

Warmup

Let $f(x_1, x_2) = 2x_1^2 + 2x_1x_2 + 2x_2^2 + 3x_1 - 4x_2$

1. Write f in the form

$$f(x) = \frac{1}{2} x^T \underset{\substack{\uparrow \\ \text{Symmetric}}}{Q} x + b^T x$$

2. Determine if f is positive definite

3. Take a deep breath

1. $f(x_1, x_2) = \frac{1}{2} (x_1, x_2) \begin{pmatrix} 4 & 2 \\ 2 & 4 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + (3 \ -4) \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$

2. (a) Principal minor $4 > 0$

$$\det \begin{pmatrix} 4 & 2 \\ 2 & 4 \end{pmatrix} = 16 - 4 = 12 > 0$$

(b) eigenvalues $\det \begin{pmatrix} 4-\lambda & 2 \\ 2 & 4-\lambda \end{pmatrix} = 0$

$$\begin{aligned} \Leftrightarrow (4-\lambda)^2 - 4 &= 0 \\ \Leftrightarrow 16 - 4 - 8\lambda + \lambda^2 &= 0 \\ 12 - 8\lambda + \lambda^2 &= 0 \end{aligned}$$

$$(\lambda - 2)(\lambda - 6) = 0$$

eigenvalues $\lambda = 2, 6 > 0$

$\therefore Q$ is positive definite

3. Left as an exercise for the reader 😊

When Q is symmetric

$$\nabla f(x) = Qx + b$$

IMPORTANT:

Not true when Q is not symmetric

$\nabla(x^T A x)$: for A not symmetric is $(A + A^T)x$

$$\nabla^2 f(x) = Q.$$

To find a minimizer, by FONC, we need a minimizer x^* to satisfy

$$\nabla f(x) = Qx + b = 0$$

$$\text{or } x^* = -Q^{-1}b$$

Why is this a minimizer?

By SOSC, $Q > 0$

$$\nabla^2 f(x)$$

Gradient Descent

- Steepest
- Fixed stepsize

Algorithm, Given f , starting point x_0

For $k=0, 1, 2, \dots$

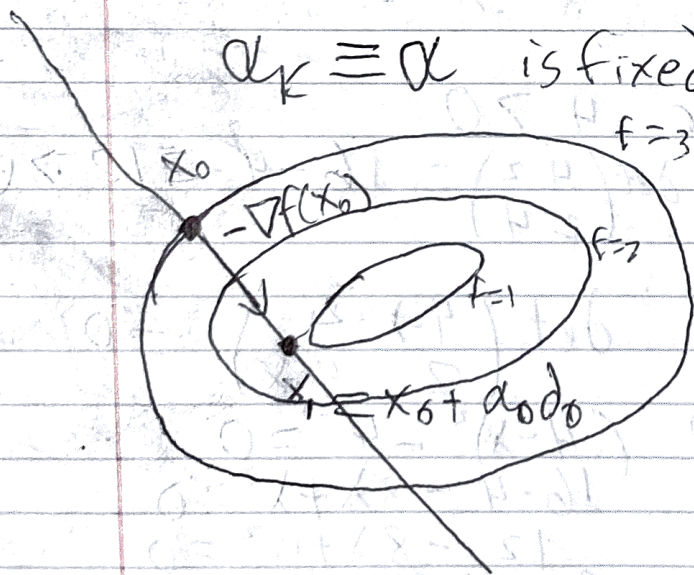
1. Let $d_k = -\nabla f(x_k)$
2. Choose stepsize α_k
3. Let $x_{k+1} = x_k + \alpha_k d_k$

For steepest Descent

$$\alpha_k = \underset{\alpha}{\operatorname{argmin}} f(x_k + \alpha d_k)$$

For fixed descent

$$\alpha_k \equiv \alpha \text{ is fixed}$$



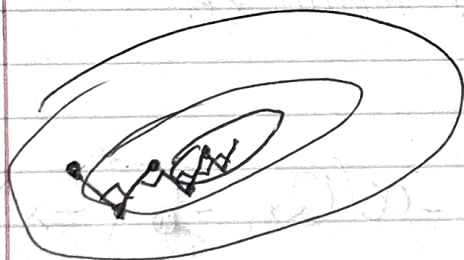
Theorem:

Consecutive directions of steepest descent are orthogonal.

Proof: Consider points x_k of steepest descent method. We have $x_{k+1} = x_k + \alpha_k d_k$ where α_k minimizes $\phi(\alpha) = f(x_k + \alpha d_k)$

Then by FONC $\phi'(\alpha) = \nabla f(x_k + \alpha d_k)^T d_k = 0$ at $\alpha = \alpha_k$.

Then we see $\nabla f(x_{k+1})^T d_k = 0$ where $d_k = -\nabla f(x_k)$. Therefore consecutive directions are orthogonal.



~~Stepsize Analysis~~

Fact: Steepest Descent is a descent method, i.e. if x_k does not satisfy $\nabla f(x_k) = 0$, then $f(x_{k+1}) < f(x_k)$

Fact: Steepest descent converges to a ~~point~~ point where $\nabla f(x_k) = 0$ (under mild conditions, e.g. $f \in C^1$, $f \rightarrow \infty$ as $\|x\| \rightarrow \infty$)

Fact: This convergence is linear

Fixed Stepsize Analysis for quadratic functions

$$x_{k+1} = x_k - \alpha \nabla f(x_k)$$

For Quadratic functions of form

~~Qx~~

$$f(x) = \frac{1}{2} x^T Q x - b^T x$$

$$\nabla f(x) = Qx - b$$

To analyze above method, we consider error $e_k = x_k - x^*$ for minimizer

$$x^* = Q^{-1}b$$

$$\text{Note } Qx^* = b$$

$$e_{k+1} = x_{k+1} - x^* = x_k - \alpha(Qx_k - b) - x^*$$

$$= e_k - \alpha(Qx_k - Qx^*)$$

$$= e_k - \alpha Q e_k$$

$$= (I - \alpha Q) e_k$$

$$= (I - \alpha Q)^{k+1} e_0$$

By spectral Theorem, can write

$e_0 = a_1 v_1 + \dots + a_n v_n$, v_i are eigenvectors of Q with eigenvalue λ_i

$$\begin{aligned} p_{k+1} &= (I - \alpha Q)^{k+1} (a_1 v_1 + \dots + a_n v_n) \\ &= a_1 (1 - \alpha \lambda_1)^{k+1} v_1 + \dots + (1 - \alpha \lambda_n)^{k+1} v_n \end{aligned}$$

For $e_k \rightarrow 0$, need all components to go to zero,

~~This occurs when~~
Recall $a^k \rightarrow 0$ when $|a| < 1$.
Need

$$|1 - \alpha \lambda_i| < 1 \quad \forall i$$

$\Leftrightarrow$

$$-1 < 1 - \alpha \lambda_i < 1$$

$$\Leftrightarrow -2 < -\alpha \lambda_i < 0$$

$\Leftrightarrow$

$$\frac{2}{\lambda_i} > \alpha > 0 \quad \forall i$$

$$0 < \alpha < \frac{2}{\lambda_{\max}}$$

Back to warmup problem

Convergence ^{guaranteed} when $0 < \alpha < \frac{2}{\lambda_{\max}} \approx \frac{1}{2}$