

**EXERCISE ONE** Consider the classic NP-hard KNAPSACK PROBLEM, where we have  $n$  objects  $a_1, \dots, a_n$ , each object has a weight  $w_i$  and cost  $c_i$ , and our bag has a weight limit of  $B$ .

Find a greedy 2-approximation algorithm for this problem.

**EXERCISE TWO** Consider SCHEDULING WITH DEPENDENCIES: we schedule jobs of different lengths on  $m$  computers ( $m$  is a part of the input), but we also have a *dependence graph* on the jobs, and we can schedule a job only when all its dependencies are completed.

Find a greedy 2-approximation algorithm for this problem.

**EXERCISE THREE** You may recall MAX SAT from the last exercise session, where we formulated a randomized approximation algorithm for it. This algorithm was effective for clauses of length 2 or more, but when there were too many clauses of type  $(x_i)$  or  $(\neg x_j)$ , it was only a  $1/2$ -approximation.

Let us prove that we can assume the input is a little bit nicer:

1. Prove the following: Suppose we have a  $c$ -approximation algorithm for a subset of MAX SAT – it only works on inputs which contain no negative mono-clauses like  $(\neg x_i)$ . Then we can transform it into a  $c$ -approximation algorithm for MAX SAT on all inputs.
2. Prove that the same holds for WEIGHTED MAX SAT, where each clause has weight  $w_i$  and we maximize the weighted sum of satisfied clauses, i.e.  $\max \sum_i w_i C_i$ .

**EXERCISE FOUR** We have learned from the previous exercise that we can only deal with MAX SAT on inputs that contain no negative mono-clauses like  $(\neg x_i)$ . We should use this fact to choose a better probability  $p$ , which we use in the randomized algorithm for setting a variable to 1:

1. Prove that if all variables  $x_i$  are randomly set to be true with probability  $p > \frac{1}{2}$ , then the probability of satisfying a clause is at least  $\min(p, 1 - p^2)$ .
2. Choose a good  $p$  and finish the analysis of the suggested randomized algorithm for MAX SAT.

**EXERCISE FIVE** We now consider MAX DICUT. On the input we get a directed graph  $G = (V, \vec{E})$  and a non-negative weight function on the edges. Our task is to find a subset of vertices  $S$  so that  $\vec{E}(S, V \setminus S)$  (the edges directed from  $S$  to the rest) have maximum possible weight.

Suggest a probabilistic  $\frac{1}{4}$ -approximation algorithm for MAX DICUT.

**EXERCISE SIX** Let us try to improve on our algorithm for MAX DICUT:

1. Suggest a natural  $\{0, 1\}$ -integer program solving MAX DICUT.
2. Choose each vertex  $v_i$  with probability  $1/4 + x_i^*/2$ , where  $x_i^*$  is the optimum of the linear relaxation of the previous integer program. Show that it is a  $1/2$ -approximation.