Machine Learning for Systems and Control

5SC28

Lecture 1A

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Control Systems Group

Department of Electrical Engineering

Eindhoven University of Technology

Academic Year: 2020-2021 (version 1.0)

EINDHOVEN UNIVERSITY OF TECHNOLOGY

Version 13/04/2021

Learning Outcomes

What is Machine Learning?

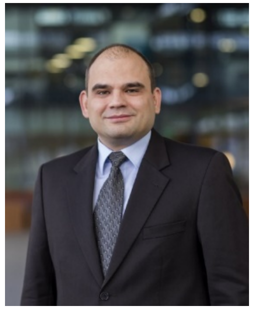
Machine Learning vs Systems & Control

Course Overview

Examination Overview

Who Are We?

dr. ir. Maarten Schoukens (FLX 5.080, m.schoukens@tue.nl)
Assistant professor – Control Systems Group
Specialization: nonlinear system identification, machine learning for systems and control
Office hours: appointment by e-mail



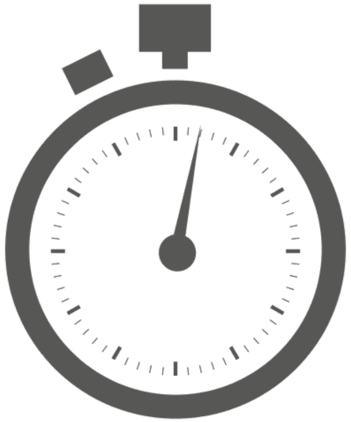
dr. ir. Roland Tóth (FLX 5.129, r.toth@thue.nl)
Associate professor – Control Systems Group
Specialization: data-driven modeling, LPV systems and control, applied machine learning
Office hours: appointment by e-mail

MSc. Gerben Beintema (g.i.Beintema@tue.nl)
PhD Candidate – Control Systems Group
Specialization: machine learning for systems and control
Office hours: appointment by e-mail

1-Minute Paper

What do you know?

What do you want to learn?



What is Machine Learning?

How can computers learn to solve problems without being explicitly programmed? In other words, how can computers be made to do what needs to be done, without being told exactly how to do it?[1]

[1] Koza, John R.; Bennett, Forrest H.; Andre, David; Keane, Martin A. (1996). *Automated Design of Both the Topology and Sizing of Analog Electrical Circuits Using Genetic Programming*. Artificial Intelligence in Design '96. Springer, Dordrecht. pp. 151–170

What is Machine Learning?

How can computers learn to solve problems without being explicitly programmed? In other words, how can computers be made to do what needs to be done, without being told exactly how to do it?[1]

Objective

Policy Learning

Feature Selection

Pattern Recognition

Prediction / Simulation

Classification

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Objective

Model / Framework

Policy Learning

Prediction / Simulation

Neural Networks

Support Vector Machines

Gaussian Processes

Genetic Programming

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Objective

Model / Framework

Learning Type

Policy Learning

Neural Networks

Supervised Learning

Prediction / Simulation

Gaussian Processes

Unsupervised Learning

Reinforcement Learning

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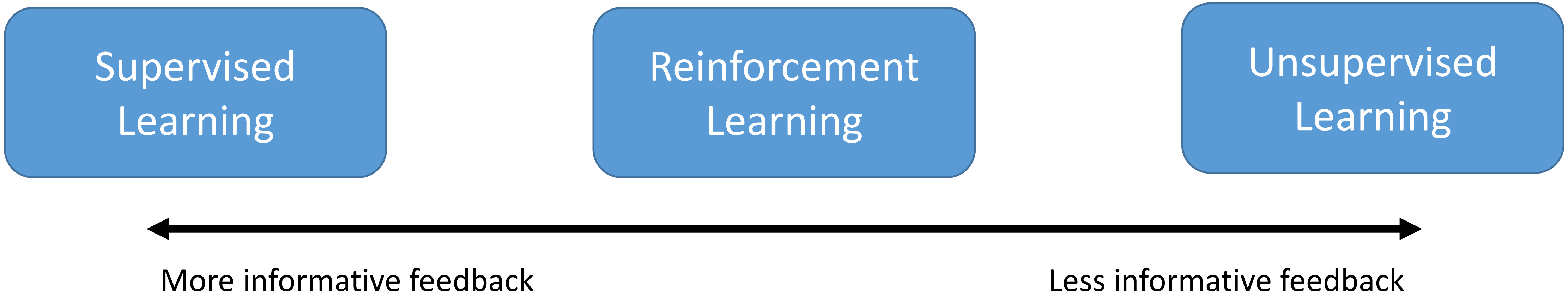
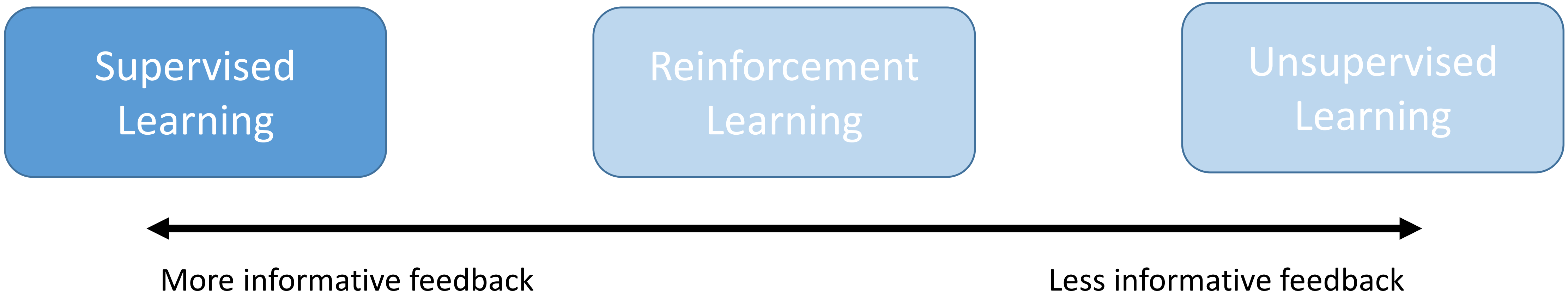
Supervised, Reinforcement and Unsupervised Learning



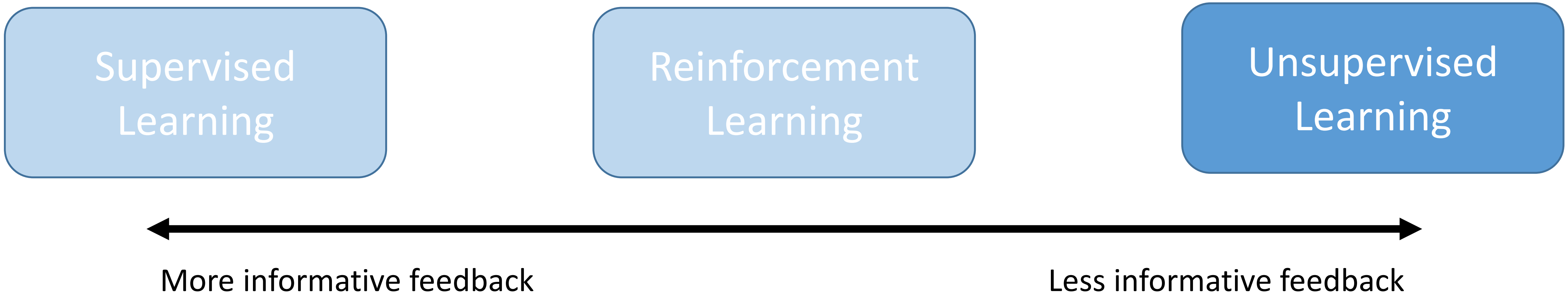
Supervised, Reinforcement and Unsupervised Learning



Inputs and outputs are known
Infer input-output relationship

e.g. function estimation

Supervised, Reinforcement and Unsupervised Learning



Only the inputs are known
Find patterns and features from data

e.g. clustering

Supervised, Reinforcement and Unsupervised Learning

Supervised Learning

Reinforcement Learning

Unsupervised Learning

More informative feedback

Less informative feedback

Correct outputs not available, only rewards

Find optimal policy / behavior / controller

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Policy Learning	Neural Networks	Supervised Learning
Prediction / Simulation	Gaussian Processes	Unsupervised Learning
		Reinforcement Learning

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Why Machine Learning?

Powerful Modelling Frameworks

Nonparametric Methods

Little User Interaction

Machine Learning vs Systems and Control

Many things in common but …

Classical Systems and Control	**Machine Learning**
Dynamic Systems (Engineering)	Static & Dynamic Systems (CS)
Theoretical Guarantees	Limited Theoretical Guarantees
Mainly Parametric Approaches	Nonparametric Approaches
High User Interaction	Low User Interaction
Noise & Uncertainties	Large-Scale Problems
System Analysis	

Example: AlphaStar

Source: https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/

Example: AlphaStar

Goal: Beat Starcraft II Pro-Gamers

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Example: AlphaStar

Goal: Beat Starcraft II Pro-Gamers

Challenges:

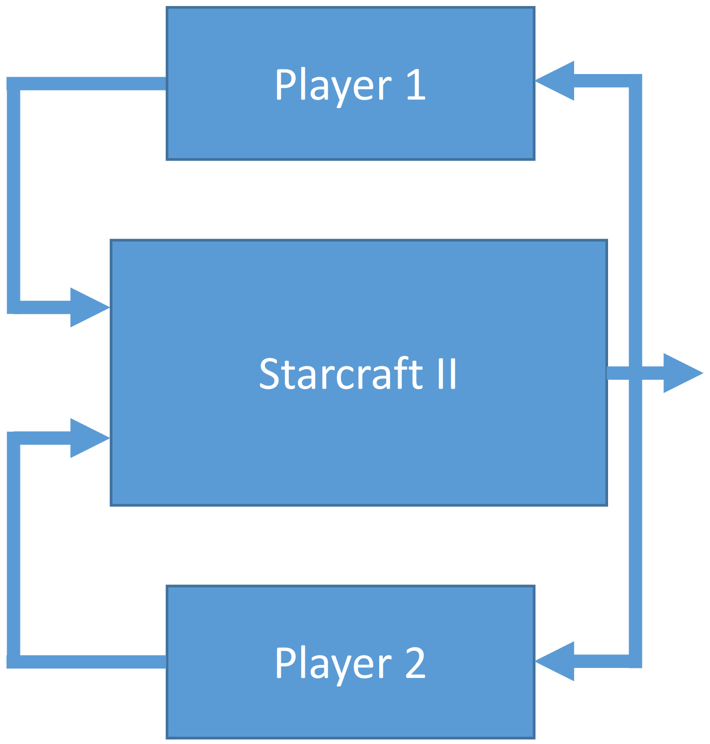
- High Decision Space
- Long-Term Dynamics
- Imperfect Information

Source: https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/

Example: AlphaStar

Goal: Beat Starcraft II Pro-Gamers

How: Learn a Policy aka ‘controller’



Example: AlphaStar

Goal: Beat Starcraft II
Pro-Gamers

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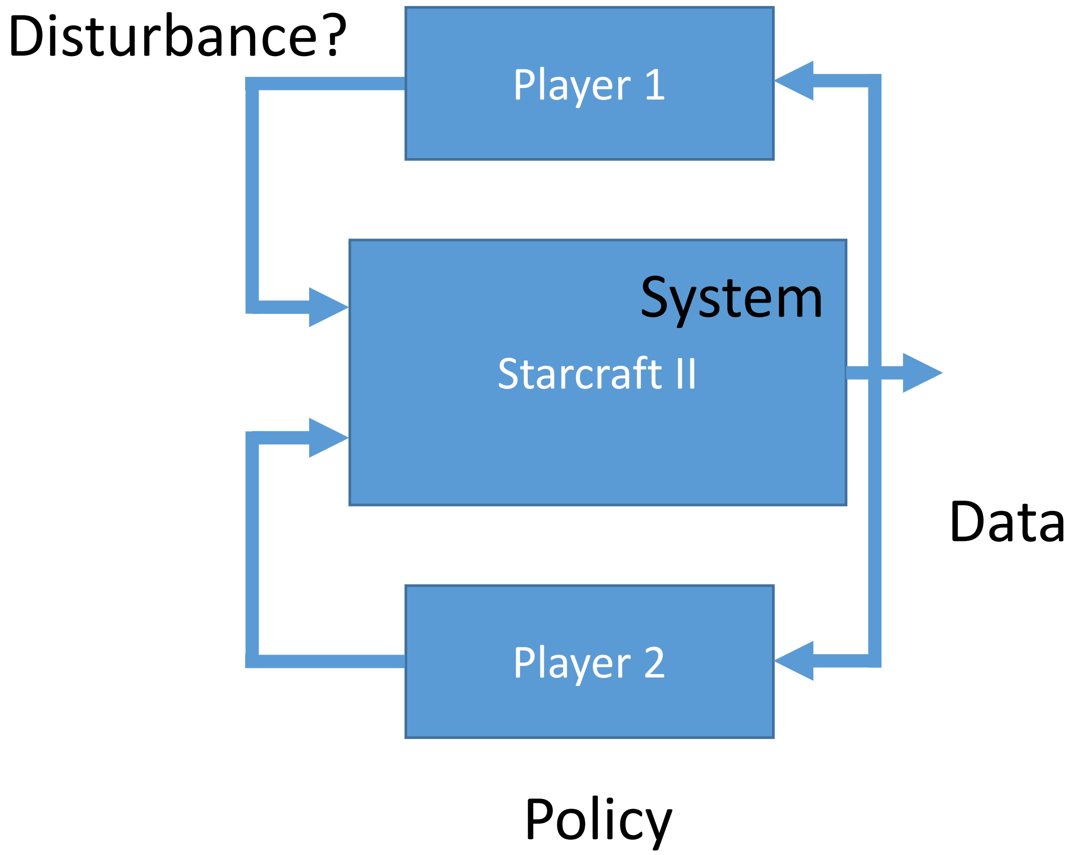


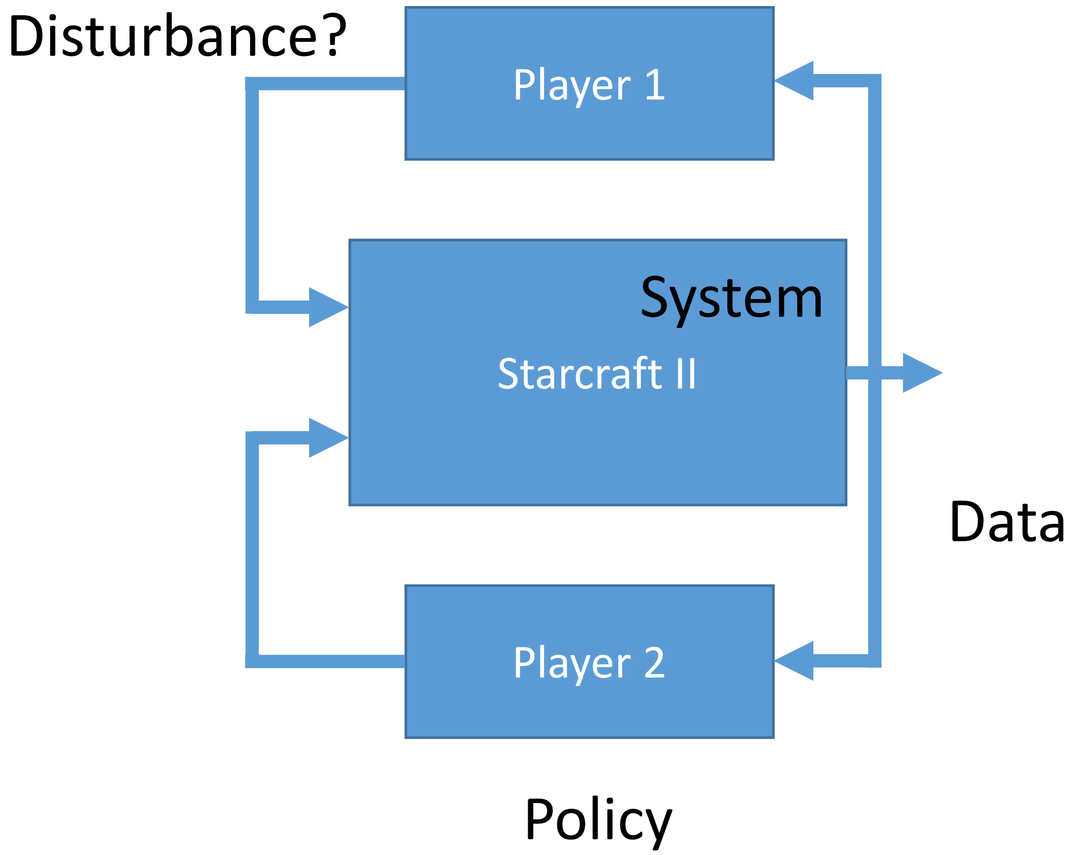
Example: AlphaStar

Goal: Beat Starcraft II Pro-Gamers

How: Learn a Policy aka ‘controller’

Framework: Neural Net

Method:
Supervised / Reinforcement Learning



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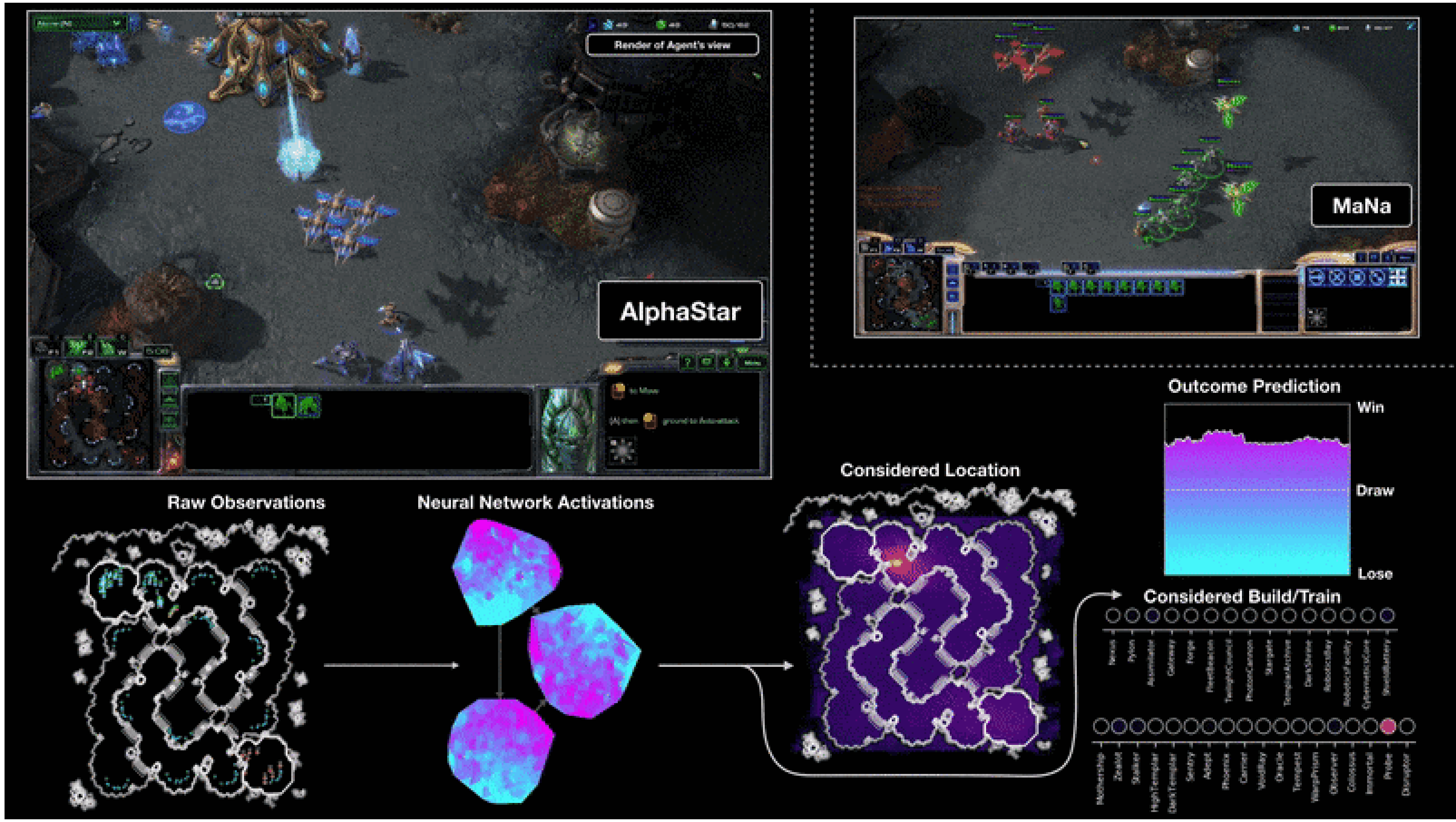


Source: https://deepmind.com/blog/alphastar-mastering-real-time-strategy-game-starcraft-ii/

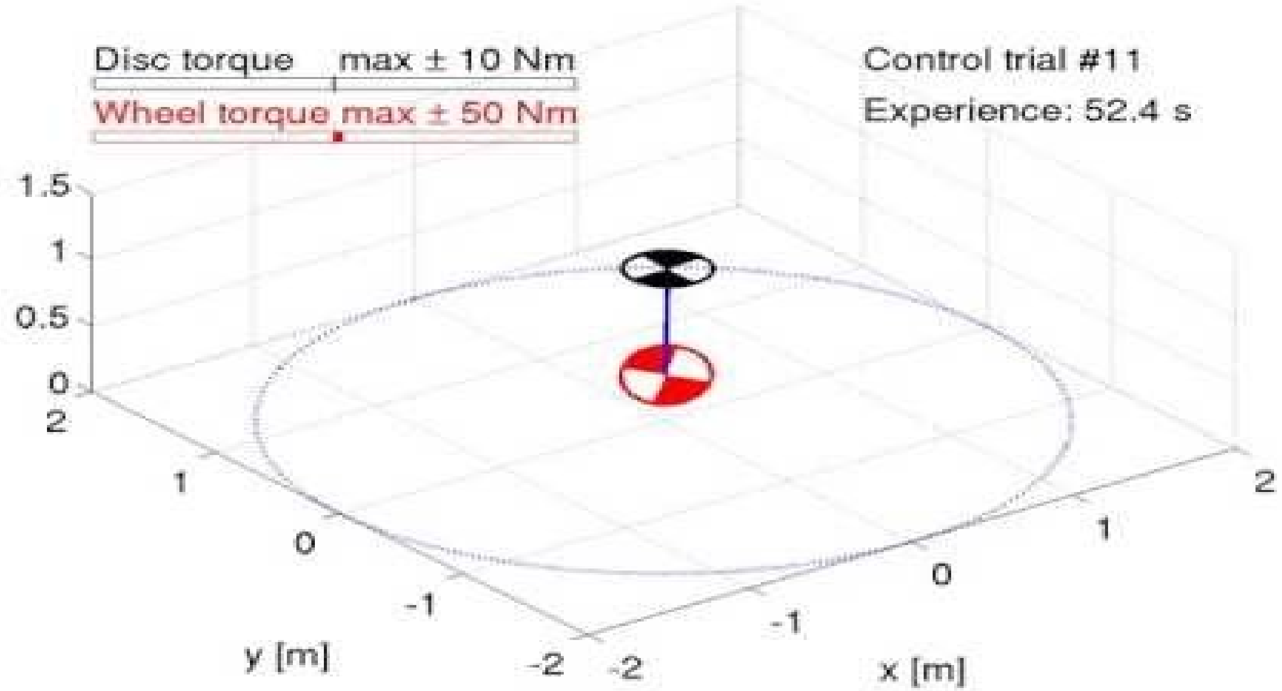
Other Examples

Cart-Pole Double-Pendulum Swing-Up

Learning to Unicycle

Throttle Valve Control

Robot Manipulator Control



Source: http://mlg.eng.cam.ac.uk/pilco/

Course Content

Data-driven modelling:	regularization, Gaussian processes
	neural networks and deep learning
Data-driven control:	basics of reinforcement learning
	actor-critic methods
	model internalization methods

Course Content

Data-driven modelling: regularization, Gaussian processes
neural networks and deep learning

Data-driven control: basics of reinforcement learning
actor-critic methods
model internalization methods

Introductory course: provide and overview of the key concepts
practical user experience

Course Information

Lectures: 8 x 2hrs

Exercises: 8 x 2hrs (Q&A) + preparation at home

Project: ~50 hrs

Exact schedule on Canvas (study guide)

Date	Details	Time
Wed, 21 Apr 2021	L1: Introduction & preliminaries	08:45-10:45
Wed, 21 Apr 2021	P1: Python introduction + Exercises based on L1	10:45-12:30
Wed, 28 Apr 2021	L2: Data-driven modelling: regularization, Gaussian Processes	08:45-10:45
Wed, 28 Apr 2021	Q&A session: theory & exercises	10:45-12:30
Wed, 12 May 2021	L3: Data-driven modelling: artificial neural networks	08:45-10:45
Wed, 12 May 2021	Q&A session: theory & exercises	10:45-12:30
Wed, 19 May 2021	L4: Data-driven modelling: deep learning and deep neural networks	08:45-10:45
Wed, 19 May 2021	Q&A session: theory & exercises	10:45-12:30
Wed, 26 May 2021	L5: Data-driven control: basics of reinforcement learning	08:45-10:45
Wed, 26 May 2021	Q&A session: theory & exercises	10:45-12:30
Wed, 02 Jun 2021	L6: Data-driven control: reinforcement learning with function approximation	08:45-10:45
Wed, 02 Jun 2021	Q&A session: theory & exercises	10:45-12:30
Wed, 09 Jun 2021	L7: Data-driven control: actor-critic reinforcement learning	08:45-10:45
Wed, 09 Jun 2021	Q&A session: theory & exercises	10:45-12:30
Wed, 16 Jun 2021	L8: Data-driven control: model internalization-based reinforcement learning	08:45-10:45
Wed, 16 Jun 2021	Q&A session: theory & exercises	10:45-12:30
Fri, 25 Jun 2021	Design Assignment Deadline	23:59
30 Jun – 01 Jul 2021	Oral Examination	/

Also available on Canvas (study guide)

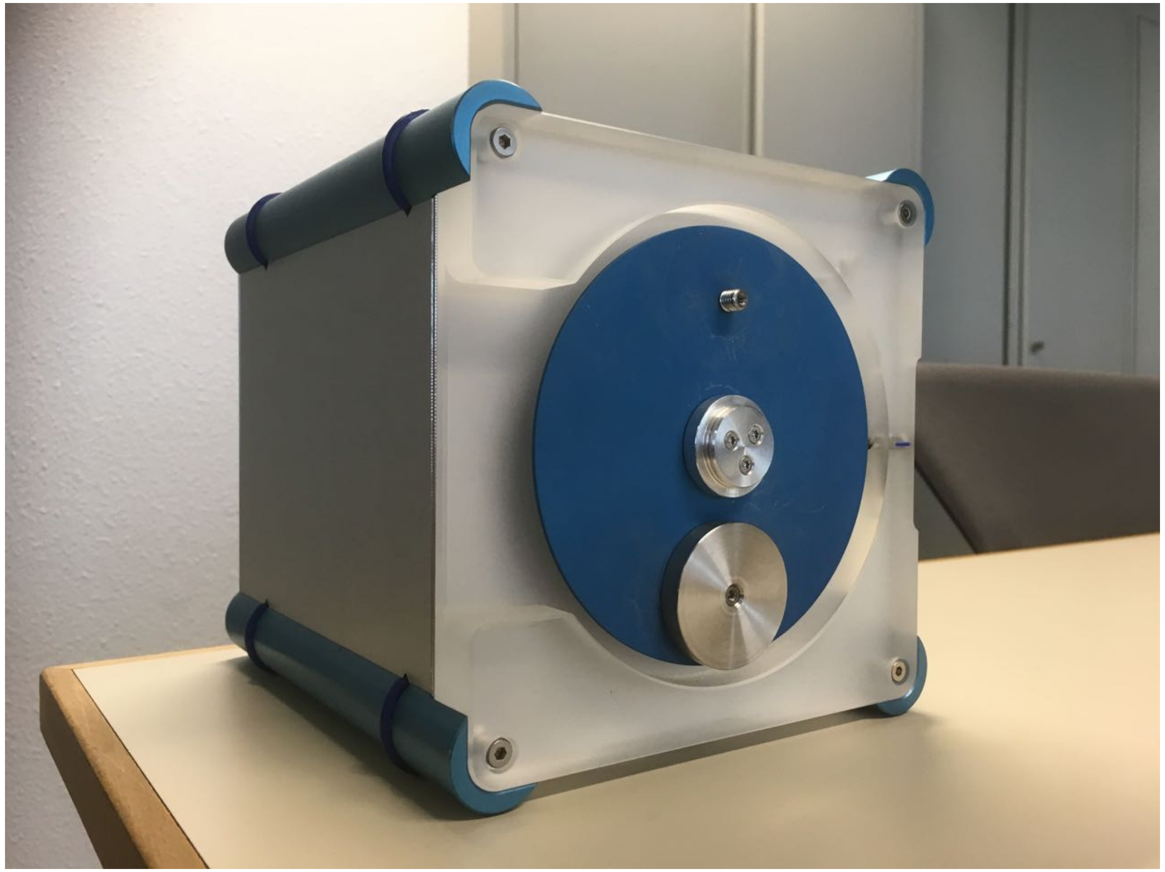
Design Project

Reinforcement Learning for an Inverted Pendulum

Obtain a policy to

1. identify pendulum dynamics
2. swing up the pendulum
3. use multiple targets & move from target to target

Tools: Reinforcement Learning
Gaussian Processes
Neural Networks



Design Project

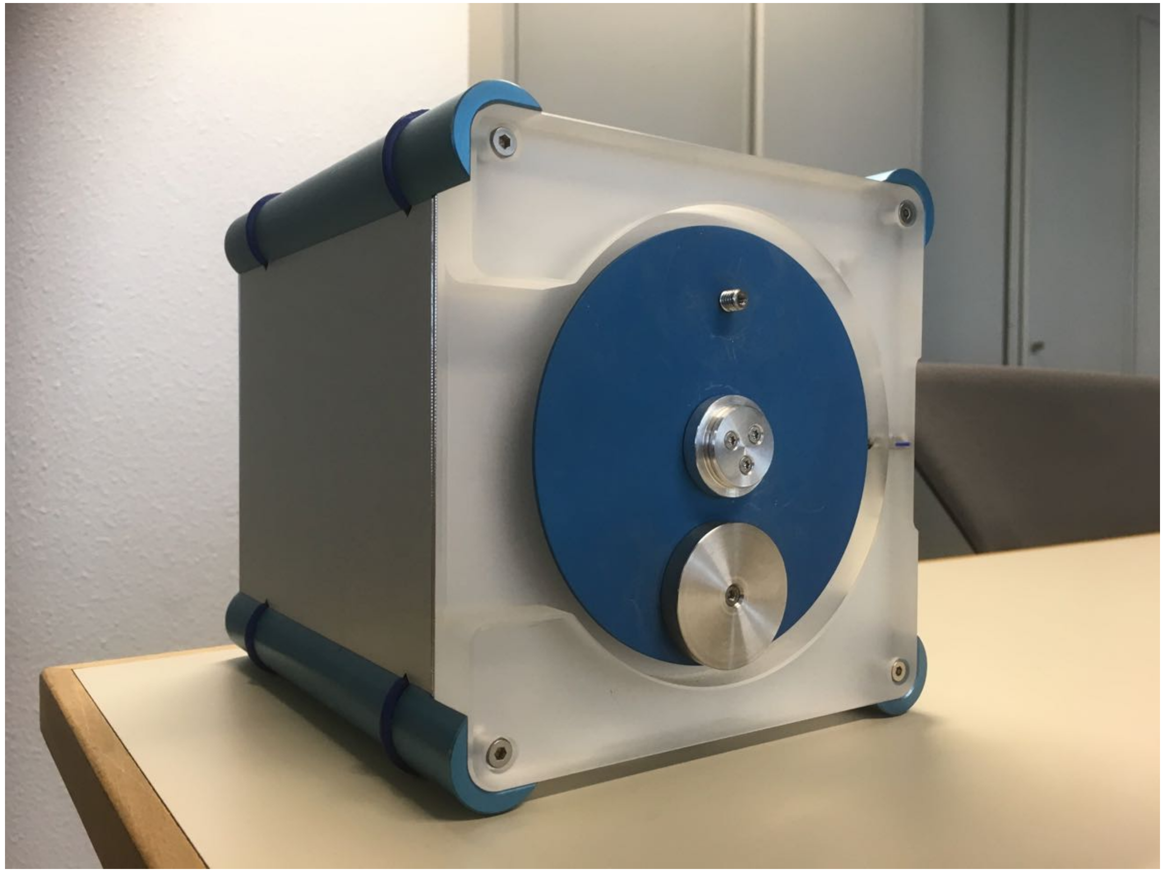
~22 Groups of 4

Registration for the groups through Canvas

6-12 pages IEEE style written report.

Each member writes 1-page group work reflection (own contribution) + rank contributions of fellow group members (template will be provided)

Oral defense (30 June – 01 July 2021)



Grading

Oral defense of the Design Project + theoretical knowledge:

a. 6-12 pages IEEE style project report (per group) + 1-page reflection reports (template will be provided)
b. 15 min group presentation + 30 min discussion of the obtained result + course theory

systematic way of obtaining the solutions
the applied and general course knowledge
correctness of the final solution
clarity of the final report and presentation

Grading

Design Assignment Report & Presentation: DARP $\in [0, 10]$

Design Assignment Implementation: DAI $\in [0, 10]$

Theory Discussion: ThD $\in [0, 10]$

Relative Individual Contribution: RIC $\in [-1, 1]$

Final Grade:

```
FP = 0.33 x DARP + 0.33 x DAI + 0.33 x ThD + RIC
if FP >= 6 then
    Min(Round(FP),10)
else
    Min(Round(FP),5)
```

Suggested Literature

Gaussian Processes

C.E. Rasmussen and C.K.I. Williams, *Gaussian Processes for Machine Learning*, the MIT Press, 2006. (http://www.gaussianprocess.org/gpml/)

Neural Networks

I. Goodfellow, Y. Bengio and A. Courville, *Deep Learning*, the MIT Press, 2016. (https://www.deeplearningbook.org/)

Reinforcement Learning

R.S. Sutton and A.G. Barto, *Reinforcement Learning: An Introduction*, MIT Press, 2018. (http://incompleteideas.net/book/the-book-2nd.html)

Continued Development of the Course

We appreciate feedback!

Ask questions! (lectures, exercise Q&A, canvas discussions)

After the course: send remarks

Questionnaire at the end

1-minute paper (already done)

Student Feedback

Student Representatives

Requiring: 2-3 volunteers

Facilitate anonymous feedback on the course and teaching

Volunteers can contact me by e-mail, chat, …

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