

CMPSCI 711: “Really Advanced Algorithms”

Lecture 11, 12, & 13 – Probability Amplification and Expanders

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Last Compiled: March 30, 2009

Outline

Probability Amplification with Two Point Sampling

Probability Amplification with Expanding Graphs

Probability Amplification with Random Walks on Expanders

Bonus Section! Connectivity and Eigenvectors

Readings

Probability Amplification

- ▶ Consider language L and randomized algorithm \mathcal{A} such that for random $r \in \{0, \dots, p-1\}$ (p is prime),
 - ▶ If $x \in L$, then $\mathbb{P}[A(x, r) = 1] \geq 1/2$
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- ▶ Easy to boost the probability of returning 1 for $x \in L$ up to $1 - 2^{-t}$ using $O(t \log p)$ random bits.
- ▶ What if we only have $O(\log p)$ bits?

Two Point Sampling

- ▶ Let p be a prime and let a, b be chosen uniformly at random from $\{0, 1, \dots, p-1\}$.
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- ▶ Hence, with $O(\log p)$ random bits, can boost probability to $1 - 1/t$ given t trials.

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- ▶ Approach is based on “sparse expanding graphs”

Theorem

For sufficiently large n , there is a bipartite graph $G = (L, R, E)$ with $|L| = n$, $|R| = 2^{\log^2 n}$ with:

- 1. Every subset of $n/2$ vertices from L has at least $2^{\log^2 n} - n$ neighbors in R .*
- 2. No vertex of R has more than $12 \log^2 n$ neighbors.*

Proof of Theorem

- ▶ By probabilistic method: For each vertex in L , pick $d = 2^{\log^2 n} (4 \log^2 n) / n$ neighbors in R (with replacement).

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$$\binom{n}{n/2} \left(2^{\log^2 n}\right)^{n/2} \left(\frac{2^{\log^2 n} - n}{2^{\log^2 n}}\right)^{dn/2}$$

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- ▶ Usual tricks shows this is $\ll 1/2$.
- ▶ Second condition: expected number of neighbors of $v \in R$ is $4 \log^2 n$.
- ▶ Chernoff bound shows that there exists $v \in R$ with more than $12 \log^2 n$ neighbors with probability $\leq |R|(e/3)^{12 \log^2 n} \ll 1/2$

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- ▶ Pick $v \in_R R$: Uses $O(\log^2 n)$ random bits.
- ▶ Consider neighbors of v .
- ▶ At least $n/2$ of nodes in L are witnesses if $x \in L$.
- ▶ Probability we find a witness is at least $1 - n/2^{\log^2 n}$.

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Expanders

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An (n, d, c) -expander is a d -regular bipartite (multi-)graph $G = (X, Y, E)$ with $|X| = |Y| = n/2$ such that for any $S \subset X$,

$$|\Gamma(S)| \geq \left(1 + c \left(1 - \frac{2|S|}{n}\right)\right) |S|.$$

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Example (Gabber-Galil expanders)

For positive integer m , let $n = 2m^2$. Each vertex in X has distinct label consisting of a pair (a, b) for $a, b \in \{0, \dots, m-1\}$. Similarly for Y . $(x, y) \in X$ has neighbors in Y with labels:

$$(x, y), (x, 2x + y), (x, 2x + y + 1), (x, 2x + y + 2)$$

$$(x + 2y, y), (x + 2y + 1, y), (x + 2y + 2, y)$$

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Eigenvalues and Algebraic Graph Theory

Fact

For symmetric $n \times n$ matrix A , there exists n orthonormal eigenvectors e_1, \dots, e_n with eigenvalues $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$: i.e.,

$$e_i A = \lambda_i e_i \quad \text{and} \quad e_i \cdot e_j = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases}$$

If A is adjacency matrix of graph G , then G connected implies $\lambda_2 < \lambda_1$. If G is d -regular and bipartite, $\lambda_1 = d$ and $\lambda_n = -d$.

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Theorem (Alon '86)

If G is an (n, d, c) -expander then $|\lambda_2| \leq d - \frac{c^2}{1024 + 2c^2}$. If $|\lambda_2| \leq d - \epsilon$ then G is an (n, d, c) -expander with $c \geq \frac{2d\epsilon - \epsilon^2}{d^2}$.

Expanders are Rapidly Mixing

Definition

Let G be an (n, d, c) -expander and let Q be transition matrix on G with $Q_{uu} = 1/2$ and $Q_{uv} = 1/(2d)$ if v is a neighbor of u . Let λ_i be eigenvalues of G and $\mu_i = (1 + \lambda_i/d)/2$ be eigenvalues of Q .

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Theorem

Consider aperiodic random walk on G defined by Q . Distribution at time t ,

$$|q^{(t)} - \pi| \leq 2\sqrt{n}\mu_2^t$$

This is at most $\sqrt{n}(1 - \epsilon/2d)^t$ if $\lambda_2 \leq d - \epsilon$.

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Lemma

For any vector $v \in \mathbb{R}^n$, $\|v\|_2 \leq \|v\|_1 \leq \sqrt{n}\|v\|_2$ where

$$\|v\|_1 = \sum_i |v_i| \text{ and } \|v\|_2 = \sqrt{\sum_i v_i^2}.$$

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- ▶ Let $x = c_1 e_1$ and using previous lemma:

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- ▶ Because $\mu_2 \geq \mu_3 \geq \dots \mu_n \geq 0$,

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BPP and Probability Amplification

- ▶ Consider language L and randomized algorithm \mathcal{A} such that for random $r \in \{0, 1\}^n$,
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$$X_0, X_1, X_2, \dots, X_{7k\beta}$$

where $\beta = O(1)$ satisfies $\lambda_2^\beta \leq 1/10$.

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Theorem

Majority of $A(x, r_0), \dots, A(x, r_{7k})$ are correct with prob. $1 - 1/2^k$.

Proof of Theorem

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- ▶ Applying claim repeatedly,

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- ▶ Probability $|A| \leq 7k/2$ is at most $2^{7k}(1/5)^{7k/2} < 1/2^k$

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- ▶ Because eigenvectors are in $[0, 1]$:

$$\|pBW\|_2 \leq \|pB\|_2 = \left\| \sum_{i \in [n]} c_i \lambda_i^\beta e_i \right\|_2 = \sqrt{\sum_{i \in [n]} c_i^2 \lambda_i^{2\beta}} \leq \sqrt{\sum_{i \in [n]} c_i^2}$$

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- ▶ Putting it together:

$$\|pB\bar{W}\|_2 \leq \|c_1 e_1 B\bar{W}\|_2 + \|yB\bar{W}\|_2 \leq (\|c_1 e_1\|_2 + \|y\|_2) \leq \|p\|_2 / 5$$

Outline

Probability Amplification with Two Point Sampling

Probability Amplification with Expanding Graphs

Probability Amplification with Random Walks on Expanders

Bonus Section! Connectivity and Eigenvectors

Readings

Connectivity and Eigenvectors

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- ▶ $e_2(u) = e_2(v)$ for all u, v if graph connected so $e_2 \not\perp e_1$

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- ▶ But x also has eigenvalue d : $xM = dx$

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For next time, please make sure you've read:

- ▶ Chapter 3.4, 5.3 [MR].
- ▶ Chapter 6 [MR] and 11.1, 11.2 from [MU]