

## 2.11.2 连续随机变量的联合熵、条件熵以及平均互信息量

将微分熵的概念推广到多个连续随机变量，可以得到联合微分熵和统计微分熵，它们与普通微分熵一样，都只有相对意义。

### 一、联合微分熵

$$h(XY) = -\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) \log f_{XY}(x, y) dx dy$$

### 二、条件微分熵

$$h(X | Y) = -\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) \log f_{X|Y}(x | y) dx dy$$

### 三、连续随机变量的平均互信息量

$$\begin{aligned} I(X; Y) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) \log \frac{f_{XY}(x, y)}{f_X(x) f_Y(y)} dx dy \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) \log \frac{f_{X|Y}(x | y)}{f_X(x)} dx dy \end{aligned}$$

注意：上式可用离散化取极限的方法严格推出，是精确的，不是舍弃无穷大项而取相对值。

四、关系 1、  $I(X;Y) = h(X) - h(X|Y)$

$$\text{推导: } I(X;Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x,y) \log \frac{f_{X|Y}(x|y)}{f_X(x)} dx dy$$

$$= - \int_{-\infty}^{\infty} \log f_X(x) dx \int_{-\infty}^{\infty} f_{XY}(x,y) dy$$

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

$$= - \int_{-\infty}^{\infty} f_X(x) \log f_X(x) dx$$

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

$$= h(X) - h(X|Y)$$

## 2、恒等关系：

$$h(XY) = h(X) + h(Y | X) = h(Y) + h(X | Y)$$

$$I(X; Y) = h(X) - h(X | Y) = h(Y) - h(Y | X) \\ = I(Y; X) \quad (\text{互易性})$$

## 3、不等关系：

$$h(X | Y) \leq h(X); \quad h(XY) \leq h(X) + h(Y)$$

$$I(X; Y) \geq 0 \quad (\text{非负性})$$

例2.12  $XY$ 是二维正态随机变量,  $E[X] = E[Y] = 0, \text{Var}[X] = \sigma_1^2, \text{Var}[Y] = \sigma_2^2, \rho = \frac{E[XY]}{\sigma_1\sigma_2}$ 。求 $h(X), h(X|Y), I(X:Y)$ 。

解：根据概率论知识，联合概率密度函数为

$$f_{XY}(x, y)$$

$$= \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} e^{-(x^2/\sigma_1^2 + y^2/\sigma_2^2 - 2\rho xy/\sigma_1\sigma_2)/2(1-\rho^2)}$$

$\rho$ 为相关系数。求出边缘密度和条件密度：



$$f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x, y) dy = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-x^2/2\sigma_1^2}$$

$$f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-y^2/2\sigma_2^2}$$

$$f_{X|Y}(x | y) = f_{XY}(x, y) / f_Y(y)$$

$$= \frac{1}{\sqrt{2\pi\sigma_1^2(1-\rho^2)}} e^{-\left(x - \frac{\sigma_1}{\sigma_2}\rho y\right)^2 / 2\sigma_1^2(1-\rho^2)}$$

再利用微分熵的定义式，得：

$$h(X) = \log \sqrt{2\pi e \sigma_1^2}$$

$$h(X | Y) = \log \sqrt{2\pi e \sigma_1^2 (1 - \rho^2)}$$

$$I(X; Y) = h(X) - h(X | Y)$$

$$= \log \sqrt{1 / (1 - \rho^2)}$$