Deep Learning

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Prof. Gilles Louppe
g.louppe@uliege.be

LIÈGE université

Philosophy

Thorough and detailed

- Understand the foundations and the landscape of deep learning.
- Be able to write from scratch, debug and run (some) deep learning algorithms.

State-of-the-art

- Introduction to materials new from research ($\leq$ 5 years old).
- Understand some of the open questions and challenges in the field.

Practical

- Fun and challenging course project.

Us

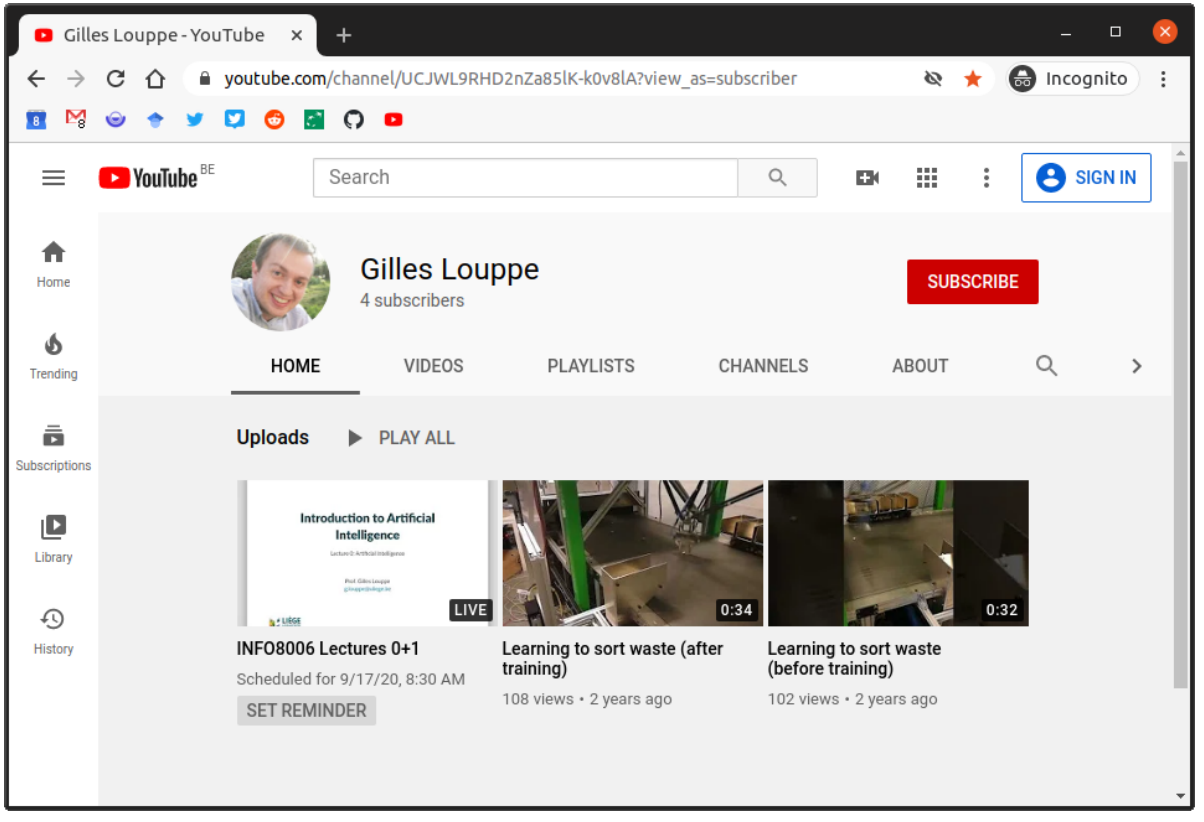
This course is given by:

- Theory: Gilles Louppe (g.louppe@uliege.be)
- Projects and guidance:
  - Matthia Sabatelli
  - Antoine Wehenkel



Materials

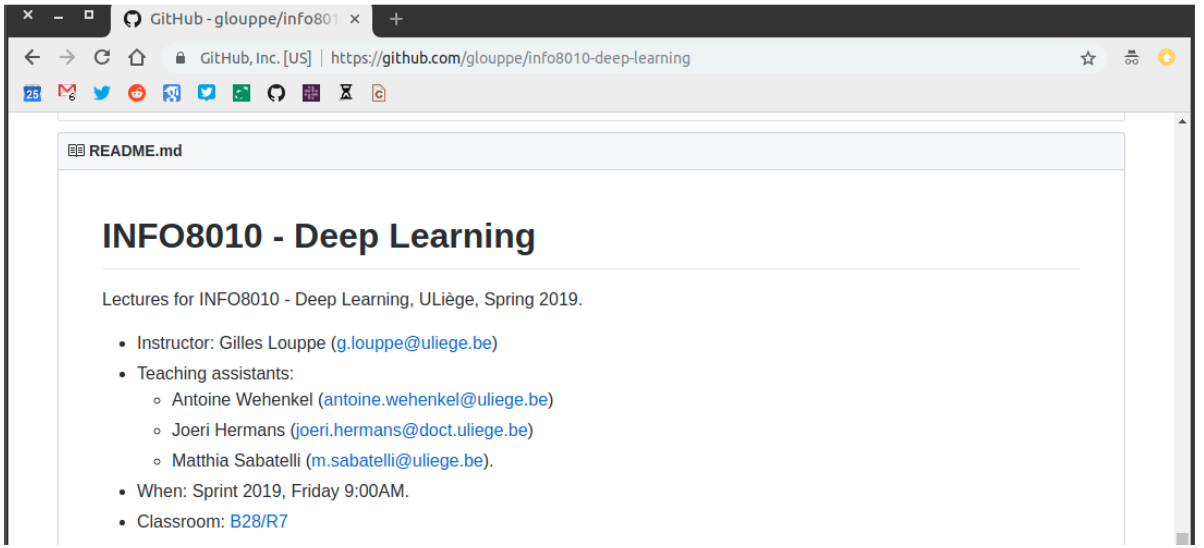
This year, the course takes place online on Youtube at https://bit.ly/3igTphO. Theoretical lectures will be streamed live.



Schedule & Slides

The schedule and slides are available at github.com/glouppe/info8010-deep-learning.

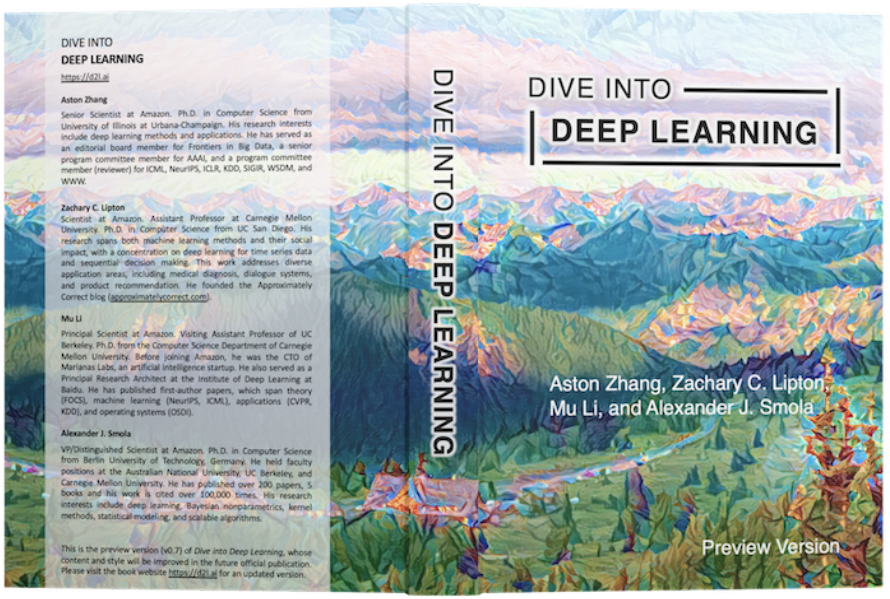
- In HTML and in PDFs.
- Posted/updated online the day before the lesson (hopefully).



Textbook

None!

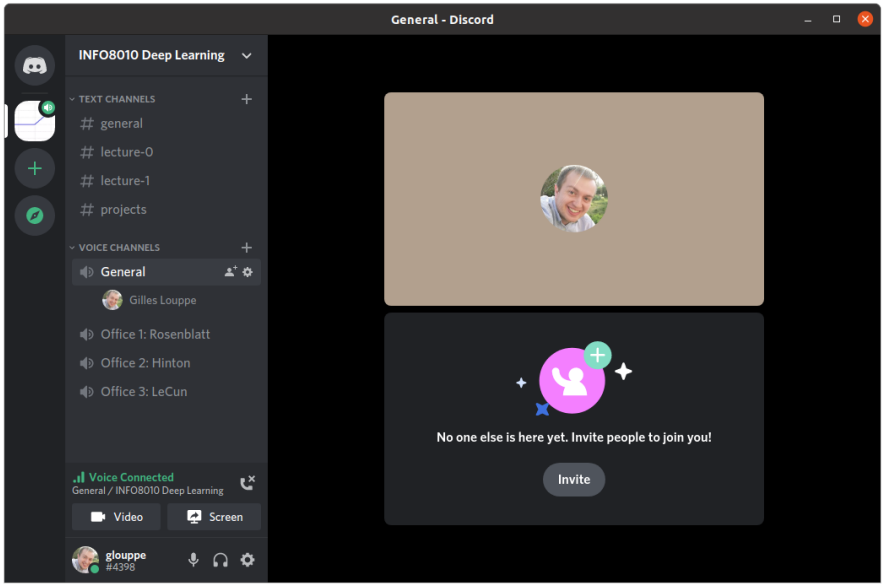
But we would recommend "Dive into Deep Learning" (d2l.ai) for a comprehensive and practical introduction to the field.



Discord

Live interactions will take place on Discord.

- Ask your questions live during the livestream (in Livestreamed Q&As).
- Ask your questions offline in the text channels.
- Don't be shy!

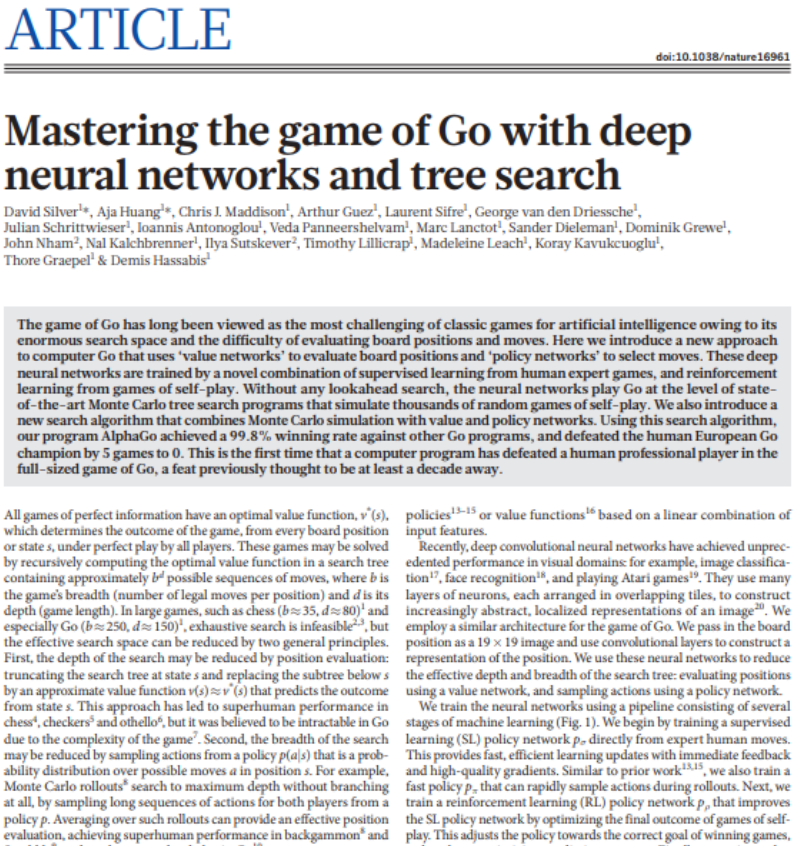


(See email for the invitation link.)

Projects

Reading assignment

Read, summarize and criticize a major scientific paper in deep learning. Details to be announced soon.



ARTICLE

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Mastering the game of Go with deep neural networks and tree search

David Silver[1]*, Aja Huang[1]*, Chris J. Maddison[1], Arthur Guez[1], Laurent Sifre[1], George van den Driessche[1], Julian Schrittwieser[1], Ioannis Antonoglou[1], Veda Panneershelvam[1], Marc Lanctot[1], Sander Dieleman[1], Dominik Grewe[1], John Nham[2], Nal Kalchbrenner[1], Ilya Sutskever[2], Timothy Lillicrap[1], Madeleine Leach[1], Koray Kavukcuoglu[1], Thore Graepel[1] & Demis Hassabis[1]

The game of Go has long been viewed as the most challenging of classic games for artificial intelligence owing to its enormous search space and the difficulty of evaluating board positions and moves. Here we introduce a new approach to computer Go that uses 'value networks' to evaluate board positions and 'policy networks' to select moves. These deep neural networks are trained by a novel combination of supervised learning from human expert games, and reinforcement learning from games of self-play. Without any lookahead search, the neural networks play Go at the level of state-of-the-art Monte Carlo tree search programs that simulate thousands of random games of self-play. We also introduce a new search algorithm that combines Monte Carlo simulation with value and policy networks. Using this search algorithm, our program AlphaGo achieved a 99.8% winning rate against other Go programs, and defeated the human European Go champion by 5 games to 0. This is the first time that a computer program has defeated a human professional player in the full-sized game of Go, a feat previously thought to be at least a decade away.

All games of perfect information have an optimal value function, $v^*(s)$, which determines the outcome of the game, from every board position or state s, under perfect play by all players. These games may be solved by recursively computing the optimal value function in a search tree containing approximately b^d possible sequences of moves, where b is the game's breadth (number of legal moves per position) and d is its depth (game length). In large games, such as chess ($b \approx 35$, $d \approx 80$)[1] and especially Go ($b \approx 250$, $d \approx 150$)[1], exhaustive search is infeasible[2,3], but the effective search space can be reduced by two general principles. First, the depth of the search may be reduced by position evaluation: truncating the search tree at state s and replacing the subtree below s by an approximate value function $v(s) \approx v^*(s)$ that predicts the outcome from state s. This approach has led to superhuman performance in chess[4], checkers[5] and othello[6], but it was believed to be intractable in Go due to the complexity of the game[7]. Second, the breadth of the search may be reduced by sampling actions from a policy $p(a|s)$ that is a probability distribution over possible moves a in position s. For example, Monte Carlo rollouts[8] search to maximum depth without branching at all, by sampling long sequences of actions for both players from a policy p. Averaging over such rollouts can provide an effective position evaluation, achieving superhuman performance in backgammon[8] and policies[13–15] or value functions[16] based on a linear combination of input features.

Recently, deep convolutional neural networks have achieved unprecedented performance in visual domains: for example, image classification[17], face recognition[18], and playing Atari games[19]. They use many layers of neurons, each arranged in overlapping tiles, to construct increasingly abstract, localized representations of an image[20]. We employ a similar architecture for the game of Go. We pass in the board position as a 19×19 image and use convolutional layers to construct a representation of the position. We use these neural networks to reduce the effective depth and breadth of the search tree: evaluating positions using a value network, and sampling actions using a policy network.

We train the neural networks using a pipeline consisting of several stages of machine learning (Fig. 1). We begin by training a supervised learning (SL) policy network p_σ directly from expert human moves. This provides fast, efficient learning updates with immediate feedback and high-quality gradients. Similar to prior work[13,15], we also train a fast policy p_π that can rapidly sample actions during rollouts. Next, we train a reinforcement learning (RL) policy network p_ρ that improves the SL policy network by optimizing the final outcome of games of self-play. This adjusts the policy towards the correct goal of winning games,

Homeworks

Short exercises to get you started with the practicals of deep learning.

Project

Project of your choosing. Details to be announced soon.

Evaluation

- Oral exam (50%)
- Reading assignment (10%)
- Projects (40%)
  - Homeworks (10%) (optional)
  - Programming project (30% or 40%)

The reading assignment and the projects are mandatory for presenting the exam.

Let's start!