

Optimal Transport: Lecture #7

Continuing our analysis of the OT problem for quadratic costs, we introduce the so-called double convexification trick:

$$\begin{aligned}x \cdot y &\leq \ell(x) + \psi(y) && \forall \text{ a.e. } x, y \\ \Rightarrow x \cdot y - \ell(x) &\leq \psi(y) && \forall \text{ a.e. } x, y \\ \Rightarrow \sup_x \{x \cdot y - \ell(x)\} &\leq \psi(y) && \forall y\end{aligned}$$

But, we can identify the LHS as the Legendre-Fenchel transform of ℓ , namely $\ell^*(y) = \sup_x \{ \langle x, y \rangle - \ell(x) \}$, noting that in \mathbb{R}^d , $\langle x, y \rangle = x \cdot y$ (\mathbb{R}^d is self-dual in this sense).

To summarize, $\psi(y) \geq \ell^*(y)$. Applying J to the pairs (ℓ, ψ) and (ℓ, ℓ^*) and recalling J is linear, we have

$$J(\ell, \psi) \geq J(\ell, \ell^*).$$

By an analogous argument, we know $(\ell, \ell^*) \in \tilde{\mathcal{D}}$, so again

$$\begin{aligned}x \cdot y &\leq \ell(x) + \ell^*(y) \\ \Rightarrow \sup_y \{x \cdot y - \ell^*(y)\} &\leq \ell(x)\end{aligned}$$

and we can identify the LHS as the Legendre-Fenchel transform of ℓ^* , namely the double dual of ℓ . ②

To summarize, ~~ℓ^{**}~~ $\ell^{**}(x) = \sup_y \{x \cdot y - \ell^*(y)\} \leq \ell(x)$

linearity
of J
 \Rightarrow

$$J(\ell^{**}, \ell^*) \leq J(\ell, \ell^*)$$

Having established the sequence of inequalities $J(\ell, \psi) \leq J(\ell, \ell^*) \leq J(\ell^{**}, \ell^*)$,

we can minimize as we want over (ℓ, ψ) and get

$$\inf_{(\ell, \psi) \in \hat{\Phi}} J(\ell, \psi) \geq \inf_{\ell \in L'(d_\mu)} J(\ell^{**}, \ell^*)$$

Why does this help us analyze the RHS? Well, as long as $(\ell^{**}, \ell^*) \in L'(d_\mu) \times L'(d_\nu)$, then we clearly have the other inequality:

$$\inf_{(\ell, \psi) \in \tilde{\Phi}} J(\ell, \psi) \leq \inf_{\ell \in L'(d_\mu)} J(\ell^{**}, \ell^*),$$

because the minimizing set on the LHS is larger than the minimizing set on the RHS.

So, the punch line is

$$\inf_{(\ell, \psi) \in \tilde{\Phi}} J(\ell, \psi) = \inf_{\ell \in L'(d_\mu)} J(\ell^{**}, \ell^*),$$

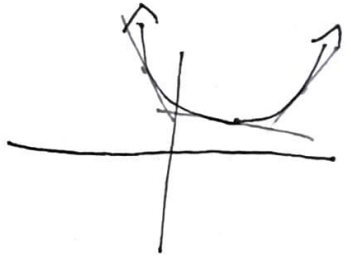
Which is an optimization over a nicer space of functions; as we shall see, \mathcal{L}^* , \mathcal{L}^{**} are both (i) convex
(ii) lower semi-continuous.

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To see this and some other nice properties we'll use later, we ~~are~~ will make a quick tour of convex analysis. Recall $\mathcal{L}: \mathbb{R}^d \rightarrow \mathbb{R} \cup \{\infty\}$ is convex if $\forall x, y \in \mathbb{R}^d, t \in [0, 1],$
$$\mathcal{L}(tx + (1-t)y) \leq t\mathcal{L}(x) + (1-t)\mathcal{L}(y)$$

• Convex functions are continuous, locally Lipschitz, and $\nabla \mathcal{L}$ exists a.e.

• Convex functions are above their tangents, in the sense that

$\forall x \in \mathbb{R}^d$ s.t. $\nabla \mathcal{L}(x)$ exists, and $\forall z \in \mathbb{R}^d, \mathcal{L}(z) \geq \mathcal{L}(x) + \nabla \mathcal{L}(x) \cdot [z-x]$



A useful corollary is that, applying this also to z (assuming $\nabla \mathcal{L}(z)$ exists) and adding the inequality gives monotonicity:

$$\langle \nabla \mathcal{L}(x) - \nabla \mathcal{L}(y), x - y \rangle \geq 0.$$

• One can handle non-differentiable \mathcal{L} through a weaker notion of subdifferentiability.

Defn: Let $\mathcal{L}: \mathbb{R}^d \rightarrow \mathbb{R}$ be convex. The subdifferential of \mathcal{L} is a set-valued

function $\partial \ell$, so that

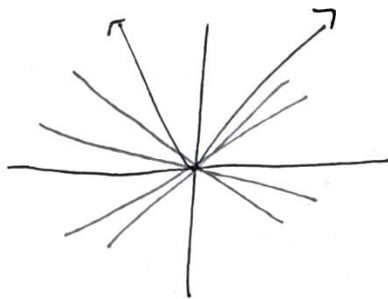
$$y \in \partial \ell(x) \Leftrightarrow \left\{ \forall z \in \mathbb{R}^d, \ell(z) \geq \ell(x) + \langle y, z-x \rangle \right\}$$

we'll use \langle, \rangle when handling \mathbb{R}^d and \mathbb{R}

We can consider the ^{set} Graph $(\partial \ell) = \{(x, y) \in \mathbb{R}^d \times \mathbb{R}^d \mid y \in \partial \ell(x)\}$.

This covers $\nabla \ell$, in that $\nabla \ell(x)$ exists $\Leftrightarrow |\partial \ell(x)| = 1$ and $\partial \ell(x) = \{\nabla \ell(x)\}$.
 But, it exists and is non-empty for all $x \in \text{dom}(\ell)$, even to points of non-differentiability.

ex: $\ell(x) = |x|$:



Subdifferentials have many useful properties (see ~~exercise~~ pp. 55-57 in Villani), and can be understood as one way to capture some notion of differentiability for non-classically differentiable functions.

An important connection between Legendre transforms and subdifferentials is:

Proposition (Connecting LT and ∂): Suppose $\ell: \mathbb{R}^d \rightarrow \mathbb{R}$ is lsc, convex, and proper (no $-\infty$, takes some non- $+\infty$ values). Then $\forall x, y \in \mathbb{R}^d$,

$$x \cdot y = \ell(x) + \ell^*(y) \Leftrightarrow y \in \partial \ell(x) \Leftrightarrow x \in \partial \ell^*(y)$$

Proof: Exercise/see Villani pp. 57.