Approximating Solutions to Hard Problems

Approximation algorithms, Probabilistically Checkable Proof Systems, and Hardness of Approximation Motivating example:

- Max SAT: Given a Boolean formula φ in conjunctive normal form, find the maximum number of clauses that can be simultaneously satisfied
- This is an optimization version of the classical SAT decision problem

Suggest simple algorithms that aim to satisfy as many clauses as possible

Approximation algorithms for Max SAT

 Greedy algorithm: assign a truth value to the variables in turn, choosing a value for variable xi that satisfies at least half of the not-yet-satisfied clauses in which xi appears

Approximation algorithms for Max SAT

 Even simpler: either the all-true or all-false assignment satisfies at least half of the clauses (why?)

Approximation algorithms for Min Vertex Cover

 Given an undirected graph G = (V,E), find a minimum vertex cover for G. A vertex cover is a set of nodes that are incident on all edges of G

Suggest simple algorithms that aim to find the smallest possible vertex cover

Greedy algorithm:

- Start with $S = \emptyset$
- Repeat until the graph has no edges:
 - Pick the vertex v that is incident on the most edges (breaking ties arbitrarily), add v to S and remove its incident edges from the graph

Approximation algorithms for Min Vertex Cover



FIGURE 9.3: The bipartite graph B_t for t = 6. The smallest vertex cover is W, but the greedy algorithm covers all the vertices in $U = \bigcup_{i=1}^{t} U_i$, and $|U|/|W| = \Theta(\log n)$.

From The Nature of Computation by Chris Moore

Conservative algorithm:

- Start with $S = \emptyset$
- Repeat until the graph has no edges:
 - Pick any edge of E, and add *both* of its endpoints to S. Delete these two vertices from the graph, as well as all incident edges

This algorithm finds a vertex cover of size at most twice the minimum – why?

An *optimization problem* \prod has the following properties: Corresponding to an instance I of the problem is a set of solutions. Corresponding to each solution is a value, which is a positive rational number.

 Π is either a *maximization* problem, in which case we want to find the solution with *maximum* value, or a *minimization* problem. Let Opt(I) be the value of the optimal solution to I.

An algorithm A is an *approximation algorithm* for \prod if given an instance I of \prod , A computes a solution of I. Let A(I) denote the value of the solution computed by A on instance I. Let

 $R_A(I) = max\{A(I)/Opt(I), Opt(I)/A(I)\}.$

Note that $1 \le R_A(I)$ and the closer $R_A(I)$ is to 1, the better A performs on input I. Algorithm A has *approximation ratio* R_A if

 $R_A \ge R_A(I)$ for all instances I of \prod .

Max 3SAT has an approximation algorithm with approximation ratio 2.

Vertex Cover has an approximation algorithm with approximation ratio log n.

Are there algorithms with better approximation ratios? Is there a limit to how good the approximation ratios can be for these and other problems?

Next we'll introduce tools to help us answer the second question here.

Gap Lemma: Let L be NP-complete. Suppose that there is a poly-time mapping from any instance x of L to instance x' of maximization problem \prod such that

 $x \in L \Rightarrow Opt(x') = g(x)$ and

 $x \notin L \Rightarrow Opt(x') < (1-c) g(x)$

where $g(x) \in \mathbb{N}$, g is poly-time computable, and 0<c<1.

If \prod has a poly-time approximation algorithm with approximation ratio 1 + c/(1-c), then NP = P.

Proof in handout.

Consider a poly-time coin-flipping verifier V which receives an input x and a proof π , and outputs either 1 (yes) or 0 (no)

Let V(x, π) denote V's output on x, π (Note that V(π , x) is a random variable)

V is a *probabilistically checkable proof system* (PCP) for language L if

 $x \in L \Rightarrow \exists \pi \in \{0,1\}^* \quad Pr[V(x,\pi) = 1] = 1$

 $x \notin L \Rightarrow \forall \pi \in \{0,1\}^* \quad \Pr[V(x,\pi) = 1] \le \frac{1}{2}$

We say that language L is in PCP(r(n), q(n)) if there is a PCP V for L such that, on all inputs x

- the verifier uses O(r(lxl)) random bits
- the verifier queries O(q(lxl)) bits of the proof
- the bits must be queried non-adaptively, i.e. the verifier decides which bits to query before seeing any of these bits

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PCP Theorem: NP = PCP(\log n, 1)
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We'll prove a weak version of this in the next class, let's look at its applications first *Max 3SAT*: Given a Boolean formula ϕ in 3-conjunctive normal form (i.e., each clause has at most three literals), find the maximum number of clauses that can be simultaneously satisfied

Max 3SAT: Given a Boolean formula ϕ in 3-conjunctive normal form (i.e., each clause has at most three literals), find the maximum number of clauses that can be simultaneously satisfied

Theorem: For some constant c > 1, if there is a polynomial time approximation algorithm for Max 3SAT with approximation ratio c, then P=NP

Proof: Let $L \in NP$, let V be a PCP for L that uses q queries, r(n) random bits, and gets a proof of length l(n). Fix instance x of L. For each string τ of length r(lxl) let $b_{\tau,1}$, $b_{\tau,2}$, ... $b_{\tau,q}$ be the positions of the proof that V queries on coin flip sequence τ .

Using V, we'll describe a mapping $x \rightarrow \Phi_X$ from instances of L to instances of Max 3SAT, and apply the Gap Lemma to conclude that Max 3SAT is hard to approximate. Useful facts (proofs will be provided in handout):

- For any Boolean function F of q variables there is an equivalent q-CNF formula (i.e., each clause has at most q literals) with at most 2^q clauses.
- For any q-CNF formula φ', there is a 3CNF formula φ such that φ' is satisfiable if and only if φ is. Moreover, the number of clauses in φ is at most q times the number of clauses in φ'.

- Hastad showed that if there is a (8/7-ε)-approximation algorithm for Max 3SAT, then NP=P.
- Karloff and Zwick provided an algorithm for Max 3SAT that seems to have approximation ratio 8/7.

- More on proving hardness of approximation, e.g., for the Clique problem
- Proof of a weak version of the PCP theorem