



# Syllabus

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## 1 Summary

**Credits** 2 (expected workload of 8 hours per week, for a half semester).

**Location and time** This course will be asynchronous and online.

**Website** [classroom.google.com](https://classroom.google.com)

**Office hours** Meetings are on demand. Send an email to schedule. We will held occasional online meetings for students Q&A on the original schedule (Tuesdays or Thursdays from 10:00 to 12:00).

**Learning objective** The student will create algorithms that can learn without labeled data (i.e., deep generative and self-supervised methods).

**Language** The course will be offered in English.

## 2 Course Description

Labeling data is a daunting task that is at times impossible. Hence, there is a need for learning algorithms that can learn without such labeled data. In this course, we will cover self-supervised learning algorithms to tackle the problem of learning without labels. We will cover recent advancements in deep generative models and self-supervised learning on several areas, such as high-dimensional representation learning; audio, text, image and video modeling; reinforcement learning; and distribution learning. We will cover the theoretical foundations and applications of these topics.

## 3 Pre-Requisites

- This course has more math than many CS courses: Linear algebra, vector calculus, probability, statistics, and optimization. Thus, a strong foundation (or concurrent work to find) about these topics is required for the course.
- A good working knowledge of C++ and/or Python. The programming assignments must be developed using one of these languages. Knowledge of Docker, version control (git), and makefiles is desired.

## 4 Topics

The following topics will be covered with online presentations and readings from our bibliography. The detailed schedule will be presented during class. Students are expected to follow the deadlines asynchronously. We will have synchronous meetups to catch up on questions from the class on several occasions to be decided with the class.

1. **Likelihood-based models.** Autoregressive, flow, and latent variable models.
2. **Compression.** Asymmetric numerical systems coding, and bits-back coding.
3. **Implicit models.** Generative adversarial networks.

**Table 1.** Grading weights per assignments.

Assignment	Grade %
HW 1	25
HW 2	25
Final Project	40
Miscellaneous	10
<b>Total</b>	<b>100</b>

**Table 2.** Grading scale conversion for postgraduates students.

Grade	Grade %
A	$\geq 85$
B	$\geq 70$
C	$\geq 50$
D	$< 50$

4. **Non-generative representation learning.**
5. **Mixture models.** Latent variable models, mixture models, parameter estimation, and EM algorithm.
6. **Semi-supervised learning.**
7. **Reinforcement learning.** Representation learning in reinforcement learning.
8. **Applications.** Applications of unsupervised learning for audio, text, images and video.

## 5 Grading

The evaluation will be done based on two homework assignments (mini-projects), and one final project. Additionally, we will have miscellaneous assignments in which their grade will be distributed proportionally (weights will be defined during the course). The miscellaneous tasks comprise daily readings and summaries. The weight of each item is shown in Table 1.

In order to get a pass in the course, students must get at least an average of 50% on the homework assignments' and project's grades. Otherwise, the student will **fail the course**. This measure is to avoid skipping projects, as they are the core activity to evaluate student's knowledge in the course. For post-graduate students, the percentage will be converted to a grade based on Table 2.

The schedule for the readings and the due dates for the projects will be announced during the course. The mini-projects have a **poster presentation** that will happen in conjunction with other graduate courses on **June 26th** (depending on the situation of the isolation).

## 6 General Information

### 6.1 Attendance

Since we have daily readings (that will be evaluated, see § 5), the attendance is highly recommended as the student will miss these evaluations. Moreover, students are highly expected to discuss and participate during class. Thus, missing classes will prevent the development of the students' knowledge during the course. Hence, a student with less than 75% attendance will **fail the course**.

### 6.2 Late Work

Every project will have two deadlines (except the final project due to time constraints during the semester). After the first one, there is a 10% accumulative penalty per 24 hours late, up to five times. After that, there will be no submission for the assignment.

### 6.3 Honesty and Integrity Policy

**Projects (reports and code) must be authored by the student or group.** Discussions and exchange of ideas among students or the professor are encouraged. Nevertheless, **the final solution (and deliverables) must be exclusively created by the student or group.** The use of libraries and pieces of code as support for a solution is valid as long as it is explicitly referenced and detailed in the work (and not banned by the professor in that work). Any other type of conduct will be considered plagiarism.

**Any instance of plagiarism, cheating, or anti-ethical behavior implies immediate failure (zero) in the course.**

## 6.4 Materials

All the materials to be used in class will be available on our website, supported by Grupo Gestor de Tecnologias Educacionais (GGTE), at the URL: <https://classroom.google.com/>. Therefore, materials will not be distributed in class.

## 7 Bibliography

There is no main textbook for this course. The relevant reading material will be posted with the lectures. You may find the complementary books in this section helpful.

### Mandatory

- [1] *Research papers*, Several research papers to be announce during the semester.

### Complementary

- [2] C. M. Bishop, *Pattern recognition and machine learning*. springer, 2006.
- [3] K. P. Murphy, *Machine learning: a probabilistic perspective*. MIT press, 2012.
- [4] T. Hastie, R. Tibshirani, and J. Friedman, *The elements of statistical learning: data mining, inference, and prediction*. Springer Science & Business Media, 2009.
- [5] S. J. Russell and P. Norvig, *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited, 2016.