

Descent Directions

$$x \in \mathbb{R}^n \rightarrow \min_x f(x)$$

✓ Unconst or

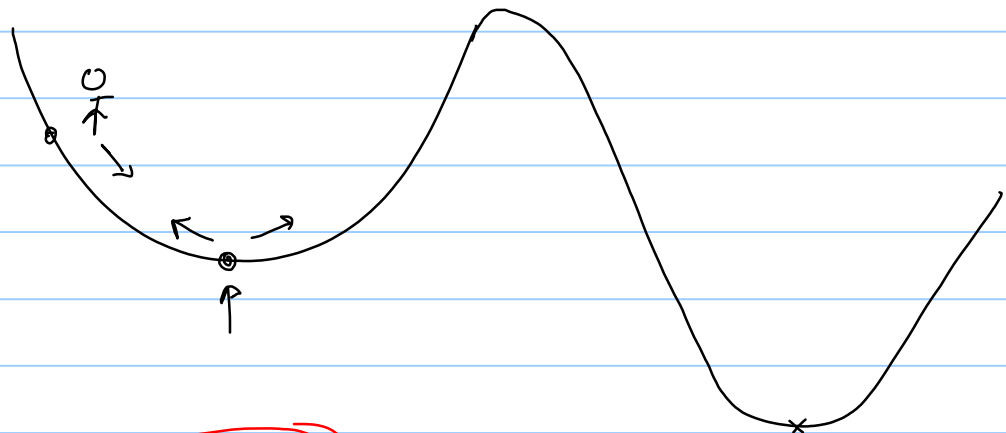
Constrained?

$$\min_x f(x)$$

x

$$\text{s.t. } g(x) \in \Gamma$$

$$\leftarrow \min_{\underline{x \in \Omega}} f(x), \text{ ~~s.t. } x \in \Omega~~$$



$\rightarrow P_N = - (\nabla^2 f)^{-1} \nabla f$, $\underline{\underline{\nabla^2 f \text{ P.D.}}}$, $\Rightarrow \lambda_i \text{'s are } > 0$ $\left[\nabla^2 f \right]$

$\underline{\underline{\nabla^2 f = Q \Lambda Q^T}}$

Properties of Descent Directions

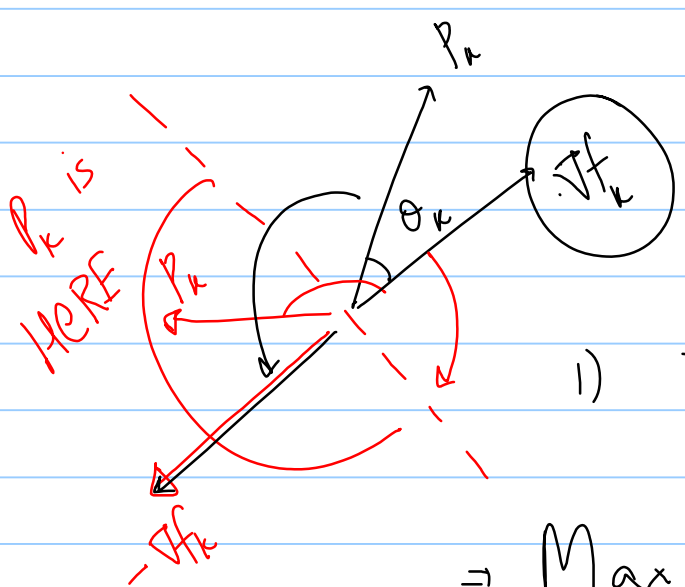
① The steepest descent direction is $-\nabla f(x_k)$

$$f(x_k + \varepsilon p_k) = f(x_k) + \boxed{\varepsilon \nabla f(x_k)^T p_k} + \boxed{O(\varepsilon^2)}$$

$$\nabla f(x_k)^T p_k = \underbrace{\|\nabla f(x_k)\|}_{\geq 0} \underbrace{\|p_k\|}_{\geq 0} \cos(\theta_k)$$

1) $f_{k+1} < f_k \Rightarrow \nabla f(x_k)^T p_k < 0$

\Rightarrow Max decrease in f happens when $\theta_k = \pi$



$$\Rightarrow p_k = \underbrace{-}_{\text{desc}} \underbrace{\nabla f_k}_{\text{grad}} \quad \text{"Steepest" descent}$$

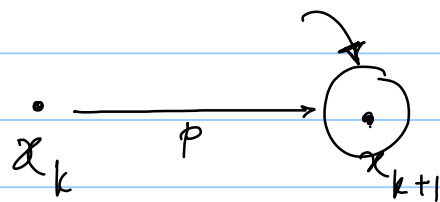
A descent direction

makes an angle $\in [-\pi/2, \pi/2]$ with $-\nabla f_k$.

Find the Newton direction

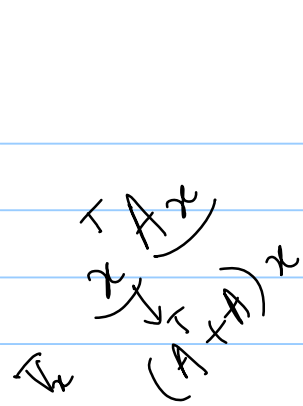
2nd order Taylor: $f(x_k + \epsilon p_k) = \underbrace{f(x_k)}_{q_k} + \epsilon \nabla f_k^T p_k + \frac{\epsilon^2}{2} \underbrace{p_k^T \nabla^2 f_k p_k}_{\text{Hessian term}} + O(\epsilon^3)$

$$\nabla f_k^T p = \left(\frac{\partial f}{\partial x_1}\right) p_1 + \left(\frac{\partial f}{\partial x_2}\right) p_2 + \dots$$



\Downarrow x_{k+1} is the soln

$$\nabla_P f(x_k + \epsilon p_k) = 0 \quad \therefore \text{Stationary pt}$$



$$\nabla_p [f(x_k + \epsilon p_k)] = \nabla_p [0] = 0 + \epsilon (\nabla f_k) + \epsilon^2 (\nabla^2 f_k) p_k + 0$$

As long as $(\nabla^2 f)$ is P.D. $\rightarrow p_k = -\frac{1}{\epsilon} (\nabla^2 f)^{-1} (\nabla f_k)$ ✓
 Left multiply by $(\nabla^2 f)^{-1}$.

$$p_N = -(\nabla^2 f)^{-1} \nabla f_k$$

Newton direction.

Is this a descent direction?

$$\begin{aligned}
 P_N^T \nabla f_k < 0 &\Rightarrow \nabla f_k^T \overbrace{\left(-(\nabla^2 f_k)^{-1} \nabla f_k \right)}^{P_N} < 0 \\
 = \nabla f_k^T P_N &\longrightarrow \nabla f_k^T \underbrace{(\nabla^2 f_k)^{-1}} \nabla f_k > 0 \\
 &\Rightarrow \underbrace{\nabla^2 f_k}_{\text{P.D.}} \text{ is P.D.} \curvearrowright \text{ is true.}
 \end{aligned}$$

Trust Region Methods

- ① Construct a model of the fn, m_k
- ② Search for a minima of m_k in the nbd of x_k .

$$\min_p m_k(x_k + p), \quad \text{s.t. } x_k + p \in T$$

$$m_k(x_k + p) = f_k + \nabla f_k^T p + \frac{1}{2} P_k^T B_k P_k$$

Hessian or its approx

→ x →

$$f(x, y) = e^{-(x-1)^2} \sin(\pi y)$$

$$x \in [0, 2], \quad y \in [0, 1]$$