

Today

- Error Redn
(ind vs pairwise)
- Sampling
- Finding linear tests.

CSS.413.1

Pseudorandomness

Lecture 05 (2021-9-7)

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Recap from last time

① Const of pw hash families.

Thm. $\forall m, n$, there exists a pw ind family of hash functions $\mathcal{H}_{m,n}$.

that requires at most $2 \max\{m, n\}$ bits to specify any $h \in \mathcal{H}_{m,n}$.

$$\mathcal{H}_{m,n} \subseteq \{h: \{0,1\}^n \rightarrow \{0,1\}^m\}.$$

② Tail Bounds:

x_1, \dots, x_t - $[0,1]$ -valued r.v

$$\bar{x} = \sum x_i / t; \quad \mu = E[\bar{x}]$$

Chernoff: x_i 's independent

$$P_x[|\bar{x} - \mu| > \epsilon] \leq 2e^{-t\epsilon^2/4}$$

Chebyshev: X_i 's are pairwise independent

$$P_n[|\bar{X} - \mu| > \epsilon] \leq \frac{1}{\epsilon^2}$$

Error Reduction of BPP Algorithms

BPP Alg that uses m -random bits
error $\leq \frac{1}{3}$

↓

Reduce error $\frac{1}{3}$ to $\frac{1}{2^k}$

$$\left(\frac{1}{3} \rightarrow 2^{-k}\right)$$

	<u>#repetitions</u>	<u>#random bits</u>
Independent	$O(k)$	$O(km)$
Pairwise Independent	$O(2^k)$	$O(k+m)$ (*)

(*) t -pairwise independent samples

$$\left\{ \begin{array}{l} \mathcal{H}_{m,n} \quad t = 2^n \\ h: \{0,1\}^n \rightarrow \{0,1\}^m \\ t = O(2^k); \end{array} \right. \left| \begin{array}{l} \# \text{ random bits} \\ = O(m+n) \\ = O(m + \log t) \\ = O(m + O(k)) \end{array} \right.$$

$$x_1, \dots, x_t \in \{0,1\}^m \text{ - } \epsilon \text{ p.w. md}$$

$$H \leftarrow \mathcal{H}_{m,n}$$

$$\underbrace{H(0^n), H(00\dots 1), \dots, H(1\dots 1)}$$

t - pairwise independent samples in $\{0,1\}^m$
 use $\mathcal{H}_{m, \log t}$

Sampling:

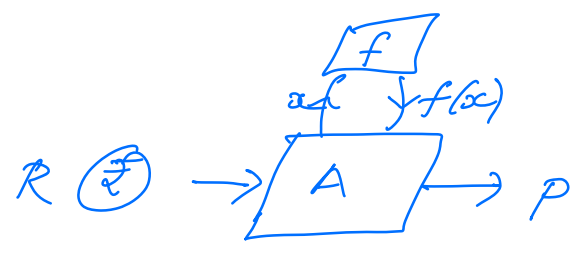
Problem: Given an oracle
 $f: \{0,1\}^m \rightarrow [0,1]$

Compute (estimate)

$$\mu = \mathbb{E}[f(U_m)] \quad \text{to within}$$

$$= \mathbb{E}[f(x)] \quad \text{an additive}$$

$$x \in \{0,1\}^m \quad \text{approximation}$$



of ϵ .

Guarantee:
 $p \in (\mu - \epsilon, \mu + \epsilon)$
 (with high probability)

A is ϵ -additive approximate sampler.

Ind. Sampler:

1. Choose $x_1 \dots x_t \leftarrow \{0,1\}^m$
2. Query Oracle f at $x_1 \dots x_t$
3. Output $\frac{\sum_{i=1}^t f(x_i)}{t}$.

Chernoff Bound.

$$\Pr_{x_1 \dots x_t} \left[\left| \frac{\sum f(x_i)}{t} - \mu \right| > \epsilon \right] \leq 2e^{-\epsilon^2/4} = \delta$$

$$\text{(set } t = O\left(\frac{1}{\epsilon^2} \log \frac{1}{\delta}\right))$$

Thm: Ind-sampler. has the following property.

$$\Pr_{R=x_1 \dots x_t} \left[\left| \text{Ind-Sampler}^+(R) - \mu \right| > \epsilon \right] \leq \delta.$$

using $t = O\left(\frac{1}{\epsilon^2} \log \frac{1}{\delta}\right)$ - samples

- $O\left(\frac{1}{\epsilon^2} \log \left(\frac{1}{\delta}\right) \cdot m\right)$ - random bits.

Pairwise Independent Sampler.

1. Set n & $t = 2^n$
2. Pick $H \leftarrow \mathcal{H}_{m,n}$.
3. Set $x_1 \dots x_t \leftarrow H(0^n), \dots, H(1^n)$
4. Query f at $x_1 \dots x_t$.
5. Output $\sum f(x_i) / t$.

Thm: Pairwise ind sampler.

$$\Pr_{(x_1, \dots, x_t) \sim \mathcal{R}} \left[\left| \text{Pairwise-Sampler}(f, \mathcal{R}) - \mu_f \right| > \epsilon \right] \leq \delta$$

by $t = \frac{1}{\epsilon^2 \delta}$ - samples.

$O(m + \log\left(\frac{1}{\epsilon}\right) + \log\left(\frac{1}{\delta}\right))$
- random bits.

Epsilon-biased Distributions.

Recall: MAXCUT examples

Analysis: pairwise independence of underlying r.v.s.

Obs: Sufficient to sample random coins from a pmf ind dist rather than independent.

In general, "property" of random coin used by alg.

Qn: Is there a smaller space of random coins that has this property?

Property: Linear tests / Linear functions

Linear function:

$l: \{0,1\}^n \rightarrow \{0,1\}$ is a linear function if there exists a set $S \subseteq [n]$ st

$$l(x_1, \dots, x_n) = \bigoplus_{i \in S} x_i$$

$$= \sum_{i \in S} x_i \pmod{2}$$

(In this case, we will denote l by l_S)

$$l_\emptyset \equiv 0.$$

$$P_{x_1 \dots x_n \leftarrow U_n} [L_S(x_1 \dots x_n) = 0] = \begin{cases} 1 & \text{if } S = \emptyset \\ \frac{1}{2} & \text{if } S \neq \emptyset \end{cases}$$

Distribution D on $\{0,1\}^n$ is ϵ -biased if for all linear functions L_S .

$$\left| P_{x_1 \dots x_n \leftarrow U_n} [L_S(x_1 \dots x_n) = 0] - P_{x_1 \dots x_n \leftarrow D} [L_S(x_1 \dots x_n) = 0] \right| \leq \epsilon$$

$$\text{i.e., } \left| P_{x_1 \dots x_n \leftarrow D} [L_S(x_1 \dots x_n) = 0] - \frac{1}{2} \right| \leq \epsilon \quad \forall S \neq \emptyset$$

U_n - 0-biased.

but it needs n -random bits to generate.

→ Construction of ϵ -biased distributions
[Alon, Goldreich, Hastad, Peretta]

Uses finite fields $GF(2^k)$

① Degree Bound:

$p(x) \in \mathbb{F}[x]$ - degree d univariate
non-zero poly

$$\Pr_{x \in \mathbb{F}} [p(x) = 0] \leq \frac{d}{|\mathbb{F}|}$$

② Non-trivial linear functions are unbiased.

$$\delta \neq \emptyset \quad \Pr_{\bar{x} \in U_n} [L(\bar{x}) = 0] = \frac{1}{2}$$

AGHP Construction of ϵ -biased $D \sim \{0,1\}^n$

Input: n, ϵ

0. Choose a field $\mathbb{F} = GF(2^k)$

where $2^k \geq \frac{n}{\epsilon}$

rand
bits
 $= 2k$
 $= O(\log n + \log \frac{1}{\epsilon})$

1. Pick $Y, Z \leftarrow \mathbb{F}$ ($2k$ bits
of rand
onness)

2. Set x_0, \dots, x_{n-1} as follows

$$x_i = \langle Y^i, Z \rangle$$

$$L(x) = \left\langle \sum_{i \in S} Y^i, x \right\rangle$$

$$Y^i = \underbrace{Y \cdot Y \cdot \dots \cdot Y}_i$$

i-times multiplication

$$Y^i \in GF(2^k) \cong \{0,1\}^k \quad \langle Y, Z \rangle$$

$$\Sigma \in GF(2^k) \cong \{0,1\}^k = \sum Y_i \cdot Z_i \pmod{2}$$

$$GF(2^k) = \mathbb{F}_2[x] / \langle f(x) \rangle \quad \text{where}$$

$$\left(\begin{array}{l} f \in \mathbb{F}_2[x] \text{ is a deg } k \\ \text{irreducible.} \\ \mathbb{F}_2^k \end{array} \right.$$

$$\emptyset \neq S$$

$$g(x) = \sum_{x \in S} X_i = \sum_{x \in S} \langle Y^i, Z \rangle$$

$$= \left\langle \sum_{x \in S} Y^i, Z \right\rangle$$

$$P_{x \in D} [g(x) = 0] = P_{Y, Z} \left[\left\langle \sum_{x \in S} Y^i, Z \right\rangle = 0 \right]$$

$$p \stackrel{\Delta}{=} P_Y \left[\sum_{x \in S} Y^i = 0 \right] \leq \frac{n}{|F|} \quad \begin{array}{l} \text{(degree} \\ \text{monia} \\ \text{since } S \neq \emptyset) \end{array}$$

$$\begin{aligned}
& P_{Y,Z} \left[\left\langle \sum_{i \in S} Y^i, Z \right\rangle = 0 \right] \\
&= P_Y \left[\sum_{i \in S} Y^i = 0 \right] \cdot P_Z \left[\left\langle \sum_{i \in S} Y^i, Z \right\rangle = 0 \mid \sum_{i \in S} Y^i = 0 \right] \\
&+ P_Y \left[\sum_{i \in S} Y^i \neq 0 \right] \cdot P_Z \left[\left\langle \sum_{i \in S} Y^i, Z \right\rangle = 0 \mid \sum_{i \in S} Y^i \neq 0 \right] \\
&= p \cdot 1 + (1-p) \cdot \frac{1}{2} \\
&= \frac{1}{2} + \frac{p}{2}.
\end{aligned}$$

Hence

$$\left| P_Z \left[\mathcal{G}(X) = 0 \right] - \frac{1}{2} \right| = \frac{p}{2} \leq \frac{\epsilon}{2}.$$

Thus X is ϵ -biased \square