CS 341 – Algorithms

Lecture 17 – Polynomial Time Reductions

21 July 2021

Today's Plan

- 1. Polynomial Time Reductions
- 2. Simple Reductions
- 3. More Simple Reductions
- 4. A Non-Trivial Reduction

Polynomial Time Reductions

Once we have learned more and more algorithms, they become our building blocks and we may not need to design algorithms for new problems from scratch.

So it becomes more and more important to be able to use existing algorithms to solve new problems.

We have already seen a few reductions.

For examples, we have reduced subset-sums to knapsack, longest increasing subsequence to longest common subsequences, and basketball league winner to maximum bipartite matching, etc.

In general, if there is an efficient reduction from problem A to problem B and there is an efficient algorithm to solve problem B, then we have an efficient algorithm to solve problem A.

Decision Problems

To formalize the notion of a reduction, it is more convenient to restrict our attention to <u>decision problems</u>, for which the output is either YES or NO, so that every problem has the same output format.

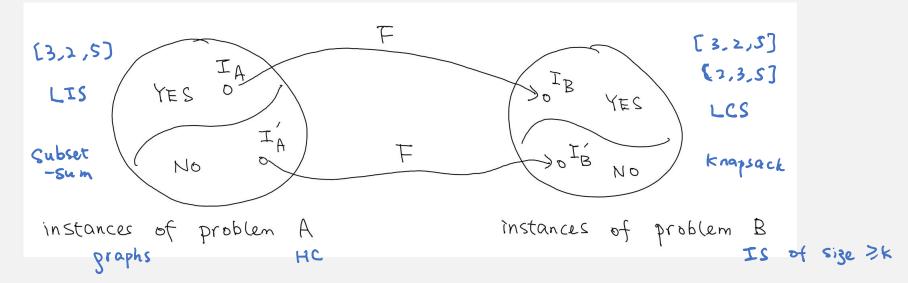
For example, instead of finding a maximum matching, we consider the decision version of the problem "Does the input graph G have a matching of size at least k?".

As we will discuss later, for all the problems that we will consider, if we know how to solve the decision version of our problem in polynomial time, then we can use the decision algorithm as a blackbox/subroutine to solve the search version of our problem in polynomial time.

e.g. max bipartite matching.
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$$k$$
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Definition (Polynomial Time Reductions)

Definition. We say a decision problem A is polynomial time reducible to a decision problem B if there is a polynomial time algorithm F that maps/transforms any instance I_A of A into an instance I_B of B (that is, $F(I_A) = I_B$) such that I_A is a YES-instance of problem A if and only if I_B is a YES-instance of problem B.



We use the notation $A \leq_p B$ to denote that such a polynomial time reduction exists, intuitively saying that problem A is not more difficult than problem B in terms of polynomial time solvability.

Algorithm (Solving Problem A by Reduction)

Input: an instance IA of problem A

Output: whether IA is a YES-instance

- 1. Use the reduction algorithm F to mapl transform I_A into $I_B = F(I_A)$ of problem B.
- 2. Return ALGB(IB).
 - Correctness: () I_A YES \Leftrightarrow $I_B = F(I_A)$ YES (reduction) (2) $Alg_B(I_B)$ is correct time complexity: F maps I_A into I_B in $p(|I_A|)$ Alg_B solves I_B in $g(|I_B|)$, then also solves A in $g(p(|I_B|))$

Proving Hardness Using Reductions

We showed $A \leq_p B$ and use an efficient algorithm for problem B to solve problem A.

This is the usual direction, but now we explore the other implication of the inequality $A \leq_p B$.

Suppose problem *A* is known to be impossible to be solved in polynomial time.

Then $A \leq_p B$ implies that problem B cannot be solved in polynomial time either.

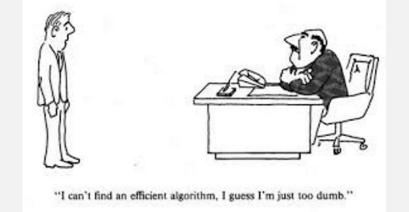
Therefore, if A is computationally hard and $A \leq_p B$, then B is also computationally hard.

By our current knowledge, however, we know almost nothing about proving a problem cannot be solved in polynomial time, so we could not draw such a strong conclusion from $A \leq_p B$.

$$A \leq p B$$
 $A \leq p B$
easy \leftarrow easy hard \rightarrow hard

Cartoon (from book by Garey and Johnson)

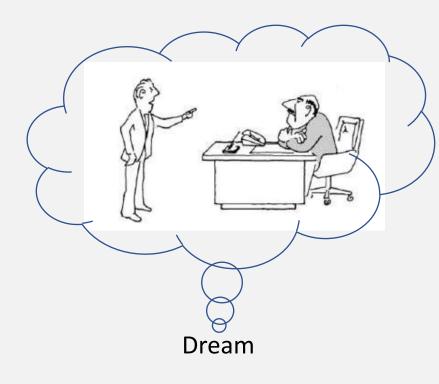
Suppose our boss gives us a problem C, but we don't know how to solve it in polynomial time.



It would be much more convincing if you could prove e.g. TSP $\leq_p C$.



"I can't find an efficient algorithm, but neither can all these famous people."



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Three Problems

Maximum Clique (Clique): A subset $S \subseteq V$ is a clique if $uv \in E$ for all $u, v \in S$.

Input: A graph G = (V, E), an integer k.

<u>Output</u>: Is there a clique with at least k vertices?



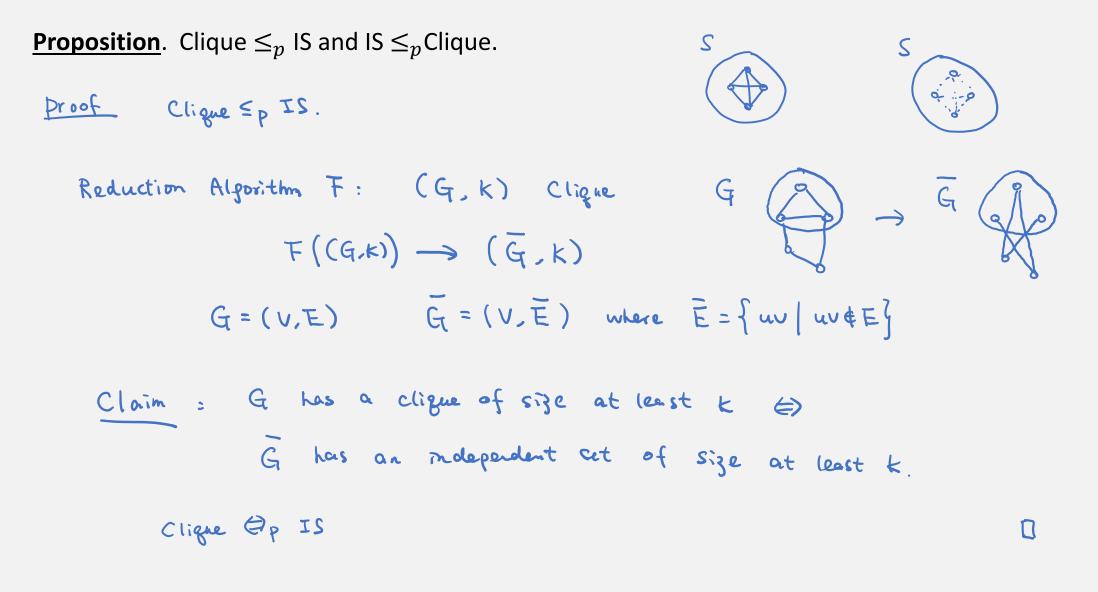
Maximum Independent Set (IS): A subset $S \subseteq V$ is an independent set if $uv \notin E$ for all $u, v \in S$. Input: A graph G = (V, E), an integer k.

<u>Output</u>: Is there an independent set with at least k vertices?

<u>Minimum Vertex Cover (VC)</u>: A subset $S \subseteq V$ is a vertex cover if $\{u, v\} \cap S \neq \emptyset$ for all $uv \in E$. <u>Input</u>: A graph G = (V, E), an integer k.

<u>Output</u>: Is there a vertex cover with at most k vertices?

Cliques and Independent Sets



Independent Sets and Vertex Cover

<u>Observation</u>. In G = (V, E), a subset $S \subseteq V$ is a vertex cover if and only if V - S is an independent set.



Polynomial Time Reductions are Transitive

<u>Proposition</u>. If $A \leq_p B$ and $B \leq_p C$, then $A \leq_p C$. $A \leq_{P} B$: $\exists F$ I_{A} YES (\exists) $I_{B} = F(I_{A})$ YES proof F can be done in p() time $B \leq PC$: $\exists H$ I_B res \Leftrightarrow $I_C = H(I_B)$ res H can be done in g() time ASPC : H(F(IA)) = IC IA YES ON IC YES H(F()) can be done g(p()).

Therefore, Clique, IS, and VC are all equivalent in terms of polynomial time solvability.

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Hamiltonian Problems

Hamiltonian Cycle (HC): A cycle is a Hamiltonian cycle if it touches every vertex exactly once.

<u>Input</u>: A graph G = (V, E).

<u>Output</u>: Does G have a Hamiltonian cycle?

Hamiltonian Path (HP): A path is a Hamiltonian path if it touches every vertex exactly once.

<u>Input</u>: A graph G = (V, E).

Output: Does G have a Hamiltonian path?

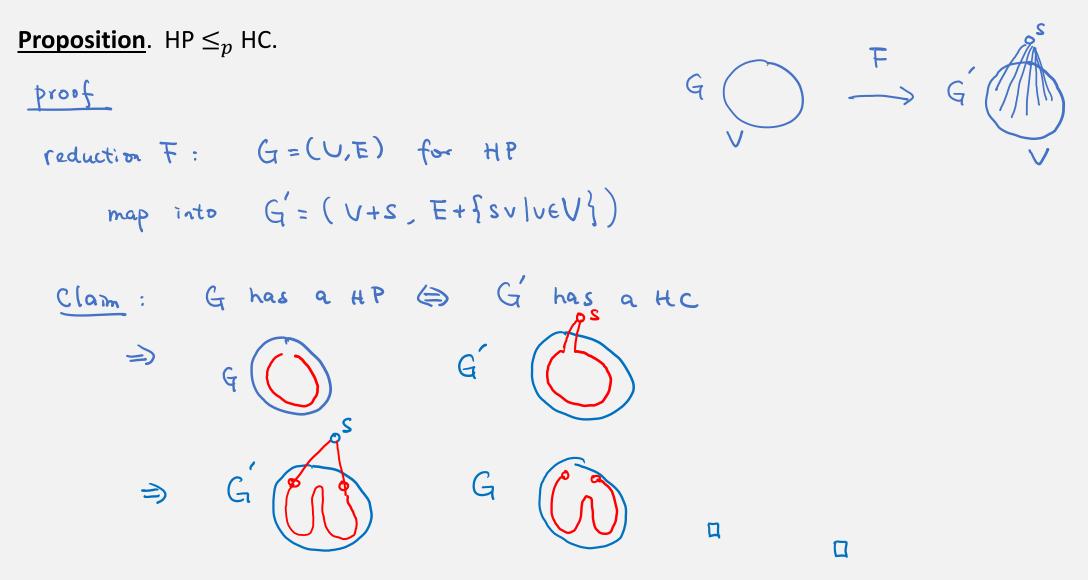
Traveling Salesman Problem (TSP):

<u>Input</u>: A graph G = (V, E), with an edge length l_e for each edge $e \in E$, and an integer L.

<u>Output</u>: Is there a Hamiltonian cycle with total length at most L?



 $\mathsf{HP} \leq_p \mathsf{HC}$

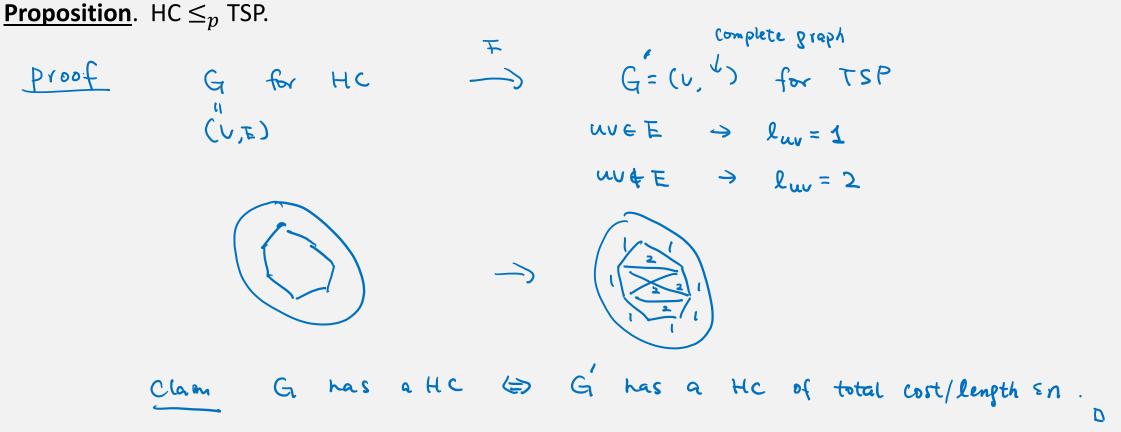


 $HC \leq_p HP$

<u>Proposition</u>. $HC \leq_p HP$. proof idea: "open up" the cycle G reduction: G = (U, E) for HC maps into $G = (V + x' + t_1 + t_2, E + \{x'v | v \in N(x)\} + t_1 x' + t_2 x)$ <u>Claim</u>: G has a HC (=) G ti has a HP x a Ptz ⇒ G G , ⇒ G A D

Traveling Salesman Problem

A common technique in doing reduction is to show that one problem is a special case of another problem. We call this technique <u>specialization</u>.



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3-Satisfiability (3SAT)

This is an important problem in the theory of NP-completeness.

We are given *n* Boolean <u>variables</u> $x_1, x_2, ..., x_n$, each can be set to be either True or False.

We are also given a formula in conjunctive normal form (CNF), where it is an AND of the <u>clauses</u>, where each clause is an OR of the <u>literals</u>, where a literal is either x_i or $\overline{x_i}$. $(X_1 \cup X_2 \cup X_3) \land (X_1 \cup \overline{X_2} \cup \overline{X_3}) \land (X_1 \cup \overline{X_2} \cup \overline{X_4}) \land (X_3 \cup \overline{X_4})$ e.g. $x_1 = T$ $x_2 = F$ $x_3 = T$ $x_4 = T/F$ clause

3-Satisfiability (3SAT)

 $(x_1 \vee x_2) \wedge (x_1 \vee \overline{x_2}) \wedge (\overline{x_1} \vee \overline{x_2}) \wedge (\overline{x_1} \vee \overline{x_2}) \leftarrow \text{not satisfiable}$

<u>Input</u>: A CNF-formula in which each clause has at most three literals.

<u>Output</u>: Is there a truth assignment to the variables that satisfies all the clauses?

 $3SAT \leq_p IS$

<u>**Theorem**</u>. $3SAT \leq_p IS$.

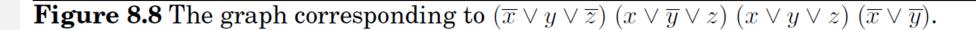
<u>Proof</u>. Given a 3SAT formula, we'd like to construct a graph G so that the formula is satisfiable if and only if the graph has an independent set of size *m* where *m* is the number of clauses. <u>Idea</u>: We would like the independent set to tell us how to satisfy the formula. $(X_1 \vee X_2 \vee \overline{X_3}) \wedge (\overline{X_2} \vee X_3 \vee \overline{X_4}) \wedge (\overline{X_1} \vee \overline{X_3} \vee X_4) \wedge (\overline{X_2} \vee \overline{X_3})$ Reduction: X2 ×, Claim X2 X formula is satisficable (\exists) praph Xz K₄ X₃ Xq X2 x, X₂ an IS of size 3m.

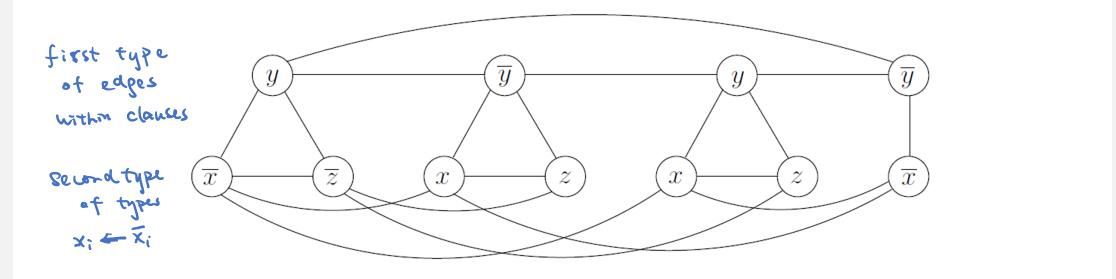
 $3SAT \leq_p IS$

<u>**Theorem**</u>. $3SAT \leq_p IS$.

Proof. Given a 3SAT formula, we'd like to construct a graph G so that the formula is satisfiable if and only if the graph has an independent set of size m where m is the number of clauses.

<u>Idea</u>: We would like the independent set to tell us how to satisfy the formula.

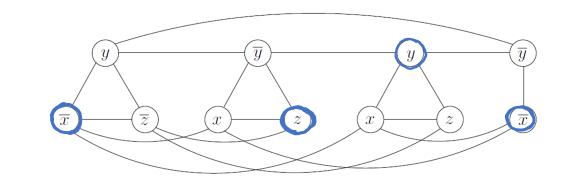




Proof

Lemma. The formula is satisfiable iff there is an independent set of size *m*.

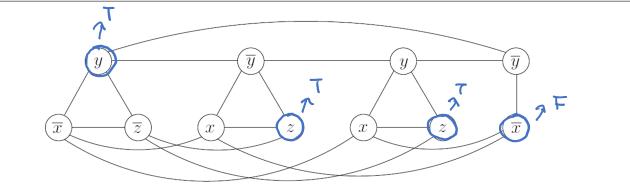
Figure 8.8 The graph corresponding to $(\overline{x} \lor y \lor \overline{z}) (x \lor \overline{y} \lor z) (x \lor y \lor z) (\overline{x} \lor \overline{y}).$



Proof

Lemma. The formula is satisfiable iff there is an independent set of size *m*.

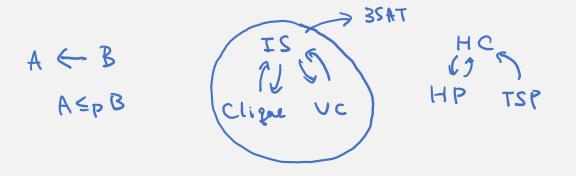
Figure 8.8 The graph corresponding to $(\overline{x} \lor y \lor \overline{z}) (x \lor \overline{y} \lor z) (x \lor y \lor z) (\overline{x} \lor \overline{y}).$



Concluding Remarks

We have introduced the notion of a polynomial time reduction, and use it to establish connections

between different problems, and so far we have



In principle, we can add new problems to relate to these problems, and slowly build up a big web of all computational problems.

As \leq_p is transitive, any strongly connected components of this big graph forms an equivalent class of problems in terms of polynomial time solvability.

Is there a better way to do it than to consider the problems one by one?