Explainable Planner Selection for Classical Planning

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36\textsuperscript{th} AAAI Conference on Artificial Intelligence

February, 2022
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

SymBA*  DecStar

0s  T

SymBA*
DecStar
Blind
Offline Portfolios

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<tbody>
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<td>T</td>
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SymBA*
DecStar
-Blind-
Offline Portfolios

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<tbody>
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<td>T</td>
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DecStar: 75%
SymBA*: 72%
Portfolio: 84%
Online Portfolio

$$f(\Pi) = \boxed{0s - T}$$
Online Portfolio

\[ f(\Pi) = \text{DecStar} \]

\[ f(\mathcal{P}) = \text{SymBA*} \]

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

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

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

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

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

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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Delfi (Katz et al., 2018)
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

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

Linear Regression

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

Linear Regression

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

Decision Tree

input

Q1
Yes  No

Q2
Yes  No

X

...
Machine Learning Techniques

Decision Tree

Q1
Yes
No

Q2
Yes
No

input

X
Machine Learning Techniques

Decision Tree

- **Q1**: Yes → Yes
- **Q1**: No → No
- **Q2**: Yes → Yes
- **Q2**: No → No
- **X**: Yes → …
- **X**: No → …
Machine Learning Techniques

Decision Tree

input

X

Q2

Yes

No

Q1

Yes

No

...
Machine Learning Techniques

Random Forest
Machine Learning Techniques

Multi-Layer Perceptron

input
Machine Learning Techniques

Multi-Layer Perceptron
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

<table>
<thead>
<tr>
<th>Function</th>
<th>Time</th>
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<tbody>
<tr>
<td>log(Time)</td>
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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

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<tr>
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### Performance

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<table>
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Performance

Min | Mean | Max
---|---|---
71.4% | 80.0% | 87.7%
77.5% | 81.9% | 84.8%
77.8% | 81.1% | 87.1%
### Planner Choices

<table>
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<tr>
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<th>CovC</th>
<th>Planner</th>
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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

- #atoms / #objects ≤ 6.9
  - true
    - #atoms ≤ 266.5
      - true: 1000s
      - false: 800s
  - false
    - median #objects per type ≤ 22.5
      - true: 500s
      - false: 100s
Single Decision Tree

#atoms / #objects ≤ 6.9

- true
  - #atoms ≤ 266.5
    - true
      - SymBA*
    - false
      - h2+DKS+iPDB
  - false
    - median #objects per type ≤ 22.5
      - true
        - SymBA*
      - false
        - h2+OSS+LM-Cut
Comparison to Delfi

Delfi1

- 86.9
- 86.2
- 86.2
- 76.8
- 70.8
- 82.7
Planner Choices

Delfi
LR
RF
DT
MLP
Opt
Planner Choices

Delfi
LR
RF
DT
MLP
Opt
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
