ECE / CS 598 SG

Special Topics in Learning-based Robotics

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Today, we will…

- Course outline
- Course logistics
- Get to know each other

Understand how we can build intelligent machines

Does that mean game playing agents?

How Google's AlphaGo Beat a Go World Champion

Inside a man-versus-machine showdown

CHRISTOPHER MOYER MARCH 28, 2016

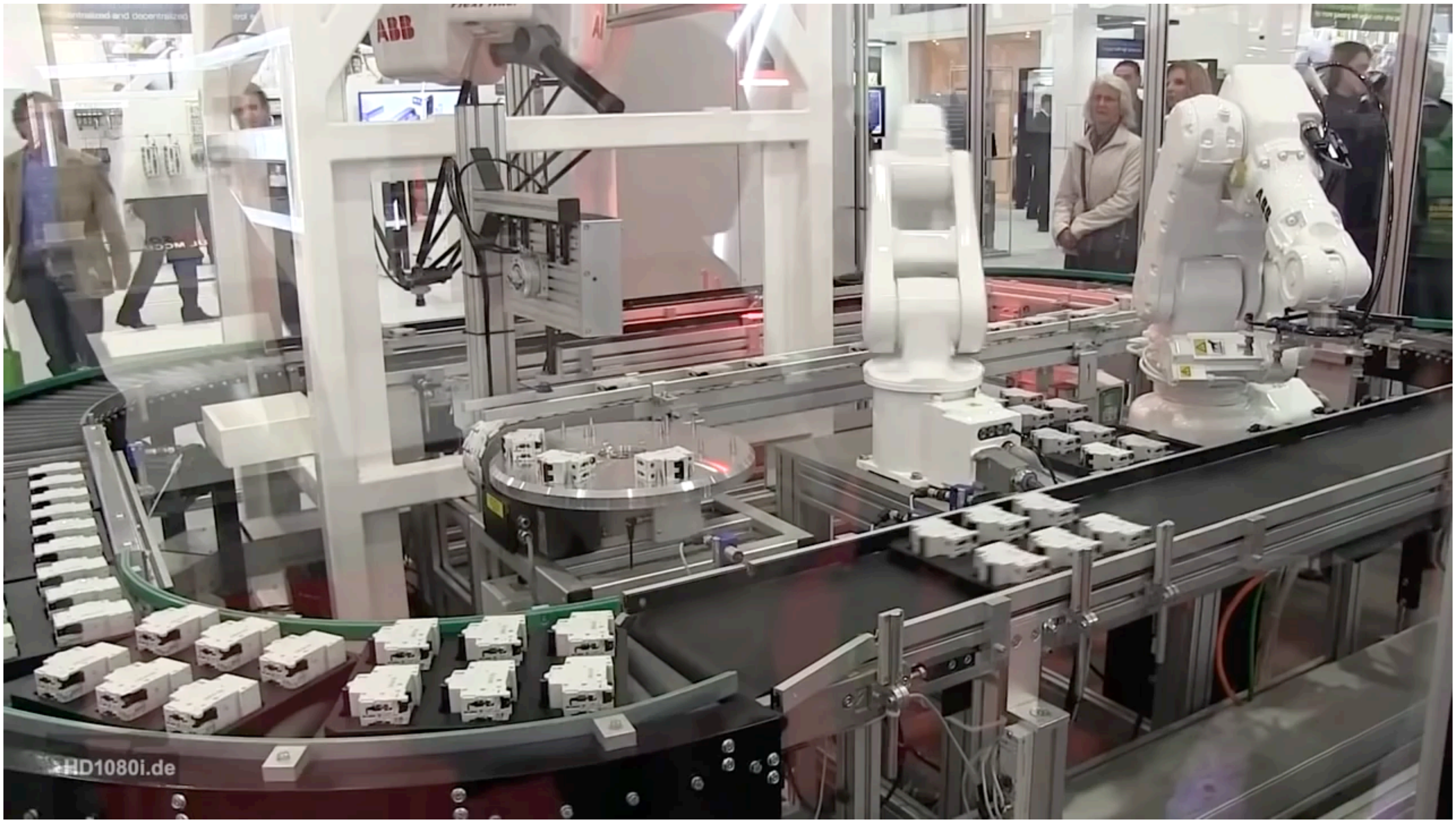
The South Korean professional Go player Lee Sedol reviews the match after finishing against Google's artificial-intelligence program, AlphaGo. (LEE JIN-MAN / AP)

Source: *The Atlantic*

Understand how we can build intelligent machines

… that can favorably change the state of the *physical* world around them.

Does that mean factory robots?



Understand how we can build intelligent machines

… that can favorably change the state of the physical world around them.

Or these fun Boston Dynamics robots?

Video credit: Boston Dynamics, CNN

Understand how we can build intelligent machines

… that can favorably change the state of *cluttered real world* environments to solve *a variety of tasks*.

Understand how far are we from making this PR1 showcase a reality.

Video credit: Pieter Abbeel

What can or can't robots do today?

Dexterous robot hands generally available.	NET 2030 BY 2040 (I hope!)
A robot that can navigate around just about any US home, with its steps, its clutter, its narrow pathways between furniture, etc.	Lab demo: NET 2026 Expensive product: NET 2030 Affordable product: NET 2035
A robot that can provide physical assistance to the elderly over multiple tasks (e.g., getting into and out of bed, washing, using the toilet, etc.) rather than just a point solution.	NET 2028

A robot that can carry out the last 10 yards of delivery, getting from a vehicle into a house and putting the package inside the front door.	Lab demo: NET 2025 Deployed systems: NET 2028

A robot that seems as intelligent, as attentive, and as faithful, as a dog.	NET 2048
A robot that has any real idea about its own existence, or the existence of humans in the way that a six year old understands humans.	NIML

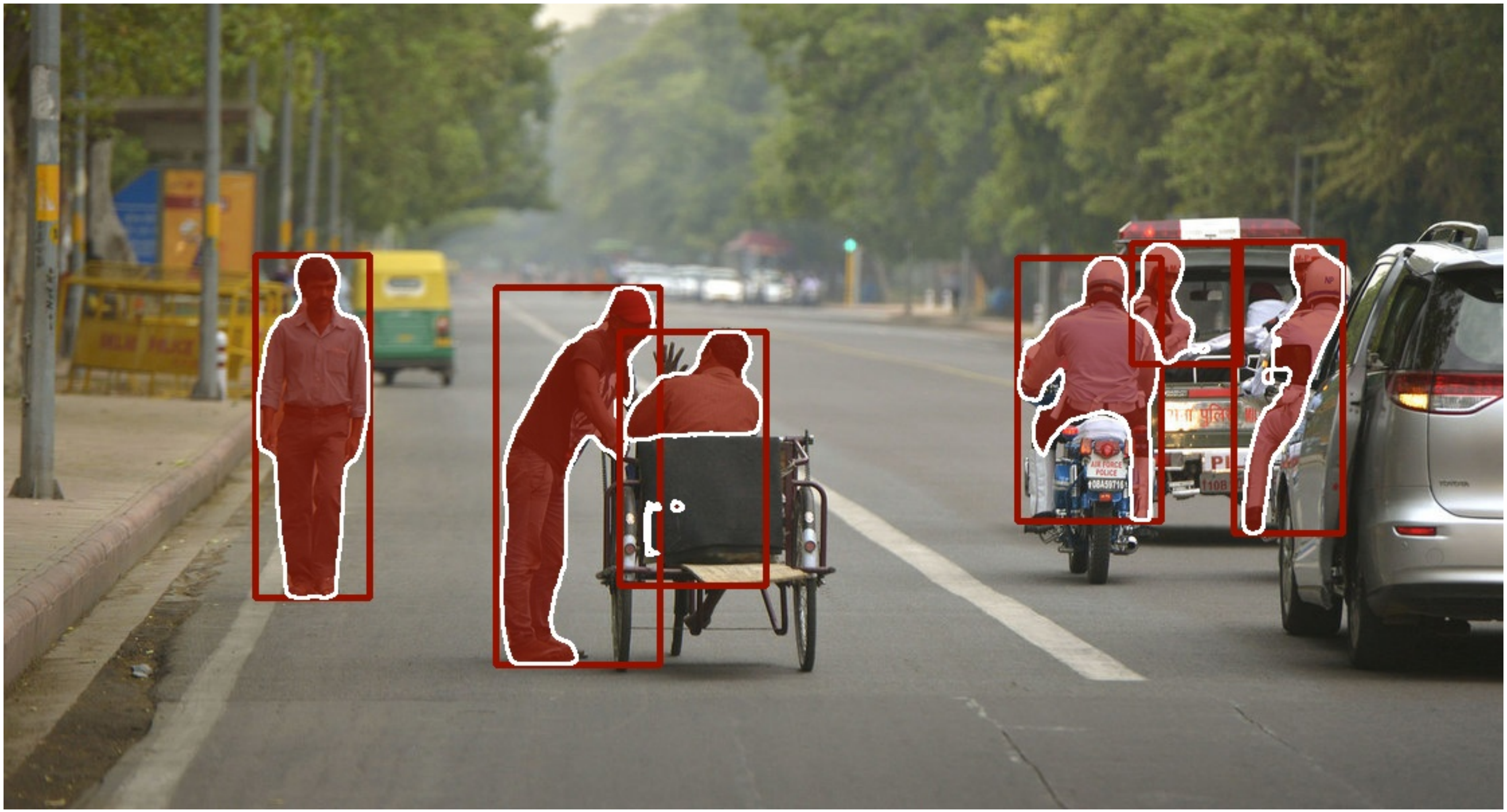
Source: Rodney Brooks: https://rodneybrooks.com/my-dated-predictions/

Goals of the Course

- Understand state-of-the-art in robotics and robot learning

Successes in Computer Vision "in the Wild"

Image Labeling Tasks

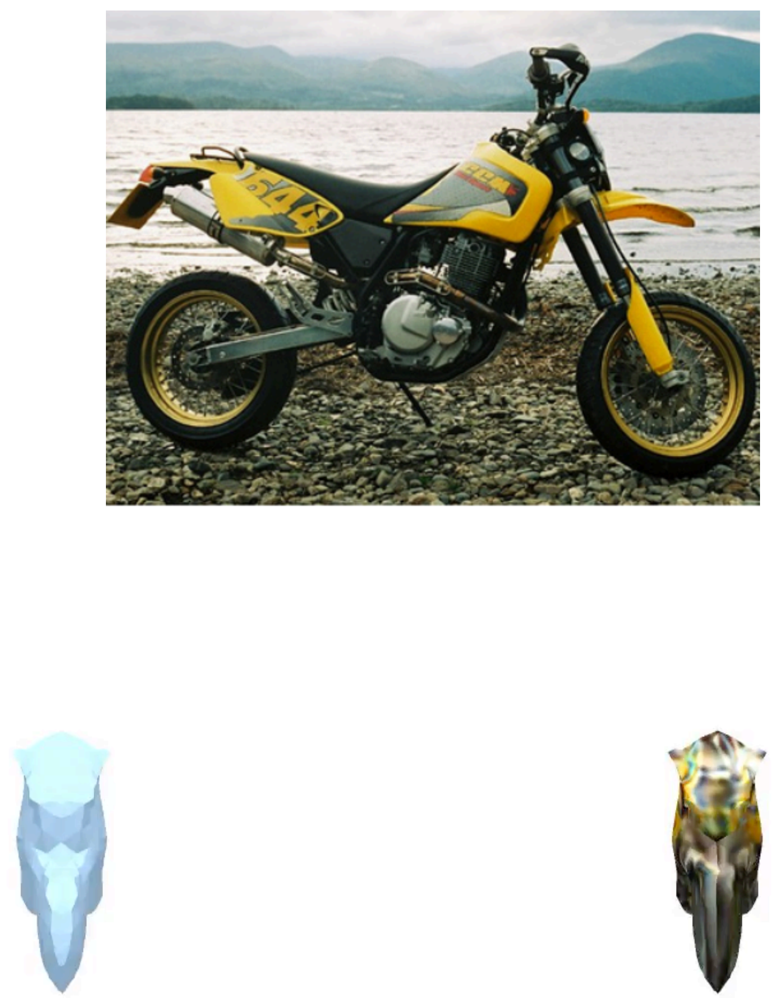


person, motorcycle, car, chair

K. He et al. **Mask R-CNN** ICCV 2017

Successes in Computer Vision "in the Wild"

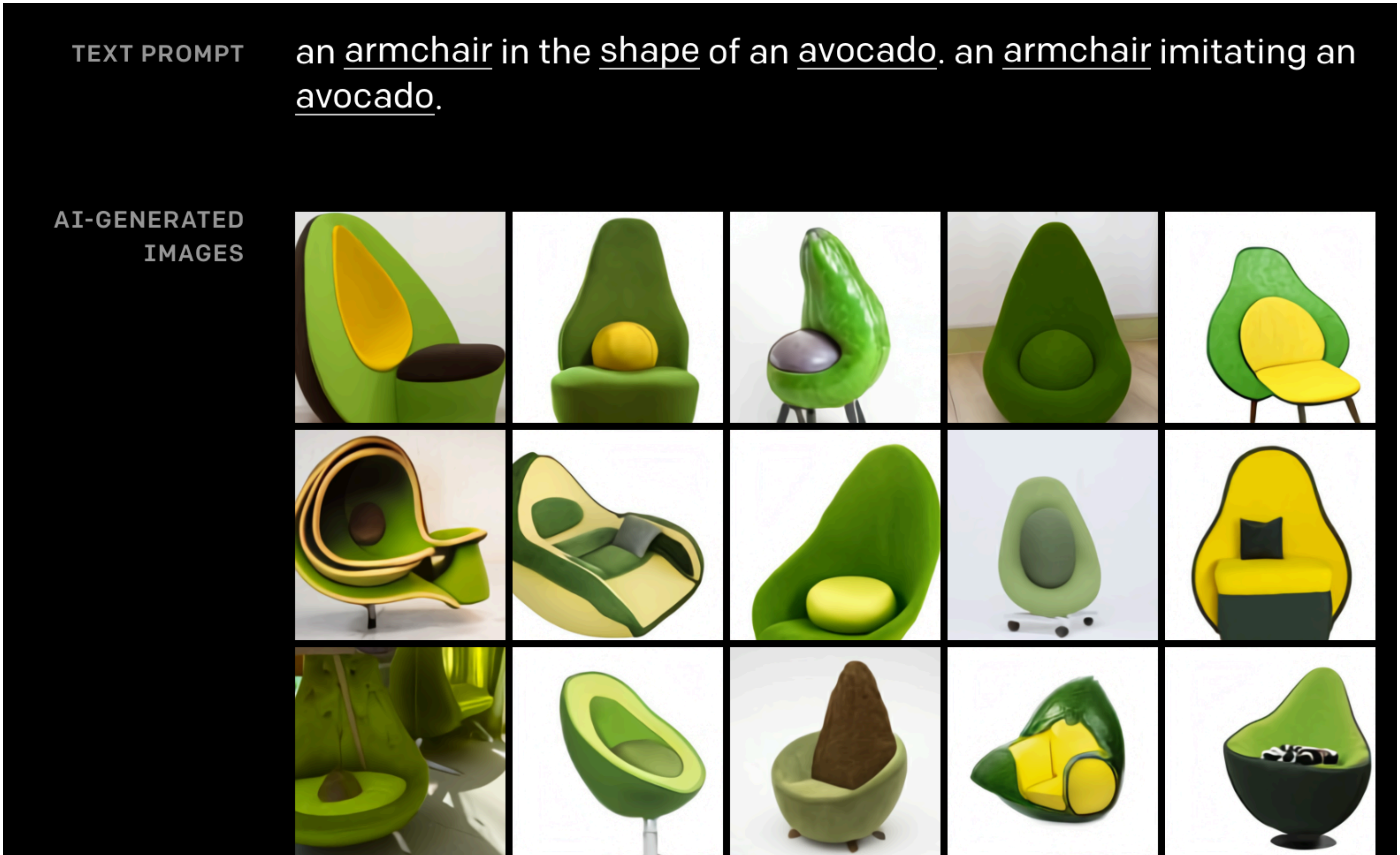
Shape and Pose Estimation for Objects and Humans



S. Goel et al. **Shape and Viewpoint without Keypoints.** ECCV 2020
A. Kanawaza et al. **End-to-end Recovery of Human Shape and Pose.** CVPR 2018

Successes in Computer Vision "in the Wild"

Image Generation

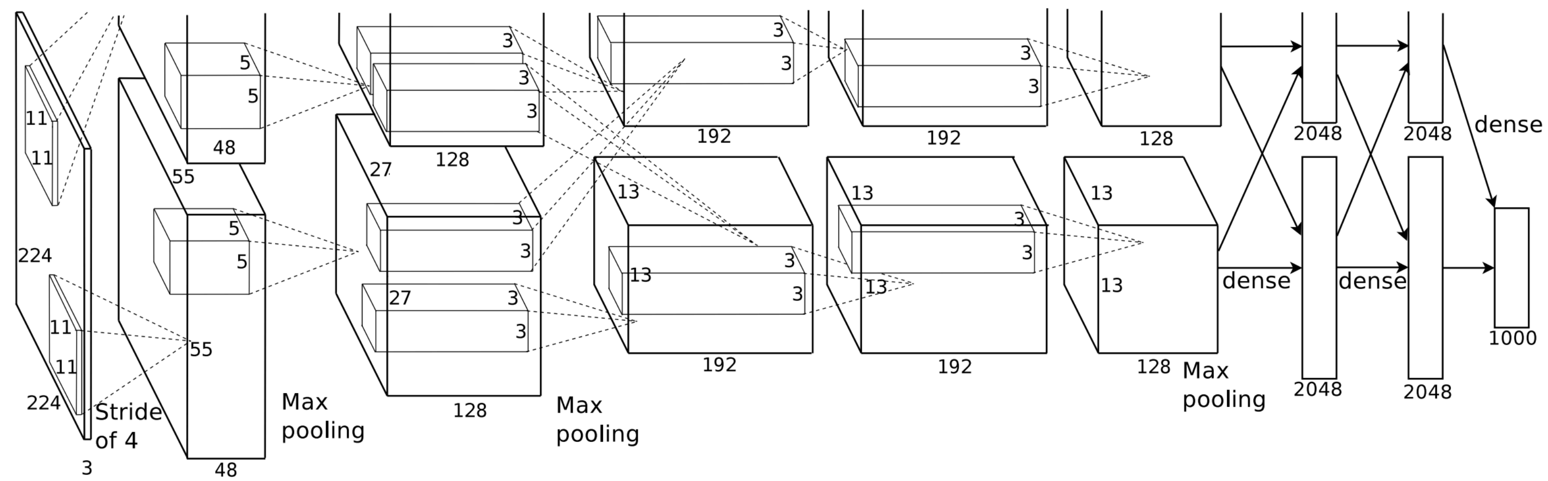


A. Ramesh et al. **Zero-Shot Text-to-Image Generation.** ECCV 2020.

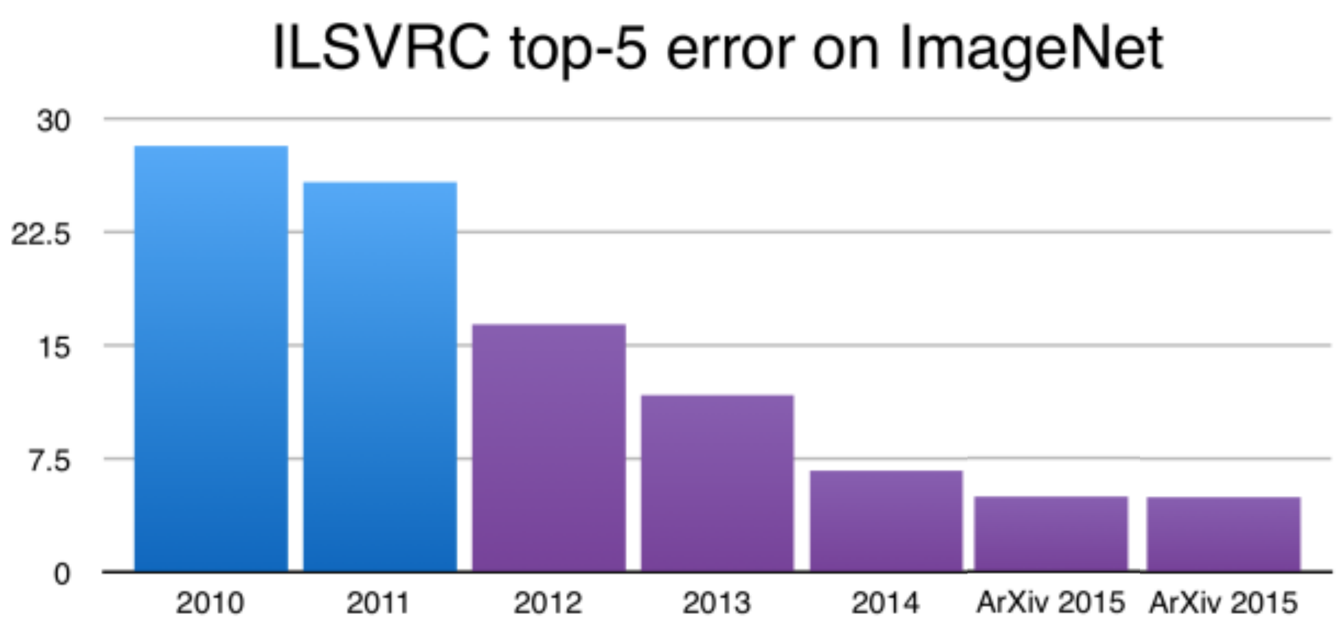
Factors Leading to Success in Computer Vision

Big models trained on big datasets

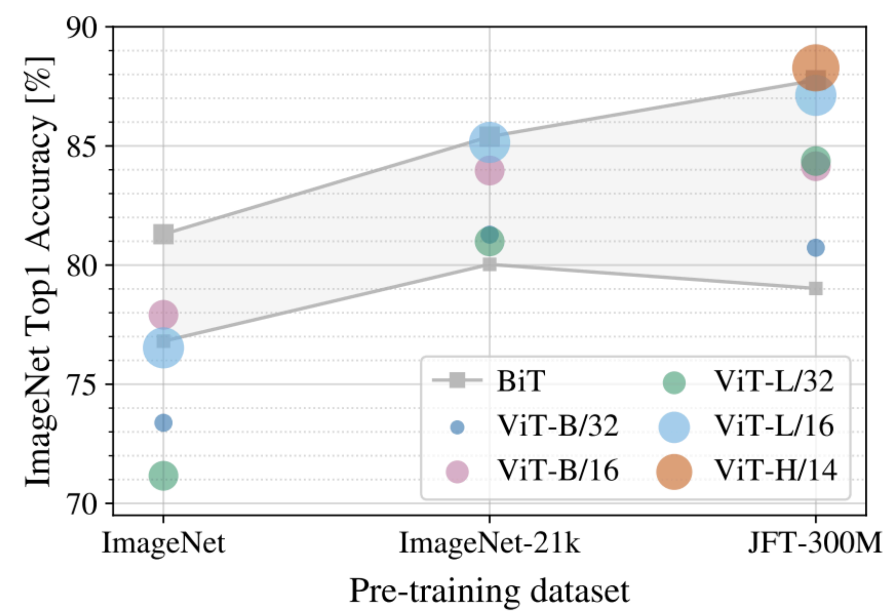
Big datasets



Big models



Hand-designed models → End-to-end learned models

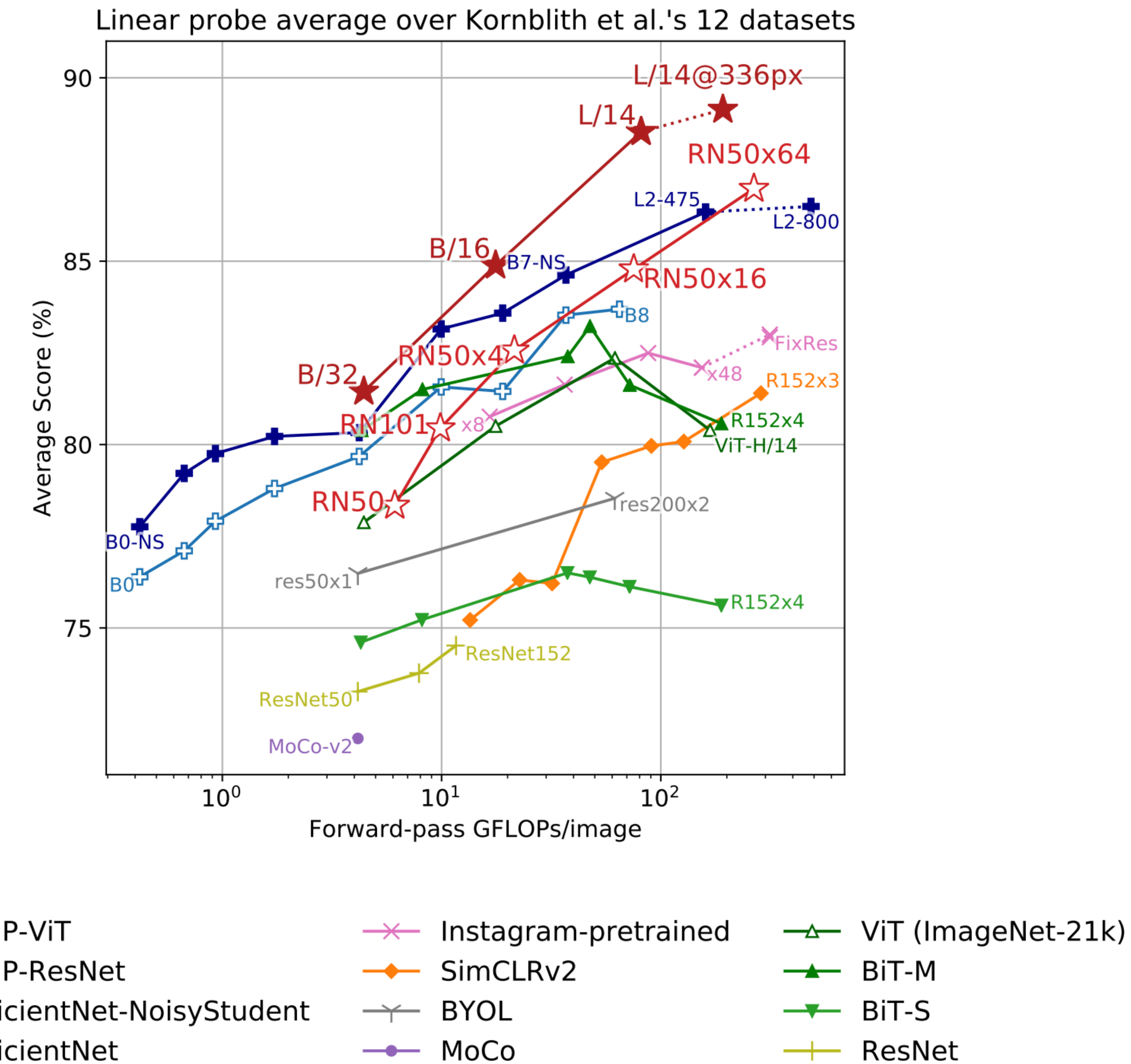


Even bigger datasets and models

A. Krizhevsky et al. **ImageNet Classification with Deep Convolutional Neural Networks.** NIPS 2012
J. Deng et al. **ImageNet: A Large-Scale Hierarchical Image Database.** CVPR 2009
A. Dosovitskiy et al. **An Image is worth 16x16 words: Transformers for Image Recognition at Scale.** ICLR 2021

Factors Leading to Success in Computer Vision

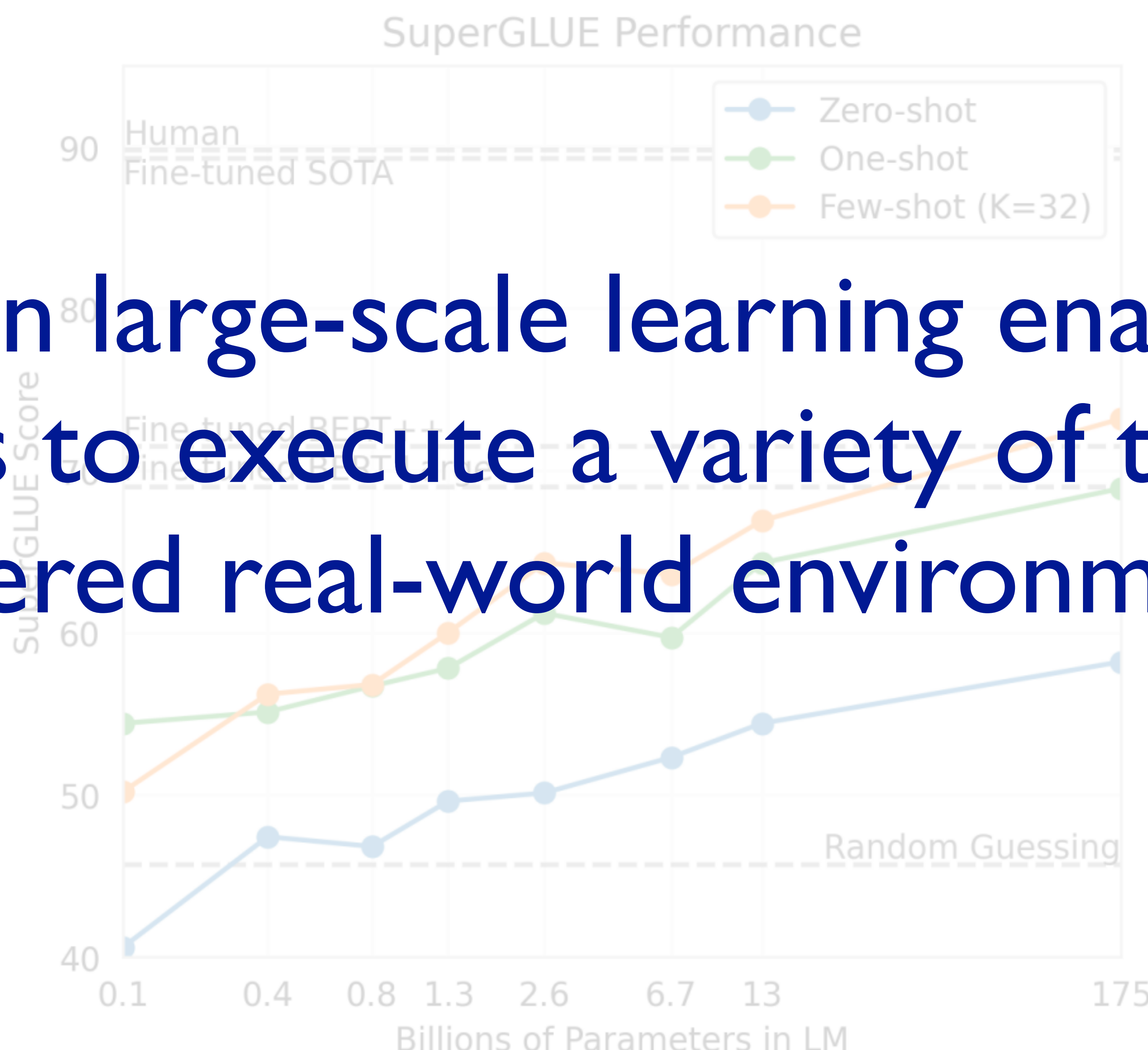
Big models trained on big datasets



A. Radford et al. **Learning Transferable Visual Models From Natural Language Supervision.** ICML 2021

Factors Leading to Success in NLP

Big models (transformers) trained on big datasets (Internet text)

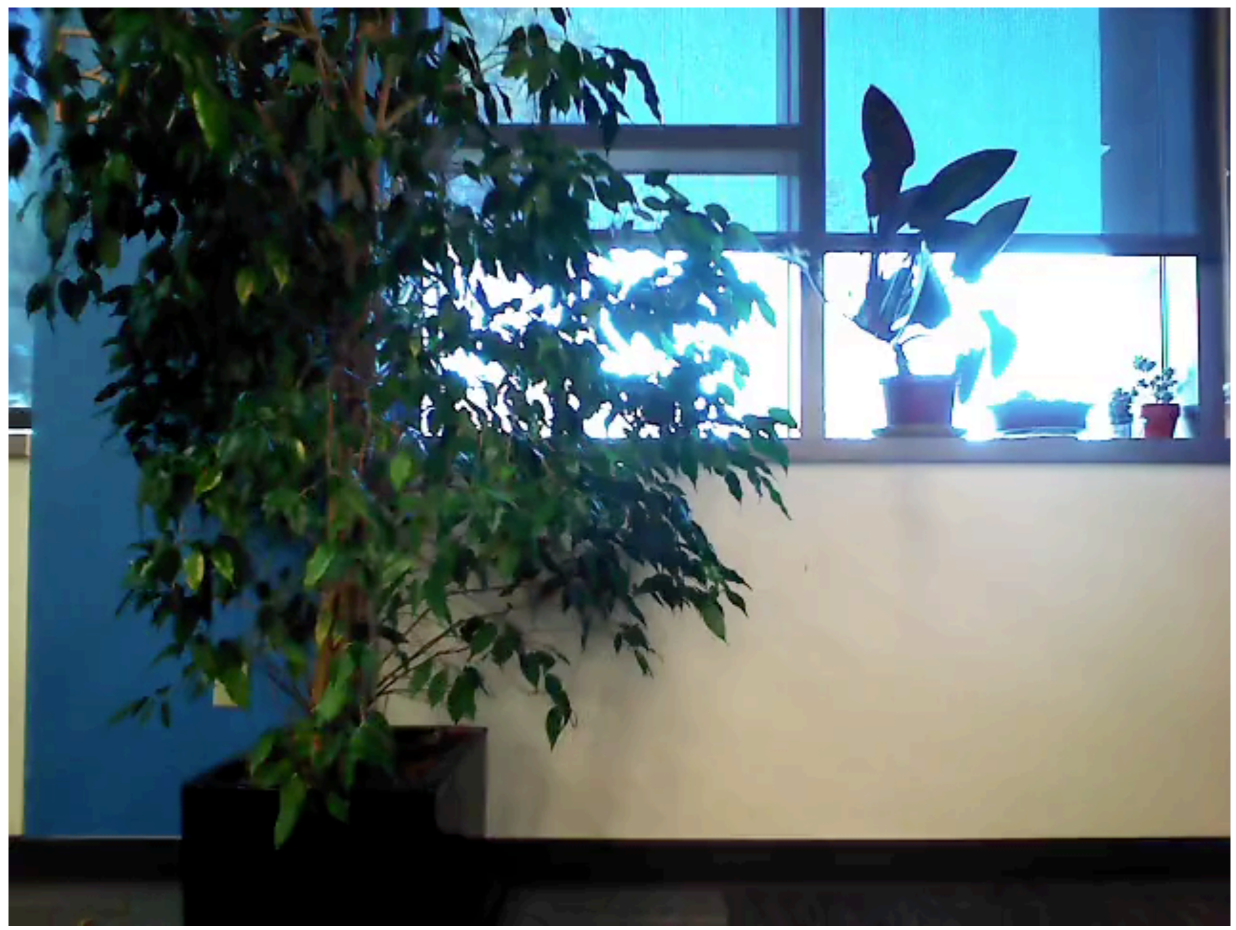


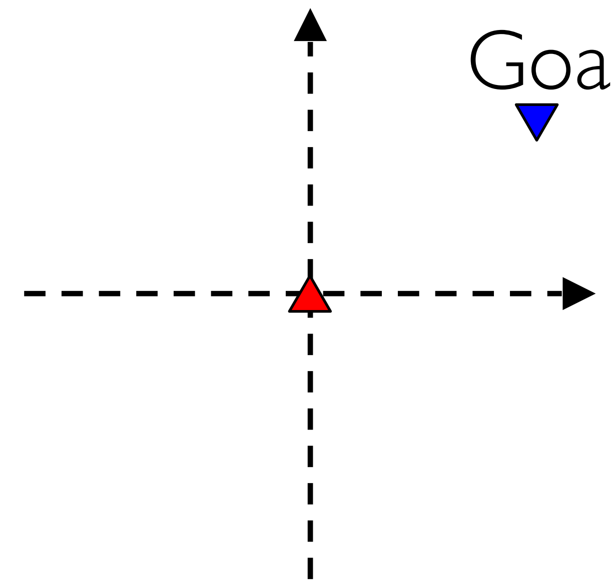
Can large-scale learning enable robots to execute a variety of tasks in cluttered real-world environments?

T. Brown et al. **Language Models are Few-shot Learners.** NeurIPS 2020

Robotic Tasks

Navigation





"Go 300 feet North, 400 feet East"

"Go Find a Chair"

Robot with a first person camera

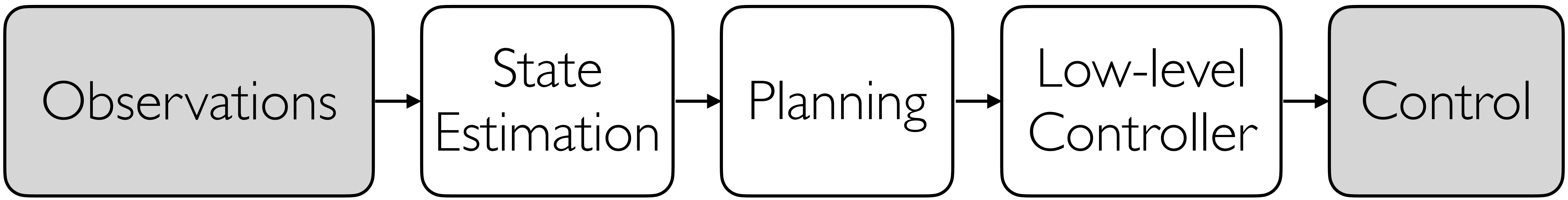
Dropped into a novel environment

Navigate around

Robotic Tasks

Manipulation

Typical Classical Robotics Pipeline



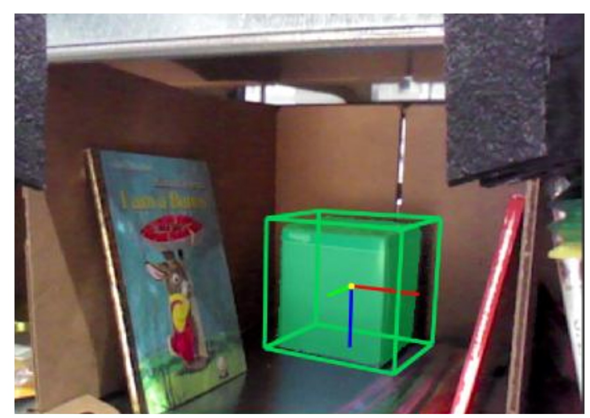
Slide adapted from S. Levine.

Typical Classical Robotics Pipeline

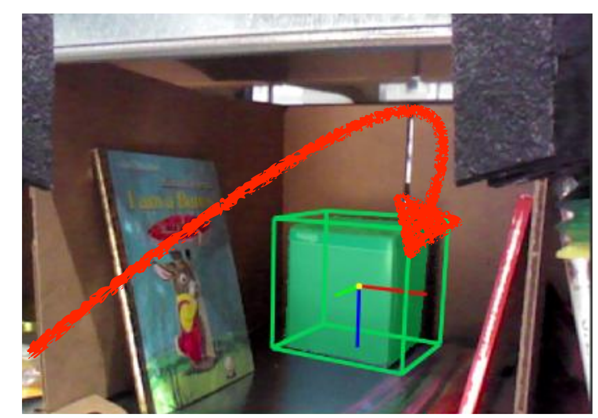
Observations → State Estimation → Planning → Low-level Controller → Control

Manipulation

Observed Images



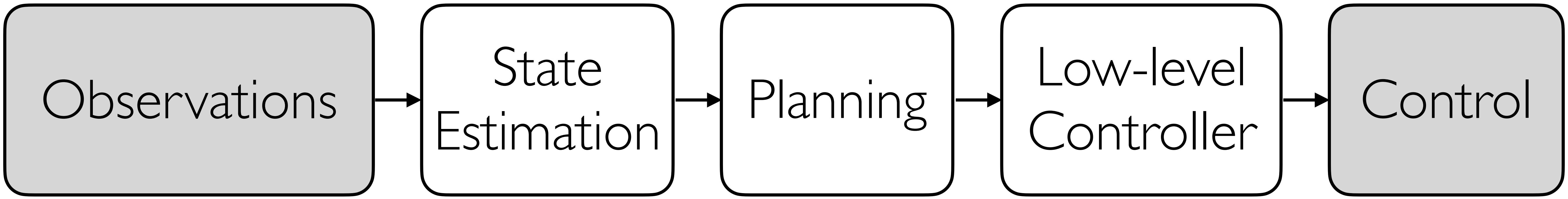
6DOF Pose



Grasp Motion Planning

Slide adapted from S. Levine.

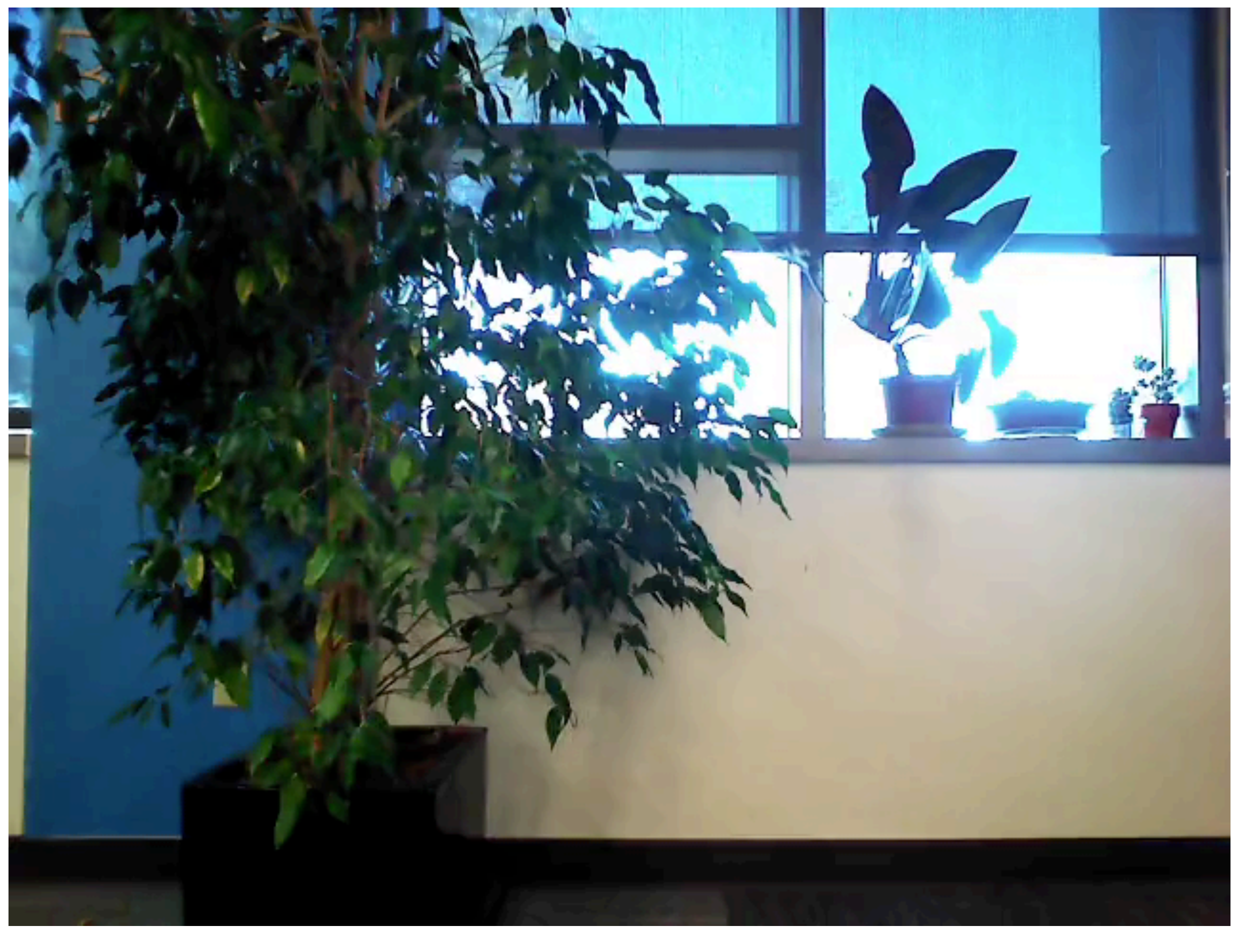
Typical Classical Robotics Pipeline

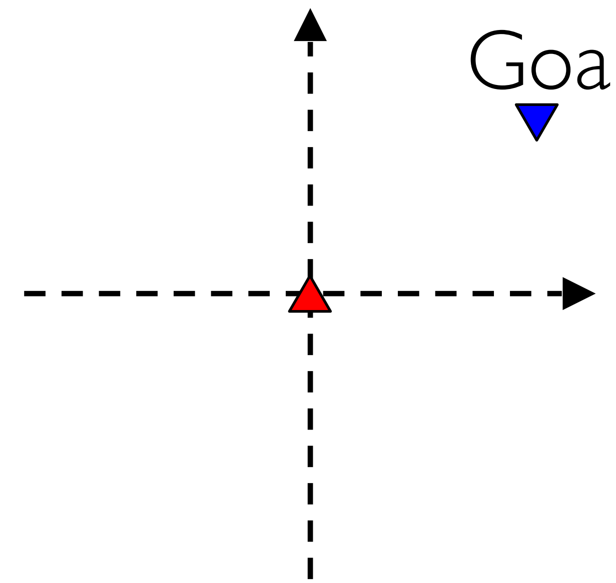


But why would learning be useful at all?

Slide adapted from S. Levine.

Robot Navigation





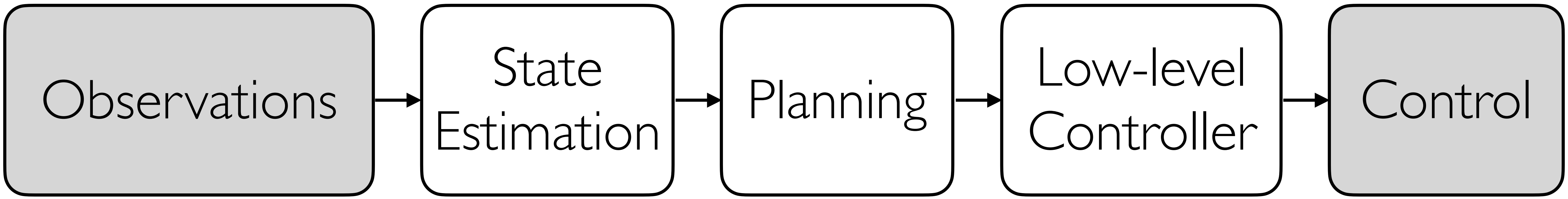
**“Go
300 feet North,
400 feet East”**

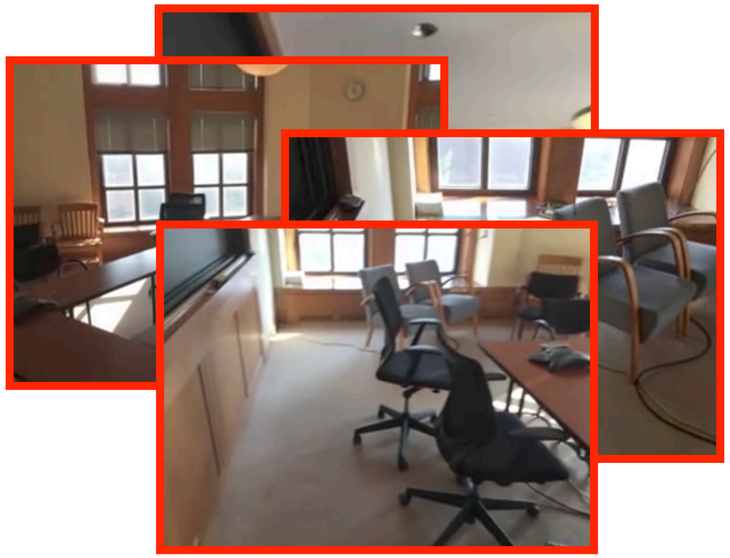
“Go Find a Chair”

Robot with a first person camera

Dropped into a novel environment

Navigate around

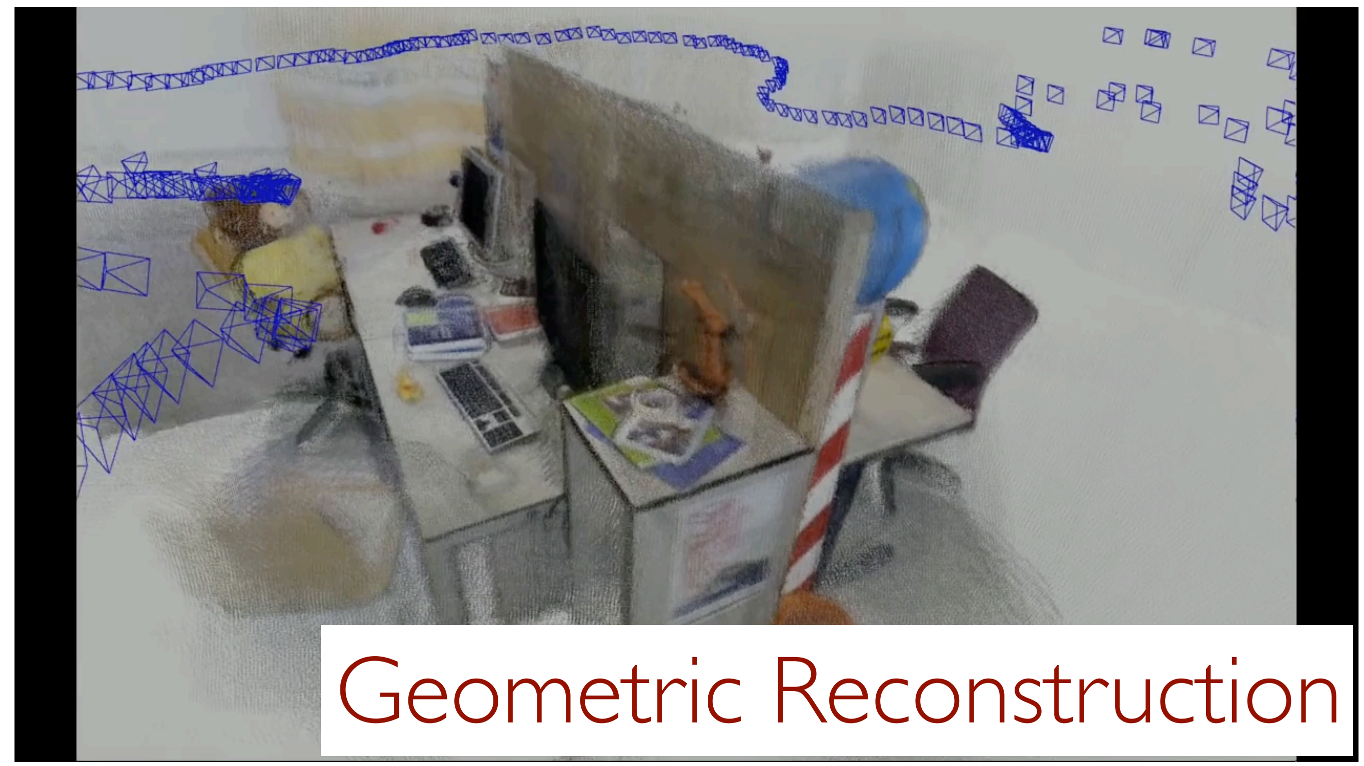


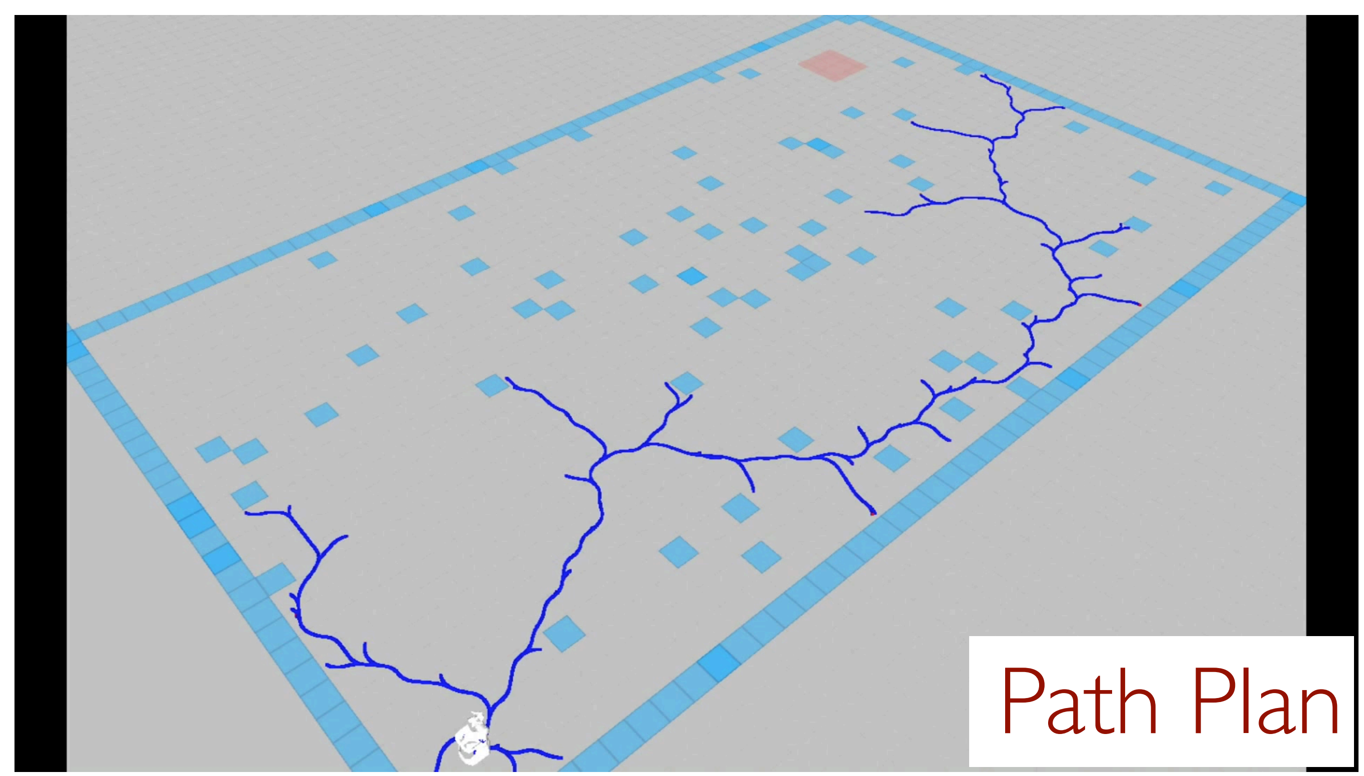


Observed Images

Mapping

Planning





Hartley and Zisserman. 2000. Multiple View Geometry in Computer Vision
Thrun, Burgard, Fox. 2005. Probabilistic Robotics

Canny. 1988. The complexity of robot motion planning.
Kavraki et al. RA1996. Probabilistic roadmaps for path planning in high-dimensional configuration spaces.
Lavalle and Kuffner. 2000. Rapidly-exploring random trees: Progress and prospects.

Video Credits: Mur-Artal et al., Palmieri et al.

Geometric 3D Reconstruction of the World

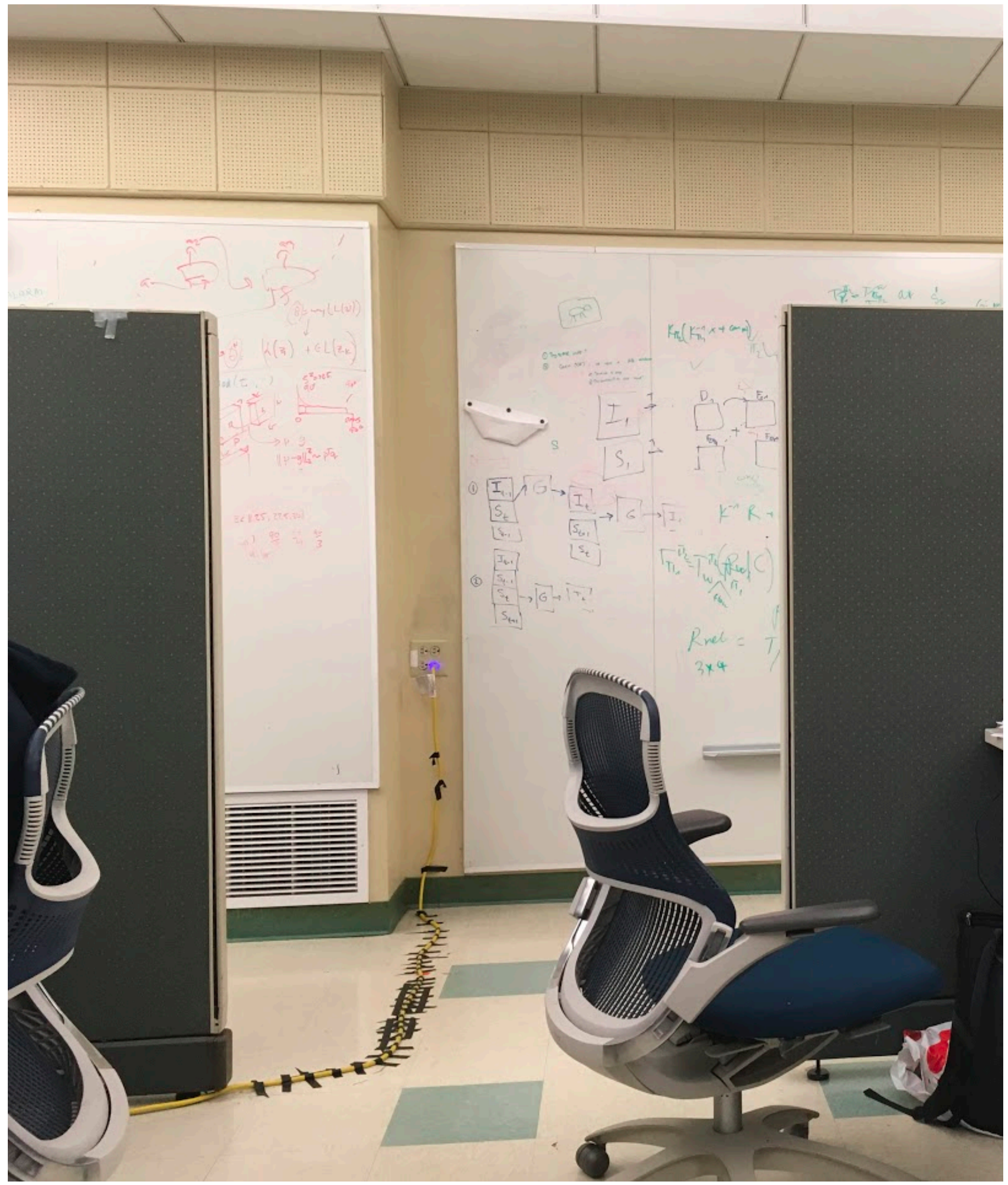
Unnecessary

Do we need to tediously reconstruct everything on this table?

Video Credit: Mur-Artal and Tardos, TRobotics 2016. ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras.

Geometric 3D Reconstruction of the World

Insufficient



Can’t speculate about space not directly observed.

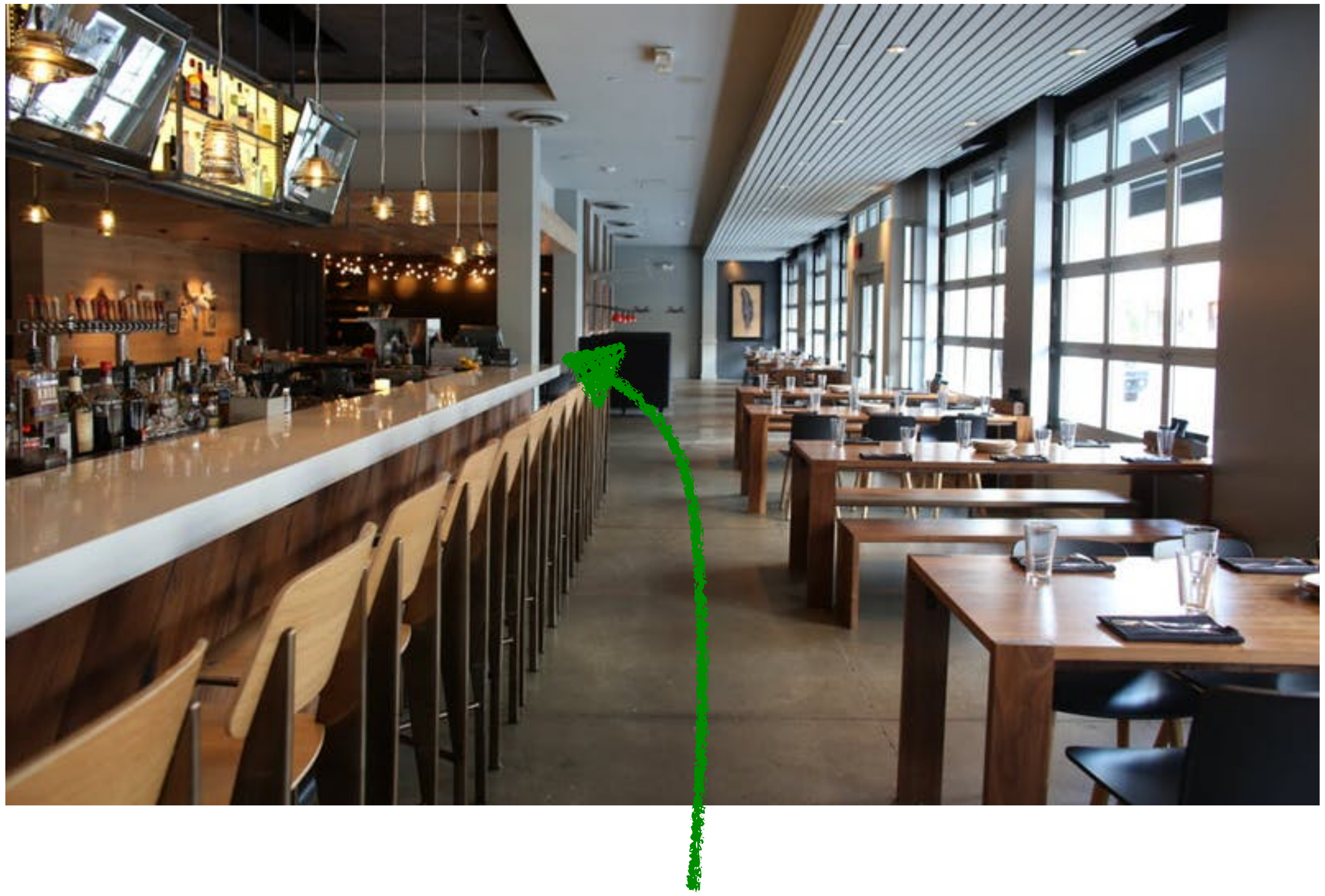
Geometric 3D Reconstruction of the World

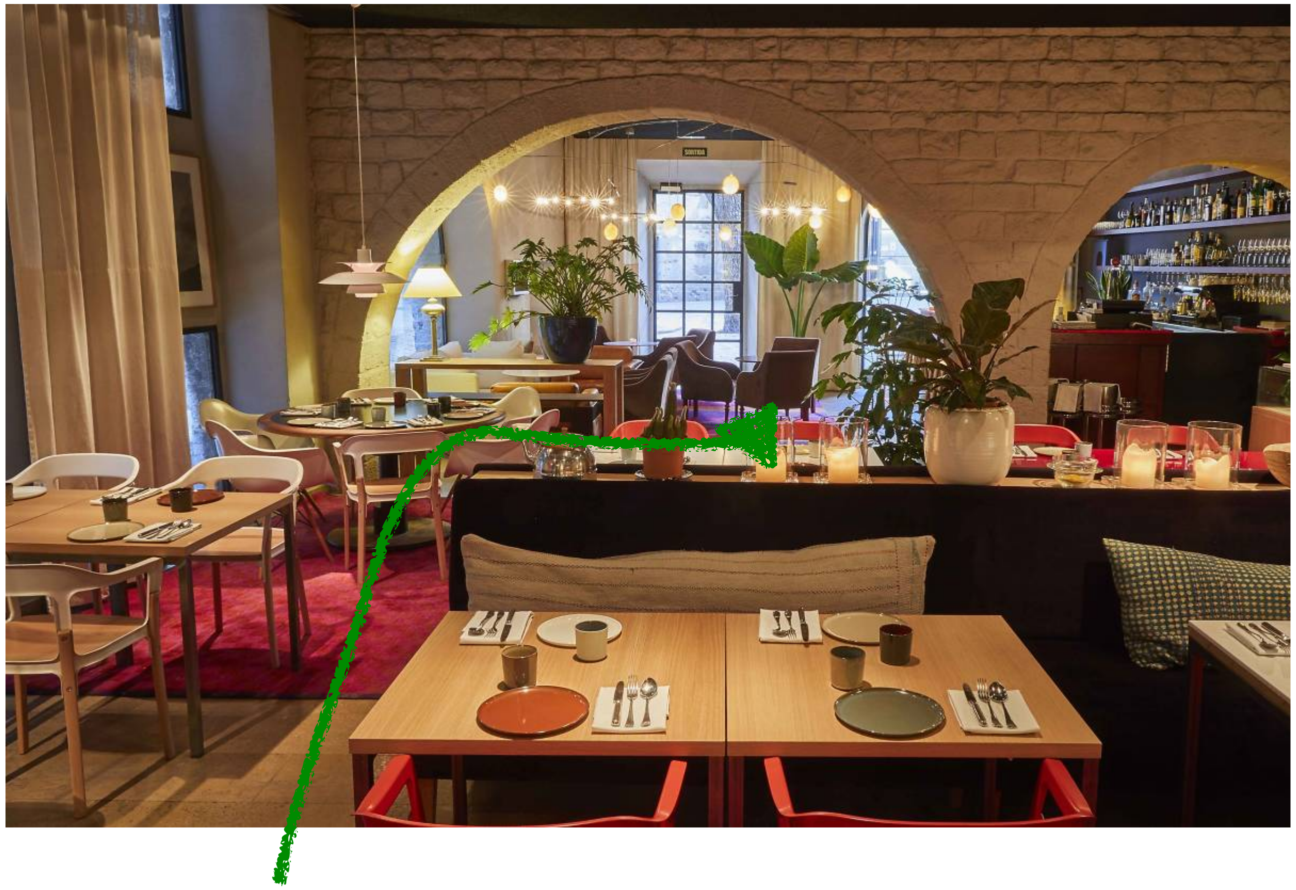
Insufficient

Can't exploit patterns in layout of indoor spaces.

Geometric 3D Reconstruction of the World

Insufficient



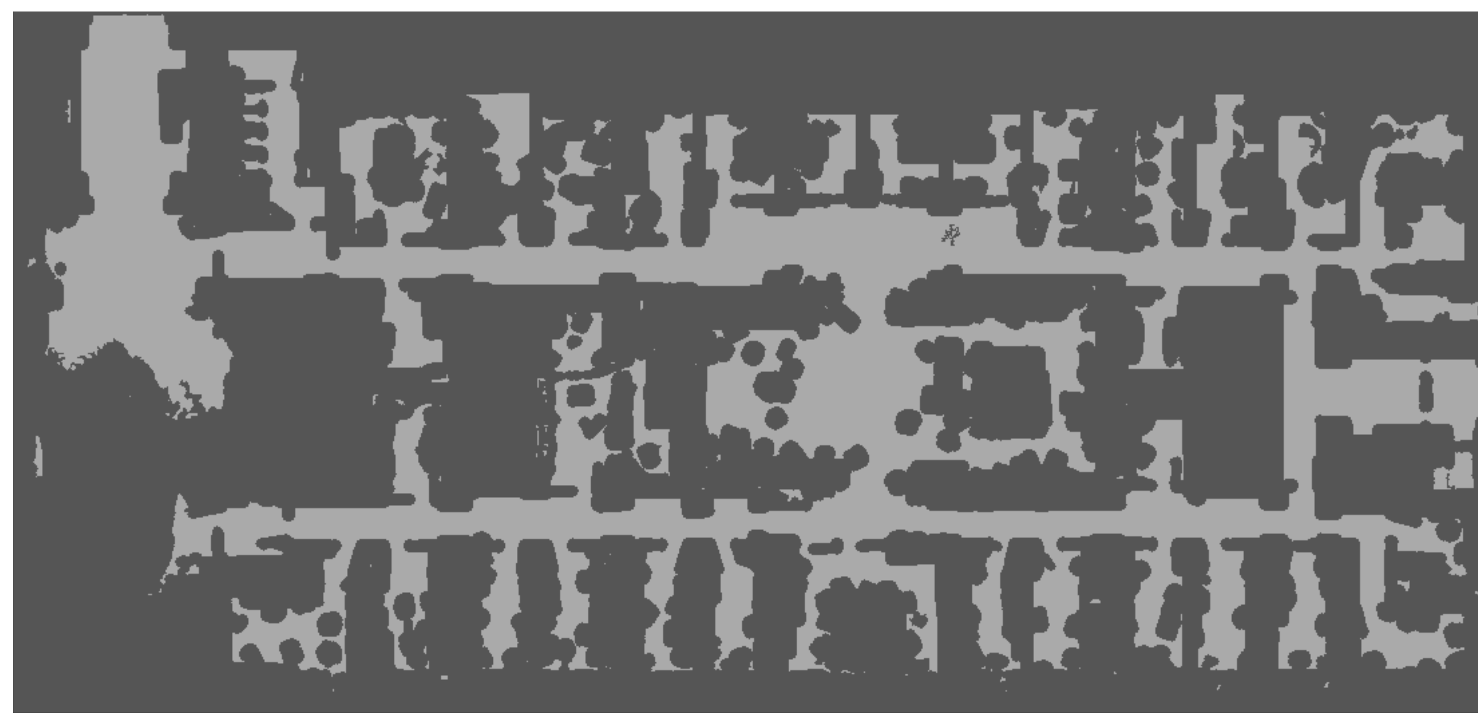


Can't exploit patterns in layout of indoor spaces.

Learn to make good decisions from partial information

Simulator based on scans of
Real World Environments

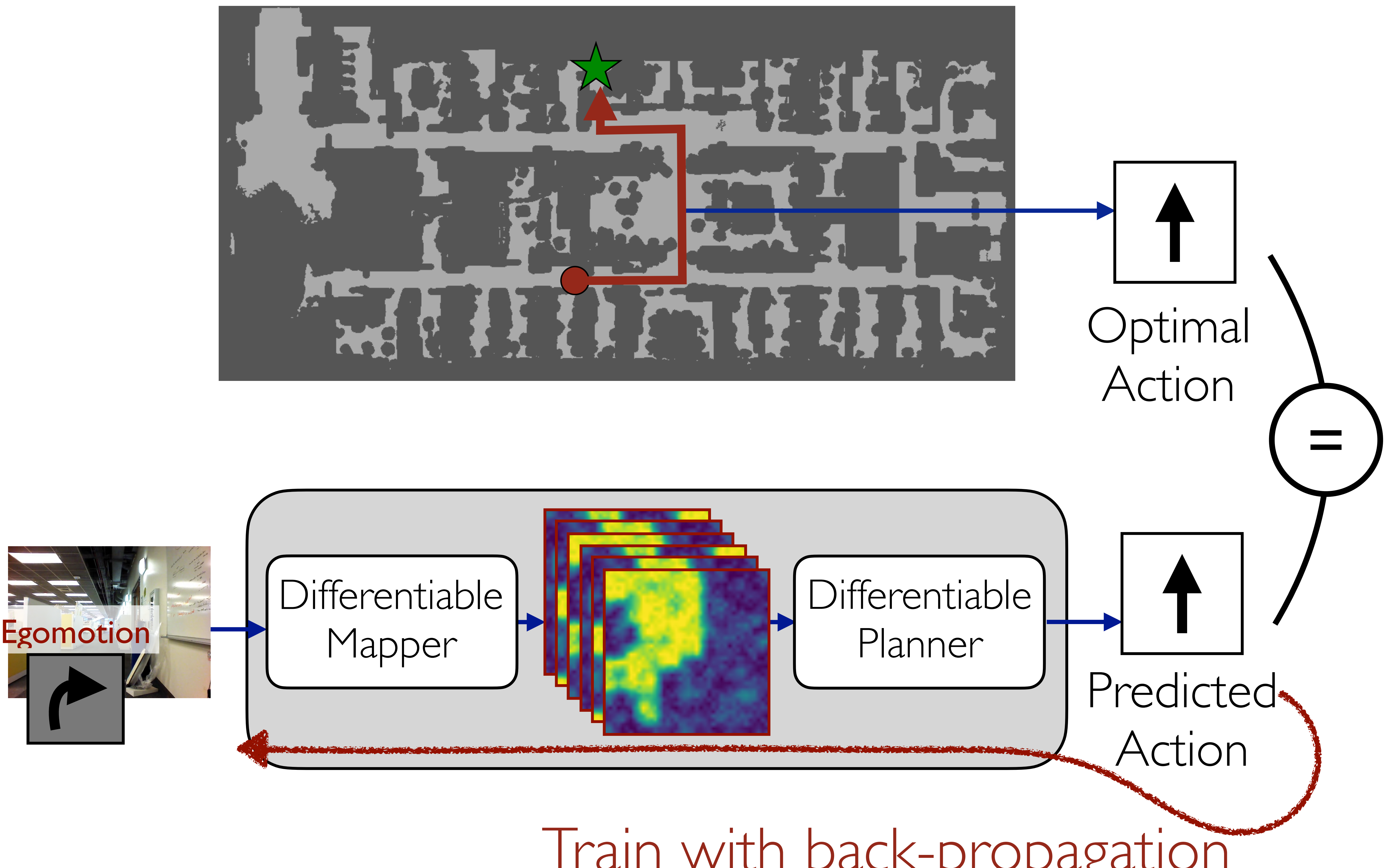
Simulate robot views
and motion



Compute ground
truth traversability

Gupta et al., CVPR 2017. Cognitive Mapping and Planning for Visual Navigation
Armeni et al. CVPR 2016. 3D Semantic Parsing of Large-Scale Indoor Spaces

Learn to make good decisions from partial information



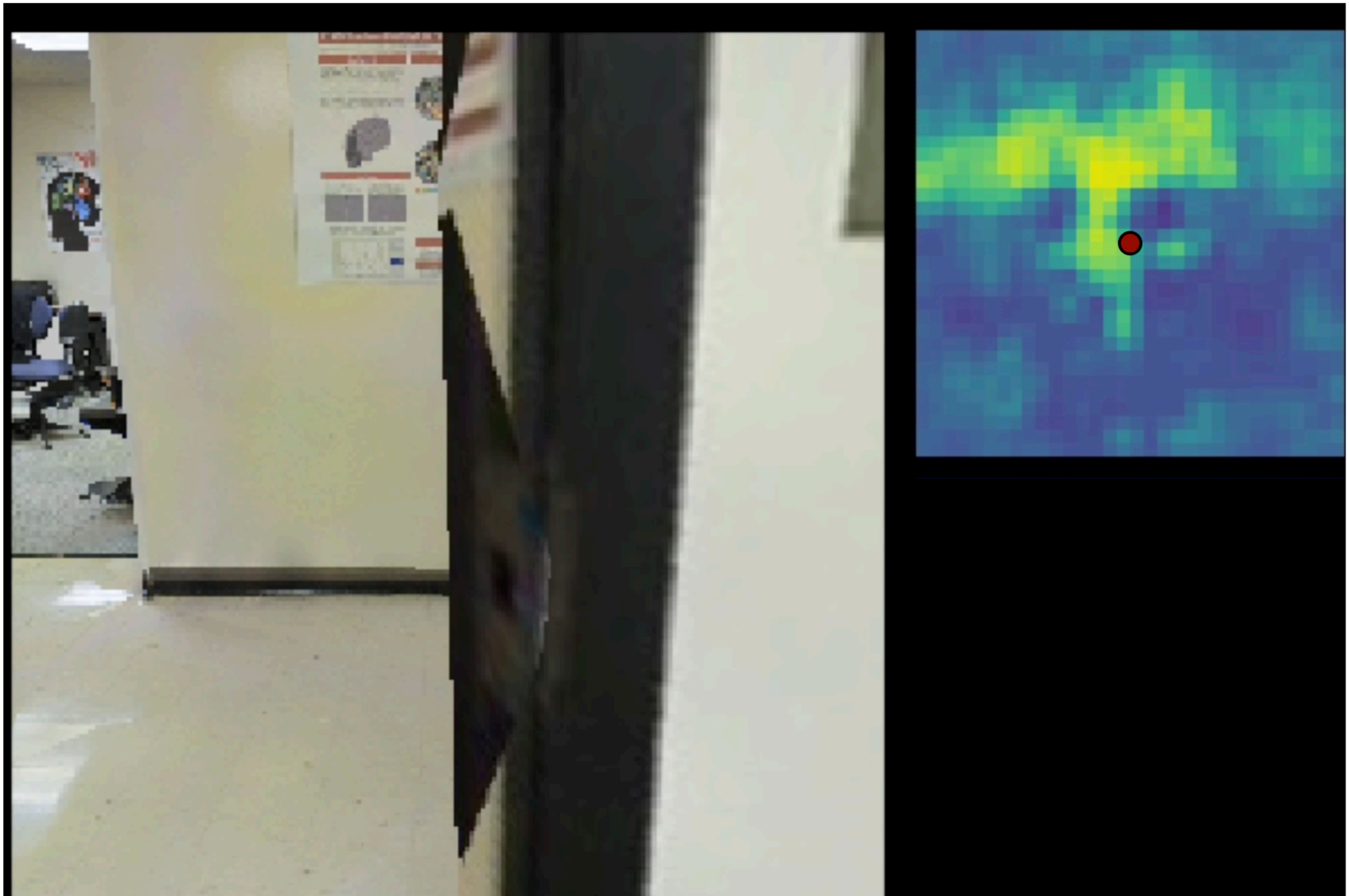
S. Gupta et al. **Cognitive Mapping and Planning for Visual Navigation.** CVPR 2017.

And, making such speculations helps!

	Goal reaching efficiency		% Area explored in 500 steps	Area explored alongside other adversarial agents
	Object Goal	Image Goal		
Without Speculation	0.46	0.33	78.2	9K cells
With Speculation	**0.53**	**0.48**	**86.2**	**14.5K cells**

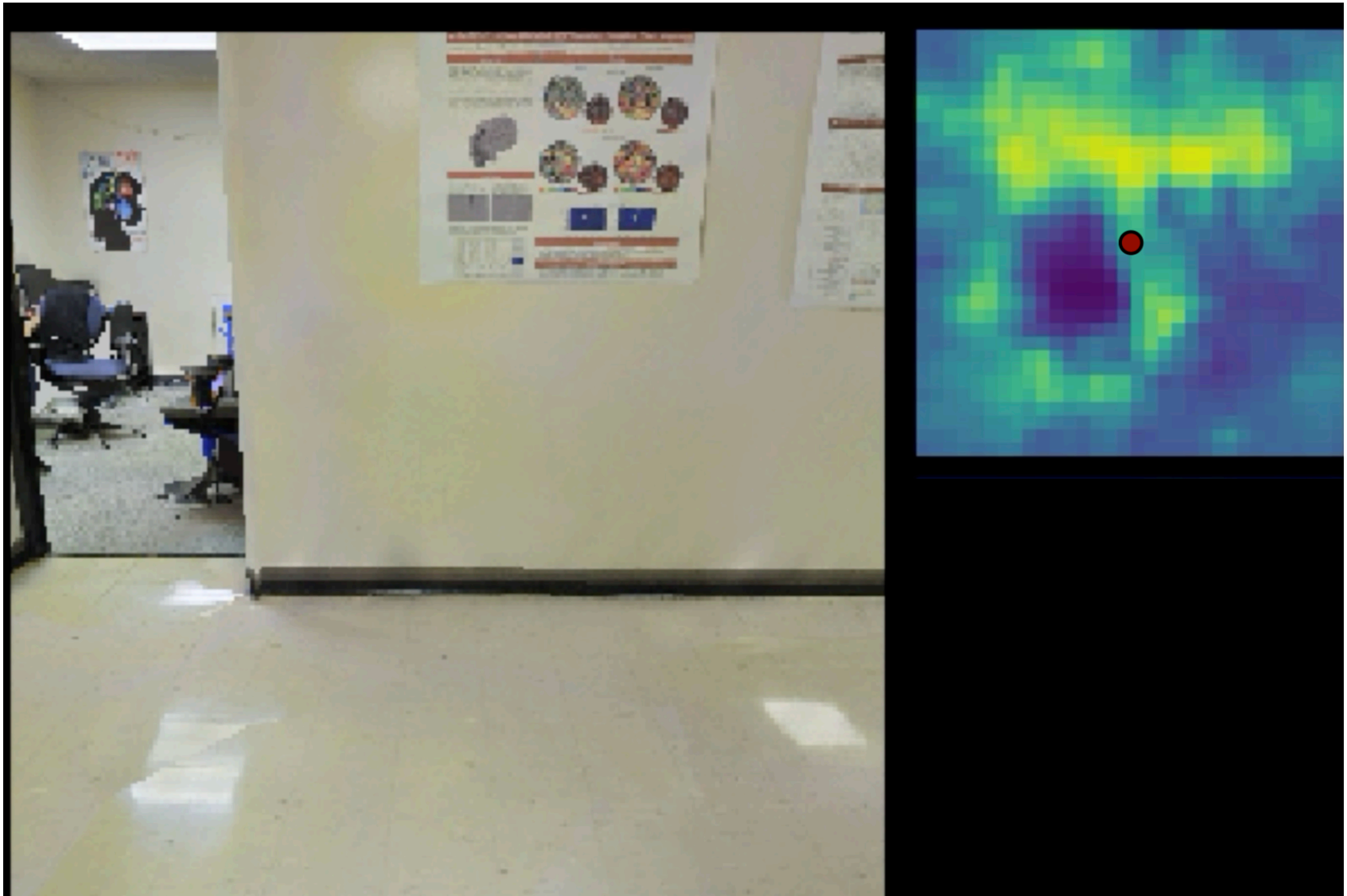
Agent can make predictions about its surroundings

Free Space

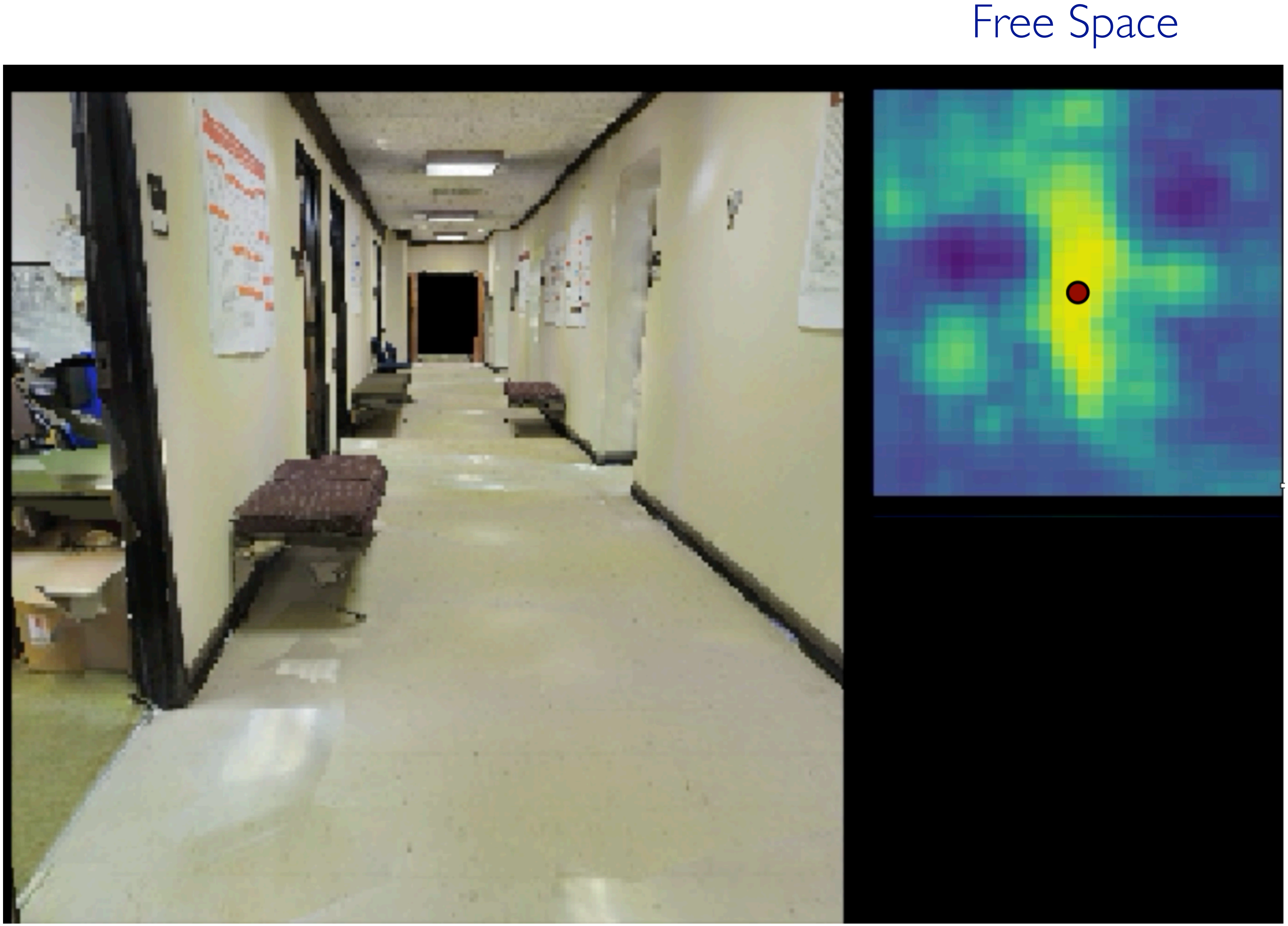


Agent can make predictions about its surroundings

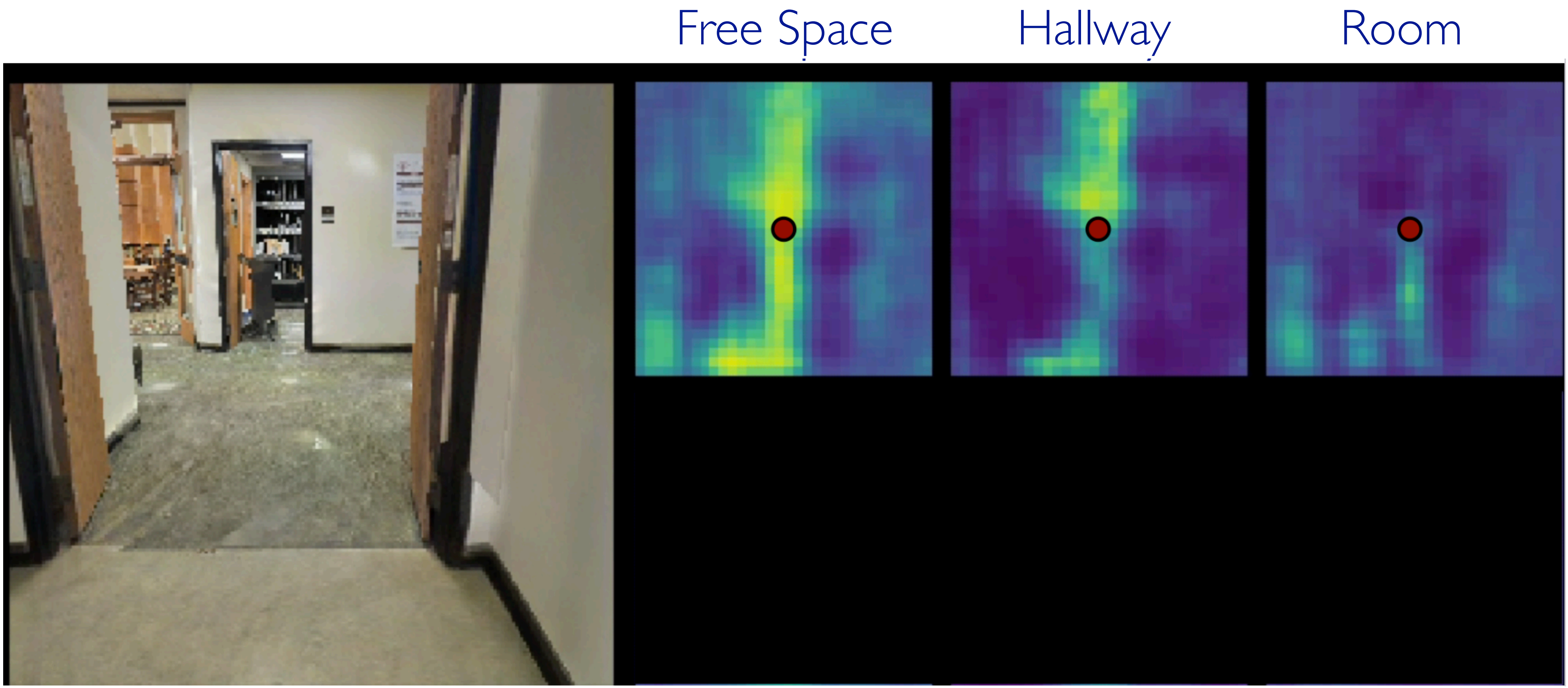
Free Space



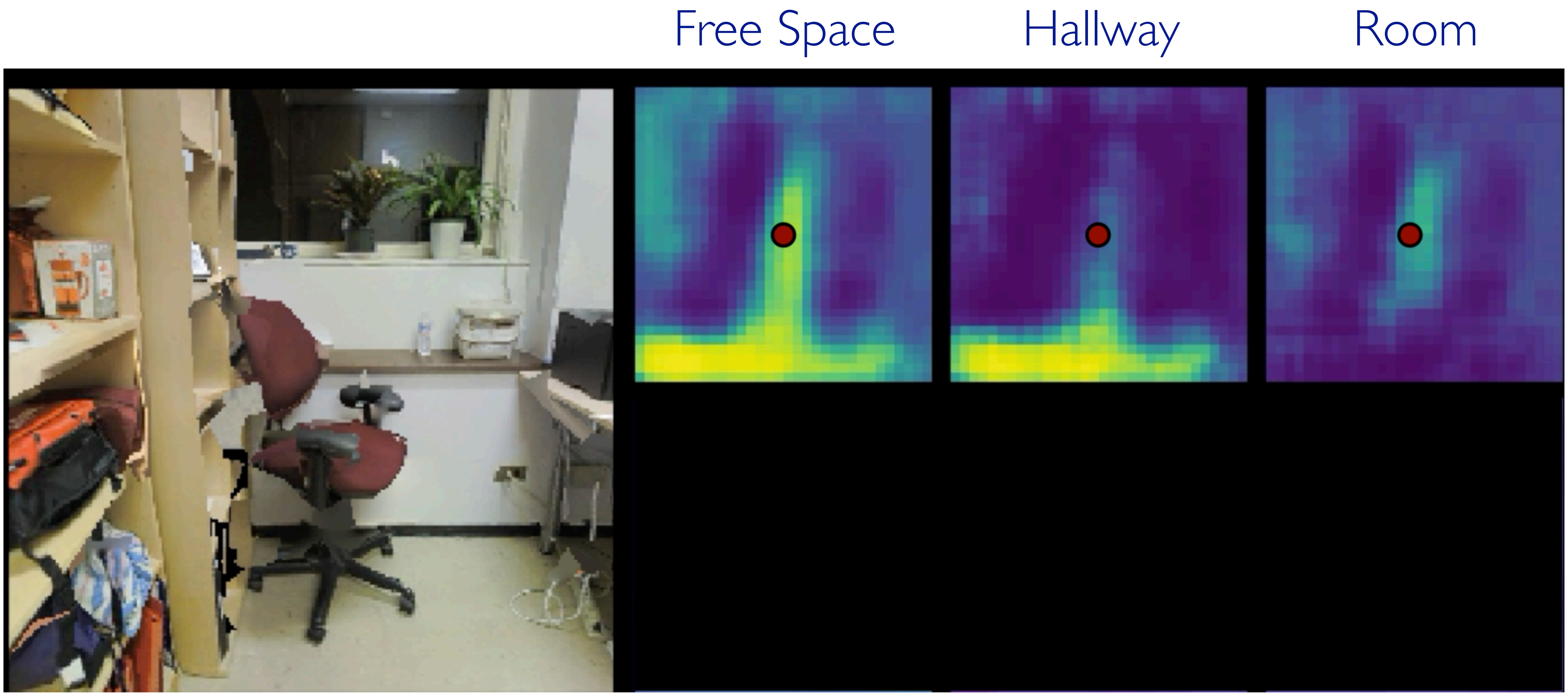
Agent can make predictions about its surroundings



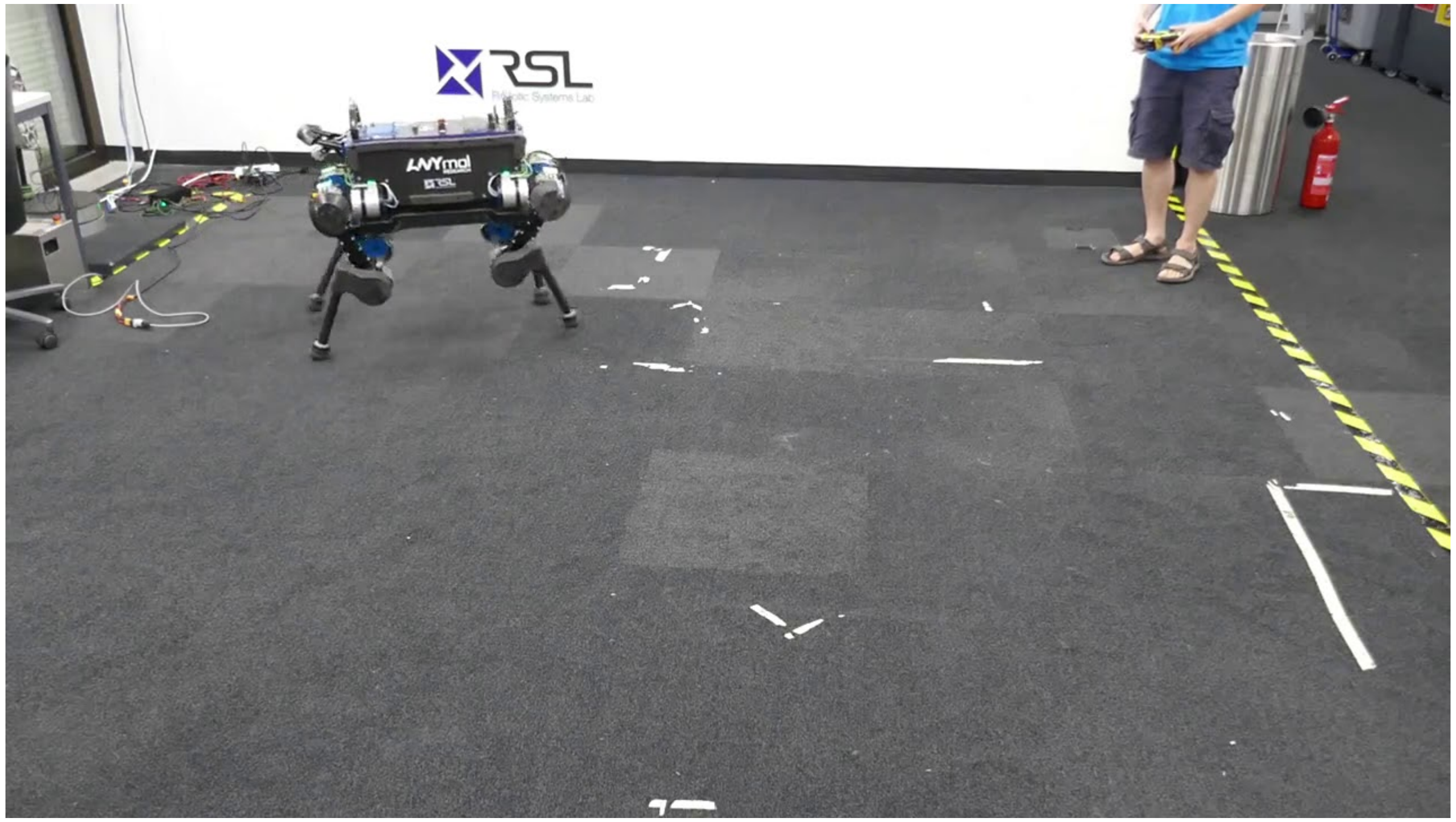
Agent can make predictions about its surroundings

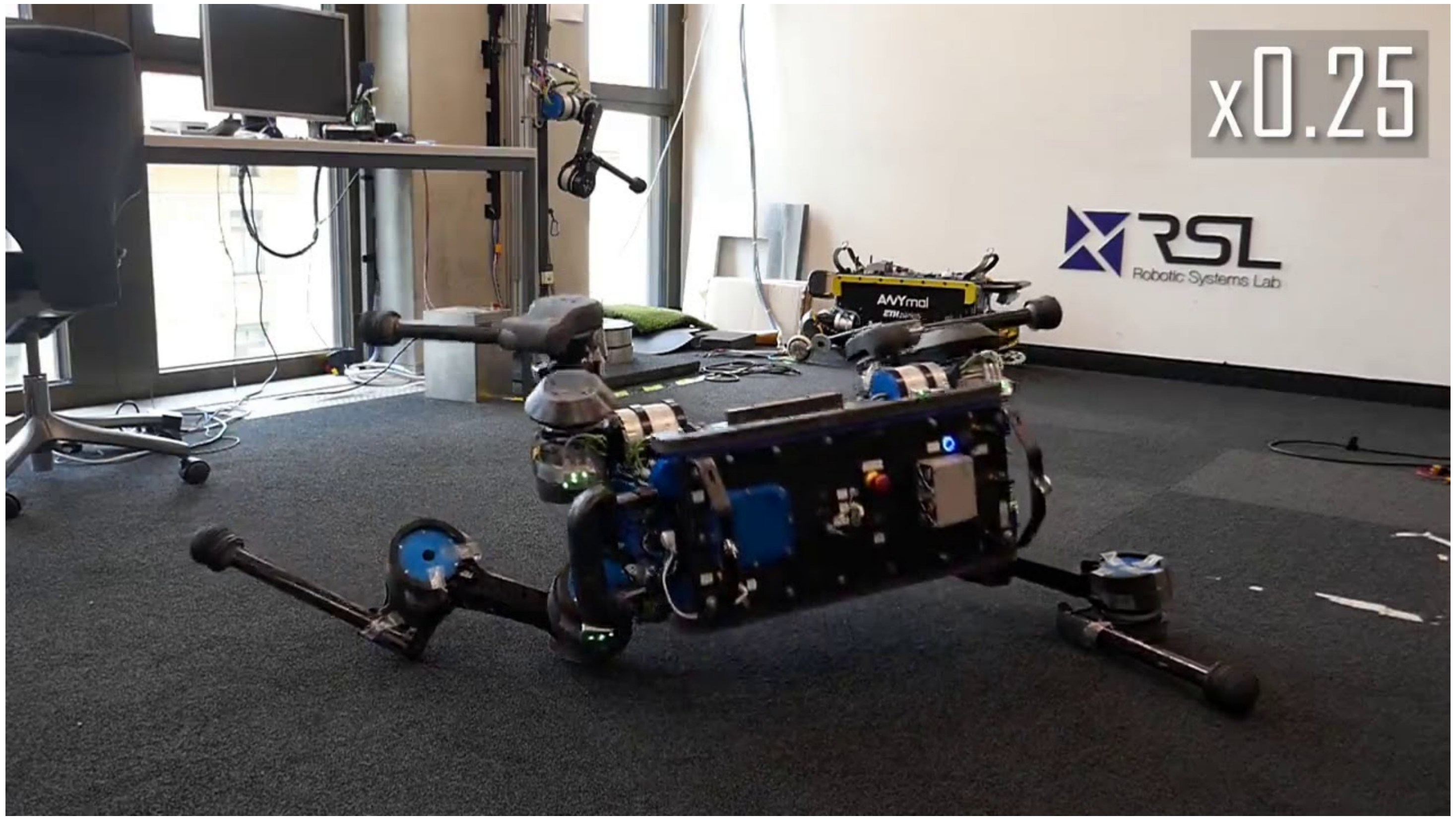


Agent can make predictions about its surroundings



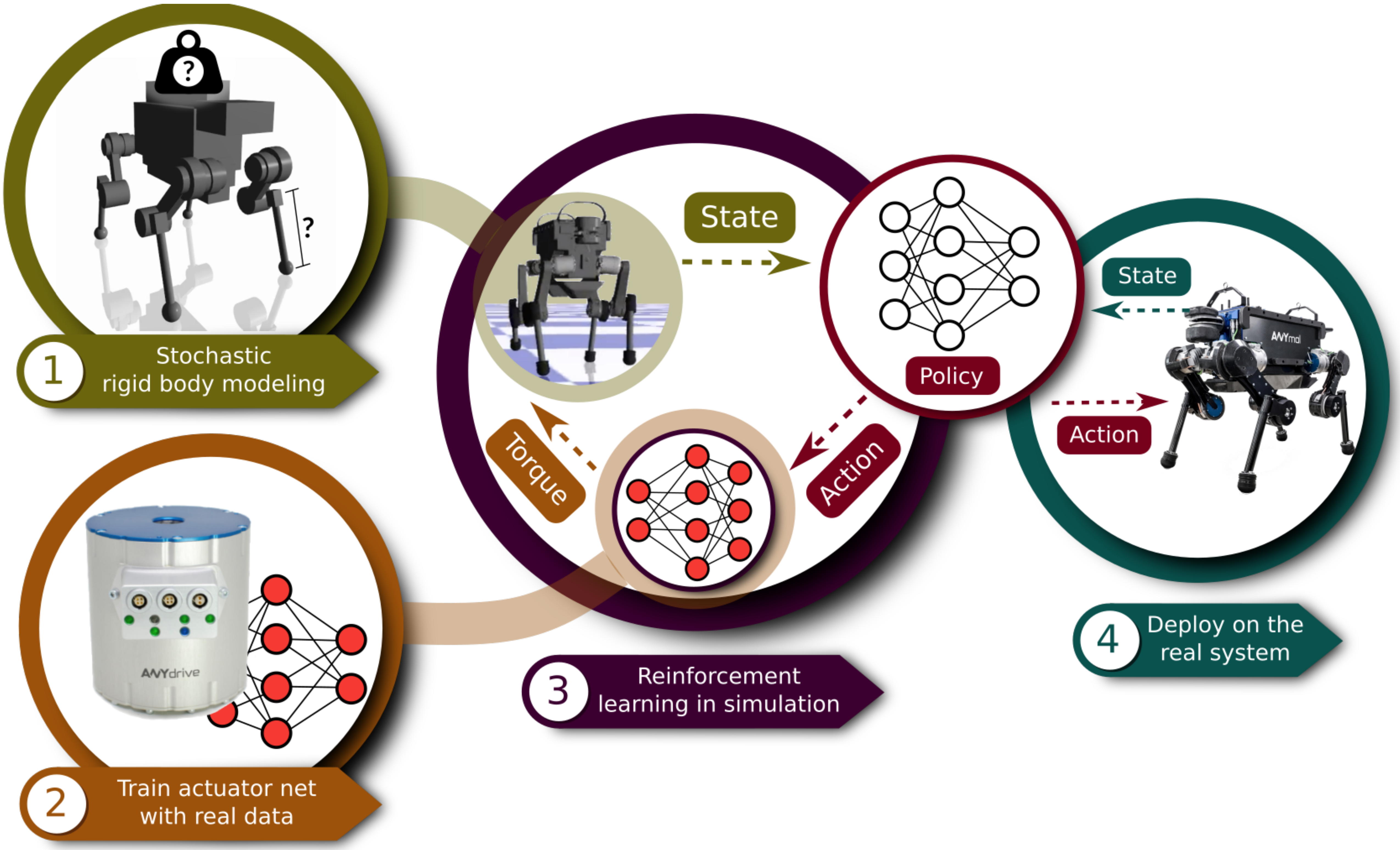
Legged Locomotion





Hard to analytically model the system

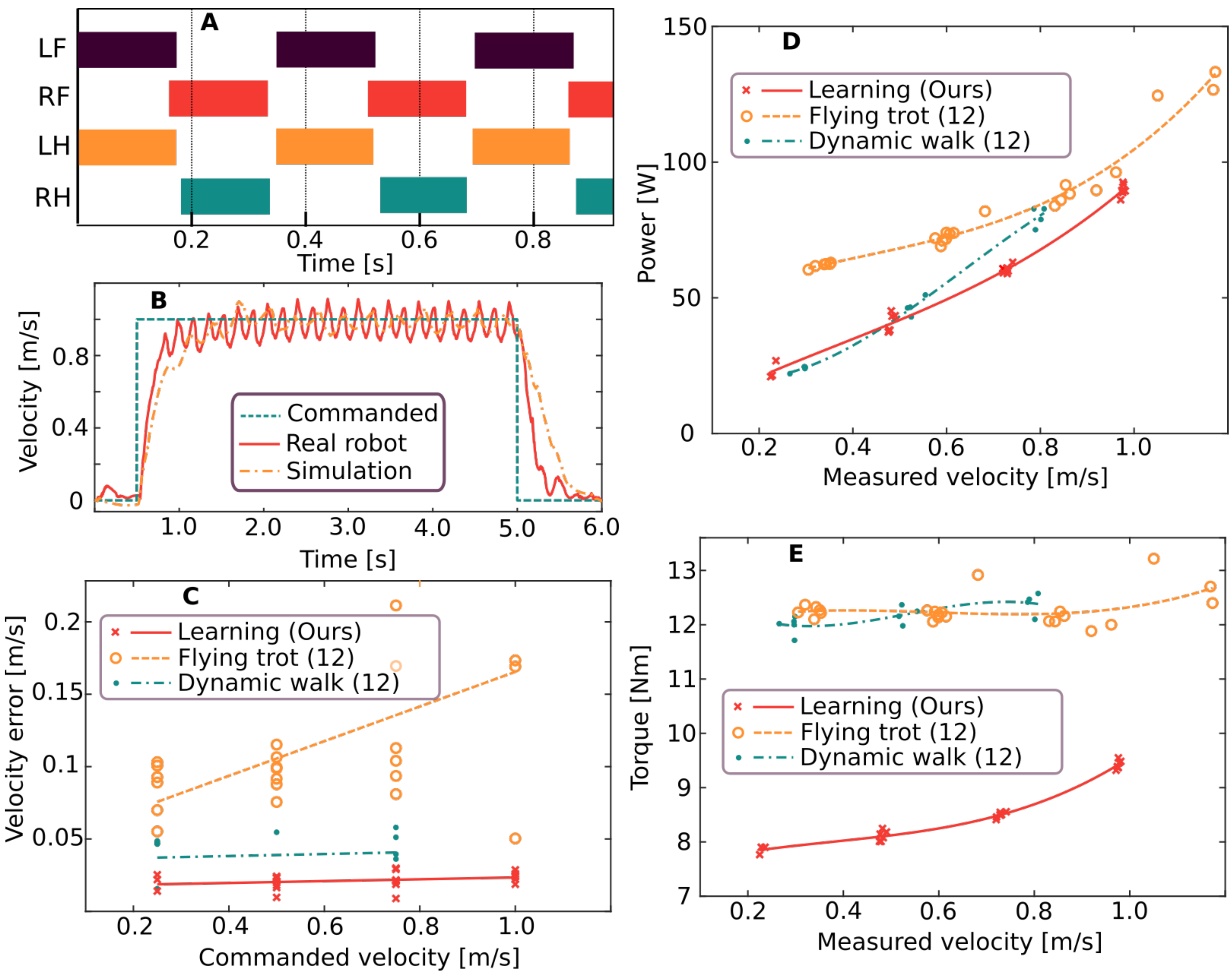
Learn a simulator and learn a policy within it



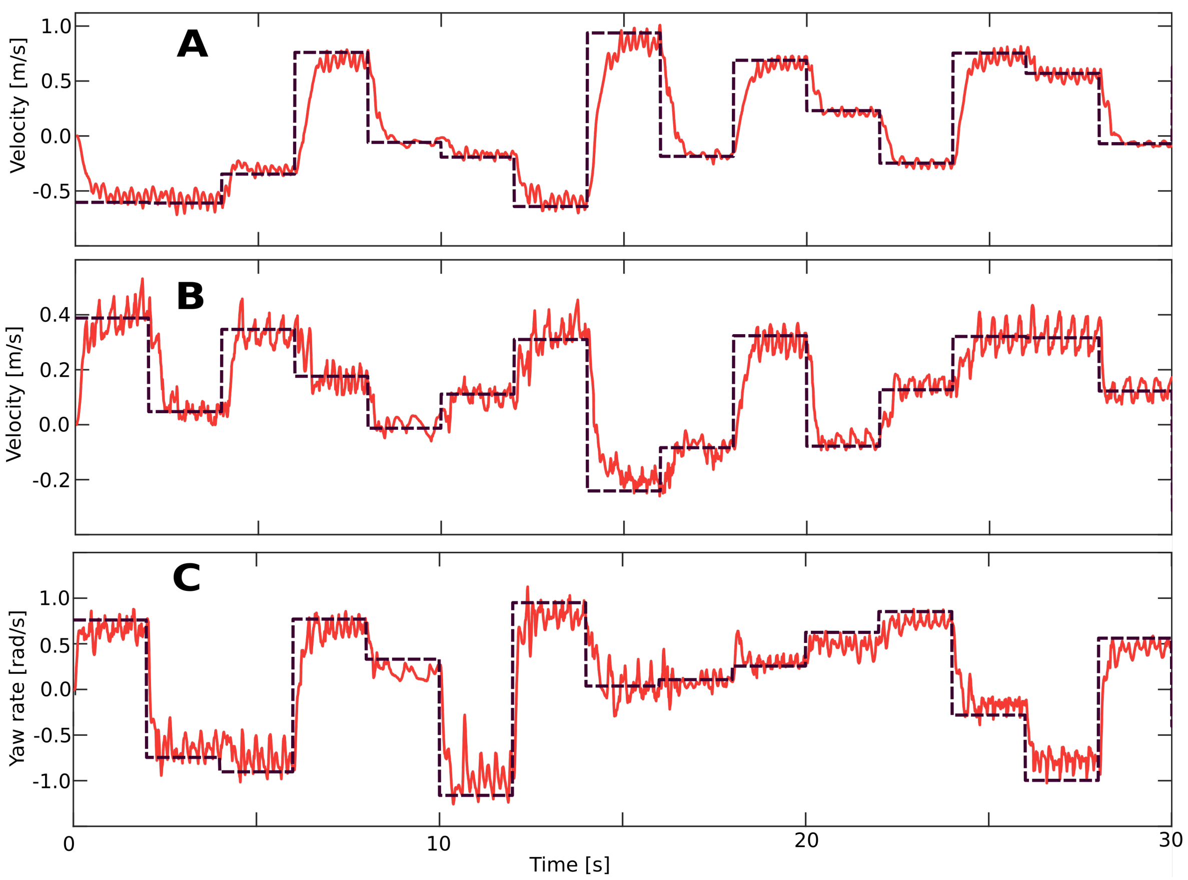
J. Hwangbo et al. **Learning Agile and Dynamic Motor Skills for Legged Robots.** Science Robotics 2019.

Control Performance at Test-time

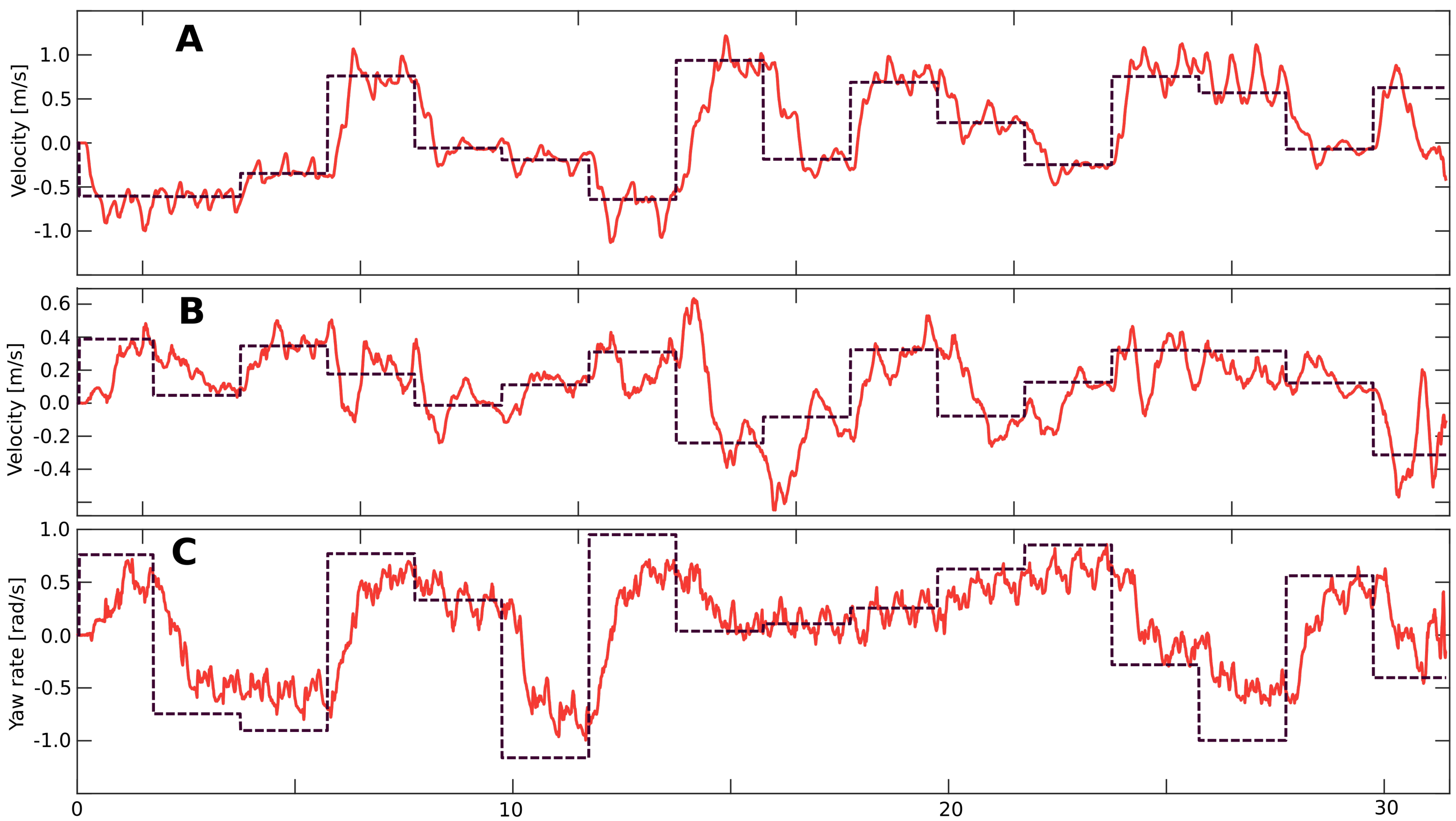
Efficient test-time motion



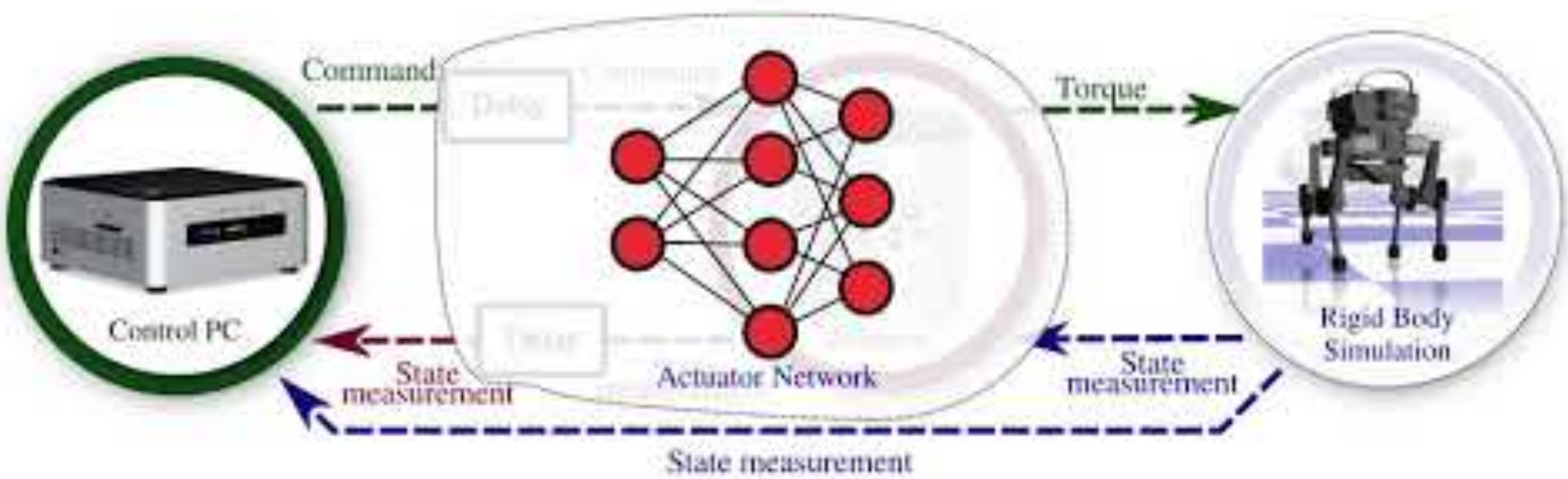
Control Performance at Test-time



ANYmal



Baseline

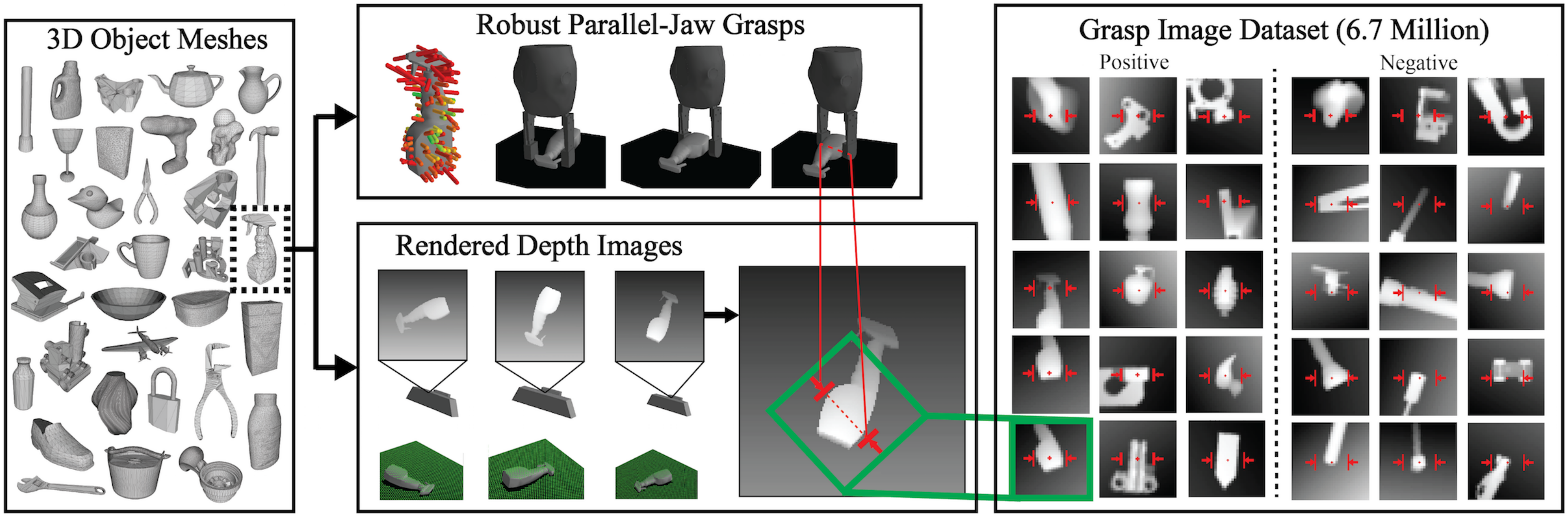


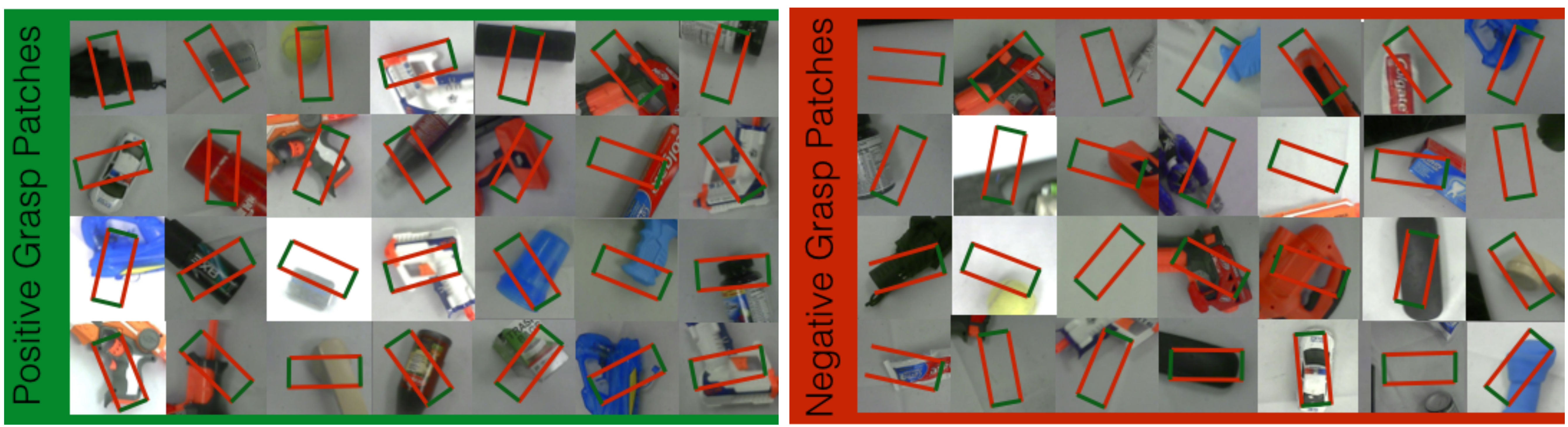
To this end, we train a neural network representing this complex dynamics with data from the real robot.

Grasping

Partial observation of environment,
hard to model agent-object interaction

Large-scale dataset of grasp outcomes





J. Mahler et al. **DexNet 2.0.** RSS 2017.
L. Pinto et al. **Supersizing Self-supervision: Learning to Grasp from 50K Tries and 700 Robot Hours.** ICRA 2016

Large-scale dataset of grasp outcomes

	IGQ	REG	GQ-Adv-Phys	GQ-Adv	GQ-S	GQ
Success Rate (%)	60±13	52±14	68±13	74±12	72±12	**80±11**
Precision (%)	N/A	N/A	68	87	92	**100**
Robust Grasp Rate (%)	N/A	N/A	100	30	48	**58**
Planning Time (sec)	1.8	3.4	0.7	0.7	0.8	0.8

	Heuristic			Learning based			
	Min eigenvalue	Eigenvalue limit	Optimistic param. select	kNN	SVM	Deep Net (ours)	Deep Net + Multi-stage (ours)
Accuracy	0.534	0.599	0.621	0.694	0.733	0.769	**0.795**

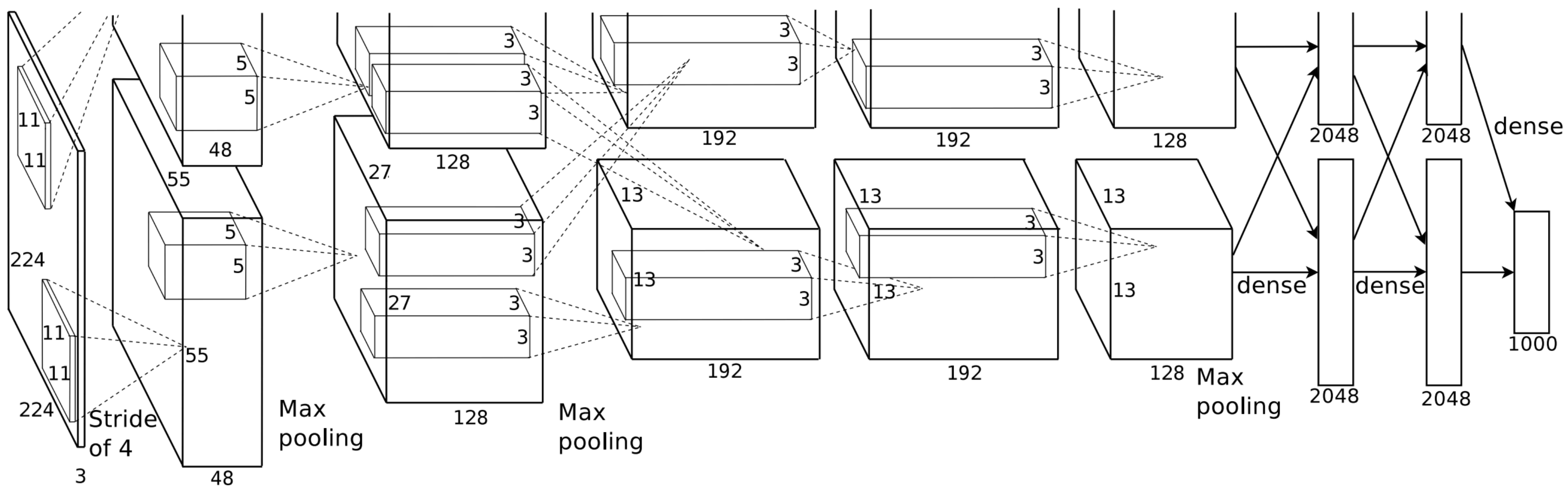
J. Mahler et al. **DexNet 2.0.** RSS 2017.
L. Pinto et al. **Supersizing Self-supervision: Learning to Grasp from 50K Tries and 700 Robot Hours.** ICRA 2016

Why Learning?

- Environments are only partially observed
- Complex systems that are hard to model
- Environments or environment-agent interactions can be hard to model
- …

How can we use learning in robotic systems?

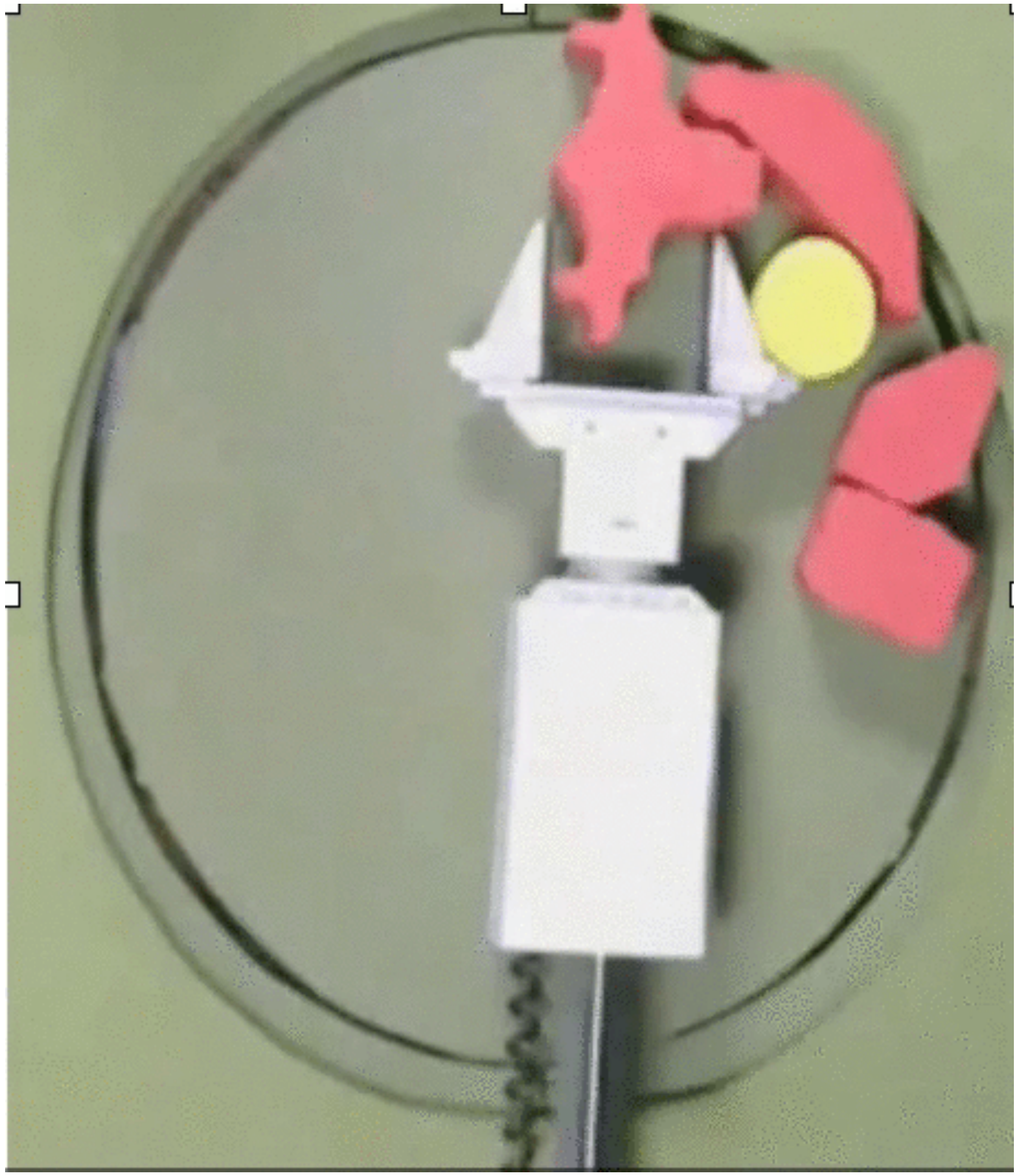
Learning in Computer Vision



person

Robot Learning vs Visual Learning

- Supervision?
  - More than one answer
  - Delayed
  - Sustainable source of supervision
- Non-stationarity
- Exploration vs exploitation



Formalism for Modeling Behavior

Reinforcement Learning

Markov Decision Process

o_t

Step Back

a_t

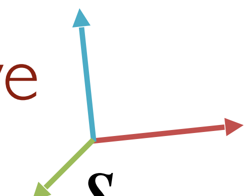
o_{t+1}

…

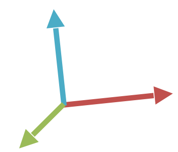
Transition Function

How you move,
how the tiger moves?

3D Relative Pose



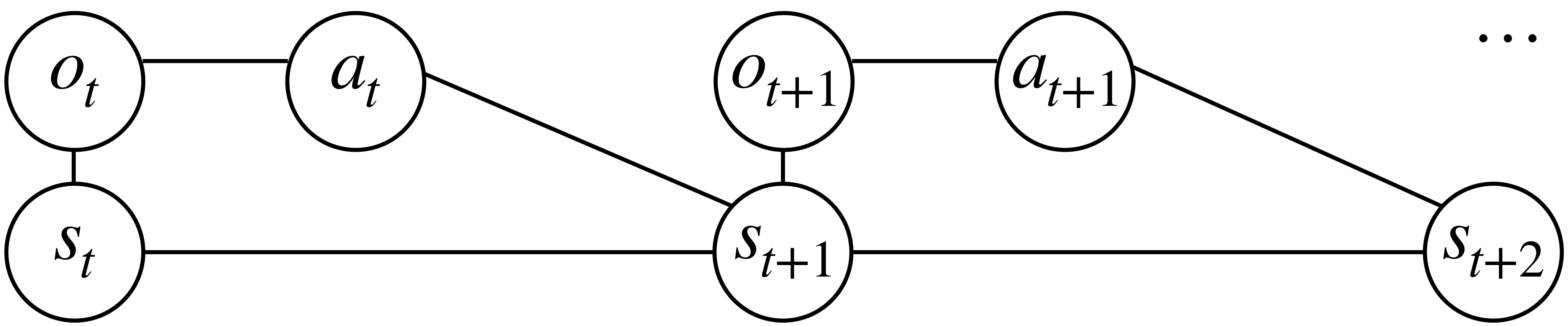
s_t



s_{t+1}

Reward Function

Survived?



Transition Function $p(s_{t+1} \mid s_t, a_t)$ $\quad$ $p(s_{t+2} \mid s_{t+1}, a_{t+1})$

Reward Function $r_t = R(s_{t+1}, s_t, a_t)$ $\quad$ $r_{t+1} = R(s_{t+2}, s_{t+1}, a_{t+1})$

Goal $\text{argmax}_{a_0,\ldots,a_T} \sum_t \gamma^t r_t$

Goals of the Course

- Understand state-of-the-art in robotics and robot learning
- Formulate robot learning problems as MDPs

Challenges with Markov Decision Process

o_t

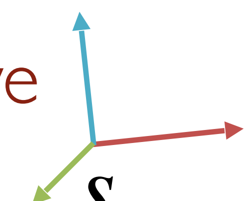
Step Back

a_t

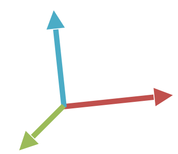
o_{t+1}

...

3D Relative Pose



s_t



s_{t+1}

Transition Function

How you move,
how the tiger moves?

Reward Function

Survived?

Need to live many many lives to learn how to live.

Credit assignment problem in RL

o_t

B

B

F

B

Yann LeCun's Cake

Alternatives to Solving MDPs

Pieter Abbeel's Cake

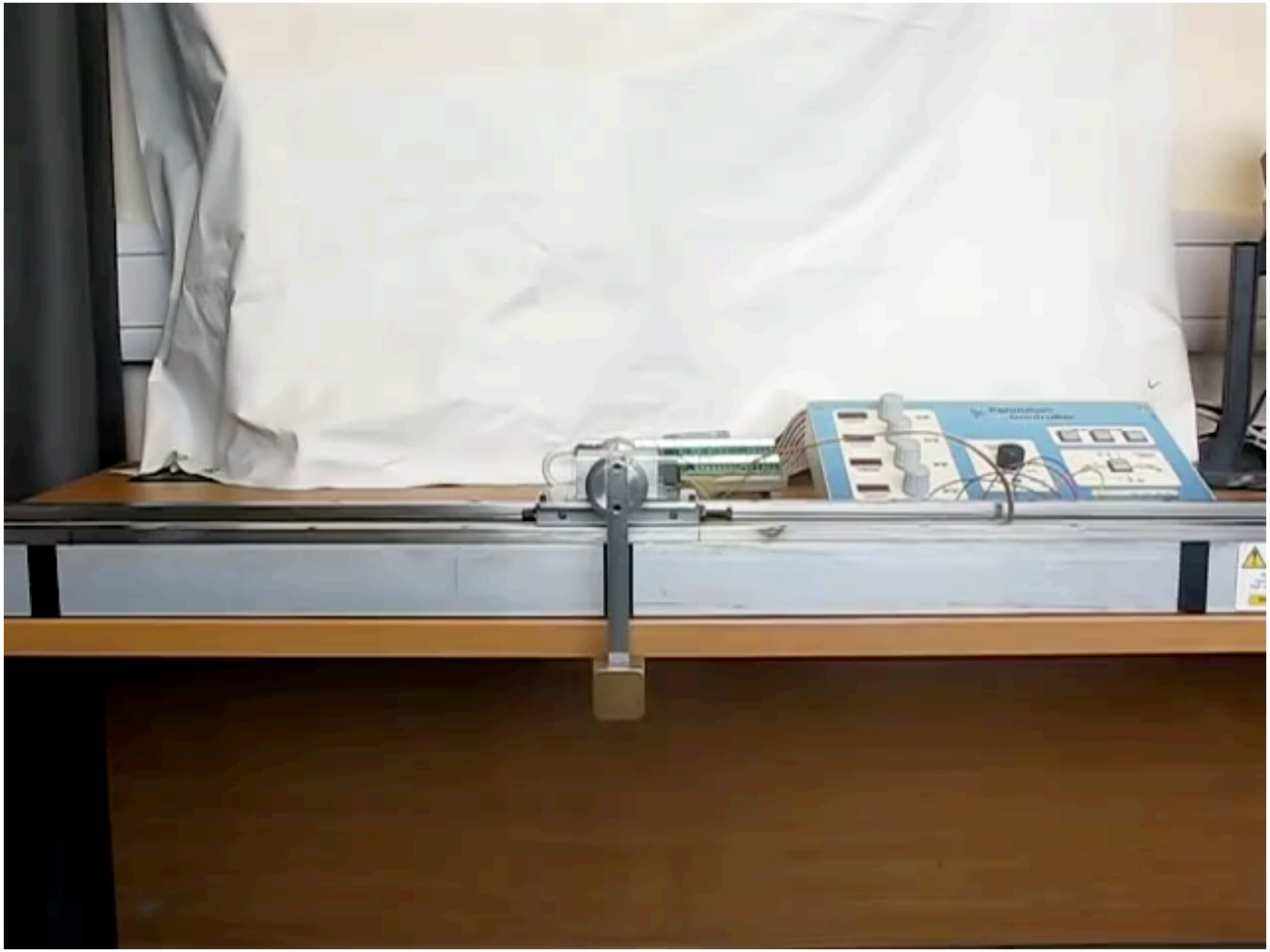
M. Andrychowicz et al. **Hindsight Experience Replay.** NeurIPS 2018.

Solve a Related but Supervision-rich Problem

S. Levine et al. **Learning Hand-Eye Coordination for Robotic Grasping with Deep Learning and Large-Scale Data Collection.** ISER 2017.

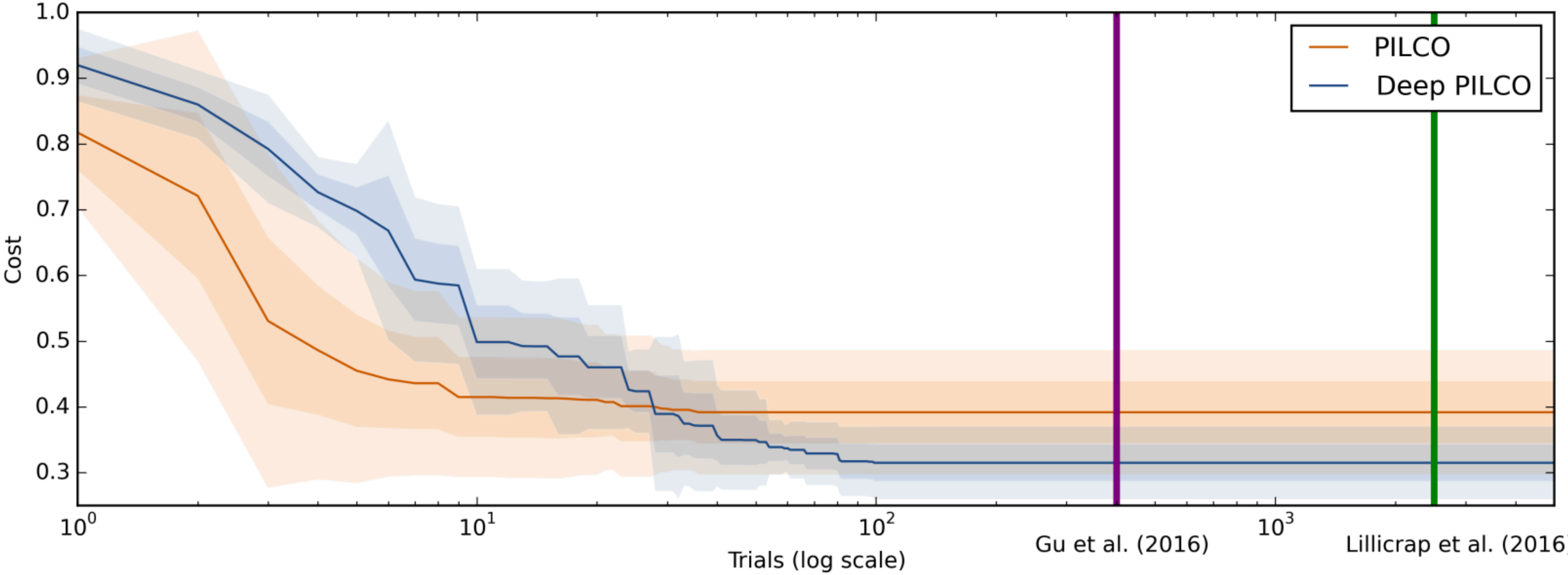
Build Models and Plan with Them

PILCO - Inverting a pendulum



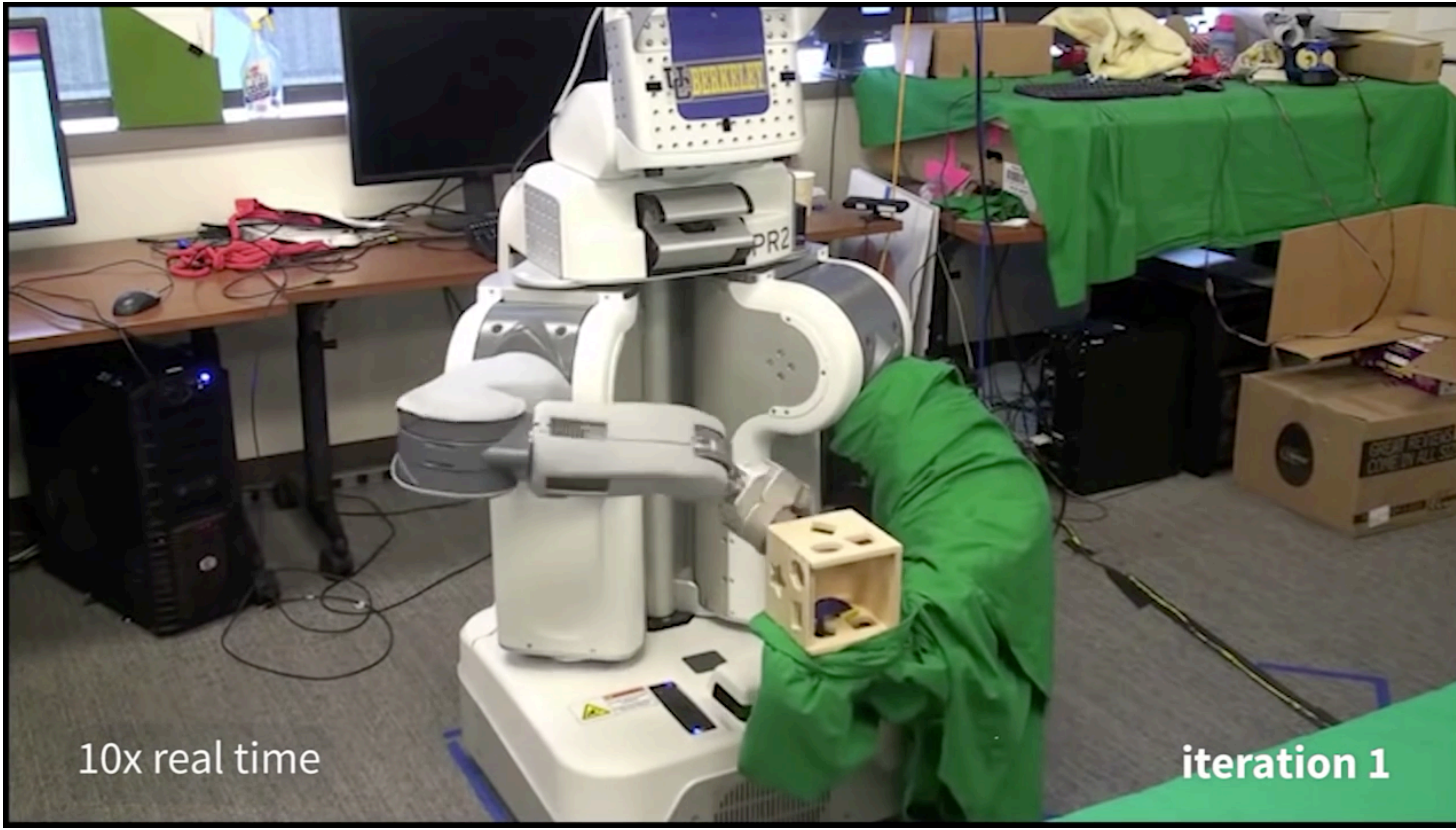
Build Models and Plan with Them

PILCO - Inverting a pendulum



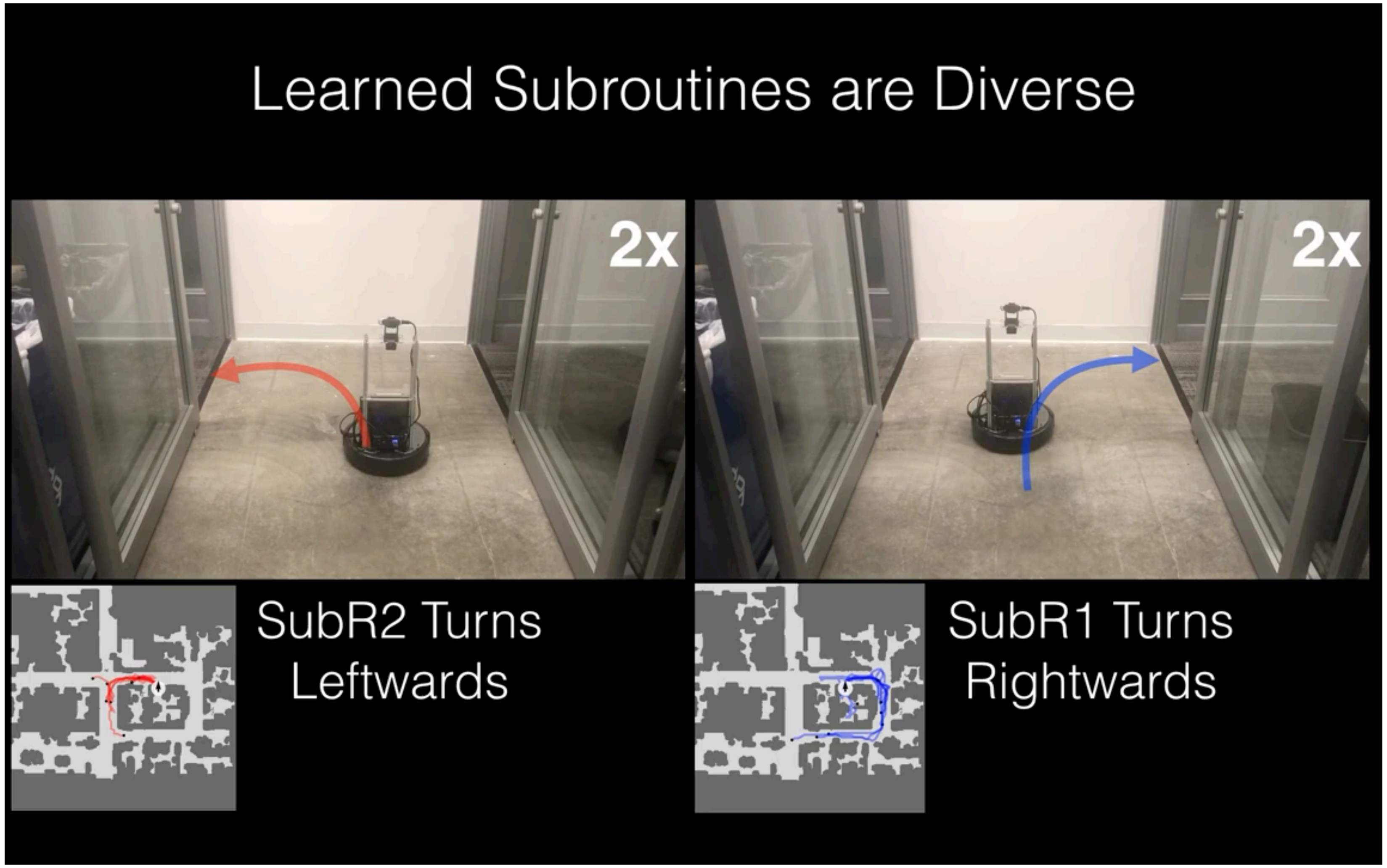
[PILCO] M. Deisenroth et al. **PILCO: A Model-based and Data-Efficient Approach to Policy Search.** ICML 2011

Learn by Imitating Experts



S. Levine et al. **End-to-End Training of Deep Visuomotor Policies.** JMLR 2016.

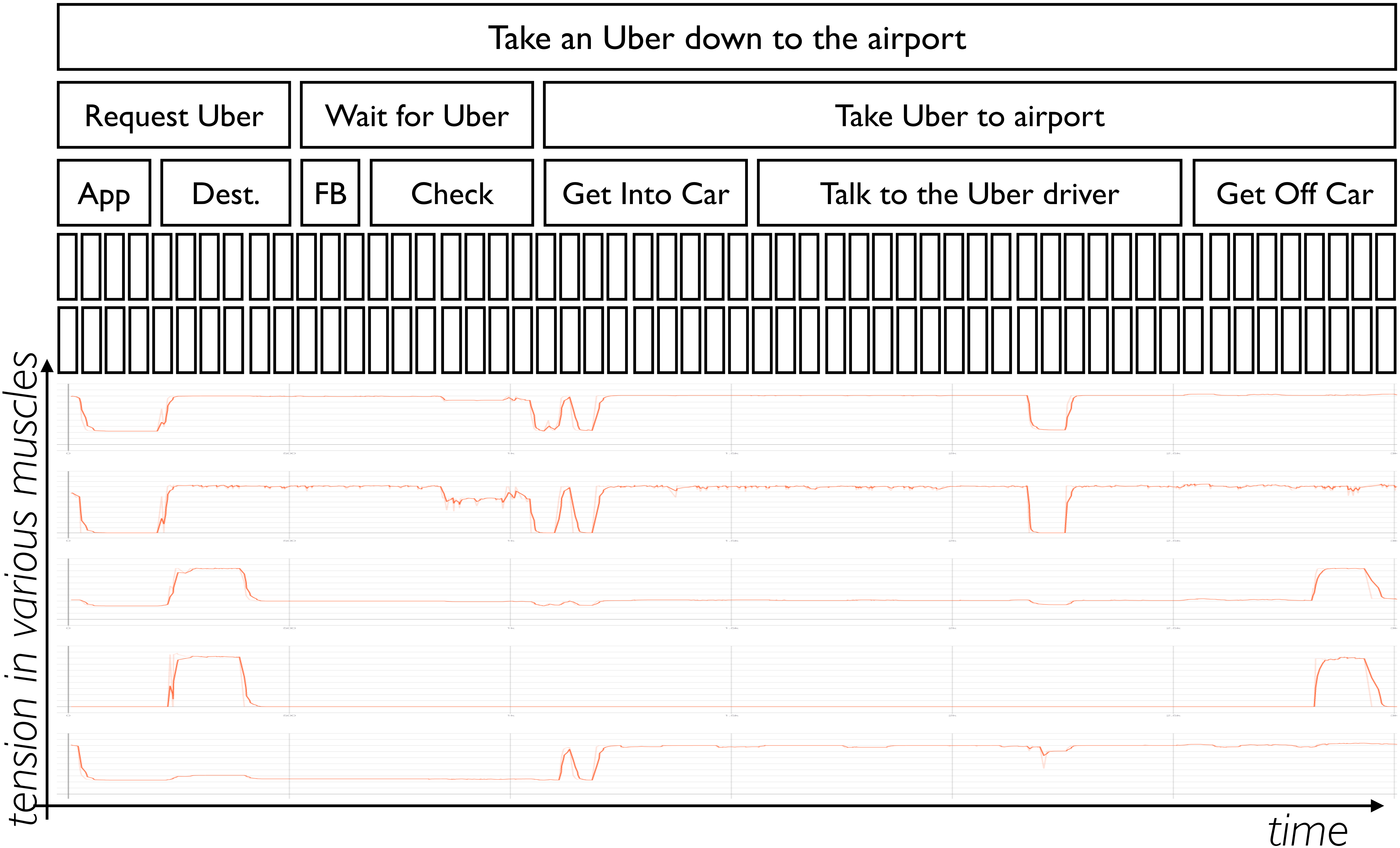
Learn by Observing Experts



A. Kumar et al. **Learning Navigation Subroutines by Watching Videos.** CoRL 2019.

Hierarchies

Think about going to the airport.



Course Outline

- Understand state-of-the-art in robotics and robot learning
- Formulate robot learning problems as MDPs
- Investigate alternative ways of solving MDPs

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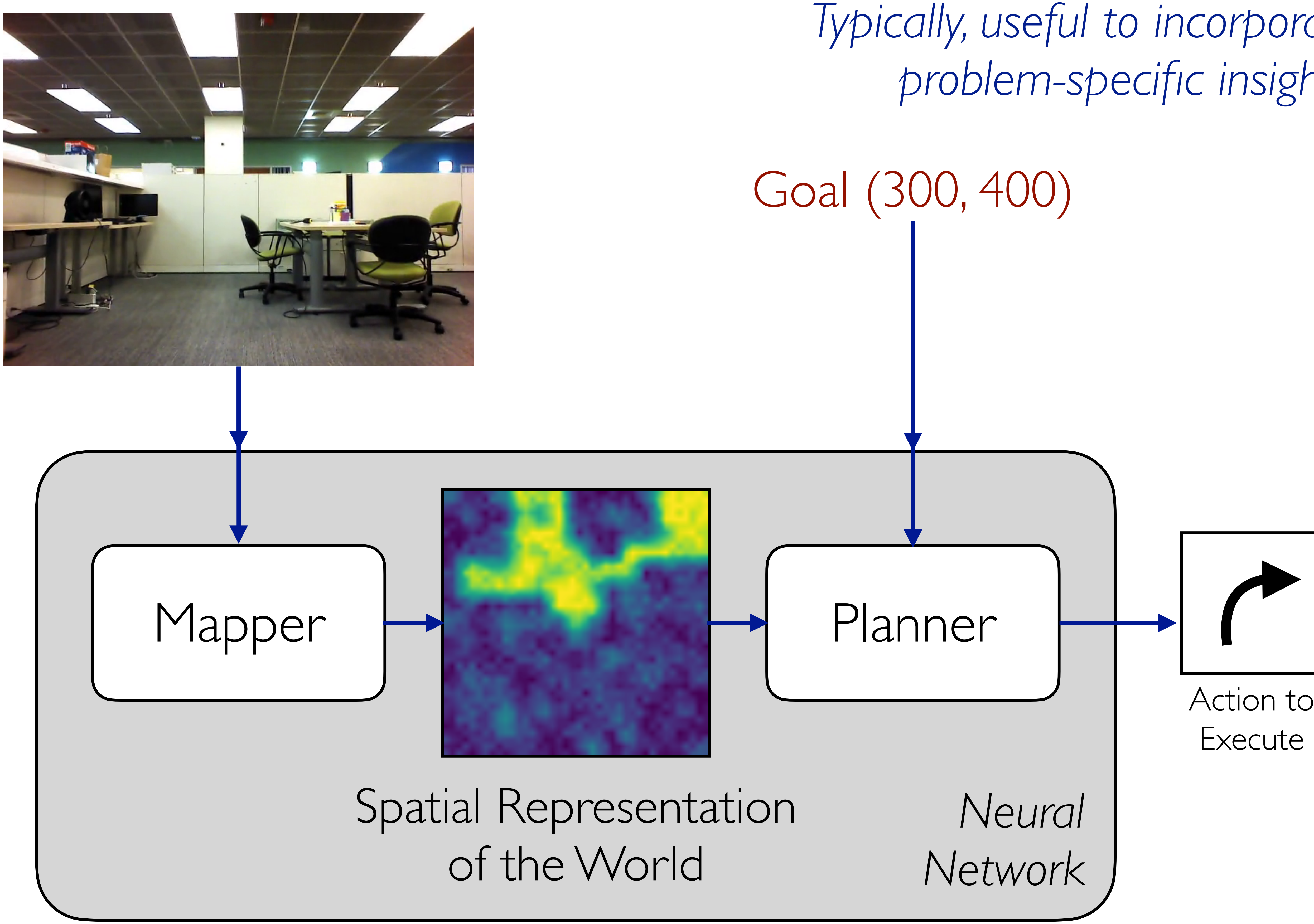
Typically, useful to incorporate problem-specific insights.

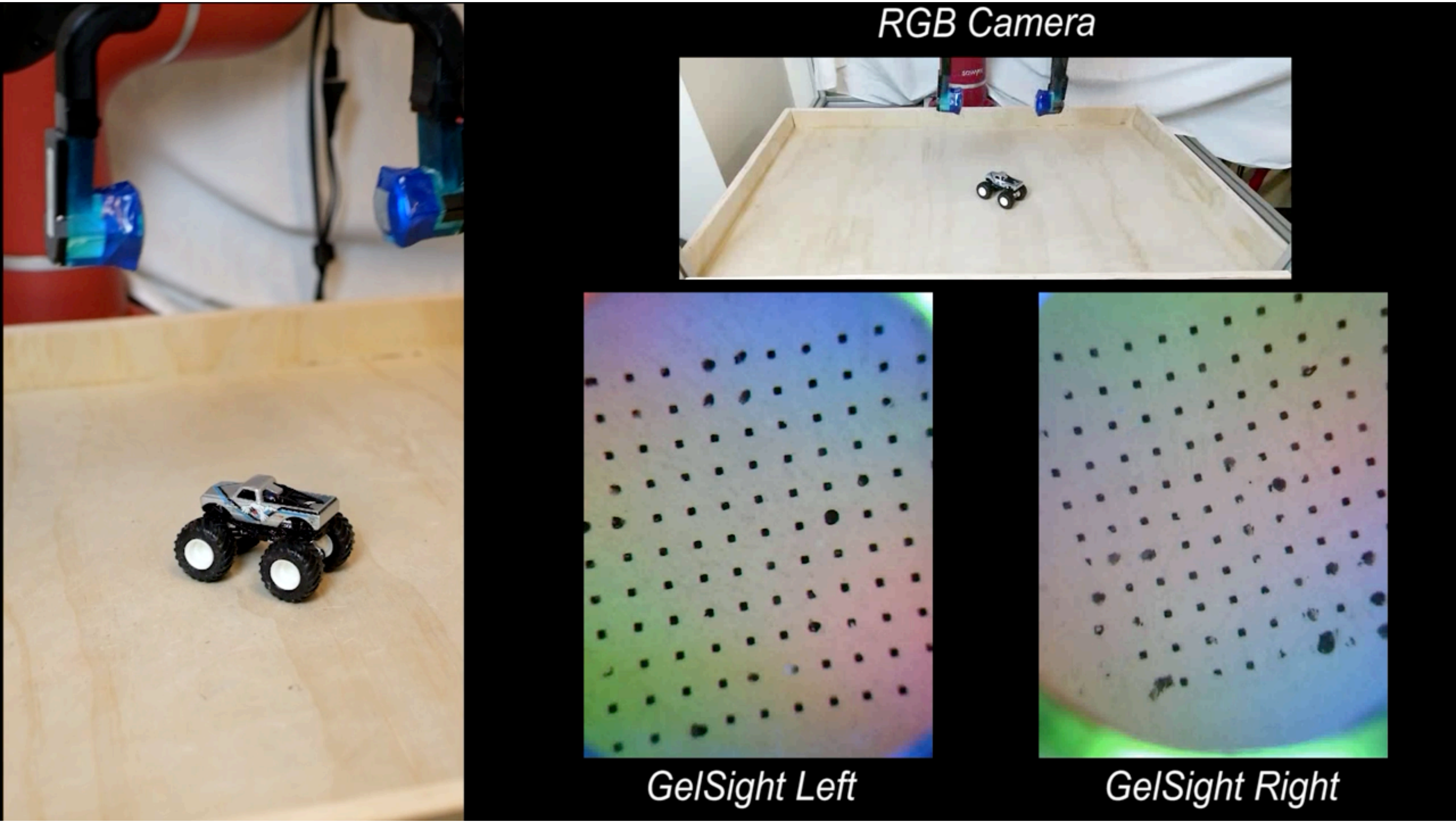


S. Gupta et al., *CVPR 2017, IJCV 2020.* Cognitive Mapping and Planning for Visual Navigation

Locomotion: Combining with low-level control

Deep Drone Racing: Learning Agile Flight in Dynamic Environments
Kaufmann, et al. CoRL 2018

Manipulation: Use of specialized hardware



Learning to Grasp and Re-grasp using Vision and Touch
Calandra, et al. RAL 2018

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- Perspectives

Perspectives

- Representations vs Behaviors
- Big Data vs Clever Algorithms
- Lessons from Cognitive Science, Psychology, Neuroscience
- …

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Today, we will…

- Course outline
- Course logistics
- Get to know each other

Course Logistics

Instructor:
Saurabh Gupta

TA:
Aditya Prakash

http://saurabhg.web.illinois.edu/teaching/ece598sg/fa2022

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Thank you