Newton's Method

- Problem Formulation
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- Globalization Techniques

Contents

Problem Formulation

Given a function $f : \mathbb{R}^n \to \mathbb{R}^n$ we are searching for solutions of the nonlinear equation

$$f(x) = 0\ .$$

Examples:

- For $f(x) = Ax - b$ this amounts to solving a linear equation system,
- For $f(x) = x^2 + 1$: no solution can be found,
- For $f(x) = x^3 - x$: three solutions exist.

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Main Idea

In order to solve the nonlinear equation $f(x)$, we start with an initial guess x_0 and solve the linear equation systems

$$f(x_k) + M(x_k)(x_{k+1} - x_k) = 0 \ ,$$

for $k \in \{0, 1, 2, \ldots\}$. Here, the matrix $M(x_k) \in \mathbb{R}^{n \times n}$ is chosen in such a way that

$$f(x_k) + M(x_k)(x - x_k) \approx f(x) \ ,$$

is an approximation of the function f. For example, if f is differentiable, we might choose $M(x_k) = f'(x_k)$, which corresponds to the so called Newton method.

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Newton (or Newton-type) method

If the matrix $M(x_k)$ is invertible, the method can also be written in the form

$$x_{k+1} = x_k - M(x_k)^{-1} f(x_k) \; ,$$

for $k \in \{0, 1, 2, \ldots\}$.

- In practice, we usually work with approximations $M(x_k) \approx f'(x_k)$.
- If $M(x_k)$ is independent of x_k, we only need to decompose M once (e.g., using LR or QR decomposition)
- Some methods try to update M at every step withough re-computing the Jacobian.

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Scaling Properties

If x^* satisfies $f(x^*) = 0$ it also satisfies $S \cdot f(x^*) = 0$, where $S \in \mathbb{R}^{n \times n}$ can be any (invertible) scaling matrix. If we apply the above recursion to the scaled equation

$$\widetilde{f}(x) = S \cdot f(x) = 0$$

we obtain the iterates $x_{k+1} = x_k - M(x_k)^{-1} S \cdot f(x_k)$, which do in general not coincide with the iterates that are obtained without scaling f. However, if we use exact Jacobians, we have

$$M(x_k) = \widetilde{f}'(x) = S \cdot f'(x) \qquad \Longrightarrow \qquad x_{k+1} = x_k - f'(x_k)^{-1} f(x_k) \; .$$

This implies that Newton's methods with exact Jacobians is invariant under scaling.

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Local Convergence Analysis

Assumptions:

- There exists a point x^* with $f(x^*) = 0$.
- The point x_0 is already in a small neighborhood of x^*.
- The scaled Jacobian matrix $M(x_k)^{-1} f'(x)$ is Lipschitz continuous w.r.t. x in a neighborhood of x^* with Lipschitz constant $\omega \geq 0$.

The basic idea is to estimate the distance of the iterates to x^*:

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\begin{aligned}
&\|x_{k+1} - x^*\| \\
&= \left\| x_k - x^* - M(x_k)^{-1} f(x_k) \right\| \\
&= \left\| x_k - x^* - M(x_k)^{-1} \int_0^1 J(x^* + s(x_k - x^*))(x_k - x^*) \mathrm{d}s \right\| \\
&\leq \left\| x_k - x^* - M(x_k)^{-1} J(x_k)(x_k - x^*) \right\| + \tfrac{\omega}{2} \|x_k - x^*\|_2^2 \ .
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Local Convergence Analysis

In summary, we find the estimate

$$\|x_{k+1} - x^*\| \leq \kappa \|x_k - x^*\| + \frac{\omega}{2} \|x_k - x^*\|_2^2 \ .$$

as long as $\left\|I - M(x_k)^{-1} J(x_k)\right\| \leq \kappa$. Here, κ can be interpreted as a bound on the accuracy of the Jacobian approximation M. If we have $\kappa < 1$ and $\|x_0 - x^*\| < \frac{2}{\omega}(1 - \kappa)$ the iterates contract and we have

$$\lim_{k \to \infty} x_k \ \to \ x^* \ .$$

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Convergence Rate

The convergence rate estimate

$$\|x_{k+1} - x^*\| \leq \kappa \|x_k - x^*\| + \frac{\omega}{2} \|x_k - x^*\|_2^2 \ .$$

implies that

- if we have $\kappa \neq 0$ the convergence rate is in general linear.
- if we choose $M(x_k) = J(x_k)$ (Newton's method), we have $\kappa = 0$ and

$$\|x_{k+1} - x^*\| \leq \frac{\omega}{2} \|x_k - x^*\|_2^2 \ .$$

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Degeneracy Handling

If the exact Jacobian $J(x^*)$ is singular (has eigenvalues that are equal to zero), Newton's method is not applicable, since the matrices $J(x_k)$ converge to a singular matrix that cannot be inverted.

If the matrix $M(x_k)$ is chosen in such a way that the convergence condition

$$\left\| I - M(x_k)^{-1} J(x_k) \right\| < 1$$

is maintained. This is possible even if J is singular, although special care has to be taken, if M is ill-conditioned. If we choose M such that

$$\left\| I - M(x_k)^{-1} J(x_k) \right\| \leq \mathbf{O}(\|x_k - x^*\|) \ ,$$

a (locally) quadratic convergence rate can be recovered.

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Nonlinear Least-Squares Problems

The unconstrained nonlinear least-squares problem is given by

$$\min_x \|f(x)\|_2^2 \ .$$

- If we can find a $x^* \in \mathbb{R}^n$ with $f(x^*) = 0$, then x^* is minimizer of the above problem.
- For $f(x) = Ax - b$ this problem is a least-squares problem in standard form.
- Makes sense for any function $f : \mathbb{R}^n \to \mathbb{R}^m$ with $m \neq n$ in general.

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Unconstrained Optimization Problems

An even more general class of problems are the unconstrained optimization problems

$$\min_x \; F(x) \; .$$

This contains the nonlinear least-squares problems as a special case, since we can choose $F(x) = \|f(x)\|_2^2$.

If F is twice Lipschitz-continuously differentiable, a minimizer can be found by applying Newton's method to

$$F'(x) = 0$$

If a solution x^* satisfies $F''(x) \succ 0$, it must be a local minimizer.

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Newton-Type Methods for Optimization

In detail, Newton-type methods for unconstrained optimization problems can be written in the form

$$x_{k+1} = x_k - M(x_k)^{-1} F'(x_k)^T \ ,$$

where $M(x_k) \approx F''(x_k)$ is a suitable Hessian approximation.

- In practice, we often choose a symmetric Hessian approximation M, since F'' is symmetric.
- If $M(x_k)$ is symmetric and positive definite, the iterate x_{k+1} is the minimizer of the quadratic function

$$\min_{x_{k+1}} \ F(x_k) + F'(x_k)(x_{k+1} - x_k) + \frac{1}{2} (x_{k+1} - x_k)^T M(x_k) (x_{k+1} - x_k) \ ,$$

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Line Search Methods

So far, we have only analyzed the local convergence properties of Newton-type methods. If we start far from a local solution, Newton type methods are often take "too big" steps and are divergent.

One way to fix this problem is to first compute a step-direction by solving

$$\min_{x_{k+1}} \; F(x_k) + F'(x_k)\Delta x_k + \frac{1}{2}\Delta x_k^T M(x_k)\Delta x_k \; ,$$

and update the iterate as

$$x_{k+1} = x_k + \alpha_k \Delta x_k \; .$$

Here, $\alpha_k \in (0,1]$ is a so-called line-search parameter, which is found by (approximately) solving the scalar optimization problem

$$\min_{\alpha_k \in [0,1]} \; F(x_k + \alpha_k \Delta x_k) \; .$$

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Armijo Line Search Conditions

In practice the line search optimization problem

$$\min_{\alpha_k \in [0,1]} F(x_k + \alpha_k \Delta x_k) \; .$$

is not solved exactly (too expensive), but only approximately.

One way to implement this is by using back-tracking until the Armijo condition

$$F(x_k + \alpha_k \Delta x_k) \leq F(x_k) + c \alpha_k F'(x_k) \Delta x_k$$

for a constant $c \ll 1$ is satisfied. This condition ensures that the line search parameter is not excessively large, although it is not sufficient to prove convergence in general.

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Armijo Line Search Conditions

If we substitute $\Delta x_k = -M(x_k)^{-1}F'(x_k)^T$ the Armijo line search condition can alternatively be written in the form

$$F(x_k + \alpha_k \Delta x_k) \leq F(x_k) - c\alpha_k F'(x_k) M(x_k)^{-1} F'(x_k)^T \ .$$

Thus, if M is positive definite, the Armijo condition ensures that we get a strict descent of the objective function whenever we apply a (damped) Newton step.

Positive definite approximations M in combination with Armijo line search work extremely well in practice, but other variants exist.

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