### Outline

Single Machine Models

#### DMP204 SCHEDULING, TIMETABLING AND ROUTING

Lecture 11 Single Machine Models, Branch and Bound

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1. Single Machine Models Branch and Bound  $1 | s_{jk} | C_{max}$ 

### Outline

Single Machine Models Branch and Bound  $1 | s_{ik} | C_{max}$ 

 $C_{max}$  1

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 $1 \mid r_j \mid L_{max}$ 

[Maximum lateness with release dates]

- Strongly NP-hard (reduction from 3-partition)
- might have optimal schedule which is not non-delay
- Branch and bound algorithm (valid also for  $1 | r_j, prec | L_{max}$ )
  - Branching:

schedule from the beginning (level k, n!/(k-1)! nodes) elimination criterion: do not consider job  $j_k$  if:

 $r_j > \min_{l \in J} \left\{ \max \left( t, r_l 
ight) + p_l 
ight\}$  J jobs to schedule, t current time

• Lower bounding: relaxation to preemptive case for which EDD is optimal

## 1. Single Machine Models

Branch and Bound  $1 | s_{jk} | C_{max}$ 

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Branch and Bound

 $1 \mid s_{jk} \mid C_{max}$ 

### Branch and Bound

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 $1 \mid s_{jk} \mid C_{max}$ 

Single Machine Models

#### Branch and Bound

S root of the branching tree

1 LIST :=  $\{S\};$ 

- U:=value of some heuristic solution; 2
- 3 current best := heuristic solution;
- while  $LIST \neq \emptyset$ 4
- 5 Choose a branching node k from LIST;
- Remove *k* from LIST; 6
- 7 Generate children child(i),  $i = 1, ..., n_k$ , and calculate corresponding lower bounds  $LB_i$ ;
- 8 for i = 1 to  $n_k$
- 9 if  $LB_i < U$  then
- if child(i) consists of a single solution then 10
- 11  $U := LB_i$ :
- current best:=solution corresponding to child(i)12
- else add  $\overline{child}(i)$  to LIST 13

[Jens Clausen (1999). Branch and Bound Algorithms - Principles and Examples.]

- Eager Strategy:
  - 1. select a node
  - 2. branch
  - 3. for each subproblem compute bounds and compare with incumbent solution
  - 4. discard or store nodes together with their bounds

(Bounds are calculated as soon as nodes are available)

- Lazy Strategy:
  - 1. select a node
  - 2. compute bound
  - 3. branch
  - 4. store the new nodes together with the bound of the processed node

(often used when selection criterion for next node is max depth)

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- Components
  - Initial feasible solution (heuristic) might be crucial!
- 1. Bounding function
- 2. Strategy for selecting
- 3. Branching
- Fathmoing (dominance test)

#### Bounding

$$\min_{s \in P} g(s) \le \left\{ \begin{array}{c} \min_{s \in P} f(s) \\ \min_{s \in S} g(s) \end{array} \right\} \le \min_{s \in S} f(s)$$

- *P*: candidate solutions;  $S \subseteq P$  feasible solutions
  - relaxation:  $\min_{s \in P} f(s)$
  - solve (to optimality) in P but with g
  - Lagrangian relaxation combines the two
  - should be polytime and strong (trade off)

Branch and Bound

#### Strategy for selecting next subproblem

best first

(combined with eager strategy but also with lazy)

- breadth first (memory problems)
- depth first

works on recursive updates (hence good for memory) but might compute a large part of the tree which is far from optimal (enhanced by alternating search in lowest and largest bounds combined with branching on the node with the largest difference in bound between the children) (it seems to perform best)

#### Branching

- dichotomic
- polytomic

#### Overall guidelines

- finding good initial solutions is important
- if initial solution is close to optimum then the selection strategy makes little difference
- Parallel B&B: distributed control or a combination are better than centralized control
- parallelization might be used also to compute bounds if few nodes alive
- parallelization with static work load distribution is appealing with large search trees

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Branch and bound vs backtracking

- = a state space tree is used to solve a problem.
- $\neq$  branch and bound does not limit us to any particular way of traversing the tree (backtracking is depth-first)
- $\neq\,$  branch and bound is used only for optimization problems.

Branch and bound  $vs A^*$ 

- $= \mbox{ In } A^* \mbox{ the admissible heuristic mimics bounding}$
- $\neq\,$  In A\* there is no branching. It is a search algorithm.

 $\neq$  A\* is best first

# $1 \mid \sum w_j T_j$

- Branching:
  - work backward in time
  - elimination criterion: if  $p_j \le p_k$  and  $d_j \le d_k$  and  $w_j \ge w_k$  then there is an optimal schedule with j before k

#### • Lower Bounding:

relaxation to preemptive case transportation problem

$$\begin{split} \min \sum_{j=1}^{n} \sum_{t=1}^{C_{max}} c_{jt} x_{jt} \\ \text{s.t.} \sum_{t=1}^{C_{max}} x_{jt} = p_j, \qquad \forall j = 1, \dots, n \\ \sum_{j=1}^{n} x_{jt} \leq 1, \qquad \forall t = 1, \dots, C_{max} \\ x_{jt} \geq 0 \qquad \forall j = 1, \dots, n; \ t = 1, \dots, C_{max} \end{split}$$

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Branch and Bound

 $|s_{jk}|C_{max}$ 

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 $[{\sf Pan} \mbox{ and Shi},\ 2007]\s lower bounding through time indexed Stronger but computationally more expensive$ 

$$\begin{split} \min \sum_{j=1}^{n} \sum_{t=1}^{T-1} c_{jt} y_{jt} \\ \text{s.t.} \\ \sum_{t=1}^{T-p_j} c_{jt} \le h_j (t+p_j) \\ \sum_{t=1}^{T-p_j} y_{jt} = 1, \qquad \forall j = 1, \dots, n \\ \sum_{j=1}^{n} \sum_{s=t-p_j+1}^{t} y_{jt} \le 1, \qquad \forall t = 1, \dots, C_{max} \\ y_{jt} \ge 0 \qquad \forall j = 1, \dots, n; \ t = 1, \dots, C_{max} \end{split}$$

## $1 \mid s_{jk} \mid C_{max}$

[Makespan with sequence-dependent setup times]

- general case is NP-hard (traveling salesman reduction).
- special case:

parameters for job j:

- $a_j$  initial state
- $b_j$  final state

such that:

$$s_{jk} \propto |a_k - b_j|$$

[Gilmore and Gomory, 1964] give an  $O(n^2)$  algorithm

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Single Machine Models Branch and Bound  $1 | s_{jk} | C_{max}$ 

- assume  $b_0 \leq b_1 \leq \ldots \leq b_n$  (k > j and  $b_k \geq b_j$ )
- one-to-one correspondence with solution of TSP with n + 1 cities city 0 has  $a_0, b_0$  start at  $b_0$  finish at  $a_0$
- tour representation  $\phi : \{0, 1, \dots, n\} \mapsto \{0, 1, \dots, n\}$ (permutation map, single linked array)
- Hence,

min 
$$c(\phi) = \sum_{i=1}^{n} c_{i,\phi(i)}$$
 (1)

$$\phi(S) \neq S \qquad \forall S \subset V \tag{2}$$

• find  $\phi^*$  by ignoring (2)

make  $\phi^*$  a tour by interchanges chosen solving a min spanning tree and applied in a certain order

• Interchange  $\delta^{jk}$ 

$$\delta^{jk}(\phi) = \{\phi' \mid \phi'(j) = \phi(k), \quad \phi(k) = \phi(j), \quad \phi'(l) = \phi(l), \quad \forall l \neq j, k\}$$

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Cost

$$\begin{aligned} c_{\phi}(\delta^{jk}) &= c(\delta^{jk}(\phi)) - c(\phi) \\ &= \| \left[ b_j, b_k \right] \cap \left[ a_{\phi(j)}, a_{\phi(k)} \right] \| \end{aligned}$$

• Theorem: Let  $\phi^*$  be a permutation that ranks the a that is k > j implies  $a_{\phi(k)} \ge a_{\phi(j)}$  then

$$c(\phi^*) = \min_{\phi} c(\phi).$$

• Lemma: If  $\phi$  is a permutation consisting of cycles  $C_1, \ldots, C_p$  and  $\delta^{jk}$  is an interchange with  $j \in C_r$  and  $k \in C_s$ ,  $r \neq s$ , then  $\delta^{jk}(\phi)$  contains the same cycles except that  $C_r$  and  $C_s$  have been replaced by a single cycle containing all their nodes.

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Branch and Bound

 $1 \mid s_{jk} \mid C_{max}$ 

• **Theorem:** Let  $\delta^{j_1k_1}, \delta^{j_2k_2}, \ldots, \delta^{j_pk_p}$  be the interchanges corresponding to the arcs of a spanning tree of  $G_{\phi^*}$ . The arcs may be taken in any order. Then  $\phi'$ ,

$$\phi' = \delta^{j_1 k_1} \circ \delta^{j_2 k_2} \circ \ldots \circ \delta^{j_p k_p} (\phi^*$$

is a tour.

- The p-1 interchanges can be found by greedy algorithm (similarity to Kruskal for min spanning tree)
- Lemma: There is a minimum spanning tree in  $G_{\phi^*}$  that contains only arcs  $\delta^{j,j+1}$ .

Step 1: Arrange  $b_i$  in order of size and renumber jobs so that

Step 3: Define  $\phi$  by  $\phi(j) = k$  where k is the j + 1-smallest of the

Step 4: Compute the interchange costs  $c_{\delta j,j+1}$ ,  $j = 0, \ldots, n-1$ 

Step 5: While G has not one single component, Add to  $G_{\phi}$  the arc

Step 6: Divide the arcs selected in Step 5 in Type I and II.

Apply the relative interchanges in the order.

 $c_{\delta j,j+1} = \| [b_j, b_{j+1}] \cap [a_{\phi(j)}, a_{\phi(j)}] \|$ 

of minimum cost  $c(\delta^{j,j+1})$  such that j and j+1 are in

Sort Type I in decreasing and Type II increasing order of

• Generally,  $c(\phi') \neq c(\delta^{j_1k_1}) + c(\delta^{j_2k_2}) + \ldots + c(\delta^{j_pk_p}).$ 

Resuming the final algorithm [Gilmore and Gomory, 1964]:

 $b_i \leq b_{i+1}, \ j = 1, \dots, n.$ 

two different components

Step 2: Arrange  $a_i$  in order of size.

 $a_i$ .

index.

node j in  $\phi$  is of  $\begin{cases}
\mathsf{Type I}, & \text{if } b_j \leq a_{\phi(j)} \\
\mathsf{Type II}, & \text{otherwise}
\end{cases}$ interchange jk is of  $\begin{cases}
\mathsf{Type I}, & \text{if lower node of type I} \\
\mathsf{Type II}, & \text{if lower node of type II}
\end{cases}$ 

• Order: interchanges in Type I in decreasing order interchanges in Type II in increasing order

- Apply to  $\phi^*$  interchanges of Type I and Type II in that order.
- **Theorem:** The tour found is a minimal cost tour.

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Summary

Single Machine Models

- $1 \mid \sum w_i C_i$ : weighted shortest processing time first is optimal
- $1 \mid \sum_{j} U_{j}$  : Moore's algorithm
- $1 \mid prec \mid L_{max}$  : Lawler's algorithm, backward dynamic programming in  $O(n^2)$  [Lawler, 1973]
- $1 \mid \sum h_j(C_j)$  : dynamic programming in  $O(2^n)$
- $1 \mid \sum w_j T_j$  : local search and dynasearch
- $1 \mid r_j, (prec) \mid L_{max}$  : branch and bound
- $1 \mid s_{jk} \mid C_{max} \,$  : in the special case, Gilmore and Gomory algorithm optimal in  $O(n^2)$
- $1 \mid \sum w_j T_j$  : column generation approaches
  - Multiobjective: Multicriteria Optimization

Branch and Bound

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## Complexity resume

Single machine, single criterion problems  $1 \mid \mid \gamma$ :

 $\begin{array}{lll} C_{max} & \mathcal{P} \\ T_{max} & \mathcal{P} \\ L_{max} & \mathcal{P} \\ h_{max} & \mathcal{P} \\ \sum C_j & \mathcal{P} \\ \sum W_j C_j & \mathcal{P} \\ \sum U & \mathcal{P} \\ \sum W_j U_j & \text{weakly $\mathcal{NP}$-hard} \\ \sum T & \text{weakly $\mathcal{NP}$-hard} \\ \sum W_j T_j & \text{strongly $\mathcal{NP}$-hard} \\ \sum h_j(C_j) & \text{strongly $\mathcal{NP}$-hard} \end{array}$ 

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