CSCI 547 – Machine Learning

Class meeting time (Spring even years): Monday/Wednesday/Friday, 9:00 – 9:50, Roberts 121

Instructor: Dr. John W. Sheppard, EPS 365, 994-4835, john.sheppard@montana.edu

Office hours: MWF, 10:00 – 11:00 or by appointment

Course Description

How can machines improve with experience? How can they discover new knowledge from a variety of data sources? What computational issues must be addressed to succeed? These are questions that are addressed in this course. Topics range from determining appropriate data representations and models for learning, understanding different algorithms for knowledge and model discovery, and using sound theoretical and experimental techniques in assessing performance. Specific approaches covered include statistical techniques (e.g., k-nearest neighbor and Bayesian learning), logical techniques (e.g., decision tree and rule induction), function approximation (e.g., neural networks and kernel methods), and reinforcement learning. The topics are discussed in the context of current machine learning research. Students will participate in seminar discussions and will complete and present the results of an individual project.

Course Dates

Monday, January 13, 2020 through Friday, May 1, 2020

Final period: May 4, 2020, 4:00 pm – 5:50 pm

Note that, since this course involves students working as *project teams*, students will not be permitted to drop after the teams have been formed (i.e., Friday 2/12/20) unless mutually agreed upon by the affected team and the instructor. Once project proposals are submitted (i.e., Monday 3/6/20), under no circumstances will drops be permitted unless the student will be dropping all courses for the semester.

Prerequisites

CSCI 447 Machine Learning is recommended but not required.

Professor Biography

Dr. Sheppard is a Norm Asbjornson College of Engineering Distinguished Professor of Computer Science and the Director of the Numerical Intelligent Systems Laboratory at MSU. Dr. Sheppard received his BS in computer science from Southern Methodist University in 1983. Later, while a full-time member of industry, he received an MS in computer science in the Johns Hopkins part time Engineering program (1990). He then continued his studies and received his Ph.D. in computer science from Johns Hopkins in the day school (1997). His research interests include model-based and Bayesian reasoning, reinforcement learning and games, evolutionary and swarm-based algorithms, and fault diagnosis/prognosis of complex systems. He has been recognized for his research as a Fellow of the IEEE "for contributions to system-level diagnosis and prognosis." Prior to entering academia full time, Dr. Sheppard was a member of industry for 20 years. His prior position was as a research fellow at ARINC.

Learning Outcomes

At the end of this course, the student will be able to:

- Formulation and assess problems in machine learning.
- Assess the strengths and weaknesses of several machine learning algorithms
- Assess and understand the key commonalities and differences in applications of machine learning to agent control and data analysis.
- Apply techniques in machine learning to problems in agent control or data analysis
- Develop a proposal for an extended research project.
- Design and conduct an experiment in machine learning
- Prepare a written, technical paper on individual research.
- Deliver a presentation describing the results of individual research

Required Course Readings

Ethem Alpaydin, *Introduction to Machine Learning*, 3/e, The MIT Press, 2014.

Lecture notes as distributed at the start of the semester.

Weekly research papers, all of which are available in D2L.

A PhD Dissertation from the list found in D2L

Anticipated Topics to be Covered

- Overview of Machine Learning
- Experimental Methods
- Computational Learning Theory
- Non-parametric Learning
- Bayesian Learning
- Artificial Neural Networks
- Reinforcement Learning
- Evolutionary Computation
- Inductive Logic Programming
- Data and Dimensionality Reduction
- Kernel Methods
- Ensemble Learning

Course Evaluation

Grading will be based on in class discussions, discussion leadership, ability to report on progress in the field through oral presentation and written critique, and the ability of the student to design and implement a research project. Students will be responsible for periodically leading class discussion and then summarizing the results of the discussion in an informal report. Each student will also conduct a research project, documented with a formal, technical paper and presentation describing the experimental method and results. The following weights will be placed on each of the course requirements:

- Discussion Leadership – 10% (See paper schedule)
- Discussion Reviews (3-5 pages) – 10% (Due *one class period prior* to when the paper is to be discussed in class. See paper schedule.)
- Project ideas (One-page summary, hardcopy, due Friday 2/12/20).
- Project Proposal – 15% (*Hardcopy handed in* Friday 3/6/20 and *discussed* in class Monday 3/9/20)
- Dissertation Critique – 15% (*Hardcopy handed in* Wednesday 3/25/20)
- Project Report – 20% (*Hardcopy handed in* Friday 4/23/20)
- Project Presentation – 10% (Scheduled during last week of class and finals, if needed)
- Class Participation – 20%

Reading List

01/13/20: Alpaydin: Chapter 1

01/15/20: Alpaydin: Chapter 1

01/17/20: Rohit Babbar and Bernard Schölkopf, "Data Scarcity, Robustness, and Extreme Multi-Label Classification," *Machine Learning* (2019) 108: 1329–1351.

01/20/20: No Class (no reading)

01/22/20: Alpaydin: Chapter 19

01/24/20: Alpaydin: Chapter 19

01/27/20: Philipp Probst, Anne-Laure Boulesteix, and Bernd Bischl, "Tunability: Importance of Hyperparameters of Machine Learning Algorithms," *Journal of Machine Learning Research* 20 (2019) 1–32.

01/29/20: Alpaydin: Chapter 2

01/31/20: Alpaydin: Chapter 2

02/03/20: Mehmet Eren Ahsen and Mathukumalli Vidyasagar, "An Approach to One-Bit Compressed Sensing Based on Probably Approximately Correct Learning Theory," *Journal of Machine Learning Research* 20 (2019) 1–23.

02/05/20: Alpaydin: Chapter 8

02/07/20: Alpaydin: Chapter 8

02/10/20: Kai Ming Ting, Ye Zhu, Mark Carman, Yue Zhu, Takashi Washio, and Zhi-Hua Zhou, "Lowest Probability Mass Neighbour Algorithms: Relaxing the Metric Constraint in Distance-Based Neighbourhood Algorithms," *Machine Learning* (2019) 108:331–376.

02/12/20: Project Ideas (no reading)

02/14/20: Alpaydin: Chapter 14

02/17/20: No Class (no reading)

02/19/20: Alpaydin: Chapter 14

02/21/20: De Wen Soh and Sekhar Tatikonda, "Learning Unfaithful K-separable Gaussian Graphical Models," *Journal of Machine Learning Research* 20 (2019) 1–30.

02/24/20: Alpaydin: Chapter 11

02/26/20: Alpaydin: Chapter 11

02/28/20: Sho Sonoda and Noboru Murata, "Transport Analysis of Infinitely Deep Neural Network," *Journal of Machine Learning Research* 20 (2019) 1–52.

03/02/20: Alpaydin: Chapter 18

03/04/20: Alpaydin: Chapter 18

03/06/20: Erwin Walraven and Matthijs T. J. Spaan, "Point-Based Value Iteration for Finite-Horizon POMDPs," *Journal of Artificial Intelligence Research* 65 (2019) 307–341.

03/09/20: Proposal Discussions (no reading)

03/11/20: Lecture Notes: Chapter 8

03/13/20: Lecture Notes: Chapter 8

03/16/20–03/20/20 Spring Break (no reading)

03/23/20: Evert Haasdijk and Jacqueline Heinerman, "Quantifying Selection Pressure," *Evolutionary Computation* 26(2):213–235.

03/25/20: Alpaydin: Chapter 9

03/27/20: NCUR: (no reading)

03/30/20: Alpaydin: Chapter 9

04/01/20: Arnaud Nguembang Fadja and Fabrizio Riguzzi, "Lifted Discriminative Learning of Probabilistic Logic Programs," *Machine Learning* (2019) 108:1111–1135.

04/03/20: Alpaydin: Chapter 6

04/06/20: Alpaydin: Chapter 7

04/08/20: David G. Harris, Shi Li, Thomas Pensyl, Aravind Srinivasan, and Khoa Trinh, "Approximation Algorithms for Stochastic Clustering," *Journal of Machine Learning Research* 20 (2019) 1–33.

04/10/20: No Class (no reading)

04/13/20: Alpaydin: Chapter 13

04/15/20: Alpaydin: Chapter 13

04/17/20: Ehsan Sadrfaridpour, Talayeh Razzaghi, and Ilya Safro, "Engineering Fast Multi-Level Support Vector Machines," *Machine Learning* (2019) 108:1879–1917.

04/20/20: Alpaydin: Chapter 17

04/22/20: Alpaydin: Chapter 17

04/24/20: Ulf Johansson, Tuve Löfström, Henrik Linusson, and Henrik Boström, "Efficient Venn Predictors Using Random Forests," *Machine Learning* (2019) 108:535–550.

04/27/20: Project Presentations (no reading)

04/29/20: Project Presentations (no reading)

05/01/20: Project Presentations (no reading)

Class Schedule

1/13/20	Introduction	1/15/20	Introduction	1/17/20	Paper 1
1/20/20	No Class	1/22/20	Experimental Methods	1/24/20	Experimental Methods
1/27/20	Paper 2	1/29/20	Learning Theory	1/31/20	Learning Theory
2/3/20	Paper 3	2/5/20	Nonparametric Learning	2/7/20	Nonparametric Learning
2/10/20	Paper 4	2/12/20	Project Ideas	2/14/20	Bayesian Learning
2/17/20	No Class	2/19/20	Bayesian Learning	2/21/20	Paper 5
2/24/20	Neural Networks	2/26/20	Neural Networks	2/28/20	Paper 6
3/2/20	Reinforcement Learning	3/4/20	Reinforcement Learning	3/6/20	Paper 7
3/9/20	Proposal Discussion	3/11/20	Evol. Comp.	3/13/20	Evol. Comp.
3/16/20	Spring Break	3/18/20	Spring Break	3/20/20	Spring Break
3/23/20	Paper 8	3/25/20	Ind. Logic Pgming	3/27/20	No Class
3/30/20	Ind. Logic Pgming	4/1/20	Paper 9	4/3/20	Data/Dim Reduction
4/6/20	Data/Dim Reduction	4/8/20	Paper 10	4/10/20	No Class
4/13/20	Kernel Methods	4/15/20	Kernel Methods	4/17/20	Paper 11
4/20/20	Ensemble Methods	4/22/20	Ensemble Methods	4/24/20	Paper 12
4/27/20	Final Presentations	4/29/20	Final Presentations	5/1/20	Final Presentations
5/4/20	Final Presentations				

Discussion Leadership

This course is formatted as a seminar in which research papers are read and discussed each week. To make the course more interesting and to encourage involvement by all students in the discussion, the seminar will be conducted such that the students will be responsible for presenting the material on one or more research papers.

When discussing a research paper, class leadership will be turned over to the assigned discussion leader. At that point the leader will present an overview of the paper for the day and formulate questions and issues for class discussion. After the overview has been presented, the class will be encouraged to engage in discussion of the issues. The instructor will participate as another member of the discussion, interjecting additional material as necessary to provide information on background and current research in the field.

A paper discussion *must* use the following format:

1. The discussion leader will take up to 15 minutes at the beginning of the session to present a summary of the main points of the paper (with PowerPoint or equivalent).
2. The discussion leader will formulate at least five substantive questions and be prepared to introduce additional ideas or questions, as necessary, to stimulate discussion.
3. The discussion leader will take up to 5 minutes at the end of the session to summarize the main points raised during the discussion.

To prepare for leading discussion, the leader should read the paper very carefully, being sensitive to issues such as

- Algorithms proposed
- Technical approach used in experiments and analyses
- Comparisons with other methods
- Claims of contributions made by the paper
- Biases of the investigators (either explicit or implicit)

- Deficiencies in the paper or the research reported
- Directions for future research
- Possible ideas for course research projects

To prepare properly, the discussion leader may need to look at related papers as indicated in the references of the assigned readings. The instructor will be able to recommend related papers as well.

The evaluation criteria for discussion leadership are as follows

- Summary of the main contributions of the papers (35%)
- Understanding of the main concepts presented in the papers (35%)
- Ability to stimulate discussion on topic/paper (30%)

Discussion Paper Summary

The discussion leader is also responsible for preparing a written summary of the class discussion. This summary will be due the class period prior to the discussion (emailed). The summary should include a review of the papers, a review of any related material either identified in the paper or arising from a personal literature review, and a review of the issues and significance of the work reported. The summary shall be provided electronically in PDF format to the instructor for posting within Desire2Learn.

The evaluation criteria for discussion summaries are as follows:

- Summary of topic (25%)
- Identification of key issues (25%)
- Discussion of the claimed contributions (25%)
- Review of related material (15%)
- Construction and readability of the summary (10%)

Dissertation Critique

Fundamentally, this is a research-oriented course, and a large number of topics will be covered as a foundation for a researcher to apply in solving complex learning problems. Furthermore, this course is oriented around introducing the student to current research in the field of machine learning. Unfortunately, in a course such as this, it is difficult during class time to explore any one topic in depth. Therefore, each student will be responsible for selecting a PhD dissertation from several provided by the instructor and writing a critique of the research reported in that dissertation. This critique should include a summary of the research reported, a discussion of the major contributions claimed, and an assessment of the significance of those contributions and of the research itself. The critique should also include a brief literature review of the topic related to the thesis, discussion of relevant algorithms, and application areas for the research reported. Where appropriate, the critique should include a comparison with other issues discussed in class. Students are encouraged to select a dissertation that is related to their course projects.

The evaluation criteria for the critique are as follows:

- Overview of the research reported (20%)
- Review of the related literature (15%)

- Major contributions of the thesis (20%)
- Understanding of techniques and algorithms (20%)
- Application areas (15%)
- Proper construction and readability of paper (10%)

Research Projects

As a semester long project, each student in this course will be responsible for conducting an independent research project in machine learning. This project will provide direct experience in proposing and executing a complete research project over the length of the course. The project can be experimental or theoretical. If an experimental project is proposed, be prepared to include enough theoretical work to explain or motivate the work. If the project is theoretical, some experimentation should be included to demonstrate whatever results are obtained.

Research Project Proposal

Each student will write a short proposal describing the intended research. The basic idea for the project must be approved by the instructor prior to commencing the major portions of the research. Obviously, some amount of research should be done to prepare the proposal. The proposal should include a brief literature survey on the topic area, a clear statement of the problem to be solved (including at least one formal hypothesis), and a description of the approach to be taken. The proposal is due around the time typical for a midterm exam.

The evaluation criteria for proposals are as follows:

- Statement of hypothesis (25%)
- Proposed approach (25%)
- Relevance and interest in topic (25%)
- Literature review (15%)
- Construction and readability of proposal (10%)

The actual execution of the project is left entirely at the discretion of the student. Any computer and programming language may be used to support the project, and additional tools for analysis and presentation (e.g., MATLAB, R, and excel) are encouraged.

Research Project Report

At the end of the project, each student will be required to submit a comprehensive research report. This report will include background and discussion of previous work done related to the topic, a clear description of the problem to be solved, discussion of the approach taken, in depth discussion of any algorithms used or developed, detailed presentation of the results obtained, discussion of the importance and implications of the results, directions for future work, and references. The student should use the research papers read in this course as guidance for what research papers look like. Note that submitting code is not required.

The evaluation criteria for the report are as follows:

- Statement of problem and hypothesis (15%)
- Approach (20%)

- Background and related work in field (15%)
- Results (15%)
- Discussion and analysis of results (20%)
- Relevant future work (5%)
- Construction and readability of report (10%)

Research Project Presentations

During the final weeks of the semester, results of research projects will be presented in class. If necessary, the finals period will also be used. Each student or group should be prepared to give a short presentation of the research performed and the results achieved. The format will be similar to a research talk given at a conference. Presentations will give the class a chance to see other projects and to provide feedback to the student. Note that the student is required to prepare visual aids (e.g., PowerPoint presentations) for their talks.

The evaluation criteria for the presentation are as follows:

- Statement of problem and hypothesis (15%)
- Approach (20%)
- Background and related work in field (15%)
- Results (15%)
- Discussion and analysis of results (20%)
- Relevant future work (5%)
- Clarity in presentation (10%)

Policy on Academic Misconduct

Academic misconduct is unacceptable. It is the responsibility of all full-time, part-time or non-degree (special) students to adhere to strict standards of integrity in their professional and scholarly activities, as well as to high standards of conduct in their non-academic activities. Students who engage in any form of academic misconduct will be reported to the Dean of Students and will receive an F for the course. Dropping the course to avoid an F resulting from academic misconduct will not be permitted under any circumstances.

Examples of academic misconduct:

- Cheating on Examinations
  - Use of unauthorized materials during examinations and in completing assignments.
  - Consultation of unauthorized materials while being excused from an examination room.
  - Discussion of an exam's contents during its administration.
  - Copying answers from another student on an examination.
  - Obtaining an examination or answers to an examination prior to its administration
  - Studying from an old exam whose circulation was prohibited by the instructor.
- Plagiarism

  - Submission of the same or substantially similar work of another person, even if re-worded
  - Use of another person's work while representing it as your own
  - Improper documentation of quotations, ideas, or paraphrased passages taken from published or unpublished works

- Reuse of Assignments
  - Submission of the same or substantially similar assignment to fulfill the requirements of more than one course.

- Improper Use of the Internet
  - Plagiarism from a published or unpublished Internet source.
  - Improper documentation of an Internet source.
  - Use of paper writing services of paper databases on the Internet.

- Improper Use of Electronic Devices
  - Consultation of unauthorized electronic devices during an examination.
  - Use of electronic devices to communicate within or outside of an examination room.
  - Storage of test answers, class notes, and other references in electronic devices during examinations.

- Unauthorized Collaboration
  - Collaboration when solving homework problems or writing lab reports, computer programs, or papers, unless explicitly approved by the professor.

- Alteration of Graded Assignments
  - Submission of an examination or assignment for a re-grade after making changes to the original answers or text.

- Forgery or Falsification
  - Falsification or invention of data in a laboratory experiment.
  - Citation of nonexistent sources or creation of false information in a written assignment.
  - Attributing to a source ideas or information that is not included in the source.
  - Forgery of university documents.
  - Impersonating a faculty member.

- Lying
  - Request for special consideration from professors or university officials based upon false information or deception.
  - Fabrication of a medical or emergency excuse.
  - Claiming falsely to have completed and/or turned in an assignment.
  - Falsely reporting an ethics violation by another student.

- Facilitating Academic Dishonesty
  - Intentionally or knowingly aiding another student to commit a violation of academic conduct.
  - Allowing another student to copy from one's own examination during its administration.

  - Providing copies of course materials whose circulation was prohibited to students enrolled in or planning to take that course.
  - Taking an examination or completing an assignment for another student, or permitting another student to do so on one's behalf.

- Unfair Competition
  - Willfully damaging the academic efforts of other students.
  - Stealing another student's academic materials.
  - Denying another student needed resources.

Policy on Assignments

This course has several assignments requiring outside work of the students. The assignments are critical for gaining understanding and experience using the materials presented in class. Due to the importance of these assignments, the following policy is set forth.

1. All assignments will be completed by the individual student and will be the original work of that student.
2. All assignments are due at the beginning of class on the dates indicated in the syllabus. No assignments will be accepted late without prior approval of the instructor (other than exceptions noted below). Approval will not be granted based on personal time-management issues.
3. Unapproved late assignments will receive no credit. Approved late assignments may still receive a penalty, depending on the circumstances. It is the responsibility of the student to ensure that the instructor is kept informed of any problems related to turning in assignments on time. Only serious, uncontrollable circumstances (such as serious illness or family tragedy) will result in accepting late assignments without prior notification. In such cases, documentation of these circumstances must be provided.
4. Attending class sessions is critical to a successful course. If an absence is anticipated, please notify the instructor beforehand by phone or email. Unexplained absences will adversely affect the final grade.
5. All written assignments are expected to be typed. Avoid hand drawn figures if at all possible. Use built-in equation editors for handling mathematical notation. If the assignments are not legible, they will be returned to the student with a grade of zero. Be sure each assignment includes name, department, daytime phone number, and email address.
6. Any language and any computer system can be used to complete the programming assignments unless otherwise specified in the assignment itself.

Policy on Class Attendance

A large amount of material will be covered in a relatively limited amount of time. In addition, a fairly large amount of work will be done by the student. Consequently, class attendance is required. If a student must miss class for any reason, he or she should notify the instructor as soon as the absence is known. In the event of emergency absences, the instructor reserves the right to request an excuse from some cognizant authority such as a supervisor or physician. Note that class attendance counts towards the class participation grade.

Policy on Personal Communications Devices

It is unfortunate, but advances in personal communications technologies have also resulted in the need for a policy concerning the use of these devices. Since students receiving and/or responding to pages or cell phone calls creates a distraction to other students, no pagers or cell phones will be permitted to be brought into the classroom without prior authorization of the instructor.