

## Approximability, Unapproximability, and Between

- KNAPSACK, NODE COVER, MAXSAT, and MAX CUT have approximation thresholds less than 1.
  - KNAPSACK has a threshold of 0 (see p. 586).
  - But NODE COVER and MAXSAT have a threshold larger than 0.
- The situation is maximally pessimistic for TSP: It cannot be approximated unless  $P = NP$  (see p. 584).
  - The approximation threshold of TSP is 1.
    - \* The threshold is  $1/3$  if the TSP satisfies the triangular inequality.
  - The same holds for INDEPENDENT SET.

## The Proof (concluded)

- Run the alleged approximation algorithm on this TSP.
- Suppose a tour of cost  $|V|$  is returned.
  - This tour must be a Hamiltonian cycle.
- Suppose a tour with at least one edge of length  $\frac{|V|}{1-\epsilon}$  is returned.
  - The total length of this tour is  $> \frac{|V|}{1-\epsilon}$ .
  - Because the algorithm is  $\epsilon$ -approximate, the optimum is at least  $1 - \epsilon$  times the returned tour's length.
  - The optimum tour has a cost exceeding  $|V|$ .
  - Hence  $G$  has no Hamiltonian cycles.

## Unapproximability of TSP<sup>a</sup>

**Theorem 75** *The approximation threshold of TSP is 1 unless  $P = NP$ .*

- Suppose there is a polynomial-time  $\epsilon$ -approximation algorithm for TSP for some  $\epsilon < 1$ .
- We shall construct a polynomial-time algorithm for the NP-complete HAMILTONIAN CYCLE.
- Given any graph  $G = (V, E)$ , construct a TSP with  $|V|$  cities with distances

$$d_{ij} = \begin{cases} 1, & \text{if } \{i, j\} \in E \\ \frac{|V|}{1-\epsilon}, & \text{otherwise} \end{cases}$$

<sup>a</sup>Sahni and Gonzales (1976).

## KNAPSACK Has an Approximation Threshold of Zero<sup>a</sup>

**Theorem 76** *For any  $\epsilon$ , there is a polynomial-time  $\epsilon$ -approximation algorithm for KNAPSACK.*

- We have  $n$  weights  $w_1, w_2, \dots, w_n \in \mathbb{Z}^+$ , a weight limit  $W$ , and  $n$  values  $v_1, v_2, \dots, v_n \in \mathbb{Z}^+$ .<sup>b</sup>
- We must find an  $S \subseteq \{1, 2, \dots, n\}$  such that  $\sum_{i \in S} w_i \leq W$  and  $\sum_{i \in S} v_i$  is the largest possible.
- Let

$$V = \max\{v_1, v_2, \dots, v_n\}.$$

<sup>a</sup>Ibarra and Kim (1975).

<sup>b</sup>If the values are fractional, the result is slightly messier but the main conclusion remains correct. Contributed by Mr. Jr-Ben Tian (R92922045) on December 29, 2004.

### The Proof (continued)

- For  $0 \leq i \leq n$  and  $0 \leq v \leq nV$ , define  $W(i, v)$  to be the minimum weight attainable by selecting some among the  $i$  first items, so that their value is exactly  $v$ .
- Start with  $W(0, v) = \infty$  for all  $v$ .
- Then
 
$$W(i + 1, v) = \min\{W(i, v), W(i, v - v_{i+1}) + w_{i+1}\}.$$
- Finally, pick the largest  $v$  such that  $W(n, v) \leq W$ .
- The running time is  $O(n^2V)$ , not polynomial time.
- Key idea: Limit the number of precision bits.

### The Proof (concluded)

- Hence

$$\sum_{i \in S'} v_i \geq \sum_{i \in S} v_i - n2^b.$$

- Because  $V$  is a lower bound on OPT (if, without loss of generality,  $w_i \leq W$ ), the relative deviation from the optimum is at most  $n2^b/V$ .
- By truncating the last  $b = \lfloor \log_2 \frac{\epsilon V}{n} \rfloor$  bits of the values, the algorithm becomes  $\epsilon$ -approximate.
- The running time is then  $O(n^2V/2^b) = O(n^3/\epsilon)$ , a polynomial in  $n$  and  $1/\epsilon$ .

### The Proof (continued)

- Given the instance  $x = (w_1, \dots, w_n, W, v_1, \dots, v_n)$ , we define the approximate instance

$$x' = (w_1, \dots, w_n, W, v'_1, \dots, v'_n),$$

where

$$v'_i = 2^b \left\lfloor \frac{v_i}{2^b} \right\rfloor.$$

- Solving  $x'$  takes time  $O(n^2V/2^b)$ .
- The solution  $S'$  is close to the optimum solution  $S$ :

$$\sum_{i \in S} v_i \geq \sum_{i \in S'} v_i \geq \sum_{i \in S'} v'_i \geq \sum_{i \in S} v'_i \geq \sum_{i \in S} (v_i - 2^b) \geq \sum_{i \in S} v_i - n2^b.$$

### Pseudo-Polynomial-Time Algorithms

- Consider problems with inputs that consist of a collection of integer parameters (TSP, KNAPSACK, etc.).
- An algorithm for such a problem whose running time is a polynomial of the input length and the *value* (not length) of the largest integer parameter is a **pseudo-polynomial-time algorithm**.<sup>a</sup>
- On p. 587, we presented a pseudo-polynomial-time algorithm for KNAPSACK that runs in time  $O(n^2V)$ .
- How about TSP (D), another NP-complete problem?

<sup>a</sup>Garey and Johnson (1978).

## No Pseudo-Polynomial-Time Algorithms for TSP (D)

- By definition, a pseudo-polynomial-time algorithm becomes polynomial-time if each integer parameter is limited to having a *value* polynomial in the input length.
- Corollary 39 (p. 304) showed that HAMILTONIAN PATH is reducible to TSP (D) with weights 1 and 2.
- As HAMILTONIAN PATH is NP-complete, TSP (D) cannot have pseudo-polynomial-time algorithms unless  $P = NP$ .
- TSP (D) is said to be **strongly NP-hard**.
- Many weighted versions of NP-complete problems are strongly NP-hard.

## Fully Polynomial-Time Approximation Scheme

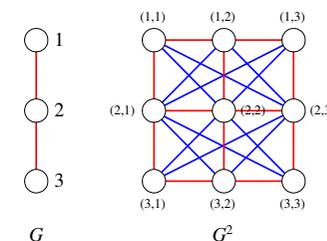
- A polynomial-time approximation scheme is **fully polynomial (FPTAS)** if the running time depends polynomially on  $|x|$  and  $1/\epsilon$ .
  - Maybe the best result for a “hard” problem.
  - For instance, KNAPSACK is fully polynomial with a running time of  $O(n^3/\epsilon)$  (p. 586).

## Polynomial-Time Approximation Scheme

- Algorithm  $M$  is a **polynomial-time approximation scheme (PTAS)** for a problem if:
  - For each  $\epsilon > 0$  and instance  $x$  of the problem,  $M$  runs in time polynomial (depending on  $\epsilon$ ) in  $|x|$ .
    - \* Think of  $\epsilon$  as a constant.
  - $M$  is an  $\epsilon$ -approximation algorithm for every  $\epsilon > 0$ .

## Square of $G$

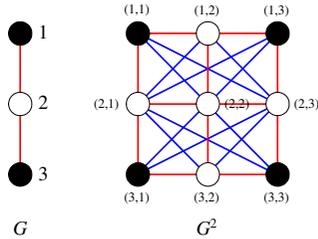
- Let  $G = (V, E)$  be an undirected graph.
- $G^2$  has nodes  $\{(v_1, v_2) : v_1, v_2 \in V\}$  and edges
 
$$\{\{(u, u'), (v, v')\} : (u = v \wedge \{u', v'\} \in E) \vee \{u, v\} \in E\}.$$



## Independent Sets of $G$ and $G^2$

**Lemma 77**  $G(V, E)$  has an independent set of size  $k$  if and only if  $G^2$  has an independent set of size  $k^2$ .

- Suppose  $G$  has an independent set  $I \subseteq V$  of size  $k$ .
- $\{(u, v) : u, v \in I\}$  is an independent set of size  $k^2$  of  $G^2$ .



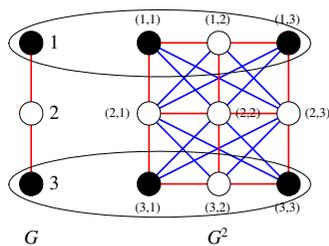
## The Proof (concluded)<sup>a</sup>

- If  $|U| \geq k$ , then we are done.
- Now assume  $|U| < k$ .
- As the  $k^2$  nodes in  $I^2$  cover fewer than  $k$  “rows,” there must be a “row” in possession of  $> k$  nodes of  $I^2$ .
- Those  $> k$  nodes will be independent in  $G$  as each “row” is a copy of  $G$ .

<sup>a</sup>Thanks to a lively class discussion on December 29, 2004.

## The Proof (continued)

- Suppose  $G^2$  has an independent set  $I^2$  of size  $k^2$ .
- $U \equiv \{u : \exists v \in V (u, v) \in I^2\}$  is an independent set of  $G$ .



- $|U|$  is the number of “rows” that the nodes in  $I^2$  occupy.

## Approximability of INDEPENDENT SET

- The approximation threshold of the maximum independent set is either zero or one (it is one!).

**Theorem 78** *If there is a polynomial-time  $\epsilon$ -approximation algorithm for INDEPENDENT SET for any  $0 < \epsilon < 1$ , then there is a polynomial-time approximation scheme.*

- Let  $G$  be a graph with a maximum independent set of size  $k$ .
- Suppose there is an  $O(n^i)$ -time  $\epsilon$ -approximation algorithm for INDEPENDENT SET.

### The Proof (continued)

- By Lemma 77 (p. 595), the maximum independent set of  $G^2$  has size  $k^2$ .
- Apply the algorithm to  $G^2$ .
- The running time is  $O(n^{2i})$ .
- The resulting independent set has size  $\geq (1 - \epsilon) k^2$ .
- By the construction in Lemma 77 (p. 595), we can obtain an independent set of size  $\geq \sqrt{(1 - \epsilon) k^2}$  for  $G$ .
- Hence there is a  $(1 - \sqrt{1 - \epsilon})$ -approximation algorithm for INDEPENDENT SET.

### Comments

- INDEPENDENT SET and NODE COVER are reducible to each other (Corollary 37, p. 286).
- NODE COVER has an approximation threshold at most 0.5 (p. 569).
- But INDEPENDENT SET is unapproximable (see the textbook).
- INDEPENDENT SET limited to graphs with degree  $\leq k$  is called  $k$ -DEGREE INDEPENDENT SET.
- $k$ -DEGREE INDEPENDENT SET is approximable (see the textbook).

### The Proof (concluded)

- In general, we can apply the algorithm to  $G^{2^\ell}$  to obtain an  $(1 - (1 - \epsilon)^{2^{-\ell}})$ -approximation algorithm for INDEPENDENT SET.
- The running time is  $n^{2^\ell i}$ .<sup>a</sup>
- Now pick  $\ell = \lceil \log \frac{\log(1-\epsilon)}{\log(1-\epsilon')} \rceil$ .
- The running time becomes  $n^{i \frac{\log(1-\epsilon)}{\log(1-\epsilon')}}$ .
- It is an  $\epsilon'$ -approximation algorithm for INDEPENDENT SET.

<sup>a</sup>It is not fully polynomial.

*On P vs NP*

## Density<sup>a</sup>

The **density** of language  $L \subseteq \Sigma^*$  is defined as

$$\text{dens}_L(n) = |\{x \in L : |x| \leq n\}|.$$

- If  $L = \{0, 1\}^*$ , then  $\text{dens}_L(n) = 2^{n+1} - 1$ .
- So the density function grows at most exponentially.
- For a unary language  $L \subseteq \{0\}^*$ ,

$$\text{dens}_L(n) \leq n + 1.$$

– Because  $L \subseteq \{\epsilon, 0, 00, \dots, \overbrace{00 \dots 0}^n, \dots\}$ .

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<sup>a</sup>Berman and Hartmanis (1977).

## Self-Reducibility for SAT

- An algorithm exploits **self-reducibility** if it reduces the problem to the same problem with a smaller size.
- Let  $\phi$  be a boolean expression in  $n$  variables  $x_1, x_2, \dots, x_n$ .
- $t \in \{0, 1\}^j$  is a **partial** truth assignment for  $x_1, x_2, \dots, x_j$ .
- $\phi[t]$  denotes the expression after substituting the truth values of  $t$  for  $x_1, x_2, \dots, x_t$  in  $\phi$ .

## Sparsity

- **Sparse languages** are languages with polynomially bounded density functions.
- **Dense languages** are languages with superpolynomial density functions.

## An Algorithm for SAT with Self-Reduction

We call the algorithm below with empty  $t$ .

- 1: **if**  $|t| = n$  **then**
- 2:   **return**  $\phi[t]$ ;
- 3: **else**
- 4:   **return**  $\phi[t0] \vee \phi[t1]$ ;
- 5: **end if**

The above algorithm runs in exponential time, by visiting all the partial assignments (or nodes on a depth- $n$  binary tree).

## NP-Completeness and Density<sup>a</sup>

**Theorem 79** *If a unary language  $U \subseteq \{0\}^*$  is NP-complete, then  $P = NP$ .*

- Suppose there is a reduction  $R$  from SAT to  $U$ .
- We shall use  $R$  to guide us in finding the truth assignment that satisfies a given boolean expression  $\phi$  with  $n$  variables if it is satisfiable.
- Specifically, we use  $R$  to prune the exponential-time exhaustive search on p. 606.
- The trick is to keep the already discovered results  $\phi[t]$  in a table  $H$ .

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<sup>a</sup>Berman (1978).

## The Proof (continued)

- Since  $R$  is a reduction,  $R(\phi[t]) = R(\phi[t'])$  implies that  $\phi[t]$  and  $\phi[t']$  must be both satisfiable or unsatisfiable.
- $R(\phi[t])$  has polynomial length  $\leq p(n)$  because  $R$  runs in log space.
- As  $R$  maps to unary numbers, there are only polynomially many  $p(n)$  values of  $R(\phi[t])$ .
- How many nodes of the complete binary tree (of invocations/truth assignments) need to be visited?
- If that number is a polynomial, the overall algorithm runs in polynomial time and we are done.

```
1: if |t| = n then
2:   return  $\phi[t]$ ;
3: else
4:   if  $(R(\phi[t]), v)$  is in table  $H$  then
5:     return  $v$ ;
6:   else
7:     if  $\phi[t0] = \text{"satisfiable"}$  or  $\phi[t1] = \text{"satisfiable"}$  then
8:       Insert  $(R(\phi[t]), 1)$  into  $H$ ;
9:       return "satisfiable";
10:    else
11:      Insert  $(R(\phi[t]), 0)$  into  $H$ ;
12:      return "unsatisfiable";
13:    end if
14:  end if
15: end if
```

## The Proof (continued)

- A search of the table takes time  $O(p(n))$  in the random access memory model.
- The running time is  $O(Mp(n))$ , where  $M$  is the total number of invocations of the algorithm.
- The invocations of the algorithm form a binary tree of depth at most  $n$ .

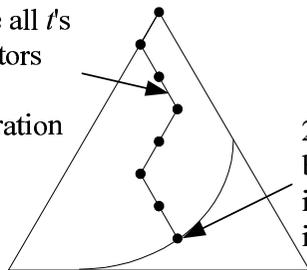
### The Proof (continued)

- There is a set  $T = \{t_1, t_2, \dots\}$  of invocations (partial truth assignments, i.e.) such that:
  - $|T| \geq (M - 1)/(2n)$ .
  - All invocations in  $T$  are **recursive** (nonleaves).
  - None of the elements of  $T$  is a prefix of another.

### The Proof (continued)

- All invocations  $t \in T$  have different  $R(\phi[t])$  values.
  - None of  $s, t \in T$  is a prefix of another.
  - The invocation of one started after the invocation of the other had terminated.
  - If they had the same value, the one that was invoked second would have looked it up, and therefore would not be recursive, a contradiction.
- The existence of  $T$  implies that there are at least  $(M - 1)/(2n)$  different  $R(\phi[t])$  values in the table.

3rd step: Delete all  $t$ 's at most  $n$  ancestors (prefixes) from further consideration



2nd step: Select any bottom undeleted invocation  $t$  and add it to  $T$

1st step: Delete leaves;  $(M - 1)/2$  nonleaves remaining

### The Proof (concluded)

- We already know that there are at most  $p(n)$  such values.
- Hence  $(M - 1)/(2n) \leq p(n)$ .
- Thus  $M \leq 2np(n) + 1$ .
- The running time is therefore  $O(Mp(n)) = O(np^2(n))$ .
- We comment that this theorem holds for any sparse language, not just unary ones.<sup>a</sup>

<sup>a</sup>Mahaney (1980).