Explainable Planner Selection for Classical Planning

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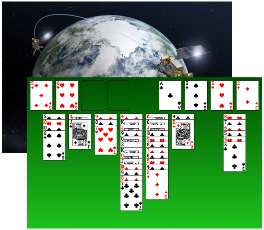
[3]Linköping University, Linköping, Sweden

36th AAAI Conference on Artificial Intelligence

February, 2022

Motivation

Motivation



Motivation

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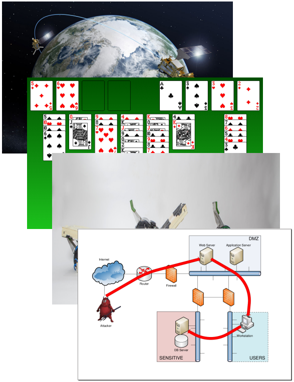

DMZ
Web Server
Application Server
Internet
Router
Firewall
Attacker
Workstation
DB Server
SENSITIVE
USERS

Motivation


DMZ
Web Server
Application Server
Internet
Router
Firewall

Motivation

SymBA*

Motivation

Smarthouse ©LemnaTec GmbH

SymBA*

DecStar

Motivation

SymBA*

DecStar

Symple-1

Smarthouse ©LemnaTec GmbH

Motivation

Smarthouse ©LemnaTec GmbH

SymBA*

DecStar

Symple-1

. . .

Motivation

?

SymBA*

DecStar

Symple-1

...

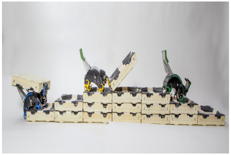
Smarthouse ©LemnaTec GmbH

Naive Solution

DecStar:	100%
SymBA*:	79%

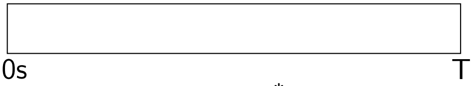
Naive Solution

DecStar:	100%
SymBA*:	79%



DecStar:	67%
SymBA*:	100%

Offline Portfolios



SymBA*

DecStar

Blind

Offline Portfolios

SymBA* DecStar

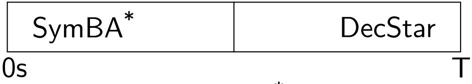
0s T

SymBA*

DecStar

~~Blind~~

Offline Portfolios

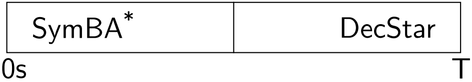


SymBA*

DecStar

~~Blind~~

Offline Portfolios



DecStar:	75%
SymBA*:	72%
Portfolio:	84%

Online Portfolio

$$f(\Pi) = \boxed{\qquad\qquad\qquad\qquad\qquad\qquad}$$

0s T

Online Portfolio

$f(\Pi) = \boxed{\qquad\qquad\qquad\qquad}$

0s T

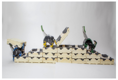
$f($  $) = \boxed{\text{DecStar}}$

0s T

Online Portfolio

$f(\Pi) =$ | |
0s T

$f($  $) =$ | DecStar |
0s T

$f($  $) =$ | SymBA* | DecStar |
0s T

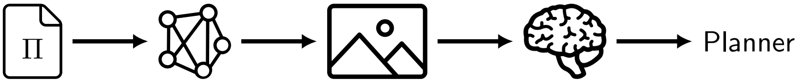
Online Portfolio

$$f(\Pi) = \boxed{\qquad\qquad\qquad\qquad\qquad\qquad}$$

0s T

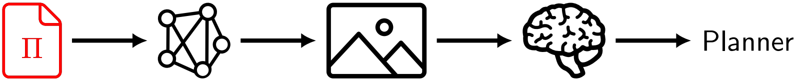
DecStar:	75%
SymBA*:	72%
Offline Portfolio:	84%
Online Portfolio:	87%

Delfi (Katz et al., 2018)



Images from the Noun Project: RomStu (file), Agni (network), Alfa Design (image), Samuel Dion-Girardeau (brain)

Delfi (Katz et al., 2018)



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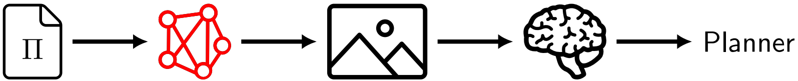

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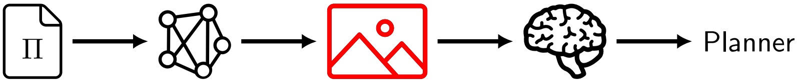

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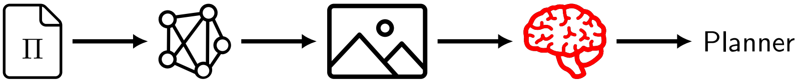

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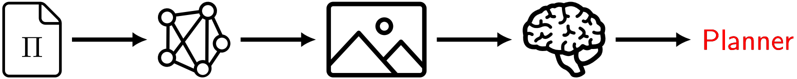


Images from the Noun Project: RomStu (file), Agni (network), Alfa Design (image), Samuel Dion-Girardeau (brain)

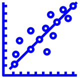
Contributions

- **explainable techniques** and **understandable features**
- identify **important features**
- investigate **which planners** are selected
- present new self-explaining decision tree

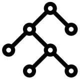
Machine Learning Techniques

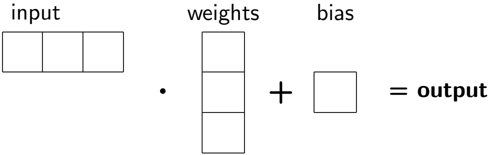
- Linear Regression
- Decision Trees
- Multi-Layer Perceptrons

Machine Learning Techniques

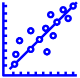


Linear Regression





Machine Learning Techniques



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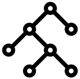

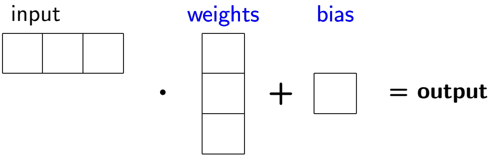

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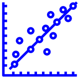

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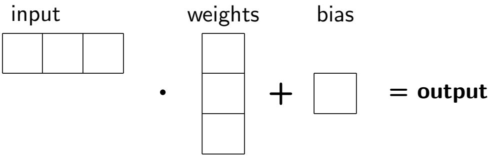

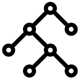

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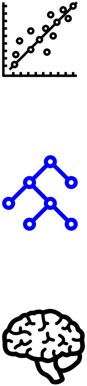
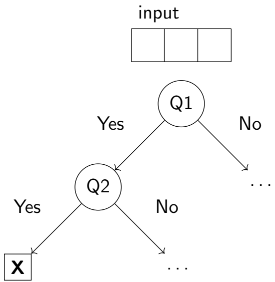


Decision Tree



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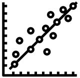
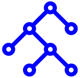
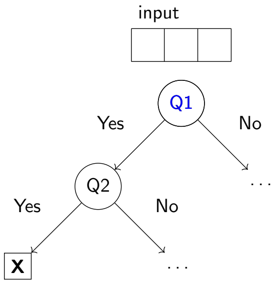
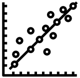


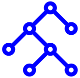


Decision Tree



Machine Learning Techniques





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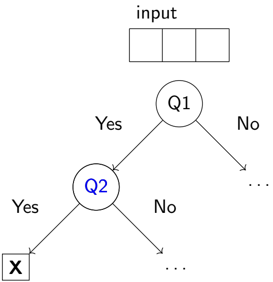

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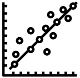

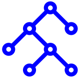

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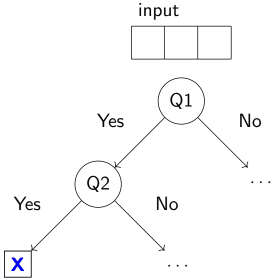

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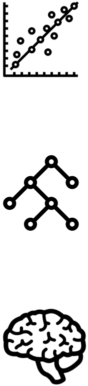
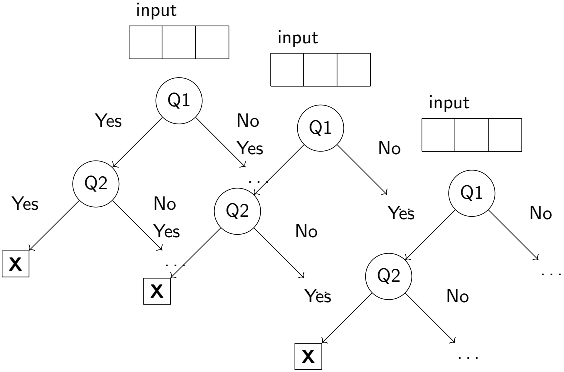
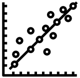
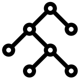


Random Forest

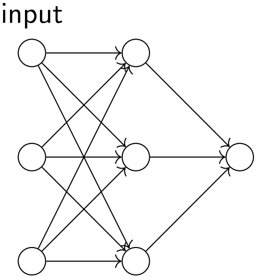


Machine Learning Techniques

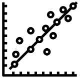


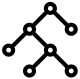


Multi-Layer Perceptron



Machine Learning Techniques





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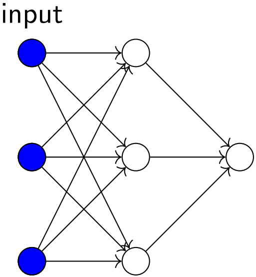

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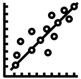

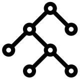

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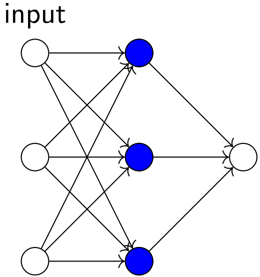

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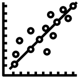

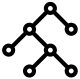

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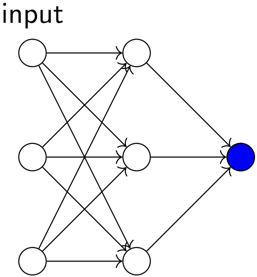


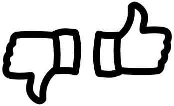
Features

$$\text{FPDDL} \subset \begin{matrix}\text{Fawcett}^1\\ \\ \text{PDDL}\end{matrix} \subset \text{Union}$$

Feature augmentations: normalize

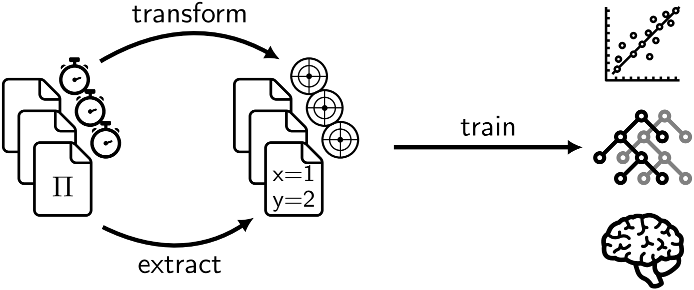
[1] The features presented by Fawcett et al. (2014)

Target Functions

	Function
	Time
	log(Time)
	Solves

Images from the Noun Project: Delwar Hossai (timer), Landan Lloyd (thumb)

Training



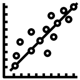
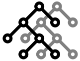
- data set by Ferber et al. (2019)
- 10-fold domain-preserving cross-validation

Noun Project: RomStu (file), Becris (Lin. Regression), Knut Synstad (Tree), Samuel Dion-Girardeau (brain)

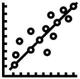
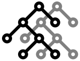
Performance

		Linear Regression					MLP		Forest
		0.0	0.1	1.0	2.0	5.0	3	5	50
FAWCETT	binary	78.6	77.2	82.1	82.4	80.9	87.1	78.2	84.8
	logtime	79.3	79.0	81.5	81.7	83.6	82.2	82.2	84.1
	time	78.6	81.8	80.5	80.4	80.3	82.2	85.3	81.8
FPDDL	binary	87.7	74.3	72.7	74.3	71.4	81.0	81.5	77.5
	logtime	82.5	84.0	78.5	77.7	80.3	78.2	79.7	82.0
	time	86.5	86.5	86.5	86.6	86.6	80.2	81.9	78.8
PDDL	binary	81.4	75.7	72.6	74.1	71.4	78.1	79.8	80.2
	logtime	82.1	79.7	80.4	79.8	77.8	79.5	78.0	82.8
	time	81.6	82.0	81.2	79.0	78.7	77.8	78.4	79.7
UNION	binary	74.8	81.0	79.4	82.4	80.9	84.7	78.3	82.1
	logtime	75.6	80.0	80.7	81.8	83.4	82.2	82.2	84.7
	time	74.8	77.3	75.7	76.1	77.1	84.3	83.6	84.0

Performance

	Random: 67.2%	Best: 73.5%
	60/60	56/60
	12/12	12/12
	24/24	24/24

Performance

	Min	Mean	Max
	71.4%	80.0%	87.7%
	77.5%	81.9%	84.8%
	77.8%	81.1%	87.1%

Planner Choices

Usage	Cov_P	Cov_C	Planner
43.7	80.1	94.4	SymBA*
12.3	82.4	89.9	h2 + OSS + LM-Cut
9.7	78.7	54.5	h2 + DKS + iPDB
9.4	78.8	88.5	h2 + OSS + iPDB
8.1	82.7	78.1	h2 + DKS + LM-Cut
5.4	67.9	74.8	DKS + M&S-MIASM-DFP
3.3	74.8	97.5	h2 + DKS + M&S-BS-sbMIASM
2.8	65.9	86.6	h2 + OSS + M&S-SCC-DFP
2.1	75.8	100	h2 + DKS + M&S-BS-SCC-DFP
1.0	67.7	84.0	OSS + M&S-MIASM-DFP

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3.3	74.8	97.5	h2 + DKS + M&S-BS-sbMIASM
2.8	65.9	86.6	h2 + OSS + M&S-SCC-DFP
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8.1	82.7	78.1	h2 + DKS + LM-Cut
5.4	67.9	74.8	DKS + M&S-MIASM-DFP
3.3	74.8	97.5	h2 + DKS + M&S-BS-sbMIASM
2.8	65.9	86.6	h2 + OSS + M&S-SCC-DFP
2.1	75.8	100	h2 + DKS + M&S-BS-SCC-DFP
1.0	67.7	84.0	OSS + M&S-MIASM-DFP

Planner Choices

Usage	Cov_P	Cov_C	Planner
43.7	80.1	**94.4**	SymBA*
12.3	82.4	89.9	h2 + OSS + LM-Cut
9.7	78.7	54.5	h2 + DKS + iPDB
9.4	78.8	88.5	h2 + OSS + iPDB
8.1	82.7	78.1	h2 + DKS + LM-Cut
5.4	67.9	74.8	DKS + M&S-MIASM-DFP
3.3	74.8	97.5	h2 + DKS + M&S-BS-sbMIASM
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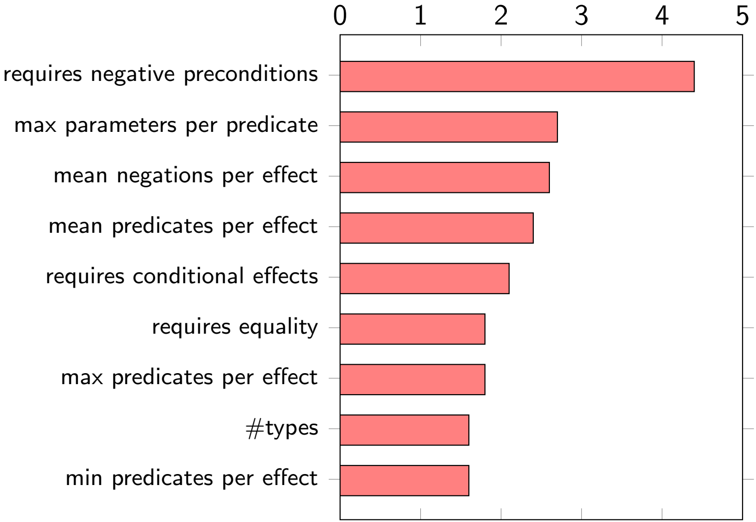
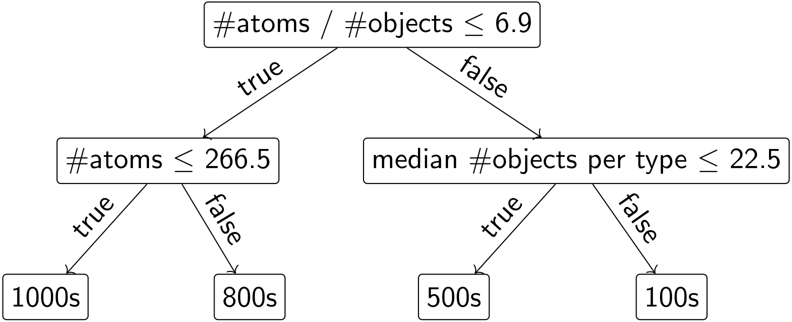
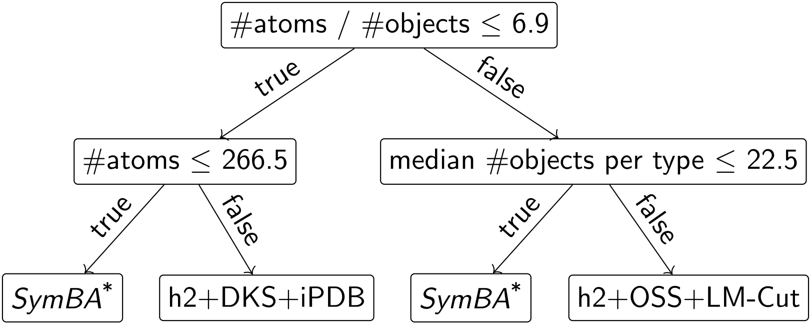
Feature Importance



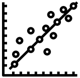
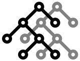
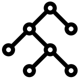
Single Decision Tree



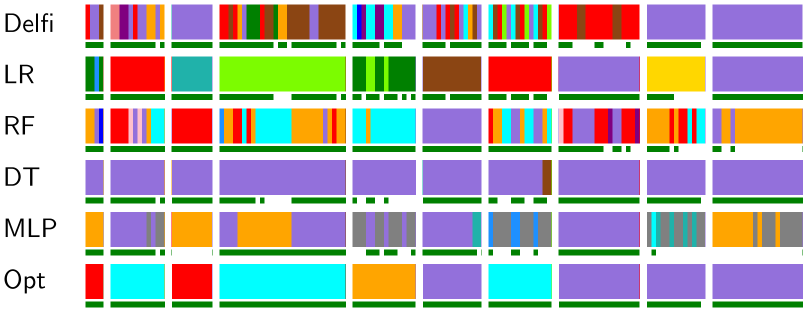
Single Decision Tree



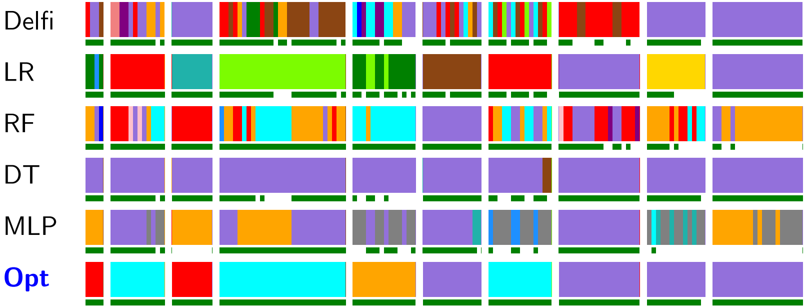
Comparison to Delfi

Delfi1	86.9
	86.2
	76.8
	70.8
	82.7

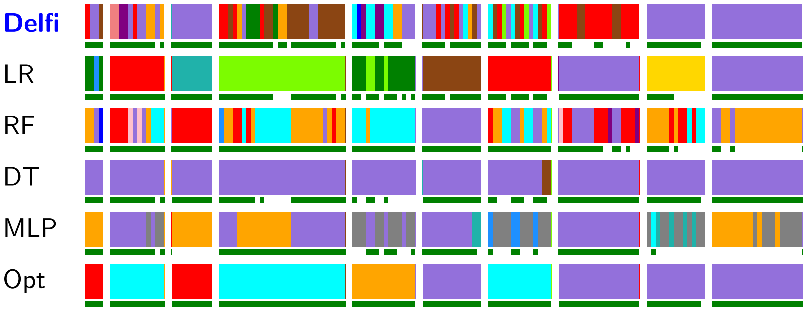
Planner Choices



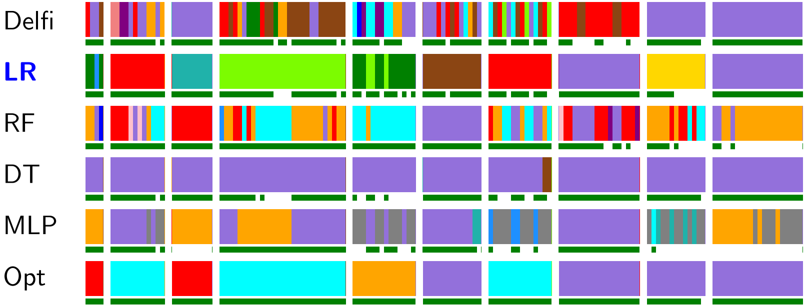
Planner Choices



Planner Choices



Planner Choices



Summary

Explainable planner selection ...

- is competitive
- let's us identify important features
- learns the right planner for a domain
- can be as simple as a single decision tree

References I

Fawcett, C.; Vallati, M.; Hutter, F.; Hoffmann, J.; Hoos, H.; and Leyton-Brown, K. 2014. Improved Features for Runtime Prediction of Domain-Independent Planners. In Chien, S.; Fern, A.; Ruml, W.; and Do, M., eds., *Proceedings of the Twenty-Fourth International Conference on Automated Planning and Scheduling (ICAPS 2014)*, 355–359. AAAI Press.

Ferber, P.; Mai, T.; Huo, S.; Chen, J.; and Katz, M. 2019. IPC: A Benchmark Data Set for Learning with Graph- Structured Data. In *In Proceedings of the ICML-2019 Workshop on Learning and Reasoning with Graph-Structured Representations*.

Katz, M.; Sohrabi, S.; Samulowitz, H.; and Sievers, S. 2018. Delfi: Online Planner Selection for Cost-Optimal Planning. In *Ninth International Planning Competition (IPC-9): Planner Abstracts*, 57–64.