

## A Proof of Theorem 1

**Lemma 1:** Let  $s_i, i = 1 \dots m$ , be real numbers such that  $0 \leq s_1 \leq s_2 \dots \leq s_m$ . Then, for all permutations  $\tau \in \mathcal{S}_m$ ,

$$\sum_{i=1}^m (i - s_i)^2 \leq \sum_{i=1}^m (i - s_{\tau(i)})^2 \quad (11)$$

**Proof:** We have

$$\begin{aligned} \sum_{i=1}^m (i - s_{\tau(i)})^2 &= \sum_{i=1}^m (i - s_i + s_i - s_{\tau(i)})^2 \\ &= \sum_{i=1}^m (i - s_i)^2 + 2 \sum_{i=1}^m (i - s_i)(s_i - s_{\tau(i)}) + \sum_{i=1}^m (s_i - s_{\tau(i)})^2. \end{aligned}$$

Expanding the last equation and exploiting that  $\sum_{i=1}^m s_i^2 = \sum_{i=1}^m s_{\tau(i)}^2$  yields

$$\sum_{i=1}^m (i - s_{\tau(i)})^2 = \sum_{i=1}^m (i - s_i)^2 + 2 \sum_{i=1}^m i s_i - 2 \sum_{i=1}^m i s_{\tau(i)}.$$

On the right-hand side of the last equation, only the last term  $\sum_{i=1}^m i s_{\tau(i)}$  depends on  $\tau$ . Since  $s_i \leq s_j$  for  $i < j$ , this term becomes maximal for  $\tau(i) = i$ . Therefore, the right-hand side is larger than or equal to  $\sum_{i=1}^m (i - s_i)^2$ , which proves the lemma.  $\square$

**Lemma 2:** Let  $\Pr(\cdot | x)$  be a probability distribution over  $\mathcal{S}_m$  and let  $p(\tau) \stackrel{\text{df}}{=} \Pr(\tau | x)$ . Moreover, let

$$s_i \stackrel{\text{df}}{=} m - \sum_{j \neq i} \Pr(\lambda_i \succ_x \lambda_j) \quad (12)$$

with

$$\Pr(\lambda_i \succ_x \lambda_j) = \sum_{\tau: \tau(j) < \tau(i)} \Pr(\tau | x). \quad (13)$$

Then,  $s_i = \sum_{j \neq i} p(\tau) \tau(i)$ .

**Proof:** We have

$$\begin{aligned}
s_i &= m - \sum_{j \neq i} \Pr(\lambda_i \succ_x \lambda_j) \\
&= 1 + \sum_{j \neq i} (1 - \Pr(\lambda_i \succ_x \lambda_j)) \\
&= 1 + \sum_{j \neq i} \Pr(\lambda_j \succ_x \lambda_i) \\
&= 1 + \sum_{j \neq i} \sum_{\tau: \tau(j) < \tau(i)} p(\tau) \\
&= 1 + \sum_{\tau} p(\tau) \sum_{j \neq i} \begin{cases} 1 & \text{if } \tau(i) > \tau(j) \\ 0 & \text{if } \tau(i) < \tau(j) \end{cases} \\
&= 1 + \sum_{\tau} p(\tau) (\tau(i) - 1) \\
&= \sum_{\tau} p(\tau) \tau(i)
\end{aligned}$$

Under the assumption that the base learners' estimates correspond exactly to the probabilities of pairwise preference, i.e.,

$$\mathcal{R}_x(\lambda_i, \lambda_j) = \mathcal{M}_{ij}(x) = \Pr(\lambda_i \succ_x \lambda_j), \quad (14)$$

$s_i \leq s_j$  is equivalent to  $S(\lambda_i) \geq S(\lambda_j)$ . Thus, ranking the alternatives according to  $S(\lambda_i)$  (in decreasing order) is equivalent to ranking them according to  $s_i$  (in increasing order).

**Theorem 1:** The expected distance

$$E(\tau') = \sum_{\tau} p(\tau) \cdot D(\tau', \tau) = \sum_{\tau} p(\tau) \sum_{i=1}^m (\tau'(i) - \tau(i))^2$$

becomes minimal by choosing  $\tau'$  such that  $\tau'(i) \leq \tau'(j)$  whenever  $s_i \leq s_j$ , with  $s_i$  given by (12).

**Proof:** We have

$$\begin{aligned}
E(\tau'_x) &= \sum_{\tau} p(\tau) \sum_{i=1}^m (\tau'_x(i) - \tau(i))^2 \\
&= \sum_{i=1}^m \sum_{\tau} p(\tau) (\tau'_x(i) - \tau(i))^2 \\
&= \sum_{i=1}^m \sum_{\tau} p(\tau) (\tau'_x(i) - s_i + s_i - \tau(i))^2 \\
&= \sum_{i=1}^m \sum_{\tau} p(\tau) [(\tau(i) - s_i)^2 - 2(\tau(i) - s_i)(s_i - \tau'(i)) \\
&\qquad\qquad\qquad + (s_i - \tau'(i))^2] \\
&= \sum_{i=1}^m \left[ \sum_{\tau} p(\tau) (\tau(i) - s_i)^2 - 2(s_i - \tau'(i)) \cdot \right. \\
&\qquad\qquad\qquad \left. \cdot \sum_{\tau} p(\tau) (\tau(i) - s_i) + \sum_{\tau} p(\tau) (s_i - \tau'(i))^2 \right]
\end{aligned}$$

In the last equation, the mid-term on the right-hand side becomes 0 according to Lemma 2. Moreover, the last term obviously simplifies to  $(s_i - \tau'(i))$ , and the first term is a constant  $c = \sum_{\tau} p(\tau) (\tau(i) - s_i)^2$  that does not depend on  $\tau'$ . Thus, we obtain  $E(\tau'_x) = c + \sum_{i=1}^m (s_i - \tau'(i))^2$  and the theorem follows from Lemma 1.  $\square$