

Problem 1: Let $\mathbf{x} \in \mathbb{R}^M$, $\mathbf{y} \in \mathbb{R}^N$ and $\mathbf{Z} \in \mathbb{R}^{P \times Q}$. The function $f : \mathbb{R}^M \times \mathbb{R}^N \times \mathbb{R}^{P \times Q} \rightarrow \mathbb{R}$ is defined as

$$f(\mathbf{x}, \mathbf{y}, \mathbf{Z}) = \mathbf{x}^T \mathbf{A} \mathbf{y} + \mathbf{B} \mathbf{x} - \mathbf{y}^T \mathbf{C} \mathbf{Z} \mathbf{D} - \mathbf{y}^T \mathbf{E}^T \mathbf{y} + \mathbf{F}.$$

What should be the dimensions (shapes) of the matrices $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}, \mathbf{E}, \mathbf{F}$ for the expression above to be a valid mathematical expression?

$$\begin{array}{ccccccccc} \mathbf{x}^T \mathbf{A} \mathbf{y} & + & \mathbf{B} \mathbf{x} & - & \mathbf{y}^T \mathbf{C} \mathbf{Z} \mathbf{D} & - & \mathbf{y}^T \mathbf{E}^T \mathbf{y} & + \mathbf{F} \\ \mathbf{1} \times \mathbf{M} & & \mathbf{N} \times \mathbf{1} & & \mathbf{1} \times \mathbf{M} & & \mathbf{M} \times \mathbf{1} & & \mathbf{1} \times \mathbf{N} & & \mathbf{P} \times \mathbf{Q} & & \mathbf{1} \times \mathbf{N} & & \mathbf{N} \times \mathbf{1} & & \mathbf{1} \times \mathbf{1} \\ \mathbf{M} \times \mathbf{N} & & & & \mathbf{N} \times \mathbf{P} & & \mathbf{Q} \times \mathbf{1} & & \mathbf{N} \times \mathbf{N} & & & & \mathbf{N} \times \mathbf{N} & & \mathbf{1} \times \mathbf{1} & & & & \mathbf{1} \times \mathbf{1} \end{array}$$

Problem 2: Let $\mathbf{x} \in \mathbb{R}^N$, $\mathbf{M} \in \mathbb{R}^{N \times N}$. Express the function $f(\mathbf{x}) = \sum_{i=1}^N \sum_{j=1}^N x_i x_j M_{ij}$ using only matrix-vector multiplications.

$$\begin{aligned} \mathbf{x}^T \mathbf{M} \mathbf{x} &= \sum_{i=1}^N \sum_{j=1}^N x_i x_j M_{ij} = \sum_{i=1}^N x_i \left(\sum_{j=1}^N x_j M_{ij} \right) \\ &= \sum_{i=1}^N x_i (\mathbf{x} \mathbf{M} \mathbf{x})_i = \mathbf{x}^T \mathbf{x} \mathbf{M} \end{aligned}$$

Problem 3: Let $\mathbf{A} \in \mathbb{R}^{M \times N}$, $\mathbf{x} \in \mathbb{R}^N$ and $\mathbf{b} \in \mathbb{R}^M$. We are interested in solving the following system of linear equations for \mathbf{x}

$$\mathbf{A}\mathbf{x} = \mathbf{b} \quad (1)$$

- Under what conditions does the system of linear equations have a **unique** solution \mathbf{x} for any choice of \mathbf{b} ?
- Assume that $M = N = 5$ and that \mathbf{A} has the following eigenvalues: $\{-5, 0, 1, 1, 3\}$. Does Equation 1 have a unique solution \mathbf{x} for any choice of \mathbf{b} ? Justify your answer.

a) $\text{rank}(\mathbf{A}\mathbf{x}) = \text{rank}(\mathbf{b}) \Rightarrow \text{unique}$

b) The rank of \mathbf{A} is equal to the number of its non-zero eigenvalues.
which here is $\text{rank}(\mathbf{A}) = 4 \Rightarrow \text{rank}(\mathbf{A}) = 4 \neq 5 \stackrel{a)}{\Rightarrow} \text{no unique solution}$

Problem 4: Let $A \in \mathbb{R}^{N \times N}$. Assume that there exists a matrix $B \in \mathbb{R}^{N \times N}$ such that $BA = AB = I$. What can you say about the eigenvalues of A ? Justify your answer.

$$AB = BA = I \Rightarrow B = A^{-1} \Rightarrow A \text{ invertible}$$

Since A is invertible and it has full rank, its eigenvalues cannot be 0.

Problem 7: Consider the following function $f : \mathbb{R} \rightarrow \mathbb{R}$

$$f(x) = \frac{1}{2}ax^2 + bx + c$$

We are interested in solving the following optimization problem

$$\min_{x \in \mathbb{R}} f(x)$$

- a) Under what conditions does this optimization problem have (i) a unique solution, (ii) infinitely many solutions or (iii) no solution? Justify your answer.
- a) Assume that the optimization problem has a unique solution. Write down the closed-form expression for x^* that minimizes the objective function, i.e. find $x^* = \arg \min_{x \in \mathbb{R}} f(x)$.

a) i) $a=1$  (unique solution is $-b$ (see b))

ii) $a=b=0$  $f'(x)=0 \Rightarrow f(x)=c \quad \forall x \in \mathbb{R}$

iii) $a=-1$  $f'(x) = -x+b$
 $f''(x) = -1 < 0$
 \Rightarrow concave \Rightarrow no minimum

b) $f'(x) = ax + b$
 $\stackrel{!}{=} 0$

$$\Rightarrow ax + b = 0$$

$$\Leftrightarrow ax = -b$$

$$\Leftrightarrow x = -\frac{b}{a}$$

Problem 8: Consider the following function $g : \mathbb{R}^N \rightarrow \mathbb{R}$

$$g(\mathbf{x}) = \frac{1}{2}\mathbf{x}^T \mathbf{A}\mathbf{x} + \mathbf{b}^T \mathbf{x} + c$$

where $\mathbf{A} \in \mathbb{R}^{N \times N}$ is a PSD matrix, $\mathbf{b} \in \mathbb{R}^N$ and $c \in \mathbb{R}$.

We are interested in solving the following optimization problem

$$\min_{\mathbf{x} \in \mathbb{R}^N} g(\mathbf{x})$$

- a) Compute the Hessian $\nabla^2 g(\mathbf{x})$ of the objective function. Under what conditions does this optimization problem have a unique solution?
- b) Why is it necessary for a matrix \mathbf{A} to be PSD for the optimization problem to be well-defined? What happens if \mathbf{A} has a negative eigenvalue?
- c) Assume that the matrix \mathbf{A} is positive definite (PD). Write down the closed-form expression for \mathbf{x}^* that minimizes the objective function, i.e. find $\mathbf{x}^* = \arg \min_{\mathbf{x} \in \mathbb{R}^N} g(\mathbf{x})$.

a) $\nabla g(\mathbf{x}) = \mathbf{A}\mathbf{x} + \mathbf{b}^T$

$$\nabla^2 g(\mathbf{x}) = \mathbf{A}$$

\mathbf{A} must be PSD \Rightarrow extreme points are all $\mathbf{b} \geq 0$
(every local minimum is a global minimum)

- b) - If \mathbf{A} is PSD, then $\nabla^2 g(\mathbf{x})$ must also be PSD and hence f is convex.
- If \mathbf{A} has an eigenvalue < 0 , then it is not PSD anymore and so not necessarily convex anymore.

c) $\nabla g(\mathbf{x}) \stackrel{!}{=} 0 \quad \arg \min g(\mathbf{x}) = \arg \max -g(\mathbf{x})$

$$\Leftrightarrow \mathbf{A}\mathbf{x} + \mathbf{b}^T = 0$$

$$\Leftrightarrow \mathbf{A}\mathbf{x} = -\mathbf{b}^T$$

$$\text{If } \mathbf{A} \text{ PD then } \mathbf{x}^* = -\mathbf{b}^T \mathbf{A}^{-1}$$

Problem 9: Prove or disprove the following statement

$$p(A|B, C) = p(A|C) \Rightarrow p(A|B) = p(A)$$

$$p(A|B, C) = p(A|C) \quad \text{Gegenbeispiel, ist falsch}$$

$$P(x=1) = P(1)$$

Problem 10: Prove or disprove the following statement

$$p(A|B) = p(A) \Rightarrow p(A|B, C) = p(A|C)$$

$$\boxed{p(A|C) = P(A \cap C)}$$

$$p(A|B) = \frac{p(B|A) p(A)}{p(B)}$$

$$P(A) = P(A|B) \stackrel{\text{Bayes}}{=} \frac{P(A, B)}{P(B)} = \frac{P(A) P(B)}{P(B)} = P(A)$$

$$P(A|B, C) = \frac{P(A, B|C)}{P(B|C)} = \frac{P(A|C) P(B|C)}{P(B|C)} = P(A|C) \quad \square$$

Problem 11: You are given the joint PDF $p(a, b, c)$ of three continuous random variables. Show how the following expressions can be obtained using the rules of probability

1. $p(a)$
2. $p(c|a, b)$
3. $p(b|c)$

$$p(a) = \iint_{b,c} p(a, b, c) \, db \, dc$$

$$p(c|a, b) = \frac{p(a, b, c)}{p(a, b)} = \frac{\int_a \int_b p(a, b, c) \, db \, da}{\int_c p(a, b, c) \, dc}$$

$$p(b|c) = \frac{p(b, c)}{p(c)} = \frac{\int_a \int_c p(a, b, c) \, dc \, da}{\int_a \int_b p(a, b, c) \, db \, da}$$

Problem 12: Researchers have developed a test which determines whether a person has a rare disease. The test is fairly reliable: if a person is sick, the test will be positive with 95% probability, if a person is healthy, the test will be negative with 95% probability. It is known that $\frac{1}{1000}$ of the population have this rare disease. A person (chosen uniformly at random from the population) takes the test and obtains a positive result. What is the probability that the person has the disease?

$$P(T) = \text{test positive} \quad P(S) = \text{sick}$$

$$P(\neg T) = \text{test negative} \quad P(\neg S) = \text{healthy}$$

$$P(T|S) = 0.95$$

$$P(S|T) ?$$

$$P(\neg T|\neg S) = 0.95$$

$$P(S|T) = \frac{P(T|S) P(S)}{P(T|S) P(S) + P(T|\neg S) P(\neg S)}$$

$$P(T|\neg S) = 0.05$$

$$= \frac{0.95 \cdot 0.001}{0.95 \cdot 0.001 + 0.05 \cdot 0.999}$$

$$\approx 0.019$$

$$= 1.9\%$$

Problem 13: Let $X \sim \mathcal{N}(\mu, \sigma^2)$, and $f(x) = ax + bx^2 + c$. What is $\mathbb{E}[f(x)]$?

$$\begin{aligned}
& \mathbb{E}[f(x)] & \mathbb{E}[x-\mu] = \mathbb{E}[x] - \mathbb{E}[\mu] = \mu - \mu = 0 \\
& = \mathbb{E}[ax + bx^2 + c] & \text{Var}[x] = \sigma^2 = \mathbb{E}[(x-\mu)^2] \\
& = \mathbb{E}[ax] + \mathbb{E}[bx^2] + \mathbb{E}[c] & = \mathbb{E}[x^2] - (\mathbb{E}[x])^2 \\
& = a\mathbb{E}[x] + b\mathbb{E}[x^2] + c & \\
& = a\mu + b \cdot \mathbb{E}[(x-\mu+\mu)^2] + c & \mathbb{E}[(x-\mu)^2] \\
& = a\mu + c + b \left(\mathbb{E}[(\underbrace{(x-\mu)+\mu}_{\phi}) (\underbrace{(x-\mu)+\mu}_{\phi})] \right) & = \mathbb{E}[x^2] - 2\mu x + \mu^2 \\
& = a\mu + c + b \left(\mathbb{E}[(\phi + \mu)^2] \right) & = \mathbb{E}[x^2] - \mu^2 \\
& = a\mu + c + b \left(\mathbb{E}[\phi^2 + 2\phi\mu + \mu^2] \right) & \text{How to get } \sigma^2? \\
& = a\mu + c + b \left(\mathbb{E}[\phi^2] + \mathbb{E}[2\phi\mu] + \mathbb{E}[\mu^2] \right) \\
& = a\mu + c + b \left(\mathbb{E}[(x-\mu)^2] + 2\mu \mathbb{E}[x-\mu] + \mathbb{E}[\mu^2] \right) \\
& = a\mu + c + b(\sigma^2 + 0 + \mu^2) \\
& = a\mu + c + b\sigma^2 + b\mu^2
\end{aligned}$$

Problem 14: Let $p(x) = \mathcal{N}(x|\mu, \Sigma)$, and $g(x) = Ax$ (where $A \in \mathbb{R}^{N \times N}$). What are the values of the following expressions:

- $\mathbb{E}[g(x)]$,
- $\mathbb{E}[g(x)g(x)^T]$,
- $\mathbb{E}[g(x)^T g(x)]$,
- the covariance matrix $\text{Cov}[g(x)]$.

$$\begin{aligned}
& \bullet \mathbb{E}[g(x)] = \mathbb{E}[Ax] = A \mathbb{E}[x] = A\mu \\
& \bullet \mathbb{E}[g(x)g(x)^T] = \mathbb{E}[Ax(Ax)^T] = A \mathbb{E}[x(Ax)^T] = A \mathbb{E}[x x^T A^T] \\
& \quad = A \mathbb{E}[x x^T] A^T = \underset{N \times N}{A} \left(\underset{N \times N}{\Sigma} + \underset{N \times N}{\mu \mu^T} \right) \underset{N \times N}{A^T} \\
& \quad = AA^T \Sigma + AA^T \mu \mu^T
\end{aligned}$$

$$\begin{aligned}
\cdot \mathbb{E}[g(x)^T g(x)] &= \mathbb{E}[(A_x)^T A_x] \\
&= \mathbb{E}[x^T A^T A x] \quad B := A^T A \\
&= \mathbb{E}\left[\sum_{i=1}^N \sum_{j=1}^N B_{i,j} x_i x_j\right] \\
&= \sum_{i=1}^N \sum_{j=1}^N B_{i,j} \mathbb{E}[x_i x_j] \\
&= \sum_{i=1}^N \sum_{j=1}^N B_{i,j} (\sigma_{i,j} + \mu_i \mu_j) \\
&= \sum_{i=1}^N \sum_{j=1}^N B_{i,j} \sigma_{i,j} + \sum_{i=1}^N \sum_{j=1}^N B_{i,j} \mu_i \mu_j \\
&= \sum_{i=1}^N (B\Sigma)_{i,i} + \mu^T B \mu \\
&= \text{tr}(A^T A \Sigma) + \mu^T A^T A \mu
\end{aligned}$$

$$\begin{aligned}
\cdot \text{Cov}[g(x)] &= \text{Cov}[A_x] \\
&= \mathbb{E}[(A_x - \mathbb{E}[A_x])(A_x - \mathbb{E}[A_x])^T] \\
&= \mathbb{E}[(A_x - A \mathbb{E}[x])(A_x - A \mathbb{E}[x])^T] \\
&= \mathbb{E}[A(x - \mathbb{E}[x])(x - \mathbb{E}[x])^T A^T] \\
&= A \mathbb{E}[(x - \mathbb{E}[x])(x - \mathbb{E}[x])^T] A^T \\
&= A \text{Cov}(x) A^T \\
&= A \Sigma A^T
\end{aligned}$$