COMP 7740/8740 EECE 7740/8740
Neural Networks
Semester and Year: Spring 2008
Instructor Name: Robert Kozma

Contact Information:

<table>
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<td>In email communications please always specify '8/7740' in the subject field</td>
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Time:
17:30 - 18:55, Tuesday
17:30 - 18:55, Thursday

Room:
Lectures: 351 Dunn Hall
Lab: 207 Dunn Hall

Office Hours:

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<th>Monday</th>
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Also by Appointment

Course Description:

COMP 7740/8740 EECE 7740/8740.

Major tools of neural networks and connectionist science are introduced, including basics of pattern recognition, multilayer perceptron and its universal mapping property, radial basis function networks; various supervised and unsupervised learning and optimization methods, backpropagation, conjugate gradient, Newton and quasi-Newton methods, Levenberg-Marquardt algorithm. Learning and generalization in NNs, including advanced Bayesian, genetic algorithm, and swarm optimization methods. Recurrent network architectures, Hopfield nets, Hebbian learning, and backpropagation through time. Static and dynamic memory principles. Structural learning for data mining and knowledge discovery. Application in signal processing and robotics, image and speech recognition, financial and biomedical signal processing, environmental sciences, etc. Implementations provided in MATLAB environment.

PREREQUISITE COMP 2150 or permission of instructor.

Why this course?

After completing this course, students are expected to be familiar with the main principles of neural computing and they should be able to use these principles in solving practical problems in their relevant area of interest and specialization.
Resources:

Textbooks:
♦ C.M. Bishop, Neural Networks for Pattern Recognition, Oxford University Press, 1999, and following editions.

Additional References:
♦ S. Haykin, Neural Networks - A Comprehensive Foundation, Prentice Hall, 1999

Journals:
♦ Neural Networks - a Journal of the International Neural Network Society
♦ IEEE Transactions on Neural Networks
♦ Neurocomputing

Websites:
♦ IEEE Computational Intelligence Society, Neural Networks Tech Committee http://ieee-cis.org/nn/ with various links to NN-related information
♦ International Neural Network Society http://www.inns.org/ page with link to SIGCOM activities on neural nets

Special Publications and Articles:
See instructor about these during the course

Evaluation:

Evaluation will be viewed as a continuous two-sided feedback process, which (a) allows students to assess themselves about their progress in learning the material/understanding the issues; and (b) allows the instructor to assess how well he is fostering the communication process with and among students. Students are expected to automatically read relevant chapters in the textbook and the supplementary references, actively participate in class discussions and perform assignments and practical lab work. After completing this course, students are expected to be familiar with the main principles of neural computing and they should be able to use these principles in solving practical problems.

Final Grades:
15%: Class Participation
20%: Assignments
15%: Midterm test
50%: Project.
Final grading is given using the +/- grading system.

Students at the 8xxx level are expected to complete their project by demonstrating the correct operation of the developed software and comparison with alternative tools.
Course Policies: Attendance:

Students are expected to attend the lectures, and actively participate in class activities.

Late Policy:

Assignments are expected at the start of the class on the deadline, handed to the lecturer in printed form. Every day late decreases the max value by 20%, so no credit beyond 5 days of being late.

Plagiarism/Cheating Policy: (These paragraphs are mandatory by CS.)

Plagiarism or cheating behavior in any form is unethical and detrimental to proper education and will not be tolerated. All work submitted by a student (projects, programming assignments, lab assignments, quizzes, tests, etc.) is expected to be a student's own work. The plagiarism is incurred when any part of anybody else's work is passed as your own (no proper credit is listed to the sources in your own work) so the reader is led to believe it is therefore your own effort. Students are allowed and encouraged to discuss with each other and look up resources in the literature (including the internet) on their assignments, but appropriate references must be included for the materials consulted, and appropriate citations made when the material is taken verbatim.

If plagiarism or cheating occurs, the student will receive a failing grade on the assignment and (at the instructor’s 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/
January 15  Orientation
January 17  Introduction to connectionism
January 22  Statistical Pattern Recognition (PR), Bayesian theory
January 24  Neural networks - the big picture, Matlab NN Toolbox
January 29  Probability density estimation
January 31  Perceptron, single-layer neural networks
February 5  Multilayer Perceptron (MLP)
February 7  Kolmogorov mapping functions
February 12  Radial basis function (RBF)
February 14  Project Outline
February 19  Error functions – sum square errors (SSE), penalty functions
February 21  Learning by backpropagation algorithm (BP)
February 26  Unsupervised learning and self organized maps
February 28  Midterm test

--- Spring Break ---

March 11  Parameter optimization, gradient, conjugate gradient, Newton, LM
March 13  Preprocessing and signal conditioning
March 18  Learning and Generalization
March 20  MLP for signal processing - speech, image processing
March 25  MLP for time series prediction - financial, biomedical
March 27  Advanced learning techniques, Bayesian, GA, swarm
April 1  Dynamics of recurrent networks
April 3  Advanced learning methods: Kalman Filter, Hebbian learning, backpropagation through time BPTT
April 8  NNs as part of intelligent information processing systems
April 10  Perception and action in biological and computational neural nets
April 15  Project Review
April 17  Project presentations
April 22  Project presentations