

## December 10

- How to prove  $\mathcal{NP}$ -completeness by reduction from known  $\mathcal{NP}$ -complete problem
- BIP-DECISION is  $\mathcal{NP}$ -complete
- SUBSET-SUM-DECISION is  $\mathcal{NP}$ -complete
- $\mathcal{NP}$ -hard and weakly  $\mathcal{NP}$ -hard problems
- Consequences of  $\mathcal{P} = \mathcal{NP}$  or  $\mathcal{P} \neq \mathcal{NP}$

Presentation differs from Wolsey

- Wolsey only assumes SATISFIABILITY  $\in \mathcal{NPC}$
- Wolsey proves BIP-DECISION  $\in \mathcal{NPC}$

## Proving $\mathcal{NP}$ -completeness

A problem  $Q$  is  $\mathcal{NP}$ -complete if

- (1)  $Q \in \mathcal{NP}$
- (2)  $\forall R \in \mathcal{NP} : R \leq_p Q$

Proving (2) is difficult, but if we already know some  $\mathcal{NP}$ -complete problem it is easier

To prove  $Q$  is  $\mathcal{NP}$ -complete

- (a) show  $Q \in \mathcal{NP}$
- (b) choose a problem  $S \in \mathcal{NPC}$
- (c) show that  $S \leq_p Q$

Proof: We have shown (1) in (a), and (2) is valid since

$$\forall R \in \mathcal{NP} : R \leq_p S \leq_p Q$$

## $\mathcal{NP}$ -hard and weakly $\mathcal{NP}$ -hard problems

A problem  $Q$  is  $\mathcal{NP}$ -complete if

- (1)  $Q \in \mathcal{NP}$
- (2)  $\forall R \in \mathcal{NP} : R \leq_p Q$

If only (2) holds we call problem  $\mathcal{NP}$ -hard.

An *optimization* problem is called  $\mathcal{NP}$ -hard if corresponding decision problem is  $\mathcal{NP}$ -complete.

A problem is *weakly*  $\mathcal{NP}$ -hard if it is  $\mathcal{NP}$ -hard but it can be solved in time polynomial in  $n$  and  $M$ , where  $n$  is length of input, and  $M$  is magnitude of coefficients.

## Binary integer programming

Integer programming plays a central role in combinatorial optimization and operations research. Hence we will prove that

$$\text{BIP-DECISION} \in \mathcal{NP}$$

Binary integer programming in decision form is defined as

$$\text{BIP-DECISION}(A, b, c, k) = \left\{ \begin{array}{l} \max \quad \sum_{j=1}^n c_j x_j \geq k \\ \text{s.t.} \quad \sum_{j=1}^n a_{ij} x_j \leq b_i, \quad i = 1, \dots, m \\ x_j \in \{0, 1\} \end{array} \right\}$$

without loss of generality we assume  $A, b, c$  integers

Equivalent formulation

$$\text{BIP-DECISION}(A, b, c, k) = \left\{ \begin{array}{l} \sum_{j=1}^n -c_j x_j \leq -k \\ \sum_{j=1}^n a_{ij} x_j \leq b_i, \quad i = 1, \dots, m \\ x_j \in \{0, 1\}, \quad j = 1, \dots, n \end{array} \right\}$$

or simply introducing new vaules of  $A, b, m$

$$\text{BIP-DECISION}(A, b) = \text{feasible} \left\{ \begin{array}{l} \sum_{j=1}^n a_{ij}x_j \leq b_i, \quad i = 1, \dots, m \\ x_j \in \{0, 1\}, \quad j = 1, \dots, n \end{array} \right\}$$

Since  $b - \sum_{j=1}^n a_{ij}x_j$  is bounded by some  $u_i$  we may add a sequence of slack variables  $x'_1 + 2x'_2 + 4x'_3 \dots$  which spans  $0 \dots, u_i$ . Hence for new  $A, b, m, n, x$

$$\text{BIP-DECISION}(A, b) = \text{feasible} \left\{ \begin{array}{l} \sum_{j=1}^n a_{ij}x_j = b_i, \quad i = 1, \dots, m \\ x_j \in \{0, 1\}, \quad j = 1, \dots, n \end{array} \right\}$$

### Step (a)

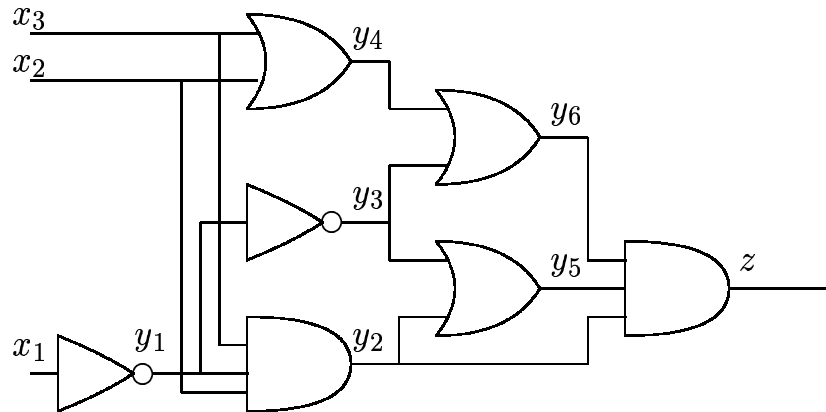
Certificate  $x$ . Check in polynomial time by checking if lefthand-side equals righthand-side.

### Step (b)

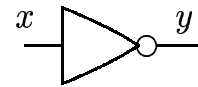
Reduce from  $\text{CIRCUIT-SAT} \in \mathcal{NP}$

**step (c)**

Given instance of CIRCUIT-SAT. Assign labels to output from each gate.



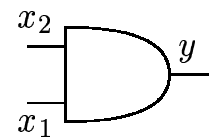
NOT-gate  $(x, y)$



$$x + y \leq 1$$

$$x + y \geq 1$$

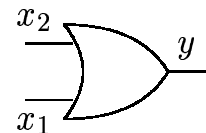
AND-gate  $(x_1, x_2, y)$



$$x_1 + x_2 - 2y \geq 0$$

$$x_1 + x_2 - y \leq 1$$

OR-gate  $(x_1, x_2, y)$



$$x_1 + x_2 - y \geq 0$$

$$x_1 + x_2 - 2y \leq 0$$

The final result should be true, add constraint

$$z = 1$$

All variables are boolean, add constraint

$$x_i, y_i, z \in \{0, 1\}$$

which completes the binary IP-model.

Check that “yes” instance is transformed to “yes” instance

$$\text{CIRCUIT-SAT}(X) = 1 \iff \text{BIP-DECISION}(f(X)) = 1$$

The resulting BIP model has  $2n$  constraints, the same amount of variables. Reduction (conversion) can be done in polynomial time and space.

## Subset-Sum is $\mathcal{NP}$ -complete

Given  $n$  weights  $w_1, \dots, w_n$ . Is it possible to choose a subset of the weights so that their weight sum equals  $c$ ?

$$\text{SUBSET-SUM-DECISION}(w, c) = \text{feasible} \left\{ \begin{array}{l} \sum_{j=1}^n w_j x_j = c \\ x_j \in \{0, 1\} \end{array} \right\}$$

Outline of proof

- (a) SUBSET-SUM-DECISION is in  $\mathcal{NP}$ .
- (b) Choose BIP-DECISION.
- (b) Prove BIP-DECISION  $\leq_p$  SUBSET-SUM-DECISION

## Reduction from BIP-DECISION

BIP-DECISION with two constraints

$$\text{BIP2-DECISION}(A, b) = \left. \begin{array}{l} \text{feasible} \left\{ \begin{array}{l} \sum_{j=1}^n a_{1j}x_j = b_1 \\ \sum_{j=1}^n a_{2j}x_j = b_2 \\ x_j \in \{0, 1\}, j = 1, \dots, n \end{array} \right. \end{array} \right\}$$

Difference between the right and left side of the constraints

$$g(x) = b_1 - \sum_{j=1}^n a_{1j}x_j,$$

$$h(x) = b_2 - \sum_{j=1}^n a_{2j}x_j,$$

Bound on  $g(x)$

$$g_{\min} = b_1 - \sum_{j=1}^n \bar{a}_j \leq g(x) \leq b_1 - \sum_{j=1}^n \underline{a}_j = g_{\max}$$

where  $\bar{a}_j = \max\{a_{1j}, 0\}$  and  $\underline{a}_j = \min\{a_{1j}, 0\}$ .

$$\lambda > \max \{ |g_{\max}|, |g_{\min}| \},$$

then

$$|g(x)| < \lambda$$

Multiply second constraint in BIP-DECISION with  $\lambda$  and add to first constraint

$$\text{BIP1-DECISION}(A, b) = \text{feasible} \left\{ \begin{array}{l} \sum_{j=1}^n (a_{1j} + \lambda a_{2j}) x_j = b_1 + \lambda b_2 = \tilde{b} \\ x_j \in \{0, 1\}, j = 1, \dots, n \end{array} \right\}$$

which is a SUBSET-SUM-DECISION problem

## Equivalence

Check that “yes” instance is transformed to “yes” instance

$$\begin{aligned} \text{BIP2-DECISION} = \text{“yes”} &\Leftrightarrow \\ \text{BIP1-DECISION} = \text{“yes”} & \end{aligned}$$

## Proof

- Assume  $\text{BIP2-DECISION}(X) = \text{“yes”}$  then obviously  $\text{BIP1-DECISION}(X) = \text{“yes”}$ .
- Assume  $\text{BIP1-DECISION}(X) = \text{“yes”}$ . Constraint in  $\text{BIP1-DECISION}$  may be written

$$g(x) + \lambda h(x) = 0$$

where

$$h(x) = K$$

must have  $K$  integer, as coefficients in  $h(x)$  integers, hence

$$g(x) + \lambda K = 0$$

Since  $|g(x)| < \lambda$ , and  $K$  integer we must have  $K = 0$

$$h(x) = 0 \quad g(x) = 0$$

so both constraints are satisfied

□

## **Time consumption**

The only computation is determination of  $\lambda$  (linear time).  
Output of BIP1-DECISION in linear time.

## **Reduction of BIP-DECISION to SUBSET-SUM-DECISION**

Assume that BIP-DECISION has  $m$  constraints. Use above algorithm  $m$  times. Resulting BIP1-DECISION will have the same set of solutions. Reduction in polynomial time.

Surprising result as SUBSET-SUM-DECISION contains all NP-problems

## What happens with the coefficients (experts)

### BIP2-DECISION to BIP1-DECISION

- all coefficients  $A, b$  in BIP2-DECISION are bounded by  $M$

- input size

$$L(X) = \Theta(n \log M)$$

as  $2n + 2$  coefficients.

- $\lambda \leq nM$

- output coefficients bounded by  $nM^2$

- output size

$$O(X) = \Theta(n \log(nM))$$

since  $n + 1$  coefficients of size  $\log(nM^2)$ .

### BIP-DECISION to SUBSET-SUM-DECISION

- assume BIP-DECISION has  $m$  constraints
- output coefficients bounded by  $n^{m-1}M^m$

## SUBSET-SUM-DECISION (experts)

- A problem is weakly  $\mathcal{NP}$ -hard if it can be solved in time polynomial in  $n$  and  $M$
- SUBSET-SUM is weakly  $\mathcal{NP}$ -hard
- We have shown  $\text{BIP-DECISION} \leq_p \text{SUBSET-SUM-DECISION}$
- Does it mean that BIP-DECISION is weakly  $\mathcal{NP}$ -hard

## More $\mathcal{NP}$ -complete problems

- Having three  $\mathcal{NP}$ -complete problems at hand it is easier to prove  $\mathcal{NP}$ -completeness of other problems
- Garey and Johnson (1979) first compendium of  $\mathcal{NP}$ -complete problems
- Crescenzi and Kann (2002) up-to-date database of  $\mathcal{NP}$ -complete problems

<http://www.nada.kth.se/viggo/problemelist/compendium.html>

link from home page

## Consequences of $\mathcal{P} = \mathcal{NP}$ or $\mathcal{P} \neq \mathcal{NP}$

- Mathematician (optimist): prove  $\mathcal{P} = \mathcal{NP}$
- Mathematician (pessimist): prove  $\mathcal{P} \neq \mathcal{NP}$
- Mathematician (thoughtful): find efficient algorithm close to optimum
- Probabilist (thoughtful): find efficient algorithm which returns optimal solution with high probability
- Engineer: heuristic algorithm
- Struggelig professor: study each problem