I work on research problems centered around the theme of using automated planning systems as mediators for human-machine teams. Automated planning – a sub-field of Artificial Intelligence that deals with reasoning and the synthesis of plans for autonomous, intelligent agents – has seen many speedup and scalability advances in the past decades. Beginning with Shakey the robot and the STRIPS planning system, automated planners now routinely handle problems of real-world scale that include scheduling for Earth Orbiting Satellites, autonomous control of interplanetary rovers, planning for large-scale logistics and delivery operations, and route planning for metropolitan scale traffic.

My work has focused on using these scale-ups in order to address two key challenges that need to be overcome when adapting automated planning methods for real-world problems. The first such challenge is that of *representation*: there must be a way of specifying all information that is salient to the problem at hand in a way that can be utilized by the automated planning system. Once sufficiently expressive representations are formulated, the second issue is that of *engineering*: the enhanced automated planning representations (and techniques thereof) must be integrated with the application in question, and any issues that arise must be addressed. In my thesis work, both of these challenges are addressed front and center via the application of automated planning to the Human-Robot Teaming problem.

Early Work

A significant portion of automated planning research in the latter part of the past decade has been directed towards understanding the implications of a scale-up in the speed of automated planners due to the adoption of heuristic search methods. One of the main effects of this scale-up has been a focus on extending the expressivity of planning representations like PDDL to better account for features that are important to solving real-world problems – like time, uncertainty, cost, and preferences. My early work in automated planning focused on one specific feature, time; and the study of actions with durations, temporal planning.

Required Concurrency: In 2007, seminal work by Cushing et al. [3] identified the notion of *required concurrency*, which separates expressive temporal action languages from simple ones. This was a breakthrough in more ways than one – not only did it show that the simpler class of temporal languages were equivalent to the STRIPS representation, it also starkly highlighted the fact that none of the existing benchmark problems on which automated planners were tested required the ability to truly handle concurrency. Later that year, we were able to contribute to the strengthening of this result [4] by conducting an analysis of existing benchmark planning domains, and showing that none of them were *capable* of modeling such required concurrency. That work provided some suggestions of real-world domains that featured required concurrency, and concluded with an argument that temporal planners ought to be evaluated on domains that exhibited this feature too. This work was variously discussed and debated within the automated planning community, and the 2011 edition of the International Planning Competition (IPC) featured for the first time domains that *required* the ability to model concurrent actions[1] – an early example of the impact of our work in the automated planning community.

G-value Plateaus: While the work on required concurrency explored issues related to increasing the expressivity of temporal planning specifications, our work on identifying the problem of G-value Plateaus [1] examined the engineering issues – specifically, a slow-down in the search process – caused by temporal planning representations. We pointed out some underlying difficulties that modern heuristic search methods would face when operating over "G-value Plateaus", which are regions in the search space over which typical search operations (like adding an new action, or advancing the current time) do not increase the g-value.[2]

This early work thus underlined the tension between extending planning representations on the one hand, and the engineering issues that are brought to the fore by such extensions on the other hand.

[1] http://www.plg.inf.uc3m.es/ipc2011-deterministic/DomainsTemporal.html

[2] The g-value is a function that gives the known distance from the starting node of the search, to the node currently under consideration – it is often denoted by the letter 'g', thus giving rise to the name. It is a part of widely used best-first search strategies such as $A^\star$ search.

Planning for Human-Robot Teaming

Human-Robot Teaming (HRT): One of the earliest motivations for the field of Artificial Intelligence was to provide autonomous control to robotic agents that carry out useful service tasks. The concept of *teaming* between humans and robots is central to many of these applications – the notion of robotic agents that support a human agent's goals while executing autonomously is a recurring theme in AI. Over the past decade, the fields of robotics and Human-Robot Interaction (HRI) have exhibited tremendous progress, both within the laboratory as well as out in the real world. Such progress has naturally made the issue of teaming between humans and robotic agents an inevitable reality. Teaming is beneficial to all parties involved: humans can delegate both menial and dangerous tasks to robotic agents, while the robots themselves can benefit from the vast store of untapped information that humans carry in their heads. This symbiotic relationship renders human-robot teams invaluable in applications ranging from military combat to urban reconnaissance, household management and even space missions. However, it is still the case that humans and robots operate with completely different models and representations of the same world (and scenario). The human-robot team may share common goals, but the individual agents' means of achieving those goals – and reasoning about the world in which they must achieve them – differ greatly. If robots are to form effective teams with humans, they must function as other humans do in human-human teams. Bridging this chasm between the agents while keeping an eye on progress towards the ultimate fulfillment of the scenario objectives requires a mediatory mechanism on the robot that can generate autonomous behaviors while taking into account the various changes thrown up by a changing world.

Planning for HRT: The level of autonomy that is desired of robotic agents involved in such teaming scenarios with humans is often achievable only by integrating them with automated planning systems [14] that can plan not just for initially specified goals, but also updates to these goals as well as changes to the world and to the agent's capabilities. Predetermined scripts and contingency trees do not (and cannot) account for all the possibilities that a real-world application scenario brings with it; instead, the planning process must be as autonomous as possible, in addition to being able to accept new input (both from the world and from other agents), and plan with that new information. At the same time, the traditional planning frameworks are themselves inadequate as they ignore the humans in the loop, and assume complete knowledge of models and objectives. Finally, pure learning-based approaches that attempt to first learn the complete models before using them are not well suited, as the robot does not have the luxury of waiting until the models become complete.

Open World Goals: All human-robot teams are constituted in the service of specific goals – either at a higher, abstract level (e.g. "humans must be rescued") or a lower, more defined level (e.g. "deliver `medbox1` to `room3`"). It makes little sense then to assume that these goals will remain static, or that they will all be specified up-front at the beginning of each scenario. Instead, a flexible framework is required that is expressive enough to denote most goals of interest, yet one that allows modifications (including addition and deletion) to goals with relative ease. Additionally, the representation used by these goals must be on a level that humans are comfortable with – too high and no goals of relevance can be defined; too low and humans will fast lose track of what the team is trying to achieve. In our work that introduces a new representational construct – *Open World Quantified Goals* [10] – we propose an extension to existing goal representations, and show that our extension results in better plans being synthesized and more goals being achieved [11]. Additionally, we explore the various issues involved in extending a planner to support this representational extension for human-robot teaming, and in integrating that planner with a robotic architecture that controls a real robot [9, 15].

Changing Worlds: Planning for HRT requires handling dynamic objectives and environments. Such tasks are characterized by the presence of highly complex, incomplete, and sometimes inaccurate specifications of the world state, problem objectives and even the model of the domain dynamics. These discrepancies may come up due to factors like plan executives, or other agents that are executing their own plans in the world. Due to this divergence, even the most sophisticated planning algorithms will eventually fail unless they offer some kind of support for replanning. These dynamic scenarios are non- trivial to handle even when planning for a single agent, but the introduction of multiple agents introduces further complications. All these agents necessarily operate in the same world, and the decisions made and actions taken by an agent may change that world for all the other agents as well. Moreover, the various agents' published plans may introduce commitments between them, due to shared resources, goals or circumstances. We thus proposed a *unified theory of replanning* [16] that takes into account: (i) the various ways in which replanning might be necessitated; (ii) the techniques that may be used to produce a new plan; and (iii) the fact that all of these techniques can be compiled into a single substrate, to enable the use of state-of-the-art planning algorithms in solving the replanning problem.

Evolving Models: As automated planning systems move into the realm of Human-Robot Teaming tasks, a recurring issue is that of incompletely specified domain theories. These shortcomings manifest themselves as reduced robustness in plans that are synthesized, and subsequent failures during execution in the world. It may be the case in many scenarios that though plan synthesis is performed using a nominal domain model, there are domain experts who specify changes to the specific problem instance and sometimes the domain model itself during the planning process. Quite often it is useful to take this new information into account, since it may help prevent grievous execution failures when the plan is put into action. Additionally, new information about the domain or the problem may open up new ways of achieving the goals specified, thus resulting in better plan quality as well as more robust plans. Our work on using natural language instructions to specify model updates during execution [2] provided a means of achieving this, by mapping natural language updates from humans to new actions that could be added to the automated planner's model.

Novel Applications of Automated Planning

In addition to my work on applying automated planning techniques to the specific problem of human-robot teaming, I have increasingly focused my attention on other important real-world problems that can benefit from automation and the application of planning techniques. In particular, the common thread that runs through all of this work is the application of cutting edge AI (and AI planning) techniques to problems that *require* automation – either due to (i) the scale of the data that has to be processed; or (ii) having to deal with humans and human knowledge.

Planning for Crowdsourcing

An emerging application of human computation and crowdsourcing concerns that all too human of activities – planning. At first glance, crowdsourced planning applications appear to have very little to do with existing automated planning methods, since they seem to depend solely on human planners. However, a deeper look at these applications shows that most of them use primitive automated components in order to enforce checks and constraints which are traditionally not the strong suit of human workers – herding the proverbial sheep, in a manner of speaking. More importantly, experiments show that even these primitive automated components go a long way towards improving plan quality, for little to no investment in terms of cost and time. While these primitive components can and should be replaced by more sophisticated automated planning techniques, adapting such technology presents several challenges. We list a few of these challenges in recent work [6, 13, 12] under two broad categories: (i) *interpretation* challenges, which include issues such as text and plan extraction, and interface design; and (ii) *steering* challenges, which range from scheduling and optimization concerns to plan recognition, synthesis, and critiquing.

Planning to Scale Information Flows for Cybersecurity

Industrial-scale network traffic monitoring software for cybersecurity, malware detection, and other critical tasks is being increasingly automated. Due to this, the rate of alerts and supporting data gathered – as well as the complexity of the underlying model – regularly exceed human processing capabilities. Many of these applications require complex models and constituent rules in order to come up with decisions that influence the operation of entire networks. In work that was conducted during my time as an intern at IBM's T.J. Watson Research Center [17], we motivated the *strategic planning* problem – one of gathering data from the world and applying the underlying model of the domain in order to come up with decisions that will monitor the system in an automated manner. We applied automated planning methods to this problem in order to achieve two objectives: (i) scale to the demands of a real-time, real world scenario; and

(ii) allow for the specification of preexisting rules and knowledge by human network admins in a high-level representation amenable to updates, such as PDDL. We devised a PDDL model of the network administration and monitoring scenario, and integrated the automated planners that produced plans (decisions) into an integrated system that monitored the flow of traffic through the network. We also conducted extensive evaluations of two different planning systems on a six month window of network data, and using a simulator.

Automated Methods for Large Data

The advent of social media platforms such as Twitter and Facebook has resulted in the generation of large-scale data that can be analyzed and used for various tasks such as prediction, promotion, propagation etc. As the scale of this data rises, it is increasingly evident that automated methods are needed to order and analyze that data to extract valuable insights. We have conducted some initial work on this in two directions: (i) *re-ordering* existing data in order to improve search on Twitter; and (ii) *analyzing* language usage patterns on Twitter.

Improving Twitter Search: The increasing popularity of Twitter renders improved trustworthiness and relevance assessment of tweets much more important for search. However, given the limitations on the size of tweets, it is hard to extract measures for ranking from the tweets' content alone. In our recent work [7, 8], we presented a novel ranking method which combines two orthogonal measures of relevance and trustworthiness of a tweet. The first measures the trustworthiness of the *source* of a tweet by extracting features from a 3-layer Twitter ecosystem consisting of users, tweets and webpages. The second measure estimates the trustworthiness of the *content* of a tweet by analyzing whether the content is independently corroborated by other tweets. We then propagate the source trustworthiness over a graph that is generated based on the content agreement between tweets, in order to arrive at a *score* for each tweet given a query. Tweets in the search results are then reordered based on this score. An evaluation of our method on 16 million tweets from the TREC 2011 Microblog Dataset showed that for top-30 precision, we achieved 53% better precision than the previous state-of-the-art on the dataset, and an improvement of 300% over Twitter's native search.

Analyzing Language Usage Patterns on Twitter: Twitter has also become the *de facto* information sharing and communication platform. Given the factors that influence language on Twitter – size limitation as well as communication and content-sharing mechanisms – there is a continuing debate about the position of Twitter's language in the spectrum of language on various established mediums. These include SMS and chat on the one hand (size limitations) and email (communication), blogs and newspapers (content sharing) on the other. To provide a way of determining this, we proposed [5] an automated computational framework that offered insights into the linguistic style of all these mediums. Our framework consisted of two parts: the first part built upon a set of linguistic features to quantify the language of a given medium; and the second part introduced a flexible factorization framework which conducted a psycholinguistic analysis of a given medium with the help of an external cognitive and affective knowledge base. Applying this analytical framework to various corpora from several major mediums, we gathered statistics in order to compare the linguistics of Twitter with those other mediums via a quantitative comparative study. This work was well-received both within the research fraternity, as well as in a wider context.[3]

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