR-XCSD-2010-2. Universitat Politècnica de Catalunya, Dec. 2010. URL: `https://www.ac.upc.edu/app/research-reports/html/research_center_index-XCSD-2010,en.html`.

Transient Solution

Example

- Assume the CTMC:

$$\begin{tikzcd} 1 \arrow[r, bend left, "1"] & 2 \arrow[r, bend left, "1"] & 3 \end{tikzcd} \qquad \mathbf{Q} = \begin{bmatrix} -1 & 1 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\pi(0) = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

- We have $\lambda_1 = 0$ and $\lambda_2 = -1$ with multiplicity 2. Thus:

$$\pi_3(t) = a + e^{-t}(b + c\,t)$$

- We have that $a = 1$, because state 3 is absorbing. Imposing $\pi_3(0) = 0$ and $\pi'_3(0) = 0$, we have $b = c = -1$, and

$$\boxed{\pi_3(t) = 1 - e^{-t}(1 + t),\ t \geq 0}$$

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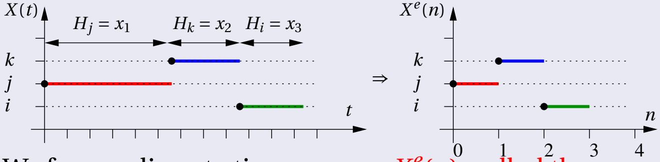
Embedded MC of a CTMC

Definition



- We form a discrete time process $X^e(n)$, called the *Embedded MC (EMC)*, by looking a CTMC at the transition time instants.

> **Theorem:** This process is a DTMC with transition probabilities:
>
> $$p^e_{ij} = \begin{cases} 0, & i = j \\ \dfrac{q_{ij}}{\sum_{j \neq i} q_{ij}}, & i \neq j \end{cases}$$

- NOTE: If i is absorbing ($q_{ii} = 0$), we define $p^e_{ii} = 1$.

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Embedded MC of a CTMC

Proof

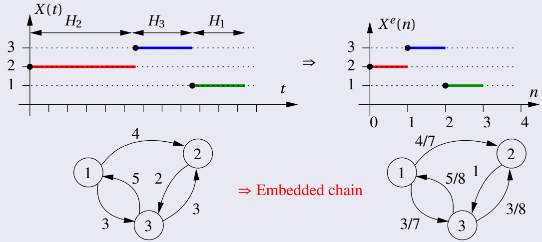
Theorem: This process is a DTMC with transition probabilities:

$$p^e_{ij} = \begin{cases} 0, & i = j \\ \dfrac{q_{ij}}{\sum_{j \neq i} q_{ij}}, & i \neq j \end{cases}$$

- The EMC satisfies the memoryless property.
- Since we look the system only upon transition to a different state: $p^e_{ii} = 0$. NOTE: it might be $p^e_{ii} \neq 0$ if we look at transitions that end up in the same state.
- The probability that there is a transition from state i to j in the CTMC is the probability that the exponentially distributed RV with parameter q_{ij} is the minimum from the independent exponentially distributed RVs with parameters $\{q_{ik}\}_{k \neq i}$. This probability is $q_{ij} / \sum_{k \neq i} q_{ik}$. □

Embedded MC of a CTMC

Example



$$\mathbf{Q} = \begin{bmatrix} -7 & 4 & 3 \\ 0 & -2 & 2 \\ 5 & 3 & -8 \end{bmatrix} \Rightarrow \quad \mathbf{P}_e = \begin{bmatrix} 0 & 4/7 & 3/7 \\ 0 & 0 & 1 \\ 5/8 & 3/8 & 0 \end{bmatrix}$$

- Each transition in the CTMC is a transition in the EMC.
- One step in i in the EMC is a sojourn time H_i in the CTMC.

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Classification of States

Irreducibility

- A state j is said to communicate with i, $i \leftrightarrow j$, if $p_{ij}(t_1) > 0$, $p_{ji}(t_2) > 0$ for some $t_1 \geq 0$, $t_2 \geq 0$.
- We define an irreducible closed set, ICS C_k as a set where all states communicate with each other, and have no transitions to other states out of the set: $i \leftrightarrow j, \forall i, j \in C_k$ and $q_{ij} = 0, \forall i \in C_k, j \notin C_k$
- An absorbing state form an ICS of only one element. This state, i, must have $q_{ij} = 0\ \forall i, j$.
- Transient states do not belong to any ICS.
- A MC is irreducible if all the states form a unique ICS.

Classification of States

Irreducibility

- Assume a MC has M ICSs: By properly numbering the states, we can write $\mathbf{P}$ as an M block diagonal matrix with the probabilities of the transient states in the last rows.
- Example, if $M = 3$:

$$\mathbf{Q} = \begin{array}{|c|c|c|c|} \hline \mathbf{Q}_1 & \multicolumn{3}{c|}{\mathbf{0}} \\ \cline{1-2} \mathbf{0} & \mathbf{Q}_2 & & \\ \cline{2-3} & & \mathbf{Q}_3 & \\ \hline \multicolumn{3}{|c|}{\text{at least one} > 0} & \mathbf{T} \\ \hline \end{array} \Rightarrow \boldsymbol{\pi}(t) = \boldsymbol{\pi}(0)\, e^{\mathbf{Q}\,t} = \boldsymbol{\pi}(0) \begin{array}{|c|c|c|c|} \hline e^{\mathbf{Q}_1 t} & \multicolumn{3}{c|}{\mathbf{0}} \\ \cline{1-2} \mathbf{0} & e^{\mathbf{Q}_2 t} & & \\ \cline{2-3} & & e^{\mathbf{Q}_3 t} & \\ \hline \multicolumn{3}{|c|}{\text{at least one} > 0} & e^{\mathbf{T} t} \\ \hline \end{array}$$

- Note that the M sub-matrices are infinitesimal generators (their rows add to 0).

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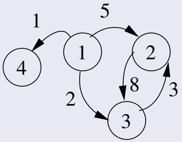
Transient and Recurrent

- Recurrent: States that, being visited, have a probability > 0 of being visited again. They are visited an infinite number of times when $t \to \infty$.
- Transient: States that, being visited, have a probability > 0 of never being visited again. They are visited a finite number of times when $t \to \infty$.
- Absorbing: A single (recurrent) state where the chain remains with probability $= 1$.



State 1 is transient
States 2 and 3 are recurrent
State 4 is absorbing

Continuous Time Markov Chains (CTMC)

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Transient and Recurrent

- To derive a classification criteria, we shall study the embedded MC (EMC), and proceed as in DTMC: Let $f_{ij}^e(n)$ the first passage prob. of the EMC, and $f_{ij}^e = \sum_{n=1}^{\infty} f_{ij}^e(n)$.
- If $f_{ii}^e = 1$ we say i is a recurrent state.
- If $f_{ii}^e < 1$ we say i is a transient state.
- When $f_{ij}^e = 1$, we define the mean recurrence time of the EMC $m_{ij}^e = \sum_{n=1}^{\infty} n f_{ij}^e(n)$. NOTE: in steps, not time units.
- If $m_{ii}^e = \infty$ the state is null recurrent.
- If $m_{ii}^e < \infty$ the state is positive recurrent.
- NOTEs: (i) Even if the EMC is periodic, there are not periodic CTMC (it has no sense). (ii) f_{ij}^e and m_{ij}^e can be computed using the recursive equations for DTMC.

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Mean recurrence time of the CTMC

- If the chain is in i at a time t, it takes an expected time to leave i equal to $1/(-q_{ii}) = 1/\sum_{j\neq i} q_{ij}$ (sojourn time exponentially distributed with rate $q_i = -q_{ii} = \sum_{j\neq i} q_{ij}$).
- Thus, if the chain is in state i, it takes a mean time to enter state j (mean first passage time):

$$\boxed{m_{ij} = \frac{1}{q_i} + \sum_{k\neq i} p^e_{ik} m_{kj}}$$

- Since: $p^e_{ij} = \begin{cases} 0, & i = j \\ \dfrac{q_{ij}}{\sum_{j\neq i} q_{ij}} = \dfrac{q_{ij}}{q_i}, & i \neq j \end{cases}$ we have:

$$\boxed{m_{ij} = \frac{1}{q_i} + \sum_{k\neq i} p^e_{ik} m_{kj} = \frac{1}{q_i} + \sum_{k\neq i} \frac{q_{ik}}{q_i} m_{kj} \text{ [time units]}}$$

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Limiting Distribution

- The probability to be in state i at time t is:
  $\pi_i(t) = P(X(t) = i) = \sum_k \pi_k(0)\, p_{ki}(t),\ t \geq 0$
- In matrix form: $\boldsymbol{\pi}(t) = \boldsymbol{\pi}(0)\,\mathbf{P}(t) = \boldsymbol{\pi}(0)\, e^{\mathbf{Q}\,t},\ t \geq 0$
- Assume that the following limit exists:

$$\boldsymbol{\pi}(\infty) = \lim_{t\to\infty} \boldsymbol{\pi}(t) = \lim_{t\to\infty} \boldsymbol{\pi}(0)\,\mathbf{P}(t) = \boldsymbol{\pi}(0) \lim_{t\to\infty} e^{\mathbf{Q}\,t}$$

- for any $\boldsymbol{\pi}(0)$, which implies

$$\lim_{t\to\infty} e^{\mathbf{Q}\,t} = \mathbf{P}(\infty) = \begin{bmatrix} \boldsymbol{\pi}(\infty) & \cdots & \boldsymbol{\pi}(\infty) \end{bmatrix}^{\mathrm{T}}$$

- If this limit exists, we call $\mathbf{P}(\infty)$ the limiting matrix, and $\boldsymbol{\pi}(\infty)$ the limiting distribution.
- $\mathbf{P}(\infty) = \begin{bmatrix} \boldsymbol{\pi}(\infty) & \cdots & \boldsymbol{\pi}(\infty) \end{bmatrix}^{\mathrm{T}}$ does not exist if the CTMC has more than one irreducible closed set (each ICS will converge to a diagonal block, and $\boldsymbol{\pi}(\infty)$ will depend on $\boldsymbol{\pi}(0)$).

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Stationary Distribution

- We have: $\boldsymbol{\pi}(t) = \boldsymbol{\pi}(0)\, e^{\mathbf{Q}\,t}$, $t \geq 0$.
- In steady state the probabilities do not change. We look for a probability vector $\boldsymbol{\pi} = \boldsymbol{\pi}(t_1)$ satisfying: $\boldsymbol{\pi}(t_1)\, e^{\mathbf{Q}\,t} = \boldsymbol{\pi}(t_1)$. In other words, for $t \geq t_1$ the probability vector reach the steady state $\boldsymbol{\pi}$, and do not change anymore. Thus:

$$\boxed{\boldsymbol{\pi} \frac{\partial e^{\mathbf{Q}\,t}}{\partial t} = \boldsymbol{\pi}\, \mathbf{Q}\, e^{\mathbf{Q}\,t} = \mathbf{0}}$$

- and we obtain that the stationary distribution $\boldsymbol{\pi}$ can be computed with the Global balance equations:

$$\boxed{\begin{array}{l} \boldsymbol{\pi}\, \mathbf{Q} = \mathbf{0} \\ \boldsymbol{\pi}\, \mathbf{e} = 1,\, \mathbf{e}^{\mathrm{T}} = (1, 1, \cdots) \end{array}}$$

- NOTE: Compare with DTMC $\boldsymbol{\pi} = \boldsymbol{\pi}\, \mathbf{P}$, $\boldsymbol{\pi}\, \mathbf{e} = 1$.

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Numerical Solution

- Replace one equation method:

$$\boxed{\begin{aligned} &\boldsymbol{\pi}\,\mathbf{Q} = \mathbf{0} \\ &\boldsymbol{\pi}\,\mathbf{e} = 1, \mathbf{e}^{\mathrm{T}} = (1, 1, \cdots) \end{aligned}}$$

- We solve the equation $\boldsymbol{\pi}\,\mathbf{Q} = 0$ replacing the last equation by $\boldsymbol{\pi}\,\mathbf{e} = 1$:

$$\boxed{\boldsymbol{\pi} \begin{bmatrix} q_{11} & q_{12} & \cdots q_{1n-1} & 1 \\ q_{21} & q_{22} & \cdots q_{2n-1} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ q_{n1} & q_{n2} & \cdots q_{nn-1} & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & \cdots & 0 & 1 \end{bmatrix}}$$

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Numerical Solution

- Replace one equation method: $\mathbf{Q} = \begin{bmatrix} -2 & 1 & 1 \\ 1 & -2 & 1 \\ 1 & 1 & -2 \end{bmatrix}$ $\quad \begin{matrix} \boldsymbol{\pi}\mathbf{Q} = 0 \\ \boldsymbol{\pi}\mathbf{e} = 1 \end{matrix}$
- Solving with octave (matlab clone):

```
octave:1> Q=[-2,1,1;1,-2,1;1,1,-2];
octave:2> s=size(Q,1); # number of rows.
octave:3> [zeros(1,s-1),1] / ...
> [Q(1:s,1:s-1), ones(s,1)]
ans =
  0.33333  0.33333  0.33333
```

- With R

```
> Q <- matrix(nc=3, byr=T, c(-2,1,1,1,-2,1,1,1,-2))
> s <- nrow(Q)
> solve(t(cbind(Q[,1:(s-1)], rep(1,s))), c(rep(0,s-1),1))
[1] 0.3333333 0.3333333 0.3333333
```

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Global balance equations

- Why are they called Global balance equations?

$$\left.\begin{array}{rr} \boldsymbol{\pi}\,\mathbf{Q} = \mathbf{0} \Rightarrow & \displaystyle\sum_{i=0}^{\infty} \pi_i q_{ij} = 0 \\ \displaystyle\sum_{i=0}^{\infty} q_{ji} = 0 \Rightarrow & \displaystyle\pi_j \sum_{i=0}^{\infty} q_{ji} = 0 \end{array}\right\} \Rightarrow \pi_j \sum_{i=0}^{\infty} q_{ji} = \sum_{i=0}^{\infty} \pi_i q_{ij}$$

$$\sum_{i=0}^{\infty} \pi_i q_{ij} \quad \Rightarrow \text{Frequency of transitions entering state } j$$

$$\pi_j \sum_{i=0}^{\infty} q_{ji} \quad \Rightarrow \text{Frequency of transitions leaving state } j$$

- In stationary regime, the frequency of transitions leaving state j is equal to the frequency of transitions entering state j.

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Solving using flux balancing

- Define the flux F_{uv} from state u to v:

$$F_{uv} = \pi_u q_{uv}$$

- and the flux from set of states U to V:

$$F(U,V) = \sum_{u \in U} \sum_{v \in V} F_{uv}$$

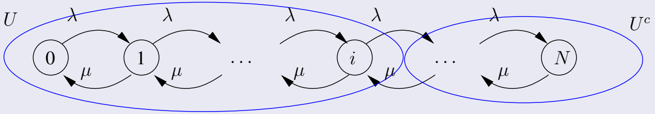
- From the Global balance equations, and reasoning exactly as in DTMC:

$$\boxed{F(U,U^c) = F(U^c,U)}$$

- NOTE: Same equation as in DTMC, changing p_{ij} by q_{ij}.

Steady State

Example: Birth-dead Process



- Flux balancing $\Rightarrow \lambda \pi_i = \mu \pi_{i+1}$
- Iterating:

$$\boxed{\pi_i = \pi_0 \rho^i, \; i = 0, 1, \cdots N-1, \; \rho = \frac{\lambda}{\mu}}$$

- Normalizing:

$$\boxed{\pi_0 = \frac{1-\rho}{1-\rho^N}}$$

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Ergodic Chains

- Ergodic state: positive recurrent ($f_{ii}^e = 1$, $m_{ii}^e < \infty$).
- Ergodic chain if all states are ergodic.
- Theorem: All states of an irreducible Markov chain are of the same type: Transient or positive/null recurrent (see [1, chapter XV]).
- Consequences:
  - Finite irreducible chains are ergodic (since all states are positive recurrent).
  - Infinite irreducible chains can be:
    - Ergodic: all the states are positive recurrent (stable chains).
    - Non ergodic: all states are null recurrent or transient (unstable chains).

[1] William Feller. *An Introduction to Probability Theory and Its Applications, Vol. 1, 3rd Edition*. Wiley, 1968.

Steady State

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Theorems for ergodic chains

- $\boldsymbol{\pi} = \boldsymbol{\pi}(\infty)$. Proof: $\boldsymbol{\pi}(\infty)$ satisfies the GBE.
- In stationary regime (when $\boldsymbol{\pi} = \boldsymbol{\pi}\, e^{\mathbf{Q}\,t}$), the mean number of time the system remains in state j during T time units is given by

$$\boxed{T\pi_j}$$

thus, π_j is the fraction of time the chain remains in state j. The proof is analogous to DTMC.
- NOTE: The relation of DTMC between mean recurrence time and stationary probabilities does not hold for CTMC. I.e., the mean number of time units between two consecutive visits to state j, m_{jj}, cannot be computed as $1/\pi_j$. It must be computed with the recursive equations (slide 35).