JEDAI Explains Decision-Making AI

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Abstract

This paper presents JEDAI, an AI system designed for outreach and educational efforts aimed at non-AI experts. JEDAI features a novel synthesis of research ideas from integrated task and motion planning and explainable AI. JEDAI helps users create high-level, intuitive plans while ensuring that they will be executable by the robot. It also provides users customized explanations about errors and helps improve their understanding of AI planning as well as the limits and capabilities of the underlying robot system.

1 Introduction

AI systems are increasingly common in everyday life, where they can be used by laypersons who may not understand how autonomous systems work or what they can and cannot do. This problem is particularly salient in cases of taskable AI systems whose functionality can change based on the tasks they are performing. In this work, we present an AI system JEDAI that can be used in outreach and educational efforts to help laypersons learn how to provide AI systems with new tasks, debug such systems, and understand their capabilities.

Three key technical challenges are addressed by the research ideas brought together in JEDAI: (i) abstracting a robot’s functionalities into high-level actions (capabilities) that the user can more easily understand; (ii) converting the user-understandable capabilities into low-level motion plans that a robot can execute; and (iii) explaining errors in a manner sensitive to the user’s current level of knowledge so as to make the robot’s capabilities and limitations clear.

JEDAI utilizes recent work in explainable AI and integrated task and motion planning to address these challenges and provides a simple interface to support accessibility. Users need to select a domain and an associated task, after which they can create a plan consisting of high-level actions (Fig. 1 left) to complete the task. The user puts together a plan in a drag-and-drop workspace, built with the Blockly visual programming library (Google 2017). JEDAI validates this plan using the Hierarchical Expertise Level Modeling algorithm (HELM) (Sreedharan et al. 2018, 2021). If the plan contains any errors, HELM computes a user-specific explanation of why the plan would fail. JEDAI converts such explanations to natural language, thus helping to identify

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Figure 1: JEDAI system with a Blockly-based plan creator on the left and a simulator window on the right.

and fix any gaps in the user’s understanding. On the other hand, if the plan given by the user is a correct solution to the current task, JEDAI uses a task and motion planner ATM-MDP (Shah et al. 2020, 2021) to convert the high-level plan, that the user understands, to a low-level motion plan that the robot can execute. The execution of this low-level motion plan by the robot is shown to the user in a simulated environment (Fig. 1 right).

Prior work on the topic includes approaches that solve the three technical challenges mentioned earlier in isolation. This includes tools for: providing visualizations or animations of standard planning domains (Magnaguagno et al. 2017; Chen et al. 2019; Aguinaldo et al. 2021; Dvorak et al. 2021; De Pellegrin et al. 2021; Roberts et al. 2021), making it easier for non-expert users to program robots with low-level actions (Krishnamoorthy et al. 2016; Weintrop et al. 2018; Huang et al. 2020; Winterer et al. 2020); and generating explanations for plans provided by the users (Grover et al. 2020; Karthik et al. 2021; Brandao et al. 2021). In addition, none of these works makes the instructions easier for the user, have the ability to automatically compute user aligned explanations, and work with real robots (or their simulators) at the same time. JEDAI addresses all three challenges in tandem by using 3D simulations for domains with real robots and their actual constraints, and providing personalized explanations that inform a user of any mistake they make while using the system.
This cost function can be changed to reflect different users' understanding of the robot's model and then uses the estimated model to compute the personalized explanations. In case of multiple errors in the user's plan, HELM generates explanation for one of the errors. This is because explaining the reason for more than one errors might be unnecessary and in the worst case might leave the user feeling overwhelmed (Miller 2019). An error is selected for explanation by HELM based on optimizing a cost function that indicates the relative difficulty of concept understandability. This cost function can be changed to reflect different users’ background knowledge.

Natural language templates Even with a user-friendly interface and personalized explanations for errors in abstract plans, the domain model syntax used for interaction with ATM-MDP presents a significant barrier to a non-expert user trying to understand the state of an environment and the capabilities of a robot. To alleviate this, JEDAI uses a simple strategy for generating natural language to make the presentation of goals, actions, and explanations more user-friendly. This strategy depends on the idea that when the structure of the planning formalism is known, any action or proposition can be talked about in natural language by filling in a generic syntactic template. E.g., the action “*pickup (plank_left)*” can be mapped to the natural language form “*pick up plank_i with the left gripper*”. These templates become more complex for conjunctions of atomic propositions, but the idea remains the same. Unfortunately, each new domain requires some amount of hand-written natural language. However, this is likely unavoidable in absence of an AI system intelligent enough to autonomously form accurate but informal sentences about the ATM-MDP’s syntax.

Implementation Any custom domain can be set up with JEDAI. We provide five built-in domains, each with one of YuMi (ABB 2015) or Fetch (Wise et al. 2016) robots. Each domain contains a set of problems that the users can attempt to solve and low-level environments corresponding to these problems. Source code for the framework, an already setup virtual machine, and the documentation are available at: [https://github.com/aaai/AAIR-JEDAI](https://github.com/aaai/AAIR-JEDAI).

3 Conclusions and Future Work

We demonstrated a novel AI tool JEDAI for helping people understand the capabilities of an arbitrary AI system and enabling them to work with such systems. JEDAI converts the user’s input plans to low level motion plans executable by the robot if it is correct, or explains to the user any error in the plan if it is incorrect. JEDAI works with off-the-shelf task and motion planners and explanation generators. This structure allows it to scale automatically with improvements in either of these active research areas.

In the future, JEDAI can be extended to work as an interface that makes AI systems compliant with Level II assistive AI – systems that makes it easy for operators to learn how to use them safely (Srivastava 2021). Extending this tool for working in non-stationary settings, and generating natural language descriptions of predicates and actions autonomously are a few promising directions of future work.
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