

CIS 5150

Fundamentals of Linear Algebra and Optimization

Syllabus

- (1) Vector Spaces, Bases, Linear Maps
 - (a) Groups, Rings, Fields and Vector Spaces
 - (b) Indexed Families
 - (c) Linear Combinations and Linear Independence
 - (d) Linear Subspaces
 - (e) Bases, the Replacement Lemma
 - (f) Matrices
 - (g) Linear Maps, Kernels, Images, Isomorphisms
- (2) Matrices and Linear Maps
 - (a) Matrix Representation of Linear Maps
 - (b) Change of Basis Matrix
 - (c) Direct Products and Direct Sums
 - (d) Multiplication by Blocks
 - (e) The Rank–Nullity Theorem and Applications
 - (f) Grassmann’s Relation
 - (g) Affine Maps
- (3) Haar Bases and Haar Wavelets
 - (a) Signal Compression
 - (b) Haar Matrices, Haar Wavelets
 - (c) Digital Signal Resolution
- (4) Determinants
 - (a) Alternating Multilinear Maps and Determinants
 - (b) Calculating Determinants via Laplace Expansion
 - (c) Invertibility and Linear Independence
 - (d) The Cayley–Hamilton Theorem

- (5) Vector Norms and Matrix Norms
 - (a) Normed Vector Spaces
 - (b) Matrix Norms
 - (c) Subordinate Norms
 - (d) Condition Number
- (6) Solving Systems of Linear Equations
 - (a) Gaussian Elimination
 - (b) LU-Factorization
 - (c) LU-PA-Factorization
 - (d) SPD Matrices and Cholesky Decomposition
 - (e) Reduced Row Echelon Form (RREF)
- (7) The Dual Space and Duality
 - (a) The Dual Space E^* and Linear Forms
 - (b) Pairing and Duality Between E and E^*
 - (c) The Bidual and Canonical Pairing
 - (d) Hyperplanes and Linear Forms
 - (e) Transpose of a Linear Map and of a Matrix
 - (f) The Four Fundamental Spaces
- (8) Euclidean and Hermitian Spaces
 - (a) Inner Products, Cauchy-Schwarz Inequality
 - (b) Orthogonality and Duality
 - (c) Adjoint of a Linear Map
 - (d) Construction of Orthonormal Bases; Gram–Schmidt Orthonormalization Procedure
 - (e) Linear Isometries and the Orthogonal Group
 - (f) Orthogonal Matrices and QR-Decomposition
 - (g) Hermitian Spaces and Unitary Transformations
- (9) Eigenvalues, Eigenvectors and the Spectral Theorems
 - (a) Eigenvalues and Eigenvectors
 - (b) Triangular Form (Schur Form)

- (c) Location of Eigenvalues (The Gershgorin Discs)
 - (d) Normal Linear Maps
 - (e) Spectral Theorem for Normal Linear Maps
 - (f) Spectral Theorem for Self-Adjoint, Skew-Adjoint and Orthogonal Linear Maps
 - (g) Matrix Versions of the Spectral Theorems
 - (h) Rayleigh Ratio, Rayley–Ritz Theorem
- (10) Singular Value Decomposition
- (a) Properties of $A^T A$ and AA^T
 - (b) SVD for Square Matrices
 - (c) Polar Form
 - (d) SVD for Rectangular Matrices
- (11) Applications of SVD
- (a) Least Squares and the Pseudo-Inverse
 - (b) Properties of the Pseudo-Inverse
 - (c) Data compression; Best Rank k Approximation.
 - (d) Principal Component Analysis (PCA)
 - (e) Best Affine Approximation
- (12) Derivatives
- (a) Open Sets and Continuity in Metric Spaces and Normed Spaces
 - (b) Limits and Continuity; Uniform Continuity
 - (c) Continuous Linear Maps and Continuous Multilinear Maps
 - (d) Directional Derivatives and Total Derivatives
 - (e) Jacobian Matrices
 - (f) Lagrange Multiplier Technique
- (13) Quadratic Optimization Problems
- (a) Unconstrained Positive Definite Optimization
 - (b) Constrained Positive Definite Optimization
 - (c) General Quadratic Optimization
 - (d) Maximizing a Quadratic Function on the Unit Sphere
- (14) Introduction to Nonlinear Optimization

- (a) Optimization Terminology
 - (b) Convex Sets and Convex Functions
 - (c) Active Constraints, Qualified Constraints
 - (d) KKT Conditions
 - (e) Duality
 - (f) Equality Constraints
 - (g) Hard Margin SVM (Support Vector Machine)
- (15) Soft Margin Support Vector Machine
- (a) Formulation of ν -Soft Margin SVM as an Optimization Problem
 - (b) Classification of Data Points
 - (c) Solving SVM Using ADMM
- (16) Regression
- (a) Ridge Regression; Learning a Linear Function
 - (b) Ridge Regression; Learning an Affine Function
 - (c) Lasso Regression; Learning a Linear Function
 - (d) Lasso Regression; Learning an Affine Function
 - (e) Elastic Net Regression; Learning an Affine Function
- (17) Introduction to Deep Learning
- (a) Deep Neural Nets
 - (b) Stochastic Gradient Descent
 - (c) Back Propagation and the Chain Rule
 - (d) Convolutional Neural Networks