



MAP7436/182A—Seminar in Applied Mathematics

Models and Convex Optimization Techniques in Data Analysis

Objective and Description of the Course:

The objective of this course is to continue our study on models and related accelerated first order methods for solving large scale convex optimization problems arising from image analysis, machine learning and neuron network computing. In this course, we will focus on the following topics. (1) Deterministic and stochastic or randomized primal dual gradient methods for a class of saddle point problems; (2). Deterministic and stochastic accelerated alternating direction method of multipliers (AADM) for equality constrained convex optimization; (3). Gradient sliding algorithm associated with fast and accelerated bundle level method for a class of composite convex optimization problems. (4). Models and algorithms for sparse convolutional network computing; (5). Models and algorithms for dynamical networks: linear model and models for information propagation. We will study the iteration complexities and practical performance of aforementioned algorithms and their applications. Students are expected to gain knowledge on mathematical theories, methods, and practical experience in solving convex optimization problems with applications to data analysis problems.

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 $O(1/k^2)$. *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. A. Chambolle and T. Pock. A first-order primal-dual algorithm for convex problems with applications to imaging. *J. Math. Imaging Vision*, 40, (2011), 120–145.
 8. 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.
 9. G. Lan and Y. Zhou, An Optimal Randomized Incremental Gradient Method, Technical Report, Department of Industrial and Systems Engineering, University of Florida, July 7.
 10. 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.
 11. 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.
 12. D. Jakovetic, J. Xavier, J. M. F. Moura, Fast Distributed Gradient Methods, [arXiv.org > cs > arXiv:1112.2972](https://arxiv.org/abs/1112.2972).
 13. 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>.
 14. Modeling Information Propagation with Survival Theory, cs.stanford.edu/people/jure/pubs/survival-icml13.pdf.
 15. Mason A. Porter, James P. Gleeson, Dynamical Systems on Networks: A Tutorial, [arXiv:1403.7663](https://arxiv.org/abs/1403.7663).
 16. Vardan Papyan, Jeremias Sulam, Michael Elad, Working Locally Thinking Globally – Part I: Theoretical Guarantees for Convolutional Sparse Coding, [arXiv:1607.02005v1](https://arxiv.org/abs/1607.02005v1)
 17. Vardan Papyan, Jeremias Sulam, Michael Elad, Working Locally Thinking Globally – Part II: Stability and Algorithms for Convolutional Sparse Coding, [arXiv.org > cs > arXiv:1607.02009](https://arxiv.org/abs/1607.02009).

Meeting Time and Rooms:

- MWF 5 at LIT 239
- Office Hours: MWF 4 or by appointment

Arrangement of the course::

- Unit 1: Accelerated methods for a class of saddle point problems (Tentatively weeks 1-5):
 1. Chambolle and T. Pock's united primal dual algorithm in reference 7;
 2. Nesterov's smoothing techniques for minimizing non-smooth convex functions in reference 4;
 3. The accelerated primal dual algorithm in reference 8;
 4. The optimal primal dual method and randomized primal dual method in reference 9.

- Unit 2: Bundle level type methods (Tentatively weeks 6-7)
 1. Fast and accelerated prox level (FAPL) method and fast uniform smooth level (FUSL) method for solving ball constrained and unconstrained convex optimization problems and a class of saddle point problems: schemes, iteration complexity analysis and applications;
 2. Gradient sliding methods associated with FAPL/FUSL for convex composite problems.
- Unit 3: Deterministic and stochastic accelerated alternating direction method of multipliers (AADMM) and AADMM type methods for distributed optimization (Tentatively weeks 8-9)
 1. Deterministic AADMM with backtracking schemes, scheme and convergence analysis;
 2. stochastic AADMM scheme and convergence analysis;
 3. AADMM type methods for distributed computing;
- Unit 4: Convolutional sparse coding (Tentatively weeks 10-13)
 1. Models for convolutional sparse coding and multi-layer convolutional sparse coding.
 2. Accelerated algorithms for convolutional sparse coding.
- Unit 5: Models and algorithms for dynamical networks (Tentatively weeks 14-16)
 1. Models and algorithms for constrained linear dynamical networks.
 2. Models and algorithms for information propagation dynamical networks.

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.

