

Randomized Algorithms

The Probabilistic Method

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The logo for the Max Planck Institute for Informatics, consisting of the letters 'mpi' in a stylized, bold, lowercase font. The 'm' and 'i' are connected, and the 'p' is taller. To the right of the letters are three vertical bars of varying heights, followed by the text 'max planck institut' and 'informatik' stacked vertically.

The Probabilistic Method in a Nutshell

Color the edges of K_n with two colors so that it has no monochromatic K_k ?

- In order to show the existence of an object with certain properties, demonstrate a sample space of objects in which the probability is positive that a randomly selected object has the property.
- Since we work with finite sample spaces, the existence proofs are, in principle, algorithmic. An object with the desired properties can be found by exhaustive search.
- Sometimes, the existence proofs can be converted into efficient randomized or even deterministic algorithms.

Lecture is based on Chapter 6 in Mitzenmacher/Upfal. The definitive book on the subject is “The Probabilistic Method” by Noga Alon and Joel Spencer.



Theorem

If $\binom{n}{k} < 2^{\binom{k}{2}-1}$, then it is possible to color the edges of K_n with two colors so that it has no monochromatic K_k .

- There are $2^{\binom{n}{2}}$ possible colorings. We pick each one with probability $2^{-\binom{n}{2}}$.
- There are $\binom{n}{k}$ different k -vertex cliques in K_n . Number them. Let A_i be the event that the i -th clique is monochromatic. Then $\Pr[A_i] = 2^{-\binom{k}{2}-1}$.
- By union bound, $\Pr[A_1 \vee \dots \vee A_{\binom{n}{k}}] \leq \binom{n}{k} 2^{-\binom{k}{2}-1} < 1$.
- Thus $\Pr[\overline{A_1} \wedge \dots \wedge \overline{A_{\binom{n}{k}}}] > 0$.

$$n = 1000, k = 20. \binom{n}{k} \leq \left(\frac{en}{k}\right)^k \leq 150^{20} \leq 2^{160}, 2^{\binom{k}{2}-1} = 2^{20 \cdot 19 / 2 - 1} = 2^{189}$$



Theorem

In an undirected graph G with m edges there is always a cut of size at least $m/2$.

- We construct a random cut by assigning the vertices randomly to the two sides of the cut.
- For an edge e , let $X_e = 1$ if the endpoints are assigned to different sides, and 0 otherwise. Then $\mathbf{E}[X_e] = 1/2$.
- Let $X = \sum_{e \in E} X_e$ be the expected size of the cut. Then $\mathbf{E}[X] = \sum_{e \in E} \mathbf{E}[X_e] = m/2$.
- Thus there exists a cut (A, B) of size $m/2$.

A Las Vegas Algorithm for Finding a Large Cut

- For a partition (A, B) of the vertices, let $C(A, B)$ be the capacity of the cut (= number of edges with one endpoint on both sides). Clearly, $C(A, B) \leq m$ always.
- Let $p = \Pr[C(A, B) \geq m/2]$. Then

$$\begin{aligned} \frac{m}{2} &= \mathbf{E}[C(A, B)] = \sum_{i < m/2} i \cdot \Pr[C(A, B) = i] + \sum_{i \geq m/2} i \cdot \Pr[C(A, B) = i] \\ &\leq (1 - p) \left(\frac{m}{2} - \frac{1}{2} \right) + pm, \end{aligned}$$

- which implies $p \geq 1/(m + 1)$.
- The algorithm is now clear: Generate a random cut and determine its capacity. Repeat until a cut of capacity at least $m/2$ has been found.
- The expected number of repetitions is $1/p = O(m)$.



Derandomization (Method of Conditional Expectations)

- Number the vertices v_1, v_2 to v_n .
- $\mathbf{E}[C(A, B) \mid x_1, \dots, x_k]$ = conditional expectation of $C(A, B)$ given that we place vertex v_i on side $x_i \in \{A, B\}$ for $1 \leq i \leq k$.
- To show: can efficiently find x_1 to x_n such that $\mathbf{E}[C(A, B)] \leq \mathbf{E}[C(A, B) \mid x_1, \dots, x_k]$ for all k .
- $k = 1$: $\mathbf{E}[C(A, B)] = \mathbf{E}[C(A, B) \mid x_1]$ since RHS does not depend on x_1 .
- Induction step: place v_{k+1} randomly. Then

$$\begin{aligned}\mathbf{E}[C(A, B) \mid x_1, \dots, x_k] &= \frac{1}{2} \mathbf{E}[C(A, B) \mid x_1, \dots, x_k, A] \\ &\quad + \frac{1}{2} \mathbf{E}[C(A, B) \mid x_1, \dots, x_k, B].\end{aligned}$$

- Compute both expectations on the right and fix x_{k+1} to choose the larger one.



Derandomization, Continued

- How to compute $\mathbf{E} [C(A, B) \mid x_1, \dots, x_k, A]$.
- for edges having both endpoints among v_1 to v_{k+1} contribution is clear.
- other edges contribute with probability $1/2$.
- contribution by other edges is the same for both placements.
- So we place v_{k+1} such that we cut at least half of the edges connecting it to vertices v_1 to v_k .
- direct analysis of deterministic algorithm: Let d'_{k+1} be the number of edges connecting v_{k+1} to $\{v_1, \dots, v_k\}$.
- Place v_1 arbitrarily and v_{k+1} , $k \geq 1$, such that at least $d'_{k+1}/2$ edges are cut. Then total number of edges cut is at least $\sum_{1 \leq k \leq n} d'_k/2 = m/2$.



Theorem

A graph $G = (V, E)$ with n vertices and m edges has an independent set of size at least $n^2/(4m)$.

- Let $d = 2m/n$ be the average degree of the vertices.
 - Delete each vertex independently with probability $1 - 1/d$.
 - For each remaining edge, remove it and one of its adjacent vertices.
- Let X be the number of vertices surviving the first step. Then $\mathbf{E}[X] = n/d$. Let Y be the number of edges surviving the first step. Then $\mathbf{E}[Y] = nd/2 \cdot \left(\frac{1}{d}\right)^2 = \frac{n}{2d}$.
- The second step removes the surviving edges and at most Y vertices. Thus alg outputs an independent set of size at least $X - Y$ and

$$\mathbf{E}[X - Y] = \frac{n}{d} - \frac{n}{2d} = \frac{n}{2d} = \frac{n^2}{4m}.$$



Graphs with Large Girth

Theorem

For every $k \geq 3$ and large n , there is a graph with n vertices, $\frac{1}{4}n^{1+1/k}$ edges, and girth (length of a shortest cycle) at least k .

- Sample a random graph $G \in \mathcal{G}_{n,p}$ with $p = n^{1/k-1}$.
Let $X = \#$ of edges. Then $\mathbf{E}[X] = \binom{n}{2} \cdot p = \frac{1}{2} \left(1 - \frac{1}{n}\right) n^{1+1/k}$.
- Let $Y =$ number of cycles in G of length at most $k - 1$.
- There are at most $\binom{n}{i} \frac{(i-1)!}{2}$ candidate cycles of length i and each one is present with probability p^i . Thus

$$\mathbf{E}[Y] = \sum_{i=3}^{k-1} \binom{n}{i} \frac{(i-1)!}{2} p^i \leq \sum_{i=3}^{k-1} n^i p^i = \sum_{i=3}^{k-1} n^{i/k} < kn^{(k-1)/k}.$$

- For each cycle of length $\leq k - 1$ in G , we remove one of its edges. The expected number of edges remaining is

$$\mathbf{E}[X - Y] \geq \frac{1}{2} \left(1 - \frac{1}{n}\right) n^{1+1/k} - kn^{(k-1)/k} \geq \frac{1}{4} n^{1+1/k}.$$

The Lovasz Local Lemma

Let E_1 to E_n be a set of “bad events” in a probability space. We want to show that the probability that no bad event occurs is **positive**. This is easy if the events are mutually independent, i.e., for any $I \subseteq \{1, \dots, n\}$

$$\Pr [\bigcap_{i \in I} E_i] = \prod_{i \in I} \Pr [E_i].$$

Then the events \overline{E}_i are also independent (prove it) and hence

$$\Pr [\bigcap_{1 \leq i \leq n} \overline{E}_i] = \prod_{1 \leq i \leq n} \Pr [\overline{E}_i] = \prod_{1 \leq i \leq n} (1 - \Pr [E_i]) > 0$$

provided that $\Pr [E_i] < 1$ for all i .

Lovasz showed that less than mutual independence suffices to show that the probability of no bad event happening is positive.



The Dependency Graph

An event E is mutually independent of the events E_1 to E_n if for any subset $I \subseteq \{1, \dots, n\}$, $\Pr[E \mid \bigcap_{i \in I} E_i] = \Pr[E]$.

Dependency Graph

A dependency graph for a set of events E_1 to E_n is a graph $G = (V, E)$ on vertex set $\{1, \dots, n\}$ such that for all i , E_i is mutually independent of the events $\{E_j \mid (i, j) \notin E\}$.

Example (Edge Disjoint Paths)

n pairs of users need to communicate in a graph. Each pair $i \in \{1, \dots, n\}$ can choose from a collection F_i of paths.

For $i \neq j$, let $E_{\{i,j\}}$ be the event that the paths chosen by pairs i and j share an edge; this is a bad event. Then $E_{i,j}$ is independent of all events $E_{\{i',j'\}}$ when $\{i,j\} \cap \{i',j'\} = \emptyset$. So each event has $< 2n$ neighbors in the dependency graph.

Note that there are $n(n-1)/2$ events.



Theorem

Let $d \in \mathbb{N}$ and $p \in \mathbb{R}$ with $4dp \leq 1$. Let E_1, \dots, E_n be events. If

1. $\Pr[E_i] \leq p$ for all i , and
2. the degree of their dependency graph is bounded by d , then

$$\Pr \left[\bigcap_{1 \leq i \leq n} \overline{E_i} \right] > 0.$$

Disjoint Paths: Assume each F_i consists of m paths. For i and j : a path in F_i intersects with at most k paths in F_j . Then

$$\Pr[E_{\{i,j\}}] \leq \frac{k}{m} \text{ and } d < 2n \text{ and hence } 4dp < \frac{8nk}{m}.$$

So if $8nk/m \leq 1$, there is a choice of paths such that the n paths are disjoint.

Theorem

Let $\varphi = C_1 \wedge \dots \wedge C_m$, where each C_i has exactly k literals. If no variable appears in more than $T = 2^k / (4k)$ clauses, φ is satisfiable.

- We assign random truth values to the variables.
- Let E_i be the event that i -th clause is false. Then $\Pr[E_i] = 2^{-k}$. Thus $p = 2^{-k}$.
- C_i is independent of C_j if they do not share a variable.
- Each of the k variables of a clause can appear in T other clauses. Hence $d \leq k \cdot T \leq 2^k / 4$.
- Thus $4pd \leq 1$ and hence a satisfying assignment exists.

Under somewhat stronger assumptions, this can be turned into an algorithm.



Proof of Local Lemma

Claim

For all $S \subseteq \{1, \dots, n\}$ and $k \notin S$

$$\Pr [E_k \mid \bigcap_{i \in S} \bar{E}_i] \leq 2p.$$

Claim \rightarrow Local Lemma

$$\begin{aligned} \Pr [\bigcap_{1 \leq j \leq n} \bar{E}_j] &= \prod_{1 \leq i \leq n} \Pr [\bar{E}_i \mid \bigcap_{1 \leq j < i} \bar{E}_j] \\ &= \prod_{1 \leq i \leq n} (1 - \Pr [E_i \mid \bigcap_{1 \leq j < i} \bar{E}_j]) \\ &\geq \prod_{1 \leq i \leq n} (1 - 2p) > 0 \end{aligned}$$



Proof of Claim

For all $S \subseteq \{1, \dots, n\}$ and $k \notin S$: $\Pr [E_k \mid \bigcap_{i \in S} \bar{E}_i] \leq 2p$.

Show $\Pr [\bigcap_{i \in S} \bar{E}_i] > 0$ as in Claim \rightarrow Local Lemma.

Use induction on $s = |S|$. $s = 0$ is trivial. Split S into $S_1 = \{i \mid k \text{ and } i \text{ are connected in dependency graph}\}$ and $S_2 = S \setminus S_1$. If S_1 is empty, full independence. So assume $|S_2| < |S|$. Let $F_{S_1} = \bigcap_{i \in S_1} \bar{E}_i$. Similarly, F_{S_2}, F_S . Note $|S_1| \leq d$.

$$\Pr [E_k \mid F_S] = \frac{\Pr [E_k \cap F_S]}{\Pr [F_S]} = \frac{\Pr [E_k \cap F_{S_1} \mid F_{S_2}] \Pr [F_{S_2}]}{\Pr [F_{S_1} \mid F_{S_2}] \Pr [F_{S_2}]}$$

$$\Pr [E_k \cap F_{S_1} \mid F_{S_2}] \leq \Pr [E_k \mid F_{S_2}] \leq p \quad E_k \text{ indep of } S_2$$

$$\begin{aligned} \Pr [F_{S_1} \mid F_{S_2}] &= \Pr [\bigcap_{i \in S_1} \bar{E}_i \mid F_{S_2}] \geq 1 - \sum_{i \in S_1} \Pr [E_i \mid F_{S_2}] \\ &\geq 1 - \sum_{i \in S_1} 2p \geq 1 - 2pd \geq 1/2. \end{aligned}$$

Summary

- In order to show the existence of an object with certain properties, demonstrate a sample space of objects in which the probability is positive that a randomly selected object has the property.
- Since we work with finite sample spaces, the existence proofs are, in principle, algorithmic. An object with the desired properties can be found by exhaustive search.
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