Generation of Explicable Plans for Robot Task Planning

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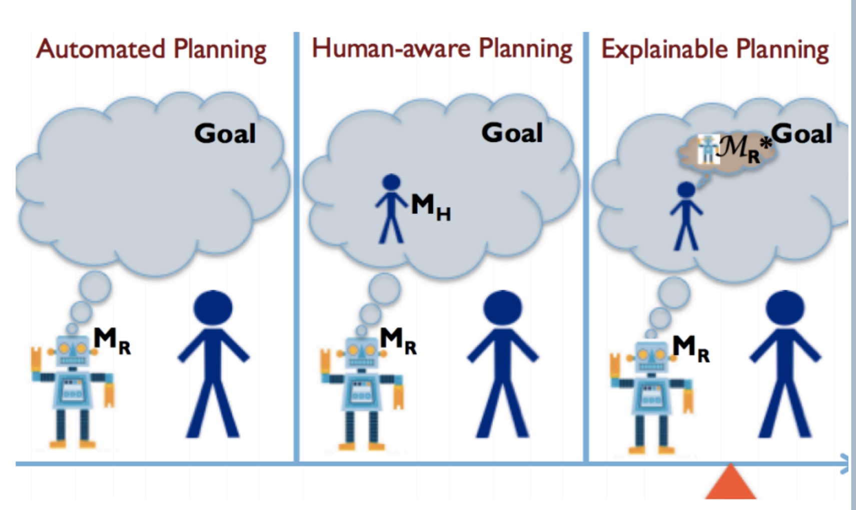
Motivation & Contributions

- For human-robot teaming scenarios, if the behaviors of robotic agents are incomprehensible to the humans, then it can impose cognitive load on humans and potentially introduce safety risks.
- In order to overcome these issues, in the plan synthesis process we not only consider planning model of the agent but also consider human's interpretation of the robot's behavior.
- This interpretation refers to human's understanding of robot's capabilities, mental states, etc.
- Differences between the actual robot model and human's interpretation of the robot model can cause confusion and surprise when the human finds robot's behavior different from his/her expectations.
- The difference in the model exists because human's understanding about the robot's model is often incomplete and inaccurate.
- A challenge in addressing this problem is that the human's understanding of the agent's model is inherently hidden and unknown.
- We propose a formulation to capture and learn this hidden model. We then integrate it in our planning process to generate plans as per human's expectation of robot plans.

Contributions:

- Introduced the concept of explicability for robot task planning.
- Incorporated explicability as a heuristic in explicable plan generation process.
- Investigated two problem scenarios:
  - Human as a passive observer
  - Human-robot peer-to-peer teams.
- Evaluated the system for both scenarios with physical robot experiments.



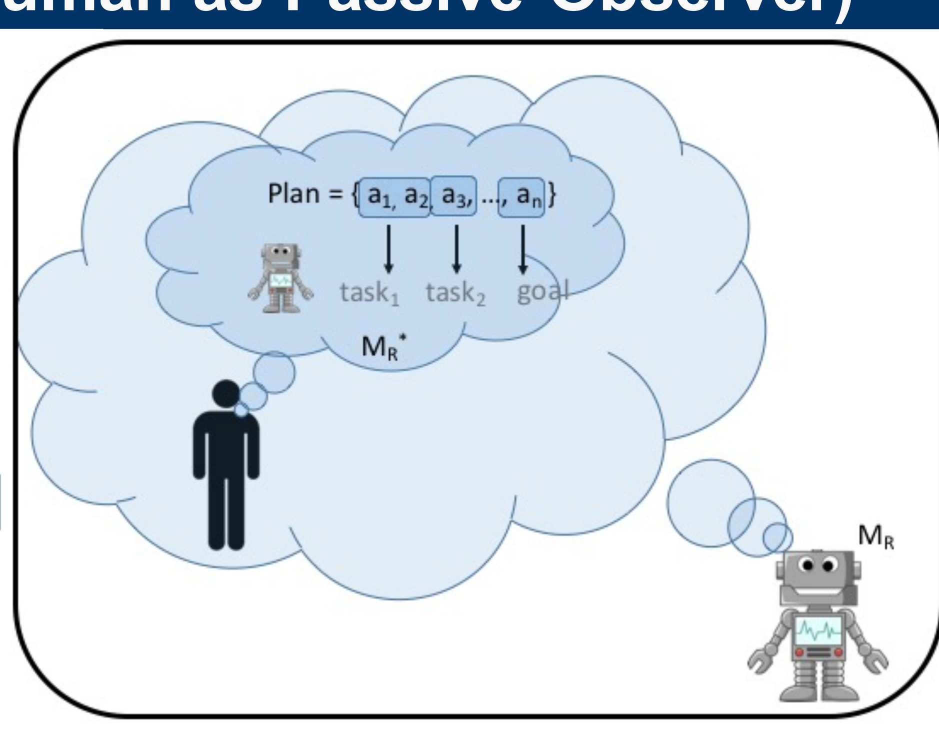
Problem Formulation (Human as Passive Observer)

Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between robot plan based on M_R and human's expectation of robot plan based on M_R*.

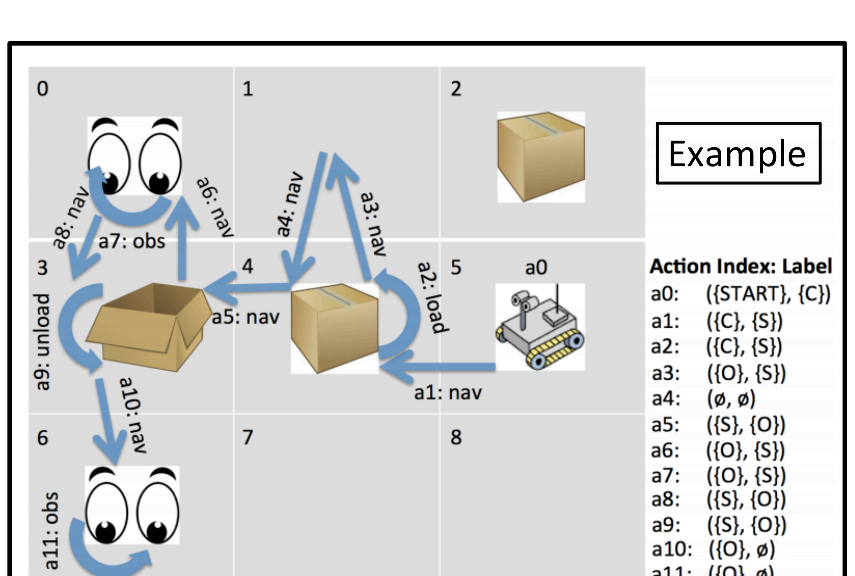
$$\underset{\pi_{M_R}}{\operatorname{argmin}}\, cost(\pi_{M_R}) + \alpha \cdot \boxed{dist(\pi_{M_R}, \pi_{\mathcal{M}_R^*})}$$

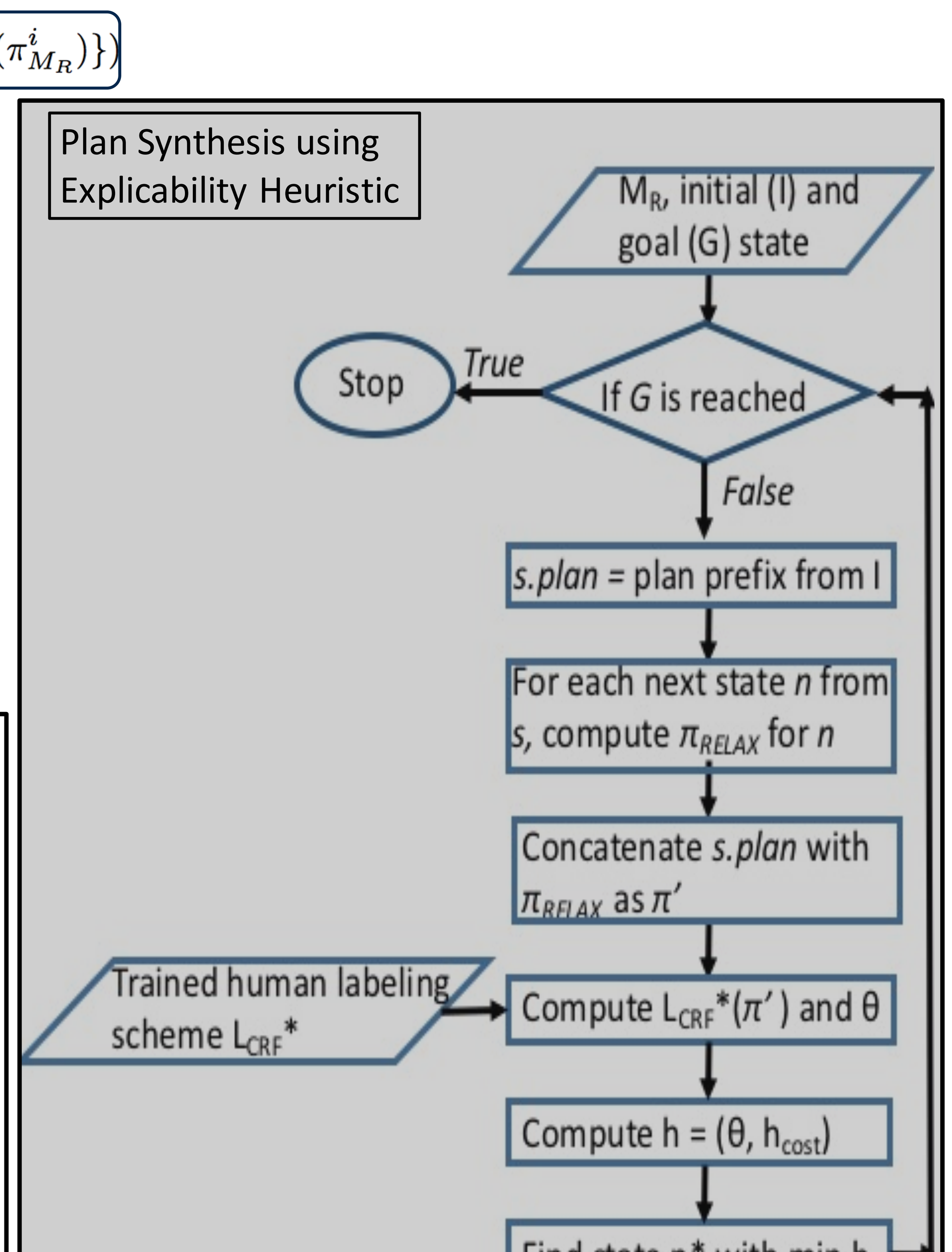
$$dist(\pi_{M_R}, \pi_{\mathcal{M}_R^*}) = F \circ \boxed{\mathcal{L}^*(\pi_{M_R})}$$

$$\underset{\pi_{M_R}}{\operatorname{argmin}}\, cost(\pi_{M_R}) + \alpha \cdot F \circ \boxed{\mathcal{L}^*_{CRF}(\pi_{M_R} | \{S_i | S_i = \mathcal{L}^*(\pi^i_{M_R})\})}$$



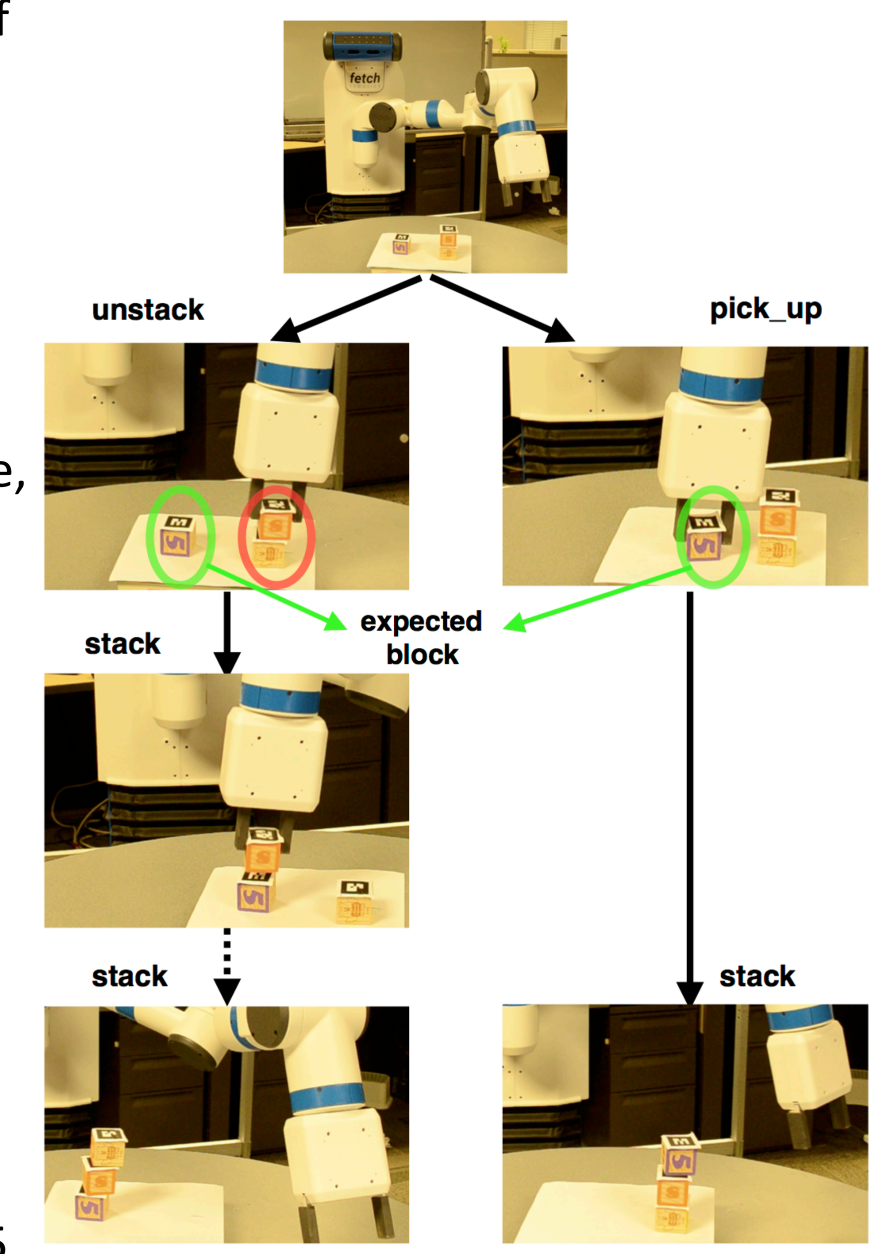
L* is the labeling scheme of the human for robot plans based on M_R*, L_{CRF}* is the learned model of L*. We use linear chain conditional random fields as the graphical model for learning because of their abilities to model sequential data.





Experimental Analysis (Human as Passive Observer)

- The robot's goal is to build a tower of a certain height using blocks.
- There are two types of blocks, light and heavy, but that information is hidden from humans.
- Picking up the heavy blocks is costly than the light blocks for the robot.
- Hence, from the human's perspective, the robot may sometimes choose seemingly more costly (i.e., longer) plans to build a tower.
- In this evaluation, we only use one task label "building tower".
- For all testing problems, the labeling process results in 77.8% explicable actions for OPT and 97.3% explicable actions for FF-EXPD.
- The average explicability measures for FF-EXPD and OPT are 0.98 and 0.78, and the average scores are 9.65 and 6.92, respectively.



Problem Formulation (Human as Active Collaborator)

- The robot has access to it's own planning model and approximate planning model of the human, M_H*.
- In the planning process, robot has to not only consider M_R* but also the actual human planning model M_H, which may be different from M_H*.
- Composite plan, π_C , captures actions performed by both human and robot to achieve their goals.

$$\arg \min_{\pi_C^{M_R, M_H^*}} cost(\pi_C^{M_R, M_H^*}) + \alpha. \boxed{dist(\pi_C^{M_R, M_H^*}, \pi_C^{M_R^*, M_H})}$$

$$\arg \min_{\pi_C^{M_R, M_H^*}} cost(\pi_C^{M_R, M_H^*}) + \boxed{\alpha. F \circ L^*_{CRF}(\pi_C^{M_R, M_H^*} | \{S_i | S_i = L^*(\pi^i_C)\})}$$

L_{CRF}* is the learned model of which takes labeled traces of composite plans as its training examples. Composite plans have alternate agent actions.