Course Introduction



- My name is Radoslav Ivanov
 Call me Rado
- Undergrad degree in CS and ECON from Colgate in 2011
- Got my PhD in CS from UPenn in 2017
- My research is on safe and secure autonomous systems
 - Verification of neural networks
 - Attack-resilient sensor fusion
 - Context-aware detection and estimation
- Started at RPI in Jan. 2022

Impressive Progress in Autonomy



Control



Boston Dynamics

Perception



YOLO v. 3

Learning

Robot Motor Skill Coordination with EM-based Reinforcement Learning

Petar Kormushev, Sylvain Calinon, and Darwin G. Caldwell

Italian Institute of Technology

Kormushev, Calinon, Caldwell, IROS'10



JPL-Caltech, DARPA Robotics Challenge



Zhu, Zhou, Daniilidis, ICCV'15



DeepMind

But we're not there yet...





Iranian assertions. "We have no indication that it was brought down by hostilsenior Pentagon official, speaking on the condition of anonymity to discuss se activity.

A 213-foot luxury yacht veered off course while cruising in the Mediterranean Sea this 4

Neural Network (NN) Vulnerabilities

- Rensselaer
- Neural networks increasingly used in safety-critical systems



Control (air traffic avoidance)



Katz et al., CAV '17

Safety concerns discovered in both domains



Goofellow et al., ICRL'15

Table 2: Verifying properties of the ACAS Xu networks.

	Networks	Result	Time	Stack	Splits
ϕ_1	41	UNSAT	394517	47	1522384
	4	TIMEOUT			
ϕ_2	1	UNSAT	463	55	88388
	35	SAT	82419	44	284515
ϕ_3	42	UNSAT	28156	22	52080
ϕ_4	42	UNSAT	12475	21	23940

Cyber-Physical Systems (CPS)



Tight coupling between **communication**, **computation** and interaction with the **physical world**

Aircraft



Autonomous Cars



Medical CPS



Military



Smart Grids



Robotics



A standard CPS design





F1/10 Autonomous Racing Competition, ES Week 2016

Problem: How do we know car won't crash?

- How do we build safe algorithms?
- How do we analyze algorithms?
- What about "black-box" components such as neural networks?
- How do we convince other people car is safe (assurance argument)?

CPS Autonomy: Problem Landscape and Complexity





Why is safe autonomy so hard?





Even navigating hallways is not easy!





Building blocks of autonomous systems

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Topics



- 1. Supervised machine learning
 - Linear regression and classification
 - Generalization
 - Deep learning
- 2. Reinforcement learning
 - Modeling, relation to standard control theory
 - Markov chains, Markov reward/decision processes
 - Policy/Value iteration
 - Q learning
 - Policy gradients
 - Actor-critic methods



- Meeting time: TF 10-noon
 - Each lecture will be split up into two 50-minute sessions,
 with a 10-minute break in between
- We will meet in Sage 3101
- Office hours: T 1-2pm, W 2-3pm, Th 11am-noon
 - Lally 309
 - Office hours will be in person unless noted otherwise



- TA: Thomas Waite
 - PhD student
 - Email: waitet@rpi.edu
- Mentor: Anthony Shaw
 - Email: shawa9@rpi.edu
- TA/Mentors will be monitoring Piazza and will be helping with grading/marking

Course Mechanics: Piazza



- We will be using Piazza for questions and discussions
- Sign-up link: https://piazza.com/rpi/fall2024/csci41606963ecse49656965
- Access code:
- Please let me know if you're having issues enrolling

Course Mechanics: LMS



- All lecture notes and slides will be posted on the website — http://cs.rpi.edu/~ivanor/rl/F24/rl.html
- Homework assignments and submissions will be through LMS
- Please use Piazza for questions and discussion
 - -I won't monitor LMS/Webex that frequently



- Lectures will be a mix of theory and practice
 - RL is inherently a statistical subject, will cover the basics of statistical learning and probability theory
- Homeworks will also be a mix
 - A few problem sets and a few programming assignments
 - Submit through LMS
 - Please make sure you have access now
 - There will be 10 homeworks total

Course Mechanics, cont'd



- Some homeworks will require significant computation
 - One big deep learning assignment
 - Classify buildings on campus
 - Charles Yu '23 and I have collected a dataset of about ~500 images per building in different weather conditions/time of day
 - One deep reinforcement learning assignment
- We will use CCI for these assignments
 - RPI/IBM's computing cluster
 - You will need a basic understanding of how to use a Unix command line and possibly use an editor over it
 - I also recommend using Ubuntu for the other assignments
 - Deep learning libraries mostly developed for Linux systems

Grading

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- Homework (100%)
- Please attend the lectures unless you have a good reason not to
 - Won't take attendance but participating in class helps you learn and helps me teach
 - It will be very hard to complete some assignments if you miss the lectures



- Hastie, Trevor, et al. The elements of statistical learning: data mining, inference, and prediction. Vol. 2. New York: springer, 2009.
 - A very comprehensive book we will cover some parts only
 - Available online: <u>https://hastie.su.domains/Papers/ESLII.pdf</u>
- James, Gareth, et al. An introduction to statistical learning. Vol. 112. New York: springer, 2013.
 - An introductory version of the above
 - Available online: <u>https://www.statlearning.com/</u>
- Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep learning. MIT press, 2016.
 - Introduction to deep learning
 - Available online: <u>https://www.deeplearningbook.org/</u>



- The RL portion will follow this book
 - Sutton, Richard S., and Andrew G. Barto. Reinforcement learning: An introduction. MIT press, 2018.
 - Available online: <u>http://incompleteideas.net/book/RLbook2020.pdf</u>
 - Good high-level overview of RL
- We will also cover parts of this very comprehensive book on Markov Decision Processes
 - Puterman, Martin L. *Markov decision processes: discrete stochastic dynamic programming*. John Wiley & Sons, 2014.
 - Physical copy available in the library
 - Solid theoretical introduction to MDPs

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- Many ML texts out there
 - Many views on which topics need to be covered
 - Some good books are:
 - Mohri, Mehryar, Afshin Rostamizadeh, and Ameet Talwalkar. *Foundations of machine learning*. MIT press, 2018.
 - Kearns, Michael J., and Umesh Vazirani. An introduction to computational learning theory. MIT press, 1994.
 - Bishop, Christopher M., and Nasser M. Nasrabadi. *Pattern* recognition and machine learning. Vol. 4. No. 4. New York: springer, 2006.
- Not as many RL resources
- Useful lecture notes by David Silver:
 - https://www.davidsilver.uk/teaching/



- Modern machine learning makes heavy use of linear algebra and probability theory
- Although this is not a theory course, there will be assignments with problem sets
 - It helps if you have some formal background, e.g., FOCS, algorithms, calculus, analysis
 - We will cover some of the basics but we can't cover all the necessary background material
- We will be using Python for programming assignments
 - If you have never used Python, this course will be very difficult for you
- Talk to me if you're not sure if this is the right course for you

Course Difficulty



- "The course got significantly harder after the drop date, which is not cool"
- Keep in mind that assignments will get harder, especially as we get deeper into RL
- RL is an advanced ML topic
 - It's a combination of control theory, dynamical systems and ML
 - ML is already an advanced topic, a combination of statistics and optimization



- Introduce yourself
 - What year are you (undergraduate/graduate)?
 - What's your major/research interest?
 - Why are you taking this course?
 - One fun fact about you