## $\{\operatorname{csci} 3|6907|$ Lecture 7$\}$

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## Announcements

- homework: hw4 due after spring break
- presentations: Apr 3 (?), io, 17, 24.
- today: probabilistic method \& derandomization

PART I $\mid$ derandomization

## Derandomization

- NAMELY, remove the randomness from randomized algorithms.
- Eliminate errors, from w.h.p. to always
- Theoretical interest: does randomness really help in the design of algorithms?
- TWO TECHNIQUES. method of conditional expectations \& pairwise independence.


## Finding a Large Cut

- THEOREM: Any graph $G$ with $m$ edges has a cut of size $\geq \frac{m}{2}$.


## LargeCut Algorithm

Input: a graph $G=([n], E)$
I. Flip $n$ coins $r_{1}, r_{2}, \ldots, r_{n}$, put vertex $i$ in $S$ if $r_{i}=0$ and in $T$ otherwise.
2. Output $(S, T)$.

- by averaging argument, there exists a choice of $r_{1}, r_{2}, \ldots, r_{n}$ that leads to a cut of size at least $\frac{m}{2}$.
- find a good sequence of coin tosses "bit by bit".


## LargeCut tree


question. How to compute labels of the "internal" nodes?

## Deterministic LargeCut

- definition. Define the conditional expectation

$$
e\left(r_{1}, r_{2}, \ldots, r_{i}\right)=\mathrm{E}_{R_{1}, \ldots, R_{n}}\left[|\operatorname{cut}(S, T)| \mid R_{1}=r_{1}, R_{2}=r_{2}, \ldots, R_{i}=r_{i}\right]
$$

- base case.e $(\lambda)=|E| / 2$.
- $\operatorname{inductive~case.~} e(\lambda)=\mathrm{E}_{R_{1}}\left[e\left(R_{1}\right)\right]$.
- more generally, $e\left(r_{1}, \ldots, r_{i}\right)=\mathrm{E}_{R_{i+1}}\left[e\left(r_{1}, \ldots, r_{i}, R_{i+1}\right)\right]$ i.e. $e\left(r_{1}, \ldots, r_{i}\right)=\frac{1}{2}\left(e\left(r_{1}, \ldots, r_{i}, 0\right)+e\left(r_{1}, \ldots, r_{i}, 1\right)\right)$
- claim. There exists $r_{1}, r_{2}, \ldots, r_{n}$ such that

$$
e(\lambda) \leq e\left(r_{1}\right) \leq e\left(r_{1}, r_{2}\right) \leq \cdots \leq e\left(r_{1}, r_{2}, \ldots, r_{n}\right)
$$

- Q. which is bigger? $e\left(r_{1}, \ldots, r_{i}, 0\right)$ vs $e\left(r_{1}, \ldots, r_{i}, 1\right)$


## Deterministic LargeCut

## Deterministic LARGECut Algorithm I

I. Set $S=\emptyset, T=\emptyset$
2. For $i=0, \ldots, n-1$ :
2.I If $|\operatorname{cut}(\{i+1\}, S)|>|\operatorname{cut}(\{i+1\}, \bar{S})|$, set $T \leftarrow T \cup\{i+1\}$,
2.2 else set $S \leftarrow S \cup\{i+1\}$.

- remark. This is the "natural" greedy algorithm. Method of conditional expectations tells us which objective function to optimize locally.


## Derandomization via pairwise independence

- ANALYSIS, REVISITED.

$$
\mathrm{E}[|\operatorname{cut}(S, T)|]=\sum_{(i, j) \in E} \operatorname{Pr}\left[R_{i} \neq R_{j}\right]=|E| / 2
$$

- observation. suffices that $\operatorname{Pr}\left[R_{i} \neq R_{j}\right]=1 / 2$ for each $i \neq j$; that is, pairwise independent
- e.g., $N=3$ vertices, $R_{1}, R_{2}$ independent, $R_{3}=R_{1} \oplus R_{2}$
- each $R_{i}$ is an unbiased random bit;
- for each $i \neq j, R_{i}$ is independent from $R_{j}$
- question. Can we generate $N$ pairwise independent bits using less than $N$ truly random bits?


## Pairwise independent bits

- construction. Let $B_{1}, \ldots, B_{k}$ be $k$ independent unbiased random bits. For each nonempty set $A \subseteq[k]$, let $R_{A}$ be the r.v. $\oplus_{i \in A} B_{i}$.
- claim. The $2^{k}-1$ random variables $R_{A}$ are pairwise independent unbiased random bits.
- Clear that each $R_{A}$ is unbiased.
- For pairwise independence, consider any $A \neq A^{\prime} \subseteq[k]$. Ahen,

$$
R_{A}=R_{A \cap A^{\prime}} \oplus R_{A \backslash A^{\prime}} ; \quad R_{A^{\prime}}=R_{A \cap A^{\prime}} \oplus R_{A^{\prime} \backslash A}
$$

- $R_{A \cap A^{\prime}}, R_{A \backslash A^{\prime}}, R_{A^{\prime} \backslash A}$ are independent and at least two are non-empty.
- Hence, $R_{A}, R_{A^{\prime}}$ takes each value in $\{0,1\}^{2}$ with prob. $1 / 4$.
- Can generate $N$ pairwise independent bits from $\lceil\log (N+1)\rceil$ independent random bits.


## Deterministic LargeCut, II

## Deterministic LargeCut Algorithm II

I. For all sequences of bits $b_{1}, b_{2}, \ldots, b_{\lceil\log (n+1)\rceil}$, run the randomized LargeCut algorithm using coin tosses $\left(r_{A}=\oplus_{i \in A} b_{i}\right)_{A \neq \emptyset}$ and choose the largest cut thus obtained.

| PART 2 | sample and modify |
| :--- | :--- |

## Sample and Modify

- stage one. Construct a random structure that does not have the required properties.
- stage two. Modify the structure to have the required property.
- application. Obtain bounds on the size of the largest independent set in a graph (set of vertices with no edges between them).


## Existence of large independent sets

- theorem: Any graph $G$ with $n$ vertices and $m$ edges has an independent set with at least $n^{2} / 4 m$ vertices (provided $m \geq n / 2$ ).
- CONSTRUCTION.
I. Delete each vertex of $G$ (and its incident edges) with prob $1-p$.

2. Remove all remaining edges along with one of its adjacent vertices.

- claim. Let $X$ and $\Upsilon$ be resp. the \# of vertices and edges that survive step i. Then, construction outputs an I.S. of size at least $X-\Upsilon$.
- analysis. $\mathrm{E}[X]=n p$ and $\mathrm{E}[\Upsilon]=m p^{2}$, so $\mathrm{E}[X-\Upsilon]=n p-m p^{2}$. maximized at $n-2 m p=0$, i.e. $p=n / 2 m$ and $\mathrm{E}[X-\Upsilon]=n^{2} / m$.

THE END $\mid$ next, random walks

