Mr. Jones — Towards a Proactive Smart Room Orchestrator

Tathagata Chakraborti,1 Kartik Talamadupula,2 Mishal Dholakia,2 Biplav Srivastava,2 Jeffrey O. Kephart,2 Rachel K. E. Bellamy2

1 Arizona State University, Tempe, AZ 85281 USA
tchakra2@asu.edu

2 IBM T. J. Watson Research Center, Yorktown Heights, NY 10598 USA
{ krtalamad, mdholak, biplavs, kephart, rachel }@us.ibm.com

Abstract

In this brief abstract we report work in progress on developing Mr. Jones—a proactive orchestrator and decision support agent for a collaborative decision making setting embodied by a smart room. The duties of such an agent may range across interactive problem solving with other agents in the environment, developing automated summaries of meetings, visualization of the internal decision making process, proactive data and resource management, and so on. Specifically, we highlight the importance of integrating higher level symbolic reasoning and intent recognition in the design of such an agent, and outline pathways towards the realization of these capabilities. We will demonstrate some of these functionalities here in the context of automated orchestration of a meeting in the CEL—the Cognitive Environments Laboratory at IBM's T.J. Watson Research Center.

Introduction

In previous work, we have described our vision of software agents that co-inhabit physical spaces with people, and use their understanding of what is happening in those spaces to act as collaborators on cognitive tasks such as decision making (Farrell et al. 2016). CELIA—the Cognitive Environments Laboratory Interactive Agent—is an early prototype of such an agent that we have implemented in our laboratory (the CEL) (Kephart and Lenchner 2015). While CELIA in its present form has drawn interest from hundreds of IBM clients and many viewers on social media (Murphy 2015), by and large the style of interaction has been command-response, i.e. users address CELIA directly by name and issue very specific instructions and goals. Since CELIA does not currently have the capability to understand the context of an interaction, it is difficult for CELIA to be proactive. To address this gap, we present a proactive agent, Mr. Jones, with an aim to make the CEL experience much more immersive and natural by adding proactive detection capabilities to assist decision-making in the smart environment.

Some of the primary responsibilities of the agent are summarized in Figure 1. These include solving problems interactively with other agents (humans) in the environment, generating summaries of events in the workspace, visualizing the decision processes of all the embedded agents and of the group (humans and agents) as a whole, proactively managing resources like background services and data; and so on. We divide the responsibilities of Mr. Jones into two processes—Engage, where plan recognition techniques are used to identify the task in progress; and Orchestrate, which involves active participation in the decision-making process via real-time plan generation, execution, and monitoring. The former process—where Mr. Jones pays attention to many modalities of sensory feedback, including speech and image recognition—is an essential capability of a proactive agent, and leads directly to the latter process. In this paper, we will demonstrate some of the system’s functionalities with respect to the Engage process, in the context of supporting a meeting in a smart room.

The contribution of this paper is two-fold—(1) We outline some of the many responsibilities of a support agent like Mr. Jones, especially from the point of view of task planning, and then we identify ways in which such capabilities can be realized in practice for real-world scenarios; and (2) We highlight the role of higher level symbolic reasoning techniques that offer easily understood explanations to human agents in the scenarios—whether those explanations are implicit from the interface, or explicit—as an essential ingredient in realizing these capabilities.

The rest of the paper is structured as follows: first, we introduce the problem of proactive decision support in multi-agent collaborative settings, and discuss the Engage and Or-
chestrate processes. We then describe the implemented architecture of Mr. Jones, and its components. We conclude with a demonstration of Mr. Jones’ current capabilities.

Proactive Decision Support for Multi-Agent Collaborative Settings

As automated devices and assistants occupy an increasingly central role in our daily lives, there is a pressing need for the integrated systems that house such devices to display some level of intelligence and responsiveness. This problem of shepherding assistants from merely automated to fully autonomous is being addressed in single-agent, passive settings – however, even in these settings, the automated assistant is merely receiving and/or recording data from the environment via the use of predefined scripts and procedures which are written to specification. However, when the automated assistant is presented with a multi-agent (non-adversarial) situation, and has to handle the additional complexity of facilitating a decision-making process within the group, it becomes imperative that the assistant cross the bridge from merely ‘automated’ system to now being an ‘autonomous’ entity. The problem that we consider in this work – proactive decision support in collaborative settings – deals with interactive scenarios featuring humans. These scenarios involve group decision-making on the part of the humans, and feature a rich space of inputs and activities that can be used to provide context to the automated assistant. The assistant in turn provides customized and intelligent support to the group throughout their decision-making, using the two processes described below:

ENGAGE The Engage process consists of the decision support assistant monitoring various inputs from the world in order to situate itself in the context of the group interaction – that is, the assistant literally engages with the world around it. The process is further divided into two stages which run in a tightly-coupled loop. First, the assistant gathers various inputs like speech transcripts, live images, and the positions of people within the room; these inputs are fed into a higher level symbolic reasoning component constructed from plan recognition algorithms. The second stage involves the assistant acting on the recommendations of the plan recognition step; it (1) requisitions resources and services that may be required to support the most likely tasks based on its recognition; (2) visualizes the decision process – this can depict both the internal process, which is the agent’s own recognition algorithm, and the external process, which is task-dependent; and (3) summarizes the group decision-making process (e.g. a meeting) in various forms. In this way, the Engage stage provides the “proactive” part of the decision support assistant.

ORCHESTRATE The Orchestrate process is the decision support assistant’s contribution to the group’s collaborative process. Once the assistant is able to identify and situate itself in the task that is being collaborated upon (during the Engage phase described above), it must contribute to the decision-making. This can be done using standard planning techniques, and can fall under the aegis of one of four actions as shown in Figure 2. These actions, some of which are discussed in more detail in (Sengupta et al. 2017), are: (1) execute, where the assistant performs an action or a series of actions related to the task at hand; (2) critique, where the assistant offers recommendations on the actions currently in the collaborative decision sequence; (3) suggest, where the assistant suggests new decisions and actions that can be discussed collaboratively; and (4) explain, where the assistant explains its rationale for adding or suggesting a particular decision. The Orchestrate process thus provides the “support” part of the decision support assistant.

The Engage and Orchestrate processes can be seen as analogues to the interpretation and steering processes defined in the crowdsourcing scenarios of (Talamadupula et al. 2013; Manikonda et al. 2017). The difference in these new scenarios is that the humans are the final decision makers, with the assistant merely supporting the decision making.
In the following section, we present the design and implementation of Mr. Jones as a decision support agent.

Architecture Design
The design of the entire system is shown in Figures 2 and 4, situating Mr. Jones in the overall context of the CEL environment and the operations of CELIA. The central component – the Orchestrator\(^1\) – regulates the flow of information and control flow across the modules that manage the various functionalities of the CEL; this is shown in Figure 4. These modules are mostly asynchronous in nature and may be: (1) services\(^2\) processing sensory information from various input devices across different modalities like audio (microphone arrays), video (PTZ cameras / Kinect), motion sensors (Myo / Vive) and so on; (2) services handling the different services of CELIA; and (3) services that attach to the Mr. Jones module. The Orchestrator is responsible for keeping track of the current state of the system as well as coordinating actuation based on the information being relayed across these modules. The actuation can be either in the knowledge or belief space, or in the actual physical space itself. The key components of the Mr. Jones module – as illustrated in Figure 2 – are discussed in more detail next.

Key Components
The design of Mr. Jones follows closely from the delimitation of tasks in the Engage and Orchestrate phases. Aside from the difference in the nature of tasks assigned to the agent in the two phases, this distinction also stems from practical considerations. The system must at once be more responsive to a broader range of tasks, yet remain robust to different levels of noise and uncertainty as well.

Knowledge Acquisition / Learning The knowledge contained in the system comes from two sources – (1) the developers and/or users of the service; and (2) the system’s own memory; as illustrated in Figure 2. One significant barrier towards adoption of higher level reasoning capabilities into such systems has been the lack of familiarity of developers and end users with the inner working of these technologies. With this in mind we provide XML-based modeling interfaces – i.e. a “system config” – where users can easily configure new environments and automatically compile the files internally used by the reasoning engines. Thus system specific information is bootstrapped into the service specifications written by expert developers, and this composite knowledge can be seamlessly transferred across task domains and physical configurations. A configuration file is presented in Figure 3 for illustration.

The memory of the system is contained in the “system logs”, and is intended to provide the rest of the domain knowledge to the planning component. This is meant to enable easily customizable and generalizable configuration of the system with a very small setup phase, as well as to let services continually learn and adapt to the dynamics of a particular environment over time. Recent literature on this topic (Zhuo, Nguyen, and Kambhampati 2013) provides techniques to learn such models on the fly.

The granularity of the information encoded in the models depends on the task at hand – for example, during the Engage phase, the system uses much higher level information (e.g. identities of agents in the room, their locations, speech intents, etc.) than during the Orchestrate phase, where more detailed knowledge is needed (e.g. how to run a discussion on Mergers and Acquisitions). This enables the system to reason at different levels of abstraction independent of each other, thus significantly improving the scalability as well as robustness of the recognition engine.

Plan Recognition Currently, the system employs the probabilistic goal / plan recognition algorithm from (Ramirez and Geffner 2010) to compute its beliefs over possible tasks that are currently underway in its environment. The algorithm internally casts the plan recognition problem as a planning problem by compiling away observations to the form of actions in a new planning problem. The solution to this new problem enforces the execution of these observation-actions in the observed order. This technique is heavily dependent on the availability of detailed and accurate models, while also being quite slow (having to solve one compiled planning problem for every hypothesis). However, it has the advantage of being able to explain the reasoning process being the belief distribution in

\(^1\)Not to be confused with the term Orchestrate from the previous section, used to describe the phase of active participation.

\(^2\)Built on top of Watson Conversation and Visual Recognition services on IBM Bluemix and other IBM internal services.
terms of the possible plans that the agent envisioned using the compilation in (Ramirez and Geffner 2010). The explanation service (visualized in the next section) is dependent on the underlying algorithm(s) used. We are currently in the process of integrating the faster but approximate plan recognition algorithm from (E.-Martín, R.-Moreno, and Smith 2015) to provide scalable support for recognition. Such an approach will still allow us to invoke the optimal algorithm in (Ramirez and Geffner 2010) on demand for explanations and traceability, yet give us the flexibility to generate faster outputs to the interface as needed.

**Plan Generation** The FAST-DOWNWARD planner (Helmert 2006) provides a suite of solutions to the forward planning problem. The planner is also required internally by the Recognition Module when using the compilation from (Ramirez and Geffner 2010), or in general to drive some of the orchestration processes. The planner reuses the compilation from the Recognition Module to compute plans that preserve the current (observed) context.

**Using Mr. Jones**

In the following section, we illustrate how the ideas presented thus far come together in the CEL – the Cognitive Environments Laboratory – at IBM’s T.J. Watson Research Center. The laboratory acts as a smart environment, equipped with various sensors and actuators to facilitate group decision making and human-agent collaboration. We first present a sample collaborative decision making task that functions as a running example, followed by a description of the Mr. Jones interface for this sample task. We then present a real-world demonstration of the system on a subset of the example, where an interaction with Mr. Jones is captured via video.

**Example Scenario**

We first present an example that demonstrates the utility of a decision support agent like Mr. Jones. This example is based on a typical usecase that the CEL is often utilized for – Mergers & Acquisitions (M&A). M&A is an enterprise usecase where (human) analysts working on behalf of a company are considering other companies as potential candidates for a merger and/or an acquisition. The CEL acts as an immersive experience to aid in the decision-making process, by providing actuators (display arrays, speakers) and sensors (microphones, cameras, pointing devices) which the analysts can use to interact with the knowledge and data being presented to them. Analysts use the CEL to evaluate various options, drill-down into the details of specific companies, and select and eliminate candidate companies.

The CEL Interactive Agent (CElia) works in concert with the humans in order to display information about companies and various alternatives that can be compared. Consider the following scenario, whose beginning is outlined in Figure 5(b). Three agents, identified by name (in red) walk into the CEL. These agents locate themselves in various locations within the space, and perform various actions within the room. They also interact with different devices in the room, and may additionally use speech in order to make their intentions known or to communicate with other agents.

Consider the transcript from the speech-based interaction between a human analyst (H) and CELIA (C), adapted from Kephart and Lenchner (2015):

**Figure 4:** Flow of control in the proposed system.
explicit invocations to – and tasking of – CELIA. This is precisely the kind of scenario where Mr. Jones can proactively identify the usecase under discussion (in this case, the M&A usecase), and intervene autonomously to provide decision support.

In the case of this running example, Mr. Jones picks up and processes various inputs from the CEL, which end up becoming observations for the plan recognition module. Specifically, the observations in the example above are:

- There are two agents in the room – Identified by processing the visual input from the cameras.
- These agents are identified as Mishal and Jeff – Processed by the face recognition module.
- The agents are located in front of the screen – Processed via the cameras.
- The agents are mentioning words and phrases that are related to the M&A usecase – Processed by speech-to-text (STT) followed by a classification from IBM Watson Conversations.

These observations are used by the plan recognition module to arrive at a high confidence in the M&A usecase; once the system is able to breach a confidence threshold, it proactively intervenes to help with the usecase.

**Interface: The Mind of Mr. Jones**

We now describe the interface of Mr. Jones, briefly referenced in previous sections. Currently we restrict ourselves to the Engage portion of the interface, since that is the process under discussion in this paper. A snapshot of the Mr. Jones Engage interface is presented in Figure 5(a). The interface itself consists of five widgets. The largest widget on the top left presents a wordcloud representation of Mr. Jones’s belief in each of the tasks; the size of the word representing that task corresponds to the probability associated with that task. The second widget, on the top right, shows the agents that are recognized as being in the environment currently – this information is used by the system to determine what kind of task is more likely. This information is obtained from four independent camera feeds that give Mr. Jones an omnispective view of the environment; this information is represented via snapshots (sampled at 10-20 Hz) in the third widget, on the bottom left. In the current example, Mr. Jones has recognized the agents named “Kartik” and “Mishal” in the scenario. Finally, the fourth widget, on the bottom right, represents a wordcloud based summarization of the audio transcript of the environment. This transcript provides a succinct representation of the things that have been said in the environment in the recent past via the audio channels. Note that this widget is merely a summarization of the full transcript, which is fed into the IBM Watson Conversation service to generate observations for the plan recognition module. The interface thus provides a (constantly updating) snapshot of the various sensory organs associated with Mr. Jones – the eyes, ears, and mind of CELIA.

**Demonstration**

**Proof-of-Concept Video** We now demonstrate via a recorded video how the Engage process evolves as agents interact in the CEL. The demonstration begins with two humans discussing the CEL environment, followed by one agent describing a projection of the Mind of Mr. Jones on the screen. The other agent then discusses how the M&A task is carried out. A video of this demonstration can be accessed at https://goo.gl/RZt4hy.

In addition to the demonstration, the video also contains a window that demonstrates the evolution of the Mr. Jones interface through the duration of the interaction. This window illustrates how Mr. Jones’s beliefs evolve dynamically in response to interactions in real-time.

**Automated Meeting Summarization** After the interaction is complete Mr. Jones automatically compiles a summarization (or minutes) of the meeting by sampling from...
the visualization of its beliefs. A video that illustrates a typical summary can be accessed at https://goo.gl/3iXuG.

This kind of visual summary provides a powerful alternative to established meeting summarization tools like text-based minutes, etc.; and allows for agents that may have missed the meeting to catch up on the proceedings. The visual summary can also be used to extract abstract insights about this one meeting, or a set of similar meetings together. Whilst merely sampling the visualization process at discrete time-intervals serves as a powerful tool towards automated summary generation, we anticipate the use of more sophisticated visualization (Dörk et al. 2010) and summarization (Shaw 2017) techniques in the future.

Work in Progress

We are currently in the initial stages of exploration with Mr. Jones, and there are a number of extensions to the current status of the system that are possible, which we list here. First, we are looking at the extension of the capabilities of Mr. Jones into other cognitive spaces that may differ from the CEL in form and tasks supported – this is to show that the system and the models that it is built on are easily generalizable. Second, we are working on smart requisition and pre-caching of services and tools that are likely to be needed by the collaborative environment in the near future based on the task insights generated by Mr. Jones. Third, we would like to focus on the planning and execution problems – as well as the models – associated with the Orchestrate stage for tasks such as M&A (used in this paper) and automated tours. Finally, one of the most promising areas for future research projects involves the use of a Mr. Jones-like interface to study multi-agent collaborations and interactions, and to consider new algorithms that can provide varying kinds of proactive support.

Conclusion

In this paper, we presented work in progress on Mr. Jones – a proactive decision support agent for the Cognitive Environments Laboratory (CEL), which is a multi-agent collaborative space. We introduced the Engage and Orchestrate processes that need to be supported by an agent that is providing proactive assistance in such scenarios. This was followed by a description of the Mr. Jones system and its key components, including knowledge acquisition, plan recognition, and plan generation. Following this we demonstrated an initial version of the system recognizing a collaborative task scenario, and producing a summary of that interaction. We concluded with a description of extensions to Mr. Jones that we are currently working on.

Acknowledgment This work was done while the first author was an intern at IBM’s T.J. Watson Research Center, Yorktown Heights, NY, USA in the summer of 2017. We thank all the members of the Human-Agent Collaboration Group there for their support. We would also like to acknowledge Sengupta et al. (2017) for their invaluable insights and suggestions with regards to the design of support agents for task planning with humans in the loop.

References

Dörk, M.; Gruen, D.; Williamson, C.; and Carpendale, S. 2010. A Visual Backchannel for Large-Scale Events. IEEE Transactions on Visualization and Computer Graphics.

E.-Martín, Y.; R.-Moreno, M. D.; and Smith, D. E. 2015. A Fast Goal Recognition Technique Based on Interaction Estimates. In IJCAI.

Farrell, R.; Lenchner, J.; Kephart, J.; Webb, A.; Muller, M.; Erickson, T.; Melville, D.; Bellamy, R.; Gruen, D.; Connell, J.; et al. 2016. Symbiotic cognitive computing. AI Mag.

Helmert, M. 2006. The fast downward planning system. Journal of Artificial Intelligence Research.

Kephart, J. O., and Lenchner, J. 2015. A symbiotic cognitive computing perspective on autonomic computing. In Autonomic Computing (ICAC), 2015 IEEE International Conference on, 109–114. IEEE.

Manikonda, L.; Chakraborti, T.; Talamadupula, K.; and Kambhampati, S. 2017. Herding the crowd: Using automated planning for better crowdsourced planning. Journal of Human Computation.

Murphy, M. 2015. Searching for Eureka: IBM’s path back to greatness, and how it could change the world. https://goo.gl/9pVyEZ.

Ramirez, M., and Geffner, H. 2010. Probabilistic plan recognition using off-the-shelf classical planners. In AAAI.

Sengupta, S.; Chakraborti, T.; Sreedharan, S.; and Kambhampati, S. 2017. RADAR - A Proactive Decision Support System for Human-in-the-Loop Planning. In ICAPS Workshop on User Interfaces for Scheduling and Planning.

Shaw, D. 2017. How Wimbledon is using IBM Watson AI to power highlights, analytics and enriched fan experiences. https://goo.gl/r6z3uL.

Talamadupula, K.; Kambhampati, S.; Hu, Y.; Nguyen, T.; and Zhuo, H. H. 2013. Herding the crowd: Automated planning for crowdsourced planning. In HCOMP.

Zhuo, H. H.; Nguyen, T. A.; and Kambhampati, S. 2013. Refining incomplete planning domain models through plan traces. In IJCAI.