Average-case Computational Complexity Algorithms and Complexity

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MPLA

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- What are some realistic distributions?
- How can we define reductions on average case?
- A class of "hard" problems (distNP) and a complete problem for that class.

Distributional Problem

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For example: SAT only on inputs with more than 10n clauses u.a.r

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distP first attempt

< L, D > is poly-time solvable on average if there is an algorithm A such that A(x) = L(x) for every x and a polynomial p such that for every n,

 $\mathbb{E}_{x \sim D_n}[time_A(x)] \leq p(n).$

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• $\mathbb{E}_{x \sim \{0,1\}^n}[time_A^2(x)] = (1 - 2^{-n})n^2 + 2^{-n}2^{2n} \ge 2^n.$

distP

A distributional problem < L, D > is in distP if there is an algorithm A for L and constants C and $\epsilon > 0$ such that for every n,

$$\mathbb{E}_{x\sim D_n}[\frac{time_A(x)^{\epsilon}}{n}] \leq C.$$

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- High probability to run in polytime. Indeed, by Markov's inequality, for every K > 1, $Prob[\frac{time_A(x)^{\epsilon}}{n} \ge KC] = Prob[time_A(x) \ge (KCn)^{1/\epsilon}]$ is at most 1/K.

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- Robust in minor changes. Indeed, for every d > 0 our definition is equivalent with: there exist ε, C, such that

$$\mathbb{E}_{x \sim D_n}[\frac{time_A(x)^{\epsilon}}{n^d}] \leq C.$$

Realistic distributions

• The world is indifferent to our algorithm.

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P-computable distributions

The P-computable distributions have an associated deterministic polynomial time machine that, given input $x \in \{0,1\}^n$, can compute the cumulative probability $\mu_{D_n}(x)$, where

$$\mu_{D_n}(x) = \sum_{y \in \{0,1\}^n : y \le x} \Pr[y].$$

P-samplable distributions

The P-samplable distributions have an associated probabilistic polynomial time machine that can produce samples from the distribution. Specifically, we say that $D = \{D_n\}$ is P-samplable if there is a polynomial p and a probabilistic p(n)-time algorithm A such that for every n, the random variables $A(1^n)$ and D_n are identically distributed.

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NOTE: The converse is not true unless $P = P^{\sharp P}$.

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Average-case reduction

We say that a distributional problem $\langle L, D \rangle$ average-case reduces to a distributional problem $\langle L', D' \rangle$, if there is a polynomial-time computable f and polynomials p,q: $\mathbb{N} \to \mathbb{N}$ satisfying:

- 1. (Correctness) For every $x \in \{0,1\}^*$, $x \in L \Leftrightarrow f(x) \in L'$.
- 2. (Length Regularity) For every $x \in \{0,1\}^*$, |f(x)| = p(|x|).
- 3. (Domination) For every $n \in \mathbb{N}$ and $y \in \{0,1\}^{p(n)}$,

$$Pr[y = f(D_n)] \le q(n)Pr[y = D'_{p(n)}].$$

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12 / 28

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If A' is for < L', D' >, we want the obvious algorithm A for < L, D > to work: on $x \sim D$, we compute f(x) = y and run algorithm A' on y.

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• We need to prove that < L, D > is in distP.

• Assume that for every x, $|f(x)| = |x|^d$.

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- It suffices to show that

$$\mathbb{E}_{x\sim D_n}[\frac{\left(\frac{1}{2}time_A(x)\right)^{\epsilon}}{q(n)n^d}] \leq C.$$

where q(n) is the polynomial in the dominating condition.

$$\mathbb{E}_{x \sim D_n}\left[\frac{\left(\frac{1}{2}time_A(x)\right)^{\epsilon}}{q(n)n^d}\right] \leq \sum_{y \in \{0,1\}^{n^d}} \Pr[y = f(D_n)]\frac{time_{A'}(y)^{\epsilon}}{q(n)n^d}$$

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Theorem 2

(Existence of a distNP-complete problem) Let U contain all tuples $\langle M, x, 1^t \rangle$ where there exists a string $y \in \{0, 1\}^l$ such that a nondeterministic TM M outputs 1 on input x on t steps. For every n, we let \mathcal{U}_n be the following distribution on length n tuples $\langle M, x, 1^t \rangle$: the string representing M is chosen at random from all strings of length at most log n, t is chosen at random in the set $\{0, ..., n - |M|\}$ and x is chosen at random from $\{0, 1\}^{n-t-|M|}$. This distribution is polynomial-time computable. Then $\langle U, \mathcal{U} \rangle$ is distNP-complete.

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- We deal with that with our next lemma

Lemma (Peak elimination)

Let $D = \{D_n\}$ be a P-computable distribution. Then there is a polynomial-time computable function $g : \{0,1\}^* \to \{0,1\}^*$ such that: 1. g is one-to-one: g(x) = g(z) iff x = z. 2. For every $x \in \{0,1\}^*$, $|g(x)| \le |x| + 1$. 3. For every string $y \in \{0,1\}^m$, $Pr[y = g(D_m)] \le 2^{-m+1}$.

• For any x of length n, h(x) is the largest common prefix of the binary numbers $\mu_{D_n}(x)$ and $\mu_{D_n}(x-1)$.

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- We know that $Pr_{D_n}[x] = \mu_{D_n}(x) \mu_{D_n}(x-1)$ and let's assume that $Pr_{D_n}[x] \ge 2^{-k}$. Then the difference must be in the first k digits, namely $|h(x)| \le k$.

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- *D* is P-computable, thus h is computable in polynomial time.
- *h* is one-to-one because only two strings can have a specific longest prefix.

$$g(x) = \left\{ egin{array}{ccc} 0x & , \ {\it Prob}_{D_n}[x] \leq 2^{-n} \ 1h(x) & , \ otherwise \end{array}
ight.$$

Example:

 $Prob_{D_n}[1010] = 0.10000$ $Prob_{D_n}[1011] = 0.10101111$

$$\Rightarrow g(1011) = 1h(1011) = 110.$$

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- If y = 0x when $Pr_{D_n}[x] \le 2^{-|x|}$, then $Pr[y = g(D_m)] \le 2^{-|y|+1}$.
- Let y = 1h(x). $Pr_{D_n}][x] > 2^{-|x|}$ and therefore $|h(x)| \le |x|$. So $Pr[y = g(D_m)] \le 2^{-|y|+1}$.

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Theorem 3

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- Domination? Yes! A legnth m tuple $\langle M', y, 1^t \rangle$ is obtained by the reduction with probability at most $2^{-|y|+1}$. This tuple is however obtained by U_m with probability at least $2^{-\log m}2^{-|y|}\frac{1}{m}$.

sampNP and its complete problems

Question:

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Theorem 4

if < L, D > is distNP-complete, then it is also sampNP-complete.

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Theorem 4

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The choice of P-computable distributions was suitable for average-case completeness results.

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Philosophical and Practical Implications

Pessiland

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- Although one-way functions exist, there are no public key encryption schemes or key exchange protocols.
- Those cryptographic applications achievalbe only by one-way functions such as private key encryption and pseudorandom generators still work.

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Cryptomania

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- We don't have general-purpose algorithms and we have to resort to heuristics, approximation, creativity and hard work.
- We have a host of exciting cryptographic applications.