

# Augmented Lagrangian Tutorial

## Canonical problem

$$\min_x f(x)$$

$$\text{s.t. } c(x) = 0$$

$$h(x) \leq 0$$

## our QP

$$\min_x \frac{1}{2} x^T Q x + g^T x$$

$$\text{s.t. } Ax - b = 0$$

$$Cx - d \leq 0$$

## Lagrangian

$$L(x, \lambda, \mu) = f(x) + \lambda^T c(x) + \mu^T h(x)$$

## KKT conditions

$$\nabla_x L = \nabla_x f + \left(\frac{\partial c}{\partial x}\right)^T \lambda + \left(\frac{\partial h}{\partial x}\right)^T \mu = 0 \quad \text{Stationarity}$$

$$Ax - b = 0$$

$$Cx - d \leq 0$$

primal feasibility

any  $x, \lambda, \mu$  that satisfies

these is a globally optimal

(this is only true of convex problems)

$$\mu \geq 0$$

dual feasibility

$$\mu_i h_i(x) = 0$$

Complementarity

## Augmented Lagrangian

$$L_p(x, \lambda, \mu, \rho) = L(x, \lambda, \mu) + \frac{\rho}{2} c(x)^T c(x) + \frac{1}{2} h(x)^T I_p h(x)$$

$I_p$  is a diagonal matrix

$$\text{if } h_i(x) < 0 \quad \&\& \quad \mu_i = 0$$

$$I_p[i, i] = 0$$

else

$$I_p[i, i] = \rho$$

this is how we make sure to only penalize active inequality constraints

## AL alg

init  $x = 0, \lambda = 0, \mu = 0, \rho = 1$

Loop

① solve  $\min_x L_p(x, \lambda, \mu, \rho)$

w/ newton's method, update  $x$  w/ the solution

② update dual variables

$$\lambda = \lambda + \rho \ell(x)$$

$$\mu = \max(0, \mu + \rho \cdot h(x))$$

↑  
element-wise max (max.() in Julia)

Update penalty

③  $\rho = \rho \cdot \phi$

④ Check convergence (KKT conditions)