CS 6501 - Learning Theory: Syllabus

Department of Computer Science
University of Virginia

SPRING 2017

Time and Location
Mondays & Wednesdays, 3:30pm–4.45pm, 340 Rice Hall.

Website: http://www.cs.virginia.edu/diochnos/teaching/
We will also be using Collab to send mass announcements and potentially assign homework and projects.

Instructor
Dimitris Diochnos, 228 Rice Hall, diochnos@virginia.edu.

Office Hours
• Tuesdays 10:00am–11:00am, 436 Rice Hall.
• Wednesdays 1:00pm–2:00pm, 436 Rice Hall.
• If you want to meet me outside of my office hours, the most reliable method is to send an email and arrange an appointment.

Prerequisite Background
Design and analysis of algorithms, basic computational complexity theory, and graduate level mathematical maturity. Tools from probability theory will be discussed (briefly) on demand as they arise.

Topics and Course Description
Learning theory is a field that develops models for capturing learning phenomena and ultimately studies the efficiency and the limitations of learning algorithms in these frameworks. The course will start with the notions of concept learning and version spaces and proceed to decision tree learning and artificial neural networks. We will then switch to the probably approximately correct (PAC) model of learning, Occam’s razor, VC theory, and ultimately prove the fundamental theorem of learning theory. We will examine the relationship between weak and strong learning (boosting). Subsequently, we will move on to online learning and learning with expert advice in the mistake bound model, where we will see algorithms such as randomized halving, weighted majority, and winnow. We will also cover theoretical aspects of learning that are related to evolution and evolution seen as a learning process drawing results from evolutionary algorithms and Valiant’s
evolvability framework. (This part of the course related to evolution can also be seen as a special type of local search optimization with PAC guarantees.) Time permitting we will cover additional models of learning or the computational approach to evolution by Adi Livnat and Christos Papadimitriou.

**Schedule of Classes**

The following schedule is indicative and is continuously subject to change. We will cover the material at a pace that is comfortable. Our first meeting is on Wednesday, January 18, 2017 and our last meeting is on Monday, May 1, 2017. The final is on Thursday, May 11, 2017 between 2:00pm and 5:00pm.

**Weeks 1-2:** Introduction, concept learning, version spaces, and search algorithms.

**Weeks 3-5** Decision tree learning and artificial neural networks.

**Weeks 6-10:** PAC learning, Occam’s razor, VC theory and sample complexity bounds. Weak and strong learning, boosting. During this period we will have the midterm. Either during the week before the spring break, or right after the break.

**Week 11:** Online models.

**Weeks 12-13:** Evolution as learning.

**Week 14:** Other topics and models in learning theory depending on our pace and how much the schedule of classes has been shifted by expanding on related subjects from probability theory or randomized algorithms.

**Week 15:** Presentations by the students.

May 1: Review for the final exam.

May 11: Final exam.

**No Classes.** No classes on the following days:

- Spring recess: Saturday, March 4 - Sunday, March 12, 2017.

**Textbook and Notes**

A big part of the course will rely on [2]. Topics not found in [2] will be based on papers or other notes that are available online or presented in class and thus all the students will have access to. Relevant references will be given through the course website(s) or mass announcements. Further, a classical resource for covering aspects relevant to the PAC model of learning is [1]. It is advised that the students take notes from the material that is covered in class.

**Grading**

Grading will be based on the following:

- 30% homework problems,
- 30% in-class presentation,
- 20% in-class midterm exam,
- 20% in-class final exam.
Regarding the in-class presentation, it will either be a presentation of a research paper, or a presentation of a project that the students undertook. In either case, students will be expected to answer questions about the presentation that they give. Students will be encouraged to upload their work on Collab, so that everyone can benefit from the work that they have done; that is, slides, source code, spreadsheets, and any other presentation-related resources.

Grades may also be adjusted slightly upward or downward depending on class participation.

**Examinations**

Both the midterm and the final exam will be closed-book written exams.

**Collaboration Policy**

Regarding homework assignments, unless otherwise specified, students may discuss problem sets with one another. However, students should afterward write the solutions on their own. Collaborators (people you speak to about an assignment) must be named at the top of the assignment. No collaboration will be allowed on exams.

Regarding the course project, students are allowed to work either alone or in pairs.

**Late Work Policy**

In general, late work will not be accepted. Problem sets are to be turned in by 4:45 pm the day they are due, either in class, or via my mailbox (on the 5th floor of Rice Hall). Any exceptions will be handled on a case-by-case basis; please communicate with me via email in advance.

**References**
