

Machine Learning for Classical Planning: Neural Network Heuristics, Online Portfolios, and State Space Topologies

Patrick Ferber
November 17, 2022



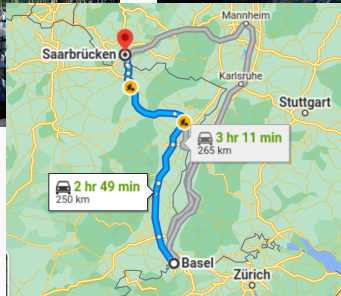
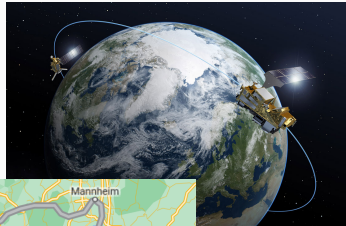
Planning



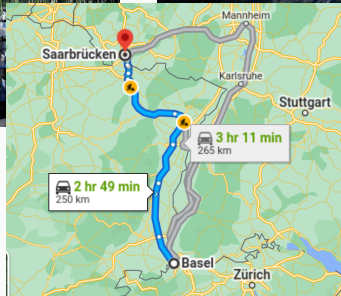
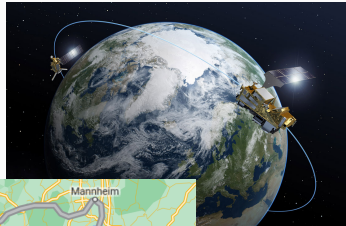
Planning



Planning

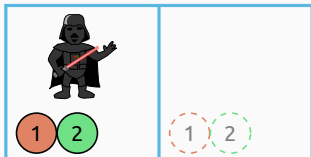


Planning

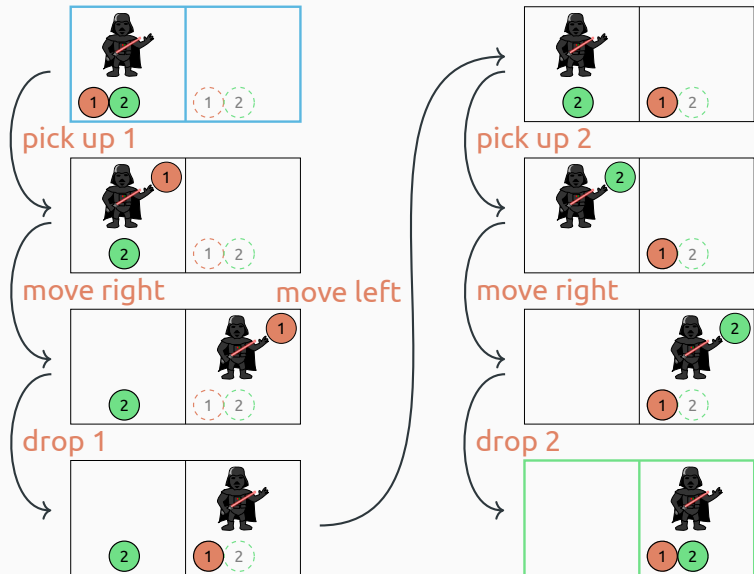


sequence of actions to satisfy a goal

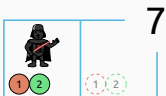
Classical Planning



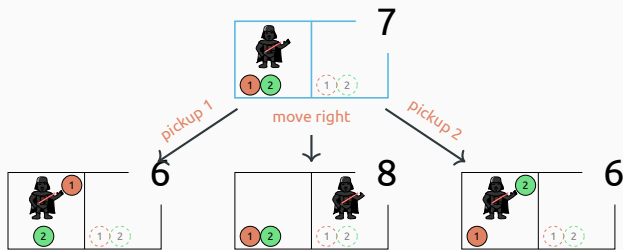
Classical Planning



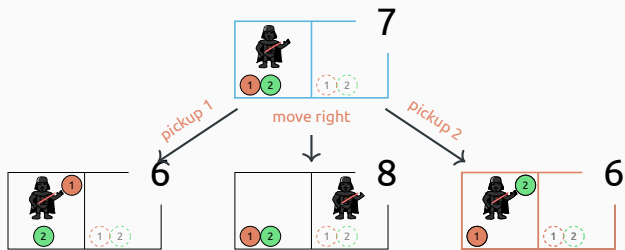
Greedy Best-First Search



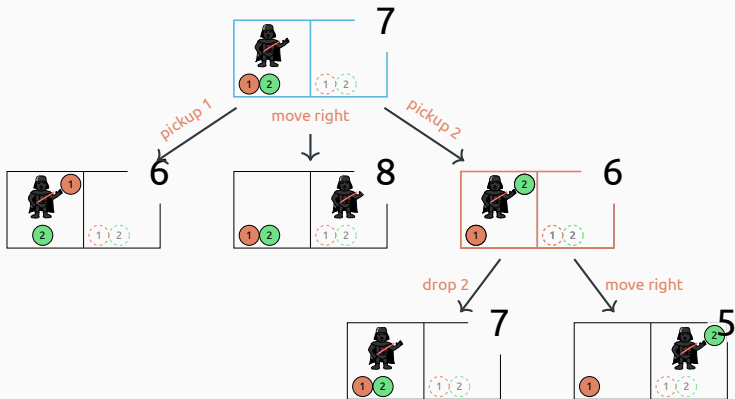
Greedy Best-First Search



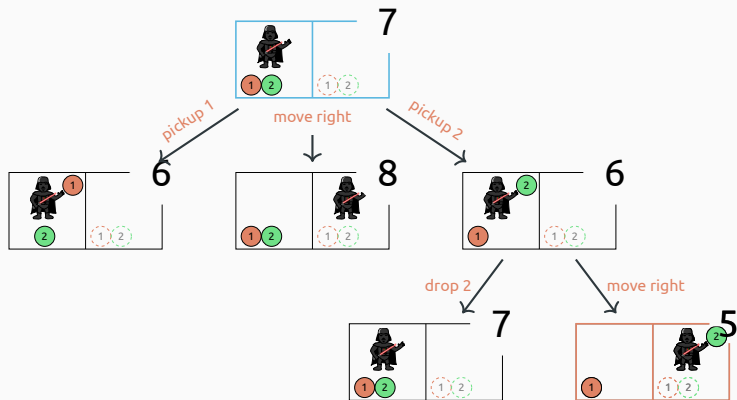
Greedy Best-First Search



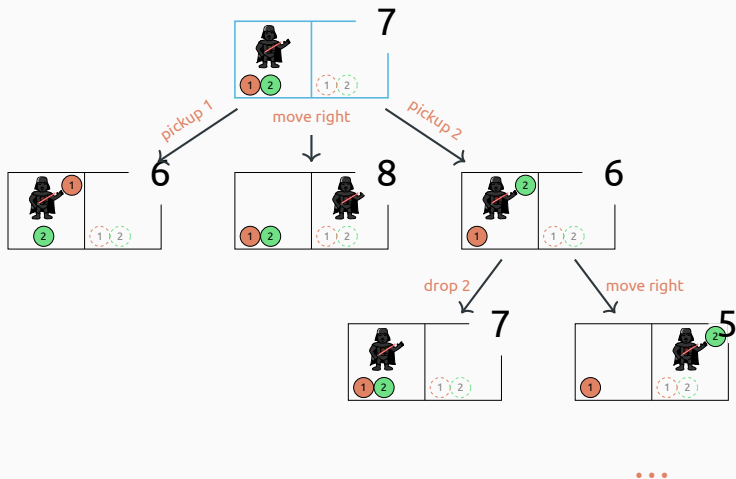
Greedy Best-First Search

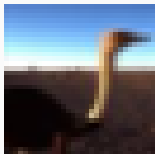


Greedy Best-First Search



Greedy Best-First Search





→ ostrich



→ car



→ ostrich



→ dog

Machine Learning

sample



→ car

sample



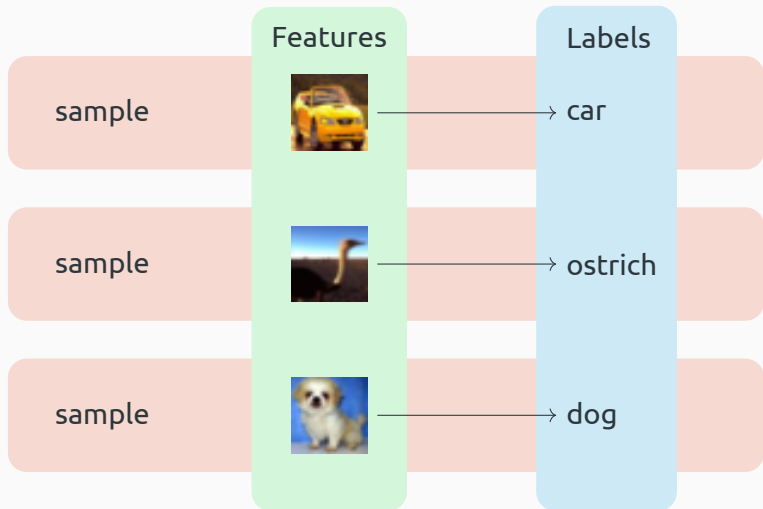
→ ostrich

sample



→ dog

Machine Learning





Heuristics

**Online
Portfolios**

**State
Space
Topologies**

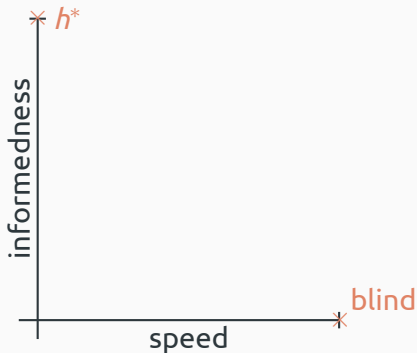


Heuristics

**Online
Portfolios**

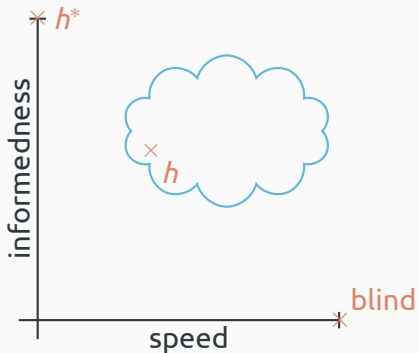
**State
Space
Topologies**

$$h\left(\begin{array}{|c|c|} \hline \text{Goblin} & \\ \hline \text{1} & \text{2} \\ \hline \end{array} \right) = 7$$



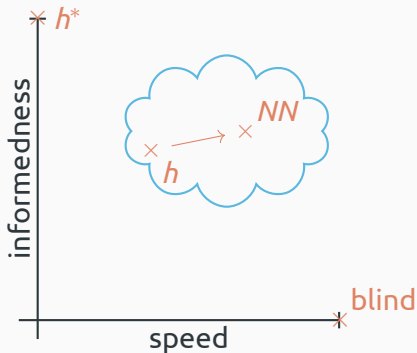
Heuristic

$$h\left(\begin{array}{|c|c|} \hline \text{robot} & \\ \hline \text{1} \text{ 2} & \text{1} \text{ 2} \\ \hline \end{array} \right) = 7$$

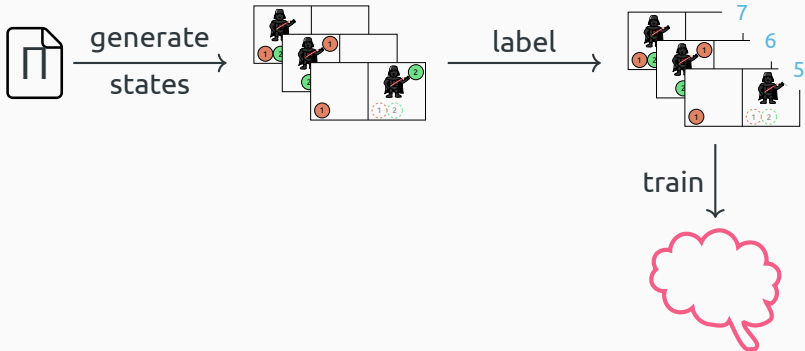


Heuristic

$$h\left(\begin{array}{|c|c|} \hline \text{Goblin} & \\ \hline \text{1 2} & \text{1 2} \\ \hline \end{array} \right) = 7$$



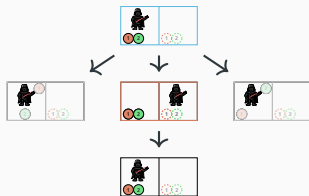
Learning Heuristics: Take I



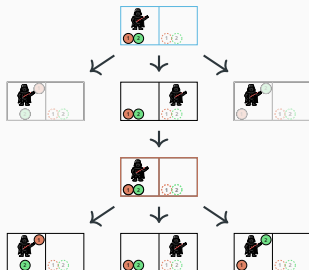
Progression Random Walks



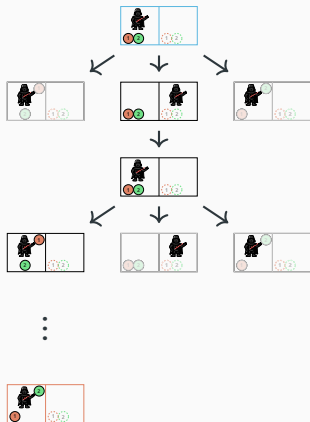
Progression Random Walks



Progression Random Walks



Progression Random Walks



Labeling States

$$h^*(\text{ [robot, 1, 2, 3, 4] })$$

$$h^{FF}(\text{ [robot, 1, 2, 3, 4] })$$

$$GBFS(\text{ [robot, 1, 2, 3, 4] } , h^{FF})$$

Labeling States

$$h^*(\text{[Diagram]})$$

$$h^{FF}(\text{[Diagram]})$$

$$GBFS(\text{[Diagram]}, h^{FF})$$

Labeling States

$$h^*(\text{ [robot, 2, 1, 2] })$$

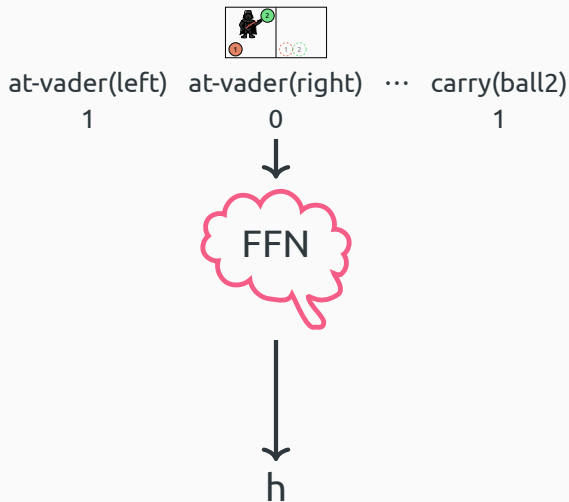
$$h^{FF}(\text{ [robot, 2, 1, 2] })$$

$$GBFS(\text{ [robot, 2, 1, 2] } , h^{FF})$$

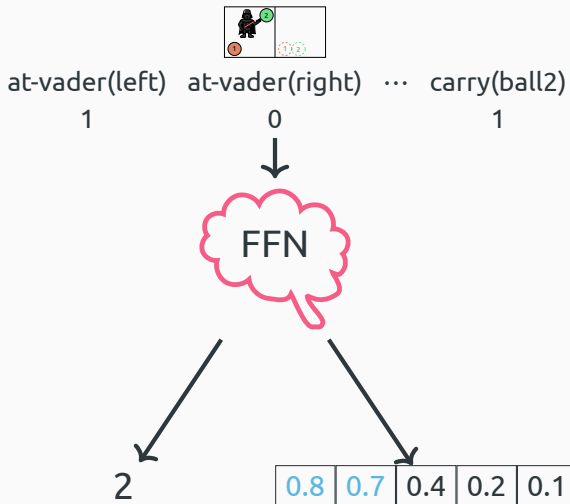
Neural Network Heuristic



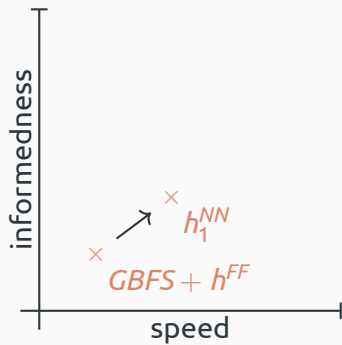
Neural Network Heuristic



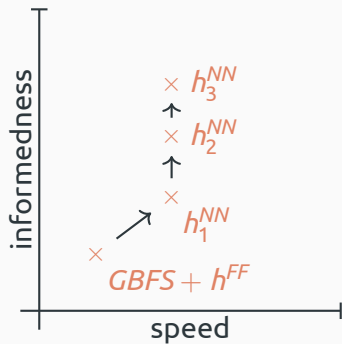
Neural Network Heuristic



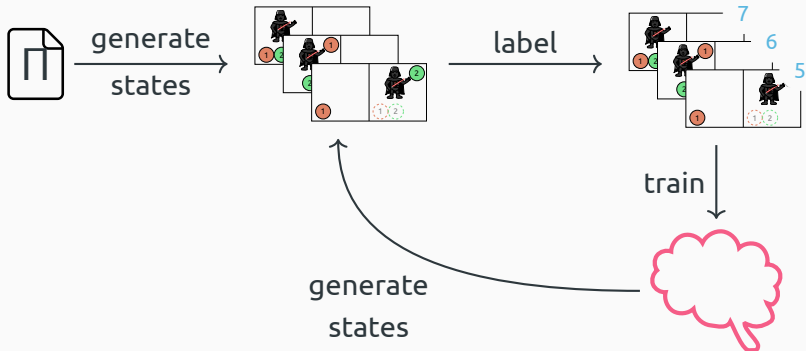
Limitation Teacher Search



Limitation Teacher Search



Learning Heuristics: Take II

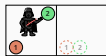


Labeling States

$GBFS(\text{Diagram}, h^{FF})$



$GBFS(\text{Diagram}, h^{NN})$



$exp(GBFS(\text{Diagram}, h^{NN}))$

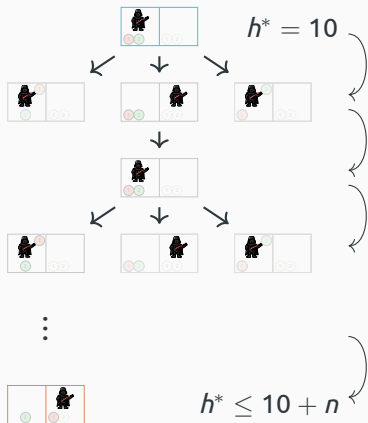


$AVI(\text{Diagram}, h^{NN})$



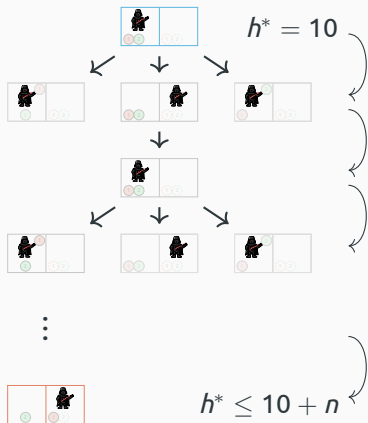
Sampling States

Progression Random Walks

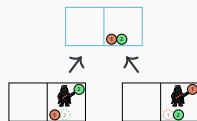


Sampling States

Progression Random Walks

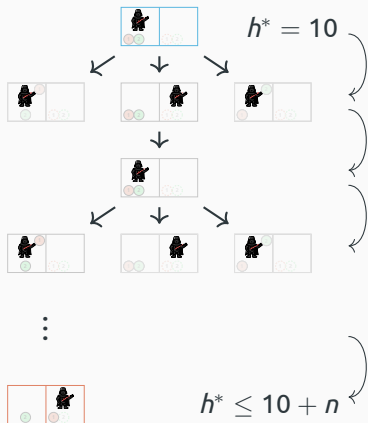


Regression Random Walks

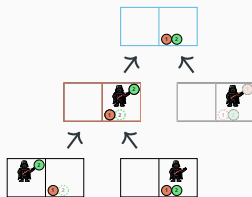


Sampling States

Progression Random Walks

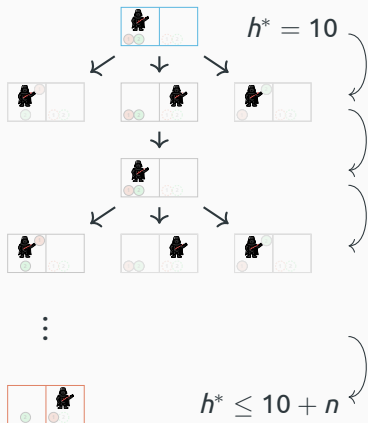


Regression Random Walks

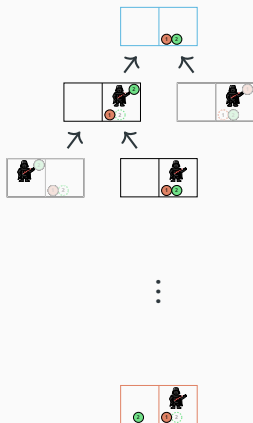


Sampling States

Progression Random Walks

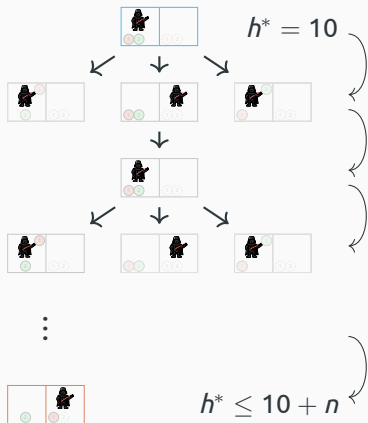


Regression Random Walks

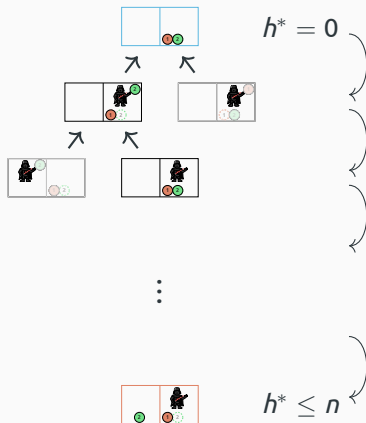


Sampling States

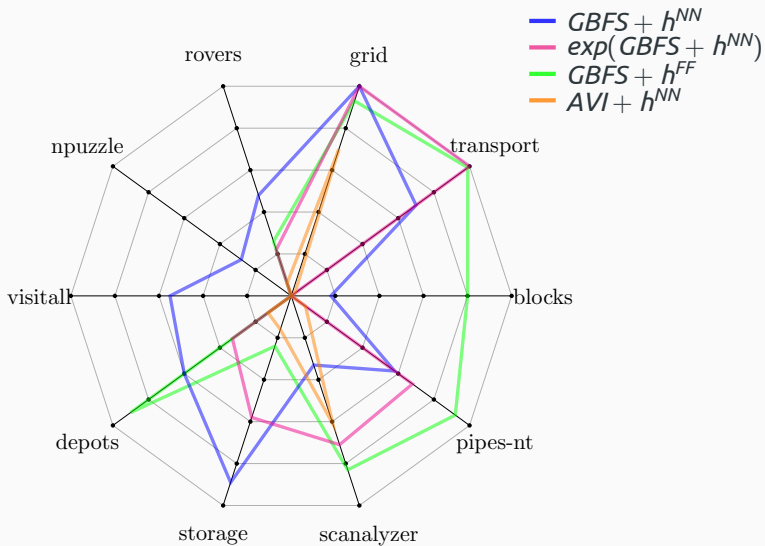
Progression Random Walks



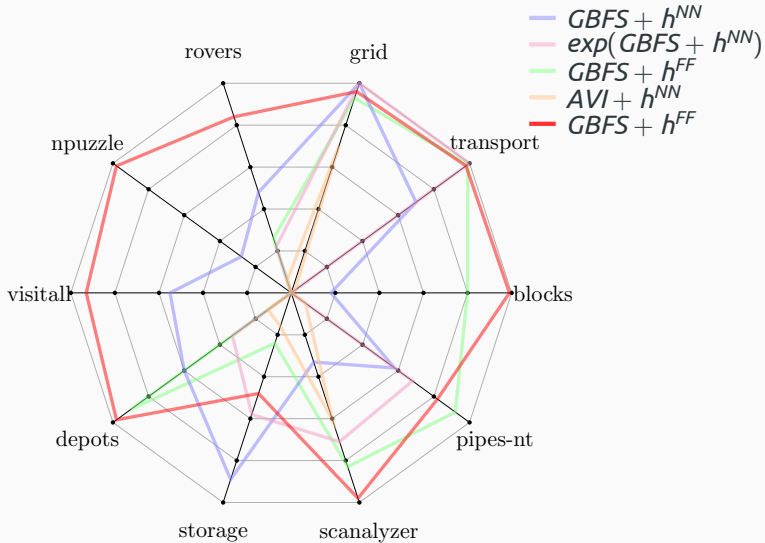
Regression Random Walks



Heuristic Coverages



Heuristic Coverages

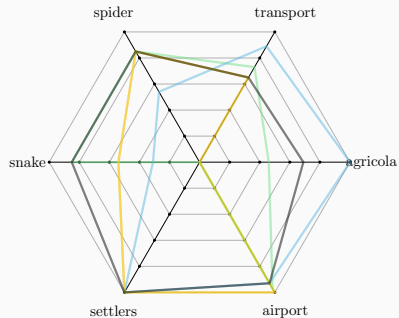


Heuristics

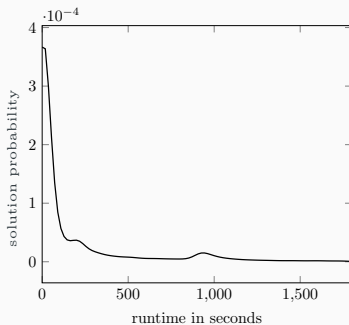
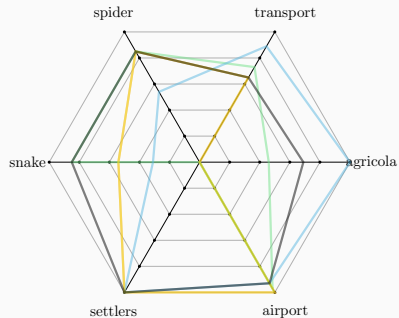
**Online
Portfolios**

**State
Space
Topologies**

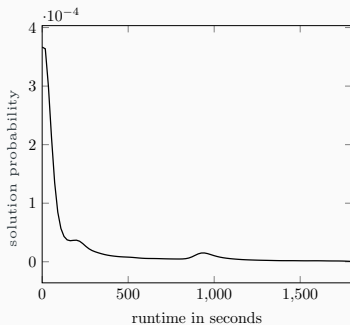
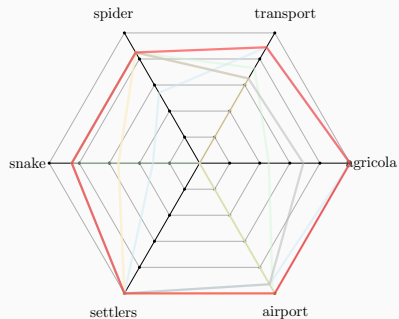
Planner Coverages



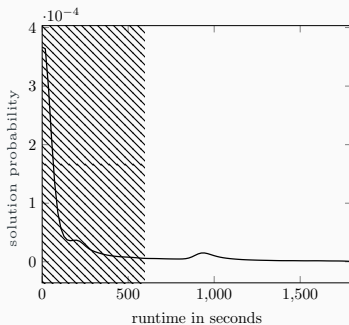
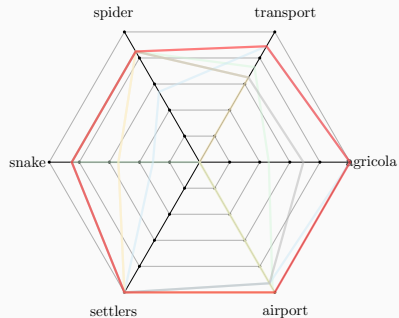
Planner Coverages

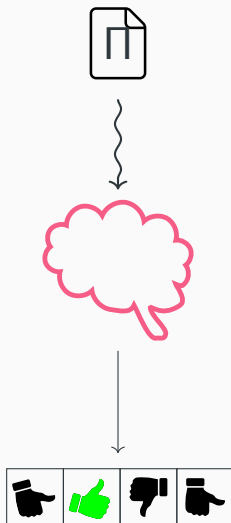


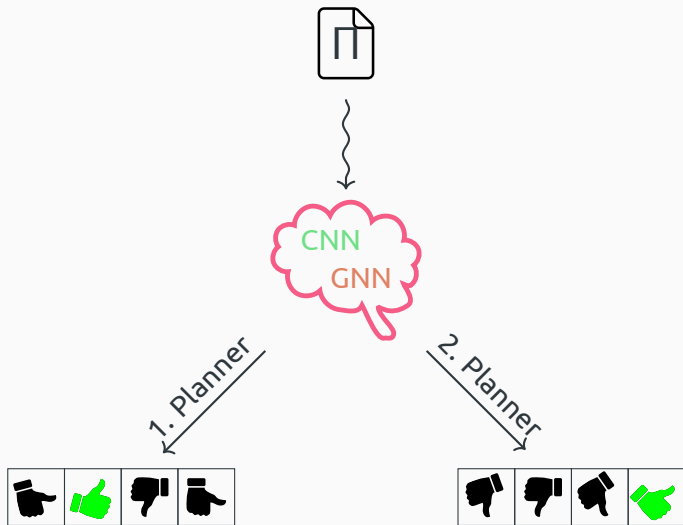
Planner Coverages



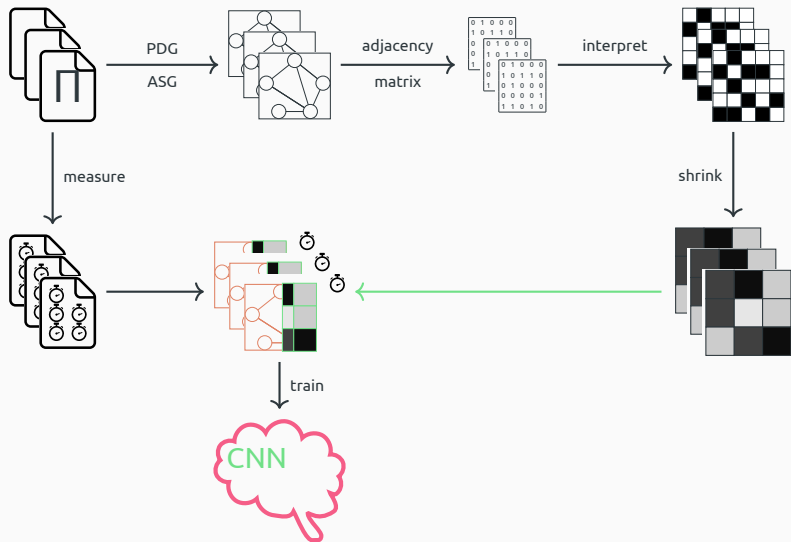
Planner Coverages



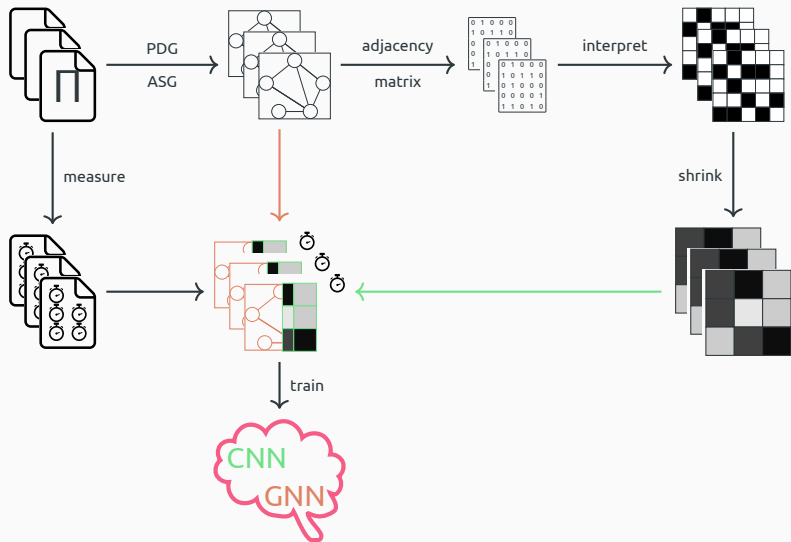




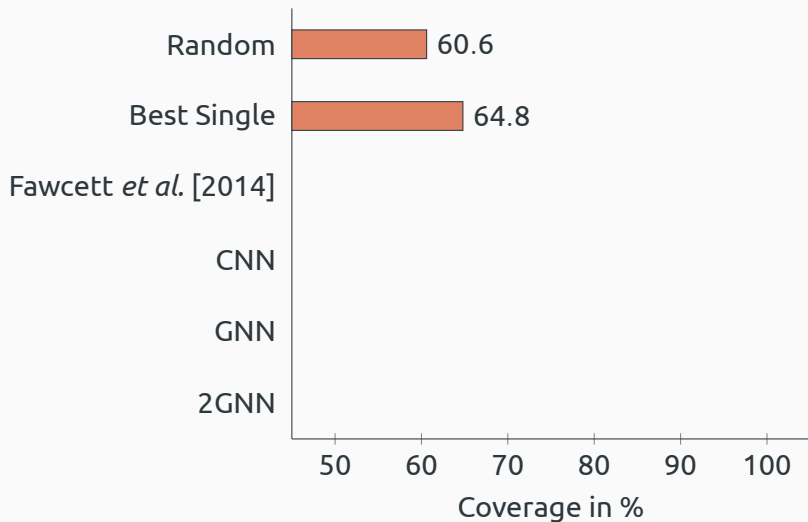
Learning Online Portfolios



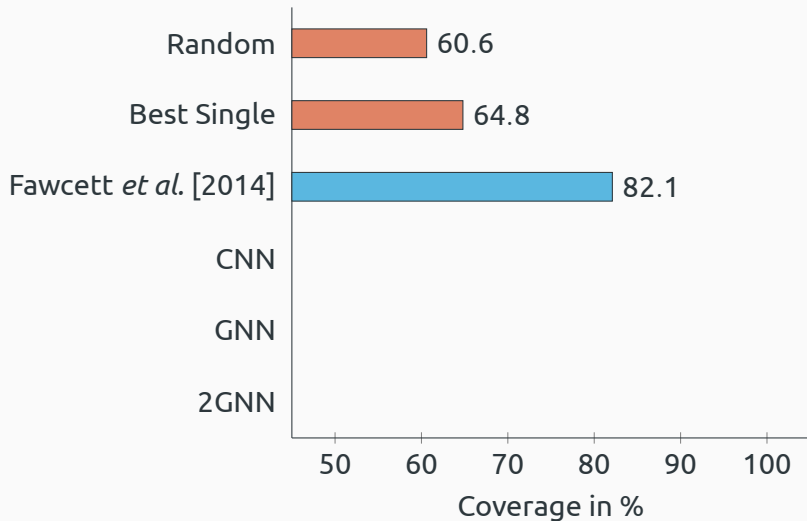
Learning Online Portfolios



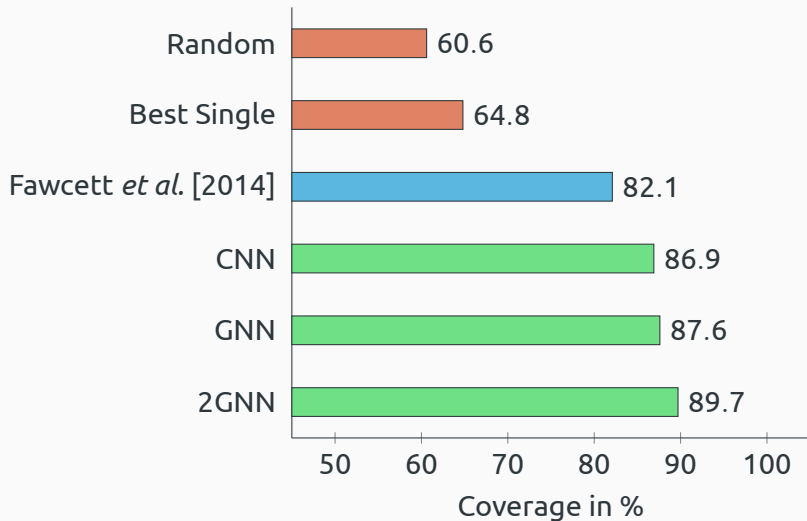
Portfolio Coverages



Portfolio Coverages



Portfolio Coverages

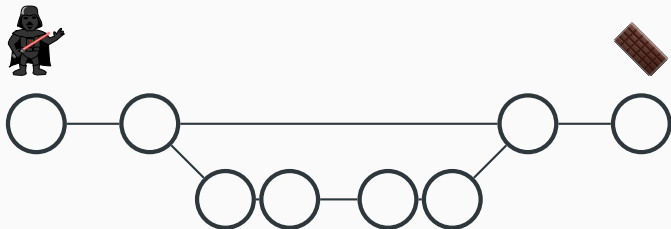


Heuristics

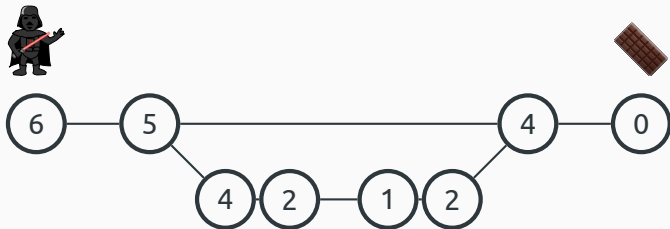
**Online
Portfolios**

**State
Space
Topologies**

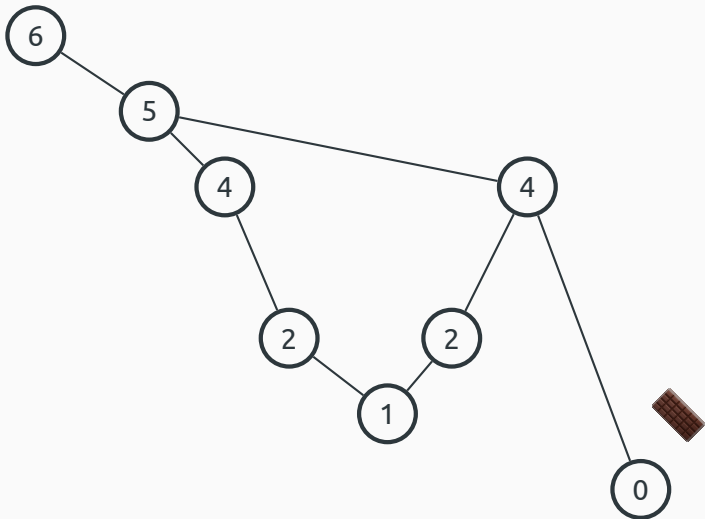
State Space Topologies



State Space Topologies



State Space Topologies



State Space Topologies



6

5

4

2

1

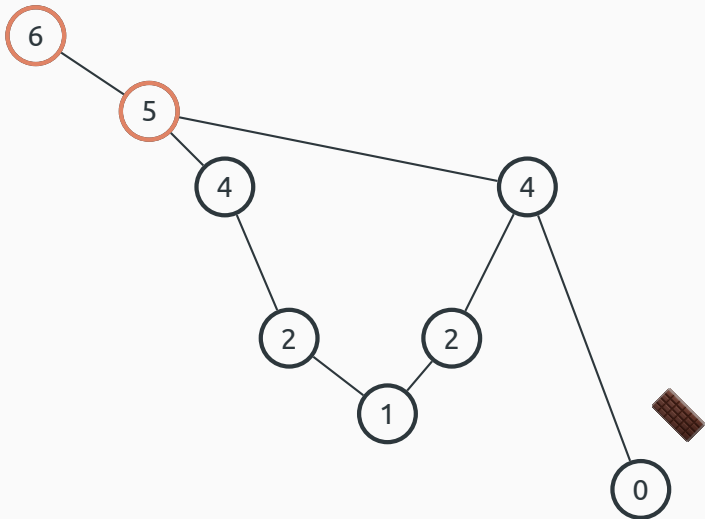
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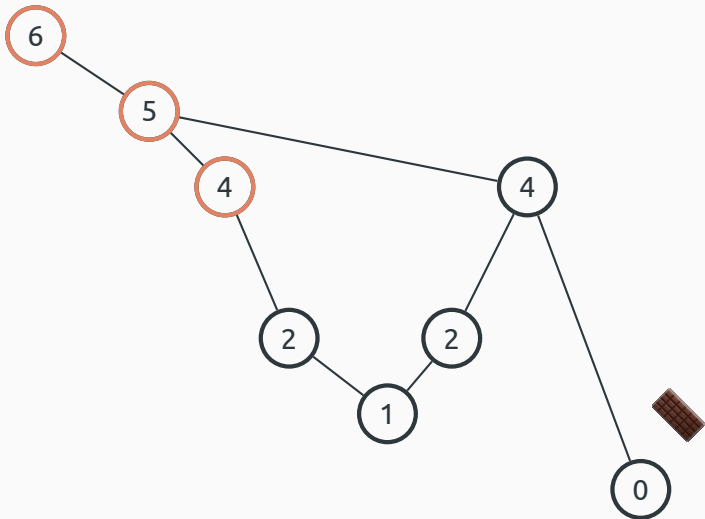
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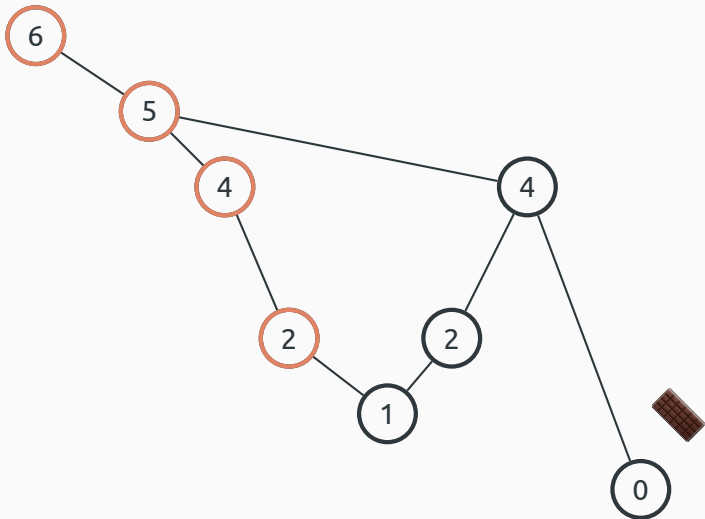
State Space Topologies



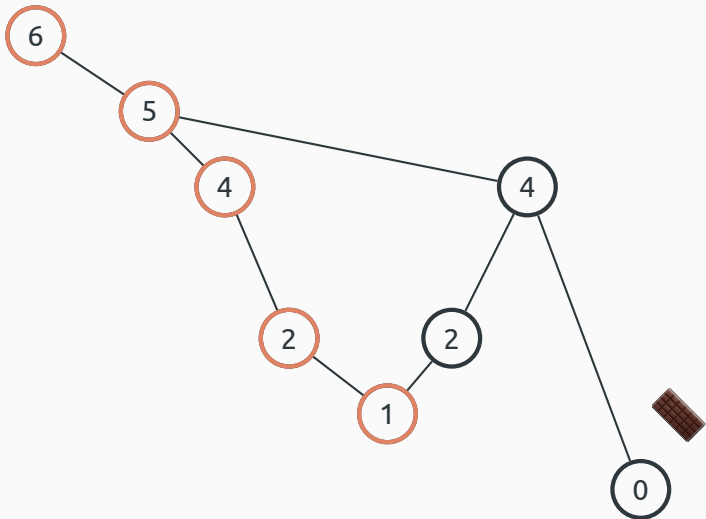
State Space Topologies



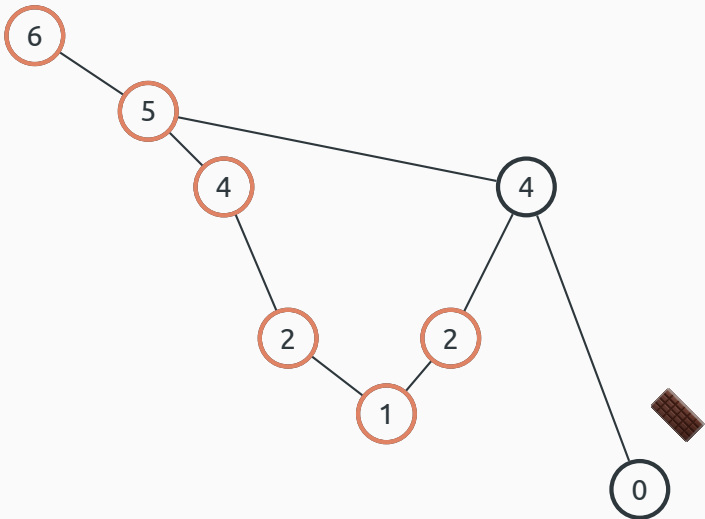
State Space Topologies



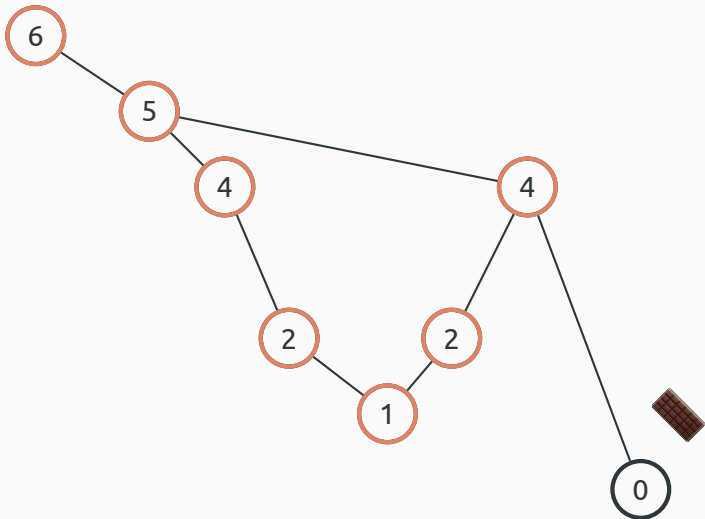
State Space Topologies



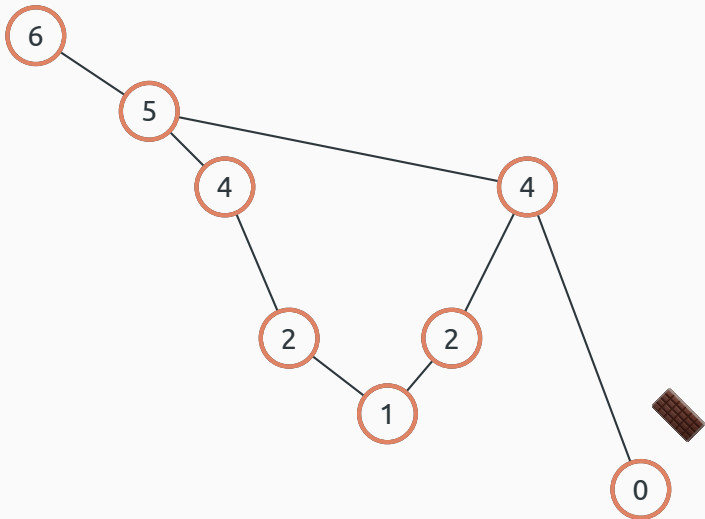
State Space Topologies



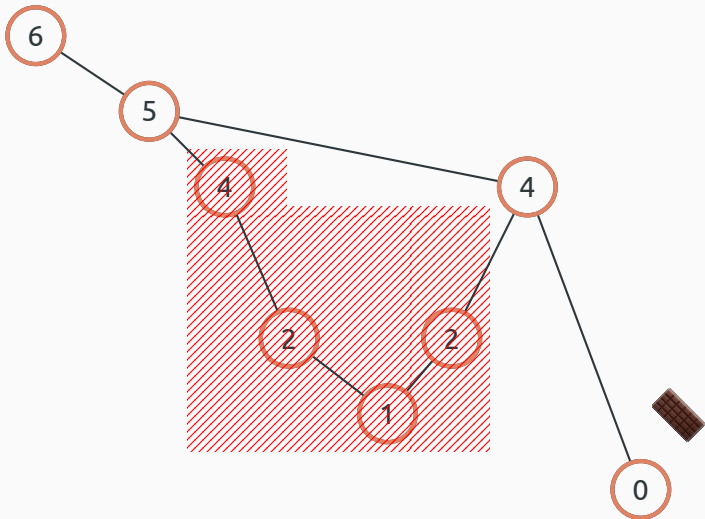
State Space Topologies



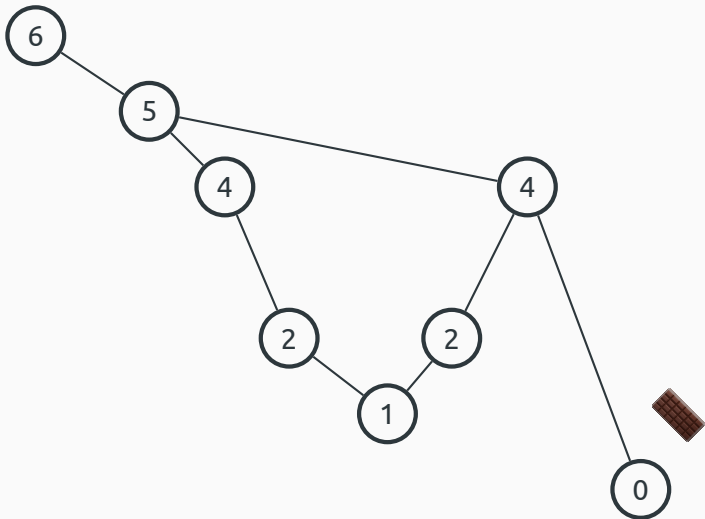
State Space Topologies



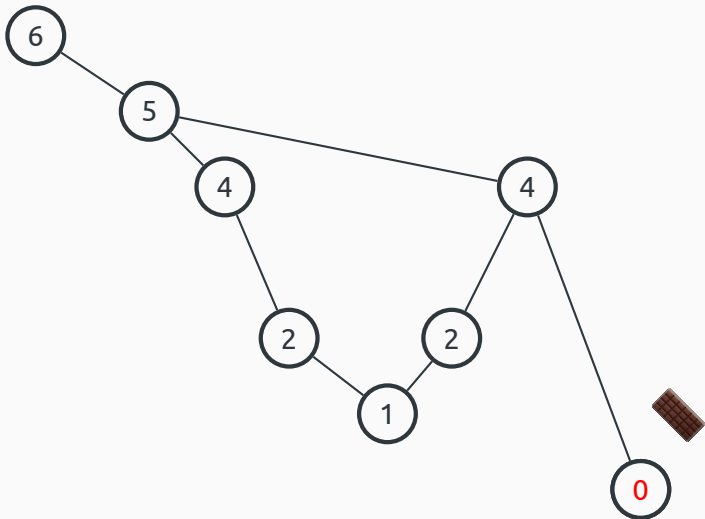
State Space Topologies



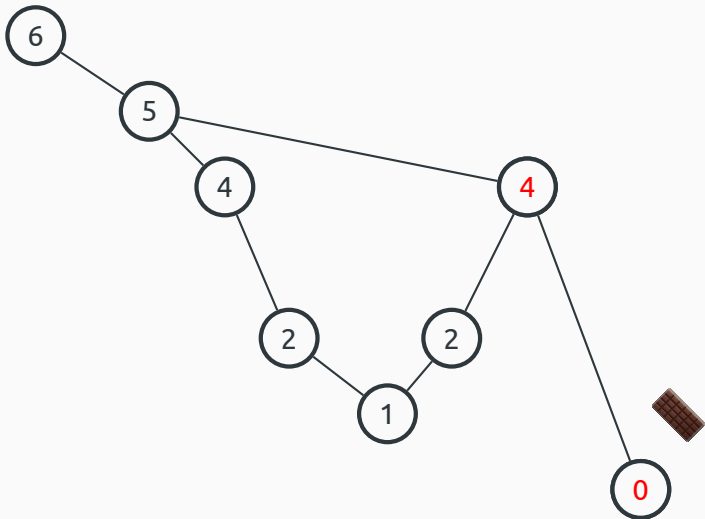
Progress States



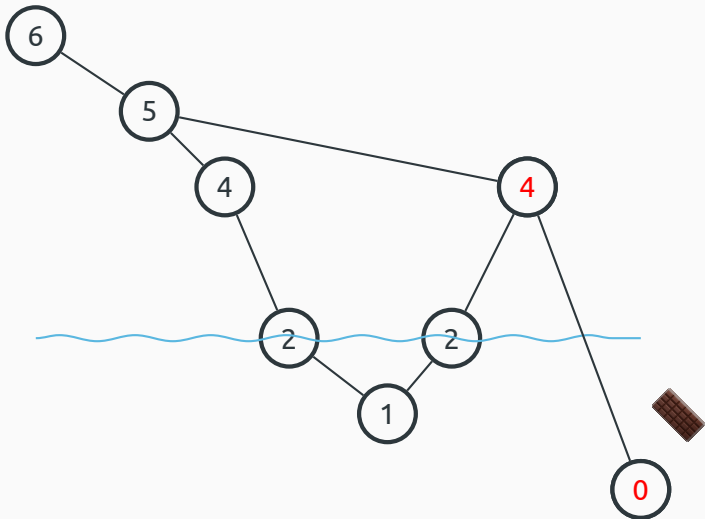
Progress States



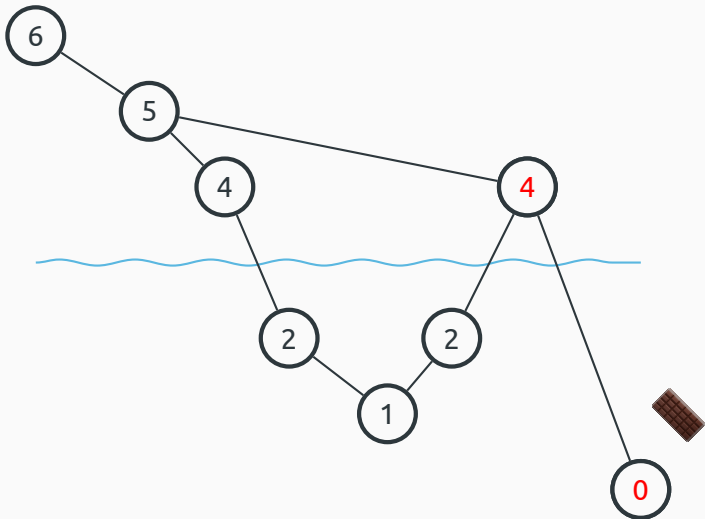
Progress States



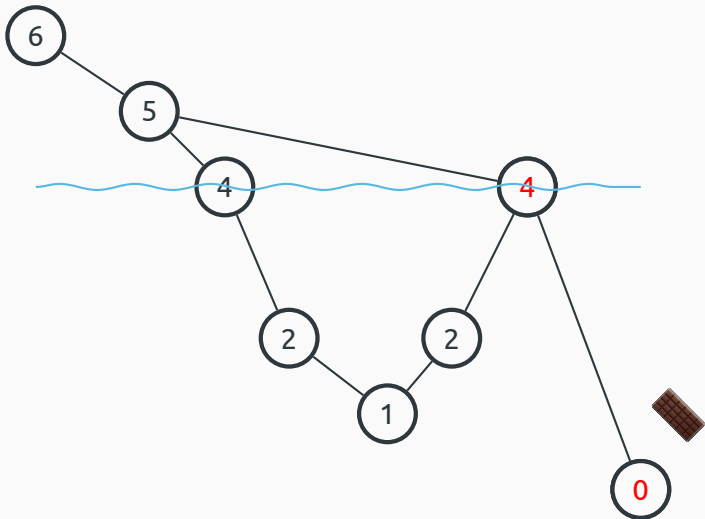
Progress States



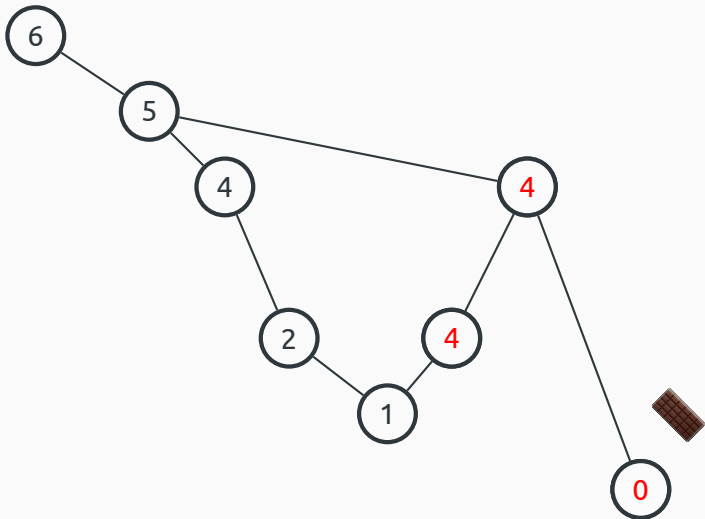
Progress States



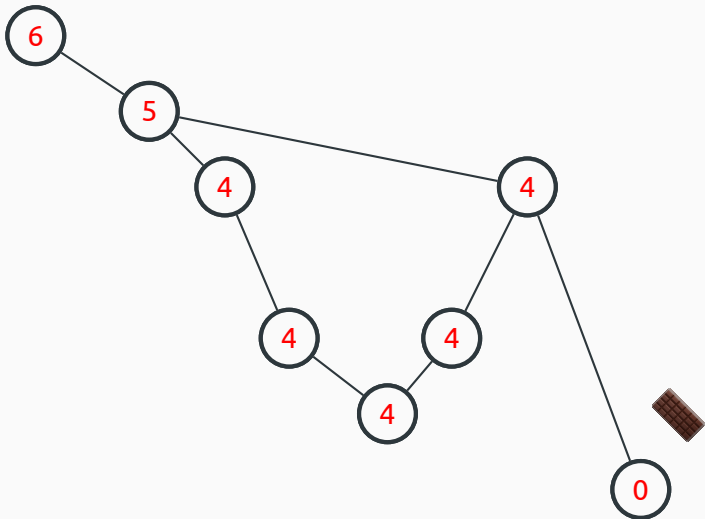
Progress States



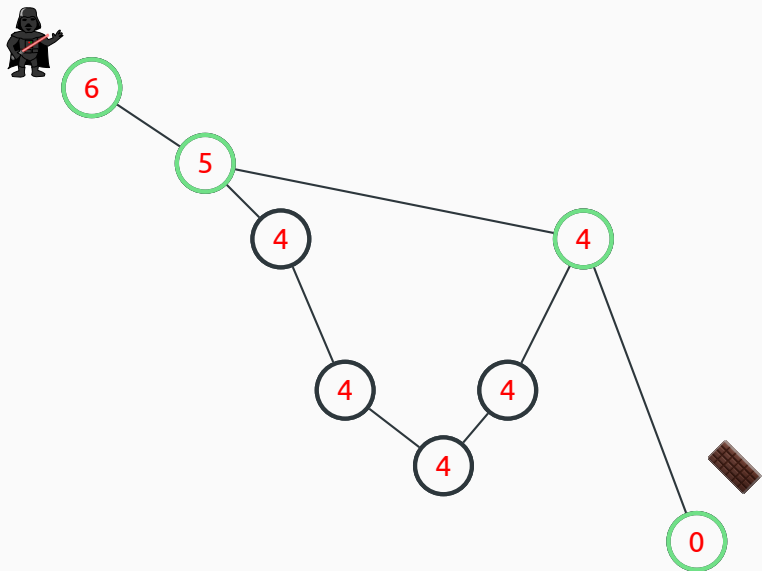
Progress States



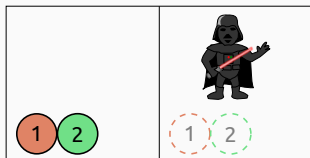
Progress States



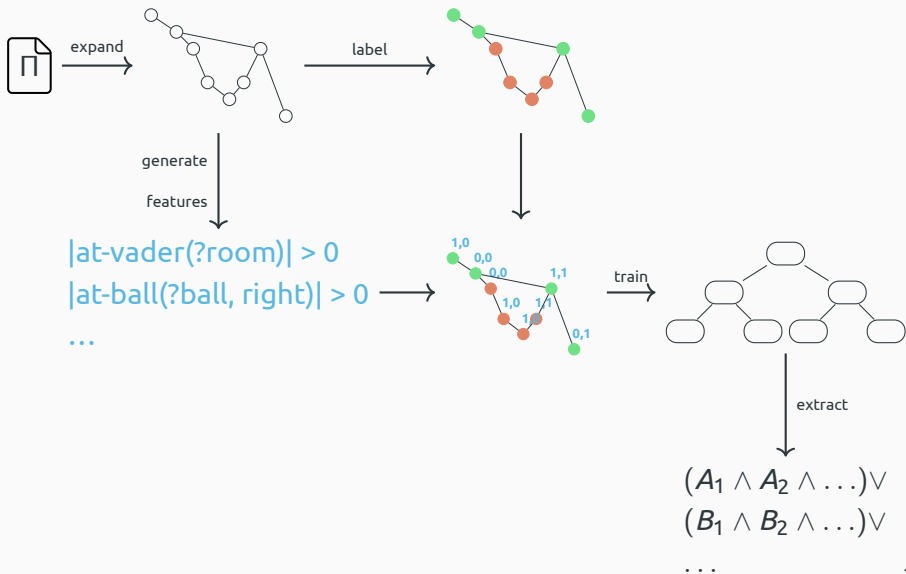
Progress States



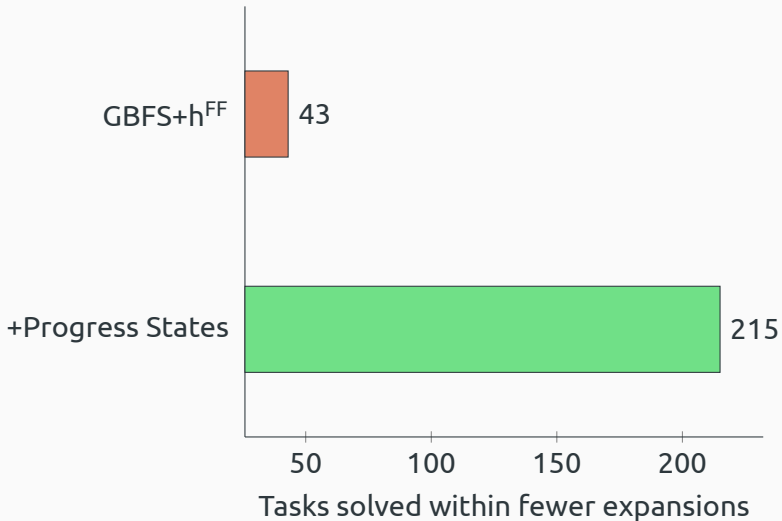
Description Logic Formulas


$$\begin{aligned} &|\text{at-ball}(\text{?ball}, \text{left})| = 0 \vee \\ &|\text{at-vader}(\text{?room}) \cap \{\text{left}\}| > 0 \wedge |\text{carry}(\text{?ball})| = 0 \vee \\ &|\text{at-vader}(\text{?room}) \cap \{\text{right}\}| > 0 \wedge |\text{carry}(\text{?ball})| > 0 \\ &\equiv \text{is-progress-state} \end{aligned}$$

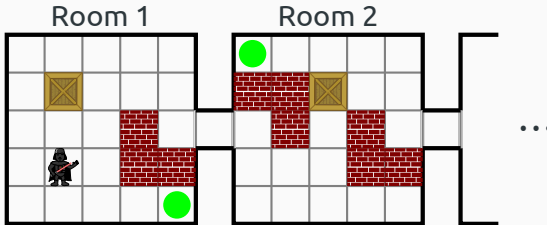
Identifying Progress States



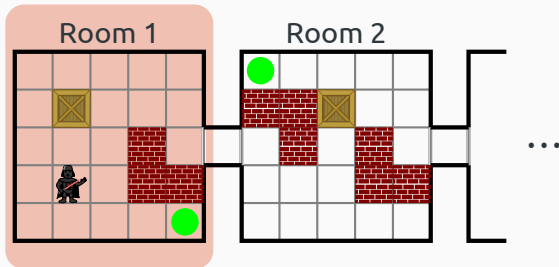
Expansions GBFS+h^{FF}



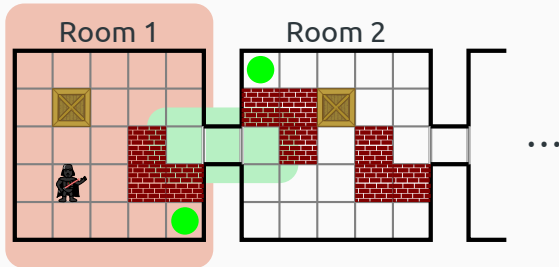
Generalized Bench Transition System



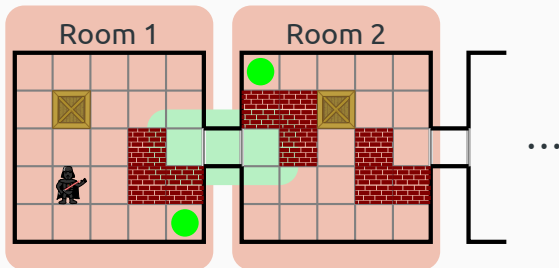
Generalized Bench Transition System



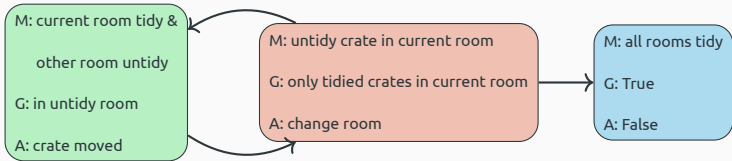
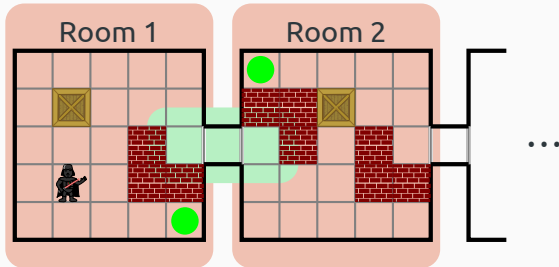
Generalized Bench Transition System



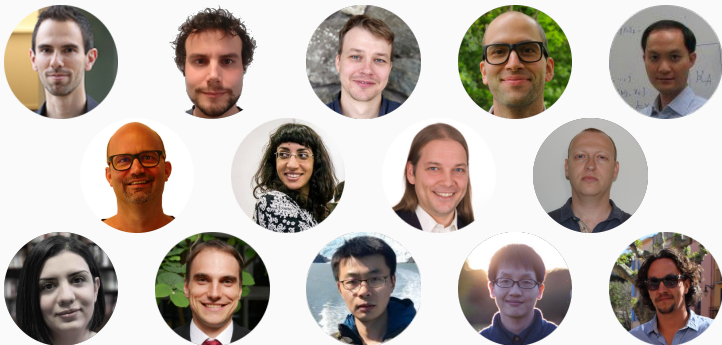
Generalized Bench Transition System



Generalized Bench Transition System



Co-Authors & Colleagues



Conclusion

Heuristics

highly
complementary

can exceed
model-based
heuristics

Online Portfolios

state of the art

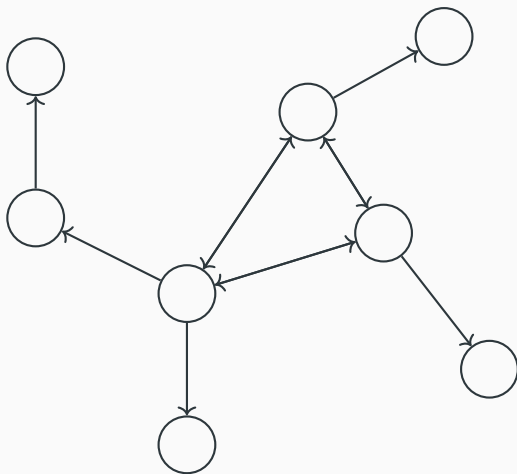
State Space Topologies

automatically
generated

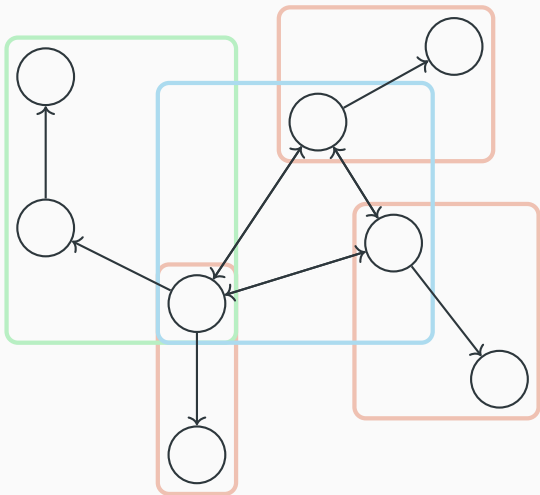
improves search

split into
subproblems

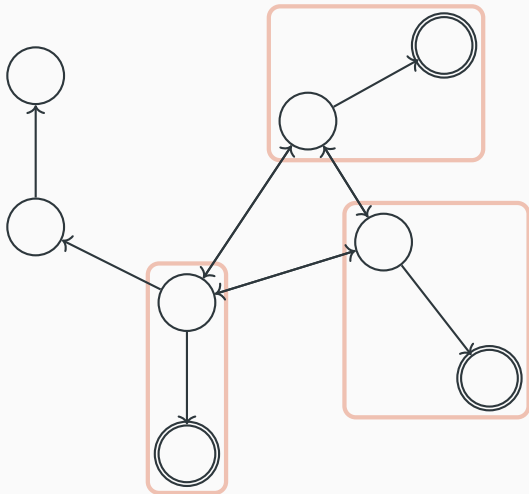
Construct GBTS



Construct GBTS

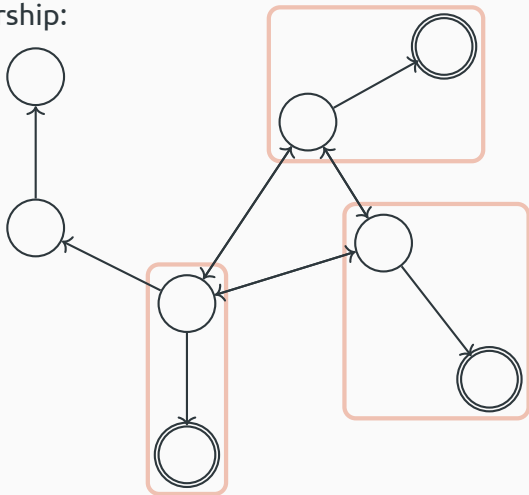


Construct GBTS



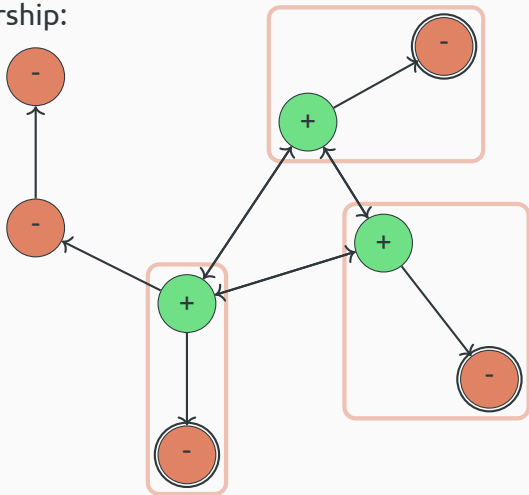
Construct GBTS

Membership:

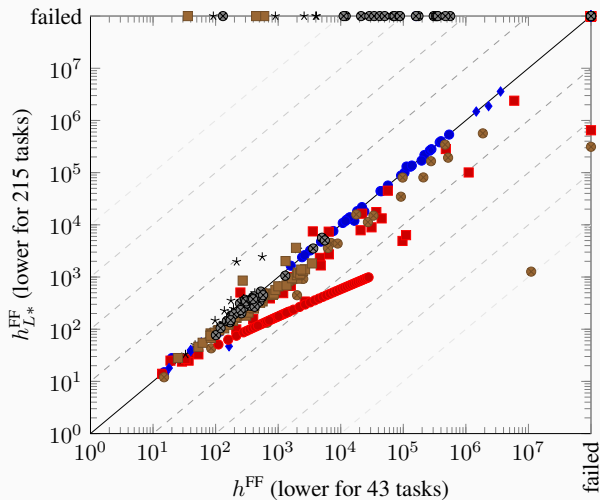


Construct GBTS

Membership:



Expansions with Progress States





References

Franz Baader, Diego Calvanese, Deborah L. McGuinness, Daniele Nardi, and Peter F. Patel-Schneider, editors. *The Description Logic Handbook: Theory, Implementation and Applications*. Cambridge University Press, 2003.

Chris Fawcett, Mauro Vallati, Frank Hutter, Jörg Hoffmann, Holger Hoos, and Kevin Leyton-Brown. Improved features for runtime prediction of domain-independent planners. In Steve Chien, Alan Fern, Wheeler Ruml, and Minh Do, editors, *Proceedings of the Twenty-Fourth International Conference on Automated Planning and Scheduling (ICAPS 2014)*, pages 355–359. AAAI Press, 2014.

References ii

- Patrick Ferber, Malte Helmert, and Jörg Hoffmann. Neural network heuristics for classical planning: A study of hyperparameter space. In Giuseppe De Giacomo, editor, *Proceedings of the 24th European Conference on Artificial Intelligence (ECAI 2020)*, pages 2346–2353. IOS Press, 2020.
- Patrick Ferber, Liat Cohen, Jendrik Seipp, and Thomas Keller. Learning and exploiting progress states in greedy best-first search. In Luc De Raedt, editor, *Proceedings of the 31th International Joint Conference on Artificial Intelligence (IJCAI 2022)*, pages 4740–4746. IJCAI, 2022.
- Patrick Ferber, Florian Geißer, Felipe Trevizan, Malte Helmert, and Jörg Hoffmann. Neural network heuristic functions for classical planning: Bootstrapping and comparison to other methods. In Sylvie Thiébaux and William Yeoh, editors, *Proceedings of the Thirty-Second International Conference on Automated Planning and Scheduling (ICAPS 2022)*, pages 583–587. AAAI Press, 2022.

References iii

- Manuel Heusner, Thomas Keller, and Malte Helmert. Best-case and worst-case behavior of greedy best-first search. In Jérôme Lang, editor, *Proceedings of the 27th International Joint Conference on Artificial Intelligence (IJCAI 2018)*, pages 1463–1470. IJCAI, 2018.
- Jörg Hoffmann and Bernhard Nebel. The FF planning system: Fast plan generation through heuristic search. *Journal of Artificial Intelligence Research*, 14:253–302, 2001.
- Jörg Hoffmann. Where ‘ignoring delete lists’ works: Local search topology in planning benchmarks. *Journal of Artificial Intelligence Research*, 24:685–758, 2005.
- Tengfei Ma, Patrick Ferber, Siyu Huo, Jie Chen, and Michael Katz. Online planner selection with graph neural networks and adaptive scheduling. In Vincent Conitzer and Fei Sha, editors, *Proceedings of the Thirty-Fourth AAAI Conference on Artificial Intelligence (AAAI 2020)*, pages 5077–5084. AAAI Press, 2020.

References iv

- Nir Pochter, Aviv Zohar, and Jeffrey S. Rosenschein. Exploiting problem symmetries in state-based planners. In Wolfram Burgard and Dan Roth, editors, *Proceedings of the Twenty-Fifth AAAI Conference on Artificial Intelligence (AAAI 2011)*, pages 1004–1009. AAAI Press, 2011.
- Silvan Sievers, Michael Katz, Shirin Sohrabi, Horst Samulowitz, and Patrick Ferber. Deep learning for cost-optimal planning: Task-dependent planner selection. In *Proceedings of the Thirty-Third AAAI Conference on Artificial Intelligence (AAAI 2019)*, pages 7715–7723. AAAI Press, 2019.
- Silvan Sievers, Gabriele Röger, Martin Wehrle, and Michael Katz. Theoretical foundations for structural symmetries of lifted PDDL tasks. In Nir Lipovetzky, Eva Onaindia, and David E. Smith, editors, *Proceedings of the Twenty-Ninth International Conference on Automated Planning and Scheduling (ICAPS 2019)*, pages 446–454. AAAI Press, 2019.

Christopher Wilt and Wheeler Ruml. Speedy versus greedy search. In Stefan Edelkamp and Roman Barták, editors, *Proceedings of the Seventh Annual Symposium on Combinatorial Search (SoCS 2014)*, pages 184–192. AAAI Press, 2014.