Course Syllabus

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Course Description. This advanced graduate course explores in depth several important classes of algorithms in modern machine learning. We will focus on understanding the mathematical properties of these algorithms in order to gain deeper insights on when and why they perform well. We will also study applications of each algorithm on interesting, real-world settings. Topics include: spectral clustering, tensor decomposition, Hamiltonian Monte Carlo, adversarial training, and variational approximation. We will supplement the lectures with paper discussions and there will be a significant research project component to the class. Prerequisites: Probability (CS 109 **(https://explorecourses.stanford.edu/search?view=catalog&filter-coursestatus-Active=on&page=0&q=CS109)**), linear algebra (Math 113 **(https://explorecourses.stanford.edu/search?view=catalog&filter-coursestatus-Active=on&page=0&q=Math113)**), machine learning (CS 229 **(https://explorecourses.stanford.edu/search?view=catalog&filter-coursestatus-Active=on&page=0&q=CS229)**), and some coding experience.

Instructor: James Zou (**jamesz@stanford.edu (mailto:jamesz@stanford.edu)**)

TA: Qijia Jiang (**qjiang2@stanford.edu (mailto:qjiang2@stanford.edu)**)

Lectures: Mondays 2:30-4:20pm in 50-52H

Paper discussions: Fridays 1:30-2:20 in McCullough 122 (starting 4/14).

Office hours: James Mondays 4:30-6pm in Packard 253.

Piazza Page: piazza.com/stanford/spring2017/cs329m/home (http://piazza.com/stanford/spring2017/cs329m/home)

Assignments (see guidelines below):

Project: 50% (team size flexible)

Scribing: 10% (teams of 3-4)

Paper presentation: 20% (teams of 3-4)

Participation (esp. in the paper discussions): 10%

Assignment: 10%

Week	**Material & Relevant Reading** (subject to change)	**Paper Presentatio**
Week 1 (4/3): **Random geometry in high dimensions and applications.**	**Material**. Random geometry in high dimensions. Johnson-Lindenstrauss projections. Locality sensitive hashing **Relevant reading**. 1. http://www.cs.cornell.edu/jeh/bookMay2015.pdf **(http://www.cs.cornell.edu/jeh/bookMay2015.pdf)** Chapter 2. 2. Charikar SimHash paper. https://www.cs.princeton.edu/courses/archive/spr04/cos598B/bib/CharikarEstim.pdf **(https://www.cs.princeton.edu/courses/archive/spr04/cos598B/bib/CharikarEstim.pdf)**	No Paper Discussio
Week 2 (4/10): **Spectral methods 1**	**Material**. SVD as best low rank approximation. Tensor decomposition for mixture of Gaussians. Power method. **Relevant reading.** 1. http://www.offconvex.org/2015/12/17/tensor-decompositions/ **(http://www.offconvex.org/2015/12/17/tensor-decompositions/)** 2. https://arxiv.org/pdf/1210.7559.pdf **(https://arxiv.org/pdf/1210.7559.pdf)**	Spectral meta-learr with-ds=yes **(http**
Week 3 (4/17): **Spectral methods 2**	**Material**. Tensor decomposition for LDA and trees. Spectral clustering. **Relevant reading.** 1. Moitra chapter 3. **http://people.csail.mit.edu/moitra/docs/bookex.pdf (http://people.csail.mit.edu/moitra/docs/bookex.pdf)** 2. Spectral methods for dimensionality reduction. https://cseweb.ucsd.edu/~saul/papers/smdr_ssl05.pdf **(https://cseweb.ucsd.edu/~saul/papers/smdr_ssl05.pdf)** . 3. Tutorial on spectral clustering. http://www.kyb.mpg.de/fileadmin/user_upload/files/publications/attachments/luxburg06_TR_v2_4139%5b1%5d.pdf **(http://www.kyb.mpg.de/fileadmin/user_upload/files/publications/attachments/luxburg06_TR_v2_4139%5b1%5d.pdf)** 4. Laplacian Eigenmap. http://yeolab.weebly.com/uploads/2/5/5/0/25509700/belkin_laplacian_2003.pdf **(http://yeolab.weebly.com/uploads/2/5/5/0/25509700/belkin_laplacian_2003.pdf)**	Tensor decomposit https://arxiv.org/pdf **(https://arxiv.org/pd**

Week 4 (4/24): **Sampling. Hamiltonian Monte Carlo**.	**Material**. Review of MCMC. Hamiltonian Monte Carlo. **Relevant reading**. 1. HMC demos. https://arogozhnikov.github.io/2016/12/19/markov_chain_monte_carlo.html 2. Conceptual overview of HMC. https://arxiv.org/pdf/1701.02434.pdf. 3. Stochastic Langevin Dynamics (Teh'11)	Firefly Monte Carlo **(https://arxiv.org/pd** carlo **(https://gith**
Week 5 (5/1): **Variational inference 1**	**Material**. Basic variational inference and examples. Stochastic variational inference. **Relevant reading.** 1. Stochastic variational inference. http://www.columbia.edu/~jwp2128/Papers/HoffmanBleiWangPaisley2013.pdf **(http://www.columbia.edu/~jwp2128/Papers/HoffmanBleiWangPaisley2013.pdf)** 2. VAE. https://arxiv.org/abs/1312.6114 **(https://arxiv.org/abs/1312.6114)** 3. normalizing flows. http://jmlr.org/proceedings/papers/v37/rezende15.pdf **(http://jmlr.org/proceedings/papers/v37/rezende15.pdf)** 4. Streaming variational Bayes. https://papers.nips.cc/paper/4980-streaming-variational-bayes.pdf **(https://papers.nips.cc/paper/4980-streaming-variational-bayes.pdf)**	Black box variation http://www.cs.colun **(http://www.cs.colu**
Week 6 (5/8): **Variational inference 2**	**Material**. Stochastic variational inference. Variational auto-encoder.	Semi-supervised le http://papers.nips.c generative-models. **supervised-learning**
Week 7 (5/15): **Project proposal presentations**	Project proposal presentation in class.	Learning from imba http://ieeexplore.iee **(http://ieeexplore.ie**
Week 8 (5/22): **Robust ML 1: adversarial training**	**Material.** Adversarial attacks. **Relevant reading.** 1. Explaining and harnessing adversarial examples. **https://arxiv.org/pdf/1412.6572.pdf (https://arxiv.org/pdf/1412.6572.pdf)** 2. https://blog.openai.com/adversarial-example-research/	Domain adversaria networks. **http://jm (http://jmlr.org/pape**
Week 9: **Holiday no class**	**Holiday, no class.**	No paper discussio with James.
Week 10 (6/5): **Robust ML 2: robust optimization, covariance shift.**	**Material.** Robust optimization. Covariance shift. **Relevant reading.** 1. Covariate shift adaptation. http://www.jmlr.org/papers/volume8/sugiyama07a/sugiyama07a.pdf **(http://www.jmlr.org/papers/volume8/sugiyama07a/sugiyama07a.pdf)** 2. Automated ML. https://papers.nips.cc/paper/5872-efficient-and-robust-automated-machine-learning.pdf **(https://papers.nips.cc/paper/5872-efficient-and-robust-automated-machine-learning.pdf)**	No paper discussio
Final Week (6/9): **Final presentation**	Oral presentation in class.	

Assignment guidelines.

Scribing: Each student should sign up to scribe one lecture **here (https://docs.google.com/spreadsheets/d/1FTjZs5QSzCV5Fzk3OybpJfBgYXGmJhRyexMD_BgCSbc/edit#gid=0)**. Students scribing the same lecture should work together to produce **one** document using the latex template provided in Files. The latex files and PDF should be emailed to **qjiang2@stanford.edu (mailto:qjiang2@stanford.edu)** by **Thursday noon of the week of the lecture**. The document will be evaluated for clarity, comprehensiveness and accuracy (i.e. no typos).

Paper presentation: Each student should sign up to present one paper **here (https://docs.google.com/spreadsheets/d/1FTjZs5QSzCV5Fzk3OybpJfBgYXGmJhRyexMD_BgCSbc/edit#gid=0)**. Students presenting the same paper should work together to prepare a **40 minutes whiteboard talk on the paper** (at most two slides is allowed). The talk should be self-contained: give background/motivation, intuition and the key results from the paper that you think are the most interesting. Do not need to cover everything; present derivations if they convey insights. Clarity will be the main evaluation criterion. **All students are expected to read the assigned paper and participate in the discussions.**

Homework assignment: Each student should submit one PDF solution. It's ok to help each other, but each person should complete his/her own assignment.

Final project: This is the main component of the course; start early! This should be an research project that is related to the course material. You are free to select your own topic and work in teams, but please check in with the instructor. The project could be empirical (e.g. applying some of the methods we discuss to your data), theoretical (e.g. proving some algorithmic properties) or developing new methods. Please use the NIPS template provided for the final write-up.

Course Summary:

Date	Details	
Thu May 4, 2017	Problem set (https://canvas.stanford.edu/courses/66218/assignments/76582)	due by 12:05pm