16-782
Planning & Decision-making in Robotics

Interleaving Planning & Execution: Real-time Heuristic Search

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Planning during Execution

- Planning is a <u>repeated</u> process!
  - partially-known environments
  - dynamic environments
  - imperfect execution of plans
  - imprecise localization

- Need to be able to re-plan fast!

- Several methodologies to achieve this:
  - anytime heuristic search: return the best plan possible within T msecs
  - incremental heuristic search: speed up search by reusing previous efforts
  - real-time heuristic search: plan few steps towards the goal and re-plan later

this lecture

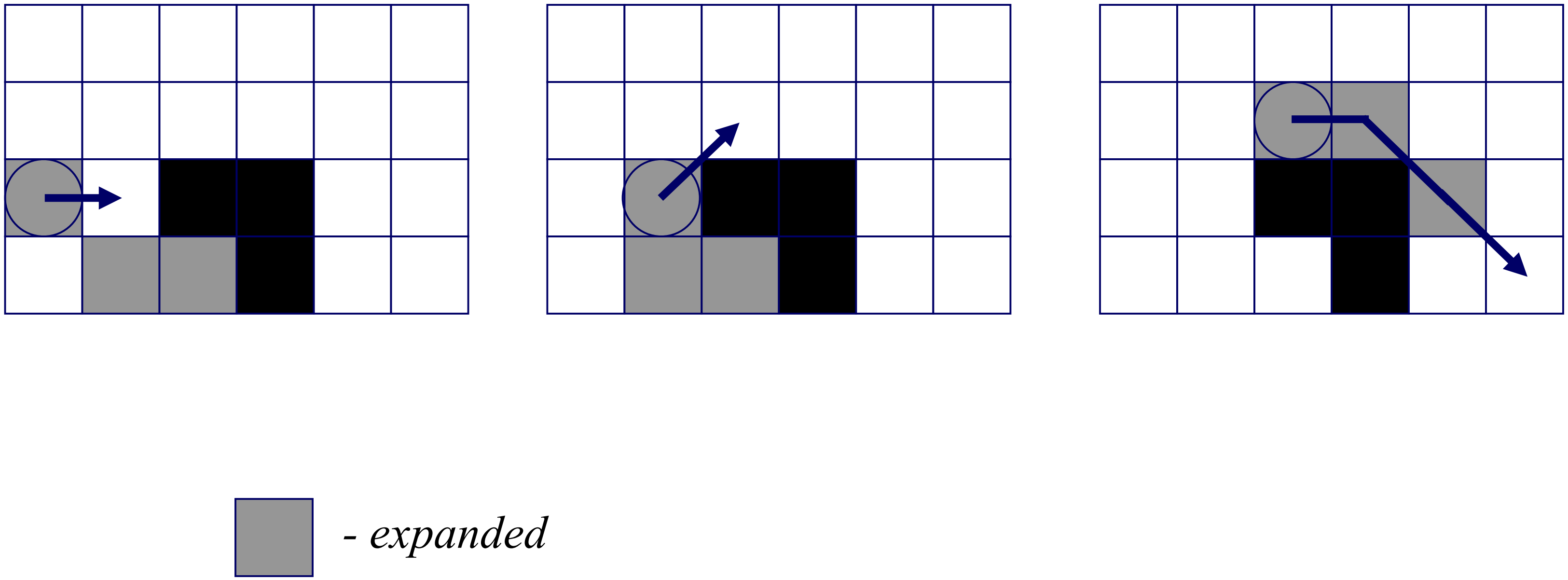
Real-time (Agent-centered) Heuristic Search

Enforce a strict limit on the amount of computations (no requirement on planning all the way to the goal)

Real-time (Agent-centered) Heuristic Search

1. Compute a partial path by expanding at most N states around the robot
2. Move once, incorporate sensor information, and goto step 1

Example in a fully-known terrain:



Real-time (Agent-centered) Heuristic Search

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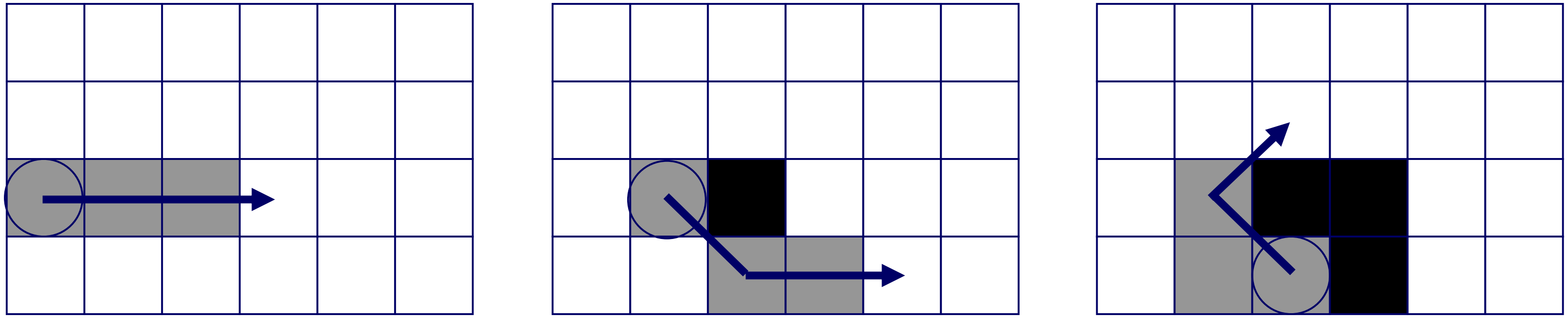
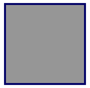
Example in an unknown terrain (planning with Freespace Assumption):



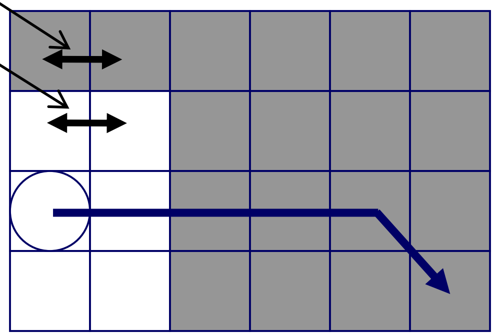


- *expanded*

Planning with Freespace Assumption [Nourbakhsh & Genesereth, '96]

- Freespace Assumption: all unknown cells are assumed to be traversable
- Planning with the Freespace Assumption: always move the robot on a shortest path to the goal assuming all unknown cells are traversable
- Replan the path whenever a new sensor information received

costs between unknown states is the same as the costs in between states known to be free



- *unknown*

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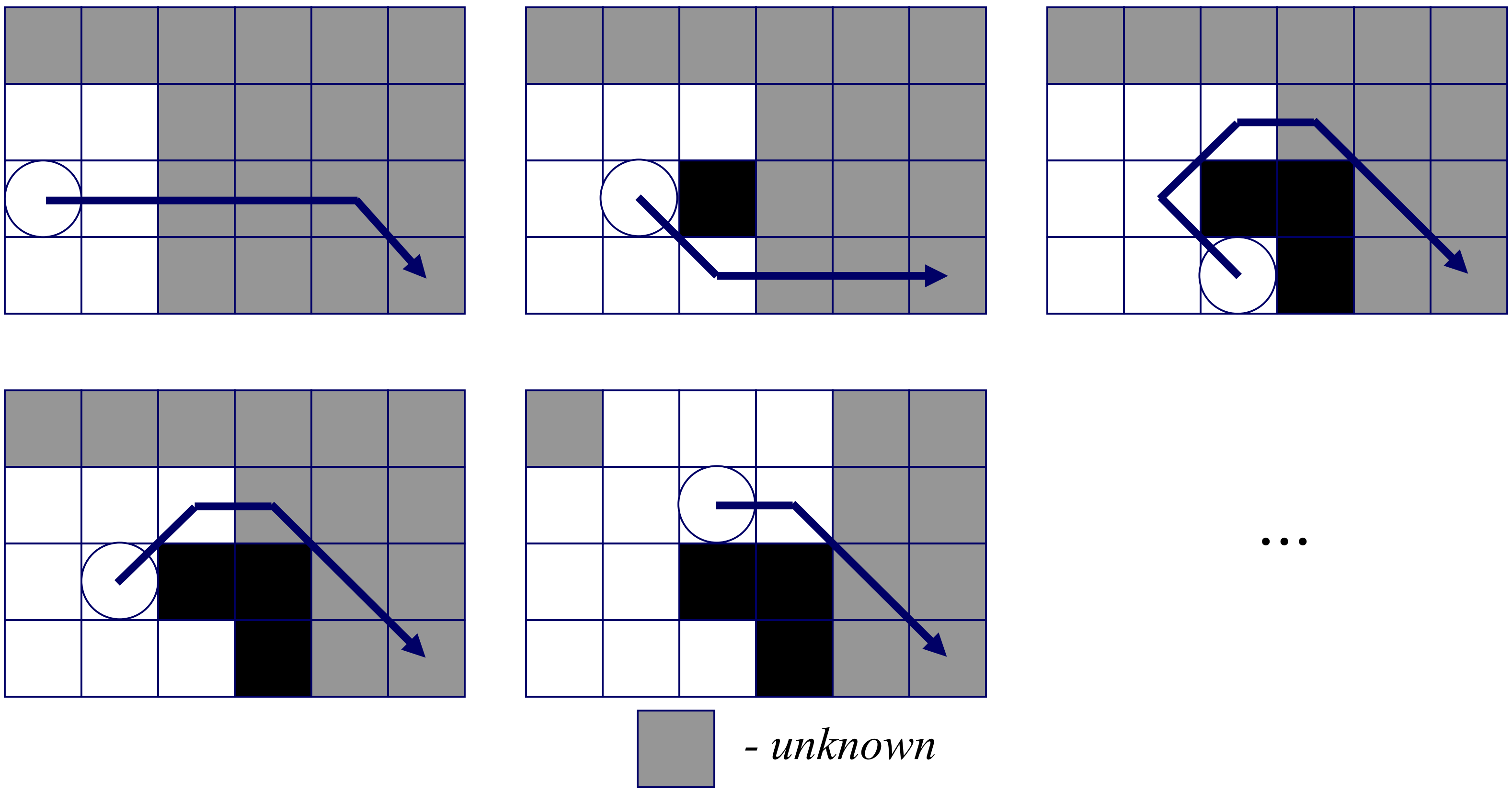

Real-time (Agent-centered) Heuristic Search

1. Compute a partial path by expanding at most N states around the robot
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Research issues:

- how to compute partial path

- how to guarantee complete behavior (guarantee to reach the goal)

- provide bounds on the number of steps before reaching the goal

Real-time (Agent-centered) Heuristic Search

1. Compute a partial path by expanding at most N states around the robot
2. Move once, incorporate sensor information, and goto step 1

Research issues:

- how to compute partial path *Any ideas?*

- how to guarantee complete behavior (guarantee to reach the goal)

- provide bounds on the number of steps before reaching the goal

Learning Real-Time A* (LRTA*) [Korf, '90]

- Repeatedly move the robot to the most promising adjacent state, using heuristics

    1. *always move as follows:* $s_{start} = \operatorname{argmin}_{s \in succ(sstart)} c(s_{start}, s) + h(s)$

$h(x,y) = max(abs(x-x_{goal}), abs(y-y_{goal})) + 0.4*min(abs(x-x_{goal}), abs(y-y_{goal}))$

6.2	5.2	4.2	3.8	3.4	3
5.8	4.8	3.8	2.8	2.4	2
5.4	4.4	3.4	2.4	1.4	1
5	4	3	2	1	0

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5.4	4.4			1.4	1
5	4	3		1	0

Any problems?

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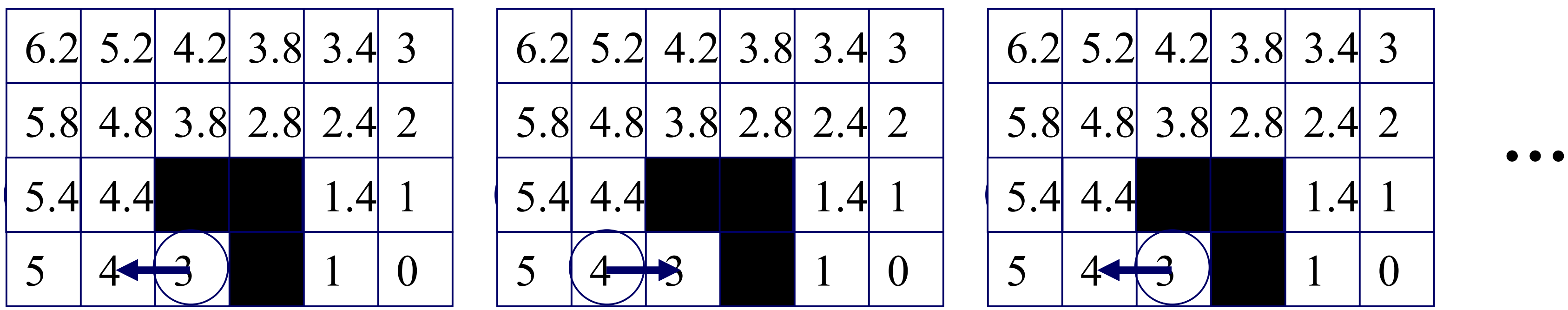

Local minima problem (myopic or incomplete behavior)

Any solutions?

Learning Real-Time A* (LRTA*) [Korf, '90]

- Repeatedly move the robot to the most promising adjacent state, using **and updating** heuristics

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makes h-values more informed

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…

h-values remain admissible and consistent

proof?

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robot is guaranteed to reach goal in finite number of steps if:

- all costs are bounded from below with $\Delta > 0$
- graph is of finite size and there exists a finite-cost path to the goal
- all actions are reversible

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- graph is of finite size and there exists a finite-cost path to the goal
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Why conditions?

Learning Real-Time A* (LRTA*)

- LRTA* with $N \geq 1$ expands [Koenig, '04]

  1. *expand N states*
  2. *update h-values of expanded states by Dynamic Programming (DP)*
  3. *move on the path to state $s = argmin_{s' \in OPEN} g(s') + h(s')$*

necessary for the guarantee to reach the goal

- expanded

Learning Real-Time A* (LRTA*)

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state *s*:

- the state that minimizes cost to it plus heuristic estimate of the remaining distance

- the state that looks most promising in terms of the whole path from current robot state to goal

- expanded

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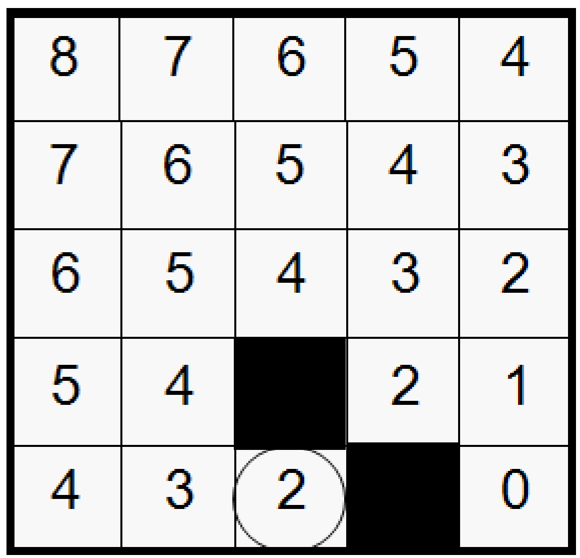

4-connected grid (robot moves in 4 directions)

example borrowed from ICAPS'06 planning summer school lecture (Koenig & Likhachev)

\- *expanded*

Learning Real-Time A* (LRTA*)

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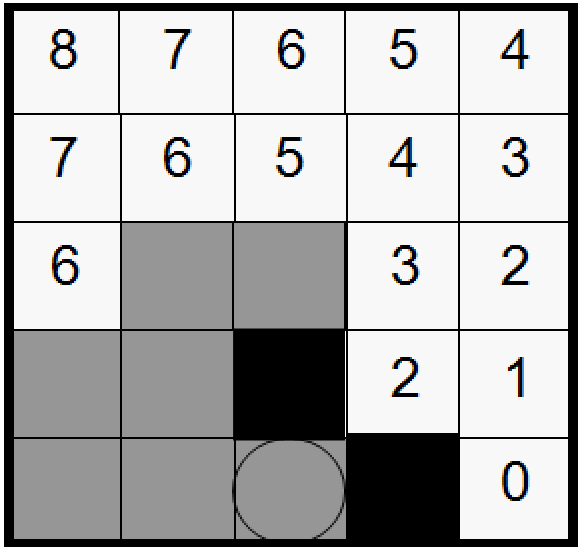
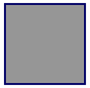


expand N=7 states



- expanded

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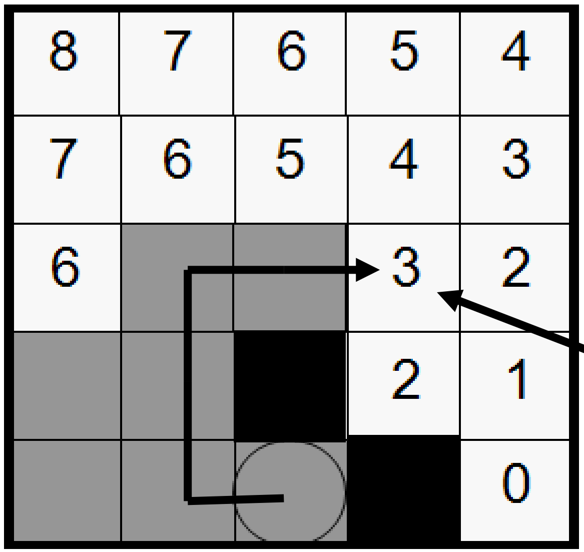

expand N=7 states

unexpanded state with smallest g + h (= 5 + 3)

- *expanded*

Learning Real-Time A* (LRTA*)

How path is found?

- LRTA* with $N \geq 1$ expands

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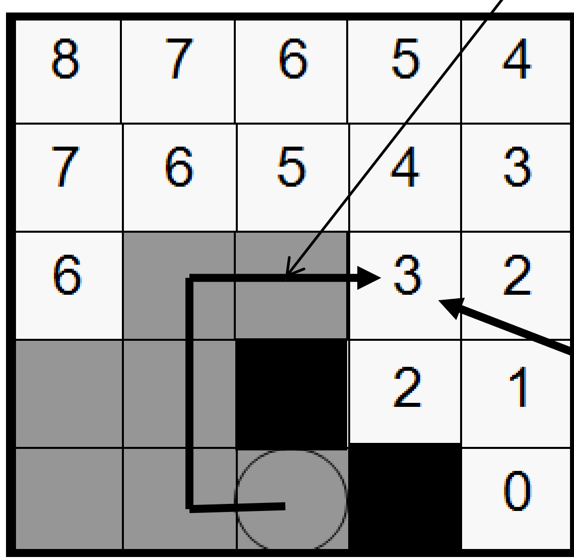

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- LRTA* with $N \geq 1$ expands

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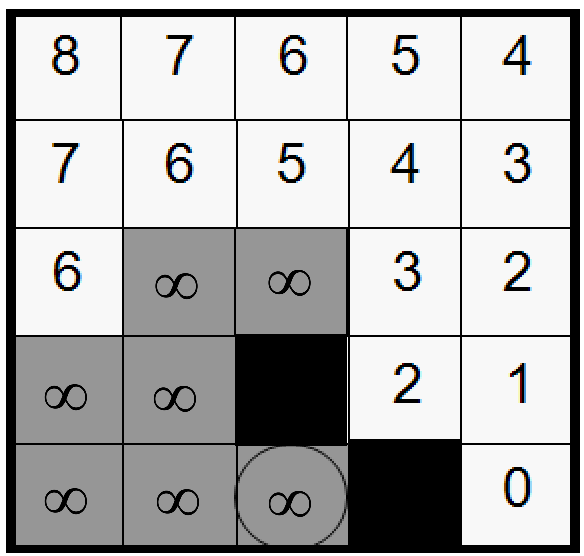

update h-values of expanded states via DP:
compute $h(s) = \min_{s' \in succ(s)} (c(s,s')+h(s'))$
until convergence

- expanded

Learning Real-Time A* (LRTA*)

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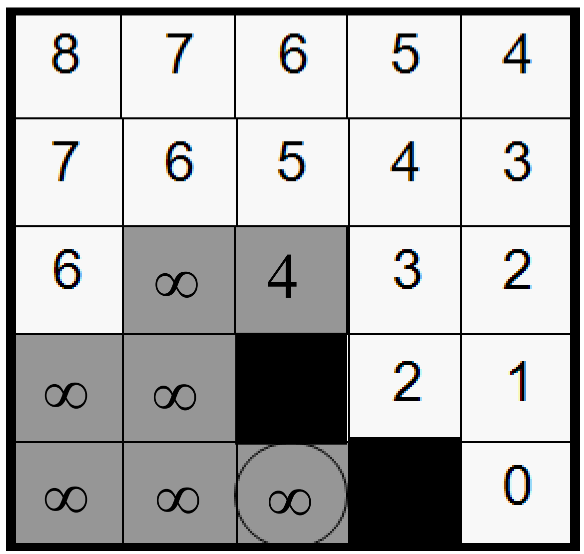

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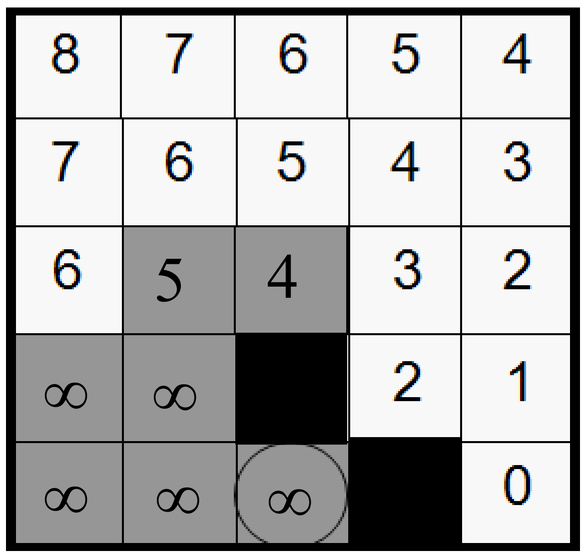

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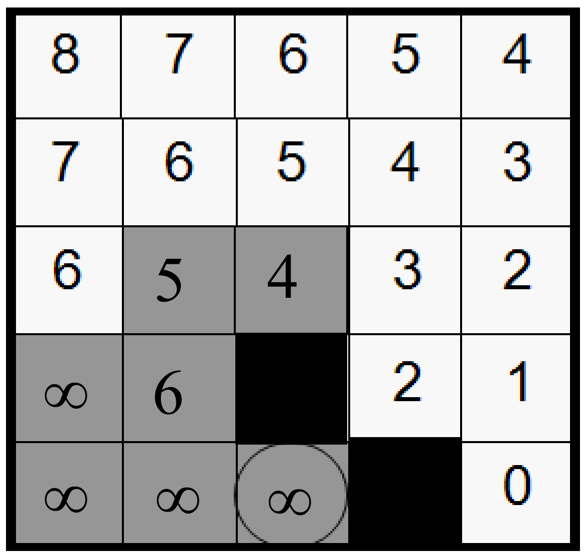

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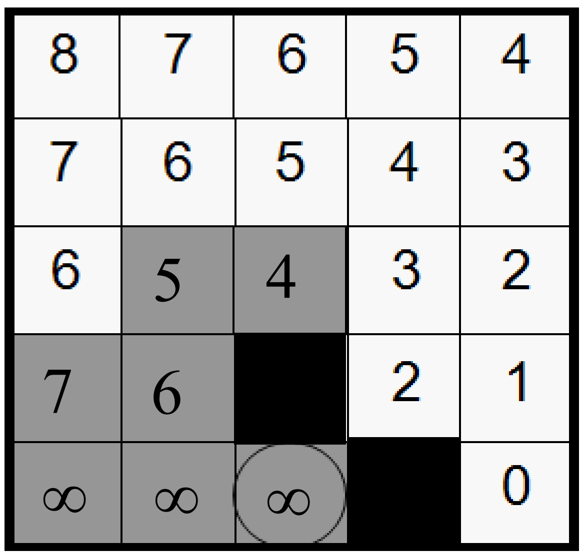

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Does it matter in what order?

- expanded

Learning Real-Time A* (LRTA*)

- LRTA* with $N \geq 1$ expands

1. expand N states

2. update h-values of expanded states by Dynamic Programming (DP)

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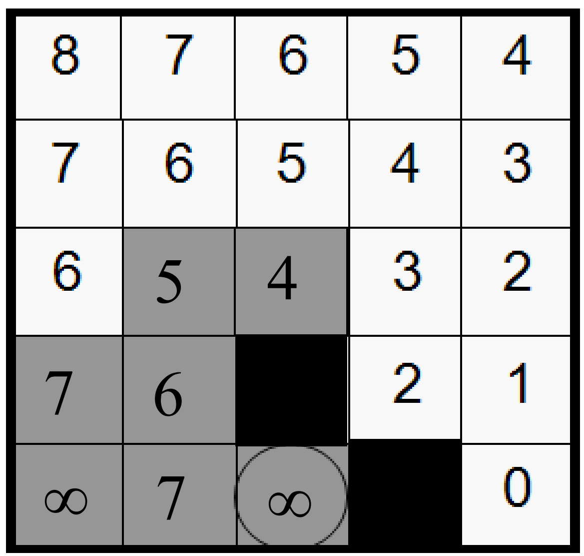

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- expanded

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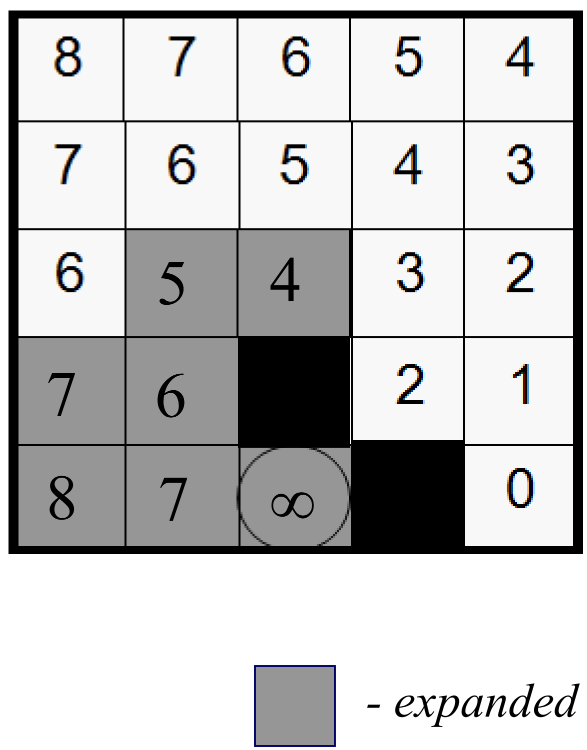

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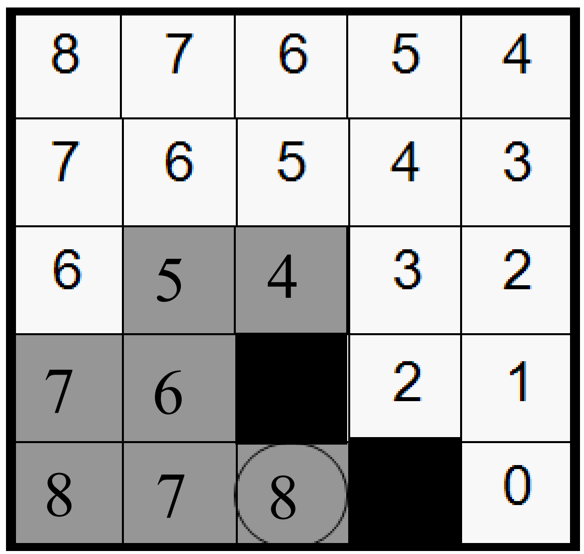

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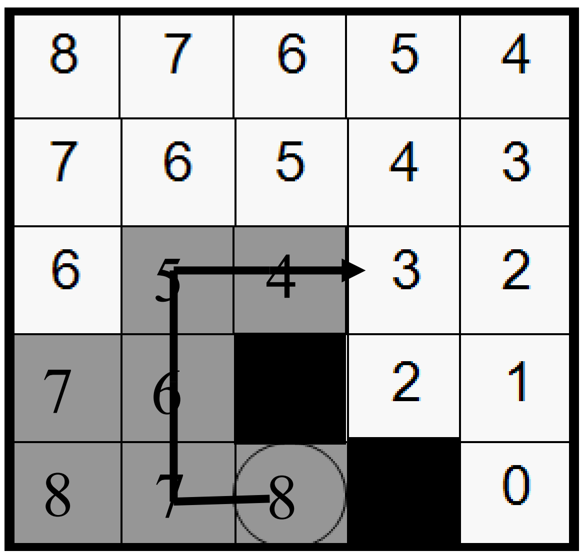


make a move along the found path and repeat steps 1-3

Drawbacks compared to A?*

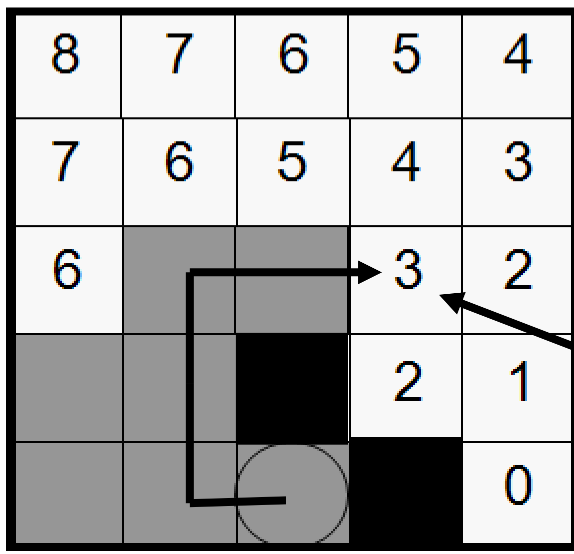
- expanded

Real-time Adaptive A* (RTAA*) [Koenig & Likhachev, '06]

- RTAA* with $N \geq 1$ expands

one linear pass,
and even that can be lazy(postponed)

1. *expand N states*
2. *update h-values of expanded states u by $h(u) = f(s) - g(u)$,*
   where $s = \operatorname{argmin}_{s' \in OPEN}\, g(s') + h(s')$
3. *move on the path to state $s = \operatorname{argmin}_{s' \in OPEN}\, g(s') + h(s')$*



expand N=7 states

unexpanded state *s* with smallest *g* + *h* (= 5 + 3)

- *expanded*

Real-time Adaptive A* (RTAA*)

- RTAA* with $N \geq 1$ expands

  1. *expand N states*
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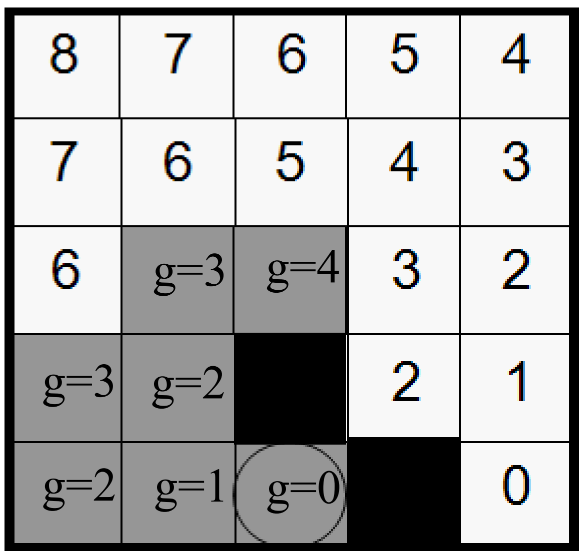

update all expanded states u:

$h(u) = f(s) - g(u)$

unexpanded state *s* with smallest *f(s) = 8*

- expanded

Real-time Adaptive A* (RTAA*)

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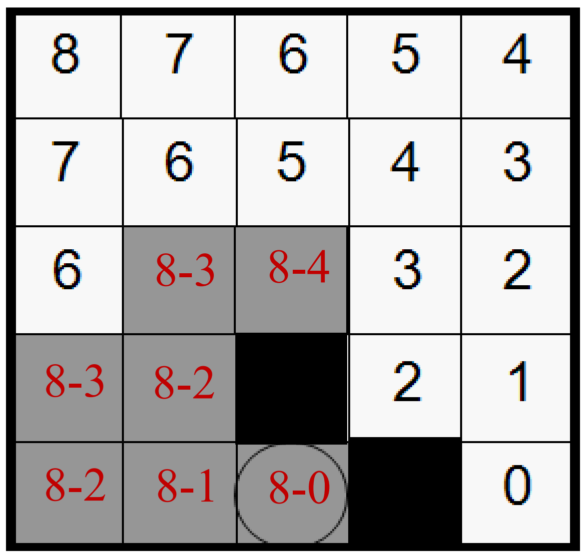

update all expanded states u:

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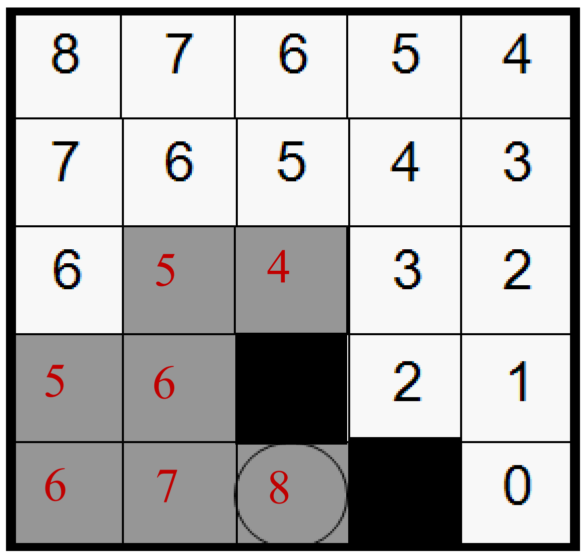
unexpanded state *s* with smallest
f(s) = *8*

- *expanded*

Real-time Adaptive A* (RTAA*)

- RTAA* with $N \geq 1$ expands

  1. *expand N states*
  2. *update h-values of expanded states u by* $h(u) = f(s) - g(u)$,
     where $s = \operatorname{argmin}_{s' \in OPEN}\, g(s') + h(s')$
  3. *move on the path to state* $s = \operatorname{argmin}_{s' \in OPEN}\, g(s') + h(s')$



update all expanded states u:

$h(u) = f(s) - g(u)$

unexpanded state *s* with smallest
f(s) = 8

- expanded

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3. *move on the path to state $s = \text{argmin}_{s' \in OPEN}\, g(s') + h(s')$*

proof of admissibility:

$h^*()$ – true cost-to-goal

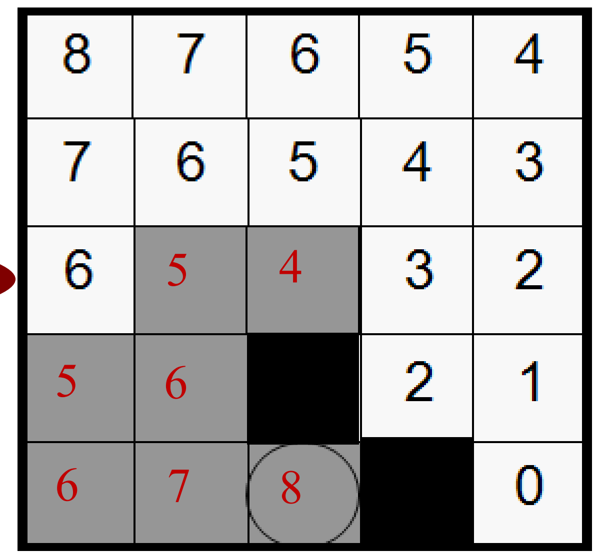
$$g(u) + h^*(u) \geq h^*(s_{start})$$

$$h^*(u) \geq h^*(s_{start}) - g(u)$$

because $f(s) \leq h^*(s_{start})$

$$h^*(u) \geq f(s) - g(u)$$

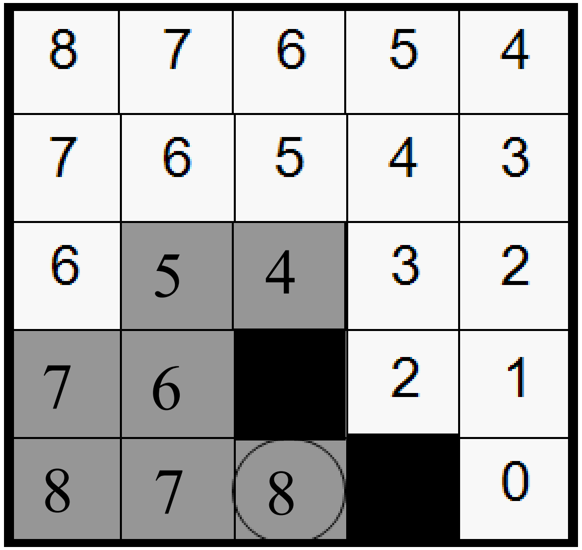
$$h^*(u) \geq h_{updated}(u)$$



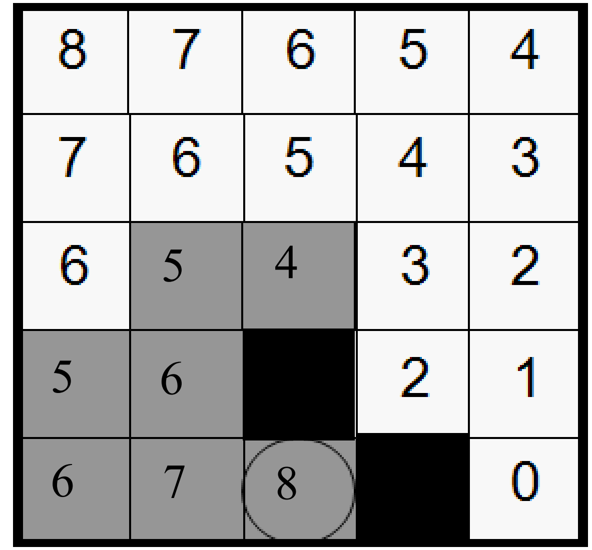
- expanded

LRTA* vs. RTAA*

LRTA*



RTAA*



- Update of *h*-values in RTAA* is much faster but not as informed
- Both guarantee adimssibility and consistency of heuristics
- For both, heuristics are monotonically increasing
- Both guarantee to reach the goal in a finite number of steps (given the conditions listed previously)

What You Should Know…

- What Freespace Assumption means
- Why we need to update heuristics in the context of Real-time Heuristic Search
- The operation of LRTA*
- Pros and cons of LRTA*
- What domains LRTA* is useful in and what domains it is not really applicable
- What RTAA* is