

# Physical Intelligence: Foundation and Systems (ESE 6510)

Instructor:  
Antonio Loquercio

Fall 2025  
University of Pennsylvania

# Today

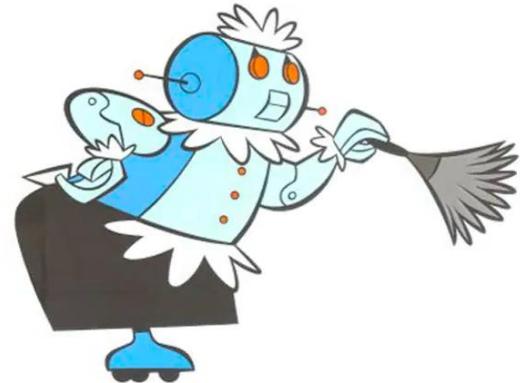
What is this class about?

- What are you getting into?
- What are you getting out of it?
- What are the expectations?

Why is now a good time to study robot learning?

How we thought  
the future would be.

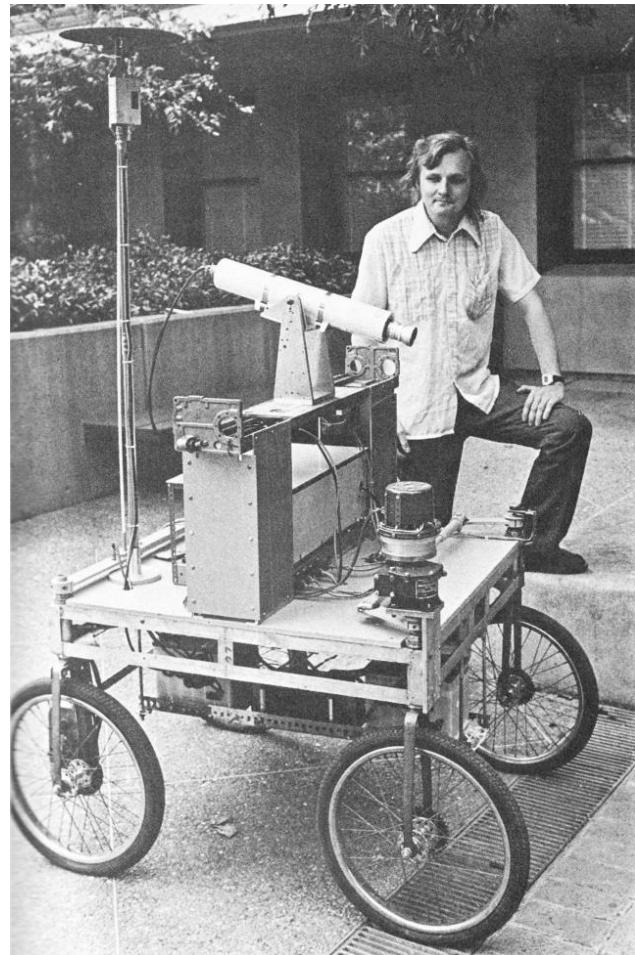
The Jetsons, ca. 1960



How the future  
is going to be.



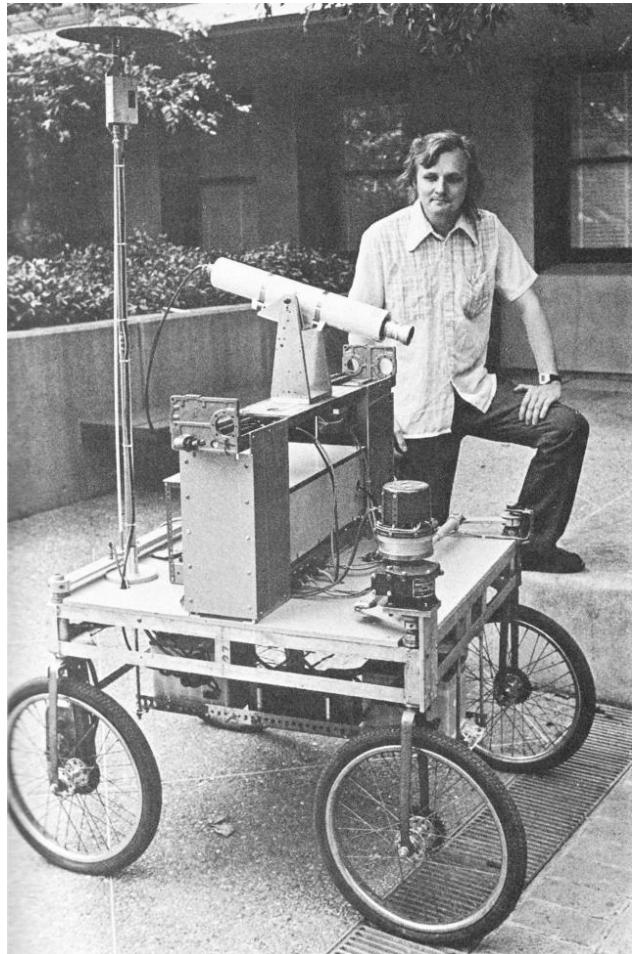
# Moravec's Paradox



*It is comparatively easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility.*

*Mind Children*, H. Moravec, 1988

# Hans Moravec's PhD Thesis



During this period a number of incoming students were assigned to the "cart project". Each correctly perceived the situation within a year, and went on to something else. The cart's reputation as a serious piece of research apparatus, never too high, sank to new depths.

# Why care about **Physical** Intelligence?

*“What’s so special about robotics?  
Surely, the same ‘foundational model’ should work for everything?”*

- In the long term, likely yes
- I don’t think we are there yet
  - We don’t have enough data
  - We don’t have the right data
  - We don’t know the right objective(s)
- Even with infinite data, there are challenges that we don’t yet know how to solve:
  - Safety (Hallucinations have significant consequences in robotics)
  - Computational efficiency
  - Stuff breaks
  - I am certainly very biased! 😅

# Why care about Physical **Intelligence**?

*“What if I don’t care about this wishy-washy learning stuff?  
I just want to make my robot go!”*

Small Reason:

If your task is well defined, other stuff might work better (e.g., Roomba)

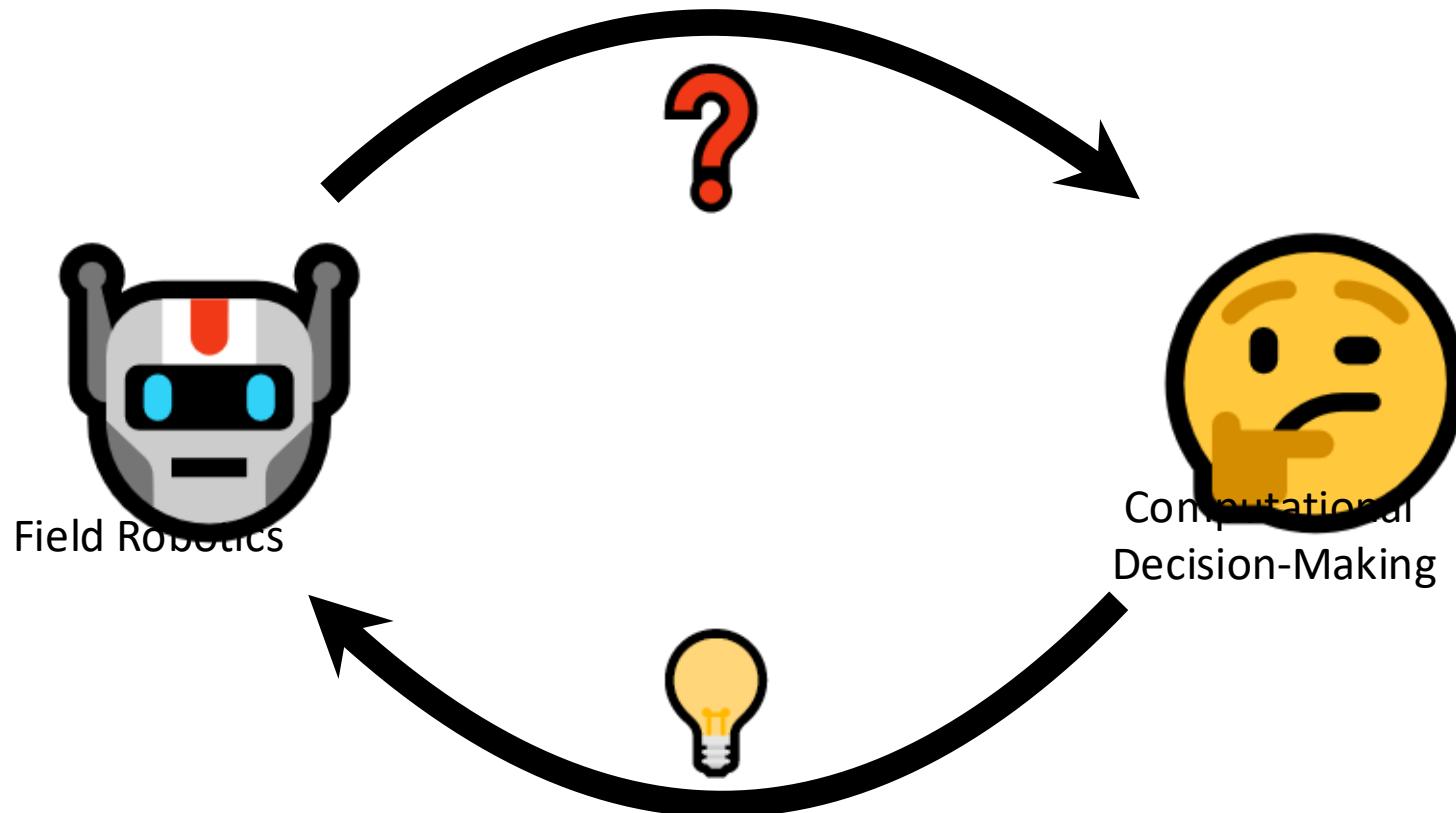
Bigger Reason:

We have not yet figured out how to build robots that are as adaptable as humans. Learning seems promising (look at CV + NLP).

Biggest Reason:

Science! Emergence of Intelligence is probably the biggest mystery in the universe. We can’t help ourselves but try to model it!

# Overreaching Theme

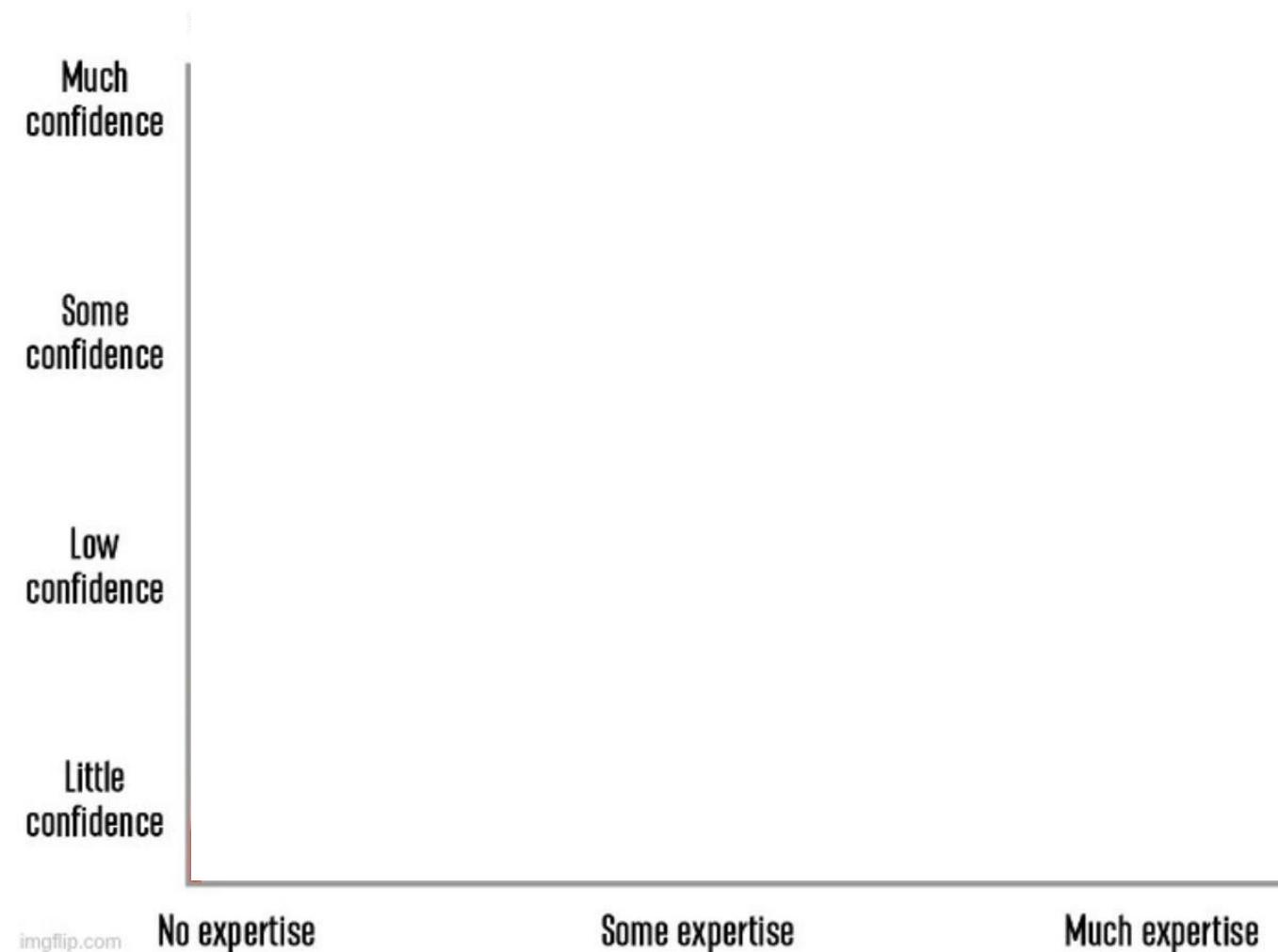


# Why care about the **Real World**?

*“Why bother with the real-world?  
I can study the exact same problem in simulations.”*

- We can't yet model everything
  - If we could, we'd be able to predict the future!
  - Unknown unknowns are often what makes a difference.
  - Need to deal with uncertainty
- Our models are limited by human cognition
  - Might be constraining if we're looking for super-human performance
- You are as smart as the environment requires
  - Can't reset or undo things
  - Intelligence  $\approx$  Reward Hacking
  - Everything works given enough constraints

# Dunning-Kruger Effect in Robotics



# What's different about this class?

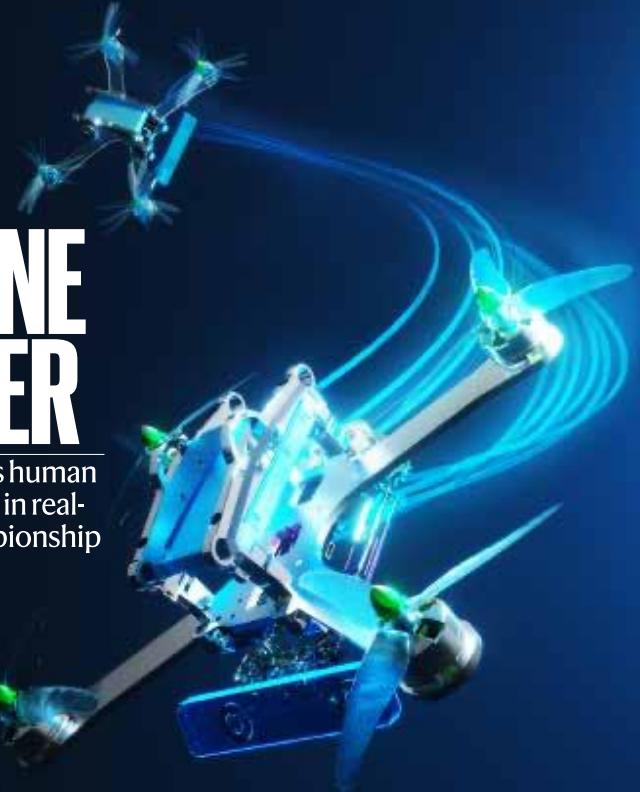
- We will see foundational concepts together with fancy systems
  - Study theoretical concepts, then come back to the nitty gritty of making something work
- Understand that hardware is as important as software
  - Contributions are sometimes not what the authors of a paper intended to
- Understand that fancy results are almost never the result of “one” idea
  - But rather, the collection of many small improvements

The international journal of science / 31 August 2023

# nature

## DRONE RACER

AI pilot beats human competitors in real-world championship



Vol. 620, No. 7996  
doi:10.1038/nature29133

Article | [Open access](#) | Published: 30 August 2023

### Champion-level drone racing using deep reinforcement learning

[Elia Kaufmann](#) [Leonard Bauersfeld](#), [Antonio Loquercio](#), [Matthias Müller](#), [Vladlen Koltun](#) & [Davide Scaramuzza](#)

*Nature* **620**, 982–987 (2023) | [Cite this article](#)

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PERCEPTION  
GROUP



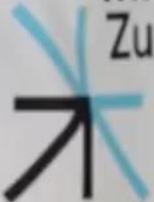
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Zürich UZH

Robotics and  
Perception Group

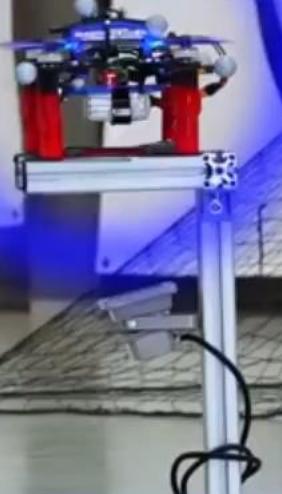
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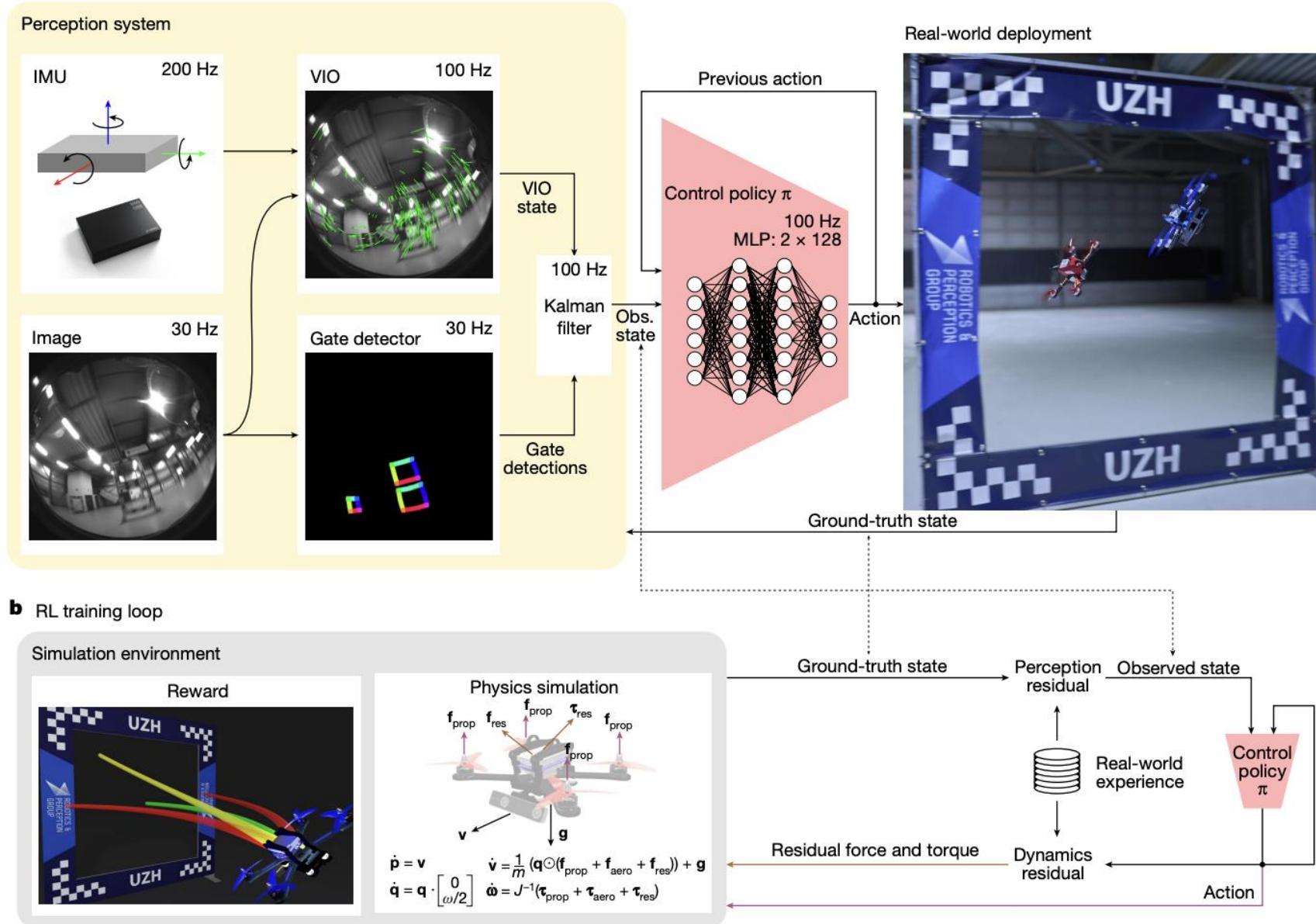
Canton of Zurich  
Department for Economic Affairs  
Office for Economy and Labour



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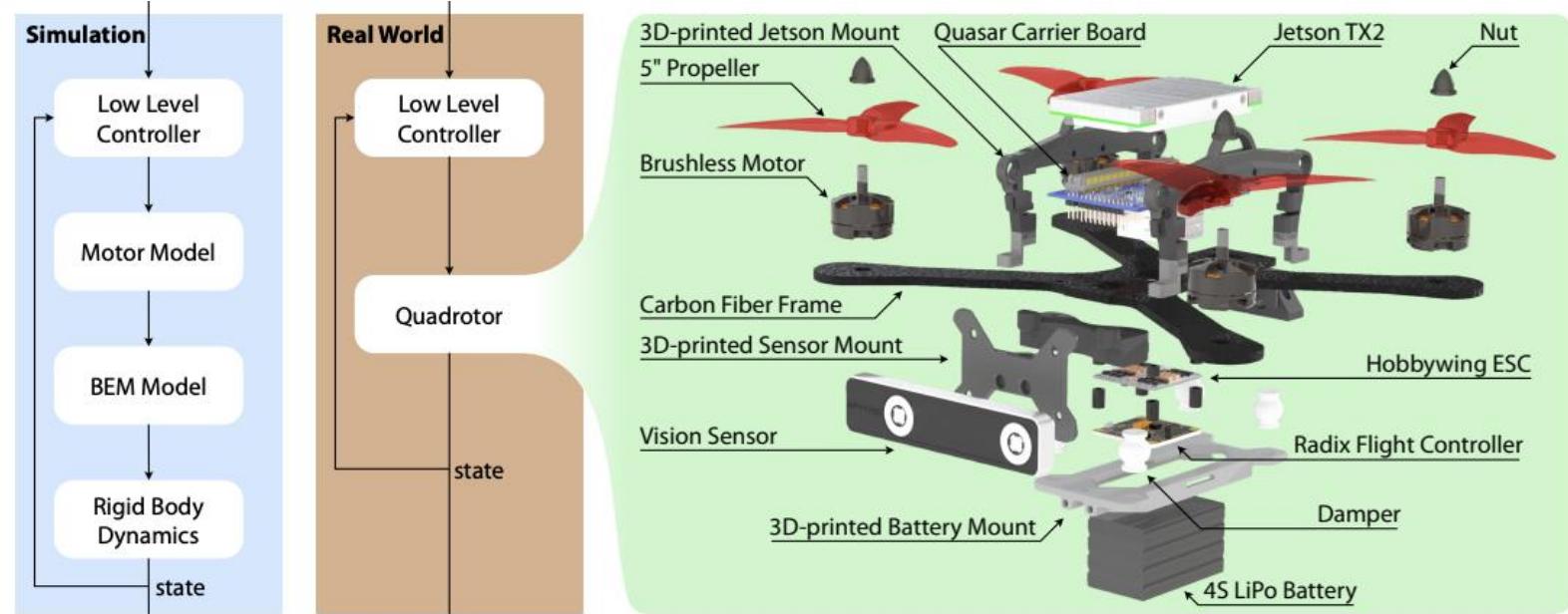
UZH

# Easy to Miss the Complexity of the System



# Easy to Miss the Complexity of the System

- The “Infrastructure” (built over three years of work)



- Latency Control
- Gaussian Mixture Models for Noise Identification
- Custom code to run vision models in embedded hardware

# Goals

- Be comfortable with the foundations of policy learning
- Get hands-on experience with robot learning
  - You never truly understand something until you have built it yourself.
- Use more learning-based techniques in your own work
- Learn how to think critically about robot learning papers and demos

# Course Material & Tools



- All learning materials will be available on this website
- We will use lot some tools to facilitate interactions:
  - Canvas for announcements
  - Ed for discussion
  - Gradescope for coursework

# Course Organization

## Grading:

1. Class Participation (5%)
  - **Attend class.** Don't skip more than 2 Quizzes. Ask questions, be involved!
2. Midterm (35%)
3. Final Exam (40%)
4. Drone Race (20%)
  - More details on this later
  - Can be done solo or in groups of 2
  - Best teams can skip the final

# Recitations (5X)

- We will do exercises/coding together in class
- There will be some quizzes during the tutorial
  - Skipping more than 2 will result in 0 points for participation.
  - Closed book (no laptop or phone)
  - Grade will be binary (1/0). You get 0 if you leave blank or write non-sense.
- You will receive additional exercises on the topic to complete at home.
- The at-home exercises will not be graded.

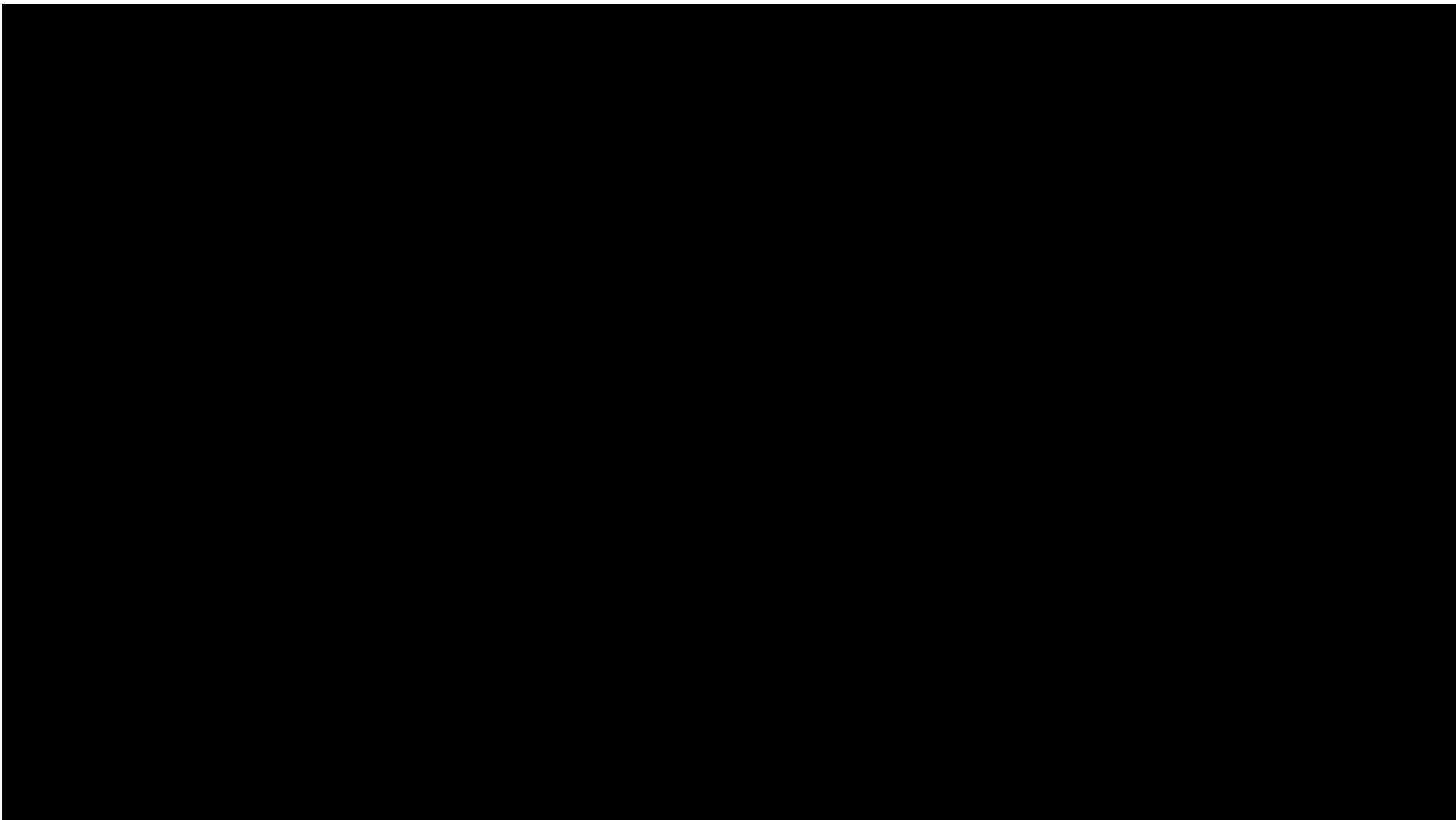
# The Drone Racing Competition: Phase I



# The Drone Racing Competition: Phase I

- Time trial, solo racing.
- All groups must participate
- Will be done in simulation.
  - More on the evaluation scheme will be announced later in the semester.
- Three grading tears
  1. The top 3 teams receive a grade bump (e.g., A -> A+).
  2. Top 10 (one bonus point)
  3. Not completing the track under a (very relaxed) maximum time (grade decided depending on what was implemented). These teams won't be able to move to the next phase.
  4. Everybody else (full score)
- Need to submit a short (1-2pp) report on what was implemented

# Phase I's Winners Last Semester



# The Drone Racing Competition: Phase II



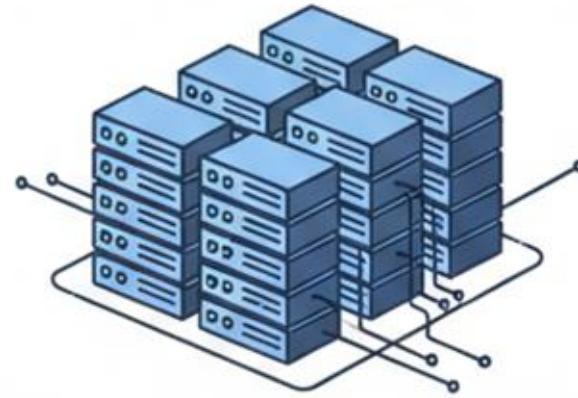
# The Drone Racing Competition: Phase II

- We will race in the real world!
- Prize: dinner in my favorite restaurant in Rome (transportation not included!) or some other worthy prizes 😊
- Two grading tears
  1. The intersection of Phase I and Phase II top-3 teams can skip the final.
  2. Top 10 get one bonus point.
  3. Everybody else (grade decided depending on what was implemented)

# Phase II's Winners Last Semester



# Compute Options for Policy Training



## **Linux Workstation (Preferred)**

### **Personal or Lab Computer**

NVIDIA GPU (RTX 3070 or better)  
32 GB RAM  
4 Cores  
50 GB SSD  
8 GB VRAM

## **HPC**

### **GRASP Cluster, PRECISE, etc**

For students that already have HPC access through a lab *and* your advisor approves of usage for a class.

## **Virtual Machine**

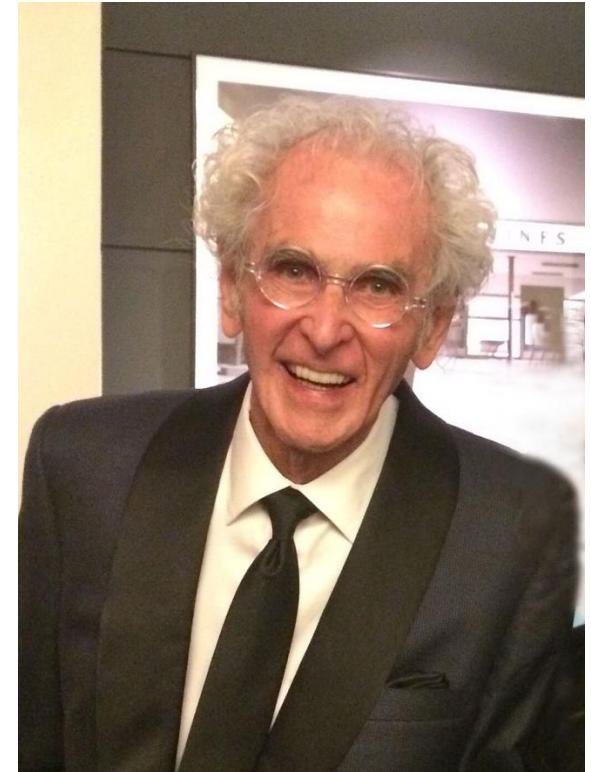
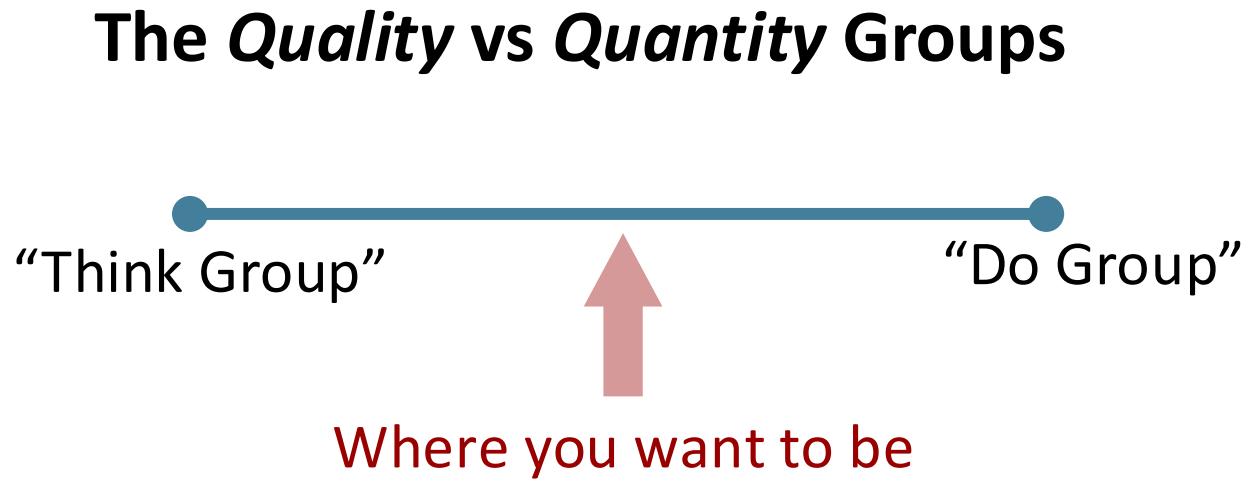
### **Google Cloud, AWS**

We will release formal instructions to run Isaac Lab within a VM using Google Cloud and/or AWS.

This is intended for students that do not have a Workstation or HPC access.

# The secret to being successful at the race

... and in Robotics in general



**Jerry Uelsmann**  
Photographer &  
Teaching Professor at UoF

# Who this class is for

- This is not an intro-level class. If you don't have previous experience with Robotics/CV/ML this might be challenging.
- We will cover the foundations of imitation and reinforcement learning, adopting a robotics-first perspective.
- Everybody is welcome to audit, but I don't think you'll get much out of it.

# ESE650 vs ESE651(This class)

- ESE650 is more about “traditional” robot learning:
  - Kalman filters
  - Optimal control
  - The connections of the above to RL
- Our class will be more focused on the latest in robot learning:
  - We will look at RL/Imitation learning theory from the eye of a roboticist.
  - Sim2real, generative imitation learning, large scale pretraining, etc.
  - A bit more hands-on.
- There will be a good overlap of topics in the RL theory part.

# Some Polls!

- Poll of backgrounds
  - Real robot experience?
  - Have you worked on drones before?
- Poll of programs
  - PhD
  - MS
  - Undergraduates

If you haven't been admitted to the class yet, please register soon.  
Make sure to fill the form when you register (otherwise I can't admit you).

# TAs



Jefferson Ng  
(Class Material)



Vaibhav Thakkar  
(Class Material)



Vineet Pasumarti  
(Race)

Some cool things I've worked on



## Learning High-Speed Flight in the Wild

**Antonio Loquercio, Elia Kaufmann, Rene Ranftl,  
Matthias Mueller, Vladlen Koltun, Davide Scaramuzza**

*Science Robotics, 2021*

# Learning to Fly From Simplified Simulators



m/h

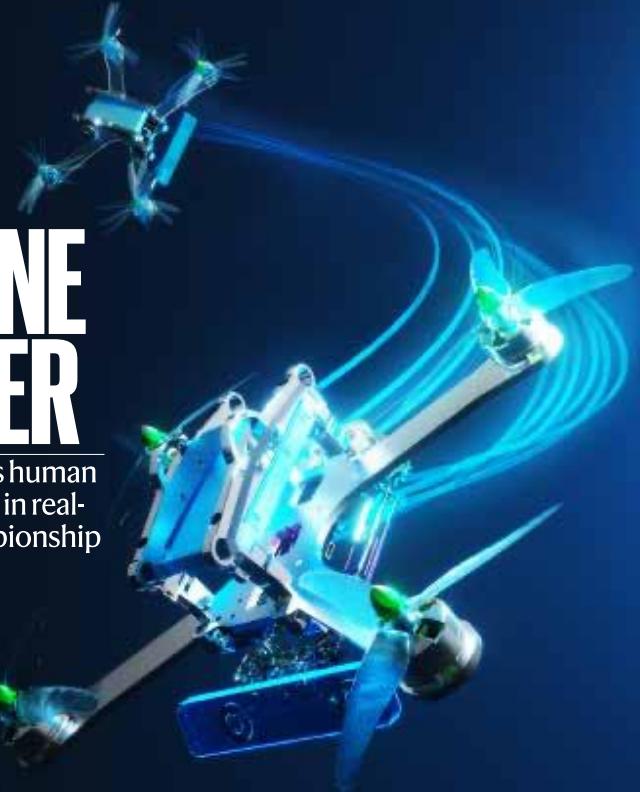


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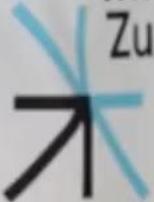
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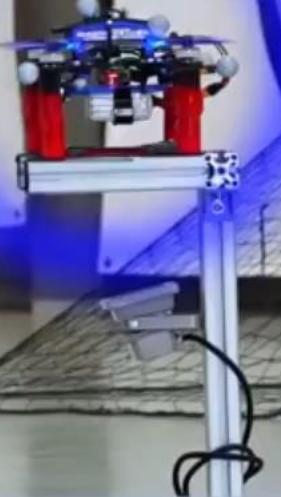
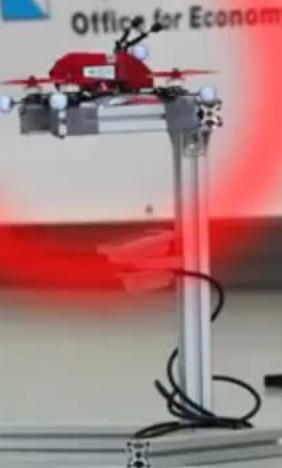
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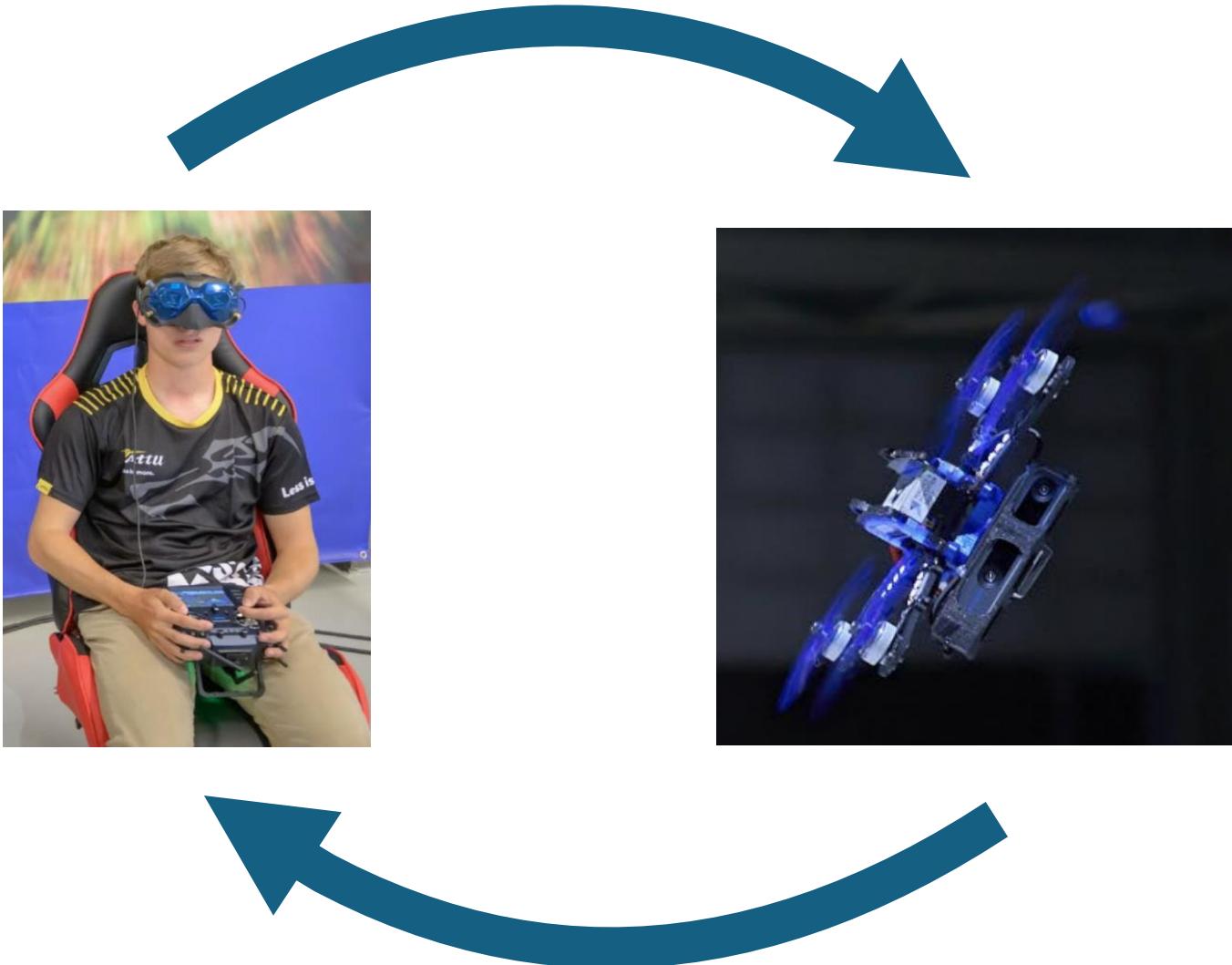
# The Human Champions







# Co-Adaptation



# Agile Flight Emerges from Multi-Agent Competitive Racing



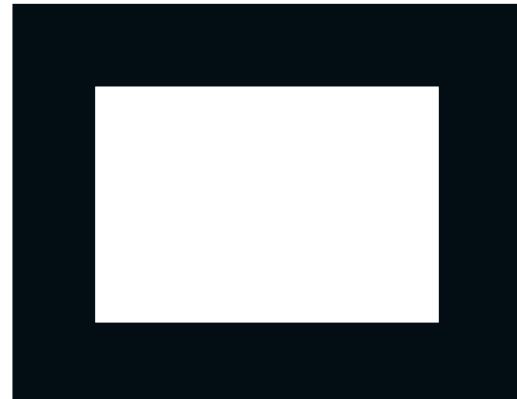
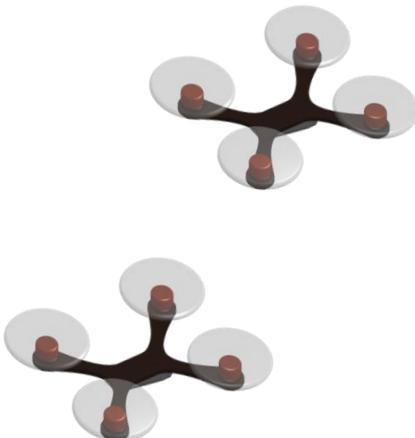
Vineet Pasumarti



Lorenzo Bianchi

# Training Agents with Sparse Competition Rewards

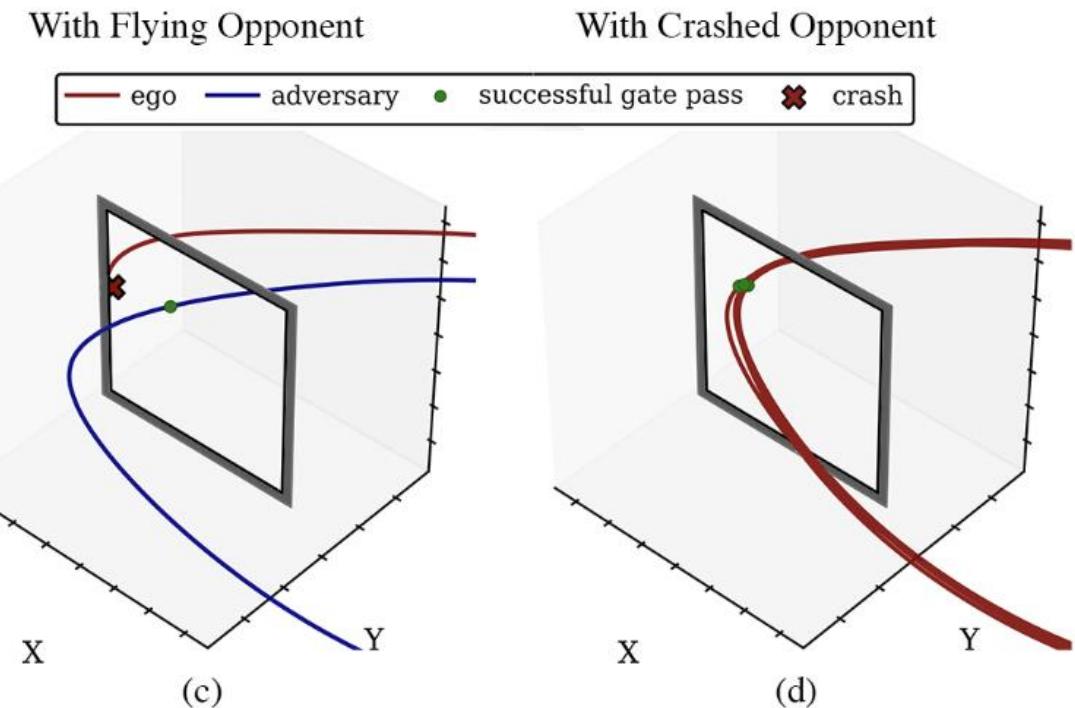
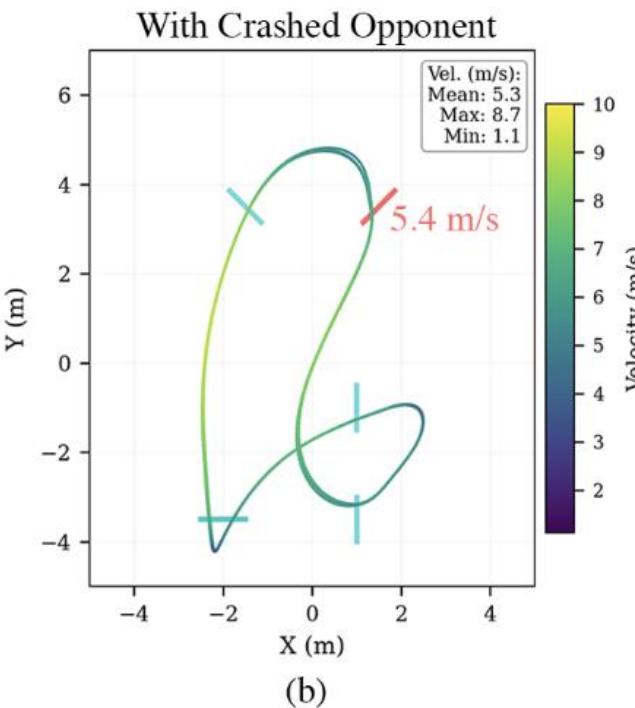
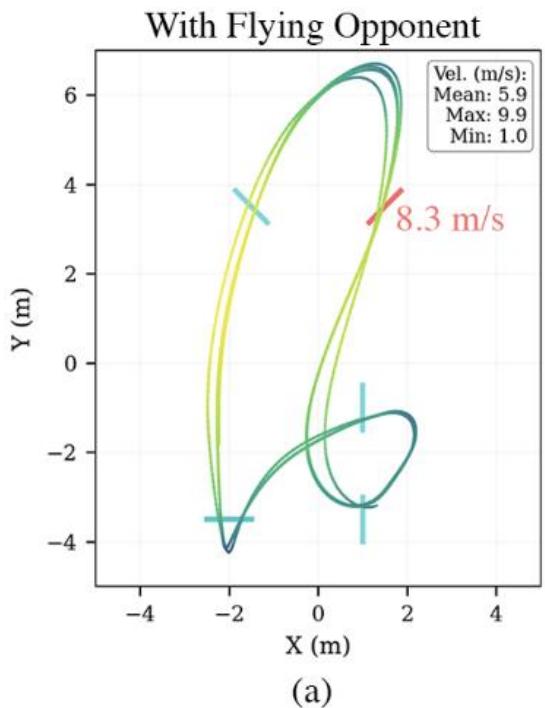
Reward 1:  
Pass every gate before your  
opponent

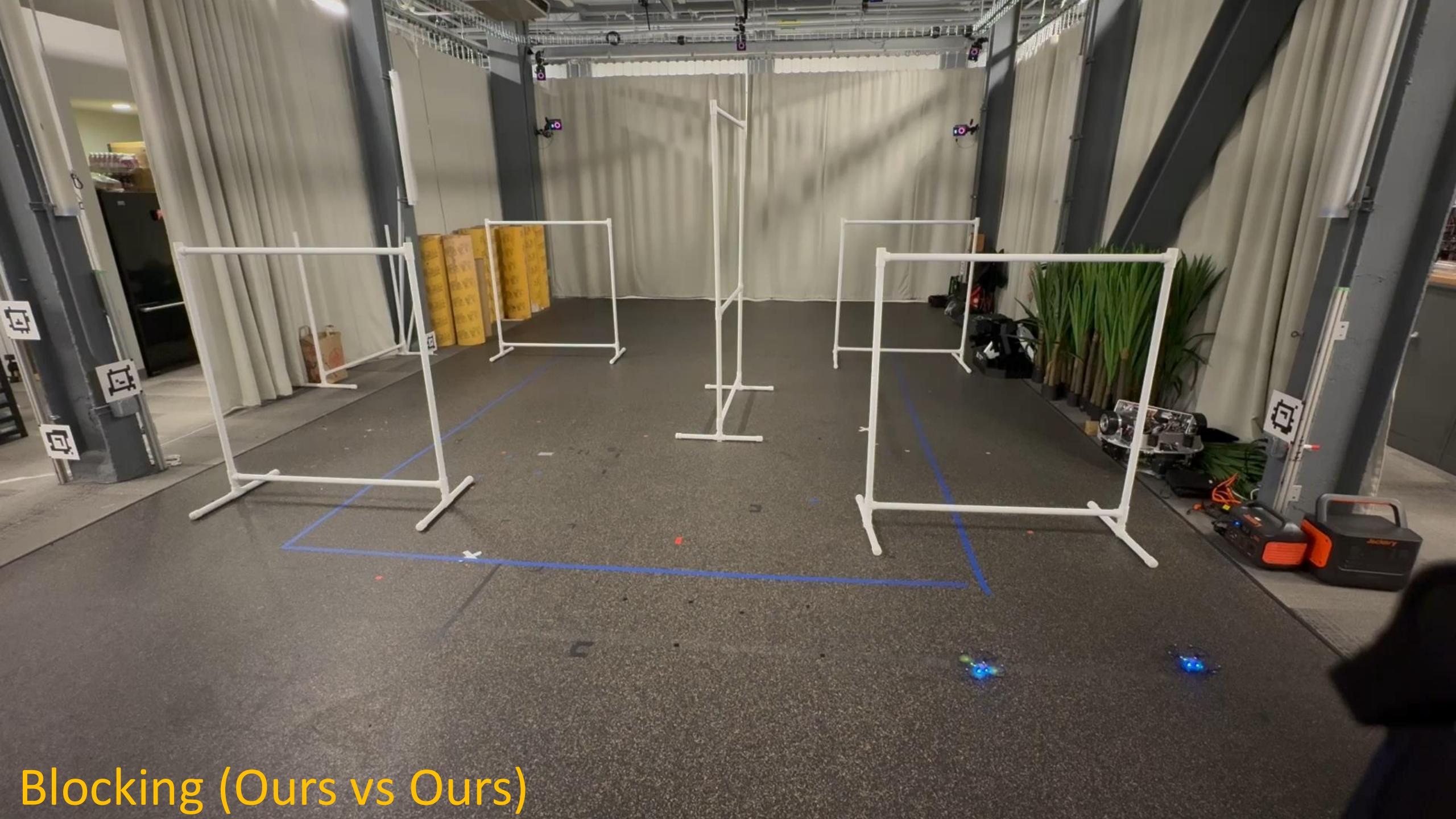


Reward 2:  
Bonus if you finish a lap first



# Competitive Behaviors Emerge





Blocking (Ours vs Ours)

Blocking (Ours vs Ours)



Physical Contact (Ours vs Ours)



Physical Contact (Ours vs Ours)

# Learning Visual Locomotion with Cross-Modal Supervision



Antonio Loquercio



Ashish Kumar



Jitendra Malik

# Day 1 (2X)



# Construction Zone





# Visual Plasticity

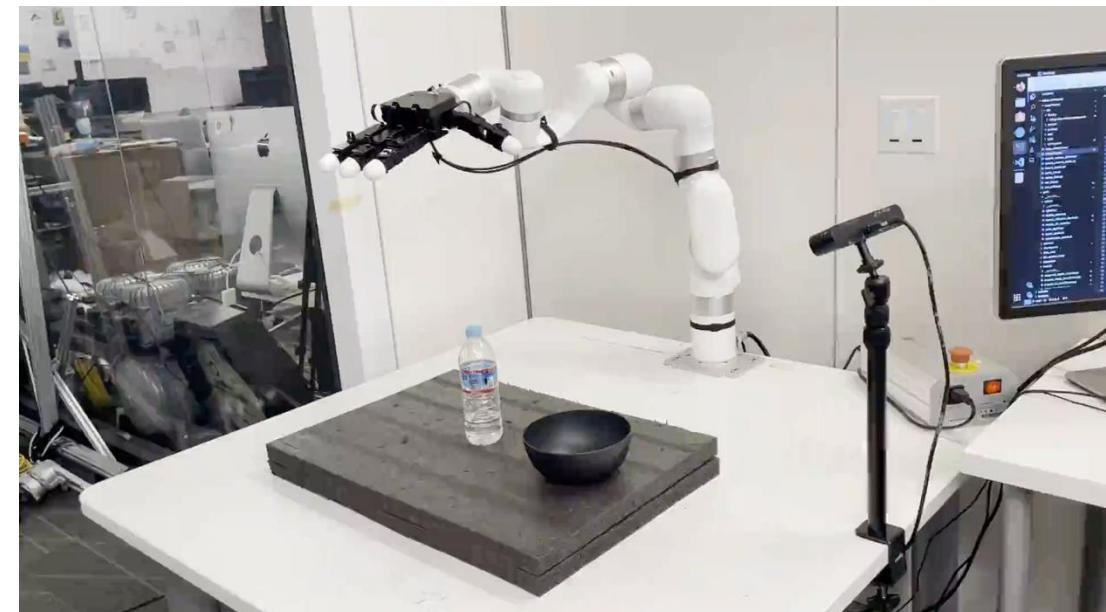
Before Adaptation



After 1min of data



# Learning from Videos



# Human videos for scaling up robot data



1. Intuitive physics
2. Contact poses
3. Pre/Post-contact trajectories
4. Human preferences
5. ....

# Sample-efficient BC Finetuning

