Part 3

Metrics of algorithmic complexity

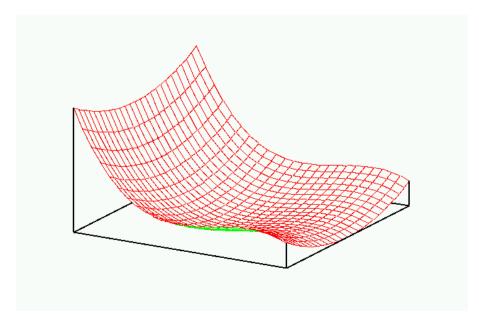
Outline of optimization algorithms

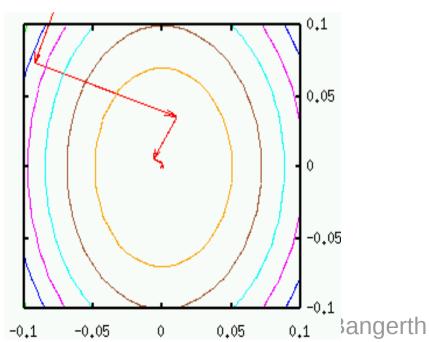
All algorithms to find minima of f(x) do so iteratively:

- start at a point x_0
- for k=1,2,...;
 - . compute an update direction $p_{\scriptscriptstyle k}$
 - . compute a step length α_k

$$. set \quad x_k \leftarrow x_{k-1} + \alpha_k \ p_k$$

set $k \leftarrow k+1$





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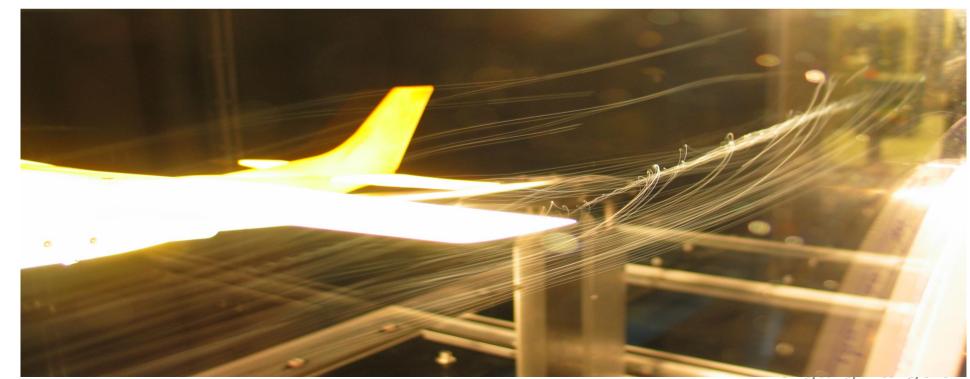
Questions:

- If x^* is the minimizer that we are seeking, does $x_k \rightarrow x^*$?
- How many iterations does it take for $||x_k x^*|| \le \epsilon$?
- How expensive is every iteration?

How expensive is every iteration?

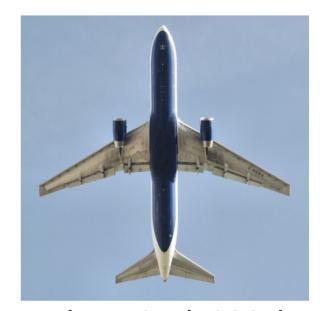
The cost of optimization algorithms is dominated by evaluating f(x), g(x), h(x) and derivatives:

- Traffic light example: Evaluating f(x) requires us to sit at an intersection for an hour, counting cars
- Designing air foils: Testing an improved wing design in a wind tunnel costs millions of dollars.



How expensive is every iteration?

Example: Boeing wing design



Boeing 767 (1980s) 50+ wing designs tested in wind tunnel



Boeing 777 (1990s)

18 wing designs
tested in wind tunnel



Boeing 787 (2000s)

10 wing designs
tested in wind tunnel

Planes today are 30% more efficient than those developed in the 1970s. Optimization in the wind tunnel and *in silico* made that happen but is *very* expensive.

How expensive is every iteration?

Practical algorithms:

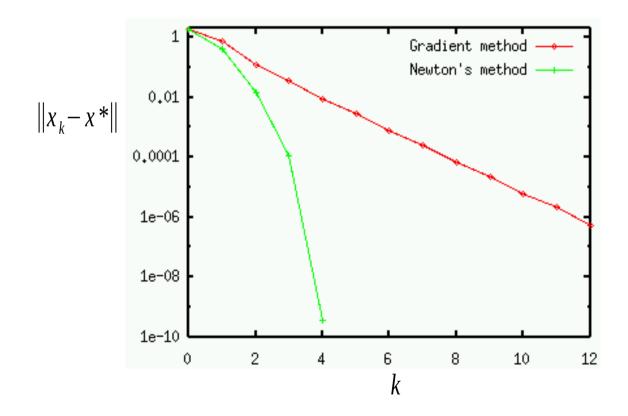
To determine the search direction p_k

- Gradient (steepest descent) method requires 1 evaluation of $\nabla f(\cdot)$ per iteration
- Newton's method requires 1 evaluation of $\nabla f(\cdot)$ and 1 evaluation of $\nabla^2 f(\cdot)$ per iteration
- If derivatives can not be computed exactly, they can be approximated by several evaluations of $f(\cdot)$ and $\nabla f(\cdot)$

To determine the step length α_k

• Both gradient and Newton method typically require several evaluations of $f(\cdot)$ and potentially $\nabla f(\cdot)$ per iteration.

Question: Given a sequence $x_k \rightarrow x^*$ (for which we *know* that $||x_k - x^*|| \rightarrow 0$), can we determine exactly *how fast the error goes to zero?*



Definition: We say that a sequence $x_k \rightarrow x^*$ is of order s if

$$||x_k - x^*|| \le C ||x_{k-1} - x^*||^s$$

A sequence of numbers $a_k \rightarrow 0$ is called of order s if

$$|a_k| \leq C |a_{k-1}|^s$$

C is called the asymptotic constant. We call $C|a_{k-1}|^{s-1}$ gain factor.

Specifically:

If s=1, the sequence is called *linearly convergent*.

Note: Convergence requires C<1. In a singly logarithmic plot, linearly convergent sequences are straight lines.

If s=2, we call the sequence *quadratically convergent*.

If 1 < s < 2, we call the sequence superlinearly convergent.

Example: The sequence of numbers

$$a_k = 1, 0.9, 0.81, 0.729, 0.6561, ...$$

is *linearly* convergent because

$$|a_k| \leq C|a_{k-1}|^s$$

with s=1, C=0.9.

Remark 1: Linearly convergent sequences can converge very slowly if *C* is close to 1.

Remark 2: Linear convergence is considered *slow.* We will want to avoid linearly convergent algorithms.

Example: The sequence of numbers

$$a_k = 0.1, 0.03, 0.0027, 0.00002187, ...$$

is *quadratically* convergent because

$$|a_k| \leq C|a_{k-1}|^s$$

with *s*=2, *C*=3.

Remark 1: Quadratically convergent sequences can converge very slowly if C is large. For many algorithms we can show that they converge quadratically if a_0 is small enough since then

$$|a_1| \leq C|a_0|^2 \leq |a_0|$$

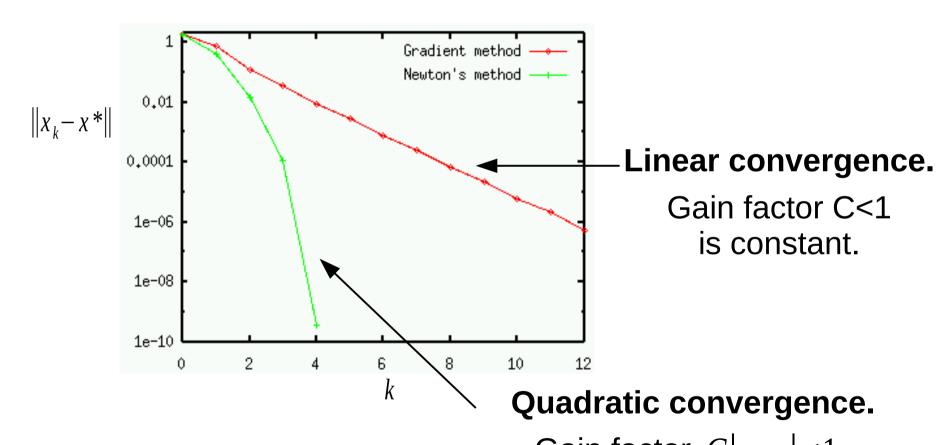
If a_0 is too large then the sequence may fail to converge since

$$|a_1| \le C|a_0|^2 \ge |a_0|$$

Remark 2: Quadratic convergence is considered *fast.* We will want to use quadratically convergent algorithms.

Wolfgang Bangerth

Example: Compare linear and quadratic convergence



Gain factor $C|a_{k-1}| < 1$ becomes better and better!

Metrics of algorithmic complexity

Summary:

- Quadratic algorithms converge faster in the limit than linear or superlinear algorithms
- Algorithms that are better than linear will need to be started close enough to the solution

Algorithms are best compared by counting the number of

- function,
- gradient, or
- Hessian evaluations

to achieve a certain accuracy. This is generally a good measure for the run-time of such algorithms.