



Artificial Intelligence Qualifying Exam

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Robots!

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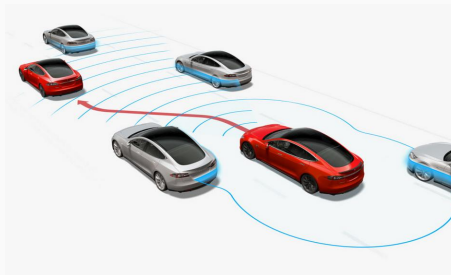
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Why Do We Care?

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

¹Gear Patrol

²US DOL

What is Needed?

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

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

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Background

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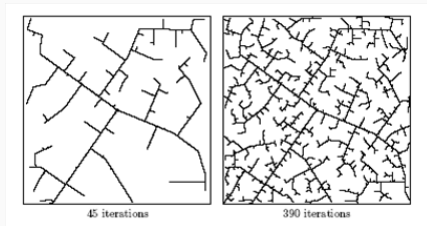
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- Given this, we can estimate the probability that a human will be able to predict *the rest of a robot's plan*, given the goal and the first t steps of the robot's plan
- Optimize plans so that the first t steps make the rest of the plan maximally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

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 $a^* = \arg \max_{a \in \mathcal{A}} \mathcal{P}_t(a)$

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How Do Humans Predict What Robots Will Do?

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

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

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

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

Optimization Using This Model

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

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

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

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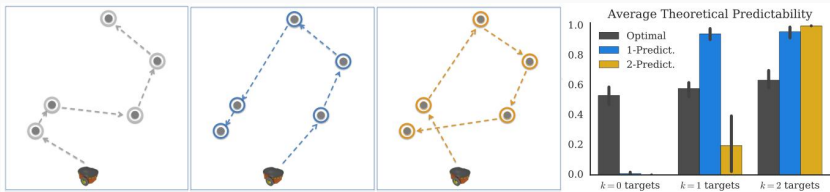
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Use branch-and-bound algorithm to reduce from factorial to exponential time.

t-Predictability



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

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

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primes people to think of shortest path: influences how they may predict what the robot does

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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.

Create 270 randomly generated layouts with five or six targets.

Environment Generation

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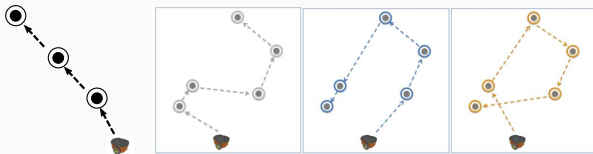
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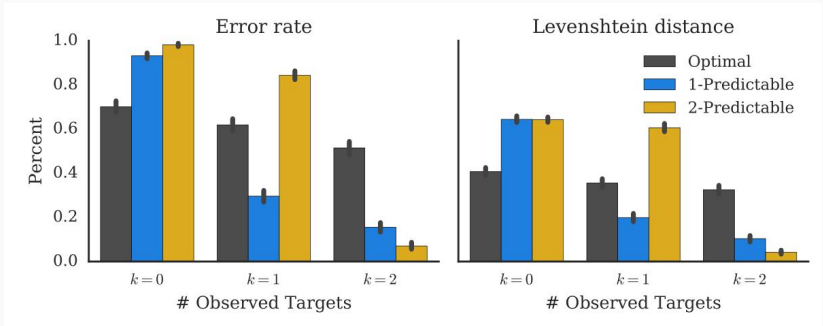
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*This planner is **most useful** in ambiguous settings*

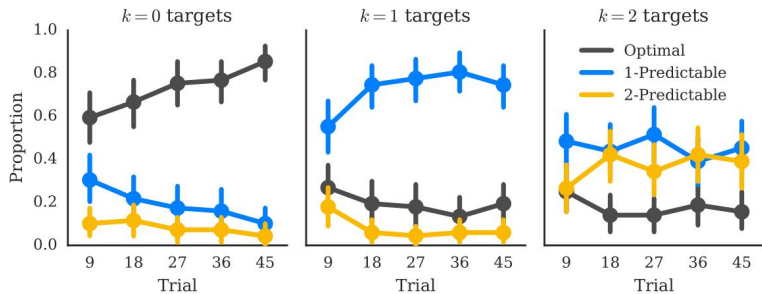


Results



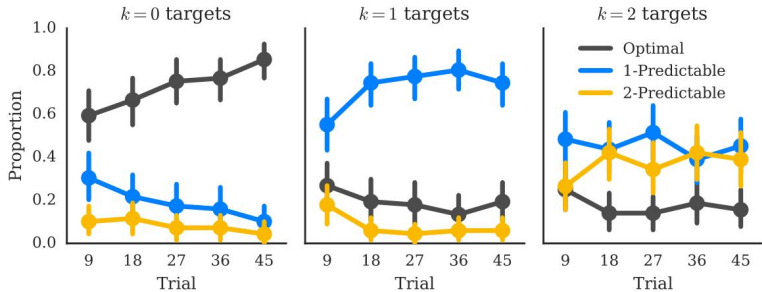
Error rate and Levenshtein distance for user-predicted paths in online experiment. Figure 4 in [1].

Preferences



User preferences over time. Figure 5 in [1].

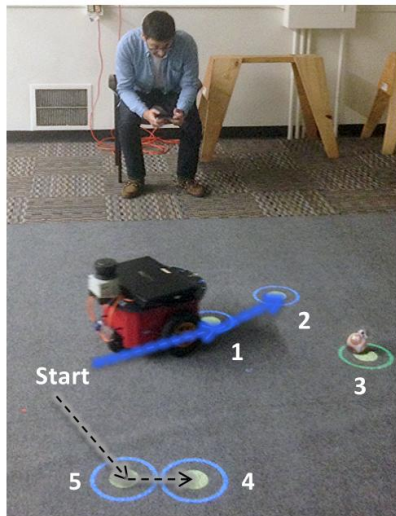
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User preferences over time. Figure 5 in [1].

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

In-Person Experiments



Results

- 1-predictable robot leads to more successful completions

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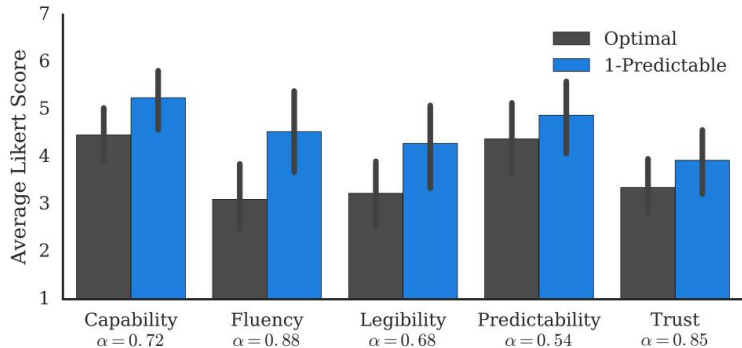
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- statistically significant evidence that this planner affects how humans predict what robots will do

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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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- want a trajectory ξ from start S to goal G

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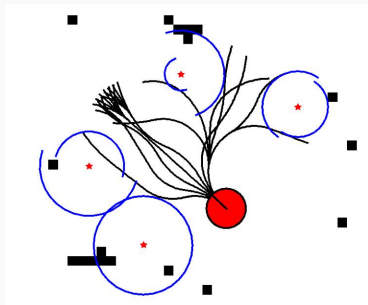
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Sample paths generated for the robot (red disk) avoiding the obstacles (black shapes). Figure 13 in *Real-Time Informed Path Sampling for Motion Planning Search* by Ross Knepper and Matt Mason, IJRR 2012 [2]

Thank you!

- [1] J. Fisac, C. Liu, J. B. Hamrick, S. Sastry, J. K. Hedrick, T. L. Griffiths, and A. D. Dragan, “Generating plans that predict themselves,” in *Workshop on the algorithmic foundations of robotics (wafr)*, 2016.
- [2] 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.