

# L10: Distances for Distributions

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# Abstract Representation

① Data point  $\rightarrow$  Set

② Data point  $\rightarrow$  Vector

Today ③ Data point  $\rightarrow$  Distribution

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## Discrete Distribution

$m$  possible outcomes

$m = 100,000$  words English

$m = 29$  countries in Gk

$\rightarrow$  vector in  $\mathbb{R}^m$  too flexible

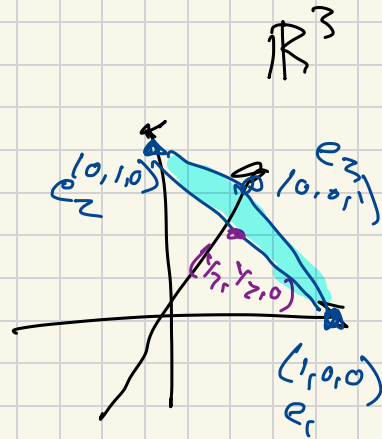
# Discret. Prob. Dist in states

$v \in \mathbb{R}^m$ , but restrict.

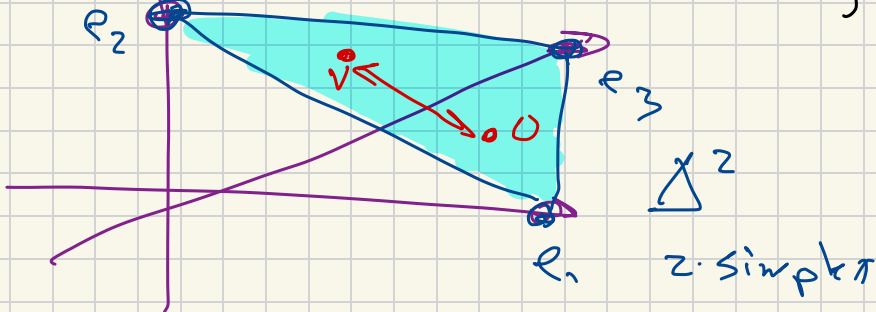
$v_j = \text{prob abs lbrs in state } j \in [m]$

$$v_j \in [0, 1]$$

$$\sum_{j=1}^m v_j = 1$$



$$\Delta^{m-1} = \left\{ x \in \mathbb{R}^m \mid x_j \geq 0, \sum_{j=1}^m x_j = \|x\|_1 = 1 \right\}$$



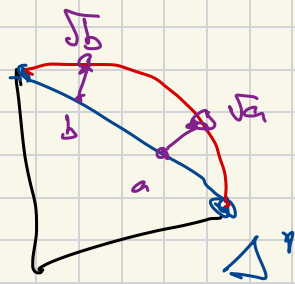
$$v, u \in \Delta^m$$

$$D(v, u) = \|v - u\|$$

2-simplex

Data  $a, b \in \Delta^{m-1}$

common distances



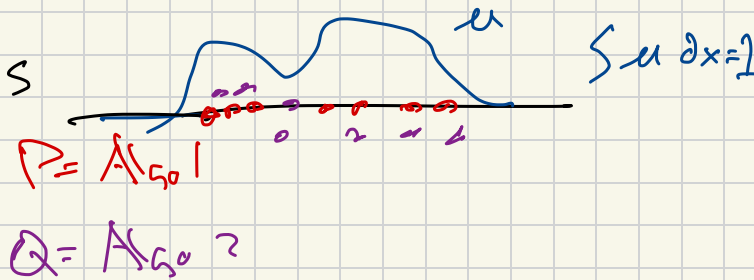
$$\bullet D_{KL}(a, b) = \sum_{j=1}^m a_j \ln(a_j/b_j)$$

$$\bullet D_H(a, b) = \frac{1}{\sqrt{2}} \sqrt{\sum_{j=1}^m (\sqrt{a_j} - \sqrt{b_j})^2}$$

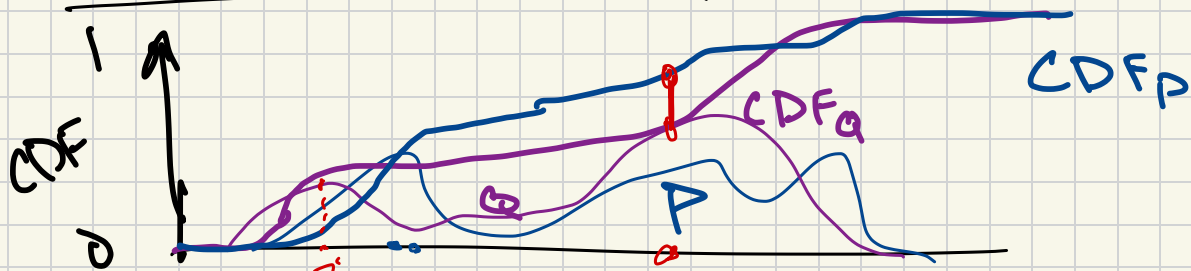
$$\bullet D_{TV}(a, b) = \max_{S \subseteq [m]} \sum_{j \in S} (a_j - b_j) = \frac{1}{2} \|a - b\|_1$$

Distribution  $\mu$  continuous

Sample  $P \sim \mu$



Kolmogorov-Smirnov (KS) Distance



$$D_{KS}(P, Q) = \max_{z \in \mathbb{R}} |CDF_P(z) - CDF_Q(z)|$$

0.321 inches

0.323 inches

Inputs continuous distributions on  $\mathbb{R}^d$

$\mu_P, \nu_Q$       $P \sim \mu_P$       $Q \sim \nu_Q$

$P, Q \subset \mathbb{R}^d$      assume  $|P| = |Q| = n$

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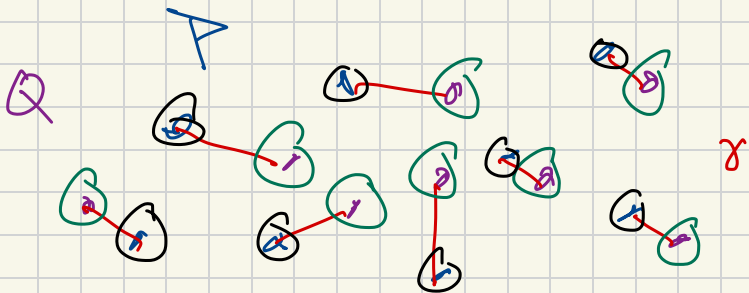
• Wasserstein

Earth Movers, Optimal Transport

• Kernel Distance

Maximum Mean Discrepancy (MMD)

Assume input  $P, Q \subset \mathbb{R}^d$ ,  $|P| = |Q| = n$



Transportation Plan  $\gamma$   
 $\gamma \in \mathcal{T}(P, Q)$

$$\min_{\gamma \in \mathcal{T}(P, Q)} \frac{\sum_{(p, q) \in \gamma} \|p - q\|}{|P|} = w_1$$

Wasserstein  $w_s$

$$w_s(P, Q) = \min_{\gamma \in \mathcal{T}(P, Q)} \left( \frac{1}{|P|} \sum_{(p, q) \in \gamma} \|p - q\|^s \right)^{1/s}$$

metric for  $s \in [1, \infty), \infty$

$$w_s(\mu, \nu) = \inf_{\gamma \in \mathcal{T}(\mu, \nu)} \left( \int_{(p, q) \in \gamma} D(p, q)^s \right)^{1/s}$$

Computation on  $w_1, w_2$

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Need to find arg min  
 $\gamma \in T(P, Q)$

Algorithms  $O(n^3 \log n)$  time

input might be  $n^2$  size

Approx  $w_2 \Rightarrow$  Sinkhorn adds entropy regularization

$\hookrightarrow$  convex optimization

$\epsilon$  approx

$O\left(\frac{1}{\epsilon} n^2 \log(n)\right)$

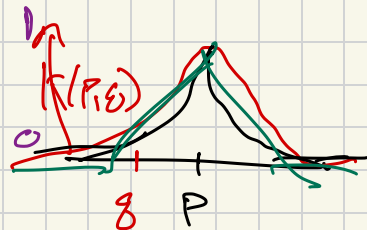


# Kernel Distance (MMD)

Similarity  $P, g \in \mathbb{R}^d$

Kernel

Gaussian  $K(p, g) = \exp(-\|p-g\|^2)$



Laplace  $K(p, g) = \exp(-\|p-g\|)$

Triangular  $= \max\{0, 1 - \|p-g\|\}$

general  $K(p, g) = \exp(-D(p, g)^2)$

[P1]  $K(p, g) \in [0, 1]$

[P2]  $K$  is positive definite

For any  $X_i$   
Gram matrix

$$G \in \mathbb{R}^{n \times n}$$

$$G_{ij} = K(x_i, x_j)$$

$G$  has all  
real, pos  
eigenvalues.

Analogy

$$\|p - g\|^2 = \|p\|^2 + \|g\|^2 - 2\langle p, g \rangle$$
$$= \langle p, p \rangle + \langle g, g \rangle - 2\langle p, g \rangle$$

Use  $K(p, g)$  as  $\langle p, g \rangle$

$$D_K(p, g) = \sqrt{K(p, p) + K(g, g) - 2K(p, g)}$$

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$$K(P, Q) = \frac{1}{|A|} \cdot \frac{1}{|Q|} \sum_{p \in P} \sum_{g \in Q} K(p, g)$$

$$D_K(P, Q) = \sqrt{K(P, P) + K(Q, Q) - 2K(P, Q)}$$

$$X = P \cup G \quad \Rightarrow \quad \text{Gram matrix} \quad G(X) \in \mathbb{R}^{2n \times 2n}$$
$$G_{ij} = \langle x_i, x_j \rangle$$

$$\text{Eigen decomposition} \quad G \rightarrow \left[ \underset{\lambda}{U}, \lambda \right] \quad U = (u_1, u_2, \dots, u_n)$$

basis

$$\text{Project} \quad X = P \cup G \rightarrow \text{basis } U.$$

$$\text{in basis for dist} = \mathcal{P}_U(P, G) = \|P - G\|_U$$

# Reproducing Kernel Hilbert Space (RKHS)

$\mathcal{H}_K =$  linear combos  $K(p, \cdot)$

$$K(p, \cdot) \in \mathcal{H}_K$$

Kernel Density Estimate  $KDE_P(x) = \frac{1}{|P|} \sum_{p \in P} K(p, x)$

$$KDE_P(\cdot) \in \mathcal{H}_K$$

$$\begin{aligned} D_K(P, Q) &= \| KDE_P(\cdot) - KDE_Q(\cdot) \|_{\mathcal{H}_K} \\ &= \left\| \mathbb{E}_{p \sim P} K(p, \cdot) - \mathbb{E}_{q \sim Q} K(q, \cdot) \right\|_{\mathcal{H}_K} \end{aligned}$$