

Lec11/12 Question 5

For any d -regular graph G , $\Phi(G) \leq \frac{1}{2} + o(1)$

Proof: Recall

$$\Phi(S) = \frac{e(S, S^c)}{|S| \cdot d} \quad S \neq \emptyset, S \neq V$$

$$\text{and } \Phi(G) = \min_{1 \leq |S| \leq n/2} \frac{e(S, S^c)}{|S| \cdot d}$$

G connected $\Leftrightarrow \Phi(G) \neq 0 \Leftrightarrow \lambda_2(G) \neq 0$

easier inequality: $\Phi(G) \leq 1$, since
 $e(S, S^c) \leq |S| \cdot d$

Back to proof:

We need to show that for any graph $G=(V, E)$, there is $S \subseteq V$ with $1 \leq |S| \leq n/2$ and

$$\Phi(S) \leq \frac{1}{2} + o(1)$$

Hint: Use probabilistic method

The randomised MAX-CUT Algorithm achieves

$$E[e(S, S^c)] = |E|/2, \text{ where}$$

$$S := \{v \in V : X_v = 1\}, \quad X_v \text{'s independent Bernoulli.}$$

Question 5 (continuation)

What about the size of S ?

$$\begin{aligned} E[|S|] &= E\left[\sum_{v \in V} X_v\right] = \sum_{v \in V} E[X_v] \\ &= n \cdot 1/2 \end{aligned}$$

We want $|S|$ to be close to $n \cdot 1/2$
and $e(S, S^c)$ to be at most $|E|/2$

\Rightarrow use concentration & union bound

Step 1: Size of S

Chernoff-Bound ("nice" form, slide 16)

$$P[|X - E[X]| \geq t] \leq 2 \cdot e^{-2t^2/n}$$

$$\begin{aligned} \Rightarrow P[| |S| - n/2 | \geq \sqrt{n \log n}] &\leq 2 \cdot e^{-2 \log n} \\ &= 2n^{-2} \end{aligned}$$

Step 2: Cut edges between S and S^c

Is this a sum of independent r.v.'s?

No! (unfortunately...)

But: $e(S, S^c) = f(X_{v_1}, X_{v_2}, \dots, X_{v_n})$,

where $X_{v_1}, X_{v_2}, \dots, X_{v_n}$ are mutually independent
 \Rightarrow Method of Bounded Differences

Question 5 (continuation)

If X_{v_i} changes, how much does $e(S, S^c)$ change?

\Rightarrow by at most $\deg(v_i) = d =: c_i$

MOBD (McDiarmid's Inequality)

$$\hookrightarrow P[e(S, S^c) \geq |E|/2 + t] \leq \exp\left(-\frac{2t^2}{\sum_{i=1}^n c_i^2}\right)$$

we choose $t = \sqrt{n \cdot \log n} \cdot d$

$$\Rightarrow P[e(S, S^c) \geq |E|/2 + \sqrt{n \log n} \cdot d] \leq n^{-2}$$

Union Bound gives:

$$\begin{aligned} & P\left[\left\{|S| - n/2\right\} \leq \sqrt{n \log n}\right] \cap \left\{e(S, S^c) \leq |E|/2 + \sqrt{n \log n} \cdot d\right\} \\ & \geq 1 - 2n^{-2} - n^{-2} \geq 1 - n^{-1} > \underline{\underline{0}} \end{aligned}$$

For any graph G , there exists $S \subseteq V$ with:

i) $||S| - n/2| \leq \sqrt{n \log n}$, and

ii) $e(S, S^c) \leq |E|/2 + \sqrt{n \log n} \cdot d$

By possibly switching $|S|$ with $|S^c|$, we get

$$i) \Rightarrow |S| \in [n/2 - \sqrt{n \log n}, n/2]$$

$$\begin{aligned} \Rightarrow \phi(G) \leq \phi(S) & \leq \frac{|E|/2 + \sqrt{n \log n} \cdot d}{(n/2 - \sqrt{n \log n}) \cdot d} = \frac{nd/4 + \sqrt{n \log n} \cdot d}{(n/2 - \sqrt{n \log n}) \cdot d} \\ & \leq \frac{1}{2} + o(1) \quad \square \end{aligned}$$

Lec 13 Question 1

Let's consider case where exactly one packet is missing

x_1, x_2, \dots, x_{n-1} be $n-1$ different IDs from $\{1, \dots, n\}$

Naive Solution: Create array of size n
 \Rightarrow space complexity $\Omega(n)$

Idea: use that $\sum_{i=1}^n i = \frac{n(n+1)}{2}$

Algorithm:

$$S_1 \leftarrow 0$$

For each packet with label x

$$S_1 \leftarrow S_1 + x$$

$$\text{Return } \frac{n(n+1)}{2} - S_1$$

\rightarrow does the job and uses only $O(\log n)$ bits of space
(if all packets are sent, we return 0)

Extension: What if two packets are missing?

$$\text{Let } S_1 = \sum_{i=1}^{n-2} x_i \quad \Rightarrow \quad x_{n-1} + x_{n-2} = \frac{n(n+1)}{2} - S_1$$

$$\text{and } S_2 = \sum_{i=1}^{n-2} x_i^2 \quad x_{n-1}^2 + x_{n-2}^2 = \frac{(2n+1)n(n+1)}{6} - S_2$$

\rightarrow solve quadratic formula

Lec 13 Question 1 (continuation)

As suggested by one student (thank you!), we can also take the XOR:

$$x_1 \oplus x_2 \oplus \dots \oplus x_{n-1} := S$$

and then return

$$1 \oplus 2 \oplus \dots \oplus n \oplus S$$

which is equal to x_n (missing element).

- this uses only $\log_2 n + 1$ space
- to cover the case where all n packets are sent, we should encode packets starting from 1 (and not 0!)

Lec 14 Question 1

Note: If we run a deterministic algorithm, the adversary specifying the data set can simulate our algorithm, in particular, can make all predictions wrong!

(Compare to pivot selection in Quick-Sort!
 Choosing pivot randomly is only so effective, since we assume the input is specified without knowing the random decisions/random bits)

$n=2$, T arbitrary

t	Exp. 1	Exp. 2	Algo Prediction	Actual Result
1	0	1	1	0
2	1	0	1	0
3	1	0	0	1
4	0	1	1	0
5	1	0	0	1
\vdots	\vdots	\vdots	\vdots	\vdots
T				

$$M^{(T)} = T, \quad m_1^{(T)} + m_2^{(T)} = T$$

$$\Rightarrow \min(m_1^{(T)}, m_2^{(T)}) \leq T/2$$

Lec 14 Question 3

For each expert i , $i=1,2,\dots,n$, create another "opposing" expert $i+n$ which always predicts the opposite of expert i .

Performance-Guarantee of RWMA:

$$\text{old: } M^{(T)} \leq 1 \cdot (1+\delta) \cdot \min_{i \in [n]} m_i^{(T)} + \frac{\ln n}{\delta}$$

$$\text{new: } M^{(T)} \leq 1 \cdot (1+\delta) \cdot \min_{i \in [n]} (m_i^{(T)}, T - m_i^{(T)}) + \frac{\ln(2n)}{\delta}$$

General Approach: can build large set of additional experts which are logical functions or even algorithms based on the original experts

- "Baseline" of mistakes by best expert improves
- Convergence becomes a bit slower due to $\ln(\cdot)$ term

Lec 14 Question 4

Naive Greedy: Always follow prediction of the best expert so far (break ties in favour of smallest ID)

Example for $n=3$:

t	m ^(t-1)			Predictions			Greedy	Result
	m ₁	m ₂	m ₃	E1	E2	E3		
1	0	0	0	1	0	0	1	0
2	1	0	0	0	1	0	1	0
3	1	1	0	0	0	1	1	0
4	1	1	1	1	0	0	1	0
5	2	1	1	0	1	0	1	0
6	2	2	1	0	0	1	1	
7	2	2	2					

For $T = n \cdot k = 3 \cdot k$, $k \in \mathbb{N}$:

$$m_i^{(T)} = \frac{1}{3} \cdot T = \frac{T}{n}, \text{ but } \underline{M^{(T)}} = T$$

← Large gap! →

A better approach is called "Follow-the-Perturbed-Leader", which adds some random noise to each $m_i^{(T)}$ ~ similar to UCB- Algo.

Lec 14 Question 4 (continuation)

We used "worst-case" tie breaking before!

What if we randomly choose one of the leaders in case of a tie?

In round 1, we have $\frac{1}{n}$ prob. of making error
" 2, " $\frac{1}{n-1}$ prob. of making error
:
" n, we have 1 prob. of making error

\Rightarrow Every n consecutive rounds, we make in expectation

$$\sum_{i=1}^n \frac{1}{n-(i-1)} \approx \ln(n)$$

many mistakes.

$$\Rightarrow E[M^{(T)}] = T \cdot \frac{\ln(n)}{n}, \text{ where } n \mid T.$$

as before: $m_i^{(T)} = \frac{T}{n} \Rightarrow$ better performance,
but there is still a large gap between $M^{(T)}$
and $\min_{i \in [n]} m_i^{(T)}$.