Lecture 1: Basic formulation of LP, hyperplane, half-space, affine set, polyhedron, lineality space, pointed polyhedron

Lecture 2: Face, minimal face, extreme point, vertex, basic feasible solution, active constraints, rank test for an extreme point

Lecture 3: Extreme points and optimality, Theorem of alternatives

Lecture 4: Farkas' Lemma (statement, proof, and geometric interpretation), Different forms of LP.

Lecture 5: Dual problems for LPs, Weak duality and strong duality for LPs Part I

Lecture 6: Strong duality Part II, examples of dual problems, complementary slackness

Lecture 7: Strict complementary, Geometric interpretation of complementary slackness, introduction of Max Flow and Min Cut problems

Lecture 8: Totally UniModular (TUM) matrices, Proving Max Flow = Min Cut by using strong duality of LPs.

Lecture 9: Convex set definition, examples of convex sets and proving their convexity (convex cone, hyperplane, polyhedron, ball, ellipsoid, norm cone, …)

Lecture 10: Operations that preserve convexity for sets, convex function (zeroth-order definition)

Lecture 11: Convex functions (1st- and 2nd-order definitions) and their properties

Lecture 12: Operations that preserve convexity for functions, conjugate function and its properties

Lecture 13: Quasi-convex and log-concave functions

Lecture 14: Convex programs, local min, global min, optimality conditions (constrained & unconstrained)

Lecture 15: Quasi-convex optimization, linear-fractional program, quadratic optimization, QCQP

Lecture 16: SOCP, Robust Linear Programming, Geometric Programming (GP)

Lecture 17: SDP, Schur complement, and connection between SOCP and SDP

Lecture 18: Lagrangian, dual function, dual problem, connection between dual function and conjugate function

Lecture 19: Weak and strong duality, Slater's condition, complementary slackness, KKT conditions

Lecture 20: Solving primal problem via its dual problem, Dual of SOCP, Dual of SDP

Lecture 21: Approximation & fitting (Norm approximation, Least-norm problems, Regularized approximation, Robust approximation) [Chapter 6]

Lecture 22: Maximum Likelihood Estimation, experiment design [Chapter 7]

Lecture 23: Classification, linear classification, SVMs [Chapter 8]

Lecture 24: Strong convexity, smoothness, their inequalities

Lecture 25: Gradient Descent, Convergence of gradient descent (GD) for smooth and strongly convex functions, convergence of GD for smooth (possibly nonconvex functions)

Lecture 26: Convergence of GD with exact line-search, Convergence of GD with backtracking line-search

Lecture 27: Newton's methods and its convergence properties