Neural Network Heuristic Functions for Classical Planning: Bootstrapping and Comparison to Other Methods

Patrick Ferber[1,3] Florian Geißer[2] Felipe Trevizan[2]
Malte Helmert[1] Jörg Hoffmann[3]



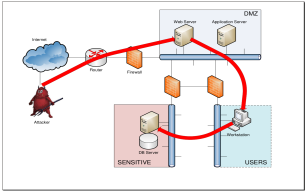


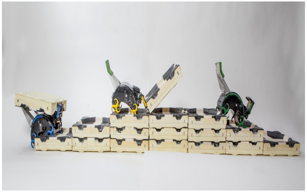
[1]University of Basel, Basel, Switzerland
[2]Australian National University, Canberra, Australia
[3]Saarland University, Saarland Informatics Campus, Saarbrücken, Germany

32nd International Conference on Automated Planning and Scheduling

2022

Motivation


DMZ
Web Server
Application Server
Internet
Router
Firewall
Attacker
Workstation
DB Server
SENSITIVE
USERS

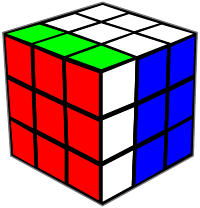


Heuristic

Heuristic

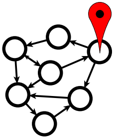
Silver et al. (2016)
Silver et al. (2017)
Silver et al. (2018)

Agostinelli et al. (2019)



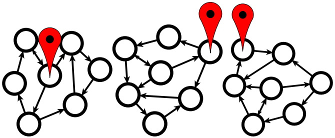
Neural Networks as Planning Heuristics

per-instance heuristics



- Ferber, Helmert, and Hoffmann (2020)
- Agostinelli et al. (2019)

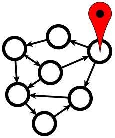
per-domain heuristics



- Shen, Trevizan, and Thiébaux (2020)
- Karia and Srivastava (2021)

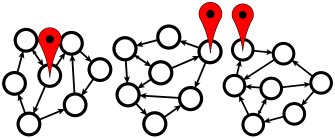
Neural Networks as Planning Heuristics

per-instance heuristics



- Ferber, Helmert, and Hoffmann (2020)
- Agostinelli et al. (2019)

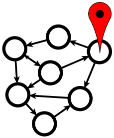
per-domain heuristics



- Shen, Trevizan, and Thiébaux (2020)
- Karia and Srivastava (2021)

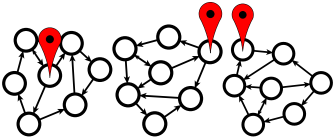
Neural Networks as Planning Heuristics

per-instance heuristics



- Ferber, Helmert, and Hoffmann (2020)
- Agostinelli et al. (2019)

per-domain heuristics

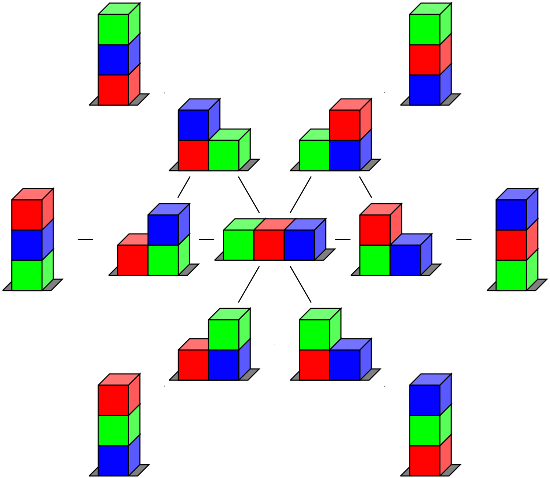


- Shen, Trevizan, and Thiébaux (2020)
- Karia and Srivastava (2021)

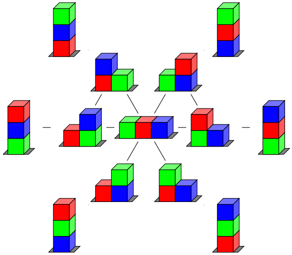
Contributions

- three *per-instance* heuristics
  - only state as input
  - curriculum learning
  - prove convergence to h^*
- comparison between state-of-the-art
  - neural network heuristics
  - model-based heuristics

Finite-Domain Representation (Helmert, 2009)



Finite-Domain Representation (Helmert, 2009)

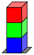


$\Pi = \langle V, O, I, g \rangle$

$V = \{ \; , \; , \; \}$

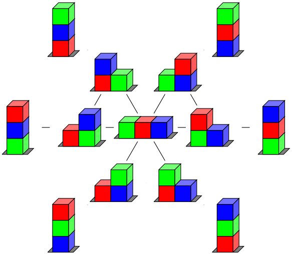
$dom(\;) = \{$on , on , on $\}$

$O = \{$move from X to Y$\}$

$I =$ 

$g = \{ \; \mapsto$ on $\}$

Finite-Domain Representation (Helmert, 2009)



$\Pi = \langle V, O, I, g \rangle$

$V = \{ , , \}$

$dom( ) = \{$on , on , on $\}$

$O = \{$move from X to Y$\}$

$I =$

$g = \{ \mapsto$ on $\}$

$\pi = \langle$move from to ,

move from to $\rangle$

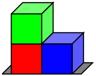
Progression & Regression

move from to

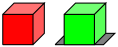
pre : { $\mapsto$ on }

eff : { $\mapsto$ on }

Progression



Regression



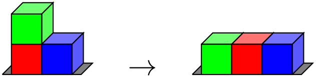
Progression & Regression

move from to

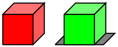
pre : $\{ \mapsto$ on $\}$

eff : $\{ \mapsto$ on $\}$

Progression



Regression



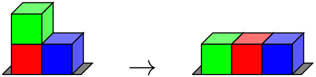
Progression & Regression

move from to

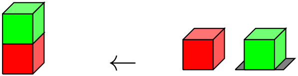
pre : $\{ \mapsto$ on $\}$

eff : $\{ \mapsto$ on $\}$

Progression



Regression

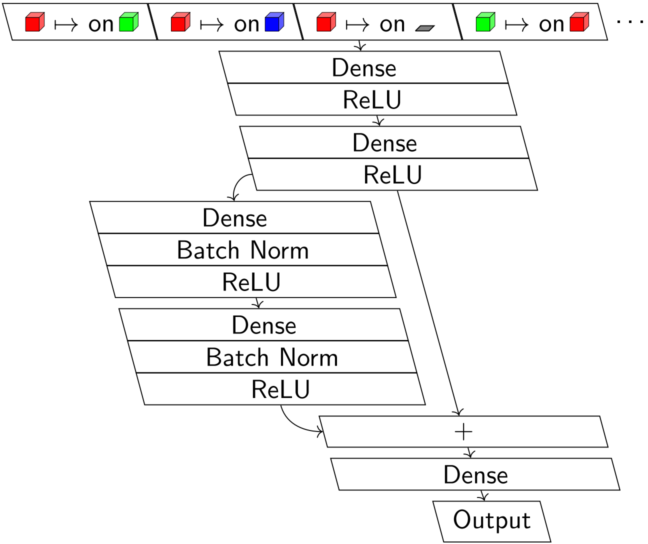


Heuristic

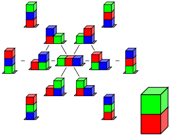
$$h : S \to \mathbb{R}_0^+ \cup \{\infty\}$$

$h^* :=$ perfect heuristic

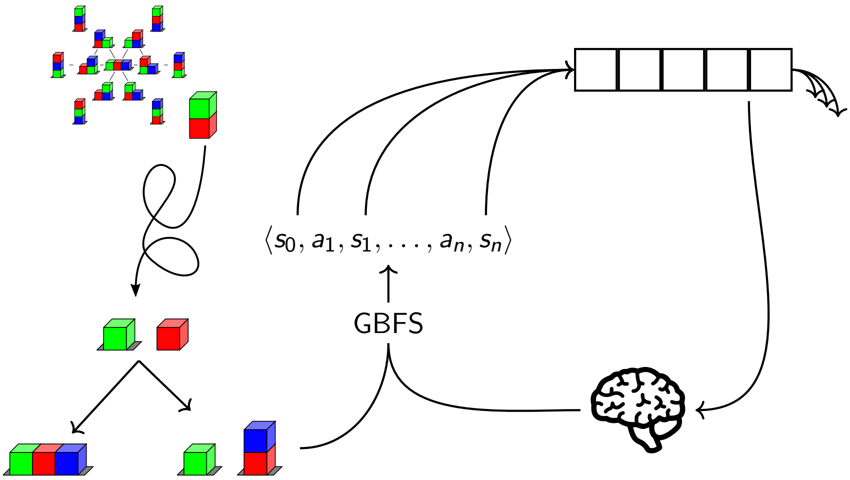
Residual Network (He et al., 2016)



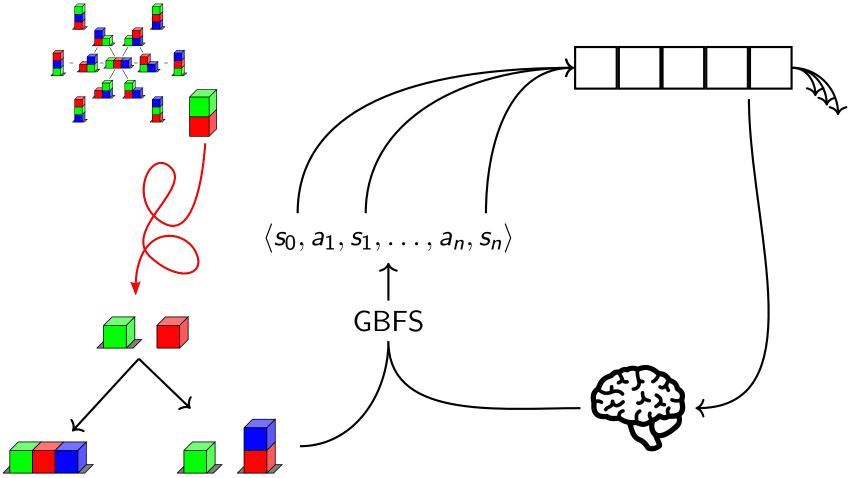
Goal-Distance Estimator



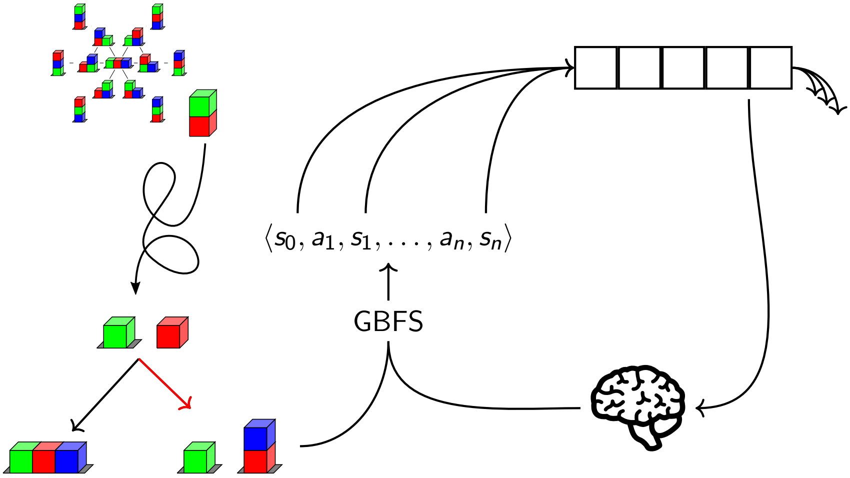
Goal-Distance Estimator



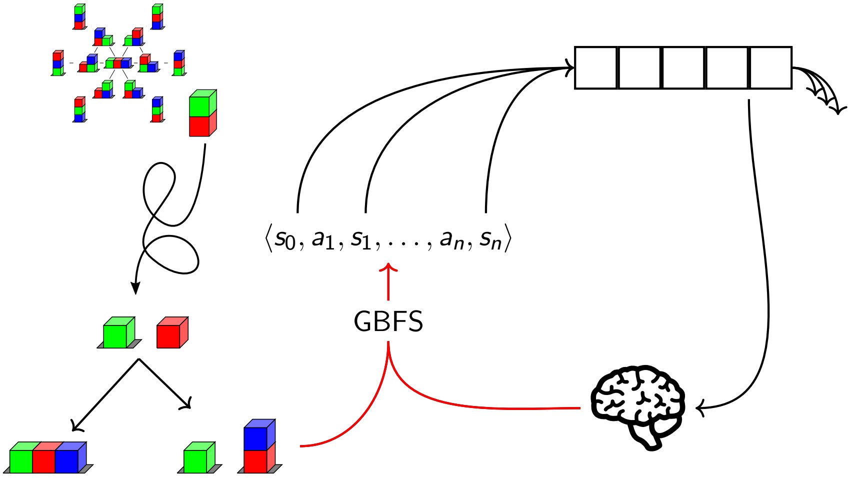
Goal-Distance Estimator



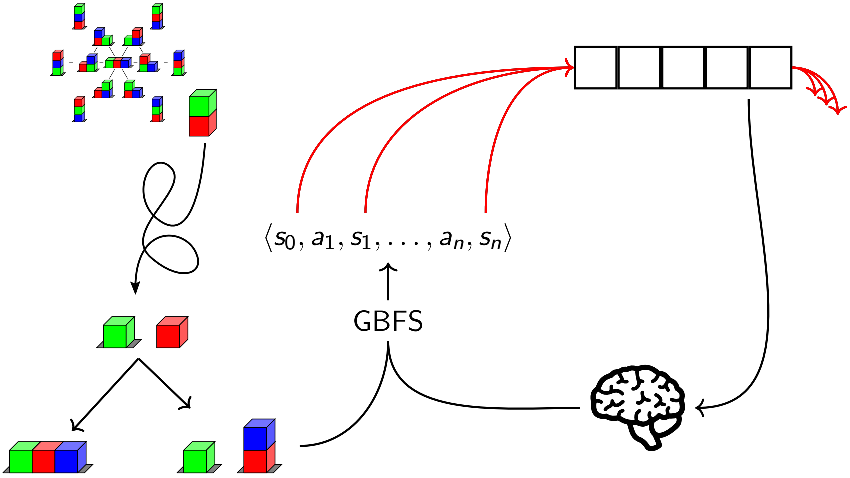
Goal-Distance Estimator



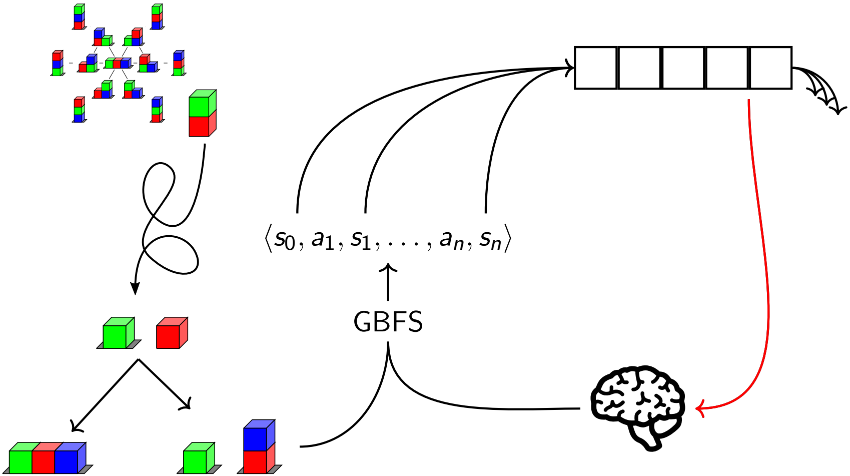
Goal-Distance Estimator



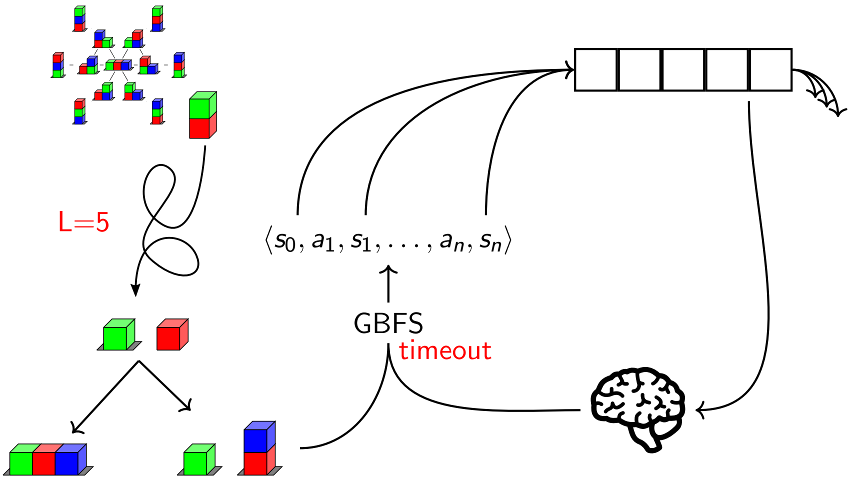
Goal-Distance Estimator



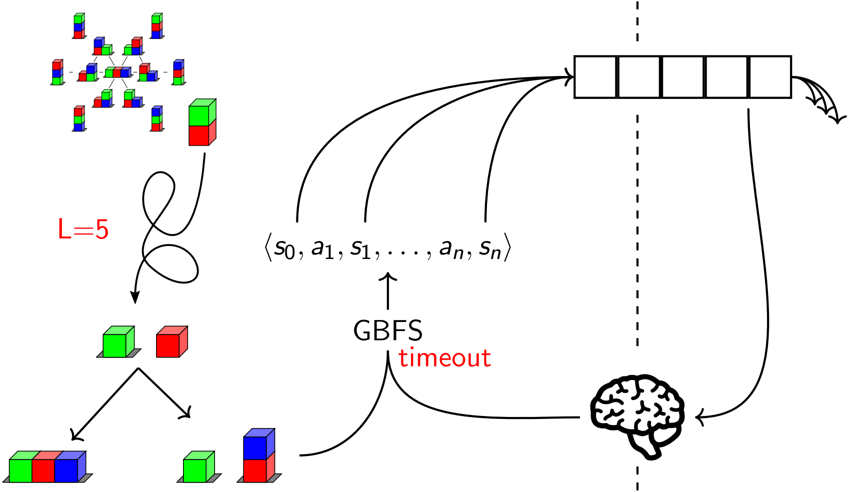
Goal-Distance Estimator



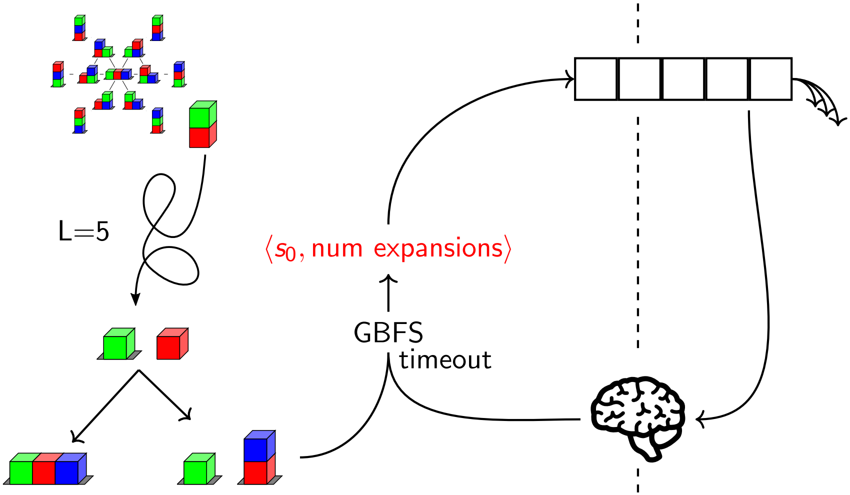
Goal-Distance Estimator



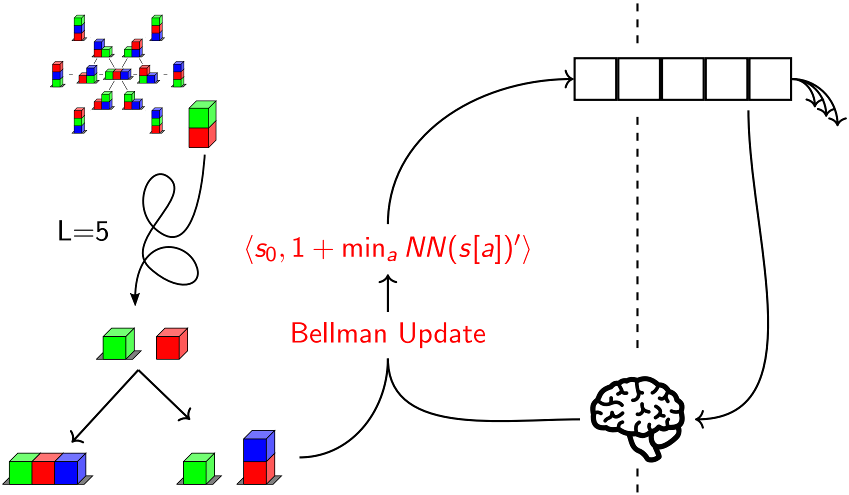
Goal-Distance Estimator



Search-Space-Size Estimator



Approximate Value Iteration



Algorithms

- h^{GD} Goal-Distance Estimator
- h^{SE} Search-Space-Size Estimator
- h^{AVI} Approximate value iteration

- h^{SL} Ferber, Helmert, and Hoffmann (2020)
- h^{HGN} Shen, Trevizan, and Thiébaux (2020)

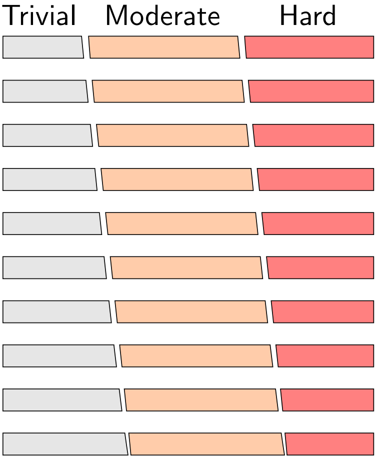
- h^{FF} Hoffmann and Nebel (2001)
- *LAMA* Richter and Westphal (2010)

Benchmarks (Ferber, Helmert, and Hoffmann, 2020)

- Blocksworld
- Depots
- Grid
- NPuzzle
- Pipesworld-NT
- Rovers
- Scanalyzer
- Storage
- Transport
- Visitall

Benchmarks (Ferber, Helmert, and Hoffmann, 2020)

- Blocksworld
- Depots
- Grid
- NPuzzle
- Pipesworld-NT
- Rovers
- Scanalyzer
- Storage
- Transport
- Visitall



Coverage (Moderate Tasks)

Domain	h^{GD}	h^{SE}	h^{AVI}
blocks	**18.0**	0.0	0.0
depots	**60.3**	32.7	54.7
grid	**100.0**	**100.0**	51.0
npuzzle	**28.0**	0.0	1.0
pipes-nt	57.8	**68.4**	50.2
rovers	**48.2**	21.8	45.0
scanalyzer	33.3	**70.7**	67.3
storage	**89.0**	57.5	69.5
transport	**100.0**	**100.0**	87.5
visitall	**55.3**	0.0	0.0

Coverage (Moderate Tasks)

Domain	h^{GD}	h^{SE}	h^{AVI}	h^{SL}	h^{HGN}
blocks	18.0	0.0	0.0	80.4	**100.0**
depots	60.3	32.7	54.7	**90.3**	0.0
grid	**100.0**	**100.0**	51.0	93.0	0.0
npuzzle	**28.0**	0.0	1.0	0.0	0.3
pipes-nt	57.8	68.4	50.2	**92.2**	7.6
rovers	**48.2**	21.8	45.0	26.0	14.0
scanalyzer	33.3	70.7	67.3	**82.7**	11.0
storage	**89.0**	57.5	69.5	24.5	0.0
transport	**100.0**	**100.0**	87.5	99.2	94.7
visitall	55.3	0.0	0.0	0.0	**100.0**

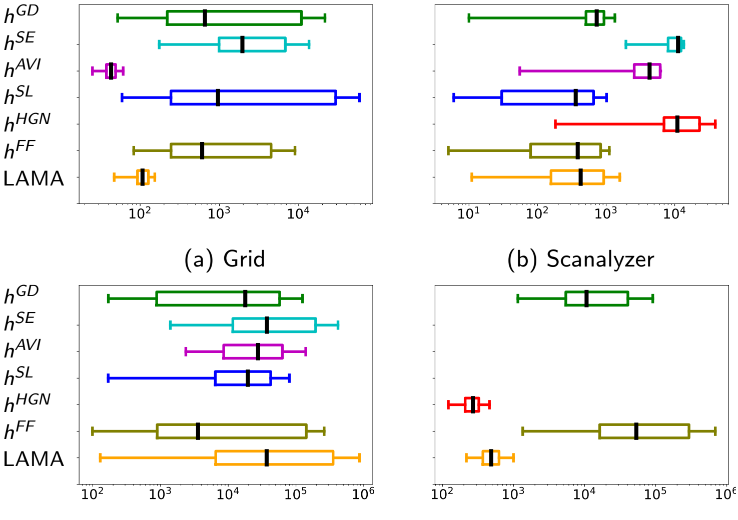
Coverage (Moderate Tasks)

Domain	h^{GD}	h^{SE}	h^{AVI}	h^{SL}	h^{HGN}	h^{FF}	*LAMA*
blocks	18.0	0.0	0.0	80.4	**100.0**	98.8	**100.0**
depots	60.3	32.7	54.7	**90.3**	0.0	98.0	**100.0**
grid	**100.0**	**100.0**	51.0	93.0	0.0	96.0	**100.0**
npuzzle	**28.0**	0.0	1.0	0.0	0.3	97.5	**100.0**
pipes-nt	57.8	68.4	50.2	**92.2**	7.6	82.4	**99.4**
rovers	**48.2**	21.8	45.0	26.0	14.0	84.2	**100.0**
scanalyzer	33.3	70.7	67.3	**82.7**	11.0	98.3	**100.0**
storage	**89.0**	57.5	69.5	24.5	0.0	**48.0**	**38.5**
transport	**100.0**	**100.0**	87.5	99.2	94.7	98.5	**100.0**
visitall	55.3	0.0	0.0	0.0	**100.0**	93.3	**100.0**

Coverage (Hard Tasks)

Domain	h^{GD}	h^{SE}	h^{AVI}	h^{SL}	h^{HGN}	h^{FF}	*LAMA*
blocks	0.0	0.0	0.0	0.0	**50.0**	61.6	**96.8**
depots	8.3	4.3	12.9	**35.4**	0.0	36.0	**82.6**
grid	87.8	**95.0**	70.5	60.2	0.0	53.2	**100.0**
npuzzle	0.0	0.0	0.0	0.0	0.0	33.2	**86.5**
pipes-nt	23.4	19.1	8.0	**48.7**	0.0	27.4	**69.3**
rovers	2.8	0.8	**6.5**	1.5	0.3	13.9	**100.0**
scanalyzer	3.3	0.0	**60.7**	60.0	0.0	98.0	**100.0**
storage	**27.2**	13.2	15.8	0.0	0.0	**13.8**	**11.5**
transport	0.0	0.0	**2.4**	0.0	0.0	0.0	**92.8**
visitall	28.0	0.0	0.0	0.0	**100.0**	74.0	**100.0**

Expansions



(a) Grid (b) Scanalyzer

(c) Storage (d) Visitall

Conclusion

- three new per-instance heuristics

- large scale comparison to previous work
  - trained heuristics highly complementary
  - in general, model-based heuristics win
  - all our heuristics superior in Storage

Paper & Supplement

References I

Agostinelli, F.; McAleer, S.; Shmakov, A.; and Baldi, P. 2019. Solving the Rubik's cube with deep reinforcement learning and search. Nature Machine Intelligence, 1: 356–363.

Ferber, P.; Helmert, M.; and Hoffmann, J. 2020. Neural Network Heuristics for Classical Planning: A Study of Hyperparameter Space. In De Giacomo, G., ed., Proceedings of the 24th European Conference on Artificial Intelligence (ECAI 2020), 2346–2353. IOS Press.

He, K.; Zhang, X.; Ren, S.; and Sun, J. 2016. Deep Residual Learning for Image Recognition. In Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition, 770–778. IEEE Computer Society.

Helmert, M. 2009. Concise Finite-Domain Representations for PDDL Planning Tasks. Artificial Intelligence, 173: 503–535.

Hoffmann, J.; and Nebel, B. 2001. The FF Planning System: Fast Plan Generation Through Heuristic Search. Journal of Artificial Intelligence Research, 14: 253–302.

References II

Karia, R.; and Srivastava, S. 2021. Learning Generalized Relational Heuristic Networks for Model-Agnostic Planning. In Leyton-Brown, K.; and Mausam, eds., Proceedings of the Thirty-Fifth AAAI Conference on Artificial Intelligence (AAAI 2021), 8064–8073. AAAI Press.

Richter, S.; and Westphal, M. 2010. The LAMA Planner: Guiding Cost-Based Anytime Planning with Landmarks. Journal of Artificial Intelligence Research, 39: 127–177.

Shen, W.; Trevizan, F.; and Thiébaux, S. 2020. Learning Domain-Independent Planning Heuristics with Hypergraph Networks. In Beck, J. C.; Karpas, E.; and Sohrabi, S., eds., Proceedings of the Thirtieth International Conference on Automated Planning and Scheduling (ICAPS 2020), 574–584. AAAI Press.

Silver, D.; Huang, A.; Maddison, C. J.; Guez, A.; Sifre, L.; van den Driessche, G.; Schrittwieser, J.; Antonoglou, I.; Panneershelvam, V.; Lanctot, M.; Dieleman, S.; Grewe, D.; Nham, J.; Kalchbrenner, N.; Sutskever, I.; Lillicrap, T.; Leach, M.; Kavukcuoglu, K.; Graepel, T.; and Hassabis, D. 2016. Mastering the Game of Go with Deep Neural Networks and Tree Search. Nature, 529(7587): 484–489.

References III

Silver, D.; Hubert, T.; Schrittwieser, J.; Antonoglou, I.; Lai, M.; Guez, A.; Lanctot, M.; Sifre, L.; Kumaran, D.; Graepel, T.; Lillicrap, T.; Simonyan, K.; and Hassabis, D. 2018. A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. Science, 362(6419): 1140–1144.

Silver, D.; Schrittwieser, J.; Simonyan, K.; Antonoglou, I.; Huang, A.; Guez, A.; Hubert, T.; Baker, L.; Lai, M.; Bolton, A.; Chen, Y.; Lillicrap, T.; Hui, F.; Sifre, L.; van den Driessche, G.; Graepel, T.; and Hassabis, D. 2017. Mastering the Game of Go Without Human Knowledge. Nature, 550(7676): 354–359.