

## 15 Polynomial reduction

**Overview.** Not surprisingly, there are many problems that are extremely hard. In particular, they do not admit polynomial time algorithms. However, for many fundamental discrete computational problems, in optimization, AI/ML, combinatorics, logic, etc, we do not know of any polynomial algorithms; on the other hand we cannot prove that no polynomial time algo exists as well.

Later people realized that a large class of problems in this “gray area” has been shown to be “equivalent” – a polynomial-time algorithm for any of them would imply the existence of a polynomial-time algorithm for all of them. These are called NP-complete problem.

In other words, all of these open questions are really a **single** open question, a single type of complexity that we don’t yet fully understand.

NP-completeness essentially means “computationally hard for all practical purpose, though we cannot prove it”.

Discovering that a problem is NP-complete provides a compelling reason to stop searching for an efficient algorithm with provable guarantees. On the other hand, it somewhat justifies the search of good heuristics (algo without guarantees)

**Polynomial reduction.** We want to say problem  $X$  is at least as hard as problem  $Y$ . We show this by the notion of “reduction” – if we have a blackbox capable of solving  $X$ , then we could also solve  $Y$ .

$Y \leq_p X$ : arbitrary instance of  $Y$  can be solved using a polynomial number of standard computational steps (reduction overhead) + a polynomial number of calls to a blackbox that solves problem  $X$ .

$Y \leq_p X$  reads “ $Y$  is polynomial-time reducible to  $X$ ” or “ $X$  is as hard as  $Y$  with respect to polynomial time”.

**The contrapositive.**  $Y \leq_p X$  gives: if  $Y$  cannot be solved in polynomial time, then  $X$  cannot be solved in polynomial time. *Be aware of the direction.*

### Problems.

- **Independent Set:** Give a graph  $G = (V, E)$ , in the **search version**, the problem is to find a subset  $S \subseteq V$  of the *maximum* size such that for any pair  $u, v \in S$ , there is *no* edge between  $u$  and  $v$ .

In the **decision version**, we also give a parameter  $k$  as an input, and ask whether there is a subset  $S \subseteq V$  of size at least  $k$  such that for any pair  $u, v \in S$ , there is *no* edge between  $u$  and  $v$ .

In the following, when we talk about reductions we always use the decision version of the problem (same for other problems).

- **Vertex Cover (decision version):** Give a graph  $G = (V, E)$  and a parameter  $k$ , we ask whether there is a subset  $S \subseteq V$  of size at most  $k$  such that for any edge  $e = (u, v) \in E$ , either  $u \in S$  or  $v \in S$ .

- *Set Cover (decision version)*: Given a set  $U$  of  $n$  elements, a collection  $S_1, \dots, S_m$  of subsets of  $U$ , and a number  $k$ , does there exist a collection of at most  $k$  of these sets whose union is equal to  $U$ ?
- *SAT and 3-SAT*: We are given a set  $X$  of  $n$  Boolean variables  $x_1, \dots, x_n$ ; each can take the value 0 or 1 (equivalently, “false” or “true”). By a *term* over  $X$ , we mean one of the variable  $x_i$  or its  $\bar{x}_i$ . Finally, a *clause* is simply a disjunction of distinct terms  $C_j = t_1 \vee t_2 \vee \dots \vee t_\ell$ , each  $t_i \in \{x_1, \dots, x_n, \bar{x}_1, \dots, \bar{x}_n\}$ . We say the clause has length  $\ell$  if it contains  $\ell$  terms. For the SAT problem, we want to determine whether there is a truth assignment for  $X$  (that is, to assign a value 0 or 1 to each  $x_i$ ), such that  $C_1 \wedge C_2 \wedge \dots \wedge C_k$  evaluates to be 1.

For 3-SAT, the only difference is that we require that each clause contains exactly 3 terms.