

1. (Optimization) Compute the gradient $\nabla f(\mathbf{x})$ and Hessian $\nabla^2 f(\mathbf{x})$ of the function (5 points)

$$f(\mathbf{x}) = (x_1 + x_2)(x_1 x_2 + x_1 x_2^2)$$

Find at least 3 stationary points of this function (3 points). Show that $[3/8, -6/8]^T$ a local maximum of this function (2 point).

$$\begin{aligned} f(\mathbf{x}) &= (x_1 + x_2)(x_1 x_2 + x_1 x_2^2) \\ &= x_1^2 x_2 + x_1^2 x_2^2 + x_1 x_2^2 + x_1 x_2^3 \end{aligned}$$

$$\textcircled{1} \quad \nabla f(\mathbf{x}) = \begin{bmatrix} \frac{df}{dx_1} = 2x_1 x_2 + 2x_1 x_2^2 + x_2^2 + x_2^3 \\ \frac{df}{dx_2} = x_1^2 + 2x_1^2 x_2 + 2x_1 x_2 + 3x_1 x_2^2 \end{bmatrix}$$

$$\text{Hessian } \nabla^2 f(\mathbf{x}) = \begin{bmatrix} \frac{d^2 f}{dx_1^2} & \frac{d^2 f}{dx_1 dx_2} \\ \frac{d^2 f}{dx_1 dx_2} & \frac{d^2 f}{dx_2^2} \end{bmatrix} = \begin{bmatrix} 2x_2 + 2x_2^2 & 2x_1 + 4x_1 x_2 + 2x_2 + 3x_2^2 \\ 2x_1 + 4x_1 x_2 + 2x_2 + 3x_2^2 & 2x_1^2 + 2x_1 + 6x_1 x_2 \end{bmatrix}$$

$$\textcircled{2} \text{ Stationary Points } \rightarrow (0, 0) (1, -1) (0, -1)$$

$$\textcircled{3} \text{ Show } \left[\frac{3}{8}, -\frac{6}{8} \right]^T \text{ a local maximum}$$

$$\begin{aligned} \nabla^2 f\left(x_1 = \frac{3}{8}, x_2 = -\frac{6}{8}\right) &= \begin{bmatrix} 2\left(-\frac{6}{8}\right) + 2\left(-\frac{6}{8}\right)^2 & 2\left(\frac{3}{8}\right) + 4\left(\frac{3}{8}\right)\left(-\frac{6}{8}\right) + 2\left(-\frac{6}{8}\right) + 3\left(-\frac{6}{8}\right)^2 \\ // & 2\left(\frac{3}{8}\right)^2 + 2 \cdot \frac{3}{8} + 6 \cdot \frac{3}{8} \left(-\frac{6}{8}\right) \end{bmatrix} \\ &= \begin{bmatrix} -0.375 & -0.1875 \\ -0.1875 & -0.65625 \end{bmatrix} \end{aligned}$$

$$\det(H) = (-0.375)(-0.65625) - (-0.1875)^2$$

$$= 0.246 - 0.035 = 0.211 > 0 \rightarrow \text{it is minima or maxima}$$

Since $\nabla^2 f(\frac{3}{8})$ and $\nabla^2 f(-\frac{6}{8})$ are smaller than zero,

it is local maximum of this function.

2. (Optimization) Show that the function $f(x) = 8x_1 + 12x_2 + x_1^2 - 2x_2^2$ has only one stationary point (4 points), and that it is neither a minimum nor a maximum, but is a saddle point (4 points).

① Show $f(x) = 8x_1 + 12x_2 + x_1^2 - 2x_2^2$ has only one stationary point.

\Rightarrow To get stationary point, have to find the x_1, x_2 value where $f'(x) = 0$.

$$f'(x_1) = 8 + 2x_1 = 0 \quad x_1 = -4$$

$$f'(x_2) = 12 - 4x_2 = 0 \quad x_2 = 3$$

$[-4 \ 3]^T$ is the only stationary point of $f(x)$.

② Show $[-4 \ 3]^T$ is a saddle point.

\Rightarrow If $\det(H(x)) < 0$, x is saddle point.

$$f''(x_1) = 2$$

$$f''(x_2) = -4$$

$$H = \begin{bmatrix} 2 & 0 \\ 0 & -4 \end{bmatrix} \quad \det(H) = 2(-4) - 0 = -8$$

Since $\det(H) = -8$ is smaller than zero, $[-4 \ 3]^T$ is the saddle point.

3. (Linear Algebra) If A and B are positive definite matrices, prove that the matrix $\begin{bmatrix} A & 0 \\ 0 & B \end{bmatrix}$ is also positive definite (7 points).

\Rightarrow Using Definition of Positive Definiteness

For symmetric matrix M , we have $x^T M x > 0$ for every x .

Let $\begin{bmatrix} A & 0 \\ 0 & B \end{bmatrix} = M$, $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ (where x_1 is a vector of same size as A and x_2 is a vector of same size as B)

$$\begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \begin{bmatrix} A & 0 \\ 0 & B \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = x_1^T A x_1 + x_2^T B x_2$$

Since A and B are positive definite, we can say $x_1^T A x_1 > 0$ and $x_2^T B x_2 > 0$.

Therefore, $x_1^T A x_1 + x_2^T B x_2$ is also bigger than zero, which proves that

$\begin{bmatrix} A & 0 \\ 0 & B \end{bmatrix}$ is positive definite.

4. (Chain Rule Calculus) Consider this function: $f(\mathbf{x}) = \mathbf{w}_2^T \text{sigmoid}(\mathbf{W}_1 \mathbf{x})$, where $\text{sigmoid}(x) = \frac{1}{1+e^{-x}}$ applies to each entry of the vector, please compute the derivatives of $\frac{\partial f}{\partial \mathbf{w}_2}$, $\frac{\partial f}{\partial \mathbf{W}_1}$, $\frac{\partial f}{\partial \mathbf{x}}$ (15 points), \mathbf{W}_1 is $c \times d$, \mathbf{x} is $d \times 1$, \mathbf{w}_2 is $c \times 1$.

$$f(x) = \mathbf{w}_2^T \cdot \frac{1}{1 + e^{-(\mathbf{w}_1 x)}}$$

$$\text{sigmoid}(\mathbf{w}_1 \mathbf{x}) = \begin{bmatrix} \end{bmatrix}_{c \times d} \begin{bmatrix} \end{bmatrix}_{d \times 1} = c \times 1$$

$$\textcircled{1} \frac{df}{d\mathbf{w}_2} = \frac{1}{1 + e^{-(\mathbf{w}_1 \mathbf{x})}} [c \times 1]$$

$$\textcircled{2} \frac{df}{d\mathbf{W}_1} = \mathbf{w}_2^T \cdot \frac{1}{(1 + e^{-(\mathbf{w}_1 \mathbf{x})})^2} (-e^{-(\mathbf{w}_1 \mathbf{x})}) (-\mathbf{x}^T)$$

$(1 \times c) \quad (c \times 1) \quad (c \times 1) \quad (1 \times d) \Rightarrow [c \times d]$

$$\textcircled{3} \frac{df}{d\mathbf{x}} = \mathbf{w}_2^T \cdot \frac{1}{(1 + e^{-(\mathbf{w}_1 \mathbf{x})})^2} (-e^{-(\mathbf{w}_1 \mathbf{x})})^T (-\mathbf{w}_1)$$

$(1 \times c) \quad (c \times 1) \quad (1 \times c) \quad (c \times d) \Rightarrow [1 \times d]$

5. (High Dimensional Statistics ("Curse of Dimensionality")) Consider N data points independent and uniformly distributed in a p -dimensional unit ball B (for every $x \in B, \|x\|^2 \leq 1$), centered at the origin. The median distance from the origin to the closest data point is given by the expression:

$$d(p, N) = \left(1 - \frac{1}{2^N}\right)^{\frac{1}{p}}$$

Prove this expression (8 points). Compute the median distance $d(p, N)$ for $N = 10,000, p = 1,000$ (2 points).

Hint: The volume of a ball in p dimensions is $V_p(R) = \frac{\pi^{\frac{p}{2}}}{\Gamma(\frac{p}{2}+1)} R^p$, where R is the radius of the ball, and Γ is the Gamma function (the exact form of it does not matter for this assignment). A point being the **closest** point to the origin means that there is **no** point that has a smaller distance to the origin than itself. What is the **probability** for that to happen with a uniform distribution in a unit ball?

Median distance (d) is the distance at which the probability that any point is closer to the origin than this distance is $\frac{1}{2}$.

For ball $B, R=1$, the volume is $V_p(1) = \frac{\pi^{\frac{p}{2}}}{\Gamma(\frac{p}{2}+1)} \cdot 1$

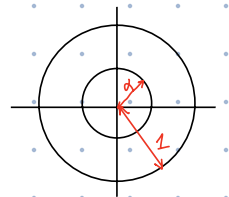
the volume of ball which $R=d$ is $V_p(d) = \frac{\pi^{\frac{p}{2}}}{\Gamma(\frac{p}{2}+1)} \cdot d^p$

And each data points are independent, therefore we can prove like below

$$\frac{1}{2} = \prod_{i=1}^N [1 - P(\|x_i\| \leq d)]$$

$$\frac{1}{2} = \prod_{i=1}^N [1 - d^p]$$

$$\frac{V_p(d)}{V_p(1)} = \frac{\cancel{\frac{\pi^{\frac{p}{2}}}{\Gamma(\frac{p}{2}+1)}} d^p}{\cancel{\frac{\pi^{\frac{p}{2}}}{\Gamma(\frac{p}{2}+1)}} 1} = d^p$$



$$\frac{1}{2} = (1 - d^p)^N$$

$$1 - d^p = \left(\frac{1}{2}\right)^{\frac{1}{N}} \rightarrow d^p = 1 - \left(\frac{1}{2}\right)^{\frac{1}{N}} \rightarrow d = \left[1 - \left(\frac{1}{2}\right)^{\frac{1}{N}}\right]^{\frac{1}{p}}$$

$$d(1000, 10000) = 0.9905$$