

MATH 6397

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Problem Set 1

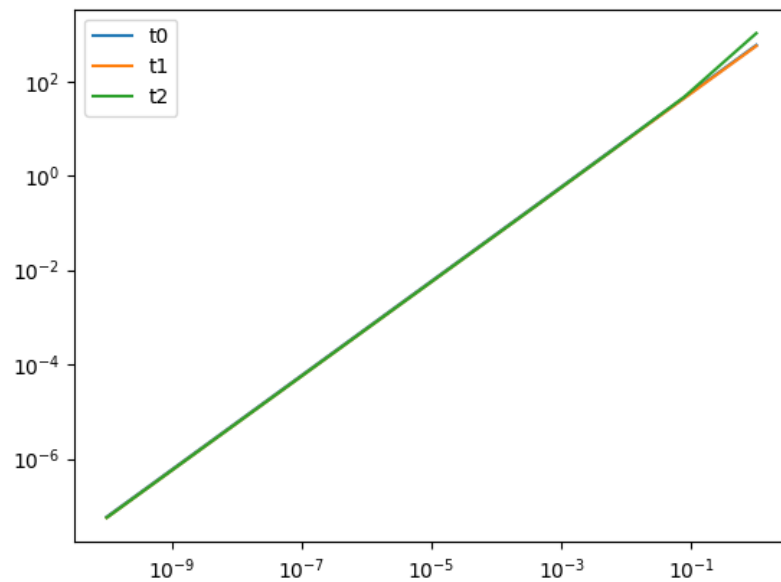
1.)

a.) We are given $f(x) = \frac{1}{2}x^T Qx + b^T x + c$

Therefore,

$$\begin{aligned}\nabla f(x) &= \frac{1}{2}(Q^T + Q)x + b, \\ \nabla^2 f(x) &= \frac{1}{2}(Q^T + Q)\end{aligned}$$

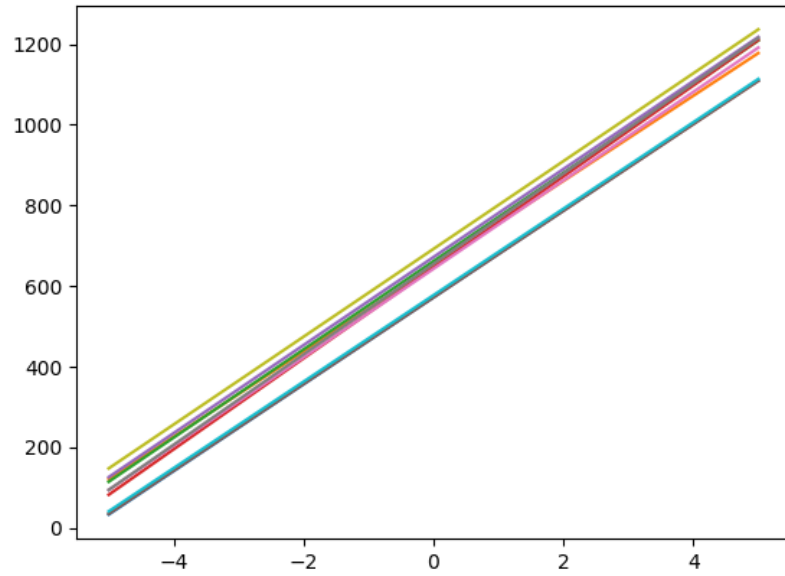
Derivative Check:



Comments: The code runs and gives us our desired result

b.)

Convexity Check:



Comments: Our function f is a convex function

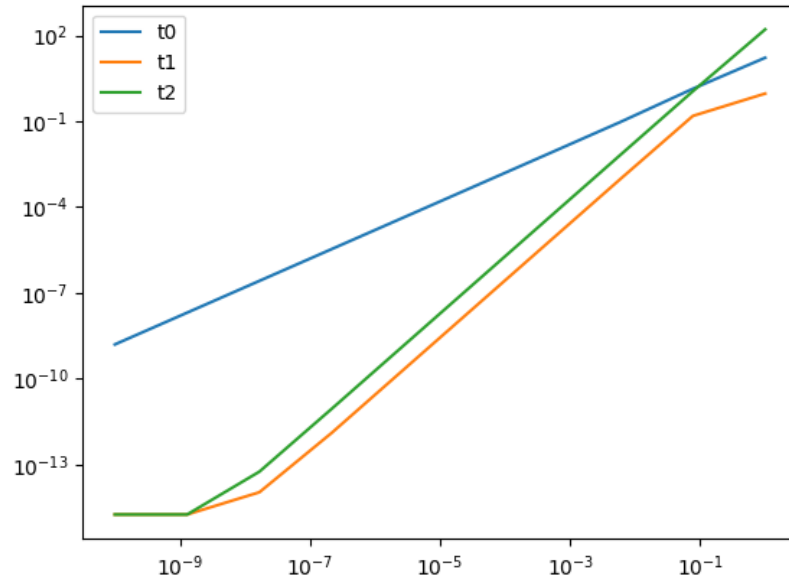
2.)

We are given $\text{minimize}_{x \in \mathbb{R}^n} \frac{1}{2} \|\sin(Ax) - b\|_2^2 + \frac{\beta}{2} \|Lx\|_2^2$

Then

$$\begin{aligned} \nabla f(x) &= A^T \text{diag}(\cos(Ax))(\sin(Ax) - b) + \beta L^T Lx, \\ \nabla^2 f(x) &= A^T A \{1 - 2\sin(Ax)(\sin(Ax))^T + b^T \sin(Ax)\} + \beta L^T L \end{aligned}$$

Derivative Check:



Comments: Our code runs and produces our desired result

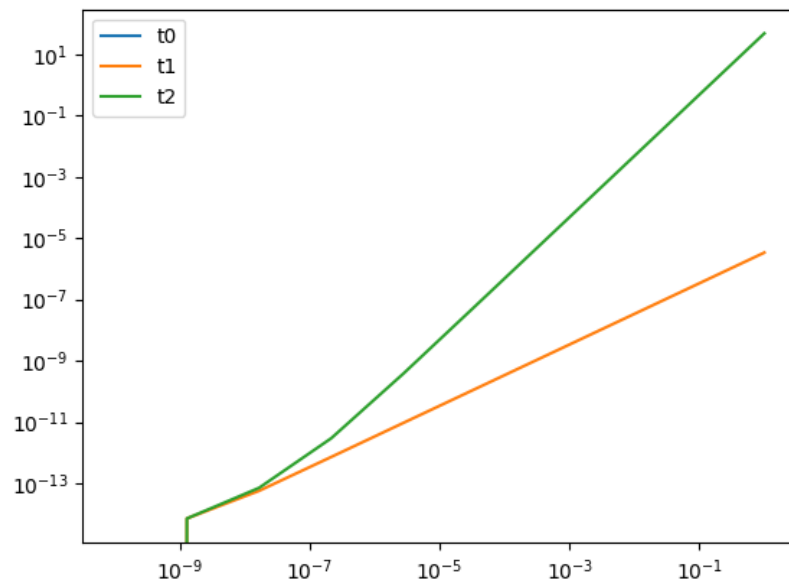
3.)

a.) We are given the optimization problem $\text{minimize}_{X \in \mathbb{R}^{m,n}} \frac{1}{2} \|\sigma(YX) - C\|_F^2$

Thus,

$$\nabla f(x) = \sum_{k=1}^m y_{ki} (1 - \sigma^2(\sum_{l=1}^n y_{kl} x_{lj})) (\sigma(\sum_{l=1}^n y_{kl} x_{lj}) - c_{kj}) = Y^T ((1 - \tanh^2(YX)) (\tanh(YX) - C))$$

Derivative Check:



Comments: This code runs

b.)

Comments: Still working on this code