Interpreting Plans with Hierarchic Language Abstractions

Tomas Trescak

Western Sydney Univeristy School of Computer Data and Mathematical Sciences Locked Bag 1797 Penrith NSW 2751, Australia t.trescak@westernsydney.edu.au

Abstract

Explainable planning systems facilitate understanding of system decisions and challenge them through investigatory dialogue, with social, selective and contrastive explanations. When aiming at end-user explanations systems often require capturing and communicating the complexities of the problem domain from various perspectives. But, the existing approaches are limited by generating explanations using a language consisting only of domain actions and variables, hindering expressivity. Our approach1 defines higher-level hierarchic abstractions composed of domain actions and variables, facilitating the interpretation of plan actions from various perspectives. Using abstractions, we can map the end users' domain knowledge, language and interests onto the plan problem domain. Moreover, the organising hierarchy of interpretations facilitates systematic decomposition from high-level perspectives to individual actions or activities.

Introduction

Explainable AI Planning (XAIP) systems are maturing, with a substantial body of work focusing on delivering robust planning systems that use explanations to help users understand and challenge system decisions. The explanations that systems generate differ based on the approach and target audience (Zhang et al. 2017). A *planning algorithm designer* is more interested in the low-level performance of the algorithm, where explanations relate to debugging activities of the programming world. Here, every instruction of the planning algorithm is essential and often, it is an algorithm itself that provides textual or even visual explanations of its inner workings (Magnaguagno et al. 2017).

The situation is different for end-users of planning systems. They are not interested in the inner working of planning algorithms but rather try to comprehend why a proposed planning scenario is their best option and what would happen if the system would consider a different alternative (Chakraborti, Sreedharan, and Kambhampati 2020). The planning system adjusts the constraints based on user input and then generates a new outcome and communicates further explanations (Fox, Long, and Magazzeni 2017). This

¹https://youtu.be/Ut7uDlgJY8k

process can occur on the *model level* (Chakraborti, Sreedharan, and Kambhampati 2020), constraining the model and analysing the outcome, or even on the *plan level*, exploring the generated plans and potentially adapting and reusing them in similar scenarios (Hammond 2012).

This paper presents the HLAM - Hierarchic Language Abstraction Model, an end-user system delivering modelbased and partially plan-based explanations. We assume that end-users of planning systems play different roles and have various levels and domains of knowledge. For example, considering a logistics planning scenario, an end-user of the planning system can be a dispatcher, driver, or client. To accommodate various end-user explanations, we propose to use language abstractions (i.e. interpretations) that facilitate plan understanding and deliver the possibility for more expressive explanations in natural language.

Hierarchic Language Abstraction Model (HLAM)

We have implemented the HLAM as a Java library², currently used with PDDL4J³ library. We have also developed a Javascript library⁴ with a web application⁵ demonstrating capabilities of our model. This application automatically generates a graphical representation of hierarchic abstractions, allowing you to drill down to the details of your plan.

Figure 2 depicts the web interface of the HLAM interpreter. On the left, you specify the plan you wish to process. You can also preload one of the example scenarios from well-known planning domains. You create (or preload) the interpretation model in the JSON format in the centre of the screen. You can see the generated HLAM model displayed as the hierarchic tree view on the right. You can collapse or expand each of the abstractions. While we create the output of our model in a tree structure, it is essential to note that the model is intrinsically defined as an oriented graph, able to capture complex dependencies between abstractions.

The graph-like structure of our model is clear from the definition of the HLAM model, where abstraction concepts (i.e. views) are defined all on one level, using references to

Copyright © 2022, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

²https://github.com/tomitrescak/pddl4j

³https://github.com/pellierd/pddl4j

⁴https://github.com/tomitrescak/hlam

⁵https://hlam.trescak.co

```
{
1
    "id": "PackageDelivery",
2
    "description": "Package Tracking",
3
    "views": [{
4
     "start": "load-plane ?id p ?pf",
5
     "goal": "unload-plane !id p ?pt",
6
     "strategy": "final",
7
     "child": "PackageTrip !id !pf !pt"
8
9
    }]
10
  },
11
   {
    "id": "PackageTrip !id !f !t",
12
    "description": "Package delivery '!
13
       id' from '!f' to '!t'",
    "views": [{
14
     "start": "load-plane !id ?p ?pf",
15
     "goal": "unload-plane !id !p ?pt",
16
     "strategy": "first",
17
     "child":"PlaneTrip !id !p !pf !pt"
18
19
    }]
  },
20
21
   {
     "id": "PlaneTrip !id !p !f !t",
22
     "description": "Plane '!p'
23
         delivery from '!f' to '!t'",
     "plan": {
24
       "sequence": [
25
         "load-plane !id !p !f",
26
         "fly-plane !p f t",
27
         "unload-plane !id !p !t"
28
29
30
     }
31
  }
```

Figure 1: JSON representation of the model for the logistics domain



Figure 2: User interface of the HLAM processor at http:// hlam.trescak.co

child concepts rather than in a tree. Figure 1 lists an excerpt from the JSON representation of the model for the logistics domain:

Please note the main parts of the HLAM model.

The PackageDelivery and PackageTrip represent hierarchic abstractions (i.e. have child abstractions PlaneTrip) of the HLAM hierarchy, and PlaneTrip extract and interpret sub-plans. The PackageDelivery has no parameters but extracts individual package journeys from the plan. Please note that we used the "final goal" strategy, selecting the last possible unload-plane line, detecting the last destination. The selected sub-plan for each extracted package journey, along with the list of bound variables, is passed to the PackageTrip abstraction. This abstraction uses the "first goal" selection strategy, extracting individual legs of the package journey. It has three parameters:

- 1. !id packageId
- 2. ! f source (from) destination of the package
- 3. !t target (to) destination of the package

As we explain in the tutorial video⁶, the abstraction binds and passes values of parameters to their child abstractions. In this case, the PackageDelivery binds the ?id and ?pf value when detecting the the start line load-plane ?id p ?pf. Detection of goal line unload-plane !id p ?pt is using the bound value of package !id and binding a ?pt value. Values of id, pf and pt are then used to create the PackageTrip !id !pf !pt abstraction.

Similarly, in the PackageTrip we consider the start line to be load-plane !id ?p ?pf, using the bound value of package !id and binding two new values: the plane p, and a source destination of the plane delivery pf. The goal, is the first matching line with unload-plane !id !p ?pt, where package !id and plane !p are bound (i.e. must be the same as in the start line), and we bind a new value ?pt, representing the target destination of this plane trip.

The model then calls the PlaneTrip child abstraction, with the bound value of !id coming from the parent node, and newly bound values !p, !pf, !pt. The PlaneTrip represents a target sub-plan selection, which selects individual plan lines. An interesting fact of this example is, that we are able to extract all individual plane trips with our package on board, starting with loading the package on board with load !id !p !f, considering all plane !p trips (note the use of unbound values for from f and to t destinations), until our package !p is unloaded from the aeroplane.

Extending HLAM

Our model considers classical planning systems but otherwise is model and domain-independent. The model's design allows extending its functionality to consider more complex scenarios. We are currently working on an extension that brings LIME-like(Ribeiro, Singh, and Guestrin 2016) approach to planning systems explanations. This extension will consider multiple plans, performing a probabilistic analysis of outcomes. This will permit the system to report conclusions such as "if you consider action A instead of B, with 80% probability it will yield to C and 90% probability it will yield to D".

⁶https://youtu.be/Ut7uDlgJY8k

References

Chakraborti, T.; Sreedharan, S.; and Kambhampati, S. 2020. The Emerging Landscape of Explainable AI Planning and Decision Making. *arXiv*.

Fox, M.; Long, D.; and Magazzeni, D. 2017. Explainable Planning. *arXiv*.

Hammond, K. J. 2012. *Case-based planning: Viewing planning as a memory task.* Elsevier.

Magnaguagno, M.; Pereira, R. F.; Móre, M. D.; and Meneguzzi, F. 2017. WEB PLANNER: A Tool to Develop Classical Planning Domains and Visualize Heuristic State-Space Search. In *ICAPS Workshop on User Interfaces and Scheduling and Planning*.

Ribeiro, M. T.; Singh, S.; and Guestrin, C. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '16, 1135–1144. New York, NY, USA: Association for Computing Machinery. ISBN 9781450342322.

Zhang, Y.; Sreedharan, S.; Kulkarni, A.; Chakraborti, T.; Zhuo, H. H.; and Kambhampati, S. 2017. Plan explicability and predictability for robot task planning. In 2017 *IEEE International Conference on Robotics and Automation* (*ICRA*), 1313–1320.