

## Solution of the quiz

Problem 1 Answer: C

Details

① Because we want to maximize the distance between the position of the vehicle at time  $T$  (given by  $E_x(T)$ ) and point  $b$ , we must minimize the negative of this quantity.

Problem 2 Answer: A

Details

① Note that all the six functions are continuous and coercive. Thus, they all have (at least) one global minimizer.

② Let's start by looking at the function in option A:  $f(x) = e^x + \frac{1}{2}|x|$ .

The candidates for being global minimizers are the points  $N \cup S$ , where

- $N$  = set of points at which  $f$  is not differentiable
- $S$  = set of stationary points of  $f$  (points at which  $\dot{f}(x) = 0$ ).

For the set  $N$ , we have  $N = \{0\}$ .

For the set  $S$ , we must solve  $\dot{f}(x) = 0$  with  $x \neq 0$ :

- case  $x > 0$  here,  $f(x) = e^x + \frac{1}{2}x$ ; thus,  $\dot{f}(x) = e^x + \frac{1}{2}$ .

This gives the equation  $e^x = -\frac{1}{2}$ , which does not have a solution for  $x > 0$  (in fact, for no  $x \in \mathbb{R}$ );

• case  $x < 0$  here,  $f(x) = e^x - 1/2x$ ; thus,  $f'(x) = e^x - 1/2$ .

This gives the equation  $e^x = 1/2$ , which has the solution  $x^* = -\log 2$  (which we accept because  $x^* < 0$ ).

The set of candidates is  $C = \{0, -\log 2\}$ .

We now evaluate  $f$  on those points:

$$\bullet f(0) = e^0 + 1/2|0| = 1$$

$$\bullet f(-\log 2) = e^{(-\log 2)} + 1/2|-\log 2| = 1/2 + 1/2 \frac{\log 2}{\approx 0.7} < 1$$

Because  $f(-\log 2) < f(0)$ , we conclude that 0 is not a global minimizer of  $f$ .

(We also found something extre: the global minimizer is  $x^* = -\log 2$ .)

③ For the functions in options B, C, D, E, and F, we always have  $N = \{0\}$  and  $S = \emptyset$ .

Thus, for those functions, we just have one candidate,  $x^* = 0$ , which must be therefore the global minimizer.

**Problem 3** Answer: C

Details ① Note that  $C(u)v = C(v)u$  for any vectors  $u, v \in \mathbb{R}^n$

(this is easily verified and highly suggested by looking at the available options)

② We have:

$$\|x - r\|_2^2 + p \sum_{k=1}^K \|C(a_k)x - b_k\|_2^2 \stackrel{\text{use ①}}{=} \|x - r\|_2^2 + p \sum_{k=1}^K \|C(a_k)x - b_k\|_2^2$$

$$\stackrel{\text{for } \alpha > 0: \alpha \|u\|^2 = \|\sqrt{\alpha}u\|^2}{=} \|x - r\|_2^2 + \sum_{k=1}^K \|\sqrt{p} C(a_k)x - \sqrt{p} b_k\|_2^2$$

for vectors  $v_1, v_2, \dots, v_K$ :

$$\left\| \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_K \end{bmatrix} \right\|_2^2 = v_1^T v_1 + v_2^T v_2 + \dots + v_K^T v_K = \|v_1\|_2^2 + \|v_2\|_2^2 + \dots + \|v_K\|_2^2$$

$$= \left\| \begin{bmatrix} \sqrt{p} C(a_1)x - \sqrt{p} b_1 \\ \vdots \\ \sqrt{p} C(a_K)x - \sqrt{p} b_K \\ x - r \end{bmatrix} \right\|_2^2$$

for matrices  $M_1, M_2, \dots, M_K$ ,  
and vector  $u$ :

$$\begin{bmatrix} M_1 u \\ M_2 u \\ \vdots \\ M_K u \end{bmatrix} = \begin{bmatrix} M_1 \\ M_2 \\ \vdots \\ M_K \end{bmatrix} u$$

$$= \left\| \underbrace{\begin{bmatrix} \sqrt{p} C(a_1) \\ \vdots \\ \sqrt{p} C(a_K) \\ I \end{bmatrix}}_A x - \underbrace{\begin{bmatrix} \sqrt{p} b_1 \\ \vdots \\ \sqrt{p} b_K \\ r \end{bmatrix}}_\beta \right\|_2^2$$

**Problem D** Answer: C

Details ① Note that  $D(u)v = D(v)u$  for any vectors  $u, v \in \mathbb{R}^n$

② We have

$$f(x) = \| (A + R D(x)) \theta + b \|_2^2$$

$$= \| R D(x) \theta + A \theta + b \|_2^2$$

use ①  $\Rightarrow$  
$$= \left\| \underbrace{R D(\theta)}_A x + \underbrace{A \theta + b}_\beta \right\|_2^2$$

observe that the given optimization problem is a least-squares problem; thus, there is a global minimizer

$$= x^T A^T A x + 2 \beta^T A x + \beta^T \beta$$

③ Because there is a global minimizer and  $f$  is differentiable everywhere,

the global minimizer is to be found in  $S = \{x : \nabla f(x) = 0\}$ .

We now focus on solving  $\nabla f(x) = 0$ :

$$\nabla f(x) = 0 \Leftrightarrow 2 A^T A x + 2 A^T \beta = 0$$

$$\Leftrightarrow D(\theta) R^T R D(\theta) x = -D(\theta) R^T \beta$$

$$\Leftrightarrow x = -(D(\theta) R^T R D(\theta))^{-1} D(\theta) R^T \beta$$

$$= -D(\theta)^{-1} (R^T R)^{-1} R^T \beta$$

$$= -D(\theta)^{-1} (R^T R)^{-1} R^T (A \theta + b)$$

OK step because the matrix  $D(\theta) R^T R D(\theta)$  is invertible: it's the product of three invertible matrices  $D(\theta)$ ,  $R^T R$ , and  $D(\theta)$ .

[ $D(\theta)$  is invertible because  $\theta_i \neq 0$  for all  $i$ ;  $R^T R$  is invertible because  $R$  is full column-rank]

if  $\phi(x) = x^T M x + p^T x$  (where  $M = M^T$ ), then  $\nabla \phi(x) = 2 M x + p$ ; in our case:  $M = A^T A$  and  $p = 2 A^T \beta$