Today

- Capturing the power of the prover in PCPs.
- Approximability and Inapproximability.
- Average-case Hardness.

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History of PCPs

Defn: Defined explicitly by Arora & Safra 1992, based on implicit definition by Feige et al. 1991. Variant defns already defined by Fortnow et al. 1988, Babai et al. 1991.

Major results:

Babai-Fortnow-Lund (1990): $NEXP \subset$ PCP[poly, poly].

Arora et al. (1992): NP $PCP[O(\log n), O(1)].$

Hastad (1997): NP = $PCP[O(\log n), 3]$.

Recall PCPs

Defn: (r, q)-restricted PCP verifier is a prob. polytime machine with access to oracle that tosses r(n) coins and queries the oracle q(n)times to decide whether it accepts x of length n.

Defn: PCP[r,q] is the class of languages Ls.t. there exists a (r,q)-restricted PCP verifier with

Completeness For every $x \in L$, there exists a proof oracle π such that $V^{\pi}(x)$ accepts w.p. 1.

Soundness For every $x \notin L$, for every proof oracle π , $V^{\pi}(x)$ accepts w.p. $\leq \frac{1}{2}$.

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Optimal proof for PCP

- Let bits of proof be variables π_1, \ldots, π_n .
- For fixed randomness, verifier's actions give a decision tree of depth 3 on variables π_1,\ldots,π_n .
- Exercise: Convert depth-3 decision tree into $\ell < 8$ clauses such that every assignment to variables satisfies at least $\ell-1$ clauses and satisfies all iff decision tree accepts.
- Create such block of clauses for every random string and take their conjunction.
- If $x \in L$ then formula satisfiable. If $x \notin L$ L then at most 15/16 fraction of clauses satisfied by any assignment.

- ullet Conclude: If you can find assignment satisfying more that 15/16 fraction of clauses in every satisfiable SAT formula, then can decide $\mathsf{PCP}[O(\log n), 3]$ and hence (by Hastad) can decide NP.
- Or equivalently, Can't approximate # satisfiable clauses by factor of 15/16 in P unless NP=P.

Complexity and Optimization

Combinatorial optimization problems: described by a triple (sol?, obj, opt), where sol?: $\{0,1\}^* \times \{0,1\}^* \to \{0,1\} \text{ and obj: } \{0,1\}^* \times \{0,1\}^* \to \mathbb{R}^+ \text{ are polytime computable, and opt} \in \{\max,\min\}.$

Given x, goal is to find solution y (i.e., sol?(x.y) = 1) so as to opt obj(x,y).

P and NP (and P?=NP) owe their popularity in large measure due to ability to explain solvability of optimization problems, in theory.

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Gap between theory and practice

- NP-completeness is not the end of the story.
- In practice people still develop heuristics.
- Typical justification: "Heuristic comes to within 99% of optimum on 95% of all cases."
- Does this contradict NP-completeness?
- No, No! On two grounds:
 - Approximation, not exact.
 - Average-case, not worst-case.

Approximability

• Given optimization problem $\Pi = (sol?,obj,opt)$ and function $\alpha : \mathbb{Z}^+ \to \mathbb{R}^+$, the (Π,α) optimization problem is that of computing a solution y to x satisfying

$$y/\alpha(|x|) \le opt \le y\alpha(|x|)$$

. (Note need $\alpha(\cdot) \geq 1$).

- NP-completeness usually gives negative results about $(\Pi,1)$. But what about $(\Pi,2)$.
- Example: (Clique,1) = (Coloring,1) = (MaxSAT,1).

- Is (Clique,2) = (Coloring, 2) = (MaxSAT,2)?
- Presumably not, since (MaxSAT,2) is in P, and (Clique,2) (thanks to your next problem set) is NP-hard!
- Need to study (Π, α) seperately for each Π and α .

PCP and (in)-approximability

- PCP theorem shows that (MaxSAT,16/15- ϵ) is NP-hard (actually (MaxSAT, 8/7 ϵ) if you are careful).
- Shows many other such results.
- Consequence: Have good understanding of this variation.

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Average-case vs. worst-case: The other objection

- NP-completeness only talks about problems on the worst-case.
- In practice, don't have to worry about the worst-case.
- Theoretical justification: Too complex for environment to compute the worst-case.
- So environment also polynomial time bounded, but maybe can toss random coins.
 If so, should only worry about average-case.
- But average-case on what distribution?

• Don't know, but will make this part of the problem.

Distributional problems

- \bullet (Π, D) , where Π is a problem and D = $\{D_n\}_n$ is a distribution on *n*-bit strings.
- ullet Can now ask: How hard is it to compute Π on distribution D?
- ullet No different from worst-case unless D is restricted (or else, consider the distribution $D = \sum_{i=1}^{\infty} 2^{-i}$ Bad input for machine M_i to solve Π).
- \bullet Restriction on D? Make it polynomial time sampleable. Can pick $x \in \{0,1\}^n$ according to D_n in time polynomial in n. Will mix notation a bit to say D_n is the sampling circuit.

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Why not just uniform?

 Chromatic number of most graphs = $n/\log n$ - so $\log n$ approximation trivial.

- Clique number of most graphs = $\log n$,

number

not

More

so $\log n$ approximation trivial.

considered easy in practice.

interesting solutions desired.

Yet Clique/Chromatic

Example: Distributed Permanent

Show Lipton's reduction.

DNP and Avg-P