# SDSC2002: CONVEX OPTIMIZATION

#### **Effective Term**

Semester A 2024/25

# Part I Course Overview

#### **Course Title**

Convex Optimization

### **Subject Code**

SDSC - Data Science

#### Course Number

2002

#### **Academic Unit**

Data Science (DS)

#### College/School

College of Computing (CC)

#### **Course Duration**

One Semester

### **Credit Units**

3

#### Level

B1, B2, B3, B4 - Bachelor's Degree

### **Medium of Instruction**

English

### **Medium of Assessment**

English

### **Prerequisites**

MA1503 Linear Algebra with Applications or MA2503 Linear Algebra and MA2508 Multi-variable Calculus

### **Precursors**

Nil

### **Equivalent Courses**

Nil

### **Exclusive Courses**

Nil

# Part II Course Details

#### **Abstract**

This is a fundamental and introductory course on optimization theory and introduces basic concepts, theories and methods of optimization techniques. It emphasizes the fundamental theories of important optimization algorithms with a focus on

applications to data science. It also equips students with computing algorithms and techniques of applying taught methods to solve practical problems.

### **Course Intended Learning Outcomes (CILOs)**

	CILOs	Weighting (if app.)	DEC-A1	DEC-A2	DEC-A3
1	Explain clearly basic concepts of convex optimization.	10	X		
2	Solve problems of convex optimization with fundamental methods by characterizing and identifying the properties of the solutions.	25	X	X	
3	Explain and apply the math theories of convex optimization without or with constraints.	25	X	X	
4	Explain the derivation and development of classic modern optimization algorithms and discuss distinctive properties of different methods.	20		Х	X
5	Apply mathematical and computational methods of optimization to solving reallife problems in context of data science and machine learning.	20		Х	X

#### A1: Attitude

Develop an attitude of discovery/innovation/creativity, as demonstrated by students possessing a strong sense of curiosity, asking questions actively, challenging assumptions or engaging in inquiry together with teachers.

### A2: Ability

Develop the ability/skill needed to discover/innovate/create, as demonstrated by students possessing critical thinking skills to assess ideas, acquiring research skills, synthesizing knowledge across disciplines or applying academic knowledge to real-life problems.

#### A3: Accomplishments

Demonstrate accomplishment of discovery/innovation/creativity through producing /constructing creative works/new artefacts, effective solutions to real-life problems or new processes.

### Learning and Teaching Activities (LTAs)

	LTAs	<b>Brief Description</b>	CILO No.	Hours/week (if applicable)
I	Lecture	Students will engage in formal lectures and demonstrations in class to gain knowledge about the stochastic optimization theories and algorithms.	1, 2, 3, 4, 5	33 hours in total
2	Take-home assignments	Students will complete the assigned problems to understand techniques of basic methods as well as their applications in solving optimization problems.	1, 2, 3, 4	after-class

3	Online applications	Students will engage	2, 3, 4, 5	6 hours in-class
		in tutorial sessions to		
		extend their knowledge		
		and apply the knowledge		
		to solving exercises of		
		optimizations		

### Assessment Tasks / Activities (ATs)

	ATs	CILO No.	Weighting (%)	Remarks (e.g. Parameter for GenAI use)
1	Test and quiz	1, 2, 3	30	Questions are designed for the part of the course to see how well the students have learned basic concepts of methods in convex optimization and recognized their applications in solving optimization problems.
2	Hand-in assignments	1, 2, 3, 4, 5	10	These are skills based assessment to enable students to demonstrate the understanding of theories and the ability of applying optimization methods in a diversity of problems.
3	Formative take-home assignments	2, 3, 4, 5	0	The assignments provide students chances to demonstrate their achievements on techniques of optimization learned in this course.

### Continuous Assessment (%)

40

### Examination (%)

60

### **Examination Duration (Hours)**

2

### **Additional Information for ATs**

Note: To pass the course, apart from obtaining a minimum of 40% in the overall mark, a student must also obtain a minimum mark of 30% in both continuous assessment and examination components.

### **Assessment Rubrics (AR)**

# **Assessment Task**

Test and quiz

### Criterion

### 4 SDSC2002: Convex Optimization

Ability to understand the basic concepts of methods in convex optimization and recognize their applications in solving optimization problems

Excellent (A+, A, A-)

High

Good (B+, B, B-)

Significant

Fair (C+, C, C-)

Moderate

Marginal (D)

Basic

Failure (F)

Not even reaching marginal levels

### **Assessment Task**

Hand-in assignments

### Criterion

Ability to apply the techniques of optimization methods in a diversity of problems

Excellent (A+, A, A-)

High

Good (B+, B, B-)

Significant

Fair (C+, C, C-)

Moderate

Marginal (D)

Basic

Failure (F)

Not even reaching marginal levels

#### **Assessment Task**

Examination

#### Criterion

Ability to solve optimization problems with fundamental methods in optimization.

Excellent (A+, A, A-)

High

Good (B+, B, B-)

Significant

Fair (C+, C, C-)

Moderate

Marginal (D)

Basic

Failure (F)

Not even reaching marginal levels

#### **Assessment Task**

Formative take-home assignments

#### Criterion

Ability to demonstrate students' achievements on techniques of optimization learned in this course

Excellent (A+, A, A-)

High

Good (B+, B, B-)

Significant

Fair (C+, C, C-)

Moderate

Marginal (D)

Basic

Failure (F)

Not even reaching marginal levels

# **Part III Other Information**

#### **Keyword Syllabus**

Review of elementary theory of (univariate and multivariate) functions, gradient, Hessian matrix, Taylor expansion and basics of numerical linear algebra (quadratic form, positive definite matrix, Lp norms);

Definitions and elementary properties of convex set and convex/concave function; strict convexity and strong convexity, examples of convex functions and log-convex functions;

Concepts in optimization theory: critical points, saddle points, local minima and global minima; local optimization and global optimization; convex/non-convex problem; constrained/unconstrained optimization;

Recognize a local minimum: first/second order necessary/sufficient condition for optimality; properties of solution to convex problem;

Examples of convex optimization problems: Least square problem in linear regression; loss function of logistic regression; Nonlinear programming algorithms: (1) gradient descent method; (2) Newton's method; (3) conjugate gradient method; Theory of convex optimization with (equality/inequality) constraints: feasible set, feasible direction, KKT conditions, KKT multiplier, Lagrangian multiplier, Lagrangian function;

Nonlinear programming algorithms with constraints: log barrier method, penalty method; method of Lagrangian multiplier;

Introductory use of one software for optimization (scipy. optimize or cvxpy).

#### **Reading List**

#### **Compulsory Readings**

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	Title
1	Lecture notes provided by the instructor

# **Additional Readings**

	Title
1	"Convex Optimization", by Stephen Boyd and Lieven Vandenberghe, Cambridge University Press, 2004"
2	Paul R. Thie, "An Introduction to Linear Programming and Game Theory", John Wiley & Sons, 1988.