## 16-886

# Embodied AI Safety

Instructor: Andrea Bajcsy





# Welcome!

# Professor



### Andrea Bajcsy (BYE-chee)

What to call me:

- Andrea (*if you are a grad student*)
- Prof. Bajcsy or Prof. B (*if you are undergrad*)

Office Location: NSH 4629 Office Hours: Wednesdays, 1-2pm Email: <u>abajcsy@cmu.edu</u>

# **Teaching Assistant**



### Ken Nakamura, PhD Student

Research Interests: *Discover synergy between* **robust optimal control** and **generative models** to allow robots to safely operate in unstructured environments.

Office Location: NSH TBA Office Hours: TBA – please take survey on Canvas so we can select OHs that suit folks best Email: <u>kensuken@andrew.cmu.edu</u>

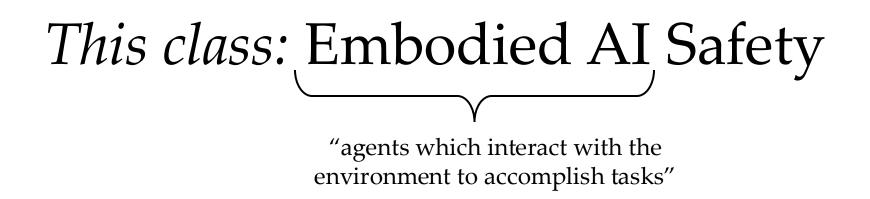
# What is next?

**Course Contents** 

**Course Logistics** 

Intro Survey

(Intro to Sequential Decision-Making)







Most examples in this class will be of these EAI systems – **robots**!

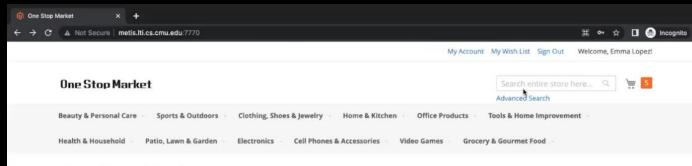
[Skydio, 2023]

#### Hello! What can I help you with?

Could you help me clean up

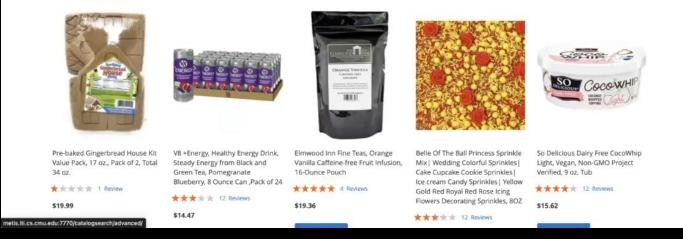


[Google, 2022]



#### One Stop Market

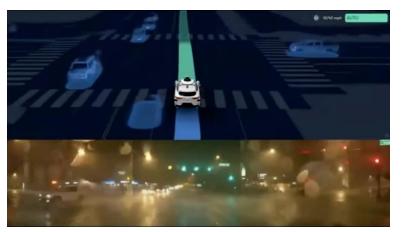
#### Product Showcases



[Zhou et al. "WebArena", arXiv 2023]

But the core ideas are also relevant to current & future EAI systems





World Models, Video Prediction Models, ...

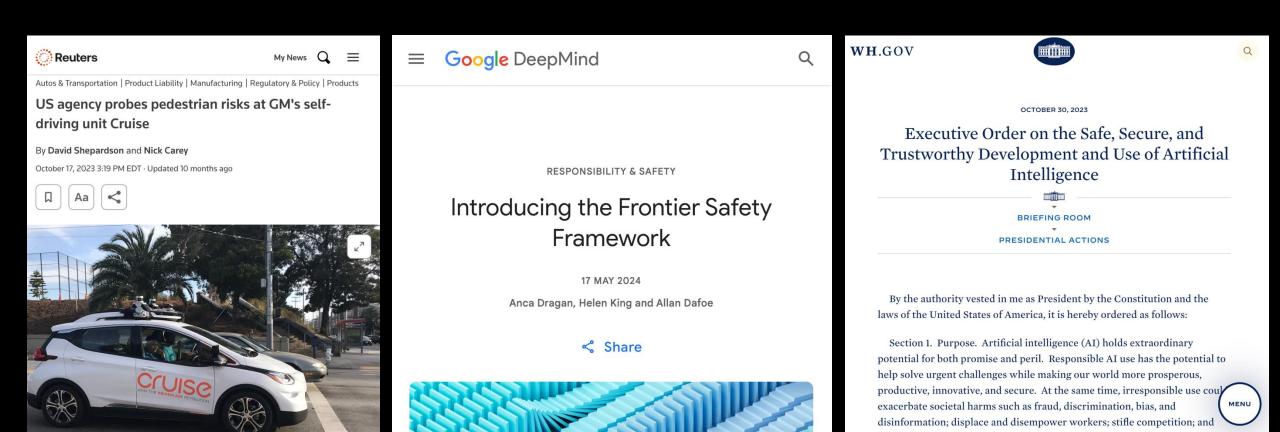


# This class: Embodied AI Safety

Some properties you will see in class:

- learned patterns instead of handdesigned ones
- high-dimensional inputs
- "End-to-end" models

# Increased capabilities & deployment have escalated concerns about safety



# This class: Embodied AI Safety What is safety?

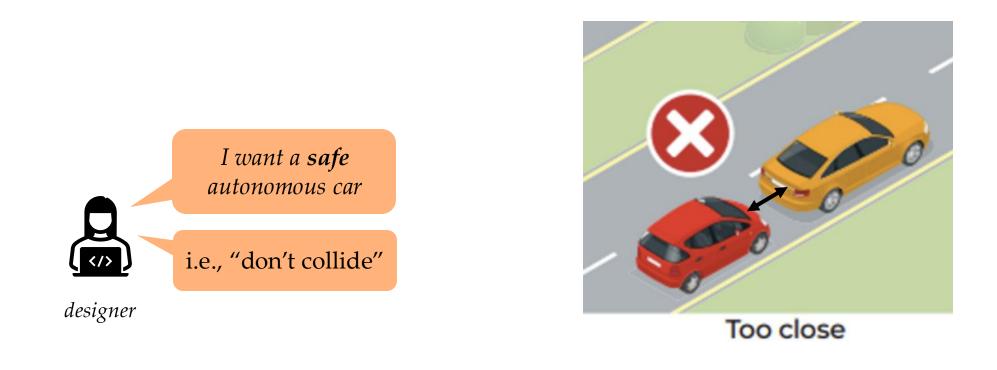


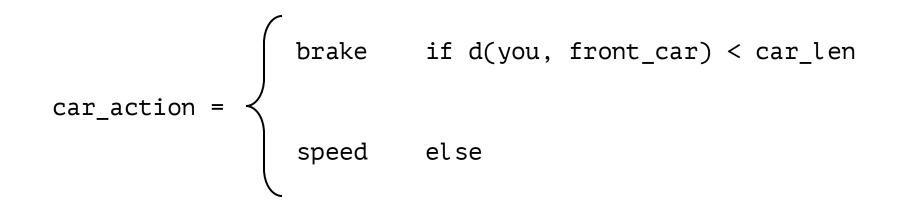
# Group exercise!

Group 1	Think of $\geq$ 3 ways you can define or specify safety for embodied AI systems. Think of the example systems from a few slides ago to motivate your ideas.
Group 2	Imagine you bought a mobile manipulator that uses an LLM-based task planner to act in your kitchen (like the one we saw from Google). What safety concerns could you imagine arising from this system?
Group 3	Imagine you are deploying a drone to help with firefighting in urban disasters. What "safety assurance" would you want from this system?
Group 4	What makes "embodied AI safety" challenging? Name $\geq$ 3 challenges you foresee.
Group 5	Name 2 <i>opportunities</i> and 2 <i>challenges</i> do foundation models (e.g., LLMs/VLMs) bring for embodied AI safety?

*unstructured, real-world environments* In the "open world", safety is a nuanced concept

### First, let's think through "simple" safety specification....



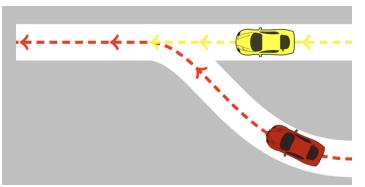


#### Env. topology

#### *Relative speed*

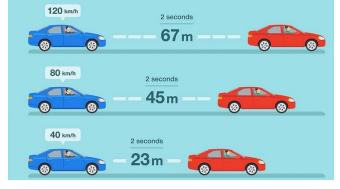


Too close



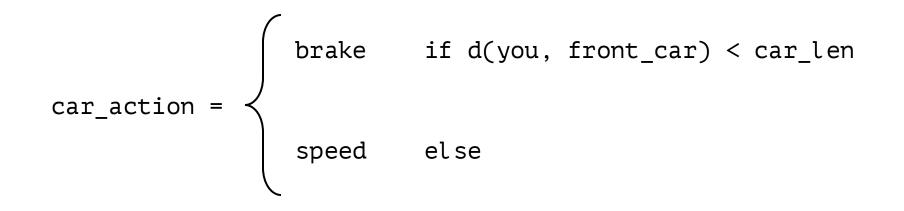
#### Weather





Many drivers





### On a Formal Model of Safe and Scalable Self-driving Cars

#### Shai Shalev-Shwartz, Shaked Shammah, Amnon Shashua

**Definition 1 (Safe longitudinal distance — same direction)** A longitudinal distance between a car  $c_r$  that drives behind another car  $c_f$ , where both cars are driving at the same direction, is safe w.r.t. a response time  $\rho$  if for any braking of at most  $a_{\max, brake}$ , performed by  $c_f$ , if  $c_r$  will accelerate by at most  $a_{\max, accel}$  during the response time, and from there on will brake by at least  $a_{\min, brake}$  until a full stop then it won't collide with  $c_f$ .

Lemma 2 below calculates the safe distance as a function of the velocities of  $c_r$ ,  $c_f$  and the parameters in the definition. In r

parame **Lemma 2** Let  $c_r$  be a vehicle which is behind  $c_f$  on the longitudinal axis. Let  $\rho$ ,  $a_{\max, brake}$ ,  $a_{\max, accel}$ ,  $a_{\min, brake}$  be as in Definition 1. Let  $v_r, v_f$  be the longitudinal velocities of the cars. Then, the minimal safe longitudinal distance that eve between the front-most point of  $c_r$  and the rear-most point of  $c_f$  is:

$$d_{\min} = \left[ v_r \, 
ho + rac{1}{2} a_{\max,\mathrm{accel}} \, 
ho^2 + rac{(v_r + 
ho \, a_{\max,\mathrm{accel}})^2}{2 a_{\min,\mathrm{brake}}} - rac{v_f^2}{2 a_{\max,\mathrm{brake}}} 
ight]_+ \, ,$$

where we use the notation  $[x]_+ := \max\{x, 0\}$ .

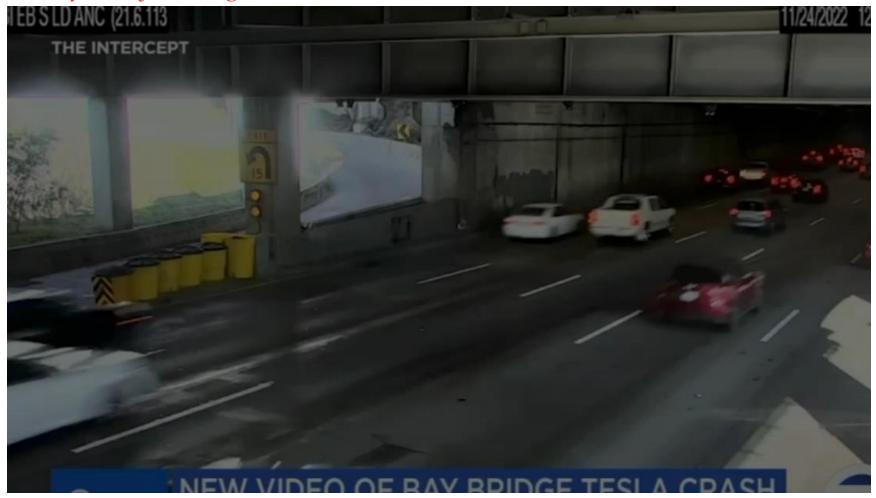




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## Even if safety specification is "simple", decision-making is hard

### Unsafe *early braking* (Tesla, 2023)



Source: https://abc7news.com/

In the open-world, many safety specifications are less obvious....

### Safety is "in the eye of the stakeholder" (also called alignment)

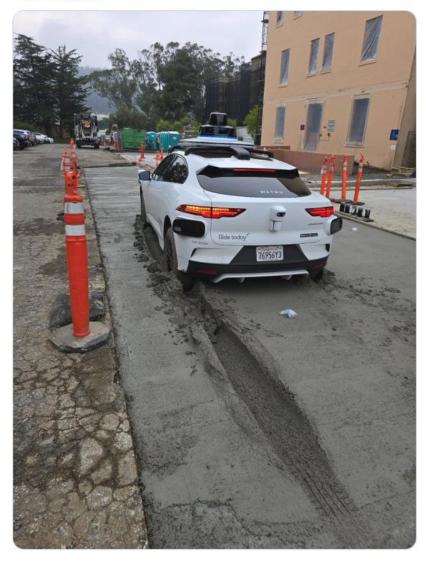


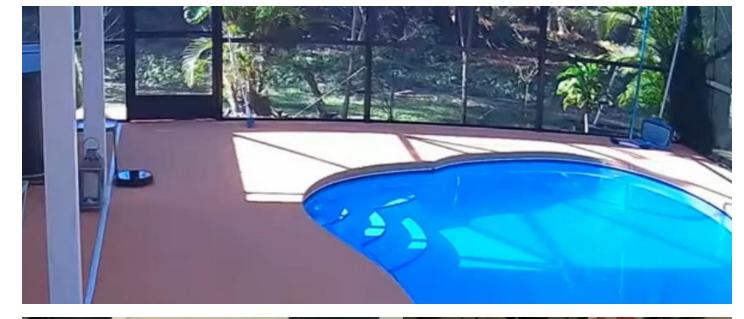
### Our representations of safety should be more than just collisions

×1 …



Oops! @Waymo

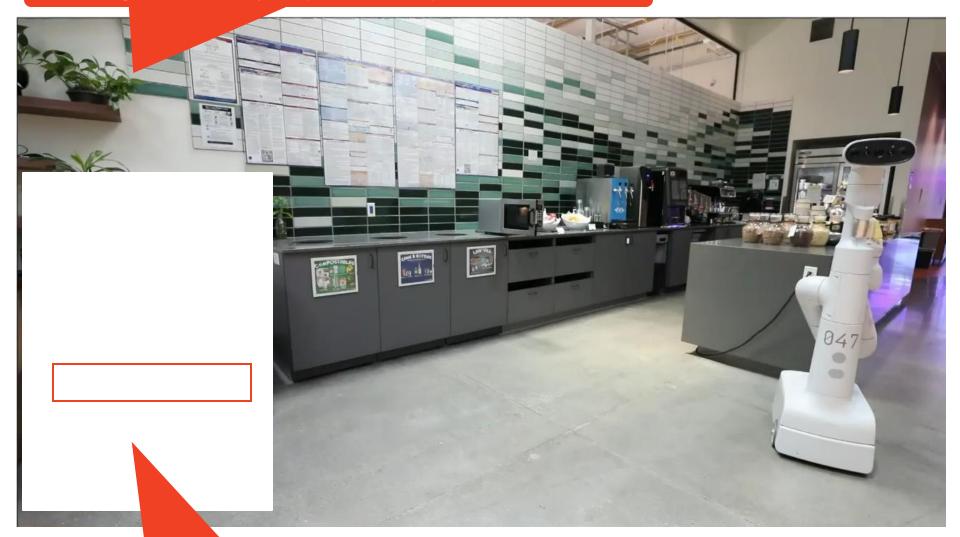






### Uncertainty and semantics play a key role in open-world safety

Knowing that its unsafe to put metal or plastic in microwave

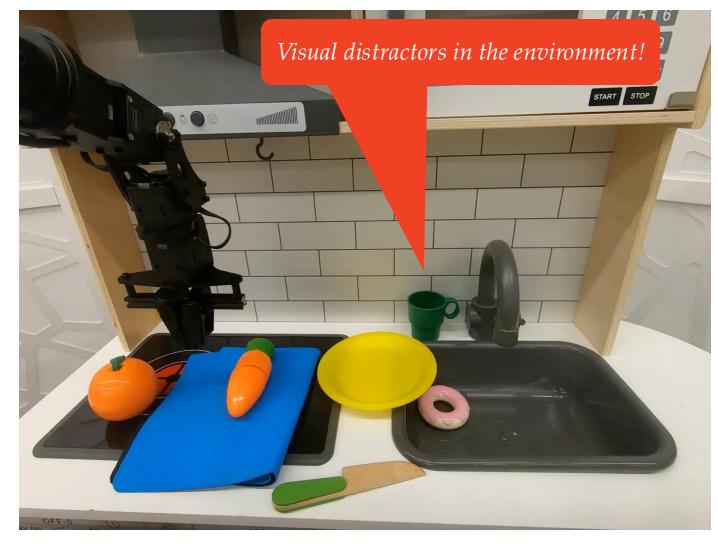


Asking for help when uncertain

[Ren, et al., "KnowNo". CoRL 2023]

### Embodied AI safety should reason about anomalous data





[Hanock, Ren, Majumdar. "BYOVLA". arXiv 2024]

# *This class:* Embodied AI Safety What is special about this?

We will formalize & study the full spectrum in the class!

## (+) Opportunities of AI Safety

infer hard-to-model low-D patterns from high-D obs

critique outcomes and steer towards good ones

enable novice stakeholders to specify safety that matters to them (e.g., language) (promise of) deployment into more unstructured or novel environments

> (promise of) generalization

### (?) Challenges of AI Safety

"misaligned" generations

how to safeguard *any* AI model?

what is OOD or anomalous?

single erroneous vision / language interpretation can lead to catastrophic action

generalize safety representations

generate (synthetic) data for stress-testing

high inference latency how to couple the detection of anomalies with mitigation actions?

## Control / Decision-Theory

how to couple the detection of anomalies with mitigation actions?

how to safeguard *any* AI model?

critique outcomes and steer towards good ones

single erroneous vision / language interpretation can lead to catastrophic action "misaligned" generations

(promise of) deployment into more unstructured or novel environments

generalize safety representations

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> high inference latency

## Machine Learning / Statistics

infer hard-to-model low-D patterns from high-D obs

enable novice stakeholders to specify safety that matters to them (e.g., language)

> (promise of) generalization

what is OOD or anomalous?

# **Course Logistics**

Format: lecture or related paper reading discussions

**Typical 80-min class:** 

~5 min attendance quiz at start 70 min lecture, invited talk, or paper discussion

# Use *course website* for up-to-date schedule & paper links

https://abajcsy.github.io/embodied-ai-safety/

#### Embodied Artificial Intelligence Safety

Spring 2025. 16-886. Monday / Wednesday 11:00-12:20.



#### Announcements

Hello! Nov 12 · 0 min read

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See you next semester! 🤓

#### **Course Overview**

Safety is a nuanced concept. For embodied systems, like robots, we commonly equate safety with collision-avoidance. But out in the "open world" it can be r more: for example, a safe mobile manipulator should understand when it is not confident about a requested task and understand that areas roped off by caul tape should never be breached. However, designing systems with such a nuanced understanding is an outstanding challenge, especially in the era of large ro behavior models.

In this araduate seminar class. we study the auestion of if (and how) the rise of modern artificial intelligence (AI) models (e.g., deep neural trajectory predicto. ...

#### Schedule (Tentative)

#### Jan. 13: **Course Overview Syllabus** Jan. 15: Sequential Decision-Making NO CLASS MLK Day Jan. 20: Jan. 22: Safety Filtering Data-Driven Safety Filters, Model Predictive Sheilding, Safety & Liveness of Filters Jan. 27: Safety Filter Synthesis via Optimal Control Jan. 29: **Robust Safety** Differential Games I, HJI **Computational Frameworks for Safety I Discounted Reachability, ISAACS** Feb. 3: Feb. 5: Computational Frameworks for Safety II HW #1 DUE DeepReach, One Filter to Deploy Them All Frontiers I Feb. 10: Semantic Safety I Safety Representations from Language, Local Updates PAPER READING Semantically Safe Robot Feb. 12: Semantic Safety II

		Manipulation, SALT
Feb. 17:	Belief-Space Safety	Deception Game, Analyzing Models that Adapt Online
Feb. 19:	Latent-Space Safety I	Dreamer, Human-Al Safety
Feb. 24:	Latent-Space Safety II	PAPER READING TBA, LS3
Feb. 26:	Failure Monitoring & Recovery via VLMs	HW #2 DUE PAPER READING 11 M Fallbacks.

# Use *Canvas* for downloading / uploading assignments



### **Recent Announcements**

**Embodied Artificial Intelligence Safety** 

🗟 Assign To 🛛 🗞 Edit 🛛 🗄



#### Welcome to 16-886: Embodied AI Safety!

Safety is a nuanced concept. For embodied systems, like robots, we commonly equate safety with collisionavoidance. But out in the "open world" it can be much more: for example, a safe mobile manipulator should understand when it is not confident about a requested task and understand that areas roped off by caution tape should never be breached. However, designing systems with such a nuanced understanding is an outstanding challenge, especially in the era of large robot behavior models.

In this graduate seminar class, we study the question of if (and how) the rise of modern artificial intelligence (AI) models (e.g., deep neural trajectory predictors, large vision-language models, and latent world models) can be harnessed to unlock new avenues for generalizing safety to the open world. From a foundations perspective, we study safety methods from two complementary communities: *control theory* (which enables the computation of safe decisions) and *machine learning* (which enables uncertainty quantification and anomaly detection). Throughout the class, there will also be several guest lectures from experts in the field. Students will practice essential research skills including reviewing papers, writing project proposals, and technical communication.

Class Website: <u>https://abajcsy.github.io/embodied-ai-safety/</u> □→

# Grading

See class syllabus on course website for detailed info

Attendance	(10%)
Homework (x3)	(30%)
Paper summaries	(10%)
Midterm project report	(10%)
Final project	(40%)

# Attendance (10%)

Expected to attend class in person—this is how we will all get the most out of the class! <u>Please show up on time</u>, especially for reading days

The way we grade this:

- <u>First 5 minutes of class</u>: we will give a **short**, **easy "quiz"** related to the last lecture's content. This is graded as 1/0.
  - e.g., "Describe what is a sequential decision-making problem."
- **Permitted 2 unexcused absences**, no questions asked, before being docked.

I understand that occasionally you may have challenges attending (e.g., illness, religious observance,..); **please let me know.** 

# Homework (30%)

HW #1: Computing & Using Safety Filters

Released:	~Jan 22
Due:	Feb 5

HW #2: Generalizing Safety Filters

Released:~Feb 10Due:Feb 26

HW #3: Conformal Prediction for Object Classification

Released:~Mar 10Due:April 2

These are coding-based homeworks in **Python** and **PyTorch**. They are *not* meant to be tedious; they are meant to **empower** you! ☺

*If you are not confident (or are rusty) with Python and Pytorch, please come see us for educational resources!* 

# Paper Summaries (10%)

### Paper discussion days: ~7 paper reading days 2 papers per reading day

	Feb. 12:	Semantic Safety II	PAPER READING Semantically Safe Robot Manipulation, SALT
	Feb. 17:	Belief-Space Safety	Deception Game, Analyzing Models that Adapt Online
	Feb. 19:	Latent-Space Safety I	Dreamer, Human-Al Safety
$\rightarrow$	Feb. 24:	Latent-Space Safety II	PAPER READING TBA, LS3
	Feb. 26:	Failure Monitoring & Recovery via VLMs	HW #2 DUE PAPER READING LLM Fallbacks, AHA

### **Before class:**

write 1-2 paragraphs of paper review / takeaway / questions (must submit on Canvas before class)

### In class:

Split you into small groups, discuss set of questions, I assign a representative from each group to present on the group's takeaways, and the whole class can engage on the answer

# Midterm Report (10%) & Final Project (40%)

### Two options:

### **Research project:**

Identify a research direction broadly relevant to this class Propose and take first steps towards an original idea

#### Literature survey:

Select a topic area and rigorous way in which you will find papers Characterize this topic area in an <u>insightful way</u> (e.g., open questions, common assumptions, tractable vs. theoretical gaps)

Can work individually, or in groups of up to 3.

#### Journal Title XX(X):1-37 Human Motion Trajectory Prediction: A C)The Author(s) 201 Survey SAGE Dariu M. Ga

Andrey Rudenko<sup>1,2</sup>, Luigi Palmieri<sup>1</sup>, Michael Herman<sup>3</sup>, Kris M. Kitani<sup>4</sup> Kai O. Arras<sup>1</sup>

#### Abstra

Example of good

*literature survey* 

ng numbers of intelligent autonomous systems in human environments, the ability of such systems to perceive, understand and anticipate human behavior becomes increasingly important. Specifically, predicting future positions of dynamic agents and planning considering such predictions are key tasks for self-driving vehicles, service robots and advanced surveillance systems. This paper provides a survey of human motion trajectory prediction. We review, analyze and structure a large selection of work from different communities and propose a taxonomy that categorizes existing methods based on the motion

modeling approach and level of contextual information used. We provide an overview of the existing datasets and performance metrics. We discuss limitations of the state of the art and outline directions for further research

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Dec Survey, review, motion prediction, robotics, video surveillance

1	Introduction
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tasks rely on the same motion modeling principles and trajectory prediction methods considered here. Within this Understanding human motion is a key skill for intelligent scope, we survey a large selection of works from differen systems to coexist and interact with humans. It involves communities and propose a novel taxonomy based on the aspects in representation, perception and motion analysis. motion modeling approaches and the contextual cues. We Prediction plays an important part in human motion analysis: categorize the state of the art and discuss typical properties

# Midterm Report (10%) & Final Project (40%)

When picking a project, make sure to answer the question:

*How does the project connect to the broader topics & context of the class?* 

*Come talk to us about your interests and we can help!* 

### Some examples:

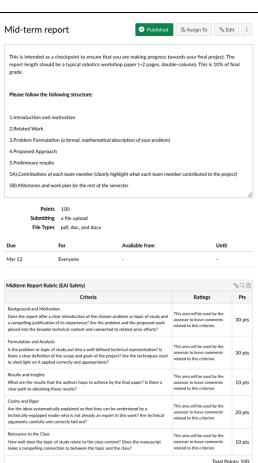
- Applying one of the techniques from class to your problem domain (*e.g., using conformal prediction to calibrate your pose estimator; using a safety filter to shield your policy, ...*)
- Comparing two methods that seek to solve the same problem (*e.g., RL vs. SSL approach to computing safety filters*)
- Posing (and solving) a new decision-theoretic safety problem for your problem domain
- Posing (and using) a new uncertainty quantification approach for your problem domain
- Challenging an assumption underlying one of the methods in the class

# Midterm Report (10%) & Final Project (40%)

Extra credit opportunity (+2%) – discuss your project with a course staff before Spring Break After you do this, write a 1 paragraph summary of your idea and discussion which you will submit to Canvas

report length should be a typical robotics workshop paper (~2 pages, double-column). This is 10% of fina Mid-term report (10%) -- due on Wed, March 12 grade Please follow the following structure 2 page writeup of progress, updated goals and timeline 1 Introduction and motivation 2.Related Work 3. Problem Formulation (a formal, mathematical description of your problem 4. Proposed Approach 5.Preliminary results 5A).Contributions of each team member (clearly highlight what each team member contributed to the proi **Oral project presentation (10%)** -- to be scheduled for April 21 & April 23 5B).Milestones and work plan for the rest of the semest Points 100 short "conference-talk" presentations (~5 minutes) Submitting a file upload File Types pdf. doc. and docx Du Available from Mar 12 Everyone

**Final project report (30%) -- due on May 1** 4-6 pages final report



## Control / Decision-Theory

#### how to couple the detection of anomalies with mitigation actions?

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# Machine Learning / Statistics

infer hard-to-model low-D patterns from high-D obs

enable novice stakeholders to specify safety that matters to them (e.g., language)

> (promise of) generalization

what is OOD or anomalous?

# What you will learn in this course

### **Control-Theoretic Safety Foundations**

Safety filtering (theory and computation) Computational frameworks for safety (RL & self-supervised learning)

### **Frontiers I**

Semantic safety & the use of VLMs Belief and latent-space safety

### **Machine Learning & Statistical Safety Foundations**

Uncertainty quantification (e.g., ensembles, conformal prediction) AI Alignment Risk and anomalies

### **Frontiers II**

Out-of-distribution detection & controlling in-distribution Statistical assurances on learned policies / models

# **Guest Lectures**

#### **Latent Safety Filters**



Ken Nakamura PhD Student @ CMU

#### **Conformal Prediction**



Anushri Dixit Prof @ UCLA

#### Mathematical Foundations of Robotic Behavior Cloning



Max Simchowitz Prof @ CMU (MLD)

#### **Out-of-Distribution & Failure Detection**

#### **Statistical Assurances for Learned Policies**



Dr. Masha Itkina Research Scientist, Toyota Research Institute



Dr. Haruki Nishimura Research Scientist, Toyota Research Institute

https://forms.gle/2eX9GZZrNPKe65T69

# Survey (5 min)



## 16-886

# Embodied AI Safety

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