Write your name:	
Write your student number:	

Exam

1. Nonconvex function. (3 points) One of the following functions $f: \mathbf{R} \to \mathbf{R}$ is <u>not</u> convex:

(A)
$$f(x) = (x^2 - x)_+ - x$$

(B)
$$f(x) = -((x_+))^2 + x^2 + x$$

(C)
$$f(x) = (x - x_+)^2 - x$$

(D)
$$f(x) = ((x_+))^2 - x^2 + x$$

(E)
$$f(x) = x_+ + x^2 - x$$

(F)
$$f(x) = (x + x_+)^2 - (x_+)^2$$

Which one?

Write your answer (A, B, C, D, E, or F) here:

2. Least-squares. (2 points) Consider the following six optimization problems:

(A)
$$\underset{x \in \mathbf{R}^n}{\text{minimize}} \quad \|A(c+x) - b\|_2^2 + \rho \|x\|_2^2$$

(B)
$$\min_{x \in \mathbf{R}^n} \|Ax - (Bx + b)\|_2^2 + \rho \|x - c\|_2^2$$

(C)
$$\min_{x \in \mathbf{R}^n} \|Ax\|_2^2 + \rho \|(B(x-c) + b)\|_2^2$$

(D)
$$\min_{x \in \mathbf{R}^n} ||(Ax - b) + \rho(Bx)||_2^2 + ||x - c||_2^2$$

(E)
$$\underset{x \in \mathbf{R}^n}{\text{minimize}} \quad (\|Ax - b\|_2 + \rho \|Bx\|_2)^2 + \|x - c\|_2^2$$

(F)
$$\underset{x \in \mathbf{R}^n}{\text{minimize}} \quad (Ax + Bx - b)^T (Ax + Bx - b) + \rho x^T x$$

In each of the six problems above, the variable to optimize is $x \in \mathbf{R}^n$. The matrices A and B, and the vector c are given. The scalar ρ is also given and is positive: $\rho > 0$.

One of the optimization problems above is **not** a least-squares problem.

Which one?

Write your answer (A, B, C, D, E, or F) here:

3. Optimal value of a constrained problem. (3 points) Consider the constrained problem

minimize
$$\underbrace{\frac{1}{2} \sum_{n=1}^{N} x_n^T R_n x_n}_{f(x_1, \dots, x_N)}$$
 subject to
$$\underbrace{x_1 + \dots + x_N}_{f(x_1, \dots, x_N)} = s,$$

where the variable to optimize is (x_1, \ldots, x_N) , with $x_n \in \mathbf{R}^d$ for $1 \leq n \leq N$. The matrices $R_n \in \mathbf{R}^{d \times d}$ are given for $1 \leq n \leq N$. Assume that each R_n is a symmetric, positive-definite matrix. The vector $s \in \mathbf{R}^d$ is also given.

One of the following expressions is the minimum value that f attains over the feasible set, that is, one of the following expressions is the number $\min\{f(x_1,\ldots,x_N)\colon x_1+\cdots+x_N=s\}$:

(A)
$$\frac{1}{2}s^T (R_1 + \cdots + R_N) s$$

(B)
$$\frac{1}{2}s^T \left(R_1^{-1} + \dots + R_N^{-1}\right)^{-1} s$$

(C)
$$\frac{1}{2}s^T \left(R_1^{-2} + \dots + R_N^{-2}\right)^{-1} s$$

(D)
$$\frac{1}{2}s^T \left(R_1^{-1} + \dots + R_N^{-1}\right)s$$

(E)
$$\frac{1}{2}s^T (R_1 + \dots + R_N)^{-1} s$$

(F)
$$\frac{1}{2}s^T (R_1^2 + \dots + R_N^2) s$$

Which one?

Write your answer (A, B, C, D, E, or F) here:

4. Sparse linear regression with asymmetric loss. (4 points) Consider the optimization problem

$$\underset{s \in \mathbf{R}^{n}, r \in \mathbf{R}}{\text{minimize}} \quad \underbrace{\sum_{k=1}^{K} \alpha \left((s^{T} x_{k} + r - y_{k})_{-} \right)^{2} + \beta \left((s^{T} x_{k} + r - y_{k})_{+} \right)^{2} + \rho \|s\|_{1}}_{f(s,r)},$$

where the variable to optimize is $(s,r) \in \mathbf{R}^n \times \mathbf{R}$. The vectors $x_k \in \mathbf{R}^n$ and the scalars $y_k \in \mathbf{R}$ are given for $1 \le k \le K$. The scalars α , β , and ρ are given and denote positive constants: $\alpha > 0$, $\beta > 0$, and $\rho > 0$. The functions $(\cdot)_-$ and $(\cdot)_+$ are defined as $(z)_- = \max\{-z, 0\}$ and $(z)_+ = \max\{z, 0\}$ for $z \in \mathbf{R}$.

Show that the function f is convex.

5. A simple control problem. (4 points) Consider the optimization problem

where the variables to optimize are $x_t \in \mathbf{R}^n$ for $1 \leq t \leq T$ and $u_t \in \mathbf{R}^p$ for $1 \leq t \leq T - 1$. The vector $x_{\text{initial}} \in \mathbf{R}^n$ and the matrices $D_t \in \mathbf{R}^{n \times p}$ are given for $1 \leq t \leq T - 1$. The scalar ρ is also given and denotes a positive constant: $\rho > 0$.

Give a closed-form solution for the optimal $\{u_t : 1 \le t \le T - 1\}$.

6. Moureau envelope. (4 points) Let $f: \mathbf{R} \to \mathbf{R}$ be a convex function. For $\lambda > 0$, we define a function $e_{\lambda}[f]: \mathbf{R} \to \mathbf{R}$ as follows: for $x \in \mathbf{R}$, the image of x under the function $e_{\lambda}[f]$ is the number $\min\{f(u) + \frac{1}{2\lambda}(u-x)^2 : u \in \mathbf{R}\}$.

That is, the function $e_{\lambda}[f]$ maps each number x to the number $e_{\lambda}[f](x)$, where $e_{\lambda}[f](x)$ is the minimum value attained by $f(u) + \frac{1}{2\lambda}(u-x)^2$ as u varies in \mathbf{R} .

Let $\lambda_1 > 0$ and $\lambda_2 > 0$. Show that

$$e_{\lambda_1}[e_{\lambda_2}[f]](x) = e_{\lambda_1 + \lambda_2}[f](x),$$

for each $x \in \mathbf{R}$.