The Steepest Descent, Coordinate Search and the Newton-Raphson Method

Lecture 3, Continuous Optimisation

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We continue to consider the unconstrained minimisation problem

$$\min_{x \in \mathbb{R}^n} f(x).$$

In Lecture 2 we considered line-search descent methods:

Algorithm 1 Choose a starting point $x_0 \in \mathbb{R}^n$ and a tolerance parameter $\epsilon > 0$. Set $k = 0$.

S1 If $\|\nabla f(x_k)\| \leq \epsilon$ then stop and output x_k as an approximate minimiser.

S2 Choose a *search direction* $d_k \in \mathbb{R}^n$ such that $\langle \nabla f(x_k), d_k \rangle < 0$.

S3 Choose a step size $\alpha_k > 0$ such that $f(x_k + \alpha_k d_k) < f(x_k)$.

S4 Set $x_{k+1} := x_k + \alpha_k d_k$, replace k by $k + 1$, and go to S1.

We proved a convergence result which only required that

- d_k is a descent direction; $\langle \nabla f(x_k), d_k \rangle < 0$,
- a line-search has to be used.

Since we already discussed the issue of choosing a step length α_k (remember the Wolfe conditions?), we can now concentrate on methods to compute good search directions d_k.

Steepest Descent: This choice of search direction was already motivated and discussed in Example 2 of Lecture 2:

$$d_k = -\nabla f(x_k).$$

- Intuitively appealing.
- Easy to apply, $-\nabla f(x_k)$ "cheap" to compute.
- $\theta(-\nabla f(x_k), d_k) \equiv 0$ in this case, and Theorem 2 of Lecture 2 implies convergence.

Regrettably, the method has major disadvantages:

- Badly affected by round-off errors.
- Badly affected by ill-conditioning, convergence can be excruciatingly slow due to excessive zig-zagging.

To illustrate this, let x^* be a strict local minimiser of f and suppose that the sufficient first and second order optimality conditions hold, i.e.,

$$\nabla f(x^*) = 0, \qquad D^2 f(x^*) \succ 0.$$

The second condition implies that the ordered eigenvalues of $D^2 f(x^*)$ satisfy

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n > 0.$$

The ratio $\kappa := \frac{\lambda_1}{\lambda_n}$ is called the *condition number* of $D^2 f(x^*)$. If κ is large, then x^* lies in a "long narrow valley" of f.

Once the steepest descent method enters this valley, it just bounces back and forth without making much progress when κ is large:

Proposition 1: Let x_0 be a starting point and let the sequence $(x_k)_{\mathbb{N}}$ be produced by

$$x_{k+1} = x_k - \alpha_k \nabla f(x_k),$$

where α_k corresponds to an exact line-search (see Lecture 2). Then

$$\|x_{k+1} - x^*\| \simeq \frac{\kappa - 1}{\kappa + 1} \|x_k - x^*\|$$

for all k large.

Coordinate Search: This method is even simpler, as the search direction cycles through the coordinate axes:

$$d_k = e_i, \quad i \equiv 1 + k \mod n.$$

- Even cheaper, as d_k does not have to be computed at all.
- Convergence even worse than steepest descent.

Newton Methods: This approach is motivated by the first order necessary optimality condition $\nabla f(x^*) = 0$ and works when $D^2 f(x)$ is non-singular for x in a neighbourhood of x^*.

- Idea: replace the nonlinear root-finding problem $\nabla f(x) = 0$ by a sequence of linear problems which are easy to solve.
- Linearisation: given x_k, the first order Taylor approximation

  $$x \mapsto \varphi(x) = \nabla f(x_k) + D^2 f(x_k)(x - x_k),$$

  approximates the nonlinear (vector valued) function $x \mapsto \nabla f(x)$ well in a neighbourhood of x_k.

- Therefore, if x_k is close to x^*, then it is reasonable to expect that the solution

  $$x_{k+1} = x_k - \left(D^2 f(x_k)\right)^{-1} \nabla f(x_k)$$

  of the linearised system of equations $\varphi(x) = 0$ lies even closer to x^*.

- $n_f(x_k) := -\left(D^2 f(x_k)\right)^{-1} \nabla f(x_k)$ is called the Newton direction.

Newton-Raphson method: given a starting point x_0, apply *exact Newton steps*

$$x_{k+1} = x_k + n_f(x_k).$$

- $n_f(x)$ is a descent direction when $D^2 f(x) \succ 0$:

  $$\langle n_f(x), \nabla f(x) \rangle = -(\nabla f(x))^{\mathsf{T}} \left(D^2 f(x_k)\right)^{-1} \nabla f(x_k) < 0,$$

  since $D^2 f(x) \succ 0 \Rightarrow (D^2 f(x))^{-1} \succ 0$. In particular, this happens when f is strictly convex (see Lecture 1).

- If $D^2 f(x) \not\succ 0$ then $n_f(x)$ may not be a descent direction and the method may converge to any point where $\nabla f(x) = 0$, which could be a minimiser, maximiser or saddle point.

- Examples can be constructed on which the method cycles through a finite number of points, that is, $x_{k+j} = x_k$ for some $k, j \in \mathbb{N}$, and the method does not converge.

- However, when x_0 is chosen sufficiently close to x^* where the first and second order optimality conditions for a minimiser hold, then the convergence is Q-quadratic, see Theorem 1 below.

Dampened Newton method:

- Uses the following search direction in Algorithm 1,

$$d_k = \begin{cases} n_f(x_k) & \text{if } \langle n_f(x_k), \nabla f(x_k)\rangle < 0, \\ -n_f(x_k) & \text{otherwise.} \end{cases}$$

- the line-search step length α_k should asymptotically become 1 (i.e., full Newton step taken) if the fast convergence rate of the Newton-Raphson method is to be picked up.

Conclusions:

- Newton's method is great for the minimisation of convex problems (or the maximisation of concave problems).

- Since f is typically strictly convex in a neighbourhood of a local minimiser x^*, it is great to switch to Newton's method in the final phase of an algorithm that otherwise relies on a line-search descent method.

Example 1: Linear Programming. Consider the linear programming problem

$$\begin{aligned} \max_{x \in \mathbb{R}^n} \; & c^{\mathsf{T}} x \\ \text{s.t. } & Ax \leq b, \\ & x \geq 0. \end{aligned}$$

Here $A \in \mathbb{R}^{m \times n}$ (a $m \times n$ matrix with linearly independent rows), $b \in \mathbb{R}^m$ and $c \in \mathbb{R}^n$ are all given, and $x \in \mathbb{R}^n$ is the vector of decision variables.

Let $\mu > 0$ and $e := \begin{bmatrix} 1 & \dots & 1 \end{bmatrix}^{\mathsf{T}}$.

At the heart of interior-point methods for linear programming lies the solution of the nonlinear system of equations

$$Ax = b \tag{1}$$
$$A^{\mathsf{T}}y + s = c \tag{2}$$
$$XSe = \mu e \tag{3}$$
$$x, s > 0, \tag{4}$$

where $x, s \in \mathbb{R}^n$, $y \in \mathbb{R}^m$, $X = \text{Diag}(x)$ and $S = \text{Diag}(s)$ are the diagonal matrices with x and s on their diagonals, and where $x, s > 0$ means that both vectors have to be component-wise strictly positive.

In order to guarantee that (4) continues to be satisfied, we use $(\Delta x, \Delta y, \Delta s)$ as a search direction and determine an updated approximate solution (x_+, y_+, s_+) as follows:

$$\alpha^* = \sup\{\alpha > 0 : x + \alpha\Delta x > 0, \; s + \alpha\Delta s > 0\},$$
$$(x_+, y_+, s_+) = (x, y, s) + \min(1, 0.99\alpha^*)(\Delta x, \Delta y, \Delta s).$$

It can be shown that the resulting sequence of intermediate solutions converges very efficiently to (x^*, y^*, s^*).

It can be shown that the system (1)-(4) has a unique solution (x^*, y^*, s^*).

Given a current approximate solution (x, y, s) such that $x, s > 0$, we can compute a Newton step $(\Delta x, \Delta y, \Delta s)$ for the unconstrained system (1)-(3) which is obtained by solving the linearised system of equations

$$\begin{aligned} A\Delta x &= b - Ax \\ A^{\mathsf{T}}\Delta y + \Delta s &= c - A^{\mathsf{T}}y - s \\ S\Delta x + X\Delta s &= \mu e - XSe. \end{aligned}$$

Theorem 1: Convergence of Newton-Raphson.
Let $f \in C^2(\mathbb{R}^n, \mathbb{R})$ with Λ-Lipschitz continuous Hessian. Let $x^* \in \mathbb{R}^n$ be such that $\nabla f(x^*) = 0$ and $D^2 f(x^*)$ nonsingular. Then there exists a neighbourhood $B_\rho(x^*)$ with the property that $x_0 \in B_\rho(x^*)$ implies $x_k \in B_\rho(x^*)$ for all k, and $x_k \to x^*$ Q-quadratically.

Proof:

- $D^2f(x^*)$ nonsingular, $x \mapsto D^2f(x)$ continuous $\Rightarrow \exists\bar{\rho} > 0$ such that $D^2f(x)$ nonsingular for all $x \in B_{\bar{\rho}}(x^*)$ and $n_f(x)$ well-defined.

- Moreover, $x \mapsto (D^2f(x))^{-1}$ is continuous, thus can choose $\bar{\rho}$ sufficiently small so that
$$\|(D^2f(x))^{-1}\| \leq 2\|(D^2f(x^*))^{-1}\| =: \beta. \tag{5}$$

- The Newton update implies
$$(x_{k+1} - x^*) = (x_k - x^*) - (D^2f(x_k))^{-1}\nabla f(x_k). \tag{6}$$

- Lipschitz continuity of D^2f implies
$$\begin{aligned} \|S\| &\leq \int_{t=0}^{1} \|D^2f(x_k) - D^2f(tx^* + (1-t)x_k)\|dt \\ &\leq \int_{t=0}^{1} \Lambda t\|x_k - x^*\|dt = \frac{\Lambda}{2}\|x_k - x^*\|. \end{aligned}$$

- Substituting this and (5) in (8),
$$\|x_{k+1} - x^*\| \leq \frac{\beta\Lambda}{2}\|x_k - x^*\|^2. \tag{9}$$

- Finally, for $\rho := \min(\bar{\rho}, 2(\beta\Lambda)^{-1})$, (9) shows that
$$x_k \in B_\rho(x^*) \Rightarrow x_k \in B_\rho(x^*),$$
so that the entire sequence $(x_k)_{\mathbb{N}}$ is well defined as long as $x_0 \in B_\rho(x^*)$.

- Using $\nabla f(x^*) = 0$, find
$$\nabla f(x_k) = \nabla f(x_k) - \nabla f(x^*) = \int_{t=0}^{1} D^2f(tx^* + (1-t)x_k)(x_k - x^*)dt$$

- Substituting into (6),
$$(x_{k+1} - x^*) = \left(D^2f(x_k)\right)^{-1} S\,(x_k - x^*), \tag{7}$$
where
$$\begin{aligned} S &:= D^2f(x_k) - \int_{t=0}^{1} D^2f(tx^* + (1-t)x_k)dt \\ &= \int_{t=0}^{1} D^2f(x_k) - D^2f(tx^* + (1-t)x_k)dt. \end{aligned}$$

- Taking norms on both sides of (7),
$$\|x_{k+1} - x^*\| \leq \|(D^2f(x_k))^{-1}\| \times \|S\| \times \|x_k - x^*\|. \tag{8}$$

Reading Assignment: Download and read Lecture-Note 3.

Note: From now on all lectures are in *Comlab 147*.