Optimisation methods

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1 P4 (max points 25)

Consider the following optimisation problem:

minimise
$$f(\mathbf{x}) = c + \mathbf{g}^{\mathsf{T}} \mathbf{x} + \frac{1}{2} \mathbf{x}^{\mathsf{T}} \mathbf{H} \mathbf{x}$$

over $\mathbf{x} \in \mathbb{R}^n$ (1)

where c is a real value, g is a n-dimensional real-valued vector and \mathbf{H} is an $n \times n$ real-symmetric matrix.

P4-i (max points 5) Assume that

$$H = \left(\begin{array}{cc} D & 0 \\ 0 & B \end{array}\right)$$

where **D** is a diagonal matrix with diagonal elements $a_1, a_2, \ldots, a_{n-2}$ and $\mathbf{B} = \begin{pmatrix} a_{n-1} & b \\ b & a_n \end{pmatrix}$.

What are the necessary and sufficient conditions for the optimisation problem (1) to be a convex optimisation problem?

P4-ii (max points 5) Write down the update equation for the gradient descent algorithm with a constant step size η for the optimisation problem (1).

P4-iii (max points 5) Assume that g = 0. Show that f is a β -smooth function and express the value of β as a function of the eigenvalues of the Hessian matrix H.

P4-iv (max points 5) Assume that g = 0 and

$$\mathbf{H} = \left(\begin{array}{cccc} 6 & 0 & 0 & 0 \\ 0 & 4 & 2 & 0 \\ 0 & 2 & 1 & 0 \\ 0 & 0 & 0 & 4 \end{array} \right).$$

Given initial value \mathbf{x}_0 , let $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T, \dots$ be updated according to gradient descent algorithm with a constant step size, and let \mathbf{x}^* denote a minimiser of f.

What is the best upper bound that can be guaranteed for $f(\mathbf{x}_T) - f(\mathbf{x}^*)$?

P4-v (max points 5) Consider the same question as in P4-iv but under assumptions that g = 0 and

$$\mathbf{H} = \left(\begin{array}{cccc} 6 & 0 & 0 & 0 \\ 0 & 4 & 2 & 0 \\ 0 & 2 & 4 & 0 \\ 0 & 0 & 0 & 4 \end{array} \right).$$