Artificial Intelligence Qualifying Exam

Alli Nilles

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University of Illinois at Urbana-Champaign

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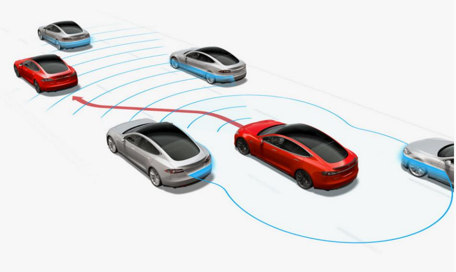
Why Do We Care?

Event Date	Event Description
01/17/2017	Employee Is Struck By Robot Arm And Sustains Fractured Stern
06/16/2013	Employee Is Struck By Axis Arm< Later Dies
03/07/2013	Maintenance Worker Is Struck And Killed By Robot
12/15/2012	Robot Crushes And Kills Worker Inside Robot Work Cell
11/29/2012	Employee Suffers Head Injures In Fall On Energized Track
08/02/2011	Employee Is Killed When Caught In Equipment
07/21/2009	Employee Is Killed By Robotic Palletizer
05/13/2007	Employee Dies After Being Struck By Robotic Arm



[1,2]

[1] Gear Patrol
[2] US DOL

What is Needed?

A better notion of what is **optimal**: encode models of human cognition into our planners and controllers!

Background

Task Planning: planning over a finite, often discrete, series of *actions*

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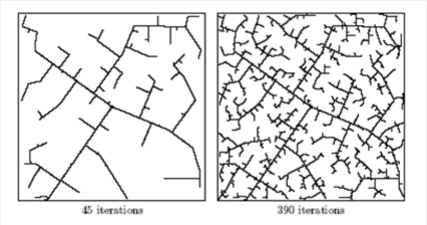

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Background: Communicating Through Action

- predictability vs. legibility[4]

HRI started in 2006, with 147 attendees, and in 2015 had 364 attendees

135/834 IROS 2016 papers had “human” in the title or keywords

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- expressiveness: Amy LaViers RAD Lab[6]

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Approach

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- Given this, we can estimate the probability that a human will be able to predict *the rest of a robot's plan*, given the goal and the first t steps of the robot's plan
- Optimize plans so that the first t steps make the rest of the plan maximally predictable

Definitions

t-predictability given a feasible plan $a = (a_1, \dots, a_T)$, *t-predictability* is the probability that an observer can correctly infer $(a_{t+1}, \dots, a_T)$ after observing $(a_1, \dots, a_t)$ and knowing the goal G.

$\mathcal{P}_t(a) = P(a_{t+1}, \dots, a_T | S, G, a_1, \dots, a_t)$

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t-predictable planner a planner which generates the plan maximizing t-predictability out of all feasible plans.
a^* such that $a^* = \arg\max_{a \in \mathcal{A}} \mathcal{P}_t(a)$

How Do Humans Predict What Robots Will Do?

For "waypoint visiting" task, assume humans will predict shortest path with some noise.

path length cost $c : \mathcal{A} \times \mathcal{S} \times \mathcal{G} \to \mathbb{R}^+$

$$P(\boldsymbol{a}|S, G) = \frac{e^{-\beta c(\boldsymbol{a}, S, G)}}{\sum_{\tilde{a} \in \mathcal{A}} e^{-\beta c(\tilde{a}, S, G)}}$$

$\beta > 0$, set to 1 for both experiments

Optimization Using This Model

$$\boldsymbol{a}^* = \arg\max_{\boldsymbol{a} \in \mathcal{A}} \frac{e^{-\beta c(\boldsymbol{a}_{t+1:T}, S^t_{\boldsymbol{a}}, G)}}{\sum_{\tilde{a}_{t+1:T} \in \mathcal{A}^t_{\boldsymbol{a}}} e^{-\beta c(\tilde{a}_{t+1:T}, S^t_{\boldsymbol{a}}, G)}}$$

Where we assume cost is linearly separable, and factor out $e^{-\beta c(\boldsymbol{a}_{1:t}, S, S^t_{\boldsymbol{a}})}$ from the top and bottom expressions.

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Search over all $\boldsymbol{a}_{1:t}$ and find $\boldsymbol{a}_{t+1:T}$ which is **most predictable**.

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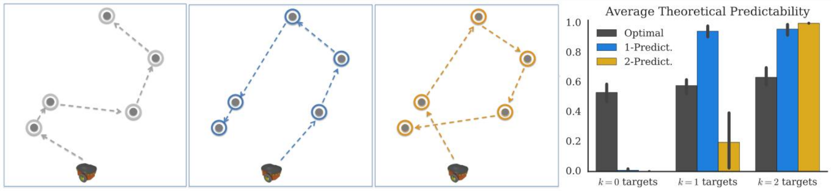
Use branch-and-bound technique to reduce from factorial to exponential time.

t-Predictability



Sample $t = 0, 1, 2$-predictable trajectories, and their theoretical predictability. Figure 2 from [4]

Online Experiment

Training Phase: click on targets, guiding human avatar to visit all targets with the shortest path

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Experimental Phase: watch robot visit $k = 0, 1, 2$ targets. Then click on targets to predict which ones robot will visit next. Then show robot's actual path.

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Create 270 randomly generated layouts with five or six targets.

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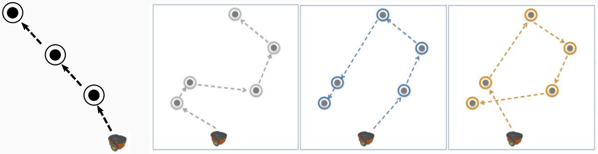
This planner is ***most useful*** *in ambiguous settings*



Results

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All hypotheses (mostly) supported:

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H3: The percieved performance of the robots will be highest when $t = k$.

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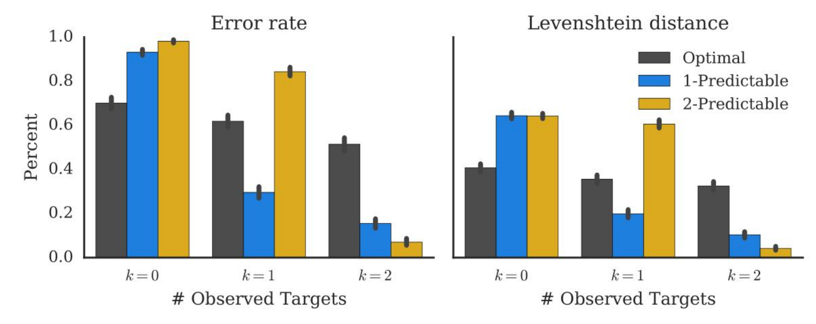
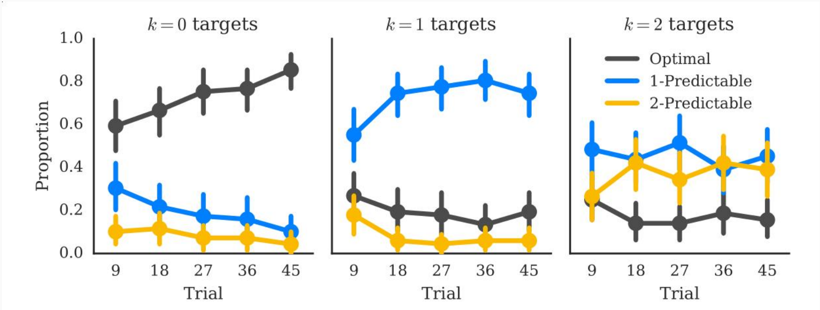


Error rate and Levenshtein distance for user-predicted paths in online experiment. Figure 4 in [4].

Preferences



User preferences over time. Figure 5 in [4].

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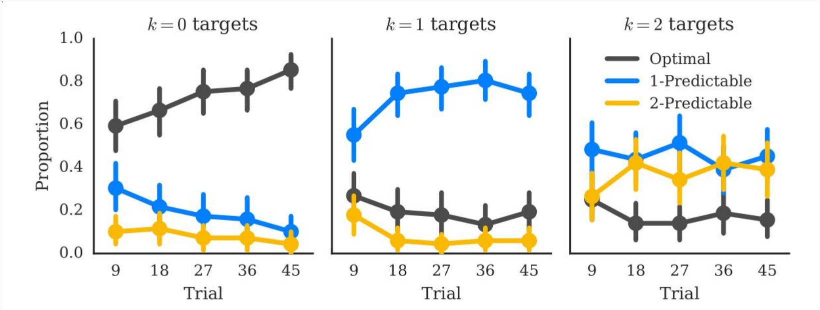
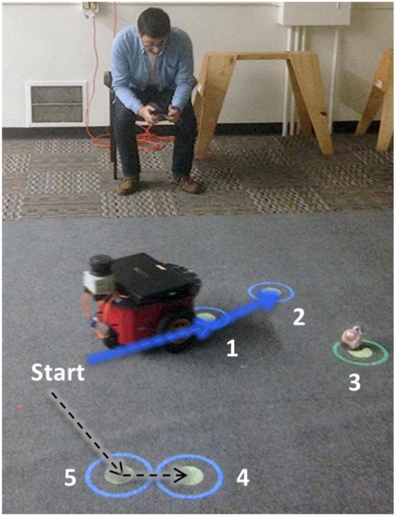


User preferences over time. Figure 5 in [4].

"This robot mostly starts out in the worst way and then goes in weird directions but eventually starts to make sense."

In-Person Experiments



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H1: The 1-predictable robot will result in more successful trials than the optimal baseline.

1-predictable robot leads to more successful completions ($z = 3.34$, $p < 0.001$)

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86% of participants prefer the predictable robot

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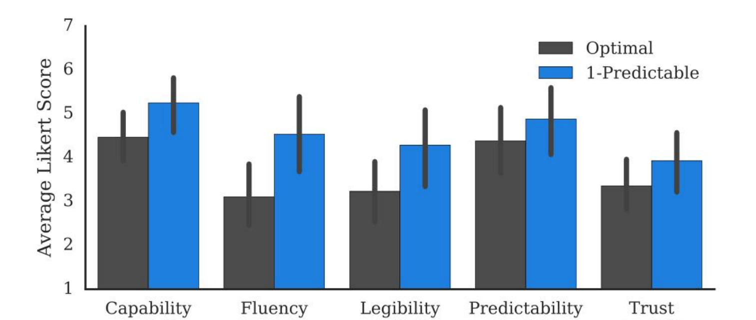

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  - very important for safety and comfort!
- statistically significant evidence that this planner affects how humans predict what robots will do
- collaboration with psychologists, thorough statistical analysis of experiments

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- Tractability: need to compute over all possible remaining action sequences
- In-person experiment is narrow in scope (but needs to be, to show effects of planner)

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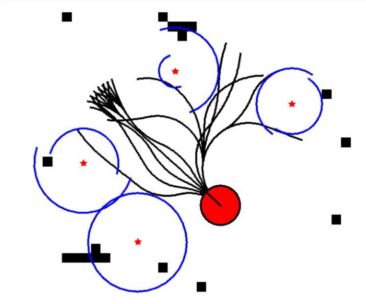

Sample paths generated for the robot (red disk) avoiding the obstacles (black shapes). Figure 13 in *Real-Time Informed Path Sampling for Motion Planning Search* by Ross Knepper and Matt Mason, IJRR 2012 [5]

Thank you!


x k c d
when we open the lab
each morning, we tell
the robot to kill
it's our little joke
but secretly
we're just afraid
to tell it to love
r munroe

References

[1] A. D. Dragan, K. C. Lee, and S. S. Srinivasa, "Legibility and predictability of robot motion," in *Human-robot interaction (hri), 2013 8th acm/ieee international conference on*, 2013, pp. 301–308.

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[5] R. A. Knepper and M. T. Mason, "Real-time informed path sampling for motion planning search," *The International Journal of Robotics Research*, vol. 31, no. 11, pp. 1231–1250, 2012.