

Exercise 2Simple functions:

1) $f(x) = x^2, x \in \mathbb{R}$

• $\text{Dom } f(x) = \mathbb{R} \checkmark$

• $\nabla f(x) = 2x$

$\nabla^2 f(x) = 2 \geq 0 \quad \forall x \in \text{Dom}(f) \checkmark$

 $\Rightarrow f(x)$ is convex

2) $f(x) = e^{x^2}, x \in \mathbb{R}$

• $\text{Dom } f(x) = \mathbb{R} \checkmark$

• $\nabla f(x) = 2xe^{x^2}$

$\nabla^2 f(x) = 4x^2 e^{x^2} + 2e^{x^2}$

$$= \underbrace{(4x^2 + 2)}_{\geq 0} \underbrace{e^{x^2}}_{\geq 0} \geq 0 \quad \forall x \in \text{Dom}(f) \checkmark$$

 $\Rightarrow \underline{f(x) \text{ convex}}$

OR by combination rule

 $\exp(g(x))$ convex if $g(x)$ convex $\Rightarrow x^2$ is $\Rightarrow \checkmark$

3) $f(x, y) = x^2 + 3xy + 2y^2, x, y \in \mathbb{R}$

• $\text{Dom } f(x) = \mathbb{R}^2 \checkmark$

• $\nabla f(x) = \begin{bmatrix} 2x + 3y & 4y + 3x \end{bmatrix}$

$\nabla^2 f(x) = \begin{pmatrix} 2 & 3 \\ 3 & 4 \end{pmatrix} = A$. Check if $A \geq 0$ is semi-definite positive or not

Method of pivots:

$$\begin{pmatrix} 2 & 3 \\ 3 & 4 \end{pmatrix} \Rightarrow \begin{pmatrix} 2 & 3 \\ 0 & -0,5 \end{pmatrix} \Rightarrow \text{One positive and one negative pivot}$$

 \Rightarrow one negative eigenvalue \Rightarrow not positive semi-definite $\Rightarrow \underline{\text{not convex}}$ Log-Sum-exp:Show that $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ is convex on \mathbb{R}^n Proof:First for $n=2$ to get an idea

$f(x) = \log(e^{x_1} + e^{x_2})$

$\nabla f(x) = \frac{1}{e^{x_1} + e^{x_2}} \begin{pmatrix} e^{x_1} \\ e^{x_2} \end{pmatrix}$

$$\nabla^2 f(x) = \frac{e^{x_1} e^{x_2}}{(e^{x_1} + e^{x_2})^2} \begin{pmatrix} 1 & -1 \\ -1 & 1 \end{pmatrix} = \underbrace{\begin{pmatrix} 1 \\ -1 \end{pmatrix}}_{\geq 0} \underbrace{(1 \quad -1)}_{= A A^T} = A A^T \checkmark$$

Now for $n \in \mathbb{R}_+$:

$$f(x) = \log \left(\sum_{i=1}^n e^{x_i} \right)$$

$$\nabla f(x) = \frac{1}{\sum_{i=1}^n e^{x_i}} \begin{pmatrix} e^{x_1} \\ \vdots \\ e^{x_n} \end{pmatrix} = \frac{1}{A} a \quad \text{where}$$

$$a = \begin{pmatrix} e^{x_1} \\ \vdots \\ e^{x_n} \end{pmatrix} \\ A = \sum_{i=1}^n e^{x_i}$$

Calculate the Hessian,

be $g_i(x)$ the i -th component:

$$g_i(x) = \frac{e^{x_i}}{\sum_{i=1}^n e^{x_i}} = \frac{a_i}{A}$$

then $\bullet \frac{\partial g_i(x)}{\partial x_i} = \frac{a_i}{A} - \frac{a_i^2}{A^2}$

$\bullet \frac{\partial g_i(x)}{\partial x_j} = \frac{-a_i a_j}{A^2} \quad j \neq i$

$$\Rightarrow \nabla^2 f(x) = \frac{1}{A^2} (A \operatorname{diag}(a) - aa^T)$$

$$= \operatorname{diag}(S(x)) - S(x)S(x)^T$$

where $S(x) = \frac{a}{A} =$

$$\begin{pmatrix} \frac{e^{x_1}}{\sum_{i=1}^n e^{x_i}} \\ \vdots \\ \frac{e^{x_n}}{\sum_{i=1}^n e^{x_i}} \end{pmatrix}$$

We want $\nabla^2 f(x) \geq 0$, be $v \in \mathbb{R}^n$

$$v^T \nabla^2 f(x) v \geq 0 \Leftrightarrow v^T \operatorname{diag}(S(x)) v \geq v^T S(x) S(x)^T v$$

We have:

$$v^T S(x) S(x)^T v = (S(x)^T v)^2$$

$$= \left(\sum_{i=1}^n S(x)_i v_i \right)^2$$

$$\leq \sum_{i=1}^n S(x)_i v_i^2$$

inequality of
Cauchy-Schwarz

$$= v^T \operatorname{diag}(S(x)) v$$

$$\Rightarrow f(x) = \log \left(\sum_{i=1}^n e^{x_i} \right) \text{ is } \underline{\text{convex}} \quad \#$$

Geometric mean:

Show that $f(x) = \left(\prod_{i=1}^n x_i \right)^{1/n}$ is concave on \mathbb{R}_{++}^n

ie. $\forall x, y \in \mathbb{R}_{++}^n, \forall \lambda \in [0, 1]$, we have $f(\lambda x + (1-\lambda)y) \geq \lambda f(x) + (1-\lambda)f(y)$

Proof:

$$f(\lambda x + (1-\lambda)y) = \left(\prod_{i=1}^n (\lambda x_i + (1-\lambda)y_i) \right)^{1/n} \stackrel{\text{Maier inequality (proven by arithmetic and geometric means)}}{\geq} \prod_{i=1}^n \lambda^{1/n} x_i^{1/n} + \prod_{i=1}^n (1-\lambda)^{1/n} y_i^{1/n}$$

$$= \left(\lambda^{1/n} \right)^n \prod_{i=1}^n x_i^{1/n} + \left((1-\lambda)^{1/n} \right)^n \prod_{i=1}^n y_i^{1/n} = \lambda f(x) + (1-\lambda)f(y) \quad \# \Rightarrow \underline{\text{concave}}$$