The (M, N)-Bhattacharyya dissimilarity

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Let $(\mathcal{X}, \mathcal{E}, \mu)$ be a measure space with μ a positive measure. Consider the Bhattacharyya distance between two probability measures P and Q with corresponding densities p and q wrt. μ :

$$D_B[p:q] := -\log \int \sqrt{p(x) q(x)} d\mu(x),$$

and more generally the skewed Bhattacharyya distance:

$$D_{B,\alpha}[p:q] := -\log \int p^{\alpha}(x) q^{1-\alpha}(x) d\mu(x).$$

Let us prove that $D_{B,\alpha}[p:q] \geq 0$ with equality iff. p=q μ -ae.:

Let us use the property that the weighted geometric mean is less or equal than the weighted arithmetic mean:

$$\underbrace{p^{\alpha}(x)q^{1-\alpha}(x)}_{:=G_{\alpha}(p(x):q(x))} \leq \underbrace{\alpha p(x) + (1-\alpha)q(x)}_{:=A_{\alpha}(p(x):q(x))},$$

with equality holding iff. p(x) = q(x).

It follows that

$$\underbrace{\int \left(p^{\alpha}(x)q^{1-\alpha}(x)\right) d\mu}_{:=\mathrm{BC}_{\alpha}[p:q]} \leq \underbrace{\int \left(\alpha p(x) + (1-\alpha)q(x)\right)}_{=1} d\mu(x),$$

where BC_{α} is the skewed Bhattacharyya coefficient in [0, 1]. Hence, we have by monotonicity of the logarithm function:

$$\log BC_{\alpha}[p:q] \le \log 1 = 0,$$

It follows that

$$D_{B,\alpha}[p:q] = -\log \mathrm{BC}_{\alpha}[p:q] \ge 0,$$

with equality iff. $p = q \mu$ -ae.

However, the Bhattacharyya distance is not strictly speaking a "mathematical distance" since it does not satisfy the triangle inequality. Thus it is a misnomer and should have been better called the Bhattacharyya dissimilarity.

In general, for an inequality $\operatorname{lhs}(p:q) \leq \operatorname{rhs}(p:q)$, we may define the following inequality gap dissimilarities: $\operatorname{rhs}(p:q) - \operatorname{lhs}(p:q)$ or $-\log \frac{\operatorname{lhs}(p:q)}{\operatorname{rhs}(p:q)} \geq 0$.

Thus we could have chosen any power mean $P_{r,\alpha}(a,b) = (\alpha a^r + (1-\alpha)b^r)^{\frac{1}{r}}$ with r < 1 and $a,b \ge 0$ (and $P_{0,\alpha} = G_{\alpha}$, the weighted geometric mean) to define a generalized Bhattacharyya distance since

$$P_{r,\alpha}(p(x):q(x)) \le A_{\alpha}(p(x):q(x)) = \alpha p(x) + (1-\alpha)q(x), r \le 1$$

and we get

$$D_{B,\alpha}[p:q] = -\log \int P_{r,\alpha}(p(x):q(x)) d\mu(x) \ge 0.$$

For two comparable weighted means $M_{\alpha} \leq N_{\alpha}$, we define

$$D_{B,\alpha}^{M,N}[p:q] := -\log \frac{\int M_{r,\alpha}(p(x):q(x)) d\mu(x)}{\int N_{r,\alpha}(p(x):q(x)) d\mu(x)} \ge 0.$$

See

- Nielsen, Frank. Generalized Bhattacharyya and Chernoff upper bounds on Bayes error using quasi-arithmetic means. Pattern Recognition Letters 42 (2014): 25-34.
- Nielsen, Frank, Ke Sun, and Stéphane Marchand-Maillet. On Hölder projective divergences. Entropy 19.3 (2017): 122.