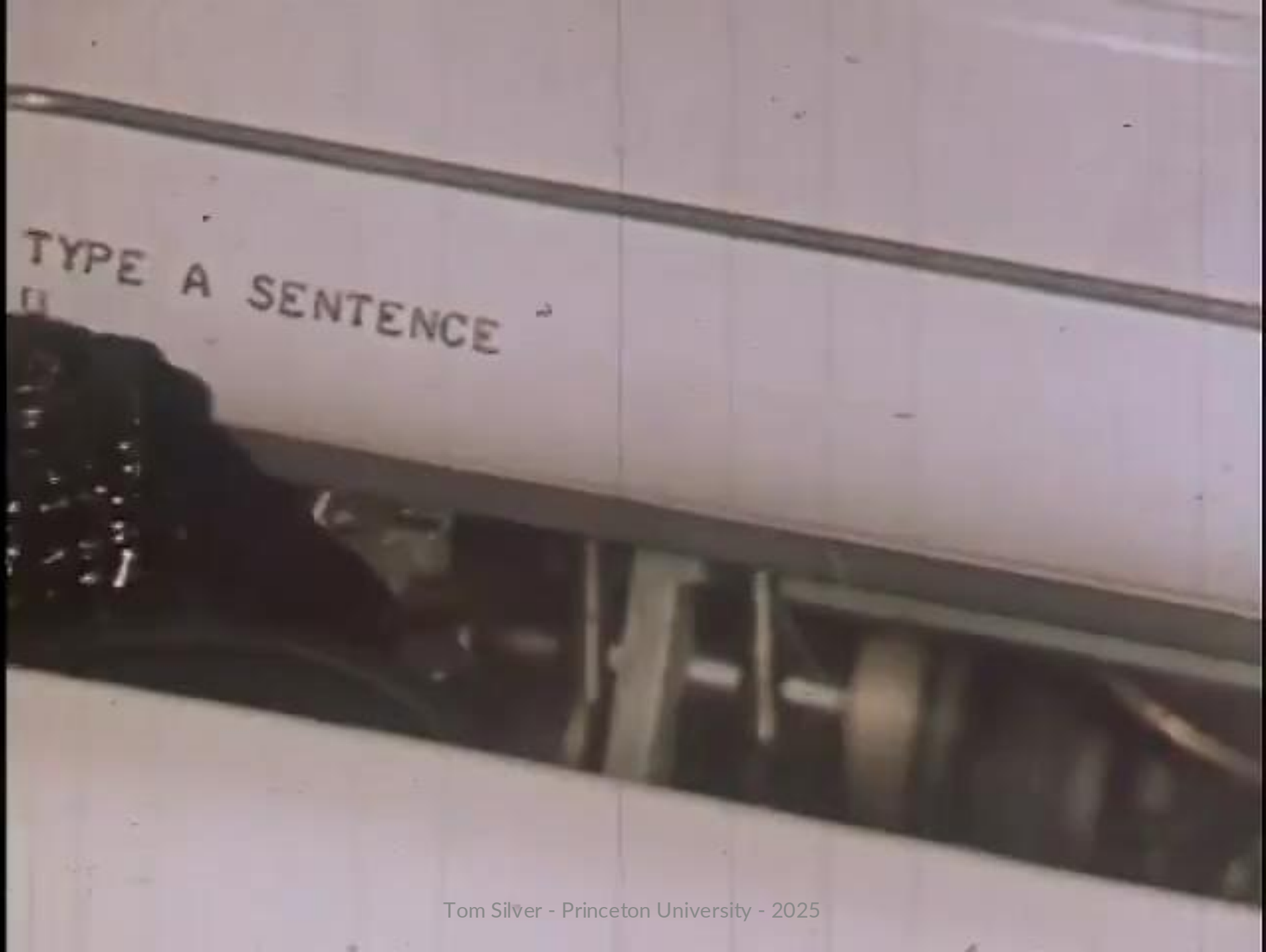
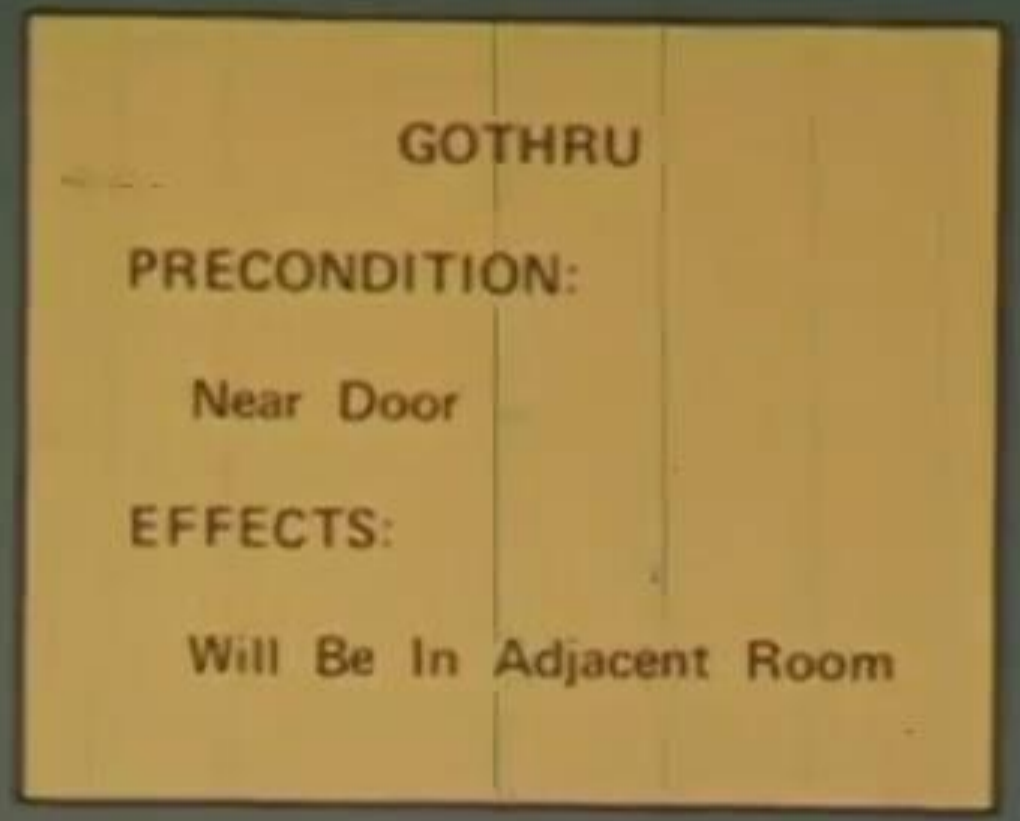
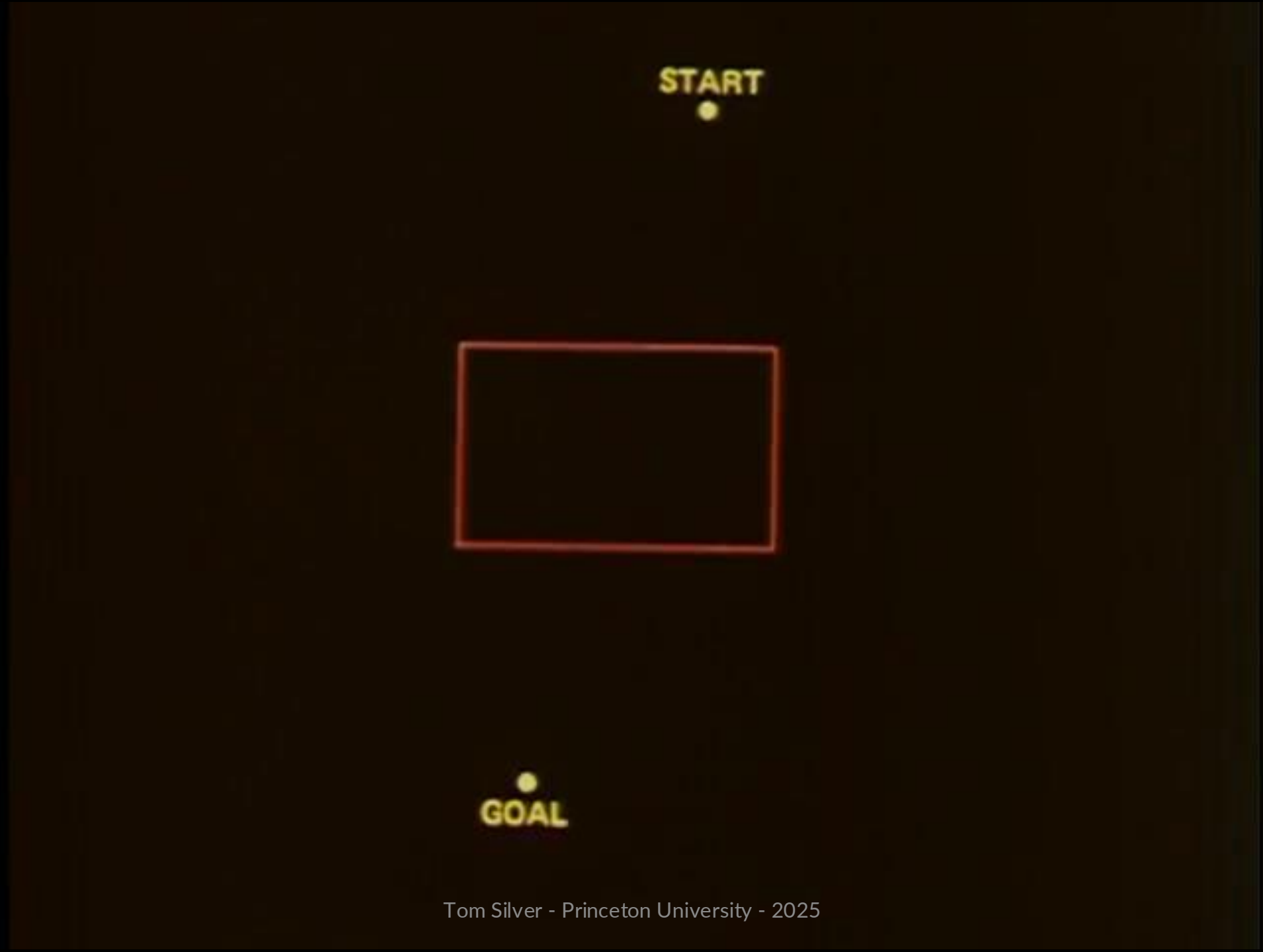
Robot Planning Meets Machine Learning

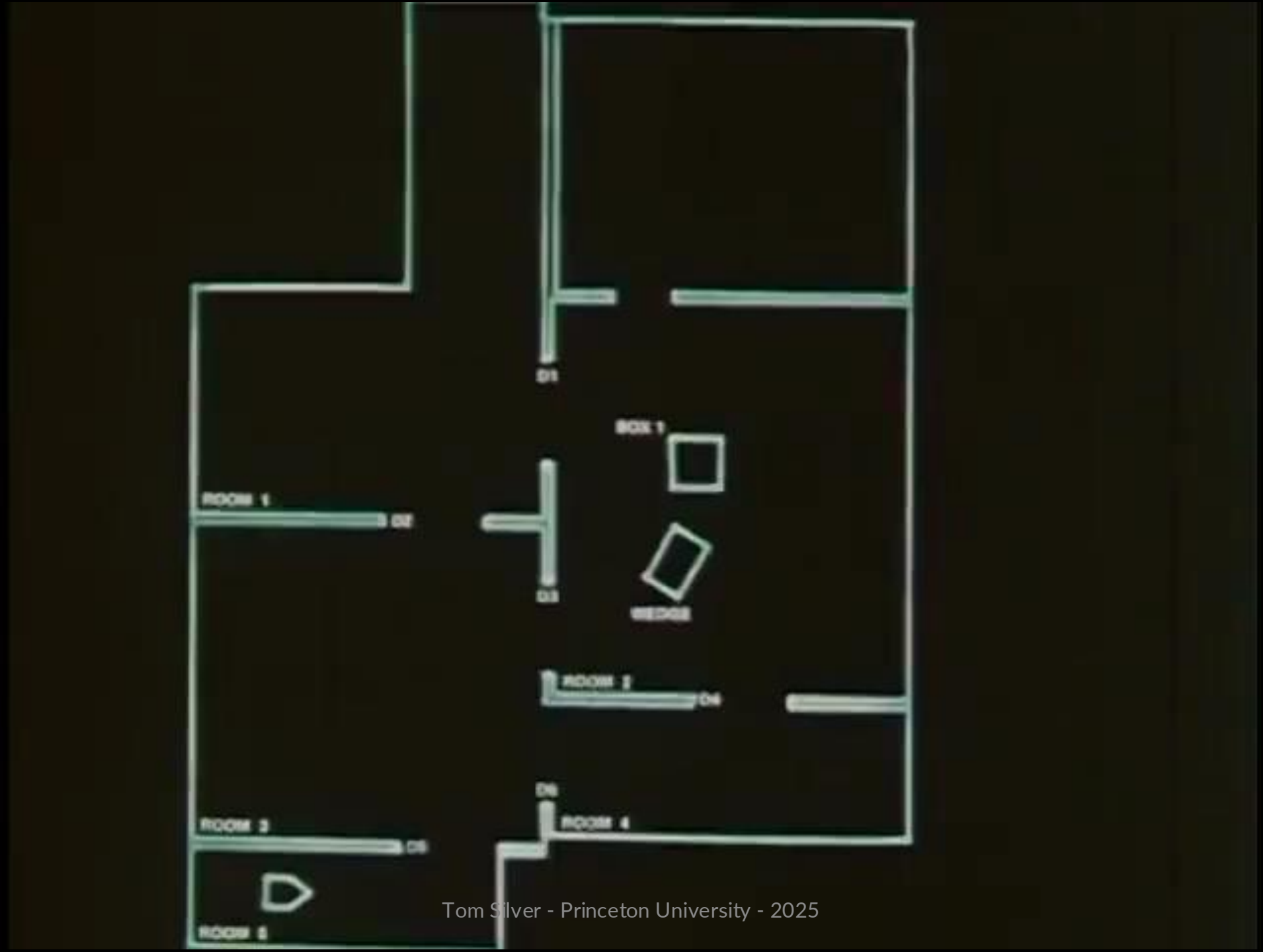
Tom Silver
Princeton University
Fall 2025

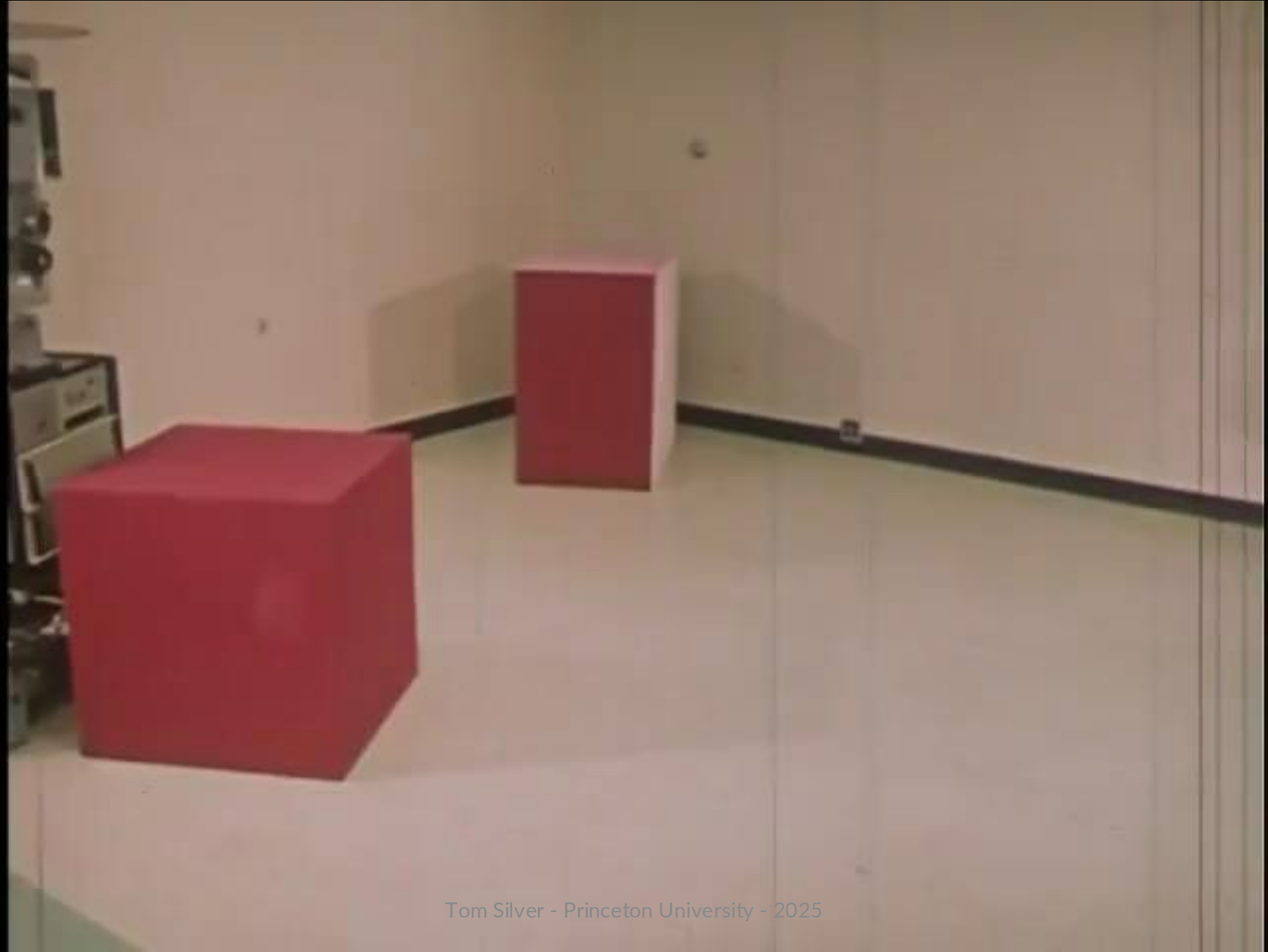

FOCUS


TYPE A SENTENCE


GOTHRU
PRECONDITION:
Near Door
EFFECTS:
Will Be In Adjacent Room


START
GOAL


D1
BOX 1
ROOM 1
D2
D3
WEDGE
ROOM 2
D4
D6
ROOM 3
D5
ROOM 4
ROOM 5



GOTO ( )

GOTHRU ( )

GOTO ( )

GOTHRU ( )

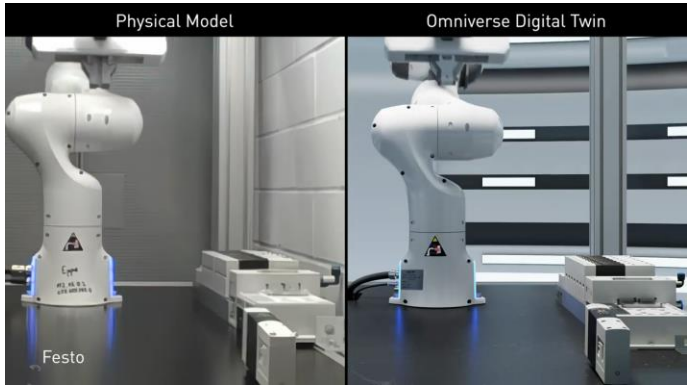
BLOCK (,)

That was 1972

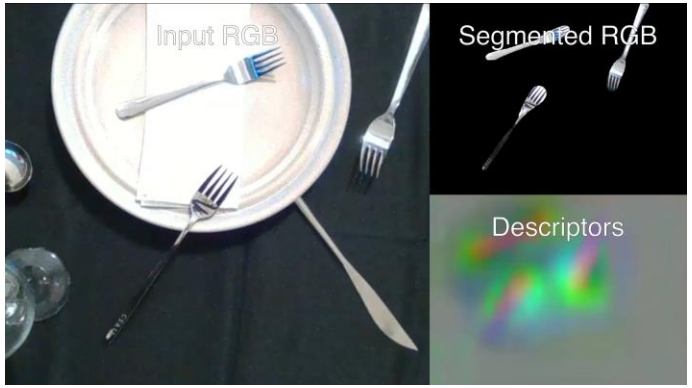
What's new?

Hardware is better

Control is better



Simulation is better



Perception is better

[1] https://openai.com/blog/learning-dexterity
[2] https://www.bostondynamics.com/resources/blog/leaps-bounds-and-backflips
[3] https://developer.nvidia.com/isaac-sim
[4] https://yenchenlin.me/nerf-supervision/

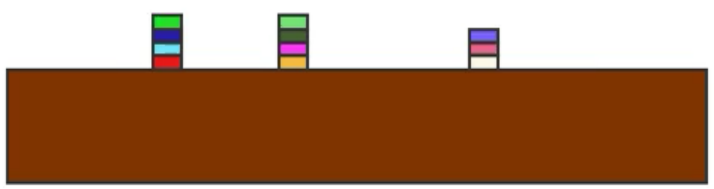
That was 1972

What's new?

Is planning better?

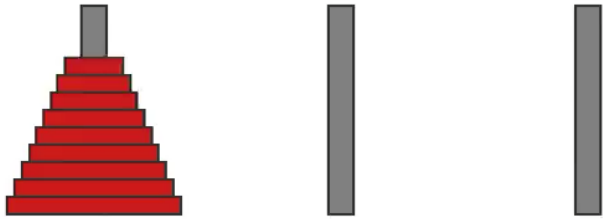
On one hand: yes, of course

Planning is Better: Task Planning



Blocks World
Plan length: 28
Planning time: 0.12 s

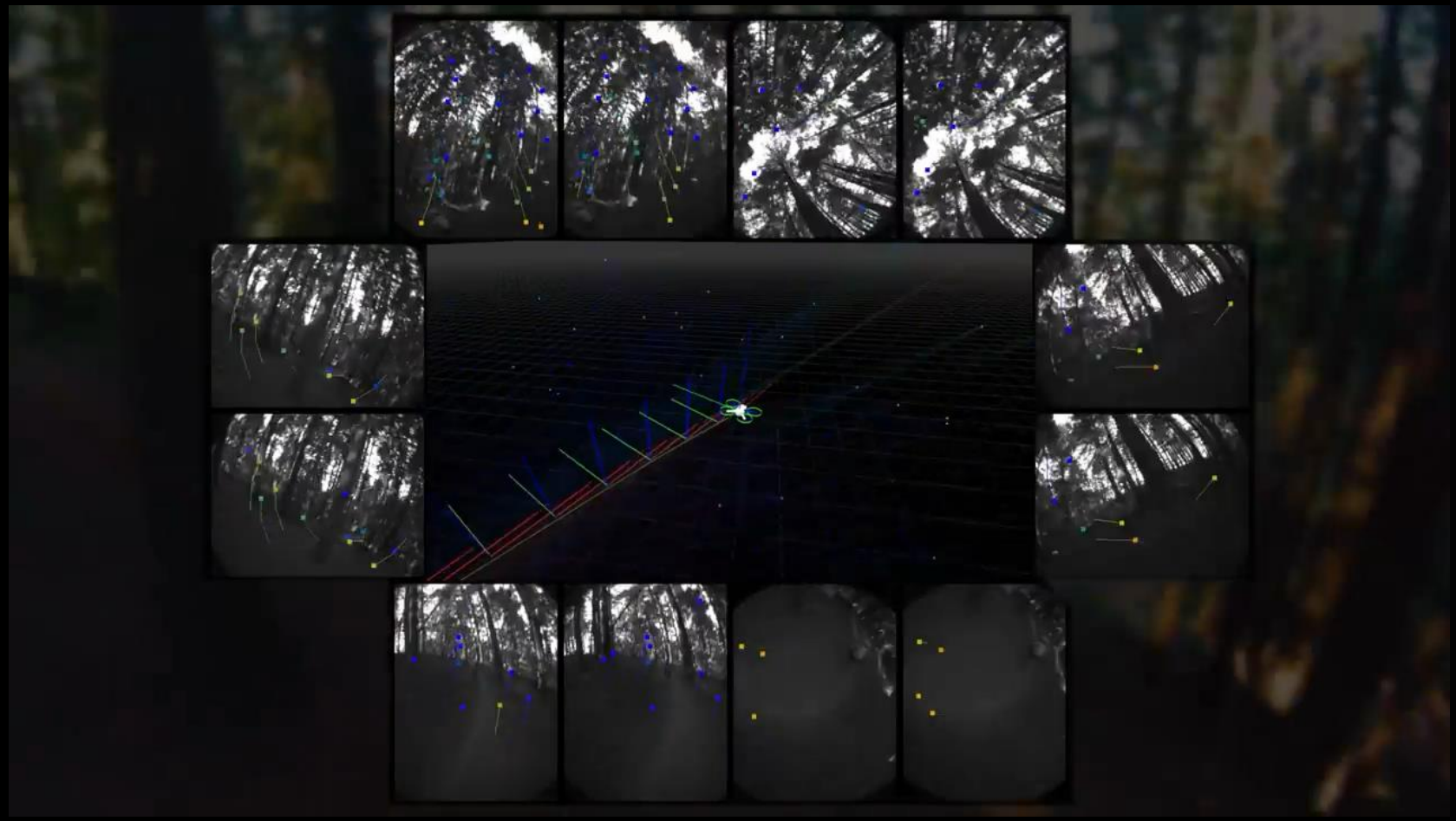
Sokoban
Plan length: 167
Planning time: 0.25 s



Hanoi
Plan length: 579
Planning time: 0.22 s

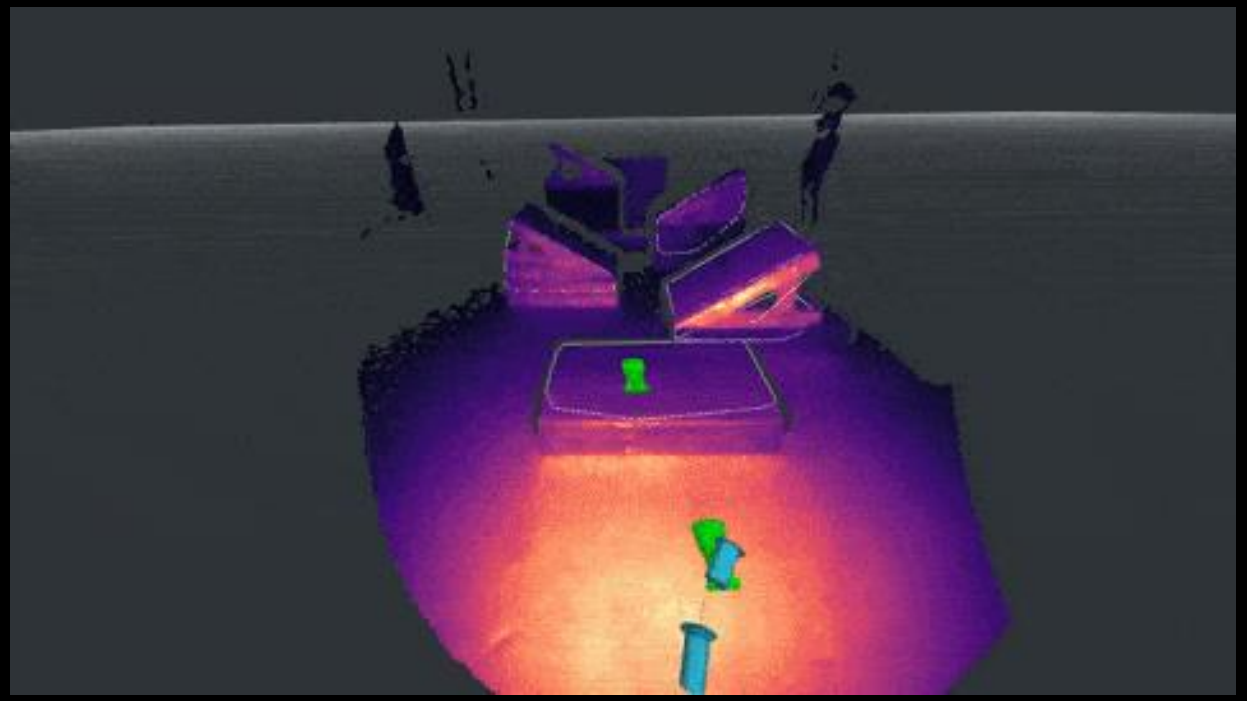
Planning with Fast Downward (https://www.fast-downward.org)
Rendering and simulation with PDDLGym (https://github.com/tomsilver/pddlgym)

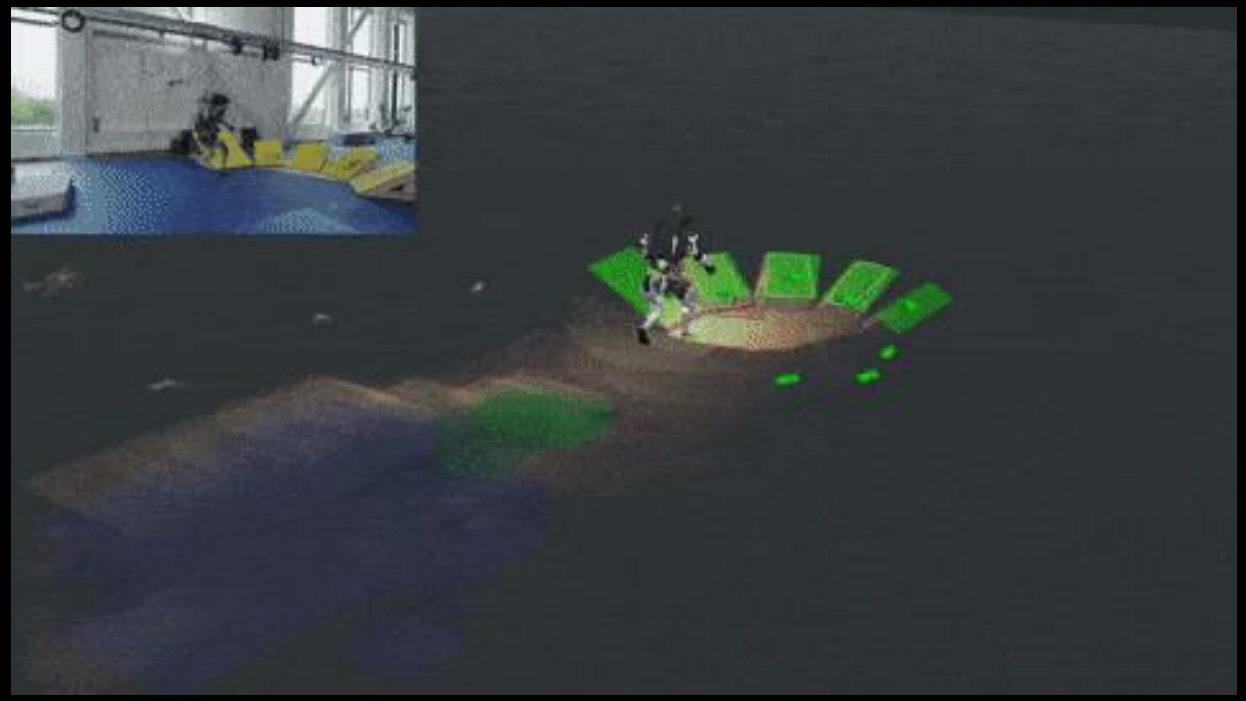
Planning is Better: Motion Planning



https://www.skydio.com/skydio-autonomy

Planning is Better: Trajectory Optimization





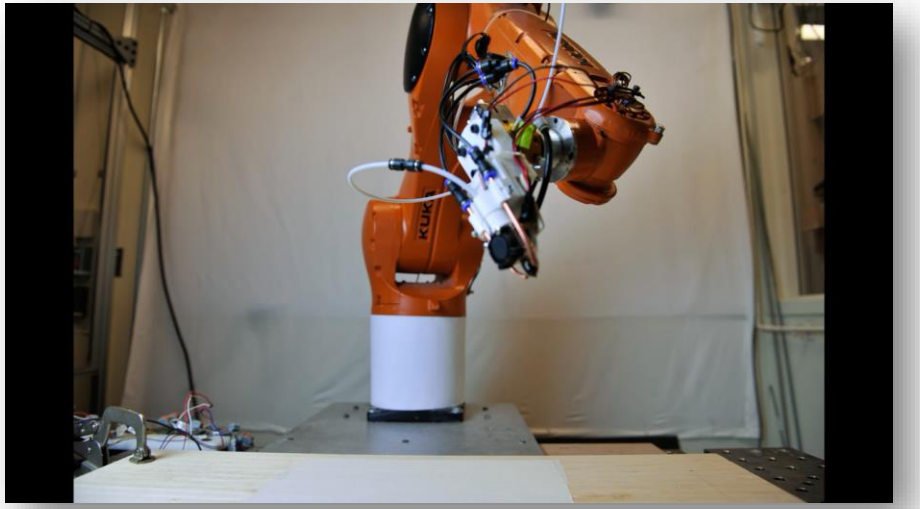
https://bostondynamics.com/blog/flipping-the-script-with-atlas/

Planning is Better: Integrated TAMP

Setting a dinner table

(Srivastava et al. 2014)

3D printing



(Garrett et al. 2020)

"Integrated Task and Motion Planning." Caelan Reed Garrett, Rohan Chitnis, Rachel Holladay, Beomjoon Kim, Tom Silver, Leslie Pack Kaelbling, and Tomás Lozano-Pérez. ARCRAS 2021.

That was 1972

What's new?

Is planning better?

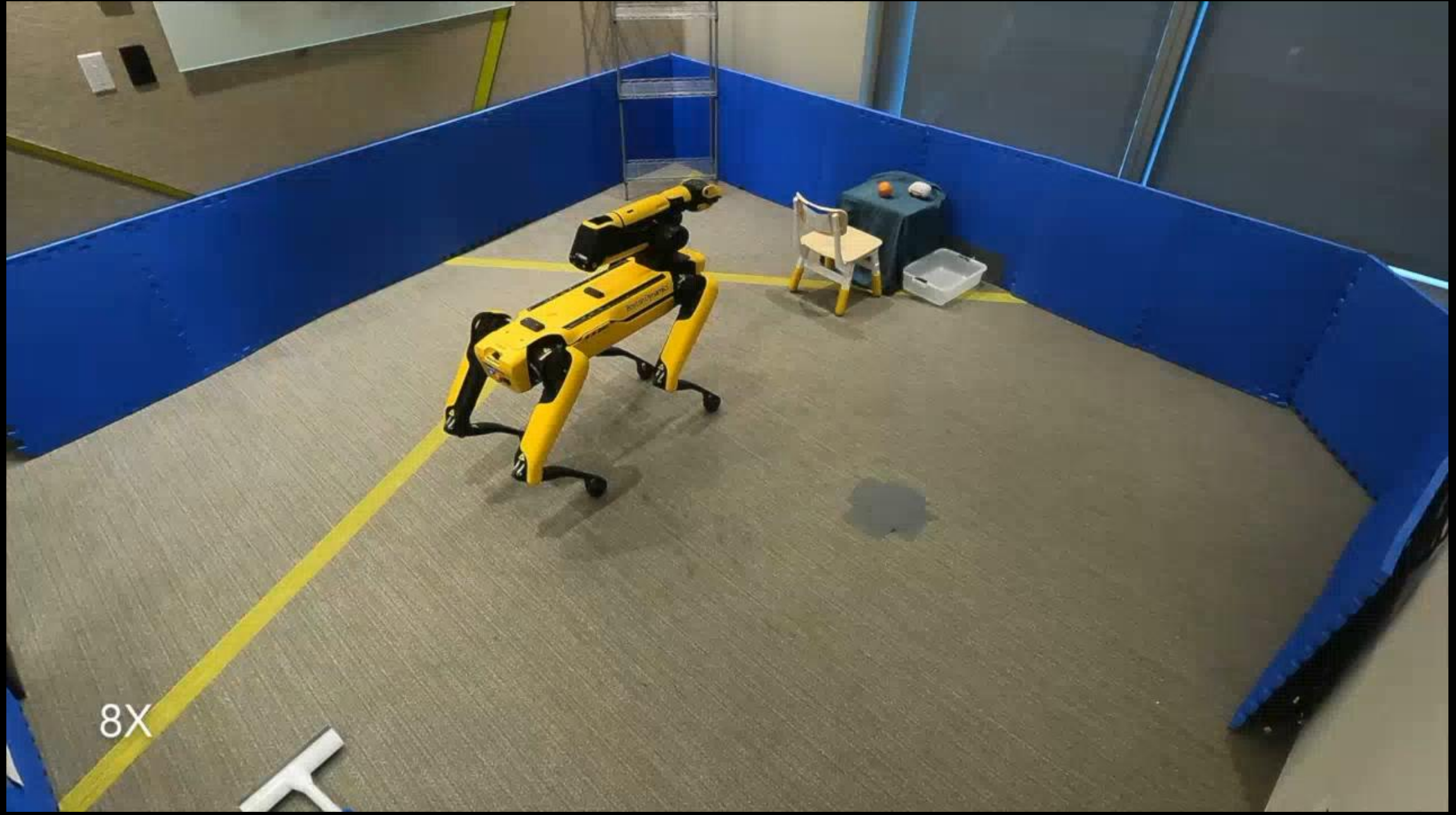
On one hand: yes, of course

On the other hand…

Our robots are still quite "Shakey"

Course thesis:

To create intelligent general-purpose robots, we need planning *and* learning, and they need each other.



Practice Makes Perfect: Planning to Learn Skill Parameter Policies

Nishanth Kumar*, **Tom Silver***, Willie McClinton, Linfeng Zhao, Stephen Proulx, Tomás Lozano-Pérez, Leslie Pack Kaelbling, Jennifer Barry

RSS 2024

FEAST: A Flexible Mealtime-Assistance System Towards In-the-Wild Personalization

Rajat Kumar Jenamani, **Tom Silver**, Ben Dodson, Shiqin Tong, Anthony Song, Yuting Yang, Ziang Liu, Benjamin Howe, Aimee Whitneck, Tapomayukh Bhattacharjee

RSS (2025) **Best Paper Award**

CART-MPC: Coordinating Assistive Devices for Robot-Assisted Transferring with Multi-Agent Model Predictive Control

Ruolin Ye, Shuaixing Chen, Yunting Yan, Joyce Yang, Christina Ge, Jose Barreiros, Kate Tsui, **Tom Silver**, Tapomayukh Bhattacharjee

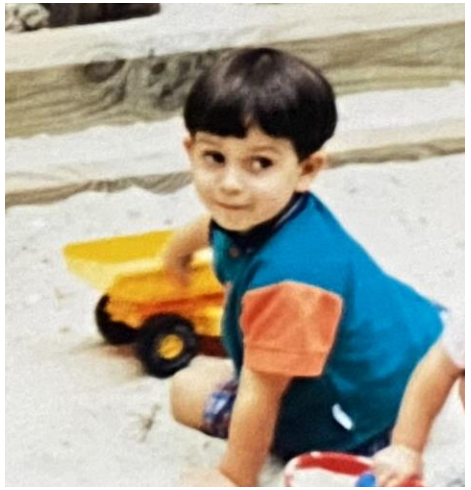
HRI 2025

Course thesis:

To create intelligent general-purpose robots, we need planning *and* learning, and they need each other.

About Me

Born and raised in Bergen County, NJ



About Me

College at Harvard

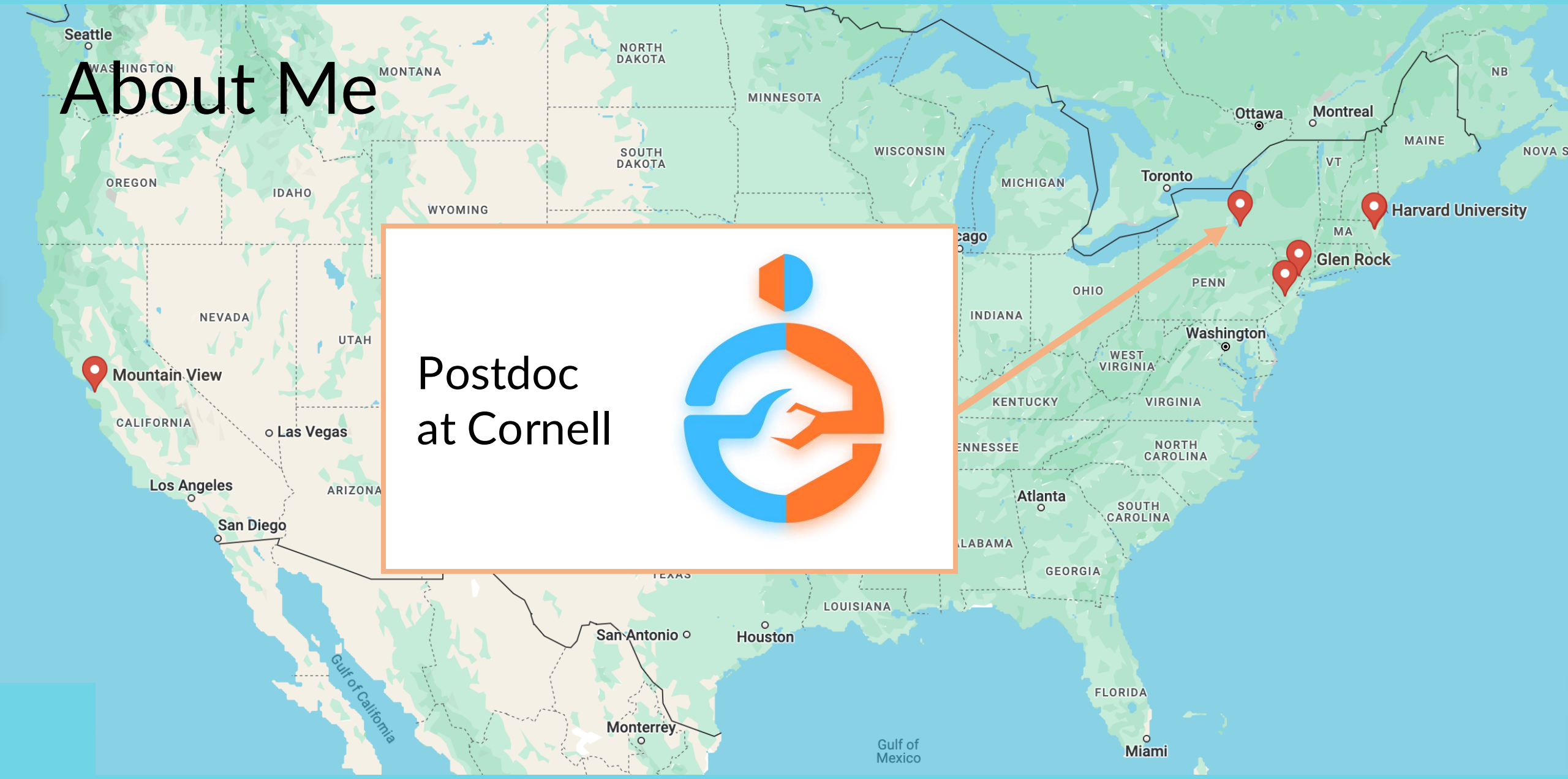
About Me

Worked at now-defunct start-up

About Me

Grad school at MIT

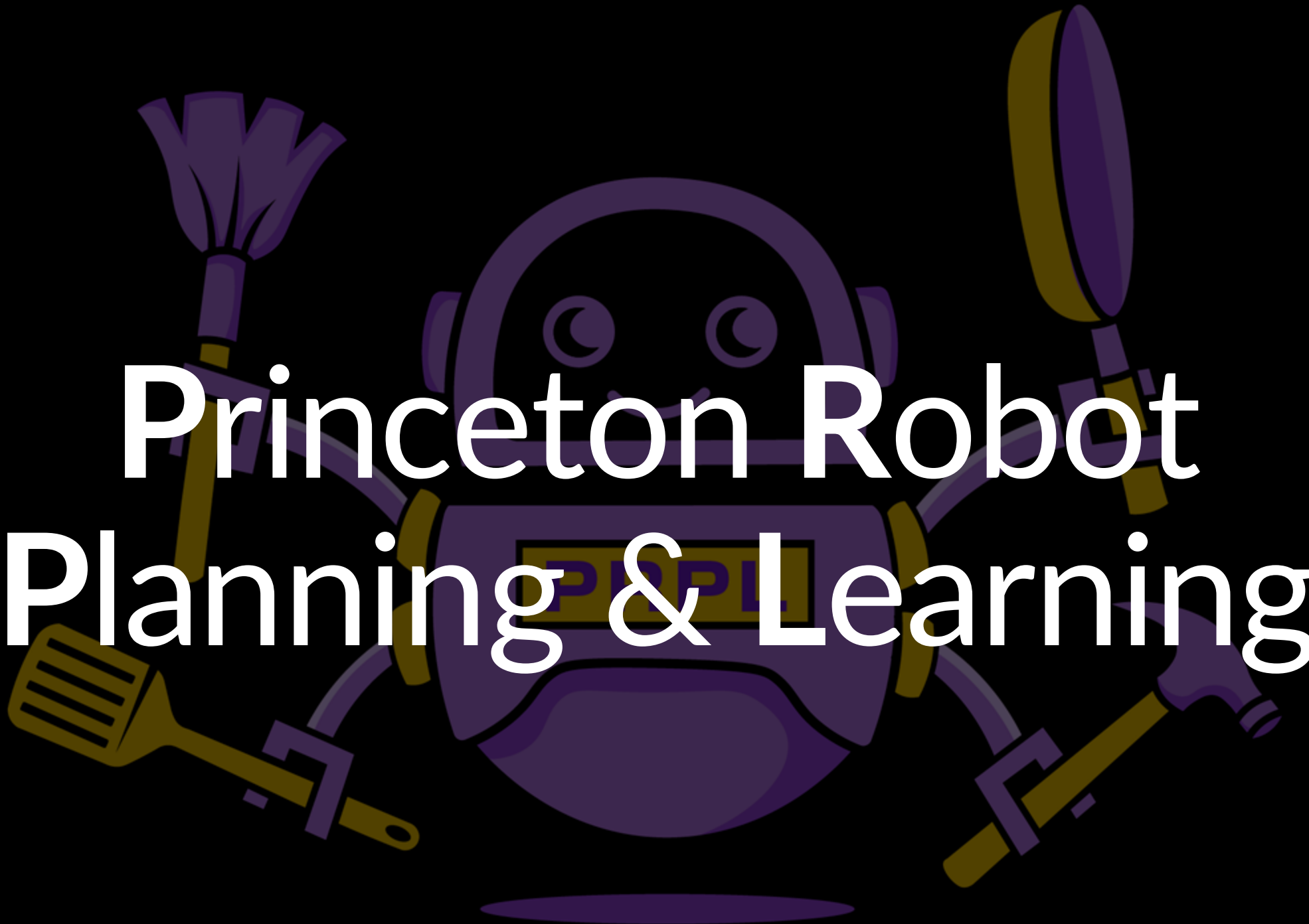
About Me



Postdoc
at Cornell

About Me

Started at Princeton Fall 2025



Princeton Robot Planning & Learning

PRPL Mission

Develop **generalist robots** that **learn** and **plan** to **help people**

robot chefs, robot lab assistants, robot house cleaners, robot beekeepers, robot toileting assistants, robot tailors, robot grocery unpackers, robot dog walkers, robot dog companions, robot bathing assistants, robot search and rescue dogs, robot traffic controllers, robot social companions, robot snowplows, robot gardeners, robot baristas, robot beach cleaners, robot construction workers, robot dressing assistants, robot forest rangers, robot personal hygiene assistants, robot barbers, robot house movers, robot personal shoppers, robot home security guards, robot appliance fixers, robot firefighters, robot medication monitors, robot recycling sorters, robot surgical tool managers, robot memory assistants, robot berry pickers, robot locksmiths…

Robot Factory

Deployment 1

Deployment 2

Deployment 3

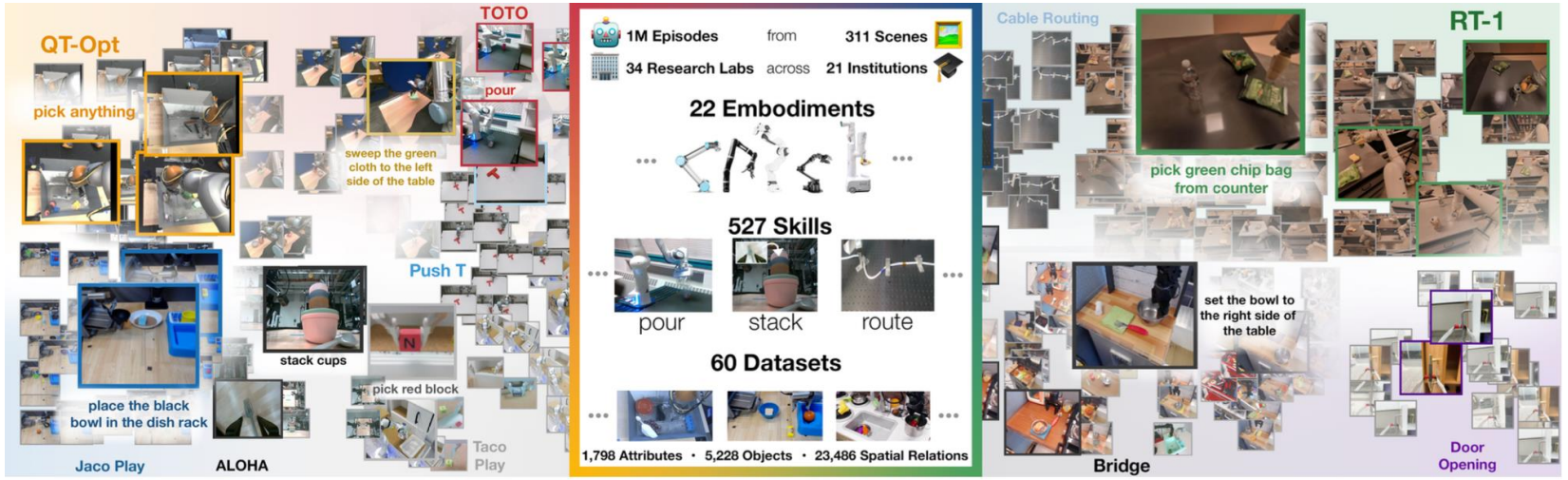
Deployment 4 ...

Robot Factory

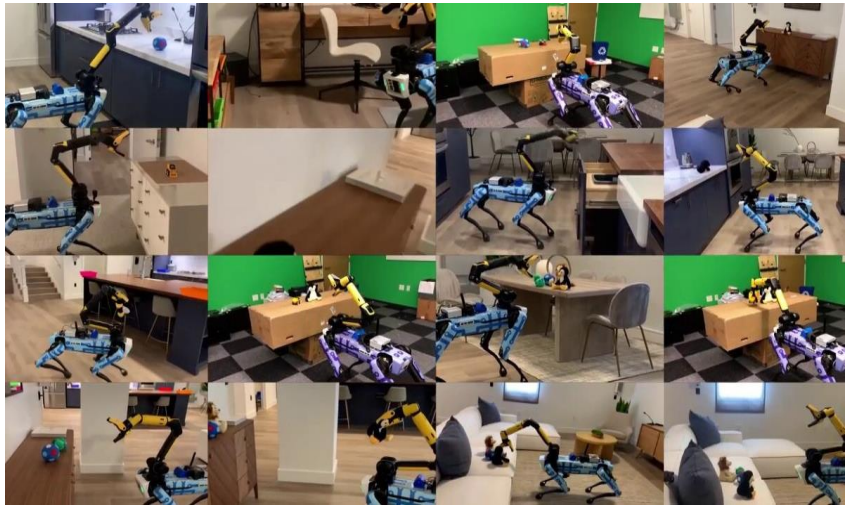
Robots that are **good in general**

General-purpose programming

Pretraining **foundation models**

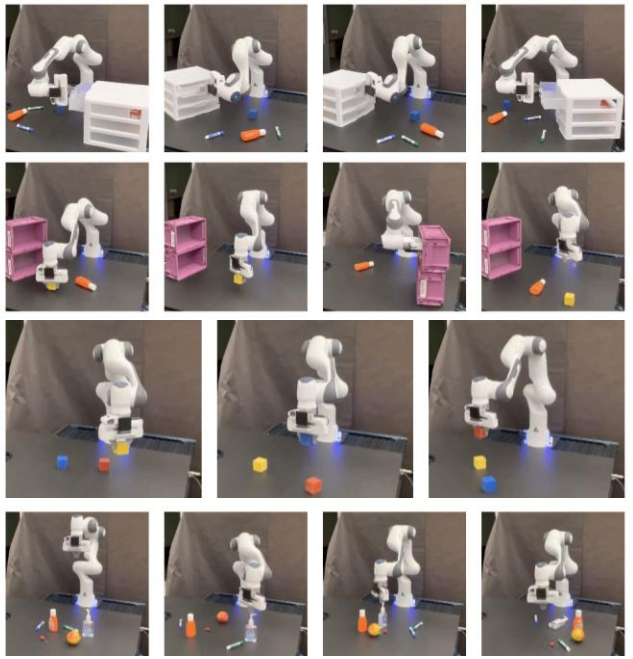


Google (RT-X, Open X-Embodiment)



Meta (Ego 4D, Adaptive Skill Coordination)

Toyota Research Institute (Diffusion Policies)



NVIDIA (RVT)

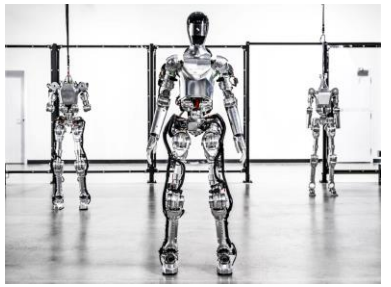
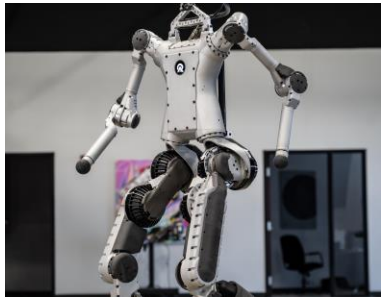
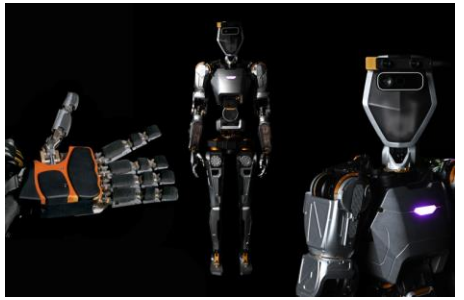


Figure AI

1X



Apptronik



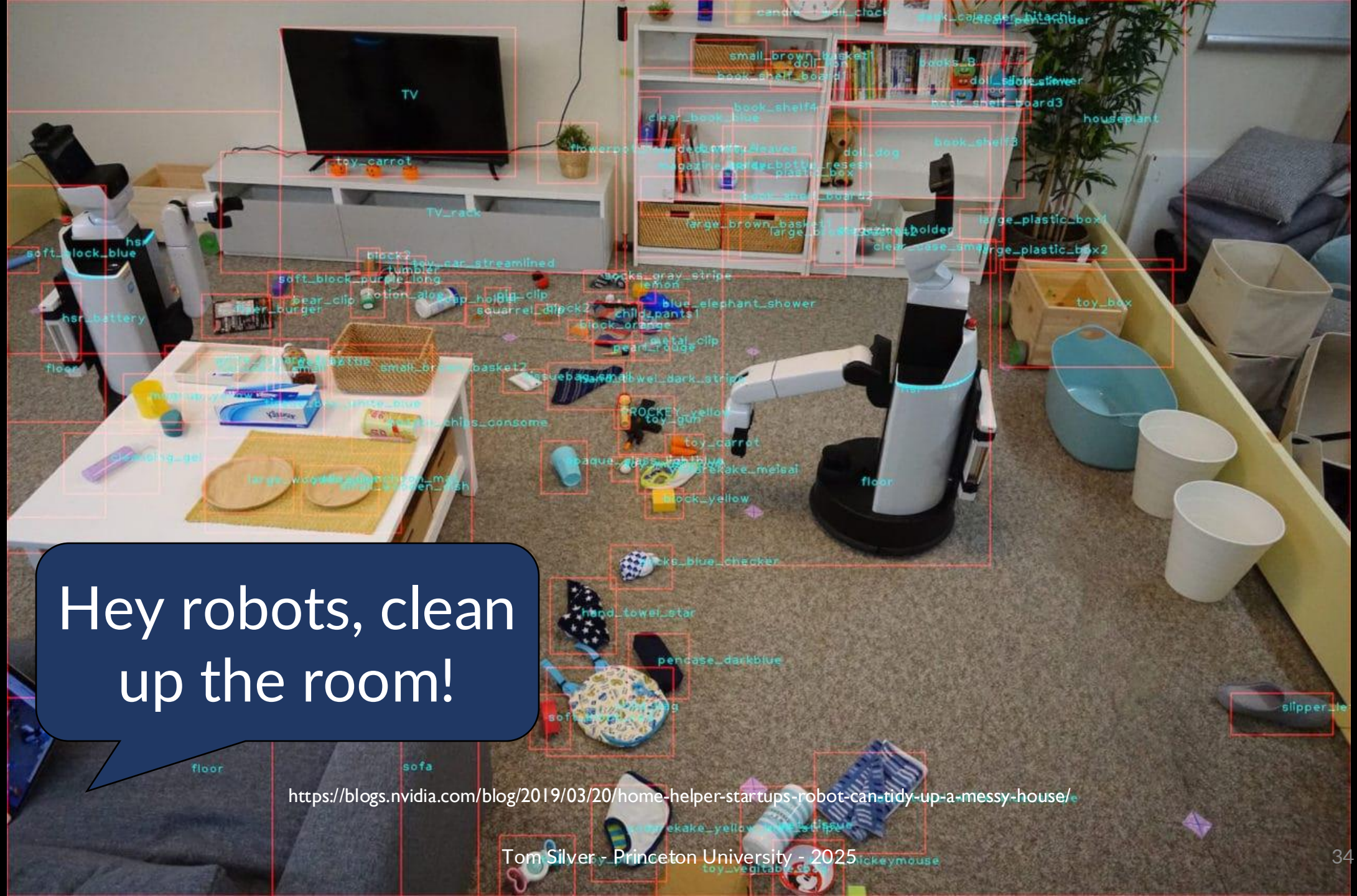
Sanctuary AI

Deployment

Robots that become **domain experts**

Learning to specialize

Planning & reasoning in the moment



https://blogs.nvidia.com/blog/2019/03/20/home-helper-startups-robot-can-tidy-up-a-messy-house/

Deployed Robots Must be **Efficient** and **Effective**

⏰ **Time efficient**: no philosopher robots

📊 **Data efficient**: learn a lot from a little

🧒🏫 **Human efficient**: our time is valuable

☑️ **Effective**: solve hard tasks

AI Planning (Task and Motion Planning)

⏰ **Time efficient**: no philosopher robots

Slow in large problems

📊 **Data efficient**: learn a lot from a little

No learning

👦🏫 **Human efficient**: our time is valuable

Need domain-specific models

☑️ **Effective**: solve hard tasks

Powerful solvers

(Srivastava et al. 2014)

(Model-Free) **Reinforcement Learning**

⏰ **Time efficient**: no philosopher robots

Fast to evaluate policy

📊 **Data efficient**: learn a lot from a little

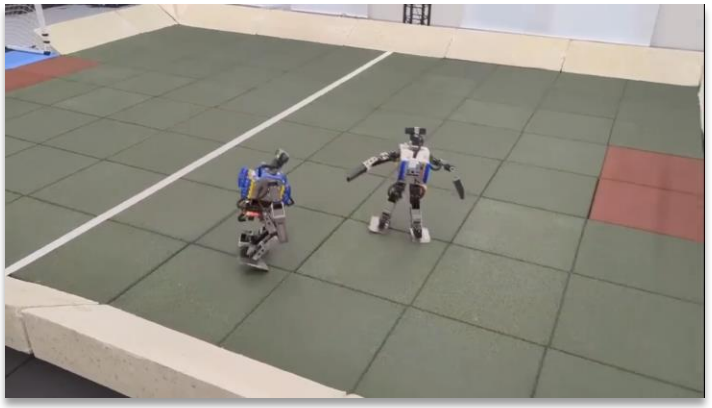
Notoriously data-hungry

🧒🏫 **Human efficient**: our time is valuable

Generally applicable

☑️ **Effective**: solve hard tasks

Narrow, short horizon



(OP3 Soccer Team, DeepMind, 2023)

Planning with **Large Language Models**

⏰ **Time efficient**: no philosopher robots

Constant time

📊 **Data efficient**: learn a lot from a little

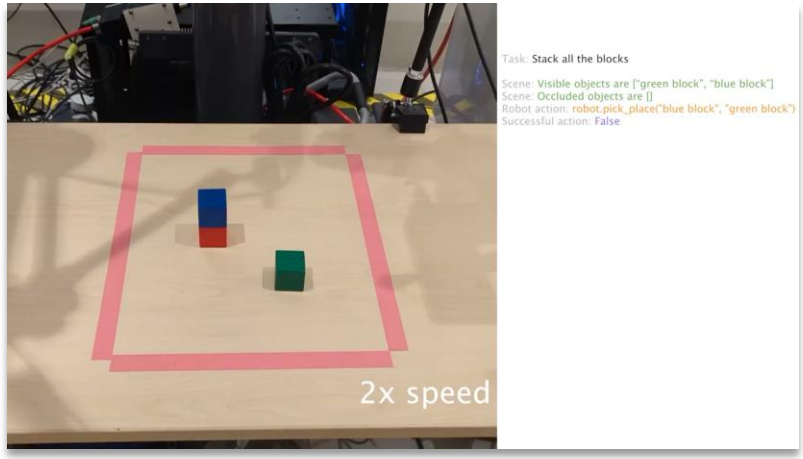
Few-shot prompting

🧒🏫 **Human efficient**: our time is valuable

Prompt engineering, validation

☑️ **Effective**: solve hard tasks

Emphasis on *hard*



(Huang et al., 2023)

This Course: **Learning + Planning**

⏰ **Time efficient**: no philosopher robots

Learning to plan *quickly*

📊 **Data efficient**: learn a lot from a little

Learning with structure

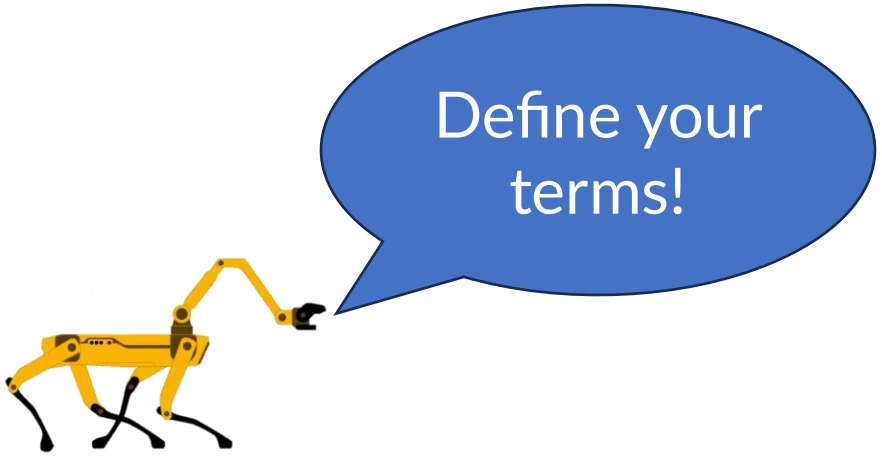
👦🏫 **Human efficient**: our time is valuable

Learning domain-specific models

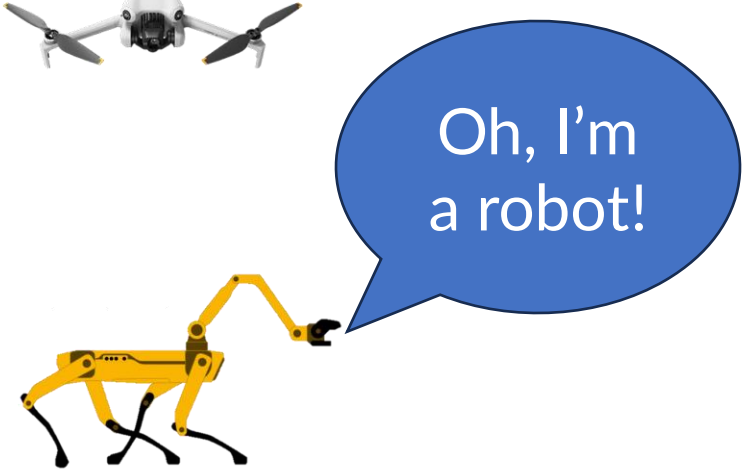
☑️ **Effective**: solve hard tasks

Powerful solvers

Robot Planning Meets Machine Learning

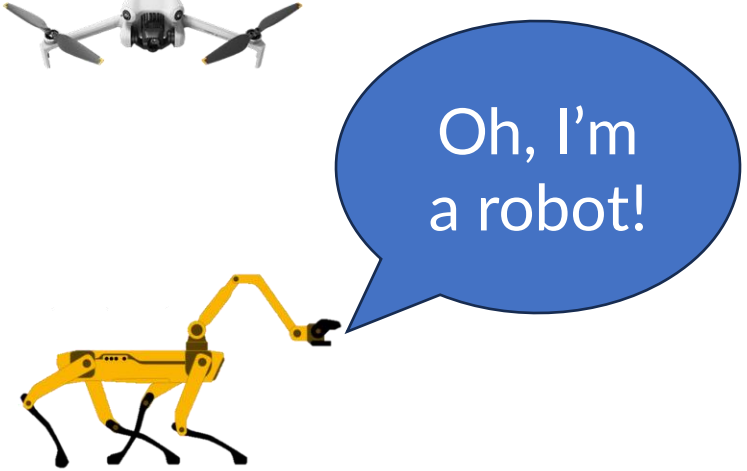


Robot: [Definition]

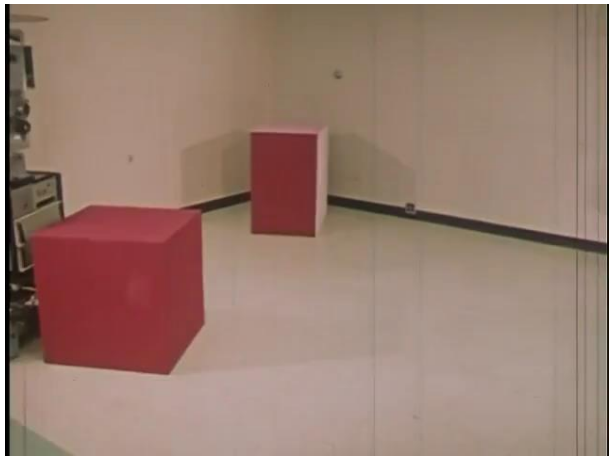


Robot: an agent that exists in our world and can sense, reason, and act.

Based on “The Robotics Primer” by Maja J Matarić (2007).



Planning: [Definition]



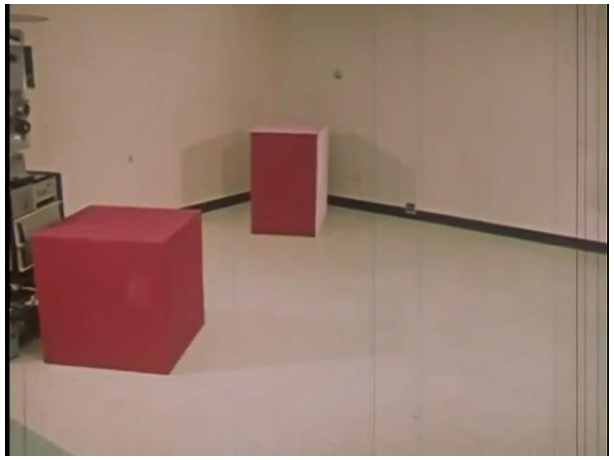
(SRI 1972)

(Srivastava et al. 2014)

(Boston Dynamics 2020)

Planning: explicit reasoning about future execution.

Based on “Robot Planning” by Drew McDermott (1992).

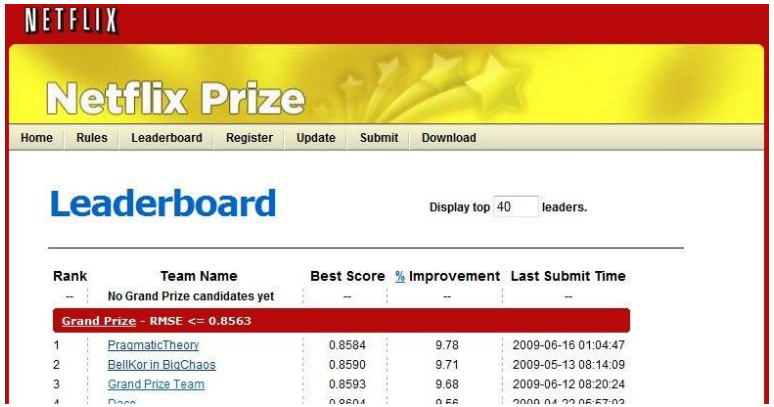


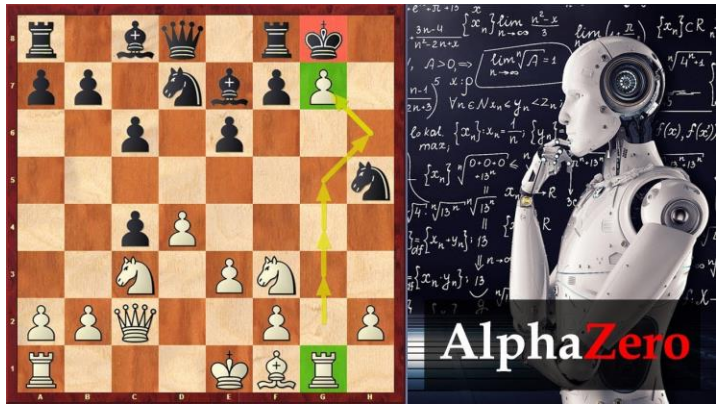
(SRI 1972)

(Srivastava et al. 2014)

(Boston Dynamics 2020)

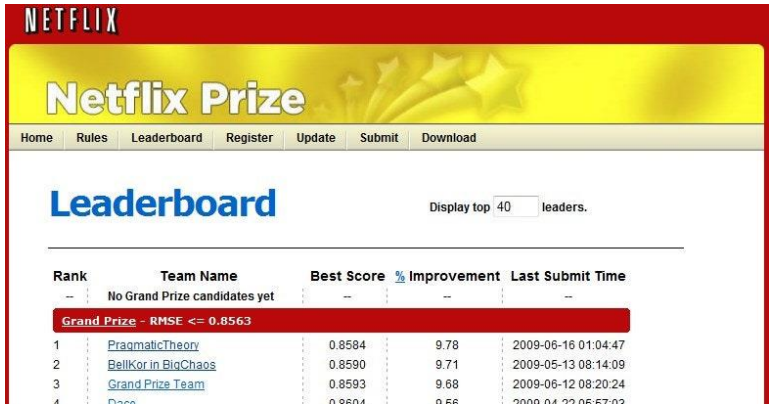
Machine learning: [Definition]

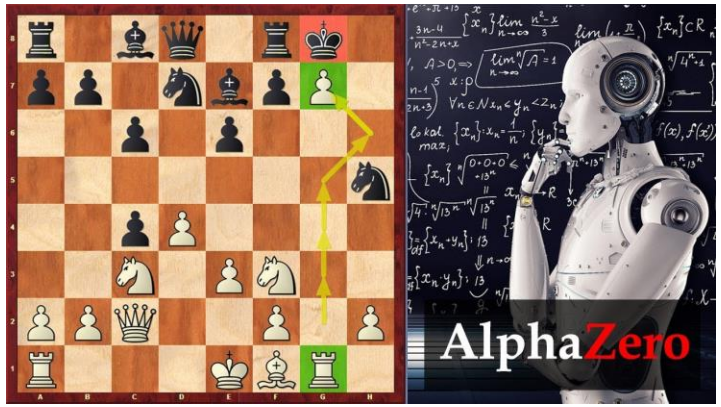




Machine learning: the automated detection of meaningful patterns in data.

Based on “Understanding Machine Learning” by Shai Shalev-Shwartz and Shai Ben-David (2014).





Key Questions for the Course

What learning and planning should happen in the *factory* vs. *wild*?

Robot Factory

Deployment

Key Questions for the Course

Where on the learning-planning spectrum should robots be?

A Human Gives the Robot a Task

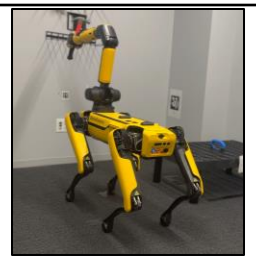
Bring me the hammer!

Time

Result

Pure Planning

Planning



...

Outcome: Success

Total Time: 800 s

Pure Learning

React!

Outcome: Failure

Total Time: 5 s

Planning + Learning

Planning with Learned Models

...

Outcome: Success

Total Time: 10 s

Key Questions for the Course

How should we taxonomize learning-for-planning methods?

Supervised learning	Unsupervised learning
Online learning	Offline learning
Analytic learning	Synthetic learning
Eureka learning	Learning through practice

...

Key Questions for the Course

What objectives should we use to train and evaluate?

⏰ **Time efficiency**: wall-clock time

📊 **Data efficient**: number of samples

🧑🏫 **Human efficient**: number of queries

☑️ **Effective**: task objective complete

...

Key Questions for the Course

To what extent are learning and planning necessary for general-purpose robotics?

Course Logistics

Course Structure

Part 1: Pure Planning

Lectures by me

Problem sets

Part 2: Planning + Learning

Paper presentations by you

Final projects

Total Output	
4 problem sets	20%
1 paper presentation	15%
Paper reviews	15%
1 final project	40%
In-class participation	10%

Course Website:

https://rpmml.github.io/

All materials will be posted on this website

All announcements will be through Piazza

All submissions will be through GradeScope

Calendar

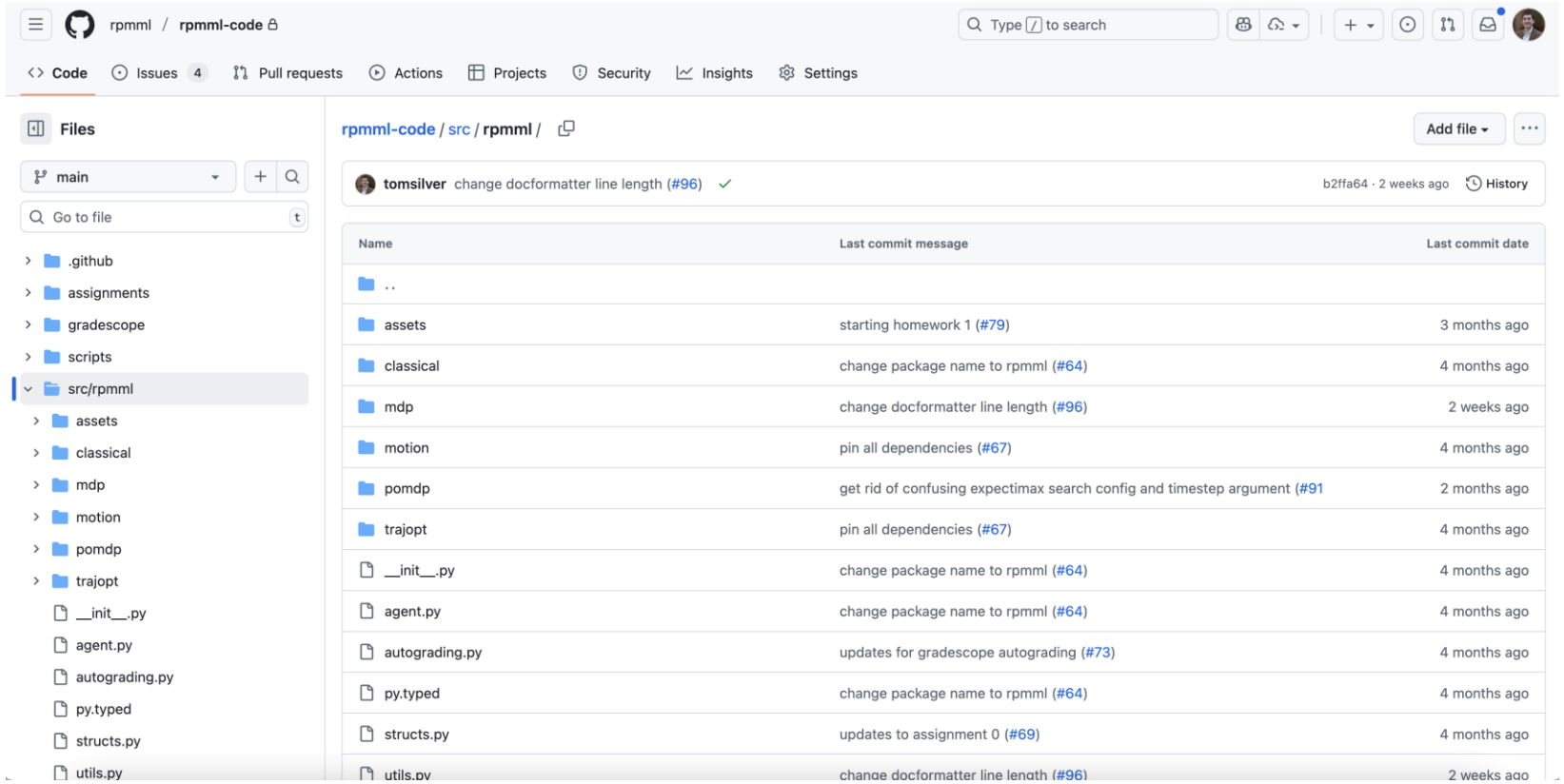
Subject to change.

Planning Foundations

Sep 2:	LECTURE	Intro	Slides
Sep 4:	LECTURE	Offline Planning in MDPs	Slides
Sep 8:	HW	HW0 Due	HW0
Sep 9:	LECTURE	Online Planning in MDPs	Slides
Sep 11:	LECTURE	Monte Carlo Methods	Slides
Sep 15:	HW	HW1 Due	HW1
Sep 16:	LECTURE	Partial Observability	Slides
Sep 18:	LECTURE	Planning and RL	Slides
Sep 22:	HW	HW2 Due	HW2
Sep 23:	LECTURE	Planning in Factored Spaces	Slides
Sep 25:	LECTURE	Motion Planning	Slides
Sep 29:	HW	HW3 Due	HW3
Sep 30:	LECTURE	Trajectory Optimization	Slides
Oct 2:	LECTURE	Hierarchy and Abstraction	Slides
Oct 6:	PROJECT	Final Project Proposal Due	Guidelines
Oct 7:	LECTURE	Guest Lecture (TBD)	Slides

HW0 due soon!

Course Code Repository



Used for homework and (optionally) final projects

TA:
Alessio Amaolo

Email:
alessioamaolo@princeton.edu

Everything is New!

With Remaining Class Time:

https://rpmml.github.io/homework_instructions/

And sign up for Piazza & GradeScope