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

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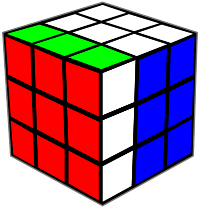
Workshop on Bridging the Gap Between AI Planning and Reinforcement Learning
(2021)

Motivation

AlphaGo

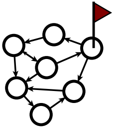
Silver et al. (2016)
Silver et al. (2017)
Silver et al. (2018)

Agostinelli et al. (2019)



Neural Networks as Planning Heuristics

per-instance heuristics



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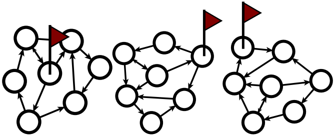
- Yu, Kuroiwa, and Fukunaga (2020)

per-domain heuristics



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- Karia and Srivastava (2021)

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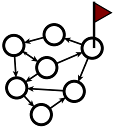

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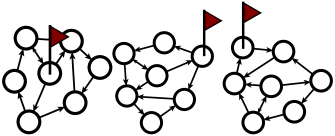

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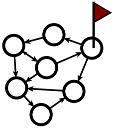

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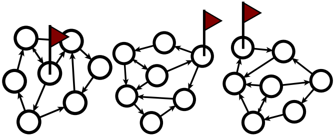

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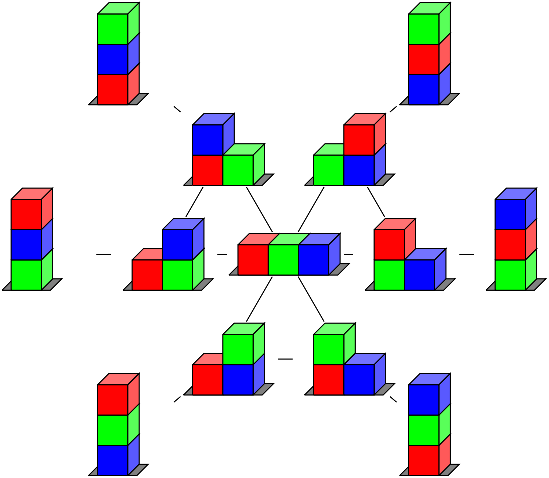
Contributions

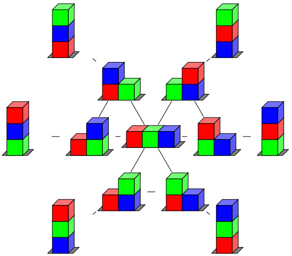
- three *per-instance* RL based heuristics
  - learned from scratch
  - only state as input
  - prove convergence to h^*

- comparison between state-of-the-art
  - neural network heuristics
  - model-based heuristics

Finite-Domain Representation (Helmert, 2009)



Finite-Domain Representation (Helmert, 2009)

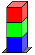


$\Pi = \langle V, O, I, g \rangle$

$V = \{ , , \}$

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

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

$I =$ 

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

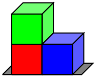
Progression & Regression

move from to

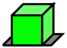
pre : $\{\ \mapsto$ on $\}$

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

Progression



Regression



Progression & Regression

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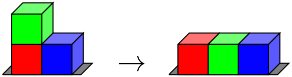
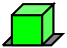
Progression



Regression



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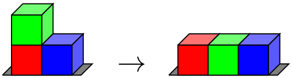
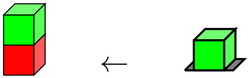
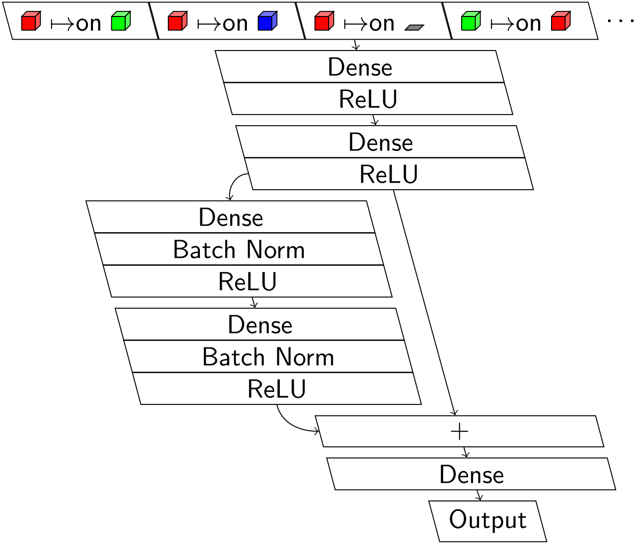
Progression



Regression



Residual Network (He et al., 2016)



Bootstrapping

```
def train(Π, NN, t_train):
    D = Buffer()

    while time() ≤ t_train:
        p = regression random walk(Π)
        s = complete to state (p)
        π = GBFS+NN(s)

        for s′ ∈ π:
            D.push(s′, distance(s′, goal(Π), π)

        NN = train(NN, D)
```

inspired by Bootstrap Learning of Arfaee, Zilles, and Holte (2011)

Bootstrapping

```
def train(Π, NN, t_train):
    D = Buffer()
    L = 5
    while time() ≤ t_train:
        p = regression random walk(Π, max_length=L)
        s = complete to state (p)
        π = GBFS+NN(s)

        for s′ ∈ π:
            D.push(s′, distance(s′, goal(Π), π)
        if frequently solves s:  L = 2 ∗ L
        NN = train(NN, D)
```

inspired by Bootstrap Learning of Arfaee, Zilles, and Holte (2011)

Bootstrapping

```
def train(Π, NN, t_train, t_search):
    D = Buffer()
    L = 5
    while time() ≤ t_train:
        p = regression random walk(Π, max_length=L)
        s = complete to state (p)
        π = GBFS+NN(s, timeout=t_search)
        if not π:  continue
        for s′ ∈ π:
            D.push(s′, distance(s′, goal(Π), π)
        if frequently solves s:  L = 2 ∗ L
        NN = train(NN, D)
```

inspired by Bootstrap Learning of Arfaee, Zilles, and Holte (2011)

Bootstrapping to Predict Expansions

```
def train(Π, NN, t_train, t_search):
    D = Buffer()
    L = 5
    while time() ≤ t_train:
        p = regression random walk(Π, max_length=L)
        s = complete to state (p)
        expansions = GBFS+NN(s,timeout=t_search)
        if not π: continue
        D.push(s, expansions)

        if frequently solves s: L = 2 * L
        NN = train(NN, D)
```

inspired by Bootstrap Learning of Arfaee, Zilles, and Holte (2011)

Approximate Value Iteration

```
def train(Π, NN, t_train):
    D = Buffer()
    while time() ≤ t_train:
        p = regression random walk(Π)
        s = complete to state (p)
        h = BellmanUpdate (s, NN)
        D.push(s, h)
        NN = train(NN, D)

def BellmanUpdate(s, NN):
    return 1 + min_{s' ∈ succ(s)} NN(s')
```

Algorithms

- h^{Boot} Bootstrapping
- h^{BExp} Bootstrapping with expansions
- 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

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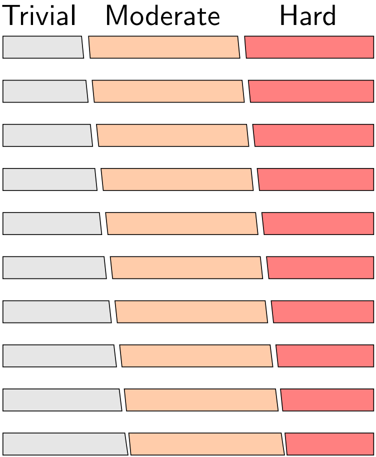


Validation (Moderate Tasks)

Domain	h^{Boot}	+V	h^{BExp}	+V	h^{AVI}	+V
blocks	0.0	+18.0	0.0	+0.0	0.0	+0.0
depots	31.7	+28.6	17.1	+15.0	**43.7**	+11.0
grid	**100.0**	+0.0	**100.0**	+0.0	51.0	+0.0
npuzzle	**27.0**	+1.0	0.0	+0.0	1.0	+0.0
pipes-nt	36.2	+21.6	**51.2**	+17.2	21.4	+28.8
rovers	**36.5**	+11.7	15.2	+6.6	34.2	+10.8
scanalyzer	33.3	+0.0	59.7	+11.0	**66.7**	+0.6
storage	**89.0**	+0.0	61.0	-3.5	67.0	+2.5
transport	**83.8**	+16.2	79.5	+20.5	70.0	+17.5
visitall	**17.0**	+38.3	0.0	+0.0	0.0	+0.0

Table: Performance of our algorithms without validation and performance change due to validation (+V).

Coverage (Moderate Tasks)

Domain	h^{Boot}	h^{BExp}	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^{Boot}	h^{BExp}	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**

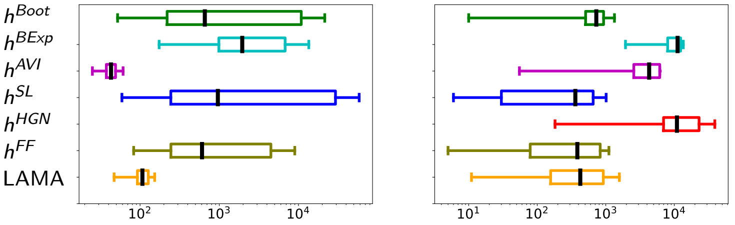
Coverage (Moderate Tasks)

Domain	h^{Boot}	h^{BExp}	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**

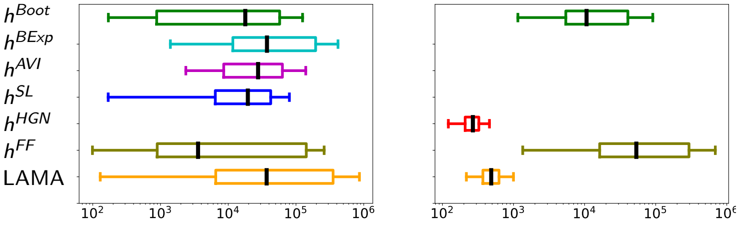
Coverage (Hard Tasks)

Domain	h^{Boot}	h^{BExp}	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 RL heuristics

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

Paper &
Supplement

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