#### **INFR11102:** Computational Complexity

Lecture 13: More on circuit models; Randomised Computation

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## 1 TM taking advices

An alternative way to characterize  $P_{/poly}$  is via TMs that take advices.

**Definition 1.** For functions  $F : \mathbb{N} \to \mathbb{N}$  and  $A : \mathbb{N} \to \mathbb{N}$ , the complexity class  $\mathsf{DTime}[F]_{/A}$  consists of languages L such that there exist a TM with time bound F(n) and a sequence  $\{a_n\}_{n\in\mathbb{N}}$  of "advices" satisfying:

- $|a_n| \leq A(n);$
- for |x| = n,  $x \in L$  if and only if  $M(x, a_n) = 1$ .

The following theorem explains the notation  $P_{/poly}$ , namely "polynomial-time with polynomial advice".

Theorem 1.  $P_{/poly} = \bigcup_{c,d \in \mathbb{N}} DTime[n^c]_{/n^d}$ .

*Proof.* If  $L \in P_{/poly}$ , then it can be computed by a family  $\mathcal{C} = \{C_1, C_2, \cdots\}$  of Boolean circuits. Let  $a_n$  be the description of  $C_n$ , and the polynomial time machine M just reads this description and simulates it. Hence  $L \in \bigcup_{c,d \in \mathbb{N}} \mathsf{DTime}[n^c]_{/n^d}$ .

For the other direction, if a language L can be computed in polynomial-time with polynomial advice, say by TM M with advices  $\{a_n\}$ , then we can construct circuits  $\{D_n\}$  to simulate M, as in the theorem  $P \subset P_{/poly}$  in the last lecture. Hence,  $D_n(x, a_n) = 1$  if and only if  $x \in L$ . The final circuit  $C_n$  just does exactly what  $D_n$  does, except that  $C_n$  "hardwires" the advice  $a_n$ . Namely,  $C_n(x) := D_n(x, a_n)$ . Hence,  $L \in P_{/poly}$ .

### 2 Karp-Lipton Theorem

Dick Karp and Dick Lipton showed that NP is unlikely to be contained in  $P_{poly}$  [KL80]. Since  $P \subset P_{poly}$ , if we could rule out the possibility that  $NP \subseteq P_{poly}$ , then we would have separated P and NP. Karp-Lipton theorem stirred a lot of effort trying to show circuit lower bounds. Indeed many successes followed, but unfortunately, we hit some barriers later on.

**Theorem 2.** If  $NP \subseteq P_{\text{poly}}$ , then  $PH = \Sigma_2^p$ .

*Proof.* As shown before, we just need to show that  $\Pi_2^p \subseteq \Sigma_2^p$  to conclude  $PH = \Sigma_2^p$ . Let  $L \in \Pi_2^p$ . Then, there exists a poly-time TM M such that

$$x \in L \Leftrightarrow \forall y \exists z, M(x, y, z) = 1$$
, and y and z are poly-size.

All strings appear in this proof actually have polynomial length, and thus we use notations  $\exists^p$  and  $\forall^p$  to denote this. Due to the Cook-Levin theorem, the expression  $\exists z, M(x, y, z) = 1$  can be converted in polynomial-time to a CNF formula  $\varphi$  such that

$$x \in L \Leftrightarrow \forall^p y, \ \varphi(x, y) \in \text{SAT.}$$
 (1)

To show  $L \in \Sigma_2^p$ , we need to somehow change the quantifier in (1).

Our assumption is that  $NP \in P_{/poly}$ , namely SAT has a polynomial-size circuit family  $C = \{C_1, C_2, \cdots\}$ .

For an input x, |x| = n, we give an  $\Sigma_2^p$  algorithm to decide whether  $x \in L$ . We first guess a circuit C for SAT. It may have two types of error:  $\varphi \in$  SAT but  $C(\varphi) = 0$  or  $\varphi \notin$  SAT but  $C(\varphi) = 1$ . There is at least one correct guess, namely  $C_{p(n)}$  where  $p(n) = |\varphi(x, y)|$ , that works correctly on  $\varphi(x, y)$  by assumption.

For any such guess C, we construct a TM M' on input  $(C, \varphi)$  so that its error is "onesided". It relies on the fact that SAT is *self-reducible*. Namely given an oracle to the decision version, we can efficiently find a solution. M' takes C as a subroutine, and if C answers "Yes", then M' proceeds to find a satisfying assignment by repeatedly asking C. If there is any inconsistency from C (namely C says that a formula is satisfiable but both assignment of some variable x make it unsatisfiable), or the final assignment is not satisfying, then M' rejects. Otherwise M' accepts if C accepts. This machine M' never accepts a formula  $\varphi \notin SAT$ , but it may reject  $\varphi \in SAT$  if C is an incorrect guess for SAT.

Now, we claim the following:

$$x \in L \Leftrightarrow \exists^p C \forall^p y, \ M'(C, \varphi(x, y)) = 1.$$
 (2)

Comparing to (1), we have changed the order of quantifiers, and the right hand side of (2) can be easily converted to a  $\Sigma_2^p$  expression (namely compute  $\varphi(x, y)$  first). What we are left to do is to verify (2).

- If  $x \in L$ , then there is a correct guess  $C_{p(n)}$  making the right hand side of (2) true.
- If  $x \notin L$ , then by (1), any  $y_0$  will make  $\varphi(x, y_0) \notin \text{SAT}$ . Recall that M', whatever the guess C is, never accepts  $\varphi \notin \text{SAT}$ . Hence, the right hand side of (2) is false.  $\Box$

Why doesn't the proof above work if we don't construct M' and simply use C?

*Remark* (Bibliographic). Karp and Lipton first proved a weaker result than Theorem 2, namely collapsing to the third level of PH. In their paper [KL80] they attribute this stronger version to Mike Sipser. The proof given here uses an idea first noted by John Hopcroft.

Relevant chapters are [AB09, Chapter 6.4] and [Pap94, Chapter 17].

# 3 Randomised computation

A great discovery in the theory of computation is the power of randomness. There are a lot of surprising randomised algorithms discovered since the 80s. Examples include, primality testing [Mil76, Rab80], polynomial identity testing [Zip79, Sch80], volume computation [DFK91], and many more.

To formalize the idea of randomised computation, we need the notion of a probabilistic Turing Machine (PTM).

A probabilistic Turing Machine is a TM with two transition functions  $\delta_0$  and  $\delta_1$ . At every step of an execution with input x, we apply  $\delta_0$  with probability 1/2, and  $\delta_1$  otherwise. For a PTM M, its output M(x) is now a random variable. We say M runs in time T(n) if for any input of length n, M halts within T(n) time regardless of the random choices made.

The standard class for efficient randomised computation is called BPP (bounded-error probabilistic polynomial-time).

**Definition 2.** A language L is in BPP if there exists a PTM P and a polynomial  $p(\cdot)$ , such that P runs in time p(n) and

- if  $x \in L$ , then  $\Pr[P(x) = 1] \ge 3/4$ ;
- if  $x \notin L$ , then  $\Pr[P(x) = 1] \le 1/4$ .

In other words, the requirement is that  $\Pr[P(x) = L(x)] \ge 3/4$ . The constant 3/4 in Definition 2 is not essential, as long as it is strictly larger than 1/2. This is captured by a notion called "amplification". On the other hand, if it is 1/2, then the class defined would be (under standard assumptions) more powerful. That class is called PP, probabilistic polynomial-time. Historically PP is defined earlier than BPP, and as it turns out, PP is the *wrong* definition for efficient randomised computation.

We also have the "one-sided" error version of  ${\tt BPP},$  called  ${\tt RP}$  (randomised polynomial-time).

**Definition 3.** A language L is in RP if there exists a PTM P and a polynomial  $p(\cdot)$ , such that P runs in time p(n) and

- if  $x \in L$ , then  $\Pr[P(x) = 1] \ge 3/4$ ;
- if  $x \notin L$ , then  $\Pr[P(x) = 1] = 0$ .

In other words, an RP algorithm never errs if  $x \notin L$ , but it may reject some  $x \in L$ .

*Remark* (Bibliographic). Relevant chapters are [AB09, Chapter 7.3, 7.4] and [Pap94, Chapter 11].

# References

- [AB09] Sanjeev Arora and Boaz Barak. Computational Complexity A Modern Approach. Cambridge University Press, 2009.
- [DFK91] Martin E. Dyer, Alan M. Frieze, and Ravi Kannan. A random polynomial time algorithm for approximating the volume of convex bodies. J. ACM, 38(1):1–17, 1991.
- [KL80] Richard M. Karp and Richard J. Lipton. Some connections between nonuniform and uniform complexity classes. In *STOC*, pages 302–309. ACM, 1980.
- [Mil76] Gary L. Miller. Riemann's hypothesis and tests for primality. J. Comput. Syst. Sci., 13(3):300–317, 1976.
- [Pap94] Christos H. Papadimitriou. Computational Complexity. Addison-Wesley, 1994.
- [Rab80] Michael O. Rabin. Probabilistic algorithm for testing primality. J. Number Theory, 12(1):128 138, 1980.
- [Sch80] Jacob T. Schwartz. Fast probabilistic algorithms for verification of polynomial identities. J. ACM, 27(4):701–717, 1980.
- [Zip79] Richard Zippel. Probabilistic algorithms for sparse polynomials. In *EUROSAM*, volume 72 of *LNCS*, pages 216–226. Springer, 1979.