Lecture notes of Stochastic Process

lectured by prof. Hsueh-I Lu

pishen

AlgoLab, CSIE, NTU

May 1, 2012

Thank list

LeoSW, windker

Stochastic Process

Definition

A Stochastic process is a set of random variables $\{X(t)|t \in T\}$ where T is a index (time) set.
State Space: possible value of X(t) for each t, which is defined as subset of R.

Markov Chain

Definition

A Stochastic Process $\mathbb{X}$ with state space S is a Markov Chain if $\exists 0 \leq p_{ij} \leq 1 \quad \forall i, j \in S$ such that

$$(a) \quad \sum_{j \in S} p_{ij} = 1 \quad \forall i \in S$$

$$(b) \quad P(X(t+1) = j | X(0) = i_0, X(1) = i_1, ..., X(t) = i) = p_{ij}$$
$$\forall t, i_0, i_1, ..., i_{t-1}$$

$\mathbb{P}$ denotes the matrix form of p_{ij} with sum of any row is 1.

Lemma: $P(X(n) = j | X(0) = i) = \mathbb{P}^n[i, j]$

Proof of lemma

We know statement is true for $(m+n)=0$. For $(m+n)>0$:

$$
\begin{aligned}
&P(X(m+n)=j|X(0)=i)\\
&\quad=\sum_{k\in S} P(X(m+n)=j \text{ and } X(m)=k|X(0)=i)\\
&\quad=\sum_{k\in S} P(X(m+n)=j|X(m)=k \text{ and } X(0)=i)\cdot\\
&\qquad P(X(m)=k|X(0)=i)\\
&\quad=\sum_{k\in S} P(X(m+n)=j|X(m)=k)\cdot P(X(m)=k|X(0)=i)\\
&\quad=\sum_{k\in S} P^n[k,j]\cdot P^m[i,k]\\
&\quad=\sum_{k\in S} P^m[i,k]\cdot P^n[k,j]\\
&\quad=\mathbb{P}^n[i,j]
\end{aligned}
$$

- $=$: conditional on $X(m)$
- $=$: definition of conditional probability
- $=$: (see next page)
- $=$: inductive hypothesis

Proof of lemma(cont)

$$
\begin{aligned}
&P(X(m+n)=j|X(m)=k \text{ and } X(0)=i)\\
&\quad= \sum_{r\in S} P(X(m+n)=j|\\
&\qquad X(m+n-1)=r \text{ and } X(m)=k \text{ and } X(0)=i)\cdot\\
&\qquad P(X(m+n-1)=r|X(m)=k \text{ and } X(0)=i)\\
&\quad= \sum_{r\in S} P(X(m+n)=j|X(m+n-1)=r)\cdot\\
&\qquad P(X(m+n-1)=r|X(m)=k)\\
&\quad= P(X(m+n)=j|X(m)=k)
\end{aligned}
$$

$=$: conditional on $X(m+n-1)$
$=$: first part by definition of Markov chain and second part by inductive hypothesis

Absorbing State

Let $\mathbb{A}$ be a set of accepting states. We would like to know the probability that $\mathbb{X}$ has ever entered some state in $\mathbb{A}$. Technique: merge all state of $\mathbb{A}$ into a new absorbing state a. Set matrix of $\mathbb{X}$ by once enter a, then probability of a goes to a is 1.

Recurrent & transient

Definition

The *recurrent probability* of state i of Markov chain $\mathbb{X}$ is

$$f_i = P(\text{there exists an index } t \geq 1 \text{ with } X(t) = i | X(0) = i)$$

- State i of $\mathbb{X}$ is *recurrent* if $f_i = 1$.
- State i of $\mathbb{X}$ is *transient* if $f_i < 1$.

Recurrent & transient (cont.)

- If state i is recurrent, by the property of Markov chain, once it re-enter the state i, we can take it as starting from $X(0)$ again. Hence we know that it will keep re-entering the state i again and again in the process.
- If state i is transient, in each period it start going from i, it may have probability $1 - f_i$ that it won't come back anymore.
  Hence the probability that the process will be in state i for exactly n periods equals ${f_i}^{n-1}(1 - f_i),\ n \geq 1$, which is a geometric distribution.

Recurrent & transient (cont.)

- From the preceding page, it follows that state i is recurrent if and only if, starting in state i, the expected number of steps that the process is in state i is infinite.
- We can also derive that, if the Markov chain has finite states, at least one state is recurrent.

Expected number of visits

Let

$$I(n) = \begin{cases} 1 & \text{if } X(n) = i \\ 0 & \text{if } X(n) \neq i \end{cases}$$

we have $\sum_{n=0}^{\infty} I(n)$ represents the number of steps that the process is in state i, and

$$\begin{aligned} E\left[\sum_{n=0}^{\infty} I(n) | X(0) = i\right] &= \sum_{n=0}^{\infty} E[I(n)|X(0) = i] \\ &= \sum_{n=0}^{\infty} 1 \cdot P(X(n) = i|X(0) = i) \\ &= \sum_{n=0}^{\infty} P_{ii}^{n} \end{aligned}$$

We set $T = \sum_{n=0}^{\infty} I(n)$

Lemma 1

From the above statements, we prove the following

Lemma

State i is

$$\textit{recurrent} \iff \sum_{n=0}^{\infty} P_{ii}^{n} = \infty,$$

$$\textit{transient} \iff \sum_{n=0}^{\infty} P_{ii}^{n} < \infty$$

Proof of Lemma 1

($\Rightarrow$:)
($\Leftarrow$:)
Suppose state i is transient($f_i < 1$), consider $P(T = k) = f_i^{k-1} \cdot (1 - f_i)$.
Since T is a geometric distribution, we have

$$
\begin{aligned}
E[T] &= \sum_{k=0}^{\infty} k \cdot f_i^{k-1} \cdot f_i \\
&= \frac{1}{1 - f_i} < \infty
\end{aligned}
$$

Communicated states

Definition

State i and j *communicate*, denoted $i \leftrightarrow j$, if there exist integers $m \geq 0$ and $n \geq 0$ such that

$$P_{ij}^{m} > 0 \text{ and } P_{ji}^{n} > 0$$

We say a Markov chain $\mathbb{X}$ is irreducible if $i \leftrightarrow j \quad \forall i, j \in S$

Lemma 2

Lemma

If $i \leftrightarrow j$, then the following statements hold.

- *State i is recurrent if and only if state j is recurrent.*
- *State i is transient if and only if state j is transient.*

Corollary: $\mathbb{X}$ is finite and irreducible $\implies$ all states are recurrent.

- *$\mathbb{X}$ is finite $\implies \exists i \in S$ is recurrent (proof later)*
- *By Lemma 2, all states are recurrent*

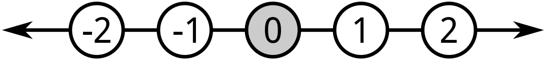
Proof

Let m and n be nonnegative integers with $P_{ij}^m, P_{ji}^n > 0$. Suppose that state j is recurrent, i.e., $\sum_{t=0}^{\infty} P_{jj}^t = \infty$. We have

$$\begin{aligned}\sum_{t=0}^{\infty} P_{ii}^t &\geq \sum_{t=0}^{\infty} P_{ii}^{m+t+n} \\ &\geq \sum_{t=0}^{\infty} P_{ij}^m \cdot P_{jj}^t \cdot P_{ji}^n \\ &= P_{ij}^m \cdot P_{ji}^n \cdot \sum_{t=0}^{\infty} P_{jj}^t = \infty\end{aligned}$$

Thus, state i is also recurrent.

Infinite drunken man problem



Let the state space consist of all integers. Let $X(0) = 0$ (i.e. at time 0 the drunken man is in state 0). The transition probabilities are such that

$$P_{i,(i+1)} = P_{i,(i-1)} = 0.5$$

holds for all states i of $\mathbb{X}$.

Gambler's ruin

Outline

1. Limiting probabilities
2. Stationary distribution
3. Long-run proportion
4. (Inverse of) Expected return time

Limiting Probabilities

Definition

Number π_j is the *limiting probability* of j if

$$\pi_j = \lim_{n\to\infty} P_{ij}^n$$

holds for all states $i \in S$ ($S \subseteq \mathbb{N}$ is the state space).

- π_j is independent of i.
- $\lim_{n\to\infty} P^n = \begin{pmatrix} \pi \\ \pi \\ \vdots \end{pmatrix}$, where $\pi = (\pi_1, \pi_2, \ldots)$

Stationary Probability Distribution

Definition

Non-negative row vector $\pi = (\pi_1, \pi_2, \ldots)$ is a *stationary probability distribution* of $\mathbb{X}$ if $\pi \times P = \pi$ holds and $\sum_{i \in S} \pi_i = 1$

- π is a normalized left eigenvector with eigenvalue $= 1$.
- If $X(0)$ has distribution π, then $X(t)$ has the same distribution π for all $t \geq 1$. π is also called as *steady-state distribution*.
- It doesn't mean that each $X(t)$ become independent. π only means the distribution of $X(t)$ when the previous random variable's value is unknown.

Theorem 1

Theorem

Let $\mathbb{X}$ be an irreducible, aperiodic, positive recurrent Markov chain, then

- *The limiting probability π_j of each state j exists.*
- *$\pi = (\pi_1, \pi_2, \ldots)$ is the unique stationary probability distribution.*

- The proof will be stated at page 38.

Expected return time

Definition

The *expected return time* of state $i \in S$ is

$$\mu_i = \sum_{n \geq 1} n \cdot f_i^{(n)}$$

where

$$f_i^{(n)} = P(\min\{t : X(t) = i, t \geq 1\} = n | X(0) = i)$$

- $f_i = \sum_{n \geq 1} f_i^{(n)}$

Positive recurrent & null recurrent

Definition

State i is *positive recurrent* if $\mu_i < \infty$

Definition

State i is *null recurrent* if $\mu_i = \infty$

- Both are recurrent states, and are *class properties*, which means that if state i and j communicate, they will share this property.
- If $\mathbb{X}$ is finite, then each recurrent state of $\mathbb{X}$ is positive recurrent. Proof stated at page 63.

Example of null recurrent

Example

For a Markov chain with n states $(1, \ldots, n)$, if

$$P(X(t+1) = i+1 | X(t) = i) = 1 - 1/n$$

and

$$P(X(t+1) = 1 | X(t) = i) = 1/n$$

According to geometric distribution (taking $p = 1/n$), the expectation value of "steps taken for state 1 to come back" will be $1/p = n$, hence $\lim_{n\to\infty} n = \infty$.

Period of a chain

Definition

The *period* of state i is d if d is the largest integer such that

$$P_{ii}^n = 0$$

holds for all n which is not divisible by d.

Definition

If each state of $\mathbb{X}$ has period 1, then $\mathbb{X}$ is called *aperiodic*.

- If $P_{ii} > 0$ for all $i \in S$, then $\mathbb{X}$ is aperiodic.
- Period can be seen as the $\gcd$ of all n that have $P_{ii}^n > 0$, note that $P_{ii}^{\gcd} > 0$ is not necessary.
- The period of drunken man problem is 2.

Lemma 1

Lemma

If state j has period 1 and is positive recurrent, then

$$\pi_{ij} \equiv \lim_{n\to\infty} P_{ij}^n$$

exists and is positive for all states $i \in S$.

- This can be proved by the Blackwell theorem in Renewal theory.
- It doesn't promise that $\pi_{ij} = \pi_{i'j}$ for any $i, i' \in S$. But they will be the same if we add the irreducible property ($i \leftrightarrow i'$).

Property of $\lim$

- The position of $\lim$ may not be switched arbitrarily in an equation.

Example

$$1 = \lim_{n\to\infty} \lim_{m\to\infty} \frac{m}{m+n} \neq \lim_{m\to\infty} \lim_{n\to\infty} \frac{m}{m+n} = 0$$

- $\lim$ would not influence the inequality.

Example

If $f(n) \geq g(n)$, then $\lim_{n\to\infty} f(n) \geq \lim_{n\to\infty} g(n)$

Property of $\lim$ (cont.)

- $\lim$ is linear operator under finite number of functions.

Example

For $m < \infty$,

$$\sum_{i=1}^{m} \lim_{n\to\infty} f_i(n) = \lim_{n\to\infty} \sum_{i=1}^{m} f_i(n)$$

need an example of $m = \infty$

Inequality 1

Inequality

$$\sum_{j \in S} \pi_{ij} \leq 1 \quad \forall i \in S$$

Proof

$$
\begin{aligned}
\lim_{m\to\infty}\sum_{j=1}^{m}\pi_{ij} &= \lim_{m\to\infty}\sum_{j=1}^{m}\lim_{n\to\infty}P_{ij}^{n}\\
&= \lim_{m\to\infty}\lim_{n\to\infty}\sum_{j=1}^{m}P_{ij}^{n}\\
&\leq \lim_{m\to\infty}\lim_{n\to\infty}\sum_{j\in S}P_{ij}^{n} = 1
\end{aligned}
$$

- The last equation works since $\sum_{j\in S} P_{ij}^{n} = 1$.

Inequality 2

Inequality

For state $j \in S$, we have

$$\pi_{ij} \geq \sum_{k \in S} \pi_{ik} P_{kj}$$

Proof

For $m \geq 1$ and $n \geq 1$,

$$P_{ij}^{n+1} = \sum_{k \in S} P_{ik}^n P_{kj} \geq \sum_{k=1}^{m} P_{ik}^n P_{kj}$$

then

$$\pi_{ij} = \lim_{n \to \infty} P_{ij}^{n+1} \geq \lim_{n \to \infty} \sum_{k=1}^{m} P_{ik}^n P_{kj} = \sum_{k=1}^{m} \lim_{n \to \infty} P_{ik}^n P_{kj} = \sum_{k=1}^{m} \pi_{ik} P_{kj}$$

hence, we know

$$\lim_{m \to \infty} \pi_{ij} = \pi_{ij} \geq \lim_{m \to \infty} \sum_{k=1}^{m} \pi_{ik} P_{kj} = \sum_{k \in S} \pi_{ik} P_{kj}$$

Equality 1

Equality

$$\pi_{ij} = \sum_{k \in S} \pi_{ik} P_{kj}$$

Proof

Assume for contradiction $\pi_{ij} > \sum_{k \in S} \pi_{ik} P_{kj}$, then

$$
\begin{aligned}
\lim_{m\to\infty} \sum_{j=1}^{m} > \lim_{m\to\infty} \sum_{j=1}^{m} \lim_{p\to\infty} \sum_{k=1}^{p} \pi_{ik} P_{kj} \\
&= \lim_{m\to\infty} \lim_{p\to\infty} \sum_{j=1}^{m} \sum_{k=1}^{p} \pi_{ik} P_{kj} \\
&= \lim_{m\to\infty} \lim_{p\to\infty} \sum_{k=1}^{p} \pi_{ik} \sum_{j=1}^{m} P_{kj} \\
&= \lim_{p\to\infty} \sum_{k=1}^{p} \pi_{ik} \lim_{m\to\infty} \sum_{j=1}^{m} P_{kj} \\
&= \lim_{p\to\infty} \sum_{k=1}^{p} \pi_{ik} \cdot 1 = \lim_{p\to\infty} \sum_{k=1}^{p} \pi_{ik}
\end{aligned}
$$

Proof (cont.)

- Since a value cannot be greater than itself, we got contradiction.
- In the 4th line, two $\lim$ can be switched because the value can only get larger when applying $\lim$ on it. not sure

Proof of theorem 1

- **Step 0**: existence of limiting probability.
- **Step 1**: existence of stationary probability distribution.
- **Step 2**: uniqueness.

0. Existence of limiting probability

Proof.

By lemma 1, we know that there exists a π_j for row i. Since the Markov chain is irreducible and all the states are positive recurrent, for any state i' other than i, we know that i' surely will visit i in finite steps. Therefore, the π_j value at row i' will equal to the π_j value at row i, which means that all the π_j for column j are the same, and is the limiting probability. □

still not clear enough

1. Existence of stationary probability distribution

We want to prove that

Target

There's a vector $s = (s_1, s_2, \ldots)$ *such that*

1. $\sum_{i \in S} s_i = 1$
2. $s \times P = s$

Proof.

By lemma 1, we know that there exists a $\pi = (\pi_1, \pi_2, \ldots)$.
And by equality 1, we know that

$$(\pi_1, \pi_2, \ldots) \times P = (\pi_1, \pi_2, \ldots)$$

Hence π can satisfy the 2nd part of our target.
Then, we take $k = \sum_{i \in S} \pi_i$. By inequality 1, we know that $k < \infty$, and can get

$$(\frac{\pi_1}{k}, \frac{\pi_2}{k}, \ldots) \times P = (\frac{\pi_1}{k}, \frac{\pi_2}{k}, \ldots)$$

where $\sum_{i \in S} \frac{\pi_i}{k} = 1$ also satisfy the 1st part of our target.
Therefore, this vector can be s, which means that it exists. $\square$

2. Uniqueness

Target

If $s = (s_1, s_2, \dots)$ is a stationary distribution of $\mathbb{X}$, then $s = \pi$.

- We'll prove this by inequality 3 & 4.

Inequality 3

Inequality

$$s_j \geq \pi_j, \forall j \in S$$

Proof.

Let the distribution of $X(0)$ be s, by the property of stationary distribution, we have

$$\begin{aligned} s_j &= P(X(n)=j) = \sum_{i\in S} P(X(n)=j|X(0)=i)P(X(0)=i) \\ &= \sum_{i\in S} P_{ij}^n \cdot s_i \\ &\geq \sum_{i=1}^{m} P_{ij}^n \cdot s_i \\ \Rightarrow s_j &= \lim_{m\to\infty}\lim_{n\to\infty} s_j \\ &\geq \lim_{m\to\infty}\lim_{n\to\infty}\sum_{i=1}^{m} P_{ij}^n \cdot s_i = \lim_{m\to\infty}\sum_{i=1}^{m}\pi_j \cdot s_i = \pi_j \end{aligned}$$

$\square$

Inequality 4

Inequality

$$s_j \leq \pi_j, \forall j \in S$$

Proof.

Similar in the proof above, $\forall m, n \geq 1$, we have

$$
\begin{aligned}
s_j &= \sum_{i \in S} P_{ij}^n \cdot s_i \\
&\leq \sum_{i=1}^{m} P_{ij}^n \cdot s_i + \sum_{i=m+1}^{\infty} s_i \\
\Rightarrow s_j &= \lim_{m \to \infty} \lim_{n \to \infty} s_j \\
&\leq \lim_{m \to \infty} \lim_{n \to \infty} \left(\sum_{i=1}^{m} P_{ij}^n \cdot s_i + \sum_{i=m+1}^{\infty} s_i \right) \\
&= \pi_j
\end{aligned}
$$

□

An example Markov chain

Example

$$P = \begin{pmatrix} \alpha & 1-\alpha \\ \beta & 1-\beta \end{pmatrix}, 0 < \alpha, \beta < 1$$

$$\pi = \left(\frac{\beta}{1+\beta-\alpha}, \frac{1-\alpha}{1+\beta-\alpha} \right)$$

Real world example: Hardy-Weinberg Law

Example

There're two kinds of allele:

- dominant: **A**
- recessive: **a**

And three kinds of senotype with population proportion as follow:

- AA: p
- aa: q
- Aa: $r = 1 - (p + q)$

Example (cont.)

$$P = \begin{array}{c} \\ AA \\ aa \\ Aa \end{array} \begin{array}{c} \begin{array}{ccc} AA & aa & Aa \end{array} \\ \begin{pmatrix} p+\frac{r}{2} & 0 & q+\frac{r}{2} \\ 0 & q+\frac{r}{2} & p+\frac{r}{2} \\ \frac{p}{2}+\frac{r}{4} & \frac{p}{2}+\frac{r}{4} & \frac{p+q+r}{2} \end{pmatrix} \end{array}$$

we get $\pi = (p, q, r)$ when

- $p = \left(p + \frac{r}{2}\right)^2$
- $q = \left(q + \frac{r}{2}\right)^2$
- $r = 2\left(p + \frac{r}{2}\right)\left(q + \frac{r}{2}\right)$

Long-run proportion

Definition

We say that r_j is the *long-run proportion* of state $j \in S$ if

$$r_j = \lim_{n \to \infty} \frac{1}{n} \sum_{1 \le t \le n} P_{ij}^t$$

holds for each state $i \in S$.

- It represents the average appearance times of state j in the whole process.
- We will show that (in theorem 3) if $\mathbb{X}$ is irreducible, then the long-run proportion of all states exist.

Theorem 2

Theorem (type 1)

If r_j exists for each $j \in S$ and $\sum_{j \in S} r_j > 0$, then $r = (r_1, r_2, \ldots)$ is the unique stationary distribution of $\mathbb{X}$.

or

Theorem (type 2)

If r_j exists for each $j \in S$ and ***a stationary distribution exists****, then $r = (r_1, r_2, \ldots)$ is the unique stationary distribution of $\mathbb{X}$.*

Proof

Existence of stationary distribution in type 1:

Let

$$R = \begin{pmatrix} r \\ r \\ \vdots \end{pmatrix} = \lim_{n\to\infty} \frac{1}{n} \sum_{1\le t\le n} P^t$$

then

$$\begin{aligned} R \times P &= \lim_{n\to\infty} \frac{1}{n} \sum_{1\le t\le n} P^{t+1} \\ &= \lim_{n\to\infty} \frac{1}{n} \sum_{1\le t\le n} P^t + \lim_{n\to\infty} \frac{1}{n}(P^{n+1} - P) \\ &= R \end{aligned}$$

As stated later, $\sum_{j\in S} r_j \le 1$, hence by normalizing r, we prove that stationary distribution exist.

- $(\lim f(n)) \cdot g(n) = \lim f(n) \cdot g(n)$?
- can replace the proof on page 40?

Proof (cont.)

Uniqueness:

Let π be an arbitrary stationary distribution, then

$$
\begin{aligned}
r &= \pi \times R \\
&= \pi \times \lim_{n\to\infty} \frac{1}{n} \sum_{1\le t\le n} P^t \\
&= \lim_{n\to\infty} \frac{1}{n} \sum_{1\le t\le n} \pi \times P^t \\
&= \lim_{n\to\infty} \frac{1}{n} \sum_{1\le t\le n} \pi \\
&= \pi
\end{aligned}
$$

can replace the proof for page 42?

Proof (cont.)

Prove that $\sum_{j\in S} r_j \le 1$:

$$\begin{aligned}
\sum_{j\in S} r_j &= \lim_{m\to\infty}\sum_{j=1}^{m}\lim_{n\to\infty}\frac{1}{n}\sum_{t=1}^{n}P_{ij}^{t} \\
&= \lim_{m\to\infty}\lim_{n\to\infty}\frac{1}{n}\sum_{t=1}^{n}\sum_{j=1}^{m}P_{ij}^{t} \\
&\le \lim_{m\to\infty}\lim_{n\to\infty}\frac{1}{n}\sum_{t=1}^{n}\sum_{j\in S}P_{ij}^{t} \\
&= \lim_{m\to\infty}\lim_{n\to\infty}\frac{1}{n}\sum_{t=1}^{n}1 = 1
\end{aligned}$$

Example 1

On a highway, if we know the probability that

- A truck is followed by a truck: $1/4$
- A truck is followed by a car: $3/4$
- A car is followed by a truck: $1/5$
- A car is followed by a car: $4/5$

We can construct a matrix

$$\begin{array}{cc} & \begin{array}{cc} T & C \end{array} \\ \begin{array}{c} T \\ C \end{array} & \begin{pmatrix} 1/4 & 3/4 \\ 1/5 & 4/5 \end{pmatrix} \end{array}$$

and get the portion of trucks and cars on the whole highway as the eigenvector $(4/19, 15/19)$ (we will know that long-run proportion exists by Theorem 3).

Example 2

For a system which has several good and bad states, we have a matrix P:

$$
\begin{array}{c c}
 & \begin{array}{cccccc} g_1 & g_2 & \cdots & b_1 & b_2 & \cdots \end{array} \\
\begin{array}{c} g_1 \\ g_2 \\ \vdots \\ b_1 \\ b_2 \\ \vdots \end{array} & \left(\begin{array}{cccccc} & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \\ & & & & & \end{array} \right)
\end{array}
$$

Example 2 (cont.)

Q1: Breakdown rate (breakdown times / total time)
The long-run frequency of going to a bad state from a good state is

$$\sum_{i \in g} \sum_{j \in b} r_i P_{ij}$$

Example 2 (cont.)

Q2: The expected time μ_G (resp. μ_B) of staying in good (resp. bad) states once we reach a good (resp. bad) state?

Ans:

For each $t = 1, 2, \ldots$, let G_t (resp. B_t) be the length of the t-th good (resp. bad) phase of consecutive good (resp. bad) states. By the strong law of large numbers,

$$P\left(\lim_{t\to\infty} \frac{G_1 + B_1 + G_2 + B_2 + \cdots + G_t + B_t}{t} = \mu_G + \mu_B\right) = 1$$

Since the reciprocal of above is the breakdown rate, we get equation (1):

$$P\left(\sum_{i\in G}\sum_{j\in B} \pi_i P_{ij} = \frac{1}{\mu_G + \mu_B}\right) = 1$$

Example 2 (cont.)

Also, with probability 1, we get equation (2):

$$P\left(\sum_{i\in G} r_i = \lim_{t\to\infty} \frac{G_1 + G_2 + \cdots + G_t}{G_1 + B_1 + \cdots + G_t + B_t} = \frac{\mu_G}{\mu_G + \mu_B}\right) = 1$$

Then, by $(2)/(1)$, we get that

$$P\left(\mu_G = \frac{\sum_{i\in G} r_i}{\sum_{i\in G}\sum_{j\in B} r_i P_{ij}}\right) = 1$$

- $\lim \frac{f(n)}{g(n)} = \frac{\lim f(n)}{\lim g(n)}$?

Theorem 3

Theorem

If $\mathbb{X}$ is irreducible, then the long-run proportion r_i exists with probability 1, moreover,

1. *If state i is positive recurrent (i.e. $0 < \mu_i < \infty$), then $P(r_i = \frac{1}{\mu_i}) = 1$.*
2. *If state i is null recurrent (i.e. $\mu_i = \infty$) or transient, then $P(r_i = 0) = 1$.*

where μ_i is the expected return time of state i

Proof

Part 1:
Suppose $X(0) = i$, T_k is the number of steps required for the k-th i goes to $(k+1)$-st i, then by the strong law of large number,

$$P\left(\lim_{k\to\infty} \frac{T_1 + T_2 + \cdots + T_k}{k} = \mu_i\right) = 1$$
$$\Rightarrow P\left(r_i = \lim_{k\to\infty} \frac{k}{T_1 + T_2 + \cdots + T_k} = \frac{1}{\mu_i}\right) = 1$$

- $\lim(A/B) = \frac{1}{\lim(B/A)}$?

Proof (cont.)

Part 2:

1. If i is transient, i will only appear finite times in the long-run, hence

$$r_i = \frac{finite}{\infty} = 0$$

2. If i is null recurrent, μ_i is ∞, then

$$P\left(\lim_{k\to\infty} \frac{T_1 + T_2 + \cdots + T_k}{k} = \infty\right) = 1$$

$$P\left(r_i = \lim_{k\to\infty} \frac{k}{T_1 + T_2 + \cdots + T_k} = 0\right) = 1$$

(The first equation is not promised by the strong law of large number. But if it's not ∞, we can say that μ_i is not ∞, which is a contradiction.)

Example 1

Example (type 1)

If $\mathbb{X}$ is **irreducible** and finite, then $\mathbb{X}$ has no null recurrent states.

Example (type 2)

If $\mathbb{X}$ is finite, then $\mathbb{X}$ has no null recurrent states.

- Finite irreducible imply positive recurrent.

Proof

- **Type 1:**
  If there's a state which is null recurrent, by irreducible, all the states will be null recurrent. Then, all states have $P(r_i = 0) = 1$. By changing the proof in page 54 into finite states version, we know that $\sum r_i = 1$. So it's impossible for finite r_i, which are all close to 0, to sum up to 1.
- **Type 2:**
  If it's not irreducible, the finite set of communicated null recurrent states still form an irreducible and finite Markov chain, which can fit the requirement of type 1.

Example 2

Example

In the drunken man problem with infinite states, no state will be positive recurrent.

- Infinite drunken man imply no positive recurrent. Note that it doesn't mean all infinite irreducible Markov chain has no positive recurrent state.

Proof

If all the states are positive recurrent, then by theorem 3, we know that all the $r_i > 0$ and is a finite value. Since each state of drunken man problem has the same structure, all the r_i has same value. We then set $r = \epsilon \cdot r_i$ $(0 < \epsilon < 1)$ such that $r_i > r > 0, \forall i$. And get

$$\sum_{i \in S} r_i > \sum_{i \in S} r = \infty > 1$$

which is contradiction to page 54.

Example 3: Poisson Hotel

Example

There's a hotel, with N representing the number of newly occupied rooms each day (N is a poisson distribution with parameter λ). And the number of consecutive check-in days of each room is a geometric distribution with probability p (p is the probability of check-out). $X(t)$ is the number of occupied rooms in day t.

Q1: $P_{ij} = ?$

We set R_i as a binomial distribution with parameter $(i, 1-p)$, which represents the number of rooms which will remain occupied in the next day, then

$$\begin{aligned}
P_{ij} &= P(R_i + N = j) \\
&= \sum_{k \geq 0} P(R_i + N = j | R_i = k) P(R_i = k) \\
&= \sum_{k \geq 0} P(N = j - k) P(R_i = k) \\
&= \sum_{0 \leq k \leq \min(i,j)} \frac{e^{-\lambda} \cdot \lambda^{j-k}}{(j-k)!} \binom{i}{k} (1-p)^k p^{1-k}
\end{aligned}$$

Q2: $r_i = ?$

We guess (by a dream?) there's a stationary distribution which is a poisson distribution with parameter λ_0. Setting $X(0)$ with this distribution. And let R as the number of rooms in $X(0)$ which remain check-in in the next day (R is a poisson distribution with parameter $\lambda_0(1-p)$). $X(1)$ will have distribution $R + N$, which is a poisson distribution with parameter $\lambda_0(1-p) + \lambda$. Then since $X(0)$ is a stationary distribution, it will have the same distribution with $X(1)$, which means that $\lambda_0 = \lambda_0(1-p) + \lambda$, and we get $\lambda_0 = \lambda/p$.
After getting r_i, we get that with probability 1,

$$\mu_i = \frac{1}{P(X(0) = i)} = \frac{i!}{e^{-\lambda/p} \cdot (\lambda/p)^i}$$

not clear enough

Corollary of theorem 2 & 3

Corollary

If $\mathbb{X}$ is irreducible, then

$$\mathbb{X} \text{ is positive recurrent } \iff \mathbb{X} \text{ admits a stationary distribution.}$$

Moving to transient states

For transient states i and j, we define the following:

1. Expected steps in a transient state:

Definition

E is a matrix where E_{ij} is the expected number of steps t with $X(t) = j$ when $X(0) = i$.

2. Probability of reaching a transient state:

Definition

F is a matrix where

$$F_{ij} = P(X(t) = j \text{ for some } t \geq 1 | X(0) = i)$$

Computing E & F

Theorem

For a Markov chain $\mathbb{X}$ consisting finite transient states,

$$E = (I - T)^{-1}$$

where I is an identity matrix, T is the induced matrix of P by all the transient states in P. Moreover,

$$F_{ij} = \frac{E_{ij} - \delta_{ij}}{E_{jj}} \text{ ,where } \delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

Proof

Conditioned on $X(1)$, we have

$$E_{ij} = \underbrace{\delta_{ij}}_{\text{step}=0} + \underbrace{\sum_k P_{ik} \cdot E_{kj}}_{\text{step}\geq 1} = \delta_{ij} + \sum_k T_{ik} \cdot E_{kj}$$

The 2nd equation works since the process will not go back to transient state once it enter a recurrent state. Then, we have

$$\begin{aligned} I \times E = E &= I + T \times E \\ \Longrightarrow (I - T) \times E &= I \\ \Longrightarrow E &= (I - T)^{-1} \end{aligned}$$

Proof (cont.)

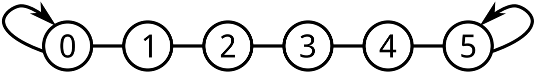
Conditioned on whether or not $X(t) = j$ holds for some $t \geq 1$, we have

$$E_{ij} = \underbrace{\delta_{ij}}_{\text{step}=0} + \underbrace{F_{ij} \cdot E_{jj}}_{\text{steps} \geq \text{the first } j}$$

therefore,

$$F_{ij} = \frac{E_{ij} - \delta_{ij}}{E_{jj}}$$

Example: Gambler's ruin



$$T = \begin{array}{c c} & \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array} & \begin{pmatrix} 0 & 0.5 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0 & 0 & 0.5 & 0 \end{pmatrix} \end{array} \quad E = \begin{pmatrix} 1.6 & 1.2 & 0.8 & 0.4 \\ 1.2 & 2.4 & 1.6 & 0.8 \\ 0.8 & 1.6 & 2.4 & 1.2 \\ 0.4 & 0.8 & 1.2 & 1.6 \end{pmatrix}$$

$$F = \begin{pmatrix} 0.375 & 0.5 & 1/3 & 0.25 \\ 0.75 & 1.75/3 & 1.9/3 & 0.5 \\ 0.5 & 1.9/3 & 1.75/3 & 0.75 \\ 0.25 & 1/3 & 0.5 & 0.375 \end{pmatrix}$$

Branching process

In the beginning, there're $X(0)$ life forms, each life form has probability p_i of becoming i life forms in the next step.

- state 0 is recurrent (absorbing).
- if $p_0 > 0$, all other states $(1, 2, \ldots)$ are transient since $P(X(t+1) = 0|X(t) = i) = {p_0}^i > 0$

We'll show that

$$E[X(n)] = \mu^n \cdot X(0)$$

where

$$\mu = \sum_{j \geq 1} j \cdot p_j = E[Z_k]$$

and Z_k is the number of offspring of the k-th life form, all Z_k are i.i.d.

Proof

$$
\begin{aligned}
E[X(n)] &= E[E[X(n)|X(n-1)]] \\
&= E\left[E\left[\sum_{k=1}^{X(n-1)} Z_k | X(n-1)\right]\right] \\
&= E[X(n-1)\cdot\mu] \\
&= \mu \cdot E[X(n-1)] \\
&= \mu^n \cdot X(0)
\end{aligned}
$$

Probability of extinction

Definition

e_i is the probability of extinction when $X(0) = i$.

Case 1: $\mu < 1$

$$
\begin{aligned}
1 - e_i &= \lim_{n\to\infty} P(X(n) \geq 1 | X(0) = i) \\
&= \lim_{n\to\infty} \sum_{j\geq 1} P(X(n) = j | X(0) = i) \\
&\leq \lim_{n\to\infty} \sum_{j\geq 1} j \cdot P(X(n) = j | X(0) = i) \\
&= \lim_{n\to\infty} E[X(n) | X(0) = i] \\
&= \lim_{n\to\infty} \mu^n \cdot i = 0
\end{aligned}
$$

Probability of extinction (cont.)

Case 2: $\mu \geq 1$

$$e_2 = {e_1}^2, \quad e_3 = e_2 \cdot e_1, \quad \ldots$$

$$\begin{aligned} e_1 &= P(\text{extinct}|X(0) = 1) \\ &= \sum_{j \geq 0} P(\text{extinct}|X(1) = j) \cdot P_{1j} \\ &= \sum_{j \geq 0} e_j \cdot p_j \\ &= \sum_{j \geq 0} {e_1}^j \cdot p_j \end{aligned}$$

We then solve the above equation to get e_1.

Example

$$p_0 = p_1 = 0.25, \quad p_2 = 0.5$$
$$\Longrightarrow \mu = 1 \cdot 0.25 + 2 \cdot 0.5 > 1$$
$$\Longrightarrow e_1 = {e_1}^0 \cdot 0.25 + {e_1}^1 \cdot 0.25 + {e_1}^2 \cdot 0.5$$
$$\Longrightarrow e_1 = \{1/2,\ 1\}$$

Since $\mu > 1$, we know $\lim_{n\to\infty} E[X(n)] = \infty$.
But if $e_1 = 1$, we have $\lim_{n\to\infty} P(X(n) = 0) = 1$, which would not make $\lim_{n\to\infty} E[X(n)] = \infty$, hence $e_1 \neq 1$.

Reversed Markov chain

Definition

Let $\mathbb{X}$ (resp. $\mathbb{Y}$) be a Markov chain with matrix P (resp. Q).
We say that $\mathbb{Y}$ is the *reversed chain* of $\mathbb{X}$ if there exists a stationary distribution π of $\mathbb{X}$ such that

$$\pi_i \cdot Q_{ij} = \pi_j \cdot P_{ji}$$

holds for all states $i,\ j \in S$.

Observation 1

Observation

The reversed sequence $\mathbb{Y}$ of $\mathbb{X}$ is a Markov chain.

Proof

$$
\begin{aligned}
&P(Y(n) = i_0 | Y(n-1) = i_1, Y(n-2) = i_2, \ldots, Y(n-k) = i_k) \\
=&P(X(n) = i_0 | X(n+1) = i_1, X(n+2) = i_2, \ldots, X(n+k) = i_k) \\
=&\frac{P(X(n) = i_0, X(n+1) = i_1, \ldots, X(n+k) = i_k)}{P(X(n+1) = i_1, \ldots, X(n+k) = i_k)} \\
=&\frac{P(X(n) = i_0) \cdot P(X(n+1) = i_1 | X(n) = i_0) \cdot P_{i_1 i_2} \cdots P_{i_{k-1} i_k}}{P(X(n+1) = i_1) \cdot P_{i_1 i_2} \cdots P_{i_{k-1} i_k}} \\
=&\frac{P(X(n) = i_0, X(n+1) = i_1)}{P(X(n+1) = i_1)} \\
=&P(X(n) = i_0 | X(n+1) = i_1) \\
=&P(Y(n) = i_0 | Y(n-1) = i_1)
\end{aligned}
$$

Observation 2

Observation

If $\mathbb{Y}$ is the reversed sequence of Markov chain $\mathbb{X}$ and π is a stationary distribution of $\mathbb{X}$, then

$$\pi_i \cdot Q_{ij} = \pi_j \cdot P_{ji}$$

holds for all $i, j \in S$, where Q is the transition matrix of $\mathbb{Y}$.

Proof

Let $\mathbb{X}$ and $\mathbb{Y}$ have distribution π

$$\begin{aligned}
\pi_i \cdot Q_{ij} &= P(Y(n-1) = i) \cdot P(Y(n) = j | Y(n-1) = i) \\
&= P(Y(n-1) = i, Y(n) = j) \\
&= P(Y(n-1) = i | Y(n) = j) \cdot P(Y(n) = j) \\
&= P(X(n+1) = i | X(n) = j) \cdot P(X(n) = j) = \pi_j \cdot P_{ji}
\end{aligned}$$

Observation 3

Observation

Let P (resp. Q) be the transition matrix of $\mathbb{X}$ (resp. $\mathbb{Y}$), if vector π satisfy the following

- $\sum_{i \in S} \pi_i = 1$
- $\pi_i \geq 0 \quad \forall i \in S$
- $\pi_i \cdot Q_{ij} = \pi_j \cdot P_{ji} \quad \forall i, j \in S$

then $\mathbb{Y}$ is the reversed sequence of $\mathbb{X}$.

- The long-run proportion of $i \to j$ in the sequence of $\mathbb{Y}$ is equal to the long-run proportion of $j \to i$ in the sequence of $\mathbb{X}$.
- Reversed Markov chain is the reversed sequence.

Proof

From the third property, we have

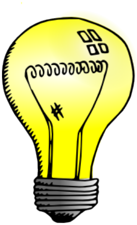
$$\sum_{j \in S} \pi_i \cdot Q_{ij} = \pi_i = \sum_{j \in S} \pi_j \cdot P_{ji} \quad \forall i \in S$$

From the 2nd equation, we know that $\pi \times P = \pi$, hence π is a stationary distribution of $\mathbb{X}$.
Then by observation 2, we know that for any π, there's a reversed sequence $\mathbb{Y}'$, whose transition matrix Q' satisfy

$$\pi_i \cdot Q'_{ij} = \pi_j \cdot P_{ji} \quad \forall i, j \in S$$

hence $\mathbb{Y} = \mathbb{Y}'$, which is a reversed sequence of $\mathbb{X}$.

Example: Bulb's life



There's a room which need to be lighted by one bulb, when the bulb in use fails, it will be replaced by a new one on next day.

- $X(n) = i$ if the bulb in use on day n is in its ith day of use.
- L is a random variable representing the lifetime of a bulb.

We want to know the stationary probability π_i of state i.

Example: Bulb's life (cont.)

$\mathbb{X}$ is a irreducible, positive recurrent, aperiodic Markov chain which has the sequence like this:

$$1, 2, 3, 1, 2, 3, 4, 5, 1, 1, 2, 1, 2, 3, 4, \ldots$$

We know that

$$P_{i1} = P(\text{buld, on its } i\text{th day of use, fails}) = \frac{P(L = i)}{P(L \geq i)} = 1 - P_{i(i+1)}$$

And the expected return time of state 1 is $E[L]$, which means that the long-run proportion of state 1 is $1/E[L]$ by page 60.

Example: Bulb's life (cont.)

Take $\mathbb{Y}$ (with matrix Q) as the reversed chain of $\mathbb{X}$, we know that for all $i \in S$,

- $Q_{(i+1)i} = 1$
- $Q_{1i} = P(L = i)$
- $\pi_1 \cdot Q_{1i} = \pi_i \cdot P_{i1}$

Hence,

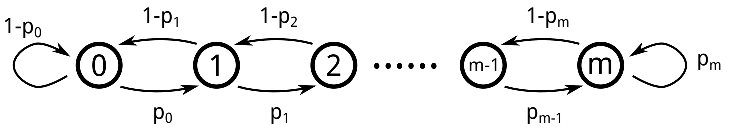
$$\pi_i = \frac{\pi_1 \cdot Q_{1i}}{P_{i1}} = \frac{P(L = i) \cdot P(L \geq i)}{E[L] \cdot P(L = i)} = \frac{P(L \geq i)}{E[L]}$$

Time-reversible

Definition

$\mathbb{X}$ is *time-reversible* if $\mathbb{X}$ is the reversed chain of $\mathbb{X}$.

Example: Reversed drunken man



- $0 < p_0 \leq 1$
- $0 \leq p_m < 1$
- $0 < p_i < 1 \quad \forall i = 1, \ldots, m-1$

The long-run proportion of transition $i \to i+1$ and $i+1 \to i$ are the same, since one must go back to i from $i+1$ in order to go to $i+1$ from i.

Hence the drunken man problem is time-reversible.

Example: Reversed drunken man (cont.)

$$
\begin{aligned}
\pi_0 \cdot p_0 &= \pi_1 \cdot (1 - p_1) \\
\pi_1 \cdot p_1 &= \pi_2 \cdot (1 - p_2) \\
&\vdots \\
\pi_{m-1} \cdot p_{m-1} &= \pi_m \cdot (1 - p_m)
\end{aligned}
$$

Thus,

$$
\begin{aligned}
\pi_1 &= \pi_0 \cdot p_0 / (1 - p_1) \\
\pi_2 &= \pi_1 \cdot p_1 / (1 - p_2) \\
&\vdots \\
\pi_m &= \pi_{m-1} \cdot p_{m-1} / (1 - p_m)
\end{aligned}
$$

Example: Reversed drunken man (cont.)

$$\pi_i = \underbrace{\frac{\prod_{j=0}^{i-1} p_j}{\prod_{j=1}^{i}(1-p_j)}}_{q_i} \cdot \pi_0 \quad \forall i = 1, \ldots m$$

$$\Longrightarrow \pi_0 + \sum_{i=1}^{m} \pi_i = 1 = \pi_0 + \sum_{i=1}^{m} q_i \cdot \pi_0$$

$$\Longrightarrow \pi_0 = \frac{1}{1 + \sum_{i=1}^{m} q_i}$$

$$\Longrightarrow \pi_k = \frac{q_k}{1 + \sum_{i=1}^{m} q_i} \quad \forall k = 0, 1, \ldots m$$

Example: Two bukkits of balls

There're two bukkits contain total m balls.
In each step, we randomly choose one ball and put it in another bukkit.
Let $X(n)$ represent the number of balls in the first bukkit, it's the Markov chain of previous example with

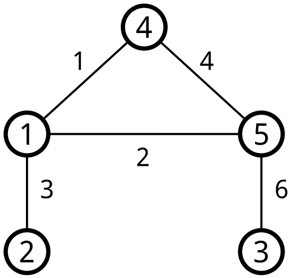
$$p_0 = 1,\ p_m = 0,\ p_i = \frac{m-i}{m} \quad \forall i = 1, \dots, m-1$$

We can get that

$$q_i = \frac{\prod_{j=0}^{i-1} \frac{m-j}{m}}{\prod_{j=1}^{i} \frac{j}{m}} = \frac{\prod_{j=0}^{i-1} m-j}{\prod_{j=1}^{i} j} = \binom{m}{i} \quad \forall i = 1, \dots m$$

$$\implies \pi_0 = \frac{1}{1 + \sum_{i=1}^{m} \binom{m}{i}} = \frac{1}{2^m} \implies \pi_k = \frac{\binom{m}{k}}{2^m} \quad \forall k = 0, 1, \dots m$$

Example: A random walk



$$P_{ij} = \frac{w(i,j)}{\sum_k w(i,k)}$$

where $w(a,b)$ is the weight of edge (a,b).
To make it as a time-reversible chain, we let

$$\pi_i = \frac{\sum_k w(i,k)}{\sum_\ell \sum_k w(\ell,k)} \quad \forall i$$

We can see that

$$\pi_i \cdot P_{ij} = \pi_j \cdot P_{ji} \quad \forall i,j$$

Hastings-Metropolis sampling algorithm

Design an irreducible Markov chain $\mathbb{X}$ such that the unique stationary distribution of $\mathbb{X}$ is the distribution of random variable Y.
Since the long-run proportion of state i is $P(Y = i)$,

$$\lim_{n\to\infty} \frac{X(1) + X(2) + \ldots + X(n)}{n} = \sum_{i \in S} i \cdot P(Y = i) = E[Y] = \mu$$

While computing μ by the law of large number is difficult (hard to sample on Y), we use this alternative method to compute μ by generating a sequence of $\mathbb{X}$, which is sometime easier.

Hastings-Metropolis sampling algorithm (cont.)

There's a random variable Y such that

$$P(Y = i) = \frac{b_i}{C}$$

for some unknown (or intractable) $C = \sum_{i \in S} b_i$.
We then design a Markov chain $\mathbb{X}$ that

- $P_{ii} = Q_{ii} + \sum_{k \in S, k \neq i} Q_{ik} \cdot (1 - q_{ik})$
- $P_{ij} = Q_{ij} \cdot q_{ij} \quad \forall j \neq i$

where

- Q is the transition matrix of an arbitrary irreducible Markov chain $\mathbb{X}$ which has the same state space as Y.
- q is a matrix to be determined later.

Hastings-Metropolis sampling algorithm (cont.)

For $n = 0, 1, \ldots,$

1. If $X(n) = i$, set Z such that $P(Z = j) = Q_{ij} \quad \forall j \in S$.
2. If $Z = j$, set $X(n+1)$ such that
   - $P(X(n+1) = j) = q_{ij}$
   - $P(X(n+1) = i) = 1 - q_{ij}$

One can see that this satisfies the requirement on previous page.

Hastings-Metropolis sampling algorithm (cont.)

Then, we let

$$
\begin{aligned}
q_{ij} &= \min\left(\frac{b_j \cdot Q_{ji}}{b_i \cdot Q_{ij}}, 1\right) \\
\Longrightarrow b_i \cdot Q_{ij} \cdot q_{ij} &= b_j \cdot Q_{ji} \cdot q_{ji} \\
\Longrightarrow \frac{b_i}{C} \cdot P_{ij} &= \frac{b_j}{C} \cdot P_{ji}
\end{aligned}
$$

By observation 3 on page 86, we know that $(b_1 / C, b_2 / C, \ldots)$ is the stationary distribution of $\mathbb{X}$.

Example: Space of permutations

Example

Let S consist of all the permutations $(x_1, x_2, \ldots, x_n)$ of $\{1, 2, \ldots, n\}$ that

$$\sum_{k=1}^{n} k \cdot x_k \geq \frac{n^3}{4}$$

- This is same as Y in page 98 with $C = |S|$ and $b_i = 1\ \forall i$.
- S is hard to compute.
- We need to design a matrix Q such that when given a permutation x, it's efficient to compute the value of $Q_{xy}\ \forall y \in S$.

Example: Space of permutations (cont.)

We let

$$Q_{xy} = \frac{1}{N(x)} \quad \text{, if } y \text{ can be obtained from } x \text{ by one swap}$$

where $N(x)$ is the number of permutations that can be obtained from x by one swap. For example:

$$\underbrace{(1,2,3,4,5)}_{y} \leftrightarrow \underbrace{(1,3,2,4,5)}_{x} \leftrightarrow \underbrace{(1,3,4,2,5)}_{y}$$

This chain is irreducible since each $x \in S$ can go to $(x_1, x_2, \ldots, x_n)$, where $x_1 \leq x_2 \leq \ldots \leq x_n$, by several swaps.
Also, given a x, finding all the obtainable y can be done efficiently.

Counting process

Definition

A collection $\mathbb{N}$ of random variables is a *counting process* if $N(t)$ denotes the total number of events that occur by time t.

- $N(t)$ is a nonnegative integer.
- The value of $N(t)$ is increasing as t increase.
- $N(t) - N(s)$ is the number of events that occur between time index s and t, where $t > s$.

Two properties

Independent increments:

Definition

A counting process is *independent increments* if the number of events in two non-overlapping time intervals are independent.

- For example, $N(s) - N(0)$ and $N(s+t) - N(s)$ are independent.

Stationary increments:

Definition

A counting process is *stationary increments* if the number of events in any time interval depends only on the length of the interval.

- For example,
$P(N(s_1 + t) - N(s_1) = k) = P(N(s_2 + t) - N(s_2) = k)$.

Poisson process

Definition

A *Poisson process* with rate λ is a counting process with independent increments and stationary increments such that

$$P(N(s+t) - N(s) = n) = \frac{e^{-\lambda t} \cdot (\lambda t)^n}{n!}$$

holds for all nonnegative integers.

- $N(s+t) - N(s)$ is Poisson distributed with parameter λt.

An operational definition

Theorem

Let $\mathbb{N}$ be a counting process with independent increments and stationary increments. Then $\mathbb{N}$ is a Poisson process if and only if the following two conditions hold:

1. $P(N(t) = 1) = \lambda \cdot t + o(t)$
2. $P(N(t) \geq 2) = o(t)$

- We say that $f(t) = o(t)$ if

$$\lim_{t \to 0} \frac{f(t)}{t} = 0$$

Proof

($\Longrightarrow$):
Since $N(t)$ is Poisson distributed with parameter λt,

$$\begin{aligned} P(N(t)=1) = \frac{(\lambda t)\cdot e^{-\lambda t}}{1!} &= \lambda t \cdot \left(1 - \frac{\lambda t}{1!} + \frac{(\lambda t)^2}{2!} - \cdots\right) \\ &= \lambda t - \lambda^2 t^2 + \cdots \\ &= \lambda t + o(t) \end{aligned}$$

$$\begin{aligned} P(N(t)=2) = \frac{(\lambda t)^2\cdot e^{-\lambda t}}{2!} &= \frac{(\lambda t)^2}{2!} \cdot \left(1 - \frac{\lambda t}{1!} + \frac{(\lambda t)^2}{2!} - \cdots\right) \\ &= o(t) \end{aligned}$$

One can prove that $P(N(t)=k) = o(t)$ for all $k \geq 2$,
hence $P(N(t) \geq 2) = o(t)$.

Proof (cont.)

($\Longleftarrow$):
The moment-generating function of a random variable X is

$$\phi(u) = E[e^{u \cdot X}]$$

We say that two random variables have the same distribution if their mement-generating function are the same.
And if X is Poisson distributed with parameter λt, then

$$E[e^{u \cdot X}] = e^{(e^u - 1) \cdot \lambda t}$$

Proof (cont.)

We define $\phi_u(t) = E[e^{u \cdot N(t)}]$, then we know that

$$\begin{aligned}
\phi_u(s+t) &= E[e^{u \cdot N(s+t)}] \\
&= E[e^{u \cdot (N(s) - N(0))} e^{u \cdot (N(s+t) - N(s))}] \\
&= E[e^{u \cdot N(s)}] \cdot E[e^{u \cdot (N(s+t) - N(s))}] \\
&= E[e^{u \cdot N(s)}] \cdot E[e^{u \cdot N(t)}] \\
&= \phi_u(s) \cdot \phi_u(t)
\end{aligned}$$

The 3rd equation is because two independent random variables X and Y will make

$$E[X \cdot Y] = E[X] \cdot E[Y]$$

Proof (cont.)

By the two conditions in page 106, we know

$$P(N(t) = 0) = 1 - \lambda t + o(t)$$

Therefore,

$$\begin{aligned}
\phi_u(t) &= E[e^{u \cdot N(t)}] \\
&= e^{u \cdot 0} \cdot (1 - \lambda t + o(t)) + e^{u \cdot 1} \cdot (\lambda t + o(t)) \\
&\quad + (e^{u \cdot 2} + e^{u \cdot 3} + \cdots) \cdot o(t) \\
&= 1 - \lambda t + e^{u} \cdot \lambda t + o(t) \\
&= 1 + (e^{u} - 1) \cdot \lambda t + o(t)
\end{aligned}$$

And

$$\phi_u(s + t) = \phi_u(s) \cdot \phi_u(t) = \phi_u(s) \cdot (1 + (e^{u} - 1) \cdot \lambda t + o(t))$$

Proof (cont.)

Differential on $\phi_u(s)$, we can get

$$\begin{aligned}\phi_u{}'(s) &= \lim_{t\to 0}\frac{\phi_u(s+t)-\phi_u(s)}{t} = \lim_{t\to 0}(\phi_u(s)\cdot(e^u-1)\cdot\lambda + o(t))\\ &= \phi_u(s)\cdot(e^u-1)\cdot\lambda\end{aligned}$$

By $\frac{\phi_u{}'(s)}{\phi_u(s)} = (e^u-1)\cdot\lambda$, we have

$$\ln\phi_u(s) = \int(e^u-1)\cdot\lambda\,\mathrm{d}s = (e^u-1)\cdot\lambda s + C$$

By $\phi_u(0)=1$ and $\ln 1 = 0$, we know $C=0$, hence

$$\phi_u(s) = e^{(e^u-1)\cdot\lambda s} \quad \forall s, u$$

which means that $N(s)$ is Poisson distributed for all s.

Inter-arrival time

Definition

The kth inter-arrival time T_k of $\mathbb{N}$ is the time interval between the $(k+1)$st and kth events.
$\mathbb{T} = T_1, T_2, \ldots$ is the sequence of inter-arrival times of $\mathbb{N}$.

- 0th event arrives at time 0.

Observation 1

Observation

If $\mathbb{N}$ is a Poisson process with rate λ, then each T_k is an independent exponential distribution with parameter λ.

Proof:
The cumulative distribution function of T_1 is

$$\begin{aligned}F_1(s) &= P(T_1 \leq s) \\ &= 1 - P(T_1 > s) \\ &= 1 - P(N(s) = 0) \\ &= 1 - e^{-\lambda s}\end{aligned}$$

The 3rd equation is because $T_1 > s \iff N(s) = 0$.
We can observe that T_1 is expenential distributed.

Proof (cont.)

$$
\begin{aligned}
P(T_2 > t | T_1 = s) &= P(N(s) = N(s+t) = 1 | T_1 = s) \\
&= P(N(s) = N(s+t) = 1) \\
&= P(N(t) = 0) \\
&= e^{-\lambda t}
\end{aligned}
$$

The 2nd equation is by independent increments.why?
The 3rd equation is by stationary increments.

Thus, T_2 is also exponential distributed with parameter λ.
And T_1, T_2 are independent.
One can prove for T_k with $k \geq 3$ by the same approach.