MATHEMATICS FOR MACHINE LEARNING

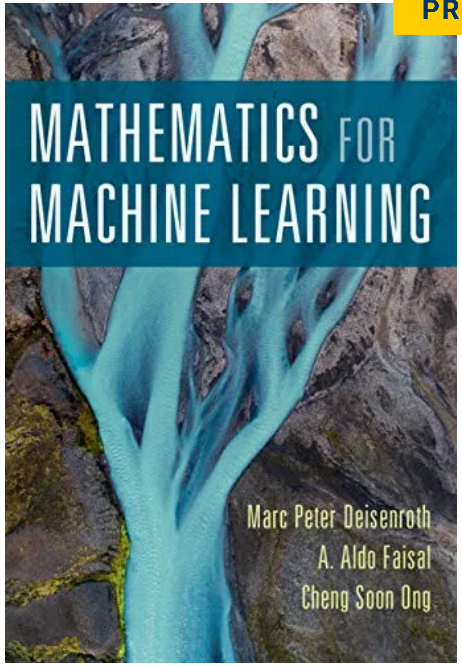
Lecture 1: Introduction

Prepared by: Mohammed Alneamri

University of Tabuk

TEXTBOOK AND REFERENCES

PRIMARY

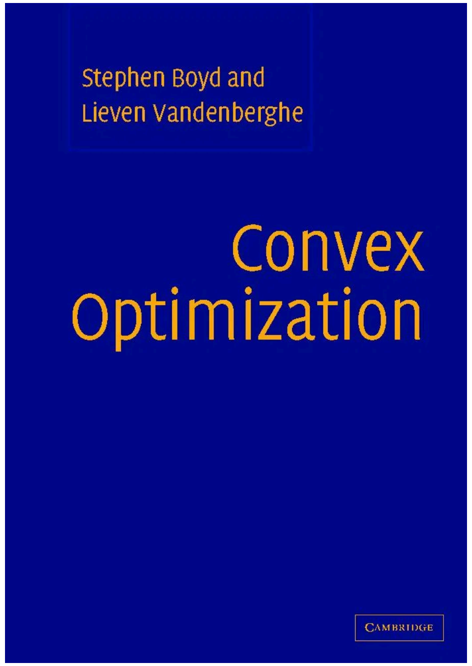


Mathematics for Machine Learning

Deisenroth, Faisal, and Ong

Cambridge University Press

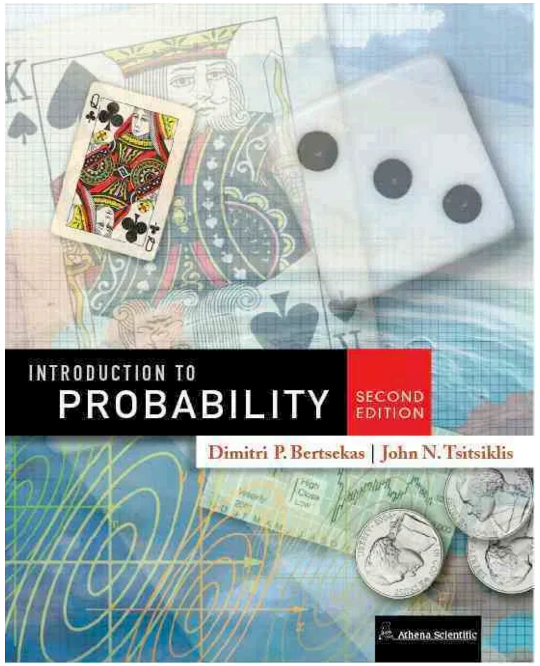
mml-book.github.io



Convex Optimization

Boyd and Vandenberghe

Cambridge University Press



Introduction to Probability

Bertsekas and Tsitsiklis

Athena Scientific (2nd Ed.)

COURSE ORGANIZATION

Part I: Mathematical Foundations

TOPIC 01

Linear Algebra

Vectors, matrices, and their operations form the computational foundation for all machine learning algorithms.

TOPIC 02

Analytic Geometry

Understanding geometric interpretations of algebraic concepts provides intuition for high-dimensional data.

TOPIC 03

Matrix Decomposition

Techniques like eigendecomposition and SVD reveal underlying structure in data and enable dimensionality reduction.

TOPIC 04

Vector Calculus

Gradients and optimization concepts are critical for training machine learning models.

TOPIC 05

Probability & Distributions

Probabilistic reasoning and statistical foundations underpin modern machine learning theory.

TOPIC 06

Optimization

Methods for finding optimal solutions are central to model training and parameter estimation.

COURSE ORGANIZATION

Part II: Machine Learning Applications

01 When Models Meet Data

Introduction to the practical aspects of applying mathematical models to real-world datasets and the challenges that arise.

02 Dimensionality Reduction

Using **Principal Component Analysis (PCA)** to reduce data complexity while preserving essential information for efficient learning.

03 Density Estimation

Probabilistic approaches to understanding data distributions and clustering using **Gaussian Mixture Models (GMM)**.

04 Classification

Geometric and optimization-based methods for supervised learning and decision boundary determination using **Support Vector Machines (SVM)**.

COURSE STRUCTURE & ASSESSMENT

6 Core Chapters (Focus)

1 **Linear Algebra**
Vectors, matrices, and operations

2 **Analytic Geometry**
Geometric interpretations

3 **Matrix Decomposition**
Eigendecomposition & SVD

4 **Vector Calculus**
Gradients & optimization

5 **Probability & Distributions**
Statistical foundations

6 **Optimization**
Model training & parameter estimation

Assessment Breakdown

Midterm Examination
20%

Final Examination
30%

Quizzes
40%
4-5 quizzes throughout course

Reading & Review Papers
10%
4-5 papers

Total Assessment
100%

TARGET AUDIENCE

UNDERGRADUATE LEVEL

Flexible Prerequisites

Students may enter with partial mathematical backgrounds (e.g., vector calculus and linear algebra). The course structure allows instructors to adjust the depth and pacing of mathematical topics based on cohort background.

Mathematical Rigor

Certain mathematical concepts are presented with rigorous proofs to develop deeper understanding and mathematical maturity.

Customizable Depth

Depending on the specific student population, the proportion of time devoted to mathematical foundations versus applications can be adjusted to optimize learning outcomes.

COURSE ADAPTABILITY

Graduate Level

Graduate students bring different preparation and learning objectives to the course:

Assumed Background

Typically completed foundational courses in linear algebra, vector calculus, probability, and optimization, allowing for efficient review rather than initial instruction.

Machine Learning Focus

Generally lack substantial machine learning experience, making the application-focused second half of the course particularly valuable.

Streamlined Math

Mathematical topics are reviewed with minimal proofs, emphasizing intuition and application over derivation.

Extended Applications

Enriched with additional machine learning problems and case studies to provide deeper exposure to practical ML challenges.

LECTURE STRUCTURE: THREE-PART APPROACH

PART 1

Concepts & Explanation

Theoretical foundations and intuitive understanding of the topic.

- Key definitions
- Conceptual framework
- Intuitive explanations
- Real-world context

PART 2

Mathematical Examples & Tutorials

Hands-on mathematical work with students through guided examples.

- Worked examples
- Step-by-step solutions
- Interactive tutorials
- Mathematical derivations

PART 3

Python Implementation

Practical coding examples implementing concepts from the lecture.

- Code examples
- Implementation details
- Practical applications
- Coding exercises

INSTRUCTOR & COURSE INFORMATION

About the Instructor

INSTRUCTOR

Mohammed Alneamri

TEACHING APPROACH

- Part 1: Concepts & Explanation
- Part 2: Mathematical Examples & Tutorials
- Part 3: Python Implementation

PHILOSOPHY

Building strong mathematical foundations combined with practical coding skills to prepare students for real-world machine learning applications.

Office Hours & Contact

OFFICE HOURS

Monday & Wednesday

10:00 AM – 12:00 PM

BY APPOINTMENT

To schedule a meeting outside regular office hours, please contact via email.

EMAIL

yiyung@gmail.com

COURSE WEBSITE

ut.edu.sa/mathml

NOTATION CONVENTIONS

SCALARS

$a, b, c, \alpha, \beta, \gamma$

VECTORS

$\mathbf{x}, \mathbf{y}, \mathbf{z}$

MATRICES

$\mathbf{X}, \mathbf{Y}, \mathbf{Z}$

SETS

A, B, C

ORDERED TUPLES

$B = (b_1, b_2, b_3)$

MATRIX OF COLUMNS

$\mathbf{B} = [\mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3]$

NUMBER SYSTEMS

$\mathbb{R}, \mathbb{C}, \mathbb{Z}, \mathbb{N}, \mathbb{R}^n$

PROBABILITY

$p(\cdot), \mathrm{P}[\cdot]$

ENJOY!

Your Learning Journey

Welcome to Mathematics for Machine Learning.
Building the foundation for your future algorithms.

QUESTIONS & SUPPORT

mnemari@gmail.com

Part of this material is adapted from the course by Yi, Yung (KAIST EE).