Lecture 20: Hardness of Approximation

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July 18, 2023

Overview

- Background and Motivation
  - Why Hardness of Approximation?
  - How do we prove Hardness of Approximation?
  - Hardness of Approximation - Example
- Proofs & Hardness of Approximation
- Conclusion
- Acknowledgements

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- Important to know the limits of efficient algorithms!

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- One of the famous NP-complete problems

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3. In our case, let's reduce it to the *Hamiltonian Cycle Problem*

Theorem

If there is an algorithm M which solves TSP without repetitions with α-approximation, then $P = NP$.

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5. Thus, M on input H will output a Hamiltonian Cycle of G, if G has one, or it will output a solution with value $\geq (1 + \alpha) \cdot |V|$

Complexity Classes

- **NP:** Set of languages $L \subseteq \{0,1\}^*$ such that there exists a poly-time Turing Machine V, such that:

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- **co-RP:** languages $L \subseteq \{0,1\}^*$ s.t. $\overline{L} \in RP$

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- $PCP[r(n), q(n)]$ consists of all languages $L \in PCP$ such that, on inputs x of length n

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The class of *Probabilistic Checkable Proofs* (PCP) consists of languages L that have a randomized poly-time verifier V such that

1. $x \in L \Rightarrow$ there exists proof w such that $\Pr[V^w(x) = 1] = 1$
2. $x \notin L \Rightarrow$ for any proof w, we have $\Pr[V^w(x) = 1] \leq 1/2$

- $PCP[r(n), q(n)]$ consists of all languages $L \in PCP$ such that, on inputs x of length n
    1. Uses $O(r(n))$ random bits
    2. Examines $O(q(n))$ bits of a proof w

Note that n *does not* depend on w, only on x.

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Theorem (PCP theorem [AS'98, ALMSS'98])

$$PCP[\log n, 1] = NP$$

PCP and Approximability of Max 3SAT

Definition (Max 3SAT)

- **Input:** a 3CNF formula φ on boolean variables $x_1, \ldots, x_n$ and m clauses
- **Output:** the maximum number of clauses of φ which can be simultaneously satisfied.

Theorem

1. *The PCP theorem implies that there is an $\varepsilon > 0$ such that there is no polynomial time $(1 + \varepsilon)$-approximation algorithm for Max 3SAT, unless $P = NP$.*
2. *Moreover, if Max 3SAT is hard to approximate within a factor of $(1 + \varepsilon)$, then the PCP theorem holds.*

- In other words, the PCP theorem and the hardness of approximation of Max 3SAT are equivalent.

PCP and Approximability of Max 3SAT

1. Let us assume the PCP theorem holds.
   - Let $L \in PCP[\log n, 1]$ be an NP-complete problem.
   - Let V be the $(O(\log n), q)$ verifier for L, where q is a constant

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3. Given an instance x of problem L, we construct 3CNF formula φ_x with m clauses such that, for some ε we have
   - $x \in L \Rightarrow \varphi_x$ is satisfiable
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4. Enumerate all random inputs R for the verifier V.
   - Length of each random string is $O(\log n)$, by definition. So number of such random inputs is poly(n).
   - For each R, V chooses q positions $i_1^R, \ldots, i_q^R$ and a boolean function $f_R : \{0,1\}^q \to \{0,1\}$ and accepts iff $f_R(w_{i_1^R}, \ldots, w_{i_q^R}) = 1$.

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2. Simulate the computation f_R of the verifier for different random inputs R and witnesses w as a Boolean formula.
   - Can be done with a CNF of size 2^q
   - Converting to 3CNF we get a formula of size $q \cdot 2^q$

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5. If $x \notin L$ then the verifier says NO for half of the random strings R.
   - For each such random string, at least one of its clauses fails
   - Thus at least $\varepsilon = \dfrac{1}{2 \cdot q \cdot 2^q}$ of the clauses of φ_x fails.

Conclusion

- Important to study hardness of approximation for NP-hard problems
- Different hard problems have different approximation parameters
- For hardness of approximation, need more *robust reductions* between combinatorial problems
- Proof systems, in particular *Probabilistic Checkable Proofs*, allows us to get such strong reductions
- Many more applications in computer science and industry!
  - Program Checking (for software engineering)
  - Zero-knowledge proofs in cryptocurrencies
  - many more...

Acknowledgement

- Lecture based largely on:
  - Section's 1-3 of Luca's survey [Trevisan 2004]
  - [Motwani & Raghavan 2007, Chapter 7]
- See Luca's survey `https://arxiv.org/pdf/cs/0409043`

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