EECE 580B – Support Vector Machines

Course Syllabus

Course Title: Support Vector Machines (3 credits)

CRN Number: 97432

Term: Spring 2010

Lecture Times: Tuesday & Thursday 2:50 pm - 4:15 pm, LH – 12

Instructors

- Jan Kodovský, email: jan.kodovsky@binghamton.edu, office phone: 607-777-5689
  - office hours: Wednesday 1pm – 3pm, office LSG – 606
- Jessica Fridrich, email: fridrich@binghamton.edu, office phone: 607-777-6177
  - office hours: Monday 1pm – 3pm, office EB – Q16

Course Website

Link: http://dde.binghamton.edu/kodovsky/svm/

Course website will contain all useful information about the course. Course materials and homeworks will be posted there as well. Blackboard system will NOT be used.

Prerequisites

There is no required course that must be completed. However, a general background of linear algebra, calculus, and elementary statistics is essential. Furthermore, basics of Matlab programming is assumed, since the course will be practically oriented and students will be often asked to use Matlab in the homework assignments. Links to several Matlab tutorials are available at the course website.

Textbook Information / Reading Materials

There is no required text. The content of the course is based mostly on the following publications:

- Learning with Kernels, *B. Schölkopf, A. J. Smola* (2002)
  - Extensive presentation of support vector machines (SVMs) and other kernel methods in general, way beyond the scope of this course. You should buy this book after completing this course, when you feel like knowing more.
  - Book's website: http://www.learning-with-kernels.org
  - Several chapters (relevant to this course) are available online at the book's website.
  - Book is on library reserve (Q325.5 .S32 2002)
- Support Vector Machines for Pattern Classification, *S. Abe* (2005)
  - Apart from two-class SVMs, a significant portion of this book is devoted to the problem of multi-class classification. Possible improvements of other classification techniques (neural networks / fuzzy classifiers) by incorporating the ideas of SVMs are also discussed.
  - Book is on library reserve (QA76.9.T48 A23 2005)

- Support Vector Machines and other kernel-based learning methods, *N. Cristianini, J. Shawe-Taylor* (2000)
  - Book's website: http://www.support-vector.net
  - If you want to buy one book, buy this one. It is a self-contained coverage of support vector classification and regression compressed into less than 200 pages.

Abovementioned books are recommended as additional reading. Furthermore, there are many SVM related materials available online. Links to these resources are available at the course website.

Course Description

Support Vector Machines belong to the class of supervised machine learning techniques. Thanks to their high performance and good generalization abilities, SVMs are becoming more and more popular among researchers of many different fields ranging from computer science through financial modeling to bioinformatics. SVMs are applicable to many different tasks, including classification, regression, pattern recognition, data mining, and predictive control.

The following topics will be covered:

- hard-margin and soft-margin SVMs
- concepts of kernels and feature spaces
- basics of optimization and quadratic programming
- elements of statistical learning theory and generalization theory
- implementation issues, SMO algorithm
- selected advanced topics (multi-classification, support vector regression)
- introduction to steganography and application of SVMs to steganalysis

Course Objectives

The focus of this course is on obtaining practical experience with using SVMs and on understanding the core concepts the theory is built on. There are many free SVM libraries available, as well as commercial packages. After this course, students will be able to pick any of these tools, and use them correctly (and optimally) in their research fields. Not as a black-box, but with understanding of the inner-workings, being aware of potential issues that may occur.

Grading / Exams

The final grade will be a weighted average of grades obtained from homework assignments and a final exam as follows:

Homework Assignments	65%
Final Exam	35%
Total	100%

Homework assignments will be posted on approximately bi-weekly basis (8–10 in total), with variable weights (the weight for every particular assignment will be announced in advance). Programming assignments have to be submitted electronically to jan.kodovsky@binghamton.edu before announced due date. No late submissions will be accepted!

The final exam will be take home and will be designed to reveal what you learned in the course. There is not going to be any midterm exam.

All students are expected to work individually on all homework assignments and the final exam. Collaboration of any sort is prohibited. Violation will result in Category I or Category II offense, see Academic Honesty Policy below.

Academic Honesty Policy

All students must adhere to the Academic Honesty Codes of Binghamton University and the Watson School:

Binghamton University Student Academic Honesty Code:

http://buweb.binghamton.edu/bulletin/program.asp?program_id=826

Watson School Academic Honesty Code:

http://www2.binghamton.edu/watson/advising/pdfs/honesty-policy.pdf

First instance violations (Category I) will result in zero credit for the assignment / exam on which the offense was commited, and in the reduction of course's final grade by one full letter grade. Record of offense will be reported to University administration. Category II violation results in course failure, and additional penalties will be determined by the Watson Academic Integrity Committee.