

Part VIII

Markov chains - random walks

Random walks on graphs are a very simple, interesting and fundamental tool with surprisingly many applications in informatics and also in mathematics and natural sciences. Design and analysis of randomized algorithms is one of them.

The concept of a random walk is closely related with that of **Markov chain/model** – one of the key concepts of discrete stochastic processes.

In physical sciences, Markov chains provide a fundamental model for the emergence of global properties from local interactions.

In informatics, random walks provide a general paradigm for random exploration of an exponentially large combinatorial structures (for example graphs), by a sequence of simple and local transitions.

- **Hidden Markov Model** (HMM) is a Markov model, with random transitions among states, extended by random outputs of the states. HMM works in such a way that an observer can see only a sequence of states' outputs and not the internal structure (states, transition and emission probabilities) of the underlying Markov model.
- Hidden Markov Model (HMM), has a lot of applications, especially in artificial intelligence.
- For example, almost all fast speech and patterns recognition systems use HMM.

The concept of Markov chain introduced Andreei Andreevich Markov in 1906, in order to consider the case of having a sequence of random experiments in which result of any experiment depends also on the result of the previous experiment.

Before that only such sequences of random experiments were considered where the result of each random experiment was fully independent from all previous experiments.

It can be also shown that any

quantum evolution

can be seen as so-called

continuous quantum walk.

Notation Let $G = (V, E)$ be a connected, undirected, graph with n nodes (in V) and m edges (in E). For a node $v \in V$, let $\Gamma_G(v)$ denote the set of neighbors of v in G .

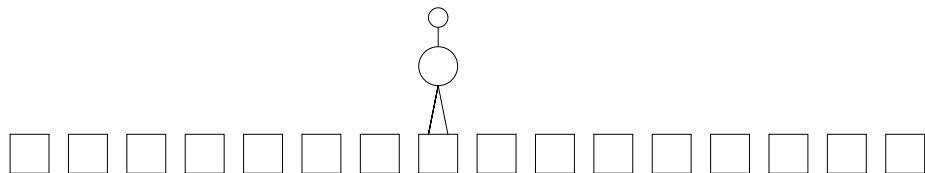
A **random walk** on G is the following sequence of moves of the process that starts in some node v_0 and then:

a neighbor v_1 of v_0 is chosen, randomly and independently, and then the process moves (walks) from v_0 to v_1 ; afterwards a neighbor v_2 of v_1 is chosen randomly and independently and the process walks from v_1 to v_2 ; the process continues to walk this way ...for ever.

Typical problems to explore for a given graph G :

- What is the expected number of steps to get from a given node u to a given node v .
- What is the expected number of steps needed to visit all nodes of G when starting in a given node u .

DRUNKARD'S WALK



Let a drunken seaman walk on a linear, both sides infinite graph, each time choosing a step right or left with the same probability.

What are the probabilities for such a drunken man to be in a particular position after some steps in case he starts in some other position.

EXAMPLE

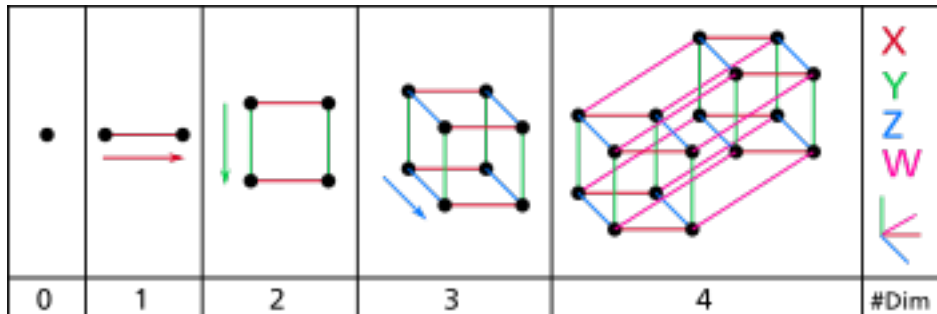
Let

- $G = K_n$ be the complete graph of n nodes
- $u \neq v$ be any two vertices of G .

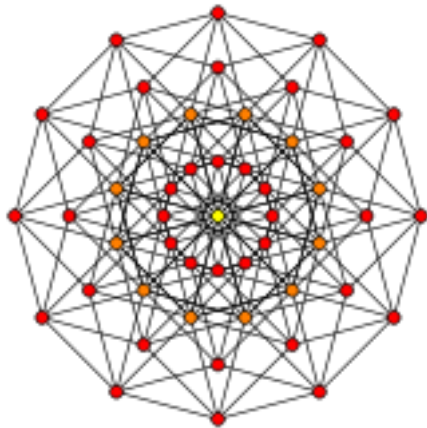
It holds:

- The expected number of steps of a random walk that begins in u and ends when first reaching v is
???????

Simple hypercubes



6-d hypercube



EXAMPLE - to finish

Let

- $G = K_n$ be the complete graph of n nodes

It holds:

- The expected number of steps of a random walk in K_n that begins in a fixed node u and ends when first reaching a fixed node v is

$$p = 1 \cdot \frac{1}{n-1} + (1+p) \cdot \frac{n-2}{n-1}$$

$$p = n - 1$$

- The expected number of steps to visit all nodes in G starting from any node u is

$$(n - 1)H_n,$$

where H_n is so called **Harmonic number**

Coupon selector problem: There are n types of coupons and at each time a coupon is chosen randomly and returned.

It has been shown that the average number of trials needed to have a coupon of each type is

$$nH_n.$$

EXAMPLE

Let us consider graph K_3 with the initial probabilities of its three nodes, say A_0, A_1, A_2 , being

$$p_0, p_1, p_2$$

and let $1/2$ be the probability of the transmission through through any edge.

If p is the initial probability of a node X , then probability of being in the same node after one step is

$$P_1 = (1 - p) \frac{1}{2} = \frac{1}{2} - \frac{p}{2},$$

after two steps is

$$P_2 = (1 - (1 - p) \frac{1}{2}) \frac{1}{2} = \frac{1}{2} - \frac{1}{4} + \frac{p}{4}$$

and after i steps the probability is

$$P_i = \sum_{j=1}^i (-1)^{j+1} \frac{1}{2^j} + (-1)^i \frac{p}{2^i}.$$

Therefore

$$\lim_{i \rightarrow \infty} P_i = \frac{1}{3}$$

EXAMPLE – 2-SATISFIABILITY

A simple polynomial-time (Monte Carlo) algorithm will be given to solve 2-SAT problem (for a formula in conjunctive normal form in which each clause having two literals) satisfiable with a single assignment.

Algorithm

- 1 Start with an arbitrary assignment.
- 2 **while** there is an unsatisfied clause C ,
choose randomly one of two literals of C and complement its value in the current assignment.

Theorem The expected number of steps of the above algorithm at finding a satisfying assignment is $\mathcal{O}(n^2)$ (where n is the number of variables).

Let A be a particular satisfying assignment.

The progress of the above algorithm can be represented by a particle moving between integers $\{0, 1, \dots, n\}$ on the real line. The position of the particle will always indicate how many variables in the current assignment have the correct value (as in A).

Crucial observation. In an unsatisfied clause at least one of two literals has an incorrect value. Therefore at each step of the algorithm with probability $\frac{1}{2}$ we increase by one the number of variables having their correct value; and with probability $\frac{1}{2}$ the number of variables having correct value is decreased by one. The motion of the particle therefore resembles a random walk on the line (that is on the linear graph).

A **stochastic process** is a sequence of random variables $\{X_t\}_{t \geq 1}$, where we think of values of X_t as values (states) of the process at time t .

Two types of stochastic processes come up over and over again in the analysis of randomized algorithms:

- 1 **Martingale**, where values of each next variable may depend, even in a complicated way, on the past history, but its expectation is 0.
- 2 **Markov chain** where next state depends always only on the current state and not on ways to get there - not on the past history.

The most useful algorithmic property of Markov chains, to be explored in the next, is their convergence to a fixed (probability) distributions on states.

MARKOV CHAINS - 1st DEFINITION

A **Markov chain** is a **discrete-time stochastic process** defined over a set of states S in terms of a matrix P of transition probabilities

$$P(i, j) = p_{ij} = \begin{array}{l} \text{the probability that the next state will be } j \\ \text{if the current state is } i. \end{array}$$

Probability conditions: For any i, j it has to hold

$$0 \leq p_{ij} \leq 1 \quad \text{and} \quad \sum_j p_{ij} = 1.$$

Denote X_t the state of the Markov chain at time t .

The stochastic process $\{X_t\}_{t=0}^{\infty}$, specifying the history of the evolution of the Markov chain at time t , has the following **memoryless property**:

The future behaviors of a Markov chain depends on its current state, and not how the chain arrived at the current state. That is, it holds, for any $t \geq 1$:

$$Pr[X_{t+1} = j | X_0 = i_0, X_1 = i_1, \dots, X_t = i_t = i] = Pr[X_{t+1} = j | X_t = i] = p_{ij}.$$

Note: Markov chains do not need to have prespecified initial states.

In general, initial states are chosen according to some probability distribution X_0 over S .

Such a distribution is called the **initial (probability) distribution**.

MARKOV CHAIN –2nd DEFINITION

A Markov chain is a discrete time stochastic process $\{X_k\}_{k \geq 0}$ of random variables with values in a countable set I such that for every $k \geq 1$ and every i_0, i_1, \dots, i_k from I we have

$$Pr[X_k = i_k | X_{k-1} = i_{k-1}, \dots, X_0 = i_0] = Pr[X_k = i_k | X_{k-1} = i_{k-1}] = p_{i_{k-1}i_k}.$$

The matrix $P(i, j) = p_{ij}$ is called the **transition matrix** of one-step **transition probabilities**.

k -steps transition probabilities $p_{ij}^{(k)}$ are defined by

$$p_{ij}^{(k)} = Pr[X_{m+k} = j | X_m = i]$$

and they do not depend on m .

If we define a matrix $P^{(k)}$ by $P^{(k)}(i, j) = p_{ij}^{(k)}$, then (**Chapman-Kolmogorov equations**)

$$P^{(k+m)} = P^{(k)}P^{(m)}.$$

The matrix $P^{(k)}$ is said to be the **k -steps transition matrix**.

DETAILS of MARKOV's CHAIN STEPS

Rows of all k -steps transition matrices have non-negative entries and sum up to 1. Such matrices are called **stochastic matrices**.

A probability distribution over states of a Markov chain with a transition matrix P at any time t can be given by a row vector X , where

$$x_i = Pr[X_t = i].$$

Distribution vector at time $t + n$ is then given by vector XP^n .

- A **state j is called reachable/accessible from the state i** if there is a $k > 0$ such that $p_{ij}^{(k)} > 0$.
- We say that **states i and j are called mutually reachable** if i is reachable from j and vice versa.
- A **Markov chain is called irreducible**, if any two of its states are mutually reachable.

GENERAL OBSERVATION

Systems represented by Markov chains change randomly and therefore it is generally impossible to determine the exact state of the system in the future.

However, we often can determine various useful statistical properties of Markov chains.

EXAMPLE - EATING HABITS

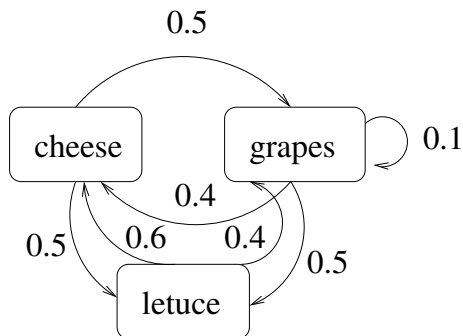
Example A creature in ZOO eats once a day, either grapes, or cheese, or lettuce, according to the following rules:

- If it ate cheese yesterday it will not eat it today and will eat lettuce and grapes with the same probability 0.5.
- If it ate grapes yesterday, it will eat today grapes with probability 0.1 cheese with probability 0.4 and lettuce with probability 0.5
- If it ate lettuce yesterday, it will eat grapes with probability 0.4 and cheese with probability 0.6.

These eating habits can be modelled by Markov chain in the next figure.

MARKOV CHAIN for EATING HABITS

Markov chains are often described by a directed graph with edges labelled by probabilities for going from one state/node to another one.



Eating habits of a creature.

One statistical property that can be computed is the percentage of days the creature eats grapes (or cheese).

EHRENFEST MODEL

There are two urns that, in total, always contain four balls. At each step, one of the balls is chosen at random and moved to other urn.

If we choose as states number of balls in the first urn, then the transition matrix, where rows and columns are labelled (from the top to bottom and from the left to right) **0, 1, 2, 3, 4** looks as follows

$$P = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 1/4 & 0 & 3/4 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 3/4 & 0 & 1/4 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

ABSORBING DRUNKARD'S WALK

A drunk man walks on a 5 nodes (0, 1, 2, 3, 4) linear graph, where leftmost node (0) is his home and rightmost one (4) is a bar. If he is at home or in bar he keeps staying there. Otherwise he moves with probability 1/2 to left node and probability 1/2 to right node.

The transition matrix has therefore the form

$$P = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

where rows and columns are labeled by 0, 1, 2, 3, 4 and $P(i, j)$ is probability that if first urn has i balls, then after one step it has j balls.

ABSORBING MARKOV CHAINS

Definition A state s_i of a Markov chain is called **absorbing** if it is impossible to leave it (i.e. $p_{ii} = 1$). A Markov chain is called **absorbing** if it has at least one absorbing state, and if from any state one can go to an absorbing state, in some number of steps.

The Drunkard's walk is an example of an absorbing Markov chain.

If the transition matrix of a Markov walk has a absorbing states and t not absorbing states, one can renumber states so that all first t rows and columns represent not absorbing states and remaining ones absorbing states. The matrix has then the following canonical form:

$$P = \begin{pmatrix} Q & R \\ \mathbf{0} & I \end{pmatrix}$$

where Q is a $t \times t$ matrix, R is a $t \times a$ matrix, $\mathbf{0}$ is a $a \times t$ zero matrix and I is a $a \times a$ identity matrix, with first t rows and columns labeled by not absorbing states. This means that for any integer n ,

$$P^n = \begin{pmatrix} Q^n & * \\ \mathbf{0} & I \end{pmatrix}$$

where $*$ is a matrix the precise form of which will not be important in the following.

BASIC CONCEPTS – I.

Given an initial state $X_0 = i$, the **probability that the first transition into state j occurs at time t** is given by

$$r_{ij}^{(t)} = Pr[X_t = j \text{ and } X_s \neq j \text{ for } 1 \leq s < t | X_0 = i].$$

Given an initial state $X_0 = i$, then the **probability that there is a visit to state j at some time $t > 0$** is given by

$$f_{ij} = \sum_{t>0} r_{ij}^{(t)}.$$

f_{ii} is the probability that Markov chain will return to the state i at least once when started in the state i .

If $f_{ii} = 1$ the state i is called **persistent/recurrent (vracajuci sa)**; otherwise it is called **transient (prechodný)**. A Markov chain is recurrent if every its state is recurrent. All states of an irreducible Markov chain are recurrent.

If $f_{ii} < 1$, then each time the chain is in the state i , with probability $1 - f_{ii}$ will never return again to i . It therefore holds:

$$Pr[\text{The number of visits to } i \text{ from } i \text{ equals } k] = f_{ii}^k (1 - f_{ii}).$$

Denote as the **hitting time (čas dosiahnutia/riešenia)** h_{ij} the expected number of steps needed to visit the state/node j for the first time when starting from the state/node i . Clearly, it holds

$$h_{ij} = \sum_{t>0} tr_{ij}^{(t)}.$$

If $h_{ii} < \infty$, then the state i is called **positive (non-null) recurrent/persistent**; otherwise it is called **null-recurrent/persistent**.

If a state i is reachable from itself, then the greatest common divisor of the set of positive k 's such that $p_{ii}^{(k)} > 0$, is called the **period** of i and is denoted by d_i .

If $d_i = 1$, then the state i is said to be **aperiodic**.

recurrent is called **ergodic**.

EQUIVALENT DEFINITIONS

A state i has a **period** k if any return to the state i must occur in time steps that are multiple of k .

A state i is called **aperiodic** - if it is not periodic for any $k > 1$.

A state i is said to be **transient**, if given that we start in the state i , there is non-zero probability that we will never return to i .

If a state i is not transient, then it is called **recurrent**.

A state i is

transient if $f_{ii} < 1$, $h_{ii} = \infty$;

null recurrent if $f_{ii} = 1$, $h_{ii} = \infty$;

non-null recurrent if $f_{ii} = 1$, $h_{ii} < \infty$.

EXAMPLE of a Markov chain with null-recurrent states

Consider a Markov chain whose states are all positive integers.

From each state i the next states are the state $i + 1$ (with probability $\frac{i}{i+1}$) and the state 1 (with probability $\frac{1}{i+1}$)

Starting at state 1, the probability of not having returned to state 1 within the first t steps is

$$\prod_{j=1}^t \frac{j}{j+1} = \frac{1}{t+1}.$$

Hence the probability of never returning to state 1 from 1 is 0, and state 1 is recurrent. It holds also

$$r_{1,1}^t = \frac{1}{t} \cdot \frac{1}{t+1} = \frac{1}{t(t+1)}.$$

However, the expected number of steps until the first return to state 1 from state 1 is

$$h_{1,1} = \sum_{t=1}^{\infty} t \cdot r_{1,1}^t = \sum_{t=1}^{\infty} \frac{1}{t+1}.$$

which is unbounded.

However, it holds: In a finite Markov chain at least one state is recurrent and all recurrent states are positive recurrent.

An equivalent definition of ergodic Markov chains.

Definition A Markov chain with a transition matrix P is called ergodic if it is possible to go from every state to every state and there is an integer n such that all entries of the matrix P^n are positive.

ERGODIC THEOREM

Let us have an ergodic Markov chain with the set of states $S = \{1, \dots, n\}$. Then, it holds:

- There exists a vector $\pi = (\pi_1, \dots, \pi_n)$ such that for every $i, j \in S$ it holds

$$\pi_j = \lim_{k \rightarrow \infty} p_{ij}^{(k)}$$

and the limit does not depend on i .

- The vector π is the only non-negative solution of the system of linear equalities

$$\pi_j = \sum_{i=1}^n \pi_i p_{ij}, \quad \sum_{j=1}^n \pi_j = 1.$$

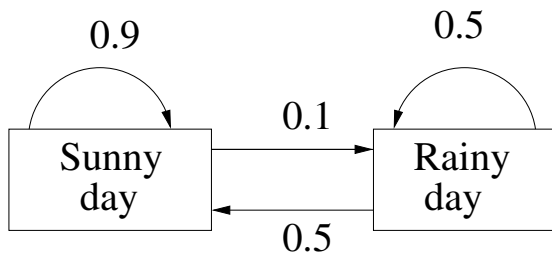
- The vector π satisfies the identity $\pi = \pi P$.
- For every $1 \leq i \leq n$, it holds that $f_{ii} = 1$ and $h_{ii} = \frac{1}{\pi_i}$.
- If $N(i, t)$ denotes the number of visits to the state i within the t first steps, then

$$\lim_{t \rightarrow \infty} \frac{N(i, t)}{t} = \pi_i.$$

Implications: Ergodic Markov chains always “forget”, after a while, their initial probability distribution.

WEATHER FORECAST

The following Markov chain depicts probabilities for going from sunny days to rainy and vice versa.



Transition matrix has the form

$$P = \begin{pmatrix} 0.9 & 0.1 \\ 0.5 & 0.5 \end{pmatrix}$$

and the stationary probability distribution is $\pi = (0.833, 0.167)$. It holds $\pi P = \pi$.

EXAMPLE - QUEUE - Q_n - I.

Let us consider, for any integer n , the bounded queue Q_n in which each time moment exactly one of the following steps happen.

- If a queue has fewer than n customers, then with probability λ a new customer joins the queue.
- If the queue is not empty, then with probability μ the head of the line is served and leaves the queue.
- With remaining probability, the queue is unchanged.

Let us consider stochastic process with X_t being the number of customers at time t . This is a Markov chain and its transition matrix has the following non-zero entries:

EXAMPLE - QUEUE - Q_n - II.

$$\begin{aligned}P_{i,i+1} &= \lambda \text{ if } i < n; \\P_{i,i-1} &= \mu \text{ if } i > 0; \\P_{i,j} &= \begin{cases} 1 - \lambda & \text{if } i = 0; \\ 1 - \lambda - \mu & \text{if } 1 \leq i \leq n - 1; \\ 1 - \mu & \text{if } i = n; \end{cases}\end{aligned}$$

This Markov chain is ergodic and therefore it has a unique stationary distribution π . It holds

$$\begin{aligned}\pi_0 &= \pi_0(1 - \lambda) + \pi_1\mu \\ \pi_i &= \pi_{i-1}\lambda + \pi_i(1 - \lambda - \mu) + \pi_{i+1}\mu, \quad 1 \leq i \leq n - 1 \\ \pi_n &= \pi_{n-1}\lambda + \pi_n(1 - \mu)\end{aligned}$$

EXAMPLE - QUEUE - Q_n - III.

From that one can show that

$$\pi_i = \pi_0 \left(\frac{\lambda}{\mu} \right)^i$$

is the solution of the above system of equations. Since

$$1 = \sum_{i=0}^n \pi_i = \sum_{i=0}^n \pi_0 \left(\frac{\lambda}{\mu} \right)^i$$

it holds

$$\pi_0 = \frac{1}{\sum_{i=0}^n (\lambda/\mu)^i}$$

MARKOV CHAINS for GRAPHS

Let $G = (V, E)$ be a connected, non-bipartite, and undirected graph with $|V| = n$ and $|E| = m$. G induces a Markov chain, denoted by M_G , states of which are nodes of G and for any two nodes $u, v \in V$

$$P(u, v) = \begin{cases} \frac{1}{d(u)}, & \text{if } (u, v) \in E; \\ 0, & \text{otherwise;} \end{cases}$$

where $d(u)$ is the degree of u (in G).

Properties of M_G

- M_G is irreducible.
- Periodicity of M_G is the greatest common divisor of the length of all closed walks in G .
- Since G is undirected, there are closed walks of length 2;
- Since G is non-bipartite, it has odd cycles and therefore the *greatest common divisor* of all closed walks is 1. Hence, M_G is aperiodic.

Ergodic theorem therefore implies that M_G has a unique stationary distribution π . This π is easy to determine. Indeed, it holds

Lemma For all $v \in V$, $\pi_v = \frac{d(v)}{2m}$. **Proof** Let $[\pi P]_v$ be the v -th component of πP . Then

$$\pi_v = [\pi P]_v = \sum_u \pi_u P(u, v) = \sum_{(u,v) \in E} \frac{d(u)}{2m} \times \frac{1}{d(u)} = \sum_{(u,v) \in E} \frac{1}{2m} = \frac{d(v)}{2m}.$$

Corollary: For all $v \in V$, $h_{vv} = \frac{1}{\pi_v} = \frac{2m}{d(v)}$.

Comment: Google's page ranking algorithm is essentially a Markov chain over the graph of the web.

APPLICATIONS of MARKOV CHAINS

- Physics - especially thermodynamics and statistical mechanics.
- Chemistry
- The PageRank of a webpage, as used by Google, is defined by a Markov chain. It is the probability to be at page i in the stationary distribution on the following Markov chain on all known webpages.

If N is the number of known webpages, and a page i has links to k_i webpages, then the probability to go to any of these pages is

$$\frac{\alpha}{k_i} + \frac{1 - \alpha}{N}$$

and the probability to go to any other page is

$$\frac{1 - \alpha}{N},$$

where the parameter α (experimentally chosen) is about 0.85.

- Economics and finance
- Social sciences
- Mathematical biology
- Algorithmic music composition

APPLICATIONS - SAMPLING

Sampling in a set S according a given probability distribution π , on elements of S , is a picking up an element $x \in S$ with probability $\pi(x)$.

- Let $Z = (X, Y)$ be a point chosen randomly in a 2×2 square centered in $(0, 0)$.
- This is equivalent to choosing X and Y randomly from interval $[-1, 1]$.
- Let Z be considered as random variable that has value 1 (0) if the point (X, Y) lies in the circle of radius 1 centered in the point $(0, 0)$.
- Clearly

$$Pr(Z = 1) = \frac{\pi}{4}$$

- If we perform such an experiment m times and Z_i be the value of Z at the i th run, and $W = \sum_{i=1}^m Z_i$, then

$$\mathbf{E}[W] = \mathbf{E}\left[\sum_{i=1}^m Z_i\right] = \sum_{i=1}^m \mathbf{E}[Z_i] = \frac{m\pi}{4}$$

and therefore $W' = (4/m)W$ is a natural estimation for π

A natural question now is how good is the estimation of π that we get from

$$\mathbf{E}[W] = \frac{m\pi}{4} \quad W' = (4/m)W$$

An application of the Chernoff bound gives:

$$\begin{aligned} \Pr(|W' - \pi| \geq \varepsilon\pi) &= \Pr\left(\left|W - \frac{m\pi}{4}\right| \geq \frac{\varepsilon m\pi}{4}\right) \\ &= \Pr([W - \mathbf{E}[W]] \geq \varepsilon \mathbf{E}[W]) \\ &\leq 2e^{-m\pi\varepsilon^2/12} \end{aligned}$$

Therefore, taking m large enough we get an arbitrarily good approx. of π

Sampling in a set S according a given probability distribution π , on elements of S , is a picking up an element $x \in S$ with probability $\pi(x)$.

HOW to do SAMPLING?

In the previous example the Monte Carlo method used a uniform sampling in a square to achieve a counting - to determine the value of π .

This method can be generalised. In many cases we can count the number of sets with a special property P in a graph in case we can generate almost uniform sample from the sets with the property P .

In various other cases we can do efficient computation provided we can implement sampling according to a fixed given probability distribution.

A Markov-chains-induced Monte Carlo method provides a very general approach to sample according to a desired probability distribution.

The basic idea is to create an Ergodic Markov Chain whose states form the sample space and whose stationary distribution is the required sampling distribution.

Let X_0, X_1, \dots be a run of such a Markov chain. The chain converges to the stationary distribution from any state X_0 and so after a sufficiently large number of steps r , the distribution of the state X_r will be close to the stationary distribution and so it can be used for a sampling. We can repeat the same argument starting with X_r and getting to X_{2r} and so on.

DESIGN of MARKOV CHAINS with UNIFORM STATIONARY DISTRIBUTION - I.

We show first how to construct a Markov Chain with a stationary distribution that is uniform over the given state space Ω .

The first step is to define on Ω a neighbourhood relation - that is to make out of Ω a graph - and in such a way that the graph obtained will be irreducible.

The second step is to define transition probabilities in such a way that the resulting stationary distribution is uniform.

The next lemma show that this can be done in case we can introduce also self-loops.

DESIGN of MARKOV CHAINS with UNIFORM STATIONARY DISTRIBUTION - II.

Notation: For any $x \in \Omega$ let $N(x)$ be the set of neighbours in the created graph and let $M > N = \max_{x \in \Omega} |N(x)|$.

Lemma: For a finite state space Ω and a given neighbourhood structure and any $M > N$ design a Markov chain such that for any $x, y \in \Omega$

$$P_{x,y} = \begin{cases} 1/M & \text{if } x \neq y, y \in N(x); \\ 0 & \text{if } x \neq y, y \notin N(x); \\ 1 - N(x)/M & \text{if } x = y; \end{cases}$$

Then if this chain is irreducible and aperiodic, then its stationary distribution is the uniform distribution.

EXAMPLE - INDEPENDENT SETS of a GRAPH - I.

A set S of nodes of a graph G is called independent if no two nodes in S are connected by an edge in G .

EXAMPLE - INDEPENDENT SETS of a GRAPH - II.

Consider a Markov chain, whose states are independent sets of a graph $G = (V, E)$.

- 1 Let X_0 be an arbitrary independent set in G .
- 2 To compute X_{i+1} do the following
 - choose a node v uniformly and randomly from V ;
 - if $v \in X_i$, then $X_{i+1} = X_i - \{v\}$;
 - if $v \notin X_i$ and if adding v to X still gives an independent set, then $X_{i+1} = X_i \cup \{v\}$;
 - otherwise set $X_{i+1} = X_i$

Using the construction from previous lemma one can show that if x, y are neighbouring independent sets then $P_{x,y} = 1/|V|$ and the stationary distribution is the uniform distribution.

- 1 From a bag of white and black balls you should pick up a white (black) ball with probability $\frac{1}{3}$ ($\frac{2}{3}$). How can you do that?
- 2 You have 11 boxes of balls. You should pick
 - a ball from the first box with probability $\frac{1}{36}$;
 - a ball from the second box with probability $\frac{2}{36}$;
 - a ball from the third box with probability $\frac{3}{36}$;
 - a ball from the fourth box with probability $\frac{4}{36}$;
 - a ball from the fifth box with probability $\frac{5}{36}$;
 - a ball from the sixth box with probability $\frac{6}{36}$;
 - a ball from the seventh box with probability $\frac{5}{36}$;
 - a ball from the eighth box with probability $\frac{4}{36}$;
 - a ball from the ninth box with probability $\frac{3}{36}$;
 - a ball from the tenth box with probability $\frac{2}{36}$;
 - a ball from the eleventh box with probability $\frac{1}{36}$;

How can you do that?

The METROPOLIS ALGORITHM

This is a general method to transform any irreducible Markov chain on a state space Ω to a Markov chain with a required stationary distribution.

Let us assume that we have already designed an irreducible state space for our Markov chain and now we want to construct a Markov chain on this state space with a stationary distribution $\pi_x = b(x)/B$, where $b(x) > 0$ for all $x \in \Omega$ and $B = \sum_{x \in \Omega} b(x)$ is finite.

Theorem For a finite state space Ω , neighbourhood structure $\{N(x) \mid x \in \Omega\}$, $N = \max_{x \in \Omega} |N(x)|$ let $M \geq N$ be any such number. For any $x \in \Omega$, let π_x be the desired probability of state x in the stationary distribution. Consider a Markov chain with

$$P_{x,y} = \begin{cases} \frac{1}{M} \cdot \min\{1, \pi_y/\pi_x\} & \text{if } x \neq y \in N(x); \\ 0 & \text{if } x \neq y \notin N(x); \\ 1 - \sum_{y \neq x} P_{x,y} & \text{if } x=y; \end{cases}$$

Then, if this chain is irreducible and aperiodic, the stationary distribution is given by probabilities π_x .

In many important applications we need to do sampling/use of elements of a set S according to a given probability distribution π on S .

One way to do that is to design such a Markov chain M on the set S that has π as the stationary distribution and then to start a random walk on M and to stop when one can expect that stationary distribution is (almost) reached.

To find time for halting we need an estimation of convergence rate of any initial distribution to the stationary one.

CONVERGENCE OF RANDOM WALKS

CONVERGENCE of RANDOM WALKS - BASICS

In the next slides we deal with the following problem: **how many steps are needed for a random walk (that starts at some node), to converge to the stationary distribution -that means to be in each node with probability specified by the stationary distribution.**

We present two techniques to deal with the above problem.

Stopping rule method calculates the rate of convergence directly by defining a proper **stopping rule**.

Coupling method reduces the problem of determining the rate of convergence to that of calculating the number of steps needed to meet another, imaginary, random walk, that starts at the stationary distribution.

PRELIMINARIES

Variation distance: $\|P - Q\|$, between two probability distributions, P and Q , on a set I of states is defined by

$$\|P - Q\| = \max_{I' \subseteq I} |P(I') - Q(I')|.$$

Lemma: Let P and Q be probability distributions over a set I of states. Then

$$\|P - Q\| = \frac{1}{2} \sum_{i \in I} |P(i) - Q(i)|.$$

STOPPING RULE (TIME)- REPETITION

Given is a sequence of random variables Z_1, Z_2, \dots , and another random variable T , whose range are natural numbers. T is a **stopping rule** for random variables Z_1, Z_2, \dots , if, for every i , the event $T = i$ is independent of variables Z_j , for all $j > i$.

The idea is that the variables Z_i are observed in the order one at each time step: at first Z_1 , then Z_2 and so on. The value of the variable T then shows the number of variables observed when such a process has to stop.

It is sometimes required that $Pr(T < \infty) = 1$, or that T is almost surely finite.

The intuition behind such a definition of the stopping rule is that at any particular time it is enough to look at the sequence so far in order to be able to tell if it is time to stop.

STOPPING RULE - OBSERVATIONS

Stopping rule can be seen as a mechanism for deciding whether to continue or to stop a process on the basis of the present position and past events, and which will always lead to a decision to stop at some time.

Examples Consider a gambler playing roulette, starting with \$ 100.

- Playing one and only one game corresponds to the stopping time $T = 1$, and this is a stopping rule.
- Playing until she either runs out of money or has played 500 games is a stopping rule.
- Playing until she doubles her money is not a stopping rule (here it is assured that betting systems has some limitations on doubling or tripling the money).
- Playing until she is the maximum amount ahead she will ever be is not a stopping rule (as it requires information about future, present and past).

STRONG UNIFORM STOPPING RULE

Given are random variables Z_1, Z_2, \dots , and a random variable T , whose range are natural numbers. T is a **stopping rule** for variables Z_1, Z_2, \dots , if, for every i , the event $T = i$ is independent of variables Z_j , for all $j > i$.

For a finite ergodic Markov chain, a **strong uniform stopping time** T is a stopping rule which satisfies the condition

$$\Pr[Z_k = i \mid T = k] = \pi_i,$$

where Z_k is the state at the k th step in the Markov chain, and π_i is the probability, under the stationary distribution, of being at the state i .

Next theorem relates strong uniform stopping rule (time) and the rate of convergence of the random walk.

Theorem Let π be the stationary distribution of a random walk, and $Q^{(t)}$ be the probability distribution after t steps. In addition, let T be a strong uniform stopping time. Then

$$\|Q^{(t)} - \pi\| \leq \Pr[T > t].$$

Proof. Let X_t be the random variable producing states from I visited by a random walk at step t .

$$\begin{aligned} \forall I' \subseteq I, Q^{(t)}(I') &= \Pr[X_t \in I'] \\ &= \left(\sum_{j \leq t} \Pr[(X_t \in I') \cap (T = j)] \right) + \Pr[(X_t \in I') \cap (T > t)] \\ &= \sum_{j \leq t} \Pr[X_t \in I' | T = j] \Pr[T = j] \\ &+ \Pr[X_t \in I' | T > t] \Pr[T > t] \\ &= \sum_{j \leq t} \pi(I') \Pr[T = j] + \Pr[X_t \in I' | T > t] \Pr[T > t] \\ &= \pi(I') (1 - \Pr[T > t]) + \Pr[X_t \in I' | T > t] \Pr[T > t] \\ &\leq \pi(I') + \Pr[T > t] \Pr[X_t \in I' | T > t] \leq \pi(I') + \Pr[T > t] \end{aligned}$$

The third equality from the end follows from the fact that T is a strong uniform stopping time and that if a random walk is in a stationary distribution, then it stays in it forever.

The last but one equality follows from the fact that

$$\sum_{j \leq t} \Pr[T = j] = \Pr[T \leq t] = 1 - \Pr[T > t].$$

Finally, the last equality implies, since both $\Pr[X_t \in I' | T > t]$ and $\pi(I')$ are at most 1,

$$\forall I' \subseteq I, |Q^{(t)}(I') - \pi(I')| \leq \Pr[T > t].$$

EXAMPLE – HYPERCUBE

We show how fast converges to the stationary distribution a special random walk on a hypercube.

Consider the following random walk

- 1 Choose uniformly a neighbor (of the currently visited node).
- 2 With probability $\frac{1}{2}$ move to the chosen node; otherwise do not move at all.

(Last trick is needed in order to have an ergodic (aperiodic) Markov chain.)

Let us define the stopping rule T to be the number of coordinates **chosen** so far (even if not all choices of coordinates yielded a move).

Note that T is a strong uniform stopping rule (informally said, this happens because we have an equal probability of being at any node after all coordinates are chosen).

In order to be able to use the last theorem we need to determine $\Pr[T > t]$. However, this is exactly the coupon selector problem, since we can see coordinates as being coupons that need to be collected.

For coupon selector problem, the expected number of trials needed to see all n coupons is $\mathcal{O}(n \lg n)$. Therefore, the expected number of steps until we choose all coordinates is $\mathcal{O}(n \lg n)$.

Using Markov's inequality we get $\Pr[T > t] \leq \frac{\mathbf{E}[T]}{t} = \mathcal{O}\left(\frac{n \lg n}{t}\right)$.

EXAMPLE – CARD SHUFFLING I.

Suppose we want to shuffle a pack of n cards, numbered $1, 2, \dots, n$, according to the following policy:

Move the top card to a random location in the pack.

How long it will take to have all cards in a random distribution (to reach the stationary distribution)?

This problem can be viewed as a random walk in a graph with $n!$ vertices corresponding to all possible permutations. Edges are determined by the shuffling policy.

Denote by **BOTTOM** the card that was originally at the bottom of the pack.

Let T be the number (name) of the card moved from the top at the last step. T is stopping rule and $T = \text{BOTTOM}$ is the stopping time.

We claim that T is strong uniform time.

This is due to the fact that once we remove **BOTTOM** from the top of the pack, we are already in the stationary distribution. (It can be shown by induction on the number of cards below **BOTTOM** that the cards below **BOTTOM** are always in a random order.) We show now that the above stopping rule behaves as a coupon collector.

Indeed, define T_i to be the number of steps until there are i cards below **BOTTOM** (including **BOTTOM**). Since $T = T_n$ we have

$$T = T_1 + (T_2 - T_1) + (T_3 - T_2) + \dots + (T_n - T_{n-1}).$$

Moreover, $T_{i+1} - T_i$ has a geometric distribution with parameter $\frac{n-i}{n}$.

This is similar to the situation in coupon selection. Indeed, let V_i denote the number of steps until we see i coupons and let $V = V_n$. Similarity between V and T follows from the fact that

$$V = V_1 + (V_2 - V_1) + (V_3 - V_2) + \dots + (V_n - V_{n-1})$$

and that $V_{i+1} - V_i$ has also geometric distribution with parameter $\frac{n-i}{n}$. Hence

$$\Pr[T > t] \leq \frac{\mathbf{E}[T]}{t} = \mathcal{O}\left(\frac{n \lg n}{t}\right).$$

The goal is again to investigate how fast a random walk X , starting at a fixed point, approaches the stationary distribution.

To do that we consider another random walk Y that starts at the stationary distribution.

Y always remains at the stationary distribution.

These two walks are correlated in the sense that once they meet, their future moves are the same.

Therefore, to determine how fast X approaches stationary distribution, it is sufficient to determine when such two random walks meet.

EXAMPLE I – HYPERCUBE II.

Let **coordinator** be a super-player that coordinates moves of two walks X and Y , at each step, as follows.

- 1 The coordinator chooses randomly an $i \in \{1, \dots, n\}$. Let X_i (Y_i) be the i th bit of the node currently visited by X (Y).
- 2 If $X_i = Y_i$, then with probability $\frac{1}{2}$ both X and Y move, and with probability $\frac{1}{2}$ both of them stay still. The move, if any, is to the neighbor that differs in the i th bit from the node currently visited.
- 3 If $X_i \neq Y_i$, then with probability $\frac{1}{2}$ player X moves and Y stay still, and with the same probability it is vice versa. (Move is again to the node that differs in the i th coordinate.)

From the point of view of both, X and Y , they perform a random walk.

It is now easy to see that the following claim holds

If, for some i , $X_i = Y_i$, then it always stays as such. If a coordinate i is chosen, (and $X_i \neq Y_i$), then $X_i = Y_i$ at the end of the step.

Hence, the random variable that counts the number of steps needed for X and Y to meet behaves as a coupon collector.

This way we get the same result as using the previous method.

EXAMPLE II – CARD SHUFFLING II.

We will consider again an n *cards shuffling problem*, but this time with a different shuffling policy.

Uniformly and randomly choose a card and put it, alternatively, either to the top or to the bottom of the pack.

To demonstrate *the coupling argument* we will consider two initial packs of cards. One that is fully ordered (first is the card number 1, last the card number n), second that is randomly ordered.

The *coordinator* chooses, randomly, a card i and in both packs the card is moved alternatively to top or to bottom.

EXAMPLE II – CARD SHUFFLING III.

Claim The stationary distribution is reached after all cards are picked. By induction, one can show that after i steps each pack can be partitioned into three parts: top, middle and bottom.

The cards in the top and bottom parts have all already been selected and appear in the same order in both packs. The cards in the middle part have not been selected yet and appear in some arbitrary order in both packs.

Therefore, after all cards have been picked at least once, the two packs are in the same order.

Observe now that the problem of picking all cards is again similar to the coupon selector problem. The expected number of steps needed to shuffle the pack is therefore $\mathcal{O}(n \lg n)$.

COMMUTE and COVER TIME

The **commute time** C_{uv} between u and v is defined as

$$C_{uv} = h_{uv} + h_{vu} = C_{vu},$$

and it is the expected time for a random walk starting at node u to return to u after at least one visit to node v .

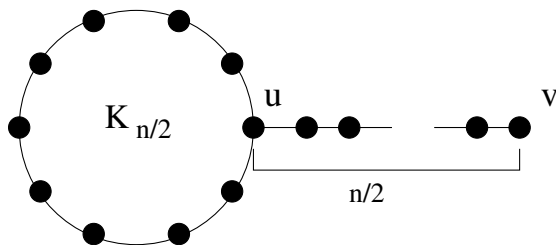
$C_u(G)$ denotes the expected length of a walk that starts at u and ends upon visiting every node in G at least once.

The **cover time** of G , notation $C(G)$, is defined by

$$C(G) = \max_u C_u(G).$$

EXAMPLES

For the **lollipop graph** (cukrátko) L_n



it holds

$$h_{uv} = \theta(n^3), \quad h_{vu} = \theta(n^2)$$

(L_n is an example showing that adding more edges can reduce the cover time – contrary to our usual intuition.)

- A chain of n vertices has the cover time $\theta(n^2)$.
- L_n has cover time $\theta(n^3)$.
- Complete graph K_n has the cover time $\theta(n \lg n)$.

COMMUTE TIME - BASIC RESULT

Lemma If $G = (V, E)$, $m = |E|$, $(u, v) \in E$, then $h_{uv} + h_{vu} \leq 2m$.

Proof: Let us assign to G a new Markov chain, M_G , states of which are oriented versions of the edges of E ($2m$ of them), and let the transition matrix Q of M_G have only the following non-zero values

$$Q_{(u,v),(v,w)} = p_{vw} = \frac{1}{d(v)}.$$

Matrix Q is **doubly stochastic** (rows and also columns sum-up to 1). Indeed, for each $v, w \in V$:

$$\sum_{x \in V, y \in \Gamma(x)} Q_{(x,y),(v,w)} = \sum_{v \in \Gamma(x)} Q_{(x,v),(v,w)} = \sum_{v \in \Gamma(x)} p_{vw} = d(v) \times \frac{1}{d(v)} = 1.$$

It can be shown, that for any Markov chain with a doubly stochastic matrix the uniform distribution on edges is stationary.

Therefore, (by ergodic theorem) stationary probability of each edge is $\frac{1}{2m}$. Consequently, the expected time between successive traversals of the directed edge (v, u) is $2m = 1/(1/2m)$.

Let us now go back to the original problem $h_{uv} + h_{vu} = ???$

Conditioned on the event that the initial entry into u was through edge (v, u) , we can conclude, from the above analysis of M_G , that the expected time to go from there to v and then back to u , along (v, u) is at most $2m$.

The memoryless property of Markov chains allows now to remove conditioning and to get the Lemma.

ELECTRICAL NETWORKS - BASICS 1/2

Many random variables associated with simple random walks on undirected graphs can be studied conveniently using concepts and language of the electrical network theory. A **resistive electrical network** is an undirected graph where to each edge an **edge resistance** (as a positive integer) is associated.

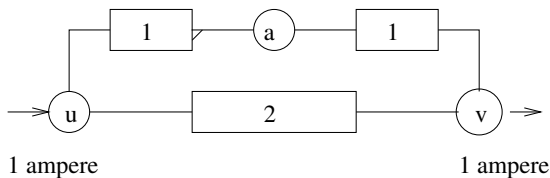


Figure: Potentials of nodes are $\phi(u) = 2$; $\phi(a) = \frac{3}{2}$; $\phi(v) = 1$; voltage difference between u and v is 1 and between a and v is $\frac{1}{2}$.

Kirchhoff law: The sum of all currents entering a node u of a network equals the sum of all currents leaving u .

Ohm law: $I = \frac{V}{R}$, where I is **current**; V is **voltage**; R is **resistance**.

For each edge e , let R_e be the resistance of e . For each node u , let i_u be the current that enters (and exits) the node u .

ELECTRICAL NETWORKS - BASICS 2/2

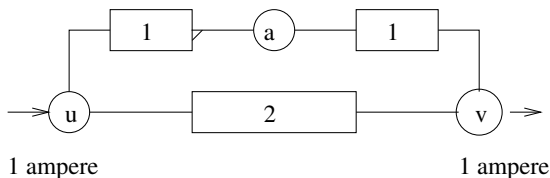


Figure: Potentials of nodes are $\phi(u) = 2$; $\phi(a) = \frac{3}{2}$; $\phi(v) = 1$; voltage difference between u and v is 1 and between a and v is $\frac{1}{2}$; resistance between u and v is 2; effective resistance is only 1.

We would like to compute the potential $\phi(v)$ for each node v and the current i_{uv} for each edge $e = (u, v)$. By Ohm's Law

$$i_{uv} = \frac{\phi(u) - \phi(v)}{R_e}.$$

Effective resistance R_{uv} between two nodes u and v is the voltage difference between u and v when one ampere is injected into u and removed from v . Hence $R_{uv} = \phi(u) - \phi(v)$.

Observe that effective resistance between nodes of an edge can be smaller than the resistance of the edge (see the above figure).

ELEKTRICKÝ POTENCIÁL a NAPÄTIE

Elektrický potenciál je práca potrebná k preneseniu jednotkového náboja z nekonečna na dané miesto silového poľa po ľubovolnej dráhe.

Elektrický potenciál je veličina charakterizujúca energetický stav v danom bode elektrického silového poľa.

Elektrické napätie je práca, ktorá sa vykoná v elektrickom poli pri prenesení jednotkového elektrického množstva po určitej dráhe.

V potenciálovom elektrickom poli nezávisí napätie na dráhe a rovná sa rozdielu potenciálov.

To each graph G we associate an electrical network $\mathcal{N}(G)$ at which the resistance of each edge is 1.

Theorem Commute time for any two vertices u and v in G is

$$C_{uv} = 2mR_{uv} = h_{uv} + h_{vu}.$$

Proof: Notation:

- $d(x)$ is the degree of any node x .
- Φ_{zv} is the potential of any node z , relative to v , when $d(x)$ units of current enter each node $x \in V$, and $2m$ units of the current exit v .

For every edge $(u, w) \in E$ it holds, by Ohm's law:

$$\Phi_{uv} - \Phi_{wv} = i_{uw}R_{uw} = i_{uw}.$$

Kirchhoff's law implies that for every $u \in V - \{v\}$

$$d(u) = \sum_{w \in \Gamma(u)} i_{uw} = \sum_{w \in \Gamma(u)} \Phi_{uw} - \Phi_{wv}.$$

On the other hand, definition of h_{uv} , $(u, v) \in E(G)$, implies that for each $u \in V - \{v\}$:

$$h_{uv} = \sum_{w \in \Gamma(u)} \frac{1}{d(u)} (1 + h_{wv}).$$

It can be shown, that both above systems of equations are in fact the same system of linear equations and therefore they have the same solution for each $u, v \in V$: $h_{uv} = \Phi_{uv}$.

DERIVATION

Kirchhoff's law implies that for every $u \in V - \{v\}$

$$d(u) = \sum_{w \in \Gamma(u)} i_{uw} = \sum_{w \in \Gamma(u)} \Phi_{uw} - \Phi_{vw}.$$

Hence,

$$d(u) = \Phi_{uv} d(u) - \sum_{w \in \Gamma(u)} \Phi_{vw}$$

and therefore

$$1 = \Phi_{uv} - \frac{1}{d(u)} \sum_{w \in \Gamma(u)} \Phi_{vw}$$

and

$$\Phi_{uv} = 1 + \frac{1}{d(u)} \sum_{w \in \Gamma(u)} \Phi_{vw}.$$

Hence

$$\Phi_{uv} = \frac{1}{d(u)} \sum_{w \in \Gamma(u)} 1 + \frac{1}{d(u)} \sum_{w \in \Gamma(u)} \Phi_{vw} = \sum_{w \in \Gamma(u)} \frac{1}{d(u)} (1 + \Phi_{vw}).$$

and so we got the same equation as $h_{uv} = \sum_{w \in \Gamma(u)} \frac{1}{d(u)} (1 + h_{vw})$.

PROOF – CONTINUATION I.1

Consider now the following network: a current of magnitude $2m$ enters u and a current of magnitude $d(x)$ exits every node $x \in V$.

If the potential of u in this network is assumed to be equal to 0, then the potential of v is equal to $-\phi_{uv} = -h_{uv}$.

Let us now perform a superposition of such a network with the network considered on previous slide (at which $d(x)$ units of current enter each node $x \in V$, and $2m$ units of the current exit v).

In the resulting network, all external currents cancel, except for those in vertices u (where the current of magnitude $2m$ enters) and v (where the current of magnitude $2m$ exits).

The difference of potentials between u and v is:

$$h_{uv} - (-h_{vu}) = h_{uv} + h_{vu} = \Phi_{uv} + \Phi_{vu} = C_{uv}.$$

Therefore, C_{uv} is the voltage between u and v in the last network.

Hence, by Ohm law

$$C_{uv} = 2mR_{uv}$$

Claim: For every pair of vertices u and v , the effective resistance R_{uv} is not more than the distance between u and v in G .

Corollary: Let $G = (V, E)$ be a graph, $n = |V|$, $m = |E|$ and $u, v \in V$.

- If $(u, v) \in \mathcal{N}(G)$, then $C_{uv} \leq 2m$;
- If $u, v \in V$, then $C_{uv} \leq 2m(n - 1)$.
- If $u, v \in V$, then $C_{uv} < n^3$.

COVER TIME

Theorem: For a graph G with n nodes and m edges $C(G) \leq 2m(n-1)$.

Proof: Let T be any spanning tree of $G = (V, E)$. Then there is a traversal of T visiting nodes

$$v_0, v_1, \dots, v_{2n-2} = v_0$$

that traverses each edge of T exactly once in each direction.

Consider a random walk that starts at v_0 , visits all nodes in the order prescribed by the traversal, and terminates after returning to v_0 .

An upper bound on the expected length of such a walk is an upper bound on $C_{v_0}(G)$.

$$C_{v_0}(G) \leq \sum_{j=0}^{2n-3} h_{v_j v_{j+1}} = \sum_{(u,v) \in T} C_{uv}.$$

Since $(v_j, v_{j+1}) \in E$, $C_{v_j v_{j+1}} \leq 2m$ by previous corollary.

Therefore

$$C_{v_0}(G) \leq 2m(n-1).$$

The above bound is independent of the choice of v_0 . Hence

$$C(G) \leq 2m(n-1).$$

SPECIAL TYPES of GRAPHS

Let us derive cover time for several special graphs.

- **A complete graph K_n .** The problem to determine cover time is essentially the Coupon Collector problem. Therefore

$$C(K_n) = n \lg n + cn.$$

- **A star graph S_n** The problem of calculating the cover time is again essentially the Coupon Collector problem. Therefore

$$C(S_n) = 2n \lg n + cn.$$

- **A line L_n :** Let u_1, u_2 be the end points of L_n . Since $R_{u_1, u_2} = n - 1$, we have

$$C_{u_1, u_2} = 2|E(L_n)|R_{u_1, u_2} = 2(n - 1)(n - 1) = 2(n - 1)^2.$$

By symmetry,

$$h_{u_1, u_2} = (n - 1)^2.$$

Then

$$C(L_n) = (n - 1)^2.$$

- **Lollipop graph L_n :** $C(L_n) = \theta(n^3)$.

The **effective resistance** $R(G)$ of a graph G is defined by

$$R(G) = \max_{\{u,v\} \subset V(G)} R_{uv}.$$

Theorem $mR(G) \leq C(G) \leq 2e^3 mR(G) \ln n + n$.

Proof. Lower bound: Let $R(G) = R_{uv}$ for some vertices $u, v \in V$. Then

$$C(G) \geq \max(h_{uv}, h_{vu}) \geq \frac{C_{uv}}{2} = \frac{2mR_{uv}}{2} = mR(G).$$

Upper bound. Create a random walk of length $2e^3 mR(G) \ln n$ and divide it into $\ln n$ **phases** of the same length.

For any vertices u and v , the hitting time h_{uv} is at most $2mR(G)$. (This is the average time to get through any of $\ln n$ phases.)

EFFECTIVE RESISTANCE of GRAPHS - III.

By Markov inequality ($Pr[Y \geq t] \leq \frac{E[Y]}{t}$), the probability that v is not visited during a single phase is at most $\frac{2mR(G)}{2e^3 mR(G)} (= \frac{h_{uv}}{2e^3 mR(G)}) = \frac{1}{e^3}$.

Therefore, the probability that v is not visited during any of the $\ln n$ phases is at most $(\frac{1}{e^3})^{\ln n} = \frac{1}{n^3}$.

Summing over n choices of v , we get that the probability that there is a node not visited within $2e^3 mR(G) \ln n$ steps is at most $\frac{1}{n^2}$.

When this happens (that is if there is a node not visited during $2e^3 mR(G) \ln n$ steps), we “continue to walk until all nodes are visited” (and n^3 steps suffices for that).

The expected total time is therefore

$$2e^3 mR(G) \ln n + \left(\frac{1}{n^2}\right)n^3 = 2e^3 mR(G) \ln n + n.$$

USTCON PROBLEM

It is the problem to decide, given an undirected graph G and two vertices s and t , whether there is a path from s to t .

Let **RLP** be the family of languages L for which there exists a probabilistic off-line log-space TM \mathcal{M} such that for any input x

$$\Pr[\mathcal{M} \text{ accepts } x] \begin{cases} \geq \frac{1}{2} & \text{if } x \in L \\ = 0 & \text{if } x \notin L \end{cases}$$

Theorem $\text{USTCON} \in \text{RLP}$.

Proof Let a log-space bounded probabilistic TM \mathcal{M} simulate a random walk of length $2n^3$ through the given graph starting from s .

If \mathcal{M} encounters t during such a walk, it outputs YES, otherwise it outputs NO. The probability of the output YES instead of NO is 0.

What is the probability that \mathcal{M} outputs NO instead of YES?

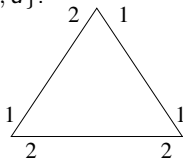
We know that $h_{st} \leq n^3$. By Markov inequality, if t is reachable from s , then the probability that t is not visited during $2n^3$ steps is at most $\frac{1}{2}$.

\mathcal{M} needs a space to count till $2n^3$ and to keep track of its position in the graph during the walk. Therefore it needs space

$$\mathcal{O}(\lg n).$$

Nonuniform, deterministic, log-space algorithms for USTCON

We will consider **regular d -degree graphs** with n nodes such that all edges of each node are labeled by labels from $\{1, 2, \dots, d\}$.



Any $\sigma \in \{1, 2, \dots, d\}^*$ or $\sigma \in \{1, 2, \dots, d\}^\infty$ and any starting node v specify a walk through the given graph.

A sequence σ is said to **traverse** a graph G if the walk it prescribes visits every node of G regardless of the starting node.

A sequence σ is said to be a **universal traverse sequence** for a class of labeled graphs if it traverses every labeled graph in the class (for any starting node).

A universal traversal sequence whose length is polynomial in n can be used by a deterministic log-space off-line TM to decide instances of USTCON.

(However, in order to be a uniform log-space algorithm, the universal traversal sequence should be constructable by a log-space TM, rather than be encoded in the machine's finite state control.)

UNIVERSAL TRAVERSAL SEQUENCE

\mathcal{G} – a family of connected regular graphs on n -nodes and m edges.

$U(\mathcal{G})$ — length of the shortest universal traversal sequence for \mathcal{G} .

$R(\mathcal{G})$ — maximum resistance between any two nodes of any graph in \mathcal{G} ,

Theorem $U(\mathcal{G}) \leq 5mR(\mathcal{G}) \lg(n|\mathcal{G}|)$.

Proof Given $G \in \mathcal{G}$, $v \in G$, let us consider a random walk of the length

$$5mR(\mathcal{G}) \lg(n|\mathcal{G}|)$$

divided into $\lg(n|\mathcal{G}|)$ sections of length $5mR(\mathcal{G})$.

The probability that the walk fails to visit v in any section is at most $\frac{2}{5}$. (Due to the Markov inequality and the fact that $C_{uv} = 2mR_{uv}$.)

Probability that v is **not** visited during any of the $\lg(n|\mathcal{G}|)$ sections is thus at most

$$\left(\frac{2}{5}\right)^{\lg(n|\mathcal{G}|)} = \left(\frac{2}{5}\right)^{(\lg_{2/5}(n|\mathcal{G}|) / \lg(2/5))} = (n|\mathcal{G}|)^{1/(\lg(2/5))} = (n|\mathcal{G}|)^{-c} \text{ for a } c > 1.$$

Summing up over n choices of v and $|\mathcal{G}|$ choices of the labeled graph G , the probability that the random walk (sequence) fails to be universal is less than 1.

As a consequence, there is a sequence of such a length that is universal for the class \mathcal{G} .
(We have just used the probabilistic method.)

HMM - HIDDEN MARKOV MODELS

Hidden Markov Model (HMM) has, similarly as Markov model considered so far, a set of states and their transition probabilities (that are given). However, in addition, it has a set of outputs each state can produce, according to its given emission probabilities, each time the system comes to that state. However, in this model states are hidden, as well as their transition and emission probabilities, before any observer.

An observer can see only the sequences of outputs states produce. The task is determine, from the large amount of such outputs, all parameters, its transition and production probabilities.

Hidden Markov Model have been very successfully used in pattern recognition, speech recognition, handwriting and gestures recognition, machine translations, gene predictions, bio-informatics, human activities recognition, as well as in many other applications.

In general, HMM can be applied when the goal is to recover a data sequence that is not immediately observable (but other data that depend on the sequence are).

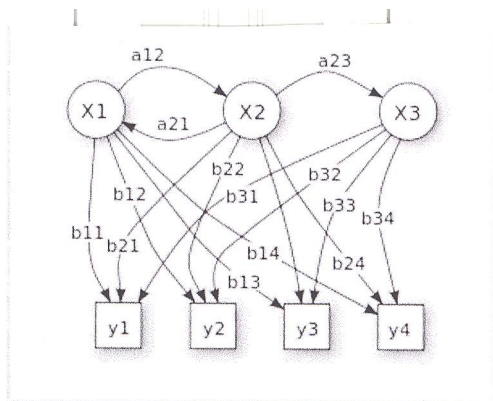


Figure 1. Probabilistic parameters of a hidden Markov model (example)

X — states

y — possible observations

a — state transition probabilities

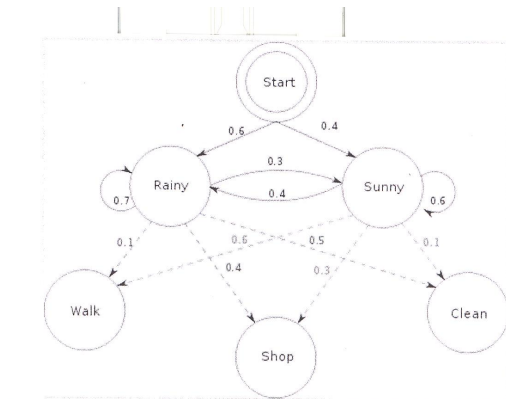
b — output probabilities

EXAMPLE: URN PROBLEM

- In a room not visible to an observer there is a genie and urns, X_1, X_2, \dots, X_n each containing a known mixture of balls labeled as $\{y_1, y_2, \dots\}$.
- Genie works as follows. Chooses randomly, according a given probability distribution, one urn, randomly draw a ball from it, emails its label to the observer, puts ball back and, according to the probability distribution associated with that urn chooses next one and the process continues.
- This process can continue many times. Observers see each time only a sequence of labels $y_{i1}, y_{i2}, \dots, y_{ik}$.
- The task for observers is to determine parameters: transition probabilities for states (as an ordinary Markov model has) and number of different balls in different urns (and emission probabilities - actually number of different balls in urns).

EXAMPLE - WEATHER

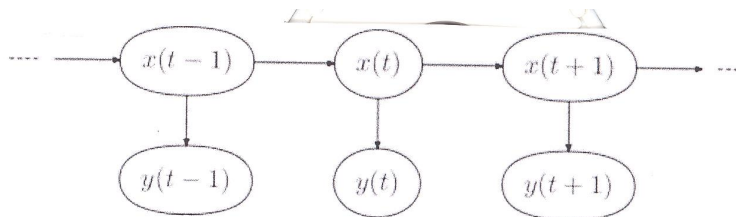
Alice and Bob live far apart from each other and talk daily about what Bob did. His actions (waking, shopping, cleaning) depend on the weather in the following way.



From their phone calls Alice tries to deduce how was and is weather in the place Bob lives.

INFERENCE PROBLEMS

In the following picture $x(t)$ is the state at time t and $y(t)$ is the output.



- **Probability of observed sequence:** The probability of observing an output sequence

$$Y = y(0), y(1), \dots, y(l-1)$$

of length l is given by

$$Pr(Y) = \sum_x Pr(Y|X)Pr(X)$$

where the sum runs over all possible hidden-node sequences

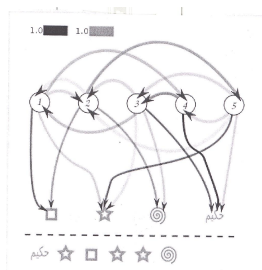
$X = x(0), x(1), \dots, x(L-1)$. This problem can be handled effectively using so called forward algorithm.

Filtering: The task is to compute, given the model's parameters and a sequence of observations, the last states at the end of observations:, i.e. to compute

$$Pr(x(t) | y(1), \dots, y(t))$$

EXAMPLE

In the following HMM and its output sequence



the following state sequences are possible:

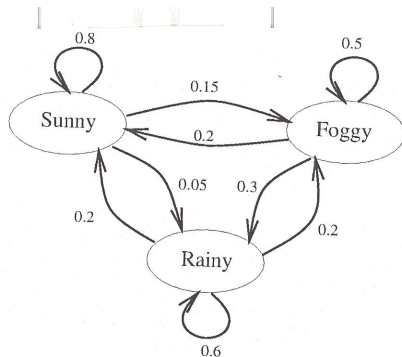
5, 3, 2, 5, 3, 2

4, 3, 2, 5, 3, 2

3, 1, 2, 5, 3, 2

EXAMPLE 2. Markov model

For Markov model



show that:

- Provided that today is sunny, show that 0.04 is probability that tomorrow is sunny and the day after is rainy.
- Show that 0.34 is probability that it will be rainy two days from now provided it is foggy today.

EXAMPLE 2. Hidden Markov Model

Let us add to the previous model two outputs "umbrella" and "no umbrella" and let probability of having umbrella be 0.1 (0.8) [0.3] for the sunny (rainy) [foggy] day. Supposed you were locked in a room for several days and you were asked about weather outside. The only piece of evidence you have is whether a man bringing you food carries umbrella or not.

- Suppose the day you were locked in was sunny. The next day man carrying food came with the umbrella. Assume that the prior probability of the man carrying an umbrella on any day is 0.5. Show that 0.08 is the probability that the second day was rainy.
- Suppose the day you were locked in the room was sunny and that man brought an umbrella on day 2 but not on day 3. Show that 0.19 is the probability that it was foggy on day 3.

HMM - speech recognition - example

In **Hierrarchical Hidden Markov Model (HHMM)** each state can itself be a HHMM.

HHMM is nowadays the basil model to model brain activities at speeach recognition and in speech recognition, creation and understanding.

A huge amount of samples of speech, from many different individuals, are applied to a HHMM to infer the hierarchy of states and all transition and transmission probabilities (essentially a simulation of neocortex for producing speech), and then the resulting HHMM is used to recognize new utterances.

APPENDIX

SECRETARY PROBLEM

The problem:

- There is a single secretariat position to fill.
- There are n applicants for the position, and the value of n is known.
- Each applicant has a unique "quality value" - the interview making committee has no knowledge of quality values of those applicants that have not been interviewed yet and no knowledge how large is the best quality value of applicants.
- The applicants are interviewed in a random order.
- After each interview, the applicant is immediately accepted or rejected.
- The decision to accept or reject an applicant can be based only on the relative "quality value" of the applicants interviewed so far.
- Rejected applicants cannot be recalled.
- The goal is to select an applicant with the best 'quality value'. The payoff is 1 for the best applicant and 0 otherwise.
- How should selection committee proceeds at the best?

Terminology: A **candidate** is an applicant who, when interviewed, is better than all the applicants interviewed previously. Since the goal in the secretary problem is to select the single best applicant, only candidates will be considered for acceptance.

Optimal policy for this problem (the stopping rule): For large n the optimal policy is to interview and reject the first $\frac{n}{e}$ applicants and then accept the next one who is better than candidates interviewed till then.

As n gets larger, the probability of selecting the best applicant goes to $\frac{1}{e}$, which is around 37%.

- Russian mathematician (1856-1922)
- Introduced Markov chains in 1906
- The original motivation was to extend the law of large numbers to dependent events.
- In 1913 he applied his findings to the first 20 000 letters of Pushkin's Eugene Onegin