

In this lecture, we expose the technique of deriving concentration inequalities with the entropy tensorization inequality. The entropy tensorization inequality enables us to bound the entropy of a function of n variables by the sum of the n entropies of this function in terms of the individual variables. The second step of this technique uses the variational formulation of the n entropies to form a differential inequality that gives an upper bound of the log-Laplace transform of the function. We can subsequently use Markov inequality to get a deviation inequality involving this function.

Let $(\mathcal{X}, \mathcal{F}, \mathbb{P})$ be a measurable space, and $u : \mathcal{X} \rightarrow \mathbb{R}^+$ a measurable function. The **entropy** of u with regard to \mathbb{P} is defined as $\text{Ent}_{\mathbb{P}}(u) \stackrel{\text{def.}}{=} \int u \log u d\mathbb{P} - \int u \cdot (\log(\int u d\mathbb{P})) d\mathbb{P}$. If \mathbb{Q} is another probability measure and $u = \frac{d\mathbb{Q}}{d\mathbb{P}}$, then $\text{Ent}_{\mathbb{P}}(u) = \int (\log \frac{d\mathbb{Q}}{d\mathbb{P}}) d\mathbb{Q}$ is the **KL-divergence** between two probability measures \mathbb{Q} and \mathbb{P} . The following lemma gives variational formulations for the entropy.

Lemma 40.1.

$$\begin{aligned} \text{Ent}_{\mathbb{P}}(u) &= \inf \left\{ \int (u \cdot (\log u - \log x) - (u - x)) d\mathbb{P} : x \in \mathbb{R}^+ \right\} \\ &= \sup \left\{ \int (u \cdot g) d\mathbb{P} : \int \exp(g) d\mathbb{P} \leq 1 \right\}. \end{aligned}$$

Proof. For the first formulation, we define x pointwisely by $\frac{\partial}{\partial x} \int (u \cdot (\log u - \log x) - (u - x)) d\mathbb{P} = 0$, and get $x = \int u d\mathbb{P} > 0$.

For the second formulation, the Laplacian corresponding to $\sup \left\{ \int (u \cdot g) d\mathbb{P} : \int \exp(g) d\mathbb{P} \leq 1 \right\}$ is $\mathcal{L}(g, \lambda) = \int (ug) d\mathbb{P} - \lambda (\int \exp(g) d\mathbb{P} - 1)$. It is linear in λ and concave in g , thus $\sup_g \inf_{\lambda \geq 0} \mathcal{L} = \inf_{\lambda \geq 0} \sup_g \mathcal{L}$. Define g pointwisely by $\frac{\partial}{\partial g} \mathcal{L} = u - \lambda \exp(g) = 0$. Thus $g = \log \frac{u}{\lambda}$, and $\sup_g \mathcal{L} = \int (u \log \frac{u}{\lambda}) d\mathbb{P} - \int u d\mathbb{P} + \lambda$. We set $\frac{\partial}{\partial \lambda} \sup_g \mathcal{L} = -\frac{\int u d\mathbb{P}}{\lambda} + 1 = 0$, and get $\lambda = \int u d\mathbb{P}$. As a result, $\inf_{\lambda} \sup_g \mathcal{L} = \text{Ent}_{\mathbb{P}}(u)$. \square

Entropy $\text{Ent}_{\mathbb{P}}(u)$ is a convex function of u for any probability measure \mathbb{P} , since

$$\begin{aligned} \text{Ent}_{\mathbb{P}}(\sum \lambda_i u_i) &= \sup \left\{ \int (\sum \lambda_i u_i \cdot g) d\mathbb{P} : \int \exp(g) d\mathbb{P} \leq 1 \right\} \\ &\leq \sum \lambda_i \sup \left\{ \int (u_i \cdot g_i) d\mathbb{P} : \int \exp(g_i) d\mathbb{P} \leq 1 \right\} \\ &= \sum \lambda_i \text{Ent}_{\mathbb{P}}(u_i). \end{aligned}$$

Lemma 40.2. [Tensorization of entropy] $\mathcal{X} = (\mathcal{X}_1, \dots, \mathcal{X}_n)$, $\mathbb{P}^n = \mathbb{P}_1 \times \dots \times \mathbb{P}_n$, $u = u(x_1, \dots, x_n)$, $\text{Ent}_{\mathbb{P}^n}(u) \leq \int (\sum_{i=1}^n \text{Ent}_{\mathbb{P}_i}(u)) d\mathbb{P}^n$.

Proof. Proof by induction. When $n = 1$, the above inequality is trivially true. Suppose

$$\int u \log u d\mathbb{P}^n \leq \int u d\mathbb{P}^n \log \int u d\mathbb{P}^n + \int \sum_{i=1}^n \text{Ent}_{\mathbb{P}_i}(u) d\mathbb{P}^n.$$

Integrate with regard to \mathbb{P}_{n+1} ,

$$\begin{aligned}
& \int u \log u d\mathbb{P}^{n+1} \\
& \leq \int \left(\overbrace{\int u d\mathbb{P}^n}^v \log \overbrace{\int u d\mathbb{P}^n}^v \right) d\mathbb{P}_{n+1} + \int \sum_{i=1}^n \text{Ent}_{\mathbb{P}_i}(u) d\mathbb{P}^{n+1} \\
& \stackrel{\text{definition of entropy}}{=} \int \overbrace{\int u d\mathbb{P}^n}^v d\mathbb{P}_{n+1} \cdot \left(\log \int \overbrace{u d\mathbb{P}^n}^v d\mathbb{P}_{n+1} \right) + \text{Ent}_{\mathbb{P}_{n+1}} \left(\overbrace{\int u d\mathbb{P}^n}^v \right) + \int \sum_{i=1}^n \text{Ent}_{\mathbb{P}_i}(u) d\mathbb{P}^{n+1} \\
& \stackrel{\text{Foubini's theorem}}{=} \int u d\mathbb{P}^{n+1} \cdot \left(\log \int u d\mathbb{P}^{n+1} \right) + \text{Ent}_{\mathbb{P}_{n+1}} \left(\int u d\mathbb{P}^n \right) + \int \sum_{i=1}^n \text{Ent}_{\mathbb{P}_i}(u) d\mathbb{P}^{n+1} \\
& \stackrel{\text{convexity of entropy}}{\leq} \int u d\mathbb{P}^{n+1} \cdot \left(\log \int u d\mathbb{P}^{n+1} \right) + \int \text{Ent}_{\mathbb{P}_{n+1}}(u) d\mathbb{P}^n + \int \sum_{i=1}^n \text{Ent}_{\mathbb{P}_i}(u) d\mathbb{P}^{n+1} \\
& = \int u d\mathbb{P}^{n+1} \cdot \left(\log \int u d\mathbb{P}^{n+1} \right) + \int \text{Ent}_{\mathbb{P}_{n+1}}(u) d\mathbb{P}^{n+1} + \int \sum_{i=1}^n \text{Ent}_{\mathbb{P}_i}(u) d\mathbb{P}^{n+1} \\
& \leq \int u d\mathbb{P}^{n+1} \cdot \left(\log \int u d\mathbb{P}^{n+1} \right) + \int \sum_{i=1}^{n+1} \text{Ent}_{\mathbb{P}_i}(u) d\mathbb{P}^{n+1}.
\end{aligned}$$

By definition of entropy, $\text{Ent}_{\mathbb{P}_{n+1}}(u) \leq \int \sum_{i=1}^{n+1} \text{Ent}_{\mathbb{P}_i}(u) d\mathbb{P}^{n+1}$. □

The tensorization of entropy lemma can be trivially applied to get the following tensorization of Laplace transform.

Theorem 40.3. *[Tensorization of Laplace transform] Let x_1, \dots, x_n be independent random variables and x'_1, \dots, x'_n their independent copies, $Z = Z(x_1, \dots, x_n)$, $Z^i = Z(x_1, \dots, x_{i-1}, x'_i, x_{i+1}, \dots, x_n)$, $\phi(x) = e^x - x - 1$, and $\psi(x) = \phi(x) + e^x \phi(-x) = x \cdot (e^x - 1)$, and I be the indicator function. Then*

$$\begin{aligned}
\mathbb{E}(e^{\lambda Z} \cdot \lambda Z) - \mathbb{E}e^{\lambda Z} \cdot \log \mathbb{E}e^{\lambda Z} & \leq \mathbb{E}_{x_1, \dots, x_n, x'_1, \dots, x'_n} e^{\lambda Z} \sum_{i=1}^n \phi(-\lambda(Z - Z^i)) \\
\mathbb{E}(e^{\lambda Z} \cdot \lambda Z) - \mathbb{E}e^{\lambda Z} \cdot \log \mathbb{E}e^{\lambda Z} & \leq \mathbb{E}_{x_1, \dots, x_n, x'_1, \dots, x'_n} e^{\lambda Z} \sum_{i=1}^n \psi(-\lambda(Z - Z^i)) \cdot I(Z \geq Z^i).
\end{aligned}$$

Proof. Let $u = \exp(\lambda Z)$ where $\lambda \in \mathbb{R}$, and apply the tensorization of entropy lemma,

$$\begin{aligned}
& \underbrace{\mathbb{E}(e^{\lambda Z} \cdot \lambda Z) - \mathbb{E}e^{\lambda Z} \cdot \log \mathbb{E}e^{\lambda Z}}_{\text{Ent}_{\mathbb{P}^n} \log u} \\
& \leq \mathbb{E} \sum_{i=1}^n \text{Ent}_{\mathbb{P}_i} e^{\lambda Z} \\
& \stackrel{\text{variational formulation}}{=} \mathbb{E} \sum_{i=1}^n \inf \left\{ \int (e^{\lambda Z} (\lambda Z - \lambda x) - (e^{\lambda Z} - e^{\lambda x})) d\mathbb{P}_i : x \in \mathbb{R}^+ \right\} \\
& \leq \mathbb{E} \sum_{i=1}^n \mathbb{E}_{x_i, x'_i} \left(e^{\lambda Z} (\lambda Z - \lambda Z^i) - (e^{\lambda Z} - e^{\lambda Z^i}) \right) \\
& = \mathbb{E} \sum_{i=1}^n \mathbb{E}_{x_i, x'_i} e^{\lambda Z} \left(e^{-\lambda(Z-Z^i)} - (-\lambda \cdot (Z - Z^i)) - 1 \right) \\
& = \mathbb{E}_{x_1, \dots, x_n, x'_1, \dots, x'_n} e^{\lambda Z} \sum_{i=1}^n \phi(-\lambda \cdot (Z - Z^i)).
\end{aligned}$$

Moreover,

$$\begin{aligned}
& \mathbb{E} e^{\lambda Z} \sum_{i=1}^n \phi(-\lambda \cdot (Z - Z^i)) \\
& = \mathbb{E} \sum_{i=1}^n e^{\lambda Z} \phi(-\lambda \cdot (Z - Z^i)) \cdot \left(\underbrace{I(Z \geq Z^i)}_{\mathbf{I}} + \underbrace{I(Z^i \geq Z)}_{\mathbf{II}} \right) \\
& = \mathbb{E} \sum_{i=1}^n \left(\underbrace{e^{\lambda Z^i} \phi(-\lambda \cdot (Z^i - Z)) \cdot I(Z \geq Z^i)}_{\text{switch } Z \text{ and } Z^i \text{ in } \mathbf{II}} + \underbrace{e^{\lambda Z} \phi(-\lambda \cdot (Z - Z^i)) \cdot I(Z \geq Z^i)}_{\mathbf{I}} \right) \\
& = \mathbb{E} \sum_{i=1}^n e^{\lambda Z} \cdot I(Z \geq Z^i) \cdot \left(\underbrace{e^{\lambda(Z^i - Z)} \cdot \phi(-\lambda \cdot (Z^i - Z))}_{\mathbf{II}} + \underbrace{\phi(-\lambda \cdot (Z - Z^i))}_{\mathbf{I}} \right) \\
& = \mathbb{E} \sum_{i=1}^n e^{\lambda Z} \cdot I(Z \geq Z^i) \cdot \psi(-\lambda \cdot (Z^i - Z)).
\end{aligned}$$

□