

Closed-Form Information-Theoretic Divergences for Statistical Mixtures

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Consider two statistical mixtures $m(x) = \sum_{i=1}^k w_i p_F(x; \theta_i)$ and $m'(x) = \sum_{i=1}^{k'} w'_i p_F(x; \theta'_i)$.

Kullback-Leibler divergence (relative entropy) *does not admit* a closed-form formula:

$$\text{KL}(m : m') = \int_{x \in \mathbb{X}} m(x) \log \frac{m(x)}{m'(x)} dx$$

→ **Stochastic approximation** using Monte-Carlo integration (costly)

$$\tilde{\text{KL}}(m : m') \approx \frac{1}{n} \sum_{\substack{x_i \sim m \\ 1 \leq i \leq n}} \left(\log \frac{m(x_i)}{m'(x_i)} + \frac{m'(x_i)}{m(x_i)} - 1 \right)$$

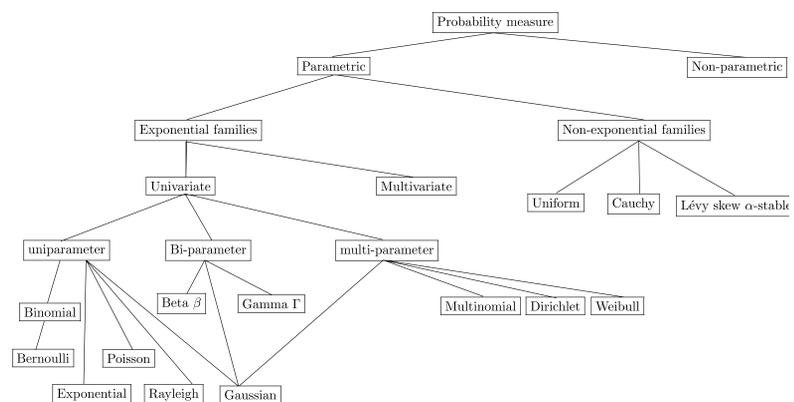
Consider alternative **Cauchy-Schwarz divergence**:

$$\text{CS}(P : Q) = -\log \frac{\int p(x)q(x)dx}{\sqrt{\int p(x)^2 dx \int q(x)^2 dx}}$$

Consider mixture components from the same exponential families

$$p_F(x; \theta) = e^{t(x, \theta) - F(\theta) + k(x)}$$

- $t(x)$ = sufficient statistics,
- θ = natural parameter,
- $F(\theta)$ = log-normalizer,
- $k(x)$ = auxiliary carrier measure



The integral of **product of mixtures** yields:

$$\int m(x)m'(x)dx = \sum_{i=1}^k \sum_{j=1}^{k'} w_i w'_j \int p_F(x; \theta_i) p_F(x; \theta'_j) dx$$

$$\int m(x)m'(x)dx = \sum_{i=1}^k \sum_{j=1}^{k'} w_i w'_j e^{\Delta_F(\theta_i, \theta'_j)}$$

$$\Delta_F(\theta_i, \theta'_j) = F(\theta_i + \theta'_j) - (F(\theta_i) + F(\theta'_j))$$

← when **natural parameter space** $\Theta = \{\theta \mid \int p_F(x; \theta) dx < \infty\}$ is a **convex cone**. Generic Cauchy-Schwarz divergence formula applies for $(k(x) = 0)$:

- mixtures of Bernoulli,
- mixtures of zero-centered Laplacian,
- mixtures of Wishart,
- mixtures of Gaussian,
- etc.

Besides Cauchy-Schwarz divergence, also closed-form solution for:

- **Square loss**: $\int (m(x) - m'(x))^2 dx = \int m^2(x) dx - 2 \int m(x)m'(x) dx + \int m'^2(x) dx$
- **total Square loss** (total Bregman divergence for $F(x) = \langle x, x \rangle$ generator)
- **Jensen-quadratic Rényi divergence**: $\text{JR}_2(m, m') = H_2\left(\frac{m+m'}{2}\right) - \frac{H_2(m) + H_2(m')}{2}$ with $H_2(m) = -\log \sum_{i=1}^k \sum_{j=1}^{k'} w_i w_j e^{\Delta_F(\theta_i, \theta_j)}$