COMP251: Dynamic programming (1)

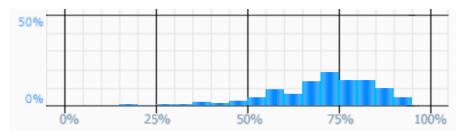
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Based on (Cormen et al., 2002) & (Kleinberg & Tardos, 2005)

Announces

Midterm:

Mean 70%, Median 72%, Best 94%.



Available for review (with solution) during my office hours.

Office hours:

Today: Moved to 3pm to 4pm.

Assignment 3:

- Deadline postponed to March 22.
- Assignment 4 will be released on Monday.

Algorithms paradigms

Greedy:

- Build up a solution incrementally.
- Iteratively decompose and reduce the size of the problem.
- Top-down approach.

Dynamic programming:

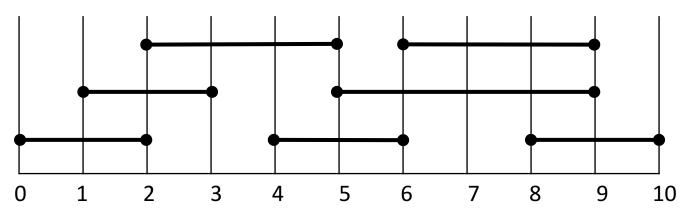
- Solve all possible sub-problems.
- Assemble them to build up solutions to larger problems.
- Bottom-up approach.

INTRODUCTION

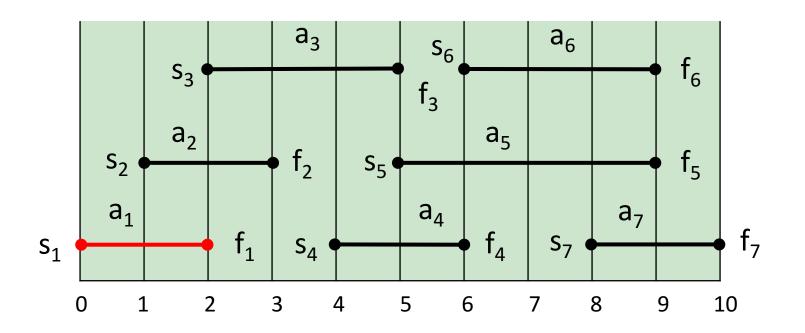
- Input: Set S of n activities, a_1 , a_2 , ..., a_n .
 - $-s_i$ = start time of activity *i*.
 - $-f_i$ = finish time of activity *i*.
- Output: Subset A of maximum number of compatible activities.
 - 2 activities are compatible, if their intervals do not overlap.

Example:

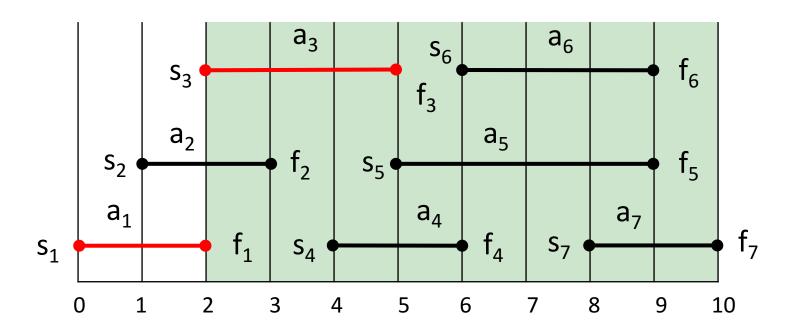
Activities in each line are compatible.



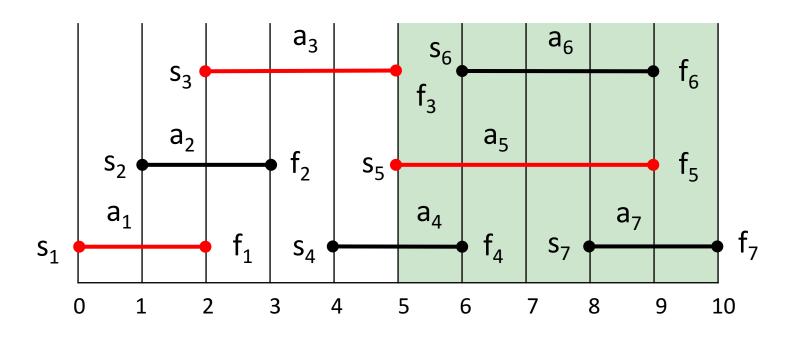
i	1	2	3	4	5	6	7
S _i	0	1	2	4	5	6	8
f_i	2	3	5	6	9	9	10



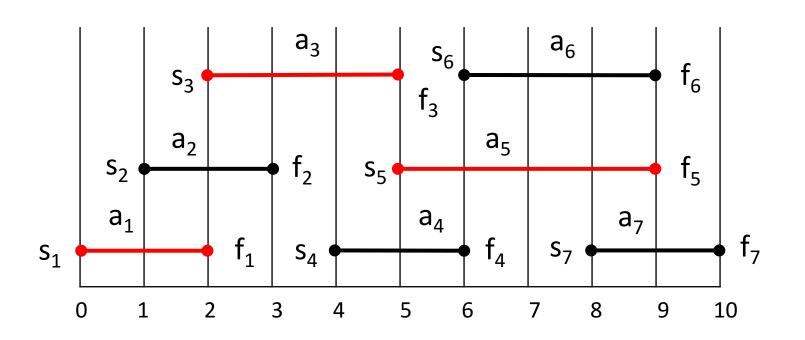
							7
				4			
f_i	2	3	5	6	9	9	10



							7
S _i	0	1	2	4	5	6	8
f_i	2	3	5	6	9	9	10



				4			
S _i	0	1	2	4	5	6	8
f_i	2	3	5	6	9	9	10



Optimal sub-structure

• Let S_{ij} = subset of activities in S that start after a_i finishes and finish before a_i starts.

$$S_{ij} = \left\{ a_k \in S : \forall i, j \quad f_i \le s_k < f_k \le s_j \right\}$$

- A_{ij} = optimal solution to S_{ij}
- $A_{ij} = A_{ik} U \{ a_k \} U A_{kj}$

Greedy choice

We can solve the problem S_{ii} top-down:

- Consider all $a_m \in S_{ij}$
- Solve S_{im} and S_{mj}
- Pick the best m such that A_{im} = A_{im} U { a_k } U A_{im}

Greedy choice

Theorem:

Let $S_{ij} \neq \emptyset$, and let a_m be the activity in S_{ij} with the earliest finish time: $f_m = \min\{f_k : a_k \subseteq S_{ii}\}$. Then:

- 1. a_m is used in some maximum-size subset of mutually compatible activities of S_{ii} .
- 2. $S_{im} = \emptyset$, so that choosing a_m leaves S_{mj} as the only nonempty subproblem.

Greedy choice

subproblems in optimal solution
choices to consider

Before theorem

2
1
1
1
1

 $A_{ii} = A_{ik} U \{ a_k \} U A_{ki}$

 $A_{ii} = \{ a_m \} U A_{mi}$

We can now solve the problem S_{ij} top-down:

- Choose $a_m \subseteq S_{ii}$ with the earliest finish time (greedy choice).
- Solve S_{mi} .

Challenges

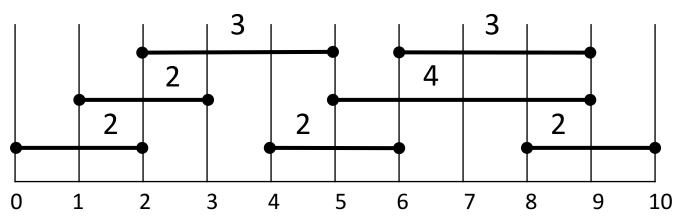
- Greedy choice is not always available.
- How to solve problem that have optimal substructures?

WEIGHTED INTERVAL SCHEDULING

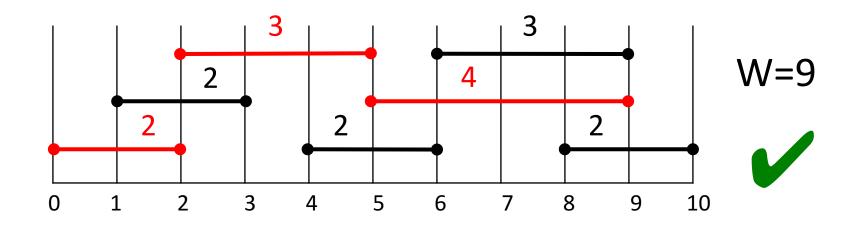
Weighted interval scheduling

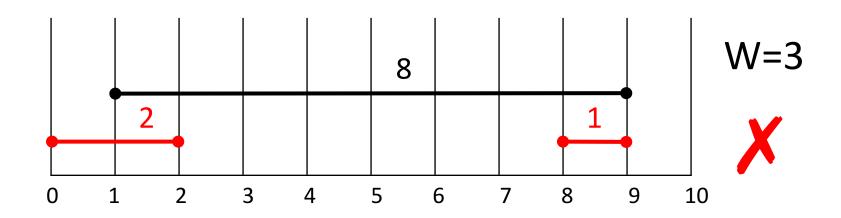
- Input: Set S of n activities, a₁, a₂, ..., a_n.
 - $-s_i$ = start time of activity *i*.
 - $-f_i$ = finish time of activity *i*.
 - w_i= weight of activity i
- Output: find maximum weight subset of mutually compatible activities.
 - 2 activities are compatible, if their intervals do not overlap.

Example:



Application of the greedy algorithm





Discussion

Optimal substructure:

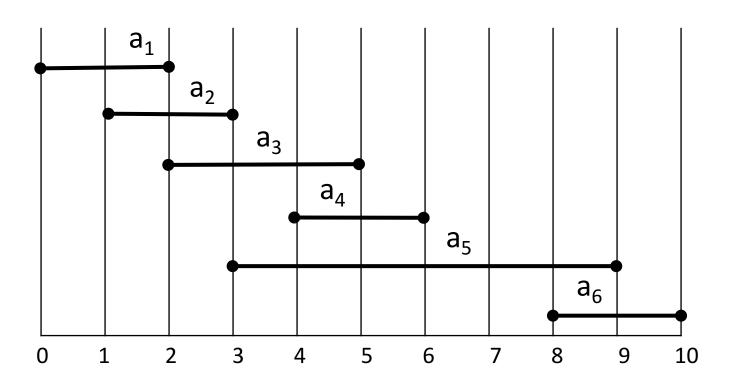
- A_{ij} = optimal solution to S_{ij}
- $A_{ij} = A_{ik} \cup \{a_k\} \cup A_{kj}$
- Greedy Choice: X
 - Select the activity with earliest finish time.

Data structure

Notation: All activities are sorted by finishing time $f_1 \le f_2 \le ... \le f_n$

Definition: p(j) = largest index i < j such that activity/job i is compatible with activity/job j.

Examples: p(6)=4, p(5)=2, p(4)=2, p(2)=0.



Binary Choice

Notation: OPT(j) = value of the optimal solution to the problem = max total weight of compatible activities 1 ... j

Case 1: OPT selects activity j

- Add weight w_i
- Cannot use incompatible activities
- Must include optimal solution on remaining compatible activities { 1, 2, ..., p(j) }.

Case 2: OPT does not select activity j

Must include optimal solution on others activities { 1, 2, ..., j-1 }.

Optimal substructure property

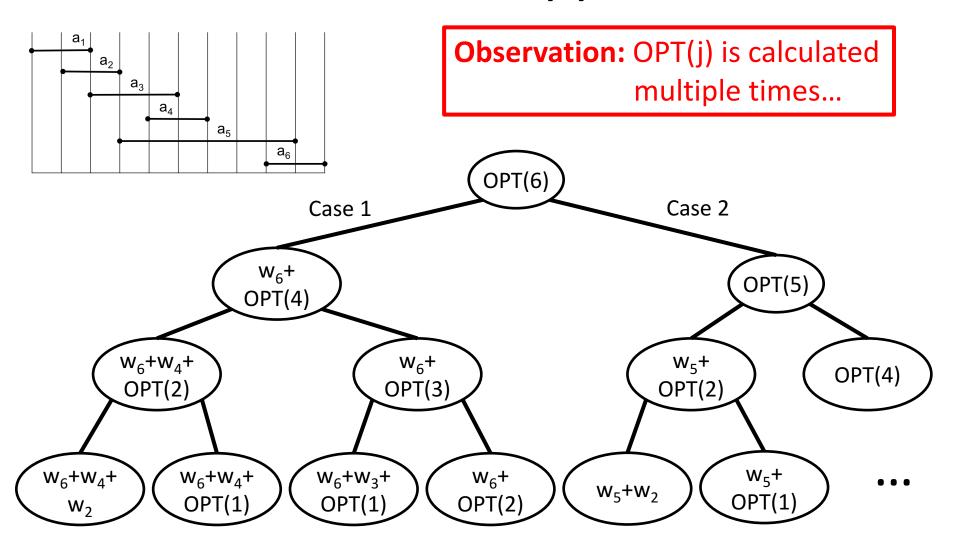
$$OPT(j) = \begin{cases} 0 & if j = 0\\ max\{w_j + OPT(p(j)), OPT(j-1)\} & Otherwise \end{cases}$$

Recursive call

```
Input: n, s[1..n], f[1..n], v[1..n]
Sort jobs by finish time so that f[1] ≤ f[2] ≤ ... ≤ f[n].
Compute p[1], p[2], ..., p[n].

Compute-Opt(j)
if j = 0
   return 0.
else
   return max(v[j] + Compute-Opt(p[j]), Compute-Opt(j-1)).
```

Brute Force Approach



Memoization

Memoization: Cache results of each subproblem; lookup as needed.

```
Input: n, s[1..n], f[1..n], v[1..n]
Sort jobs by finish time so that f[1] \le f[2] \le ... \le f[n].
Compute p[1], p[2], ..., p[n].
for j = 1 to n
   M[j] \leftarrow empty.
M[0] \leftarrow 0.
M-Compute-Opt(j)
if M[j] is empty
   M[j] \leftarrow \max(v[j]+M-Compute-Opt(p[j]),
                 M-Compute-Opt(j-1).
return M[j].
```

Running time

Claim. Memoized version of algorithm takes $O(n \log n)$ time.

- Sort by finish time: $O(n \log n)$.
- Computing $p(\cdot)$: $O(n \log n)$ via sorting by start time.
- M-COMPUTE-OPT(j): each invocation takes O(1) time and either
 - (i) returns an existing value M[j]
 - (ii) fills in one new entry M[j] and makes two recursive calls
- Progress measure $\Phi = \#$ nonempty entries of M[].
 - initially $\Phi = 0$, throughout $\Phi \leq n$.
 - (ii) increases Φ by $1 \Rightarrow$ at most 2n recursive calls.
- Overall running time of M-Compute-Opt(n) is O(n).

Remark. O(n) if jobs are presorted by start and finish times.

DYNAMIC PROGRAMMING

Bottom-up

Observation: When we compute M[j], we only need values M[k] for k < j.

```
BOTTOM-UP (n; s1, ..., sn; f1, ..., fn; v1, ..., vn)

Sort jobs by finish time so that f1 \le f2 \le ... \le fn.

Compute p(1), p(2), ..., p(n).

M[0] \leftarrow 0

for j = 1 TO n

M[j] \leftarrow \max \{ vj + M[p(j)], M[j-1] \}
```

Main Idea of Dynamic Programming: Solve the sub-problems in an order that makes sure when you need an answer, it's already been computed.

Finding a solution

Dyn. Prog. algorithm computes optimal value.

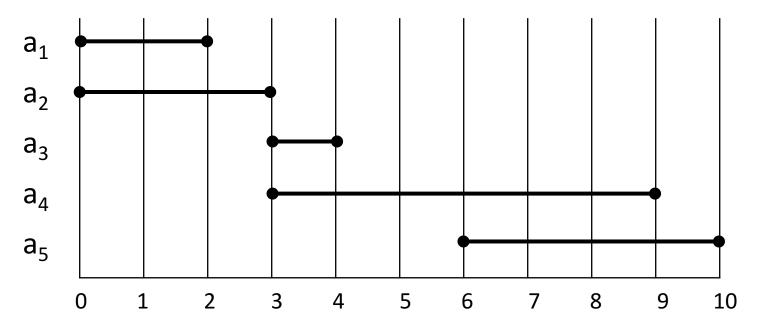
Q: How to find solution itself?

A: Bactrack!

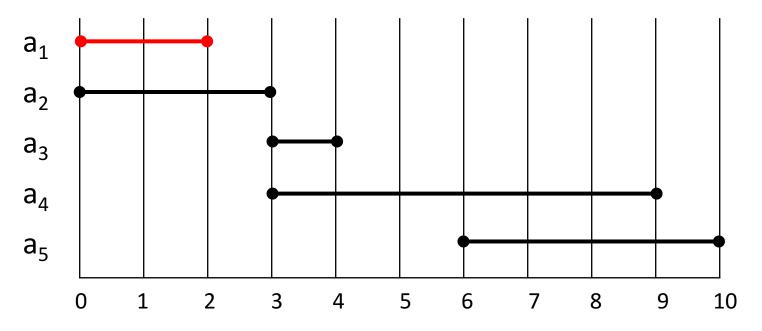
```
Find-Solution(j)
if j = 0
  return ∅.
else if (v[j] + M[p[j]] > M[j-1])
  return { j } ∪ Find-Solution(p[j])
else
  return Find-Solution(j-1).
```

Analysis. # of recursive calls $\leq n \Rightarrow O(n)$.

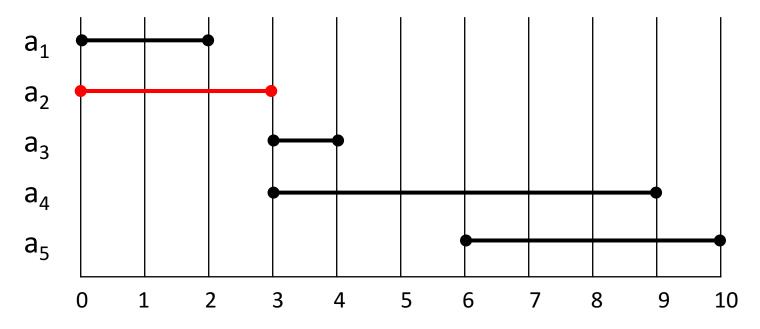
activity	1	2	3	4	5
predecessor	0	0	2	2	3
Best weight M	-	-	-	-	_
$V_j+M[p(j)]$	-	-	-	_	-
M[j-1]	-	-	-	_	-



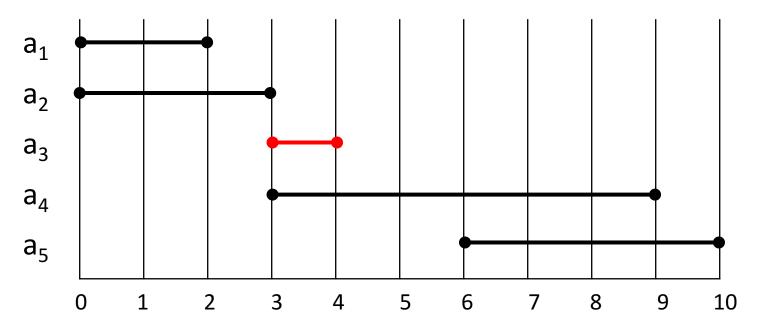
activity	1	2	3	4	5
predecessor	0	0	2	2	3
Best weight M	2	-	-	-	-
$V_j+M[p(j)]$	2	-	_	_	-
M[j-1]	0	-	-	_	-



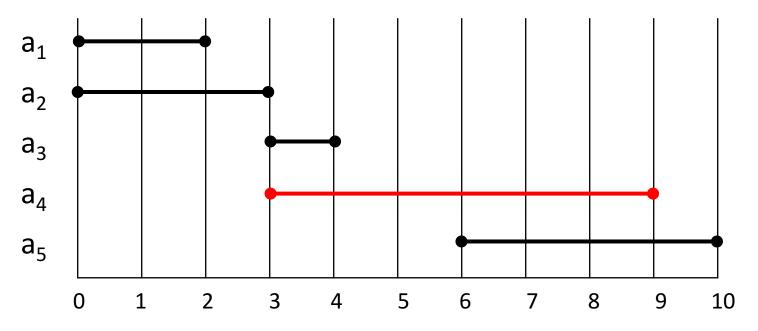
activity	1	2	3	4	5
predecessor	0	0	2	2	3
Best weight M	2	3	-	-	-
$V_j+M[p(j)]$	2	3	-	_	-
M[j-1]	0	2	_	_	-



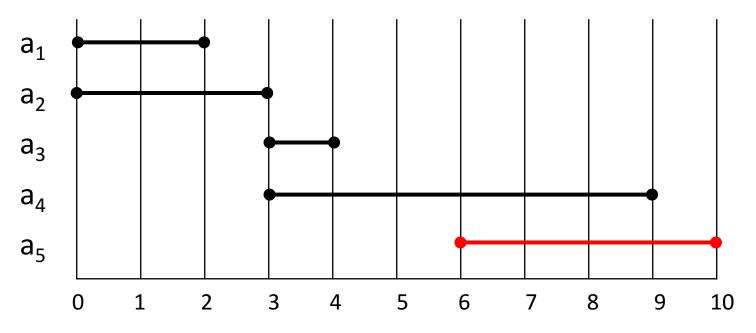
activity	1	2	3	4	5
predecessor	0	0	2	2	3
Best weight M	2	3	4	-	_
$V_j+M[p(j)]$	2	3	4	_	-
M[j-1]	0	2	3	_	-



activity	1	2	3	4	5
predecessor	0	0	2	2	3
Best weight M	2	3	4	9	-
$V_j+M[p(j)]$	2	3	4	9	-
M[j-1]	0	2	3	4	_

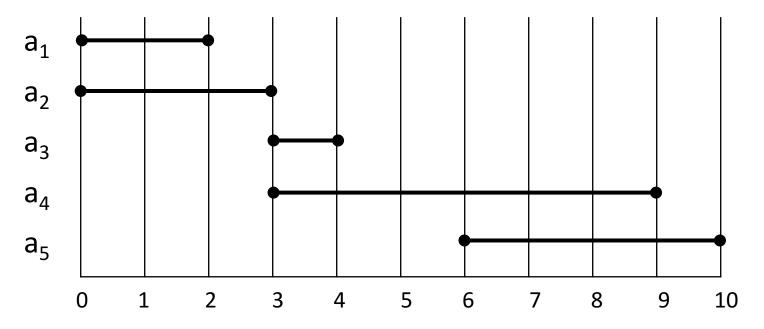


activity	1	2	3	4	5
predecessor	0	0	2	2	3
Best weight M	2	3	4	9	9
$V_j+M[p(j)]$	2	3	4	9	8
M[j-1]	0	2	3	4	9



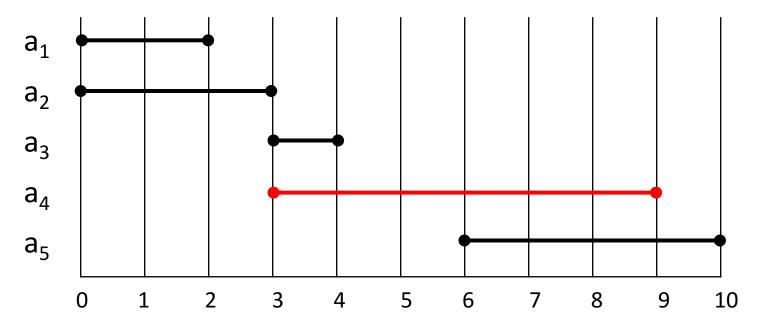
Example: Reconstruction

activity	1	2	3	4	5
predecessor	0	0	2	2 \	3
Best weight M	2	3	4	9	9
$V_j+M[p(j)]$	2	3	4	9	8
M[j-1]	0	2	3	4	\ 9



Example: Reconstruction

activity	1	2	3	4	5
predecessor	0	0	2	2	3
Best weight M	2	3	4	9	9
$V_j+M[p(j)]$	2	3	4	9	8
M[j-1]	0	2	3	4	9



Example: Reconstruction

activity	1	2	3	4	5
predecessor	0	0	2	2	3
Best weight M	2	3	4	9	9
$V_j+M[p(j)]$	2	3	4	9	8
M[j-1]	0	2	3	4	9

