COMP 7745/8745
Machine Learning
Spring 2016

Instructor: Deepak Venugopal

Time and Location: T, Th 2:30-3:55pm, Dunn Hall 107

Email: dvngopal@memphis.edu

Office Hours: T, Th 1:30-2:30 PM, Dunn Hall 317

TA: Kyle Cherry (kcherry2@memphis.edu)

TA Office Hours: TBA

Course Textbook: Machine Learning, *Tom Mitchell*, McGraw Hill, 1997

References:

- Pattern Classification, David G. Stork, Peter E. Hart, and Richard O. Duda, Wiley, 2000
- Pattern Recognition and Machine Learning, Chris Bishop, Springer-Verlag, 2006
- Elements of Statistical Learning, Trevor Hastie, Robert Tibshirani and Jerome Friedman, Springer, 2009
- Machine Learning: A Probabilistic Perspective, Kevin Murphy, MIT press

Pre-Requisites

Discrete Mathematics, Probability Theory, Algorithm Analysis and Data Structures.

Learning Objectives

The aim of this course is to study, analyze and apply fundamental techniques in Machine Learning. Both theoretical and empirical aspects of Machine learning will be emphasized. At the end of this course, students should have the necessary background to build practical machine learning systems and also be able to apply machine learning in their own research.

Topics

1. Concept Learning
2. Basic Supervised Learning Techniques
    - Decision Trees

- Linear classifiers: Logistic Regression, Perceptrons
- Neural Networks and Backpropagation
- Naive Bayes

3. Evaluation
   - Statistical Bounds
   - Bias vs Variance tradeoff
   - Cross-Validation
4. Computational Learning Theory
   - PAC Learning
   - VC-Dimension
5. Instance based learning: K-nearest neighbors
6. Advanced Supervised Learning Techniques
   - Support Vector Machines and kernels
   - Boosting Weak Learners (AdaBoost)
7. Unsupervised Learning
   - K-Means clustering
   - The EM algorithm
8. Reinforcement Learning: Q Learning
9. Advanced Topics (depending on remaining time)
   - Introduction to Probabilistic Graphical Models
   - Introduction to Deep Learning

Evaluation

1. Midterm (closed books with cheat-sheet): 30% (March 1)
2. Final (closed books with cheat-sheet): 30% (last day of class)
3. 4 Homeworks (Each homework will also have a practical component): 40%
4. For 8000-level Ph.D. students: Research paper presentation (10%)

- Select a paper from one of the following conferences (preferably published within the last 5 years): NIPS, ICML, KDD, UAI, AISTATS
- Send me the paper that you wish to present by Feb 18. I will break ties if there are any and try to make sure we have a good overall schedule
- Presentations in the last two weeks of class. Schedule will be announced later.
- Note: If you want to present your own work related to machine learning by tying it to your research, it is highly encouraged. However, it should be current, i.e., you should perform the research during this semester and not previous work. In this case, by Feb 18th, please send me a proposal of your intended research.

Grading

Grading: $A+ \geq 95\%$, $A \geq 90\%$, $A- \geq 85\%$, $B+ \geq 80\%$, $B \geq 75\%$, $B- \geq 65\%$, $C \geq 50\%$
Note: A modified curve may be used for determining the grades at the discretion of the instructor.

Policies

1. Both midterm and final exams are closed book and closed notes. One double-sided cheat sheet will be allowed.

2. No late homeworks will be accepted unless well-documented reasons are presented

3. All homeworks must be individual work. Plagiarizing assignments or code sharing is not permitted. If plagiarism or cheating occurs, the student will receive a failing grade on the assignment and (at the instructors discretion) a failing grade in the course. The course instructor may also decide to forward the incident to the University Judicial Affairs Office for further disciplinary action. For further information on U of M code of student conduct and academic discipline procedures, please refer to: http://www.people.memphis.edu/ jaffairs/

4. Regular class attendance is mandatory. There is a strong correlation between regular attendance and obtaining a good grade. Instructor reserves the right to lower grades for lack of attendance. Students are responsible for any material and contents of missed lectures.

5. No early or late exams will be given unless under extreme situations

6. Any grading errors in assignments should be notified within a week to the TA