

$$\begin{aligned}
 I(X;Y) &= h(X) - h(X|Y) \\
 &= - \int f(x) \log f(x) dx + \iint f(x,y) \log f(x,y) dx dy \\
 &= \iint f(x,y) \log \frac{f(x,y)}{f(x)} dx dy \\
 &= \iint f(x,y) \log \frac{f(x,y)}{f(x)f(y)} dx dy \quad (*)
 \end{aligned}$$

also showing interchangeability of X and Y .

Def. 2.5.6. The relative entropy or Kulback-Leibler divergence between two densities f and g is defined as

$$D(f \parallel g) = \int f(x) \log \frac{f(x)}{g(x)} dx \quad \underline{\quad}$$

From (*) it follows that

$$I(X;Y) = D(f(x,y) \parallel f(x) \cdot f(y)) \quad (**)$$

Th. 2.5.7. $D(f \parallel g) \geq 0$

with equality iff $f=g$ (almost everywhere, a.e.) $\underline{\quad}$

Proof. Let $S = \{x \mid f(x) > 0\}$ the support of f . Then

$$\begin{aligned}
 -D(f \parallel g) &= \int_S f \log \frac{g}{f} \\
 &\leq \log \int_S f \frac{g}{f} \quad (\text{Jensen inequality, La 2.1.6}) \\
 &\quad (f \text{ concave: } E f(X) \leq f(EX)) \\
 &= \log \int_S g \leq \log 1 = 0
 \end{aligned}$$

Equality holds iff $f=g$ a.e. \square

Corollary 2.5.8.

- a) $I(X; Y) \geq 0$ with equality iff X and Y are independent.
- b) $h(X|Y) \leq h(X)$ with equality iff X, Y are independent.
- c) $-\int f \log f \leq -\int f \log g$

Proof. a) follows from (**)

b) $I(X; Y) = h(X) - h(X|Y) \geq 0$ by a)

c) By Def. of $D(f||g)$. □

Th. 2.5.9. (Chain rule for diff. entropy)

$$h(X_1, \dots, X_n) = \sum_{i=1}^n h(X_i | X_1, \dots, X_{i-1}) \quad \square$$

Proof. From the definition it follows that

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

This implies

$$h(X_1, \dots, X_i) = h(X_1, \dots, X_{i-1}) + h(X_i | X_1, \dots, X_{i-1}) \quad \forall i \in \mathbb{N}$$

The assertion follows by induction. □

Corollary 2.5.10.

$$h(X_1, \dots, X_n) \leq \sum_{i=1}^n h(X_i)$$

with equality iff X_1, \dots, X_n are stoch. independent. □

Th. 2.5.11. Let $X \in \mathbb{R}^n$ with density $f(x)$,
 $A \in \mathbb{R}^{n \times n}$ of full rank, $b \in \mathbb{R}^n$. Then

$$h(AX+b) = h(X) + \log |A|. \quad \square$$

(Note that $|A| = |\det A|$)

Proof. If $X \sim f(x)$, then $Y = AX+b \sim \frac{1}{|A|} f(A^{-1}(y-b))$,
 $x, y \in \mathbb{R}^n$.

$$\begin{aligned} & - \int \frac{1}{|A|} f(A^{-1}(y-b)) \log \left(\frac{1}{|A|} f(A^{-1}(y-b)) \right) dy \\ &= - \log \frac{1}{|A|} - \int \frac{1}{|A|} f(A^{-1}y) \log (f(A^{-1}y)) dy \\ &= - \log \frac{1}{|A|} - \int f(x) \log f(x) dx \\ &= \log |A| + h(X). \quad \square \end{aligned}$$

Th. 2.5.12. Let $X \in \mathbb{R}^n$ abs. cont. with ~~$f(x)$~~ density $f(x)$ and $\text{Cov}(X) = C$, C pos. definite. Then

$$h(X) \leq \frac{1}{2} \ln \left((2\pi e)^n |C| \right),$$

i.e., $N_n(\mu, C)$ has largest entropy amongst all r.v. with pos. def. covariance matrix C .

Proof. W.l.o.g. assume $EX = 0$ (see Th. 2.5.11)

Let $\varphi(x) = \frac{1}{(2\pi)^{n/2} |C|^{1/2}} \exp\left\{-\frac{1}{2} x^T C^{-1} x\right\}$ density of $N_n(0, C)$.

Let $X \sim f(x)$, $EX = 0$, $\text{Cov}(X) = E(XX^T) = \int x x^T f(x) dx$.

$$\begin{aligned} h(X) &= - \int f(x) \ln f(x) dx \\ &\leq - \int f(x) \ln \varphi(x) dx \quad (\text{Cor. 2.5.8 c}) \\ &= - \int f(x) \ln \left[\frac{1}{(2\pi)^{n/2} |C|^{1/2}} \exp\left\{-\frac{1}{2} x^T C^{-1} x\right\} \right] dx \\ &= - \ln \left[\frac{1}{(2\pi)^{n/2} |C|^{1/2}} \right] + \frac{1}{2} \int x^T C^{-1} x f(x) dx \\ &= \ln \left((2\pi)^{n/2} |C|^{1/2} \right) + \frac{1}{2} \int \text{tr}(C^{-1} x x^T) f(x) dx \\ &= \ln \left((2\pi)^{n/2} |C|^{1/2} \right) + \frac{1}{2} \text{tr} C^{-1} \underbrace{\int x x^T f(x) dx}_{= C} \\ &= \ln \left((2\pi)^{n/2} |C|^{1/2} \right) + \frac{n}{2} \\ &= \ln \left((2\pi e)^{n/2} |C|^{1/2} \right). \quad \square \end{aligned}$$