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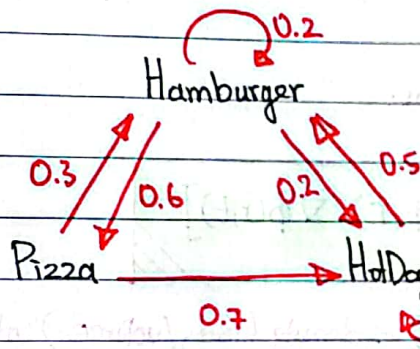
No.

## ② Prerequisite: Markov Chain.

→ Markov Chain (or Markov Process) is a Stochastic Model describing a sequence of possible events in which the probability of each event depends only on the state attained on the previous event.

↓ Markov Property.

→ Example of Markov Chains:



→ Let say there is a restaurant serving Hamburger, Pizza and Hot dog and there is a rule: What is being served today is dependent on what is served yesterday (Graph of prob on the left).

→ Example:  $P(\text{Hamburger} | \text{Pizza}) = 0.3$   
 $P(\text{Hotdog} | \text{Pizza}) = 0.7$  }  $\Sigma = 1$  (Bc of probability).

→ Random Walk along the Markov Chain:

;) Hamburger → Pizza → Hamburger → Hotdog → ...

→ Starting from a point in the Markov Chain (Hamburger), recursively generate new state based on the previous state. → Random Walk.

→ The question is, what will be the probability of each individual state if the walk goes on to infinitely many steps?

(\*)  $[P(\text{Hamburger}), P(\text{Pizza}), P(\text{Hotdog})] = [\lambda_1, \lambda_2, \lambda_3]$

↳  $\lambda_i$  = Eigenvalues of adjacency matrix.

Adjacency matrix  $A =$

	Ham	Pizza	Hotdog	
Ham	0.2	0.6	0.2	
Pizza	0.3	0	0.7	
Hotdog	0.5	0	0.5	





### ③ Prerequisite: Diffusion Equation.

↳ Definition (Diffusion Eq): Diffusion equation is a parabolic differential equation. In physics, it is used to describe the behaviours of particles in Brownian Motion.

\*) Brownian motion is the random motion of particles trapped in a medium (liquid / gas / ...).

↳ The equation is usually written as:

$$\frac{\partial \phi(r, t)}{\partial t} = \nabla \cdot [D(\phi, r) \cdot \nabla \phi(r, t)]$$

\* Where  $\left\{ \begin{array}{l} \phi(r, t) = \text{density (mass/volume) at location } r, \text{ time } t. \\ D(\phi, r) = \text{diffusion coefficient for } \phi \text{ at location } r. \\ \nabla \phi(r, t) = \text{gradient of density.} \end{array} \right.$

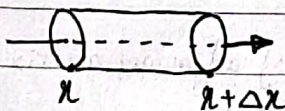
↳ If  $D(\phi, r)$  depends on  $\phi$  then the equation is non-linear.  
... Otherwise it's linear ( $D = \text{const}$ ).

↳ How to derive the diffusion equation:

↳ A newer notation of diffusion equation:

$$\frac{\partial u(x, t)}{\partial t} = \text{div} [D(u, t) \cdot \nabla u(x, t)]$$

\* In the GRAND paper  $u$  and  $x$  switches though.



→ Let's examine the diffusion of liquid inside through a very small length  $\Delta x$  of a pipe.



→ We define  $u(x,t)$  = concentration (density) at location  $x$ , time  $t$ .

→ The mass inside the tiny pipe can be approximated as:

$$M \approx u(x,t) \Delta x$$

→ According to Fick's law of diffusion:

$$(1) \quad \frac{\partial M}{\partial t} = \text{flux in} - \text{flux out}$$

Where the diffusion flux is defined as:

$$(2) \quad J(x,t) = -D \frac{\partial u(x,t)}{\partial x}$$

→ (1) & (2)  $\Rightarrow$

$$\Rightarrow \frac{\partial M}{\partial t} = D \left( \frac{\partial u(x+\Delta x, t)}{\partial x} - \frac{\partial u(x, t)}{\partial x} \right)$$

$$= D(u_x(x+\Delta x, t) - u_x(x, t))$$

$$\Rightarrow \Delta x \frac{\partial u(x,t)}{\partial t} = D(u_x(x+\Delta x, t) - u_x(x, t))$$

$$\Rightarrow \frac{\partial u(x,t)}{\partial t} = D \frac{u_x(x+\Delta x, t) - u_x(x, t)}{\Delta x}$$

$$\Rightarrow \text{As } \Delta x \rightarrow 0 \Rightarrow \frac{\partial u(x,t)}{\partial t} = D u_{xx}(x,t) \quad \#$$





#### ④ Prerequisite: Dynamical System.

↳ Definition (Dynamical system): A dynamical system is a system whose state evolves with time over a statespace according to a fixed rule.

↳ Dynamical systems are generally described as a system of differential equations:

$$\frac{dx}{dt} = f(\bar{x}, t, u; \beta)$$

Diagram annotations for the equation above:

- $\bar{x}$ : State (vectors)
- $f$ : Dynamics (Vector field).
- $u$ : actuation (control)
- $\beta$ : Other variables.

$$y = g(x, t)$$

Diagram annotations for the equation above:

- $y$ : Measurements.
- $g$ : (Some times we may not have direct control/access to the whole state).

#### ↳ Challenges:

- ) Unknown dynamics  $f$ . E.g: A pendulum, spread of disease, ...
- ) Non-linear dynamics.
- ) High-dimensional, complex state space  $x$ .
- ) Multiscale.
- ) Chaotic dynamics.
- ) Hidden / latent variables.
- ) Noise / disturbance.