CSE 591: Human-aware Robotics

Instructor: Dr. Yu ("Tony") Zhang

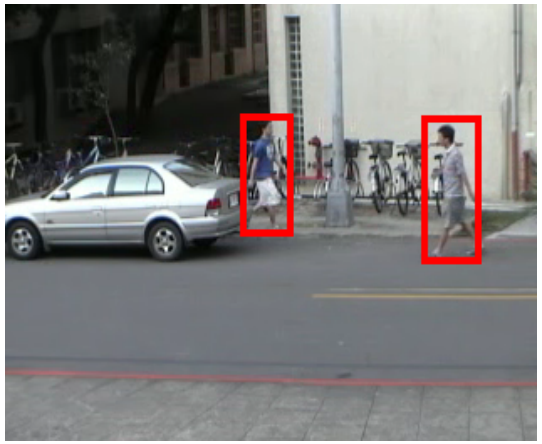
Location & Times: CAVC 359, Tue/Thu, 9:00--10:15 AM
Office Hours: BYENG 558, Tue/Thu, 10:30--11:30AM

Nov 10, 2016

Slides adapted from Subbarao Kambhampati, Heni Ben Amor

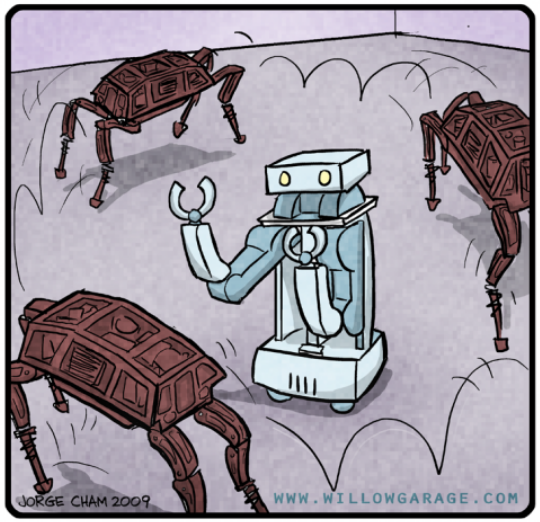
Challenges in human-aware robotics

- **Perception of humans**
  Human recognition, human tracking, and activit recognition



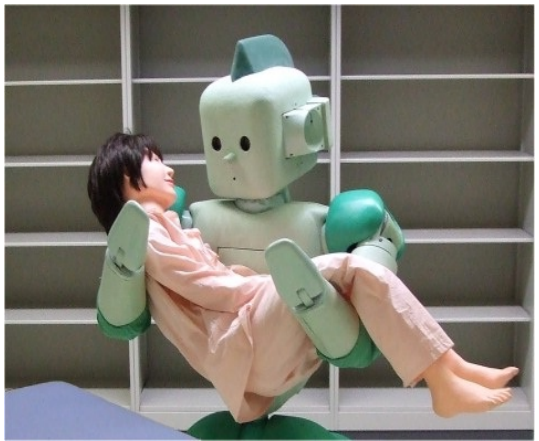
- **Modeling of humans**
  Goal and intent recognition, human decision and behavioral models, expectation, model learning

- **Human-robot interface**
  Command recognition, gestu recognition



"SIT, BOY, SIT! SIT, I SAY, SI... OH, FORGET IT."

- **Human-aware decision making**
  Human-aware planning, reinforcement learning and inverse reinforcement learning.



Dimensions of HIL Planning

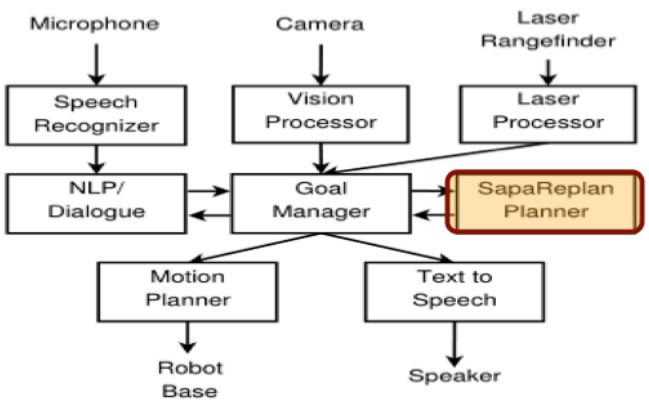
Human aware robot planning

	Cooperation Modality	Communication Modality	What is Communicated	Knowledge Level
Crowdsourcing	Interaction (Advice from planner to humans)	Custom Interface	Critiques, subgoals	Incomplete Preferences Incomplete Dynamics
Human-Robot Teaming	Teaming/ Collaboration	Natural Language Speech implicit	Goals, Tasks, Model information	Incomplete Preferences Incomplete Dynamics (Open World)
"Grandpa Hates Robots"	Awareness (pre-specified constraints)	Prespecified (Safety / Interactio Constraints)	No explicit communication Interaction constraints	Incomplete Preferences Complete Dynamics
MAPGEN	Interaction (Planner takes binding advice from human)	Direct Modification of Plans	Direct modifications, decision alternatives	Incomplete Preferences Complete Dynamics

Decision theoretic Assistance,
Resource conflicts and plan for serendipity
Grandpa hates robots

Model Updates
(via natural language)

- "To go into a room when you are at a closed door, push it one meter."
  - Precondition: "you are at a closed door"
  - Action definition: "push it one meter"
  - Effect: "go into a room"



- NLP Module
  i. Reference resolution
  ii. Parsing
  iii. Background knowledge
  iv. Action submission (to planner)

[Cantrell, Talamadupula et al., HRI 2012]

[In collaboration with hrilab, Tufts University]

Dimensions of HIL Planning

Human aware robot planning

	Cooperation Modality	Communication Modality	What is Communicated	Knowledge Level
Crowdsourcing	Interaction (Advice from planner to humans)	Custom Interface	Critiques, subgoals	Incomplete Preferences Incomplete Dynamics
Human-Robot Teaming	Teaming/ Collaboration	Natural Language Speech implicit	Goals, Tasks, Model information	Incomplete Preferences Incomplete Dynamics (Open World)
"Grandpa Hates Robots"	Awareness (pre-specified constraints)	Prespecified (Safety / Interactio Constraints)	No explicit communication Interaction constraints	Incomplete Preferences Complete Dynamics
MAPGEN	Interaction (Planner takes binding advice from human)	Direct Modification of Plans	Direct modifications, decision alternatives	Incomplete Preferences Complete Dynamics

Decision theoretic Assistance,
Resource conflicts and plan for serendipity
Grandpa hates robots + …

Challenges in Human-Aware Planning & Decision Making

- Interpret what humans are doing
  - Plan/goal/intent/preference/capability recognition (Expectation)
- Plan with incomplete domain models
  - Robust planning with "lite" models
  - (Learn to improve domain models)

- Continual planning/Replanning
  - Commitment sensitive to ensure coherent interaction
- Explanations/Excuses
  - Excuse generation can be modeled as the (conjugate of) planning problem
- Asking for help/elaboration
  - Reason about the information value

Explicability among Humans

- We, as humans, while interacting make an effort (behave explicably) to be understood.
- Explicability is crucial for good team performance.

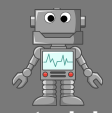
"You clumsy ape! I ask for a hemostat and you hand me a banana. Where'd you go to med school, the Bronx Zoo?"

Explicability

Explicability is not only important for human-human teams but also for human-robot teams.

Explicability → **Human's expectation of agent behavior** → **Hidden in human's mind**

Goal: Clear a cluttered table

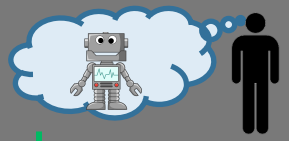


Move to the table

Push the items off the table

Pick and place

Table is clear



Move to the table

Keep books on shelf

Remove the coffee mug

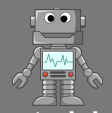
Place pen in pen holder

Explicability

Explicability is not only important for human-human teams but also for human-robot teams.

Explicability → **Human's expectation of agent behavior** → **Hidden in human's mind**

Goal: Clear a cluttered table

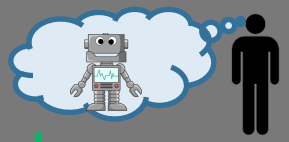


Move to the table

Push the items off the table

Pick and place

Table is clear



Move to the table

Keep books on shelf

Remove the coffee mug

Place pen in pen holder

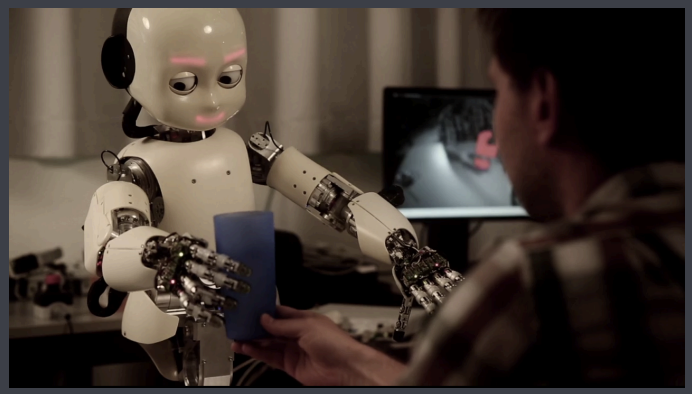
expectations are not met

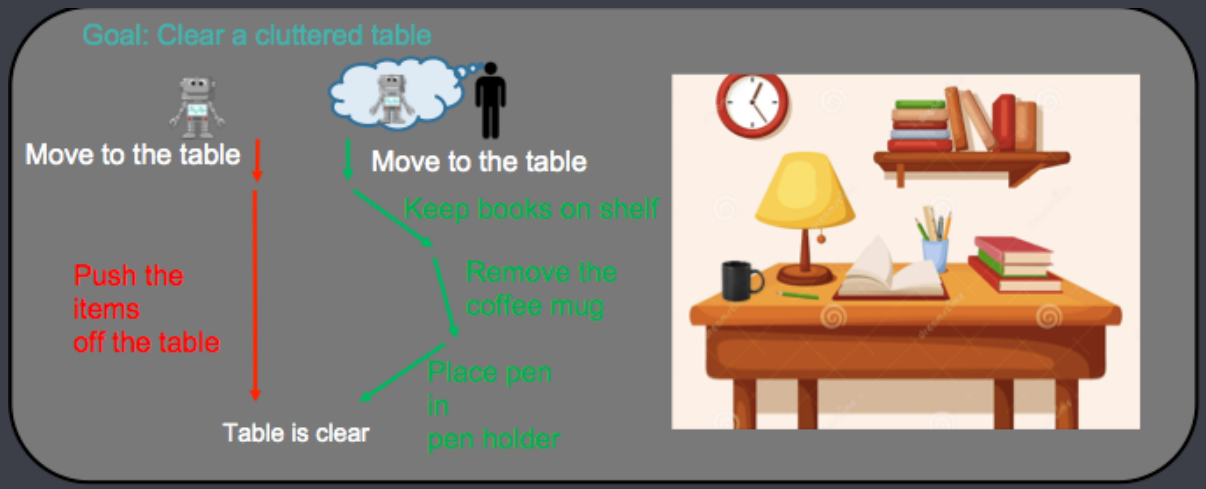
Inexplicable

- **Confusion and surprise**
- **Cognitive load**
- **Safety concerns**

Crucial for an agent to understand other agent's interpretation of itself.

Plan Explicability for Autonomous Robots





Autonomously construct task plans

Candidate plan #1 (Cost optimal plan)

Candidate plan #2

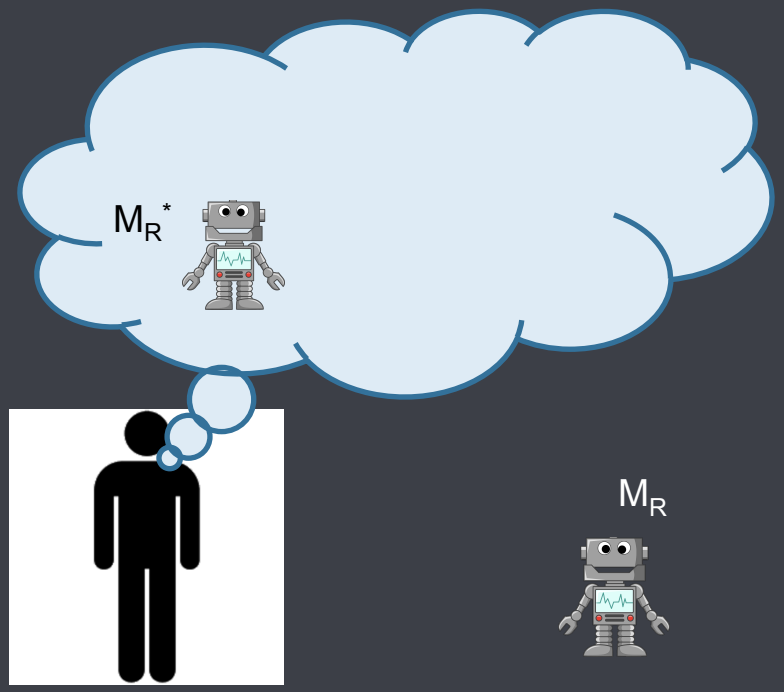
...

Filtered by **plan explicability measure**

Explicable Plan

How do we compute the plan explicability measure?

Plan Explicability



How do we compute the plan explicability measure?

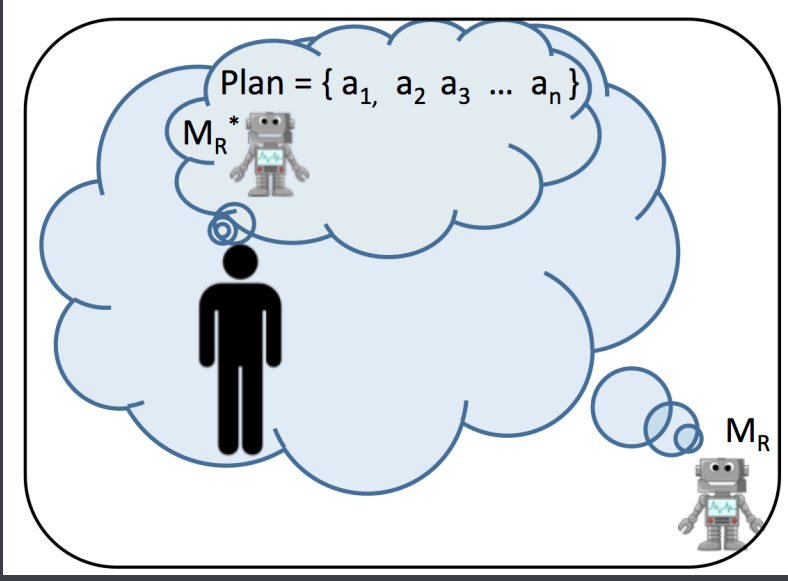
- Human's expectation of an agent is associated with another model of the agent in **human's mind**
- Plan explicability can be interpreted as a "distance" between the plans generated by M_R and M_R^*

Problem Formulation

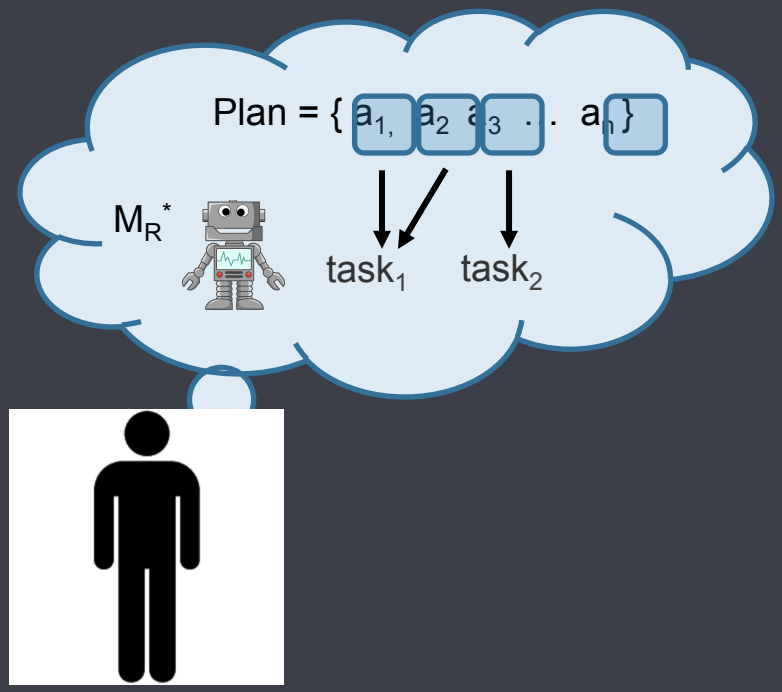
Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between the robot plan and human's expectation of the robot plan):

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

How do we obtain M_R*?



Problem Formulation



How do we obtain M_R*?

- Human's understanding of the other agents' behavior is related to how we associate it with tasks

The easier it is for humans to associate tasks/sub-goals to a plan, the more explicable the plan is.

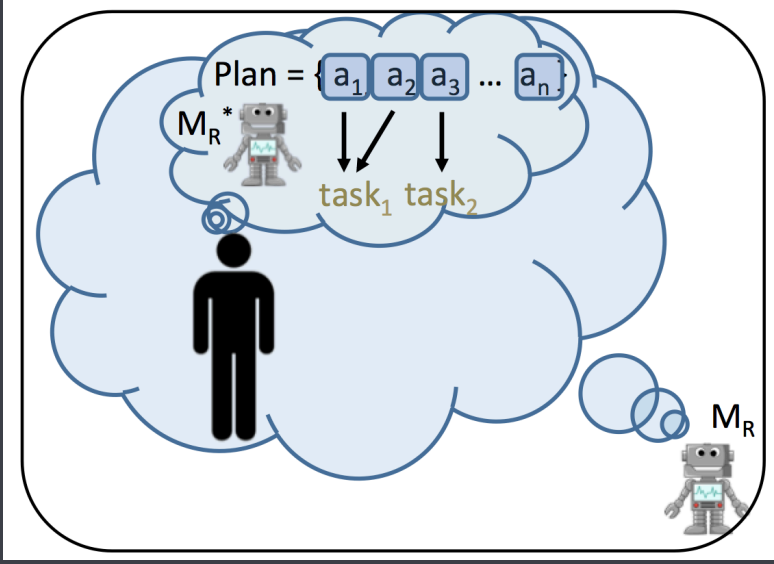
Psychological Studies: G. Csibra and G. Gergel 2007, R. Vallacher and D. Wegner, 1987.

Problem Formulation

Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between the robot plan and human's expectation of the robot plan):

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

Hidden model



Problem Formulation

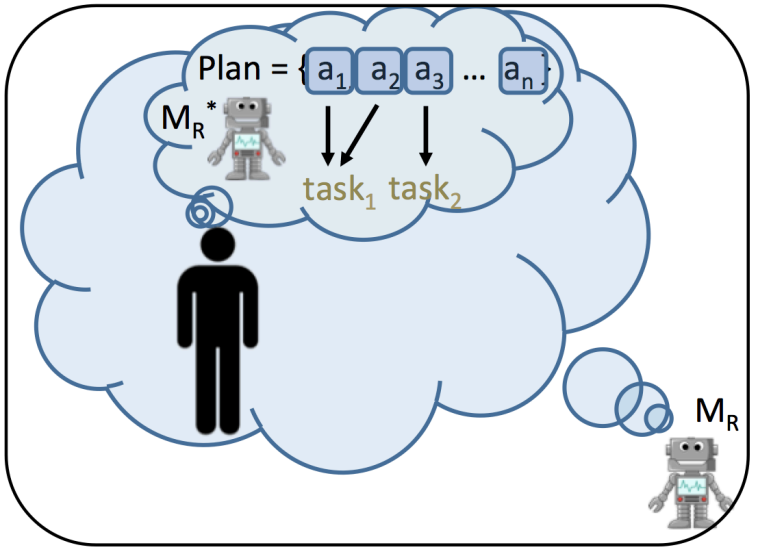
Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between the robot plan and human's expectation of the robot plan):

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

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

Function that takes plan labels as input

Human's labeling scheme for robot plans



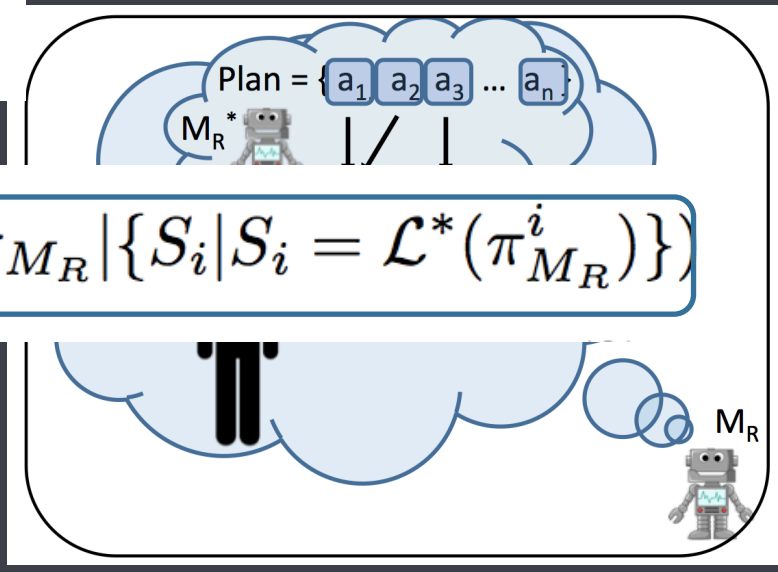
Problem Formulation

Given a goal, the objective is to find a robot plan that minimizes a weighted sum of cost of robot plan and differences between the robot plan and human's expectation of the robot plan):

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

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

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

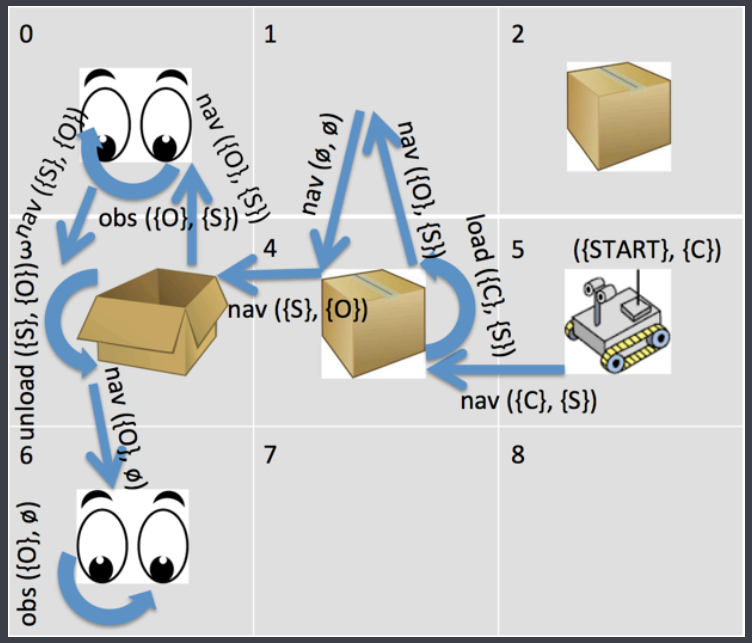


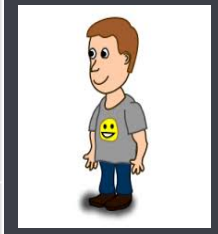
Learned labeling scheme function using linear chain Conditional Random Fields

Explicability labeling for obtaining training samples

Task labels for actions. For example:

- Collect
- Store
- Observe





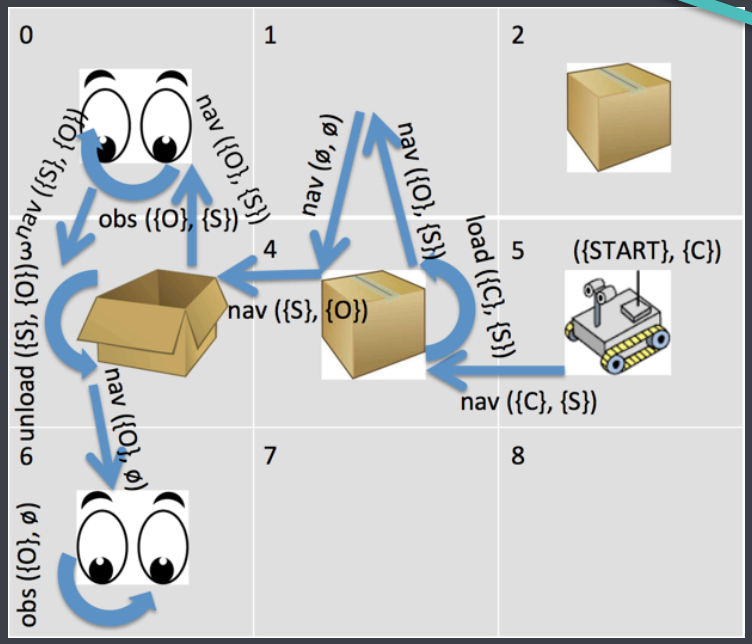
$$\underset{\pi_{M_R}}{\operatorname{argmin}}\, cost(\pi_{M_R}) + \alpha \cdot \boxed{F \circ \mathcal{L}^*_{CRF}(\pi_{M_R} | \{S_i | S_i = \mathcal{L}^*(\pi^i_{M_R})\})}$$

Learning using CRF

Model:

- Conditional Random Fields (CRF)

$$p(\mathbf{x}, \mathbf{y}) = \frac{1}{Z} \Pi_A \Phi(\mathbf{x}_A, \mathbf{y}_A)$$

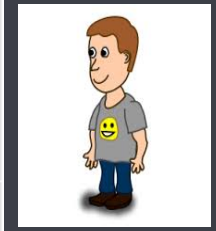


Task labels for actions. For example:

- Collect
- Store
- Observe

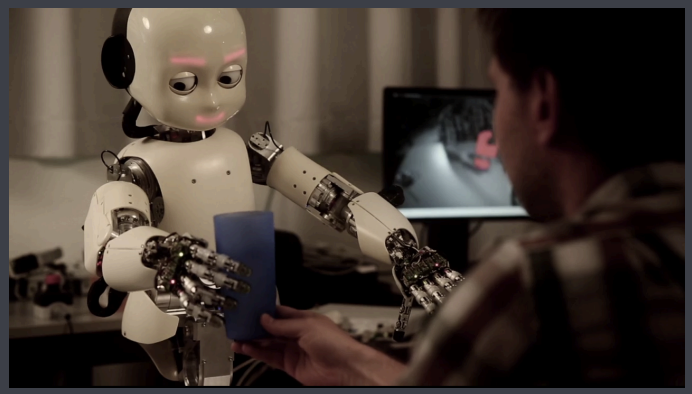
Features:

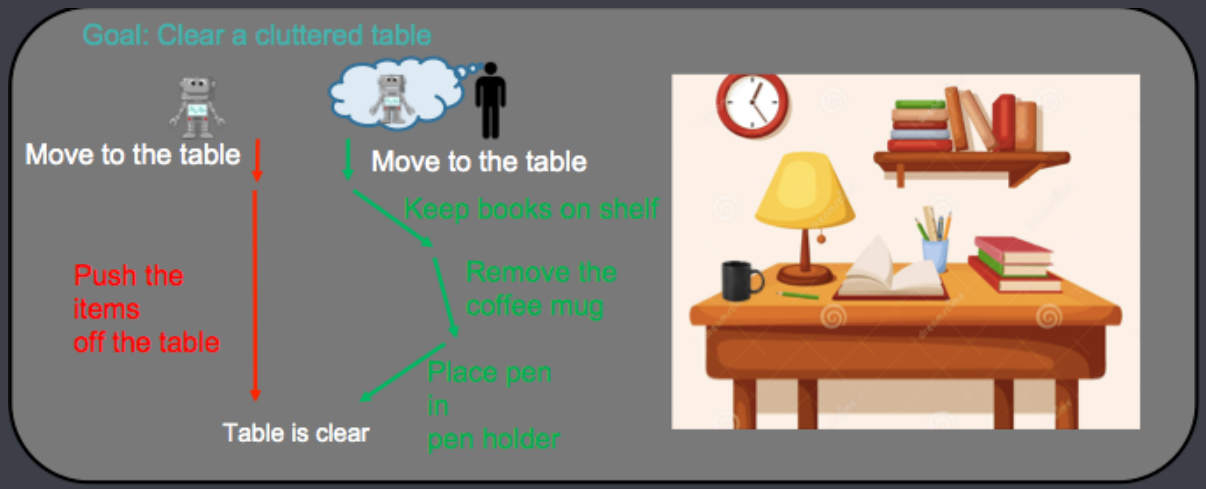
- Plan features: state, e.g., at rover 5; action name, e.g., rover



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

Plan Explicability for Autonomous Robots





Autonomously construct task plans

Given N candidate plans

Candidate plan #1 (Cost optimal plan) $\pi_{MR}(1)$

...**Candidate plan #k** $\pi_{MR}(k)$

...

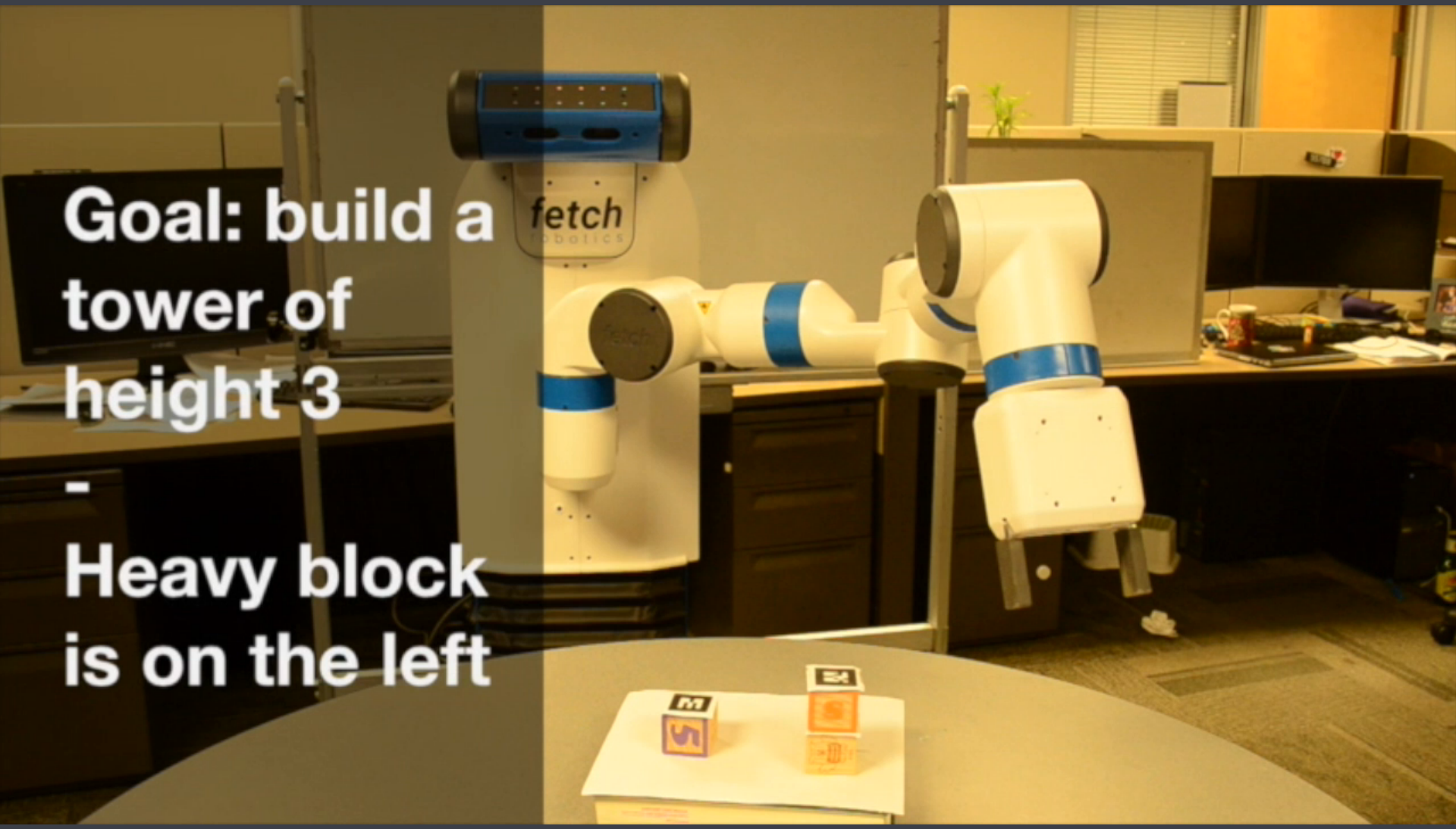
$\pi_{MR}(N)$

Filtered by **plan explicability measure**

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

Explicable Plan

Implemented Scenario



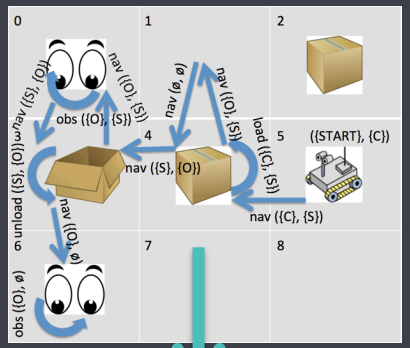
www.youtube.com/watch?v=AAAwSVbAV7s

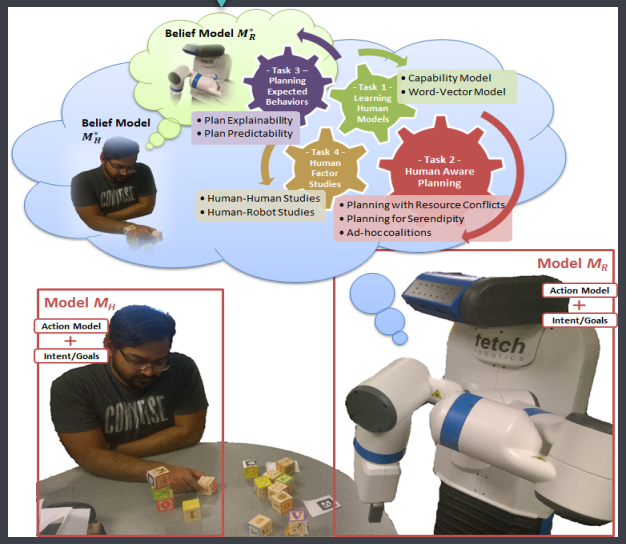
Interactive teaming

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

$$\underset{\pi_C^{M_R,\widetilde{M_H}}}{\arg\min}\; cost(\pi_C^{M_R,\widetilde{M_H}})$$

$$+\alpha.dist(\pi_C^{M_R,\widetilde{M_H}}, \pi_C^{\mathcal{M}_R^*,M_H})$$



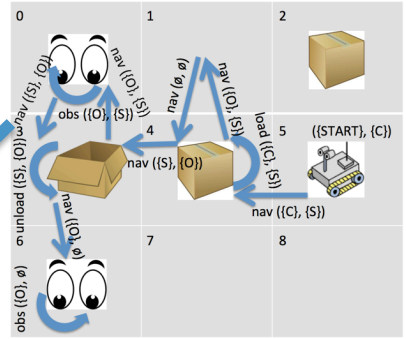


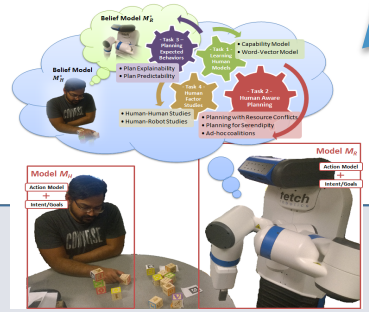
$$\underset{\pi_{M_R}}{\operatorname{argmin}}\, cost(\pi_{M_R}) + \alpha \cdot F \circ \mathcal{L}^*_{CRF}(\pi_{M_R} | \{S_i | S_i = \mathcal{L}^*(\pi^i_{M_R})\})$$

$$\underset{\pi_C^{M_R,\widetilde{M_H}}}{\arg\min}\; cost(\pi_C^{M_R,\widetilde{M_H}})$$

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

Interactive teaming





(Team) working on a tower

S_1 S_k

Class labels

Fetch next block

t_1^R t_2^H t_{m-1}^H t_m^R

Task labels

Pickup A

Stack A

a_1^R a_2^H a_3^R a_{n-2}^H a_{n-1}^R a_n^R

Actions

Robot in action

Related work

- There exists work on generating legible robot motions
- Two different task plans may map to the exact same motions

➢ Plan explicability is focusing on task planning

- Model learning via learning from demonstration, inverse reinforcement learning, cross-training, and tutoring systems
- Previous approaches are about how one agent teaches the other agent in terms of its plan preference
- Note that a preferred plan may not always be an expected plan; similarly, an expected plan may not always be a preferred plan

➢ We are addressing the question of what humans would expect the robot to do rather than what humans themselves would do

Dimensions of HIL Planning

Human aware robot planning

	Cooperation Modality	Communication Modality	What is Communicated	Knowledge Level
Crowdsourcing	Interaction (Advice from planner to humans)	Custom Interface	Critiques, subgoals	Incomplete Preferences Incomplete Dynamics
Human-Robot Teaming	Teaming/ Collaboration	Natural Language Speech implicit	Goals, Tasks, Model information	Incomplete Preferences Incomplete Dynamics (Open World)
"Grandpa Hates Robots"	Awareness (pre-specified constraints)	Prespecified (Safety / Interactio Constraints)	No explicit communication Interaction constraints	Incomplete Preferences Complete Dynamics
MAPGEN	Interaction (Planner takes binding advice from human)	Direct Modification of Plans	Direct modifications, decision alternatives	Incomplete Preferences Complete Dynamics

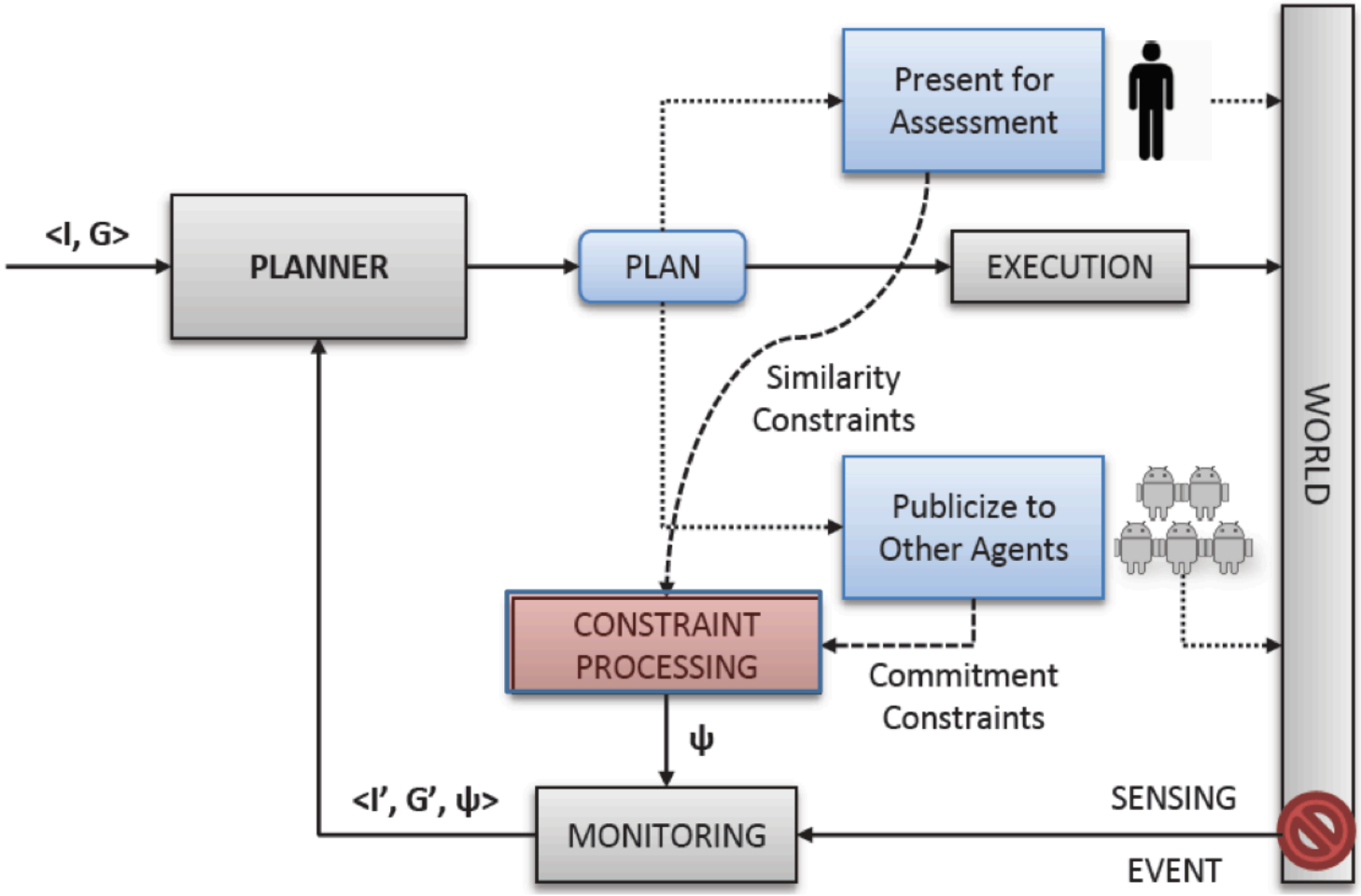
Decision theoretic Assistance,
Resource conflicts and plan for serendipity
Grandpa hates robots + …

Challenges in Human-Aware Planning & Decision Making

- Interpret what humans are doing
  - Plan/goal/intent/preference/capability recognition (Expectation)
- Plan with incomplete domain models
  - Robust planning with "lite" models
  - (Learn to improve domain models)

- Continual planning/Replanning
  - Commitment sensitive to ensure coherent interaction
- Explanations/Excuses
  - Excuse generation can be modeled as the (conjugate of) planning problem
- Asking for help/elaboration
  - Reason about the information value

A Generalized Model of Replanning



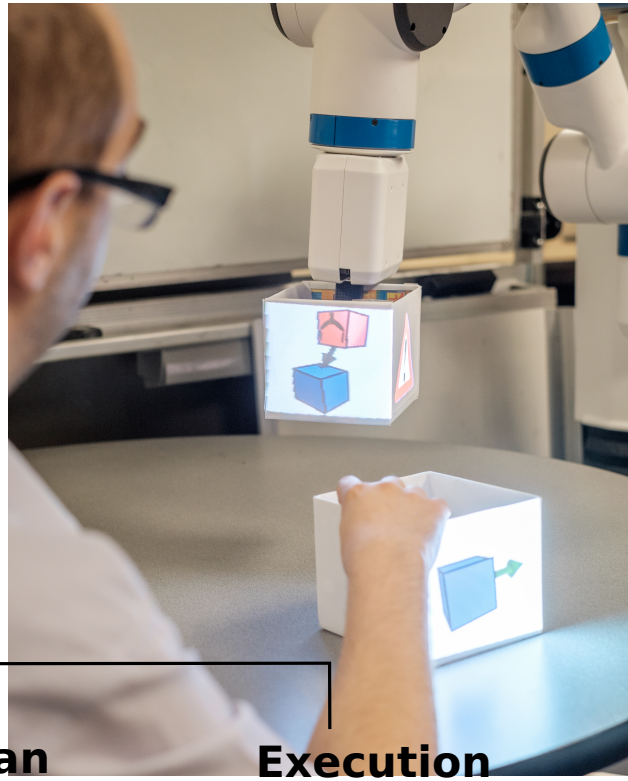
Failures in Planner-Based Systems

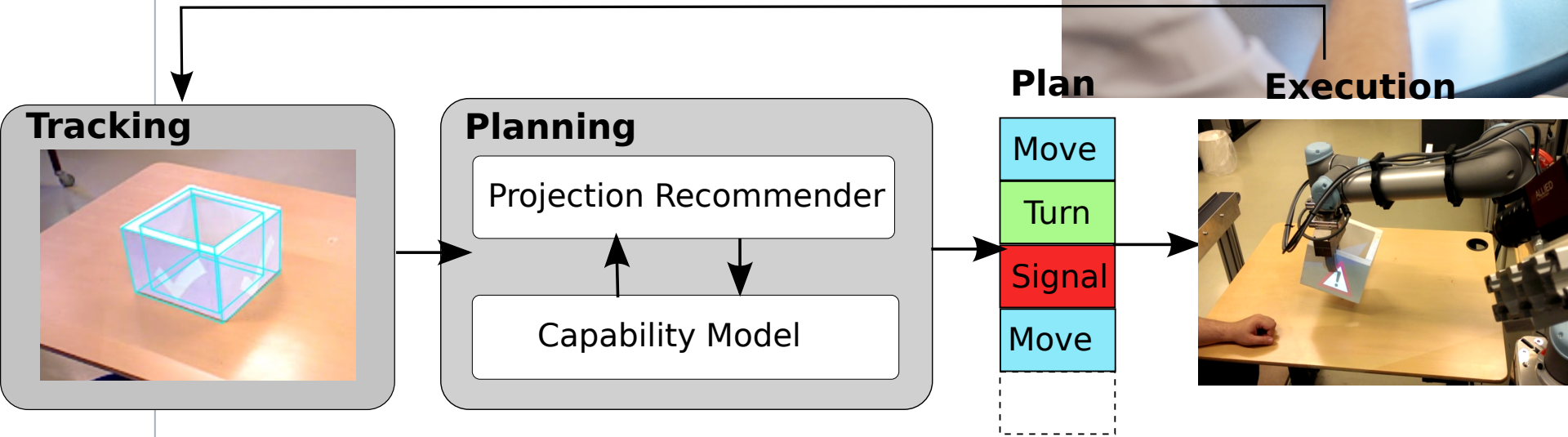
When acting in a uncertain, dynamic environment, things can go wrong:

- Execution failures
  - Error diagnosis
  - Continual Planning
- Planning failures
  - Domain is incorrectly modelled
  - Incomplete world knowledge
  - Missing resources
  - Maybe the task is just unsolvable

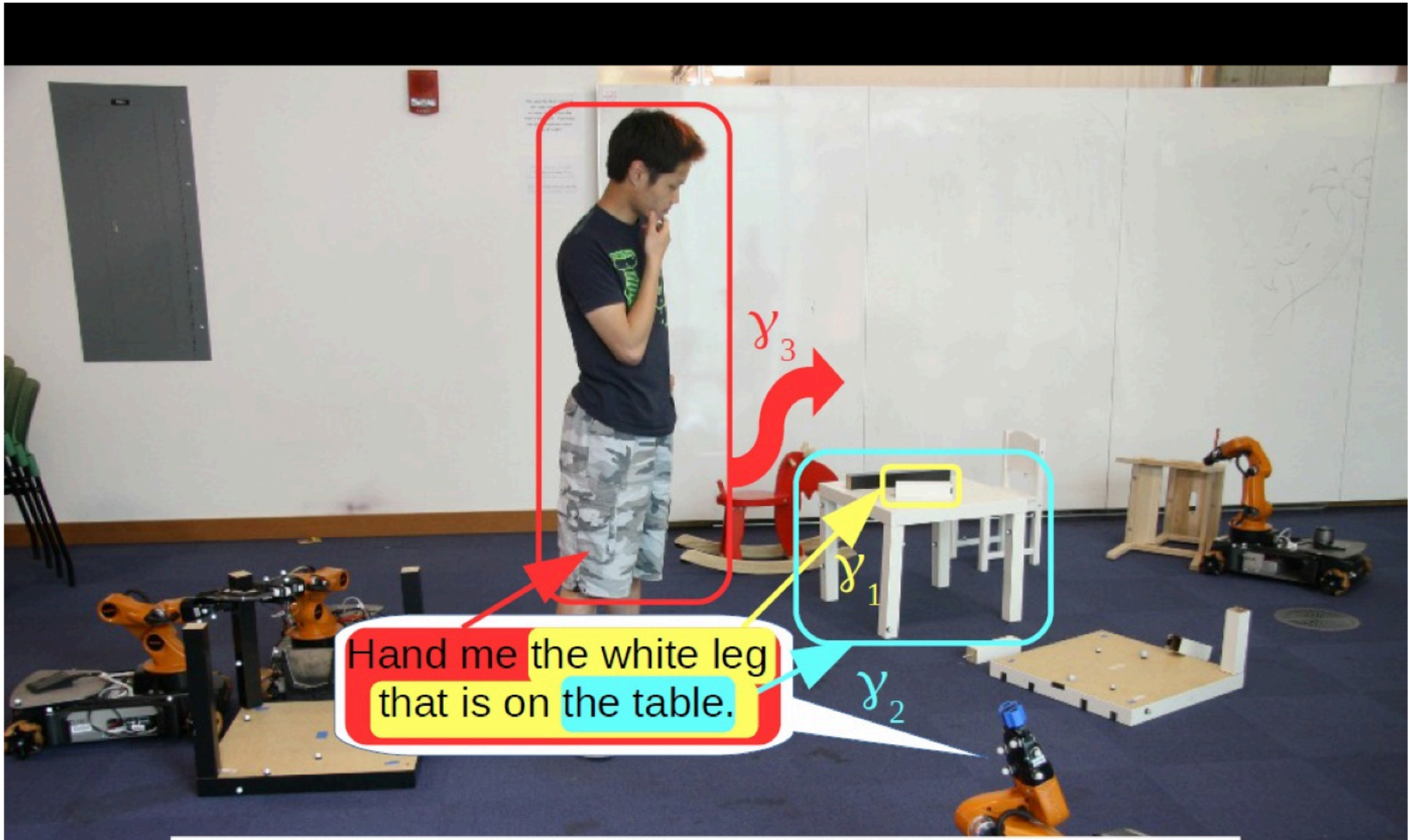
Coming up With Good Excuses
Göbelbecker, Keller, Eyerich, Brenner & Nebel (2010)

Projecting robot intents






Asking for Help Using Inverse Semantics
Tellex, Knepper, Li, Rus & Roy
?
Thursday, Jan 29 2015, 1:55pm – 3:10pm
Session: Science and Systems 2014 (RSS) Presentations 2
Asking for Help Using Inverse Semantics
Stefanie Tellex, Ross Knepper, Adrian Li, Daniela Rus, Nicholas Roy



γ_k are *groundings*, or objects, places, paths, and events in the external world. Each γ_k corresponds to a constituent phrase in the language.

Other Challenges in Human-aware Robotics

Trust in human-robot teaming

Trust building

When to trust

Emergencies

In emergencies, don't trust a robot too much

Published 1 March 2016

Share

In emergencies, people may trust robots too much for their own safety, a new study suggests. In a mock building fire, test subjects followed instructions from an "Emergency Guide Robot" even after the machine had proven itself unreliable — and after some participants were told that robot had broken down.

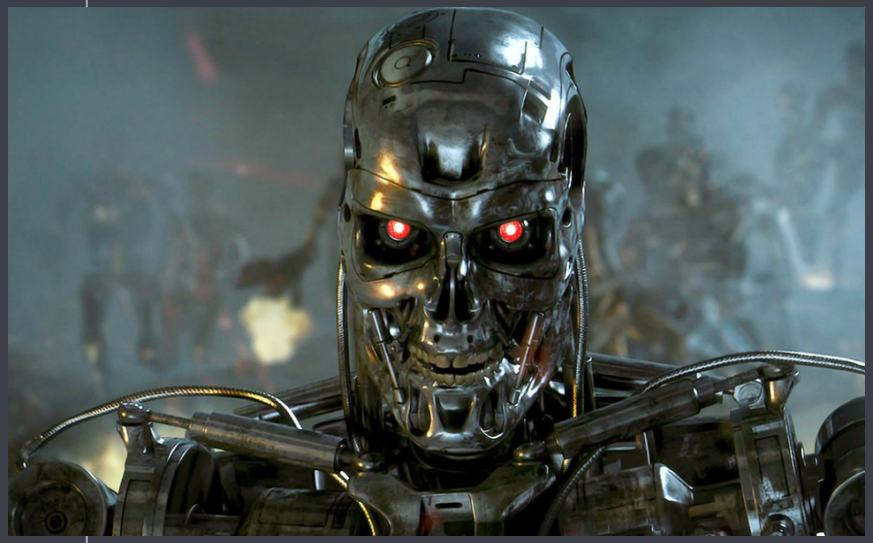
Simulation of rescue robot in operation // Source: gatech.edu

In emergencies, people may trust robots too much for their own safety, a new study suggests. In a mock building fire, test subjects followed instructions from an "Emergency Guide Robot" even after the machine had proven itself unreliable — and after some participants were told that robot had

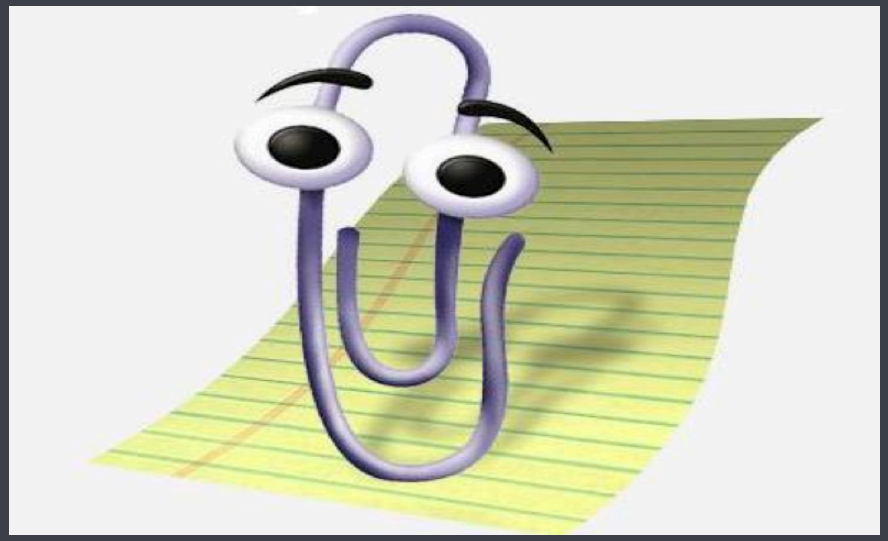
Mutual trust

Cyber-physical systems

Safety in Human-robot Teaming



1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings, except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.



AI MAGAZINE 1984

HOME ABOUT LOGIN SEARCH CURRENT AR
ANNOUNCEMENTS AAAI

Home > Vol 5, No 2 > **Nilsson**

Artificial Intelligence, Employment, and Income

Nils J. Nilsson

Abstract

Artificial intelligence (AI) will have profound societal effects. It prom
benefits (and may also pose risks) in education, defense, business,
this article we explore how AI is likely to affect employment and the
income. We argue that AI will indeed reduce drastically the need of
also note that some people fear the automation of work by machine
of unemployment. Yet, since the majority of us probably would rath
activities other than our present jobs, we ought thus to greet the w
consequences of AI enthusiastically. The paper discusses two reaso

Technology

Intelligent Machines: The jobs robots will steal first

By Jane Wakefield
Technology reporter

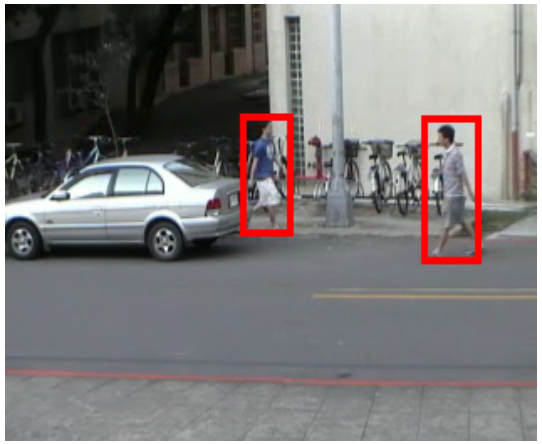
14 September 2015 | Technology

Our days at the office could be numbered as an increasing range of jobs are done more efficiently by a machine

If you are sitting at a desk, driving a taxi or carrying a hod, stop for a moment and ask: could a robot or machine do this job better?

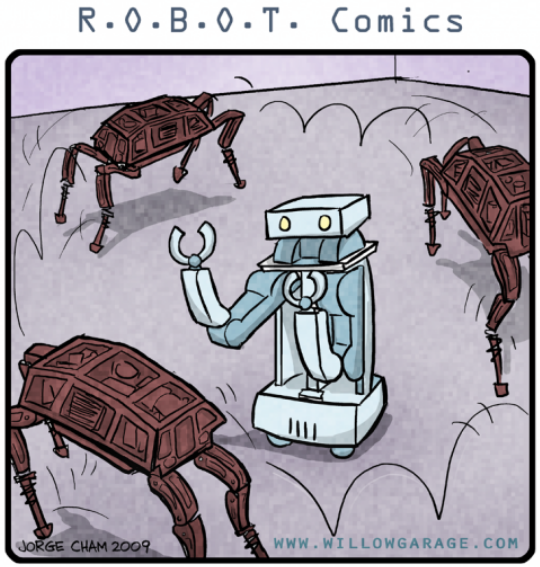
Challenges in human-aware robotics

- **Perception of humans**
  Human recognition, human tracking, and activit recognition



- **Modeling of humans**
  Goal and intent recognition, human decision and behavioral models, expectation, model learning

- **Human-robot interface**
  Command recognition, gestu recognition



"SIT, BOY, SIT! SIT, I SAY, SI... OH, FORGET IT."

- **Human-aware decision making**
  Human-aware planning, reinforcement learning and inverse reinforcement learning.