Towards harmonious mobility in pedestrian environments

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Successful robotics paradigm

Jens Schlueter/Getty images

Amazon/Kiva

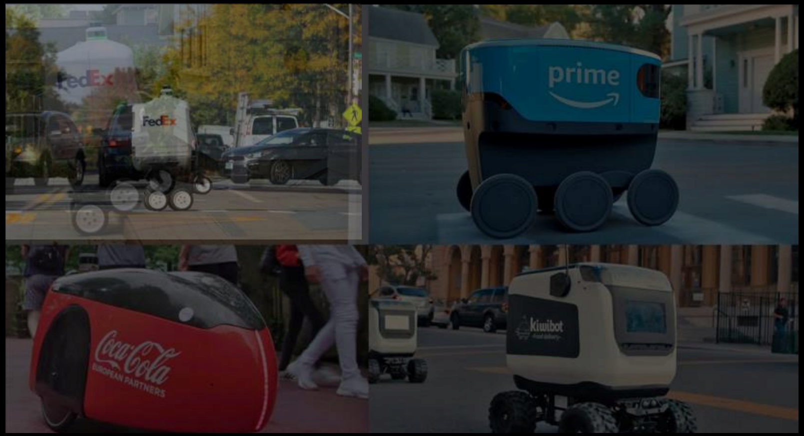
A new paradigm

Patrick T. Fallon / AFP via Getty Images

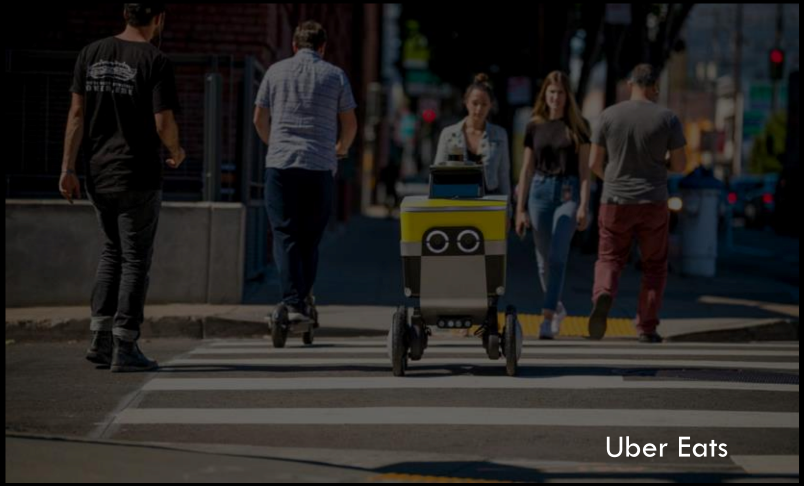

Uber Eats


Pablo Martinez Monsivais / AP

A new paradigm



Social navigation: an essential skill



Uber Eats

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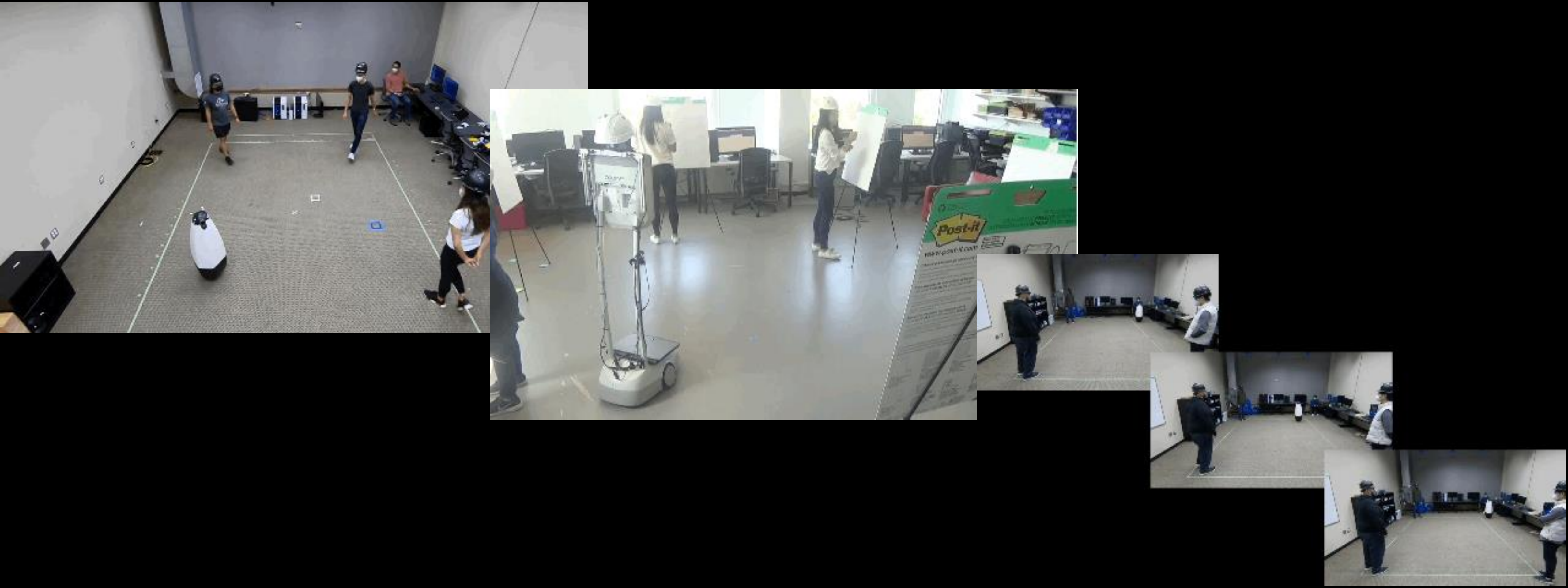
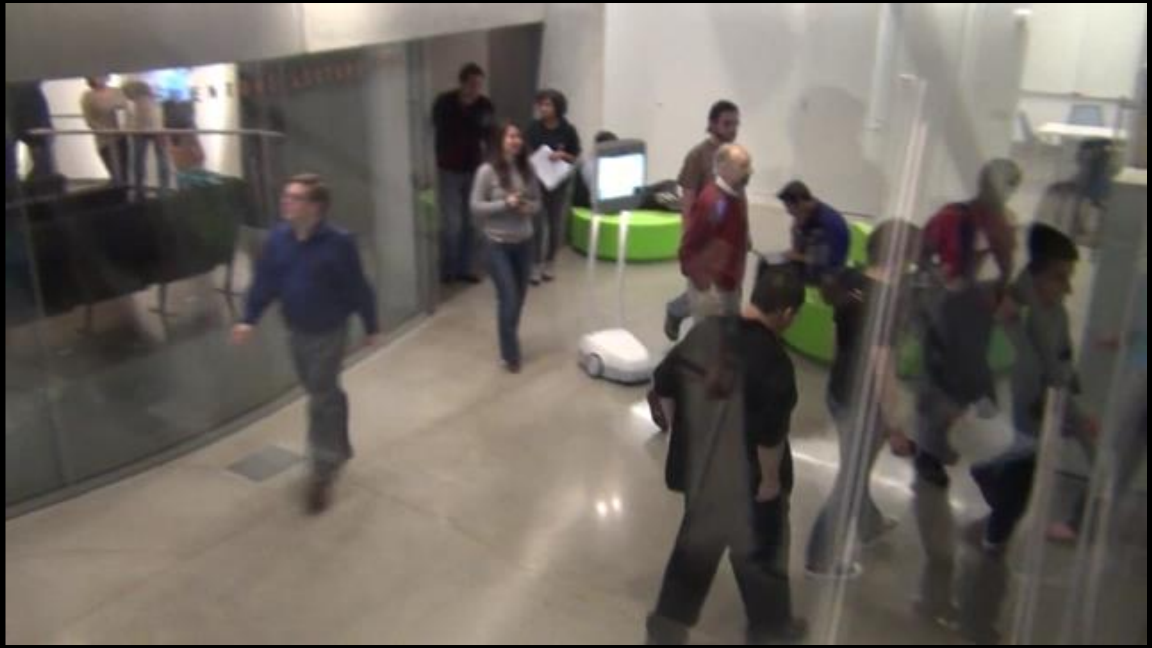
Full-stack approach to social navigation



Social robot navigation

The challenge

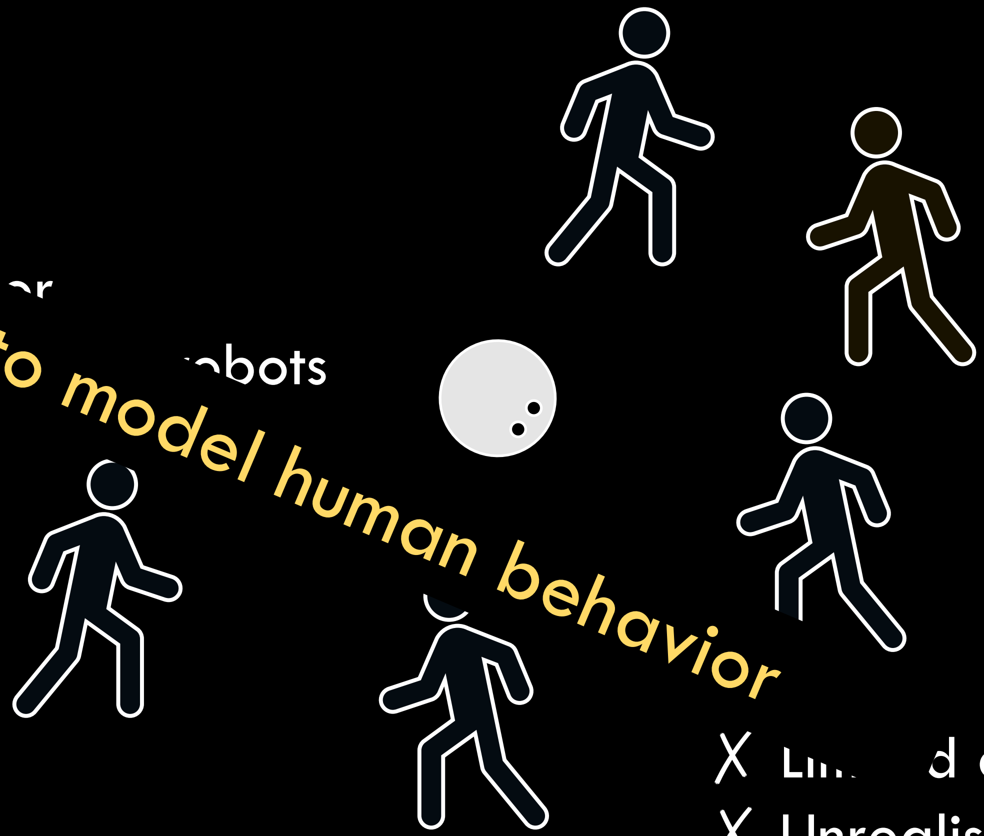


Gates Hall, Cornell University, 2015

The challenge

- ✗ Rich context
- ✗ Large space c … ior
- ✗ Limited mental mod … bots
- ✗ No rules

Hard to model human behavior



- ✗ Li … d datasets
- ✗ Unrealistic simulators


How do humans do it?

Wolfinger '95

Pedestrian interaction is inherently complex yet observably ordered. For order to be possible, people must behave like competent pedestrians and must expect copresent others to act accordingly. Although many researchers have examined pedestrian behavior, few have considered exactly how pedestrians develop and sustain the expectation that others will indeed behave like competent pedestrians. Using ethnographic data, the author shows how these expectations emerge in the specific practices that comprise pedestrian behavior. Various researchers have attributed pedestrian order to the existence of a tacit contract between users of public space. The author's findings extend the implications of this work by explicating the social and collaborative processes by which users of public space come to trust each other to act like competent pedestrians.

PASSING MOMENTS

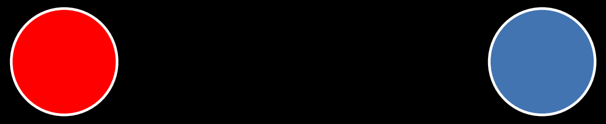
Some Social Dynamics of Pedestrian Interaction

Insight

Enabling robots to represent passing could mitigate lack of accurate models

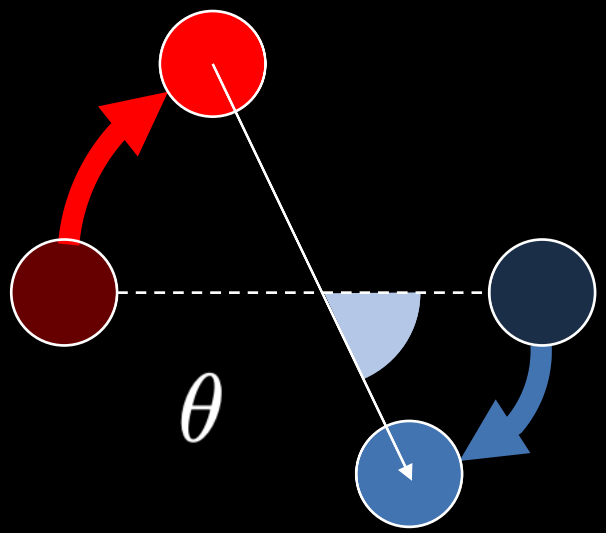
How can we formalize passing?

Passing as rotation

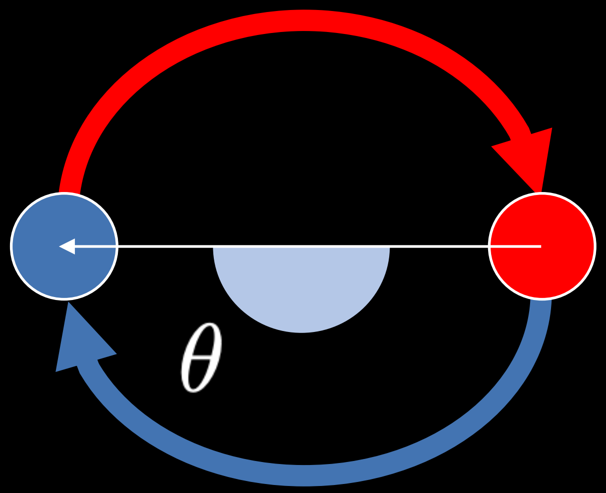


Passing as rotation

Passing as rotation



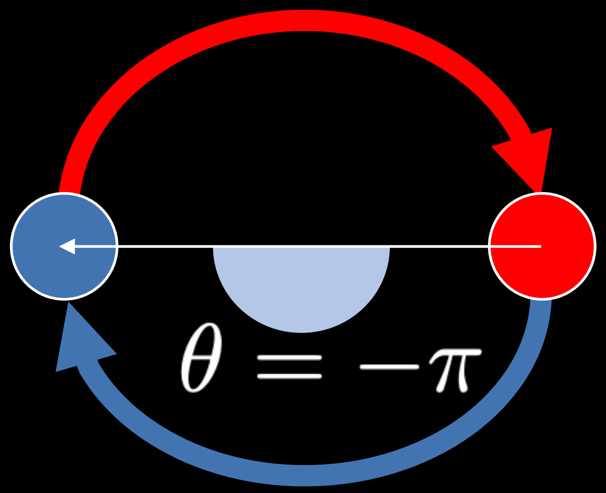
Passing as rotation



Passing as rotation

$$\lambda = \frac{1}{2\pi}\int d\theta$$

Winding number



Progress

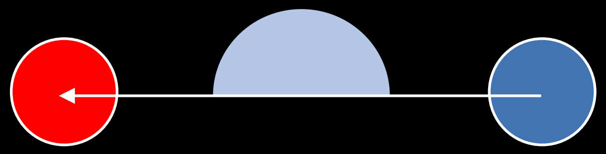
Side

$$\lambda = -0.5$$

Passing as rotation

$$\lambda = \frac{1}{2\pi}\int d\theta$$

Winding number



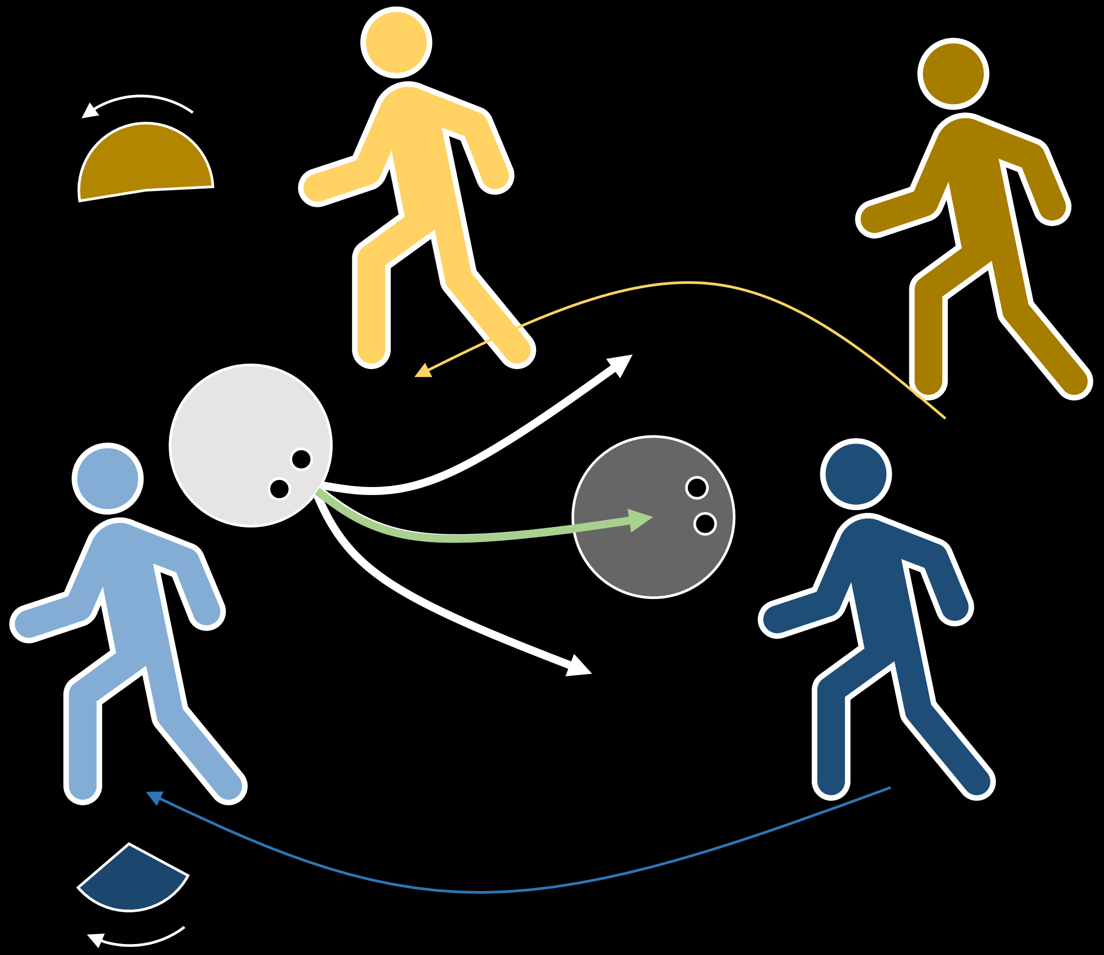
$$\theta = \pi$$

Progress

Side

$$\lambda = +0.5$$

Monitor and expedite passing

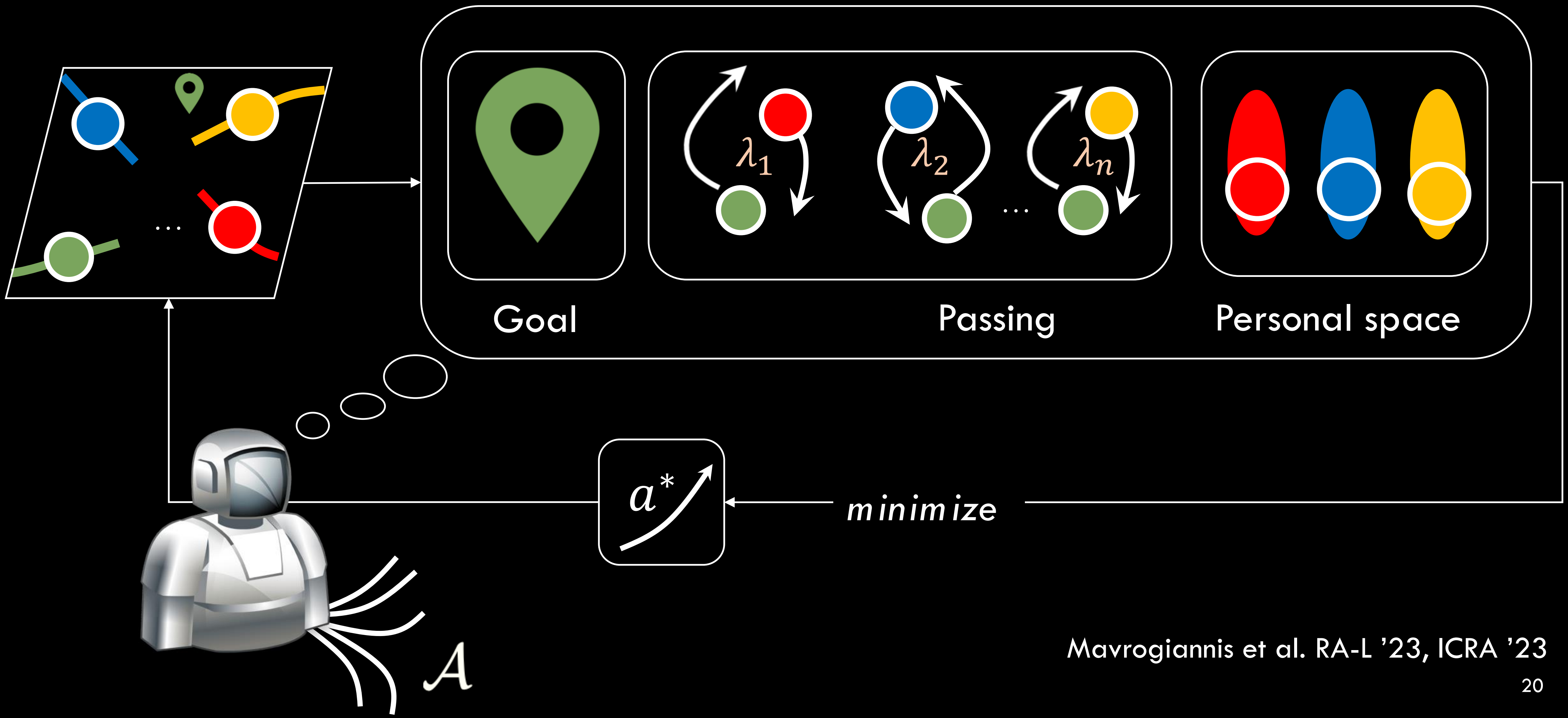


$$\mathcal{J} = -\frac{1}{n}\sum_{i=1}^{n}\lambda_i^2$$

Motivate actions
that maximize passing progress

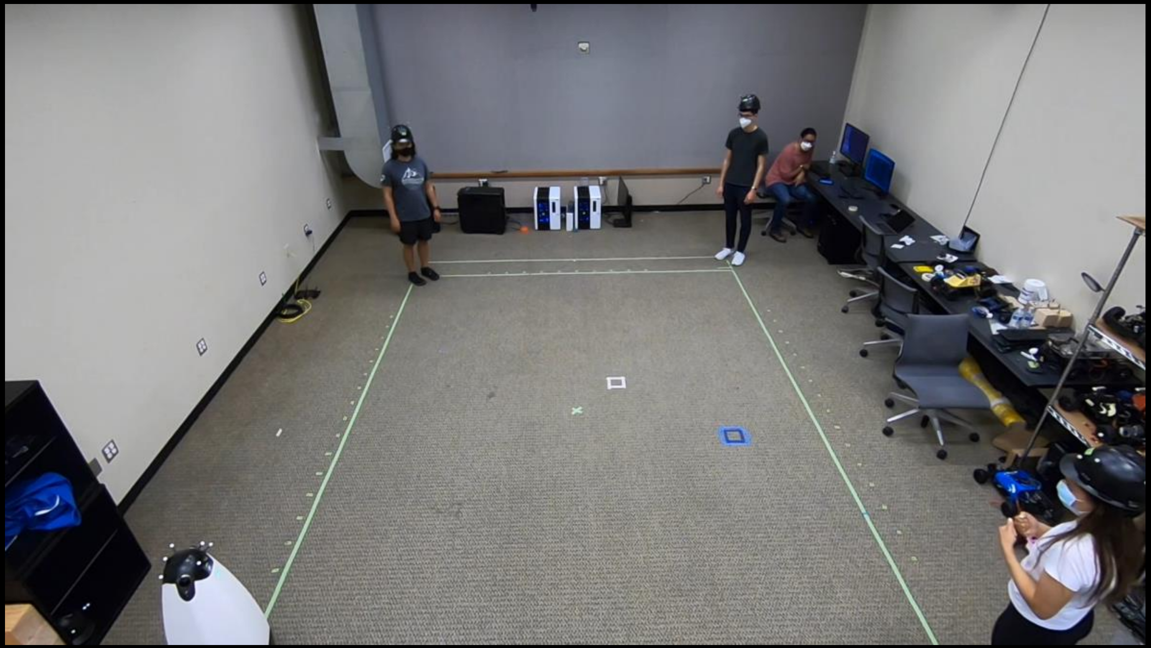
A passing-aware MPC

Constant velocity prediction!

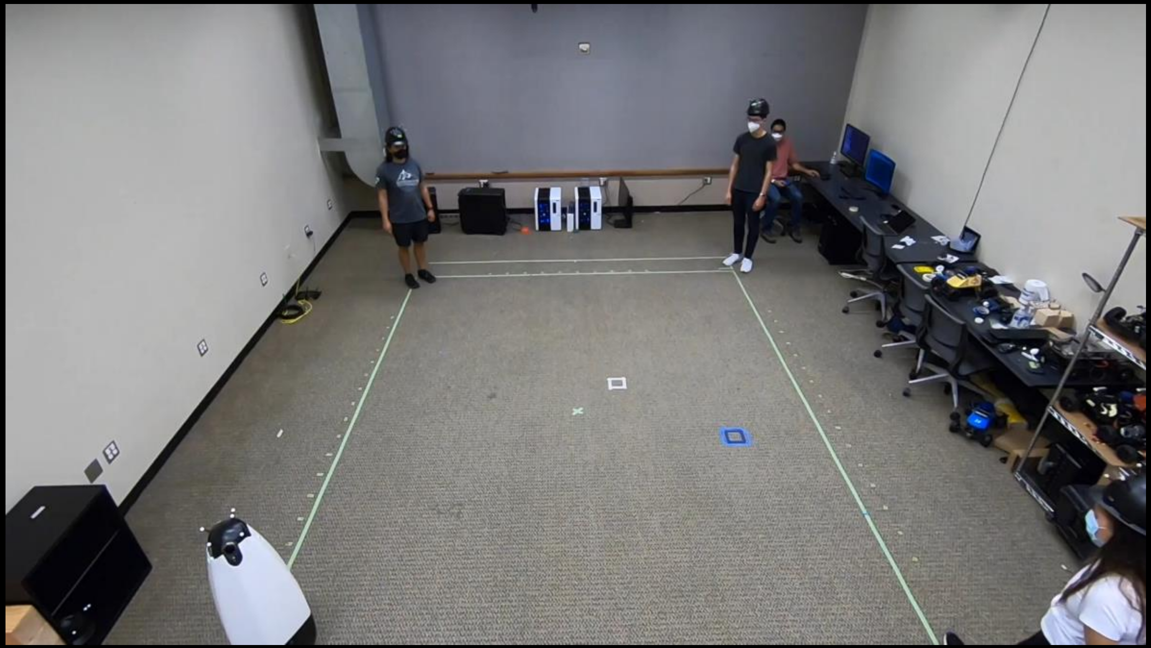


Mavrogiannis et al. RA-L ’23, ICRA ’23

Safe, efficient navigation in dense crowds

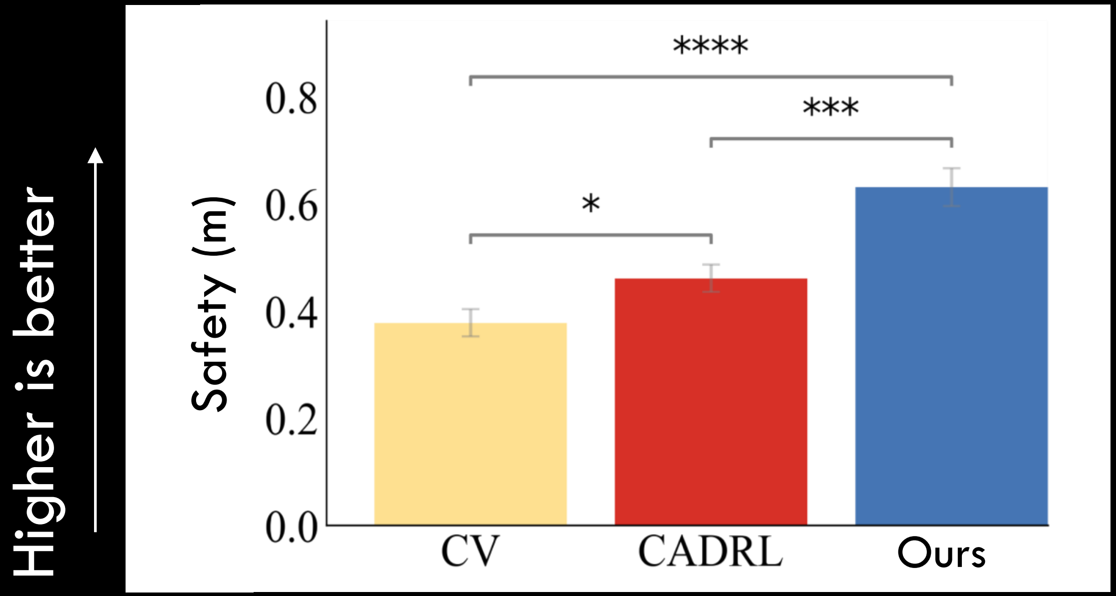


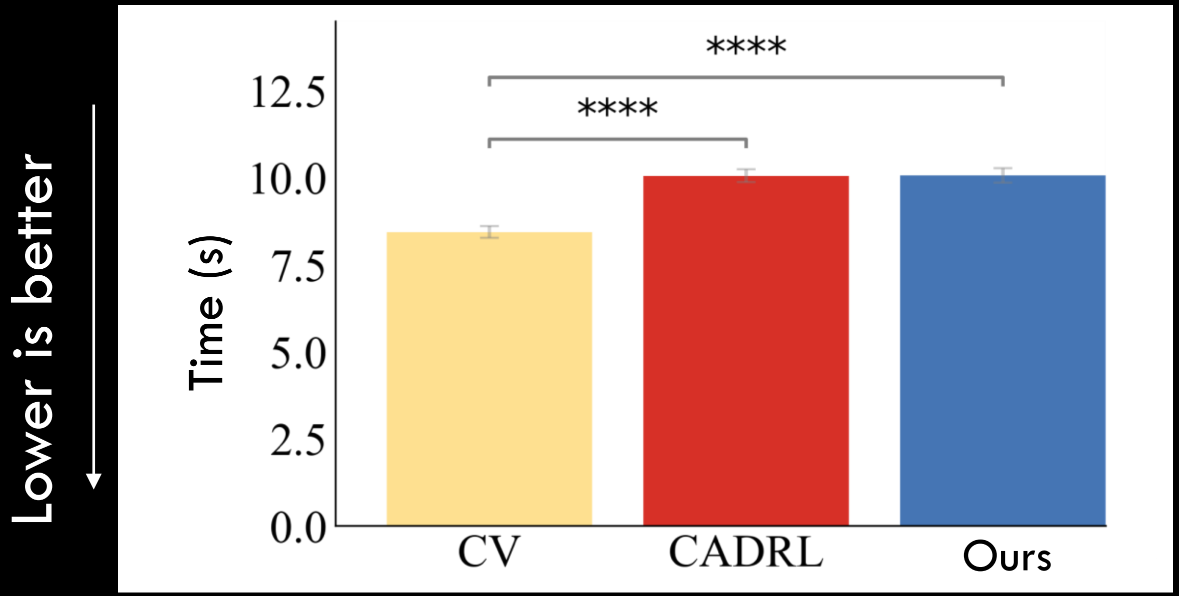
CADRL [Everett et al., IROS ’18]



Ours [Mavrogiannis et al. RAL ’23, ICRA ’23]

Safe, efficient navigation in dense crowds





✓ Domain knowledge & math insights empower simple models

✗ Simple models might struggle with more complex settings

Sriyash Poddar

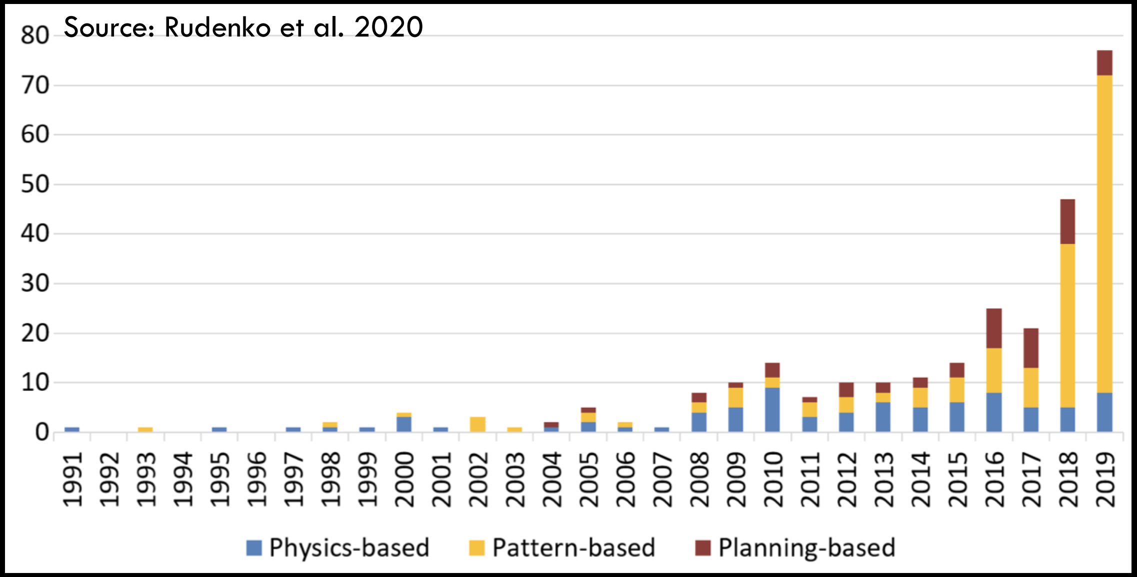
Scaling to complex settings

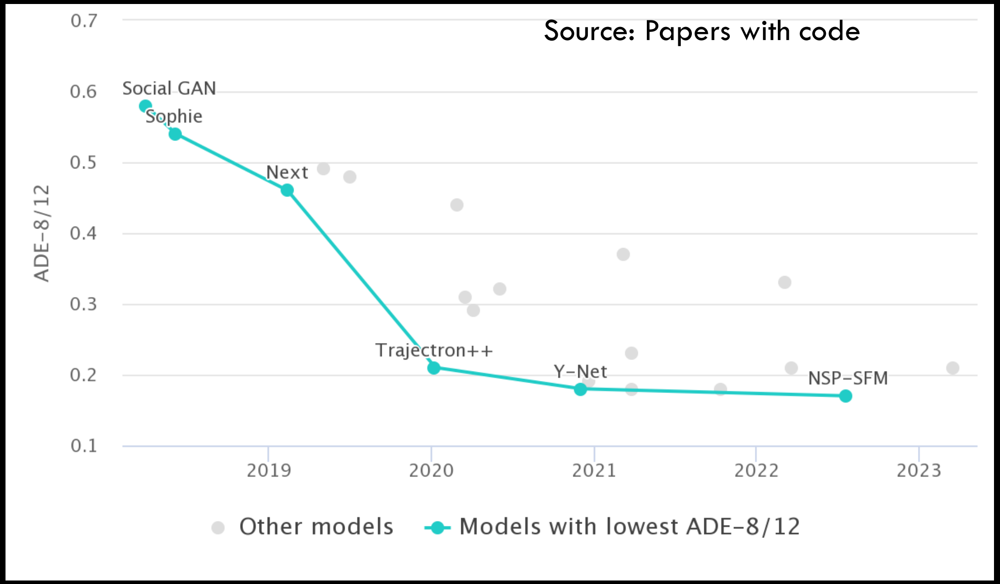
"From crowd motion prediction to robot navigation in crowds"

Poddar, Mavrogiannis, Srinivasa

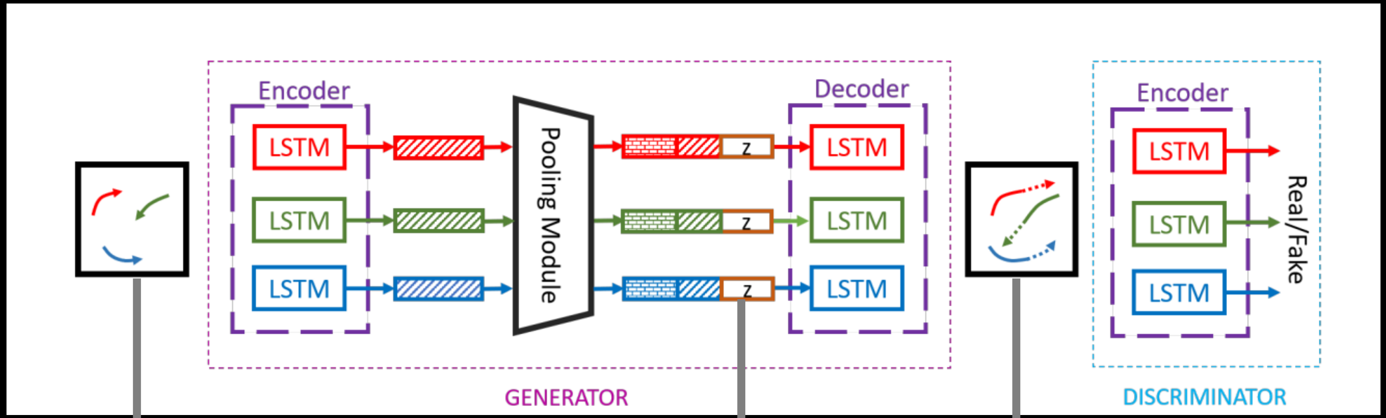
Motion and Path Planning IV; 14:48-14:54, Paper TuBT9.9

Human motion prediction





Probabilistic prediction based on S-GAN



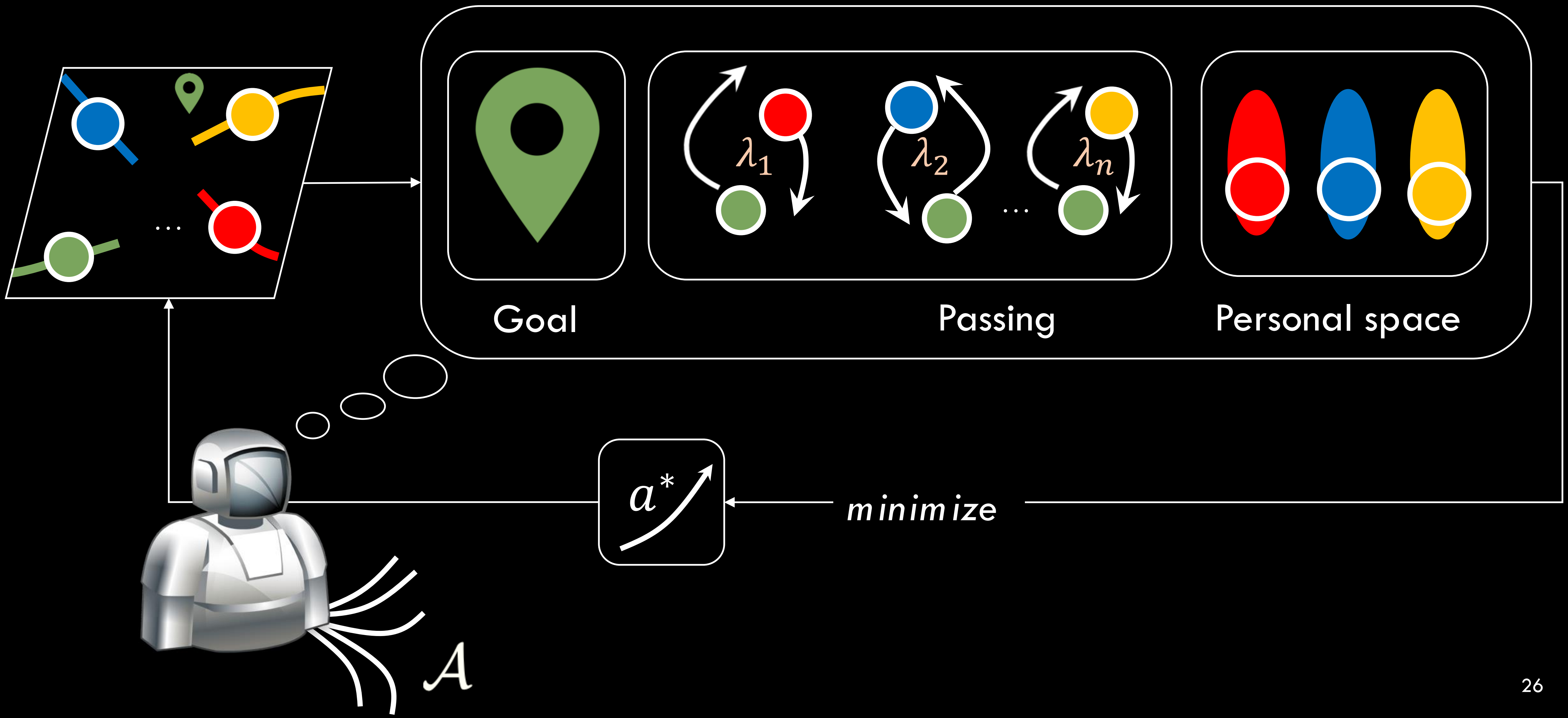
$$f(\boldsymbol{s}^{1:n}_{t-h:t}) = \mathcal{G}(\boldsymbol{s}^{1:n}_{t-h:t}, z) \sim p(\hat{\boldsymbol{s}}^{1:n} | \boldsymbol{s}^{1:n}_{t-h:t})$$

Conditional distribution over future trajectories given window of the past

S-GAN. Gupta et al. 2018

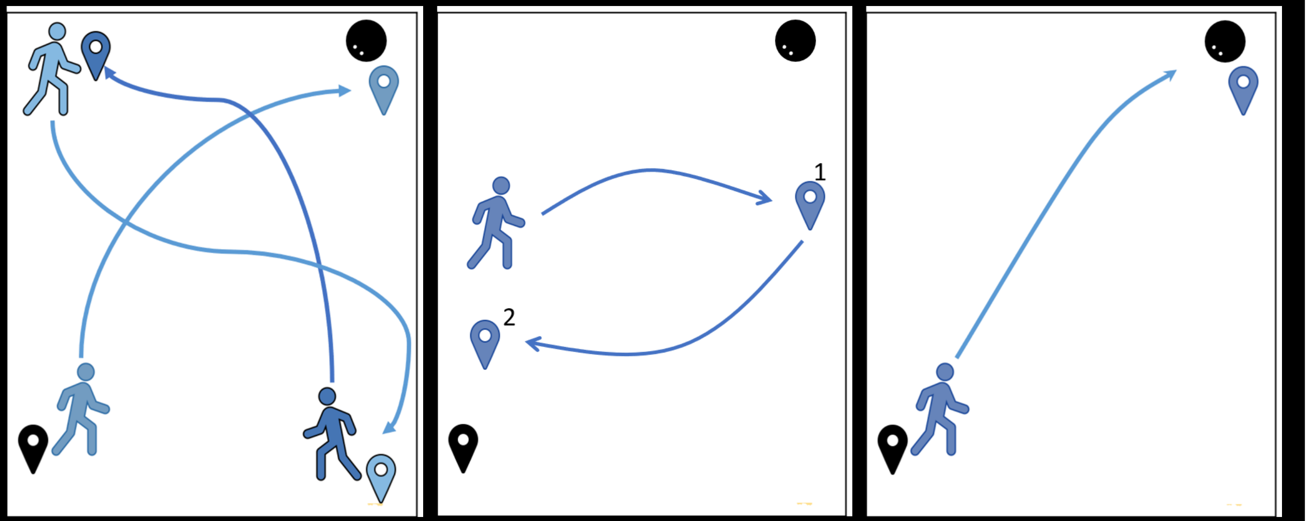
S-GAN based probabilistic prediction!

A passing-aware MPC



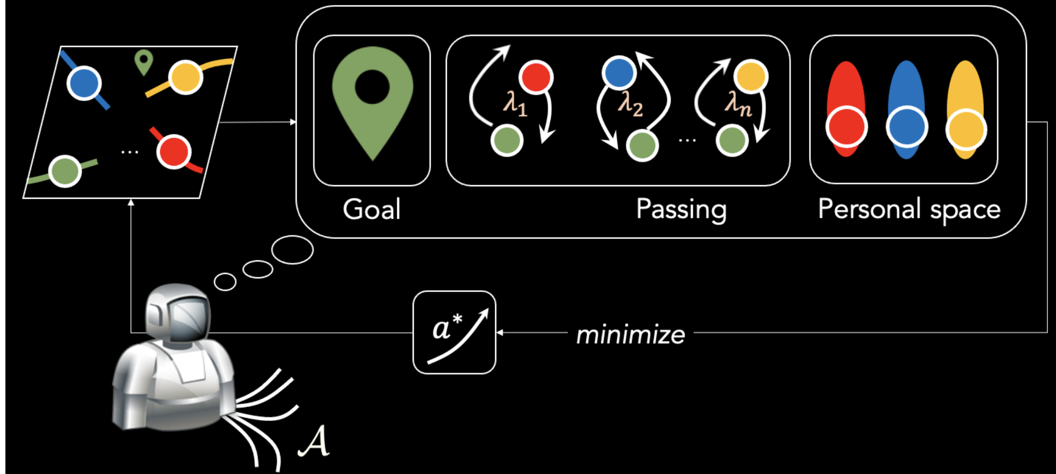
Lab experiments

3 Conditions



Cooperative Distracted Aggressive

3 MPC variants



S-GAN-1

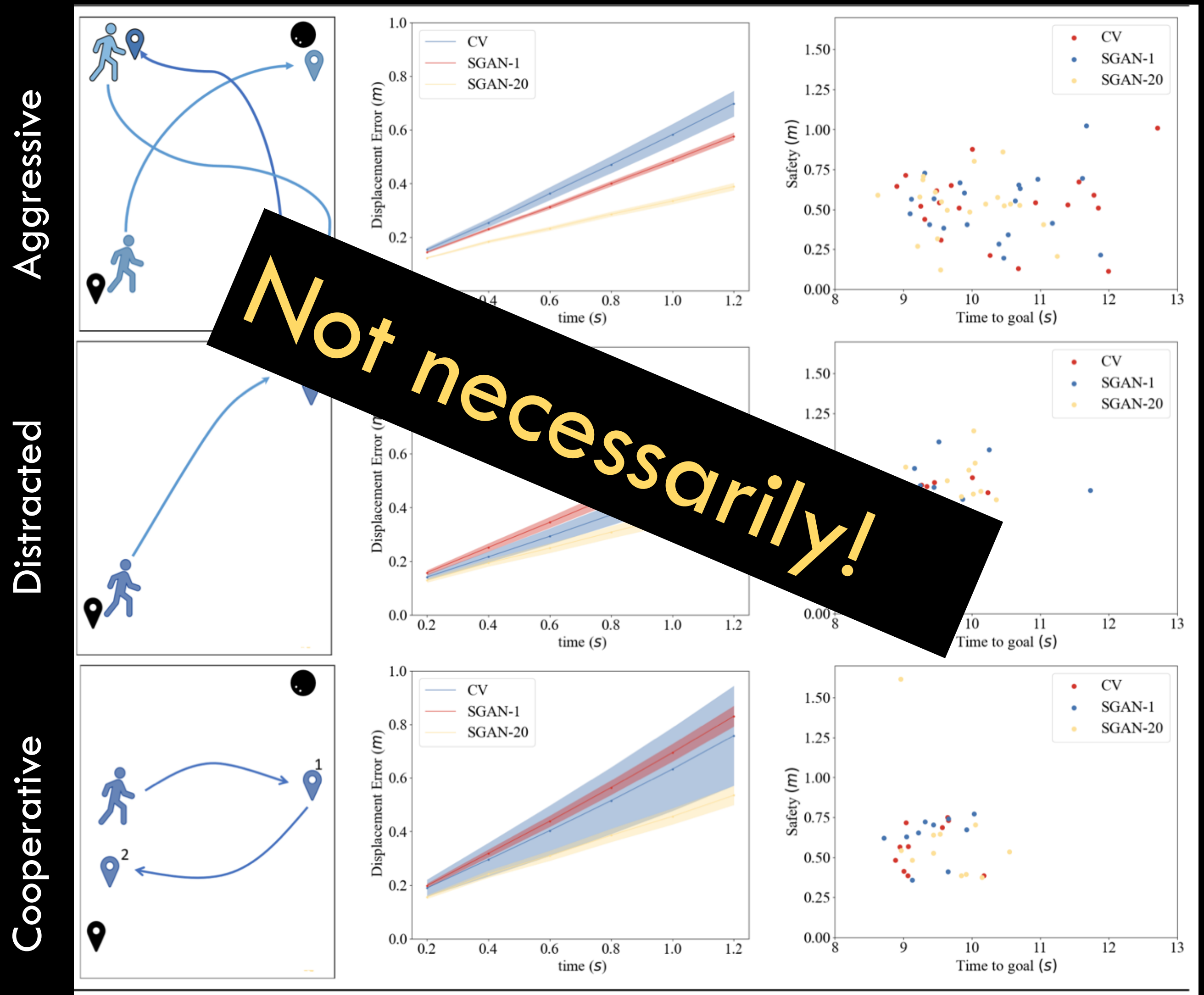
S-GAN-20

CV [Mavrogiannis et al. 2023]

Cooperative

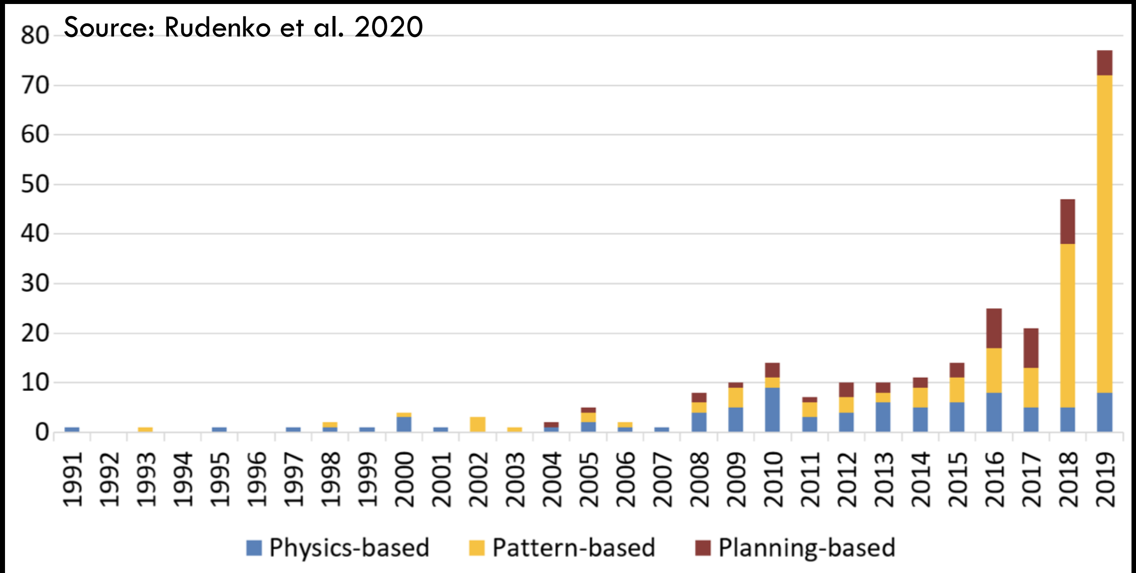
Better prediction ⇒ better navigation?

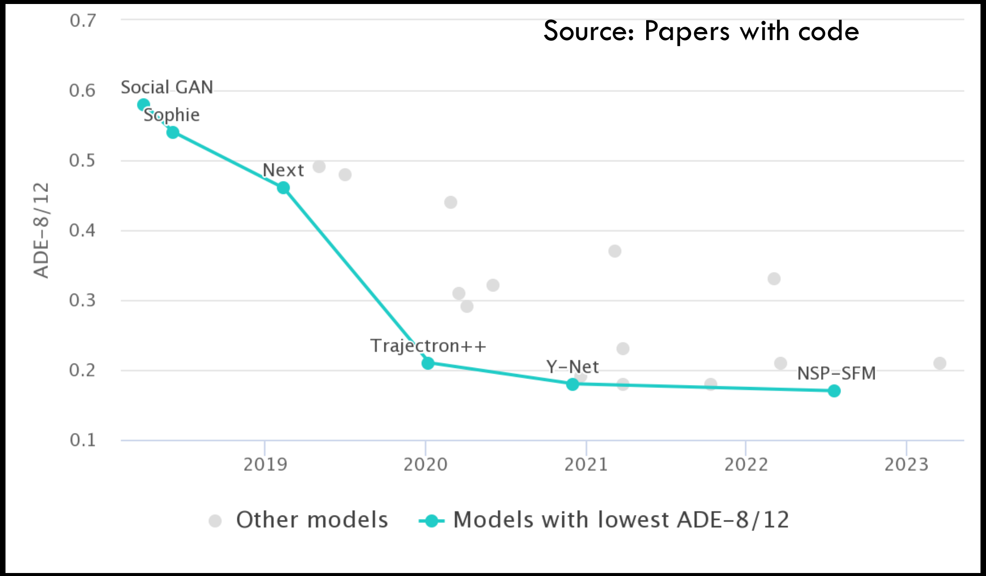
Prediction error | Safety vs Efficiency



CV ~ S-GAN

Human motion prediction: relevance to social robot navigation?





Better benchmarks/metrics

Better datasets/simulators

Deeper user understanding

Understanding users’ perceptions

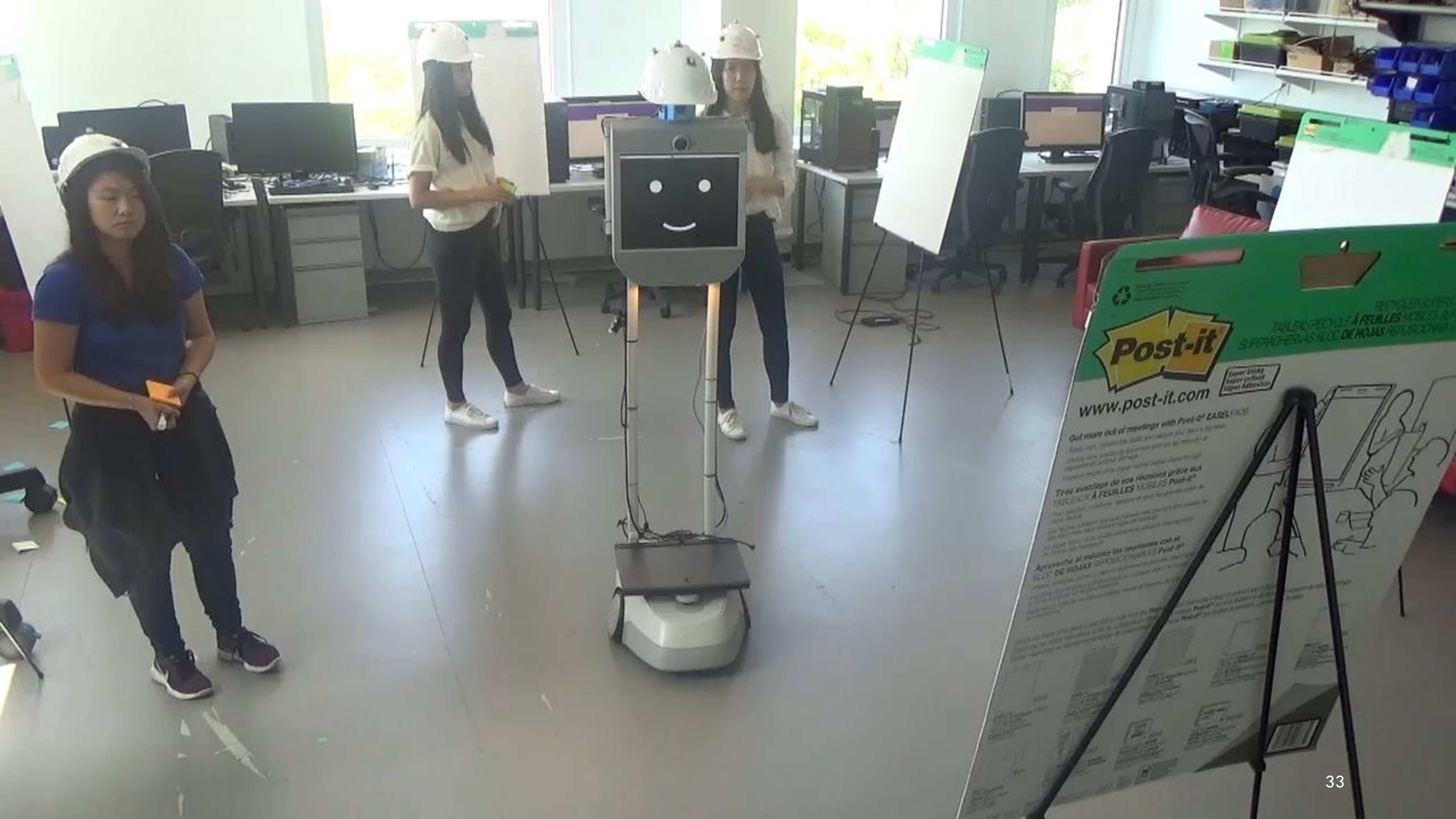
Mavrogiannis et al. HRI ’19, T-HRI ’22

Experiment design for social navigation

Natural walking

Crowded space

Challenging interactions


Post-it
www.post-it.com

Within subjects, 3 conditions

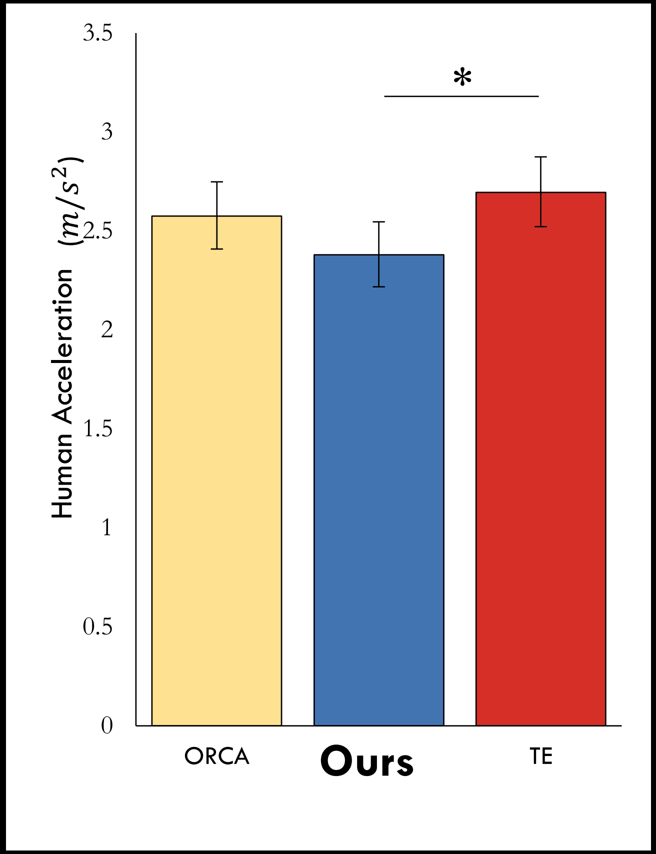
Ours
[Mavrogiannis et al., ’18]

ORCA
[Van den Berg et al., ’09]

Teleoperation (TE)

105 users walked more comfortably

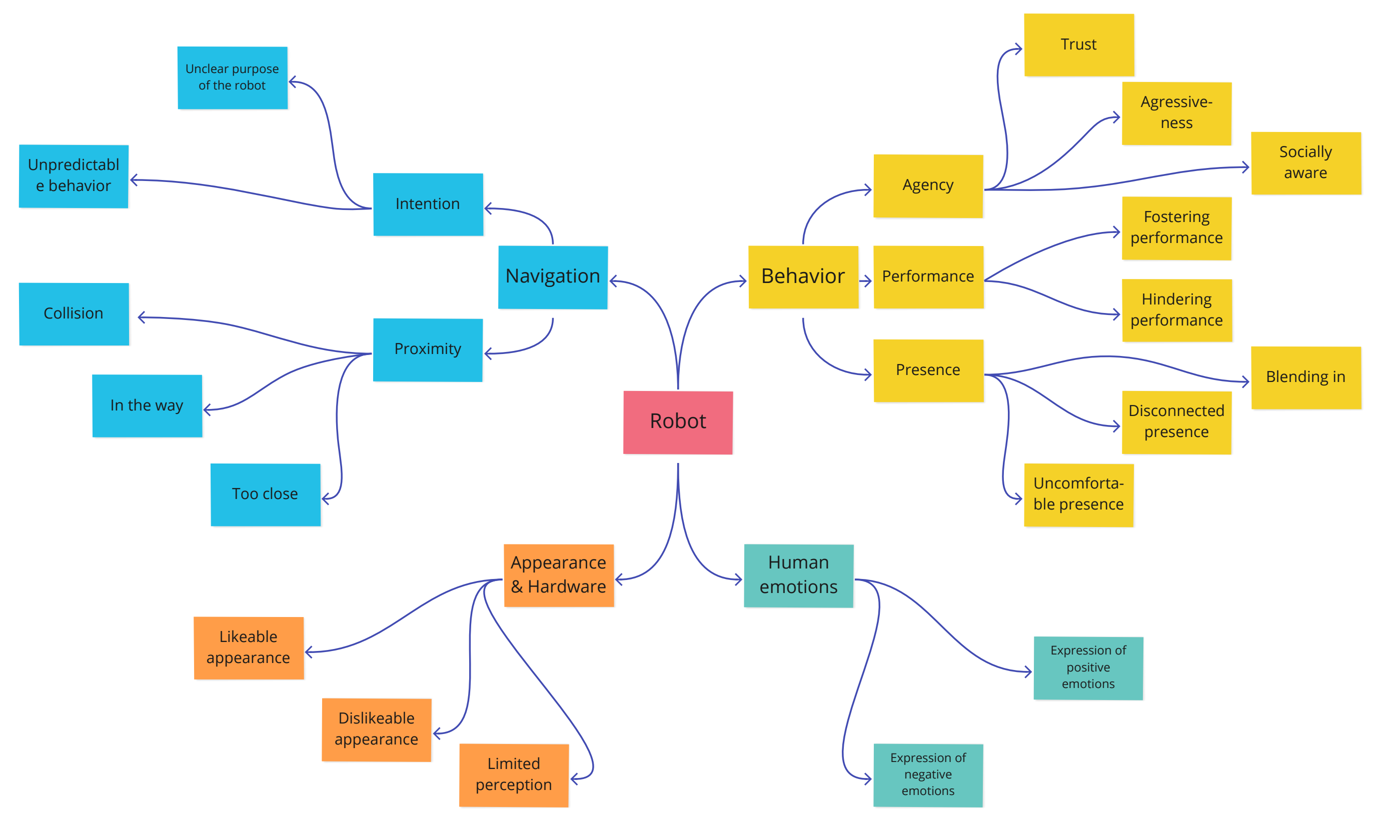
Lower is better



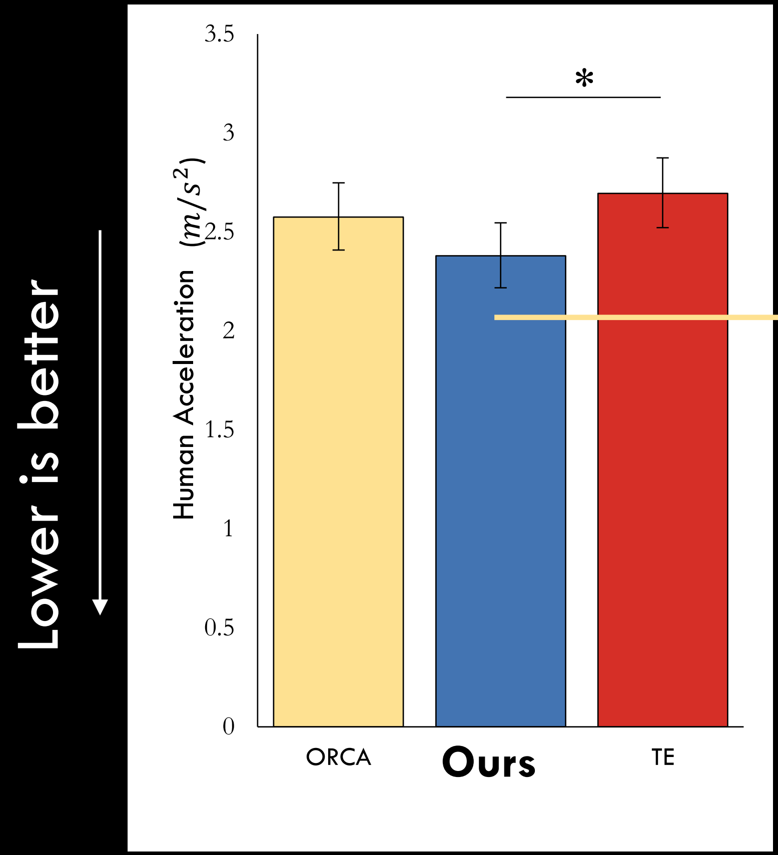
Lower acceleration

Users were less disturbed by the robot

Thematic analysis of short responses



105 users walked more comfortably



"I barely noticed the robot when I was performing the tasks"
(Ours)

"I had no idea what the robot was doing"
(TE)

"I felt the robot was in my personal space"
(ORCA)

There is more to human perceptions…

Many additional challenges

Qualitative↔quantitative

User-centered benchmarking

Core Challenges of Social Robot Navigation: A Survey

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Robot navigation in crowded public spaces is a complex task that requires addressing a variety of engineering and human factors challenges. These challenges have motivated a great amount of research resulting in important developments for the fields of robotics and human-robot interaction over the past three decades. Despite the significant progress and the massive recent interest, we observe a number of significant remaining challenges that prohibit the seamless deployment of autonomous robots in crowded environments. In this survey article, we organize existing challenges into a set of categories related to broader open problems in robot planning, behavior design, and evaluation methodologies. Within these categories, we review past work, and offer directions for future research. Our work builds upon and extends earlier survey efforts by a) taking a critical perspective and diagnosing fundamental limitations of adopted practices in the field and b) offering constructive feedback and ideas that could inspire research in the field over the coming decade.

CCS Concepts: • **Computing methodologies** → **Simulation evaluation**; **Reinforcement learning**; **Robotic planning**; • **Computer systems organization** → **Robotics**; **Robotic control**; • **Human-centered computing** → *User studies.*

Additional Key Words and Phrases: Social robot navigation, motion planning, motion prediction, multiagent systems, social robotics, benchmarking

Mavrogiannis et al. T-HRI 2023

Insights

Domain insights empower simple models

Scaling requires expressive models

But transfer on real robots is nontrivial

Need for extensive user validation & benchmarks

A new paradigm

Patrick T. Fallon / AFP via Getty Images

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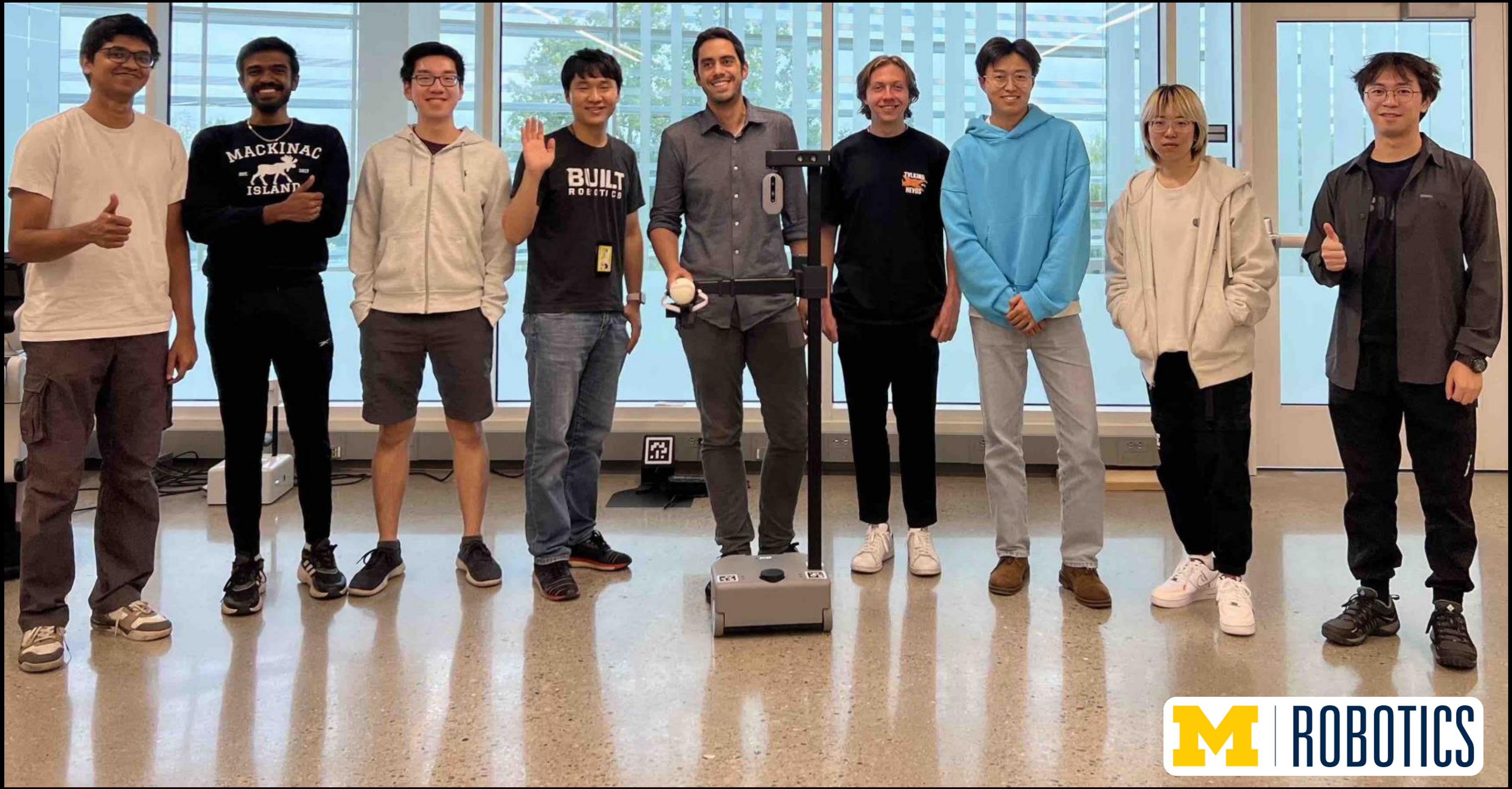
The Fluent Robotics Lab



fluent.robotics.umich.edu

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