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Overview

- Markov Chain
- Example
- Stationary Distribution
- Banach Fixed Point Theorem
- Application: Page Rank

Markov Process

• Markov Property: The state of the system at time *t*+1 depends only on the state of the system at time *t*

$$\Pr[X_{t+1} = x_{t+1} / X_1 \cdots X_t = x_1 \cdots x_t] = \Pr[X_{t+1} = x_{t+1} / X_t = x_t]$$

$$\boxed{X_1 \quad X_2 \quad X_3 \quad X_4 \quad X_5}$$

Transition probabilities are independent of time

$$\Pr[X_{t+1}=b/X_t=a]=p_{ab}$$

Markov Chain : A Simple Example

Weather:

raining today



40% rain tomorrow 60% no rain tomorrow

not raining today



20% rain tomorrow80% no rain tomorrow



Markov Chain : A Simple Example

Weather:





40% rain tomorrow 60% no rain tomorrow

not raining today

20% rain tomorrow 80% no rain tomorrow

The transition matrix:

$$P = \begin{pmatrix} 0.4 & 0.6 \\ 0.2 & 0.8 \end{pmatrix}$$

Rows sum up to 1

Markov Property

"Future" is independent of "Past" and depend only on "Present"

In other words: Memoryless

Useful for modeling and analyzing many real systems

Coke vs Pepsi example

- Given that a person's last cola purchase was Coke, there is a 90% chance that his next cola purchase will also be Coke.
- If a person's last cola purchase was Pepsi, there is an 80% chance that his next cola purchase will also be Pepsi.



Coke vs Pepsi example

Given that a person is currently a Pepsi purchaser, what is the probability that he will purchase Coke two purchases from now?

 $\Pr[\operatorname{Pepsi} \rightarrow ? \rightarrow \operatorname{Coke}] =$

Pr[Pepsi→Coke] + Pr[Pepsi→ Pepsi→Coke] =

0.2 * 0.9 + 0.8 * 0.2 = 0.34

$$P = \begin{bmatrix} 0.9 & 0.1 \\ 0.2 & 0.8 \end{bmatrix} \begin{bmatrix} 0.9 \\ 0.2 \\ 0.8 \end{bmatrix} = \begin{bmatrix} 0.83 & 0.17 \\ 0.34 & 0.66 \end{bmatrix}$$

Coke vs Pepsi example

Given that a person is currently a Coke purchaser, what is the probability that he will purchase Pepsi **three** purchases from now?

$$P^{3} = \begin{bmatrix} 0.9 & 0.1 \\ 0.2 & 0.8 \end{bmatrix} \begin{bmatrix} 0.83 & 0.17 \\ 0.34 & 0.66 \end{bmatrix} = \begin{bmatrix} 0.781 & 0.219 \\ 0.438 & 0.562 \end{bmatrix}$$

Coke vs Pepsi example

- •Assume each person makes one cola purchase per week
- •Suppose 60% of all people now drink Coke, and 40% drink Pepsi
- •What fraction of people will be drinking Coke three weeks from now?

$$P = \begin{bmatrix} 0.9 & 0.1 \\ 0.2 & 0.8 \end{bmatrix} \qquad P^3 = \begin{bmatrix} 0.781 & 0.219 \\ 0.438 & 0.562 \end{bmatrix}$$

 $\Pr[X_3 = \text{Coke}] = 0.6 * 0.781 + 0.4 * 0.438 = 0.6438$

 π_k - the distribution in week k $\pi_0 = (0.6, 0.4)$ - initial distribution $\pi_3 = \pi_0 * P^3 = (0.6438, 0.3562)$

Coke vs Pepsi example



Stationary Distribution

Note that

$$\pi_{k+1} = \pi_k P$$

Stationary Distribution:
$$\pi = \lim_{k \to \infty} \pi_k$$
 for any π_0 .

If such π exists, it satisfies that for all j, $\sum_{i} \rho_{ij} \pi(i) = \pi(j)$ and $\sum_{i} \pi(i) = 1$

Special case : Contraction Map

Let (X,d) be a metric space, $f: X \to X$ is called a contraction if there is a $\rho \in [0,1)$ such that

$$d(f(x), f(y)) \le \rho d(x, y) \quad \forall x, y \in X$$

A Markov Chain is a contraction if for any two initial distributions π_1, π_2 ,

$$\mathsf{d}(\pi_1\mathsf{P},\pi_2\mathsf{P}) \leq \rho \mathsf{d}(\pi_1,\pi_2)$$

Banach Fixed Point Theorem

Let (X,d) be a complete metric space, and $f: X \to X$ be a contraction. Then f has a fixed point. Further, this fixed point is unique.

• So if $d(\pi_1 P, \pi_2 P) \le \rho d(\pi_1, \pi_2)$ for some $\rho \in [0,1)$, then the Markov Chain P has a unique stationary distribution (fixed point).

PageRank: Markov Chain over the Web

- If a user starts at a random web page and surfs by clicking links and randomly entering the new web page, what is the probability that a random user is found at a web page?
- The PageRank of a page captures this notion
 "popular" web page get a higher rank
 This gives a rule for a random walk on The Web graph (a directed graph).

PageRank: Formula

Given page A, and pages T_1 ,..., T_j linking to A, PageRank PR(A) of A is defined as the solution of :

 $PR(A) = (1-\rho) + \rho(PR(T_1)/D(T_1) + ... + PR(T_j)/C(T_j))$

D(T) is the out-degree of page T
 ρ is the "random URL" factor (=0.85)

Then, PR/n is the stationary distribution of the corresponding Markov chain, where n is the total number of web pages.



 $PR(A)=(1-\rho) + \rho^{*}(PR(T1)/D(T1) + PR(T2)/D(T2) + PR(T3)/D(T3))$ =0.15+0.85*(0.5/3 + 0.3/4+ 1.5/5)

PageRank: Computation

This Markov Chain is a contraction with ρ=0.85, and PR is its stationary distribution.

Banach fixed point theorem holds

Hence PR can be calculated iteratively :

$$\mathsf{PR}_{i+1} (\mathsf{A}) = (1-\rho) + \rho(\mathsf{PR}_i(\mathsf{T}_1)/\mathsf{C}(\mathsf{T}_1) + \dots + \mathsf{PR}_i(\mathsf{T}_n)/\mathsf{C}(\mathsf{T}_n))$$

- Each page distributes its PR_i to all pages it links to. Linkees add up their awarded ranks to compute their PR_{i+1}.
- PR_i converges exponentially fast over i.