

Probability Metrics

we've seen the total variation metric on $\text{Prob}(S, \mathcal{B})$

$$d_{TV}(\mu, \nu) = \sup_{B \in \mathcal{B}} |\mu(B) - \nu(B)|$$

This is an example of a (dual) probability metric:

$$d(\mu, \nu) = \sup_{h \in \mathcal{H}} |\int h d\mu - \int h d\nu|$$

↑ some class of functions on S .

Always a pseudo-metric; genuine metric if

\mathcal{H} is sufficiently rich.

Eg. Kolmogorov metric: $d_{Kol}(\mu, \nu) = \sup_{t \in \mathbb{R}} |F_{\mu}(t) - F_{\nu}(t)|$
(on $\text{Prob}(\mathbb{R}, \mathcal{B}(\mathbb{R}))$)

Wasserstein L¹ Distance

On $\text{Prob}(\mathbb{R}, \mathcal{B}(\mathbb{R}))$, define

$$d_{w_1}(\mu, \nu) = \sup_{\|f\|_{\text{Lip}} \leq 1} \left| \int f d\mu - \int f d\nu \right|$$

↖ ie. $\mathcal{H} = \text{Lip}_1(\mathbb{R})$

That doesn't look like what we called the Wasserstein metric in [Lecture 21.2]. But it actually is.

Prop: $d_{w_1}(\mu, \nu) = \sup_{\|f\|_{\text{Lip}} \leq 1} \left| \int f d\mu - \int f d\nu \right|$

$$= \int_{-\infty}^{\infty} |F_{\mu}(t) - F_{\nu}(t)| dt$$

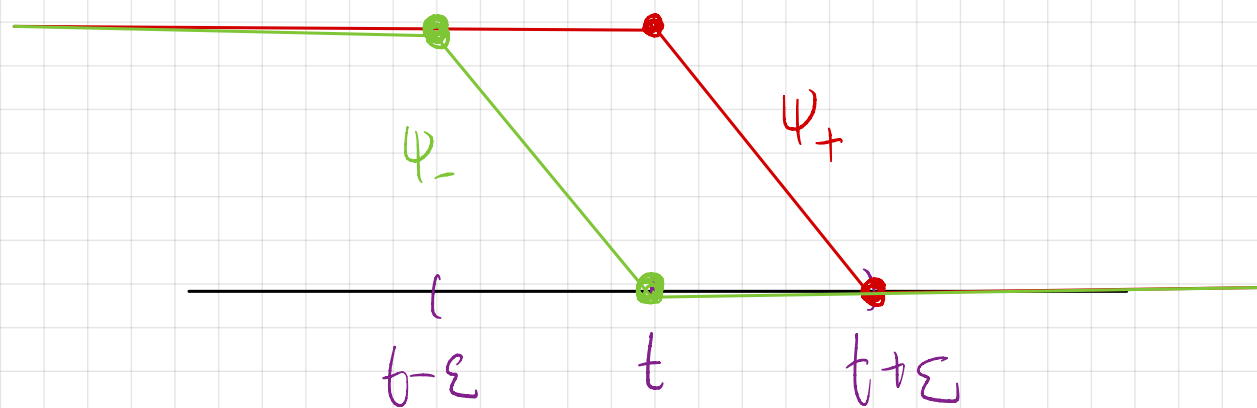
$$= \inf \{ \mathbb{E}[|X - Y|] : (X, Y) \text{ is a coupling of } \mu, \nu \}$$

The Wasserstein distance controls the Kolmogorov distance - at least when one of the measures has a bounded density.

Prop: If $d\nu = \rho dx$ and $\rho \leq C < \infty$, then for any $\mu \in \text{Prob}(\mathbb{R}, \mathcal{B}(\mathbb{R}))$,

$$d_{\text{Kol}}(\mu, \nu) \leq 2\sqrt{C} d_{\text{W}_1}(\mu, \nu).$$

Pf. Fix $t \in \mathbb{R}$, $\varepsilon > 0$, and define two continuous approximations to $\mathbb{1}_{(-\infty, t]}$:



$$\psi_- \leq \mathbb{1}_{(-\infty, t]} \leq \psi_+$$

$$\therefore \int \mathbb{1}_{(-\infty, t]} d\mu - \int \mathbb{1}_{(-\infty, t]} d\nu$$

$$\begin{aligned} & \mu(-\infty, t] - \nu(-\infty, t] \\ & \leq \int \psi_+ d\mu - \int \psi_+ d\nu + \int (\psi_+ - \mathbb{1}_{(-\infty, t]}) d\nu \end{aligned}$$

$$\therefore \mu(-\infty, t] - \nu(-\infty, t] \leq \frac{1}{\varepsilon} d_{w_1}(\mu, \nu) + C\varepsilon, \text{ for all } \varepsilon > 0.$$



$$\therefore \leq 2\sqrt{C d_{w_1}(\mu, \nu)}$$

↙ optimize over $\varepsilon > 0$.

Now use ψ_- to prove the reverse ineq. for $\nu(-\infty, t] - \mu(-\infty, t]$.

$$\therefore \sup_{t \in \mathbb{R}} |\mu(-\infty, t] - \nu(-\infty, t]| \leq 2\sqrt{C d_{w_1}(\mu, \nu)}$$

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As usual, we apply a metric on measures to random variables by $d(X, Y) := d(\mu_X, \mu_Y)$.

Cor: If $Z \stackrel{d}{=} \mathcal{N}(0, 1)$, then for any random variable X ,

$$d_{\text{kol}}(X, Z) \leq 2 \sqrt{d_{\text{W}_1}(X, Z)}$$

One of our goals is to prove (a version of) the:

Berry - Esseen Theorem:

Let $\{X_n\}_{n=1}^{\infty}$ be iid. L^3 random variables, with $\mathbb{E}[X_j] = 0$, $\mathbb{E}[X_j^2] = 1$, $\mathbb{E}[|X_j|^3] = \sigma^3$.

Let $S_n = X_1 + \dots + X_n$. If $Z \stackrel{d}{=} \mathcal{N}(0, 1)$, then

$$d_{\text{kol}}\left(\frac{S_n}{\sqrt{n}}, Z\right) \leq C \frac{\sigma^3}{\sqrt{n}}$$