

Q2 BV 9.5.

Q3 BV 9.6

Q5.

Recall the backtracking rule:

Given a descent direction  $\Delta x$  for  $f$  at  $x \in \text{dom } f$ ,

$\alpha \in (0, 1/2)$ ,  $\beta \in (0, 1)$ ,

$t \leftarrow 1$

↖ decrease of  $f$  is not enough.

While  $f(x + t \Delta x) > f(x) + \alpha t \nabla f(x)^T \Delta x$

set  $t \leftarrow \beta t$ .

$f$ : strongly convex with  $mI \preceq \nabla^2 f(x) \preceq MI \quad \forall x$ .  
 $M$ -smooth.

Find backtracking stopping condition:

$\nabla^2 f(x) \preceq MI \Rightarrow f(x + t \Delta x) = f(x) + t \nabla f(x)^T \Delta x + \frac{t^2}{2} \Delta x^T \underbrace{\nabla^2 f(z)}_{\preceq MI} \Delta x$   
 $z$  between  $x$  &  $x + t \Delta x$ .

$$f(x + t \Delta x) \leq f(x) + t \nabla f(x)^T \Delta x + \frac{Mt^2}{2} \|\Delta x\|^2.$$

We terminate whenever

$$f(x + t \Delta x) \leq f(x) + \alpha t \nabla f(x)^T \Delta x$$

A sufficient condition is:

$$\cancel{f(x)} + t \nabla f(x)^T \Delta x + \frac{Mt^2}{2} \|\Delta x\|^2 \leq \cancel{f(x)} + \alpha t \nabla f(x)^T \Delta x$$

$$\cancel{t(1-\alpha)} \nabla f(x)^T \Delta x + \frac{Mt^2}{2} \|\Delta x\|^2 \leq 0.$$

That is the exit condition holds with  $t \in [0, t_0]$

$$1 \geq t_0 = -2(1-\alpha) \frac{\nabla f(x)^T \Delta x}{M \|\Delta x\|^2} \geq - \frac{\nabla f(x)^T \Delta x}{M \|\Delta x\|^2} \stackrel{= t_0}{\geq 0}.$$

$\begin{matrix} \leq 1 \\ \uparrow \\ 0 \leq \alpha \leq \frac{1}{2} \end{matrix}$

How many iterations s.t.  $t \leq t_0$

$$\beta^k \cdot 1 \leq t_0 \Rightarrow k \log \beta \leq \log t_0$$

$$k \geq \frac{\log t_0}{\log \beta} = \frac{\log (1/t_0)}{\log (1/\beta)}$$

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Q3. BV 9.6  $f(x) = \frac{1}{2} (x_1^2 + \gamma x_2^2)$

$$x^* = (x_1^*, x_2^*) = (0, 0)$$

$$\nabla f(x) = \begin{bmatrix} x_1 \\ \gamma x_2 \end{bmatrix}$$

$$\begin{aligned} x^{(k+1)} &= x^{(k)} - t \nabla f(x^{(k)}) \\ &= \begin{bmatrix} x_1^{(k)} \\ x_2^{(k)} \end{bmatrix} - t \begin{bmatrix} x_1^{(k)} \\ \gamma x_2^{(k)} \end{bmatrix} = \begin{bmatrix} (1-t)x_1^{(k)} \\ (1-t\gamma)x_2^{(k)} \end{bmatrix}. \end{aligned}$$

$$x^{(0)} = \begin{bmatrix} \gamma \\ 1 \end{bmatrix}$$

$$x^{(1)} = \begin{bmatrix} (1-t)\gamma \\ (1-t\gamma) \cdot 1 \end{bmatrix}, \quad x^{(2)} = \begin{bmatrix} (1-t)^2\gamma \\ (1-t\gamma)^2 \end{bmatrix}, \dots, x^{(k)} = \begin{bmatrix} (1-t)^k\gamma \\ (1-t\gamma)^k \end{bmatrix}.$$

Find the  $t > 0$  that min

$$g(t) := f(x^{(k-1)} - t \nabla f(x^{(k-1)}))$$

$$\gamma^2 (1-t)^{2k}$$

$$x^{(k)}$$

$$f(x) = \frac{1}{2} (x_1^2 + \gamma x_2^2)$$

$$g(t) = \frac{1}{2} \left[ ((1-t)^k \gamma)^2 + \gamma (1-t\gamma)^{2k} \right]$$

$$g'(t) = \frac{1}{2} \left[ 2k(1-t)^{2k-1} (-1) \gamma^2 + \gamma \cdot 2k \cdot (1-t\gamma)^{2k-1} \cdot (-\gamma) \right] = 0.$$

$$-(1-t)^{2k-1} = (1-t\gamma)^{2k-1}$$

$\Downarrow$

$$-(1-t) = 1-t\gamma$$

$\Downarrow$

$$t^* = \frac{2}{1+\gamma}$$

$$x^{(k)} = \begin{bmatrix} (1-t)^k \gamma \\ (1-t \cdot \frac{2}{1+\gamma})^k \end{bmatrix} = \left( \frac{1-\gamma}{1+\gamma} \right)^k \begin{bmatrix} \gamma \\ 1 \end{bmatrix}.$$

Find out how  $f(x^{(k)})$  evolves.

$$f(x) = \frac{1}{2} (x_1^2 + \gamma x_2^2) = \frac{\gamma(\gamma+1)}{2} \left( \frac{1-\gamma}{1+\gamma} \right)^{2k}$$

If  $\gamma \approx 1$ , then  $\frac{1-\gamma}{1+\gamma} \approx 0$

If  $\gamma \approx 0$ , then  $\frac{1-\gamma}{1+\gamma} \approx 1$

If  $\gamma \approx 10^6$ , then  $\frac{1-\gamma}{1+\gamma} \approx -1$

5. 
$$f(x) = \|x\|_2^{2+\beta} = \left( (x_1^2 + \dots + x_n^2)^{\frac{1}{2}} \right)^{2+\beta} \\ = (x_1^2 + \dots + x_n^2)^{1+\beta/2}.$$

$$\begin{aligned} \frac{\partial f}{\partial x_i} &= (\nabla f(x))_i = (1 + \frac{\beta}{2}) (x_1^2 + \dots + x_n^2)^{\beta/2} (2x_i) \\ &= (2+\beta) \|x\|^\beta x_i \quad \forall i=1, \dots, n. \end{aligned}$$

$$\nabla f(x) = (2+\beta) \|x\|^\beta \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = (2+\beta) \|x\|^\beta x$$

GD with step size  $s > 0$ .

$$x^{(k+1)} = x^{(k)} - s \nabla f(x^{(k)})$$

$$\begin{aligned}
 &= x^{(k)} - s(2+\beta) \|x^{(k)}\|^\beta x^{(k)} \\
 &= x^{(k)} [1 - s(2+\beta) \|x^{(k)}\|^\beta].
 \end{aligned}$$

Claim: If  $\|x^1\| < \|x^0\|$ , then  $\|x^{k+1}\| < \|x^k\|$  for all  $k \geq 1$ .

Pf: Suppose  $\|x^1\| < \|x^0\|$ . Assume  $\|x^k\| < \|x^{k-1}\|$  for all  $k \leq n$ ,  $n \geq 2$ .

$$\frac{\|x^{n+1}\|}{\|x^n\|} = |1 - s(2+\beta) \|x^n\|^\beta|$$

We only need to show that  $|1 - s(2+\beta) \|x^n\|^\beta| < 1$ .

$$|a| < 1 \Leftrightarrow -1 < a < 1$$

$$-1 < 1 - s(2+\beta) \|x^n\|^\beta < 1$$

$$0 < s(2+\beta) \|x^n\|^\beta < 2$$

By the induction hypothesis,

$$\frac{\|x^n\|}{\|x^{n-1}\|} < 1 \Rightarrow \underline{0 < s(2+\beta) \|x^{n-1}\|^\beta < 2} \quad \text{have}$$

$$0 < s(2+\beta) \|x^n\|^\beta \stackrel{\text{I.H.}}{<} s(2+\beta) \|x^{n-1}\|^\beta < 2.$$

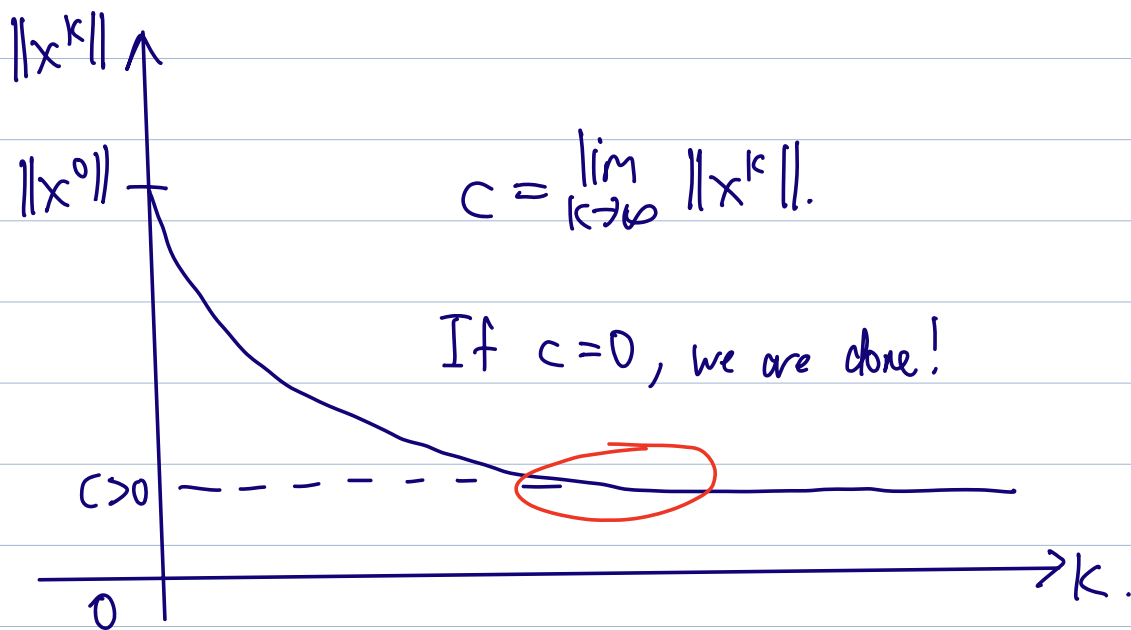
Claim: If  $\|x^1\| < \|x^0\|$ , then  $\|x^{k+1}\| < \|x^k\|$  for all  $k \geq 1$ .

$$x^1 = (1 - s(2+\beta)\|x^0\|^\beta) x^0$$

Thus for the GD method to converge, we need  $\|x^1\| < \|x^0\|$ .

$$|1 - s(2+\beta)\|x^0\|^\beta| < 1. \quad (*)$$

If  $(*)$  is satisfied  $\{\|x^k\|\}$  is monotonically decreasing.



$$|1 - s(2+\beta)\|x^0\|^\beta| < 1. \quad (*)$$

$$\|x^0\| \geq c, \quad 0 < s(2+\beta)\|x^0\|^\beta < 2$$

$$\Rightarrow 0 < s(2+\beta)c^\beta < 2.$$

$$\Rightarrow |1 - s(2+\beta)c^\beta| < 1 \quad (**)$$

$$\lim_{k \rightarrow \infty} \frac{\|x^{k+1}\|}{\|x^k\|} = 1$$

Combining (\*\*) with the iterations, we see that

$$\lim_{k \rightarrow \infty} \frac{\|x^{k+1}\|}{\|x^k\|} = \underbrace{\left| 1 - s(2+\beta)c^\beta \right|}_{\lim_{k \rightarrow \infty} \|x^k\|}^{(*)} < 1 \Rightarrow \Leftarrow$$

$c$  cannot be  $> 0$ .  $\Rightarrow c = 0$ .

$$x^{k+1} = x^k \left( 1 - s(2+\beta)\|x^k\|^\beta \right).$$

$$\begin{aligned} \lim_{k \rightarrow \infty} \frac{\|x^{k+1}\|}{\|x^k\|} &= \lim_{k \rightarrow \infty} \left| 1 - s(2+\beta)\|x^k\|^\beta \right| \\ &= \left| 1 - s(2+\beta)c^\beta \right|. \end{aligned}$$