

# Approximation Algorithms Lecture 13

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## 1 Recap

Fully polynomial time approximation scheme (FPTAS) for knapsack problem

## 2 Content

### 2.1 APTAS for bin packing

We will exhibit an APTAS for bin packing with the solution  $\leq (1 + \varepsilon)\mathbf{OPT} + 1/\varepsilon^2 + 2$ .

We will first write an integer program for bin packing.

Given  $n_i$  objects of size  $s_i$ ,  $1 \leq i \leq k$ , and  $\sum_i n_i = m$ .

A configuration  $c$  is a  $k$ -tuple  $(o_1^c, o_2^c, \dots, o_k^c)$  such that  $\sum_i o_i s_i \leq 1$ , and  $o_i \in \mathbb{Z}_{\geq 0}$ .

Let  $x_c$  be the number of bins which have configuration  $c$ . Then  $x_c \in \mathbb{Z}_{\geq 0}$ .

Then we need to minimize  $\sum_c x_c$ .

There is another constraint:  $\sum_c x_c o_i^c \geq n_i$  for all  $1 \leq i \leq k$ , which is the integer program.

Relax the integrality constraint on  $x_c$  to  $x_c \geq 0$ , and this will give us a linear program.

Note that in a linear program, the optimal answer is at a vertex. Let the number of different configurations be  $\alpha$  (this is also the "dimension" of the LP). Then the optimal solution lies at the intersection of  $\alpha$  hyperplanes (inequalities).

We have  $\alpha + k$  inequalities in all and at a vertex, we set  $\alpha$  inequalities as equalities. At least  $\alpha - k$  configurations are set to 0, and so at most  $k$  configurations have non-zero  $x_c$ .

Our algorithm then becomes:

1. Solve the LP and round up all  $x_c$  variables.

Note that solution is  $\leq$  LP value +  $k$  (since rounding will increase by at most  $k$ ), which is at most  $\mathbf{OPT} + k$ .

Note that  $k$  is large, and we want to reduce it.

We will group objects to reduce number of distinct sizes as follows: remove all objects of size  $\leq \varepsilon$ , order objects by decreasing size and form groups of  $g$  objects.

Redefine  $k$  as the number of distinct sizes now. (Verify this later on). Round up each object in a group to the size of the largest object in that group.

Let  $I'$  be this new instance.

If we run the earlier algorithm on  $I'$  then we get a solution with number of bins  $\leq \mathbf{OPT}' + \lceil \frac{k}{g} \rceil$ .

In going from  $I$  to  $I'$  we only increased the object sizes, hence the solution for  $I'$  can also pack the objects in  $I$ .

How does  $\mathbf{OPT}'$  relate to  $\mathbf{OPT}$ ?

**Claim 0.1**

$$\mathbf{OPT}' \leq \mathbf{OPT} + g$$

*Proof.* Consider a solution which requires  $\mathbf{OPT}$  bins to pack objects of  $I$ .

The objects of  $I'$ , except those of  $g_1$  can be packed in the spaces occupied by the objects of  $I$ . To see this, we can just construct a mapping from  $g_i$  to  $g_{i-1}$ , and put object  $f(o)$  where  $o$  is put in  $I$ .

Now each group 1 object can be packed in a separate bin, so we are done.  $\square$

So all objects can be packed in  $\mathbf{OPT}' + g + \lceil \frac{k}{g} \rceil$  bins.

Here  $k$  is the number of distinct sizes obtained after throwing away all objects of size  $\leq \varepsilon$ . We will choose  $g = \lceil \varepsilon^2 k \rceil$ , i.e.,  $g \leq \varepsilon^2 k + 1$ .

So the solution we get is  $\leq \mathbf{OPT} + \varepsilon^2 k + 1 + \lceil \frac{1}{\varepsilon^2} \rceil \leq \mathbf{OPT} + \varepsilon^2 k + \frac{1}{\varepsilon^2} + 2$ .

We have  $\varepsilon \leq \frac{\mathbf{OPT}}{k}$  since we have at least  $k$  objects of size  $\varepsilon$ , so the total volume is  $\geq \varepsilon k$ , whence the total number of bins is at least  $\lceil \varepsilon k \rceil$ . Then this gets us an upper bound of  $(1 + \frac{1}{\varepsilon}) \mathbf{OPT} + \frac{1}{\varepsilon^2} + 2$ .

How to handle small objects of size  $\leq \varepsilon$ ?

1. Consider small objects in any order.
2. For each object, check if it can fit into one of the bins. If not, open a new bin.

Note that if I open a new bin, then each bin has objects of size at least  $1 - \varepsilon$ . Suppose we had  $r$  bins opened earlier, then the total size of objects is at least  $(1 - \varepsilon)r$ , which means that  $\mathbf{OPT} \geq (1 - \varepsilon)r$ .

This means that  $r \leq \frac{\mathbf{OPT}}{1 - \varepsilon}$ .

So number of bins in my solution is  $r + 1 \leq \frac{\mathbf{OPT}}{1 - \varepsilon} + 1 \leq \mathbf{OPT}(1 + \varepsilon) + 1$ . (fix this later on using  $\mathbf{OPT}'$ ).

Note that the running time is dictated by the time required by solving the LP.

Now we need to bound the time taken.

Let's look at how many configurations  $C = (o_1, \dots, o_k)$  are possible.  $k = 1/\varepsilon^2$  after removing stuff.

Each  $o_i$  is between 0 and  $\frac{1}{\varepsilon}$  (since bin size is 1 and each object has size  $\geq \varepsilon$ ).

So the number of configurations possible is  $\leq (1 + \frac{1}{\varepsilon})^{\frac{1}{\varepsilon^2}} \approx (\frac{1}{\varepsilon})^{\frac{1}{\varepsilon^2}}$  which is the number of variables.

Number of non-trivial constraints =  $\lceil k/g \rceil = 1/\varepsilon^2$ . So the time required to solve the LP is  $O((N + M)^3 + n) = O((1 + \frac{1}{\varepsilon})^{\frac{3}{\varepsilon^2}} + n)$  where  $n$  is the number of objects.

See prof's notes for linear programming.