Notes on Optimal Transport
ENSAE
3A

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Last updated: Wednesday 6^{th} February, 2019 at 19:00

1 Introduction

These are notes I gathered from a seminar session given by Shuangjian Zhang at ENSAE and from lectures given by Marco Cuturi at MLSS 2019 in South Africa.

Likelihood maximization is an instance of generative modeling: given data points $x_1, \dots, x_N \in \mathbb{R}^d$ and a family of densities $(f_\theta)_{\theta \in \Theta}$, we look for the f_θ that matches the most the empirical data distribution defined as $\nu_{\text{data}} := \frac{1}{N}\sum_{i=1}^N \delta_{x_i}$. This is done by maximizing the log-likelihood $\frac{1}{N}\sum_{i=1}^N \log f_\theta(x_i)$. This quantity exists only if $f_\theta(x_i) > 0$ for all i, which forces the densities to have the whole of $\mathbb{R}^d$ as support. Likelihood maximization can be given a geometric interpretation: if one overlooks that ν_{data} and f_θ are not absolutely continuous with respect to the same measure (the former is discrete), minimizing the Kullback-Leibler divergence between the two writes as

$$\begin{aligned}\operatorname{argmin}_{\theta\in\Theta} \mathrm{KL}(\nu_{\text{data}}||f_\theta) &= \operatorname{argmin}_{\theta\in\Theta} E_{X\sim\nu_{\text{data}}}[\log(f_{\text{data}}(X)) - \log(f_\theta(X))] \\ &= \operatorname{argmin}_{\theta\in\Theta} -E_{X\sim\nu_{\text{data}}} \log(f_\theta(X)) \\ &= \operatorname{argmax}_{\theta\in\Theta} \frac{1}{N}\sum_{i=1}^N \log f_\theta(x_i)\end{aligned}$$

A weakness of likelihood maximization is its poor scalability to high-dimensional settings, which are commonplace. For instance, a 100×100 image with 3 color channels lives in $\mathbb{R}^{30.000}$. Instead of working directly in the data space $\mathbb{R}^d$, we may rather consider a latent space $(\mathbb{R}^p, \mathcal{B}(\mathbb{R}^p), \mu)$ with $p \ll d$, and measurable functions $g_\theta : \mathbb{R}^p \to \mathbb{R}^d$ (e.g deconvolution networks). We define the pushforward measure $g_{\theta\sharp}\mu$ by $\forall B \in \mathcal{B}(\mathbb{R}^d), g_{\theta\sharp}\mu(B) := \mu(g_\theta \in B)$ and we look for θ such that $g_{\theta\sharp}\mu$ matches ν_{data}. This requires setting a metric on the space of probability measures, and fortunately, many exist: Hellinger, Kantorovitch, MMD, Wasserstein... Some of these metrics arise from the theory of optimal transport.

2 Optimal transport

2.1 Monge problem and its Kantorovitch relaxation

Let μ and ν be probability measures on $(\mathbb{R}^d, \mathcal{B}(\mathbb{R}^d))$ and $c : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}_+$ a cost function. Monge's optimal transportation problem is the following:

$$\inf_{\substack{T \text{ measurable} \\ T_\sharp\mu = \nu}} \int c(x, T(x)) d\mu(x) \tag{MP}$$

In words, T is a transportation mapping that assigns to each x exactly one location $T(x)$, implying that the mass at x cannot be split to several locations. $T_\sharp\mu = \nu$ is the transportation constraint, and the objective $\int c(x, T(x))d\mu(x)$ measures the total transportation cost.

The Kantorovitch relaxation allows for mass splitting by considering couplings. A probability measure P on $\mathbb{R}^d \times \mathbb{R}^d$ is said to be a coupling of (μ, ν) if for any $A, B \in \mathcal{B}(\mathbb{R}^d)$, $P(A \times \mathbb{R}^d) = \mu(A)$ and $P(\mathbb{R}^d \times B) = \nu(B)$. Let $\Pi(\mu, \nu)$ denote the set of such couplings. $\Pi(\mu, \nu)$ is clearly non-empty since it contains the product measure $\mu \otimes \nu$.
Kantorovitch's optimal transportation problem is the following:

$$\inf_{P \in \Pi(\mu,\nu)} \int\int c(x,y) dP(x,y) \tag{KP-primal}$$

It is important to note that (KP-primal) provides a lower bound for (MP). Indeed, if T verifies $T_\sharp \mu = \nu$ and we let $P = (\mathrm{Id}, T)_\sharp \mu$, it is easy to check that P is a coupling. A theorem of integration with respect to pushforward measures yields $\int\int c(x,y)dP(x,y) = \int c \circ (\mathrm{Id}, T)(x) d\mu(x) = \int c(x, T(x)) d\mu(x)$, hence the claim.

The dual of (KP-primal) is defined as follows:

$$\sup_{\substack{\varphi \in L_1(\mu) \\ \psi \in L_1(\nu) \\ \forall (x,y),\ \varphi(x) + \psi(y) \leq c(x,y)}} \int \varphi d\mu + \int \psi d\nu \tag{KP-dual}$$

Theorem 2.1. *If c is lower semi-continuous, then (KP-primal) and (KP-dual) share the same optimal value. Moreover, the infimum in (KP-primal) is attained.*

Proof. We give a partial proof of the first part of the theorem. Let $\varphi \oplus \psi : (x,y) \mapsto \varphi(x) + \psi(x)$ and

$$\iota_\Pi(P) := \sup_{\substack{\varphi \in L_1(\mu) \\ \psi \in L_1(\nu)}} \int \varphi d\mu + \int \psi d\nu - \int \varphi \oplus \psi dP$$

Let $P \in \Pi(\mu, \nu)$. If we let π_1 and π_2 denote the projections respectively on the first and last d coordinates, then $\int \varphi \oplus \psi dP = \int \varphi \circ \pi_1 dP + \int \psi \circ \pi_2 dP$. For $\varphi = 1_A$,

$$\int \varphi \circ \pi_1 dP = \int 1_{\pi_1^{-1}(A)} dP = P(\pi_1^{-1}(A)) = P(A \times \mathbb{R}^d) = \mu(A)$$

Therefore $\int \varphi d\mu + \int \psi d\nu - \int \varphi \oplus \psi dP = 0$ when φ and ψ are indicators, and a standard limit argument shows that it remains 0 for arbitrary integrable φ and ψ. Thus $\iota_\Pi(P) = 0$ when P is a coupling.
If $P \notin \Pi(\mu, \nu)$, WLOG there exists some $A \in \mathcal{B}(\mathbb{R}^d)$ such that $P(A \times \mathbb{R}^d) \neq \mu(A)$. If $P(A \times \mathbb{R}^d) < \mu(A)$, consider $\varphi = \lambda 1_A$ with $\lambda > 0$ and $\psi = 0$. Then

$$\int \varphi d\mu + \int \psi d\nu - \int \varphi \oplus \psi dP = \lambda(\mu(A) - P(A \times \mathbb{R}^d)) \xrightarrow[\lambda \to \infty]{} \infty$$

Hence $\iota_\Pi(P) = \infty$. The other case is similar.

If we let $\mathcal{M}^+$ denote the set of positive measures on $\mathbb{R}^d \times \mathbb{R}^d$, then (KP-primal) turns into

$$\begin{aligned}
\inf_{P \in \mathcal{M}^+} \int\int c\, dP + \iota_\Pi(P) &= \inf_{P \in \mathcal{M}^+} \sup_{\substack{\varphi \in L_1(\mu) \\ \psi \in L_1(\nu)}} \int c\, dP + \int \varphi d\mu + \int \psi d\nu - \int \varphi \oplus \psi dP \\
&= \inf_{P \in \mathcal{M}^+} \sup_{\substack{\varphi \in L_1(\mu) \\ \psi \in L_1(\nu)}} \int c - \varphi \oplus \psi\, dP + \int \varphi d\mu + \int \psi d\nu \\
&= \sup_{\substack{\varphi \in L_1(\mu) \\ \psi \in L_1(\nu)}} \inf_{P \in \mathcal{M}^+} \left[\int c - \varphi \oplus \psi\, dP \right] + \int \varphi d\mu + \int \psi d\nu
\end{aligned}$$

Switching the inf and the sup is the technical hurdle of the proof. In [1] Villani provides a rigorous justification that is quite technical.

Next, $\inf_{P\in\mathcal{M}^+}\int c-\varphi\oplus\psi\, dP$ can be rewritten more simply. If $c-\varphi\oplus\psi\geq 0$, 0 is a lower bound for the integral, and it is attained for $P=0$. Hence $c-\varphi\oplus\psi\geq 0 \implies \inf_{P\in\mathcal{M}^+}\int c-\varphi\oplus\psi\, dP=0$. Otherwise, if there exists (x_0,y_0) such that $c(x_0,y_0)-\varphi\oplus\psi(x_0,y_0)<0$, consider $P=\lambda\delta_{(x_0,y_0)}$ and let $\lambda\to\infty$ to get $\inf_{P\in\mathcal{M}^+}\int c-\varphi\oplus\psi\, dP=-\infty$.
Thus (KP-primal) can be written as

$$\sup_{\substack{\varphi\in L_1(\mu)\\ \psi\in L_1(\nu)\\ \varphi\oplus\psi\leq c}}\int\varphi d\mu+\int\psi d\nu$$

which is exactly (KP-dual). $\square$

References

[1] Cédric Villani. *Topics in optimal transportation.* Number 58. American Mathematical Soc., 2003.