

Lecture 7

more on random walks
maybe begin pairwise independence motivation

- Saving random bits in amplification
via random walks
- if time: begin pairwise independence
start with algorithm for max-cut
that we will derandomize next
time via pairwise independence

Reducing Randomness via

Random Walks:

For language L ,

let A be algorithm using r bits
of randomness s.t.

1-sided error

$$(1) \forall x \in L \quad \Pr_{w \in A's \text{ coins}} [A_w(x) = 1] \geq 99/100$$

usually correct

$$(2) \forall x \notin L \quad \Pr_{w \in A's \text{ coins}} [A_w(x) = 0] = 1$$

always correct

To get error $< 2^{-k}$

Method

random bits used

1) run k times on independently chosen bits

$k \cdot r$

• output " $x \notin L$ " if see 0
else output " $x \in L$ "

2) today: use random walks to choose bits

$r + O(k)$

↑
not independent

Plan

- \forall (random) string $w \in \{0,1\}^r$, assign it to node in graph G ← we pick!

- picking random n -bit string
 \Leftrightarrow picking random node in G
easier?



picking several random n -bit strings

- \Leftrightarrow picking several random nodes in G
easier?



picking several strings, one of which is
"good"

- \Leftrightarrow picking several nodes, one of which
is "good" Easier!!



The graph G : ← we get to pick G !!!

- constant degree d -regular, connected, nonbipartite

- transition matrix P for r.w. on G

has $|\lambda_2| \leq \frac{1}{10}$

Since < 1
implies
 G is
connected!

→ $\lambda_2 + d$ -reg \Rightarrow stat dist Π is uniform

- # nodes = 2^r

corresponds to all
possible choices of r
random bits

The Algorithm

Random bits

• Pick random start node $w \in \{0, 1\}^r$

r

• Repeat K times:

$w \leftarrow$ random nbr of w

run $A_w(x)$ with w as random bits.

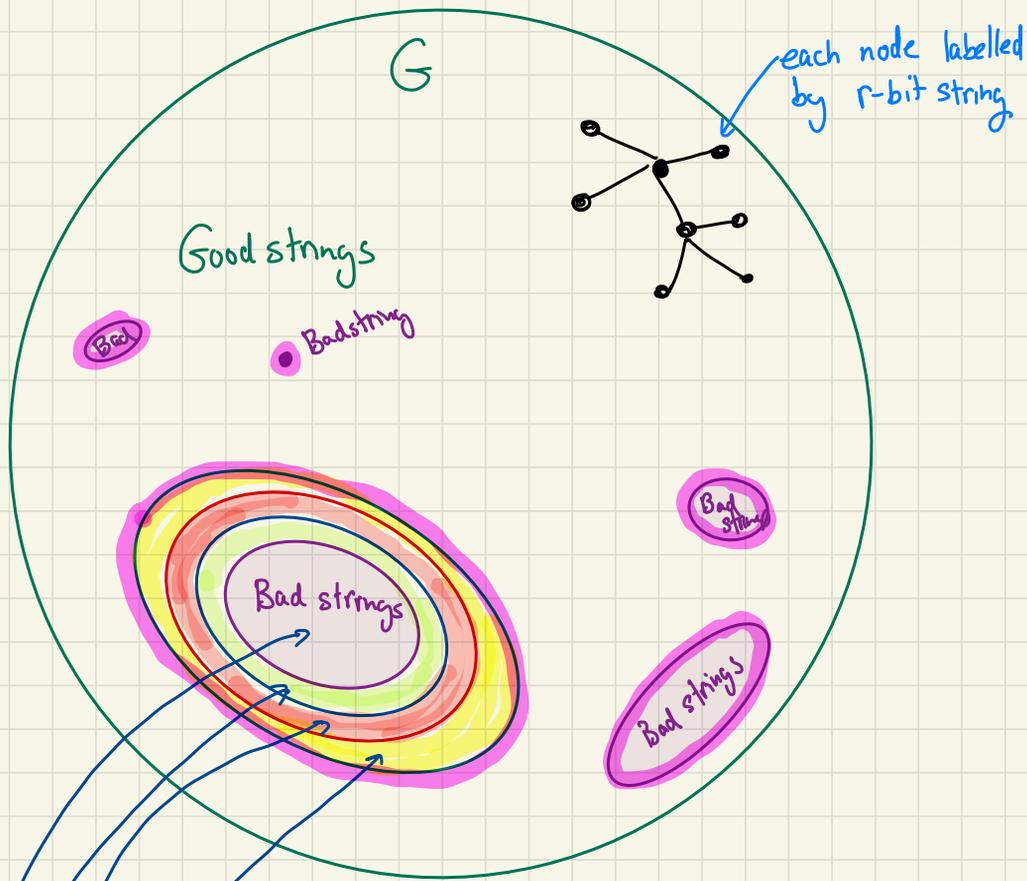
If $A_w(x) = 0$, output " $x \notin L$ " & halt
else continue

$O(1) \times K$
↑ ↑
 d # loops
is const

• Output " $x \in L$ "

total: $r + O(K)$

Behavior: Claim: error of new algorithm is $\leq (\frac{1}{3})^k$ for $x \in L$
(still 0 error for $x \notin L$)



each node labelled by r -bit string

Good strings

Bad

Bad string

Bad strings

Bad strings

Bad strings

bad, but likely to hit good string after 1 step

after 2 steps

after 3 steps

after k steps

if $|\lambda_2| \ll 1$ then fewer & fewer of these as k gets bigger

Main Idea
 unlikely to pick start location that is likely bad after k -steps

bad case: walk only on "bad strings" & never reach good strings
 why is this possible if G arbitrary? e.g. line

λ_2 is close to 1

Proof of Claim

$x \notin L$: algorithm never errs (no bad strings)

$x \in L$:

most random bits say $x \in L$: $\geq \frac{99}{100} \cdot 2^r$ ($A(x)=1$)

define $B \equiv \left\{ w \mid A_w(x) \text{ with random bits } w \right.$
is incorrect.
i.e. says $x \notin L$
"bad w's"

$$|B| \leq \frac{2^r}{100}$$

need lin. alg. way of describing walks that
stay in bad set:

define N diagonal matrix

$$N_w = \begin{cases} 1 & \text{if } w \in B \quad \leftarrow \text{incorrect} \\ 0 & \text{o.w.} \quad \leftarrow \text{correct} \end{cases}$$

Can compose:

$$\|g \cdot PN\|_1 = \Pr_{w \in g} [\text{start at } g, \text{ take a step \& land on "bad"}]$$

⋮

$$\|g(PN)^k\|_1 = \Pr_{w \in g} [\text{start at } g, \text{ take } k \text{ steps \& each is "bad"}]$$

ignores whether start node bad. this just hurts vs, so ok to ignore.

Lemma $\forall \pi \quad \|\pi PN\|_2 \leq \frac{1}{5} \|\pi\|_2$

First: how do we use lemma?

answer incorrect only if always see bad w's

$$\Rightarrow \Pr [\text{incorrect}] \leq \|p_0 (PN)^k\|_1$$

$$\leq \sqrt{2^r} \|p_0 (PN)^k\|_2$$

since $\|p\|_1 \leq \sqrt{\text{domain size}} \cdot \|p\|_2$

$$\leq \sqrt{2^r} \|P_0\|_2 \left(\frac{1}{5}\right)^k \quad \text{apply lemma } k \text{ times}$$

$$= \frac{1}{\sqrt{2^r}} \quad \text{since start at uniform } \& \text{ } L_2 \text{ norm of uniform}$$

$$= \sqrt{\sum \left(\frac{1}{2}\right)^2} = \sqrt{\frac{1}{2}}$$

$$= \left(\frac{1}{5}\right)^k \quad \checkmark \quad \text{great! our algorithm works!}$$

Proof of lemma:

let $V_1 \dots V_{2^r}$ be e-vects of P that are orthonormal
 $\& V_1$ is s.t. $\|V_1\|_2 = 1$ (so $V_1 = \left(\frac{1}{\sqrt{2^r}}, \dots, \frac{1}{\sqrt{2^r}}\right)$)

then $\Pi = \sum_{i=1}^{2^r} \alpha_i V_i$

note: 1) $\|\Pi\|_2 = \sqrt{\sum \alpha_i^2}$ by (*) proved previously

2) $\forall w \quad \|wN\|_2 = \sqrt{\sum_{i \in S} w_i^2} \leq \sqrt{\sum_i w_i^2} = \|w\|_2$

So:

$$\begin{aligned}\|TPN\|_2 &= \left\| \sum_{i=1}^{2^n} \alpha_i v_i PN \right\|_2 \\ &= \left\| \sum_{i=1}^{2^n} \alpha_i \lambda_i v_i N \right\|_2\end{aligned}$$

since any TP is lin comb of basis vectors

$$\leq \underbrace{\|\alpha, \lambda, v, N\|_2}_{\textcircled{A}} + \underbrace{\left\| \sum_{i=2}^{2^n} \alpha_i \lambda_i v_i N \right\|_2}_{\textcircled{B}}$$

Cauchy-Schwarz

bound \textcircled{A} :

$$\|\alpha, \lambda, v, N\|_2 = \|\alpha, v, N\|_2 \quad \text{since } \lambda_i = 1$$

$$= |\alpha_1| \cdot \sqrt{\sum_{i \in B} \left(\frac{1}{\sqrt{2^r}}\right)^2} \quad \text{since } v_i = \left(\frac{1}{\sqrt{2^r}}, \dots, \frac{1}{\sqrt{2^r}}\right)$$

uses that uniform dist is unlikely to be on a bad string

$$= |\alpha_1| \cdot \sqrt{\frac{|B|}{2^r}}$$

$$\leq \frac{|\alpha_1|}{10}$$

$$\leq \frac{\|T\|_2}{10}$$

$$\star N = \begin{pmatrix} \alpha_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \alpha_n \end{pmatrix}$$

$$\text{since } \frac{|B|}{2^r} \leq \frac{1}{100}$$

$$\text{since } \|T\|_2 = \sqrt{\sum_{i=1}^n \alpha_i^2}$$

bound (B):

$$\left\| \sum_{i=2}^{2^r} \alpha_i \lambda_i v_i N \right\|_2 \leq \left\| \sum_{i=2}^{2^r} \alpha_i \lambda_i v_i \right\|_2$$

from note

uses

"mixing"
of v_i 's
for $i > 2$.

These could be
"heavy" in bad
areas, but won't
stay for long!!

$$= \sqrt{\sum (\alpha_i \lambda_i)^2}$$

$$\leq \sqrt{\sum \alpha_i^2 \cdot \left(\frac{1}{10}\right)^2}$$

$$\lambda_i \leq 1/10$$

$$\leq \frac{1}{10} \cdot \|\Pi\|_2$$

$$\text{So: } \|\Pi P N\|_2 \leq \frac{\|\Pi\|_2}{5} \quad \blacksquare$$

Pairwise Independence & Derandomization

Let's start with a simple algorithm for MaxCut:

Max Cut:

given: $G = (V, E)$

output: partition V into S, T

to maximize $|\underbrace{\{(u, v) \mid u \in S, v \in T\}}_{\text{size of S-T cut}}|$

NP hard

Randomized Algorithm:

Flip coins $r_1 \dots r_n$

Put node i on side r_i to get S, T

if $r_i = 0$ add i to S
else $r_i = 1$ add i to T

Analysis:

Let $1_{u,v} = \begin{cases} 1 & \text{if } r_u \neq r_v \\ 0 & \text{o.w.} \end{cases}$ ↓ u, v on opposite sides of cut

$$\text{Cut size} = \sum_{(u,v) \in E} 1_{u,v}$$

$$E[\text{cut size}] = E\left[\sum_{(u,v) \in E} 1_{u,v}\right]$$

$$= \sum_{(u,v) \in E} E[1_{u,v}] = \sum_{(u,v) \in E} \Pr[1_{u,v} = 1]$$

$$= \sum_{(u,v) \in E} \Pr[(r_u = 1 \wedge r_v = 0) \text{ or } (r_u = 0 \wedge r_v = 1)]$$

$$= |E| \cdot \left[\frac{1}{4} + \frac{1}{4}\right] = \frac{|E|}{2}$$

So expect $\frac{1}{2}$ the edges to cross cut!

$$\text{Note: } E[\text{cut size}] = \frac{|E|}{2} \Rightarrow \exists \text{ cut of size } \frac{|E|}{2}$$

average cut size produced by algorithm

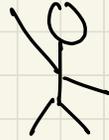
must be one that is at least as big as the average

Why is $\frac{|E|}{2}$ considered a success?



Oh, right...

the best you can do is $|E|$



Gives multiplicative approximation
to within a factor of 2

Previous lecture

Derandomization via Enumeration

Given: probabilistic algorithm A + input x

Algorithm:

Run A on every possible random
string of length $r(n)$

Output majority answer

Randomized Max Cut Algorithm:

Flip coins r_1, \dots, r_n

Put node i on side r_i to get S, T

Derandomization: first attempt

Use "derandomization via enumeration"

Run A on every possible random string of length $r(n)$

Output majority answer

here $r(n) = n$, so need 2^n runs of A 😞

Hope: reduce $r(n)$?

still use "derandomization via enumeration"

find subset $S \subseteq \{0,1\}^{r(n)}$ of random strings that "works"

↕ only enumerate over S