- Suppose we have an instance with polynomially bounded processing times  $p_i \le q(n)$
- We set  $k := \lceil 2na(n) \rceil \ge 2 \text{ OPT}$
- Then

$$ALG \le \left(1 + \frac{1}{k}\right) OPT \le OPT + \frac{1}{2}$$

- ▶ But this means that the algorithm computes the optimal solution as the optimum is integral.
- ▶ This means we can solve problem instances if processing times are polynomially bounded
- ▶ Running time is  $\mathcal{O}(\text{poly}(n,k)) = \mathcal{O}(\text{poly}(n))$
- ▶ For strongly NP-complete problems this is not possible unless P=NP



17.2 Scheduling Revisited

357

# **Bin Packing**

Given n items with sizes  $s_1, \ldots, s_n$  where

$$1 > s_1 \ge \cdots \ge s_n > 0$$
.

Pack items into a minimum number of bins where each bin can hold items of total size at most 1.

### Theorem 5

There is no  $\rho$ -approximation for Bin Packing with  $\rho < 3/2$  unless P = NP.

### **More General**

Let  $OPT(n_1, ..., n_A)$  be the number of machines that are required to schedule input vector  $(n_1, \ldots, n_A)$  with Makespan at most T (A: number of different sizes).

If  $OPT(n_1, ..., n_A) \leq m$  we can schedule the input.

 $OPT(n_1,\ldots,n_A)$ 

$$= \begin{cases} 0 & (n_1, \dots, n_A) = 0 \\ 1 + \min_{(s_1, \dots, s_A) \in C} \mathrm{OPT}(n_1 - s_1, \dots, n_A - s_A) & (n_1, \dots, n_A) \geq 0 \\ \infty & \mathrm{otw.} \end{cases}$$

where C is the set of all configurations.

 $|C| \leq (B+1)^A$ , where B is the number of jobs that possibly can fit on the same machine.

The running time is then  $O((B+1)^A n^A)$  because the dynamic programming table has just  $n^A$  entries.

# **Bin Packing**

#### Proof

In the partition problem we are given positive integers  $b_1, \dots, b_n$  with  $B = \sum_i b_i$  even. Can we partition the integers into two sets S and T s.t.

$$\sum_{i \in S} b_i = \sum_{i \in T} b_i ?$$

- We can solve this problem by setting  $s_i := 2b_i/B$  and asking whether we can pack the resulting items into 2 bins or not.
- A  $\rho$ -approximation algorithm with  $\rho < 3/2$  cannot output 3 or more bins when 2 are optimal.
- ▶ Hence, such an algorithm can solve Partition.

EADS II

359

## **Bin Packing**

### **Definition 6**

An asymptotic polynomial-time approximation scheme (APTAS) is a family of algorithms  $\{A_{\epsilon}\}$  along with a constant c such that  $A_{\epsilon}$  returns a solution of value at most  $(1+\epsilon)OPT + c$  for minimization problems.

- ▶ Note that for Set Cover or for Knapsack it makes no sense to differentiate between the notion of a PTAS or an APTAS because of scaling.
- ▶ However, we will develop an APTAS for Bin Packing.

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361

Choose  $\gamma = \epsilon/2$ . Then we either use  $\ell$  bins or at most

$$\frac{1}{1 - \epsilon/2} \cdot \text{OPT} + 1 \le (1 + \epsilon) \cdot \text{OPT} + 1$$

bins.

It remains to find an algorithm for the large items.

# **Bin Packing**

Again we can differentiate between small and large items.

#### Lemma 7

Any packing of items into  $\ell$  bins can be extended with items of size at most y s.t. we use only  $\max\{\ell, \frac{1}{1-\gamma} SIZE(I) + 1\}$  bins, where  $SIZE(I) = \sum_{i} s_{i}$  is the sum of all item sizes.

- If after Greedy we use more than  $\ell$  bins, all bins (apart from the last) must be full to at least  $1 - \gamma$ .
- ▶ Hence,  $r(1 \gamma) \leq SIZE(I)$  where  $\gamma$  is the number of nearly-full bins.
- ► This gives the lemma.

17.3 Bin Packing

362

# **Bin Packing**

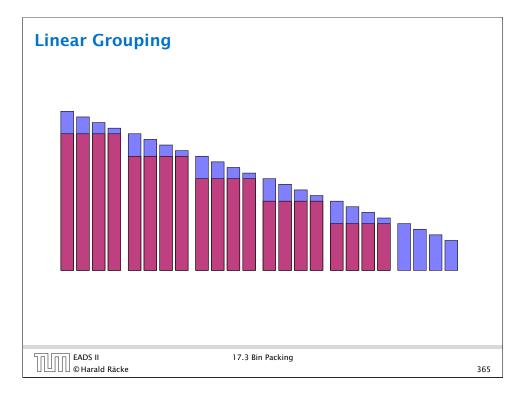
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### **Linear Grouping:**

Generate an instance I' (for large items) as follows.

- Order large items according to size.
- Let the first k items belong to group 1; the following k items belong to group 2; etc.
- Delete items in the first group;
- ▶ Round items in the remaining groups to the size of the largest item in the group.



### Lemma 9

 $OPT(I') \le OPT(I) \le OPT(I') + k$ 

### Proof 2:

- ightharpoonup Any bin packing for I' gives a bin packing for I as follows.
- ▶ Pack the items of group 1 into *k* new bins;
- ▶ Pack the items of groups 2, where in the packing for *I'* the items for group 2 have been packed;
- ▶ ...

### Lemma 8

 $OPT(I') \le OPT(I) \le OPT(I') + k$ 

#### Proof 1:

- ightharpoonup Any bin packing for I gives a bin packing for I' as follows.
- ▶ Pack the items of group 2, where in the packing for *I* the items for group 1 have been packed;
- ▶ Pack the items of groups 3, where in the packing for *I* the items for group 2 have been packed;
- ...

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17.3 Bin Packing

366

Assume that our instance does not contain pieces smaller than  $\epsilon/2$ . Then  ${\rm SIZE}(I) \ge \epsilon n/2$ .

We set  $k = \lfloor \epsilon \text{SIZE}(I) \rfloor$ .

Then  $n/k \le n/\lfloor \epsilon^2 n/2 \rfloor \le 4/\epsilon^2$  (here we used  $\lfloor \alpha \rfloor \ge \alpha/2$  for  $\alpha \ge 1$ ).

Hence, after grouping we have a constant number of piece sizes  $(4/\epsilon^2)$  and at most a constant number  $(2/\epsilon)$  can fit into any bin.

We can find an optimal packing for such instances by the previous Dynamic Programming approach.

cost (for large items) at most

$$OPT(I') + k \le OPT(I) + \epsilon SIZE(I) \le (1 + \epsilon)OPT(I)$$

running time  $\mathcal{O}((\frac{2}{\epsilon}n)^{4/\epsilon^2})$ .