

Lecture 9

Proposition 10. $R(\text{Simon}_n) = \Omega(\sqrt{n})$.

We will need the following lemma.

Lemma 6. Let $f, T: D := D_0 \dot{\cup} D_1 \subseteq \Sigma^n \rightarrow \{0, 1\}$. Let $f(D_0) = \{0\}$ and $f(D_1) = \{1\}$. Suppose μ_0 is a distribution on D_0 and μ_1 is a distribution on D_1 . Let μ denote the distribution on D such that $x \leftarrow \mu$ is defined by $b \leftarrow \{0, 1\}$ and $x \leftarrow \mu_b$. Let $P_1 \subseteq D_1$. Suppose that for all $b \in \{0, 1\}$,

$$\Pr[T(x) = b \mid x \leftarrow \mu_0] = \Pr[T(x) = b \mid x \in P_1, x \leftarrow \mu_1]. \quad (94)$$

Then

$$\Pr[T(x) = f(x) \mid x \leftarrow \mu] \leq \frac{1}{2} + \frac{1}{2} \Pr[x \notin P_1 \mid x \leftarrow \mu_1]. \quad (95)$$

Proof.

$$\begin{aligned} & \Pr[T(x) = f(x) \mid x \leftarrow \mu] \\ &= \frac{1}{2} \Pr[T(x) = 0 \mid x \leftarrow \mu_0] + \frac{1}{2} \Pr[T(x) = 1 \mid x \leftarrow \mu_1] && \text{definition of } \mu \\ &= \frac{1}{2} \Pr[T(x) = 0 \mid x \leftarrow \mu_0] + \frac{1}{2} (\Pr[T(x) = 1 \mid x \in P_1, x \leftarrow \mu_1] \Pr[x \in P_1 \mid x \leftarrow \mu_1] \\ &\quad + \frac{1}{2} \Pr[T(x) = 1 \mid x \notin P_1, x \leftarrow \mu_1] \Pr[x \notin P_1 \mid x \leftarrow \mu_1]) && \text{law of total probability} \\ &\leq \frac{1}{2} \Pr[T(x) = 0 \mid x \leftarrow \mu_0] + \frac{1}{2} \Pr[T(x) = 1 \mid x \leftarrow \mu_0] + \frac{1}{2} \Pr[x \notin P_1 \mid x \leftarrow \mu_1] && \text{by lemma condition} \\ &= \frac{1}{2} + \frac{1}{2} \Pr[x \notin P_1 \mid x \leftarrow \mu_1], \end{aligned}$$

as required. □

Comment: Apply this lemma to $f = \text{Simon}_n$ and T the (function induced by the) decision tree.

Proof of proposition 10. (A more rigorous version of de Wolf's exposition.) By the averaging argument/easy direction of Yao's principle (i.e., the arguments we used at the beginning of the randomized lower bound proof for OR_n), it suffices to show the following. There exists a distribution μ over D such that if a DDT T satisfies

$$\Pr[T(x) = \text{Simon}_n(x) \mid x \leftarrow \mu] \geq 2/3, \quad (96)$$

then the depth d of T is at least $\Omega(\sqrt{n})$.

We assume without loss of generality (wlog) that

1. T never queries x at the same index twice, i.e., in all paths from root to leaf, the labels of the nodes are distinct.
2. T is balanced, i.e., every root-to-leaf path is length d .

This is wlog since any T without these properties can be simulated by another DDT with these two properties of no greater depth.

To define μ , we first define two distributions μ_0 and μ_1 on D_0 and D_1 respectively by the following sampling procedures. Then we define $x \leftarrow \mu$ by $b \leftarrow \{0, 1\}$ and $x \leftarrow \mu_b$.

1. Definition of $x \leftarrow \mu_0$. For each $s \in \{0, 1\}^k$, pick a distinct value in $\{0, 1, \dots, n-1\}$ for $x(s)$ uniformly at random. (So x is a uniformly random permutation of $\{0, 1, \dots, n-1\}$.)
2. Definition of $x \leftarrow \mu_1$. Pick $a \leftarrow \{0, 1\}^k - \{0^k\}$, then for each set $\{s, s \oplus a\}$, where $s \in \{0, 1\}^k$, pick a distinct value in $\{0, 1, \dots, n-1\}$ for $x(s) = x(s \oplus a)$ uniformly at random. *Comment:* the distribution defined is independent of how the "for each" loop is ordered.

Case $x \leftarrow \mu_0$. The sequence of d responses to the d queries T makes is a uniformly random sequence of d distinct elements in $\{0, 1, \dots, n-1\}$.

Case $x \leftarrow \mu_1$. Let $t \in \{1, \dots, d\}$. Let $v_1, \dots, v_{t-1} \in \{0, 1, \dots, n-1\}$ be distinct. Let s_1, \dots, s_t denote the sequence of indices that T queries on x given $x(s_1) = v_1, \dots, x(s_{t-1}) = v_{t-1}$. (Note s_1, \dots, s_t are uniquely defined, in particular, s_1 is the

label of the root of T .) Say the sequence $x(s_1), \dots, x(s_t)$ is good if all its values are all distinct. Writing \Pr for probability over $x \leftarrow \mu_1$, we have

$$\begin{aligned} & \Pr[x(s_1), \dots, x(s_t) \text{ is good} \mid x(s_1) = v_1, \dots, x(s_{t-1}) = v_{t-1}] \\ &= \Pr[x(s_t) \notin \{x(s_1) = v_1, \dots, x(s_{t-1}) = v_{t-1}\} \mid x(s_1) = v_1, \dots, x(s_{t-1}) = v_{t-1}] \\ &= \Pr[a(x) \notin \{s_1 \oplus s_t, \dots, s_{t-1} \oplus s_t\} \mid x(s_1) = v_1, \dots, x(s_{t-1}) = v_{t-1}] \quad a(x) = \text{the } a \text{ corresp. to } x \end{aligned}$$

Comment: the point of conditioning like this is to explicitly see that s_t is *fixed* and not a function of x ; without such conditioning, the queried indices are generally functions of x and we would need to argue why, e.g., we can't have $s_1 = 0^k$ and $s_t = a(x)$, so that $a(x)$ is always in $\{s_1 \oplus s_t\}$. This is why I have chosen to be more rigorous here than de Wolf's exposition. The set $\{s_1 \oplus s_t, \dots, s_{t-1} \oplus s_t\}$ in the last equation is the set that contains $t-1$ elements: $s_i \oplus s_t$ where $i \in [t-1]$. In class, I got confused and thought $\{s_1 \oplus s_t, \dots, s_{t-1} \oplus s_t\}$ was a set containing $\binom{t-1}{2}$ elements, which led to the confusion later on that got corrected by Victor.

Since the v_i s are distinct, conditioning on $x(s_1) = v_1, \dots, x(s_{t-1}) = v_{t-1}$ implies that $a(x)$ cannot belong to $\{s_i \oplus s_j \mid i, j \in [t-1], i \neq j\} \cup \{0^k\}$ but can take any other value. Since a is initially chosen uniformly from $\{0, 1\}^k - \{0^k\}$, $a(x)$ is uniformly distributed over the set of other values, i.e.,

$$\{0, 1\}^k - \{0^k\} - \{s_i \oplus s_j \mid i, j \in [t-1], i \neq j\}, \quad (97)$$

which has at least $2^k - 1 - \binom{t-1}{2}$ elements. Therefore, by the union bound,

$$\Pr[a(x) \notin \{s_1 \oplus s_t, \dots, s_{t-1} \oplus s_t\} \mid x(s_1) = v_1, \dots, x(s_{t-1}) = v_{t-1}] \geq 1 - \frac{t-1}{2^k - 1 - \binom{t-1}{2}}. \quad (98)$$

Write x is t -good if the responses to the first t queries T makes on x are distinct. Then, since the above analysis holds for all distinct v_1, \dots, v_{t-1} , we have

$$\Pr[x \text{ is } k\text{-good} \mid x \text{ is } (k-1)\text{-good}] \geq 1 - \frac{t-1}{2^k - 1 - \binom{t-1}{2}}, \quad (99)$$

using the fact that $\Pr[A \mid \dot{\cup}_i B_i] \geq \min_i \Pr[A \mid B_i]$.

Therefore, since the last inequality holds for all $t \in \{1, \dots, d\}$,

$$\begin{aligned} \Pr[x \text{ is } d\text{-good}] &\geq \prod_{t=1}^d \left(1 - \frac{t-1}{2^k - 1 - \binom{t-1}{2}}\right) \\ &\geq 1 - \sum_{t=1}^d \frac{t-1}{2^k - 1 - \binom{t-1}{2}} \quad \forall a, b \in [0, 1], (1-a)(1-b) \geq 1-a-b. \end{aligned}$$

Assume wlog that d is such that $1 + \binom{d-1}{2} \leq 2^k/2$ (else we're done) so

$$\Pr[x \text{ is } d\text{-good}] \geq 1 - \frac{2}{2^k} \frac{1}{2} d(d-1) \geq 1 - \frac{d^2}{2^k}. \quad (100)$$

Conditioned on the event that x is d -good, the sequence of d responses to the d queries T makes is a uniformly random sequence of d distinct elements in $\{0, 1, \dots, n-1\}$, just like in the case $x \leftarrow \mu_0$. Comment: this is intuitively clear from the definition of μ_1 but can also verify this by computing a product of conditional probabilities.

Therefore, for all $b \in \{0, 1\}$,

$$\Pr[T(x) = b \mid x \leftarrow \mu_0] = \Pr[T(x) = b \mid x \in P_1, x \leftarrow \mu_1]. \quad (101)$$

Finally, letting $P_1 := \{x \in D_1 \mid x \text{ is } d\text{-good}\}$, we can apply lemma 6 to find that

$$\Pr[T(x) = \text{Simon}_n(x) \mid x \leftarrow \mu] \leq \frac{1}{2} + \frac{1}{2} \frac{d^2}{2^k}. \quad (102)$$

Therefore, we must have $d \geq \sqrt{2^k/3} = \Omega(\sqrt{n})$, as required. \square

Remark 11. The D_0 of Simon_n is the same as the D_0 of Collision_n (when n is a power of 2). On the other hand, the D_1 of Simon_n is a subset of D_1 of Collision_n . Therefore, any randomized decision tree that computes Collision_n (with bounded-error $1/3$) can also be used to compute Simon_n (with bounded-error $1/3$). Therefore $R(\text{Collision}_n) \geq R(\text{Simon}_n)$. Therefore $O(\sqrt{n}) \geq R(\text{Collision}_n) \geq R(\text{Simon}_n) \geq \Omega(\sqrt{n})$, where the first inequality is from a few lectures ago and the last inequality is what we just proved. So $R(\text{Simon})$, $R(\text{Collision}) = \Theta(\sqrt{n})$.