

Newton's Method I

Roots and Stationary Points of Univariate Scalar Functions

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Informatik 12:
Software and Tools for Computational Engineering

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Objective and Learning Outcomes

Recall

- Linearization
- Intermediate Value Theorem

Newton's Method

- Roots of Nonlinear Equations
- Stationary Points and Local Optima

Summary and Next Steps

Objective and Learning Outcomes

Recall

Linearization

Intermediate Value Theorem

Newton's Method

Roots of Nonlinear Equations

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Summary and Next Steps

Objective

- ▶ Introduction to Newton's method for scalar functions.

Learning Outcomes

- ▶ You will understand
 - ▶ roots of nonlinear functions
 - ▶ linearization
 - ▶ convergence
 - ▶ stationary points and local optima
- ▶ You will be able to
 - ▶ implement Newton's method
 - ▶ investigate convergence of Newton's method.

Objective and Learning Outcomes

Recall

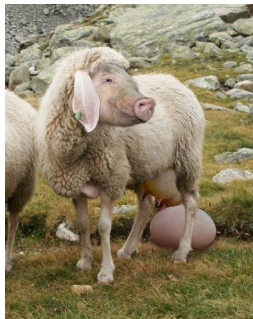
- Linearization
- Intermediate Value Theorem

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Summary and Next Steps

The solution of linear equations amounts to simple scalar division. The solution of nonlinear equations can be challenging.



"Egg-Laying, Wool-Bearing, Milk-Giving Sow"
© Georg Mittenecker @ Wikipedia

Many numerical methods for nonlinear problems are built on local (at \tilde{x}) replacement of the target function with a **linear** (affine; in Δx) **approximation** derived from the truncated Taylor series expansion and “hoping” that

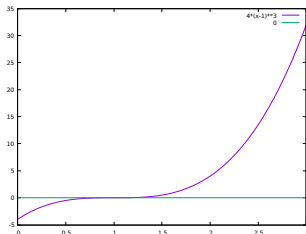
$$f(\tilde{x} + \Delta x) \approx f(\tilde{x}) + f'(\tilde{x}) \cdot \Delta x ,$$

i.e. hoping for a reasonably small remainder.

The solution of a sequence of linear problems is then expected to yield an iterative approximation of the solution to the nonlinear problem. Newton's method is THE example.

Intermediate Value Theorem and Bisection

Let $y = f(x)$ be continuous within a neighborhood $x + \Delta x$ of x taking values $f(x)$ and $f(x + \Delta x)$ at the endpoints of the interval. Then f takes all values between $f(x)$ and $f(x + \Delta x)$ over the same interval.



If $f(x)$ and $f(x + \Delta x)$ have different signs, then f has a root within the interval bounded by x and $x + \Delta x$, i.e., $\exists \tilde{x} : f(\tilde{x}) = 0$.

The simplest possible root finding algorithm follows from iterative / recursive **bisection** of the the interval $[x, x + \Delta x]$.

Unfortunately, the bisection algorithm converges slowly and does not generalize to higher dimensions. Hence, we are going to investigate superior alternatives.

Note: \tilde{x} not necessarily unique; f can take values outside of $[f(x), f(x + \Delta x)]$

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Consider a nonlinear equation $y = f(x) = 0$ at some (starting) point x .

Building on the assumption that $f(x + \Delta x) \approx f(x) + f'(x) \cdot \Delta x$ the root finding problem for f can be replaced locally by the root finding problem for the linearization

$$\bar{f}(\Delta x) = f(x) + f'(x) \cdot \Delta x .$$

The right-hand side is a straight line intersecting the y -axis in $(\Delta x = 0, \bar{f}(\Delta x) = f(x))$.

Solution of

$$\bar{f}(\Delta x) = f(x) + f'(x) \cdot \Delta x = 0$$

for Δx yields

$$\Delta x = -\frac{f(x)}{f'(x)}$$

implying $f(x + \Delta x) \approx 0$.

If the new iterate is not close enough to the root of the nonlinear function, i.e., $|f(x + \Delta x)| > \epsilon$ for some measure of accuracy of the numerical approximation $\epsilon > 0$, then it becomes the starting point for the next iteration yielding the recurrence

$$x = x - \frac{f(x)}{f'(x)}$$

Convergence of this **Newton[-Raphson] method** is not guaranteed in general. **Damping** of the magnitude of the next step may help.

$$x = x - \alpha \cdot \frac{f(x)}{f'(x)} \quad \text{for } 0 < \alpha \leq 1 .$$

The damping parameter α is often determined by **line search** (e.g., recursive bisection yielding $\alpha = 1, 0.5, 0.25, \dots$) such that decrease in absolute function value is ensured.

```
1 template<typename T> T f(const T &x);
2 template<typename T> T dfdx(const T &x);
3
4 template<typename T>
5 void solve(T& x, const T& eps) {
6     while (fabs(f(x))>eps) x-=f(x)/dfdx(x);
7 }
8
9 int main(int, char *v[]) {
10     double x=std::stof(v[1]);
11     solve(x,1e-12);
12     std::cout << "x=" << x << std::endl
13             << "f(x)=" << f(x) << std::endl
14             << "dfdx(x)=" << dfdx(x) << std::endl
15     return 0;
16 }
```

Newton's method can be regarded as a fixed point iteration

$$x = g(x) = x - \frac{f(x)}{f'(x)} .$$

If at the solution

$$|g'(x)| < 1 ,$$

then there exists a neighborhood containing values of x for which the fixed-point iteration converges to this solution.

The convergence rate of a fixed-point iteration grows linearly with decreasing values of $|g'(x)|$.

For $|g'(x)| = 0$ we get at least **quadratic convergence**; cubic for $|g'(x)| = |g''(x)| = 0$ and so forth.

Newton's method becomes

$$x = g(x) = x - \frac{f(x)}{f'(x)}$$

yielding

$$g'(x) = f(x) \cdot \frac{f''(x)}{(f'(x))^2} \cdot$$

At the solution $f(x) = 0$ implies $g'(x) = 0$. Assuming a **simple root** ($f(x) = 0$, $f'(x) \neq 0$) the second derivative of g becomes equal to

$$g''(x) = f'(x) \cdot \frac{f''(x)}{(f'(x))^2} + \underbrace{f(x)}_{=0} \cdot (\dots)$$

implying **quadratic convergence** within the corresponding neighborhood of the solution if $f''(x) \neq 0$ as well as convergence after a single iteration for linear f .

Let $f(x) = \cos(x)$. from

$$x = g(x) = x - \frac{f(x)}{f'(x)} = x - \frac{\cos(x)}{-\sin(x)}$$

follows

$$g'(x) = f(x) \cdot \frac{f''(x)}{(f'(x))^2} g'(x) = \cos(x) \cdot \frac{-\sin(x)}{(\cos(x))^2} \cdot$$

At $\tilde{x} = 1$ we get $|g'(x)| \approx 0.41$ and hence convergence to the nearest root at $\frac{\pi}{2} \approx 1.57$.

At $\tilde{x} = 3$ we get $|g'(x)| \approx 49.21$ suggesting divergence. However, the second iterate $\tilde{x} \approx -4.02$ yields $|g'(x)| \approx 0.69$ resulting in convergence to the root closest to -4.02 , that is, $-\frac{3 \cdot \pi}{2} \approx -4.71$.

Let $y = f(x)$ be twice continuously differentiable over the domain of interest.

- ▶ \tilde{x} is a stationary point (necessary condition for local optimality) of f if

$$f'(\tilde{x}) \equiv \frac{df}{dx}(\tilde{x}) = 0$$

- ▶ \tilde{x} is a local minimum (sufficient condition for local optimality) of f if

$$f''(\tilde{x}) \equiv \frac{d^2f}{dx^2}(\tilde{x}) > 0 \quad (\text{strict convexity})$$

- ▶ \tilde{x} is a local maximum (sufficient condition for local optimality) of f if

$$f''(\tilde{x}) \equiv \frac{d^2f}{dx^2}(\tilde{x}) < 0 \quad (\text{strict concavity})$$

$f'' = 0$ indicates a **non-simple stationary point**.

Consider the nonlinear optimization problem

$$\min_{x \in \mathcal{R}} f(x)$$

for $f : \mathcal{R} \rightarrow \mathcal{R}$.

Starting from some initial estimate for the stationary point \tilde{x} the **steepest descent** method iteratively takes steps into descent directions. In the scalar case the choice is between stepping toward $-\infty$ or ∞ .

The first derivative $f'(x)$ indicates local increase ($f'(\tilde{x}) > 0$) or decrease ($f'(\tilde{x}) < 0$) of the the function value.

Aiming for decrease the next step should be toward $-\infty$ if $f' > 0$ or toward ∞ if $f' < 0$. No further local decrease in the function value can be achieved for $f' = 0$ (necessary optimality condition).

The step size is typically **damped** in order to ensure continued progress toward $\min_{x \in R} f(x)$ yielding the recurrence

$$x := x - \alpha \cdot f'(x) \quad \text{while } |f'(x)| > \epsilon$$

Comments on line search apply as above.

Validation of a local minimum at \tilde{x} requires $f''(\tilde{x}) > 0$. Similarly, a local maximum is found if $f''(\tilde{x}) < 0$.

```
1 template<typename T> T f(const T &x);
2 template<typename T> T dfdx(const T &x);
3 template<typename T> T ddfdx(const T &x);
4
5 template<typename T>
6 void solve(T& x, const T& eps) {
7     T g=dfdx(x), y=f(x), y_prev;
8     while (fabs(g)>eps) {
9         y_prev=y;
10        double alpha=2.;
11        while (y_prev<=y&&alpha>eps) {
12            T x_trial=x; alpha/=2;
13            x_trial-=alpha*g; y=f(x_trial);
14        }
15        x-=alpha*g; g=dfdx(x);
16    }
17 }
```

Consider the nonlinear optimization problem

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

for $f : \mathbb{R} \rightarrow \mathbb{R}$.

Application of Newton's method to

$$f'(x) = 0$$

yields

$$x = x - \frac{f'(x)}{f''(x)}.$$

Comments on convergence and line search apply as above.

Validation of a local minimum at \tilde{x} requires $f''(\tilde{x}) > 0$. Similarly, a local maximum is found if $f''(\tilde{x}) < 0$.

```
1 template<typename T> T f(const T &x);  
2 template<typename T> T dfdx(const T &x);  
3 template<typename T> T ddfdx(const T &x);  
4  
5 template<typename T>  
6 void solve(T& x, const T& eps) {  
7     while (fabs(dfdx(x))>eps)  
8         x-=dfdx(x)/ddfdxx(x);  
9 }
```

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Summary

- ▶ Newton's method for scalar functions
- ▶ roots of nonlinear equations
- ▶ stationary points and local optima

Next Steps

- ▶ Inspect sample code.
- ▶ Run further experiments.
- ▶ Continue the course to find out more ...