

(A)

Method of Steepest Descent

Gradient descent is derived from 1st order Taylor approx:

$$f(x) \approx f(x^{(t)}) + \underbrace{\nabla f(x^{(t)})^T}_{\text{arrow}} (x - x^{(t)})$$

To min. $f(x)$, we want to make $\underbrace{\hspace{10em}}$ as small as possible.

For GD, we pick $x^{(t+1)} - x^{(t)} = -\mu \nabla f(x^{(t)})$
which gives

$$f(x^{(t+1)}) \approx f(x^{(t)}) - \mu \|\nabla f(x^{(t)})\|_2^2$$

Another interpretation: we want to find direction p that minimizes $\nabla f(x^{(t)})^T p$.

$$\Rightarrow \left(\min_{\|p\|=\delta} \nabla f(x^{(t)})^T p \right) \text{ for some } \delta > 0.$$

↑

we add $\|p\|=\delta$ to bound the problem and also because we are really only interested in the direction

This is equivalent to:

$$\min_p \frac{\delta \nabla f(x^{(t)})^T p}{\|p\|}$$

By Cauchy-Schwarz inequality :

$$-\|\nabla f(x^{(t)})\| \cdot \|p\| \leq \nabla f(x^{(t)})^T p \leq \|\nabla f(x^{(t)})\| \cdot \|p\|$$

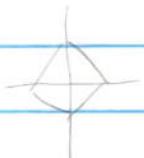
$$\rightarrow \left\{ -\|\nabla f(x^{(t)})\| \leq \frac{\nabla f(x^{(t)})^T p}{\|p\|} \right\}$$

Smallest possible value of \uparrow

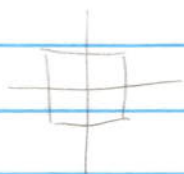
Assume we are using the two-norm and let $S = \|\nabla f(x^{(t)})\|$. Then the direction p that achieves the minimum value is :

$$\left\{ p^* = -\nabla f(x^{(t)}) \right\} \text{ (ie. we get gradient descent)}$$

Different norms give different methods of steepest descent :



L1-norm : $\|x\|_1 = \sum_{i=1}^n |x_i|$ (sum of absolute values of x)



L-infinity-norm : $\|x\|_\infty = \max_{i=1 \dots n} |x_i|$ (max abs. value in x)

$$\text{sign}(y) = \begin{cases} +1 & y > 0 \\ 0 & y = 0 \\ -1 & y < 0 \end{cases}$$

(c)

For 1-norm

$$\min_P \frac{\nabla f(x^{(t)})^T P}{\|P\|_1} \Rightarrow P^* = -\text{sign}(\nabla_j f(x^{(t)})) \begin{pmatrix} 0 \\ \vdots \\ \delta \\ \vdots \\ 0 \end{pmatrix} \leftarrow \text{row } j$$

$$\text{where } \delta = \|\nabla f(x^{(t)})\|_\infty = |\nabla_j f(x^{(t)})|$$

↑
jth element of ∇f has
the largest magnitude

This is aka "coordinate descent". We are moving
along one axis at each iteration.

For ∞ -norm

$$\min_P \frac{\nabla f(x^{(t)})^T P}{\|P\|_\infty} \Rightarrow P^* = -\delta \begin{pmatrix} \text{sign}(\nabla_1 f(x^{(t)})) \\ \text{sign}(\nabla_2 f(x^{(t)})) \\ \vdots \\ \text{sign}(\nabla_n f(x^{(t)})) \end{pmatrix}$$

where $\delta = \|\nabla f(x^{(t)})\|_1$ and the sign of
each ± 1 matches the sign of $\nabla f(x^{(t)})$.

$$\left(\text{if } \nabla_i f(x^{(t)}) \neq 0 \forall i, P^* = -\delta \begin{pmatrix} \pm 1 \\ \vdots \\ \pm 1 \end{pmatrix} \right)$$