

204

Choosing a step size

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Optimization on manifolds, MATH 512 @ EPFL

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Decrease without knowing L ?

We make a **Lipschitz-like assumption** about f and R together:

$$\mathbf{A2} \quad f(R_x(s)) \leq f(x) + \langle \text{grad} f(x), s \rangle_x + \frac{L}{2} \|s\|_x^2 \text{ for all } (x, s) \in \text{TM}.$$

With $x_{k+1} = R_{x_k}(-\alpha \text{grad} f(x_k))$, this implies:

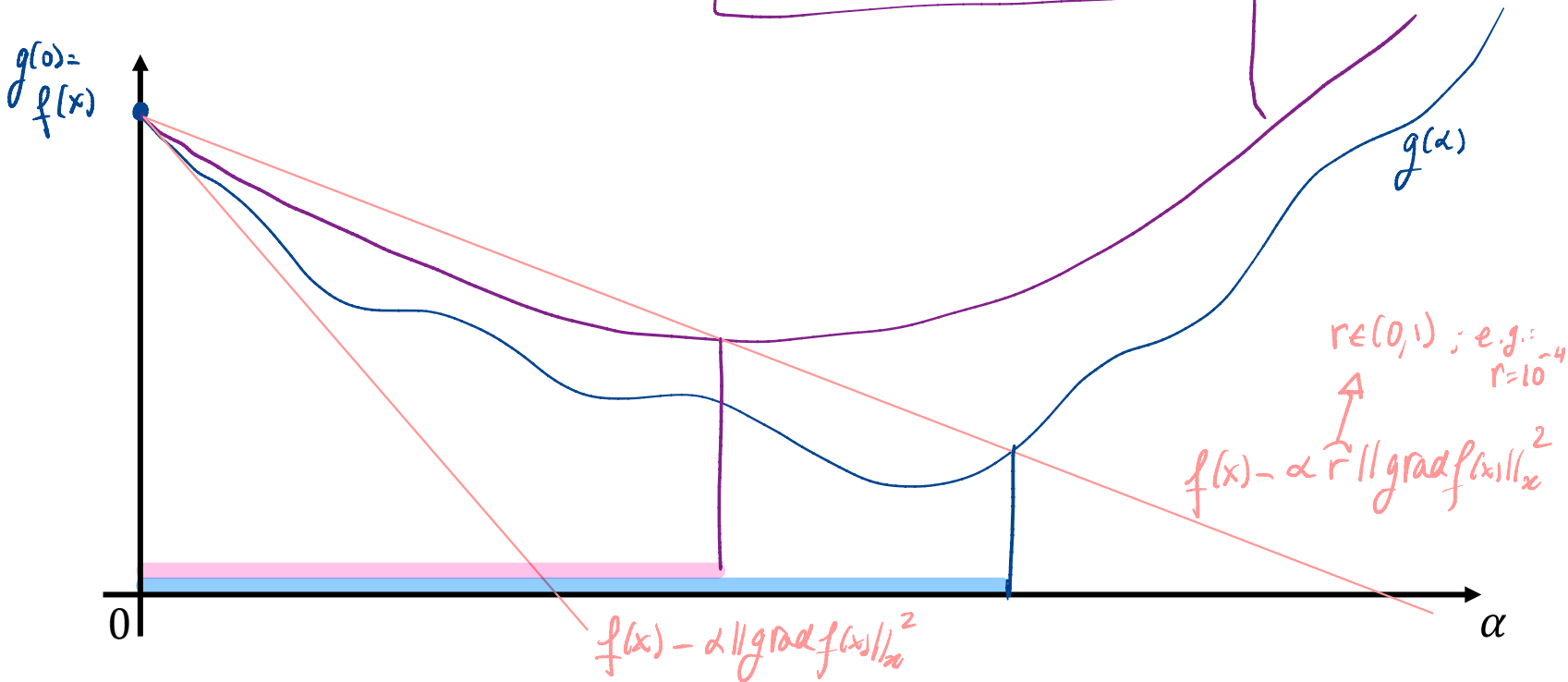
$$\mathbf{A3} \quad \text{Sufficient decrease: } f(x_k) - f(x_{k+1}) \geq c \|\text{grad} f(x_k)\|_{x_k}^2 \quad \forall k$$

where $c = \alpha \left(1 - \frac{\alpha L}{2}\right)$. Positive if $\alpha \in (0, 2/L)$. But rarely know L ...

$$g'(0) = Df(x)[-gradf(x)] = -\|gradf(x)\|_x^2$$

Backtracking line-search

$$g(\alpha) \stackrel{\text{def}}{=} f(R_x(-\alpha gradf(x))) \stackrel{A2}{\leq} f(x) - \alpha \|gradf(x)\|_x^2 + \frac{\alpha^2 L}{2} \|gradf(x)\|_x^2$$



I accept α if $g(\alpha) \leq f(x) - \alpha r \|\text{grad} f(x)\|_x^2 \equiv f(x) - f(R_x(-\alpha \text{grad} f(x))) \geq \alpha r \|\text{grad} f(x)\|_x^2$

Armijo backtracking for gradient descent

Parameters: $\tau \in (0, 1)$, $r \in (0, 1)$ (for example, $\tau = \frac{1}{2}$ and $r = 10^{-4}$)

Input: $x \in \mathcal{M}$, $\bar{\alpha} > 0$

Algorithm: Let $\alpha \leftarrow \bar{\alpha}$

While $f(x) - f(R_x(-\alpha \text{grad} f(x))) < r\alpha \|\text{grad} f(x)\|_x^2$

$\alpha \leftarrow \tau\alpha$

Output α

Theorem: If **A2** holds, then **A3** holds with $c = r \min\left(\bar{\alpha}, \frac{2\tau(1-r)}{L}\right)$.

“While” loops at most $\max\left(1, 2 + \log_{\tau^{-1}}\left(\frac{\bar{\alpha}L}{2(1-r)}\right)\right)$ times.