

## SW9 ##

Speed of convergence:

↖ Gradient descent

- Linear Convergence: The distance to the optimal is getting better every step. The speed is depending  $C$

$$\|x^* - x^{i+1}\| \leq C \|x^* - x^i\|$$

↖ Newton's method

- Superlinear convergence:

Repetition of the sequence  $\{C_i\}_{i \in \mathbb{N}}$  with  $\lim_{n \rightarrow \infty} \text{times}(n)$

- Quadratic convergence ↖ Broyden's method

There is  $C > 0$  and  $i_0 \in \mathbb{N}$  such that for all  $i \geq i_0$  we have

$$\|x^* - x^{i+1}\| \leq C \|x^* - x^i\|^2$$

Approximating partial derivatives:

Sometimes it's hard to find the derivatives. Then just get two points of the function and calculate the differences over the stepsize. To get the best approx. get the point you want the derivative and go one step right, one step left and divide by two step sizes:

$$\frac{\partial f(x)}{\partial x_1} \approx \frac{f(x_1, x_2, \dots, x_i + \epsilon, \dots, x_n) - f(x_1, x_2, \dots, x_i - \epsilon, \dots, x_n)}{2\epsilon}$$

Second derivative:

$$\frac{\partial^2 f(x)}{\partial x_1^2} \approx \frac{f(x_1, \dots, x_i + \epsilon, \dots, x_n) - 2f(x_1, \dots, x_n) + f(x_1, \dots, x_i - \epsilon, \dots, x_n)}{\epsilon^2}$$

→ Derivative of the first expression.

Second partial derivative with two variables:

$$\frac{\partial^2 f(x)}{\partial x_i \partial x_j} \approx \frac{1}{4\epsilon^2} \cdot \left( f(x_1, \dots, x_i + \epsilon, \dots, x_j + \epsilon, \dots, x_n) \right. \\ \left. - f(x_1, \dots, x_i + \epsilon, \dots, x_j - \epsilon, \dots, x_n) \right. \\ \left. - f(x_1, \dots, x_i - \epsilon, \dots, x_j + \epsilon, \dots, x_n) \right. \\ \left. + f(x_1, \dots, x_i - \epsilon, \dots, x_j - \epsilon, \dots, x_n) \right)$$

## Brayden's method:

Idea: Computing and inverting the Hessian-Matrix is expensive.  
In this method, we do just an approximation.

Hence it make sense to require that the approximation  $A^i$  satisfies:

$$A^i(x^i - x^{i-1}) = \nabla f(x^i) - \nabla f(x^{i-1})$$

Brayden's method fullfills this fact with following equation:

$$A^i = A^{i-1} + \frac{((\nabla f(x^i) - \nabla f(x^{i-1})) - A^{i-1}(x^i - x^{i-1}))(x^i - x^{i-1})^T}{\|x^i - x^{i-1}\|^2}$$

And without getting the invert  $A^{-1}$  in each step, we can compute  $(A^i)^{-1}$  directly from  $(A^{i-1})^{-1}$ :

$$(A^i)^{-1} = \left( A^{i-1} + \frac{(g^i - A^{i-1}d^i)d^iT}{\|d^i\|^2} \right)^{-1} \quad // \text{Sherman-Morrison}$$

$$\stackrel{SM}{=} A^{-1} - \frac{A^{-1} v u^T A^{-1}}{1 + u^T A^{-1} v}$$

! Final Formula / procedure of the Brayden's method:

- Initialization: Start with  $x^0$

Compute  $\nabla f(x^0)$  and the inverse of the Hessian matrix  $H_f(x^0)$ ,  
and set  $(A^0)^{-1} := (H_f(x^0))^{-1}$ . Use this to compute

$$x^1 = x^0 - (A^0)^{-1} \nabla f(x^0)$$

- Iteration step: To compute  $x^{i+1}$  from  $x^i$ , compute first  $\nabla f(x^i)$ ,  
 $g^i = \nabla f(x^i) - \nabla f(x^{i-1})$  and  $d^i = x^i - x^{i-1}$ , then

$$(A^i)^{-1} = (A^{i-1})^{-1} - \frac{((A^{i-1})^{-1}g^i - d^i)(d^i)^T (A^{i-1})^{-1}}{(d^i)^T (A^{i-1})^{-1}g^i}$$

and set  $x^{i+1} = x^i - (A^i)^{-1} \nabla f(x^i)$

### Aitken's acceleration method:

if the scalar sequence  $\{x_i\}_{i \in \mathbb{N}}$  converges linearly toward  $x^*$ ,  
then

$$\frac{x^* - x^{i-1}}{x^* - x^{i-2}} \approx \frac{x^* - x^i}{x^* - x^{i-1}} \quad // \text{Konvergiert gleichm\"assig zu } x^*$$

Assuming this, we get

$$x^* = x^i - \frac{(x^i - x^{i-1})^2}{x^i - 2x^{i-1} + x^{i-2}}$$

Now create a new sequence  $\{y_i\}_{i \in \mathbb{N}}$  from the previous sequence  $\{x_i\}_{i \in \mathbb{N}}$ .

$$y_i = x^i - \frac{(x^i - x^{i-1})^2}{x^i - 2x^{i-1} + x^{i-2}} = x^i - \frac{(\Delta x^i)^2}{\Delta^2 x^i} \quad // \text{with this, } \{y_i\}_{i \in \mathbb{N}, i \geq 2} \text{ converges quadratically towards the same limit } x^*.$$