

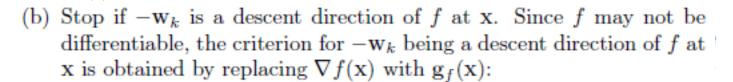
By Weistrass' thm, $\leq 19-P1$ (max f(z) - min f(x)) $f(z) = x \in C_8$ Jis ets 4 since C8 is 8 dosed & bounded, fattains extrema on Cs Similarly, we get $f(p) - f(q) \leq \frac{\|p-q\|}{8} \left(\max_{z \in C_8} f(z) - \min_{z \in C_8} f(z) \right)$ Combining () & 2), we get (f(p)-f(q)) < L (1p-91) Where $L = \frac{max f(z) - min f(x)}{2EC_8}$

- As discussed in the class, director d is a descent direction of a function f at a point x if the directional derivative of f along d is strictly negative. That is $\mathbf{d}^T \nabla f(\mathbf{x}) < 0$. In this exercise, we provide a method for generating descent direction in cases in which obtaining a single subgradient is relatively simple.
 - (a) Let $\mathbf{g}_{f}^{(i)}(\mathbf{x})$ be a subgradient of f at \mathbf{x} in the i^{th} step of the algorithm. (For i=0, you just pick any subgradient.) Let \mathbf{w}_{k} be the vector of minimum p-norm (for any $p \geq 1$) in the convex hull of $\mathbf{g}_f^{(1)}(\mathbf{x}), \mathbf{g}_f^{(2)}(\mathbf{x}), \dots \mathbf{g}_f^{(k-1)}(\mathbf{x})$. Present an algorithm for computing \mathbf{w}_k when p=2. What about the case of any other value of p?

... $g_f(x^{(k-1)})$.

(4 Marks)

((4 Marks)	
MS.	Mr= MIU	$ M _{\mathcal{D}}$
	K d'M	
	st w=	$= d_1 g_1^{(i)}(x) + d_2 g_1^{(2)}(x) - d_{k-1}g_1^{(k-1)}(x)$
		107



$$-\mathbf{w}_k^T \mathbf{g}_f(\mathbf{x}) < 0$$

If the stopping criterion is not met, let $g_f^{(k)}(\mathbf{x}) \in \partial f$ such that

$$w_k^T \mathbf{g}_f^{(k)}(\mathbf{x}) = \min_{\mathbf{g} \in \partial f} w_k^T \mathbf{g}$$

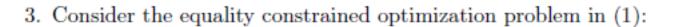
Prove that this process returns a descent direction of f at x in a finite number of iterations. You can assume that ∂f is compact. (Note that since $\partial f \subseteq \Re^n$, this is equivalent to saying that ∂f is closed and bounded).

(7 Marks)

Ans:	Firstly, ω_{k} is the projection of the origin on the set $(\alpha n)(g_{f}^{(i)}(x), g_{f}^{(i)}(x), -g_{f}^{(k-i)}(x))$
	the set $(\alpha \sqrt{9})(\alpha)$ $9((\alpha))$ $-2((\alpha))$
	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
	By the projection theorem on slide 9 of
http:/	//www.cse.iitb.ac.in/~CS709/notes/eNotes/first-order-descent-pr
oject	//www.cse.iitb.ac.in/~CS709/notes/eNotes/first-order-descent-pr ionMethod-annotated.pdf, we have $\forall g \in conv(g_{\xi}(x), \dots, g_{\xi}(x))$
	$(g-W_k)^T(O-W_k) \leq O$
\Rightarrow	(9-Wx) Wx > 0 > 9 Wx > 11 wx/12 min 11911=119*112
	(9-wx) Twx > 0 >) 9 Twx > 11wx 2 min 1911 = 119 x 12
	(x) $(x-1)$
Both	(9f. 9f) 4 Note: WKE If(x) WK-1) are sequences 49 CDf(x) (s subgradient with minimum norm
(ω,,	Will are sequences for Cof(a) is subgradient
lying	Wk-1) are sequences fg CDf(x) is subgradient with minimum norm

> Since of 13 closed, 11911>0, since if gx=0 limit points of W1. - WK-1

Los (9f. - 9f) then is already an optimal point should both lie in of if $\lim_{k\to\infty} w_k = \widehat{w} \& \lim_{k\to\infty} g^{(k)} = \widehat{g}_f$ then we expect 930>0 But if none of wk's are descent directions so fair, we have -wkgf=min wkg = max -wkg >0
gedf gedf gedf re witgest o sletting k-so, we get a contradiction => Some Wx should become a descent direction



minimize
$$\frac{1}{2}\mathbf{x}^TQ\mathbf{x} + \mathbf{c}^T\mathbf{x} + \beta$$

subject to $A\mathbf{x} = \mathbf{b}$ (1)

Assume that A has full row rank (that is no equality is redundant/conflicting). Let N be the basis for the null space of A. Show that this optimization problem is unbounded below if N^TQN has negative eigenvalues.

(5 Marks)

(5 Marks)			
M3:	Let us write KKT conditions for this problem		
	Qx+c+A7x=0		

factional loss thru a hoxizontal 7 FOO DL=3000 Ft = 1 KN H=4FLV2 valory nuts to be estimated 10 Vist/inin Mality m3/5. h term. 9.8 m/32 of beclass to hea d = WOH Dens. M & 73 Din m3/5 4000 likes 1:2 1100 /4e ~ 1/z HP = 375 kg m/s