

# Large Scale Matrix Computation and Machine Learning CSCI 6971/4971

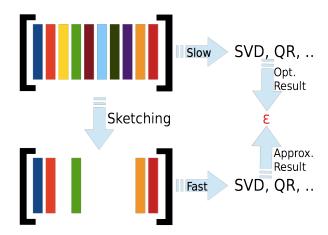
Mondays and Thursdays, 2pm-3:50pm, Lally 102

**Alex Gittens** 

Office Hours: Mon, Thurs 4pm-5pm or by appointment (use the link on my website)

Lally 316 gittea@rpi.edu

http://www.cs.rpi.edu/~gittea/



Course Description: Modern machine learning routinely deals with millions of points in high-dimensional spaces. Classical linear algebra and optimization algorithms can be prohibitively costly in such applications, as they aim at machine precision and/or scale super-linearly in the size of the input data. Randomization can be used to bring the costs of machine learning algorithms closer to linear in the size of the input data; this is done by sacrificing, in a principled manner, computational accuracy for increased speed. This course surveys modern randomized algorithms and their applications to machine learning, with the goal of providing a solid foundation for the use of randomization in large-scale machine learning. Topics covered will include time-accuracy tradeoffs, stochastic first-order and second-order methods, applications of low-rank approximation, approximate kernel learning, distributed optimization, and hyperparameter optimization.

Course Website: http://www.cs.rpi.edu/~gittea/teaching/spring2019/csci6971-and-4971. html Note that this document supercedes any statements made on the website.

**Course Text(s):** None required. As necessary, links to papers and other reading materials will be provided.

**Course Learning Outcomes for CSCI4971:** Students who successfully complete this course will be able to:

• Identify convex optimization problems, their optimality conditions, and properties relevant

to the selection and performance of optimization algorithms such as strong convexity and smoothness.

- Use stochastic first- and second-order optimization techniques to tackle large-scale machine learning problems that are inefficient or intractable with classical deterministic optimization algorithms.
- Identify the trade-offs of using stochastic optimization techniques in machine learning and linear algebra.
- Use randomized low-rank approximation techniques to speed the training of kernel machines.

**Course Learning Outcomes for CSCI6971:** Students who successfully complete this course will be able to:

- Identify convex optimization problems, their optimality conditions, and properties relevant
  to the selection and performance of optimization algorithms such as strong convexity and
  smoothness.
- Use stochastic first- and second-order optimization techniques to tackle large-scale machine learning problems that are inefficient or intractable with classical deterministic optimization algorithms.
- Identify the trade-offs of using stochastic optimization techniques in machine learning and linear algebra.
- Use randomized low-rank approximation techniques to speed the training of kernel machines.
- Read the contemporary literature on randomized approaches to problems in large-scale machine learning, evaluate the theoretical guarantees and empirical performance of novel methods, and effectively share their conclusions.
- Understand, reproduce, and extend arguments guaranteeing the performance of stochastic optimization algorithms used in large-scale machine learning.
- Understand, reproduce, and extend arguments guaranteeing the performance of randomized low-rank approximation algorithms.

#### **Grading Criteria:**

Homeworks 50% In-class Pop Quizzes 20% Project 30%

Students in 4971 and 6971 will be graded according to different rubrics on each assignment, as the time at which they are assigned and due will be shared, but the assignments themselves will vary between the two courses. Students are expected to have writing supplies on hand in each class to complete the in-class pop quizzes. If you are an athlete or for some other reason are not able to attend each class, make alternative arrangements with the instructor in the first two weeks of the course.

Letter grades will be computed from the semester average. Maximum lower bound cutoffs for A, B, C and D grades are 90%, 80%, 70%, and 60%, respectively. These bounds may be moved lower

at the instructor's discretion.

## **Homework Policy**

All assignments must be typeset and are due, via email, at the start of class (the first 15 minutes). Late homeworks will be penalized and accepted at the discretion of the instructor. There will be no makeup homeworks.

#### **Project Policy**

A presentation project will be assigned during the second half of the semester. It will entail reading a paper, summarizing the guarantees established in the paper, implementing the main algorithm and appropriately empirically evaluating it, then delivering a 15 minute presentation before the class.

## **Academic Integrity**

The Rensselaer Handbook of Student Rights and Responsibilities and The Graduate Student Supplement define various forms of Academic Dishonesty and you should make yourself familiar with these. In this course, all assignments that are turned in for a grade must represent the students own work. In cases where help was received, or teamwork was allowed, a notation on the assignment should indicate your collaboration.

Submission of any assignment that is in violation of this policy will result in an administrative grade of F for the course.

If you have any question concerning this policy before submitting an assignment, please ask for clarification.