



Robotics

Spring 2023

Abhishek Gupta

TAs: Yi Li, Srivatsa GS

Course Logistics

- Where: MEB 242
- When: 11:30-1 Tu/Thu
- Who:
 - Abhishek Gupta (Instructor)
 - Yi Li (TA)
 - Srivatsa GS (TA)
- Office hours:
 - Abhishek: Gates 215, Friday 4-5pm
 - Yi: Gates 152, Thursday 3-4pm
 - Srivatsa: Gates 152, Monday 3-4pm

Course Logistics - Grading

- Grading:
 - 50% of grade is on Final Project
 - 15% of grade is on HW1
 - 15% of grade is on HW2
 - 15% of grade is on HW3
 - 5% participation
- Communications through EdStem/e-mail
- Every week: 2 lectures by Abhishek
- Final projects will be presented in a poster session.
 - Intermediate project proposals and milestone check ins.
- Please participate, otherwise it will be boring for all of us!

Course Logistics - Project

- Final project (50% of grade):
 - Project proposal (1 page)
 - Milestone report (3-4 pages)
 - Final report (6-8 pages)
- Project can be investigating any question related to robotics:
 - New algorithm
 - Performant/stable implementation
 - Empirical investigation
 - New robotic application
 - ...
- Can be done in groups of 1-2 students.

Course Logistics – Homeworks

- 3 homeworks covering 3 class modules:
 - Estimation: EKF/UKF/Particle filtering for localization
 - Control and Planning: RRT/RRT*/A*/D* for motion planning
 - End to end learning: Behavior cloning, Dagger, policy gradient, actor critic
- Homeworks are all in Python, using pybullet or pytorch

Course Logistics - Integrity

- Late policy

You are allowed to use **6 late days throughout the quarter**. After this, assignments turned in late will incur a penalty of 20%, for each day. Please plan ahead.

- Academic Honesty Policy

While we **encourage students to discuss homeworks, each student must write up their own solution**. It's fine to use a source for generic algorithms (with attribution), but it is not allowed to copy solutions to the problems. Additionally, **students may not post their code online**. If we determine that a student posted their code online, they will get an automatic 50% reduction on the entire assignment (math + code) and if they copy code for the problems from another student or from online, they will get an automatic 0% for the entire assignment (and possibly reported to the college).

Please don't cheat, make my life easier

Who am I?



- New assistant professor in CSE
- Grew up in Oregon/India, last 10 years in Berkeley
- Undergrad Berkeley, Ph.D. Berkeley, Postdoc MIT.
- Interests: RL/robotics/optimization and control/robustness and generalization
- Outside of work: Tennis/soccer/sketching/dog enthusiast

Who is Yi?

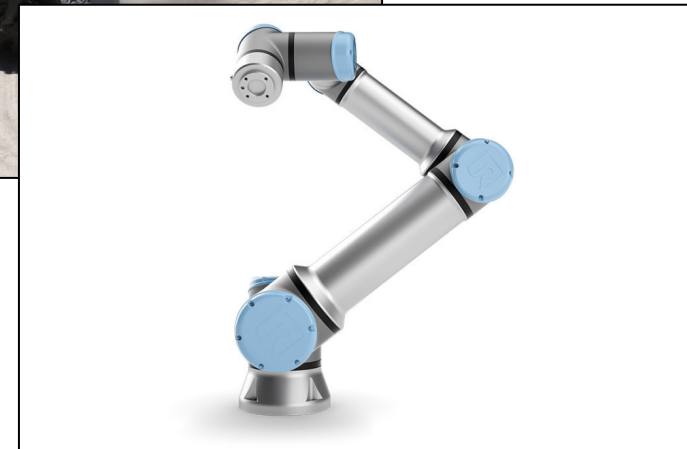
TA: Yi Li

- PhD student in RSElab
- Office hour: Thursday 3-4 pm
- Location: Gates 152
- Email: yili18@cs.washington.edu
- Research Experience:
 - Unseen Object Instance Segmentation and Tracking
 - Object 6D Pose Estimation
 - Instance Segmentation
 - Object Detection



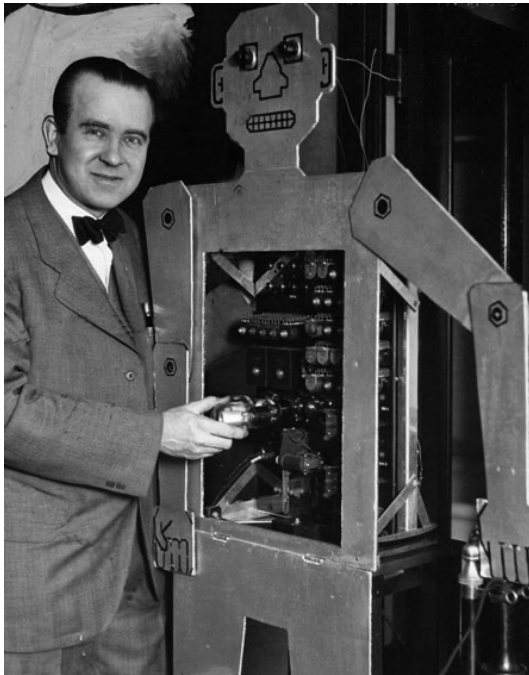
Who is Srivatsa?

- 2nd Year Masters Student in ME
 - Working on Visual Odometry and SLAM on the RACER project.
 - Previously worked on 6Dof Grasp generation and packing in UW-Amazon manipulation research and at Voaige Inc.
 - Office hours: Gates 152, Monday 3-4pm

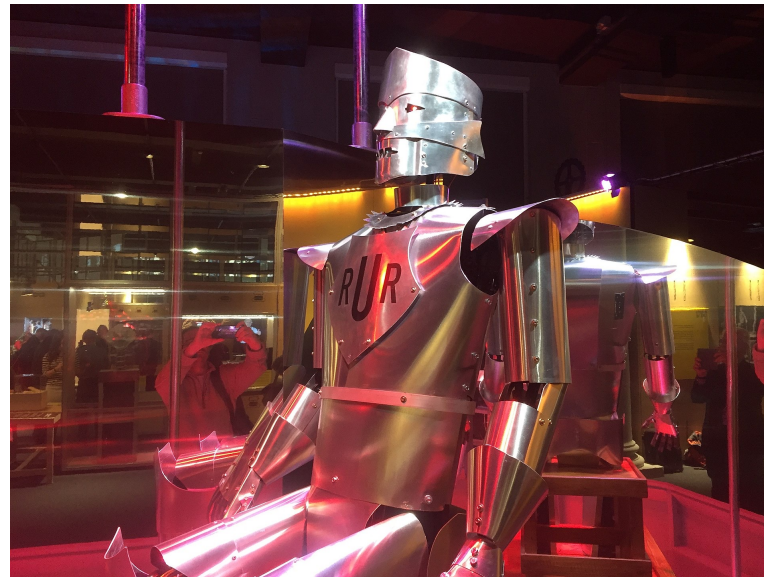


What is a robot?

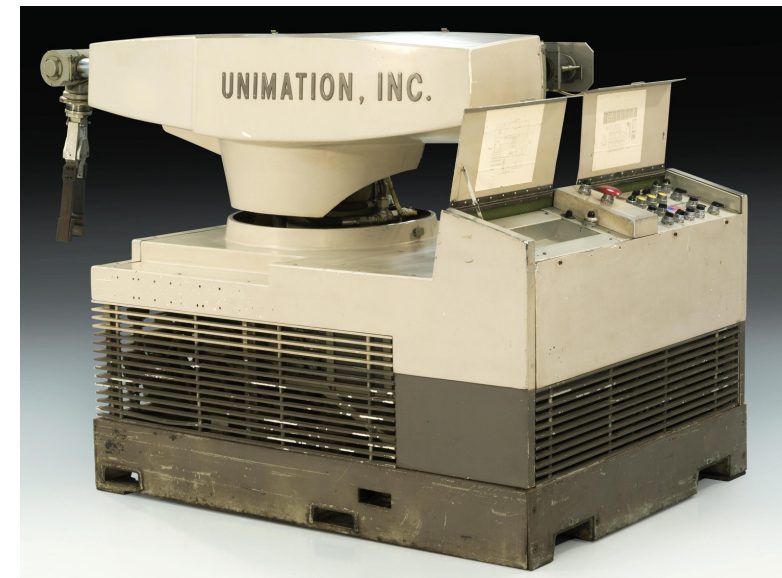
- First definitions:
 - Karel Capek → robots were biological beings performing unpleasant labor.



Herbert Televox(1927)



Eric (1928)

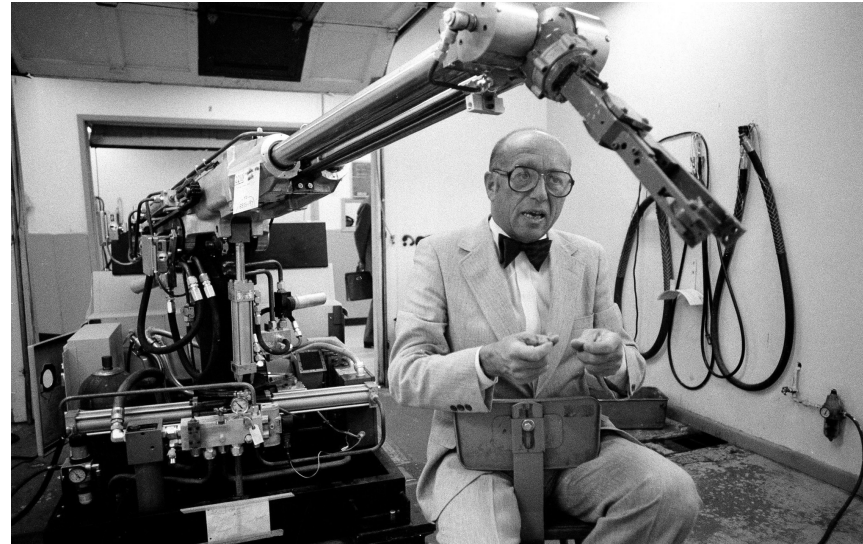


Unimate (1961)

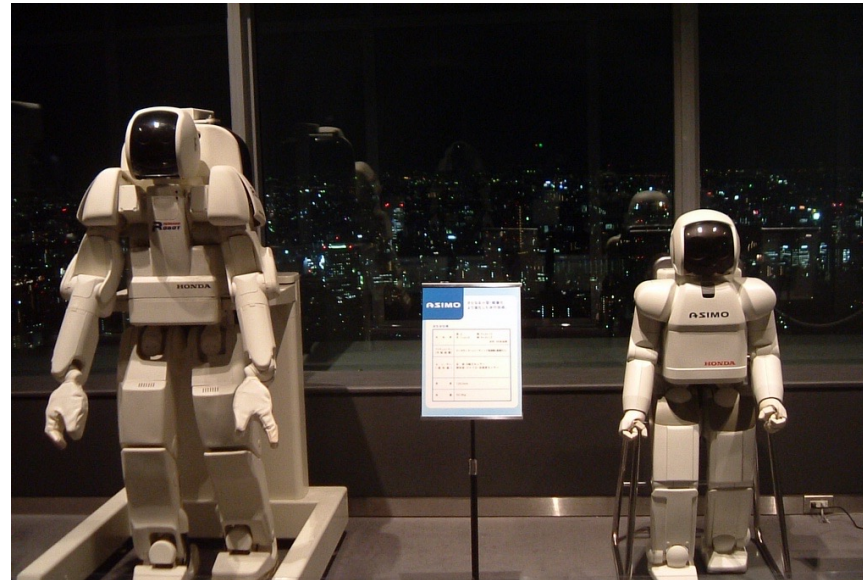
The first wave of robots



Shakey

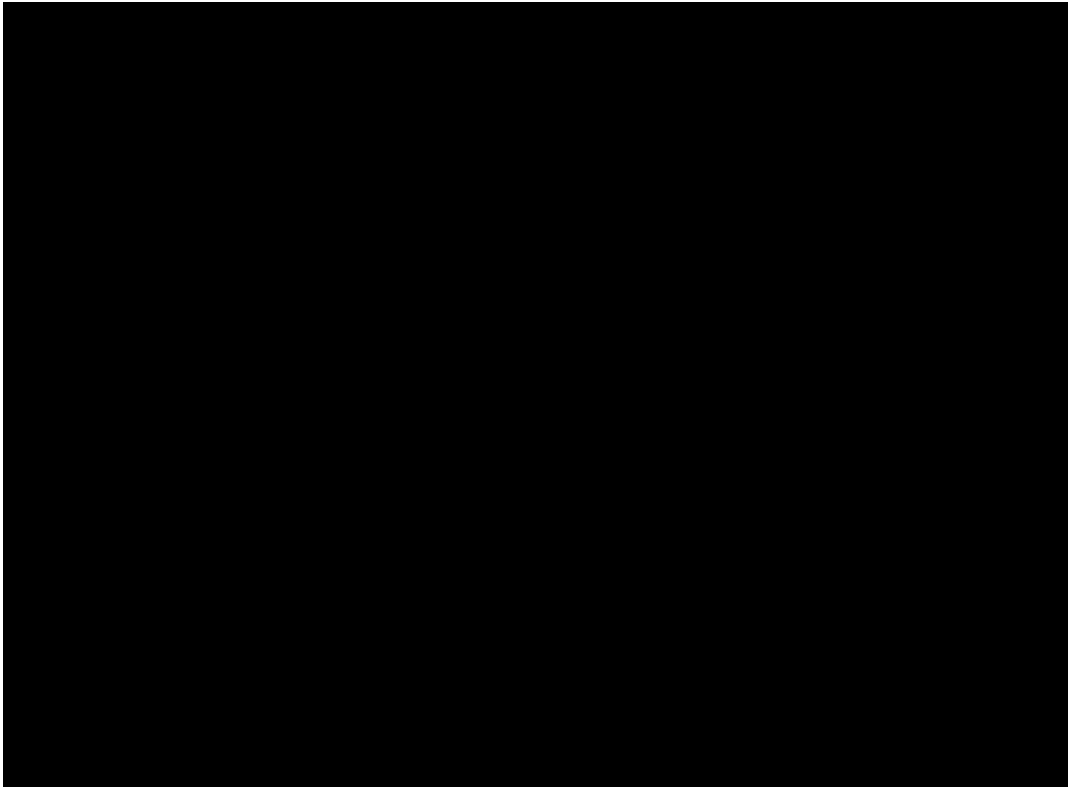


Engelberger
(Unimate ++)



Honda P series

The second wave of robots

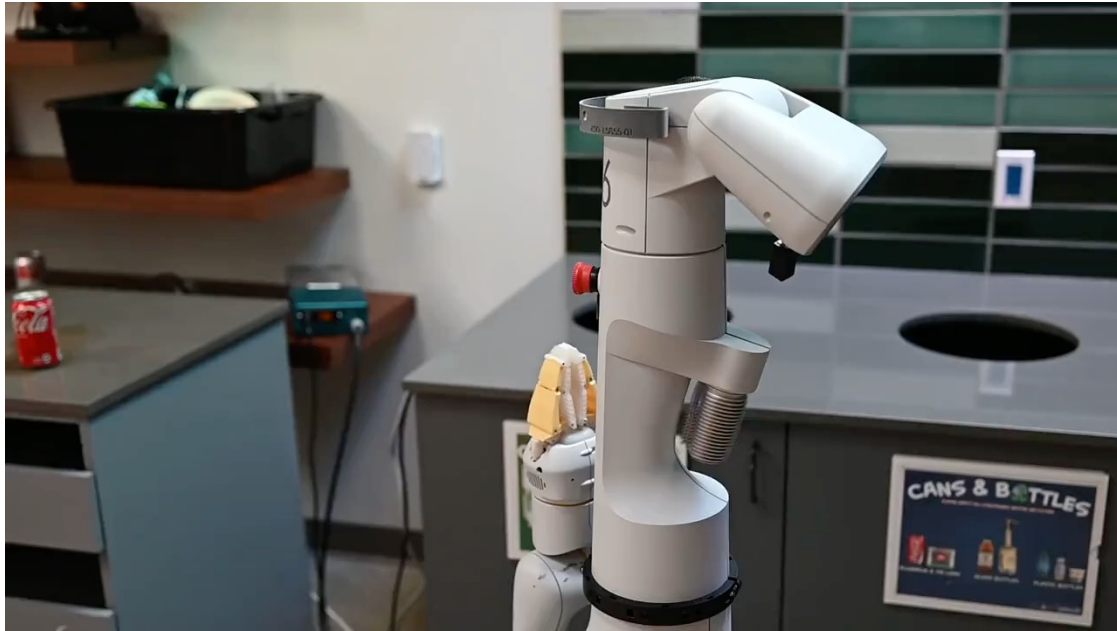


DARPA Grand Challenge



PR1 Robot

Robots Today



Everyday Robotics - Google



Atlas – Boston Dynamics

Robotics Spans Applications and Industries

- Applicable in a variety of industries and spaces:
 - Industry:
 - Industrial manufacturing
 - Warehouse navigation
 - Outdoor navigation/locomotion:
 - Legged locomotion
 - Outdoor navigation
 - Last mile delivery
 - Self driving cars
 - Home and office manipulation
 - Mobile manipulation
 - Dexterous manipulation

Industrial Robotics

Industrial Robotics Today



Industrial Pick and Place



Robotics
星猿哲科技

Robots in Warehouses



Navigation

CMU NavLab



DARPA Urban Challenge 2007



Self-Driving Cars



Outdoor Off-Road Autonomy



Locomotion

Boston Dynamics BigDog (2008)



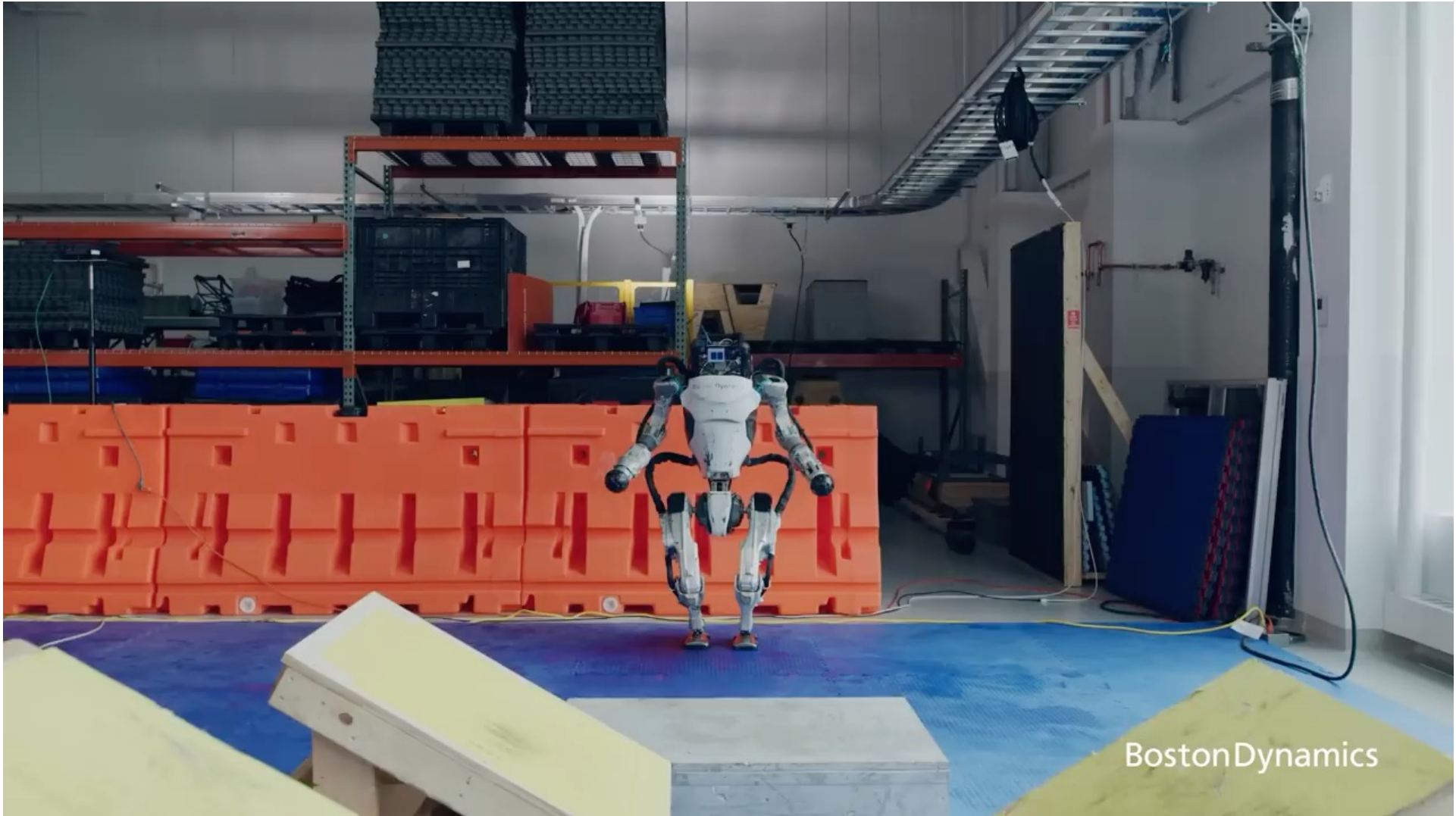
RoboCup



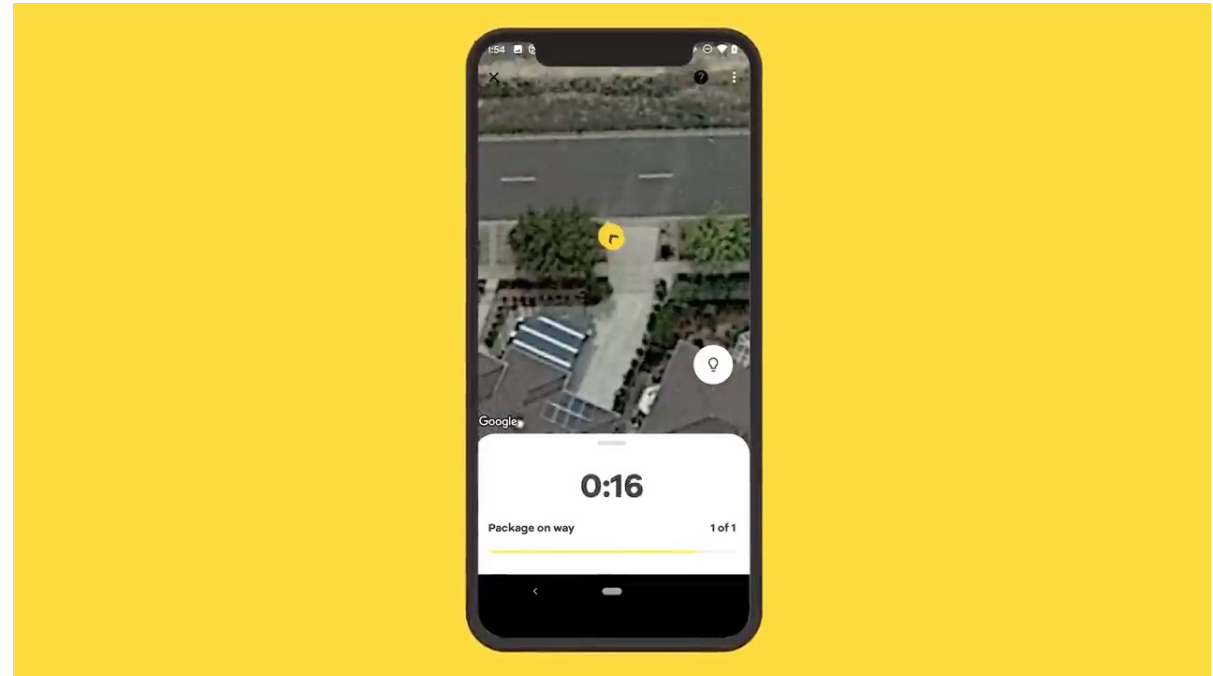
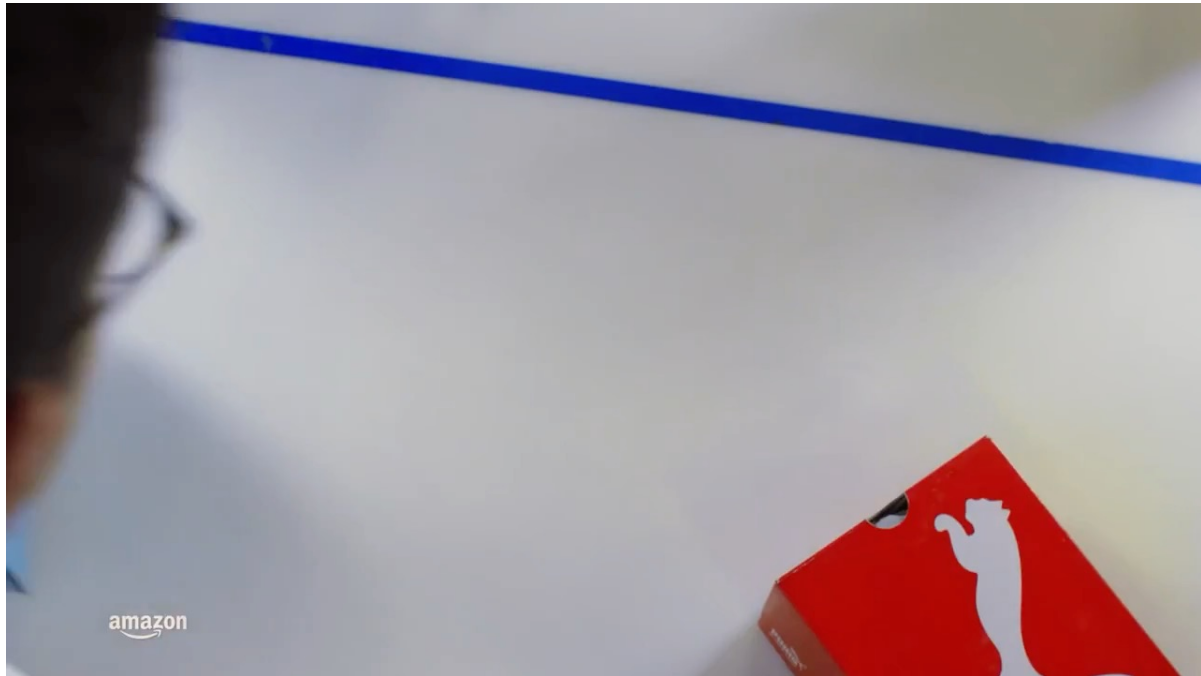
Boston Dynamics Spot



Humanoid Parkour



Drone Delivery

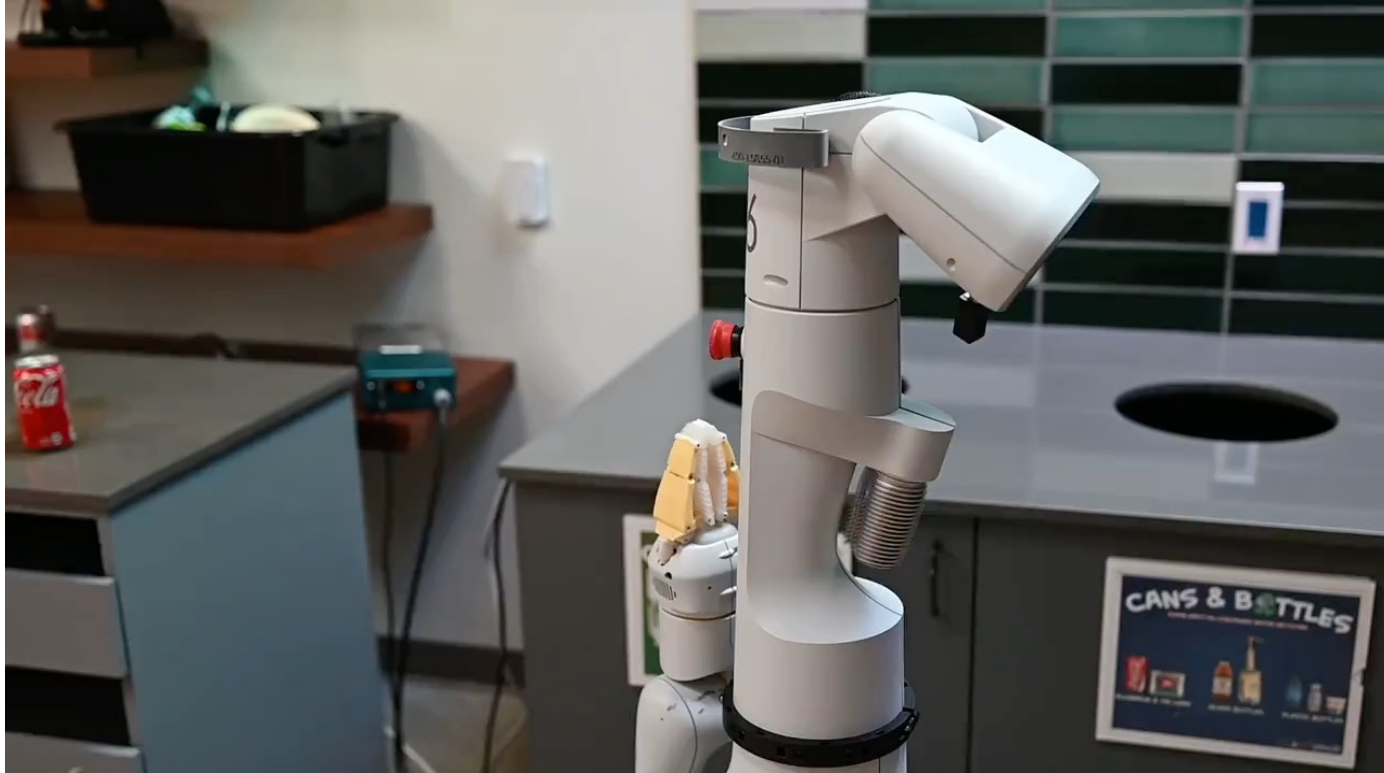


Indoor Manipulation

Dexterous Manipulation



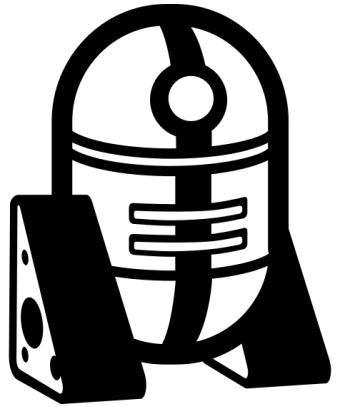
Mobile Manipulation



HaptX Dataglove



How should we start to formalize the robotics problem?

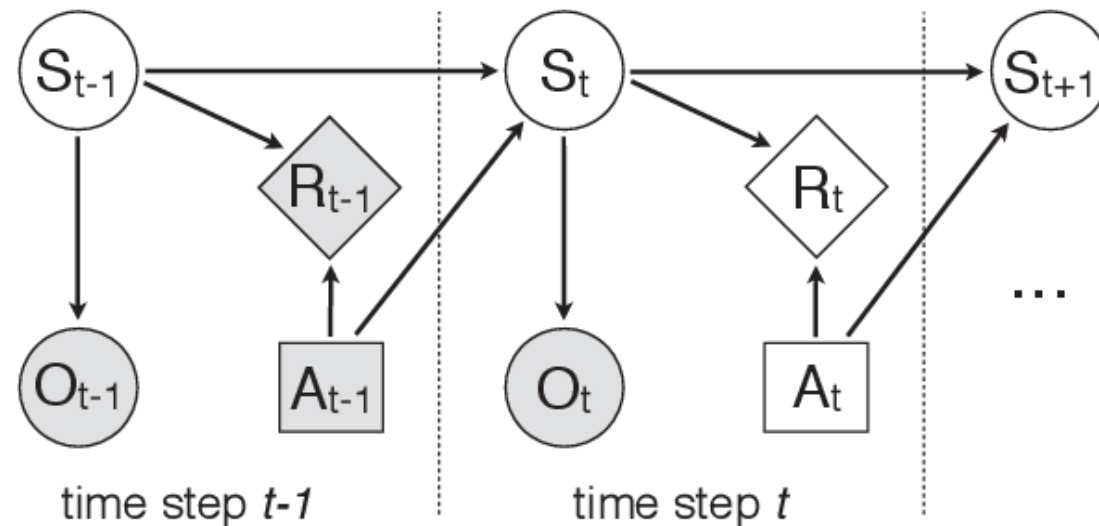


- Agent: Rational entity equipped with sensors and actuators
- Environment: accepts actuation commands and steps forward according to some dynamics



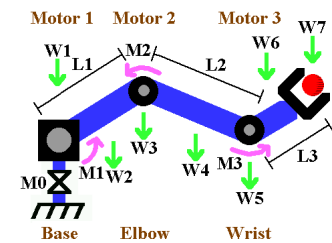
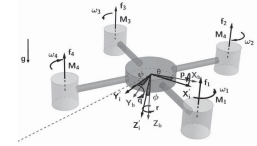
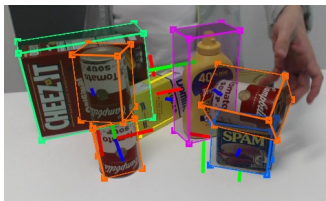
Graphical Model of Robotics

- State: Minimum sufficient statistic encapsulating the world, sufficient for prediction
- Measurement/Observation: Current sensor readings, potentially partially observed
- Action: Actuators that agent can use to affect the state



Graphical Model of Robotics

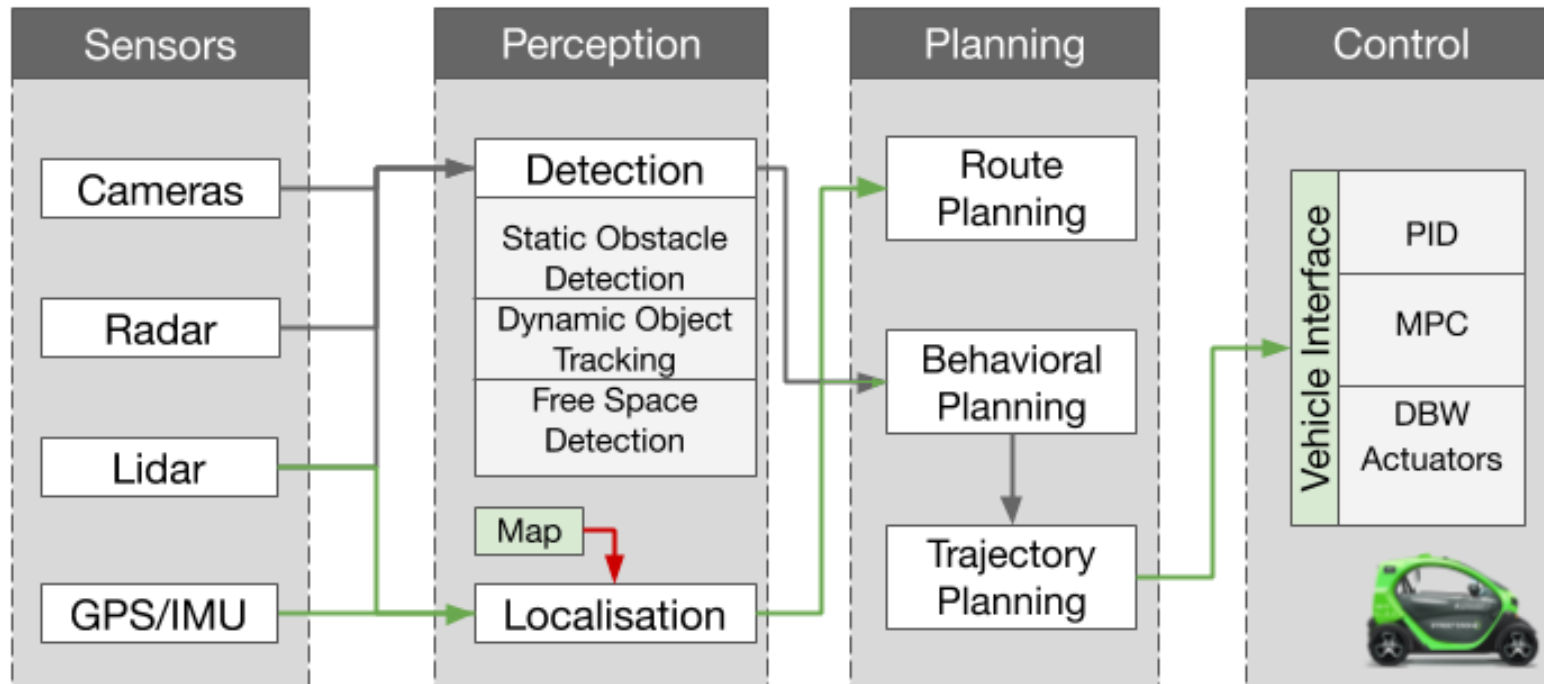
- State: sufficient statistic encapsulating the world, sufficient for prediction (this is a choice)
- Measurement/Observation: Current sensor readings, potentially partially observed (this is a choice)
- Action: Actuators that agent can use to affect the state (this is a choice)



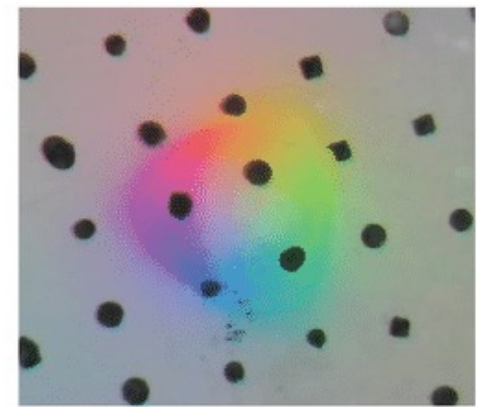
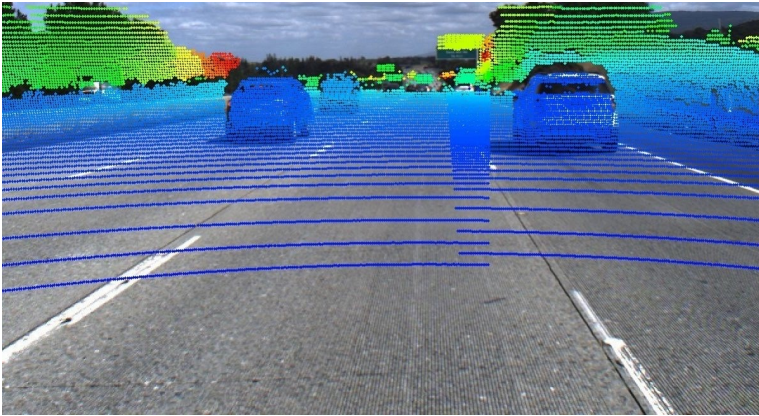
Sense-Plan-Act Framework

Robotics has three primary subpieces:

1. Sensing → from measurements
2. Planning → from models
3. Acting → in the world



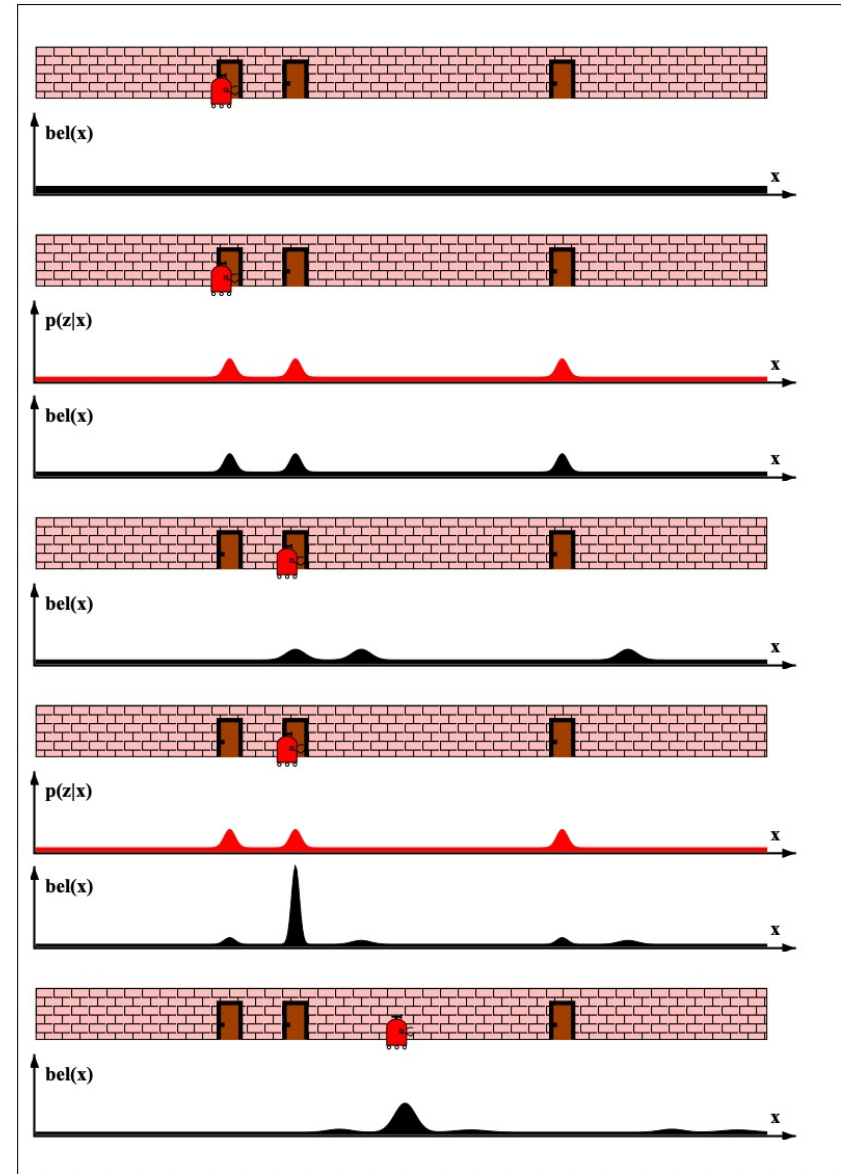
Sensing: Why is it nontrivial?



- Sensors have overwhelming amounts of information
- Partially observed
- Noisy and prone to drift

Sensing: Why is it nontrivial?

State is never perfectly known, only a **belief** over state can be estimated



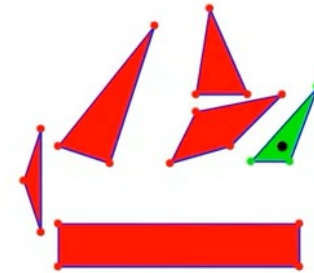
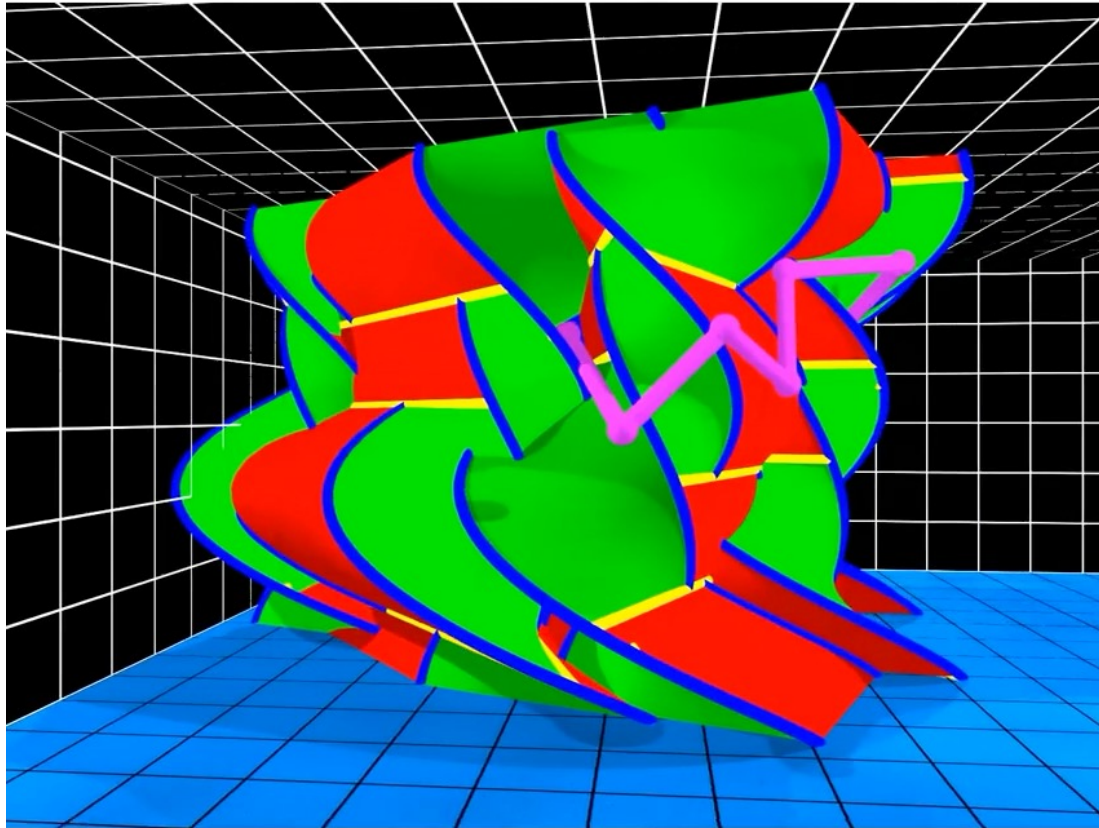
Probabilistic Robotics

A robot that carries a notion of its own uncertainty and that acts accordingly is superior to one that does not.

- Maintaining uncertainty allows for
 - Information gathering
 - Robustness to imperfect sensing and actuation
 - Interpretability
 - Exploration

Planning: Why is it nontrivial?

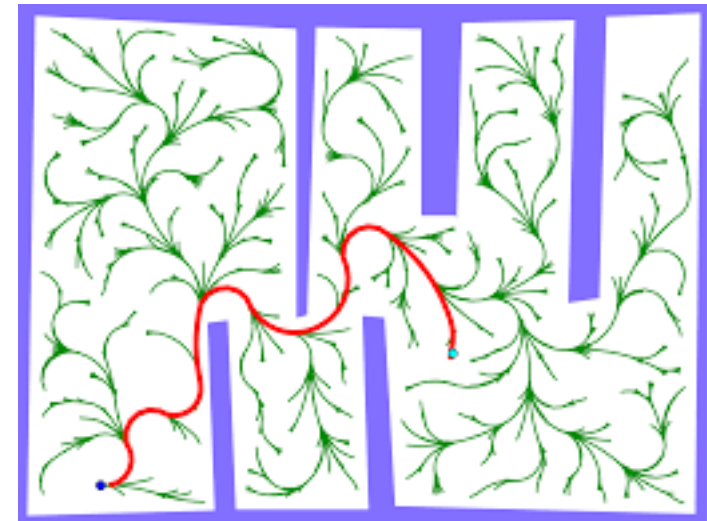
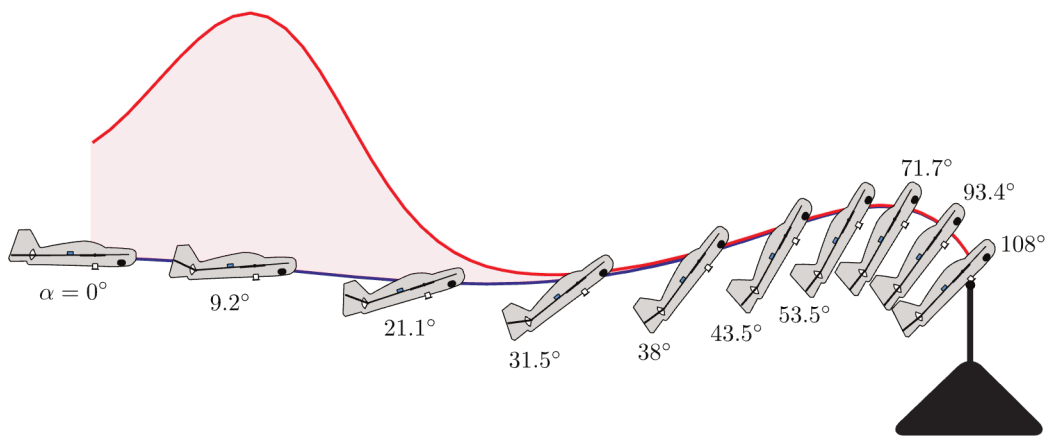
- Searching/Optimization through a complex non-convex space
- Combination of discrete/continuous optimization



Overview

Rational Agents and Utility Maximization

- How do we even formulate planning?
 - Utility maximization: trajectory optimization
 - Search: shortest path finding
- Viewing planning through the lens of rationality allows us to use tools from optimization



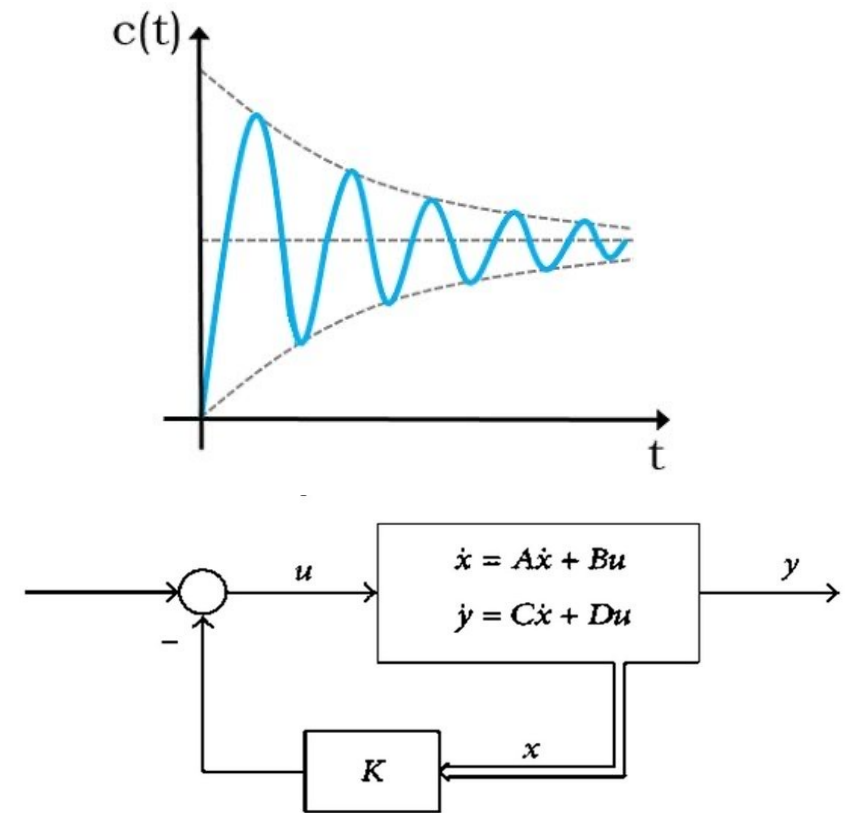
Acting: Why is it nontrivial?

- Robot systems in the real world are subject to significant perturbations/noise → need to be stable in the face of these perturbations



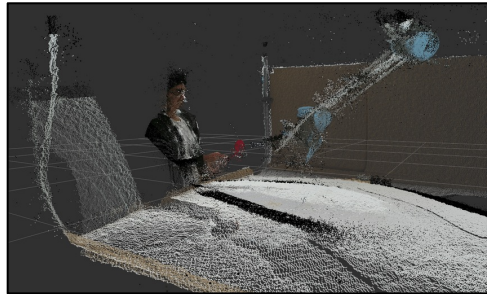
Low-level control and Stabilization

- Unstable/suboptimal systems can be catastrophic



Robotics: Integrated System Research

Focus on addressing all problems at once



$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} = \boldsymbol{\tau}_g(\mathbf{q}) + \mathbf{B}\mathbf{u},$$

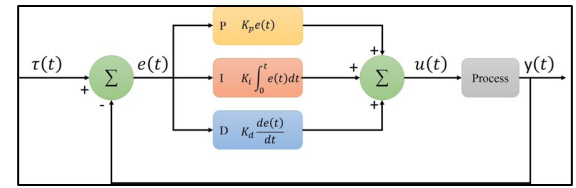
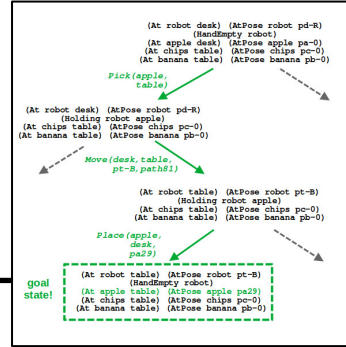
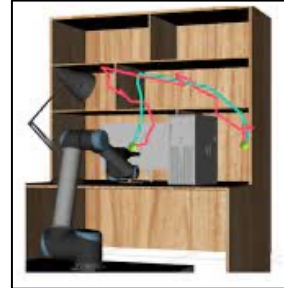
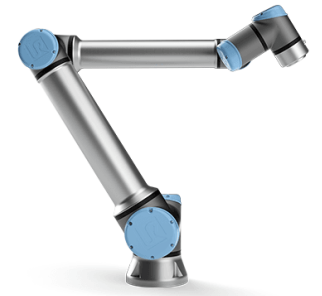
State Estimation

Modeling and Prediction

High-level planning

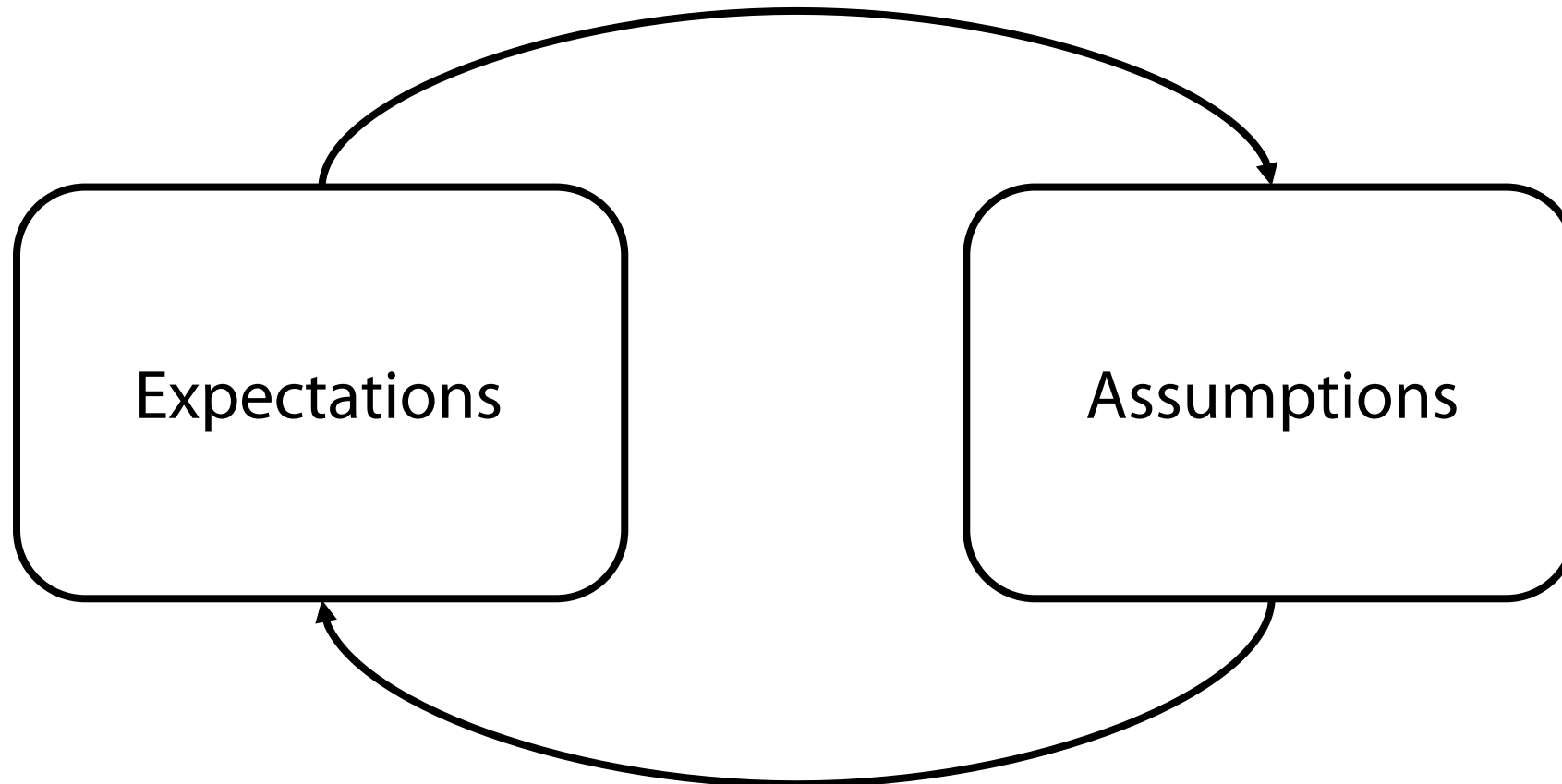
Low-level planning

Low-level control



What makes robotics hard?

Unique interplay of expectations and assumptions



Expectations

- Significantly larger set of tasks being performed
- Failure can be catastrophic and unsafe
- Precision required may be much larger than other decision making problems
- Multi-step decision making problems



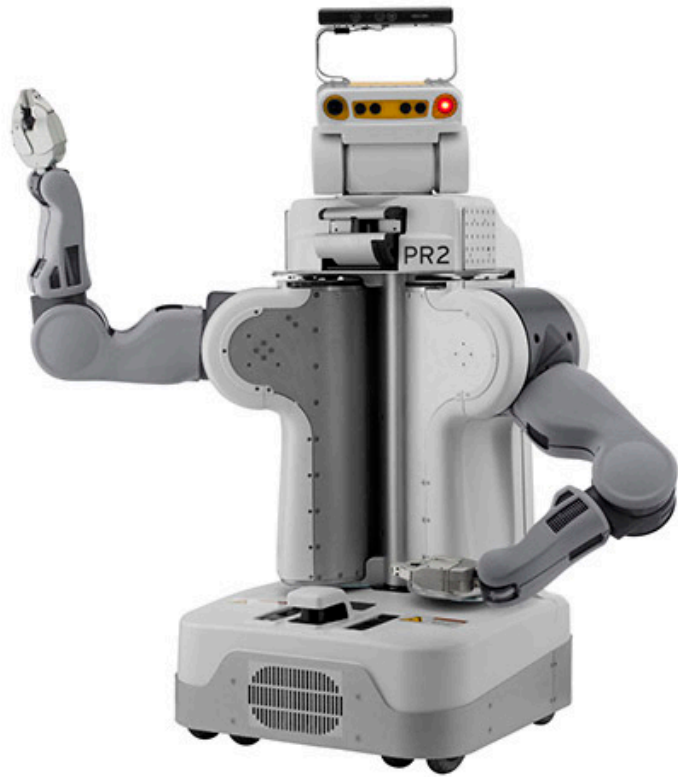
Assumptions

- Limited data due to the real world
- No perfect simulator
- Chicken and egg problem on deployment
- Evaluation is difficult



Why now?

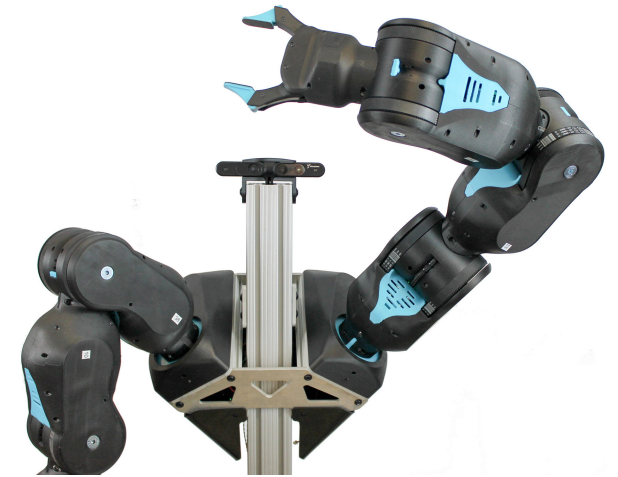
Hardware is getting cheaper and more accessible



400K



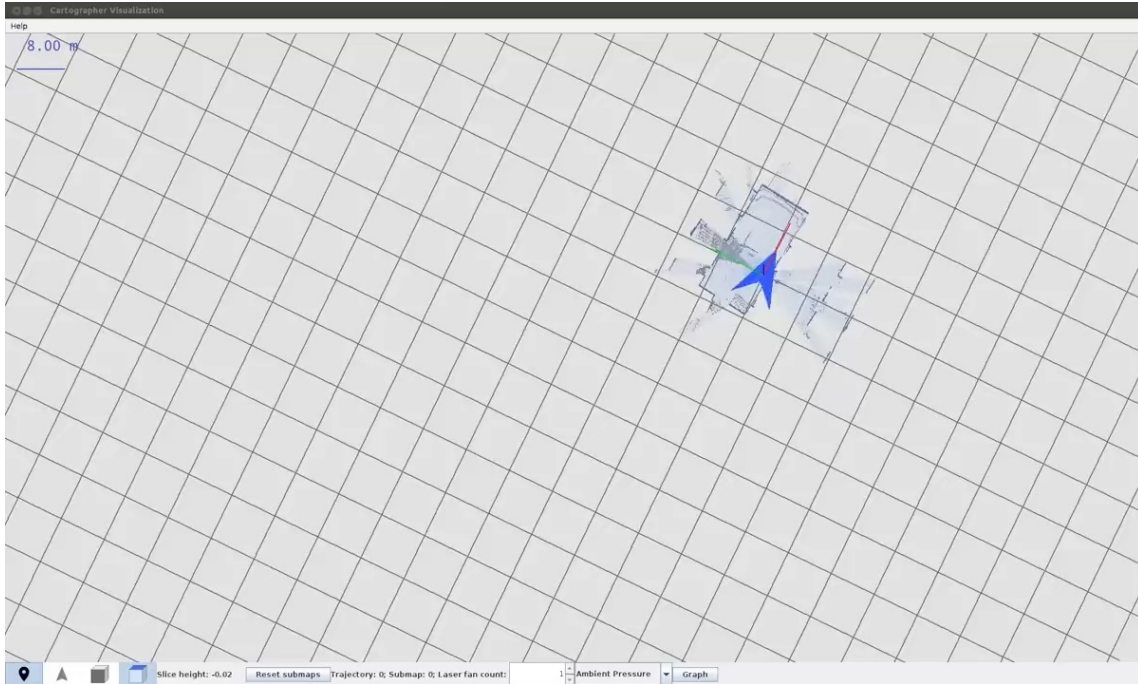
30K



5K

Why now?

Algorithms/models have started maturing/stabilizing

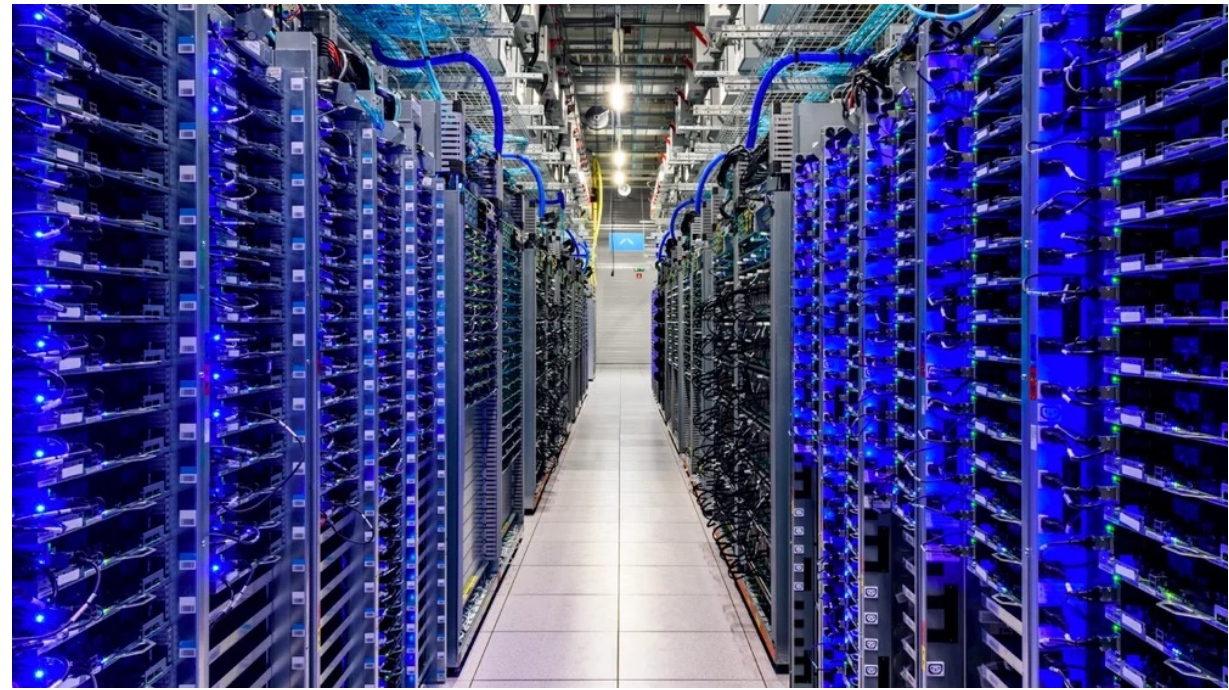


**Discovery of Complex Behaviors
through Contact-Invariant Optimization**

Submitted to SIGGRAPH 2012
Submission ID: 0480

Why now?


Data/compute is now available at a scale not possible before



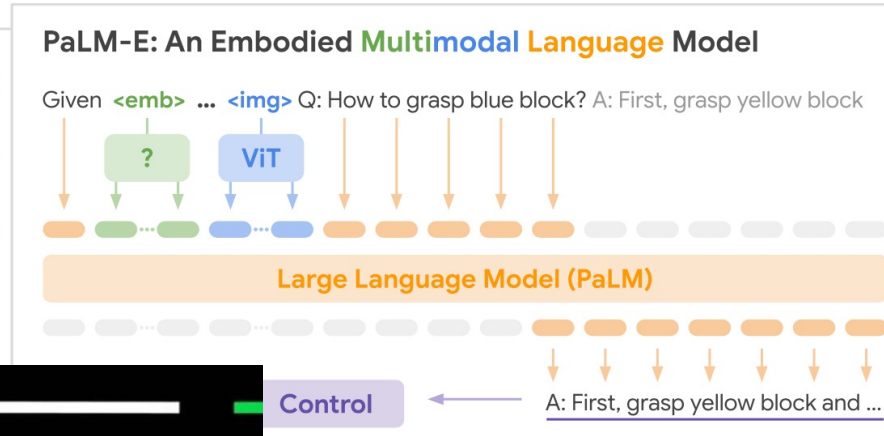
Why now?

Adjacent fields are showing remarkable progress

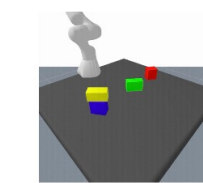
Mobile Manipulation



Human: Bring me the rice chips from the drawer. Robot: 1. Go to the drawers, 2. Open top drawer. **** 3. Pick the green rice

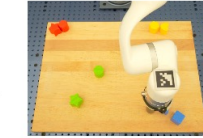


Task and Motion Planning



Given **<emb>** Q: How to grasp blue block? A: First grasp yellow block and place it on the table, then grasp the blue block.

Tabletop Manipulation



Given **** Task: Sort colors into corners. Step 1. Push the green star to the bottom left. Step 2. Push the green circle to the green star.

Describe the following
>
g jumping over a
e at a dog show.

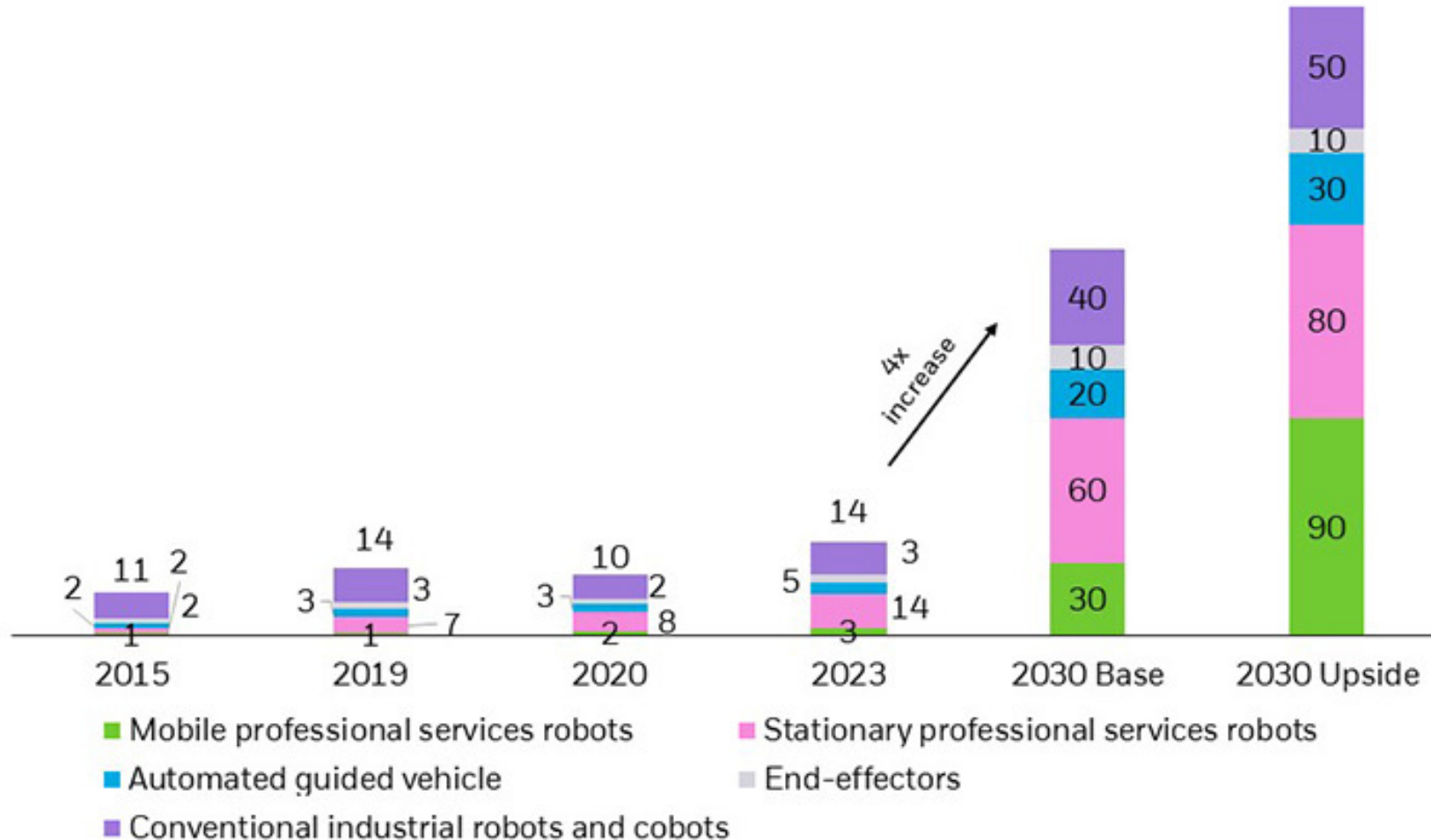
Language Only Tasks

Q: Miami Beach borders which ocean? A: Atlantic. Q: What is 372 x 18? A: 6696. Q: Write a Haiku about embodied LLMs. A: Embodied language. Models learn to understand. The world around them.



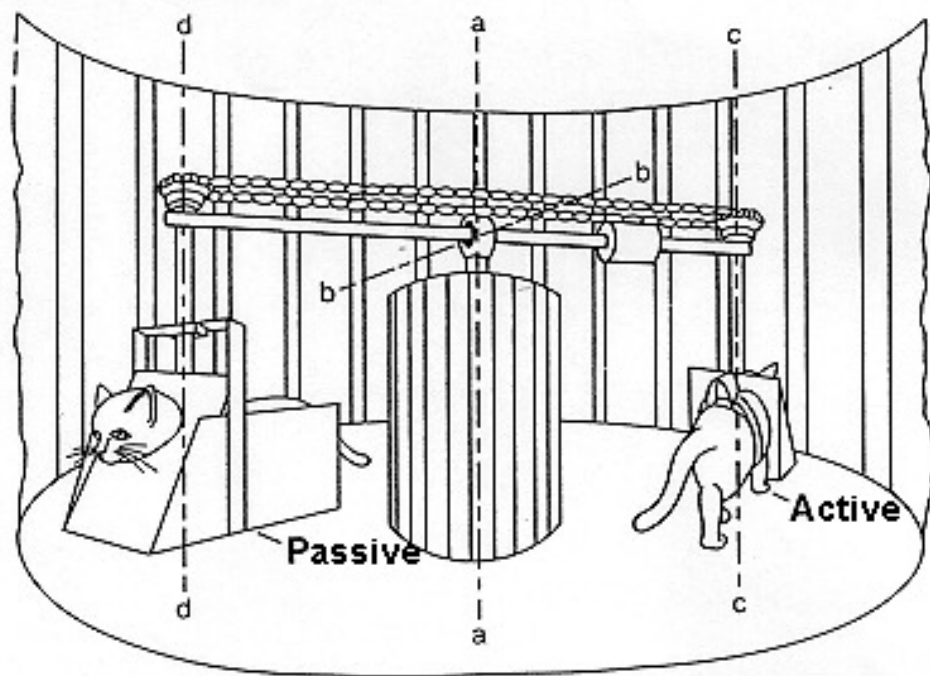
Why now?

- Fast growing investment into automation/robotics



Is robotics useful to study beyond applications?

Arguably intelligence needs embodiment



- visually-guided paw placement:
- avoidance of a visual cliff
- blink to an approaching object:
- visual pursuit of a moving object:
- pupillary reflex to light:
- tactual placing response

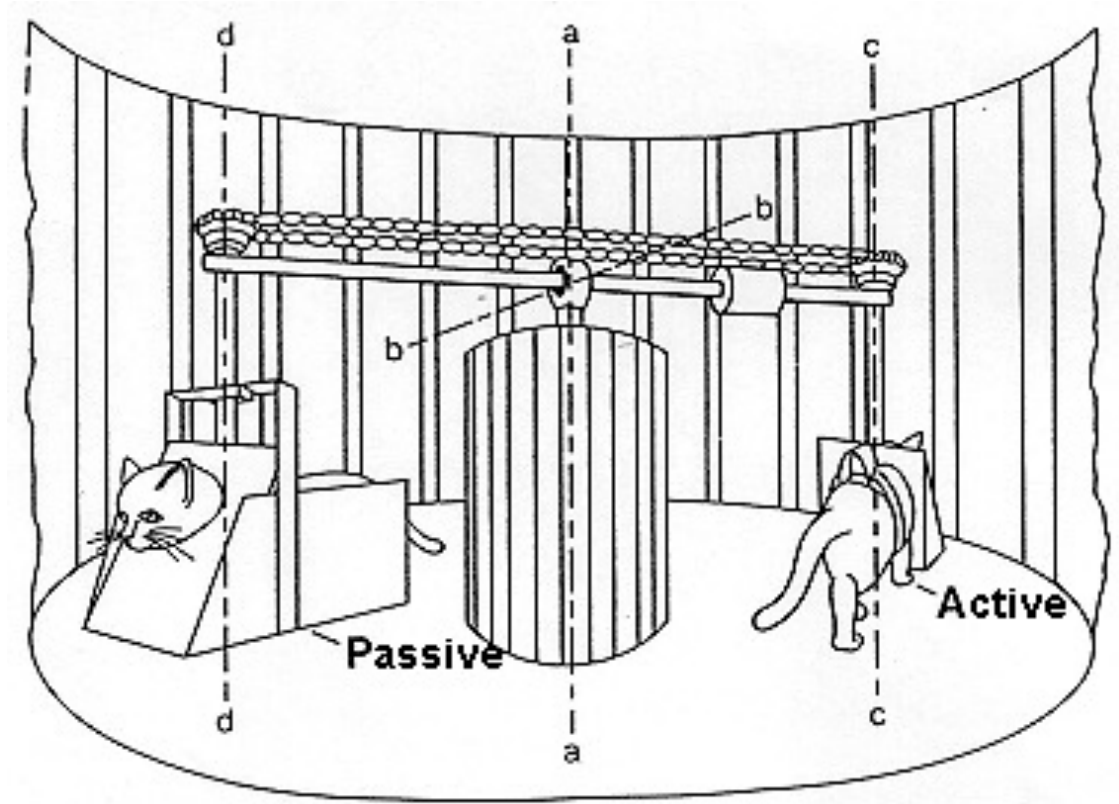
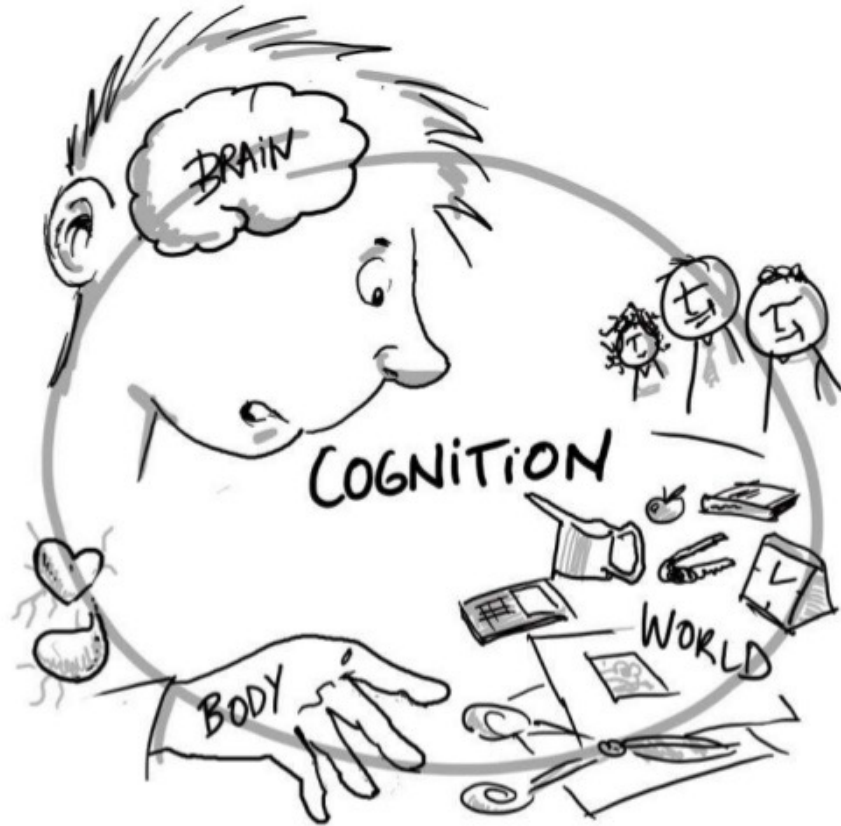
Table 1 Responses on the visual cliff

Active kittens		Passive kittens	
shallow	deep	shallow	deep
12	0	6	6
12	0	4	8
12	0	7	5
12	0	6	6
12	0	7	5
12	0	7	5
12	0	5	7
12	0	8	4
12	0	6	6
12	0	8	4

Robotics may be a way to study fundamental intelligence

Zooming out – why this matters for the study of intelligence?

Hypothesis: Intelligence with and without embodiment looks drastically different



Elephants don't play chess!

Separation Principle

Under certain assumptions, the optimal state estimation + optimal deterministic control yields an optimal system

$$\begin{aligned}\dot{x} &= Ax + Bu \\ y &= Cx\end{aligned}$$

$$\begin{aligned}u &= -K\hat{x} \\ u &= -Kx\end{aligned}$$

Not always true!

$$\begin{aligned}\hat{\dot{x}} &= A\hat{x} + Bu + L(y - C\hat{x}) \\ \dot{e} &= (A - LC)e\end{aligned}$$

Control as if you had perfect state

Estimate as if you didn't care about control

Why do we care?

Module 1: Estimation

$$\begin{aligned}\hat{\dot{x}} &= A\hat{x} + Bu + L(y - C\hat{x}) \\ \dot{e} &= (A - LC)e\end{aligned}$$

Filtering/Smoothing

Localization

Mapping

SLAM

Why do we care?

Module 2: Planning/Control

$$u = -K \hat{x}$$
$$u = -K x$$

Search

Motion Planning

Trajectory Optimization

Stability/Certification

When does this not hold?

$$u = -K \hat{x}$$
$$u = -K x$$

Not always true!

$$\dot{\hat{x}} = A \hat{x} + B u + L(y - C \hat{x})$$
$$\dot{e} = (A - LC)e$$

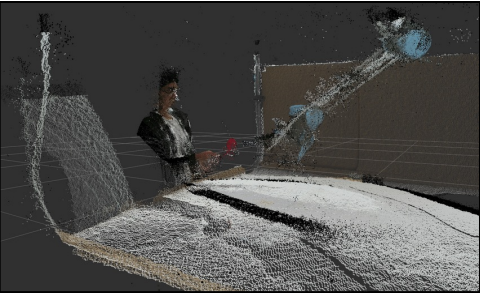
Imperfect and arbitrarily non-linear systems

MDPs and Reinforcement Learning

Imitation Learning

Solving POMDPs

How does a typical robotics pipeline look?



$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} = \boldsymbol{\tau}_g(\mathbf{q}) + \mathbf{B}\mathbf{u},$$

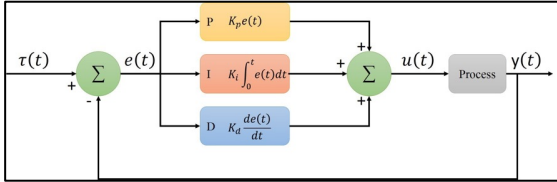
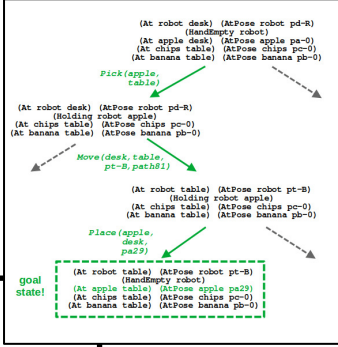
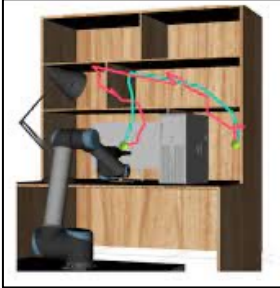
State Estimation

Modeling and Prediction

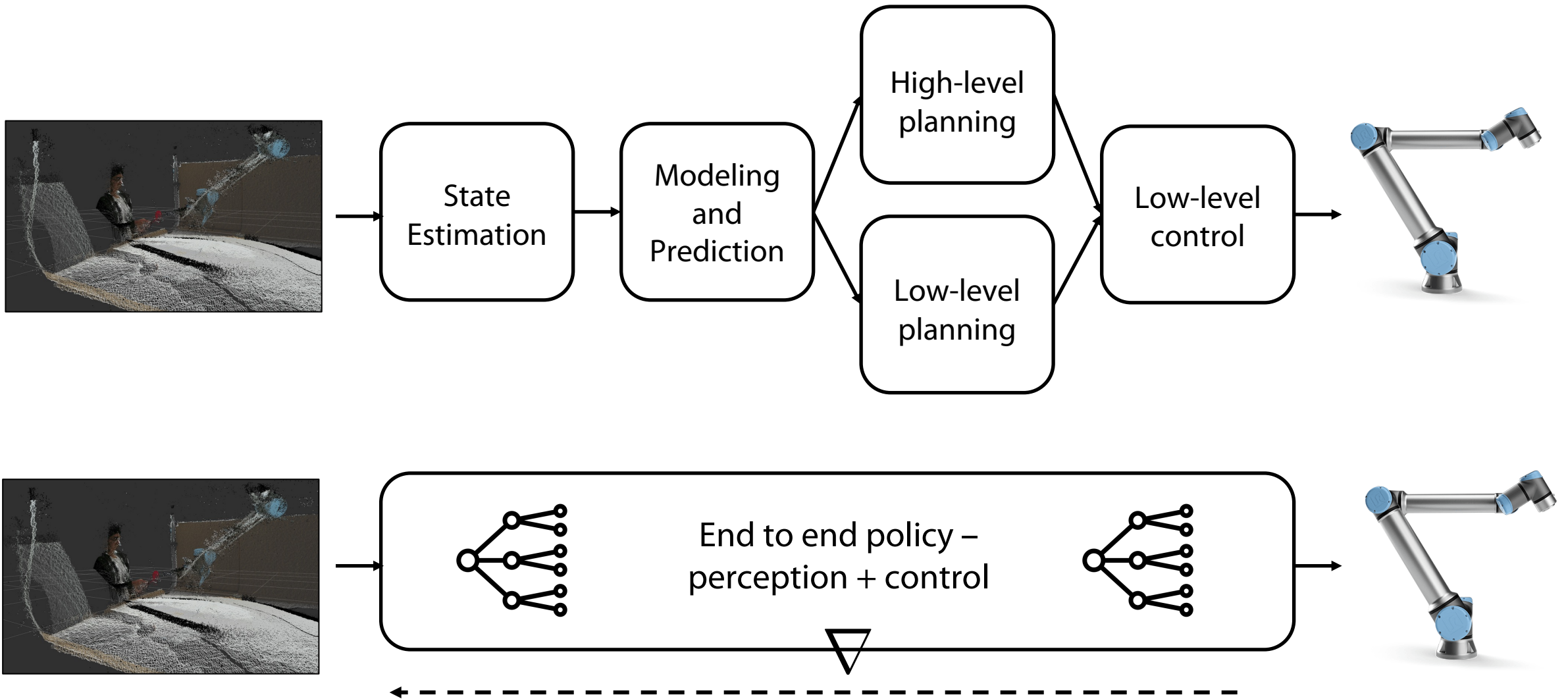
High-level planning

Low-level planning

Low-level control



Deep reinforcement learning pipeline for robotics



Not quite so simple, agent environment interface must be chosen!

Why might we not want to do this?

Modules compensate for each other

Avoids hand-designing and supervising interfaces

Often more performant/less biased

Lack of Interpretability

Lack of Reusability

Often data inefficient

Course Outline

Filtering/Smoothing

Localization

Mapping

SLAM

Search

Motion Planning

TrajOpt

Stability/Certification

MDPs and RL

Imitation Learning

Solving POMDPs

Goal of this course

- Understand what makes robotics so challenging
- Cover fundamental techniques and provide historical context on methods in robotics estimation and planning
- Provide exposure to state of the art and modern techniques in robotics and control

What broader tools will we learn?

Estimation:

Bayesian Inference

Maximum likelihood inference

End to end:

Statistical inference

Deep neural networks

Reinforcement Learning

Control:

Discrete search

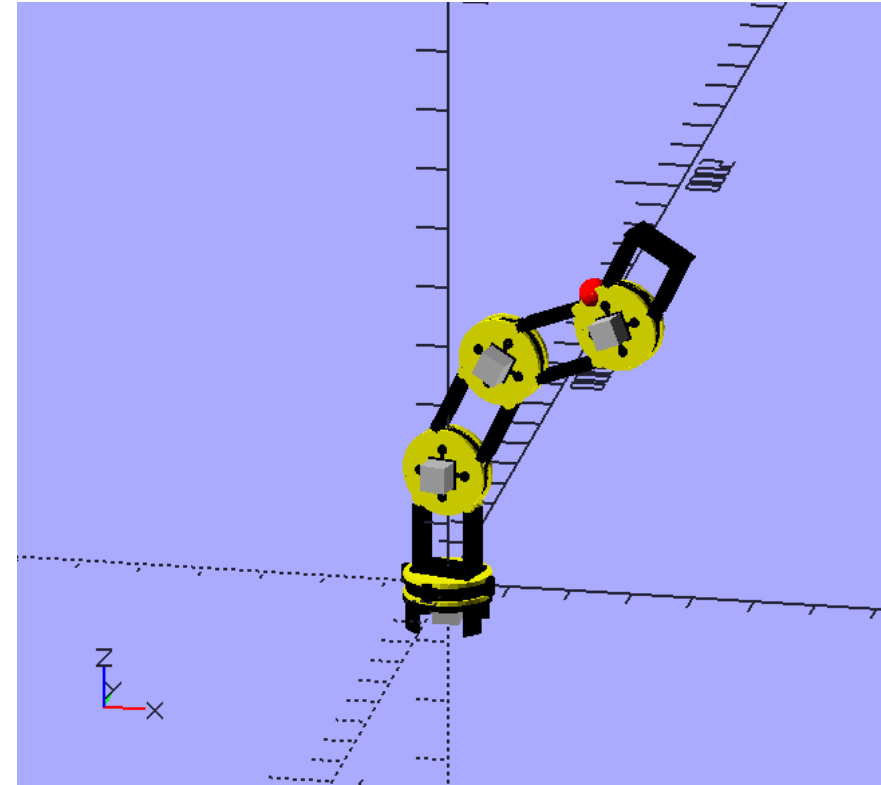
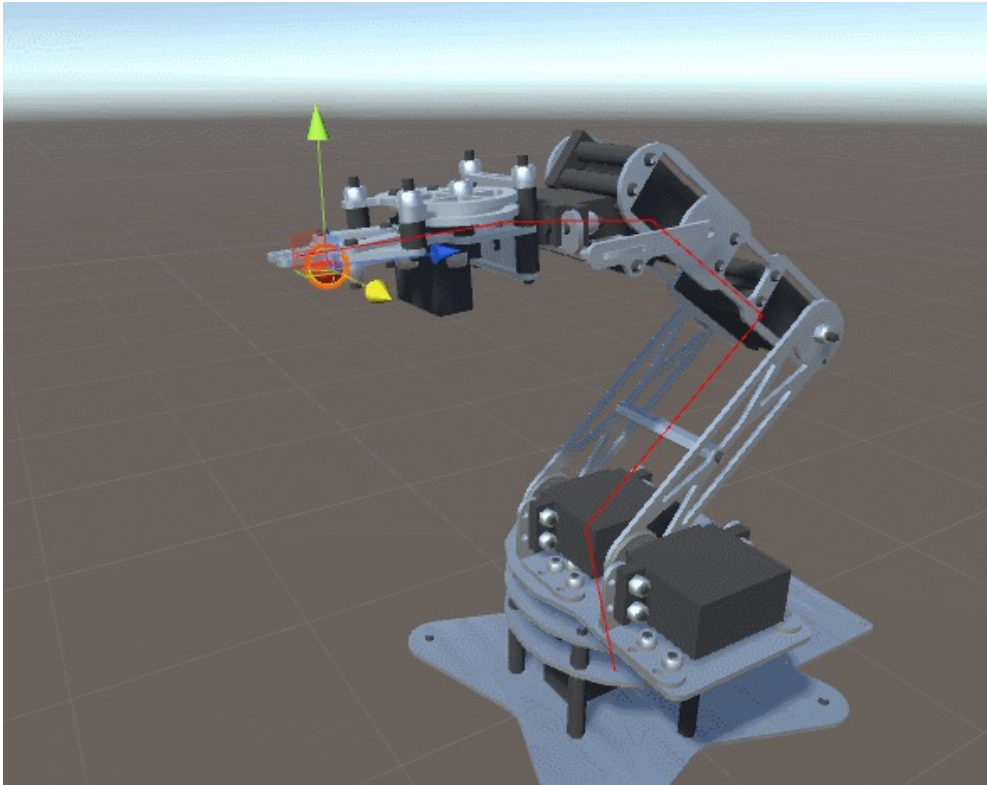
Convex optimization

Dynamic Programming

Useful beyond robotics across decision making problems

What we will not cover?

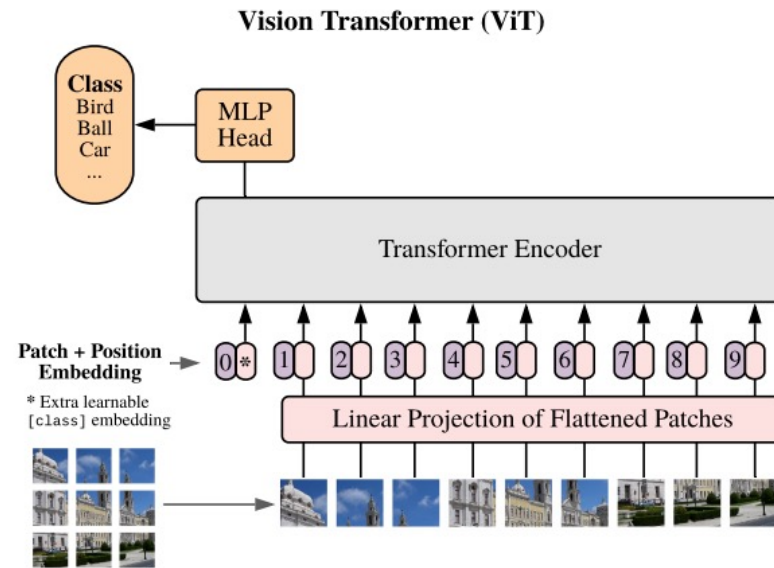
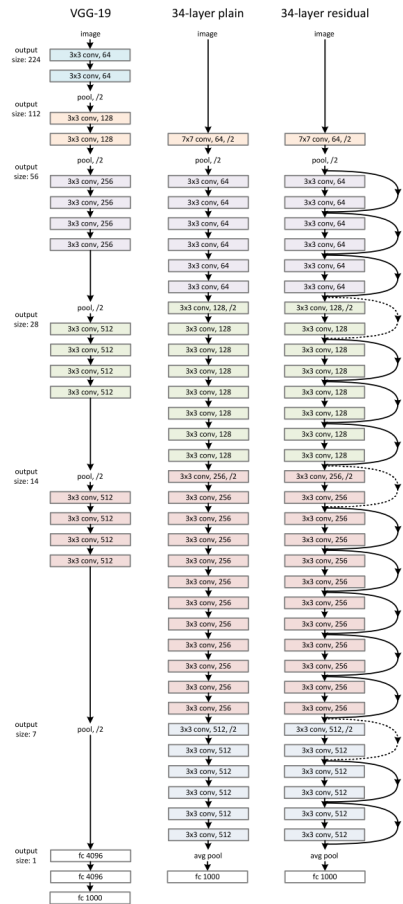
Kinematics or Dynamics Modeling



$$\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} = \boldsymbol{\tau}_g(\mathbf{q}) + \mathbf{B}\mathbf{u},$$

What we will not cover?

Advances in Computer Vision



What we will not cover?

Task and Motion Planning

Humanoid Manipulation Planning using
Backward-Forward Search

by

Michael X. Grey and Caelan R. Garrett

advised by

C. Karen Liu, Aaron D. Ames, and

Andrea L. Thomaz

