

### Ex. 3.1:

#### New variant of Greedy:

Sort items s.t.  $U_1/s_1 \geq U_2/s_2 \geq \dots \geq U_n/s_n$

Choose  $k$  s.t.  $\sum_{i=1}^k s_i \leq B$ , but  $\sum_{i=1}^{k+1} s_i > B$

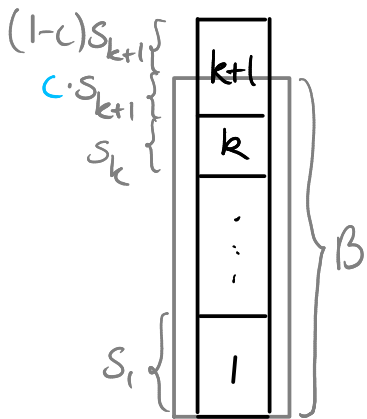
Choose  $i^*$  s.t.  $U_{i^*} = \max_{1 \leq i \leq n} U_i$

If  $\sum_{i=1}^k U_i > U_{i^*}$

Return  $\{1, \dots, k\}$

Else

Return  $\{i^*\}$



Since no solution has more value per size unit than the "solution" containing items  $1, \dots, k$  and a  $c$ -fraction of item  $k+1$ :

$$\text{OPT} \leq \sum_{i=1}^k U_i + c \cdot U_{k+1}$$

$$< \sum_{i=1}^k U_i + U_{k+1}, \text{ since } c < 1$$

$$\leq \sum_{i=1}^k U_i + U_{i^*}, \text{ since } U_{i^*} \geq U_{k+1}$$

$$\max \left\{ \sum_{i=1}^k U_i, U_{i^*} \right\} \geq \frac{1}{2} \left( \sum_{i=1}^k U_i + U_{i^*} \right)$$

$$\geq \frac{1}{2} \cdot \text{OPT}$$

## Section 3.3: Bin Packing

### Bin Packing

Input:  $n$  items with sizes between 0 and 1.

Objective: Pack items in bins of size 1, using as few bins as possible.

Last time we discussed simple approximation algorithms. Today we will develop an approximation scheme:

### $A_\epsilon(I)$

Split input  $I$  into

- $I_s$ : items smaller than  $\epsilon/2$  (small items)
- $I_\ell$ : remaining items (large items)

1. Pack large items:

a. Round up item sizes ( $I_\ell \rightarrow I'_\ell$ )

$\Rightarrow O(\frac{1}{\epsilon^2})$  different sizes

b. Do dyn. prg. on  $I'_\ell$

$\Rightarrow A_\epsilon(I'_\ell) = \text{OPT}(I'_\ell)$

2. Add small items to the packing using First-fit (or any other Any-fit alg.)

The rounding scheme (1.a.) will be described later.

## Adding small items to the packing (2.)

### Lemma 3.10

$$A_\varepsilon(I) \leq \max \left\{ A_\varepsilon(I_\varepsilon), \underbrace{\frac{2}{2-\varepsilon}}_{\leq 1+\varepsilon, \text{ for } \varepsilon \leq 1} \cdot \underbrace{\text{size}(I)}_{\leq \text{OPT}(I)} + 1 \right\}$$

Proof:

If no extra bin is needed for adding the small items,  $A_\varepsilon(I) = A_\varepsilon(I_\varepsilon)$ .

Otherwise, all bins, except possibly the last one, are filled to more than  $1 - \varepsilon/2$ .

In this case,

$$\begin{aligned} A_\varepsilon(I) &\leq \left\lceil \frac{\text{size}(I)}{1 - \varepsilon/2} \right\rceil < \frac{\text{size}(I)}{1 - \varepsilon/2} + 1 \\ &= \frac{2}{2-\varepsilon} \text{size}(I) + 1 \end{aligned}$$

□

Thus, we just need to ensure that  $A_\varepsilon(I_\varepsilon) \leq (1+\varepsilon) \text{OPT}$ .

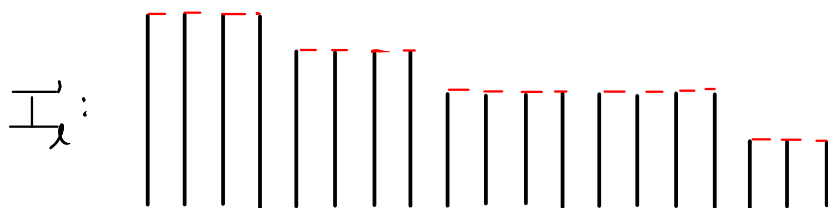
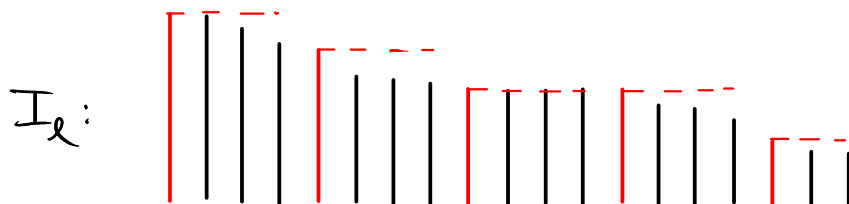
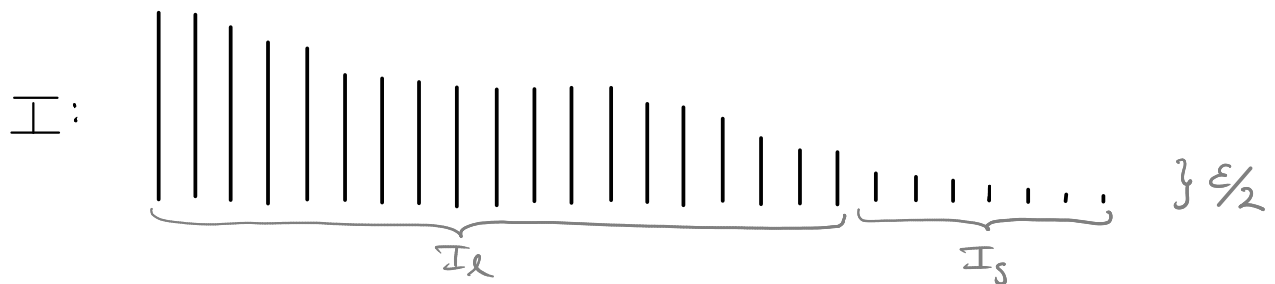
## Rounding scheme (1.a.)

Last time we saw that a rounding scheme similar to the one we used for Knapsack would at best yield an approx. factor of 1.5. Instead, we will use:

### Linear grouping:

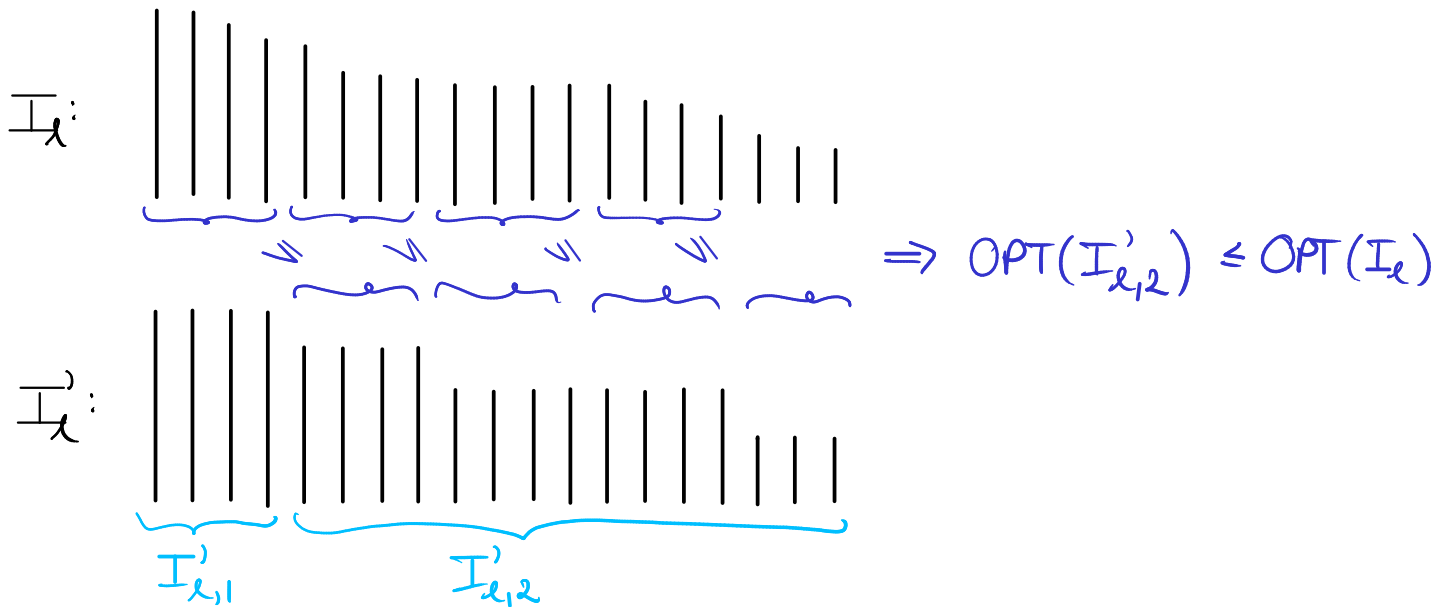
- Sort items in  $I_\epsilon$  by decreasing sizes.
  - Partition sorted  $I_\epsilon$  in groups of  $k$  consecutive items. ( $k$  will be determined later.)
  - For each group, round up item sizes to largest size in the group.
- The result is called  $I'_\epsilon$ .

Ex: ( $k=4$ )



# Approximation

Each item in the  $i$ 'th group of  $I_\ell$  is at least as large as any item in the  $(i+1)$ st group of  $I_\ell$ :



$$\text{OPT}(I'_\ell) \leq \underbrace{\text{OPT}(I'_{\ell,1})}_{\leq k} + \underbrace{\text{OPT}(I'_{\ell,2})}_{\leq \text{OPT}(I_\ell)}$$

since  $|I'_{\ell,1}| = k$

This proves:

Lemma 3.11:  $\text{OPT}(I'_\ell) \leq \text{OPT}(I_\ell) + k$

$= A_\ell(I'_\ell)$

Thus, letting  $k = \lfloor \varepsilon \cdot \text{size}(I) \rfloor \stackrel{(*)}{\leq} \varepsilon \cdot \text{OPT}(I)$   
 will ensure that

$$\begin{aligned}
 A_\varepsilon(I) &= A_\varepsilon(I_\ell) \\
 &= \text{OPT}(I_\ell) \\
 &\leq \text{OPT}(I_\ell) + k, \quad \text{by Lemma 3.11} \\
 &\leq \text{OPT}(I_\ell) + \varepsilon \cdot \text{OPT}(I), \quad \text{by } (*) \\
 &\leq (1+\varepsilon) \cdot \text{OPT}(I), \quad \text{since } I_\ell \subseteq I
 \end{aligned}$$

Now, by Lemma 3.10,

$$\begin{aligned}
 A_\varepsilon(I) &\leq \max \left\{ \underbrace{A_\varepsilon(I_\ell)}_{\leq (1+\varepsilon)\text{OPT}(I)}, \underbrace{\frac{2}{2-\varepsilon} \cdot \text{size}(I) + 1}_{\leq (1+\varepsilon)\text{OPT} + 1} \right\} \\
 &\leq (1+\varepsilon)\text{OPT}(I), \quad \leq (1+\varepsilon)\text{OPT} + 1 ;
 \end{aligned}$$

as just  
shown

$$\frac{2}{2-\varepsilon} \leq 1+\varepsilon \Leftrightarrow$$

$$2 \leq (1+\varepsilon)(2-\varepsilon) \Leftrightarrow$$

$$2 \leq 2 + \varepsilon - \varepsilon^2 \Leftrightarrow$$

$$\varepsilon \leq 1$$

Thus,  $A_\varepsilon(I) \leq (1+\varepsilon) \cdot \text{OPT}(I) + 1$

asymptotic approximation scheme

## Packing $I'_\epsilon$ using dynamic programming (l.b.)

At most  $2/\epsilon$  items fit into one bin,  
since all items in  $I'_\epsilon$  have size at least  $\epsilon/2$ .

There are  $N \leq \lceil n/k \rceil$  different sizes  $s_1, \dots, s_N$  in  $I'_\epsilon$ .

Hence, any packing of a bin can be represented by a vector  $(m_1, \dots, m_N)$ , where  $m_i$ ,  $1 \leq i \leq N$ , is the # items of size  $s_i$  in the bin and  $0 \leq m_i \leq 2/\epsilon$ . A vector representing the contents of a bin is called a **configuration**.

Let  $\mathcal{B}$  denote the set of possible bin configurations.

Note that  $|\mathcal{B}| < (\frac{2}{\epsilon})^N$

Let  $n_i$  be the # items of size  $s_i$  in  $I'_\epsilon$

For the dyn. prg. we use an  $N$ -dimensional table  $B$  with  $n_i+1$  rows in the  $i$ 'th dimension.

$B[m_1, \dots, m_N]$  will be the minimum #bins required to pack  $m_i$  items of size  $s_i$ ,  $1 \leq i \leq N$ .

Ex:

$$I = \langle 0.6, 0.5, 0.5, 0.4, 0.4, 0.4, 0.3, \underbrace{0.1, 0.1}_{< \epsilon/2} \rangle$$

$$\epsilon = 0.4, \quad k = 4$$

$$I_\lambda = \langle 0.6, 0.5, 0.5, 0.4, 0.4, 0.4, 0.3 \rangle$$

$$I'_\lambda = \langle 0.6, 0.6, 0.6, 0.6, 0.4, 0.4, 0.4 \rangle$$

$$s_1 = 0.6$$

$$s_2 = 0.4$$

$$n_1 = 4$$

$$n_2 = 3$$

$$\mathcal{C} = \{ (0,1), (0,2), (1,0), (1,1) \}$$

0.4 / 0.6	0	1	2	3
0	0	1		
1	1	1		
2	2	2	$\rightarrow \leq 3$	$\rightarrow \leq 3$
3	3	$\downarrow \leq 3$	$\downarrow \leq 3$	
4	4			

0.4 / 0.6	0	1	2	3
0	0	1	1	
1	1	1	2	
2	2	2	2	
3	3	3	3	
4	4	4		

0.4 / 0.6	0	1	2	3
0	0	1	1	2
1	1	1	2	3
2	2	2	2	3
3	3	3	3	3
4	4	4	4	4

$$B[4,3] = 1 + \min_{(m_1, m_2) \in \mathcal{C}} \{ B[4-m_1, 3-m_2] \}$$

$$= 1 + \min \{ \underset{\leftarrow}{B[4,2]}, \underset{\leftarrow}{B[4,1]}, \underset{\uparrow}{B[3,3]}, \underset{\nwarrow}{B[3,2]} \}$$

$$= 1 + B[3,2] = 4$$

In general:

$$B[m_1, \dots, m_N] = 1 + \min_{(c_1, \dots, c_N) \in \mathcal{C}} \{ m_1 - c_1, \dots, m_N - c_N \}$$



0.4	0	1	2	3
0.6	0	1	2	3
0	0	1	1	2
1	1	1	2	3
2	2	2	2	3
3	3	3	3	3
4	4	4	4	4

0.4	0	1	2	3
0.6	0	1	2	3
0	0	1	1	2
1	1	1	2	3
2	2	2	2	3
3	3	3	3	3
4	4	4	4	4

$I_e'$

0.4	0.4	0.4	
0.6	0.6	0.6	0.6

0.4	0.4		0.4
0.6	0.6	0.6	0.6

$I_e$

0.4	0.4	0.3	
0.6	0.5	0.5	0.4

$I$

0.4	0.4	0.3	
0.6	0.5	0.5	0.4

# Running time

Let  $n_\ell = |I_\ell|$ . Then,

$$\text{size}(I) \geq \text{size}(I_\ell) \geq n_\ell \cdot \frac{\epsilon}{2}, \quad (*)$$

since  $I_\ell$  contains only large items.

Thus,

$$k = \lfloor \epsilon \cdot \text{size}(I) \rfloor \geq \lfloor n_\ell \cdot \frac{\epsilon^2}{2} \rfloor \geq n_\ell \cdot \frac{\epsilon^2}{4} \quad (**)$$

Hence,

$$N \leq \left\lceil \frac{n_\ell}{k} \right\rceil \leq \left\lceil \frac{4}{\epsilon^2} \right\rceil \quad (***)$$

by (\*)

by (\*\*)

$$\text{Table size} \leq n_\ell^N \leq n^N$$

$$\text{Time per entry } O(|\mathcal{B}|) \leq O\left(\left(\frac{2}{\epsilon}\right)^N\right)$$

$$\text{Running time } O\left(n^N \cdot \left(\frac{2}{\epsilon}\right)^N\right) = O\left(\left(\frac{2n}{\epsilon}\right)^N\right) \leq O\left(\left(\frac{2n}{\epsilon}\right)^{\left\lceil \frac{4}{\epsilon^2} \right\rceil}\right)$$

not fully  
poly. time

by (\*\*\*)

Hence,  $\{A_\epsilon\}$  is an

Asymptotic Poly. Time Approx. Scheme (APTAS)

This proves:

Thm 3.12: There is an APTAS for Bin Packing

There is no PTAS for Bin Packing:

### Theorem 3.8

No alg. for Bin Packing has an absolute approx. ratio better than  $\frac{3}{2}$ , unless  $P=NP$

Proof:

Reduction from Partition Problem:

Given a set  $S$  of integers,  
can  $S$  be partitioned into two sets  $S_1$  and  $S_2$ ,  
such that  $\sum_{s \in S_1} s = \sum_{s \in S_2} s$ ?

For a given instance  $S$  of the partition problem, let  
 $B = \sum_{s \in S} s$  and  $I = \{s \cdot \frac{2}{B} \mid s \in S\}$ .

Then,  $\sum_{i \in I} i = B \cdot \frac{2}{B} = 2$

If we use  $I$  as input for the bin packing problem,

- at least 2 bins are needed, and
- 2 bins suffice, iff  $S$  is a yes-instance for the partition problem.

If we had a bin packing alg. with an approx. factor  $< \frac{3}{2}$ , it would always use only 2 bins, whenever 2 bins suffice

Thus, the alg. could be used to decide any instance of the partition problem.

□