Explainable Planner Selection for Classical Planning

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Motivation
Motivation
Motivation
Motivation
Motivation
Motivation

SymBA*
Motivation

SymBA*

DecStar
Motivation

SymBA*
DecStar
Symple-1
Motivation

SymBA*

DecStar

Symple-1

...
Motivation

? SymBA*

DecStar

Symple-1

...
Naive Solution

DecStar: 100%
SymBA*: 79%
Naive Solution

DecStar: 100%
SymBA*: 79%

DecStar: 67%
SymBA*: 100%
Offline Portfolios

0s

SymBA*
DecStar
Blind

T
Offline Portfolios

\[
\begin{array}{c|c}
\text{SymBA}^* & \text{DecStar} \\
0s & T \\
\end{array}
\]

SymBA*
DecStar
Blind
Offline Portfolios

| SymBA* | DecStar |
|--------|---------|
| 0s     | T       |

SymBA*  
DecStar  
- Blind -
Offline Portfolios

| SymBA* | DecStar |
|--------|---------|
| 0s     | T       |

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

\[ f(\Pi) = \]

\[
\begin{array}{c}
0s \\
T
\end{array}
\]
Online Portfolio

\[ f(\Pi) = \begin{array}{c}
0s \\
T
\end{array} \]

\[ f(\text{DecStar}) = \begin{array}{c}
0s \\
T
\end{array} \]

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

\[ f(\Pi) = \begin{array}{c}
\text{0s} \\
\text{T}
\end{array} \]

\[ f(\text{DecStar}) = \begin{array}{c}
\text{DecStar} \\
\text{0s} \\
\text{T}
\end{array} \]

\[ f(\text{SymBA}^* \text{DecStar}) = \begin{array}{c}
\text{SymBA}^* \\
\text{DecStar} \\
\text{0s} \\
\text{T}
\end{array} \]
Online Portfolio

\[ f(\Pi) = \frac{\text{DecStar}}{0s} \quad \frac{\text{SymBA}^*}{T} \]

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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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

input · weights + bias = output
Machine Learning Techniques

Linear Regression

\[
\text{input} \cdot \text{weights} + \text{bias} = \text{output}
\]
Machine Learning Techniques

Linear Regression

\[
\text{input} \cdot \text{weights} + \text{bias} = \text{output}
\]
Machine Learning Techniques

Decision Tree

input

Q1
Yes
No

Q2
Yes
No

X

...
Machine Learning Techniques

Decision Tree

input

Q1
Yes
Yes
No
No

Q2
Yes
No

X

Yes
No

…

…
Machine Learning Techniques

Decision Tree

input

Q1
Yes No

Q2
Yes No

X
Machine Learning Techniques

Decision Tree

Q1

Q2

Yes

Yes

No

No

Yes

No

X

...
Machine Learning Techniques

Random Forest
Machine Learning Techniques

**Multi-Layer Perceptron**

![Diagram of a multi-layer perceptron](image)
Machine Learning Techniques

Multi-Layer Perceptron

[Diagram of a multi-layer perceptron network]
Machine Learning Techniques

Multi-Layer Perceptron
Machine Learning Techniques

Multi-Layer Perceptron

input
Features

FPDDL ⊂ Fawcett\(^1\) ⊂ PDDL ⊂ Union

**Feature augmentations:** normalize

\(^1\) The features presented by Fawcett et al. (2014)
Target Functions

| Function      | Solves |
|---------------|--------|
| Time          |        |
| log(Time)     |        |

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  |
|----------|------|------|------|
| Experiments 1 | 71.4% | 80.0% | 87.7% |
| Experiments 2 | 77.5% | 81.9% | 84.8% |
| Experiments 3 | 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          |
### Planner Choices

| Usage | Cov<sub>P</sub> | Cov<sub>C</sub> | Planner                                      |
|-------|----------------|----------------|----------------------------------------------|
| 43.7  | 80.1           | 94.4           | □ SymBA*                                     |
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| 9.7   | 78.7           | 54.5           | □ h2 + DKS + iPDB                            |
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## Planner Choices

| Usage | Cov_P | Cov_C | Planner                      |
|-------|-------|-------|-----------------------------|
| 43.7  | 80.1  | 94.4  | SymBA*                      |
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## 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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| 2.1   | 75.8    | 100     | h2 + DKS + M&S-BS-SCC-DFP                       |
| 1.0   | 67.7    | 84.0    | OSS + M&S-MIASM-DFP                             |

*SymBA*
## Planner Choices

| Usage | CovP | CovC | Planner |
|-------|------|------|---------|
| 43.7  | 80.1 | 94.4 | SymBA*  |
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| 2.1   | 75.8 | 100  | h2 + DKS + M&S-BS-SCC-DFP |
| 1.0   | 67.7 | 84.0 | OSS + M&S-MIASM-DFP |
Feature Importance

- requires negative preconditions
- max parameters per predicate
- mean negations per effect
- mean predicates per effect
- requires conditional effects
- requires equality
- max predicates per effect
- #types
- min predicates per effect
Single Decision Tree

\[
\frac{\#\text{atoms}}{\#\text{objects}} \leq 6.9
\]

- **true**
  - \(\#\text{atoms} \leq 266.5\)
    - **true**
      - 1000s
    - **false**
      - 800s
- **false**
  - median \(\#\text{objects per type} \leq 22.5\)
    - **true**
      - 500s
    - **false**
      - 100s
Single Decision Tree

- \#atoms / \#objects \leq 6.9
  - true: \#atoms \leq 266.5
    - SymBA*
    - h2+DKS+iPDB
  - false: median \#objects per type \leq 22.5
    - SymBA*
    - h2+OSS+LM-Cut
Comparison to Delfi

|          |     |     |     |     |     |
|----------|-----|-----|-----|-----|-----|
| Delfi1   | 86.9| 86.2| 76.8| 70.8| 82.7|

Delfi1 86.9
Planner Choices

- Delfi
- LR
- RF
- DT
- MLP
- Opt
### Planner Choices

| Planner | Delfi | LR | RF | DT | MLP | Opt |
|---------|-------|----|----|----|-----|-----|

![Heatmap of Planner Choices](chart)
| Planner Choices |
|-----------------|
| **Delfi**       |
| **LR**          |
| **RF**          |
| **DT**          |
| **MLP**         |
| **Opt**         |
Planner Choices

Delfi
LR
RF
DT
MLP
Opt
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
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.

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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.