

Dynamic Programming

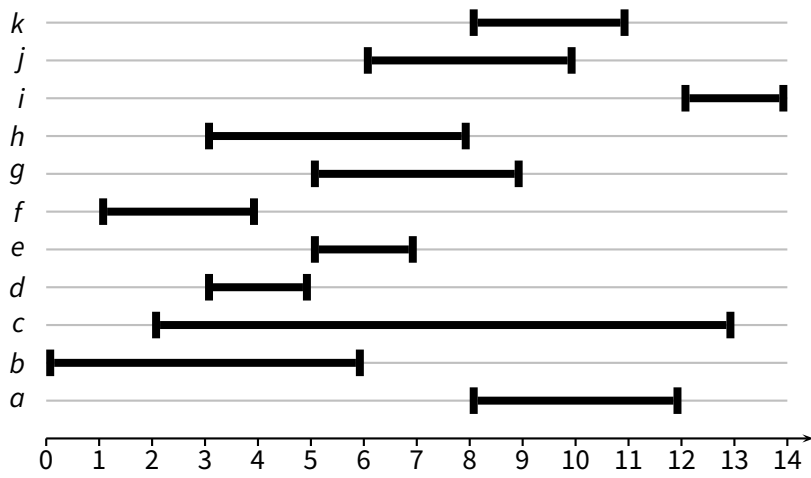
Antonio Carzaniga

Faculty of Informatics
Università della Svizzera italiana

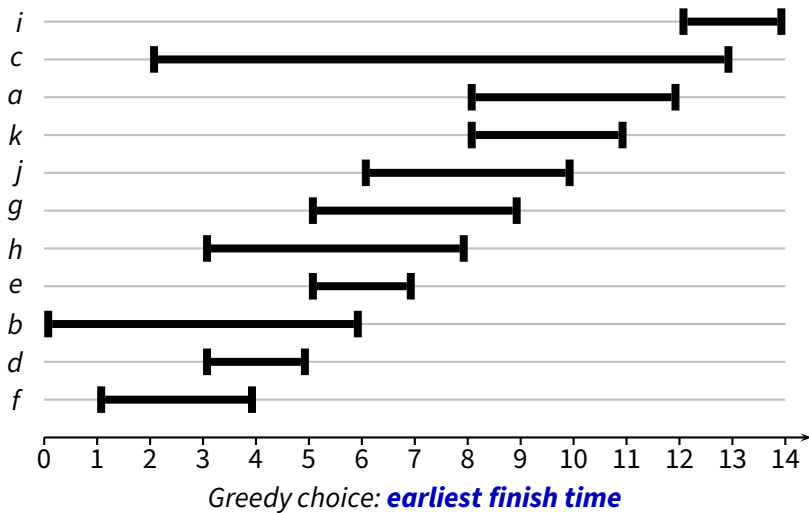
May 21, 2024

- Examples
- Dynamic programming strategy
- More examples

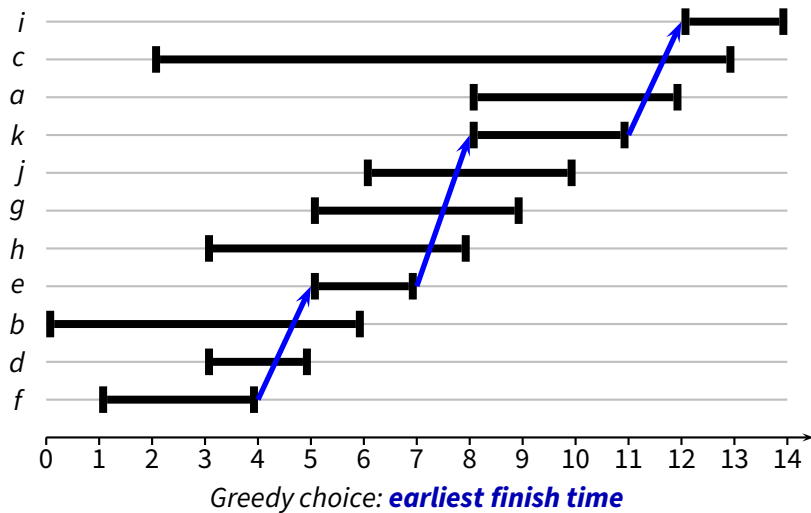
Activity-Selection Problem



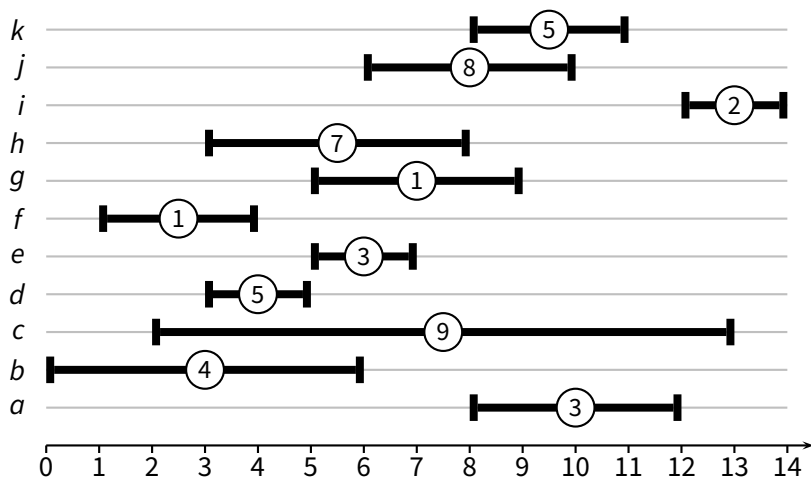
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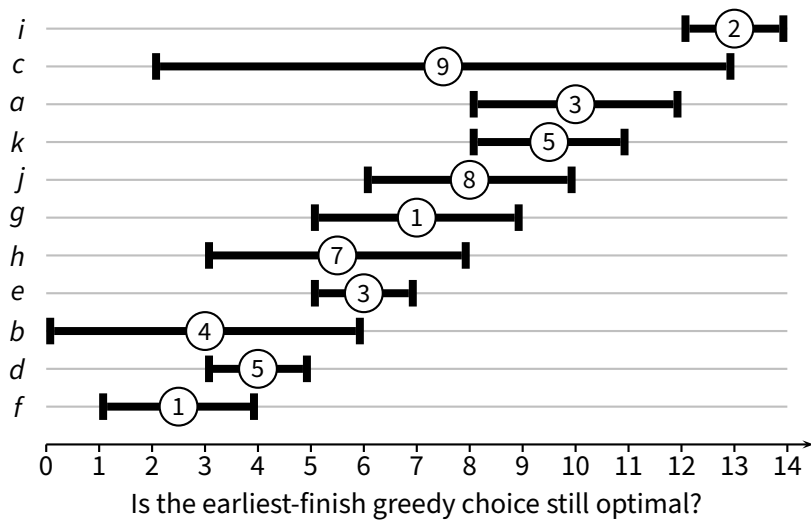
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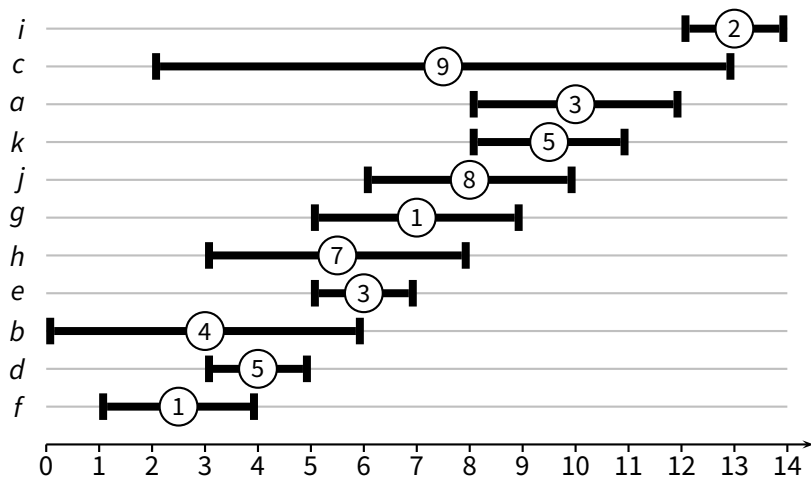
Weighted Activity-Selection Problem



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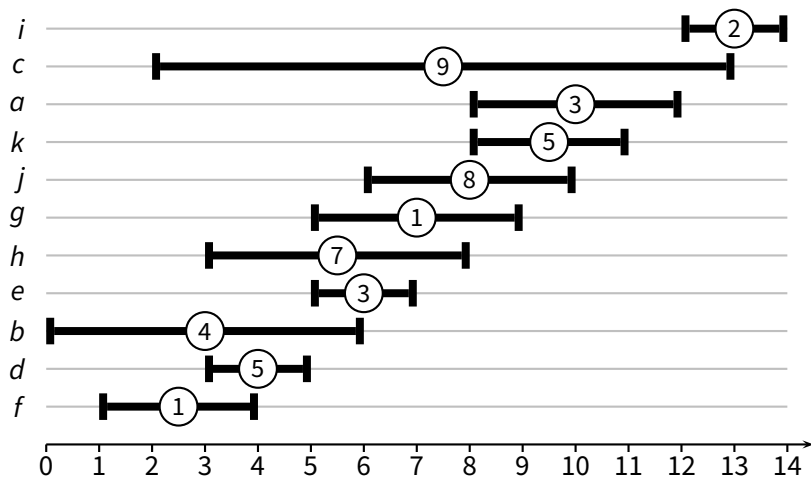


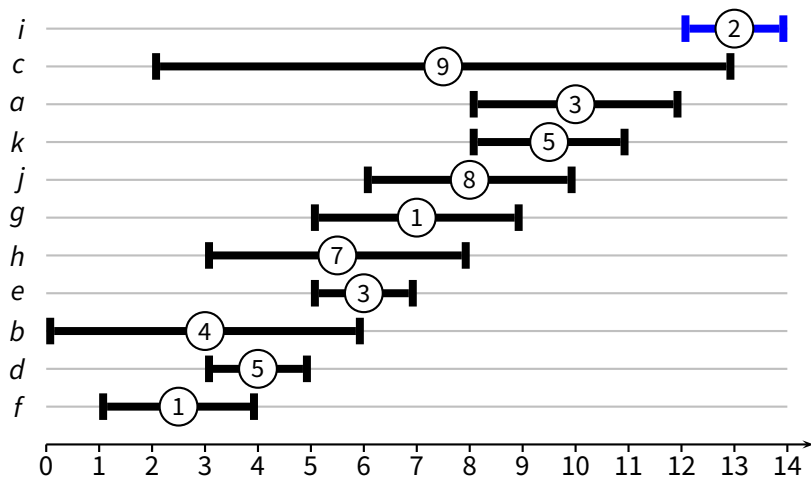
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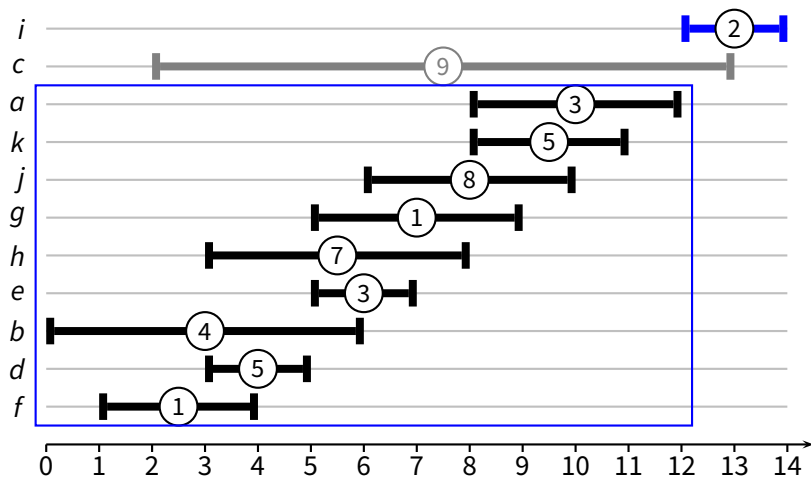
Is the earliest-finish greedy choice still optimal?

Is *any* greedy choice optimal?

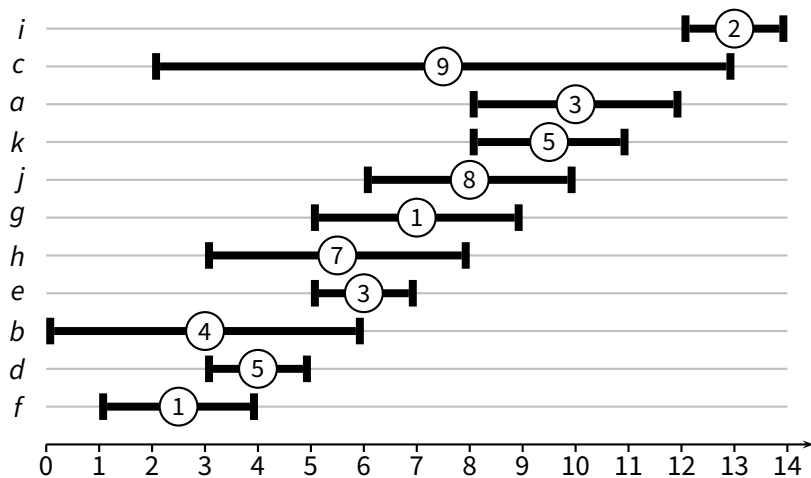


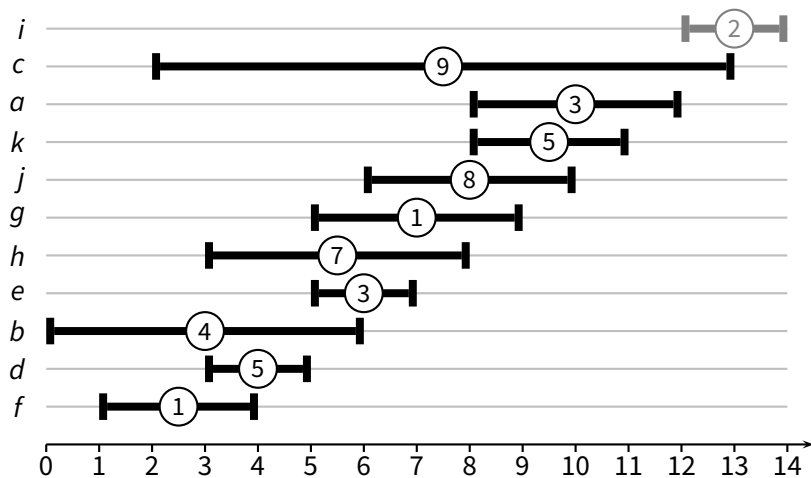


Case 1: activity i is in the optimal schedule

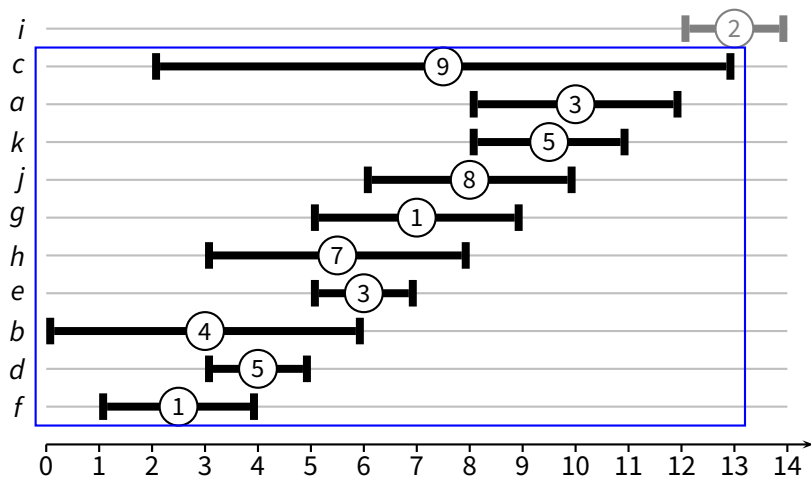


Case 1: activity *i* is in the optimal schedule





Case 2: activity *i* is not in the optimal schedule



Case 2: activity *i* is not in the optimal schedule

Bellman-Ford Algorithm

- Given a graph $G = (V, E)$ and a weight function w , we compute the shortest distance $D_u(v)$, from $u \in V$ to $v \in V$, using the *Bellman-Ford equation*

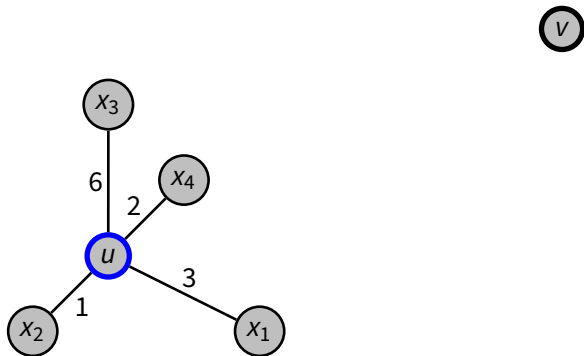
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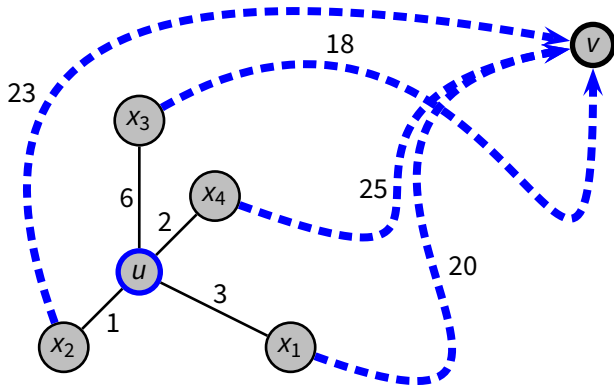
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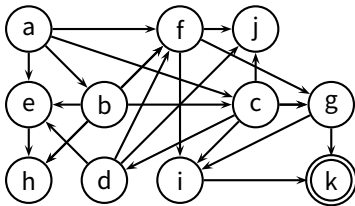
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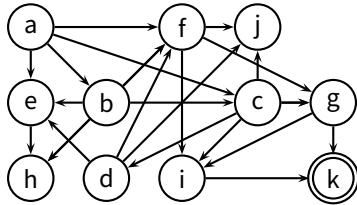
Shortest Paths on DAGs

- Given a *directed acyclic graph* $G = (V, E)$, this one with unit weights, find the shortest distances to a given node

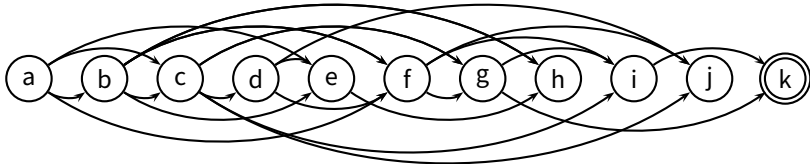


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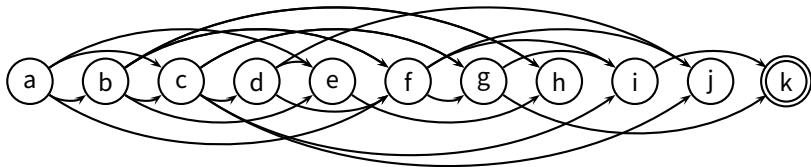
- Considering V in **topological order**...



Shortest Paths on DAGs (2)

- Considering V in *topological order*

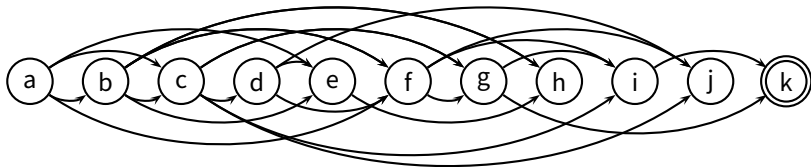
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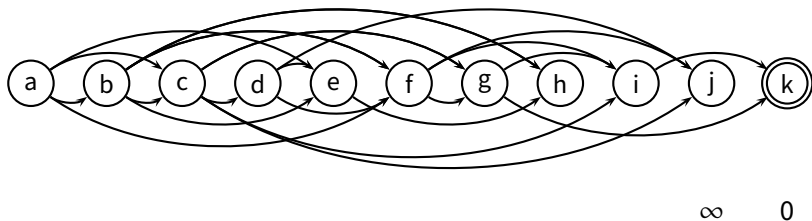


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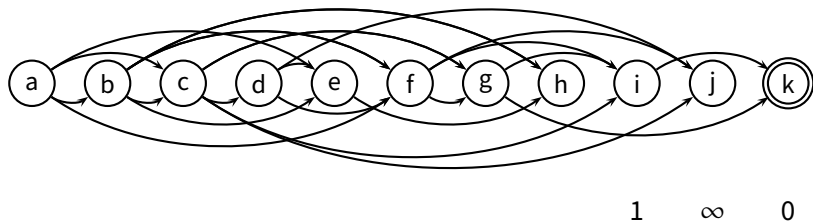
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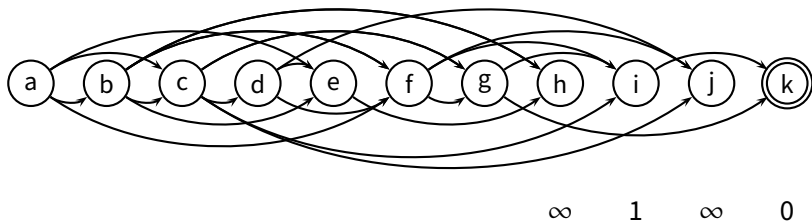
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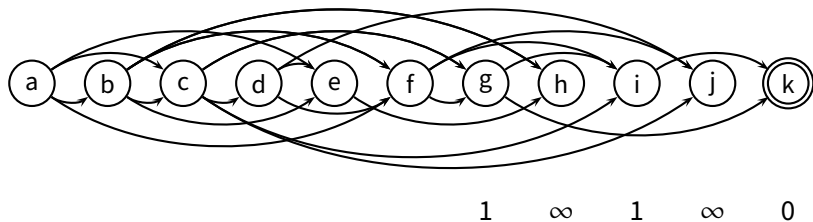
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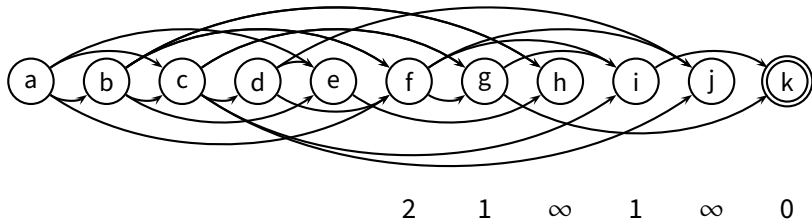
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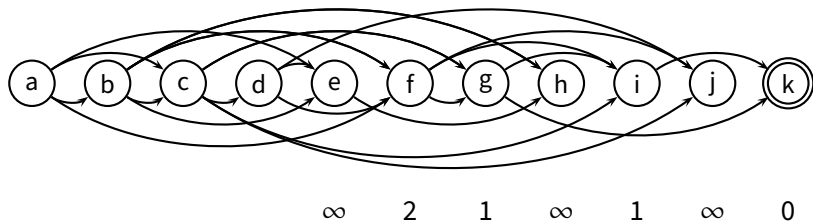
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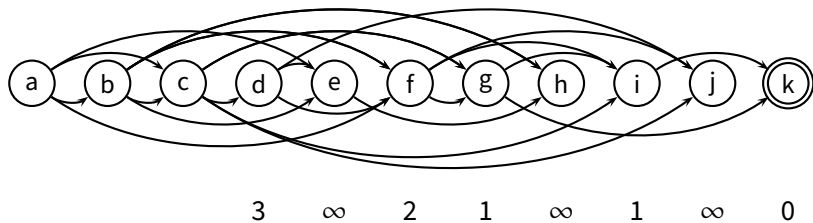
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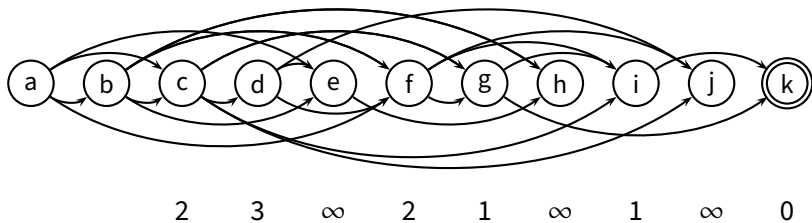
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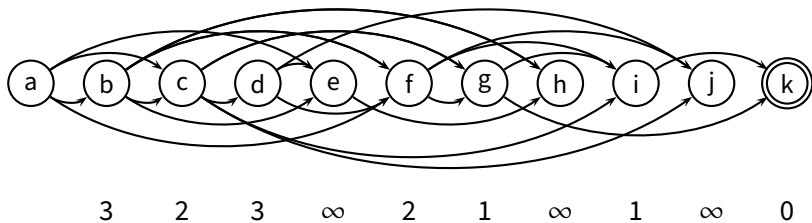
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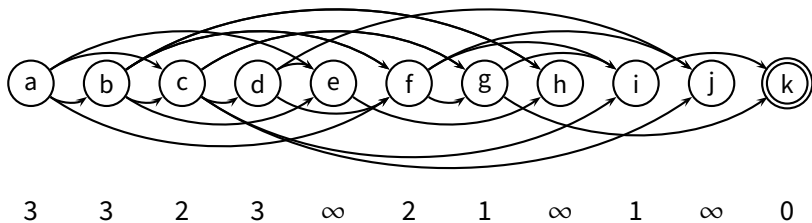
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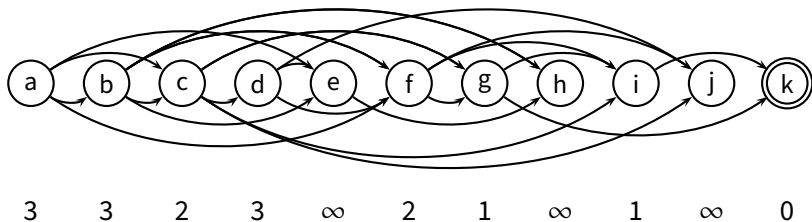
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- Since G is a DAG, computing D_y with $y \in \text{Adj}(x)$ can be considered a *subproblem* of computing D_x
 - ▶ we build the solution bottom-up, storing the subproblem solutions

Longest Increasing Subsequence

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- Given a sequence of numbers a_1, a_2, \dots, a_n , an *increasing subsequence* is any subset $a_{i_1}, a_{i_2}, \dots, a_{i_k}$ such that $1 \leq i_1 < i_2 < \dots < i_k \leq n$, and such that

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A maximal-length subsequence is

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- Combining the subproblems

$$L(j) = 1 + \max\{L(i) \mid i < j \wedge a_i < a_j\}$$

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 - ▶ derive the solution from (one of) the solutions to the subproblems

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 - ▶ **exercise:** find a counter-example

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 - ▶ in dynamic programming, it is typical to reduce $L(j)$ into $L(j - 1)$
 - ▶ this is one reason why recursion does not work so well for dynamic programming
- Divide-and-conquer splits the problem into ***independent subproblems***
 - ▶ in dynamic programming, subproblems typically overlap
 - ▶ pretty much the same argument as above

Dynamic Programming vs. Greedy

- Greedy: requires the *greedy-choice property*
 - ▶ greedy: *greedy choice* plus *one subproblem*
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 - ▶ greedy: ***greedy choice*** plus ***one subproblem***
 - ▶ greedy choice typically *before* proceeding to the subproblem
 - ▶ no need to store the result of each subproblem
- Dynamic programming: ***more general***
 - ▶ does not need the greedy-choice property
 - ▶ typically looks at several subproblems
 - ▶ “dynamically” choose one of them to obtain a global solution
 - ▶ typically works bottom-up
 - ▶ typically reuses solutions of the subproblems

- Prefix/suffix subproblems

- ▶ *Input:* x_1, x_2, \dots, x_n
- ▶ *Subproblem:* x_1, x_2, \dots, x_i , with $i < n$
- ▶ $O(n)$ subproblems

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L u g a n o

Z u r i g o

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⇓		+	+		-	-	
Z		r	i				
L	u			g	a	n	o
Z	u	r	i	g			o

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Z	u	r	i	g		o		Z	u	r	i	g	o

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	↓		+	+		-	-
Z		r		i			
L	u				g	a	n
							o
Z	u	r		i	g		o

	↓		↓	↓	↓
Z		r		i	g
L	u	g		a	n
					o
Z	u	r		i	g
					o

- Align the two strings x and y , possibly inserting “gaps” between letters
 - ▶ a gap in the source means *insertion*
 - ▶ a gap in the destination means *deletion*
 - ▶ two different character in the same position means *modification*

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- This suggests a way to combine the subproblems; let $diff(i, j) = 1$ iff $x[i] \neq y[j]$ or 0 otherwise

$$E(i, j) = \min\{1 + E(i - 1, j), \\ 1 + E(i, j - 1), \\ diff(i, j) + E(i - 1, j - 1)\}$$

■ Problem definition

- ▶ *Input:* a set of n objects with their weights w_1, w_2, \dots, w_n and their values v_1, v_2, \dots, v_n , and a maximum weight W
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■ Dynamic-programming solution

- ▶ let $K(w, j)$ be the maximum value achievable at maximum capacity w using the first j items (i.e., items $1 \dots j$)
- ▶ considering the j th element, we can either “use it or loose it,” so

$$K(w, j) = \max\{K(w - w_j, j - 1) + v_j, K(w, j - 1)\}$$

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- **Idea:** “cache” the results

```
PINGALA( $n$ )  
1  if  $n \leq 2$   
2      return  $n$   
3  if  $(n, x) \in H$  // a hash table  $H$  “caches” results  
4      return  $x$   
5  else  $x = \mathbf{PINGALA}(n - 1) + \mathbf{FIBONACCI}(n - 2)$   
6      INSERT( $H, n, x$ )  
7      return  $x$ 
```

- Idea also known as *memoization*

■ *Greedy*

1. start with the greedy choice
2. add the solution to the remaining subproblem

A nice tail-recursive algorithm

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3. in practice, solve the subproblems bottom-up

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 - ▶ Yes, because $2 + 134 + 78 = 214$
- **Puzzle 1:** is it possible to insert some '+' signs in the strings of digits to obtain the corresponding target number?

<i>digits</i>	<i>target</i>
646805736141599100791159198	472004
6152732017763987430884029264512187586207273294807	560351
48796142803774467559157928	326306
195961521219109124054410617072018922584281838218	7779515