MATH130165h: Homework 5.
20207100005.

$$[i] f_{i}(x) = b^{T} x \qquad \frac{\partial f_{i}(x)}{\partial x_{i}} = b_{i} \qquad (. \nabla f_{i}(x)) = b.$$

$$\frac{\partial \chi_i \partial \chi_j}{\partial \chi_i \partial \chi_j} = 0 \quad \forall i,j \qquad \therefore \quad H(f_i) = 0$$

$$\begin{bmatrix} 2 \end{bmatrix} f_{\lambda}(x) = x^{T}A \times \frac{\partial f_{\lambda}(x)}{\partial x_{i}} = \frac{\partial (x^{T}A)}{\partial x_{i}} \times + x^{T}A \frac{\partial x}{\partial x_{i}} = (x^{T}A)_{[i,j]} \times + x^{T}A e_{i}$$

$$= A_{[i,j]} \cdot x + (x^{T}A)_{[i,j]} = A_{[i,j]} \times + A^{T}x_{[i,j]}$$

$$(. \nabla f_{\lambda(x)}) = A \times + A^{T} \times = (A + A^{T}) \times.$$

$$\frac{\partial (\partial f_{2}(x))}{\partial x_{1}} = A_{[i,j]} + A_{[i,j]}^{T} \Rightarrow \frac{\partial (\partial f_{2}(x))}{\partial x} = A + A^{T}$$

And
$$H(f_{\nu})_{[ij]} = \frac{\partial^2 f_{\nu}(x)}{\partial x_j \partial x_i} = \frac{\partial (\partial f_{\nu}(x))}{\partial x_j}$$
 \(\frac{1}{2} \text{H}(f_{\nu}) = A+A^T\)

$$\frac{|P_{ro}blem 2|}{|P_{ro}blem 2|} = \sum_{i=1}^{n} (B^{T}X)_{E,i,i} = \sum_{i=1}^{n} (\sum_{k=1}^{n} B_{ik}^{T} X_{ki}) = \sum_{i=1}^{n} (\sum_{k=1}^{n} B_{ik} X_{ki})$$

$$\frac{\partial f_{i}(X)}{\partial X_{ki}} = B_{ki} \qquad \angle \nabla f_{i}(X) = B.$$

$$\frac{\partial f_{i}(X)}{\partial X_{ki}} = (X^{T}AX) = \sum_{i=1}^{n} (X^{T}AX)_{E,i,j} = \sum_{i=1}^{n} X_{E,i,j}^{T} A X_{E,i,j}$$

$$\frac{\partial f_{i}(X)}{\partial X_{E,i,j}} = (A^{T}+A) X_{E,i,j} \qquad \angle \nabla f_{i}(X) = A^{T}+A$$

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$$\frac{\partial f_{i}(X)}{\partial X_{i,j}} = \nabla f_{i}(X) \times F_{i}(X)$$

$$\frac{\partial f_{i}(X)}{\partial X_{i,j}} = \nabla f_{i}(X)$$

$$\frac{\partial f$$

First, we know from the calculus rule that:

$$\frac{\partial tr[AXBXC]}{\partial X} = \frac{\partial tr[AXD]}{\partial X} + \frac{\partial tr[EXC]}{\partial X} = A^TD^T + E^TC^T$$

$$= A^T(BXC)^T + E^T(BXC)^T$$

$$= A^T(BXC)^T + E^T(BXC)^T$$

$$D = CAX$$
Thus,
$$\frac{\partial tr(BX^TAXX^TBX^T)}{\partial X} = AXX^TBX^TB + \frac{\partial tr(CAXX^TBX^T)}{\partial X} = BX^TAX$$

$$\Rightarrow = (CA)^{\mathsf{T}}(X^{\mathsf{T}}BX^{\mathsf{T}})^{\mathsf{T}} + \frac{\partial \mathsf{Tr}(DX^{\mathsf{T}}BX^{\mathsf{T}})}{\partial X}$$

Problem 3

$$\frac{1}{2} f(x) = f(x) - \frac{M}{2} ||x||^2$$
 is convex

$$1, \beta[xx+(-x)y] \leq xg(x)+(-x)g(y)$$

$$= \chi_{\{1x\}} + (1-\alpha)f_{\{1y\}} - \frac{M}{2} \left[\alpha_{11}x_{11}^{2} - 11\alpha x + (1-\alpha)y_{11}^{2} + (1-\alpha)y_{11}^{2} \right]$$

$$= \chi_{\{1x\}} + (1-\alpha)f_{\{1y\}} - \frac{M}{2} \left[\alpha_{x}^{7}x - \left[\alpha_{x}^{7}x + (1-\alpha)y_{1}^{7}\right] \left[\alpha_{x}x + (1-\alpha)y_{1}^{7}\right] + (1-\alpha)y_{1}^{7}y_{1}^{7} \right]$$

$$= \chi_{\{1x\}} + (1-\alpha)f_{\{1y\}} - \frac{M}{2} \left[-\alpha(1-\alpha)(x_{1}^{7}x + y_{1}^{7}x) + \alpha(1-\alpha)x_{1}^{7}x + (1-\alpha)x_{1}^{7}y_{1}^{7} \right]$$

=
$$x f(x) + (1-x) f(y) - \frac{1}{2}(1-x) = x^{T}x + y^{T}y - x^{T}y - y^{T}x$$

=
$$\alpha f(x) + (+\alpha) f(y) - \frac{\pi}{2} (1-\alpha) \propto ||x-y||^2 + \chi_{,y}, \forall \alpha \in [0,1]$$

1 1 = 3

$$[\nabla f(x) - \nabla f(y)]^T(x-y) > \mu(x^T-y^T)(x-y)$$

$$([\nabla g (x) - \nabla g (y)]^T (x-y) > 0.$$
 \(\nabla g (x) = \nabla f(x) - \mu x)

Suppose X_1 , X_2 are the global minimizers of f. $f(x_1) = f(x_1) \leq f(x_1) \quad \forall x \in D$ $f(x_1) = f(x_1) \leq f(x_1) \quad \forall x \in D$ $f(x_1 + (1-t)x_1) \leq f(x_1) + (1-t)f(x_1) \leq f(x_1) + (1-t)f(x_1) = f(x_1)$ $\forall x_1 + (1-t)x_2 \quad \text{is a globel minimizer if } f$ That is, $x_1, x_2 \in M$, $\forall t \in [0,1]$, $\forall x_1 + (1-t)x_2 \in M$

- The set of global minimizers are convex.

Problem 5

$$\nabla f(x) = Ax - b$$
. 1. update rule: $\chi_{k+1} = \chi_k - \alpha (A\chi_k - b)$

$$\sqrt{1+(x')} = 0 \quad \chi^* = A^{-1}b$$

$$e_{1c+1} = \chi_{1c+1} - \chi^* = (I - \alpha A)\chi_{k+\alpha}b - A^{-1}b$$

Thus, to converge, the spectral radius of
$$I-dA < 1$$

$$P(I-\alpha A) < 1 \qquad \Rightarrow \alpha \in (0, \frac{2}{\lambda_{max}})$$

The norm of I-AA is a constant, so the convergence rate is linear.



$$S(X_XCD + \frac{9(EBCX_XC)}{9}$$

XCEBC + (EBCXT)T (C)T