

CS 159

Predictive Control & Neural Network Theory

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Instructors & TAs



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Course Details

- Website: <https://1five9.github.io/>
- Office Hours and Q&A via Discord
 - (ask instructors for invite)
- Assignments via Gradescope

- 4 Homework Assignments (20% total grade)
- Final Research Project (80% total grade)
- Work in teams of 2-3 for everything

Structure of the Course

- Two Topics:
 - Machine Learning for Predictive Control (Ugo Rosolia)
 - Neural Network Theory (Jeremy Bernstein)
 - TBA: guest lectures related to these two topics
- 6 Lectures (3 weeks) per topic
- 2 Assignments per topic
- Final project on topic of your choice
 - Instructors and TAs can help you choose a good project direction

Recap of CS 155

Supervised Learning

Linear Models

Overfitting

Loss Functions

Non-Linear Models

Learning Algorithms
& Optimization

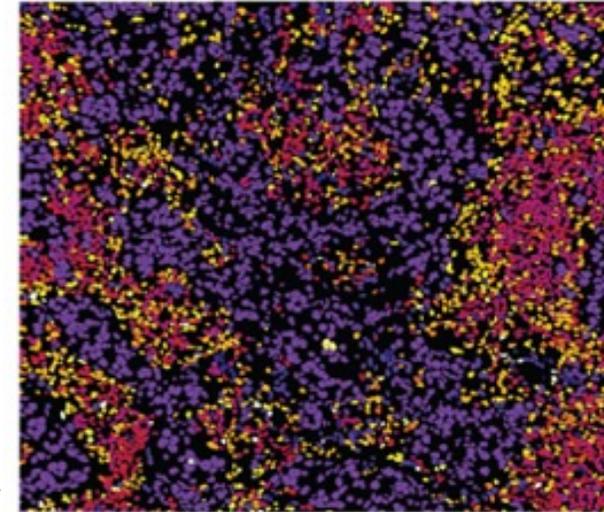
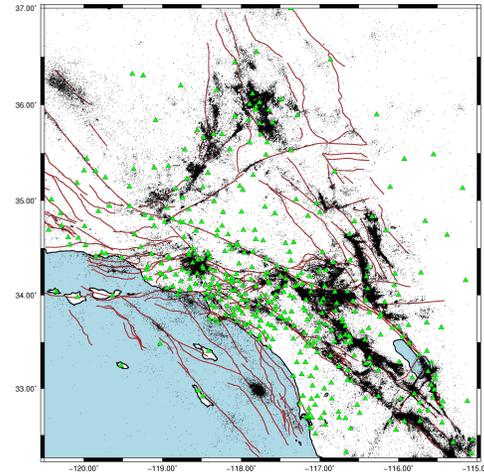
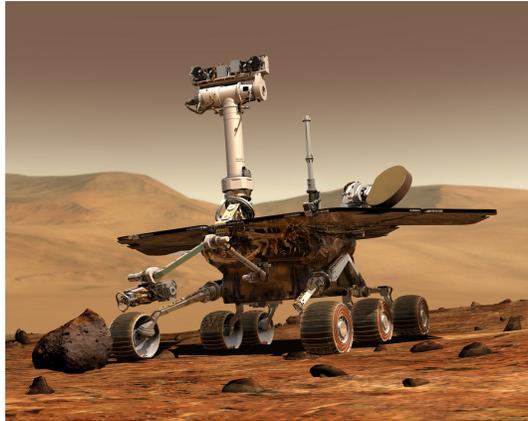
Probabilistic Modeling

Unsupervised Learning

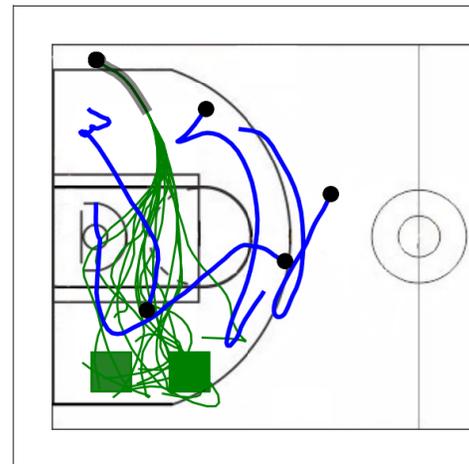
Main Lessons from CS 155

- Requirements for reliable learning:
 - Large dataset
 - Supervised learning signal
- Outcome:
 - Reasonably good performance on validation/test set

Machine Learning for the Real World

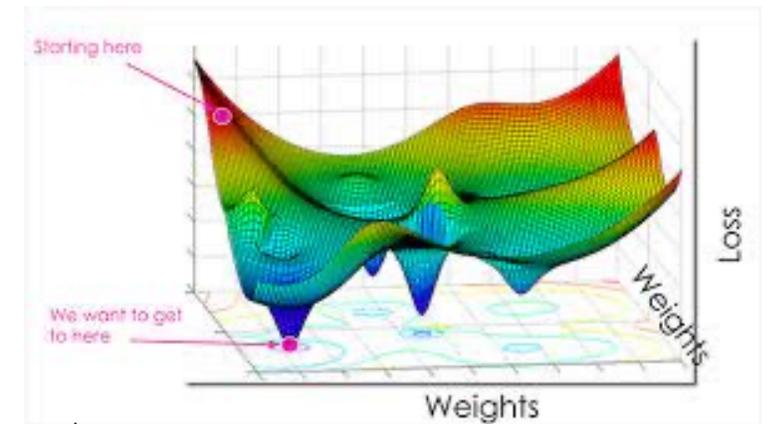


Mesenchyme
Tumor
CD4+ T-cells
CD8+ T-cells
CD3+ T-cells
B-cells
Macrophages



Course Topics

- Predictive Control
 - Sequential decision making
 - Design controllers using learning
 - Safety considerations
 - Distribution shift
- Neural Network Theory
 - Designing reliable learning algorithms
 - Minimize hyperparameter tuning
 - Thinking about generalization
 - Deep learning can memorize training set
 - What about overfitting?



Img src:

<https://www.pyimagesearch.com/2019/10/14/why-is-my-validation-loss-lower-than-my-training-loss/>

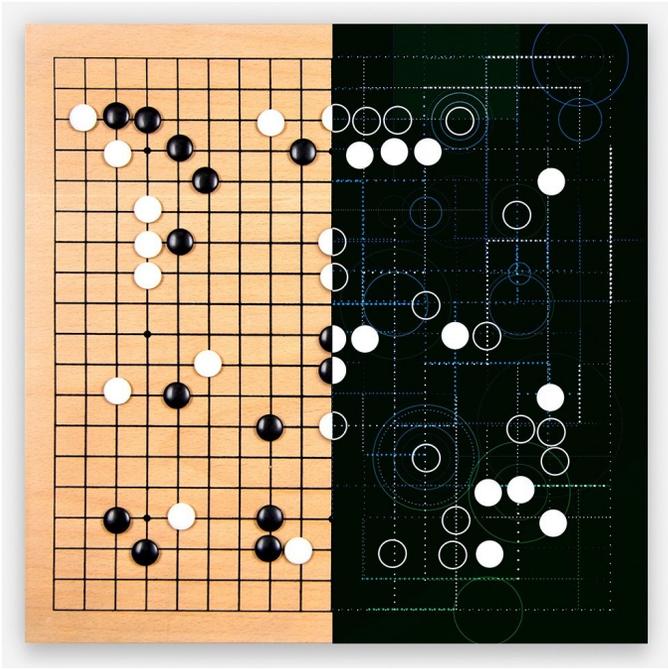
Questions?

First Challenge: Dynamics & Control

- Sequential decision making
- Your “state” evolves based on actions
- Training data may not cover test instances
- Constraints such as safety



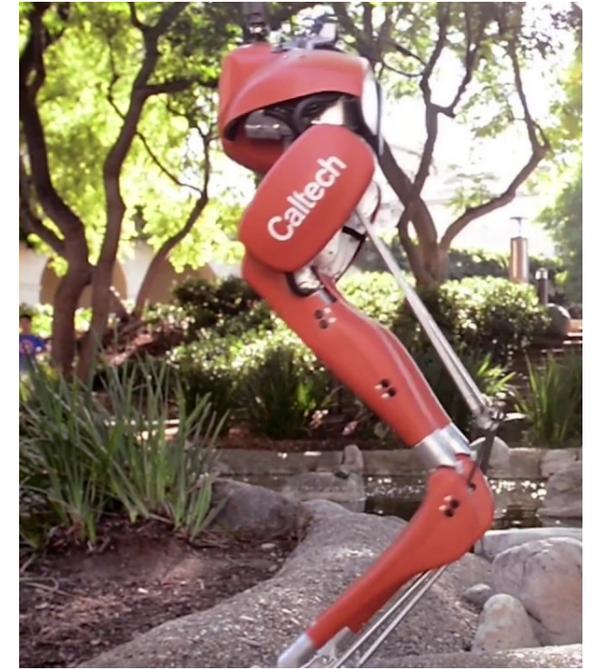
First Topic: Predictive control & model-based RL



Discrete State Space



Continuous State Space

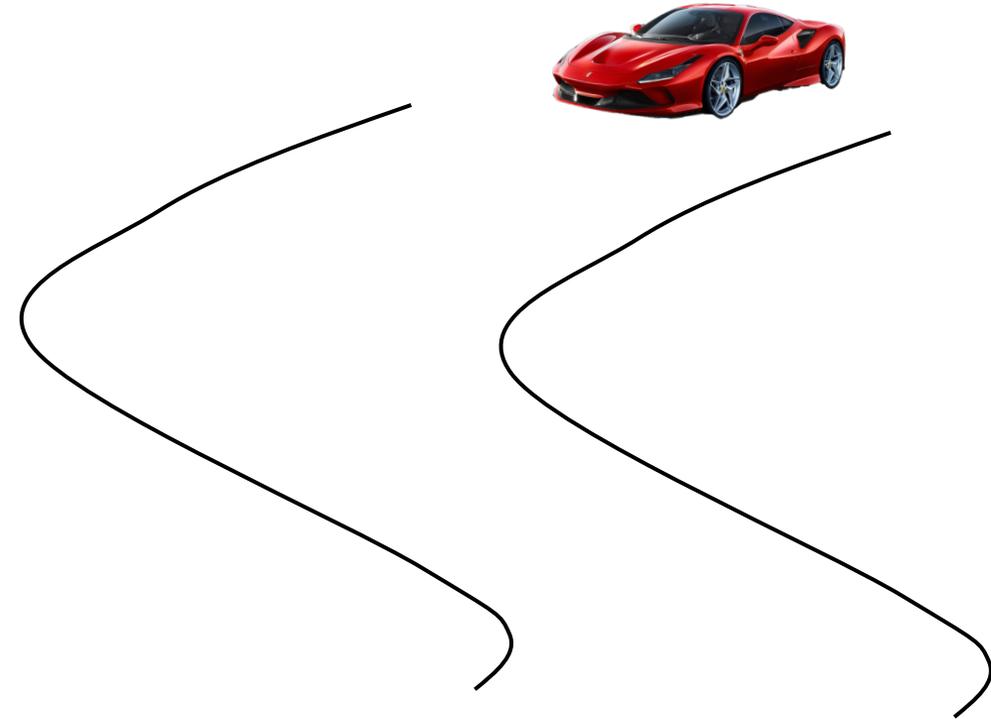


Hybrid State Space

Main Focus: Continuous State Spaces

Why?

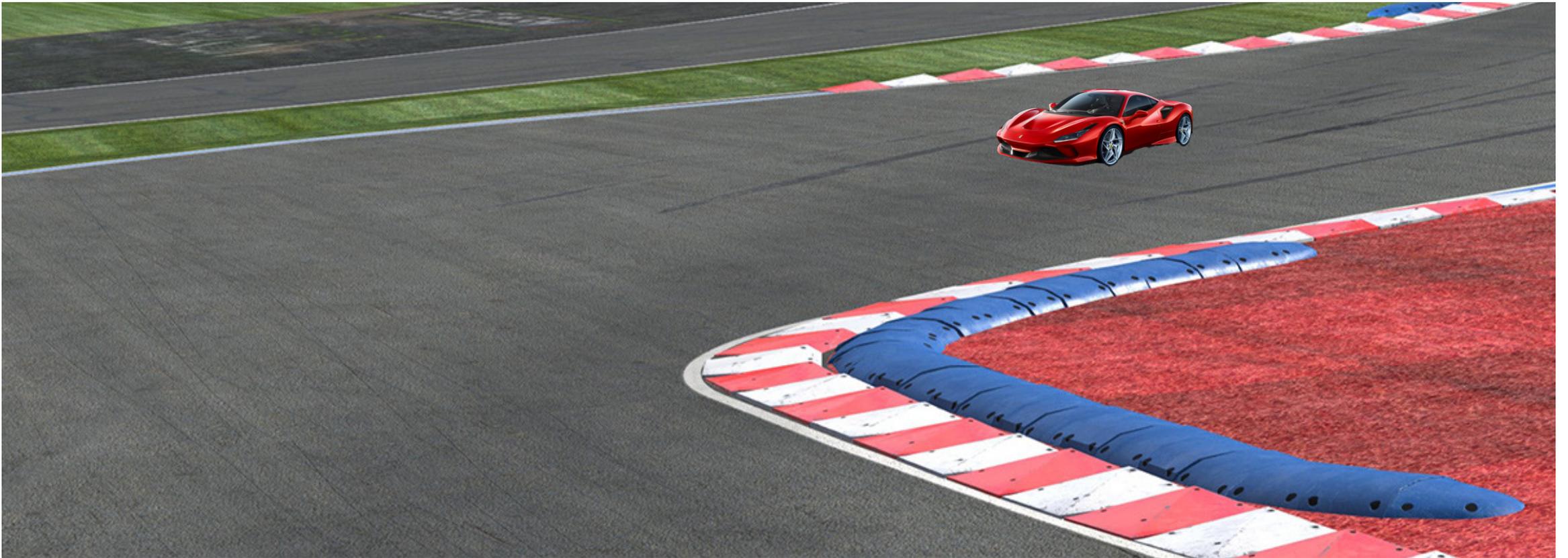
- ▶ Easy to express constraints.
 - ▶ e.g., stay within the lane boundaries.
- ▶ Low-level control actions are continuous.
 - ▶ e.g. torque send to the engine.
- ▶ Performance metrics are easy to specify.
 - ▶ e.g., minimize the derivative of the acceleration.



Main Focus: Continuous State Spaces

Tools:

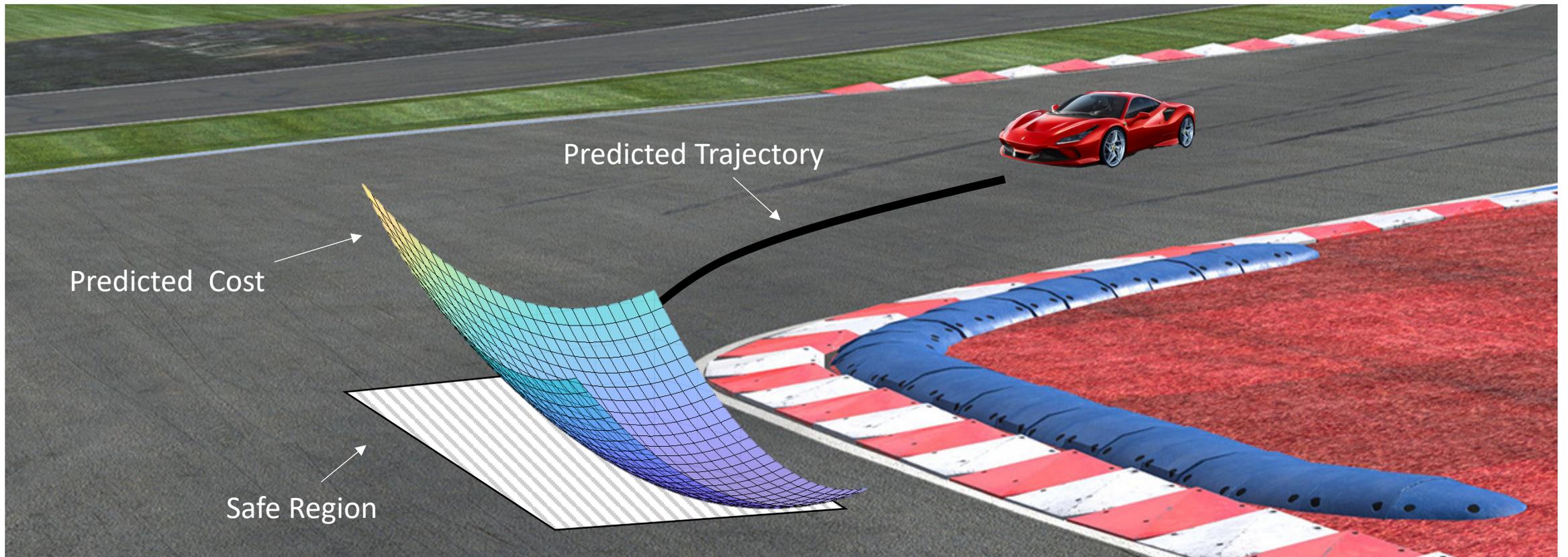
- ▶ Model Predictive Control
- ▶ System Identification (aka “supervised” model learning)
- ▶ Model-based Approximate Dynamic Programming (aka Model-based RL)



Main Focus: Continuous State Spaces

Tools:

- ▶ Model Predictive Control
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Learning Model Predictive Controller full-size vehicle experiments

Credits: Siddharth Nair, Nitin Kapania and Ugo Rosolia

Outline

Week #1:

- ▶ Discrete MDPs
- ▶ Optimal Control

Week #2:

- ▶ Model Predictive Control
- ▶ Model Predictive Control: Feasibility and Stability

Week #3:

- ▶ Learning Model Predictive Control (LMPC)
- ▶ Uncertain LMPC

Quick Recap:

1. Dynamic Programming
2. Optimal Control

MPC fundamentals

Learning + MPC

Spoiler Alert: In the continuous settings, we will use ideas inspired by the discrete case!

Homework

Homework:

- ▶ Mostly coding given a python template.
- ▶ Goal: get familiar with optimization-based controllers.

Office hours:

- ▶ Monday and Wednesday @ 3PM
- ▶ For email CS159 in the subject!

Slides:

- ▶ More details than what we will cover in class.
- ▶ Use them as lectures notes.
- ▶ HW will be only on topics covered in class.

Final Project:

- ▶ Based on research interests.
- ▶ Encouraged to combine **Part I** and **Part II** of this class.
- ▶ Review project is also an option (Review and code existing RL algorithms. Reach out to instructors for details).

```
def buildIneqConstr(self):  
    # Hint 1: consider building submatrices and then stack them together  
    # Hint 2: most likely you will need to use auxiliary variables  
    ...  
    G_in = ...  
  
    ...  
    E_in = ...  
  
    ...  
    w_in = ...  
  
    if self.printLevel >= 2:  
        print("G_in: ")  
        print(G_in)  
        print("E_in: ")  
        print(E_in)  
        print("w_in: ", w_in)  
  
    self.G_in = sparse.csc_matrix(G_in)  
    self.E_in = E_in  
    self.w_in = w_in.T
```



Questions?