Review

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Probability Theory

A **σ-algebra** $\mathcal{F}$ is a collection of subsets of the sample space Ω such that the following requirements are satisfied:

S1 The empty set is contained in $\mathcal{F}$.

S2 If a set E is contained in $\mathcal{F}$, then its complement E^c is contained in $\mathcal{F}$.

S3 The countable union of sets in $\mathcal{F}$ is contained in $\mathcal{F}$.

Let $\mathcal{F}$ be a σ-algebra over the sample space Ω. A **probability measure** on $\mathcal{F}$ is a function $\Pr\colon \mathcal{F} \to [0,1]$ satisfying

P1 The certain event satisfies $\Pr[\Omega] = 1$.

P2 If the events $E_1, E_2, \ldots$ in $\mathcal{F}$ are mutually disjoint, then

$$\Pr[\bigcup_{k=1}^{\infty} E_k] = \sum_{k=1}^{\infty} \Pr[E_k].$$

Exercise

The smallest (with respect to inclusion) non-empty events belonging to a σ-algebra $\mathcal{F}$ are called **atoms**. *Show that if $\mathcal{F}$ is a finite σ-algebra, then each event A in $\mathcal{F}$ is the union of finitely many atoms.*

Solution

Seeking a contradiction, suppose that C *is an event in* $\mathcal{F}$ *that is not a union of finitely many atoms.*

Let $\mathcal{A}$ *denote the family of all atoms of* $\mathcal{F}$. *Let* $B = \bigcup \mathcal{A}$.

Since $\mathcal{F}$ *is finite, the event* $C \setminus B$ *must contain an atomic event* A. *However, this is impossible, since* B *is the (finite) union of all atomic events.*

Random Variables

Definition

Let $\mathcal{F}$ be a σ-algebra over the sample space Ω. A **random variable** X is a function $X\colon \Omega \to \mathbf{R}$ such that the preimage $X^{-1}(B)$ of each Borel set B in $\mathbf{R}$ is an event in $\mathcal{F}$.

It suffices to show that

$$\{z \in \Omega \mid X(z) \leqslant x\}$$

is an event contained in $\mathcal{F}$ for all $x \in \mathbf{R}$.

Let $(\Omega, \mathcal{F})$ be a measurable space.

Let A be a subset of Ω. Then the indicator function $I_A : (\Omega, \mathcal{F}) \to \mathbf{R}$ given by

$$I_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{otherwise.} \end{cases}$$

is a random variable if and only if $A \in \mathcal{F}$. We call I_A the **indicator random variable** of the event A.

Simple Random Variable

A random variable is called **simple** if and only if it is a linear combination of a finite number of indicator random variables with disjoint support.

In other words, if X is a simple random variable, then there exist pairwise disjoint events $A_1, \ldots, A_n$ and real numbers $s_1, \ldots, s_n$ such that

$$X = \sum_{k=1}^{n} s_k I_{A_k}.$$

Any nonnegative random variable can be approximated by a sequence of simple random variables.

A **discrete random variable** is a random variable with countable range, which means that the set $\{X(z) \mid z \in \Omega\}$ is countable.

The convenience of a discrete random variable X is that one can define events in terms of values of X, for instance in the form $X \in A$ which is short for

$$\{z \in \Omega \mid X(z) \in A\}.$$

If the set A is a singleton, $A = \{x\}$, then we write $X = x$.

Exercise

Let $\Omega = \{1, 2, 3, 4\}$ *and* $\mathcal{F} = \{\emptyset, \Omega, \{1\}, \{2, 3, 4\}\}$. *Is* $X(x) = 1 + x$ *a random variable with respect to the* σ*-algebra* $\mathcal{F}$*?*

Solution

The preimage of $\{3\}$ *is*

$$X^{-1}(\{3\}) = \{2\},$$

but this is not an event in $\mathcal{F}$*. So* X *is not a random variable.*

Expectation and Variance

Expectation Value

Definition

Let X be a discrete random variable over the probability space $(\Omega, \mathcal{F}, \Pr)$. The **expectation value** of X is defined to be

$$\mathrm{E}[X] = \sum_{\alpha \in X(\Omega)} \alpha \Pr[X = \alpha],$$

when this sum is unconditionally convergent in $\overline{\mathbf{R}}$, the extended real numbers.

The expectation value is also called the **mean** of X.

Proposition

For random variables $X_1, X_2, \ldots, X_n$, we have

$$E[X_1 + X_2 + \cdots + X_n] = E[X_1] + E[X_2] + \cdots + E[X_n].$$

For any real number a, we have

$$E[aX_k] = aE[X_k].$$

Pigeonhole Principle of Expectation

Proposition

A random variable cannot always be less than its expected value.

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Proof.

Seeking a contradiction, suppose that X is a discrete random variable that has values always less than $\mu = \mathrm{E}[X]$. Then

$$\mathrm{E}[X] = \sum_{\alpha \in X(\Omega)} \alpha \Pr[X = \alpha] < \sum_{\alpha \in X(\Omega)} \mu \Pr[X = \alpha] = \mathrm{E}[X],$$

contradiction. $\square$

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contradiction. $\square$

Similarly, a random variable cannot always be larger than its expected value.

Exercise

Consider the complete graph K_n on n vertices. Show that there exists a tournament on K_n that has at least $n!/2^{n-1}$ Hamiltonian paths.

A **tournament** T_n is a directed graph that is obtained from K_n by orienting each edge. This is a round robin tournament with no draws, where an edge (u, v) in the graph T_n means that player u was beating player v.

A **Hamiltonian path** is a path of $n - 1$ edges that visits each vertex of T_n precisely once, $v_1 \to v_2 \to v_3 \to \cdots \to v_n$.

The exercise asserts that some combinatorial structure exists that has a certain property. It asserts that there exists a tournament on n points that has many (namely $n!/2^{n-1}$) Hamiltonian paths.

For $n = 10$, the exercise asserts that there exists a tournament with

$$\frac{n!}{2^{n-1}} = \frac{10!}{2^9} > 7000$$

Hamiltonian paths. Of course, not all tournaments on n points will have that many Hamiltonian paths.

Solution

Construct a tournament on K_n by randomly orienting each edge in K_n with probability $1/2$. Consider a random permutation π on n points. The vertices $(v_{\pi 1}, v_{\pi 2}, \ldots, v_{\pi n})$ form a Hamiltonian path if and only if $v_{\pi k}$ beats $v_{\pi(k+1)}$ for all k in the range $1 \leqslant k \leqslant n-1$. Let X_π denote the indicator random variable for the event that π yields a Hamiltonian path. Then

$$\mathrm{E}[X_\pi] = \Pr[X_\pi = 1] = 1/2^{n-1}.$$

Let $X = \sum X_\pi$ be the random variable counting Hamiltonian paths. Since there are $n!$ permutations, the expected number of Hamiltonian paths is

$$\mathrm{E}[X] = \sum_{\pi \in S_n} \mathrm{E}[X_\pi] = n!/2^{n-1}.$$

By the pigeonhole principle of expectation, it follows that some tournament must have at least $n!/2^{n-1}$ Hamiltonian paths.

Concentration Inequalities

Markov's Inequality

Theorem (Markov's Inequality)

If X is a nonnegative random variable and t a positive real number, then

$$\Pr[X \geqslant t] \leqslant \frac{\mathrm{E}[X]}{t}.$$

Corollary (Markov's Inequality)

If X is a nonnegative random variable and t a positive real number, then

$$\Pr[X \geqslant t\mathrm{E}[X]] \leqslant \frac{1}{t}.$$

Chebychev's Inequality

Theorem (Chebychev's inequality)

If X is a random variable, then

$$\Pr[|X - E[X]| \geqslant t] = \Pr[(X - E[X])^2 \geqslant t^2] \leqslant \frac{\mathrm{E}[(X - E[X])^2]}{t^2} = \frac{\mathrm{Var}[X]}{t^2}.$$

Theorem (Chernoff Bounds)

Let X be the sum of n independent indicator random variables $X_1, X_2, \ldots, X_n$, where $\mathrm{E}[X_k] = p_k$. Let $\mu = \mathrm{E}[X] = \sum_{k=1}^{n} \mathrm{E}[X_k]$. Then

$$\Pr[X > (1+\delta)\mu] \leqslant e^{-\delta^2\mu/3},$$
$$\Pr[X < (1-\delta)\mu] \leqslant e^{-\delta^2\mu/2}.$$

Naming of the Bounds

Exercise

Who first proved Markov's, Chebychev's, and Chernoff's inequality?

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Solution

1. *Markov's inequality was first proved by Chebychev.*

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1. *Markov's inequality was first proved by Chebychev.*
2. *Chebychev's inequality was first proved by Bienaymé.*

Naming of the Bounds

Exercise

Who first proved Markov's, Chebychev's, and Chernoff's inequality?

Solution

1. *Markov's inequality was first proved by Chebychev.*
2. *Chebychev's inequality was first proved by Bienaymé.*
3. *Chernoff's inequality was first proved by Rubin.*

Conditional Expectation

Conditional Expectation given an Event

Definition

The **conditional expectation** of a discrete random variable X given an event A is denoted as $\mathrm{E}[X \mid A]$ and is defined by

$$\mathrm{E}[X \mid A] = \sum_x x \Pr[X = x \mid A].$$

We can compute the expected value of X as a sum of conditional expectations. This is similar to the law of total probability.

Proposition

If X and Y are discrete random variables, then

$$\mathrm{E}[X] = \sum_y \mathrm{E}[X \mid Y = y] \Pr[Y = y].$$

Definition

Let X and Y be two discrete random variables.

The **conditional expectation** $\mathrm{E}[X \mid Y]$ of X given Y is the random variable defined by

$$\mathrm{E}[X \mid Y](\omega) = \mathrm{E}[X \mid Y = Y(\omega)].$$

Law of the Iterated Expectation

Proposition

$$\mathrm{E}[\mathrm{E}[X \mid Y]] = \mathrm{E}[X].$$

Proof.

$$\begin{aligned}
\mathrm{E}[\mathrm{E}[X \mid Y]] &= \sum_y \mathrm{E}[\,\mathrm{E}[X \mid Y] | Y = y]\,\Pr[Y = y] \\
&= \sum_y \mathrm{E}[X \mid Y = y]\,\Pr[Y = y] \\
&= \mathrm{E}[X]
\end{aligned}$$

□

Wald's Theorem

Theorem

Suppose that $X_1, X_2, \ldots$ *are independent random variables, all with the same mean. Suppose that* N *is a nonnegative, integer-valued random variable that is independent of the* X_i*'s. If* $\mathrm{E}[X_1] < \infty$ *and* $\mathrm{E}[N] < \infty$*, then*

$$\mathrm{E}\left[\sum_{k=1}^{N} X_i\right] = \mathrm{E}[N]\mathrm{E}[X_1].$$

Probability Generating Functions

Definition

Let X be a discrete random variable defined on a probability space with probability measure Pr. Assume that X has non-negative integer values. The **probability generating function** of X is defined by

$$G_X(z) = \mathrm{E}[z^X] = \sum_{k=0}^{\infty} \Pr[X = k] z^k.$$

This series converges for all z with $|z| \leqslant 1$.

Expectation

The expectation value can be expressed by

$$E[X] = \sum_{k=1}^{\infty} k \Pr[X = k] = G_X'(1), \tag{1}$$

where $G_X'(z)$ denotes the derivative of $G_X(z)$.

Indeed, $G_X'(z) = \sum_{k=0}^{\infty} k \Pr[X = k] z^{k-1} = \sum_{k=1}^{\infty} k \Pr[X = k] z^{k-1}$.

Complexity Classes

The Class **RP** of Randomized Polynomial Time DP

Definition

Let ε be a constant in the range $0 \leqslant \varepsilon \leqslant 1/2$.

The class **RP** consists of all languages L that do have a polynomial-time randomized algorithm A such that

1. $x \in L$ implies $\Pr[A(x) \text{ accepts}] \geqslant 1 - \varepsilon$,
2. $x \notin L$ implies $\Pr[A(x) \text{ rejects}] = 1$.

One-Sided Error

Randomized algorithms in **RP** may err on 'yes' instances, but not on 'no' instances.

Definition

Let ε be a constant in the range $0 \leqslant \varepsilon \leqslant 1/2$.
The class **co-RP** consists of all languages L whose complement $\overline{L}$ is in **RP**. In other words, L is in **co-RP** if and only if there exists a polynomial-time randomized algorithm A such that

1. $x \in L$ implies $\Pr[A(x) \text{ accepts}] = 1$,
2. $x \notin L$ implies $\Pr[A(x) \text{ rejects}] \geqslant 1 - \varepsilon$.

One-Sided Error

Randomized algorithms in **co-RP** may err on 'no' instances, but not on 'yes' instances.

The Class **ZPP** of Zero-Error Probabilistic Polynomial Time DP

Definition

The class **ZPP** consists of all languages L such that there exists a randomized algorithm A that always decides L correctly and runs in expected polynomial time.

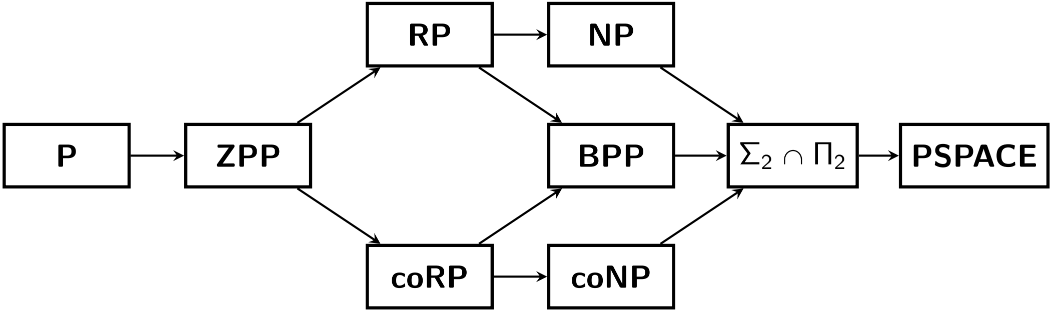
Definition

Let ε be a constant in the range $0 \leqslant \varepsilon < 1/2$.

The class **BPP** consists of all languages L such that there exists a polynomial-time randomized algorithm A such that

1. $x \in L$ implies $\Pr[A(x) \text{ accepts}] \geqslant 1 - \varepsilon$,
2. $x \notin L$ implies $\Pr[A(x) \text{ rejects}] \geqslant 1 - \varepsilon$.

Overview



Randomized Algorithms

Karger's Minimum Cut Algorithm

Contract(G)

Require: A connected loopfree multigraph $G = (V, E)$ with at least 2 vertices.

while $|V| > 2$ **do**
  Select $e \in E$ **uniformly at random**;
  G := G/e;
end while
return $|E|$.

Ensure: An upper bound on the minimum cut of G.

Main Idea of the Analysis

Iterated conditional probabilities:

$$\Pr\left[\bigcap_{\ell=1}^{n} E_\ell\right] = \left(\prod_{m=2}^{n} \Pr\left[E_m \middle| \bigcap_{\ell=1}^{m-1} E_\ell\right]\right) \Pr[E_1].$$

Karger's Minimum Cut Algorithm

Karger's contraction algorithm is the prototypical example of a Monte Carlo type algorithm. Study it carefully!

Quicksort

Suppose that we want to sort an array $A[1..n]$ of length n.

Quicksort picks a **pivot** element p uniformly at random.

Then partitions the array A into three parts: **left**, **pivot**, an d **right**.

$< p$	$< p$	$\cdots$	$< p$	p	$> p$	$> p$	$\cdots$	$> p$

Partition requires $n - 1$ comparisons with the pivot element p.

Then quicksort recursively sorts left and right parts.

Proposition

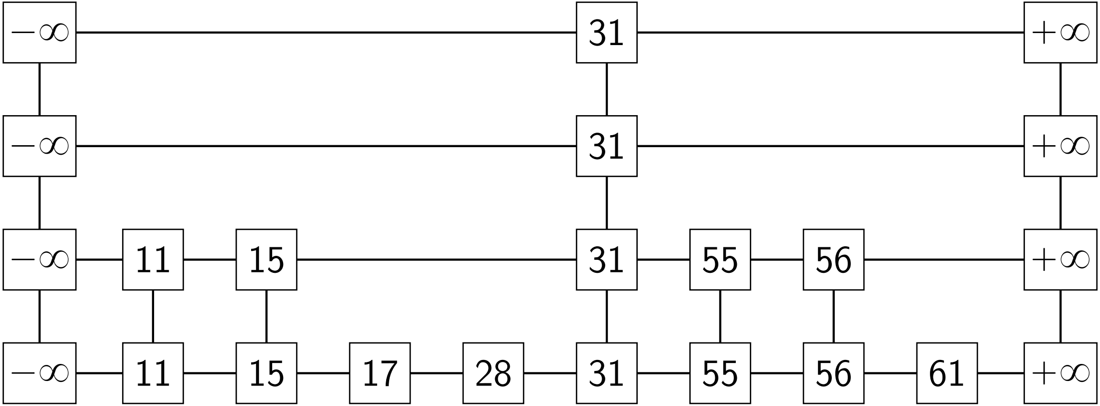
The expected number of comparisons made by randomized quicksort on an array of size n is at most $2n \ln n$.

Quicksort

Randomized quicksort is the prototypical example of a Las Vegas algorithm. Study the analysis carefully!

Randomized Data Structures

Skip Lists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