MAP7436/C213–Seminar in Applied Mathematics

Introduction to Convex Optimization and Applications

References:

- Introductory Lectures on Convex Optimization, by Y. Nesterov, Kluwer, Boston, 2004
- Convex Analysis, by R. T. Rockafellar, Princeton University Press, Princeton, NJ, 1970.
- Mathematical Problems in Image Processing – PDE and the Calculus of Variations by Gilles Aubert and Pierre Kornprobst;
- The Handbook of Mathematical Models in Computer Vision by Nikos Paragios, Yunmei Chen, and Olivier Faugera
- Related papers:

1. Beck and M. Teboulle, A fast iterative shrinkage-thresholding algorithm for linear inverse problems, SIAM J. Imaging Sci., 2 (2009), pp. 183– 202.
2. Beck and M. Teboulle, Gradient-based algorithms with applications to signal recovery problems. In: Convex Optimization in Signal Processing and Communications, Edited by Y. Eldar and D. Palomar, Cambridge University Press, (2010).
3. Y. Nesterov. A method for solving the convex programming problem with convergence rate O(1/k2). Dokl. Akad. Nauk SSSR, 269(3):543–547, 1983.
4. Y. Nesterov, Smooth minimization of non-smooth functions, Math. Program., 103 (2005), pp. 127–152.
5. Y. Nesterov, Gradient methods for minimizing composite objective function, http://www.ecore.beDPs/dp1191313936.pdf (2007).
6. P. Tseng, On Accelerated Proximal Gradient Methods for Convex-Concave Optimization, Technical report, Department of Mathematics, University of Washington, Seattle, WA; available online from http://www.math.washington.edu/~tseng/papers.html.
7. Y. Chen, G. Lan, and Y. Ouyang, Optimal primal-dual methods for a class of saddle point problems, SIAM J. Optim., 24 (2014), pp. 1779–1814.
8. K. Scheinberg, D. Goldfarb and X. Bai, Fast First-Order Methods for Composite Convex Optimization with Backtracking, Foundations of Computational Mathematics 14 (2014) pp. 389–417.
9. Y.Ouyang, Y.Chen, G.Lan and E.Pasiliao Jr., An Accelerated Linearized Alternating Direction Method of Multipliers, SIAM Journal on Imaging Sciences}, 8 (1) (2015), pp. 644-681.
10. S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, Distributed optimization and statistical learning via the alternating direction method of multipliers, Foundations and Trends in Machine Learning, 3 (2011), pp. 1–122.
11. D. Jakovetic, J. Xavier, J. M. F. Moura, Fast Distributed Gradient Methods, arXiv.org > cs > arXiv:1112.2972.
12. Y.Chen, G.Lan, Y.Ouyang, and W.Zhang, Fast Bundle-Level Type Methods for Unconstrained and Ball-constrained Convex Optimization, http://arxiv.org/submit/1131766.
13. C. I. Fabian, Bundle-type methods for inexact data. Central European Journal of Operations Research, 8(1), 2000.

Meeting Time and Rooms:

- MWF 5 at LIT 233
- *Office Hours:* MWF 4 or by appointment

Objective and Description of the Course:

The objective of this course is to introduce several popular classes of the first order methods for solving large scale convex optimization problems arising from image analysis, machine learning, neuron network computing, and related data analysis problems. In this course, we will review Nesterov's fast gradient methods for smooth convex optimizations and Nesterov's smoothing techniques for non-smooth optimizations. Then, we will study the generations of Nesterov's for minimizing composite convex functions and some recently developed accelerated first order methods that adopted the main idea of the Nesterov's fast gradient methods. They are the accelerated primal dual method for solving a class of saddle point problems; the accelerated alternating direction method of multipliers (ADMM) for solving certain classes of convex optimization problems with equality constrains; the accelerated bundle level (BL) type methods for solving certain classes of smooth and non-smooth, constrained and unconstrained convex optimization problems. The iteration complexities of those algorithms will be analyzed, and some methods to improve their practical performance will be introduced, such as the backtracking and gradient sliding techniques. Moreover, we will study the ADMM and accelerated ADMM in distributed optimization. Students are expected to gain knowledge on mathematical theories, methods, and practical experience in solving convex optimization problems with applications to data analysis problems.

Arrangement of the course:

- Unit 1: Nesterov's Optimal Gradient Methods (Tentatively weeks 1-4):

  1. Optimal gradient methods for minimizing smooth convex functions;

  2. Smoothing techniques for minimizing non-smooth convex functions;

  3. Generalization of Nesterov's accelerated gradient methods for minimizing a class of composite convex functions consisting of a smooth function and a simple non-smooth function, such as the fast iterative shrinkage/thresholding algorithm (FISTA);

  4. Backtracking variants of the FISTA to improve practical performance.

- Unit 2: Bundle Level Type Methods (Tentatively weeks 5-9)

  1. Bundle level type methods and
  accelerated bundle level methods: schemes, iteration complexity analysis;

  2. Fast accelerated bundle level method and its variants for solving unconstrained convex optimization problems: schemes, iteration complexity analysis, comparisons and applications;

  3. Fast accelerated bundle level method for solving a class of constrained convex optimization problems: scheme, iteration complexity analysis;

  4. Gradient sliding method for fast accelerated bundle level method for minimizing a class of composite convex functions consisting of a smooth function and a non-smooth function.

- Unit 3: Alternating Direction Method of Multiplies (ADMM) and Accelerated ADMM (AADMM) for distributed optimization (Tentatively weeks 10-13)

1. ADMM and AADMM: schemes, and convergence analysis;

2. Deterministic and stochastic
AADMM in distributed optimization;

3. General form consensus optimization and sharing;

4. Comparisons with FISTA based distributed optimization methods.

- Unit 4: Applications of the fast first order methods in large scale data analysis (Tentatively weeks 14-16)

1. Applications in imaging.

2. Applications in neuron network computing.

3. Applications in machine learning.

Grading:
Students will be required to present one to two papers and the projects related to the course content. These projects may be related to problems of particular interest to the individual student. Grades will be assigned on the basis of the presentations or projects. Current UF grading policies can be found from the following link http://www.registrar.ufl.edu/catalog/policies/regulationgrades.html

Teaching Evaluation:
Students are expected to provide feedback on the quality of instruction in this course based on 10 criteria. These evaluations are conducted online at https://evaluations.ufl.edu.

Academic Honesty*:*
The course will be conducted in accordance with the University honor code and academic honesty policy, which can be found in the student guide

Accommodation for Student with Disabilities:
Students requesting classroom accommodation must first register with the Dean of Students Office. The Dean of Students Office will provide documentation to the student who must then provide this documentation to the Instructor when requesting accommodation.

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