CS4400
DEEP REINFORCEMENT LEARNING

Lecture 13: Course Summary

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Content of this lecture

13.1

Course Summary

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13.1 Course summary

- Modern neural network architectures
  - modules represent structural constraints (equivariances)
  - implicit equivariances mostly responsible for generalization
- Modern deep reinforcement learning methods
  - on-policy, off-policy, offline, multi-agent, exploration
  - how to implement the core parts
- Underlying deep reinforcement learning concepts
  - continuous actions, partial observations
  - value propagation, robustness, deep exploration
  - how to formalize, derive and prove these things
- When reinforcement learning fails
  - instability, distribution shift, value bias, catastrophic forgetting
  - random expl., relative overgen., communication, zero-shot coord.
  - sim2real transfer, out-of-distribution generalization

13.2

Course Summary

Beyond this course

13.2 Is reinforcement learning realistic?

- Standard setup: train and test in stationary environment
  - online learning makes overfitting impossible
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  - but does it *generalize* or *memorize*?

Is reinforcement learning realistic?

- Standard setup: train and test in stationary environment
  - online learning makes overfitting impossible
  - learns after many many environmental interactions
  - but does it *generalize* or *memorize*?
- Real world applications differ significantly
  - finite training samples
  - catastrophic actions
  - observation noise
  - varying background activity
  - one agent multiple tasks

13.2 How would "realistic RL" look like?

- Conventional machines
  - robustness/multi-functionality/generalization
  - guarantees/constraints/ethics
  - reliability/explainability/responsibility

  → application breakthroughs within 10 years?

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- Biology-like machines
  - life-long learning: keeps learning in the wild
  - learning without tasks and without terminal states
  - develops abstractions and switches between them

  → basic terminology develops right now

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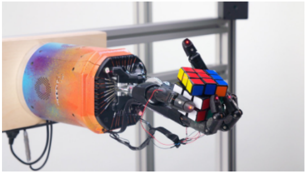
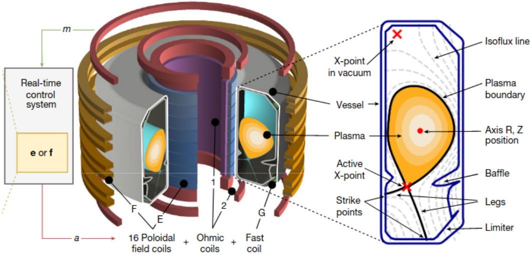
  → basic terminology develops right now
- Sentience (artificial general intelligence)
  - merges sequential (symbolic) and reflexive (pattern recognition) AI

  → we don’t even know what questions to ask

The coolest deep RL applications

- Atari (Mnih et al., 2013, 2015, and many, many follow-ups)
- Go, Shogi, Chess (Silver et al., 2016, 2017, 2018)
- StarCraft II (Vinyals et al., 2019)
- MOBAs (Berner et al., 2019; Ye et al., 2020)
- Robotic Rubik's cube (OpenAI et al., 2019)
- Traffic signals (Cabrejas-Egea et al., 2021)
- Fusion reactors (Degrave et al., 2022)
- Parkour robot (Cheng et al., 2023)





13.2 What do we need to work on?

- Data efficiency
  - breakthroughs in offline RL will allow RL in robotics soon
  - model-based RL, network architecture, Bayesian optimization
- Safety
  - uncertainty, Bayesian RL, safe exploration
  - constrained RL, interpretable RL, formal verification
- Generalization
  - network architectures, inference from multiple abstractions
- Lifelong learning
  - learning w/o task boundaries, self-motivated learning
- Social agents
  - zero-shot coordination, interaction with humans, communication

13.2 What to do next?

- RL research @ TU-Delft

SDM Wendelin Böhmer: anything deep RL
SDM Matthijs Spaan: RL and uncertainty
SDM Frans Oliehoek: Bayesian RL, model-based RL, multi-agent RL
ALG Anna Lukina: verifiable ML & RL
INSY Luciano Siebert: inverse RL for responsible and ethical AI
INSY Pradeep Murukannaiah: interactive AI
INSY Catharine Oertel: dialogue AI
3ME Jens Kober: RL from demonstrations for robots
3ME Javier Alonso-Mora: RL for robot motion planning
3ME Laura Ferranti: RL for reliable robot control
AS/EWI BIOlab: AI and RL for neuroscience & biomedical applications

- Get in touch with RL @ TU-Delft: reinforceAI.net
  - CS4210-B: AIDM Project (Q4)
  - CS4345: formal methods for learned system (Q3)
  - CS4240: deep learning (no RL, Q3)
  - RL reading group Thursdays 15:00 [mattermost]
  - ELLIS unit: get involved with Delft's AI community

Next lecture

- This is the last lecture!
- Ask questions now!
- Shy? Ask questions here: answers.ewi.tudelft.nl

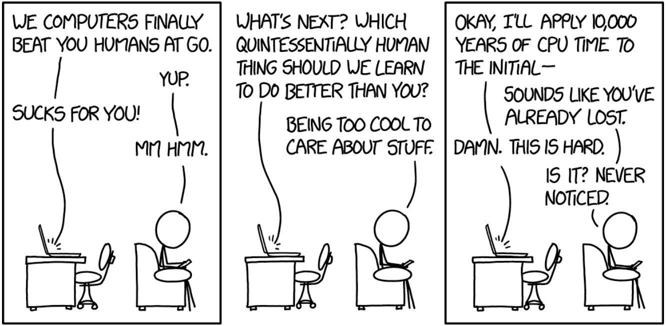


image source: xkcd.com

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