

Lecture 7. Monday, 4/11/2022

- Entropic regularization
- Kullback-Leibler divergence
- Generalization.

Regularized (discrete) OT

Given $a \in \mathcal{P}_m$ and $b \in \mathcal{P}_n$, $C \in \mathbb{R}^{m \times n}$ with $C \geq 0$.

Def. $\mathcal{A}(a, b) = \{P = [P_{ij}] \in \mathbb{R}^{m \times n} : P \geq 0, \sum_{j=1}^n P_{ij} = a_i, \forall i; \sum_{i=1}^m P_{ij} = b_j, \forall j\}$

OT: $W_C(a, b) := \min_{P \in \mathcal{A}(a, b)} \langle P, C \rangle$. $E[P] \stackrel{\Delta}{=} \langle P, C \rangle$.

Regularization: Consider $E_\varepsilon[P] = \langle P, C \rangle + \varepsilon h(P)$ for some h . Hope that $E_\varepsilon[P]$ is easier to minimize and as $\varepsilon \rightarrow 0$ minimizer/minimum value of E_ε converge to those of E ($= E_0$).

Call h a regularizer. (How to choose h ?)

⊙ (Component wise) convex \Rightarrow uniqueness for each $\varepsilon > 0$.

⊙ (component wise) minimum of h is inside $(0, 1)$ so that the constraints will be satisfied.

Entropic regularization: For $\varepsilon > 0$, define

$$\begin{aligned} E_\varepsilon[P] &= \langle C, P \rangle + \varepsilon \langle P(\log P - 1), \mathbf{1}_{m \times n} \rangle \\ &= \sum_{i=1}^m \sum_{j=1}^n P_{ij} C_{ij} + \varepsilon \underbrace{\sum_{i=1}^m \sum_{j=1}^n P_{ij} (\log P_{ij} - 1)}_{h(P)}. \end{aligned}$$

Notation:

⊙ $P(\log P - 1) \in \mathbb{R}^{m \times n}$: $[P(\log P - 1)]_{ij} = P_{ij}(\log P_{ij} - 1) \forall ij$

⊙ $\mathbf{1}_{m \times n} \in \mathbb{R}^{m \times n}$: all entries = 1. (Not $\mathbf{1}_{n \times n}$)

Remarks ⊙ If $f: \mathbb{R}^d \rightarrow \mathbb{R}$ satisfies $f \geq 0$ in \mathbb{R}^d

and $\int_{\mathbb{R}^d} f dx = 1$ then $H(f) = - \int_{\mathbb{R}^d} f \log f dx$ is called the entropy of f .

If $p = (p_i) \in \mathcal{P}_d$: all $p_i \geq 0$, $\sum_{i=1}^d p_i = 1$, then $S = -\sum_{i=1}^d p_i \log p_i$ is called the entropy of p .

In thermodynamics, the free energy is $F = U - TS$ with U, T, S being internal energy, temperature, and entropy. $S = -\frac{\partial F}{\partial T}$.

In statistical mechanics, entropy $S = -k_B \log \mathcal{Z}$, where \mathcal{Z} is the partition function.

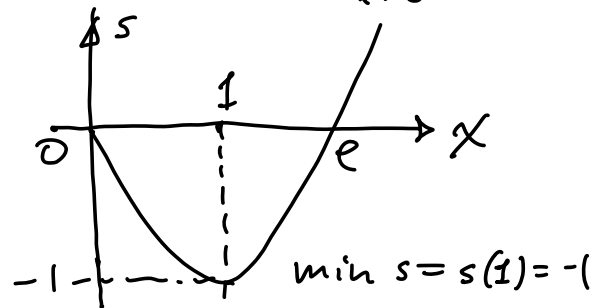
② Define $s(x) = x \log x - x$ ($x > 0$). $s(0) = 0 = \lim_{x \rightarrow 0^+} s(x)$.

So, s is cont. on $[0, \infty)$. $s(e) = 0$

$$s'(x) = \log x = 0 \Rightarrow x = 1$$

$$0 < x < 1 \Rightarrow s'(x) < -1$$

$s''(x) = \frac{1}{x} > 0$. So, s is strictly convex on $[0, 1]$.



Fix i, j . denote $c = C_{ij}$, and consider

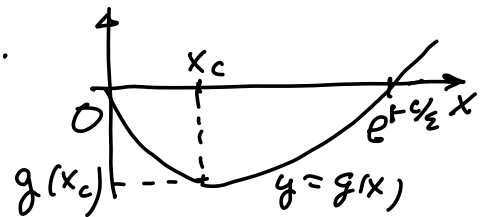
$$g(x) = cx + \varepsilon x (\log x - 1) \quad (0 \leq x \leq 1). \quad g'(x) = 0, x > 0 \Rightarrow x = e^{-\frac{c}{\varepsilon}}$$

$$g'(x) = c + \varepsilon \log x. \quad g'(x) = 0 \Rightarrow \boxed{x_c = e^{-\frac{c}{\varepsilon}} \in (0, 1)}$$

$$g(x_c) = c e^{-\frac{c}{\varepsilon}} + \varepsilon (-c/\varepsilon) = c(e^{-\frac{c}{\varepsilon}} - 1).$$

$$0 < \varepsilon < 1, c > 0 \Rightarrow x_c \approx 0.$$

$$g''(x) = \frac{\varepsilon}{x}. \quad g \text{ is convex.}$$



Recall for $\varepsilon = 0$, the original OT has minimizers but may not be unique. Denote

$$\mathcal{M}_c(a, b) = \{ \hat{p} \in \mathcal{A}(a, b) : \langle C, \hat{p} \rangle = W_c(a, b) \}.$$

This is the set of all optimal plans. We showed before that $\mathcal{M}_c(a, b) \neq \emptyset$ is convex and compact.

Proposition There exists a unique $P_0 \in \mathcal{M}_c(a,b)$ such that

$$h(P_0) = \min_{P \in \mathcal{M}_c(a,b)} h(P).$$

Proof Since $h(P) = \langle P(\log P - 1), \mathbb{1}_{\text{supp}} \rangle$ is continuous and $\mathcal{M}_c(a,b)$ is compact, there exists $\operatorname{argmin}_{\mathcal{M}_c(a,b)} h(\cdot)$.

Suppose P_0 and $Q_0 \in \mathcal{M}_c(a,b)$ satisfy $h(P_0) = h(Q_0) \leq h(P) \forall P \in \mathcal{M}_c(a,b)$. Let $R_\lambda = (1-\lambda)P_0 + \lambda Q_0$ ($0 \leq \lambda \leq 1$).

Then $R_\lambda \in \mathcal{M}_c(a,b)$ since $\mathcal{M}_c(a,b)$ is convex. Moreover, the convexity of h implies that $h(R_\lambda) \leq (1-\lambda)h(P_0) + \lambda h(Q_0) \leq \min_{\mathcal{M}_c(a,b)} h(\cdot)$. Hence, $R_\lambda = \operatorname{argmin}_{\mathcal{M}_c(a,b)} h(\cdot)$ and $f(\lambda) := h(R_\lambda) = \text{const.}$

Suppose $P_0 \neq Q_0$. We examine $f'(\lambda)$, $f''(\lambda)$ for λ close to 0. If $P_{0,ij} = Q_{0,ij} = 0$ then $s(R_{\lambda,ij}) = 0$. ($s(x) = x \log x - x$).

If $Q_{0,ij} > 0$ then $\frac{d}{d\lambda} \Big|_{\lambda=0} s(R_{\lambda,ij})$ exists and is finite.

For any (i,j) , if $Q_{0,ij} = 0$ and $P_{0,ij} > 0$, then $\frac{d}{d\lambda} s(R_\lambda) = \frac{d}{d\lambda} s(\lambda P_{0,ij}) \rightarrow -\infty$ as $\lambda \rightarrow 0$. But $f' \equiv 0$ as $f = \text{const.}$ Hence $P_{0,ij} = Q_{0,ij} = 0$ or $P_{0,ij} > 0$ and $Q_{0,ij} > 0$ for any (i,j) . Thus, $h(R_\lambda) = \sum_{i,j} s(R_{\lambda,ij})$ is a $C^2([0,1])$ -function of λ . Now, direct calculations lead to

$$f''(0) = \frac{d^2}{d\lambda^2} \Big|_{\lambda=0} s(R_\lambda) = \sum_{i,j}' \frac{1}{Q_{0,ij}} (P_{0,ij} - Q_{0,ij})^2 > 0,$$

where $\sum_{i,j}'$ sums over all (i,j) with $P_{0,ij} > 0$ and $Q_{0,ij} > 0$.

But $f(\lambda) = \text{const. on } [0,1]$. So $f''(0) = 0$, a contradiction. QED

Theorem (1) For any $\varepsilon > 0$, there exists a unique $P_\varepsilon \in \mathcal{A}(a,b)$ such that $E_\varepsilon[P_\varepsilon] = \min_{P \in \mathcal{A}(a,b)} E_\varepsilon[P]$.

$$(2) \quad \lim_{\varepsilon \rightarrow 0^+} P_\varepsilon = P_0 = \operatorname{argmin}_{P \in \mathcal{M}_c(a,b)} h(P).$$

$$(3) \quad \lim_{\varepsilon \rightarrow 0^+} E_\varepsilon[P_\varepsilon] = \lim_{\varepsilon \rightarrow 0^+} E[P_\varepsilon] = E[P_0] = V_C(a,b).$$

Proof (1) $E_\varepsilon: \mathcal{A}(a,b) \rightarrow \mathbb{R}$ is continuous and $\mathcal{A}(a,b)$ is compact. Hence, $\exists P_\varepsilon = \arg \min_{\mathcal{A}(a,b)} E_\varepsilon$. The uniqueness can be shown by the same argument in the proof of Proposition above.

(2) It suffices to show that any convergent sequence $\{P_{\varepsilon_k}\} (\varepsilon_k \downarrow 0)$ has the same limit P_0 . Assume $P_{\varepsilon_k} \rightarrow \bar{P}$. Clearly, $\bar{P} \in \mathcal{A}(a,b)$. Now, $E_{\varepsilon_k}[P_{\varepsilon_k}] \leq E_{\varepsilon_k}[P_0]$, i.e.,

$$E[P_{\varepsilon_k}] + \varepsilon_k h(P_{\varepsilon_k}) \leq E[P_0] + \varepsilon_k h(P_0).$$

Since h is bounded and continuous, we have for $k \rightarrow \infty$ that $E[\bar{P}] \leq E[P_0] = W_C(a,b)$, i.e., $\bar{P} \in \mathcal{N}_C^2(a,b)$. Now,

$$E_{\varepsilon_k}[P_{\varepsilon_k}] = E[P_{\varepsilon_k}] + \varepsilon_k h(P_{\varepsilon_k}) \leq E_{\varepsilon_k}[P_0] = E[P_0] + \varepsilon_k h(P_0) \\ \leq E[P_{\varepsilon_k}] + \varepsilon_k h(P_0).$$

Hence, $h(P_{\varepsilon_k}) \leq h(P_0)$. Taking $k \rightarrow \infty$, we get $h(\bar{P}) \leq h(P_0)$.

By the above Proposition, $\bar{P} = P_0$.

(3) Since $P_\varepsilon \rightarrow P_0$, $E_\varepsilon[P_\varepsilon] = E[P_\varepsilon] + \varepsilon h(P_\varepsilon) \rightarrow E[P_0] = W_C(a,b)$. QED

Theorem (Cominetti-San Martin 1994) The convergence

$P_\varepsilon \rightarrow P_0$ in the above Thm is exponential, i.e.,

$P_\varepsilon = P_0 + G(\varepsilon)$ for $0 < \varepsilon \leq \varepsilon_0$ for some ε_0 and

$G(\varepsilon)$ satisfies $\lim_{\varepsilon \rightarrow 0^+} \frac{G_{ij}(\varepsilon)}{e^{-\mu/\varepsilon}} = 0 \quad \forall i, j$.

for some $\mu > 0$. QED

A different prob, $\min_{P \in \mathcal{A}(a,b)} \langle P \log P^{-1}, \mathbb{1}_{\text{max}} \rangle$.

Answer: the unique minimizer is $a \otimes b$, and the minimum is

$$\sum_{i,j} a_i b_j [\log(a_i b_j) - 1] = \sum_{i,j} [a_i b_j (\log a_i + \log b_j - 1)]$$

$$= \sum_i a_i \log a_i + \sum_j b_j \log b_j - 1.$$

"Proof" Denote $h(P) = \langle P \log P - 1, \mathbb{1} \rangle = \sum_{i,j} s(P_{ij})$, $P \in \mathcal{A}(a, b)$
 Since h is continuous and $\mathcal{A}(a, b)$ is compact, there exists a minimizer, which is a critical point of the Lagrangian

$$\mathcal{L}(P, \lambda) = h(P) + \sum_{i=1}^m f_i \left(\sum_{j=1}^n P_{ij} - a_i \right) + \sum_{j=1}^n g_j \left(\sum_{i=1}^m P_{ij} - b_j \right), \quad \lambda = (f, g).$$

$$\partial_{f_i} \mathcal{L} = 0 \Rightarrow \sum_j P_{ij} = a_i \quad \forall i, \quad \sum_i P_{ij} = b_j \quad \forall j.$$

$$\partial_{P_{kl}} \mathcal{L} = 0 \Rightarrow \log P_{kl} - f_k - g_l = 0 \quad \text{or} \quad P_{kl} = 0 \quad \forall k, l.$$

So, if $P_{kl} > 0$ then $P_{kl} = e^{f_k + g_l} = \alpha_k \beta_l$, $\alpha_k = e^{f_k}$, $\beta_l = e^{g_l}$.

If $P_{kl} = 0$ then $P_{kl} = \alpha_k \beta_l$ with $\alpha_k = 0$ or $\beta_l = 0$. So, $P_{kl} = \alpha_k \beta_l$ with $\alpha_k \geq 0$, $\beta_l \geq 0$. Let $\alpha = \sum_k \alpha_k$, $\beta = \sum_l \beta_l$. Since $P \in \mathcal{A}(a, b)$

$$a_k = \sum_l P_{kl} = \sum_l \alpha_k \beta_l = \alpha_k \beta. \quad b_l = \alpha \beta_l. \quad \sum_k a_k = 1 \Rightarrow \alpha \beta = 1.$$

$$\sum_j b_j = 1 \Rightarrow \alpha \beta = 1. \quad \text{So, } P_{kl} = \alpha_k \beta_l = \alpha_k \beta \cdot \beta_l \alpha = a_k b_l. \quad \underline{\text{QED}}$$

Remark The above proof is not rigorous as the inequality constraints $P_{ij} \geq 0 \quad \forall i, j$ are not included in the Lagrangian. A similar but correct proof should use the KKT conditions for minimizing a convex function with equalities and inequality constraints.

$\lambda = (f, g)$ for the equality constraints

$\mu = (\mu_{ij})$ for the inequality constraints.

Then, necessary conditions $\Rightarrow P_{kl} = e^{f_k + g_l - \mu_{kl}}$

$$\sum_l P_{kl} = a_k, \quad \sum_k P_{kl} = b_l \quad \forall k, l. \quad \mu_{kl} \geq 0. \quad \text{ALSO,}$$

the complementarity condition $\Rightarrow \mu_{ij} P_{ij} = 0 \quad \forall i, j$

Hence, all $\mu_{ij} = 0 \Rightarrow P_{kl} = e^{f_k + g_l}$. As above,

$p_{ue} = a_u b_e$. Finally, check that the sufficient conditions. QED

Corollary If $P = [P_{ij}] \in \mathcal{A}(a, b)$ then

$$\sum_{i,j} P_{ij} \log P_{ij} \geq \sum_i a_i \log a_i + \sum_j b_j \log b_j.$$

Pf. $\sum_{i,j} P_{ij} (\log P_{ij} - 1) \geq \sum_{i,j} a_i b_j [\log(a_i b_j) - 1]$

$$\sum_{i,j} P_{ij} = 1 \Rightarrow \sum_{i,j} P_{ij} \log P_{ij} \geq \sum_{i,j} a_i b_j \log a_i + \sum_{i,j} a_i b_j \log b_j = \sum_i a_i \log a_i + \sum_j b_j \log b_j. \quad \text{QED}$$

Lagrange multiplier and Kullback-Leibler divergence (or: relative entropy).

$\min_{\mathcal{A}(a,b)} E_\varepsilon$. Define the Lagrange multiplier

$\lambda = (f, g) \in \mathbb{R}^m \times \mathbb{R}^n$ and the Lagrangian

$$\begin{aligned} \mathcal{L}_\varepsilon(P, \lambda) &= \sum_{i,j} P_{ij} c_{ij} + \varepsilon \sum_{i,j} P_{ij} (\log P_{ij} - 1) \\ &\quad - \sum_{i=1}^m f_i \left(\sum_{j=1}^n P_{ij} - a_i \right) - \sum_{j=1}^n g_j \left(\sum_{i=1}^m P_{ij} - b_j \right). \end{aligned}$$

Minimizers of E_ε are extreme points of \mathcal{L}_ε .

$$\partial_{f_k} \mathcal{L}_\varepsilon = 0 \Rightarrow \sum_{j=1}^n P_{kj} = a_k \quad \forall k.$$

$$\partial_{g_l} \mathcal{L}_\varepsilon = 0 \Rightarrow \sum_{i=1}^m P_{il} = b_l \quad \forall l.$$

$$\partial_{p_{kl}} \mathcal{L}_\varepsilon = 0 \Rightarrow c_{kl} + \varepsilon \log P_{kl} - f_k - g_l = 0$$

$$\Rightarrow P_{kl} = e^{-\frac{1}{\varepsilon}(c_{kl} - f_k - g_l)} \quad \forall k, l.$$

Denote $K_{\varepsilon, ij} = e^{-c_{ij}/\varepsilon} \quad \forall i, j$. $K_\varepsilon = [K_{\varepsilon, ij}] \in \mathbb{R}^{m \times n}$

Define $KL(P|K_\varepsilon) = \sum_{i,j} \left[P_{ij} \left(\log \frac{P_{ij}}{K_{\varepsilon, ij}} - 1 \right) + K_{\varepsilon, ij} \right]$.

Call it the Kullback-Leibler divergence of P relative to K_ε , or the relative entropy of P relative to K_ε .

What is this quantity?

$$\begin{aligned} KL(P|K_\varepsilon) &= \sum_{i,j} p_{ij}(\log p_{ij} - 1) - \sum_{i,j} p_{ij} \log K_{\varepsilon,ij} + \sum_{i,j} K_{\varepsilon,ij} \\ &= \sum_{i,j} p_{ij}(\log p_{ij} - 1) + \frac{1}{\varepsilon} \sum_{i,j} p_{ij} c_{ij} + \sum_{i,j} K_{\varepsilon,ij} \\ &= \frac{1}{\varepsilon} [\langle P, C \rangle + \varepsilon \langle P(\log P - 1), \mathbb{1}_{m \times n} \rangle] + \langle K_\varepsilon, \mathbb{1}_{m \times n} \rangle \\ &= \frac{1}{\varepsilon} E_\varepsilon[P] + \langle K_\varepsilon, \mathbb{1}_{m \times n} \rangle. \end{aligned}$$

Proposition $E_\varepsilon[P] = \varepsilon KL(P|K_\varepsilon) - \varepsilon \langle K_\varepsilon, \mathbb{1}_{m \times n} \rangle$. $\forall P \in \mathcal{A}(a,b)$

Hence, the unique minimizer of E_ε over $\mathcal{A}(a,b)$ is the unique minimizer of $KL(\cdot|K_\varepsilon)$ over $\mathcal{A}(a,b)$. QED

General regularized OT problem

Let $h \in C([0,1]) \cap C^1(0,1)$ with $h'' > 0$ on $(0,1)$.

$$\begin{aligned} \text{Consider } E_\varepsilon[P] &= \langle C, P \rangle + \varepsilon \langle h(P), \mathbb{1}_{m \times n} \rangle \\ &= \sum_{i,j} c_{ij} p_{ij} + \varepsilon \sum_{i,j} h(p_{ij}), \quad P \in \mathcal{A}(a,b) \\ E[P] &= \langle C, P \rangle, \quad P \in \mathcal{A}(a,b) \end{aligned}$$

Recall $a \in \mathcal{P}_m, b \in \mathcal{P}_n, C \in \mathbb{R}^{m \times n}, C \geq 0$.

$$\mathcal{A}(a,b) = \{P \in \mathbb{R}^{m \times n} : P \geq 0, \sum_i p_{ij} = b_j \forall j, \sum_j p_{ij} = a_i \forall i\}$$

$$W_C(a,b) = \min_{\mathcal{A}(a,b)} E[\cdot].$$

$$\mathcal{M}(a,b) = \{\hat{P} \in \mathcal{A}(a,b) : \langle C, \hat{P} \rangle = W_C(a,b)\}.$$

Thm. (1) $\exists! P_n \in \mathcal{M}(a,b)$ such that $h(P_n) \in h(\hat{P})$ for any $\hat{P} \in \mathcal{M}(a,b)$.

(2) For each $\varepsilon > 0$, there exists a unique e
 $P_\varepsilon = \arg \min_{P \in \mathcal{D}(a,b)} F_\varepsilon[P]$.

(3) $\lim_{\varepsilon \rightarrow 0^+} P_\varepsilon = P_h$ and $\lim_{\varepsilon \rightarrow 0^+} F_\varepsilon[P_\varepsilon] = W_C(a,b)$. QED

Examples (1) Entropic regularization.

$$h(P) = \sum_{i,j} P_{ij} (\log P_{ij} - 1).$$

(2) Quadratic regularization: $h(P) = \sum_{i,j} \frac{1}{2} P_{ij}^2$.

(3) Binary entropic regularization

$$h(P) = \sum_{i,j} [P_{ij} \log P_{ij} + (1 - P_{ij}) \log (1 - P_{ij})].$$