CPSC 633-600 Machine Learning: Spring 2009

Syllabus

NEWS: *1/20/09, 09:04PM (Tue)*

- [01/20/09] slide01 uploaded. Bring to class.
- [01/20/09] Course web page goes online.

Read-Only Bulletin Board.: 1/20/09, 08:21PM (Tue)

Page last modified: 1/21/09, 08:56AM Wednesday.

General Information | Resources | Reading List | Weekly Schedule | Lecture Notes

I. General Information

Instructor:

Dr. Yoonsuck Choe
Email: choe(a)tamu.edu
Office: HRBB 322B
Phone: 845-5466
Office hours: 10:10am-11:10am, MWF

TA: N/A

Prerequisite/Restrictions:

CPSC 420, 625, or consent of instructor.

Lectures:

MWF 9:10am–10:00am HRBB 126.

Introduction:

Machine learning is the study of self-modifying computer systems that can acquire new knowledge and improve their own performance; survey machine learning techniques, which include induction from examples, Bayesian learning, artificial neural networks, instance-based learning, genetic algorithms, reinforcement learning, unsupervised learning, and biologically motivated learning algorithms. Prerequisite: CPSC 420 or 625.

Goal:

The goal of this course is to

1. learn various problems and solution strategies in machine learning.
2. learn practical methodology for applying ML algorithms to problem domain of your choice.

Textbook:

- Tom Mitchell (1997) Machine Learning, McGraw-Hill. [Book home page]

Administrative Trivia:

1. Computer accounts: if you do not have a unix account, ask for one on the CS web page.
2. Programming languages permitted: C/C++, Java, or Matlab (or octave), and must be executable on CS unix hosts or any public system in the departmental lab.

Topics to be covered:

See the Weekly Schedule section for more details. The content will closely reflect Mitchell (1997).

Grading:

1. 3 assignments (including written and programming components), 18% each = 54%
2. 2 exams (in class), 15% each = 30%
3. Mini project 16%

The cutoff for an 'A' will be at most 90% of total score, 80% for a 'B', 70% for a 'C', and 60% for a 'D'. However, these cutoffs might be lowered at the end of the semester to accomodate the actual distribution of grades.

Academic Integrity Statement:

AGGIE HONOR CODE: An Aggie does not lie, cheat, or steal or tolerate those who do.

Upon accepting admission to Texas A&M University, a student immediately assumes a commitment to uphold the Honor Code, to accept responsibility for learning, and to follow the philosophy and rules of the Honor System. Students will be required to state their commitment on examinations, research papers, and other academic work. Ignorance of the rules does not exclude any member of the TAMU community from the requirements or the processes of the Honor System.

For additional information please visit: http://www.tamu.edu/aggiehonor/

Local Course Policy:

- All work should be done **individually** and **on your own** unless otherwise allowed by the instructor.
- Discussion is only allowed immediately before, during, or immediately after the class, or during the instructor's office hours.
- If you find solutions to homeworks or programming assignments on the web (or in a book, etc.), you may (or may not) use it. Please check with the instructor.

Students with Disabilities:

The Americans with Disabilities Act (ADA) is a federal anti-discrimination statute that provides comprehensive civil rights protection for persons with disabilities. Among other things, this legislation requires that all students with disabilities be guaranteed a learning environment that provides for reasonable accommodation of their disabilities. If you believe you have a disability requiring an accommodation, please contact the Department of Student Life, Services for Students with Disabilities, in Cain Hall or call 845-1637.

Resources:

1. UCI Machine Learning Repository: datasets to test machine learning algorithms.
2. Research resources page
3. Ganeral reading list (u: p:): includes short blurb about how to find, read, and critique others' work. This list is **not** the course reading list.

III. Weekly Schedule and Class Notes

- **Lecture notes (in PDF format)**: all notes will be uploaded in this directory.

- It is **your responsibility** to download, print, and bring the notes to the class. Notes will be available 24 hours before each class.
- See the **2009 Spring TAMU Calendar** for breaks, etc. May 1 is the last class day (note that it is Tuesday, but our class will meet).

Week	Date	Topic	Reading	Assignments	Notices and Dues	Notes
1	1/19	MLK Day (Holiday)				
1	1/21	Introduction	1.1–1.2, 1.3–1.5			slide01.pdf
1	1/23	Concept learning	2.1–2.4			slide02.pdf
2	1/26	Concept learning	2.5–2.6			slide02.pdf
2	1/28	Concept learning	2.7–2.8			slide02.pdf
2	1/30	ANN	4.1–4.4			slide03.pdf
3	2/2	ANN	4.5–4.6			slide03.pdf
3	2/4	ANN	4.7–4.9			slide03.pdf
3	2/6	ANN (applications)	TBA			slide03.pdf
4	2/9	Decision tree	3.1–3.4			slide04.pdf
4	2/11	Decision tree	3.5–3.8			slide04.pdf
4	2/13	Reinforcement learning	13.1–13.3.3			slide05.pdf
5	2/16	Reinforcement learning	13.3.4–13.5			slide05.pdf
5	2/18	Reinforcement learning	13.6–13.8			slide05.pdf
5	2/20	Reinforcement learning (autonomous semantics)				slide06.pdf
6	2/23	Reinforcement learning (autonomous semantics)				slide06.pdf
6	2/25	**Midterm Exam**				
6	2/27	Genetic algorithms	9.1–9.3			slide07.pdf
7	3/2	Genetic algorithms	9.4–9.8			slide07.pdf
7	3/4	Genetic algorithms (neuroevolution)	TBA			slide08.pdf
7	3/6	Evaluating hypotheses	5.1–5.3			slide09.pdf
8	3/9	Evaluating hypotheses	5.4–5.7			slide09.pdf
8	3/11	Bayesian learning	6.1–6.4			slide10.pdf
8	3/13	**Guest lecture**			Trip to DC (PI meeting)	
9	3/16	**Spring break**				
9	3/18	**Spring break**				
9	3/20	**Spring break**				
10	3/23	Bayesian learning	6.5–6.9			slide10.pdf
10	3/25	Bayesian learning	6.11–6.13			slide10.pdf
10	3/27	Bayesian learning	6.11–6.13			slide10.pdf
11	3/30	**Guest lecture**			Conference trip	
11	4/1	**Guest lecture**			Conference trip	
11	4/3	Bayesian learning	6.11–6.13			slide10.pdf
12	4/6	Bayesian learning	6.11–6.13			slide10.pdf
12	4/8	Computational learning theory	7.1–7.3			slide11.pdf
12	4/10	**No class**	Reading day			
13	4/13	Computational learning theory	7.4–7.6			slide11.pdf
13	4/15	Instance-based learning	8.1–8.3; 8.4–8.7			slide12.pdf
13	4/17	Committee machines (ensemble averaging and boosting)	Haykin (1999), Chapter 7			slide15.pdf
14	4/20	**Final exam**				
14	4/22	Imitation learning	Rao et al. (2004) [PDF]			slide13.pdf
14	4/24	Learning in biological vision	Miikkulainen et al. (2005)			slide14.pdf
15	4/27	Learning in biological vision	Miikkulainen et al. (2005)			slide14.pdf
15	4/29	Unsupervised learning				slide16.pdf
15	5/1	Project presentation				
16	5/4	Project presentation				
16	5/5	Project presentation				

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