

Motivation: Histograms/Density \rightarrow Comparing them, optimizing over them
 Measures: On a set X $A \subset X \rightarrow \mu(A) \in \mathbb{R}$ (total size/Measure)

Positive: $\mu(A) \geq 0$ Probab: $\mu(X) = 1$
 $(\mu(A \cup B) = \mu(A) + \mu(B))$ if $A \cap B = \emptyset$
 (should extend to countable union)

Radon measure: to speak about convergence, one needs a distance (of pts & measures)

- ① Needs all balls $\mu(B) < \infty$ (small ones)
- ② $\mu(A) = \sup \{ \mu(K) : K \subset A \}$ compact

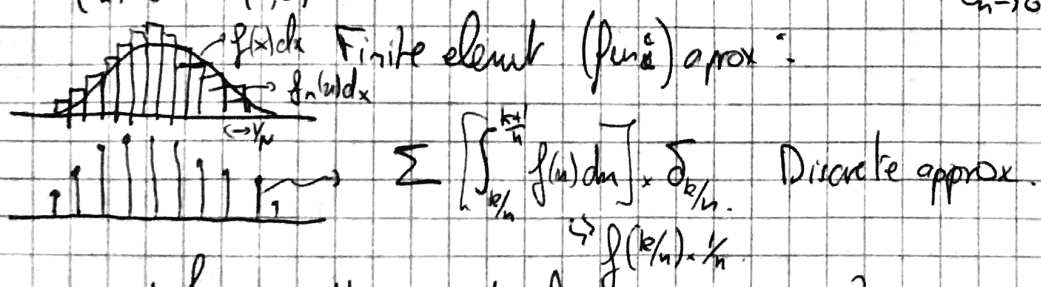
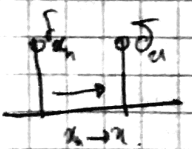
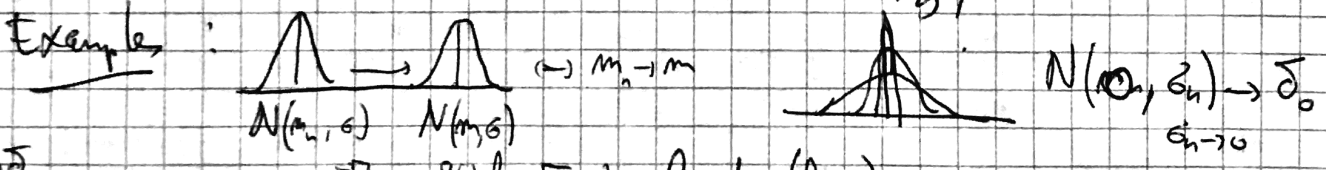
\Rightarrow Allows to define $\int f d\mu$ for $f \in C(X)$ continuous

Radon measure & Random variables: $Z: (\Omega, \mathcal{P}) \rightarrow X$ random var
 associated measure $\mu(A) = \mathbb{P}_Z(A) \triangleq \mathbb{P}(Z \in A)$
 Z is "push-forwarding" \mathbb{P} to \mathbb{P}_X

Convergence of Random variables: convergence law \Leftrightarrow weak convergence
 Measures

$\mu_n \xrightarrow{w} \mu \Leftrightarrow \forall A, \mu_n(A) \rightarrow \mu(A)$
 $\mathbb{P}_{Z_n} \rightarrow \mathbb{P}_Z \Leftrightarrow \forall f \in C(X), \int f d\mu_n \rightarrow \int f d\mu$

Weak than the **STRONG** convergence of the density $\mu_n = g_n dx$ $g_n \xrightarrow{L^1} g \Rightarrow \mu \rightarrow \nu$
 (μ_n & μ might not be ~~have~~ densities)



Key question: Quantifying the speed of convergence? $D(\mu, \nu)$ "distance" like
 First requirement: $\mu_n \rightarrow \mu \Leftrightarrow D(\mu_n, \mu) \xrightarrow{n} 0$
 $\Leftrightarrow D$ defines the weak topology
WARNING: is 0-dimensional (and in particular if D is not a norm)
 (D_1, D_2) same topology \Leftrightarrow equivalent $\Leftrightarrow \exists c, D_1/c \leq D_2 \leq cD_1$
 i.e. convergence rates depend on the distance!

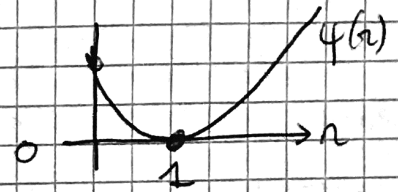
Statistical divergence

① Comparing density: if $\mu = f dx$ then compute $D(\mu, \nu) = \int |f(x) - g(x)|^p dx = \|f - g\|_p^p$
 if $\nu = g dx$ Prblm: strong assumption
 • Not continuous with weak topology
 $D(\mu + \epsilon \delta, \nu)$ not defined

② Comparing relative density: ~~ψ~~ ψ-divergence / Csiszar divergence

Comparing $\frac{d\mu}{d\nu} = f$ (ie $d\mu(x) = f(x) d\nu$) with 1

$$D(\mu|\nu) \triangleq \int_X \psi\left(\frac{d\mu}{d\nu}(x)\right) d\nu(x)$$

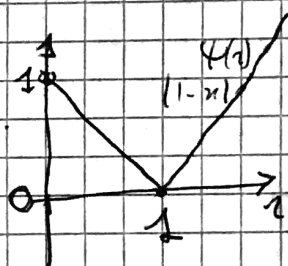


ψ convex ~~ψ~~
 $\psi(1) = 0$
 $D(\mu|\nu) = 0 \iff \mu = \nu$
 D convex of (μ, ν) !

examples: $\psi(x) = |x-1|$

$$D(\mu|\nu) = \int \left| \frac{d\mu}{d\nu} - 1 \right| d\nu = \int \left| \frac{d\mu}{d\nu} - \frac{d\nu}{d\nu} \right| d\nu = \int \left| \frac{d\mu}{d\nu} - \frac{d\nu}{d\nu} \right| d\nu$$

it is a norm!!



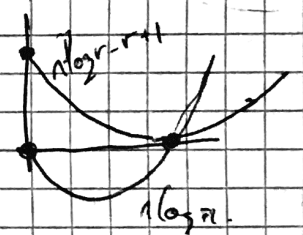
examples: $\psi(x) = x \log x$
 KL divergence

$$D(\mu|\nu) = \int \log\left(\frac{d\mu}{d\nu}\right) d\mu$$

("generalized" KL)

$$\psi(x) = x \log x - x + 1 \quad D(\mu|\nu) = \int \log\left(\frac{d\mu}{d\nu}\right) d\mu + \int (d\nu - d\mu)$$

useful to make it also a Bregman divergence
 same if $S_{d\mu} = S_{d\nu}$



③ Hilbertian norm using lifting: For simplicity, $X = \mathbb{R}^d, \int 1 = 1$

Convolution/Kernel density estimator: $\mu * h$ as a density
 ($h(x)$ smooth $\int h = 1$)
 ex $\mu = \sum \alpha_k \delta_{x_k} \rightarrow \sum \alpha_k h(x - x_k)$

$$D(\mu, \nu)^2 = \|\mu * h - \nu * h\|_2^2 = \int_{\mathbb{R}^d} \left[\int_{\mathbb{R}^d} h(x-y) d\zeta(y) \right]^2 dx \triangleq \|\mu - \nu\|_K^2$$

seems intractable even for discrete μ and ν
 $= \int_{\mathbb{R}^d} \int_{\mathbb{R}^d} h(x-y) h(x-y') d\zeta(y) d\zeta(y') dx$ [Fubini]
 Max Mean (MMD)
 Discrepancy

ex $h(x) = e^{-\|x\|_2^2 / 2\sigma^2} \rightarrow K(y, y') = \exp(-\|y - y'\|_2^2 / 4\sigma^2)$
 $K(y, y') \triangleq \int_{\mathbb{R}^d} h(x-y) h(x-y') dx$
 Kernel

Ex $K(y, y') = -\|y - y'\|$ also correspond to $h(x) = \frac{1}{\|x\|}$ (3)

So $D(\mu, \nu)^2 = \iint K(y, y') (d\mu(y) - d\nu(y)) (d\mu(y') - d\nu(y'))$

ex $\mu = \sum a_i \delta_{x_i}$
 $\nu = \sum b_j \delta_{y_j}$ $\rightarrow D(\mu, \nu)^2 = -2 \sum_{j,i} k(x_i, y_j) a_i b_j = E(k(X, X')) + E(k(Y, Y')) - 2E(k(X, Y))$

$+ \sum_{i,i'} k(x_i, x_{i'}) a_i a_{i'}$
 $+ \sum_{j,j'} k(y_j, y_{j'}) b_j b_{j'}$



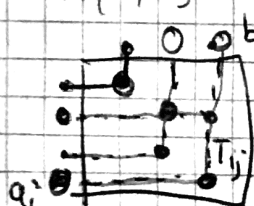
Thm: $\|\cdot\|_K$ metrizes weak convergence

Optimal Transport

Special discrete case: $\mu = \sum a_i \delta_{x_i}$ $\nu = \sum b_j \delta_{y_j}$ "Grains of masses"
 $a_i, b_j \geq 0, \sum a_i = \sum b_j (=1)$

Coupling: $\Pi(a, b) = \left\{ P \in \mathbb{R}_+^{n \times m} : \forall_i \sum_j P_{ij} = a_i, \forall_j \sum_i P_{ij} = b_j \right\}$ cvx
Blytuf

$P \mathbf{1} = a$ $P^T \mathbf{1} = b$



OT: $\mathcal{C}_p(\mu, \nu) = \min_{P \in \Pi(a, b)} \sum c_{ij} P_{ij}$ ↳ Lin Prog
↳ Combinatorial optm
↳ Sinkhorn approx

Wasserstein dist: if $c_{ij} = d(x_i, y_j)^p, p \geq 1, W_p(\mu, \nu) \triangleq \mathcal{C}_p(\mu, \nu)^{1/p}$

Thm: W_p is a distance & it metrizes weak convergence

MMD: \oplus Simple \oplus Good sample exity \oplus Reflects less the distance $\|\mu - \mu \circ \tau\| = O(\sqrt{p})$

OT: \ominus Cpx \ominus Bad sample exity \oplus More geometrical

$|D(\mu, \nu) - D(\hat{\mu}_n, \hat{\nu}_n)| \sim \frac{1}{n^q}$ MMD: $q = 1/2$ OT: $q = 1/2$