

Lecture 3: Information Inequalities

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1 Information Theory Basics

1.1 Entropy, Relative Entropy, and Mutual Information

- **Definition (*Shannon Entropy*)** [Cover and Thomas, 2006]

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space and $X : \mathbb{R} \rightarrow \mathcal{X}$ be a random variable. Define $p(x)$ as *the probability density function* of X with respect to a base measure μ on \mathcal{X} . **The Shannon Entropy** is defined as

$$\begin{aligned} H(X) &:= \mathbb{E}_p [-\log p(X)] \\ &= \int_{\Omega} -\log p(X(\omega)) d\mathbb{P}(\omega) \\ &= - \int_{\mathcal{X}} p(x) \log p(x) d\mu(x) \end{aligned}$$

- **Definition (*Conditional Entropy*)** [Cover and Thomas, 2006]

If a pair of random variables (X, Y) follows the joint probability density function $p(x, y)$ with respect to a base product measure μ on $\mathcal{X} \times \mathcal{Y}$. Then **the joint entropy** of (X, Y) , denoted as $H(X, Y)$, is defined as

$$H(X, Y) := \mathbb{E}_{X, Y} [-\log p(X, Y)] = - \int_{\mathcal{X} \times \mathcal{Y}} p(x, y) \log p(x, y) d\mu(x, y)$$

Then **the conditional entropy** $H(Y|X)$ is defined as

$$\begin{aligned} H(Y|X) &:= \mathbb{E}_{X, Y} [-\log p(Y|X)] = - \int_{\mathcal{X} \times \mathcal{Y}} p(x, y) \log p(y|x) d\mu(x, y) \\ &= \mathbb{E}_X [\mathbb{E}_Y [-\log p(Y|X)]] = \int_{\mathcal{X}} p(x) \left(- \int_{\mathcal{Y}} p(y|x) \log p(y|x) d\mu(y) \right) d\mu(x) \end{aligned}$$

- **Proposition 1.1 (*Properties of Shannon Entropy*)** [Cover and Thomas, 2006]
Let X, Y, Z be random variables.

1. (**Non-negativity**) $H(X) \geq 0$;
2. (**Chain Rule**)

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

Furthermore,

$$H(X, Y|Z) = H(X|Z) + H(Y|X, Z)$$

3. (**Sub-Additivity**)

$$H(X, Y) \leq H(X) + H(Y)$$

4. (**Concavity**) $H(p) := \mathbb{E}_p [-\log p(X)]$ is a concave function in terms of p.d.f. p , i.e.

$$H(\lambda p_1 + (1 - \lambda) p_2) \geq \lambda H(p_1) + (1 - \lambda) H(p_2)$$

for any two p.d.fs p_1, p_2 on \mathcal{X} and any $\lambda \in [0, 1]$.

- **Definition (*Relative Entropy / Kullback-Leibler Divergence*)** [Cover and Thomas, 2006]

Suppose that P and Q are *probability measures* on a measurable space \mathcal{X} , and P is *absolutely continuous* with respect to Q , then the relative entropy or the Kullback-Leibler divergence is defined as

$$\mathbb{KL}(P \parallel Q) := \mathbb{E}_P \left[\log \left(\frac{dP}{dQ} \right) \right] = \int_{\mathcal{X}} \log \left(\frac{dP(x)}{dQ(x)} \right) dP(x)$$

where $\frac{dP}{dQ}$ is the *Radon-Nikodym derivative* of P with respect to Q . Equivalently, the KL-divergence can be written as

$$\mathbb{KL}(P \parallel Q) = \int_{\mathcal{X}} \left(\frac{dP(x)}{dQ(x)} \right) \log \left(\frac{dP(x)}{dQ(x)} \right) dQ(x)$$

which is *the entropy of P relative to Q* . Furthermore, if μ is a base measure on \mathcal{X} for which densities p and q with $dP = p(x)d\mu$ and $dQ = q(x)d\mu$ exist, then

$$\mathbb{KL}(P \parallel Q) = \int_{\mathcal{X}} p(x) \log \left(\frac{p(x)}{q(x)} \right) d\mu(x)$$

- **Definition (*Mutual Information*)** [Cover and Thomas, 2006]

Consider two random variables X, Y on $\mathcal{X} \times \mathcal{Y}$ with joint probability distribution $P_{(X,Y)}$ and marginal distribution P_X and P_Y . The mutual information $I(X; Y)$ is *the relative entropy* between *the joint distribution $P_{(X,Y)}$* and *the product distribution $P_X \otimes P_Y$* :

$$I(X; Y) = \mathbb{KL}(P_{(X,Y)} \parallel P_X \otimes P_Y) = \mathbb{E}_{P_{(X,Y)}} \left[\log \frac{dP_{(X,Y)}}{dP_X \otimes dP_Y} \right]$$

If $P_{(X,Y)}$ has a probability density function $p(x, y)$ with respect to a base measure μ on $\mathcal{X} \times \mathcal{Y}$, then

$$I(X; Y) = \int_{\mathcal{X} \times \mathcal{Y}} p(x, y) \log \left(\frac{p(x, y)}{p_X(x)p_Y(y)} \right) d\mu(x, y)$$

- **Proposition 1.2 (*Properties of Relative Entropy and Mutual Information*)** [Cover and Thomas, 2006]

Let X, Y be random variables.

1. (**Non-negativity**) Let $p(x), q(x)$ be probability density function of P, Q .

$$\mathbb{KL}(P \parallel Q) \geq 0$$

with equality if and only if $p(x) = q(x)$ almost surely. Therefore, the mutual information is non-negative as well:

$$I(X; Y) \geq 0$$

with equality if and only if X and Y are independent.

2. (**Finite Cardinality Domain**) Let $|\mathcal{X}|$ be the number of elements in domain \mathcal{X} and X is a discrete random variables in \mathcal{X} . Then the relative entropy of probability distribution p with respect to uniform distribution u on \mathcal{X} is

$$\begin{aligned}\text{KL}(p \parallel u) &= \log |\mathcal{X}| - H(X) \geq 0 \\ \Rightarrow H(X) &\leq \log |\mathcal{X}|\end{aligned}$$

3. (**Symmetry**) $I(X; Y) = I(Y; X)$
4. (**Information Gain via Conditioning**) The mutual information $I(X; Y)$ is the reduction in the uncertainty of X due to the knowledge of Y (and vice versa)

$$\begin{aligned}I(X; Y) &= H(X) - H(X|Y) \\ &= H(Y) - H(Y|X) \\ &= H(X) + H(Y) - H(X, Y)\end{aligned}\tag{1}$$

5. (**Shannon Entropy as Self-Information**) $I(X; X) = H(X)$

1.2 Chain Rules for Entropy, Relative Entropy, and Mutual Information

- **Proposition 1.3 (Conditioning Reduces Entropy)** [Cover and Thomas, 2006]
From non-negativity of mutual information, we see that the entropy of X is non-increasing when conditioning on Y

$$H(X|Y) \leq H(X)\tag{2}$$

where equality holds if and only if X and Y are independent.

- **Proposition 1.4 (Chain Rule for Entropy)** [Cover and Thomas, 2006]
Let X_1, X_2, \dots, X_n be drawn according to $p(x_1, x_2, \dots, x_n)$. Then

$$H(X_1, X_2, \dots, X_n) = \sum_{i=1}^n H(X_i | X_{i-1}, \dots, X_1)\tag{3}$$

- **Proposition 1.5 (Sub-Additivity of Entropy)** [Cover and Thomas, 2006]
Let X_1, X_2, \dots, X_n be drawn according to $p(x_1, x_2, \dots, x_n)$. Then

$$H(X_1, X_2, \dots, X_n) \leq \sum_{i=1}^n H(X_i)\tag{4}$$

with equality if and only if the X_i are independent.

- **Proposition 1.6 (Chain Rule for Mutual Information)** [Cover and Thomas, 2006]
Let X_1, X_2, \dots, X_n, Y be drawn according to $p(x_1, x_2, \dots, x_n, y)$. Then

$$I(X_1, X_2, \dots, X_n; Y) = \sum_{i=1}^n H(X_i; Y | X_{i-1}, \dots, X_1)\tag{5}$$

where **the conditional mutual information** is defined as

$$I(X; Y|Z) := H(X|Z) - H(X|Y, Z) = \text{KL}(P_{(X,Y|Z)} \parallel P_{X|Z} \otimes P_{Y|Z})$$

- **Proposition 1.7 (Chain Rule for Relative Entropy)** [Cover and Thomas, 2006]
Let $P_{(X,Y)}$ and $Q_{(X,Y)}$ be two probability measures on product space $\mathcal{X} \times \mathcal{Y}$ and $P \ll Q$. Denote the marginal distributions P_X, Q_X and P_Y, Q_Y on \mathcal{X} and \mathcal{Y} , respectively. $P_{Y|X}$ and $Q_{Y|X}$ are conditional distributions (Note that $P_{Y|X} \ll Q_{Y|X}$). Define **the conditional relative entropy** as

$$\mathbb{E}_X [\text{KL}(P_{Y|X} \parallel Q_{Y|X})] := \mathbb{E}_X \left[\mathbb{E}_{P_{Y|X}} \left[\log \left(\frac{dP_{Y|X}}{dQ_{Y|X}} \right) \right] \right].$$

Then the relative entropy of joint distribution $P_{(X,Y)}$ with respect to $Q_{(X,Y)}$ is

$$\text{KL}(P_{(X,Y)} \parallel Q_{(X,Y)}) = \text{KL}(P_X \parallel Q_X) + \mathbb{E}_X [\text{KL}(P_{Y|X} \parallel Q_{Y|X})] \quad (6)$$

In addition, let P and Q denote two joint distributions for X_1, X_2, \dots, X_n , let $P_{1:i}$ and $Q_{1:i}$ denote the marginal distributions of X_1, X_2, \dots, X_i under P and Q , respectively. Let $P_{X_i|1\dots i-1}$ and $Q_{X_i|1\dots i-1}$ denote the conditional distribution of X_i with respect to X_1, X_2, \dots, X_{i-1} under P and under Q .

$$\text{KL}(P \parallel Q) = \sum_{i=1}^n \mathbb{E}_{P_{1:i-1}} [\text{KL}(P_{X_i|1\dots i-1} \parallel Q_{X_i|1\dots i-1})] \quad (7)$$

1.3 Log-Sum Inequalities and Convexity

- **Proposition 1.8 (Log-Sum Inequalities)** [Cover and Thomas, 2006]
For non-negative numbers a_1, \dots, a_n and b_1, \dots, b_n ,

$$\sum_{i=1}^n a_i \log \frac{a_i}{b_i} \geq \left(\sum_{i=1}^n a_i \right) \log \frac{\sum_{i=1}^n a_i}{\sum_{i=1}^n b_i} \quad (8)$$

with equality if and only if $\frac{a_i}{b_i}$ is constant.

- **Proposition 1.9 (Joint Convexity of Relative Entropy)** [Cover and Thomas, 2006]
 $\text{KL}(p \parallel q)$ is **convex** in the pair (p, q) ; that is, if (p_1, q_1) and (p_2, q_2) are two pairs of probability density functions, then for $\lambda \in [0, 1]$,

$$\text{KL}(\lambda p_1 + (1 - \lambda)p_2 \parallel \lambda q_1 + (1 - \lambda)q_2) \leq \lambda \text{KL}(p_1 \parallel q_1) + (1 - \lambda) \text{KL}(p_2 \parallel q_2) \quad (9)$$

- **Proposition 1.10** [Cover and Thomas, 2006]
Let $(X, Y) \sim p(x, y) = p(x)p(y|x)$. The mutual information $I(X; Y)$ is a **concave** function of $p(x)$ for fixed $p(y|x)$ and a **convex** function of $p(y|x)$ for fixed $p(x)$.

1.4 Data Processing Inequality

- **Definition (Data Processing Markov Chain)**
Random variables X, Y, Z are said to **form a Markov chain** in that order (denoted by $X \rightarrow Y \rightarrow Z$) if the conditional distribution of Z depends only on Y and is **conditionally independent** of X . Specifically, X, Y , and Z form a Markov chain $X \rightarrow Y \rightarrow Z$ if the joint probability mass function can be written as

$$p(x, y, z) = p(x)p(y|x)p(z|y)$$

- **Proposition 1.11** (*Data Processing Inequality*) [Cover and Thomas, 2006]
If $X \rightarrow Y \rightarrow Z$, then

$$I(X; Z) \leq I(X; Y)$$

- **Corollary 1.12** [Cover and Thomas, 2006]
In particular, if $Z = g(Y)$, we have

$$I(X; g(Y)) \leq I(X; Y)$$

- **Corollary 1.13** [Cover and Thomas, 2006]
If $X \rightarrow Y \rightarrow Z$, then

$$I(X; Y|Z) \leq I(X; Y)$$

Thus, the dependence of X and Y is **decreased** (or remains unchanged) by the observation of a “**downstream**” random variable Z .

2 Information Inequalities

2.1 Han’s Inequality

- **Proposition 2.1** (*Han’s Inequality*) [Cover and Thomas, 2006, Boucheron et al., 2013]
Let X_1, X_2, \dots, X_n be random variables. Then

$$\begin{aligned} H(X_1, X_2, \dots, X_n) &\leq \frac{1}{n-1} \sum_{i=1}^n H(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n) \\ &\Leftrightarrow H(X) \leq \frac{1}{n-1} \sum_{i=1}^n H(X_{(-i)}) \end{aligned} \quad (10)$$

Proof: For any $i = 1, \dots, n$, by the definition of the conditional entropy and the fact that conditioning reduces entropy,

$$\begin{aligned} H(X_1, X_2, \dots, X_n) &= H(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n) + H(X_i | X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n) \\ &\leq H(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n) + H(X_i | X_1, \dots, X_{i-1}). \end{aligned}$$

Summing these n inequalities and using the chain rule for entropy, we get

$$\begin{aligned} nH(X_1, X_2, \dots, X_n) &\leq \sum_{i=1}^n H(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n) + \sum_{i=1}^n H(X_i | X_1, \dots, X_{i-1}) \\ &= \sum_{i=1}^n H(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n) + H(X_1, X_2, \dots, X_n) \end{aligned}$$

which is what we wanted to prove. ■

- **Proposition 2.2** (*Han’s Inequality for Relative Entropy*) [Boucheron et al., 2013]
Let $(\mathcal{X}, \mathcal{B})$ be a measurable space, and P and Q be probability measures on \mathcal{X}^n such that $P = P_1 \otimes \dots \otimes P_n$ is a **product measure**. We denote the element of \mathcal{X}^n by $x = (x_1, \dots, x_n)$

and write $x_{(-i)} := (x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n)$ for the $(n-1)$ -vector obtained by **leaving out the i -th component of x** (i.e. the i -th Jackknife sample of x). Denote $Q_{(-i)}$ and $P_{(-i)}$ the marginal distributions of Q and P . Let $p_{(-i)}$ and $q_{(-i)}$ denote the corresponding probability density function with respect to base measure μ on \mathcal{X} .

$$\begin{aligned} q_{(-i)}(x_{(-i)}) &= \int_{y \in \mathcal{X}} q(x_1, \dots, x_{i-1}, y, x_{i+1}, \dots, x_n) d\mu(y) \\ p_{(-i)}(x_{(-i)}) &= \int_{y \in \mathcal{X}} p(x_1, \dots, x_{i-1}, y, x_{i+1}, \dots, x_n) d\mu(y) \\ &= \prod_{j \neq i} p_j(x_j). \end{aligned}$$

Then

$$\text{KL}(Q \parallel P) \geq \frac{1}{n-1} \sum_{i=1}^n \text{KL}(Q_{(-i)} \parallel P_{(-i)}) \quad (11)$$

or equivalently,

$$\text{KL}(Q \parallel P) \leq \sum_{i=1}^n (\text{KL}(Q \parallel P) - \text{KL}(Q_{(-i)} \parallel P_{(-i)})) \quad (12)$$

Proof: From Han's inequality, we have

$$-H(Q) \geq -\frac{1}{n-1} \sum_{i=1}^n H(Q_{(-i)}).$$

Since

$$\text{KL}(Q \parallel P) = -H(Q) + \mathbb{E}_Q[-\log P(X)]$$

and

$$\text{KL}(Q_{(-i)} \parallel P_{(-i)}) = -H(Q_{(-i)}) + \mathbb{E}_{Q_{(-i)}}[-\log P_{(-i)}(X_{(-i)})],$$

it suffices to show that

$$\mathbb{E}_Q[-\log P(X)] = \frac{1}{n-1} \sum_{i=1}^n \mathbb{E}_{Q_{(-i)}}[-\log P_{(-i)}(X_{(-i)})].$$

This may be seen easily by noting that by the product property of P , we have $p(x) = p_{(-i)}(x_{(-i)})p_i(x_i)$ for all i , and also $p(x) = \prod_i p_i(x_i)$, and therefore

$$\begin{aligned} \mathbb{E}_Q[-\log P(X)] &= \frac{1}{n} \sum_{i=1}^n \mathbb{E}_Q[-\log P_{(-i)}(X_{(-i)}) - \log P_i(X_i)] \\ &= \frac{1}{n} \sum_{i=1}^n \mathbb{E}_Q[-\log P_{(-i)}(X_{(-i)})] + \frac{1}{n} \sum_{i=1}^n \mathbb{E}_Q[-\log P_i(X_i)] \\ &= \frac{1}{n} \sum_{i=1}^n \mathbb{E}_Q[-\log P_{(-i)}(X_{(-i)})] + \frac{1}{n} \mathbb{E}_Q[-\log P(X)]. \end{aligned}$$

Rearranging, we obtain

$$\begin{aligned}\mathbb{E}_Q [-\log P(X)] &= \frac{1}{n-1} \sum_{i=1}^n \mathbb{E}_Q [-\log P_{(-i)}(X_{(-i)})] \\ &= \frac{1}{n-1} \sum_{i=1}^n \mathbb{E}_{Q_{(-i)}} [-\log P_{(-i)}(X_{(-i)})] . \quad \blacksquare\end{aligned}$$

2.2 Applications of Han's Inequality

2.2.1 Combinatorial Entropies

2.2.2 Edge Isoperimetric Inequality on the Binary Hypercube

2.3 Φ -Entropy

- **Definition (Φ -Entropy)** [Boucheron et al., 2013]

Let $\Phi : [0, \infty) \rightarrow \mathbb{R}$ be a **convex** function, and assign, to every **non-negative integrable random variable** X , the Φ -entropy of X is defined as

$$H_\Phi(X) = \mathbb{E} [\Phi(X)] - \Phi(\mathbb{E} [X]). \quad (13)$$

- **Remark** The Φ -entropy is a **functional** of *distribution* P_X instead of a function of X .
- **Remark** By Jensen's inequality, the Φ -entropy is *non-negative*

$$\begin{aligned}\Phi(\mathbb{E} [X]) &\leq \mathbb{E} [\Phi(X)] \\ \Rightarrow H_\Phi(X) &= \mathbb{E} [\Phi(X)] - \Phi(\mathbb{E} [X]) \geq 0.\end{aligned}$$

- **Example (*Special Examples for Φ -Entropy*)**

1. For $\Phi(x) = x^2$, the Φ -entropy of X is the **variance** of X :

$$H_\Phi(X) = \mathbb{E} [X^2] - (\mathbb{E} [X])^2 = \text{Var}(X).$$

2. For $\Phi(x) = -\log(x)$, the Φ -entropy of $Y = e^{\lambda X}$ is the **logarithm of moment generating function** of $X - \mathbb{E} [X]$:

$$H_\Phi(e^{\lambda X}) = -\lambda \mathbb{E} [X] + \log \left(\mathbb{E} [e^{\lambda X}] \right) = \log \mathbb{E} [e^{\lambda(X - \mathbb{E} [X])}] := \psi_{X - \mathbb{E} [X]}(\lambda). \quad (14)$$

3. For $\Phi(x) = x \log x$, the Φ -entropy of X is defined as the **entropy** of X

$$H_\Phi(X) = \text{Ent}(X) := \mathbb{E} [X \log X] - \mathbb{E} [X] \log (\mathbb{E} [X]). \quad (15)$$

Let (Ω, \mathcal{B}) be measurable space, and P and Q are probability measures on Ω with $P \ll Q$. Define a random variable X by the *Radon-Nikodym derivative* of P with respect to Q ; that is,

$$X(\omega) := \begin{cases} \frac{dP}{dQ}(\omega) & Q(\omega) > 0 \\ 0 & \text{o.w.} \end{cases}.$$

We see that X is Q -measurable and $dP = X dQ$ with $\mathbb{E}_Q [X] = 1$. Then the entropy of X is the relative entropy of P with respect to Q .

$$\text{Ent}(X) = \text{KL}(P \parallel Q) \quad (16)$$

2.4 Sub-Additivity of Φ -Entropy

- **Remark (*Sub-Additivity of Shannon Entropy*)**

Let X_1, X_2, \dots, X_n be drawn according to $p(x_1, x_2, \dots, x_n)$. Then

$$H(X_1, X_2, \dots, X_n) \leq \sum_{i=1}^n H(X_i)$$

with equality if and only if the X_i are independent.

- **Proposition 2.3 (*Sub-Additivity of The Entropy*)** [Boucheron et al., 2013]

Let $\Phi(x) = x \log x$, for $x > 0$ and $\Phi(0) = 0$. Let Z_1, Z_2, \dots, Z_n be independent random variables taking values in \mathcal{X} , and let $f : \mathcal{X}^n \rightarrow [0, \infty)$. Letting $X = f(Z_1, Z_2, \dots, Z_n)$, we have

$$\mathbb{E}[\Phi(X)] - \Phi(\mathbb{E}[X]) \leq \sum_{i=1}^n \mathbb{E}[\mathbb{E}_{(-i)}[\Phi(X)] - \Phi(\mathbb{E}_{(-i)}[X])], \quad (17)$$

where $\mathbb{E}_{(-i)}[\cdot]$ is the conditional expectation operator conditioning on $Z_{(-i)}$. Introducing the notation $\text{Ent}_{(-i)}(X) = \mathbb{E}_{(-i)}[\Phi(X)] - \Phi(\mathbb{E}_{(-i)}[X])$, this can be re-written as

$$\mathbb{E}[\Phi(X)] - \Phi(\mathbb{E}[X]) \leq \mathbb{E}\left[\sum_{i=1}^n \text{Ent}_{(-i)}(X)\right]. \quad (18)$$

Proof: The proposition is a direct consequence of Han's inequality for relative entropies. First note that if the inequality is true for a random variable X , then it is also true for cX where c is a positive constant. Hence, we may assume that $\mathbb{E}[X] = 1$. Now define the probability measure P on \mathcal{X}^n by its probability density function p given by

$$p(z) = f(z)q(z), \quad \forall z \in \mathcal{X}^n$$

where q denote the probability density of $Z := (Z_1, Z_2, \dots, Z_n)$ and Q the corresponding probability measure. Then

$$\text{Ent}(X) := \mathbb{E}[X \log X] - \mathbb{E}[X] \log(\mathbb{E}[X]) = \text{KL}(P \parallel Q)$$

which, by Han's inequality for relative entropy

$$\text{Ent}(X) = \text{KL}(P \parallel Q) \leq \sum_{i=1}^n (\text{KL}(P \parallel Q) - \text{KL}(P_{(-i)} \parallel Q_{(-i)}))$$

However, straightforward calculation shows that

$$\sum_{i=1}^n (\text{KL}(P \parallel Q) - \text{KL}(P_{(-i)} \parallel Q_{(-i)})) = \sum_{i=1}^n \mathbb{E}[\mathbb{E}_{(-i)}[\Phi(X)] - \Phi(\mathbb{E}_{(-i)}[X])]$$

and the statement follows. ■

- **Remark** The Efron-Stein inequality is the special case of the inequality when $\Phi(x) = x^2$,

$$\begin{aligned} \mathbb{E}[\Phi(X)] - \Phi(\mathbb{E}[X]) &\leq \sum_{i=1}^n \mathbb{E}[\mathbb{E}_{(-i)}[\Phi(X)] - \Phi(\mathbb{E}_{(-i)}[X])] \\ &\Rightarrow \text{Var}(X) \leq \sum_{i=1}^n \mathbb{E}[\text{Var}_{(-i)}(X)] \end{aligned}$$

- **Remark (*Tensorization of Entropy*)**

The inequality in (17) or (18) is also called the *tensorization of entropy* in [Wainwright, 2019]

- **Proposition 2.4 (*Sub-Additivity of Φ -Entropy*)** [Boucheron et al., 2013]

Let \mathcal{C} denote the class of functions $\Phi : [0, \infty) \rightarrow \mathbb{R}$ that are **continuous** and **convex** on $[0, \infty)$, **twice differentiable** on $(0, \infty)$, and such that either Φ is **affine** or Φ'' is **strictly positive** and $1/\Phi''$ is **concave**. For all $\Phi \in \mathcal{C}$, the **entropy functional** H_Φ is **sub-additive**. That is,

$$\begin{aligned} \mathbb{E} [\Phi(X)] - \Phi(\mathbb{E} [X]) &\leq \sum_{i=1}^n \mathbb{E} [\mathbb{E}_{(-i)} [\Phi(X)] - \Phi(\mathbb{E}_{(-i)} [X])] , \\ \Leftrightarrow H_\Phi(X) &\leq \mathbb{E} \left[\sum_{i=1}^n H_\Phi^{(-i)}(X) \right] \end{aligned} \quad (19)$$

where $H_\Phi^{(-i)}(X) := \mathbb{E}_{(-i)} [\Phi(X)] - \Phi(\mathbb{E}_{(-i)} [X])$ is the conditional entropy and, $\mathbb{E}_{(-i)} [\cdot]$ denotes conditional expectation conditioned on the $(n-1)$ -vector $Z_{(-i)} := (Z_1, \dots, Z_{i-1}, Z_{i+1}, \dots, Z_n)$.

- **Remark *The sub-additivity property*** of H_Φ is equivalent to what we could call *the Jensen property*

$$\begin{aligned} H_\Phi \left(\int f(z, Z_2) d\mu_1(z) \right) &\leq \int H_\Phi(f(z, Z_2)) d\mu_1(z) \\ \Leftrightarrow H_\Phi(\mathbb{E}_{Z_1} [f(Z_1, Z_2)]) &\leq \mathbb{E}_{Z_1} [H_\Phi(f(Z_1, Z_2))] \end{aligned} \quad (20)$$

This implies that in order to prove sub-additivity of a Φ -entropy, it suffices to show that it has the Jensen property.

2.5 Duality and Variational Formulas

- **Lemma 2.5** *The Legendre transform (or convex conjugate) of $\Phi(x) = x \log(x)$ is e^{u-1} . That is,*

$$\sup_{x>0} \{u x - x \log(x)\} = e^{u-1}$$

Proof: Solve the supremum on the left-hand side by taking derivative of the objective function and setting it as zero:

$$\begin{aligned} \nabla g(x) &= u - \log(x) - 1 = 0 \\ \Rightarrow x^* &= e^{u-1} \\ \Rightarrow \sup_x \{u x - x \log(x)\} &= g(x^*) = u e^{u-1} - e^{u-1}(u-1) = e^{u-1} \quad \blacksquare \end{aligned}$$

- **Remark** If $\Phi(X) = X \log(X)$ is integrable, and $\mathbb{E} [e^U] = 1$, we have

$$UX \leq X \log(X) + \frac{1}{e} e^U.$$

Therefore, U_+X is integrable, and one can always define $\mathbb{E} [UX] = \mathbb{E} [U_+X] - \mathbb{E} [U_-X]$ for positive and negative part of U . Thus the $\mathbb{E} [UX]$ is well-defined.

• **Theorem 2.6 (Duality Formula of Entropy)** [Boucheron et al., 2013]

Let X be a non-negative random variable defined on a probability space (Ω, \mathcal{A}, P) such that $\mathbb{E}[\Phi(X)] < \infty$. Then we have **the duality formula**

$$\text{Ent}(X) = \sup_{U \in \mathcal{U}} \mathbb{E}[UX] \quad (21)$$

where the supremum is taken over the set \mathcal{U} of all random variables $U : \Omega \rightarrow \mathbb{R} \cup \{\infty\}$ with $\mathbb{E}[e^U] = 1$. Moreover, if U is such that $\mathbb{E}[UX] \leq \text{Ent}(X)$ for all non-negative random variable X such that $\Phi(X)$ is integrable and $\mathbb{E}[X] = 1$, then $\mathbb{E}[e^U] \leq 1$.

Proof: Note that for any random variable U such that $\mathbb{E}[e^U] = 1$, we have

$$\begin{aligned} \text{Ent}(X) - \mathbb{E}_P[UX] &= \mathbb{E}_P[X \log(X)] - \mathbb{E}_P[X \log(\mathbb{E}_P[X])] - \mathbb{E}_P[UX] \\ &= \mathbb{E}_P[X(\log(X) - U)] - \mathbb{E}_P[X \log(\mathbb{E}_P[X])] \\ &= \mathbb{E}_P[X \log(Xe^{-U})] - \mathbb{E}_P[X \log(\mathbb{E}_P[X])] \\ &= \mathbb{E}_{e^U P}[Xe^{-U} \log(Xe^{-U})] - \mathbb{E}_{e^U P}[Xe^{-U} \log(\mathbb{E}_{e^U P}[Xe^{-U}])] \\ &= \text{Ent}_{e^U P}(Xe^{-U}) \end{aligned}$$

Note that due to $\mathbb{E}[e^U] = 1$, $\int e^U dP = 1$, thus $e^U P$ is a proper probability measure. This shows that

$$\begin{aligned} \text{Ent}_{e^U P}(Xe^{-U}) &\geq 0 \\ \Rightarrow \text{Ent}(X) &\geq \mathbb{E}_P[UX] \end{aligned}$$

with equality whenever $e^U = X/\mathbb{E}_P[X]$. This proves the duality formula.

Conversely, let U be such that $\mathbb{E}_P[UX] \leq \text{Ent}(X)$ for all non-negative random variables such that $\Phi(X)$ is integrable. If $\mathbb{E}[e^U] = 0$, then there is nothing to prove. Otherwise, given a positive integer n large enough to ensure that $x_n = \mathbb{E}[e^{\min\{U, n\}}] > 0$, one may define $X_n = e^{\min\{U, n\}}/x_n$, so that $\mathbb{E}[X_n] = 1$, which leads to

$$\mathbb{E}[UX_n] \leq \text{Ent}(X_n),$$

and therefore

$$\begin{aligned} \frac{1}{x_n} \mathbb{E}[Ue^{\min\{U, n\}}] &\leq \text{Ent}(e^{\min\{U, n\}}/x_n) \\ &= \frac{1}{x_n} [\mathbb{E}[\min\{U, n\} e^{\min\{U, n\}}] - \log(x_n)] \end{aligned}$$

Hence

$$\log(x_n) \leq 0$$

and taking the limit when $n \rightarrow \infty$, we show by monotonicity that $\mathbb{E}[e^U] \leq 1$. ■

• **Theorem 2.7 (Alternative Duality Formula of Entropy)** [Boucheron et al., 2013]

$$\text{Ent}(X) = \sup_T \mathbb{E}[X(\log(T) - \log(\mathbb{E}[T]))] \quad (22)$$

where the supremum is taken over all non-negative and integrable random variables.

Proof: From (21), taking $U = \log \frac{T}{\mathbb{E}[T]}$, so that $\mathbb{E}[e^U] = \mathbb{E}\left[\frac{T}{\mathbb{E}[T]}\right] = 1$. This gives us (22). ■

- **Corollary 2.8 (Duality Formula of Log Moment Generating Function)** [Cover and Thomas, 2006, Boucheron et al., 2013]
Let X be a real-valued integrable random variable. Then for every $\lambda \in \mathbb{R}$,

$$\log \mathbb{E}_Q \left[e^{\lambda(X - \mathbb{E}_Q[X])} \right] = \sup_{P \ll Q} \{ \lambda(\mathbb{E}_P[X] - \mathbb{E}_Q[X]) - \text{KL}(P \parallel Q) \}, \quad (23)$$

where the supremum is taken over all probability measures P absolutely continuous with respect to Q , and $\mathbb{E}_P[\cdot]$ denotes integration with respect to the measure P (recall that $\mathbb{E}_Q[\cdot]$ is integration with respect to Q).

Proof: Let $P \ll Q$. Taking $Y := \frac{dP}{dQ}$ and $U := \lambda(X - \mathbb{E}_Q[X]) - \psi_{X - \mathbb{E}_Q[X]}(\lambda)$ where $\psi_X(\lambda) := \log \mathbb{E}_Q[e^{\lambda X}]$. Note that $\mathbb{E}_Q[Y] = 1$ and $\mathbb{E}[e^U] = 1$. It follows from the duality formula that

$$\begin{aligned} \text{KL}(P \parallel Q) &= \text{Ent}(Y) \geq \mathbb{E}[UY] = \mathbb{E}[\lambda(X - \mathbb{E}_Q[X])Y] - \psi_{X - \mathbb{E}_Q[X]}(\lambda) \\ &= \lambda(\mathbb{E}_P[X] - \mathbb{E}_Q[X]) - \psi_{X - \mathbb{E}_Q[X]}(\lambda) \end{aligned}$$

or equivalently

$$\psi_{X - \mathbb{E}_Q[X]}(\lambda) \geq \lambda(\mathbb{E}_P[X] - \mathbb{E}_Q[X]) - \text{KL}(P \parallel Q),$$

therefore

$$\log \mathbb{E}_Q \left[e^{\lambda(X - \mathbb{E}_Q[X])} \right] \geq \sup_{P \ll Q} \{ \lambda(\mathbb{E}_P[X] - \mathbb{E}_Q[X]) - \text{KL}(P \parallel Q) \}.$$

Conversely, setting

$$U = \lambda(X - \mathbb{E}_Q[X]) - \sup_{P \ll Q} \{ \lambda(\mathbb{E}_P[X] - \mathbb{E}_Q[X]) - \text{KL}(P \parallel Q) \}$$

for every non-negative random variable Y such that $\mathbb{E}[Y] = 1$,

$$\mathbb{E}[UY] \leq \text{Ent}(Y).$$

Hence, $\mathbb{E}[e^U] \leq 1$ by duality theorem, which means that

$$\log \mathbb{E}_Q \left[e^{\lambda(X - \mathbb{E}_Q[X])} \right] \leq \sup_{P \ll Q} \{ \lambda(\mathbb{E}_P[X] - \mathbb{E}_Q[X]) - \text{KL}(P \parallel Q) \}. \quad \blacksquare$$

- **Corollary 2.9 (Duality Formula of Kullback-Leibler Divergence)** [Cover and Thomas, 2006, Boucheron et al., 2013]
Let P and Q be two probability distributions on the same space. Then

$$\text{KL}(P \parallel Q) = \sup_X \{ \mathbb{E}_P[X] - \log \mathbb{E}_Q[e^X] \}, \quad (24)$$

where the supremum is taken over all random variables such that $\mathbb{E}_Q[\exp(X)] < \infty$.

Proof: If $P \ll Q$, $\mathbb{KL}(P \parallel Q) = \text{Ent}(dP/dQ)$ and the corollary follows from the alternative formulation of the duality formula. Let $Y = dP/dQ$ and $X = \log(T)$ so that

$$\begin{aligned} \mathbb{KL}(P \parallel Q) &= \text{Ent}(Y) = \sup_T \mathbb{E} [dP/dQ (\log(T) - \log(\mathbb{E}[T]))] \\ &= \sup_X \{ \mathbb{E}_P[X] - \log \mathbb{E}_Q[e^X] \}. \end{aligned}$$

If $P \not\ll Q$, then there exists an event A such that $P(A) > 0 = Q(A)$, $\mathbb{KL}(P \parallel Q) = \infty$, and choosing $X_n = n\mathbb{1}\{A\}$ and letting n tend to infinity, we observe that the supremum on the right-hand side is infinite. ■

- **Remark** This corollary asserts that if Q remains fixed, $\mathbb{KL}(P \parallel Q)$ is the **convex dual** of the functional $X \rightarrow \log \mathbb{E}_Q[e^X]$.
- **Theorem 2.10 (The Expected Value Minimizes Expected Bregman Divergence)** [Boucheron et al., 2013]
Let $I \subseteq \mathbb{R}$ be an open interval and let $f : I \rightarrow \mathbb{R}$ be **convex** and **differentiable**. For any $x, y \in I$, the **Bregman divergence** of f from x to y is $f(y) - f(x) - f'(x)(y - x)$. Let X be an I -valued random variable. Then

$$\mathbb{E}[f(X) - f(\mathbb{E}[X])] = \inf_{a \in I} \mathbb{E}[f(X) - f(a) - f'(a)(X - a)] \quad (25)$$

- **Corollary 2.11 (Duality Formula of Entropy via Bregman Divergence)** [Boucheron et al., 2013]
Let X be a non-negative random variable such that $\mathbb{E}[\Phi(X)] < \infty$. Then

$$\text{Ent}(X) = \inf_{u > 0} \mathbb{E}[X(\log(X) - \log(u)) - (X - u)] \quad (26)$$

2.6 Wasserstein Distance and Information Inequality

- **Proposition 2.12 (Wasserstein Distance and Information Inequality)** [Boucheron et al., 2013]
Let X be a real-valued integrable random variable. Let ϕ be a **convex** and **continuously differentiable** function on a (possibly unbounded) interval $[0, b)$ and assume that $\phi(0) = \phi'(0) = 0$. Define, for every $x \geq 0$, the **Legendre transform** $\phi^*(x) = \sup_{\lambda \in (0, b)} (\lambda x - \phi(\lambda))$, and let, for every $t \geq 0$, $\phi^{*-1}(t) = \inf\{x \geq 0 : \phi^*(x) > t\}$, i.e. the **generalized inverse** of ϕ^* . Then the following two statements are equivalent:

1. for every $\lambda \in (0, b)$,

$$\psi_{X - \mathbb{E}[X]}(\lambda) \leq \phi(\lambda)$$

where $\psi_X(\lambda) := \log \mathbb{E}_Q[e^{\lambda X}]$ is the logarithm of moment generating function;

2. for any probability measure P absolutely continuous with respect to Q such that $\mathbb{KL}(P \parallel Q) < \infty$,

$$\mathbb{E}_P[X] - \mathbb{E}_Q[X] \leq \phi^{*-1}(\mathbb{KL}(P \parallel Q)). \quad (27)$$

In particular, given $\nu > 0$,

$$\psi_{X - \mathbb{E}[X]}(\lambda) \leq \frac{\nu \lambda^2}{2}$$

for every $\lambda > 0$ **if and only if** for any probability measure P absolutely continuous with respect to Q and such that $\text{KL}(P \parallel Q) < \infty$,

$$\mathbb{E}_P[X] - \mathbb{E}_Q[X] \leq \sqrt{2\nu \text{KL}(P \parallel Q)}. \quad (28)$$

Proof: As a direct consequence of Corollary 2.8, we see that (1) holds if and only if for every distribution $P \ll Q$,

$$\begin{aligned} \psi_{X-\mathbb{E}[X]}(\lambda) &\leq \phi(\lambda) \\ \Leftrightarrow \lambda(\mathbb{E}_P[X] - \mathbb{E}_Q[X]) - \text{KL}(P \parallel Q) &\leq \phi(\lambda), & \forall P \ll Q \\ \Leftrightarrow \mathbb{E}_P[X] - \mathbb{E}_Q[X] &\leq \frac{\phi(\lambda) + \text{KL}(P \parallel Q)}{\lambda}, & \forall P \ll Q, \lambda \in (0, b) \\ \Leftrightarrow \mathbb{E}_P[X] - \mathbb{E}_Q[X] &\leq \inf_{\lambda \in (0, b)} \left\{ \frac{\text{KL}(P \parallel Q) + \phi(\lambda)}{\lambda} \right\} & \forall P \ll Q \end{aligned}$$

Note that

$$\phi^{*-1}(t) = \inf_{\lambda \in (0, b)} \left\lceil \frac{t + \phi(\lambda)}{\lambda} \right\rceil$$

Setting $t = \text{KL}(P \parallel Q)$, we have

$$\begin{aligned} \psi_{X-\mathbb{E}[X]}(\lambda) &\leq \phi(\lambda) \\ \Leftrightarrow \mathbb{E}_P[X] - \mathbb{E}_Q[X] &\leq \phi^{*-1}(\text{KL}(P \parallel Q)). \end{aligned}$$

which shows that (i) is equivalent to (ii). Applying the previous result with $\phi(\lambda) = \lambda^2\nu/2$ for every $\lambda > 0$ leads to the stated special case of equivalence since then $\phi^{*-1}(t) = \sqrt{2\nu t}$. ■

- **Remark** (*The Quadratic Transportation Cost Inequality / The Information Inequality*) [Boucheron et al., 2013, Wainwright, 2019]

The inequality (??) and (28) are called **information inequality** in [Wainwright, 2019] due to the role of Kullback-Leibler Divergence in information theory.

The inequality (28) is related to what is usually termed a **quadratic transportation cost inequality**. If Ω is a *metric space*, the probability measure Q is said to satisfy a *quadratic transportation cost inequality* if the last inequality holds for every X which is *Lipschitz* on Ω with *Lipschitz norm* at most 1.

$$\mathcal{W}_1(P, Q) = \sup_{X \in \text{Lip}_1} \{\mathbb{E}_P[X] - \mathbb{E}_Q[X]\} \leq \sqrt{2\nu \text{KL}(P \parallel Q)}. \quad (29)$$

where $\text{Lip}_1 = \{f \in \mathbb{R}^\Omega : |f(x) - f(y)| \leq L \|x - y\|, \ L \leq 1\}$.

2.7 Pinsker's Inequality

2.8 Birgé's Inequality

2.9 The Brunn-Minkowski Inequality

References

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