

Markovian and non-Markovian processes and Master Equation

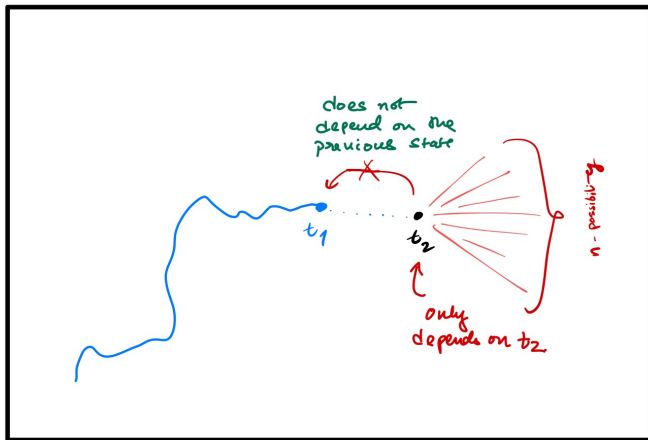
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Motivation

A Markov process assumes that the next state of a process only depends on the present state and not the past states.



Markov process

Chapman Kolmogorov

Master Equation

Fermi's golden rule

Non markovian process

Lindblad's equation

The **weak law of large numbers** states that if you have a sample of independent and identically distributed random variables, as the sample size grows larger, the sample mean will tend toward the population mean. .

Nekrasow's claim - independence is a necessary condition for the weak law of large numbers.

Markov's modification of Bernoulli's experiment

Markov proved that dependence of variables on previous state can also lead to convergence.

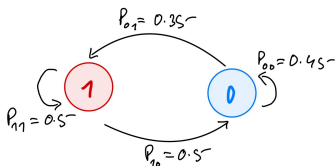
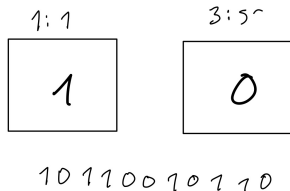


Figure 2: An example of a stochastic process with dependence on the last example

Definition: A stochastic process where the future state only depends on the present state and all the past states are eliminated.

$$P_{1|n-1}(y_n, t_n \mid y_1, t_1; \dots; y_{n-1}, t_{n-1}) = P_{1|1}(y_n, t_n \mid y_{n-1}, t_{n-1})$$

$$\begin{aligned} P_3(y_1, t_1; y_2, t_2; y_3, t_3) &= P_2(y_1, t_1; y_2, t_2) P_{1|2}(y_3, t_3 \mid y_1, t_1; y_2, t_2) \\ &= P_1(y_1, t_1) P_{1|1}(y_2, t_2 \mid y_1, t_1) P_{1|1}(y_3, t_3 \mid y_2, t_2) \end{aligned}$$

where $t_1 < t_2 < t_3$

Chapman Kolmogorov

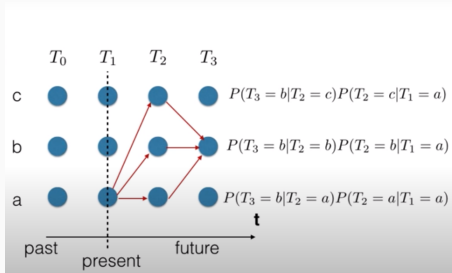


Figure 3: Two step transition probability

[3]

The Chapman–Kolmogorov equation provides the two step transition probability

$$P_2(y_1, t_1; y_3, t_3) = P_1(y_1, t_1) \int P_{1|1}(y_2, t_2 | y_1, t_1) P_{1|1}(y_3, t_3 | y_2, t_2) dy_2$$

$$P_2(y_1, t_1; y_3, t_3) = P_1(y_1, t_1) \int P_{2|1}(y_2, t_2 | y_1, t_1) P_{1|1}(y_3, t_3 | y_2, t_2) dy_2$$

Use Bayes theorem

[5] Divide both sides by $P_1(y_1, t_1)$

$$P_{11}(y_3 | t_3 | y_1, t_1) P_1(y_1, t_1) = \int P_{1|1}(y_3, t_3 | y_2, t_2) P_{1|1}(y_2, t_2 | y_1, t_1) dy_2$$

$$P_{1|1}(y_3, t_3 | y_1, t_1) = \int P_{1|1}(y_3, t_3 | y_2, t_2) P_{1|1}(y_2, t_2 | y_1, t_1) dy_2$$

Stationary Markov process

When the states of the system $P_1(t)$ is not affected by a time shift , then $P_1(t)$ is a stationary Markov process . origin of time does not matter since it is a function of elapsed time .[4]

Transition probability depends on time interval between two states

$$P_{1|1}(y_2, t_2 | y_1, t_1) = T_{\tau}(y_2 | y_1) \quad \text{with } \tau = t_2 - t_1, \tau' = t_3 - t_2$$

Stationary Markov process

Chapman-kolmogorov equation is

$$P_{1|1}(y_3, t_3 | y_1, t_1) = \int P_{1|1}(y_3, t_3 | y_2, t_2) P_{1|1}(y_2, t_2 | y_1, t_1) dy_2$$

Chapman-Kolmogorov equation then becomes ($\tau, \tau' > 0$)

$$T_{\tau+\tau'}(y_3 | y_1) = \int T_{\tau'}(y_3 | y_2) T_{\tau}(y_2 | y_1) dy_2$$

since it is already product of two matrices

$$T_{\tau+\tau'} = T_{\tau'} T_{\tau} \quad (\tau, \tau' > 0)$$

$$P_2(y_1, t_1; y_2, t_2) = T_{\tau}(y_2 | y_1) P_1(y_1)$$

$$\text{As } t \rightarrow \infty \quad P_2(y_2, t_2 - t_1 | y_1) = P_1(y_2)$$

Homogeneous Markov Process

A stationary process $Y(t)$ such that $P_1(y_1)$ and $T_\tau(y_2 | y_1)$ is given. t_0 and y_0 is a fixed time and fixed value. $Y^*(t)$ is a non stationary markov process for $y \geq t_0$ [4]

$$P_1^*(y_1, t_1) = T_{t_1-t_0}(y_1 | y_0)$$

$$P_{1|1}^*(y_2, t_2 | y_1, t_1) = T_{t_2-t_1}(y_2 | y_1)$$

Homogeneous Markov Process

One can extract a process $Y(t)$ at t_0 from $P(t_0)$ and are distributed according to $P(y_0)$

$$P_1^*(y_1, t_1) = \int T_{t_1-t_0}(y_1 | y_0) p(y_0) dy_0$$

$$P_{1|1}^*(y_2, t_2 | y_1, t_1) = T_{t_2-t_1}(y_2 | y_1)$$

These processes being non stationary but their transition probability depends on time difference, hence it is homogeneous markov process

Markov chain

We have three states A, B and C where the particle can travel . P_{AB} is the probability of a particle to go from state A to state B.

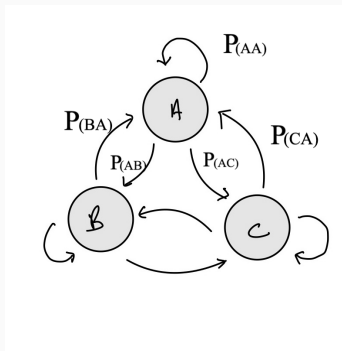


Figure 4: Markov chain

Transition Probability matrix

The transition probability $T_\tau(y_2 | y_1)$ is a $N \times N$ matrix . The Transition Probability matrix is given as

$$\begin{bmatrix} P_{AA} & P_{AB} & P_{AC} \\ P_{BA} & P_{BB} & P_{BC} \\ P_{CA} & P_{CB} & P_{CC} \end{bmatrix}$$

$$P_{AA} + P_{AB} + P_{AC} = 1 \quad \text{where all rows add up to 1}$$

The Markovian Master equation

$$\frac{dp_n(t)}{dt} = \sum_n \{W_{nn'}p_{n'}(t) - W_{n'n}p_n(t)\}$$

They are differential equations that describe the evolution of probability with respect to time . The master equation is a gain loss equation for the probabilities of separate states n.[5]

Long Time Limit

As $t \rightarrow \infty$ all solutions tend to the stationary solution.

For a closed isolated system in equilibrium , all transitions per unit time into any state n must be balanced by transitions into n'.[5]

$$W_{nn'}p_{n'}^e = W_{n'n}p_n^e$$

Any process that depends on all the past states is a non Markovian process, which implies that the memory of the previously visited sites changes the distribution.

Lindblad Master Equation

Describes a non-unitary evolution of the density operator ρ

$$\rho = |\psi\rangle\langle\psi|$$

For shorter time interaction with the environment compared to the internal time scale of system, we use the Markovian assumption[1]

$$\frac{\partial \rho(t)}{\partial t} = \mathcal{L}[\rho(t)]$$

H is the Hamiltonian of the system and L_μ are called Lindblad operators. The superoperator $\mathcal{L}$ is called Liouvillian.

$$\mathcal{L}[\rho] = -i[H, \rho] + \sum_{\mu} \left[L_{\mu} \rho L_{\mu}^{\dagger} - \frac{1}{2} \left\{ L_{\mu}^{\dagger} L_{\mu}, \rho \right\} \right]$$

The Markovian approximation is not accurate when the interactions inside the environment have comparable strengths to the interactions inside the system.

Nakajima Zwangzig master equation

NZ is used as non Markovian master equation[1]

$$\frac{\partial \rho(t)}{\partial t} = -i[H, \rho(t)] + \int_0^t ds \mathcal{K}_{r-s}^{-\text{NZ}}[\rho(s)] + I(t)$$

$\mathcal{K}_t^{\text{NZ}}$ is memory kernel the above equation describes non-Markovian processes, because the state at time $t + dt$ depends not only $\rho(t)$ but also on the states $\rho(s)$ for $s < t$

$$\frac{\partial \rho(t)}{\partial t} = -i[H, \rho(t)] + \int_0^t ds N_{t \rightarrow -1}^{-2(x)}[\rho(t)] + I(t)$$

Summary

1. Defined Markov Process, stationary and homogeneous process
2. Derived Chapman Kolmogorov and Master Equation
3. Proved that system weakly coupled by the heat bath gives similar transition probability to Fermi's Golden rule
4. Non Markov process defined
5. Lindblad's Master Equation
6. Nakajima Zwanzig master equation defined

References

- [1] In: (2018). DOI: [10.1088/1367-2630/aaf749](https://doi.org/10.1088/1367-2630/aaf749). URL: <https://doi.org/10.1088/1367-2630/aaf749>.
- [2] Gunter M. Schütz and Steffen Trimper. “Elephants can always remember: Exact long-range memory effects in a non-Markovian random walk”. In: *Physical Review E* 70.4 (Oct. 2004). ISSN: 1550-2376. DOI: [10.1103/PhysRevE.70.045101](https://doi.org/10.1103/PhysRevE.70.045101). URL: <http://dx.doi.org/10.1103/PhysRevE.70.045101>.
- [3] Gareth Tribello. *Chapman Kolmogorov*. URL: <https://www.youtube.com/watch?v=W5P4kCpdhho&t=453s>.

- [4] N.G. VAN KAMPEN. "Chapter IV - MARKOV PROCESSES". In: *Stochastic Processes in Physics and Chemistry (Third Edition)*. Ed. by N.G. VAN KAMPEN. Third Edition. North-Holland Personal Library. Amsterdam: Elsevier, 2007, pp. 73–95. DOI: <https://doi.org/10.1016/B978-044452965-7/50007-6>. URL: <https://www.sciencedirect.com/science/article/pii/B9780444529657500076>.
- [5] N.G. VAN KAMPEN. "Chapter V - THE MASTER EQUATION". In: *Stochastic Processes in Physics and Chemistry (Third Edition)*. Ed. by N.G. VAN KAMPEN. Third Edition. North-Holland Personal Library. Amsterdam: Elsevier, 2007, pp. 96–133. DOI: <https://doi.org/10.1016/B978-044452965-7/50008-8>. URL: <https://www.sciencedirect.com/science/article/pii/B9780444529657500088>.