

## Lecture Notes 11

### 27 Statistical Closeness

Let  $X = \{X_n\}_{n \in \mathbb{N}}$ ,  $Y = \{Y_n\}_{n \in \mathbb{N}}$  be probability ensembles.  $X, Y$  are *statistically close* if their statistical difference  $\Delta(n)$  is negligible, where

$$\Delta(n) = \frac{1}{2} \sum_{\alpha} |\Pr[X_n = \alpha] - \Pr[Y_n = \alpha]|.$$

**Theorem 1** *If  $X, Y$  are statistically close, then  $X, Y$  are indistinguishable in polynomial time.*

Here's the proof that I only sketched in class.

**Proof:** We prove the contrapositive. Suppose  $X, Y$  are not indistinguishable in polynomial time. Then there exists a p.p.t. algorithm  $D$  and a positive polynomial  $p(\cdot)$  such that for infinitely many  $n$ ,

$$|\Pr[D(X_n, 1^n) = 1] - \Pr[D(Y_n, 1^n) = 1]| \geq \frac{1}{p(n)} \quad (1)$$

For  $\alpha$  a length- $n$  string, let  $p(\alpha) \stackrel{\text{df}}{=} \Pr[D(\alpha, 1^n) = 1]$ . Then

$$\Pr[D(X_n, 1^n) = 1] = \sum_{\alpha} p(\alpha) \cdot \Pr[X_n = \alpha]. \quad (2)$$

$$\Pr[D(Y_n, 1^n) = 1] = \sum_{\alpha} p(\alpha) \cdot \Pr[Y_n = \alpha]. \quad (3)$$

Plugging (2) and (3) into (1) gives

$$\frac{1}{p(n)} \leq \left| \sum_{\alpha} p(\alpha) \cdot \Pr[X_n = \alpha] - \sum_{\alpha} p(\alpha) \cdot \Pr[Y_n = \alpha] \right| \quad (4)$$

$$= \left| \sum_{\alpha} p(\alpha) \cdot (\Pr[X_n = \alpha] - \Pr[Y_n = \alpha]) \right| \quad (5)$$

$$\leq \sum_{\alpha} p(\alpha) \cdot |\Pr[X_n = \alpha] - \Pr[Y_n = \alpha]| \quad (6)$$

$$\leq \sum_{\alpha} |\Pr[X_n = \alpha] - \Pr[Y_n = \alpha]| \quad (7)$$

$$= 2\Delta(n). \quad (8)$$

Thus,  $\Delta(n)$  is not negligible, so  $X, Y$  are not statistically close. ■

The converse to theorem 1 does not hold.

**Theorem 2** *There exists  $X = \{X_n\}_{n \in \mathbb{N}}$  that is indistinguishable from the uniform ensemble  $U = \{U_n\}_{n \in \mathbb{N}}$  in polynomial time, yet  $X$  and  $U$  are not statistically close. Furthermore,  $X_n$  assigns all probability mass to a set  $S_n$  consisting of at most  $2^{n/2}$  strings of length  $n$ .*

**Proof:** We construct the ensemble  $X = \{X_n\}_{n \in \mathbb{N}}$  by choosing for each  $n$  a set  $S_n \subseteq \{0, 1\}^n$  of cardinality  $N = 2^{n/2}$  and letting  $X_n$  be the uniformly distributed on  $S_n$ . Thus,  $\Pr[X_n = \alpha] = 1/N$  for  $\alpha \in S_n$ , and  $\Pr[X_n = \alpha] = 0$  for  $\alpha \notin S_n$ .

The fact that  $X, U$  are not statistically close is immediate from the above. Using the facts that  $2^n = N^2$  and  $|S_n| = N$ , and  $|\overline{S_n}| = N^2 - N$ , we get

$$\begin{aligned} \Delta(n) &= \frac{1}{2} \sum_{\alpha} |\Pr[X_n = \alpha] - \Pr[U_n = \alpha]| \\ &= \frac{1}{2} \left( \sum_{\alpha \in S_n} \left| \Pr[X_n = \alpha] - \frac{1}{N^2} \right| + \sum_{\alpha \notin S_n} \left| \Pr[X_n = \alpha] - \frac{1}{N^2} \right| \right) \\ &= \frac{1}{2} \left( \sum_{\alpha \in S_n} \left| \frac{1}{N} - \frac{1}{N^2} \right| + \sum_{\alpha \notin S_n} \left| 0 - \frac{1}{N^2} \right| \right) \\ &= \frac{1}{2} \cdot \left( N \cdot \left( \frac{1}{N} - \frac{1}{N^2} \right) + (N^2 - N) \frac{1}{N^2} \right) \\ &= 1 - \frac{1}{N} \end{aligned}$$

The proof in the textbook supplies the low-level details needed to establish this theorem, but it is a little unclear about the construction itself, particularly about how the set  $S_n$  is chosen.

We wish to choose a set  $S_n$  for which the corresponding distribution  $X_n$  is indistinguishable from  $U_n$  by every polynomial size circuit  $C$ . We do this by diagonalizing over all circuits of size  $2^{n/8}$ . We start with all size  $2^N$  subsets of  $\{0, 1\}^n$  as candidates for  $S_n$ . For each such circuit  $C$ , we discard from consideration all candidates on which  $C$  is too successful at distinguishing the corresponding ensemble from uniform. By a counting argument, we show that not very many candidates get thrown out at each stage—so few in fact that there are still candidates left after all of the size  $2^{n/8}$  circuits have been considered. We choose any remaining candidate for  $S_n$  and conclude that no size  $2^{n/8}$  circuit is very successful at distinguishing  $X_n$  from  $U_n$ .

More precisely, here's how to determine which candidates to discard. First, consider an  $n$ -input circuit  $C$  with at most  $2^{n/8}$  gates. Let  $p_C$  be  $C$ 's expected output on uniformly chosen inputs. Then  $C(x) = 1$  for a  $p_C$  fraction of all length  $n$  strings, and  $C(x) = 0$  for the remainder.

Let  $\mathcal{S}_n = \{S \subseteq \{0, 1\}^n \mid |S| = 2^N\}$ . This is the initial family of candidate sets. Let  $f_C : \mathcal{S}_n \rightarrow \{0, 1\}$ , where

$$f_C(S) = \left| \frac{\sum_{s \in S} C(s)}{N} - p_C \right|.$$

Thus,  $f_C(S)$  is the amount that the average value of  $C(s)$  taken over strings  $s \in S$  differs from the average value of  $C(u)$  taken over all length- $n$  strings  $u$ . By the law of large numbers, we would expect  $f_C(S)$  to be very small with high probability for randomly chosen  $S \in \mathcal{S}$ . Call a set  $S$  *bad* for  $C$  if  $f_C(S) \geq 2^{-n/8}$ . Using the Chernoff bound, one shows that the fraction of sets  $S \in \mathcal{S}_n$  that are bad for  $C$  is less than  $2^{-2^{n/4}}$ . (Details are in the book.)

Next, one argues that there are at most  $2^{2^{n/4}}$  circuits of size  $2^{n/8}$ . (This is by a counting argument. Details are not in the book and should be verified.) From this, it follows that there is at least one set  $S_n \in \mathcal{S}_n$  which is not bad for any such circuit. Fix such a set.

Now, let  $X_n$  be uniformly distributed over  $S_n$ . Observe that the following three quantities are all the same: the expected value of  $C(X_n)$ ,  $\Pr[C(X_n) = 1]$ , and  $\sum_{s \in S} C(s)/N$ . Hence, for all circuits  $C$  of size at most  $2^{n/8}$ , we have  $|\Pr[C(X_n) = 1] - \Pr[C(U_n) = 1]| = f_C(S_n) < 2^{-n/8}$ , which

grows more slowly than  $1/p(n)$  for any polynomial  $p(\cdot)$ . We conclude that the probabilistic ensembles  $U$  and  $X$  are indistinguishable by polynomial-size circuits, which also implies polynomial-time indistinguishability by probabilistic polynomial-time Turing machines. ■

We remark that a consequence of theorem 2 is that the set  $S_n$  on which  $X_n$  has non-zero probability mass cannot be recognized in polynomial time. Assume to the contrary that it could be recognized by some polynomial time algorithm  $A$ , that is,  $A(x) = 1$  if  $x \in S_n$  and  $A(x) = 0$  otherwise. Then  $A$  itself would distinguish  $X_n$  from  $U_n$ . Clearly,  $\Pr[A(X_n) = 1] = 1$  but  $\Pr[A(U_n) = 1] = |S_n|/2^n$ . Since  $|S_n| = 2^{n/2}$ , these two probabilities differ by  $1 - \frac{1}{2^{n/2}}$  which is greater than  $\frac{1}{2}$  for all sufficiently large  $n$ . (Note that the constant 2 is also a polynomial!)

## 28 Indistinguishability by Repeated Sampling

The definition of polynomial time indistinguishability given in section 26 gives the distinguishing algorithm  $D$  a single random sample from either  $X$  or  $Y$  and compare the two probabilities of it outputting a 1. We can generalize that definition in a straightforward way by providing  $D$  with multiple samples, as long as the number of samples is itself bounded by a polynomial  $m(n)$ . If the difference in output probabilities in this case is a negligible function, we say that  $X, Y$  are *indistinguishable by polynomial-time sampling*. See Definition 3.2.4 of the textbook for details

Giving  $D$  multiple samples allows for new possible distinguishing algorithms. For example, consider the algorithm  $\text{Eq}(x, y)$  that outputs 1 if  $x = y$  and 0 otherwise.  $\text{Eq}$  able to distinguish the ensemble  $X$  of Theorem 2 from  $U$ . Let's analyze the probabilities.

$$\Pr[\text{Eq}(X_n^1, X_n^2) = 1] = \frac{1}{N}$$

since no matter what value  $X_n^1$  assumes, there is a  $1/N$  chance that the second (independent) sample is equal to it. (Recall that  $N = 2^{n/2}$ .) On the other hand,

$$\Pr[\text{Eq}(U_n^1, U_n^2) = 1] = \frac{1}{N^2}.$$

The difference of these two probabilities is clearly non-negligible.

However, it turns out that multiple samples are only helpful in cases such as this where at least one of the distributions cannot be constructed in polynomial time, as we shall see.

### 28.1 Efficiently constructible ensembles

We say that an ensemble  $X = \{X_n\}_{n \in \mathbb{N}}$  is *polynomial-time constructible* if there exists a polynomial-time probabilistic algorithm  $S$  such that the output distribution  $S(1^n)$  and  $X_n$  are identically distributed.

### 28.2 Multiple samples don't help with constructible ensembles

**Theorem 3** *Let probability ensembles  $X, Y$  be indistinguishable in polynomial time, and suppose both are polynomial-time constructible. Then  $X, Y$  are indistinguishable by polynomial-time sampling.*

**Proof:** The proof is an example of the *hybrid technique*, also sometimes called an *interpolation* proof. Here's the outline of it.

Assume  $X, Y$  are distinguishable by  $D$  using  $m = m(n)$  samples. Let  $X_n^{(1)}, \dots, X_n^{(m)}$  be independent random variables identically distributed to  $X_n$  and similarly for  $Y$ . Let

$$p(X) = \Pr[D(X_n^{(1)}, \dots, X_n^{(m)}) = 1],$$

and let

$$p(Y) = \Pr[D(Y_n^{(1)}, \dots, Y_n^{(m)}) = 1].$$

By assumption,  $D$  can distinguish  $X, Y$ , so the difference  $\delta(n) = |p(x) - p(y)|$  is non-negligible.

We now construct a sequence of hybrid  $m$ -tuples of random variables for  $k = 0, \dots, m$ :

$$H_n^k \stackrel{\text{df}}{=} (X_n^{(1)}, \dots, X_n^{(k)}, Y_n^{(k+1)}, \dots, Y_n^{(m)})$$

Clearly,  $H_n^0$  consists of all  $Y$ 's, and  $H_n^m$  consists of all  $X$ 's. Hence,  $D$  distinguishes between  $H_n^0$  and  $H_n^m$  with probability  $\delta(n)$ .

Now let  $\delta_k(n)$  be the absolute value of the difference in  $D$ 's probability of outputting a 1 given  $H_n^k$  and  $H_n^{k+1}$ . It is easily seen that  $\sum_{k=0}^{m-1} \delta_k(n) \geq \delta(n)$ ; hence, for some particular value of  $k = k_0$ ,

$$\delta_{k_0}(n) \geq \frac{\delta(n)}{m}.$$

We now describe a single-sample distinguisher  $D'$ . On input  $\alpha$ , it first chooses a random number  $k$  from  $\{0, \dots, m-1\}$ . Next, it generates  $k$  independent random numbers  $x_1, \dots, x_k$  distributed according to  $X_n$  and  $m-k-1$  random numbers  $y_{k+2}, \dots, y_m$  distributed according to  $Y_n$ . It can do this by the assumption that  $X$  and  $Y$  are polynomial-time constructible. It then constructs  $h = (x_1, \dots, x_k, \alpha, y_{k+2}, \dots, y_m)$ , runs  $D(h)$ , and outputs the result.

Note that  $h$  is distributed according to  $H_n^k$  if  $\alpha$  was chosen according to  $Y$ , and  $h$  is distributed according to  $H_n^{k+1}$  if  $\alpha$  was chosen according to  $X$ . Thus, the probability that  $D'$  outputs 1 given a sample from  $X$  or a sample from  $Y$  is at least  $1/m$ , the probability that  $D'$  chooses  $k = k_0$ , times  $\delta_{k_0}(n)$ . Hence,  $D'$  distinguishes with probability difference at least  $\delta(n)/m^2$ , which contradicts the assumption that  $X, Y$  are indistinguishable in polynomial time. ■