Sistemi Intelligenti Corso di Laurea in Informatica, A.A. 2019-2020 Università degli Studi di Milan

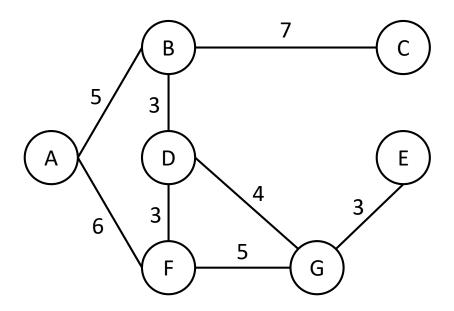


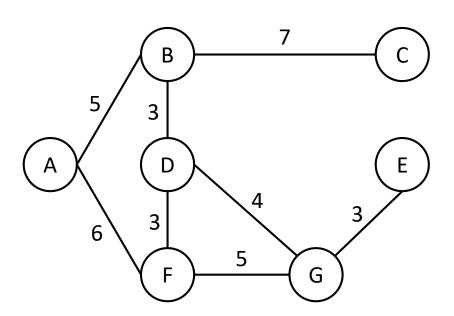
Search algorithms for planning

Nicola Basilico

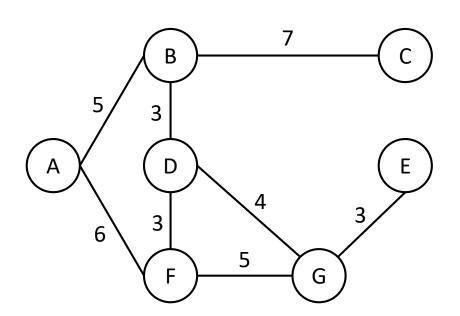
Dipartimento di Informatica Via Celoria 18- 20133 Milano (MI) Ufficio 4008 nicola.basilico@unimi.it

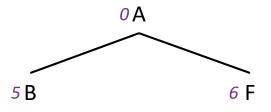
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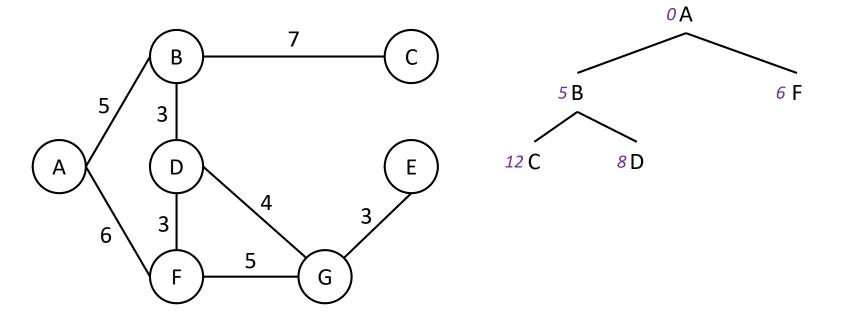


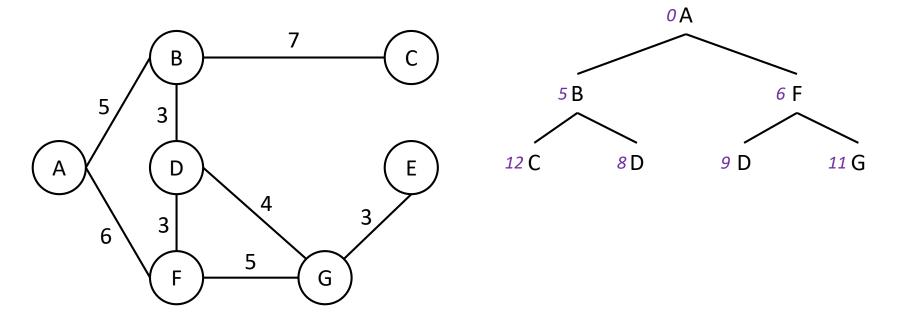


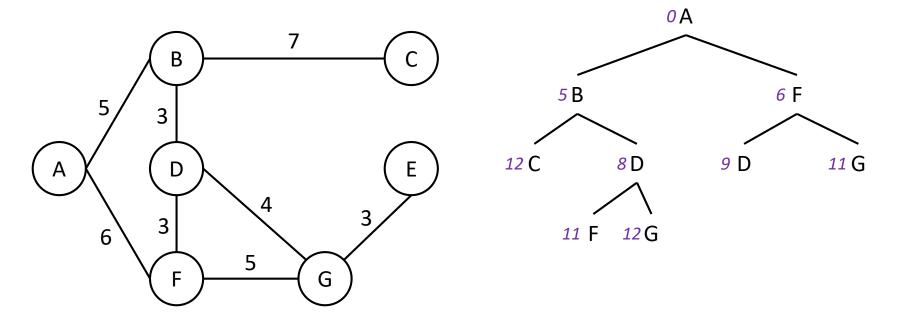
0 A

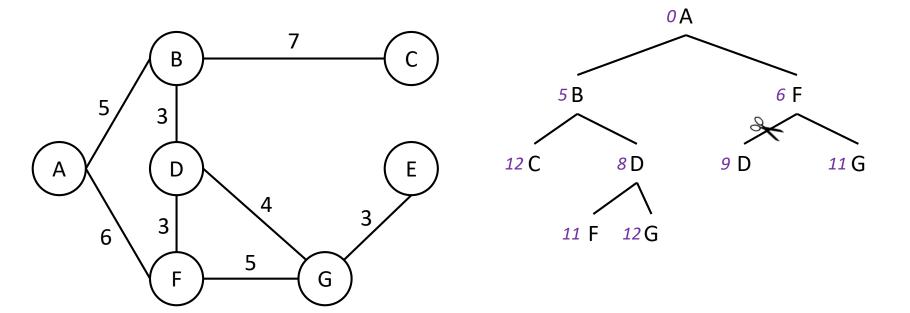


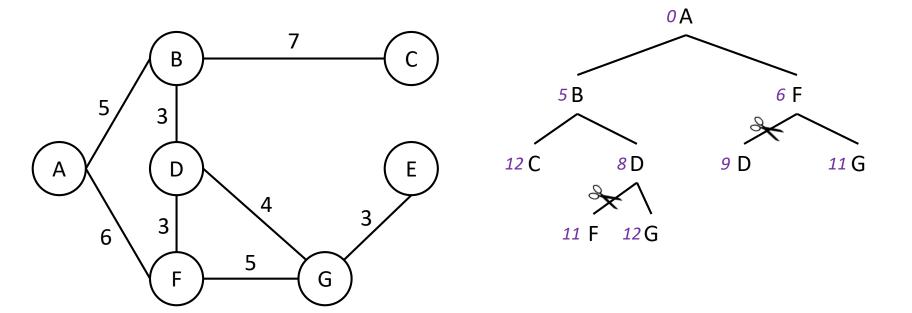


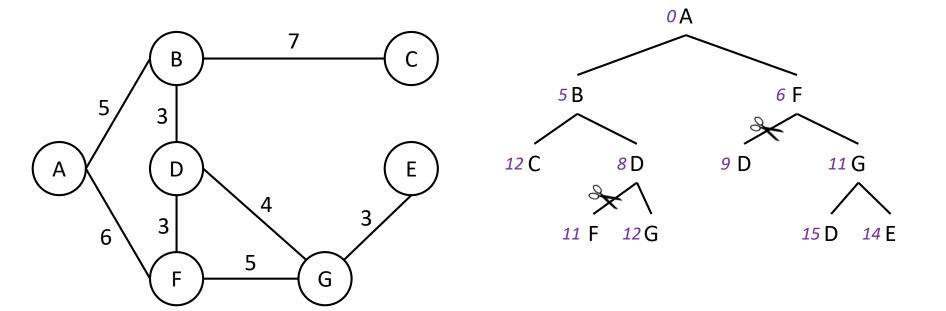


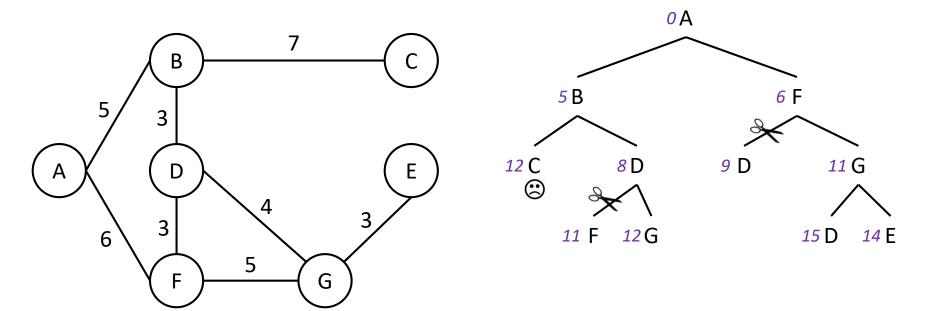


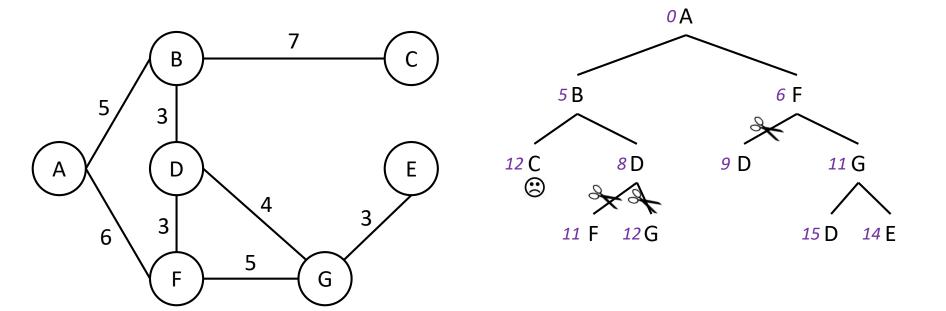


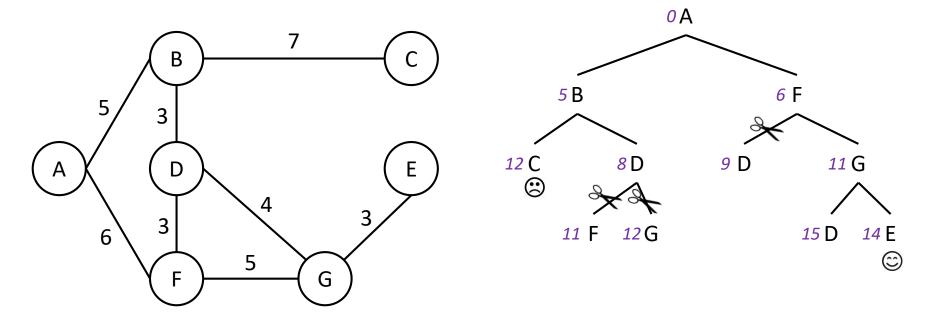






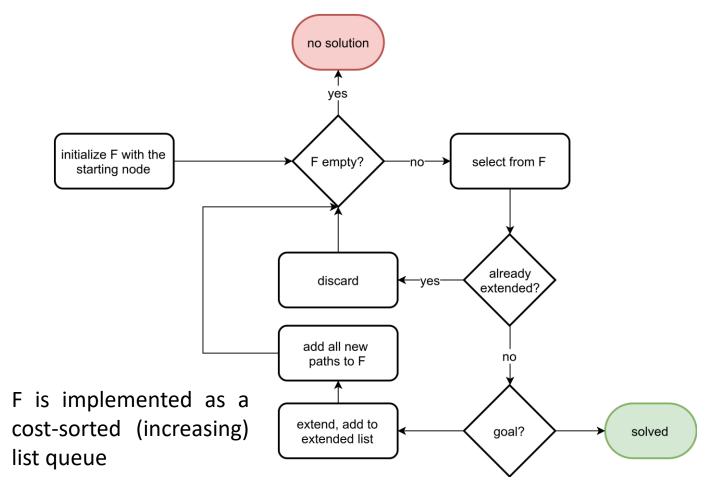






Thanks to the extended list we can prune two branches

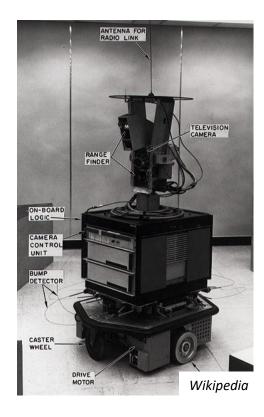
Implementation

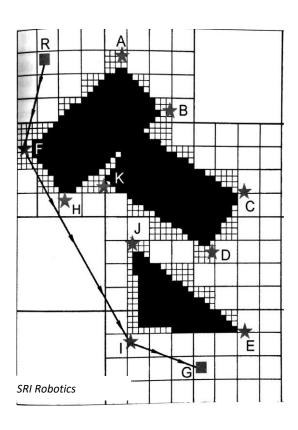


The goal check is done when the node is selected (not when is generated)

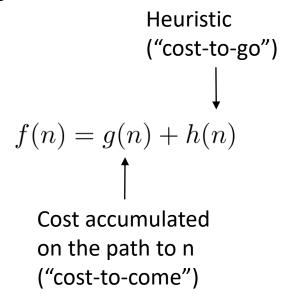
Question: is this search informed?

- The informed version of UCS is called A*
- Very popular search algorithm
- It was born in the early days of mobile robotics when, in 1968, Nilsson, Hart, and Raphael had to face a practical problem with Shakey (one of the ancestors of today's mobile robots)





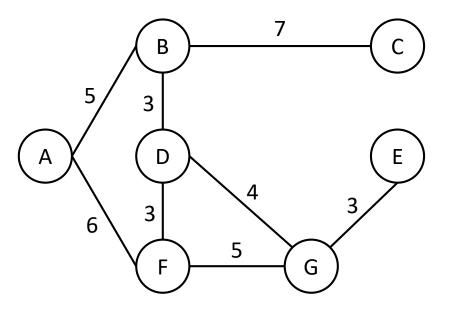
 The idea behind A* is simple: perform a UCS, but instead of considering accumulated costs consider the following:



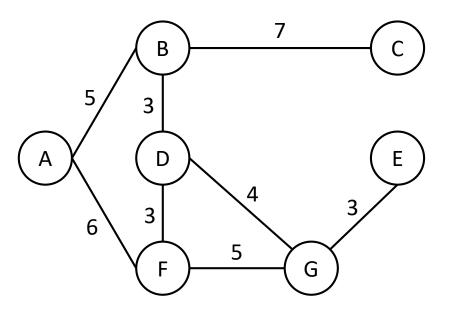
• To guarantee that the search is sound and complete we need to require that the heuristic is **admissible**: it is an optimistic estimate or, more formally:

 $h(n) \leq$ Cost of the minimum path from n to the goal

 If the heuristic is not admissible we might discard a path that could actually turn out to be better that the best candidate found so far

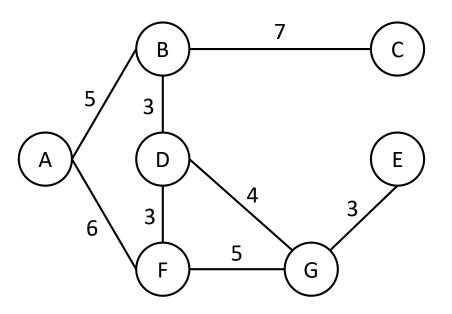


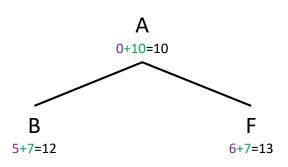
$\mathrm{node}\ v$	h(v)
A	10
В	7
\mathbf{C}	1
D	3
${f E}$	0
${ m F}$	7
G	2



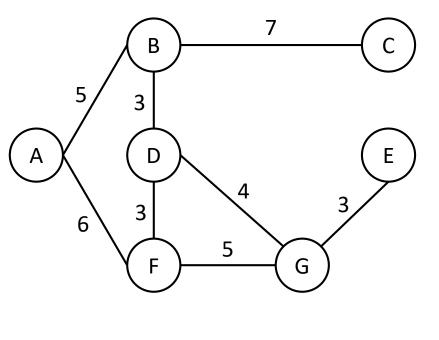
Α	
0+10=10	

node v	h(v)
A	10
В	7
\mathbf{C}	1
D	3
${ m E}$	0
${ m F}$	7
G	2

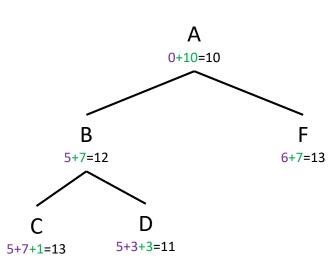


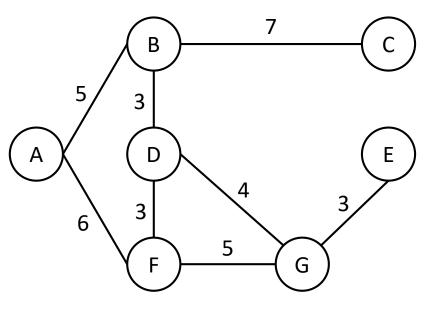


node v	h(v)
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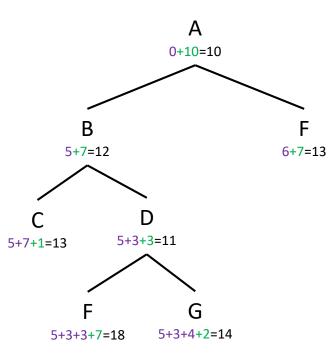


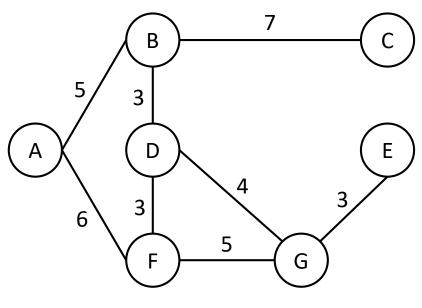
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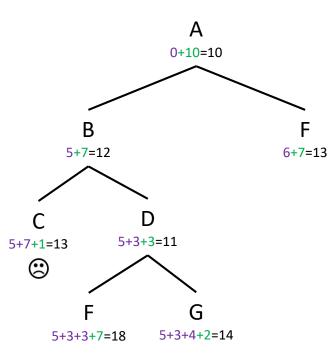


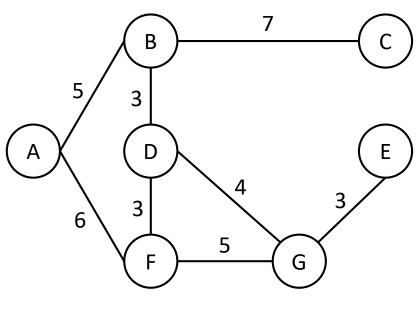
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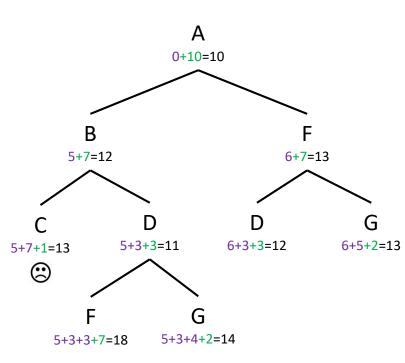


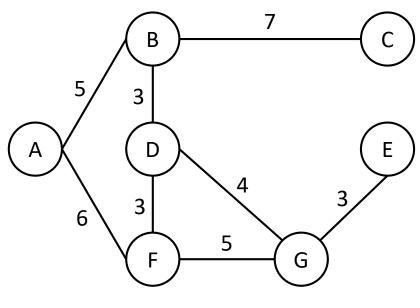
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G	2



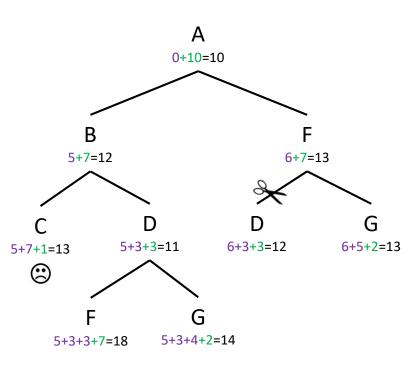


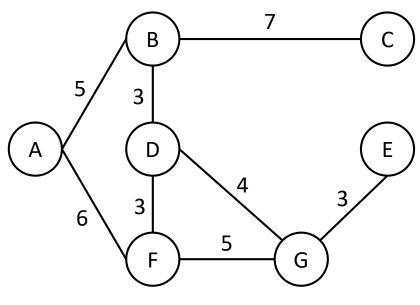
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G	2



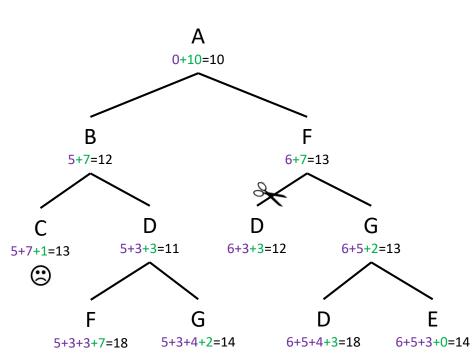


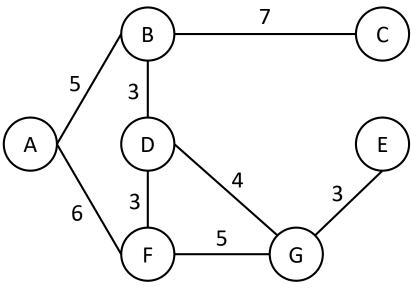
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${ m F}$	7
G	2



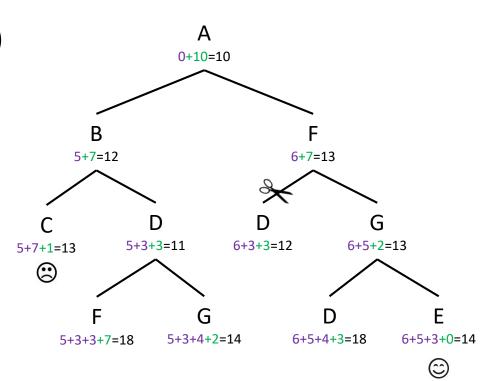


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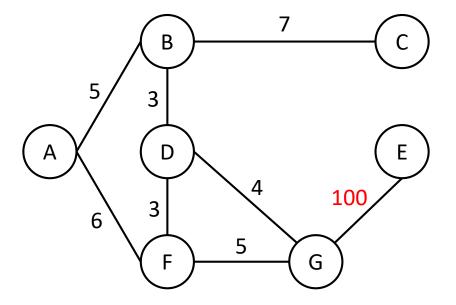




$\mathrm{node}\ v$	h(v)
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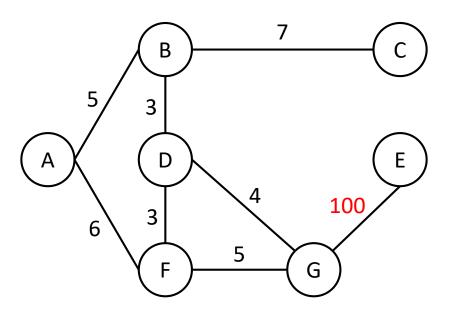


- Problem: if we work with an extended list, admissibility is not enough!
- Let's consider this "pathological" instance:



$\mathrm{node}\ v$	h(v)
A	10
В	0
\mathbf{C}	1
D	0
\mathbf{E}	0
\mathbf{F}	100
G	0

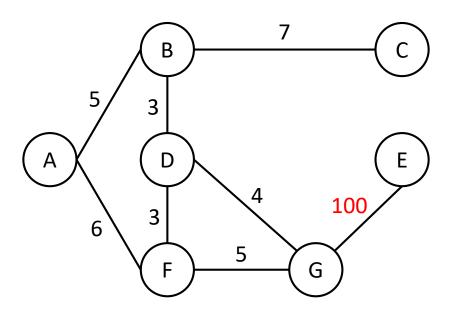
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A	10
В	0
\mathbf{C}	1
D	0
${ m E}$	0
${ m F}$	100
G	0

A 0+10=10

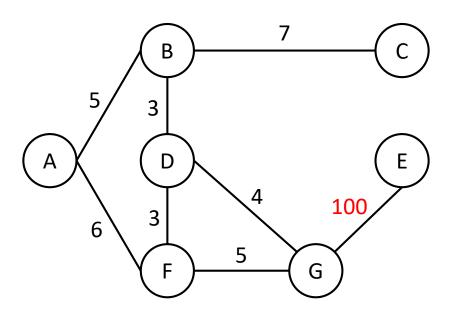
- Problem: if we work with an extended list, admissibility is not enough!
- Let's consider this "pathological" instance:



	A
0+1	LO=10
В	F
5+0=5	6+100=106

node v	h(v)
A	10
В	0
\mathbf{C}	1
D	0
${ m E}$	0
\mathbf{F}	100
G	0

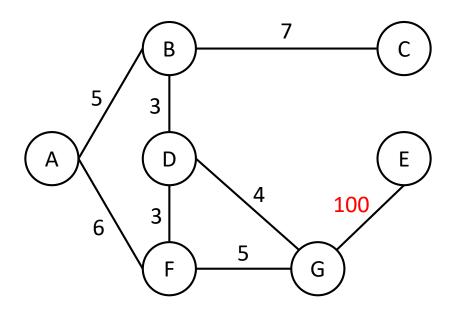
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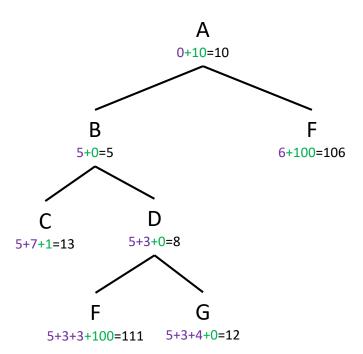
106

node v	h(v)
A	10
В	0
\mathbf{C}	1
D	0
${ m E}$	0
${ m F}$	100
\mathbf{G}	0

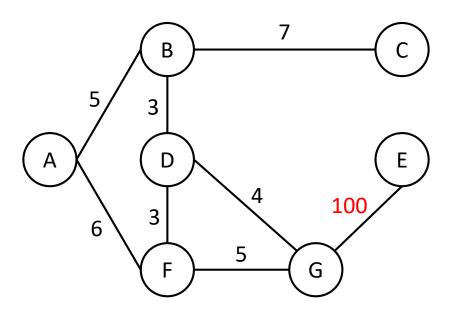
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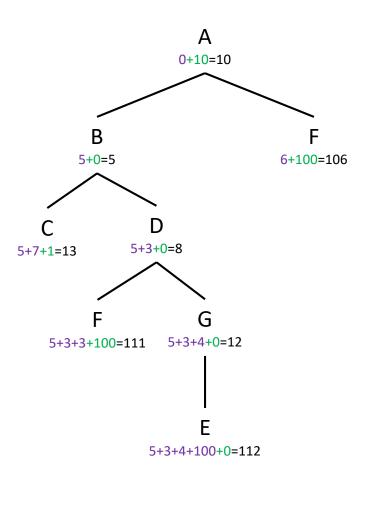
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A	10
В	0
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D	0
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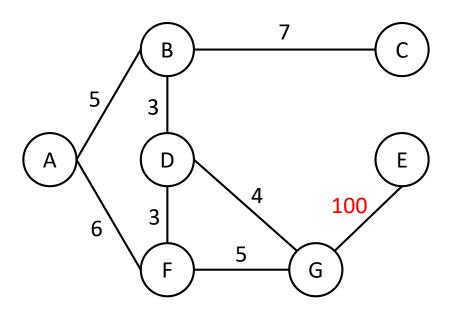
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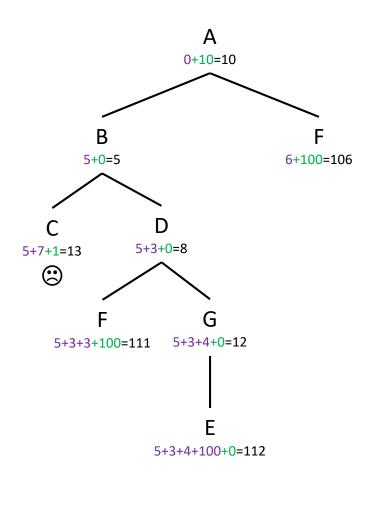
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A	10
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G	0



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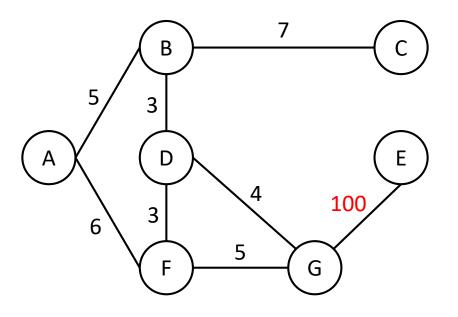


node v	h(v)
A	10
В	0
\mathbf{C}	1
D	0
\mathbf{E}	0
${ m F}$	100
G	0

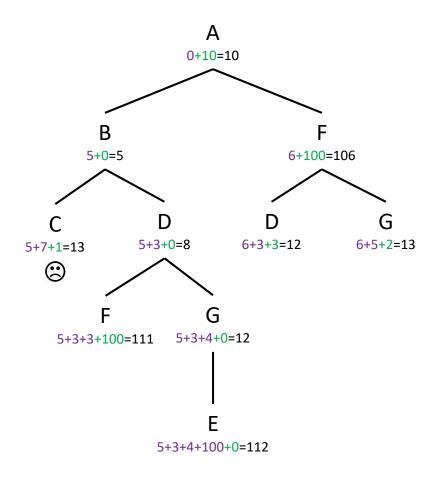


Δ*

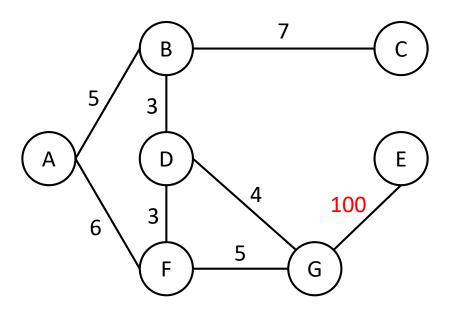
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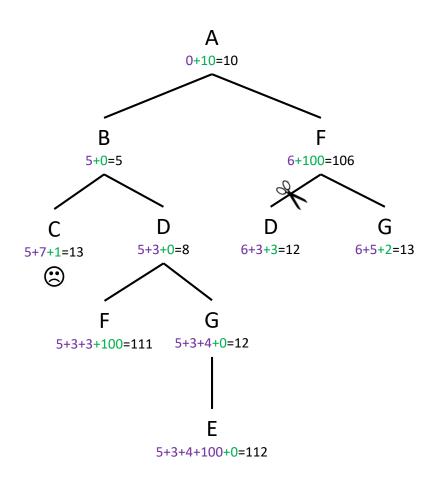
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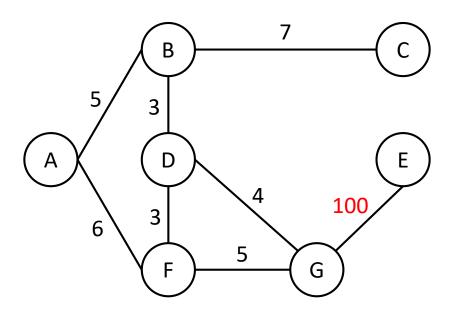
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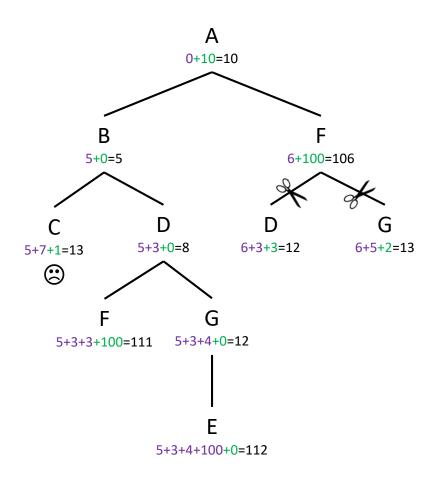
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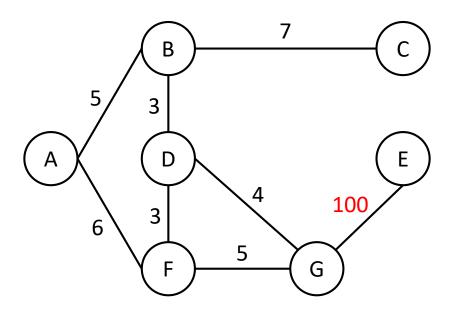
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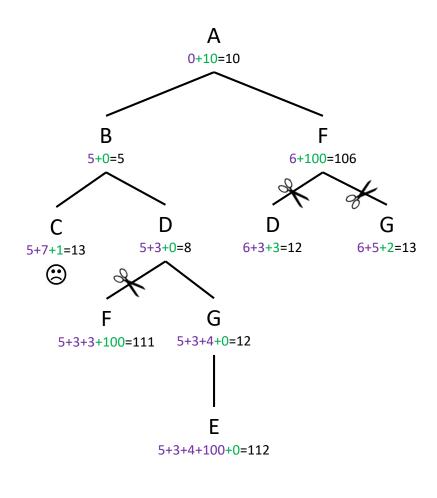
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В	0
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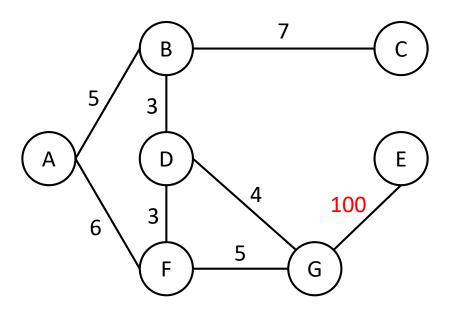
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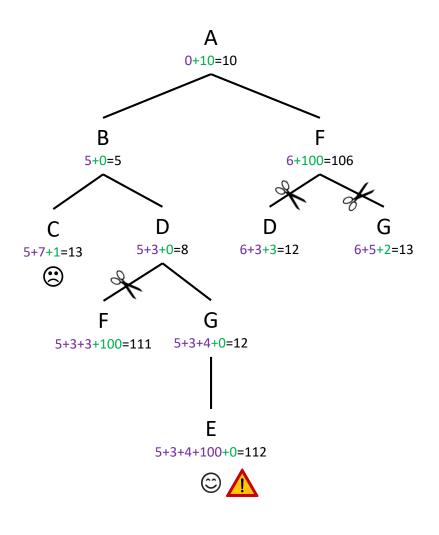
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A	10
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G	0



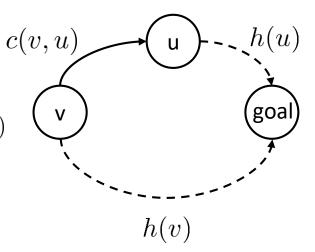
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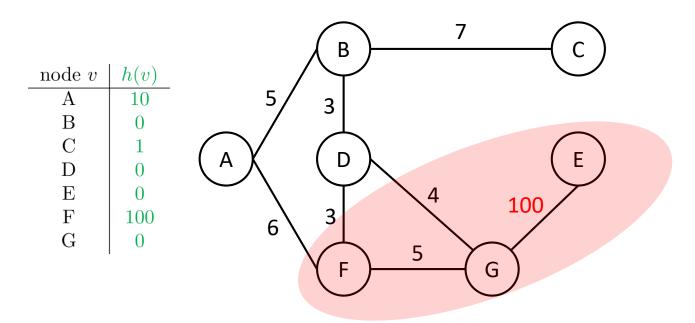
$\mathrm{node}\ v$	h(v)
A	10
В	0
\mathbf{C}	1
D	0
${ m E}$	0
\mathbf{F}	100
G	0



- We need to require a stronger property: consistency
- For any connected nodes u and v: $h(v) \le c(v, u) + h(u)$



It's a sort of triangle inequality, let's reconsider our pathological instance:



Optimality of A*

$$f(v) = g(v) + h(v)$$

$$f(u) = g(u) + h(u) = g(v) + c(v, u) + h(u) \ge g(v) + h(v)$$

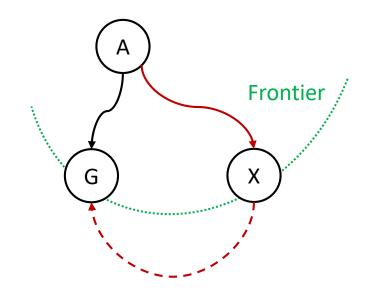
consistency

$$f(u) \ge f(v)$$
 \longrightarrow f is non-decreasing along any search trajectory

Hypotheses:

- 1. A* selects from the frontier a node G that has been generated through a path p
- 2. p is not the optimal path to G

Given 2 and the frontier separation property, we know that there must exist a node X on the frontier that is on a better path to G



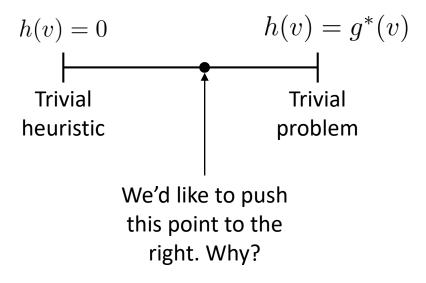
f is non-decreasing: $f(G) \ge f(X)$

A* selected G: f(G) < f(X)

When A* selects a node for expansion, it discovers the optimal path to that node

Evaluating heuristics

How to evaluate if an heuristic is good?



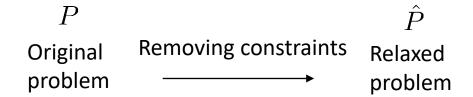
- A* will expand all nodes v such that: $f(v) < g^*(goal) \longrightarrow h(v) < g^*(goal) g(v)$
- If, for any node v $h_1(v) \leq h_2(v)$ then A* with h_2 will not expand more nodes than A* with h_1 , in general h_2 is better (provided that is consistent and can be computed by an efficient algorithm)
- If we have two consistent heuristics h_1 and h_2 we can define $h_3(v) = \max\{h_2(v), h_1(v)\}$

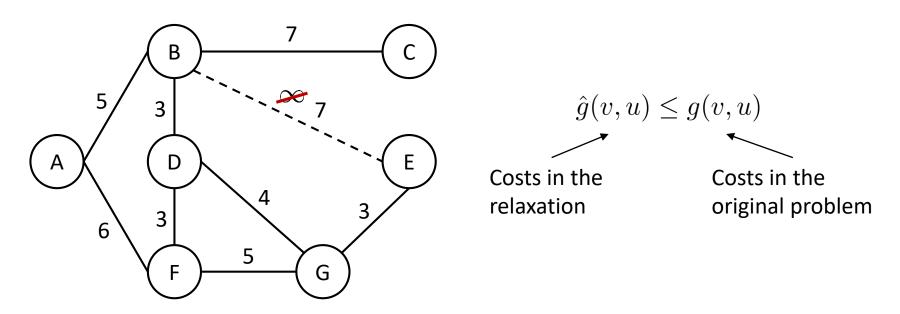
Building good heuristics

- The "larger heuristics are better" principle is not a methodology to define a good heuristic
- Such a task, seems to be rather complex: heuristics deeply leverage the inner structure of a problem and have to satisfy a number of constraints (admissibility, consistency, efficiency) whose guarantee is not straightforward
- When we adopted the straight-line distance in our route finding examples, we were sure it was a good heuristic
- Would it be possible to generalize what we did with the straight-line distance to define a method to *compute* heuristics for a problem?
- Good news: the answer is yes

Relaxed problems

 Given a problem P, a relaxation of P is an easier version of P where some constraints have been dropped





• In our route finding problems removing the constraint that movements should be over roads (links) means that some costs pass from an infinite value to a finite one (the straight-line distance)

Relaxed problems

• Idea:

Define a relaxation of P:
$$\hat{P}$$
 Apply A* to every node and get $\hat{h}^*(v)$ Set $h(v) = \hat{h}^*(v)$ in the original problem and run A*

- We can easily define a problem relaxation, it's just matter of removing constraints/rewriting costs
- But what happens to soundness and completeness of A*?

$$\hat{h}^*(v) \leq \hat{g}(v,u) + \hat{h}^*(u)$$
 Path costs are optimal

$$h(v) \leq \hat{g}(v,u) + h(u) \qquad \text{From our idea}$$

$$\hat{g}(v,u) \leq g(v,u)$$
 From the definition of relaxation

$$h(v) \le g(v,u) + h(u)$$
 h is consistent

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