

Code name: **JB**  
 Argument type: Parameter

## 1 Jensen-Bregman divergence

### 1.1 Definitions

The *Jensen-Bregman divergence*<sup>1</sup> (first introduced in April 2010<sup>2</sup>) between parameters  $p$  and  $q$  has been historically designed as a symmetrization of Bregman divergences generalizing the renown Jensen-Shannon divergence<sup>3</sup>. The Jensen-Bregman divergence defined by:

$$\text{JB}_F(p; q) = \frac{1}{2} \left( B_F \left( p : \frac{p+q}{2} \right) + B_F \left( q : \frac{p+q}{2} \right) \right) \quad (1)$$

where  $F \in \mathcal{F}_B$  is a Bregman function generator.

The Jensen-Bregman divergence amounts to a Jensen divergence (also called a Burbea-Rao divergence):

$$\text{JB}_F(p; q) = \frac{F(p) + F(q)}{2} - F \left( \frac{p+q}{2} \right) = J_F(p : q) = \text{BR}_F(p; q) \quad (2)$$

Notice that the terms with the gradients  $\nabla F(\frac{p+q}{2})$  in the BD expressions cancel out (proof given later on for skew versions).

Choosing  $F(x) = -H(x)$ , the Shannon information, we recover the Jensen-Shannon divergence:

$$\text{JB}_{-H}(p; q) = H \left( \frac{p+q}{2} \right) - \frac{H(p) + H(q)}{2} = \text{JS}(p; q) \quad (3)$$

Let  $K_F(p : q) = B_F(p : \frac{p+q}{2})$  (generalizing Lin's K divergence for the Kullback-Leibler divergence). Then we have:

$$\text{JB}_F(p; q) = \frac{1}{2}(K_F(p : q) + K_F(q : p)).$$

For  $\alpha \in \mathbb{R}$ , we define the *skew Jensen-Bregman divergence*<sup>4</sup>:

$$\text{JB}_F^{(\alpha)}(p : q) = \alpha B_F(p : \alpha p + (1 - \alpha)q) + (1 - \alpha) B_F(p : \alpha p + (1 - \alpha)q). \quad (4)$$

<sup>1</sup>Frank Nielsen and Sylvain Boltz. “The Burbea-Rao and Bhattacharyya centroids”. In: *IEEE Transactions on Information Theory* 57.8 (2011), pp. 5455–5466.

<sup>2</sup>Frank Nielsen and Sylvain Boltz. “The Burbea-Rao and Bhattacharyya centroids”. In: *CoRR* abs/1004.5049 (Apr. 2010). URL: <http://arxiv.org/abs/1004.5049>.

<sup>3</sup>Jianhua Lin. “Divergence measures based on the Shannon entropy”. In: *IEEE Transactions on Information theory* 37.1 (1991), pp. 145–151.

<sup>4</sup>Frank Nielsen and Richard Nock. “Jensen-Bregman Voronoi diagrams and centroidal tessellations”. In: *International Symposium on Voronoi Diagrams in Science and Engineering (ISVD)*. IEEE. 2010, pp. 56–65.

The skew Jensen-Bregman divergence amounts to a skew Jensen divergence (and vice-versa):

$$\text{JB}_F^{(\alpha)}(p : q) = \alpha F(p) + (1 - \alpha)F(q) - F(\alpha p + (1 - \alpha)q), \quad (5)$$

$$= J_F^{(\alpha)}(p : q). \quad (6)$$

*Proof.* Let  $m_\alpha = \alpha p + (1 - \alpha)q$  denote the weighted mixture of parameters  $p$  and  $q$ . A direct expansion of  $\text{JB}_F^{(\alpha)}(p : q)$  yields

$$\begin{aligned} \text{JB}_F^{(\alpha)}(p : q) &= \\ &\alpha F(p) - \alpha F(m_\alpha) - \alpha \langle p - m_\alpha, \nabla F(m_\alpha) \rangle \\ &+ (1 - \alpha)F(q) - (1 - \alpha)F(m_\alpha) - (1 - \alpha) \langle q - m_\alpha, \nabla F(m_\alpha) \rangle \end{aligned}$$

Reordering the terms, we get:

$$\text{JB}_F^{(\alpha)}(p : q) = \alpha F(p) + (1 - \alpha)F(q) - F(m_\alpha) + \langle \nabla F(m_\alpha), -\alpha(p - m_\alpha) - (1 - \alpha)(q - m_\alpha) \rangle$$

Since  $p - m_\alpha = (1 - \alpha)(p - q)$  and  $q - m_\alpha = -\alpha(p - q)$ , we have  $-\alpha(p - m_\alpha) - (1 - \alpha)(q - m_\alpha) = -\alpha(1 - \alpha)(p - q) + (1 - \alpha)\alpha(p - q) = 0$  in the second argument of the inner product, and the inner product is 0. Thus  $\text{JB}_F^{(\alpha)}(p : q) = \alpha F(p) + (1 - \alpha)F(q) - F(\alpha p + (1 - \alpha)q) = J_F^{(\alpha)}(p : q)$ .  $\square$

Define the *scaled skew Bregman-Jensen divergences* and *scaled skew Jensen divergences* for  $\alpha \in \mathbb{R} \setminus \{0, 1\}$ :

$$\text{JB}'_F^{(\alpha)}(p : q) = \frac{1}{\alpha(1 - \alpha)} \text{JB}_F^{(\alpha)}(p : q) = \text{JB}_F^{(\alpha)}(p : q) \quad (7)$$

In the limit cases  $\alpha \rightarrow 0$  or  $\alpha \rightarrow 1$ , the scaled skew JBD tend to a sided Bregman divergence<sup>5</sup>:

$$\lim_{\alpha \rightarrow 0} \text{JB}'_F^{(\alpha)}(p : q) = J'_F^{(\alpha)}(p : q) = B_F(p : q) \quad (8)$$

$$\lim_{\alpha \rightarrow 1} \text{JB}'_F^{(\alpha)}(p : q) = J'_F^{(\alpha)}(p : q) = B_F(q : p) \quad (9)$$

(A straightforward proof for the scaled skew Jensen divergence follows from the equivalence with the scaled skew Jensen-Bregman divergence, and by using the definition of the scaled skew Jensen-Bregman divergence.)

Those definitions extend straightforwardly to matrix types<sup>6</sup>: For example, by considering the von Neumann information (negative of the von Neumann entropy)  $F(X) = \text{tr}(X \log X - X)$  or the log-det information  $F(X) = -\log |X|$ .

<sup>5</sup>Nielsen and Boltz, “The Burbea-Rao and Bhattacharyya centroids”.

<sup>6</sup>Nielsen and Nock, “Jensen-Bregman Voronoi diagrams and centroidal tessellations”.

**Remark 1.** Although  $B_F(p : q) = B_{F^*}(q^* : p^*)$  (from Young's equality  $F(x) + F^*(x^*) = \langle x, x^* \rangle$ ), we cannot easily express a relationship between  $JB_F^{(\alpha)}(p : q)$  and  $JB_{F^*}^{(\alpha)}(p^* : q^*)$  because  $m_\alpha^* = \nabla F(m_\alpha)$  does not express in terms of  $p^*$  and  $q^*$  (except for the case of the quadratic information  $F(x) = \frac{1}{2}\langle x, x \rangle$ ).

We extend the skew Jensen-Bregman divergence to weighted convex combination of points using the Jensen-Bregman diversity:

$$JB_F(p_1, \dots, p_n; w_1, \dots, w_n) := \sum_{i=1}^n w_i B_F(p_i : m_w), \quad m_w = \sum_{i=1}^n w_i p_i \quad (10)$$

The Jensen-Bregman diversity amounts to a Jensen diversity:

$$JB_F(p_1, \dots, p_n; w_1, \dots, w_n) = J_F(p_1, \dots, p_n; w_1, \dots, w_n), \quad (11)$$

with the Jensen diversity defined as:

$$J_F(p_1, \dots, p_n; w_1, \dots, w_n) := \sum_{i=1}^n w_i F(p_i) - F\left(\sum_{i=1}^n w_i p_i\right) \quad (12)$$

*Proof.* We have  $\sum_{i=1}^n w_i B_F(p_i : m_w)$ ,  $m_w = \sum_{i=1}^n w_i p_i = (\sum_i w_i F(p_i)) - F(\bar{p}) - \sum_{i=1}^n w_i \langle (\sum_i w_i(p_i - \bar{p}), \nabla F(\bar{p})) \rangle$ . Since  $\sum_i w_i(p_i - \bar{p}) = (\sum_i w_i p_i) - (\sum_i w_i)\bar{p} = 0$ , the inner product terms vanish, and we have the Jensen-Bregman diversity that equals the Jensen diversity.  $\square$

In Bregman  $k$ -means clustering<sup>7</sup>, the Jensen(-Bregman) diversity is called the *Bregman information*: It generalizes the notion of variance of a cluster (that is obtained by considering the squared Euclidean distance, a Bregman divergence).

Sided information radius: For a given weighted set, let  $R_F(x) = \sum_i w_i B_F(p_i : x)$  and  $L_F(l) = \sum_i w_i B_F(x : p_i)$ . Let  $r = \arg \min R_F(x)$  and  $l = \arg \min L_F(x)$ . Then  $R_F(r; p_i, w_i) = L_{F^*}(r^*; p_i^*, w_i)$  and  $L_F(l; p_i, w_i) = R_{F^*}(l^*; p_i^*, w_i)$ . In general, the sided information radii do not coincide (except when the generator is  $F(x) = \frac{1}{2}\langle x, x \rangle$ )

## 1.2 Properties

- $\sqrt{JB_F(p; q)}$  is a metric iff  $F(p + q)$  is a Conditionally Positive Definite (CPD) kernel<sup>8</sup>.

<sup>7</sup>Frank Nielsen and Richard Nock. "Sided and symmetrized Bregman centroids". In: *IEEE transactions on Information Theory* 55.6 (2009), pp. 2882–2904.

<sup>8</sup>Sreangsu Acharyya, Arindam Banerjee, and Daniel Boley. "Bregman Divergences and Triangle Inequality". In: *Proceedings of the 13th SIAM International Conference on Data Mining, May 2-4, 2013. Austin, Texas, USA..* 2013, pp. 476–484. DOI: 10.1137/1.9781611972832.53. URL: <http://dx.doi.org/10.1137/1.9781611972832.53>.

### 1.3 Further extensions

Jensen-Bregman log det divergence<sup>9</sup>, total Jensen-Bregman divergences<sup>10</sup> that are equivalent to total Jensen divergences.

### 1.4 Historical notes

See:<sup>11</sup>, matrix Jensen-Bregman log-det divergence<sup>12</sup>

See also:<sup>13</sup>

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<sup>9</sup>Anoop Cherian et al. “Jensen-Bregman LogDet divergence with application to efficient similarity search for covariance matrices”. In: *IEEE transactions on pattern analysis and machine intelligence* 35.9 (2013), pp. 2161–2174.

<sup>10</sup>Meizhu Liu et al. “Shape retrieval using hierarchical total Bregman soft clustering”. In: *IEEE transactions on pattern analysis and machine intelligence* 34.12 (2012), pp. 2407–2419.

<sup>11</sup>Nielsen and Boltz, “The Burbea-Rao and Bhattacharyya centroids”; Nielsen and Nock, “Jensen-Bregman Voronoi diagrams and centroidal tessellations”; Frank Nielsen and Richard Nock. “Skew Jensen-Bregman Voronoi diagrams”. In: *Transactions on Computational Science XIV*. Springer, 2011, pp. 102–128.

<sup>12</sup>Cherian et al., “Jensen-Bregman LogDet divergence with application to efficient similarity search for covariance matrices”.

<sup>13</sup>Frank Nielsen. “A family of statistical symmetric divergences based on Jensen’s inequality”. In: *CoRR* abs/1009.4004 (2010). URL: <http://arxiv.org/abs/1009.4004>.