New Results in Bounded-Suboptimal Search

Maximilian Fickert[1] and Tianyi Gu[2] and Wheeler Ruml[2]

1 UNIVERSITÄT DES SAARLANDES

2 University of New Hampshire

Planning as Heuristic Graph Search

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heuristic search: a planning approach

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heuristic search: a planning approach

planning is a model-based AI method, it models the environment as a state space and finds a sequence of actions that accomplishes some objective

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heuristic search: a planning approach

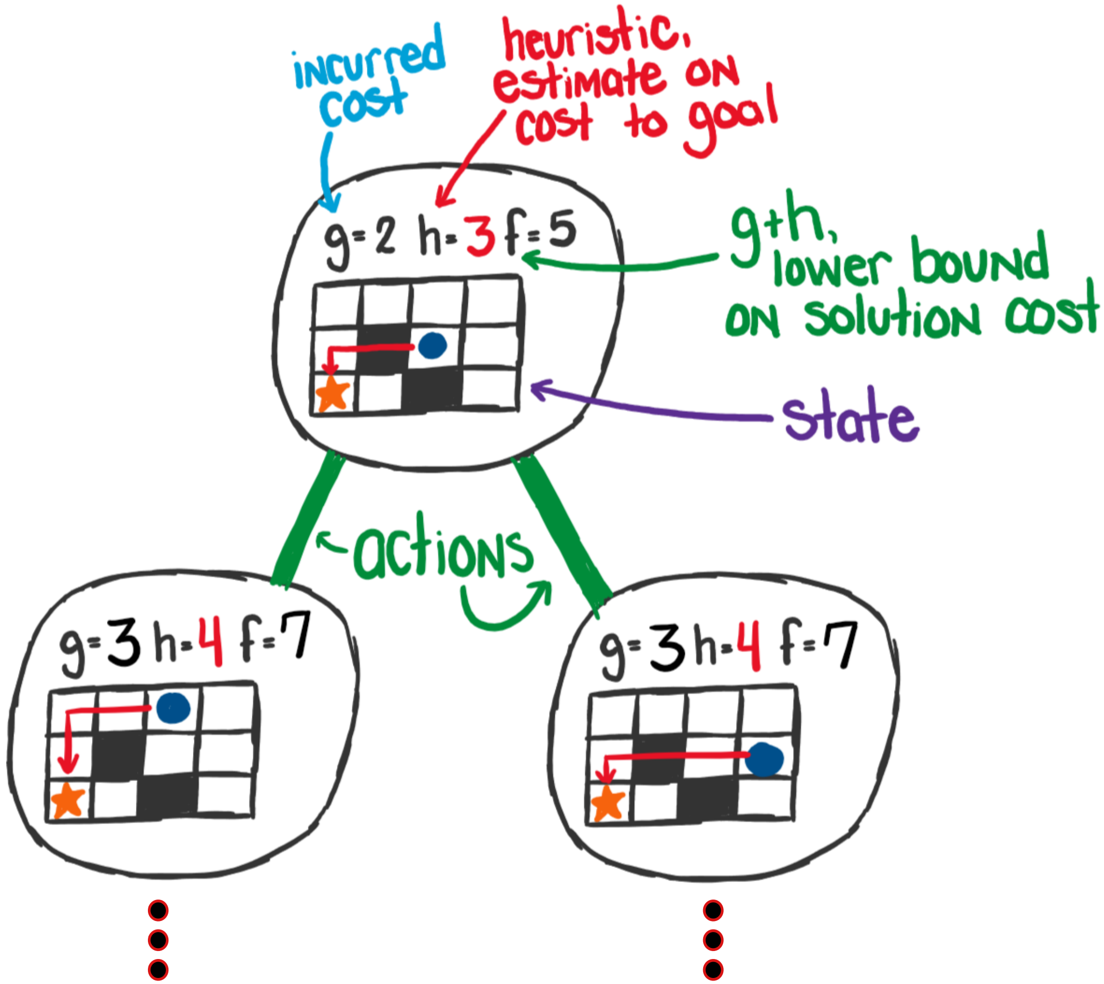
planning is a model-based AI method, it models the environment as a state space and finds a sequence of actions that accomplishes some objective

heuristic search:

$\{$states, actions$\} \rightarrow \{$V, E$\}$
planning problem $\rightarrow$ find a path from s_{init} to $\{s_{goal}\}$
guide graph search by a heuristic estimate of cost-to-goal

Planning as Heuristic Graph Search

heuristic search associates costs with states,
used to guide search



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A*: expands the node with minimal f value
returns optimal path
optimal search can take too long!
because it must expand every node with $f < C^*$[1]

[1] How Good is Almost Perfect, Malte Helmert and Gabriele Roger, AAAI, 2008.

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What if we don't have time?

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Alternatives to Optimal Search: Problem Settings

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optimal: minimize solution cost

expand every node with $f < C^*$

greedy: minimize solving time

anytime: incrementally converge to optimal

bounded-suboptimal: minimize time subject to relative cost bound (factor of optimal)

bounded-cost: minimize time subject to absolute cost bound

contract: minimize cost subject to absolute time bound

utility function: minimize utility function of cost and time

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Bounded-Suboptimal Search: The Problem Setting

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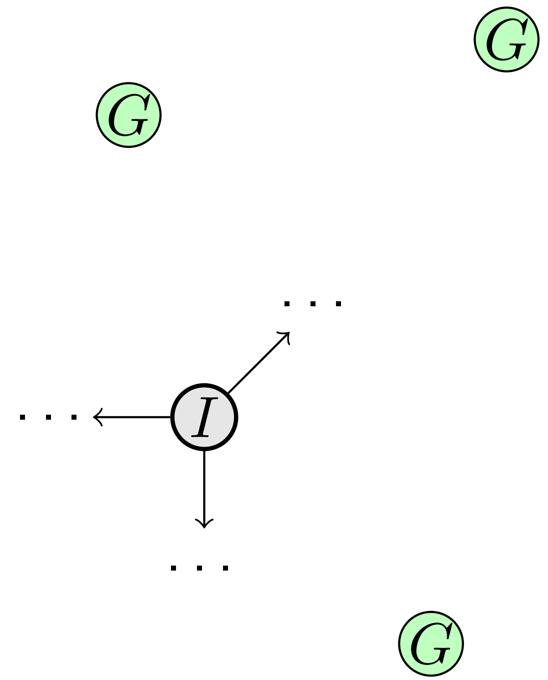

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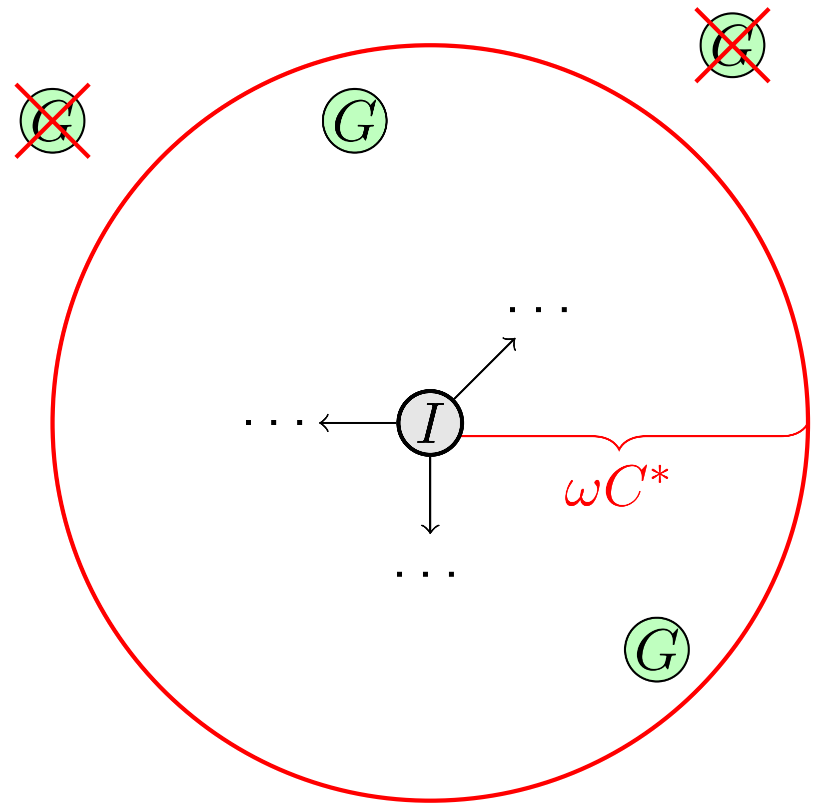

Objective: Find a plan with cost at most ωC^* as fast as possible.

State-of-The-Art: 1/2 EES (Thayer and Ruml, 2011)

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Three source of heuristic information:

h: a lower bound on cost-to-go

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

traditional A$*$ lower bound

$\hat{h}$: an estimate of cost-to-go

$$\hat{f} = g(n) + \hat{h}(n)$$

unbiased estimates can be more informed

$\hat{d}$: an estimate of distance-to-go

nearest goal is the easiest to find

State-of-The-Art: 1/2 EES (Thayer and Ruml, 2011)

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Three source of heuristic information: h, $\hat{h}$, $\hat{d}$

EES search strategy:

$best_f$: open node giving lower bound on cost
$best_{\hat{f}}$: open node giving estimated optimal cost
$best_{\hat{d}}$: estimated $\omega-$suboptimal node with minimum $\hat{d}$

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node to expand next:

1. pursue the nearest goal estimated to lie within the bound
2.
3.

in other words:

1. **if** $\hat{f}(best_{\hat{d}}) < \omega \cdot f(best_f)$ **then** $best_{\hat{d}}$
2.
3.

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node to expand next:

1. pursue the nearest goal estimated to lie within the bound
2. pursue the estimated optimal solution
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in other words:

1. **if** $\hat{f}(best_{\hat{d}}) < \omega \cdot f(best_f)$ **then** $best_{\hat{d}}$
2. **else if** $\hat{f}(best_{\hat{f}}) < \omega \cdot f(best_f)$ **then** $best_{\hat{f}}$
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State-of-The-Art: 1/2 EES (Thayer and Ruml, 2011)

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$best_f$: open node giving lower bound on cost
$best_{\hat{f}}$: open node giving estimated optimal cost
$best_{\hat{d}}$: estimated $\omega-$suboptimal node with minimum $\hat{d}$

node to expand next:

1. pursue the nearest goal estimated to lie within the bound
2. pursue the estimated optimal solution
3. raise the lower bound on optimal solution cost

in other words:

1. **if** $\hat{f}(best_{\hat{d}}) < \omega \cdot f(best_f)$ **then** $best_{\hat{d}}$
2. **else if** $\hat{f}(best_{\hat{f}}) < \omega \cdot f(best_f)$ **then** $best_{\hat{f}}$
3. **else** $best_f$

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Other EES variants:

1. **if** $\hat{f}(best_{\hat{d}}) < \omega \cdot f(best_f)$ **then** $best_{\hat{d}}$
2. ~~**else if** $\hat{f}(best_{\hat{f}}) < \omega \cdot f(best_f)$ **then** $best_{\hat{f}}$~~ ?
3. **else** $best_f$

see paper for more details.

State-of-The-Art: 1/2 EES (Thayer and Ruml, 2011)

Three source of heuristic information: h, $\hat{h}$, $\hat{d}$

EES search strategy:

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3. **else** $best_f$

Problem:

- EES does not consider the uncertainty of its estimates (brittle)
- EES does not spend enough effort on estimating the bound

State-of-The-Art: 2/2 DPS (Gilon, Felner, and Stern, 2016)

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Best first search on “potential”:

$$ud(n) = \frac{\omega \cdot f_{min} - g(n)}{h(n)}$$

State-of-The-Art: 2/2 DPS (Gilon, Felner, and Stern, 2016)

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Best first search on "potential":

$$ud(n) = \frac{\omega \cdot f_{min} - g(n)}{h(n)}$$

does not explicitly optimize search time

Bounded-Cost: XES (Fickert, Gu, and Ruml, 2021)

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Best first search on expected search effort:

$$xe(n) = \frac{T_n}{p(n)}$$

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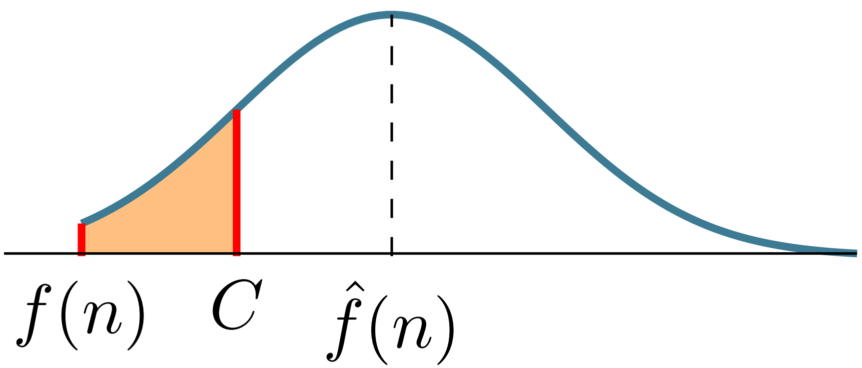
Best first search on expected search effort:

$$xe(n) = \frac{T_n}{p(n)}$$

$T(n)$: totoal search effort, estiamted by $d(n)$
$p(n)$: the probability of finding a solution within the bound, estimated by:



Bounded-Cost: XES (Fickert, Gu, and Ruml, 2021)

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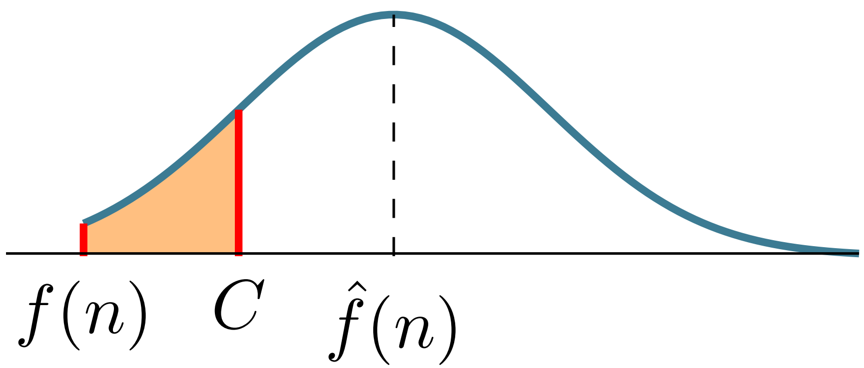

XES performs better than BEES and PS.
Can we adpat XES to bounded-suboptimal setting?

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Our Approach: 1/2 Dynamic XES

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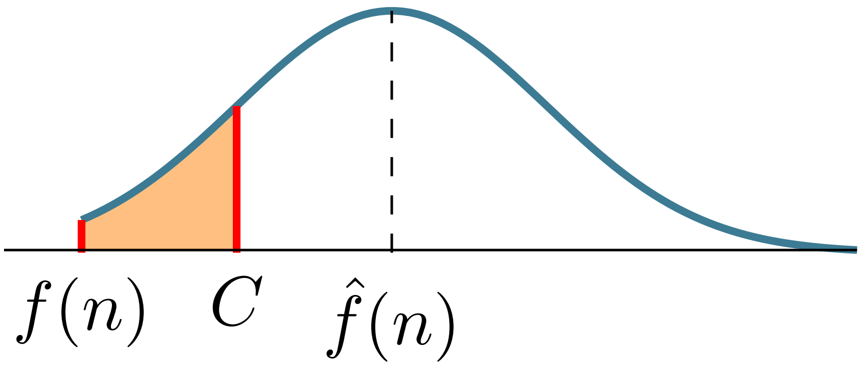

hard to estimate when raising the bound is useful!

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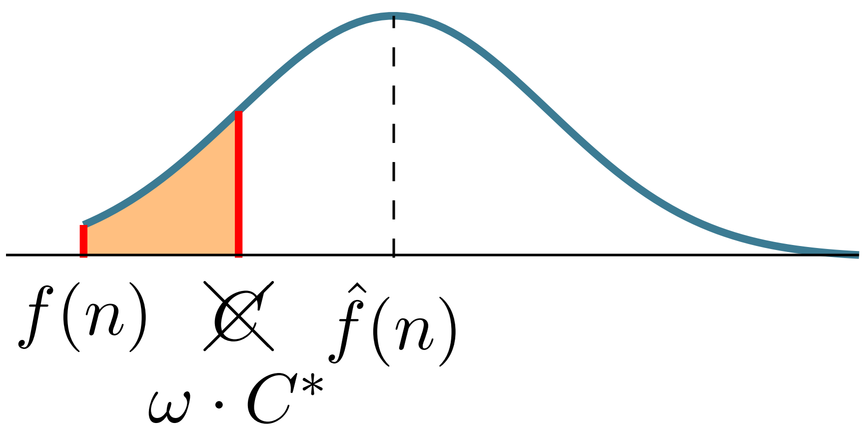

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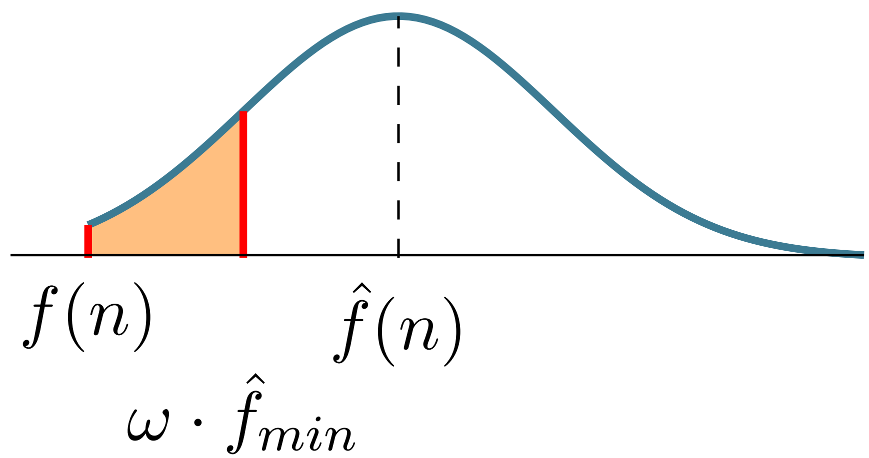

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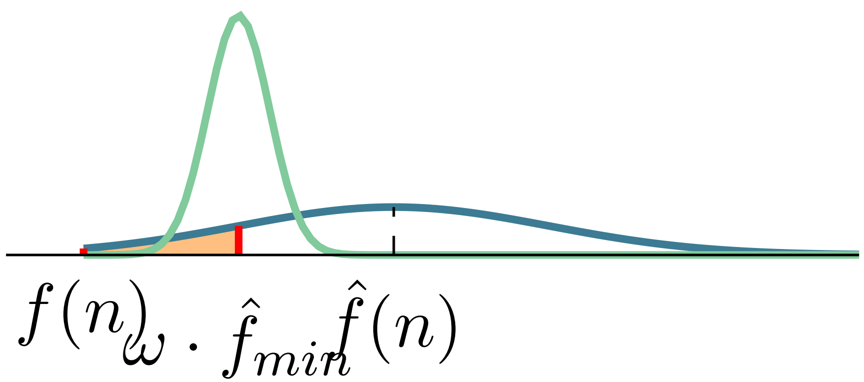

hard to estimate when raising the bound is useful!

Our Approach: 2/2 A Round-Robin Scheme

Round-Robin on:

- **focal list:** sorted by d(EES) or ud(DPS) or xe(DXES)
- **open list:** sorted by $\hat{f}$
- **cleanup list:** sorted by f

focal and open condition: $f(n) < \omega \cdot f_{min}$

Simple but work well emparically!

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Planning Domains:

- Implementation in Fast Downward[2]
- Benchmarks:
  IPS optimal tracks (48 domains)

Search Domains:

- Sliding-Tile Puzzle, Vaccum World, Pancake, Racetrack

[2] Helmert 2006.

IPC Coverage ($\omega = 1.5$)

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Coverage	WA*	EES	DPS	DXES	RR-d	RR-DPS	RR-DXES
Sum (1652)	995	967	1012	894	1025	982	**1052**
Normalized(%)	58.7	57.0	60.0	51.5	60.7	57.9	**62.5**
Expansions	569	558	472	734	383	665	**371**

$\rightarrow$ RR-DXES and RR-d perform best overall.

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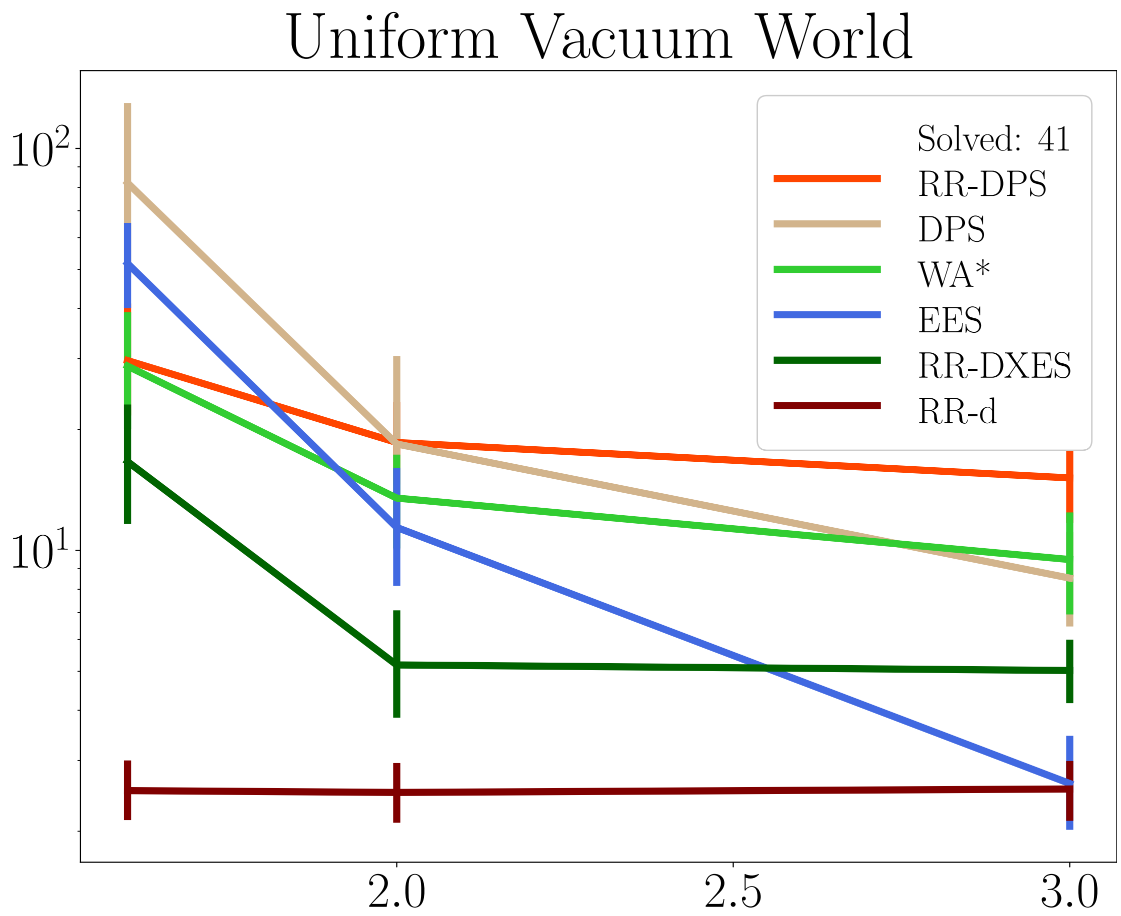

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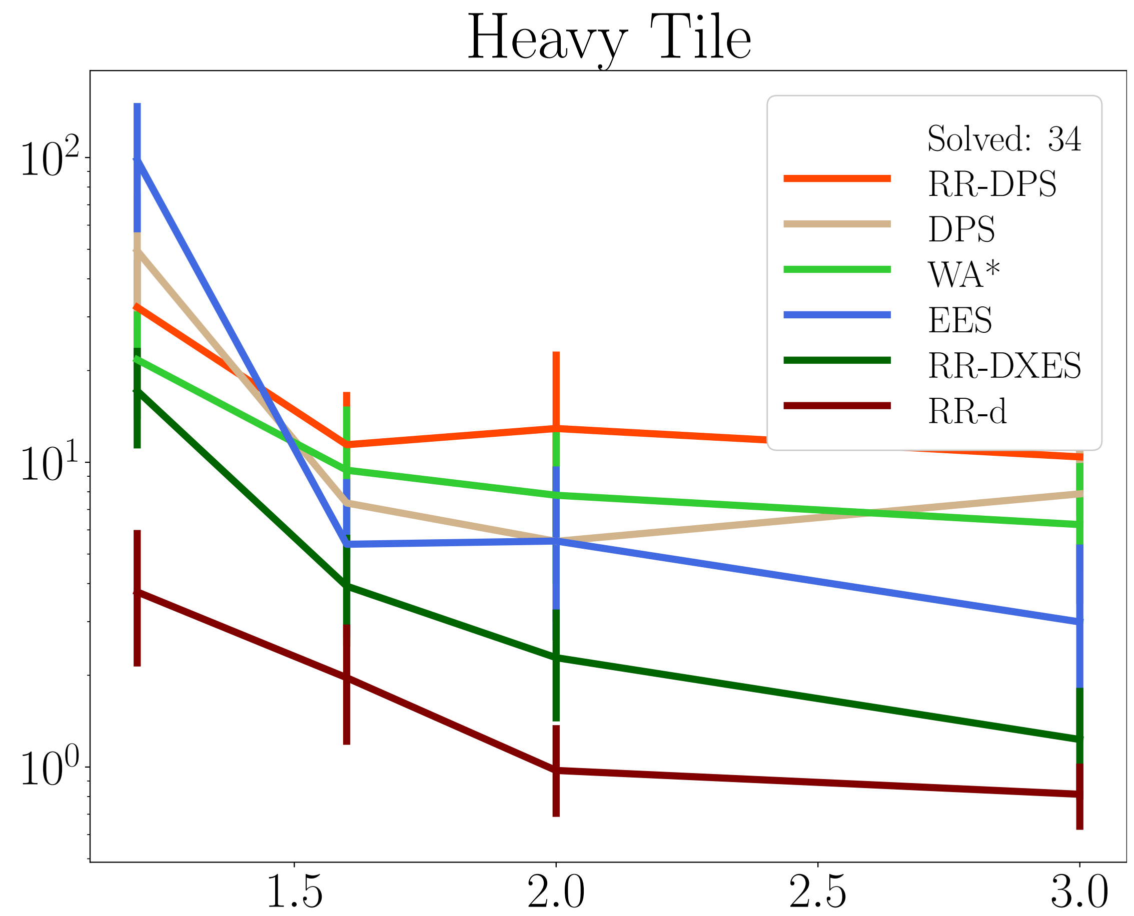

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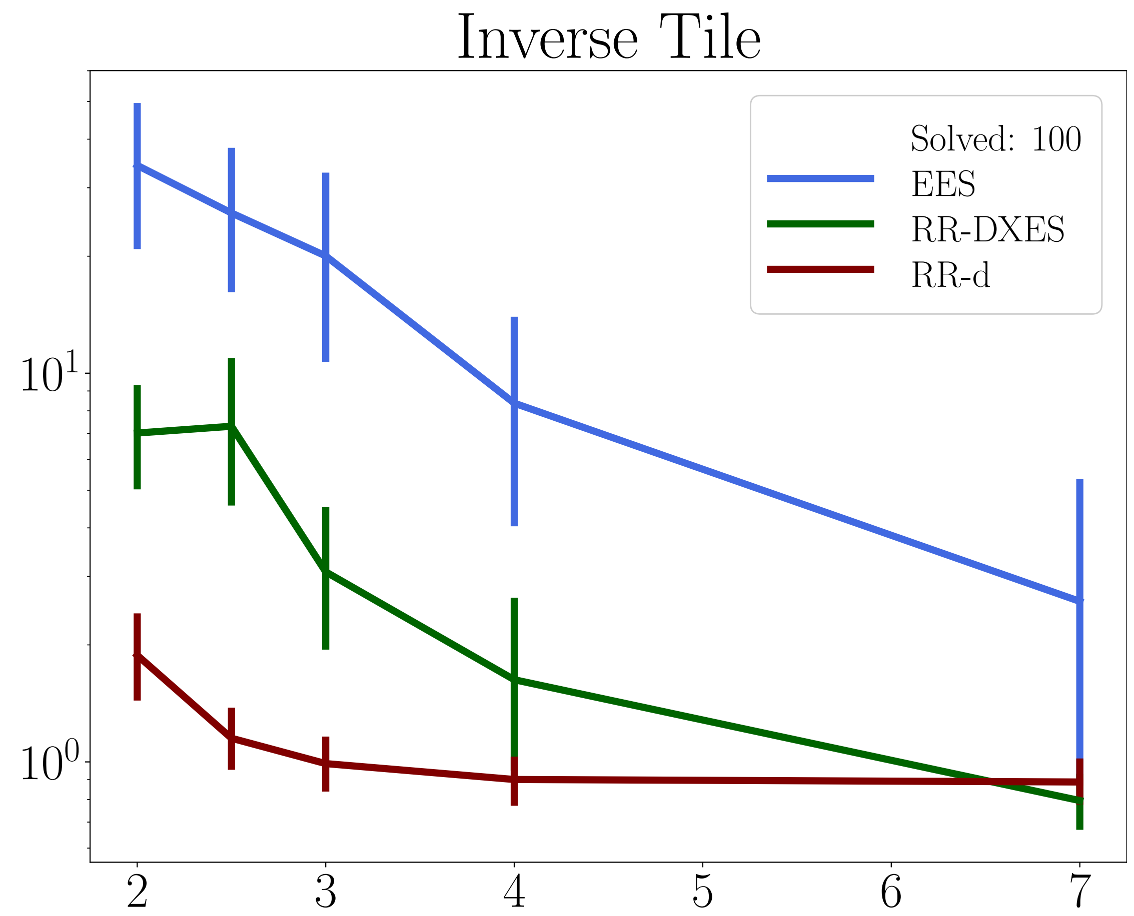

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What to do for bounded-suboptimal search:

- Weighted-A* is the first thing to try
- Round-Robin on d, $\hat{f}$, f is the next to try

Summary

What to do for bounded-suboptimal search:

- Weighted-A* is the first thing to try
- Round-Robin on d, $\hat{f}$, f is the next to try

What's next:

- When to raise bound, and when to pursue solution?
- DXES should help, but not quite, why?

Questions?

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