MO435— Probabilistic Machine Learning
INSTITUTO DE COMPUTAÇÃO — UNICAMP
1st Semester 2020

Syllabus

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1 Summary

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

Location and time IC3.5 352, Tuesday and Thursday from 10:00 to 12:00.

Website classroom.google.com

Office hours Meetings are on demand. Send an email to schedule.

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

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.
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.

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

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 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, occasional quizzes, and participation in class and online. 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**. (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 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. 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

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.