

REOP - Session 2: Shortest paths

I/ Homework

~~Ex 3.2~~ Ex 3.3 Ex 3.10
Prop 3.2 (\Leftrightarrow Ex 3.5) sorry

Ex 3.3

Adjacency matrix $A_{uv} = \begin{cases} 1 & \text{if } \exists \text{ an edge } (u, v) \\ 0 & \text{otherwise} \end{cases}$

$(A^2)_{uv} = \sum_{w \in V} \underbrace{A_{uw} A_{wv}}_{= 1 \text{ iff both edges } (u, w) \text{ \& } (w, v) \text{ exist}} = \sum_{w \in V} \mathbb{1}_{\{\text{the path } (u, w, v) \text{ exists}\}}$

$A^2_{uv} =$ nb of paths of length 2 in G from u to v

The result can be proved by induction

$$A_{uv}^k = (A^{k-1} * A)_{uv} = \sum_w \underbrace{A_{uw}^{k-1}}_{\text{by ind, = nb of } (k-1)\text{-paths } u \rightsquigarrow w} \underbrace{A_{wv}}_{\text{existence of edge } (w,v)}$$

Ex 3.10

S is a stable \Leftrightarrow no edge has both endpoints in S
 \Leftrightarrow every edge has at least 1 endpoint in $V \setminus S$
 \Leftrightarrow the vertices of $V \setminus S$ cover every edge
 $\Leftrightarrow V \setminus S$ is a vertex cover

S is the largest stable $\Leftrightarrow V \setminus S$ is the smallest vertex cover

$$\alpha(G) = |S| = |V| - |V \setminus S| = |V| - \tau(G)$$

II/ Shortest paths

1) Statement

Input: - a graph $G = (V, E)$
- a cost function $c: E \rightarrow \mathbb{R}$
- two vertices o (origin) & d (destination)

Question: Find an $o \rightsquigarrow d$ path P of minimum cost $c(P) = \sum_{e \in P} c(e)$
(or a proof that none exists)

We denote by $c(v)$ the cost of a shortest $o \rightsquigarrow v$ path

2) Integer Programming Formulation

Reminders

A linear Program (LP) is an optimization problem with a linear objective & linear constraints

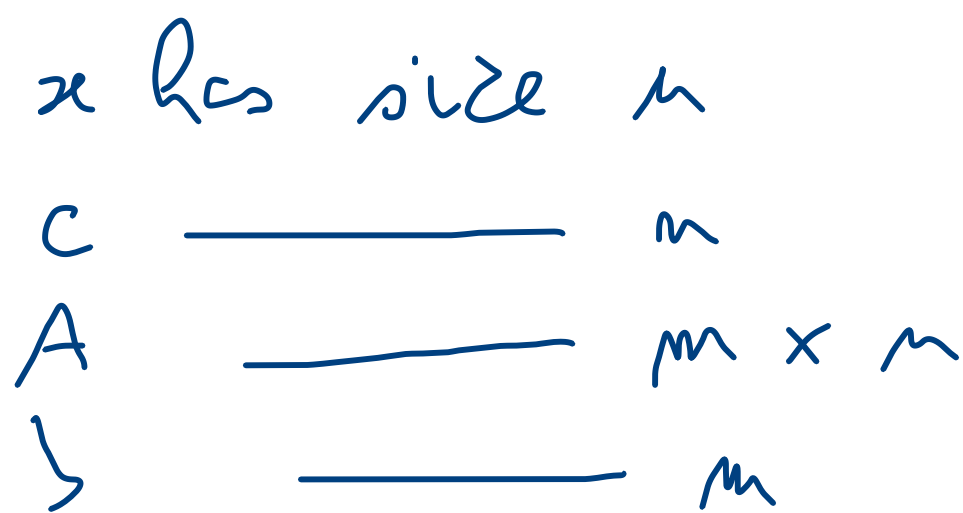
(LP) $\min c^T x$ s.t. $Ax \leq b$ | $x \in \mathbb{R}^n$ variable
 A, b, c are params

A Mixed Integer Linear Program is a Linear Program where some of the variables are constrained to take integer values

$$\min c^T x \quad \text{s.t.} \quad Ax \leq b$$

$x \in \mathbb{R}^{m-1} \times \mathbb{Z}^1$

$Rq: Ax \leq b$
 is a vector inequality
 It means
 $\forall i \in [1, m], (Ax)_i \leq b_i$



$m = nb$ of variables
 $m = nb$ of constraints

Writing a MILP doesn't mean writing A, b, c explicitly

$$\min 5x + 2y \quad \text{s.t.} \quad x \in \mathbb{Z}, y \in \mathbb{R}$$

$$c = \begin{pmatrix} 5 \\ 2 \end{pmatrix}$$

many constraints:
 write them separately
 & symbolically

$$\begin{aligned} 3x + 3y &\leq 1 \\ x - y &\in \mathbb{Z} \end{aligned}$$

$$A = \begin{pmatrix} 3 & 3 \\ 1 & -1 \end{pmatrix} \quad b = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$

In theory solving a MILP is (NP-)HARD

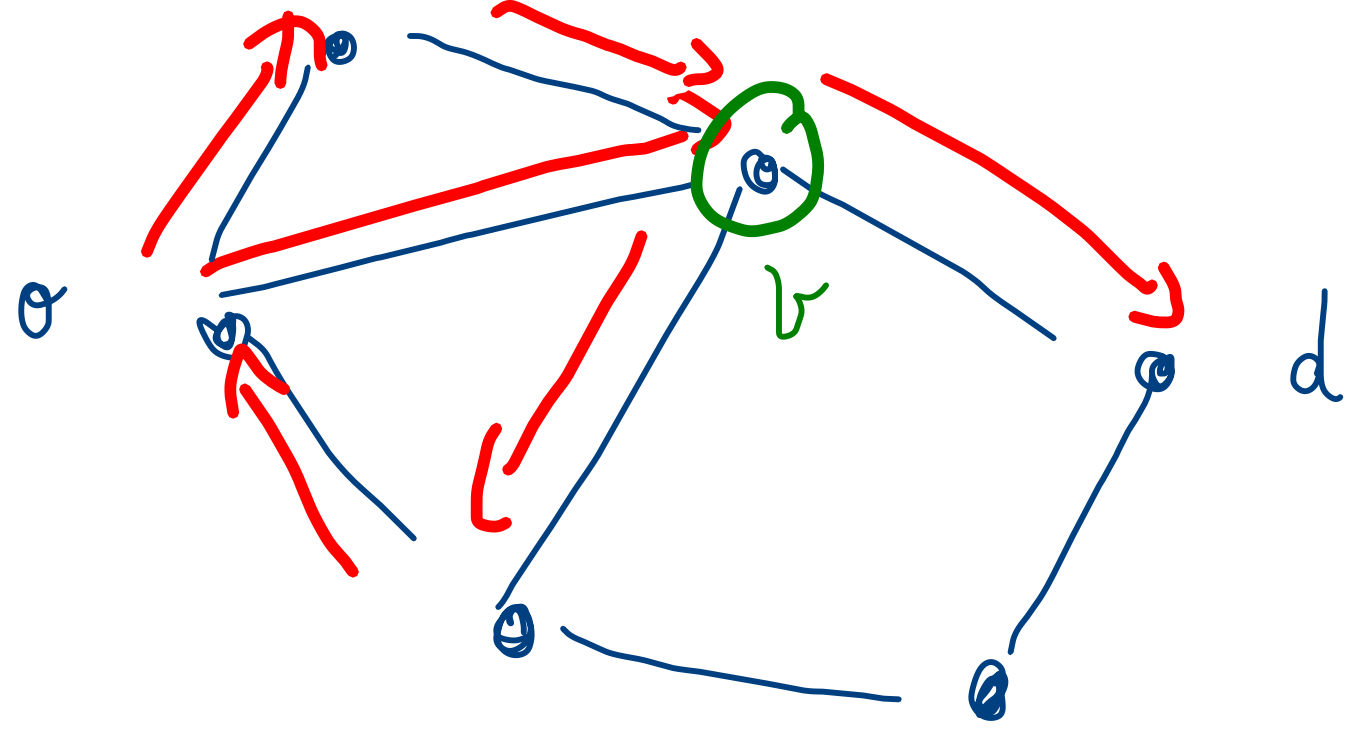
- BUT
- they are a really useful modeling tool
 - there are very efficient industrial (or open source) solvers

Formulation of "shortest path" as a MILP

Let x_{uv} be a binary variable = 1 iff the edge (u, v) is selected in a path

Objective: $\min \underbrace{\sum_{(u,v) \in E} x_{uv} c(u,v)}_{c(P_x)}$

Constraints: $x \in \{0, 1\}^E$ "defines an s-d path"



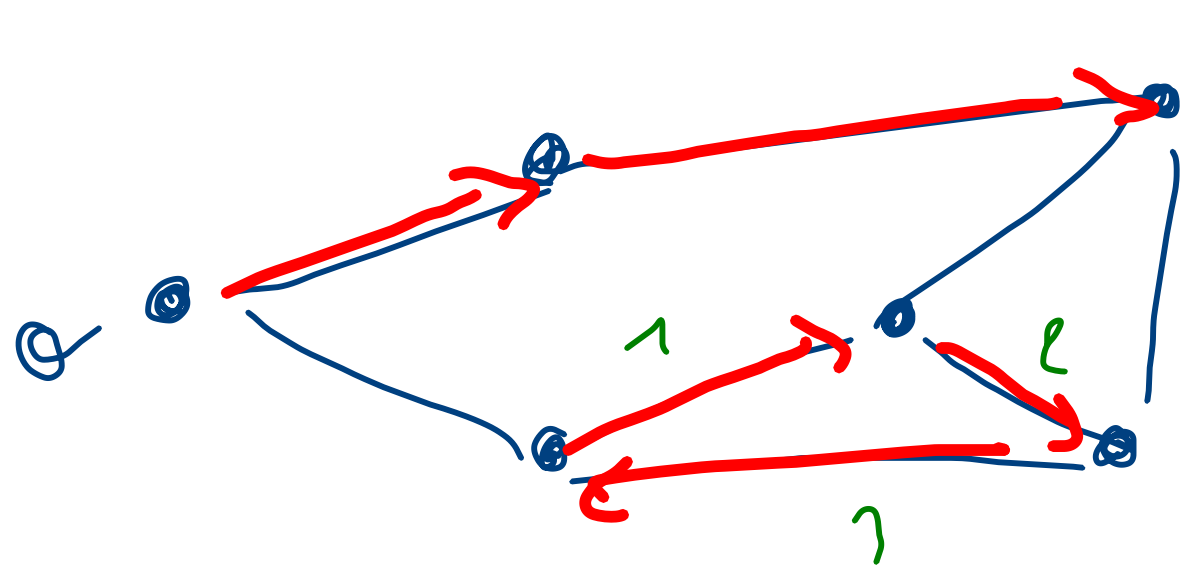
If a vertex $v \notin \{s, d\}$ is crossed, it should have as many edges going in and out

This means $\forall v, \sum_{u \in N^-(v)} x_{uv} - \sum_{w \in N^+(v)} x_{vw} = \begin{cases} 0 & \text{if } v \notin \{s, d\} \\ 1 & \text{if } v = d \\ -1 & \text{if } v = s \end{cases}$

$(x \in \{0, 1\}^{V \times V} \rightarrow \text{additional ctr})$

Rq: since $x \in \{0, 1\}^E$ we are actually modeling a shortest simple path (no repeated edge)

Rq: all the solutions are not paths but (in the nice cases)



the optimal solutions are $c > 0$ optimal solution has no cycle

3) Complexity

Thm: The shortest path pb is NP hard in the general case
polynomial in nice cases

Why? → If there are cycles with < 0 cost in G then the "shortest" path is not defined
→ Then we look for the shortest simple path but it is at least as hard as the Hamiltonian path

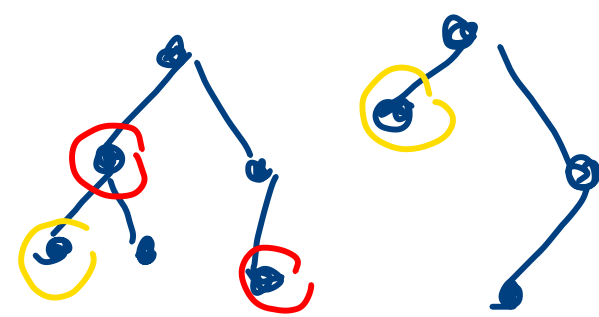


Nice cases:

≠ Depth-First

• Unweighted graphs ($c=1$) → Breadth First Search (BFS)

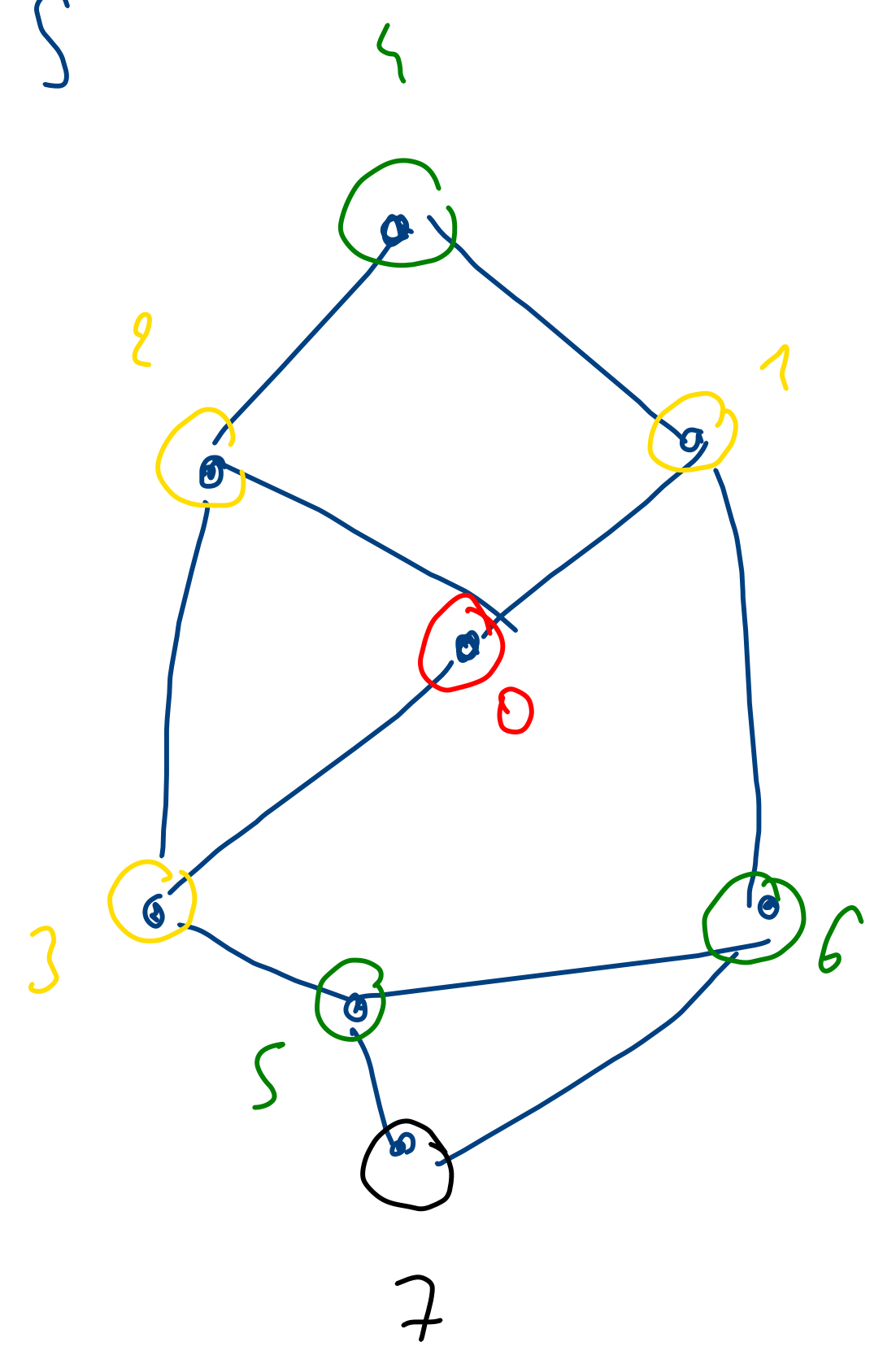
• Acyclic graphs:
- Undirected: forest (at most 1 simple path $s-d$)
- Directed: topological sort ← DFS



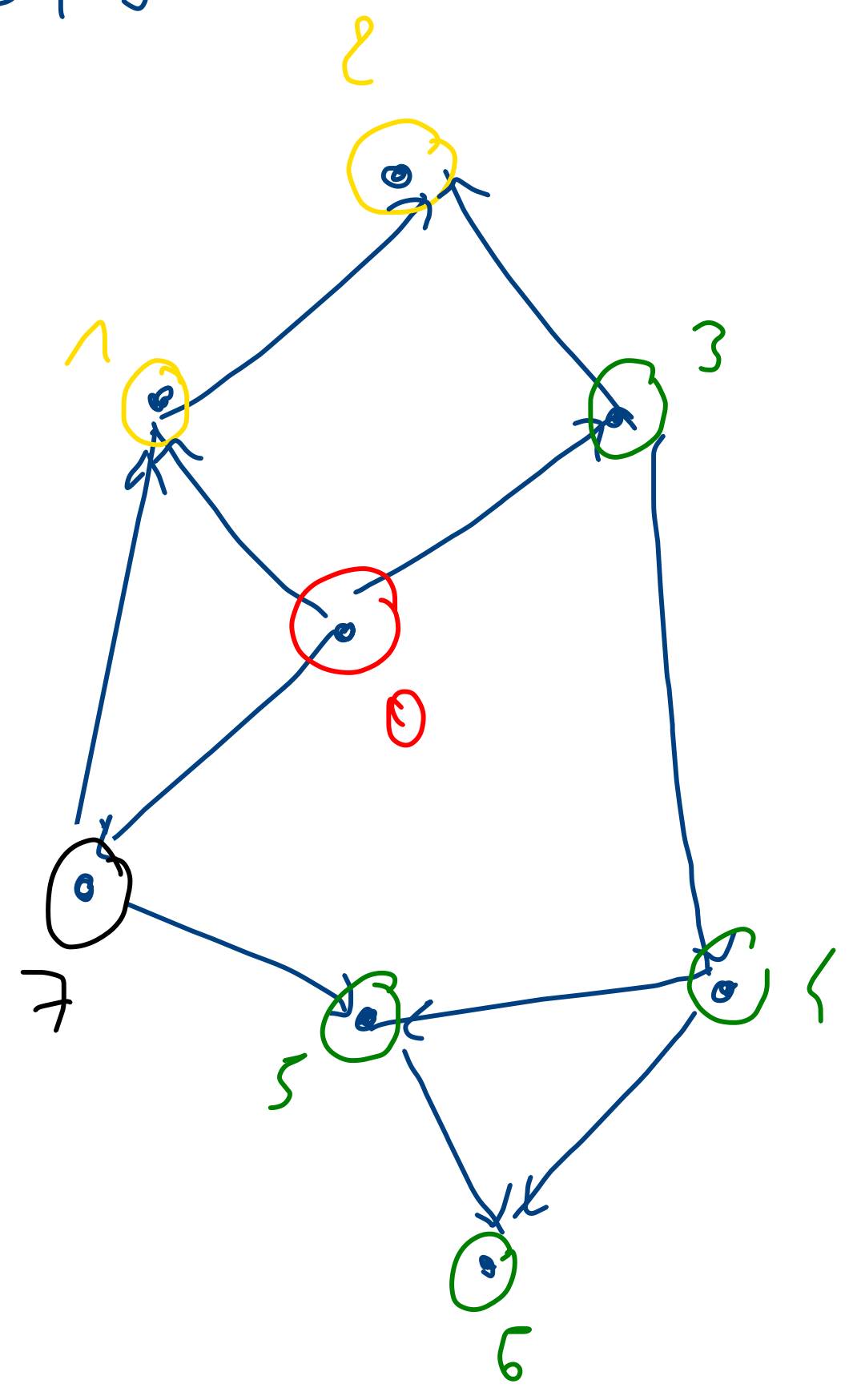
• $c > 0$: Dijkstra's algorithm ← program

• No negative cycles:
- Directed: Bellman-Ford ←
- Undirected: T-joint (reason 2)

BFS



DFS



4) Generalizations

- Single origin, single destination
 - Single origin, mult destinations
 - Multiple origins, mult destinations
- 1 o, 1 d
1 o, all possible d's
all pairs (Floyd-Warshall)

Variants:

- Shortest paths with resource constraints (A. Parnert)
- Multi-criteria
- Transportation networks (timed trips)

III / Algorithms

1) Dynamic Programming

Invented by Bellman. Principle:

A subtrajectory of an optimal trajectory is also optimal

In order to solve a problem, you generalize it. This is done by changing the bounds or varying some constants

2) Bellman - Ford algorithm

Setting: Directed graphs with no cycles of negative cost

We want to compute the cost $c(d)$ of a shortest $s-d$ path
Generalization: we will compute

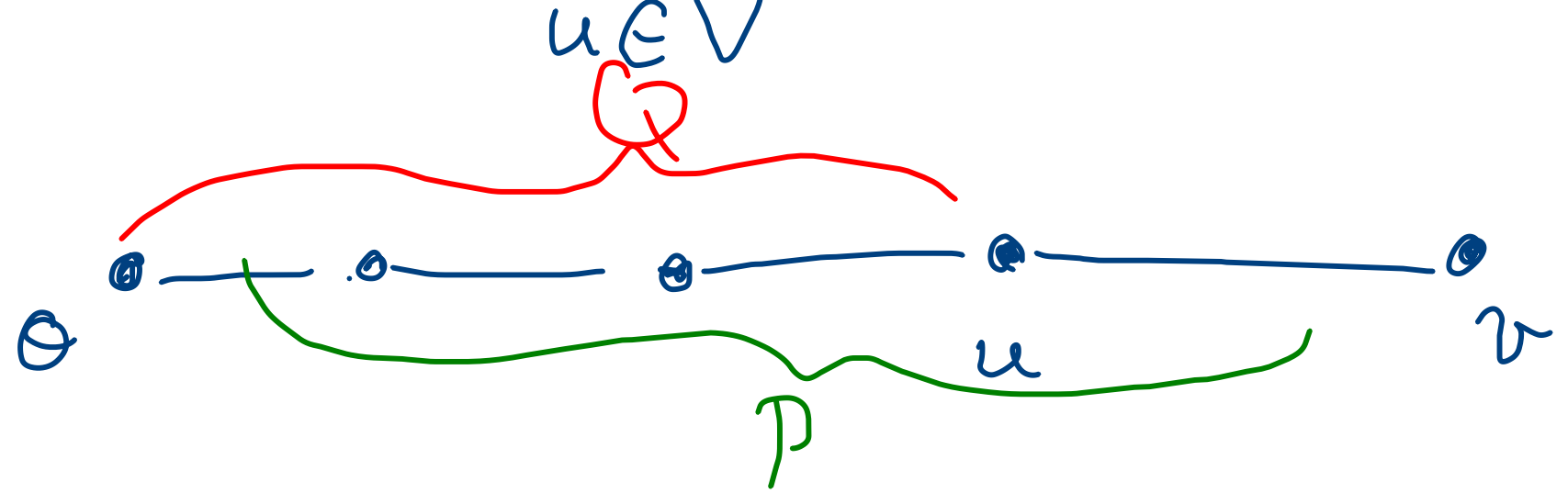
$c_k(v)$ = the cost of a shortest $s-v$ path
with exactly k edges (if it exists)

We can retrieve the info we want by taking the minimum
of all the $c_k(d)$ values for $k \dots$ in $[1, M]$
Since there are no negative cycles, a shortest path will be acyclic
and have at most $n-1$ edges (trees have $\leq n-1$ edges)
(there will be at least one such shortest path)

Bellman equation / recursion:

to build P $c_k(v) = \min_{u \in V} (c_{k-1}(u) + c(u, v))$

we use Q \rightarrow & extend it by 1



(TS)

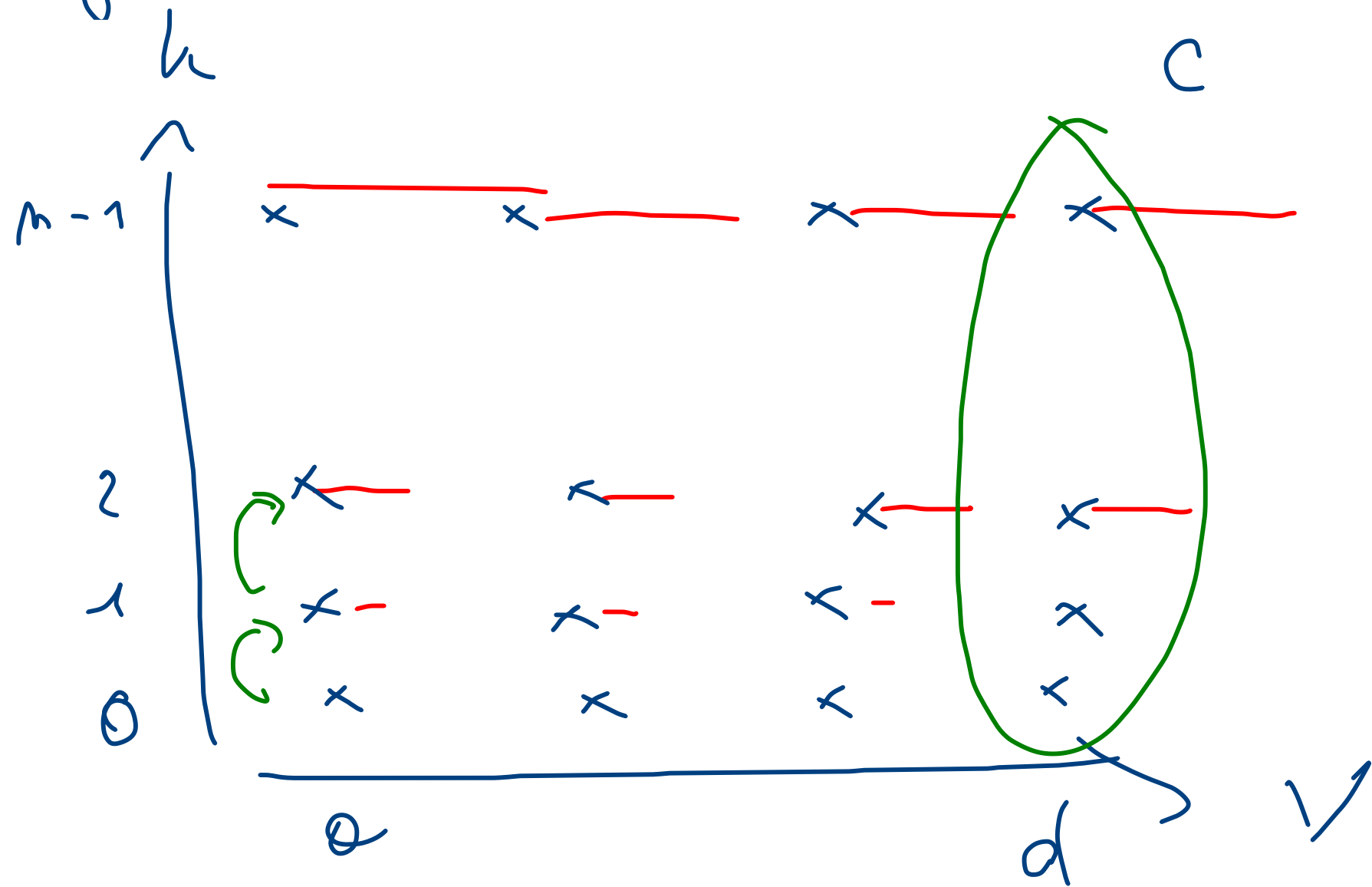
compute $c_u(v)$
remember $(v, k) \rightarrow u$

Why? If P is a shortest k-path from s to v ,
and if u is the vertex just before v on P, then
Q is a shortest $(k-1)$ -path from s to u

$$c_0(v) = \begin{cases} 0 & \text{if } v = s \\ \infty & \text{otherwise} \end{cases}$$

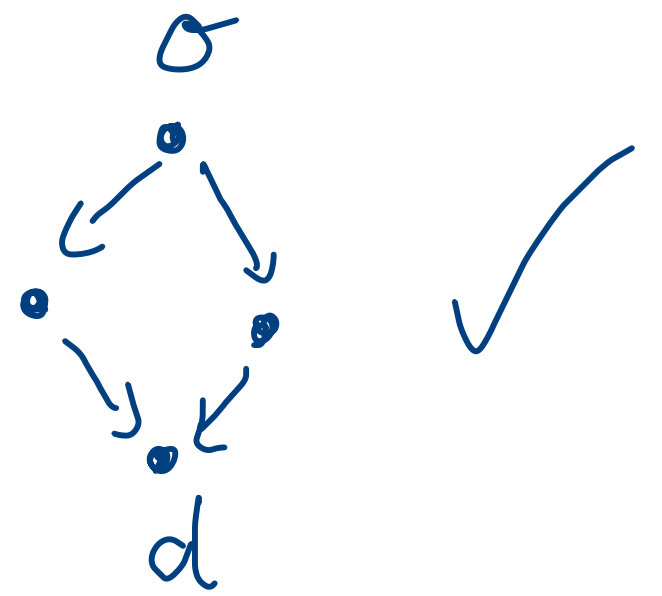
We have the cost, now how do we get the path?
 At each iteration of the recursion, store the vertex u that achieves the minimum in (B)
 For each (v, k) , we know the penultimate vertex on an optimal path u . Then we look it up for $(u, k-1)$ etc and we go back to \emptyset

Building a matrix



2) Topological sort

Setting: DAGs (Directed Acyclic Graphs)



In a DAG, all paths are elementary

(B)

Bellman equation : $c(v) = \min_{u \in V} (c(u) + c(u, v))$

$u \in N^-(v)$ parents of v

Before computing $c(v)$, we need to have computed $c(u)$

Find an order on the vertices such that children nodes always come after their parents

! This is possible because we are in a DAG

using topological sorting (see notes)

Topological sort \Leftrightarrow Depth-First Search

DFS(v) is a procedure that

- opens v
- scans its children (applies DFS to them)
- closes v

} consistent
bc
no
cycles

The order in which nodes are closed is a reverse topological order

3) Dijkstra's algorithm

Setting: $c > 0$ see Algorithm 3

U = set of visited vertices

$d(v)$ = "tentative" distance $\geq c(v)$

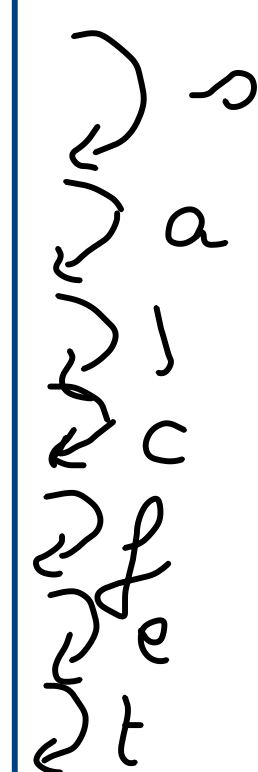
↳ updated iteratively until it reaches the true distance

Lemma: For all $u \in U$, $d(u) = c(u)$

Ex 5.8

Evolution of the tentative distance

s	a	b	c	d	e	f	g	h	t
0	∞	∞	∞	∞	∞	∞	∞	∞	∞
0	1	2	3	∞	∞	∞	∞	∞	∞
0	1	2	3	∞	∞	3	∞	∞	∞
0	1	2	3	∞	7	3	∞	∞	∞
0	1	2	3	7	5	3	∞	∞	∞
0	1	2	3	7	4	3	6	∞	∞
0	1	2	3	6	4	3	6	7	∞
0	1	2	3	6	4	3	6	7	5



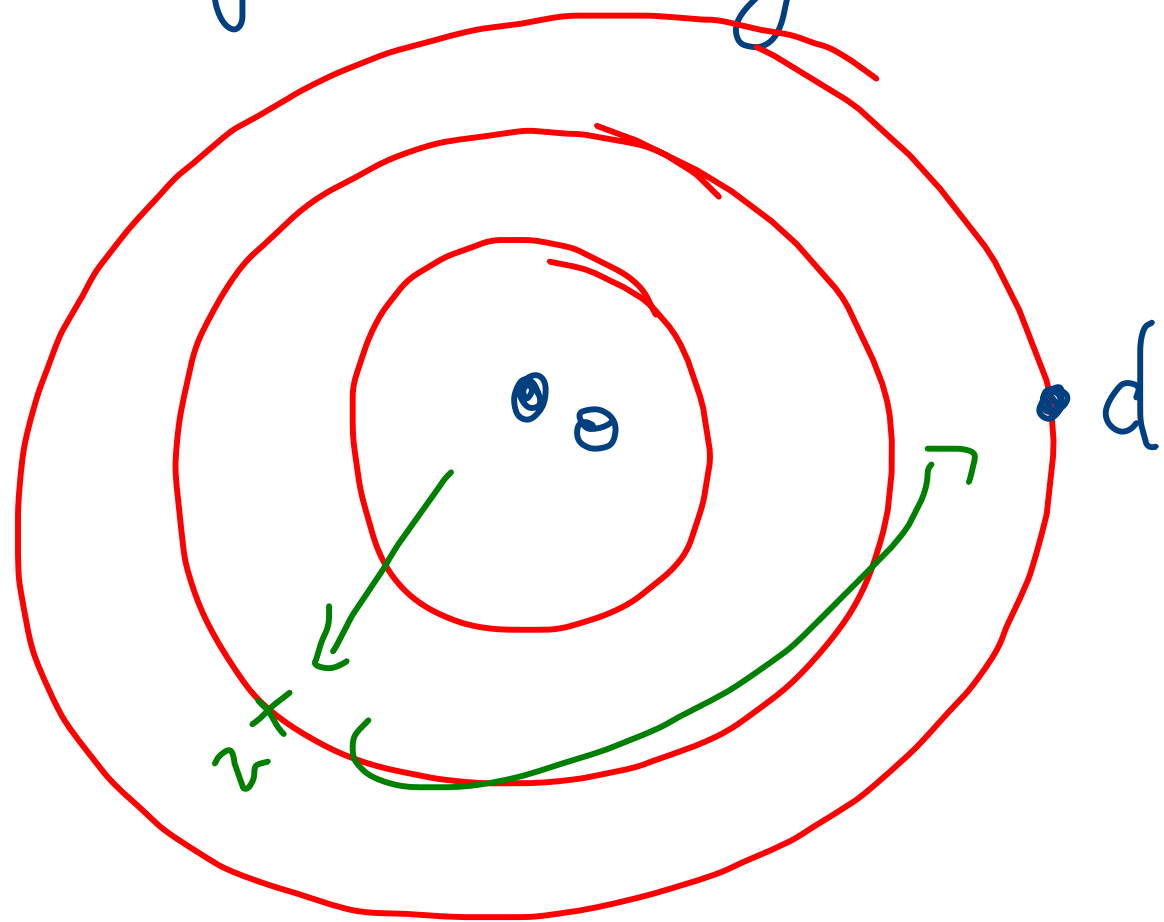
We only visited vertices v s.t. $c(v) \leq c(d)$

To get the shortest path, same as in Bellman-Ford

line 6 of the code: either update or leave unchanged
 when you update, store a pointer $w \rightarrow v$

"the best path $s \rightarrow u$ we know for now ends with v "

A* algorithm: Dijkstra on steroids



A* alg. guides the search towards d
by changing the vertex selection
method

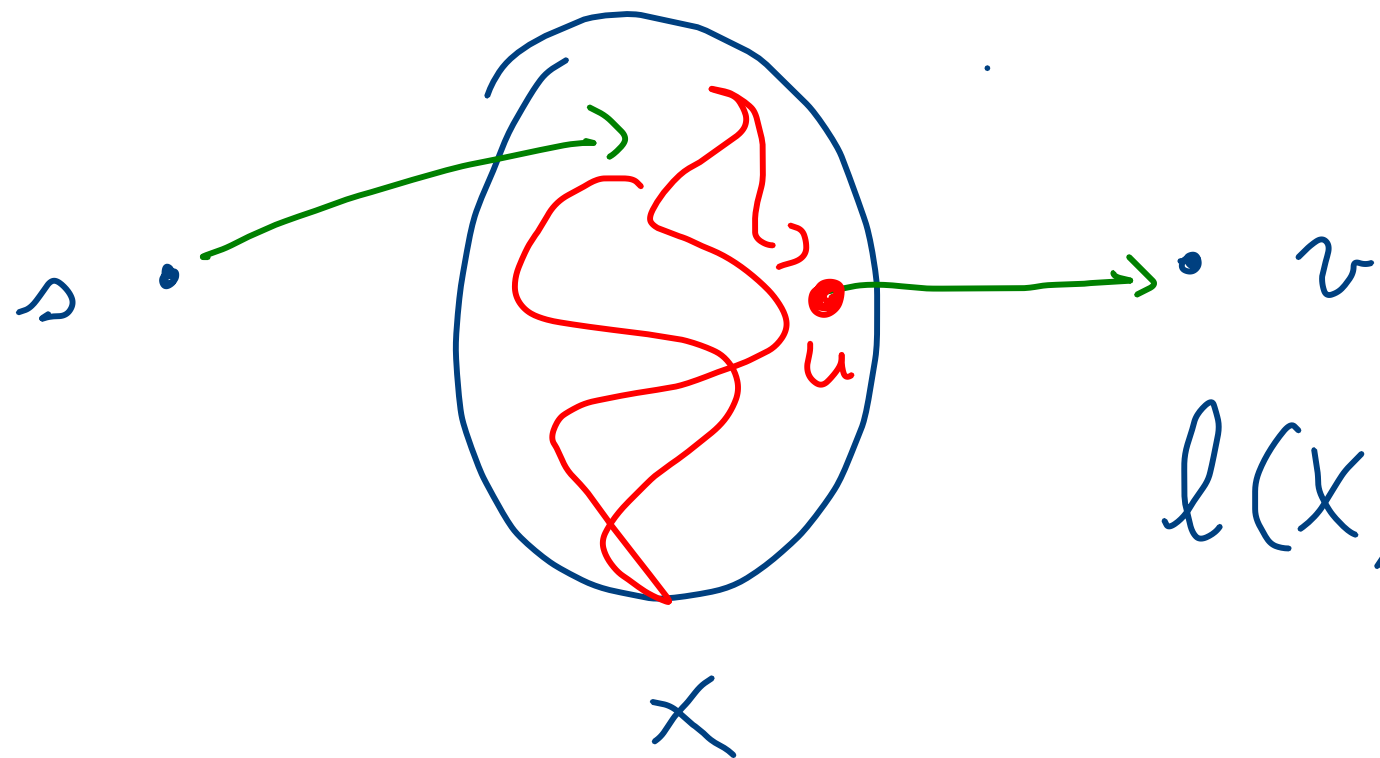
Dijkstra : criterion = $d(v)$

A* : criterion = $d(v) + h(v, d)$

choose the right heuristic

Ex 5.20 : Held-Karp algorithm for TSP

$l(X, v)$ = the cost of a shortest path from s to v
that visits every $x \in X$ exactly once



Bellman equation

$$l(X, v) = \min_{u \in X} \{ l(X \setminus \{u\}, u) + c(u, v) \}$$

Compute $l(X, v)$ for increasing subset size

TV/ Homework

- Find the complexity in Ex 5.20
- Ex 3.5 (Eulerian graphs) \rightarrow solutions in the notes on my website
- Ex 5.12 & Ex 5.19