

Quadratic Programming Assignment

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Abstract—This document contains the solution to Question 27 of Exercise 5 in Chapter 6 of the class 12 NCERT textbook.

1) The point on the curve

$$x^2 = 2y \quad (1)$$

which is nearest to the point $\mathbf{P} = \begin{pmatrix} 0 \\ 5 \end{pmatrix}$ is

a) $\begin{pmatrix} 2\sqrt{2} \\ 4 \end{pmatrix}$

b) $\begin{pmatrix} 2\sqrt{2} \\ 0 \end{pmatrix}$

c) $\begin{pmatrix} 0 \\ 0 \end{pmatrix}$

d) $\begin{pmatrix} 2 \\ 2 \end{pmatrix}$

Solution: We need to find

$$\min_{\mathbf{x}} g(\mathbf{x}) = \|\mathbf{x} - \mathbf{P}\|^2 \quad (2)$$

$$\text{s.t. } h(\mathbf{x}) = \mathbf{x}^\top \mathbf{V} \mathbf{x} + 2\mathbf{u}^\top \mathbf{x} = 0 \quad (3)$$

where

$$\mathbf{V} = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}, \quad \mathbf{u} = \begin{pmatrix} 0 \\ -1 \end{pmatrix} \quad (4)$$

First, we show that (3) is nonconvex. Indeed, suppose \mathbf{x}_1 and \mathbf{x}_2 satisfy $h(\mathbf{x}) = 0$. Then,

$$\mathbf{x}_1^\top \mathbf{V} \mathbf{x}_1 + 2\mathbf{u}^\top \mathbf{x}_1 + f = 0 \quad (5)$$

$$\mathbf{x}_2^\top \mathbf{V} \mathbf{x}_2 + 2\mathbf{u}^\top \mathbf{x}_2 + f = 0 \quad (6)$$

Then, for any $0 \leq \lambda \leq 1$, substituting

$$\mathbf{x}_\lambda \leftarrow \lambda \mathbf{x}_1 + (1 - \lambda) \mathbf{x}_2 \quad (7)$$

into (3), we get

$$h(\mathbf{x}_\lambda) = \lambda(\lambda - 1)(\mathbf{x}_1 - \mathbf{x}_2)^\top \mathbf{V}(\mathbf{x}_1 - \mathbf{x}_2) + f \neq 0 \quad (8)$$

Hence, the optimization problem is nonconvex. The constraints throw an error when `cvxpy` is used, as shown in the erroneous Python code `codes/parab_cvx.py`.

We use the method of Lagrange multipliers instead to find the optima. Here, we need to find $\lambda \in \mathbb{R}$ such that there exists a \mathbf{x} satisfying

$$\nabla g(\mathbf{x}) = \lambda \nabla h(\mathbf{x}) \quad (9)$$

$$\implies 2(\mathbf{x} - \mathbf{P}) = 2\lambda(\mathbf{A}\mathbf{x} + \mathbf{u}) \quad (10)$$

$$\implies (\mathbf{I} - \lambda \mathbf{A})\mathbf{x} = \lambda \mathbf{u} + \mathbf{P} \quad (11)$$

$$\implies \begin{pmatrix} 1 - \lambda & 0 \\ 0 & 1 \end{pmatrix} \mathbf{x} = \begin{pmatrix} 0 \\ 5 - \lambda \end{pmatrix} \quad (12)$$

From (12), we have two cases:

a) $\lambda \neq 1$. In this case, we form the augmented matrix

$$\begin{pmatrix} 1 - \lambda & 0 & 0 \\ 0 & 1 & 5 - \lambda \end{pmatrix} \xrightarrow{R_1 \leftarrow \frac{R_1}{1 - \lambda}} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 5 - \lambda \end{pmatrix} \quad (13)$$

and get that

$$\mathbf{x}_m = \begin{pmatrix} 0 \\ 5 - \lambda \end{pmatrix} \quad (14)$$

Substituting in (3) gives $\lambda = 5$. Thus, $\mathbf{x}_m = \mathbf{0}$.

b) $\lambda = 1$. In this case, (12) becomes

$$\begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \mathbf{x} = \begin{pmatrix} 0 \\ 4 \end{pmatrix} \quad (15)$$

$$\implies \mathbf{e}_2^\top \mathbf{x} = 4 \quad (16)$$

Substituting (16) into (3) becomes

$$(\mathbf{e}_1^\top \mathbf{x})^2 = 8 \quad (17)$$

$$\implies \mathbf{e}_1^\top \mathbf{x} = \pm 2\sqrt{2} \quad (18)$$

Using (18) and (16),

$$\mathbf{x}_m = \begin{pmatrix} \pm 2\sqrt{2} \\ 4 \end{pmatrix} \quad (19)$$

Using these values of \mathbf{x}_m , the distances are

$$\left\| \begin{pmatrix} 0 \\ 5 \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \end{pmatrix} \right\| = 5 \quad (20)$$

$$\left\| \begin{pmatrix} 0 \\ 5 \end{pmatrix} - \begin{pmatrix} \pm 2\sqrt{2} \\ 4 \end{pmatrix} \right\| = 3 \quad (21)$$

Thus, the correct answer is **a**).

We demonstrate both of the minima in (21) is obtained using constrained gradient descent in Fig. 1, plotted using the Python code `codes/grad_pits.py`.

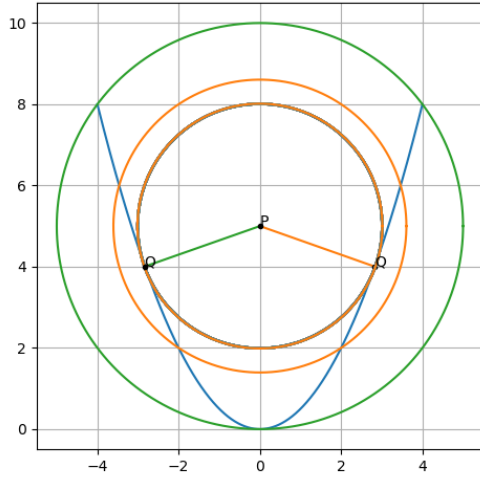


Fig. 1: Gradient descent for a nonconvex optimization problem.