Mirror Descent with Relative Smoothness in Measure Spaces, with application to Sinkhorn and Expectation-Maximization (EM)

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Joint work with Pierre-Cyril Aubin-Frankowski and Flavien Léger (INRIA).

Outline

Optimisation over the space of measures

Let $\mathcal{X} \subset \mathbb{R}^d$ and consider $\mathcal{P}(\mathcal{X})$ the space of probability measures on $\mathcal{X}$

Let $\mathcal{F} : \mathcal{P}(\mathcal{X}) \to \mathbb{R} \cup \{+\infty\}$ convex and $C \subset \mathcal{M}(\mathcal{X})$ is a convex set:

$$\min_{\nu \in C} \mathcal{F}(\nu)$$

Many problems in machine learning can be cast as the latter optimization problem, where $\mathcal{F}(\cdot) = \mathrm{D}(\cdot|\bar{\mu})$ where $\bar{\mu}$ is a fixed target distribution on $\mathbb{R}^d$.

Example 1 and 2

We will consider the following examples:

- Sinkhorn's algorithm
- Expectation-Maximization algorithm

Example 3 - Bayesian inference

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(2) Assume an underlying model parametrized by $x \in \mathbb{R}^d$, e.g.:

$$y = g(w, x) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \mathrm{Id}).$$

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Step 1. Compute the Likelihood:

$$p(\mathcal{D}|x) \overset{(1)}{\propto} \prod_{i=1}^p p(y_i|x, w_i) \overset{(2)}{\propto} \exp\left(-\frac{1}{2}\sum_{i=1}^p \|y_i - g(w_i, x)\|^2\right).$$

Step 2. Choose a prior distribution (initial guess) on the parameter:

$$x \sim p_0, \quad \text{e.g. } p_0(x) \propto \exp\left(-\frac{\|x\|^2}{2}\right).$$

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Step 3. Bayes' rule yields the formula for the posterior distribution over the parameter x:

$$p(x|\mathcal{D}) = \frac{p(\mathcal{D}|x)p_0(x)}{Z} \quad \text{where} \quad Z = \int_{\mathbb{R}^d} p(\mathcal{D}|x)p_0(x)dx$$

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Denoting $\bar{\mu} := p(\cdot|\mathcal{D})$ the posterior on parameters $x \in \mathbb{R}^d$, we have:

$$\bar{\mu}(x) \propto \exp\left(-V(x)\right), \quad V(x) = \frac{1}{2}\sum_{i=1}^{p}\|y_i - g(w_i, x)\|^2 + \frac{\|x\|^2}{2}.$$

i.e. $\bar{\mu}$'s density is known "up to a normalization constant".

The posterior $\bar{\mu}$ is interesting for

- measuring uncertainty on prediction through the distribution of $g(w, \cdot)$, $x \sim \bar{\mu}$.
- prediction for a new input w:

$$\hat{y} = \underbrace{\int_{\mathbb{R}^d} g(w, x) d\bar{\mu}(x)}_{\text{"Bayesian model averaging"}}$$

i.e. predictions of models parametrized by $x \in \mathbb{R}^d$ are reweighted by $\bar{\mu}(x)$.

Can be cast as:

$$\min_{\nu \in C} \mathrm{KL}(\nu|\bar{\mu})$$

where KL is the "Kullback-Leibler divergence" or relative entropy":

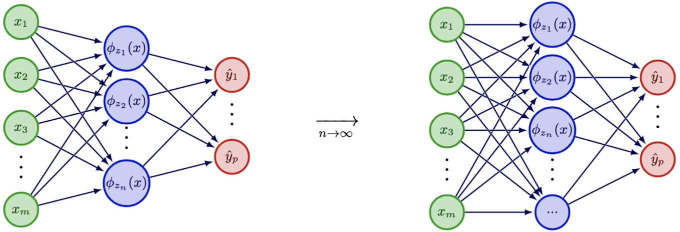
$$\mathrm{KL}(\mu|\bar{\mu}) = \begin{cases} \int_{\mathbb{R}^d} \log\left(\frac{\mu}{\bar{\mu}}(x)\right) d\mu(x) & \text{if } \mu \ll \bar{\mu} \\ +\infty & \text{else.} \end{cases}$$

The KL as an objective is convenient since it **does not depend on the normalization constant** Z (unknown in Bayesian inference)!

Recall that writing $\bar{\mu}(x) = e^{-V(x)}/Z$ we have:

$$\mathrm{KL}(\mu|\bar{\mu}) = \int_{\mathbb{R}^d} \log\left(\frac{\mu}{e^{-V}}(x)\right) d\mu(x) + \log(Z).$$

Example 4 - Optimisation of 1 hidden layer neural networks



$$\min_{z_1,\dots,z_n\in\mathbb{R}^d} \mathbb{E}_{(x,y)\sim P_{data}}\left[\left\|y - \frac{1}{n}\sum_{i=1}^{n}\phi_{z_i}(x)\right\|^2\right] \quad \xrightarrow[n\to\infty]{} \quad \min_{\nu\in\mathcal{P}(\mathbb{R}^d)} \mathbb{E}_{(x,y)\sim P_{data}}\left[\left\|y - \int_{\mathbb{R}^d}\phi_z(x)d\mu(z)\right\|^2\right]$$

Assume $\exists\bar{\mu}$, $\mathbb{E}[y|X=x] = \int \phi_z(x) d\bar{\mu}(z)$.

The problem can be cast as:

$$\min_{\nu \in C} \mathrm{MMD}^2(\nu, \bar{\mu})$$

where MMD is the Maximum Mean Discrepancy:

$$\mathrm{MMD}^2(\mu, \pi) = \mathbb{E}_{\substack{z \sim \mu \\ z' \sim \mu}}[k(z, z')] + \mathbb{E}_{\substack{z \sim \pi \\ z' \sim \bar{\mu}}}[k(z, z')] - 2\mathbb{E}_{\substack{z \sim \mu \\ z' \sim \bar{\mu}}}[k(z, z')],$$

with $k : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ is a kernel.

Mirror Descent with relative smoothness over the space of measures

To solve

$$\min_{\nu \in C} \mathcal{F}(\nu)$$

we consider the **mirror descent algorithm** [Beck and Teboulle, 2003], a first-order optimization method based on **Bregman divergences.**

Its convergence analysis classically requires **strong convexity and smoothness.**

However, the latter is not satisfied for the KL, hence we consider **relative convexity and smoothness.**

For now assume $C = \mathcal{M}(\mathcal{X})$.

Outline

Space of measures

Let $\mathcal{X} \subset \mathbb{R}^d$, and fix a vector space of (signed) measures $\mathcal{M}(\mathcal{X})$.

It could be $L^1(\mathrm{d}\rho)$, $L^2(\mathrm{d}\rho)$ where ρ is a reference measure, or the space of Radon measures $\mathcal{M}_r(\mathcal{X})$ with the total variation (TV) norm.

Let $\mathcal{M}^*(\mathcal{X})$ the dual of $\mathcal{M}(\mathcal{X})$.

For $\mu \in \mathcal{M}(\mathcal{X})$ and $f \in \mathcal{M}^*(\mathcal{X})$, we denote

$$\langle f, \mu \rangle = \langle f, \mu \rangle_{\mathcal{M}^*(\mathcal{X}) \times \mathcal{M}(\mathcal{X})} = \int_{\mathcal{X}} f(x)\mu(dx).$$

Derivative of $\mathcal{F}$

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The difficulty is to choose the right notion of derivative.

Recall that Gâteaux and Fréchet derivatives have to be defined in every direction:

Definition 1

The function $\mathcal{F}$ is said to be Gâteaux differentiable at ν if there exists a linear operator $\nabla F(\nu) : \mathcal{M}(\mathcal{X}) \to \mathbb{R}$ such that for any direction $\mu \in \mathcal{M}(\mathcal{X})$:

$$\nabla \mathcal{F}(\nu)(\mu) = \lim_{h \to 0} \frac{\mathcal{F}(\nu + h\mu) - \mathcal{F}(\nu)}{h}. \tag{1}$$

The operator $\nabla \mathcal{F}(\nu)$ is called the Gâteaux derivative of $\mathcal{F}$ at ν, and if it exists, it is unique.

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We thus consider first a weaker notion of directional derivatives.

Then, the notion of first variation will allow to perform all the computations we need, as if the function was Gâteaux differentiable.

Definition 2 (Directional derivative)

If it exists, the *directional derivative* of $\mathcal{F} : \mathcal{M}(\mathcal{X}) \to \mathbb{R} \cup \{\pm\infty\}$ at a point $\nu \in \mathrm{dom}(\mathcal{F})$ in the direction $\mu \in \mathcal{M}(\mathcal{X})$ is defined as

$$d^+\mathcal{F}(\nu)(\mu) = \lim_{h \to 0^+} \frac{\mathcal{F}(\nu + h\mu) - \mathcal{F}(\nu)}{h}. \tag{2}$$

Definition 3 (First variation)

If it exists, the *first variation* of $\mathcal{F}$ evaluated at $\mu \in \mathrm{dom}(\mathcal{F})$ is the element $\nabla\mathcal{F}(\mu) \in \mathcal{M}^*(\mathcal{X})$, unique up to orthogonal components to $\mathrm{span}(\mathrm{dom}(\mathcal{F}) - \mu)$, s.t.:

$$\langle \nabla\mathcal{F}(\mu), \xi \rangle = d^+\mathcal{F}(\mu)(\xi) \tag{3}$$

for all $\xi = \nu - \mu \in \mathcal{M}(\mathcal{X})$, where $\nu \in \mathrm{dom}(\mathcal{F})$.

Bregman divergences

Let $\phi : \mathcal{M}(\mathcal{X}) \to \mathbb{R} \cup \{+\infty\}$ be a convex functional. For $\mu \in \mathrm{dom}(\phi)$, the ϕ-*Bregman divergence* is defined for all $\nu \in \mathrm{dom}(\phi)$ by

$$D_\phi(\nu|\mu) = \phi(\nu) - \phi(\mu) - d^+\phi(\mu)(\nu - \mu) \in [0, +\infty], \qquad (4)$$

and $+\infty$ elsewhere. The function ϕ is referred to as *the Bregman potential*.

Properties:

- $D_\phi(\cdot|\mu)$ is convex if ϕ has a first variation (last term is linear)
- D_ϕ separates measures for ϕ strictly convex
- linearity $D_{\phi+\psi} = D_\phi + D_\psi$ (since d^+ is linear)
- idempotence: $D_{D_\phi(\cdot|\xi)}(\nu|\mu) = D_\phi(\nu|\mu)$ for any $\xi \in \mathrm{dom}(\phi)$ assuming $\nabla\phi(\xi)$ exists.

Relative smoothness and convexity

$\mathcal{F}$ is L-smooth relative to ϕ if, for any $\mu, \nu \in \text{dom}(\mathcal{F}) \cap \text{dom}(\phi)$, we have

$$D_{\mathcal{F}}(\nu|\mu) = \mathcal{F}(\nu) - \mathcal{F}(\mu) - d^{+}\mathcal{F}(\mu)(\nu - \mu) \leq L D_{\phi}(\nu|\mu).$$

Conversely, we say that $\mathcal{F}$ is l-strongly convex relative to ϕ, for some scalar $l \geq 0$, if we have

$$D_{\mathcal{F}}(\nu|\mu) \geq l D_{\phi}(\nu|\mu).$$

- Since $D_{\mathcal{F}}(\nu|\mu) = \mathcal{F}(\nu) - \mathcal{F}(\mu) - d^{+}\mathcal{F}(\mu)(\nu - \mu)$, convexity of $\mathcal{F}$ writes $D_{\mathcal{F}}(\nu|\mu) \geq 0$.
- Smoothness can be written as

$$\|\nabla \mathcal{F}(\mu) - \nabla \mathcal{F}(\nu)\| \leq L\|\mu - \nu\|$$

which implies

$$\mathcal{F}(\nu) - \mathcal{F}(\mu) - d^{+}\mathcal{F}(\mu)(\nu - \mu) \leq L\|\nu - \mu\|^2$$

- A Bregman divergence objective $\mathcal{F}(\cdot) = D_{\phi}(\cdot|\xi)$ is always 1-relatively smooth and strongly convex w.r.t. ϕ (due to the idempotence: $D_{D_{\phi}(\cdot|\xi)}(\nu|\mu) = D_{\phi}(\nu|\mu)$)

Case of the KL

The KL is not smooth:

- the "gradient of the KL": $\mu \mapsto \log(\mu|\bar{\mu})(.)$ typically is not Lipschitz
- traditional smoothness cannot hold because KL diverges for Dirac masses, thus does not have subquadratic growth with respect to any norm on measures.

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Fact: Let $\phi_e(\mu) = \int_{\mathcal{X}} \ln(\mu(x))\mu(x)d\rho(x)$ the **negative entropy**. The KL can be written as a Bregman divergence of ϕ_e, if $\mu \ll \bar{\mu} \ll \rho$, i.e.

$$D_{\phi_e}(\mu|\bar{\mu}) = \mathrm{KL}(\mu|\bar{\mu}).$$

Hence the KL is always 1-relatively smooth with respect to the negative entropy.

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Remark: It is a strong Bregman divergence. For instance, for a bounded kernel k, $\mathrm{MMD}(\mu, \nu) \leq c_k \mathrm{KL}(\mu|\nu)$.

Outline

Relative smoothness :
$\mathcal{F}(\nu) \leq \mathcal{F}(\mu) + d^{+}\mathcal{F}(\mu)(\nu - \mu) + LD_{\phi}(\nu|\mu)$.

Mirror descent can be written **in its minimal formulation** as the proximal scheme

$$\mu_{n+1} = \underset{\nu \in C}{\operatorname{argmin}} \{ d^{+}\mathcal{F}(\mu_n)(\nu - \mu_n) + LD_{\phi}(\nu|\mu_n) \} \qquad (5)$$

Remark: If $\mathcal{F}$ and ϕ were Gâteaux differentiable at μ_n, then provided μ_{n+1} exists, the first-order optimality condition for (5) would give

$$\nabla\phi(\mu_{n+1}) - \nabla\phi(\mu_n) = -\frac{1}{L}\nabla\mathcal{F}(\mu_n). \qquad (6)$$

Remark: If $\phi = \phi_e$, $\nabla\phi_e(\mu) = \log(\mu) + 1$ which leads to the famous multiplicative update $\mu_{n+1} = \mu_n e^{-\frac{1}{L}\nabla\mathcal{F}(\mu_n)}$.

Convergence result for mirror descent

Theorem: Assume that $\mathcal{F}$ is l-strongly convex and L-smooth relative to ϕ, with $l, L \geq 0$. Consider the mirror descent scheme (5), and assume that for each $n \geq 0$, $\nabla\phi(\mu_n)$ exists. Then for all $n \geq 0$ and all $\nu \in \mathrm{dom}(\mathcal{F}) \cap \mathrm{dom}(\phi)$:

$$\mathcal{F}(\mu_n) - \mathcal{F}(\nu) \leq \frac{l D_\phi(\nu|\mu_0)}{\left(1 + \frac{l}{L-l}\right)^n - 1} \leq \frac{L}{n} D_\phi(\nu|\mu_0)$$

Remark: mirror descent rates with strong (standard) convexity and smoothness lead to $\mathcal{O}(1/\sqrt{n})$ rate with a decreasing step-size $\propto 1/\sqrt{n}$.

Outline

Preliminaries

Notations:

- $\Pi(\bar{\mu}, *)$ the set of couplings having first marginal $\bar{\mu}$
- $\Pi(*, \bar{\nu})$ the set of couplings having second marginal $\bar{\nu}$
- $\Pi(\bar{\mu}, \bar{\nu}) = \Pi(\bar{\mu}, *) \cap \Pi(*, \bar{\nu})$ the couplings with marginals $(\bar{\mu}, \bar{\nu})$

For any $\pi \in \mathcal{P}(\mathcal{X} \times \mathcal{Y})$, we can write $\pi = p_{\mathcal{X}}\pi \otimes K_{\pi}$ where $K_{\bar{\pi}}(x, dy) = {\bar{\pi}(dx,dy)}/{p_{\mathcal{X}}\bar{\pi}(dx)}$.

Hence we have the decomposition:

$$\begin{aligned} \mathrm{KL}(\pi|\bar{\pi}) &= \int \log\left(\frac{\pi}{\bar{\pi}}\right) d(p_{\mathcal{X}}\pi \otimes K_{\pi}) \\ &= \mathrm{KL}(p_{\mathcal{X}}\pi|p_{\mathcal{X}}\bar{\pi}) + \int_{\mathcal{X}} \mathrm{KL}(K_{\pi}|K_{\bar{\pi}})\, dp_{\mathcal{X}}\pi \\ &= \mathrm{KL}(p_{\mathcal{X}}\pi|p_{\mathcal{X}}\bar{\pi}) + \mathrm{KL}(\pi|p_{\mathcal{X}}\pi \otimes K_{\bar{\pi}}). \end{aligned} \quad (7)$$

It will be crucial for assessing the (relative) smoothness and convexity two objective functions F_{S} and F_{EM} we will consider.

Consider a cost function $c \in L^\infty(\mathcal{X} \times \mathcal{Y}, \bar{\mu} \otimes \bar{\nu})$ and a regularization parameter $\epsilon > 0$.

The **entropic optimal transport problem** is the minimization problem

$$\mathrm{OT}_\epsilon(\bar{\mu}, \bar{\nu}) = \min_{\pi \in \Pi(\bar{\mu}, \bar{\nu})} \mathrm{KL}(\pi | e^{-c/\epsilon} \bar{\mu} \otimes \bar{\nu}). \tag{8}$$

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We say that a coupling π is cyclically invariant, and write $\pi \in \Pi_c$, if denoting by $(\mu, \nu) = (p_\mathcal{X}\pi, p_\mathcal{Y}\pi)$ its marginals we have

$$\mathrm{KL}(\pi | e^{-c/\epsilon} \mu \otimes \nu) = \min_{\tilde{\pi} \in \Pi(\mu, \nu)} \mathrm{KL}(\tilde{\pi} | e^{-c/\epsilon} \mu \otimes \nu). \tag{9}$$

Moreover when $\pi \in \Pi_c$, there exist $f \in L^\infty(\mathcal{X})$ and $g \in L^\infty(\mathcal{Y})$ such that $\pi = e^{(f+g-c)/\epsilon} \mu \otimes \nu$.

The Sinkhorn algorithm in its primal formulation searches for the solution of (8) by alternative (entropic) projections on $\Pi(\bar{\mu}, *)$ and $\Pi(*, \bar{\nu})$, i.e. initializing with $\pi_0 \in \Pi_c$, iterate

$$\pi_{n+\frac{1}{2}} = \underset{\pi \in \Pi(\bar{\mu}, *)}{\operatorname{argmin}} \operatorname{KL}(\pi | \pi_n), \tag{10}$$

$$\pi_{n+1} = \underset{\pi \in \Pi(*, \bar{\nu})}{\operatorname{argmin}} \operatorname{KL}(\pi | \pi_{n+\frac{1}{2}}). \tag{11}$$

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Define the constraint set $C = \Pi(*, \bar{\nu})$ and the objective function

$$F_{\mathrm{S}}(\pi) = \mathrm{KL}(p_{\mathcal{X}}\pi | \bar{\mu}). \tag{12}$$

Sinkhorn algorithm as mirror descent

Proposition: The Sinkhorn iterations (10) can be written as a mirror descent with objective F_S and Bregman divergence KL over the constraint $C = \Pi(*, \bar{\nu})$,

$$\pi_{n+1} = \underset{\pi \in C}{\operatorname{argmin}} \langle \nabla F_S(\pi_n), \pi - \pi_n \rangle + \mathrm{KL}(\pi|\pi_n)$$
$$\text{with } \nabla F_S(\pi_n) = \ln(d\mu_n/d\bar{\mu}) \in L^\infty(\mathcal{X} \times \mathcal{Y}). \quad (13)$$

where $\mu_n = p_{\mathcal{X}}\pi_n$.

Proof: We have the identity:

$$F_S(\pi_n) + \langle \nabla F_S(\pi_n), \pi - \pi_n \rangle + \mathrm{KL}(\pi|\pi_n) = \mathrm{KL}(\pi|\bar{\mu} \otimes {}^{\pi_n}/_{\mu_n}) = \mathrm{KL}(\pi|\pi_{n+\frac{1}{2}}).$$

We conclude by taking the argmin over $\pi \in C$.

(Relative) smoothness and convexity of F_S

Lemma: The functional F_S is convex and is 1-relatively smooth w.r.t. the negative entropy ϕ_e over $\mathcal{P}(\mathcal{X} \times \mathcal{Y})$.

Proof: Let $\pi, \tilde{\pi} \in \mathcal{P}(\mathcal{X} \times \mathcal{Y})$ with $p_{\mathcal{X}}\tilde{\pi} \ll p_{\mathcal{X}}\pi \ll \bar{\mu}$. Then:

- with straightforward computations, $D_{F_S}(\tilde{\pi}|\pi) = \mathrm{KL}(p_{\mathcal{X}}\tilde{\pi}|p_{\mathcal{X}}\pi) \geq 0$, so F_S is convex
- applying the disintegration formula, we obtain that $D_{F_S}(\tilde{\pi}|\pi) \leq \mathrm{KL}(\tilde{\pi}|\pi)$. **(KL of joint distributions is smaller than KL of marginals)**

Consequence: this already yields a $\mathcal{O}(1/n)$ rate for Sinkhorn's algorithm.

(Relative) strong convexity of F_{S}

Proposition Let
$D_c := \frac{1}{2}\sup_{x,y,x',y'}[c(x,y) + c(x',y') - c(x,y') - c(x',y)] < \infty$.
For $\tilde{\pi}, \pi \in \Pi_c \cap C$, we have that

$$\mathrm{KL}(\tilde{\pi}|\pi) \leq (1 + 4e^{3D_c/\epsilon})\,\mathrm{KL}(p_{\mathcal{X}}\tilde{\pi}|p_{\mathcal{X}}\pi),$$

in other words F_{S} is $(1 + 4e^{3D_c/\epsilon})^{-1}$-relatively strongly convex w.r.t. KL over $\Pi_c \cap C$.

Consequence: this yields a linear rate for Sinkhorn's algorithm.

We recover (known) rates for Sinkhorn

Proposition: For all $n \geq 0$, the Sinkhorn iterates verify, for π_* the optimum of:

$$\mathrm{OT}_\epsilon(\bar{\mu}, \bar{\nu}) = \min_{\pi \in \Pi(\bar{\mu}, \bar{\nu})} \mathrm{KL}(\pi | e^{-c/\epsilon} \bar{\mu} \otimes \bar{\nu}).$$

and μ_* its first marginal,

$$\mathrm{KL}(\mu_n | \mu_*) \leq \frac{\mathrm{KL}(\pi_* | \pi_0)}{(1 + 4e^{\frac{3D_c}{\epsilon}}) \left(\left(1 + 4e^{-\frac{3D_c}{\epsilon}}\right)^n - 1 \right)} \leq \frac{\mathrm{KL}(\pi_* | \pi_0)}{n}.$$

Outline

EM

Goal: fit a parametric distribution to some observed data Y (e.g. a mixture of Gaussians approximating the data), where one needs to estimate both

- the latent variable distribution on X (e.g. weights of each Gaussian)
- parameters of conditionals $P(Y|X = x)$ (e.g. means and covariances of each Gaussian)

Consider the following probabilistic model: we have a latent, hidden random variable $X \in (\mathcal{X}, \bar{\mu})$, an observed variable $Y \in \mathcal{Y}$ distributed as $\bar{\nu}$.

We posit a joint distribution $p_q(dx, dy)$ parametrized by an element q of some given set $\mathcal{Q}$. The goal is to infer q by solving

$$\min_{q \in \mathcal{Q}} \mathrm{KL}(\bar{\nu} | p_{\mathcal{Y}} p_q), \tag{14}$$

where $p_{\mathcal{Y}} p_q(dy) = \int_{\mathcal{X}} p_q(dx, dy)$.

For any $\pi \in \Pi(*, \bar{\nu})$, by the disintegration formula:

- $\mathrm{KL}(\bar{\nu}|p_{\mathcal{Y}}p_q) \leq \mathrm{KL}(\pi|p_q)$
- with equality if $\pi(dx, dy) = p_q(dx, dy)\bar{\nu}(dy)/p_{\mathcal{Y}}p_q(dy)$

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EM then proceeds by alternate minimizations of $\mathrm{KL}(\pi, p_q)$ [Neal and Hinton, 1998]:

$$q_n = \operatorname*{argmin}_{q \in \mathcal{Q}} \mathrm{KL}(\pi_n|p_q), \tag{15}$$

$$\pi_{n+1} = \operatorname*{argmin}_{\pi \in \Pi(*, \bar{\nu})} \mathrm{KL}(\pi|p_{q_n}). \tag{16}$$

The above formulation consists in (15), optimizing the parameters q_n at step n (M-step), and then (16), optimizing the joint distribution π_{n+1} at step $n+1$ (E-step, which is explicit).

Define the constraint set $C = \Pi(*, \bar{\nu})$ and

$$F_{\mathrm{EM}}(\pi) = \inf_{q \in \mathcal{Q}} \mathrm{KL}(\pi | p_q). \tag{17}$$

Proposition: EM can be written as a mirror descent iteration:

$$\pi_{n+1} = \operatorname*{argmin}_{\pi \in C} \langle \nabla F_{\mathrm{EM}}(\pi_n), \pi - \pi_n \rangle + \mathrm{KL}(\pi | \pi_n)$$
$$\text{with } \nabla F_{\mathrm{EM}}(\pi_n) = \ln(d\pi_n / dp_{q_n}). \tag{18}$$

Proof: Use the envelope theorem to differentiate F_{EM} and find that $\nabla F_{\mathrm{EM}}(\pi_n) = \ln(d\pi_n / dp_{q_n})$. Then for any coupling π, we have the identity

$$F_{\mathrm{EM}}(\pi_n) + \langle \nabla F_{\mathrm{EM}}(\pi_n), \pi - \pi_n \rangle + \mathrm{KL}(\pi | \pi_n) = \mathrm{KL}(\pi | p_{q_n}).$$

Thus the MD iteration matches (16).

Latent EM

F_{EM} is in general non-convex. However, writing $p_q(dx, dy) = \mu(dx)K(x, dy)$ and optimizing only over its first marginal makes F_{EM} convex.

Define $F_{\text{LEM}}(\pi) := \inf_{\mu \in \mathcal{P}(\mathcal{X})} \text{KL}(\pi|\mu \otimes K)$
($F_{\text{LEM}}(\pi) = \text{KL}(\pi|p_{\mathcal{X}}\pi \otimes K)$ by the disintegration formula).

Proposition: Latent EM can be written as mirror descent with objective F_{LEM}, Bregman potential ϕ_e and the constraints $C = \Pi(*, \bar{\nu})$,

$$\pi_{n+1} = \underset{\pi \in C}{\text{argmin}} \langle \nabla F_{\text{LEM}}(\pi_n), \pi - \pi_n \rangle + \text{KL}(\pi|\pi_n)$$

$$\text{with } \nabla F_{\text{LEM}}(\pi_n) = \ln\left(\frac{d\pi_n}{d(\mu_n \otimes K)}\right) \in L^\infty. \quad (19)$$

Rate for Latent EM

Proposition Set $\mu_* \in \operatorname{argmin}_{\mu \in \mathcal{P}(\mathcal{X})} \mathrm{KL}(\bar{\nu} | T_K(\mu))$ where $T_K : \mu \in \mathcal{P}(\mathcal{X}) \mapsto \int_{\mathcal{X}} \mu(dx) K(x, \cdot) \in \mathcal{M}(\mathcal{Y})$.

The functional F_{LEM} is convex and 1-smooth relative to ϕ_e.

Moreover for $\pi_0 \in \Pi(*, \bar{\nu})$,

$$\mathrm{KL}(\bar{\nu} | T_K \mu_n) \leq \mathrm{KL}(\bar{\nu} | T_K \mu_*) + \frac{\mathrm{KL}(\mu_* | \mu_0) + \mathrm{KL}(\bar{\nu} | T_K \mu_*) - \mathrm{KL}(\bar{\nu} | T_K \mu_0)}{n}.$$

Conclusion

- rigorous proof of convergence of mirror descent under relative smoothness and convexity, which holds in the infinite-dimensional setting of optimization over measure spaces
- provides a new and simple way to derive rates of convergence for Sinkhorn's algorithm
- new convergence rates for EM when restricted to the latent distribution, obtaining similar but complementary rates to [Kunstner et al., 2021].

Questions?

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