

Problem 1 ✓ f is convex. According to Jensen's inequality, $f(\lambda_1 x_1 + \lambda_2 x_2) \leq \lambda_1 f(x_1) + \lambda_2 f(x_2)$
 $f(\sum_{i=1}^k \lambda_i x_i) = f(\lambda_1 + (1-\lambda_1) \sum_{i=2}^k \frac{\lambda_i}{1-\lambda_1} x_i) \leq \lambda_1 f(x_1) + (1-\lambda_1) f(\sum_{i=2}^k \frac{\lambda_i}{1-\lambda_1} x_i)$
 Since $\sum_{i=2}^k \frac{\lambda_i}{1-\lambda_1} = 1$, we can induce that, $\lambda_1 f(x_1) + \dots + \lambda_k f(x_k) \geq f(\lambda_1 x_1 + \dots + \lambda_k x_k)$.

2 ✓ $\max\{f, g\} = \begin{cases} f, & f \geq g \\ g, & f < g \end{cases}$. $\because f$ and g are both convex
 $\therefore \max\{f, g\}$ must be convex.

$\because f$ & g are convex, $\therefore \begin{cases} \lambda f(x_1) + (1-\lambda)f(x_2) \geq f(\lambda x_1 + (1-\lambda)x_2) \\ \lambda g(x_1) + (1-\lambda)g(x_2) \geq g(\lambda x_1 + (1-\lambda)x_2) \end{cases}$
 $f+g: \lambda(f(x_1) + g(x_1)) + (1-\lambda)(f(x_2) + g(x_2)) \geq f(\lambda x_1 + (1-\lambda)x_2) + g(\lambda x_1 + (1-\lambda)x_2)$
 $\therefore f+g$ is also convex

3 ✓ let $f(x) = -\log x$. by AM-GM inequality, we have $\frac{x_1+x_2}{2} \geq \sqrt{x_1 x_2}$
 $f(x) = -\frac{1}{x} < 0$. $\therefore f(x)$ decreases. $\therefore f(\frac{x_1+x_2}{2}) \leq f(\sqrt{x_1 x_2})$
 thus, $\because f'(x) = -\frac{1}{x^2} < 0$, $\therefore f(x)$ decreases, $\therefore f(\frac{x_1+x_2}{2}) \leq f(\sqrt{x_1 x_2})$
 $\therefore -\log(\frac{x_1+x_2}{2}) \leq -\frac{1}{2} \log x_1 - \frac{1}{2} \log x_2$. $\therefore f(x)$ is convex over $(0, \infty)$
 $\therefore -f(x) = \log x$. $\therefore \log x$ is concave over $(0, \infty)$

4 ✓ $e^x: \frac{e^{x_1} + e^{x_2}}{2} \geq \sqrt{e^{x_1} \cdot e^{x_2}} = e^{\frac{x_1+x_2}{2}}$. $\therefore e^x$ is convex.

$e^{-x}: \frac{e^{-x_1} + e^{-x_2}}{2} \geq \sqrt{e^{-x_1} \cdot e^{-x_2}} = e^{-\frac{x_1+x_2}{2}}$, $\therefore e^{-x}$ is convex
 thus, e^x and e^{-x} are both convex over \mathbb{R} .

5 ✓ from question 3 we know, $-\log x$ is convex.

$$\therefore -\frac{x_1}{x_1+x_2} \log \frac{y_1}{x_1} - \frac{x_2}{x_1+x_2} \log \frac{y_2}{x_2} \geq -\log(\frac{y_1}{x_1+x_2} + \frac{y_2}{x_1+x_2}) = -\log(\frac{y_1+y_2}{x_1+x_2})$$

$$\therefore \frac{x_1}{x_1+x_2} \log \frac{x_1}{y_1} + \frac{x_2}{x_1+x_2} \log \frac{x_2}{y_2} \geq \log \frac{x_1+x_2}{y_1+y_2}. \therefore x_1 \log \frac{x_1}{y_1} + x_2 \log \frac{x_2}{y_2} \geq (x_1+x_2) \log \frac{x_1+x_2}{y_1+y_2}$$

Problem 2 ✓ $\because 0 < p_k \leq 1$, $H(P) = -\sum p_k \log p_k$. $\therefore H(P) = -\sum p_k \log p_k \geq 0$

According to Jensen's inequality, $\sum p_k \log \frac{1}{p_k} \leq \log \sum p_k \cdot \frac{1}{p_k} = \log K$

$\therefore 0 \leq H(P) \leq \log K$

2 ✓ $H(P) = -\sum p_k \log p_k$, according to Jensen's inequality,
 $H(P) \geq -\log(\sum p_k^2)$.

Problem 2/3/ from problem 1.5 we know, $x_1 \log \frac{x_1}{y_1} + x_2 \log \frac{x_2}{y_2} \geq (x_1 + x_2) \log \left(\frac{x_1 + x_2}{y_1 + y_2} \right)$
 let $x_1 = p_x$, $x_2 = q_x$, $y_1 = y_2 = 1$, we have $p_x \log p_x + q_x \log q_x \geq (p_x + q_x) \log \left(\frac{p_x + q_x}{2} \right)$
 thus, $\sum_x p_x \log p_x + \sum_x q_x \log q_x \geq \sum_x (p_x + q_x) \log \left(\frac{p_x + q_x}{2} \right)$
 thus, $-\frac{1}{2} \sum_x (p_x + q_x) \log \left(\frac{p_x + q_x}{2} \right) \geq -\frac{1}{2} (\sum_x p_x \log p_x + \sum_x q_x \log q_x)$
 we have $1 + \left(\frac{p_x + q_x}{2} \right) \geq \frac{1}{2} (H(p) + H(q))$.

Problem 3/1/ $N(\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$, we know $N(\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} = \frac{1}{\sqrt{2\pi\sigma^2}} (*)$
 differentiate (*) on μ , we have: $\mu \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx = \int_{-\infty}^{+\infty} x \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$
 that is, $\int_{-\infty}^{+\infty} x \cdot N(\mu, \sigma^2) dx = \mu \cdot 1 = \mu$. and this is the def. of expectation
 $\therefore N(\mu, \sigma^2)$'s expectation is μ .

Problem 3 ✓

$$E(X+Y) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} (x+y) f_{XY}(x,y) dx dy = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x f_{XY}(x,y) dx dy + \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} y f_{XY}(x,y) dx dy \\ = E(X) + E(Y).$$

$$\text{Var}(X+Y) = E((X+Y-\mu)^2) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} (x+y-\mu)^2 f_{XY}(x,y) dx dy = \sigma_x^2 + \sigma_y^2$$

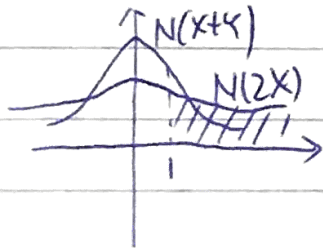
$$E(aX) = \int_{-\infty}^{+\infty} ax f_X(x) dx = a E(X)$$

$$\text{Var}(aX) = \int_{-\infty}^{+\infty} (ax - E(ax))^2 f_X(x) dx = \int_{-\infty}^{+\infty} (ax - a\mu)^2 f_X(x) dx = \int_{-\infty}^{+\infty} a^2 (x-\mu)^2 f_X(x) dx \\ = a^2 \int_{-\infty}^{+\infty} (x - E(X))^2 f_X(x) dx = a^2 \sigma^2$$

∴ Distribution of $X+Y$: $N(X+Y) \sim (0, 2)$

----- $2X$: $N(2X) \sim (0, 4)$

3 ✓



I'll choose $2X$, because $N(2X)$ variance is bigger, and its expected value is 0, which means it has more chance to get number larger than 1.

problem 4 ✓ $f(x, y) = x^2 + y^2$ (distance function). constraint: $x + 2y - 10 = 0$

we get $(x, y) = \lambda(1, 2)$. therefore, $x = \frac{y}{2} = \lambda$. and $x + 2y - 10 = 0$

$\therefore \lambda = 2$. closest point: $(2, 4)$

3 ✓ $\varphi(x, y) = x^2y + y^2 - xy$. $\nabla \varphi = \left(\frac{\partial \varphi}{\partial x}, \frac{\partial \varphi}{\partial y} \right) = (2xy - y, x^2 + 2y - x)$.

at $(1, 1)$, $\nabla \varphi = 1 + 2 = 3$

Problem 43

constraint: $(x-3)^2 + (y-2)^2 = C$ ($0 \leq C \leq 1$)

(let $f(x, y, \lambda) = x^2 + y^2 + \lambda((x-3)^2 + (y-2)^2 - C)$)

$$\begin{cases} \frac{\partial f}{\partial \lambda} = 0 \\ \frac{\partial f}{\partial x} = 0 \\ \frac{\partial f}{\partial y} = 0 \end{cases} \Rightarrow \begin{cases} (x-3)^2 + (y-2)^2 = C \\ 2x + 2\lambda(x-3) = 0 \\ 2y + 2\lambda(y-2) = 0 \end{cases}$$

$$\therefore \begin{cases} x_1 = 3(1 + \sqrt{\frac{C}{13}}) \\ y_1 = 2(1 + \sqrt{\frac{C}{13}}) \\ \frac{1}{1+\lambda_1} = 1 + \sqrt{\frac{C}{13}} \end{cases} \quad \& \quad \begin{cases} x_2 = 3(1 - \sqrt{\frac{C}{13}}) \\ y_2 = 2(1 - \sqrt{\frac{C}{13}}) \\ \frac{1}{1+\lambda_2} = 1 - \sqrt{\frac{C}{13}} \end{cases}$$

$f(x_1, y_1, \lambda_1) = (\sqrt{C} + \sqrt{13})^2$. min ($C=0$), $f_{\min} = 13$.

$C=1$, $f_{\max} = 14 + 2\sqrt{13}$

$f(x_2, y_2, \lambda_2) = (\sqrt{C} - \sqrt{13})^2$. $C=0$, $f_{\max} = 13$

$C=1$, $f_{\min} = 14 - 2\sqrt{13}$

\therefore min: $14 - 2\sqrt{13}$.

max: $14 + 2\sqrt{13}$