# 3.4 CONVEX OPTIMIZATION

# **Convexity**

Convex set:  $C \subset \mathbf{R}^n$  is convex if

$$
x, y \in C, \quad \lambda \in [0, 1] \quad \Rightarrow \quad \lambda x + (1 - \lambda)y \in C
$$



Convex Functions:  $f : \mathbf{R}^n \to \mathbf{R}$  is convex if

$$
x, y \in \mathbf{R}^{n}, \quad \lambda \in [0, 1]
$$

$$
f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)
$$



# Convexity (Continued)



Notice that  $\{x : g(x) \le 0\}$  is convex if g is convex.

Theorem: If  $f$  and  $g$  are convex any local optimum is globally optimal.

### Linear Programs

$$
\min_{x \in \mathbf{R}^n} a^T x
$$

subject to

 $Bx \leq b$ 

Linear program is a convex program.

Feasible basic solution: feasible solution that satisfies  $n$  of the constraints as equalities.

Fact: If an optimal solution exists, there exists a feasible basic solution that is optimal.



# Quadratic Programs

$$
\min_{x \in \mathbf{R}^n} \frac{1}{2} x^T H x + g^T x
$$

subject to

 $Ax \leq b$ 



Quadratic program is convex if  $H$  is positive semi-definite.

#### **ALGORITMS FOR CONSTRAINED** 3.5 OPTIMIZATION PROBLEMS

### Algorithms for Linear Program

Simplex Method

Motivation: There always exists a basic optimal solution.

Main Idea:

- Find a basic solution.
- $\bullet$  Find another basic solution with lower cost function value.
- $\bullet$  Continue until another basic solution with lower cost function value cannot be found.

Simplex algorithm always finds a basic optimal solution.

# Algorithms for Linear Program (Continued)

Interior Point Method

Main Idea:

• Define barrier function:

$$
B=-\sum_{i=1}^m\frac{1}{c_i^Tx-b_i}
$$

Form the unconstrained problem:

$$
\min_x a^T x + \frac{1}{K} B(x)
$$

- $\bullet$  Solve the unconstrained problem using Newton method.
- $\bullet$  Increase  $K$  and solve the unconstrained problem again until the solution converges.
- $\bullet$  Kemarkably, problems seem to converge between 5 to 50  $\,$ Newton steps regerdless of the problem size.
- $\bullet$  Can exploit structures of the problem (e.g. sparsity) to reduce computation time per Newton step.
- $\bullet$  Can be extended to general nonlinear convex problems such as quadratic programs.

# Algorithms for Quadratic Program

Active Set Method

Main Idea:

- $\bullet$  Determine the active constraints and set them as equality constraints.
- $\bullet$  Solve the resulting problem.
- $\bullet$  Check the Kuhn-Tucker condition that is also suffucuent for QP.
- $\bullet$  If Kuhn-Tucker condition is not satisfied, try another set of active constraints.

Interior Point Method

 $\bullet$  The main idea of interior point method for QP is the same as that for LP.

# Generalized Reduced Gradient Method for Constrained Nonlinear Programs

Main idea:

- 1. Linearize the equality constraints that are possibly obtained adding slack variables
- 2. Solve the resulting linear equations for  $m$  variables
- 3. Apply the steepest descent method with respect to  $n m$ variables

Linearization of Constraints:

$$
\nabla_y h(y, z) dy + \lambda^T \nabla_z h(y, z) dz = 0
$$
  

$$
\Downarrow
$$
  

$$
dy = -[\nabla_y h(y, z)]^{-1} \lambda^T \nabla_z h(y, z) dz
$$

Generalized Reduced Gradient of Objective Function:

$$
df(y, z) = \nabla_y f(y, z) dy + \lambda^T \nabla_z f(y, z) dz
$$

$$
= [\lambda^T \nabla_z f(y, z) - \nabla_y f(y, z) [\nabla_y h(y, z)]^{-1} \lambda^T \nabla_z h(y, z)] dz
$$

$$
\Downarrow
$$

$$
r = \frac{df}{dz} = \lambda^T \nabla_z f(y, z) - \nabla_y f(y, z) [\nabla_y h(y, z)]^{-1} \lambda^T \nabla_z h(y, z)
$$

#### Penalty Method for Constrained Nonlinear Programs

Main idea: Instead of forcing the constraints, penalize the violation of the constraints in the objective.

$$
\min_x f(x) - c_k g(x) = (P_k)
$$

where  $c_k > 0$ .

Theorem: Let  $x_k$  be the optimal solution of  $(P_k)$ . Then as  $c_k \to \infty$ ,  $x_k \rightarrow x^*$ .



# Successive QP Method

## for Constrained Nonlinear Programs

Main idea:

- 1. Approximate the ob ject function by quadradic function and constraints linear function.
- 2. Solve the resulting quadratic problem

Approximate Quadratic Program:

$$
\min \nabla f dx + \frac{1}{2} dx^T \nabla^2 f dx
$$

sub ject to

$$
g(x) + \nabla g(x) dx \le 0
$$



# Nonconvex Programs

The aforementioned optimization algorithms indentify only one local optimum.

However, a nonconvex optimization problem may have a number of local optima.



 $\downarrow$ 

Algorithms that indentifies a global optimum are necessary

# A Global Optimization Algorithm for Noconvex Programs

Branch and bound type global optimization algorithm:



- $\bullet$  Branching Step: split the box at the optimum
- $\bullet$  Bounding Step: find the box where the optimum is lowest  $\hspace{0.1mm}$