AMSI
AUSTRALIAN MATHEMATICAL SCIENCES INSTITUTE

ACE Network Subject Information Guide

Methods and Theory of Modern Optimisation

Semester 2, 2019

Administration and contact details

Host Department	Mathematical Sciences, School of Science
Host Institution	RMIT University
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Subject details

Handbook entry URL	NA
Subject homepage URL	TBA
Honours student hand-out URL	NA
Start date:	TBA (likely the week of 22 July)
End date:	TBA (likely the week of 20th October)
Contact hours per week:	3hours
Lecture day and time:	TBA
Description of electronic access arrangements for students (for example, WebCT)	Will be via a dedicate web page on the RMITOpt website (only accessible to students)

Subject content

1. Subject content description

Nonlinear optimisation is the arguably the backbone of data science, where it finds application in the training of deep learning architectures. This problem involves the use of data sets to train a neural network before deployment. From the perspective of mathematical optimisation, this involves the application of an algorithm known as stochastic gradient descent, which itself is a version of the classical gradient descent method. A renewed interest in first order gradient based convex optimisation has arisen out of the study of this and similar problems. The nonsmooth version arises in other problems found in Machine learning such as the regularised risk minimisation with binary hinge loss. In the area signal process similar nonsmooth problems are faced when recovering corrupted signals with sparce support (compressed sensing). Moreover, the general area of optimisation under uncertainty also draws its techniques from the same well with methods used to solve stochastic optimisation problems exploiting decomposition methods, to create parallel programming approaches based on constrained convex optimisation, the so call alternating direction method of multipliers (ADMM). Other feasibility methods based on projection-based methods also can be viewed as arising out of special cases of these general methods.

In the course we will take a modern view point of the study of these and related problems and algorithms used to solve them. You will be introduced to the language of convex and nonsmooth optimisation and shown how this powerful mathematical machinery allows one to analyses optimisation problems and develop algorithms for the solution of these problems. We will study the application of ADMM to various problem sets including stochastic optimisation and feasibility problems. The ability to apply these techniques within the hyperspace of symmetric matrices allows the same methods to be applicable to a wider class of problems and this aspect will also be explored.

Ultimately, we will look at the use of these techniques to some of the areas of application discussed above. Depending on the background of the student, scope is available in this course for projects involving theoretical work and\or more practical work involving the coding of methods.

2. Week-by-week topic overview

Week 1: Convexity Preserving Operations, inner product spaces, symmetric matrices and Frobenius norm.
Week 2: Supports, Separation, relative interior and Subdifferentiability
Week 3: Fenchel Conjugate, Fenchel duality and Application in Optimization
Week 4: Lagrangian Duality and Penalty methods
Week 5: Introduction to Positive Semi-Definite problems.
Week 6: Simple subgradient methods, step size for methods and convergence
Week 7: Using subgradient methods in LPs and LR. Improvements when we have a gradient.
Week 8: The method of multipliers and alternating direction method of multipliers (ADMM).
Week 9: Using ADMM: Linear and Quadratic Programming Convex optimisation and Alternating Projections.
Week 10: Stochastic optimisation. Feasibility problems i.e. matrix completion
Week 11: Applications in Machine learning
Week 12: Inverse problems and Compressed sensing

3. Assumed prerequisite knowledge and capabilities

Necessary: Any under graduate courses in real analysis, basic vector calculus and linear algebra.
Desirable: Familiarity with a computer programming language like Matlab or Julia.

4. Learning outcomes and objectives

On completion of this course student should have gained:

1. Knowledge of advanced mathematical techniques in convex optimisation
2. The ability to reformulate problems and identify and\or develop numerical algorithms for the solution of these problems
3. Exposure to important classes of real work problems in areas like machine learning and signal processing.

AQF specific Program Learning Outcomes and Learning Outcome Descriptors (if available):

AQF Program Learning Outcomes addressed in this subject	Associated AQF Learning Outcome Descriptors for this subject
Problem Solving - You will have the ability to apply knowledge and skill to characterise, analyse and solve a wide range of problems.	**S1: cognitive skills to review, analyse, consolidate and synthesise knowledge to identify and provide solutions to complex problem with intellectual independence** **S2: cognitive and technical skills to demonstrate a broad understanding of a body of knowledge and theoretical concepts with advanced understanding in some areas** **A2: to adapt knowledge and skills in diverse contexts**

5. Learning resources

Insert texts, printed notes and/or software required
Students will be provided with a full set of lecture notes will be provided that are typeset in Latex. Preferred computing platforms include Matlab, Julia and Python.

6. Assessment

Exam/assignment/classwork breakdown					
Exam	50%	**Assignment**	50%	**Class work**	NA
Assignment due dates		TBA.	TBA	TBA	TBA.

Approximate exam date	Week of 5th November

Institution Honours program details

Weight of subject in total honours assessment at host department	**12.5%**
Thesis/subject split at host department	**25% thesis/75% course work**
Honours grade ranges at host department:	
H1	**80-100 %**
H2a	**75-79 %**
H2b	**70-74 %**
H3	**65-69 %**