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

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 model problems probabilistically, and create algorithms that learn such models from data.

Language The course will be offered in English.

2 Course Description

Probabilistic models are used in several areas of engineering and science, such as perception-based problems (language and vision), healthcare, finances, biology, climate, among others. This course is an advanced introduction to probabilistic models of data, their inference, and optimization methods used to learn such models.

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. **Gaussian models.** Gaussian distributions, parameter estimation and fitting.
2. **Probabilistic models.** Regression, generative classification, and discriminative classification.
3. **Generalized linear models.** Linear models, and exponential family.
4. **Directed graphical models.** Definition of graphical models, chain rule, and conditional independence.

Table 1. Grading weights per assignments.

Assignment	Grade %
HW 1	25
HW 2	25
Exam	40
Miscellaneous	10
Total	**100**

Table 2. Grading scale conversion for postgraduates students.

Grade	Grade %
A	≥ 85
B	≥ 70
C	≥ 50
D	< 50

5. **Mixture models.** Latent variable models, mixture models, parameter estimation, and EM algorithm.
6. **Gaussian processes.** GP for regression, GP and Gaussian Linear Models, and connection with other models.
7. **Variational inference.** Interpretation of VI, mean field method, Variational Bayes, and Variational Bayes EM.
8. **Monte Carlo inference.** sampling, importance sampling, particle filtering, MCMC, Gibbs sampling, and annealing methods.
9. **Clustering.** Dirichlet process, affinity propagation, spectral clustering, and hierarchical clustering.

5 Grading

The evaluation will be done based on two homework assignments (mini-projects), and one final (take home) exam. 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' 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 an optional **poster presentation** that will happen in conjunction with other graduate courses on **June 26th** (depending on the situation of the isolation). (Since this course comprises the first half of the semester, you are invited, but not required, to participate.)

6 General Information

6.1 Attendance

Since we are proceeding with an online version of the course, attendance will not be mandatory.

6.2 Late Work

Every project will have two deadlines. 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 Take Home Exam

The exam will be released to the students with detailed instructions on duration (superior to 24 hours) and how to submit it. The exam is design for individual work, and we expect that students follow our honesty and integrity policy. The exam will be open-book and will allow for consults to other sources. The tentative date for the start of the exam April 28th.

6.4 Honesty and Integrity Policy

Projects (reports and code) and exams 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.

6.5 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/`.

7 Bibliography

Mandatory

[1] C. M. Bishop, *Pattern recognition and machine learning*. springer, 2006.

[2] K. P. Murphy, *Machine learning: a probabilistic perspective*. MIT press, 2012.

[3] D. Barber, *Bayesian reasoning and machine learning*. Cambridge University Press, 2012.

Complementary

[4] S. J. Russell and P. Norvig, *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited, 2016.