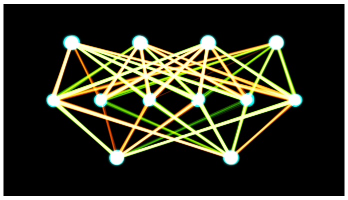
UNIVERSITY OF MONTANA

CSCI447/547
Machine Learning
TR, 12:30PM-2:00PM, GBB108



Instructor: Doug Brinkerhoff
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Office: SS403
Office Hours: TWR, 9:00-11:00
(E-mail for an appointment, or my door is always open when I'm in)

Course Description: As a society we have reached a point where the amount of information available to us exceeds our capacity to analyze it without the assistance of the very computers that have made the collection of such vast sums of data possible. In this course we will explore the techniques required to turn these data into predictive models of varying complexity, from the modest linear regression to the vaunted deep neural network, with many other methods in between.

Learning Outcomes: At the completion of this course, students will be able to:
1. Understand the meaning of the phrase 'machine learning' in the context of contemporary data analysis.
2. Understand fundamental principles such as overfitting, validation, and Bayesian probability.
3. Select models and error metrics appropriate for the structure and subject of problems being considered.
4. Implement a bestiary of machine learning algorithms, both from scratch and with the assistance of high performance libraries like Google's TensorFlow.
5. Apply these algorithms to problems in their primary field of study.

Course Organization: This course employs an 'active learning' strategy. Class time will be roughly proportioned between interactive lectures and sessions in which you will work with your classmates to implement and/or test a machine learning method, or apply one to a new dataset. This in class work will not be graded *per se*, but participation is a substantial portion of your grade. There will additionally be a weekly assignment on which you are encouraged to work with your classmates if so desired; however submissions must be individual. Grad students will have the enviable experience of answering an extra advanced problem on each assignment.

Graduate Increment Graduate students will have two additional requirements. First will be the proposal and execution of a project, either the implementation of a new machine learning algorithm or the application of one of our class examples to a non-trivial dataset. The last two class periods will be dedicated to presentation of the results of these projects. Second will be the identification, reading, and summarization of two primary pieces of literature on machine learning. The clever student will choose these papers synergistically with their implementation project.

Computers, Software, and Online Material: If possible, I would suggest bringing a laptop to class. A tentative list of the software that we'll be using is as follows:
1. Python 3
2. Numpy/Scipy/Matplotlib: http://www.scipy.org/install.html

3. Jupyter: http://jupyter.org/install
4. scikit-learn: http://scikit-learn.org/stable/install.html
5. Keras: https://keras.io/
6. tensorflow: https://www.tensorflow.org/install/

All teaching material will be presented in Python, and I think that everyone will be happier if you do your assignments in Python as well. An important exception to this is the final project, where you are welcome to use whatever language/tools that you want (subject to approval of your proposal).

We will utilize many online resources throughout the course, from software libraries to external reading. These will generally be linked from the course's Moodle page. All internal course material (assignments, lecture notes and slides, Jupyter notebooks, etc.) will be available on Moodle.

Assignments will be disseminated and collected via GitHub classroom. Details will be presented separately.

Prerequisite(s): Officially, CSCI232: Data Structures and Algorithms. In reality, this course requires a commitment to making up any knowledge gaps that the student might have with respect to the course material. Because of the nature of the subject, ML borrows heavily from topics in calculus, statistics, discrete math, and programming. It is unlikely that anyone is going to be comfortable with the course material all the time. Don't get too bent out of shape about it.

Text(s):

1. *Pattern Recognition and Machine Learning*, Christopher M. Bishop, Springer, ISBN-13:978-0387310732.
   Freely available at https://www.microsoft.com/en-us/research/uploads/prod /2006/01/Bishop-Pattern-Recognition-and-Machine-Learning-2006.pdf
2. *Bayesian Reasoning and Machine Learning*, David Barber,
   Freely available at http://web4.cs.ucl.ac.uk/staff/D.Barber/pmwiki/pmwiki.php?n=Brml.HomePage

Grade Distribution:

(Graduate student distribution in parentheses)

Course Participation and Attendance	40 (30)%
Assignments	60 (50) %
Project	(20)%

Letter Grade Distribution:

>= 93.00	A	73.00 - 76.99	C
90.00 - 92.99	A-	70.00 - 72.99	C-
87.00 - 89.99	B+	67.00 - 69.99	D+
83.00 - 86.99	B	63.00 - 66.99	D
80.00 - 82.99	B-	60.00 - 62.99	D-
77.00 - 79.99	C+	<= 59.99	F

Attendance Policy: Attendance is generally required, as participation is a significant portion of your grade. However, I also understand that there are lots of good reasons for not being able to make it to class; just talk to me about it and chances are we can work something out.

Late Assignments: I will not accept late assignments unless an extension was agreed upon well in advance of the due date or in extenuating circumstances to be determined at my sole discretion.

Academic Integrity: All students must practice academic honesty. Academic misconduct is subject to an academic penalty by the course instructor and/or a disciplinary sanction by the University. All students need to be familiar with the Student Conduct Code. I will follow the guidelines given there. In cases of academic dishonesty, I will seek out the maximum allowable penalty. In general, there will not be many options for cheating in this course: Assignments will not come from the book, you are generally welcome to collaborate with your classmates, and any piracy of your final project will be painfully obvious for me and for everyone else. Look, this is a 400/500 level class, and if you're reading this you're probably looking to have a career in CS or a related field. When you're at a job interview, don't be sitting there regretting that you didn't learn anything in Machine Learning because you were cheating the whole time. Nobody wants that.

Disabilities: Students with disabilities may request reasonable modifications by contacting me. The University of Montana assures equal access to instruction through collaboration between students with disabilities, instructors, and Disability Services for Students. Reasonable means the University permits no fundamental alterations of academic standards or retroactive modifications.

Tentative Course Schedule: The following is subject to change according to the rate at which we proceed through the material, the moon and tides, and the results of my horoscope for the week.

Date	**Topic**
Aug 26– Aug 30	What does it mean to learn? • The vocabulary of optimization • Linear regression as a first example
Sep 2 – Sep 6	Distributions • The meaning of probability • The normal distribution • the Bernoulli distribution
Sep 9 – Sep 13	Known knowns, known unknowns, and unknown unknowns. • Bayes' theorem • Naive Bayes • Expectation maximization

Sep 16 – Sep 20	Drawing a line in the sand • Classification versus regression • Logistic regression • Gradient descent
Sep 23 – Sep 27	Three's a crowd • Generative vs. discriminative models • Softmax regression • PCA
Sep 30 – Oct 4	A mind like a steel trap, Pt. 1 • The multilayer perceptron • Artificial neural networks
Oct 7 – Oct 11	A mind like a steel trap, Pt. 2 • The backpropagation algorithm • Regularization
Oct 14 – Oct 18	Does everybody know what time it is? • Tool time • Tensorflow • Keras
Oct 21 – Oct 25	The bottleneck • Autoencoders
Oct 28 – Nov 1	Filter feeders • Convolutional neural networks • for classification • for segmentation
Nov 4 – Nov 8	Making funny faces • Variational autoencoders • Generative adversarial networks
Nov 11 – Nov 15	Talk the talk • Sequential data • Markov models

Nov 18 – Nov 22	Like a monkey with a miniature cymbal • LSTM • Embeddings
Dec 2 – Dec 6	Grad student presentations