

\LaTeX Mini Project 3

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1. Problem 1

$$\begin{aligned} \ln P(E) &= \ln \sum_H P(H, E) \\ &= \ln \sum_H Q(H|E) \cdot \frac{P(H, E)}{Q(H|E)} \\ &\geq \sum_H Q(H|E) \ln \frac{P(H, E)}{Q(H|E)} \end{aligned}$$

The difference between the inequality is given by KL divergence $D(Q||P)$. which is $= - \sum Q(H|E) \ln \frac{P(H|E)}{Q(H|E)}$ as we have

$$\ln P(E) = \sum_H Q(H|E) \ln \frac{P(E, H)}{Q(H|E)} - \sum_H Q(H|E) \ln \frac{P(H|E)}{Q(H|E)}$$

from the Bayes theorem.

We cannot consider $D(P||Q)$ as KL divergence is not symmetric, i.e. $D(P||Q) \neq D(Q||P)$

2. Problem 2

3. Problem 3

For a fixed x_i , y_i are i.i.d random variables with $y_i \sim N(w_1 x_i + w_0, \sigma^2)$. So the probability distribution of y_1, y_2, \dots is defined by:

$$\begin{aligned} f(y_1, \dots, y_n | w_1, w_0) &= \pi_{i=1}^n f(y_i | w_1, w_0) \\ &= \pi_{i=1}^n \frac{1}{(2\sigma^2)^{\frac{n}{2}}} \exp \frac{-(y_i - w_1 x_i - w_0)^2}{2\sigma^2} \\ &= \frac{1}{(2\sigma^2)^{\frac{n}{2}}} \exp \frac{-1}{(2\sigma^2)^{\frac{n}{2}}} \sum_{i=1}^n (y_i - w_1 x_i - w_0)^2 \end{aligned}$$

To get the MLE estimates of w_1 and w_0 we will set $\frac{\partial f}{\partial w_1} = 0$ and $\frac{\partial f}{\partial w_0} = 0$ which leads to the equations:

$$\sum_{i=1}^n x_i (y_i - w_1 x_i - w_0) = 0$$

$$\sum_{i=1}^n (y_i - w_1 x_i - w_0) = 0$$

Solving the second equation for w_0 yields $w_0 = y - w_1 x$ and replacing w_0 in the first equation yields:

$$\sum_{i=1}^n (x_i - \bar{x} + \bar{x})(y_i - w_1 x_i - \bar{y} + w_1 \bar{x}) = 0$$

which in turn leads to

$$w_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$