Hapori Explainable Decision Tree

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Abstract

Hapori Explainable Decision Tree[1] is a portfolio planner which participated in the optimal, satisficing, and agile tracks of the International Planning Competition (IPC) 2023. It uses the single-model planner selection via a decision tree by Ferber and Seipp (2022) to predict over IPC 2018 planners which planner to execute for a task.

Introduction

No planner excels at all tasks, but each has its individual strength and weaknesses (Roberts and Howe 2009). Thus, planner portfolios try to combine multiple planners to dip into the strength of each one. Delfi (Katz et al. 2018b; Sievers et al. 2019) is an example of an online portfolio. Given a task, Delfi converts it to an image and then uses a convolutional neural network (CNN) to predict the best planner for the task. Delfi is highly successful and won the classical, optimal track of the International Planning Competition (IPC) 2018. Delfi is not only successful, but also unexplainable. Experts understand neither which properties of a planning tasks can be seen in the constructed images nor which rules the CNN learned. The graph convolution based successor of Delfi (Ma et al. 2020) improved upon the first issue, but the second one remained. Ferber and Seipp (2022) successfully train explainable portfolios with a similar performance to Delfi. One of their portfolios is based on a single decision tree which receives a set of numeric, explainable features as input and outputs the name of the planner to execute. Here, we retrained this portfolio using a larger set of benchmarks tasks and the planners from the IPC 2018.

Method

Let $\mathcal{O}$ be the set of possible observations (in our case the set of all possible PDDL tasks). Let F be a list of *numeric features* such that each feature $f \in F$ is a function $f : \mathcal{O} \to \mathbb{R}$. A feature vector $\vec{x} \in \mathbb{R}^{|F|}$ for an observation o holds the evaluation of the features on the observation, i.e. $\vec{x}_i = F_i(o)$ for $1 \leq i \leq |F|$. A decision tree (Breiman et al. 1984) D trained on the features F is a binary tree where every internal node i is associated with a condition C_i over F and every leaf node l is associated with a prediction P_l (see Figure 1). Every condition C_i is a function $C_i(\vec{x}) = \vec{x}_j \leq t$ where $1 \leq j \leq |F|$ and $t \in \mathbb{R}$ is some threshold value. To evaluate the decision tree T on the feature vector $\vec{x}$, we set the root node as current node n. If n is an internal node, then we traverse to the first child if $C_n(\vec{x})$ holds and to the second child otherwise. If n is a leaf node, the decision tree evaluates to P_n.

[1]Hapori is the Maori word for community.

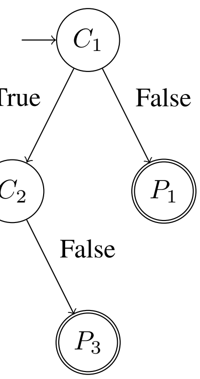

Figure 1: Schema of a decision tree. Each internal node is associated with a condition C_i on the input features. Each leaf node is associated with a prediction outcome P_j.

To train a decision T as portfolio, we specify the list of numeric features F, a set of training tasks T, and a list of planners P. For every task $t \in T$, we compute the feature vector $\vec{x}_t$ and the label vector $\vec{y}_t \in \mathbb{B}^{|P|}$ with $\vec{y}_{t,i} = \top$ iff the planner P_i find a solution for the task t within some resource limits. Our training data D consits of all pairs $\langle \vec{x}_t, i \rangle$ such that $t \in T$ and $\vec{y}_{t,i} = \top$. This data representation allows us to use any standard algorithm to train decision trees. A drawback of the representation is that the more planners solve a task, the more the task appears in the training data. Thus, tasks are not equally impactful during training. As a counter measure, we weight every sample $\langle \vec{x}_t, i \rangle$ by $1/n$ where n is the number of planners which solve t.

Components and Training Data

Planners. As the pool of planners for our portfolios to choose from, we used all planners from the IPC 2018. If an IPC 2018 planner was already a portfolio, we used its component planners instead. We only considered each planner once (some portfolios included planners that were also submitted separately and several portfolios included the same planners).

For the optimal track, we had to exclude maplan-1, maplan-2, and MSP because they use CPLEX, and Complementary1 because it generates suboptimal solutions. Furthermore, the FDMS planners and Metis1 were covered by Delfi already. This results in the following list of planners (or their components):

- Complementary2 (Franco, Lelis, and Barley 2018)
- components of DecStar (Gnad, Shleyfman, and Hoffmann 2018)
- components of Delfi (Delfi1 and Delfi2 have the same components; Katz et al., 2018b)
- Metis2 (Sievers and Katz 2018)
- Planning-PDBs (Moraru et al. 2018)
- Scorpion (Seipp 2018b)
- SymBA*1 (IPC 2014; Torralba et al., 2014)
- Symple-1 and Symple-2 (Speck, Geißer, and Mattmüller 2018)

All planners participating in the satisficing track also participated in the agile track (except for Fast Downward Stone Soup 2018), with an identical code base but possibly with different configurations. We thus only have one set of planners but multiple configurations for these two tracks. We had to exclude alien because we could not get it to run, and freelunch-doubly-relaxed, fs-blind and fs-sim because they have a large number of dependencies which results in planner images too large to be included in our pool. Furthermore, IBaCoP-2018 and IBaCoP2-2018 use a large number of planners or portfolios of which newer and stronger versions participated in IPC 2018 as standalone planners, or which we failed to get to run, so we only cover the component planners Jasper, Madagascar, Mercury, and Probe. This results in the following list of planners (or their components):

- Cerberus and Cerberus-gl (Katz 2018)
- components of DecStar (Gnad, Shleyfman, and Hoffmann 2018)
- components of Fast Downward Remix (Seipp 2018a)
- components of Fast Downward Stone Soup 2018 (Seipp and Röger 2018)
- Jasper (IPC 2014; Xie, Müller, and Holte, 2014)
- LAPKT-DUAL-BFWS, LAPKT-POLYNOMIAL-BFWS, LAPKT-DFS+, and LAPKT-BFWS-Preference (Francès et al. 2018)
- Madagascar (IPC 2014; Rintanen, 2014)
- Mercury2014 (Katz and Hoffmann 2014)
- MERWIN (Katz et al. 2018a)
- OLCFF (Fickert and Hoffmann 2018)
- Probe (IPC 2014; Lipovetzky et al., 2014)
- Grey Planning configuration of Saarplan (Fickert et al., 2018; rest covered by DecStar)
- Symple-1 and Symple-2 (Speck, Geißer, and Mattmüller 2018)

Benchmarks and Runtime. For training the portfolios, we used all tasks and domains from previous IPCs, from Delfi (Katz et al. 2018b), and from the 21.11 Autoscale collection Torralba, Seipp, and Sievers (2021), leading to a set of 92 domains with 7330 tasks. We used Downward Lab (Seipp et al. 2017) to run all planners on all benchmarks on AMD EPYC 7742 2.25GHz processors, imposing a memory limit of 8 GiB and a time limit of 30 minutes for optimal planners and 5 minutes for satisficing and agile planners. For each run, we stored its outcome (plan found, out of memory, out of time, task not supported by planner, error), the execution time, the maximum resident memory, and if the run found a plan, the plan length and plan cost. This data set is online available.[2] As training data for our optimal (respectively satisficing/agile) portfolios, we selected from each domain the 30 tasks which are solved by the fewest optimal (or satisficing/agile) planners, which results in 1926 (optimal) and 2377 (satisficing/agile) remaining tasks.

Features. Ferber and Seipp (2022) showed that their models performed best when trained on the 49 PDDL features of Fawcett et al. (2014). Thus, we also train our models on those features. Among others, those include the number of objects, the number of actions, and the mean number of parameters per predicate. For each task in our benchmark collection, the PDDL features are also available online.

Executing Predictive Portfolios

Given a task, the portfolio selector computes the values of its input features. Then, it evaluates the output of the trained model with respect to the values of the features. Next, it interprets the model output, e.g., if the model directly predicts a planner, then this planner is selected; if it predicts for each planner the probability that it solves the given task, then the planner with highest probability is selected. Finally, it executes the the selected planner for the whole time limit.

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