

Algorithms and Computability

Lecture 1 *Intro & Dynamic Programming*

SW6/DVML8 spring 2025

Simonas Šaltenis



AALBORG UNIVERSITY
DENMARK

People



- Lecturers:

- First 6 lectures: Simonas Šaltenis
 - ♦ Email: simas@cs.aau.dk
 - ♦ Office: 3.2.05
- Last 7 lectures: Christian Schilling
 - ♦ Email: christianms@cs.aau.dk
 - ♦ Office: 1.2.14



- Teaching assistant:

- Victor Doré Hansen vdha20@student.aau.dk

Location, Time, Structure



- Location: 0.1.95 + Fib16, FRB7H, Kst3,...
- Time: Tuesdays, 12:30–14:15 (Exercises: 14:30–16:15)
 - Self-studies and mini-projects other days – see the schedule.
 - Please, check the schedule on Moodle for any changes.
- A total of 16 sessions:
 - 13 regular sessions + 3 self-study sessions
 - A regular session = 2-hour lecture + 2-hour exercises
 - A self-study exercise session = 4 hours of exercises

Workload

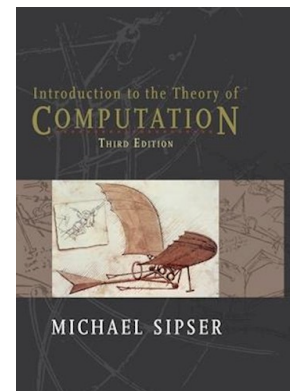
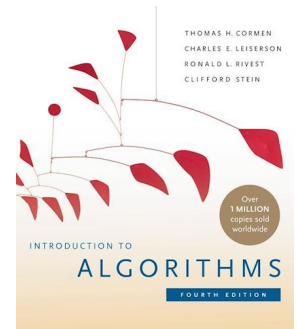
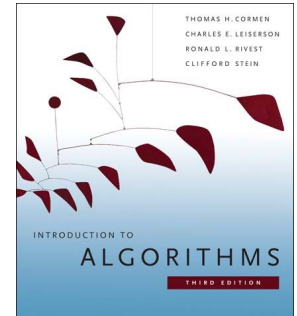


- This is a 5 ECTS course \approx 150 hours of your effort
 - 13 regular sessions:
 - ♦ 2h lecture + 2h exercises + 3.5h preparing. In total, $13 \times (2+2+3.5) = 97.5\text{h}$
 - 3 self-studies:
 - ♦ 4h solving exercise + 3h preparing/feedback. In total = 21h
- Exam and preparation for it \approx 31.5h
- In total: $97.5 + 21 + 31.5 = 150\text{h}$

Textbook



- First six lectures:
 - T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein. *Introduction to Algorithms*, **3rd edition**, The MIT Press. ISBN:9780262533058
 - ...or **4th edition**. ISBN: 9780262046305
 - On the Moodle, I use CLRS for both editions, or CLRS3/CLRS4 when there is a difference.
 - Additional notes and videos.
- Last seven lectures:
 - Michael Sipser. *Introduction to the Theory of Computation*, **Third International Edition**. Thomson Course Technology. ISBN: 9781133187790



Advice, Exam



- **Prepare** for lectures: read, watch videos.
- Be active during lectures, have paper and pen – there will be mini-exercises/quizzes.
- **Exercises, self-studies, and mini-projects** are very important:
 - The exam will consist of a set of exercises / questions
 - Some parts of exam exercises can directly relate to selected parts of self-studies/mini-projects.
 - Make sure you understand all exercises by **YOURSELF** even if working on them in a group.
- Your feedback, positive and negative, is always welcome!
- The **exam** will be a 4-hour Moodle-based digital exam with notes and books.

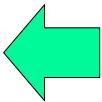
What is it about?



- The course is about *algorithms and algorithmic problems*
 - The first six lectures cover some selected *algorithms*, algorithm *design techniques*, and algorithm *analysis techniques* for problems with known efficient algorithms
 - ♦ We continue where the AD course left off, but focus a bit more on the design of algorithms rather than just understanding them “as is”.
 - We focus on the *efficiency of algorithms*, i.e., on the *upper bounds*.
 - The last seven lectures focus on characterizing how hard the *problems* are:
 - ♦ How to formalize computation?
 - ♦ Do all problems have an algorithmic solution?
 - ♦ How do we show that one problem is as hard as the other?
 - ♦ We focus on *hardness of problems*, i.e., on the *lower bounds*.

Course content



-
- Lecture 1: Dynamic programming 
 - Lecture 2: Greedy algorithms
 - Lecture 3: Maximum flow
 - Lecture 4: External-memory algorithms
 - Lecture 5: Parallel algorithms
 - Lecture 6: Amortized analysis
 - Lecture 7: Turing machines
 - Lecture 8: The Church-Turing thesis
 - Lecture 9: Decidability
 - Lecture 10: Reducibility
 - Lecture 11: Time complexity – the complexity class P
 - Lecture 12: NP and NP-completeness
 - Lecture 13: NP-complete problems

{ Self-study

{ Self-study

{ Self-study

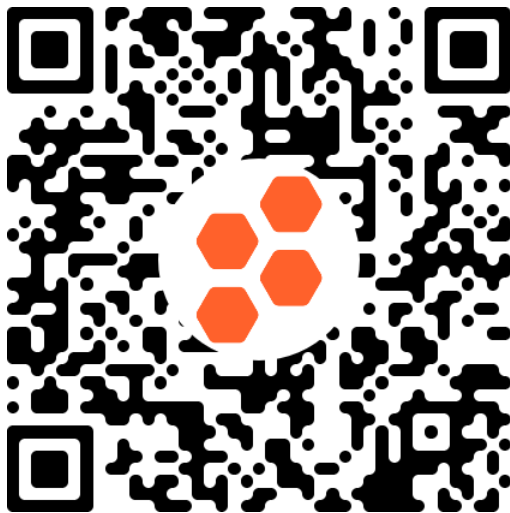
Mini-quiz 1



1.2. (3 points) $700 \cdot n^2 + 999 \cdot n^2 \lg n + 0.1 \cdot n^2 \lg^2 n$ is:

☐ a) $\Theta(n^2 \lg n)$ ☐ b) $\Omega(n^2 \lg n)$ ☐ c) $\Theta(n^2)$ ☐ d) $\Theta(n^2 \cdot \lg^2 n)$

- Go to [Socrative](#) and vote (the link is also on course Moodle)
 - Multiple choices could be correct



Mini-quiz 2



- From the reading material for today: “... *would take* $\omega(1)$ *time...*” What does it mean?
 - A: Would take *constant time* (not dependent on problem size)
 - B: Would take *more than constant time*
 - C: Would take *constant time or more*
- Go to [Socrative](#) and vote (the link is also on course Moodle)

Mini-quiz 3



- Have you prepared for the lecture today? (be honest)
 - A: Read everything and watched the two videos
 - B: Read some of it and watched the two videos
 - C: Did not read anything, but watched the two videos
 - D: Watched some (parts) of the videos and read some of it
 - E: Did not have time/energy/desire to prepare at all
- Go to [Socrative](#) and vote (the link is also on course Moodle)

Dynamic Programming



- Goals of this lecture:
 - *to understand the **principles** of dynamic programming;*
 - *to understand how an algorithm for **edit distance** works;*
 - *to be able to **apply** the dynamic programming algorithm design technique.*

Optimization problems



- Many problems can be framed as *optimization problems*:
 - Find the *shortest route* from A to B .
 - Find the *items* that give *most value* and can fit into a knapsack.
- Two things that we need to find:
 - *Compute* the optimum *value*:
 - ♦ Length of a route
 - ♦ Total value of items in the knapsack.
 - *Construct an object* that has that optimum value (i.e., proof of the value):
 - ♦ Route
 - ♦ The set of items

Dynamic programming



- *Dynamic programming*:
 - A powerful technique to solve *optimization problems*
- Structure:
 - To arrive at an optimal solution *a number of choices* are made
 - Each *choice generates* a number of *sub-problems*
 - Which choice to make is decided by looking at all possible choices and the solutions to sub-problems that each choice generates.
 - The solution to a specific sub-problem is used many times in the algorithm
 - Subproblems are *overlapping*
 - *First*, think how to compute the value of a variable that we optimize,
 - *Then*, augment your algorithm to remember the choices made.
 - *Finally*, the choices can be traced back to build an optimal solution corresponding to an optimal value.

DP algorithm design roadmap



- Construction:
 - Which choices have to be considered in each step of the algorithm?
 - What are the sub-problems? Which parameters define each sub-problem?
 - How are the trivial sub-problems solved?
 - (In which order do we have to solve the sub-problems?)
 - Or write a *memoized* version of the algorithm
 - Remember the (optimal) choices made
 - Use the remembered choices to construct a solution
- Analysis:
 - How many different sub-problems are there in total?
 - How many choices have to be considered in each step of the algorithm?

Recurrence for
the optimal value

Constructing
a solution

Edit Distance



- Problem definition:
 - Two strings: $s[1..m]$, and $t[1..n]$
 - Find *edit distance* $dist(s,t)$ – the smallest number of edit operations that turns s into t
 - Edit operations:
 - **Replace** one letter with another
 - **Delete** one letter
 - **Insert** one letter
- Example:

ghost	delete g
host	insert u
houst	replace t by e
house	

Sub-problems



- What are the sub-problems?
 - *Goal 1*: To have as few sub-problems as possible
 - *Goal 2*: Solution to the sub-problem should be possible by combining solutions to smaller sub-problems.
- Sub-problem:
 - $d_{i,j} = \text{dist}(s[1..i], t[1..j])$
 - Then $\text{dist}(s, t) = d_{m,n}$

Making a choice



- *How can we solve a sub-problem by looking at solutions of smaller sub-problems to make a choice?*
 - Let's look at the last symbol: $s[i]$ and $t[j]$. There are three options, do whatever is cheaper:
 - If $s[i] = t[j]$, then turn $s[1..i-1]$ to $t[1..j-1]$, else **replace** $s[i]$ by $t[j]$ and turn $s[1..i-1]$ to $t[1..j-1]$
 - **Delete** $s[i]$ and turn $s[1..i-1]$ to $t[1..j]$
 - **Insert** insert $t[j]$ at the end of $s[1..i]$ and turn $s[1..i]$ to $t[1..j-1]$

Recurrence



$$d_{i,j} = \min \begin{cases} d_{i-1,j-1} + \begin{cases} 0 & \text{if } s[i] = t[j] \\ 1 & \text{else} \end{cases} \\ d_{i-1,j} + 1 \\ d_{i,j-1} + 1 \end{cases}$$

- *How do we solve trivial sub-problems?*
 - To turn empty string to $t[1..j]$, do j **inserts**
 - To turn $s[1..i]$ to empty string, do i **deletes**
- *(In which order do we have to solve the sub-problems?)*

Algorithm, memoized



EditDistance(s[1..m], t[1..n])

01 **for** i = 0 **to** m **do**

02 **for** j = 0 **to** n **do**

03 dist[i, j] = ∞

04 **return** EditDistR(s, t, m, n)

$$d_{i,j} = \min \begin{cases} d_{i-1,j-1} + \begin{cases} 0 & \text{if } s[i] = t[j] \\ 1 & \text{else} \end{cases} \\ d_{i-1,j} + 1 \\ d_{i,j-1} + 1 \end{cases}$$

EditDistR(s, t, i, j)

01 **if** dist[i, j] == ∞ **then**

02 **if** j == 0 **then** dist[i, j] = i

03 **else if** i == 0 **then** dist[i, j] = j

04 **else**

05 **if** s[i] == t[j] **then**

06 dist[i, j] = min(EditDistR(s, t, i-1, j-1),

 EditDistR(s, t, i-1, j)+1,

 EditDistR(s, t, i, j-1)+1)

07 **else**

08 dist[i, j] = 1 + min(EditDistR(s, t, i-1, j-1),

 EditDistR(s, t, i-1, j),

 EditDistR(s, t, i, j-1))

09 **return** dist[i, j]

Algorithm



```
EditDistance(s[1..m], t[1..n])
01 for i = 0 to m do dist[i,0] = i
02 for j = 0 to n do dist[0,j] = j
03 for i = 1 to m do
04     for j = 1 to n do
05         if s[i] = t[j] then
06             dist[i,j] = min(dist[i-1,j-1], dist[i-1,j]+1,
                                dist[i,j-1]+1)
07         else
08             dist[i,j] = 1 + min(dist[i-1,j-1], dist[i-1,j],
                                dist[i,j-1])
09 return dist[m,n]
```

- *What is the running time of this algorithm?*
- *How do we modify it to remember the edit operations?*

Let's run the algorithm



$$d_{i,j} = \min \begin{cases} d_{i-1,j-1} + \begin{cases} 0 & \text{if } s[i] = t[j] \\ 1 & \text{else} \end{cases} \\ d_{i-1,j} + 1 \\ d_{i,j-1} + 1 \end{cases}$$

			G	H	O	S	T
	j\i	0	1	2	3	4	5
	0	0	1 _D	2 _D	3 _D	4 _D	5 _D
H	1	1 _I	1 _R				
O	2	2 _I					
U	3	3 _I					
S	4	4 _I					
E	5	5 _I					

I : insert
 D: delete
 R: replace
 C: do nothing

Let's run the algorithm



$$d_{i,j} = \min \begin{cases} d_{i-1,j-1} + \begin{cases} 0 & \text{if } s[i] = t[j] \\ 1 & \text{else} \end{cases} \\ d_{i-1,j} + 1 \\ d_{i,j-1} + 1 \end{cases}$$

			G	H	O	S	T
	j\i	0	1	2	3	4	5
	0	0	1 _D	2 _D	3 _D	4 _D	5 _D
H	1	1 _I	1 _R	1 _C			
O	2	2 _I					
I	3	3 _I					

I : insert
D: delete
R: replace
C: do nothing

- Fill the next cell!
- Go to [Socrative](#) and write in your answer (the link is also on course Moodle)

Let's run the algorithm



$$d_{i,j} = \min \begin{cases} d_{i-1,j-1} + \begin{cases} 0 & \text{if } s[i] = t[j] \\ 1 & \text{else} \end{cases} \\ d_{i-1,j} + 1 \\ d_{i,j-1} + 1 \end{cases}$$

			G	H	O	S	T
	j\i	0	1	2	3	4	5
	0	0	1 _D	2 _D	3 _D	4 _D	5 _D
H	1	1 _I	1 _R	1 _C	2 _D		
O	2	2 _I					
U	3	3 _I					
S	4	4 _I					
E	5	5 _I					

I : insert
 D: delete
 R: replace
 C: do nothing

Elements of Dynamic Programming



- Dynamic programming is used for optimization problems
 - A number of choices have to be made to arrive at an optimal solution
 - At each step, consider all possible choices and solutions to sub-problems induced by these choices (compare to greedy algorithms)
 - The order of solving of the sub-problems is important – from smaller to larger
- Usually a table of sub-problem solutions is used

Elements of Dynamic Programming

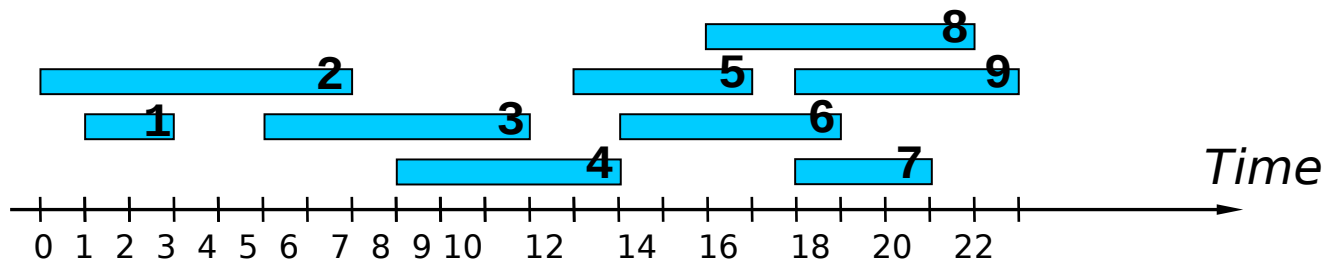


- To be sure that the algorithm finds an optimal solution, the *optimal sub-structure* property has to hold
 - the simple “cut-and-paste” argument usually works:
 - **If** an optimal solution includes a choice that we consider **then** it includes optimal solutions to the subproblems that this choice generates.
 - but not always! Longest simple unweighted path example – no optimal sub-structure!
 - The subproblems have to be *independent*.

Activity-Selection Problem



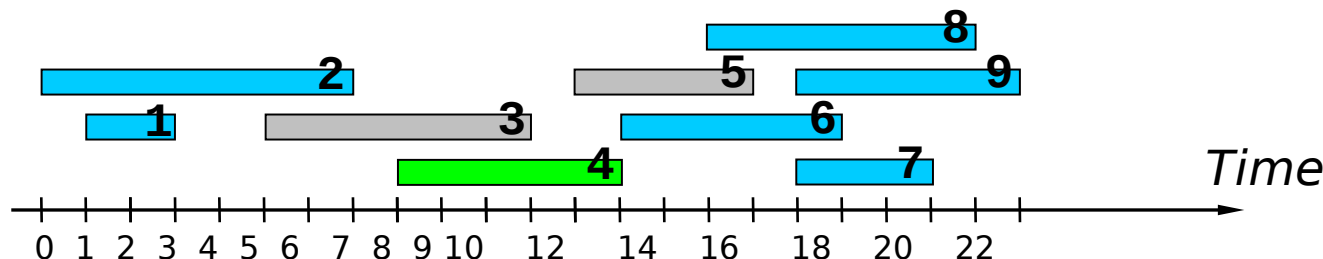
- Input:
 - A set of n activities, each with start and end times: $A[i].s$ and $A[i].f$. The activity lasts during the period $[A[i].s, A[i].f)$
- Output:
 - The **largest** subset of mutually *compatible* activities
 - Activities are compatible if their intervals do not intersect



“Straight-forward” solution



- Let's just pick (schedule) one activity $A[k]$
 - This generates two set's of activities compatible with it:
 $Before(k)$, $After(k)$
 - E.g., $Before(4) = \{1, 2\}$; $After(4) = \{6, 7, 8, 9\}$



- Solution:

$$MaxN(A) = \begin{cases} 0 & \text{if } A = \emptyset, \\ \max_{a \in A} \{ MaxN(Before(a)) + MaxN(After(a)) + 1 \} & \text{if } A \neq \emptyset. \end{cases}$$

Dynamic Programming Alg.



- The recurrence results in a dynamic programming algorithm
 - Sort activities on the end time (for simplicity assume also “sentinel” activities $A[0]$ and $A[n+1]$)
 - Let S_{ij} – a set of activities after $A[i]$ and before $A[j]$ and compatible with $A[i]$ and $A[j]$.
 - Let's have a two-dimensional array, s.t., $c[i, j] = \text{MaxN}(S_{ij})$:

$$c[i, j] = \begin{cases} 0 & \text{if } S_{ij} = \emptyset, \\ \max_{a_k \in S_{ij}} \{c[i, k] + c[k, j] + 1\} & \text{if } S_{ij} \neq \emptyset. \end{cases}$$

- $\text{MaxN}(A) = \text{MaxN}(S_{0, n+1}) = c[0, n+1]$

Dynamic Programming Alg. II



- Does it really work correctly?
 - We have to prove the optimal sub-structure:
 - *If an optimal solution A to S_{ij} includes $A[k]$, then it also includes optimal solutions to S_{ik} and S_{kj}*
 - To prove use “cut-and-paste” argument
- What is the running time of this algorithm?

Activity Selection DP Alg. 2.0



- Alternative way of thinking about it – **binary choice**:
 - Sort activities on the start time (have “sentinel” activity $A[n+1]$ after all the other activities)
 - Let $next(i) = \min \{k \mid k > i \wedge \neg overlaps(A[i], A[k])\}$
 - The subproblem is then to schedule all the activities starting with i and after.

$$c[i] = \begin{cases} 0 & \text{if } i > n, \\ \max(1 + c[next(i)], c[i+1]) & \text{otherwise.} \end{cases}$$

- $MaxN(A) = c[1]$
- *What is the running time and space used?*