Optimization Theory and Algorithms

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Outline

- Equality constrained minimization
- Reduction to an unconstrained minimization
- Newton's method with equality constrained

Equality constrained minimization problem

min
$$f(x)$$

s.t. $Ax = b$

- *f* is convex and twice continuously differentiable
- Assume optimal point x^* exists. Let $p^* = f(x^*)$ be the optimal value.

Optimality condition (KKT conditions): x^* is optimal iff there exists a v^* such that

$$\nabla f(x^*) + A^T v^* = 0, \quad Ax^* = b$$

Solution methods:

- Elimination method
- Dual method
- Newton's method

reduce to an unconstrained minimization

Elimination equality constraints

$${x \mid Ax = b} = {Fz + x' \mid z \in \mathbb{R}^{n-p}}$$

- Rank(A)=p
- $F \in \mathbb{R}^{n \times (n-p)}$ is any matrix whose range is the nullspace of A.
- x' is any particular solution of Ax = b.

equality constrained minimization

$$\min_{x} f(x)$$

s.t. $Ax = b$



unconstrained minimization

$$\min_{\mathbf{z}} f(F\mathbf{z} + x')$$

Dual method

Primal problem

(equality constrained)

min
$$f(x)$$

s.t. $Ax = b$



Dual function:

$$g(v) = -b^T v + \min_{x} (f(x) + v^T Ax)$$

Dual problem

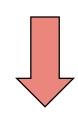
 $\max g(v)$

(unconstrained)

Newton's method with equality constraints

Newton's method with no constraints

$$\min_{\Delta x} f(x + \Delta x) \approx f(x) + \nabla f(x)^T \Delta x + \frac{1}{2} \Delta x^T \nabla^2 f(x) \Delta x$$



set the gradient to zero

$$\Delta x_{nt} = -\nabla^2 f(x)^{-1} \nabla f(x)$$

Newton's method with equality constraints

$$\min_{\Delta x} f(x + \Delta x) \approx f(x) + \nabla f(x)^T \Delta x + \frac{1}{2} \Delta x^T \nabla^2 f(x) \Delta x$$

s.t. $A(x + \Delta x) = b$



$$\nabla f(x) + \nabla^2 f(x) \Delta x_{nt} + A^T v^* = 0$$
$$A \Delta x_{nt} = 0$$



Newton's method with equality constraints

Newton's method with no constraints min f(x)

Optimality condition:

$$\nabla f(x^*) = 0$$

$$x^* = x + \Delta x_{nt}$$
Taylor approximation
$$\nabla f(x) + \nabla^2 f(x) \Delta x_{nt} = 0$$

 $\Delta x_{nt} = -\nabla^2 f(x)^{-1} \nabla f(x)$

Newton's method with equality constraints

min
$$f(x)$$

s.t. $Ax = b$

Optimality conditions (KKT conditions):

$$\nabla f(x^*) + A^T v^* = 0, \quad Ax^* = b$$

$$x^* = x + \Delta x_{nt}$$
Taylor approximation

$$\nabla f(x) + \nabla^2 f(x) \Delta x_{nt} + A^T v^* = 0, A(x + \Delta x_{nt}) = b$$



$$\nabla f(x) + \nabla^2 f(x) \Delta x_{nt} + A^T v^* = 0, \ A \Delta x_{nt} = 0$$



$$\begin{bmatrix} \nabla^2 f(x) & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} \Delta x \\ \nu \end{bmatrix} = \begin{bmatrix} -\nabla f(x) \\ 0 \end{bmatrix}$$

Newton's method with equality constraints

- Given a starting point $x \in \operatorname{dom} f$
- Repeat
- 1. Compute the *Newton step* and decrement:

$$\begin{bmatrix} \nabla^2 f(x) & A^T \\ A & 0 \end{bmatrix} \begin{bmatrix} \Delta x \\ v \end{bmatrix} = \begin{bmatrix} -\nabla f(x) \\ 0 \end{bmatrix} \qquad \lambda = \left(\nabla f(x)^T \nabla^2 f(x)^{-1} \nabla f(x) \right)^{1/2}$$

- 2. Stopping criterion: if $\lambda^2/2 \le \varepsilon$, break
- 3. Line search: choose a step size t via backtracking line search.
- 4. Update: $x \leftarrow x + t\Delta x_{nt}$