

Optimization Theory and Algorithms

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Outline

- General descent method
- Line search method
- Gradient descent method
- Newton's method

Unconstrained minimization problem

$$\begin{array}{ll}\min & f(x) \\ \text{s.t.} & x \in \mathbb{R}^n\end{array}$$

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

Necessary and sufficient condition of optimality:

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

- Special case: directly solve $\nabla f(x^*) = 0$ and obtain a closed-form solution
- General case: an iterative algorithm

A sequence of points $x^{(0)}, x^{(1)}, \dots \in \mathbf{dom} f$ with $f(x^{(k)}) \rightarrow p^*$ as $k \rightarrow \infty$

Examples

Convex quadratic minimization

$$\min f(x) = \frac{1}{2}x^T Qx + b^T x$$

Optimality condition: $\nabla f(x^*) = Qx^* + b = 0$

- Case 1: unique solution. $x^* = -Q^{-1}b$ (**closed-form** solution)
- Case 2: infinitely many solutions.
- Case 3: no solution, i.e., $\min f_0(x) = -\infty$.

Convex geometric programming

$$\min f(x) = \log \left(\sum_{i=1}^m \exp(a_i^T x + b_i) \right)$$

Optimality condition: $\nabla f(x^*) = \frac{1}{\sum_{j=1}^m \exp(a_j^T x^* + b_j)} \sum_{i=1}^m \exp(a_i^T x^* + b_i) a_i = 0$

No closed-form solution. Rely on an **iterative algorithm** to find the solution.

Descent methods

Minimizing sequence

$$x^{(k+1)} = x^{(k)} + t^{(k)} \Delta x^{(k)}, \quad k = 1, 2, \dots$$

- k is the iterative number
- $\Delta x^{(k)}$ is the step, or search direction at iteration k
- $t^{(k)}$ is the step size at iteration k
- $x^{(k+1)}$ is the output of iterative method at iteration k

Descent method:

$$f(x^{(k+1)}) < f(x^{(k)})$$

- For convex f , $f(x^{(k+1)}) < f(x^{(k)})$ implies $\nabla f(x^{(k)})^T \Delta x^{(k)} < 0$

Algorithm

- Given a starting point $x \in \text{dom } f$
- **Repeat**
 1. Determine a **descent direction** Δx
 2. *Line search*. Choose a **step size** t
 3. **Update** $x \leftarrow x + t\Delta x$
- Until stopping criterion is satisfied (convergence)



descent direction

Gradient descent method

Set descent direction as $\Delta x = -\nabla f(x)$

$$\nabla f(x)^T \Delta x = -\nabla f(x)^T \nabla f(x) < 0$$

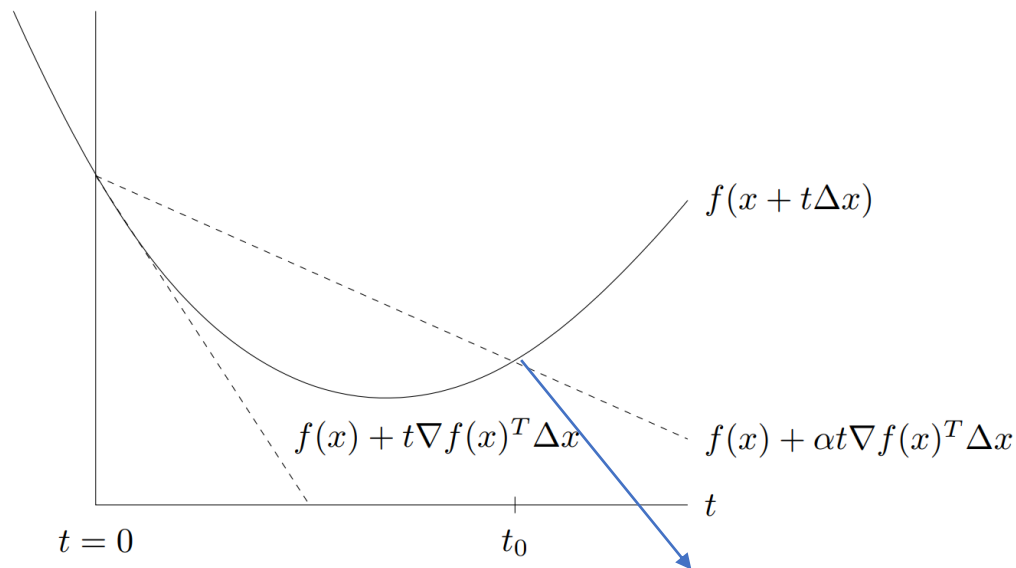
- Given a starting point $x \in \mathbf{dom} f$
- **Repeat**
 1. Determine a **descent direction**: $\Delta x = -\nabla f(x)$
 2. Line search. Choose a step size t .
 3. Update $x \leftarrow x - t\nabla f(x)$
- Until stopping criterion is satisfied (convergence)

Line search

Exact line search $t = \operatorname{argmin}_{s \geq 0} f(x + s\Delta x)$

Backtracking line search (inexact method)

- Given a descent direction Δx for f at $x \in \mathbf{dom} f$, $\alpha \in (0, 0.5)$, $\beta \in (0, 1)$
- $t = 1$
- While $f(x + t\Delta x) > f(x) + \alpha t \nabla f(x)^T \Delta x$:
 $t = \beta t$



Terminates when $f(x + t\Delta x) \leq f(x) + \alpha t \nabla f(x)^T \Delta x$

Gradient descent method

- Given a starting point $x \in \mathbf{dom} f$
- **Repeat**
 1. Determine a **descent direction**: $\Delta x = -\nabla f(x)$
 2. *Line search*. Choose a **step size** t via *exact line search* or *backtracking line search*.
 3. Update $x \leftarrow x - t\nabla f(x)$
- Until stopping criterion is satisfied (convergence)

Stopping criterion: $\|\nabla f(x)\|_2 \leq \varepsilon$ for small ε .

Interpretation of gradient descent

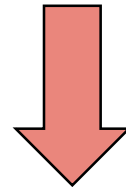
Quadratic approximation:

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



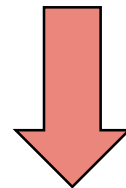
Replaced by $\frac{1}{t} I$

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



Set the gradient with respect to Δx as zero

$$\nabla f(x) + \frac{1}{t} \Delta x = 0$$



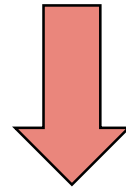
$$\Delta x = -t \nabla f(x)$$

The next point that minimizes quadratic approximation is $x + \Delta x = x - t \nabla f(x)$

Newton's method

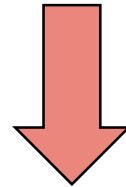
Minimize quadratic approximation:

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



Set the gradient with respect to Δx as zero

$$\nabla f(x) + \nabla^2 f(x) \Delta x = 0$$



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

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

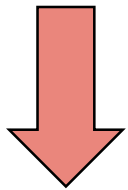
Newton's method

Interpretation: solution of linearized optimality condition

$$\begin{array}{ll}\min & f(x) \\ \text{s.t.} & x \in \mathbb{R}^n\end{array}$$

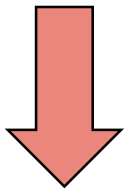
Optimality condition:

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

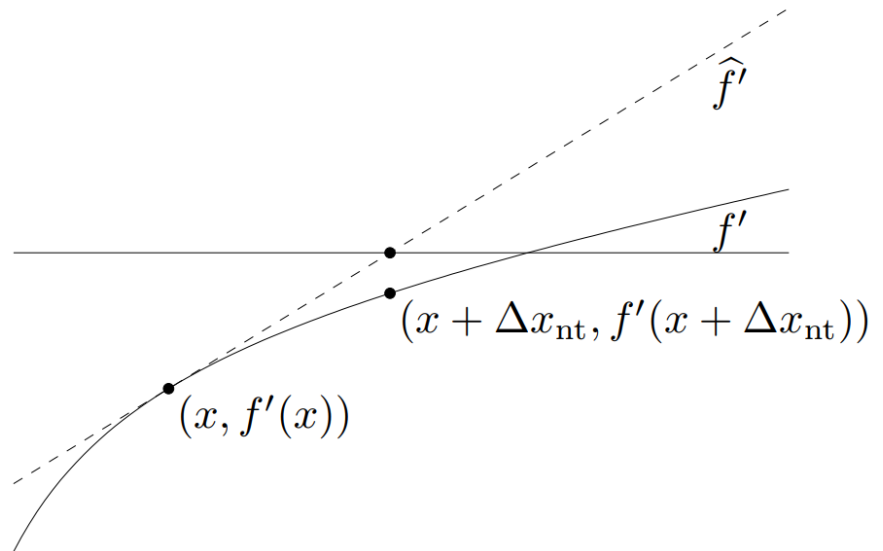


Taylor approximation

$$\nabla f(x + v) + \nabla^2 f(x)v = 0$$



$$v = -\nabla^2 f(x)^{-1} \nabla f(x)$$



Newton's method

- Given a starting point $x \in \mathbf{dom} f$
 - **Repeat**
 1. Compute the *Newton step* $\Delta x_{nt} = -\nabla^2 f(x)^{-1} \nabla f(x)$
 2. *Line search*. Choose a step size t via *backtracking line search*.
 3. Update $x \leftarrow x + t \Delta x_{nt}$
- Until stopping criterion is satisfied (convergence)



Rely on Newton decrement

Newton decrement: $\lambda(x) = (\nabla f(x)^T \nabla^2 f(x)^{-1} \nabla f(x))^{1/2}$

- Gives an estimate of $f(x) - p^*$, using quadratic approximation \hat{f}
$$f(x) - \left(f(x) + \nabla f(x)^T \Delta x_{nt} + \frac{1}{2} \Delta x_{nt}^T \nabla^2 f(x) \Delta x_{nt} \right) = \frac{1}{2} \lambda(x)^2$$



$$f(x) - p^* \approx \frac{1}{2} \lambda(x)^2$$

Newton's method

- Given a starting point $x \in \mathbf{dom} f$
- **Repeat**
 1. Compute the *Newton step* and decrement
$$\Delta x_{nt} = -\nabla^2 f(x)^{-1} \nabla f(x); \quad \lambda = \left(\nabla f(x)^T \nabla^2 f(x)^{-1} \nabla f(x) \right)^{1/2}$$
 2. **Stopping criterion:** if $\lambda^2/2 \leq \varepsilon$, break
 3. *Line search:* choose a step size t via *backtracking line search*.
 4. Update: $x \leftarrow x + t\Delta x_{nt}$

Drawback: high complexity of computing Hessian matrix

Solution: Quasi-Newton method