

First steps in random walks

(a brief introduction to Markov chains)

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Step 1

Random variables

Before the walk

Measurable spaces

A **measurable space** is a set Ω equipped with a family of sets

$$A \subseteq \Omega$$

called the **events** of the space, such that

- (i) the set Ω is an event
- (ii) if A_1, A_2, \dots are events, then $\bigcup_{i=1}^{\infty} A_i$ is an event
- (iii) if A is an event, then its complement $\Omega \setminus A$ is an event

Illustration

Every topological space Ω induces a measurable space whose events

$$A \subseteq \Omega$$

are defined by induction:

- the events of level 0 are the **open sets** and the **closed sets**,
- the events of level $k + 1$ are the **countable** unions and intersections

$$\bigcup_{i=1}^{\infty} A_i$$

$$\bigcap_{i=1}^{\infty} A_i$$

of events A_i of level k .

Typically...

The measurable space \mathbb{R} equipped with its **borelian** events

Probability spaces

A measurable set Ω equipped with a **probability measure**

$$A \mapsto \mathbf{P}(A) \in [0, 1]$$

which assigns a value to every event, in such a way that

- (i) the event Ω has probability $\mathbf{P}(\Omega) = 1$
- (ii) the event $\bigcup_{i=1}^{\infty} A_i$ has probability

$$\mathbf{P}\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \mathbf{P}(A_i)$$

when the events A_i are pairwise disjoint.

Random variable

A **random variable** on a measurable space Υ

$$X : \Omega \rightarrow \Upsilon$$

is a **measurable** function from a probability space

$$(\Omega, \mathbf{P})$$

called the **universe** of the random variable.

Notation for an event A of the space Υ :

$$\{ X \in A \} := \{ \omega \in \Omega \mid X(\omega) \in A \} = X^{-1}(A)$$

Conditional probabilities

Given two random variables

$$X, Y : \Omega \longrightarrow \Upsilon$$

and two events A, B such that

$$\mathbf{P} \{ Y \in B \} \neq 0$$

the **probability** of $\{ X \in A \}$ **conditioned** by $\{ Y \in B \}$ is defined as

$$\mathbf{P} \{ X \in A \mid Y \in B \} := \frac{\mathbf{P} \{ X \in A \cap Y \in B \}}{\mathbf{P} \{ Y \in B \}}$$

where

$$\{ X \in A \cap Y \in B \} = X^{-1}(A) \cap Y^{-1}(B).$$

Expected value

The **expected value** of a random variable

$$X : \Omega \longrightarrow \mathbb{R}$$

is defined as

$$\mathbf{E} (X) = \int_{\Omega} X \, d\mathbf{P}$$

when the integral converges absolutely.

In the case of a random variable X with finite image:

$$\mathbf{E} (X) = \sum_{x \in \mathbb{R}} x \, \mathbf{P} \{ X = x \}$$

Step 2

Markov chains

Stochastic processes

Finite Markov chains

A **Markov chain** is a sequence of random variables

$$X_0, X_1, X_2, \dots : \Omega \longrightarrow \Upsilon$$

on a measurable space Υ such that

$$\mathbf{P} \{ X_{n+1} = y \mid X_1 = x_1, \dots, X_n = x_n \} = \mathbf{P} \{ X_{n+1} = y \mid X_n = x_n \}$$

Every Markov chain is described by its **transition matrix**

$$P(x, y) := \mathbf{P} \{ X_{n+1} = y \mid X_n = x \}$$

Stationary distribution

A **stationary distribution** of the Markov chain

P

is a probability measure π on the state space \mathcal{Y} such that

$$\pi = \pi P$$

A stationary distribution π is a fixpoint of the transition matrix P

Reversible Markov chains

A probability distribution π on the state space Υ satisfies the

detailed balance equations

when

$$\pi(x) P(x, y) = \pi(y) P(y, x)$$

for all elements x, y of the state space Υ .

Property. Every such probability distribution π is stationary.

Proof of the statement

Suppose that

$$\pi(x) P(x, y) = \pi(y) P(y, x)$$

for all elements x, y of the state space Υ . In that case,

$\pi P(x)$	$=$	$\sum_{y \in \Upsilon} \pi(y) P(y, x)$	by definition
	$=$	$\sum_{y \in \Upsilon} \pi(x) P(x, y)$	detailed balance equation
	$=$	$\pi(x)$	property of the matrix P

Irreducible Markov chains

A Markov chain is **irreducible** when for any two states

$$x, y \in \Omega$$

there exists an integer

$$t \in \mathbb{N}$$

such that

$$P^t(x, y) > 0$$

where P^t is the transition matrix P composed t times with itself.

Step 3

Random walk

A concrete account of reversible Markov chains

Networks

A finite undirected connected graph

$$G = (V, E)$$

where every edge $e = \{x, y\}$ has a **conductance**

$$c(e) \in \{ x \in \mathbb{R} \mid x > 0 \}.$$

The inverse of the conductance

$$r(e) = \frac{1}{c(e)}$$

is called the **resistance** of the edge.

Weighted random walk

Every network defines a Markov chain

$$P(x, y) = \frac{c(x, y)}{c(x)}$$

where

$$c(x) = \sum_{x \sim y} c(x, y)$$

Here, $x \sim y$ means that $\{x, y\}$ is an edge of the graph G .

A stationary probability

Define the probability distribution

$$\pi(x) = \frac{c(x)}{c_G}$$

where

$$c_G = \sum_{x \in V} \sum_{x \sim y} c(x, y)$$

The Markov chain P is reversible with respect to the distribution π .

Consequence.

the distribution π is **stationary** for the Markov chain P .

Conversely...

Every Markov chain P on a finite set Υ reversible with respect to the probability π may be recovered from the random walk on the graph

$$G = (V, E)$$

with set of vertices

$$V = \Upsilon$$

and edges

$$\{x, y\} \in E \iff P(x, y) > 0$$

weighted by the conductance

$$c(x, y) = \pi(x) P(x, y).$$

Step 4

Harmonic functions

Expected value of hitting time is harmonic

Harmonic functions

A function

$$h : \Omega \longrightarrow \mathbb{R}$$

is **harmonic** at a vertex x when

$$h(x) = \sum_{y \in \Omega} P(x, y) h(y)$$

Here, P denotes a given transition matrix.

Harmonic functions at a vertex x define a vector space

Expected value

The **expected value** of a random variable on \mathbb{R} is defined as

$$\mathbf{E} (X) = \int_{\Omega} X \, d\mathbf{P}$$

In the finite case:

$$\mathbf{E} (X) = \sum_{x \in \mathbb{R}} x \, \mathbf{P} \{ X = x \}$$

Hitting time

The hitting time τ_B associated to a set of vertices B is defined as

$$\tau_B = \min \{ t \geq 0 \mid X_t \in B \}$$

This defines a random variable

$$X_{\tau_B} : \Upsilon \longrightarrow B$$

which maps every $v \in \Upsilon$ to the first element b it reaches in the set B .

Proof of the statement

$$X_{\tau_B}^{-1}(b) = \bigcup_{n=0}^{\infty} \mathbf{Hit}_n(b)$$

where

$$\mathbf{Hit}_0(b) = X_0^{-1}(b)$$

$$\mathbf{Hit}_1(b) = X_1^{-1}(b) \setminus X_0^{-1}(B)$$

$$\mathbf{Hit}_{n+1}(b) = X_{n+1}^{-1}(b) \setminus \bigcup_{b \in B} \mathbf{Hit}_n(b)$$

This establishes that each $X_{\tau_B}^{-1}(b)$ is an event of the universe Ω , and thus that X_{τ_B} is a random variable.

Expected value

Given a function

$$h_B : B \longrightarrow \mathbb{R}$$

define the random variable:

$$h_B \circ X_{\tau_B} : \Upsilon \longrightarrow \Omega \longrightarrow \mathbb{R}$$

whose expected value at the vertex x is denoted

$$\mathbf{E}_x [h_B \circ X_{\tau_B}]$$

Existence of an harmonic function

Observation: the function

$$h : x \mapsto \mathbf{E}_x [h_B \circ X_{\tau_B}]$$

- (i) coincides with h_B on the vertices of B
- (ii) is harmonic on every vertex x in the complement $\Omega \setminus B$.

Proof of the statement

$$\mathbf{E}_b [h_B \circ X_{\tau_B}] = h_B(b)$$

$$\begin{aligned} \mathbf{E}_x [h_B \circ X_{\tau_B}] &= \sum_{y \in \Omega} P(x, y) \mathbf{E}_x [h_B \circ X_{\tau_B} \mid X_1 = y] \\ &= \sum_{y \in \Omega} P(x, y) \mathbf{E}_y [h_B \circ X_{\tau_B}] \\ &= \sum_{y \sim x} \mathbf{E}_y [h_B \circ X_{\tau_B}] \end{aligned}$$

Uniqueness of the harmonic function

There exists a unique function

$$h : \Omega \longrightarrow \mathbb{R}$$

such that

- (i) coincides with h_B on the vertices of B
- (ii) is harmonic on every vertex x in the complement $\Omega \setminus B$.

Proof of the statement

First, reduce the statement to the particular case

$$h_B = 0$$

Then, consider a vertex $x \in \Omega \setminus B$ such that

$$h(x) = \max \{ h(z) \mid z \in \Omega \}$$

Then, for every vertex y connected to x , one has

$$h(y) = \max \{ h(z) \mid z \in \Omega \}$$

because the function h is harmonic.

Step 5

Electric networks

Expected values as conductance

Idea

Now that we know that

$$h : x \mapsto \mathbf{E}_x [h_B \circ X_{\tau_B}]$$

defines the **unique** harmonic function on the vertices of $\Omega \setminus B...$

let us find **another way** to define this harmonic function!

Voltage

We consider a source a and a sink z and thus define

$$B = \{ a, z \}$$

and define a **voltage** as any function

$$W : V \longrightarrow \mathbb{R}$$

harmonic on the vertices of $V \setminus \{a, z\}$.

A voltage W is determined by its boundary values $W(a)$ and $W(z)$

Flows

A flow θ is a function on **oriented edges** of the graph, such that

$$\theta(x\vec{y}) = -\theta(y\vec{x})$$

The **divergence**

$$\mathbf{div} \theta : x \mapsto \sum_{y \sim x} \theta(x\vec{y})$$

Observe that

$$\sum_{x \in V} \mathbf{div} \theta(x) = 0$$

Flows from source to sink

A flow from a to z is a flow such that

- (i) Kirchnoff's node law: $\mathbf{div} \theta (x) = 0$
- (ii) the vertex a is a source: $\mathbf{div} \theta (a) \geq 0$

Observe that

$$\mathbf{div} \theta (z) = - \mathbf{div} \theta (a)$$

Current flow

The current flow I induced by a voltage W is defined as

$$I(\vec{x}\vec{y}) = \frac{W(x) - W(y)}{r(x, y)} = c(x, y) [W(x) - W(y)]$$

From this follows Ohm's law:

$$r(\vec{x}\vec{y}) I(\vec{x}\vec{y}) = W(y) - W(x)$$

Main theorem

$$\mathbf{P}_a (\tau_z < \tau_a^+) = \frac{1}{c(a) \mathcal{R} (a \leftrightarrow z)} = \frac{C (a \leftrightarrow z)}{c(a)}$$

where

$$\mathcal{R} (a \leftrightarrow z) = \frac{W(a) - W(z)}{\| I \|} = \frac{W(a) - W(z)}{\mathbf{div} \theta (a)}$$

Edge-cutset

An edge-cutset separating a from z is a set of vertices

Π

such that every path from a to z crosses Π .

If Π_k is a set of disjoint edge-cutset separating sets, then

$$\mathcal{R}(a \leftrightarrow z) \geq \sum_k \left(\sum_{e \in \Pi_k} c(e) \right)^{-1}$$

Energy of a flow

The energy of a flow is defined as:

$$\mathcal{E}(\theta) = \sum_e [\theta(e)]^2 r(e)$$

Theorem. (Thompson's Principle) For any finite connected graph,

$$\mathcal{R}(a \leftrightarrow z) = \inf \{ \mathcal{E}(\theta) \mid \theta \text{ is a unit flow from } a \text{ to } z \}$$

where a unit flow θ is a flow from a to z such that

$$\operatorname{div} \theta(a) = 1.$$