

Probability Metrics

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

$$\begin{aligned} d_{TV}(\mu, \nu) &= \sup_{B \in \mathcal{B}} |\mu(B) - \nu(B)| \\ &= \frac{1}{2} \sup_{h \in \mathcal{B}_1(S, \mathcal{B})} |\int h d\mu - \int h d\nu| \end{aligned}$$

(bounded \mathcal{B} -measurable $\Leftrightarrow \sup|h| \leq 1$)

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.

too strong for weak convergence

Eg. Kolmogorov metric: $d_{Kd}(\mu, \nu) = \sup_{t \in \mathbb{R}} |F_\mu(t) - F_\nu(t)|$

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

$$= \sup_{t \in \mathbb{R}} \left| \int_{\mathbb{R}} \mathbb{1}_{(-\infty, t]} d\mu - \int_{\mathbb{R}} \mathbb{1}_{(-\infty, t]} d\nu \right|$$

Wasserstein L' Distance

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

$$d_{W_1}(\mu, \nu) = \sup_{\|f\|_{\text{Lip}} \leq 1} |\int f d\mu - \int f d\nu|$$

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



$$\begin{aligned}\mathcal{H} &= \{f: \mathbb{R} \rightarrow \mathbb{R} : |f(x) - f(y)| \leq L|x-y| \forall x, y \in \mathbb{R}\} \\ \|f\|_{\text{Lip}} &= \sup |f'|.\end{aligned}$$

It's a metric (by the Portmanteau theorem)

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

$$\text{Prop: } d_{W_1}(\mu, \nu) = \sup_{\|f\|_{\text{Lip}} \leq 1} |\int f d\mu - \int f d\nu|$$

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

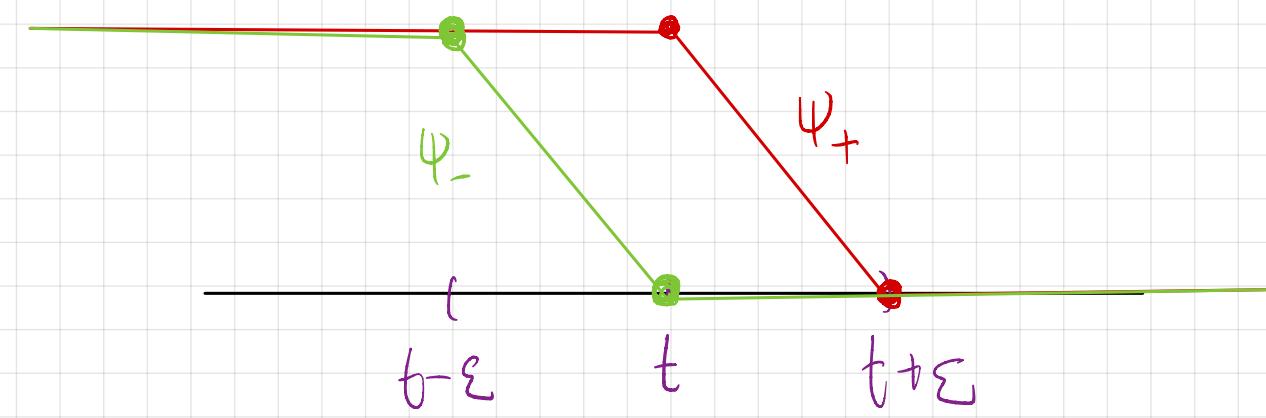
$$= \inf \{ \mathbb{E}[|X-Y|] : (X, Y) \text{ is a coupling of } \mu, \nu \}$$

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 $\mu \in \text{Prob}(\mathbb{R}, \mathcal{B}(\mathbb{R}))$,

$$d_{\text{Kol}}(\mu, \nu) \leq 2\sqrt{C d_{W_1}(\mu, \nu)}.$$

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



$$\leftarrow \text{slope } \frac{1}{\varepsilon}$$

$$\|\varepsilon \Psi_{\pm}\|_{\text{Lip}} \leq \frac{1}{\varepsilon}.$$

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

$$\|\varepsilon f\|_{\text{Lip}} = \sup_{x \neq y} \frac{|f(x) - f(y)|}{|x - y|}$$

$$= \varepsilon \|f\|_{\text{Lip}}$$

$$\|\varepsilon \Psi_{\pm}\| \leq 1.$$

$$\therefore \underbrace{\int \mathbb{1}_{(-\infty, t]} dy}_{\lesssim \Psi_+} - \int \mathbb{1}_{(-\infty, t]} dv$$

$$\leq \int \Psi_+ d\mu - \int \Psi_+ dv + \int \Psi_+ dv - \int \mathbb{1}_{(-\infty, t]} dv$$

$$\begin{aligned}
& \mu(-\infty, t] - \nu(-\infty, t] \\
& \leq \int \Psi_+ d\mu - \int \Psi_+ d\nu + \underbrace{\int (\Psi_+ - \mathbb{1}_{(-\infty, t]}) d\nu}_{\substack{\uparrow \\ \mathbb{1}_{(t, t+\varepsilon]} \\ \rho dx}} \\
& = \frac{1}{\varepsilon} \left(\int \varepsilon \Psi_+ d\mu - \int \varepsilon \Psi_+ d\nu \right) \\
& \leq \frac{1}{\varepsilon} d_{W_1}(\mu, \nu) \quad \substack{\uparrow \\ C \\ C\varepsilon}
\end{aligned}$$

$$\therefore \mu(-\infty, t] - \nu(-\infty, t] \leq \frac{1}{\varepsilon} d_{W_1}(\mu, \nu) + C\varepsilon, \text{ for all } \varepsilon > 0.$$

$$\begin{array}{c}
\downarrow \\
\therefore \leq 2 \sqrt{C d_{W_1}(\mu, \nu)}
\end{array}$$

$$\begin{array}{c}
\downarrow \text{optimize over } \varepsilon > 0 \\
\varepsilon = \sqrt{\frac{d_{W_1}(\mu, \nu)}{C}}
\end{array}$$

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

$$d_{KL}(\mu, \nu) = \therefore \sup_{t \in \mathbb{R}} |\mu(-\infty, t] - \nu(-\infty, t)| \leq 2 \sqrt{C d_{W_1}(\mu, \nu)}$$

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

$$d_{\text{Kol}}(X, Z) \leq 2 \sqrt{d_{W_1}(X, Z)} \quad \text{b/c } F_Z(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

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 $E[X_j] = 0$, $E[X_j^2] = 1$, $E[X_j^3] = o\vartheta^3$.

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

$$d_{\text{Kol}}\left(\frac{S_n}{\sqrt{n}}, Z\right) \leq C \frac{o\vartheta^3}{\sqrt{n}} \leftarrow \text{rate = optimal}$$

$$\sup_{t \in \mathbb{R}} |\bar{F}_{S_n/\sqrt{n}}(t) - F_Z(t)| \quad \text{best known } C < 0.4748$$

$\mathbb{R} \Phi(t) = \text{Erf}(t)$