

* Other basic descent methods:

There are other descent methods for which you can guarantee:

$$f(x_{k+1}) \leq f(x_k) - \frac{\beta}{2} \|\nabla f(x_k)\|_2^2 \text{ for some } \beta > 0.$$

* Examples:

1) Preconditioned methods:

$$\underline{x_{k+1} = x_k - \alpha S_k \nabla f(x_k)}, \text{ where } S_k \text{ is a PD matrix w/ eigenvalues in } [\gamma_1, \gamma_2] \\ 0 < \gamma_1 < \gamma_2 < \infty.$$

From Lemma 2.2:

$$\begin{aligned} f(x_{k+1}) &\leq f(x_k) + \langle \nabla f(x_k), x_{k+1} - x_k \rangle + \frac{L}{2} \|x_{k+1} - x_k\|_2^2 \\ &= f(x_k) - \alpha \underbrace{\langle S_k \nabla f(x_k), \nabla f(x_k) \rangle}_{\geq \gamma_1 \|\nabla f(x_k)\|_2^2} \\ &\quad + \frac{L}{2} \alpha^2 \underbrace{\|S_k \nabla f(x_k)\|_2^2}_{\leq \gamma_2^2 \|\nabla f(x_k)\|_2^2} \\ &\leq f(x_k) - \underbrace{\left(\alpha \gamma_1 - \frac{L}{2} \gamma_2^2 \alpha^2 \right)}_{> 0 \text{ for suff. small } \alpha} \|\nabla f(x_k)\|_2^2. \end{aligned}$$

Newton's method uses $S_k = (\nabla^2 f(x_k))^{-1}$; need $\nabla^2 f(x_k)$ to have positive evals for this work

2) Gauss-Southwell (greedy coordinate descent)

$$x_{k+1} = x_k - \alpha \underbrace{\nabla_{i_k} f(x_k)}_{-p_k} e_{i_k}, \quad e_{i_k} = [0, 0, \dots, \underbrace{1}_{i_k \text{ position}}, \dots, 0]$$

$$\star \boxed{i_k = \arg \max_{1 \leq i \leq n} |\nabla_i f(x_k)|}$$

$$\|p_k\|_2 \geq \frac{1}{\alpha} \|\nabla f(x_k)\|_2$$

3) Randomized coordinate descent (HW #2)

4) Stochastic gradient descent, where

$$p_k = -g(x_k, \tilde{z}_k), \quad \mathbb{E}_{\tilde{z}_k} [g(x_k, \tilde{z}_k)] = \nabla f(x_k)$$

\downarrow
 i.i.d. r.v.

$$x_{k+1} = x_k + \alpha p_k,$$

under certain assumptions.

* Convergence of basic descent methods:

* Assume:

$$f(x_{k+1}) \leq f(x_k) - \frac{\alpha}{2} \|\nabla f(x_k)\|_2^2.$$

① nonconvex case:

$$\min_{0 \leq i \leq k} \|\nabla f(x_i)\|_2 \leq \sqrt{\frac{2(f(x_0) - f_*)}{\alpha(k+1)}},$$

where $f(x) \geq f_* > -\infty, \forall x$.

② Convex f .

convexity:

$$\forall x: f(x^*) \geq f(x) + \langle \nabla f(x), x^* - x \rangle$$

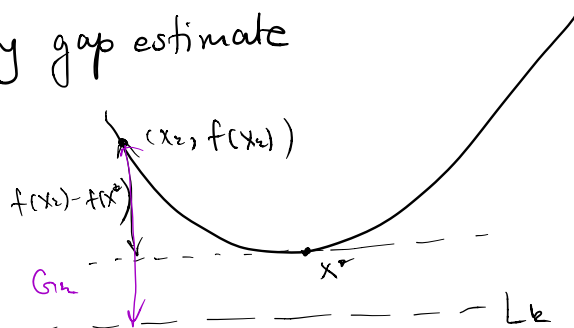
$$f(x_{k+1}) - f(x^*) \leq \overline{G}_k$$

optimality gap estimate

$$f(x^*) \geq \underline{L}_k$$

lower bound

Let \underline{L}_k be a strictly increasing positive numbers.



Goal:

$$A_k G_k - A_{k-1} G_{k-1} \leq \underbrace{E_k}_{\text{"error"}}$$

$$\Rightarrow A_k G_k \leq A_0 G_0 + \sum_{i=0}^k E_i$$

$$\underbrace{f(x_{k+1}) - f(x^*)}_{\text{bounded}} \leq G_k \leq \underbrace{\frac{A_0 G_0}{A_k}}_{\text{bounded}} + \underbrace{\frac{\sum_{i=0}^k E_i}{A_k}}_{\text{want it to grow slowly compared to } A_k}$$

Lower bound on $f(x^*)$:

$$f(x^*) \geq f(x_i) + \langle \nabla f(x_i), x^* - x_i \rangle$$

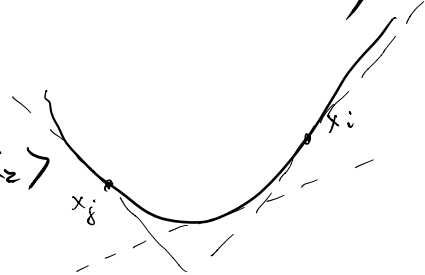
Let $\{a_i\}_{i=0}^k$ be a sequence of positive numbers
s.t. $A_k = \sum_{i=0}^k a_i$ so that $\frac{1}{A_k} \sum_{i=0}^k a_i = 1$.

$$\underbrace{\sum_{i=0}^k a_i}_{A_k} f(x^*) \geq \sum_{i=0}^k a_i (\langle \nabla f(x_i), x^* - x_i \rangle + f(x_i))$$

$$f(x^*) \geq \frac{1}{A_k} \sum_{i=0}^k a_i (\langle \nabla f(x_i), x^* - x_i \rangle + f(x_i)) =: L_k$$

$$\underline{A_k L_k - A_{k-1} L_{k-1} = a_k f(x_k)}$$

$$+ a_k \langle \nabla f(x_k), x^* - x_k \rangle$$



$$G_k = \underline{f(x_{k+1}) - L_k}$$

$$A_k G_k - A_{k-1} G_{k-1} = A_k f(x_{k+1}) - A_{k-1} f(x_k) - a_k f(x_k) - a_k \langle \nabla f(x_k), x^* - x_k \rangle$$

$$A_k = A_{k-1} + a_k$$

$$= A_k (f(x_{k+1}) - f(x_k)) - a_k \langle \nabla f(x_k), x^* - x_k \rangle$$

"Descent Lemma"

$$\leq -\frac{A_k \alpha}{2} \|\nabla f(x_k)\|_2^2 - \alpha_k \langle \nabla f(x_k), x^* - x_k \rangle$$

$$\stackrel{\text{C.S.}}{\leq} -\frac{A_k \alpha}{2} \|\nabla f(x_k)\|_2^2 + \alpha_k \|\nabla f(x_k)\|_2 \cdot \|x^* - x_k\|_2$$

Useful inequality: $-\frac{p^2}{2} + pq \leq \frac{q^2}{2}$

$$p = \sqrt{\alpha A_k} \|\nabla f(x_k)\|_2, \quad q = \frac{\alpha_k}{\sqrt{\alpha A_k}} \|x^* - x_k\|_2$$

$$A_k G_k - A_{k-1} G_{k-1} \leq \frac{\alpha_k^2}{2\alpha A_k} \|x^* - x_k\|_2^2 = E_k$$

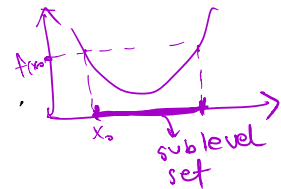
$$\text{Ex. } A_0 G_0 \leq \frac{\alpha_0^2}{2\alpha A_0} \|x^* - x_0\|_2^2$$

$$\Rightarrow f(x_{k+1}) - f(x^*) \leq G_k \leq \frac{1}{A_k} \sum_{i=0}^k \frac{\alpha_i^2}{2\alpha A_i} \|x^* - x_i\|_2^2$$

Define $R = \max \{ \|x^* - x\|_2 : f(x) \leq f(x_0) \}$

sublevel set: $\{x : f(x) \leq f(x_0)\}$

$$\Rightarrow f(x_{k+1}) - f(x^*) \leq \frac{R^2}{2\alpha A_k} \sum_{i=0}^k \frac{\alpha_i^2}{A_i}$$



How should we choose α_i ($A_i = \sum_{j=0}^i \alpha_j$) ?

$\alpha_i \propto i^p$, $p > 0$, for k large enough $A_k \propto \frac{k^{p+1}}{p+1}$.

(for integer p , Faulhaber's formula)

One particular choice

$$\alpha_i = \frac{i+1}{2}; \quad A_i = \frac{(i+1)(i+2)}{4}$$

$$\frac{\alpha_i^2}{A_i} \leq 1$$

$$\Rightarrow f(x_{k+1}) - f(x^*) \leq \frac{2R^2}{\alpha(k+2)}.$$