# Optimization

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### Stationary points

Stationary point (critical point, equilibrium point)

$$\nabla F(x) = 0 \tag{1}$$

### Theorem (First-order necessary conditions for minimum)

If  $x^*$  is a local minimizer and f is continuously differentiable in an open neighborhood of  $x^*$ , then  $\nabla F(x^*) = 0$ 

### Theorem (Second-order necessary conditions for minimum)

If  $x^*$  is a local minimizer and  $\nabla^2 F$  is continuous in an open neighborhood of  $x^*$ , then  $\nabla F(x^*) = 0$  and  $\nabla^2 F(x^*)$  is positive semidefinite

### Stationary points

#### Theorem (Second-order sufficient conditions)

Suppose that  $\nabla^2 F$  is continuous in an open neighborhood of  $x^*$  and that  $\nabla F(x^*) = 0$ . If  $\nabla^2 F(x^*)$  is

- positive definite, then  $x^*$  is a strict local minimizer of f.
- negative definite, then  $x^*$  is a strict local maximizer of f.
- indefinite, then  $x^*$  is a saddle point.
- singular, then various pathological situations can occur.

## Stationary points

$$\begin{vmatrix} a_{11} \end{vmatrix}, \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix}, \dots \begin{vmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{n1} & \dots & a_{nn} \end{vmatrix}$$

If sequence of signs of determinants is

- all positive  $\Rightarrow A$  positive definite  $\Rightarrow$  minimum
- alternates, starting from negative ⇒ A negative definite ⇒ maximum
- any sign is wrong  $\Rightarrow A$  indefinite  $\Rightarrow$  saddle point.
- no sign is wrong, but one or more terms is 0 ⇒
   A is positive semidefinite or negative semidefinite ⇒
   more delicate work is needed

## Methods

| Solving equations         | Optimization                       |
|---------------------------|------------------------------------|
| bisection method          | golden section search              |
| secant method             | successive parabolic interpolation |
| Newton's method           | Newton's method                    |
| Conjugate Gradient method | Conjugate Gradient method          |

## Convergence of optimization methods

#### Convergence

linear

$$\lim_{n \to \infty} \frac{||x_{n+1} - x^*||}{||x_n - x^*||} = C, \quad 0 < C < 1$$
 (2)

superlinear

$$\lim_{n \to \infty} \frac{||x_{n+1} - x^*||}{||x_n - x^*||} = 0, \quad 1 (3)$$

quadratic

$$\lim_{n \to \infty} \frac{||x_{n+1} - x^*||}{||x_n - x^*||^2} = C \tag{4}$$

• convergence of order p at rate  $\mu$ 

$$\lim_{k \to \infty} \frac{||x_{n+1} - x^*||}{||x_n - x^*||^p} = C$$
 (5)

## Convergence of optimization methods

Linear order of convergence (p = 1):

$$||x_n - x^*|| = O(\lambda^n)$$

Quadratic order of convergence (p = 2):

• the number of correct digits approximately doubles at each iteration.

# Convergence of optimization methods

| Method                             | Convergence                   |
|------------------------------------|-------------------------------|
| coordinate descent method          | no convergence                |
| golden section search              | linear, $r=1,$ $Cpprox 0.618$ |
| successive parabolic interpolation | superlinear, $rpprox 1.324$   |
| steepest descent                   | linear, $r=1$                 |
| Newton's method                    | quadratic, $r=2$              |
| Quasi-Netwon methods               | superlinear                   |
| -BFGS                              | superlinear                   |
| Conjugate Gradient method          | linear                        |

### Steepest descent with line search

- $f: \mathbb{R}^n \to \mathbb{R}$
- $x_k \in \mathbb{R}^n$
- $\alpha_k \in \mathbb{R}$

Steepest descent

$$x_{k+1} = x_k - \alpha_k \nabla f(x_k) \tag{6}$$

Line search

$$\min_{\alpha} f(x_k - \alpha_k \nabla f(x_k)) \tag{7}$$

### Newton's methods

$$H_{f}(x) = \begin{bmatrix} \frac{\partial^{2} f(x)}{\partial x_{1}^{2}} & \frac{\partial^{2} f(x)}{\partial x_{1} \partial x_{2}} & \cdots & \frac{\partial^{2} f(x)}{\partial x_{1} \partial x_{n}} \\ \frac{\partial^{2} f(x)}{\partial x_{2} \partial x_{1}} & \frac{\partial^{2} f(x)}{\partial x_{2}^{2}} & \cdots & \frac{\partial^{2} f(x)}{\partial x_{2} \partial x_{n}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^{2} f(x)}{\partial x_{n} \partial x_{1} +} & \frac{\partial^{2} f(x)}{\partial x_{n} \partial x_{2}} & \cdots & \frac{\partial^{2} f(x)}{\partial x_{n}^{2}} \end{bmatrix}$$
(8)

$$H_f(x_k)s_k = -\nabla f(x_k)$$

$$x_{k+1} = x_k + s_k$$
(9)

### References

- [1] http://heath.cs.illinois.edu/scicomp/notes/cs450\_ chapt06.pdf
- [2] Jorge Nocedal, Stephen J. Wright, Numerical Optimization, 2006, https://doi.org/10.1007/978-0-387-40065-5
- [3] http: //www.benfrederickson.com/numerical-optimization