Coordinate descent

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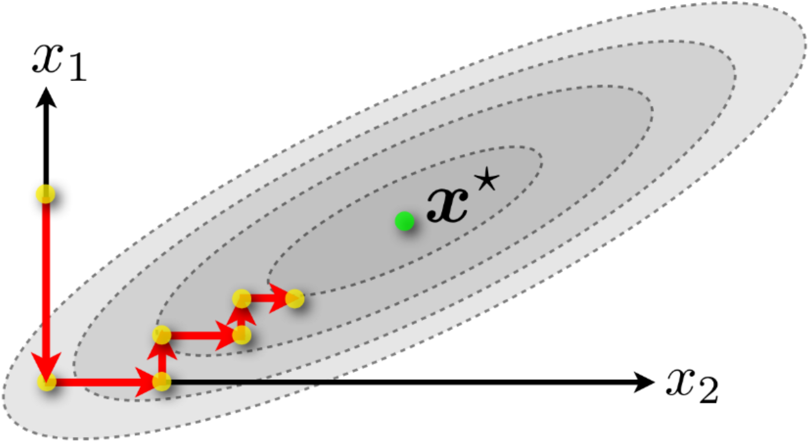
1. Introduction

Coordinate Descent

Goal: Find $x^* \in \mathbb{R}^d$ minimizing $f(x)$.



Figure

Coordinate Descent

Modify only one coordinate per step:

$$\text{select } i_k \in \{1, \ldots, d\}$$
$$x_{k+1} = x_k + \gamma e_{i_k}$$

where e_i is the i-th unit basis vector. Two main variants:

- Gradient-based stepsize:

$$x_{k+1} = x_k - \frac{1}{L} \nabla_{i_k} f(x_k) e_{i_k}$$

- Exact coordinate minimization:
  Solve the scalar problem $\arg\min_{\gamma \in \mathbb{R}} f(x_k + \gamma e_{i_k})$.
  - *hyperparameter free*

Randomized Coordinate Descent

How to choose the coordinate?

select $i_k \in \{1, \ldots, d\}$ uniformly at random

$$x_{k+1} = x_k + \gamma e_{i_k}$$

- Faster convergence than gradient descent
  (if coordinate step is d times cheaper than full gradient step)

Technical assumptions

Coordinate-wise smoothness:

$$f(x + \gamma e_i) \leq f(x) + \gamma \nabla_i f(x) + \frac{L}{2}\gamma^2, \quad \forall x \in \mathbb{R}^d, \forall \gamma \in \mathbb{R}, \forall i \in [d]$$

Is equivalent to coordinate-wise Lipschitz gradient:

$$|\nabla_i f(x + \gamma e_i) - \nabla_i f(x)| \leq L|\gamma|$$

- Additionally we assume strong convexity

Convergence: Linear rate

Theorem

Let f be coordinate-wise smooth with constant L and μ-strongly convex, Then coordinate descent with stepsize $1/L$

$$x_{k+1} = x_k - \frac{1}{L}\nabla_{i_k} f(x_k) e_{i_k}$$

where $i_k \sim Unif(1, \ldots, d)$

$$\mathbb{E}[f(x_k) - f^*] \le \left(1 - \frac{\mu}{dL}\right)^k (f(x_0) - f^*)$$

Proof

By using smoothness we obtain

$$f(x_{k+1}) \leq f(x_k) - \frac{1}{2L}\|\nabla_{i_k} f(x_k)\|^2$$

Taking the expectation w.r.t. i

$$\begin{aligned}
\mathbb{E}[f(x_{k+1})] &\leq f(x_k) - \frac{1}{2L}\mathbb{E}[|\nabla_{i_k} f(x_k)|^2] \\
&= f(x_k) - \frac{1}{2L}\frac{1}{d}\sum_i |\nabla_i f(x_k)|^2 \\
&= f(x_k) - \frac{1}{2dL}\|\nabla f(x_k)\|^2.
\end{aligned}$$

Lemma strong convexity implies PL: $\frac{1}{2}\|\nabla f(x)\|^2 \geq \mu(f(x) - f^*)$ Therefore, by subtracting f^* on both sides we get the statement of the theorem.

Polyak-Lojasiewicz (PL) Condition

Definition

f satisfies the PL condition if the following holds for some $\mu > 0$

$$\frac{1}{2}\|\nabla f(x)\|^2 \geq \mu(f(x) - f^*)$$

Lemma

Strong convexity implies PL.

Proof Strong convexity gives

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2}\|x - y\|^2.$$

Minimizing each side w.r.t. y gives

$$f(x^*) \geq f(x) - \frac{1}{2\mu}\|\nabla f(x)\|^2$$

Linear convergence without strong convexity

Examples satisfying PL

$f := g \circ A$ for strongly convex g and *arbitrary* matrix A, see least squares regression.

Corollary (Linear convergence for PL)

Same conditions as before but PL instead of strong convexity yields:

$$\mathbb{E}[f(x_k) - f^*] \leq \left(1 - \frac{\mu}{dL}\right)^k (f(x_0) - f^*)$$

Importance sampling

Uniform random selection is not always the best!

- Individual smoothness constants L_i for each coordinate i

$$f(x+\gamma e_i) \leq f(x) + \gamma \nabla_i f(x) + \frac{L_i}{2}\gamma^2$$

Coordinate descent using this modified selection probabilities $P[i_k = i] = \frac{L_i}{\sum_i L_i}$ with stepsize $1/L_{i_k}$ converges with the faster rate

$$\mathbb{E}[f(x_k) - f^*] \leq \left(1 - \frac{\mu}{d\bar{L}}\right)^k (f(x_0) - f^*)$$

where $\bar{L} = \frac{1}{d}\sum_{i=1}^d L_i$.

Often $\bar{L} \ll L = \max_i L_i$

Steepest Coordinate Descent

Selection rule given by

$$i_k = \arg\max_{i \in [d]} |\nabla_i f(x_k)|$$

"Greedy" or steepest coordinate descent.
Drawback: requires computation of full gradient if you do not have additional knowledge.

Convergence of Steepest Coordinate Descent

Has same convergence rate as for random coordinate descent! Use the fact that *max* is larger than *average*

$$\max_i |\nabla_i f(x)|^2 \geq \frac{1}{d} \sum_{i=1}^{d} |\nabla_i f(x)|^2,$$

Corollary

Steepest Coordinate Descent with stepsize $1/L$

$$f(x_k) - f^* \leq \left(1 - \frac{\mu}{d\bar{L}}\right)^k (f(x_0) - f^*)$$

Faster Convergence of Steepest Coordinate Descent

Faster convergence when measuring strong convexity of f w.r.t 1-norm instead of the standard Euclidean norm, i.e.

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu_1}{2} \|x - y\|_1^2.$$

Theorem

Let f be coordinate-wise smooth with constant L and μ_1-strongly convex, w.r.t. the 1-norm. Then steepest coordinate descent with stepsize $1/L$

$$f(x_k) - f^* \leq \left(1 - \frac{\mu}{L}\right)^k (f(x_0) - f^*)$$

Contraction factor i d times larger. But only in the extreme

$$\frac{\mu}{d} \leq \mu_1 \leq \mu$$