Hapori Delfi

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Abstract

The cost-optimal planner *Delfi* has successfully participated in the International Planning Competition (IPC) 2018. Its success can be attributed to two main factors: the use of state-of-the-art cost-optimal planners in its portfolio and the ability to predict which of these planners is a good fit for a given planning task. Following that prior success, here we extend the set of planners in the portfolio. The learning methodology is adapted according to the prior work, applied now not only to cost-optimal, but also to agile and satisficing planning.

Introduction

The cost-optimal planner *Delfi* (Katz et al. 2018b) was rated first in the cost-optimal track of the International Planning Competition (IPC) 2018. It uses a so-called online portfolio approach (Cenamor, de la Rosa, and Fernández 2016; Sievers et al. 2019a) to overcome the limitations of any individual planner, predicting which out of the collection of planners will work well on the planning task at hand. That collection included 17 planners of mostly similar configurations, varying mostly in the heuristic used. The prediction was done with the help of a deep learning tool, specifically convolutional neural network (CNN) (LeCun, Bengio, and Hinton 2015), predicting whether a planner will solve a planning task, represented by an image, within the predefined time limit of 30 minutes. The image representation was obtained based on a structural representation of a planning task called *abstract structure graph* (ASG) (Sievers et al. 2019b), casting the graph as an adjacency matrix, condensing and turning into a grayscale image.

In this work, we construct a new, community based version of Delfi, which we now call *Hapori Delfi* [1]. We extend the collection of planners in the portfolio and adopt the best performing learning methodology and architecture according to the post-IPC 2018 investigation (Sievers et al. 2019a). Specifically, we discretize the time interval into three equal size intervals and predict whether the planner will solve the task within that time interval. We use the same image-based planning task representation as in the original *Delfi* and retrain the CNN for the new collection of planners. Additionally, we go beyond just cost-optimal planning, preparing versions of *Hapori Delfi* also for the agile and satisficing tracks. In the rest of the paper we describe the differences from the original *Delfi* for each of the tracks we participate in, specifically in the components used and the training data.

[1] Hapori is the Maori word for community.

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.

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[2] URL to be published

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