MO436A - Topics in Machine Learning / MC934B - Tópicos em Engenharia de Computação
Institute of Computing - Unicamp
Second Semester 2021

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Course Information - Syllabus

1 Summary

The course will be conducted through online tools. We will adopt Google Classroom (https://classroom.google.com) as our main tool. To get access to Google Classroom, students must use their DAC accounts. Invites to the course page with access codes will be sent to your e-mails.

Credits:	2
Class hours:	The discipline will happen synchronously but the lectures will be available for future study. Attendance is not required but is encouraged
Website:	https://classroom.google.com and http://www.ic.unicamp.br/~esther/teaching/2020s2/mo436
Support to students:	The support will happen through virtual channels scheduled with the professor
Course Goals:	By the end of the course, the students must understand the main concepts related to Reinforcement Learning, define the key features of RL that distinguishes it from AI and other machine learning paradigms. They should also be able to build models using Reinforcement Learning as a basis.

Every Monday	14:00-16:00h	Course online meeting

2 Syllabus

Topics to be presented in the course include:

- Introduction to RL
- Markov Decision Processes
- Dynamic Programming
- Model-Free Prediction and Control
- Value-based Methods
- Policy Gradient Methods
- Exploration and Exploitation
- RL Topics: Imitation Learning
- RL Topics: Meta-RL
- RL applications

3 Programming languages

We will use Python as the course reference programming language.

4 Course Page and Activity Submission

The course material will be available on Google Classroom. Practical work and projects carried out during the course must be submitted through Google Classroom in the area corresponding to the course.

5 Evaluation

The evaluation of the discipline will be conducted based on the following activities:

- A set R of varied tasks that will have grades distributed proportionally. Tasks may include quizzes, readings, reviews of recommended articles and online tests:
  - $R = \frac{R_1+R_2+...+R_n}{n}$, where n is the number of activities carried out throughout the semester
- Two projects, $P1$ and $P2$ with weights 40% and 55%, respectively
  - Groups must have 4 students
  - The reports for the project must present the adopted solution, discussing the results achieved, in the model proposed by the professor
  - The code and the reports must be delivered via Google Classroom
- The final grade, MF, will be calculated as: $MF = 0.5R + 0.40P1 + 0.55P2$
- The student will be approved if his final grade is $MF \geq 5.0$ Otherwise, he/she will fail.
- For graduate students, the grade range will be:
  - A: >=8.5
  - B: >=7.0 and <8.5
  - C: >=5 e <7.0
  - D: <5

5.1 Deadlines

- Project 1 ($P1$): 08/11/2021
- Project 2 ($P2$): 12/12/2021

6 Bibliography

Some of the references considered important for the fulfillment of the proposed content are listed below. The complementary material to be used will be indicated on the course page.

1. Reinforcement Learning: An Introduction, Sutton and Barto, 2nd Edition. This is available for free in http://incompleteideas.net/book/RLbook2018.pdf.
2. Reinforcement Learning: State-of-the-Art, Marco Wiering and Martijn van Otterlo, Eds.
3. Artificial Intelligence: A Modern Approach, Stuart J. Russell and Peter Norvig.
4. Deep Learning, Ian Goodfellow, Yoshua Bengio, and Aaron Courville.
5. David Silver's course on Reinforcement Learning.

Observations

- There will be no substitute projects.
- This discipline has no final exam.
- **Any fraud attempt on the projects will result in a final score of $MF = 0$ (zero) for all involved.**