Combining absolute and relative information in studies on food quality

Marc Sader, Raúl Pérez-Fernández, and Bernard De Baets

KERMIT, Department of Data Analysis and Mathematical Modelling,
Ghent University, Coupure links 653, 9000 Gent, Belgium
{marc.sader,raul.perezfernandez,bernard.debaets}@ugent.be

Abstract. A common problem in food science concerns the assessment of the quality of food samples. Typically, a group of panellists is trained exhaustively on how to identify different quality indicators in order to provide absolute information, in the form of scores, for each given food sample. Unfortunately, this training is expensive and time-consuming. For this very reason, it is quite common to search for additional information provided by untrained panellists. However, untrained panellists usually provide relative information, in the form of rankings, for the food samples. In this paper, we discuss how both scores and rankings can be combined in order to improve the quality of the assessment.

Keywords: Consensus evaluation; Absolute information; Relative information.

1 Introduction

We consider the problem in which several panellists are asked to score a food sample on a given ordinal scale, the goal being to reach a consensus evaluation of the sample. This problem commonly appears in food science, for instance, when identifying the degree of spoilage [1, 2] or when evaluating the appearence [3, 4] of a given sample. Unfortunately, training and (subsequently) collecting information from panellists usually carries big expenses. For this reason, there usually is a limited amount of data available to reach a consensus evaluation. It is thus quite common to invoke untrained panellists and to gather some additional information [5]. However, untrained panellists are obviously not as skilled as trained panellists, and might be unable to accurately evaluate a given sample. Since it is a conceptually easier task, untrained panellists are then just asked to rank different samples according to their personal appreciation. In this paper, we propose to combine both types of information in order to improve the quality of the assessment. Moreover, we illustrate our proposal by discussing an experiment concerning the freshness of raw Atlantic salmon (*Salmo salar*) [6].

The remainder of the paper is organized as follows. In Section 2, we recall the well-known notions of median and Kemeny median. Section 3 is devoted to the introduction of a method for reaching a consensus evaluation of the given samples while combining both scoring and ranking information. We end with some conclusions in Section 4.

2 Preliminaries

2.1 Obtaining a consensus vector of scores

We consider the setting where n_T trained panellists are asked to assign a score on a k-point scale to each (food) sample in a set $X = \{x_1, \ldots, x_n\}$ of n (food) samples. The goal is to agree on the consensus score that should be assigned to each of the samples based on the scores provided by the trained panellists. For any $i \in \{1, \ldots, n_T\}$, we denote by $\mathbf{s}_i$ the vector of scores assigned by the i-th panellist. The scale we use throughout this paper is shown in Figure 1.

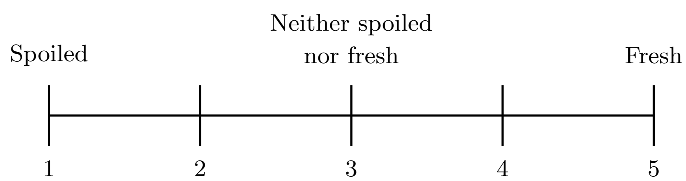

Fig. 1. Example of a 5-point scale, where the extreme scores of "1" and "5" represent spoiled and fresh, respectively, and the intermediate score of "3" represents a neutral response of neither spoiled nor fresh.

A common method for determining the consensus vector of scores is based on the minimization of a distance, i.e., the consensus vector of scores $\mathbf{s}^*$ should satisfy

$$\mathbf{s}^* = \mathop{\arg\min}_{\mathbf{s} \in \{1,\ldots,k\}^n} \sum_{i=1}^{n_T} d(\mathbf{s}, \mathbf{s}_i)\,,$$

where d is a fixed distance function on the set of vectors of scores. Note that there can be multiple minimizers $\mathbf{s}^*$.

One could note that several examples of this procedure are commonly used in practice. For instance, when we consider the sum of zero-one distances[1] over

[1] The zero-one distance function is defined as $d_0(s, s') = 0$ if $s = s'$ and $d_0(s, s') = 1$ otherwise.

all components, the preceding method amounts to identifying the mode(s). Similarly, when we consider the sum of ℓ_1-distances[2], the preceding method amounts to identifying the median(s), and, when we consider the sum of ℓ_2-distances[3], it amounts to identifying the mean(s). One could note that the latter method presumes the existence of a certain notion of distance between labels, something that is not advisable in case the considered scale is defined by abstract words [7].

Example 1. Consider the set of $n = 4$ samples $X = \{x_1, x_2, x_3, x_4\}$ and the vectors of scores on the fixed 5-point scale provided by $n_T = 10$ trained panellists shown in Table 1. Note that these data come from a real-life dataset concerning an experiment on raw Atlantic salmon (*Salmo salar*) [6].

	$\mathbf{s}_1$	$\mathbf{s}_2$	$\mathbf{s}_3$	$\mathbf{s}_4$	$\mathbf{s}_5$	$\mathbf{s}_6$	$\mathbf{s}_7$	$\mathbf{s}_8$	$\mathbf{s}_9$	$\mathbf{s}_{10}$
x_1	5	4	5	2	3	3	5	5	2	4
x_2	5	2	1	2	4	2	5	4	3	3
x_3	2	1	5	2	2	4	3	2	2	2
x_4	3	1	2	1	2	2	2	3	3	1

Table 1. The scores assigned to samples x_1, x_2, x_3 and x_4 by the trained panellists.

For each of the 625 possible vectors of scores, we compute the sum of ℓ_1-distances to the vectors of scores provided by the trained panellists. We conclude that the vector of scores that minimizes this value is $\mathbf{s}^* = (4, 3, 2, 2)$. As expected, this vector coincides with the one obtained by identifying the median for each of the samples. $\triangleleft$

2.2 Obtaining a consensus ranking

We consider the setting where n_U untrained panellists are asked to rank all the samples on the considered set $X = \{x_1, \dots, x_n\}$ of n samples. Untrained panellists are asked to provide a complete ranking of the samples, however, they are allowed to express ties in case they consider two or more samples to be equally suitable. The goal is to agree on the consensus ranking that should be assigned to each of the samples based on the scores provided by the trained panellists. For any $i \in \{1, \dots, n_U\}$, we denote by $\precsim_i$ the ranking assigned by the i-th panellist, which can be split into the usual symmetric $\sim_i$ and antisymmetric $\prec_i$ parts. We denote by $\mathcal{W}$ the set of all rankings (with ties) on X.

[2] The ℓ_1-distance function is defined as $d_1(s, s') = |s - s'|$.
[3] The ℓ_2-distance function is defined as $d_2(s, s') = (s - s')^2$.

A common method for determining the consensus ranking is due to Kemeny [8] in which a consensus ranking $\precsim^*$ is one that satisfies

$$\precsim^* = \arg\min_{\precsim \in \mathcal{W}} \sum_{i=1}^{n_U} K(\precsim, \precsim_i)\,,$$

where $K(\precsim^1, \precsim^2)$ denotes the Kemeny distance between two rankings $\precsim^1$ and $\precsim^2$. We recall that the Kemeny distance[4] between two rankings is computed as follows. For each pair of samples $\{x_u, x_v\}$, if both rankings agree on the order of the samples, we write down 0; if, in one ranking, x_u is ranked above x_v (or x_v is ranked above x_u) and, in the other ranking, x_u and x_v are tied, we write down 1; and, if, in one ranking, x_u is ranked above x_v and, in the other ranking, x_v is ranked above x_u, we write down 2. After writing down the numbers for all $n(n-1)/2$ possible pairs, the Kemeny distance between the two rankings equals the sum of these numbers.

Example 2. Consider the same set of $n = 4$ samples $X = \{x_1, x_2, x_3, x_4\}$ of Example 1, and the rankings provided by $n_U = 28$ untrained panellists shown in Table 2. Note that these data also come from the experiment on raw Atlantic salmon (*Salmo salar*) in [6].

i	$\precsim_i$	i	$\precsim_i$
1	$x_2 \sim x_4 \prec x_3 \sim x_2$	15	$x_2 \prec x_1 \prec x_4 \prec x_3$
2	$x_4 \prec x_3 \prec x_2 \prec x_1$	16	$x_4 \prec x_3 \sim x_2 \prec x_1$
3	$x_4 \prec x_2 \prec x_3 \sim x_1$	17	$x_4 \prec x_3 \sim x_2 \prec x_1$
4	$x_1 \prec x_4 \prec x_3 \prec x_2$	18	$x_4 \prec x_3 \sim x_2 \prec x_1$
5	$x_1 \sim x_4 \prec x_3 \prec x_2$	19	$x_2 \prec x_4 \prec x_3 \prec x_1$
6	$x_4 \prec x_3 \sim x_1 \sim x_2$	20	$x_4 \prec x_3 \prec x_2 \prec x_1$
7	$x_4 \sim x_3 \prec x_1 \sim x_2$	21	$x_1 \sim x_4 \prec x_3 \sim x_2$
8	$x_4 \prec x_1 \sim x_2 \prec x_2$	22	$x_1 \sim x_2 \prec x_3 \prec x_4$
9	$x_1 \prec x_3 \sim x_2 \prec x_4$	23	$x_4 \prec x_3 \prec x_2 \prec x_1$
10	$x_2 \prec x_4 \prec x_1 \prec x_3$	24	$x_4 \prec x_1 \prec x_2 \prec x_3$
11	$x_4 \prec x_2 \prec x_3 \prec x_1$	25	$x_4 \prec x_2 \prec x_3 \prec x_1$
12	$x_4 \prec x_1 \prec x_3 \sim x_2$	26	$x_1 \prec x_4 \prec x_3 \prec x_2$
13	$x_2 \sim x_4 \sim x_3 \prec x_1$	27	$x_4 \prec x_2 \prec x_3 \prec x_1$
14	$x_2 \prec x_4 \prec x_1 \prec x_3$	28	$x_4 \prec x_2 \prec x_3 \prec x_1$

Table 2. The rankings expressed by the untrained panellists.

For each of the 75 possible rankings, we compute the sum of Kemeny distances to the rankings provided by the untrained panellists. We conclude that the ranking that minimizes this value is $\precsim^* = x_4 \prec x_3 \sim x_2 \prec x_1$. $\triangleleft$

[4] When the rankings contain no ties, the Kemeny distance is equal to the double of the Kendall distance [9].

3 Combining scores and rankings

We now consider the setting where n_T trained panellists each have assigned a score to each of the n samples in X and n_U untrained panellists each have ranked the n samples in X. The goal is to combine both types of information in order to improve the quality of the assessment of the consensus vector of scores and/or ranking. We propose to consider a combination of the median and the Kemeny median.

3.1 Improving the quality of the assessment of a consensus vector of scores

To compute the 'distance'[5] between each possible vector of scores $\mathbf{s}$ and the rankings provided by the untrained panellists, we define the set $\theta_{\mathbf{s}}$ of all possible rankings that do not contradict $\mathbf{s}$, as follows:

$$\theta_{\mathbf{s}} = \left\{ \precsim \in \mathcal{W} \,\middle|\, (\forall i, j \in \{1, \ldots, n\}) \big(\mathbf{s}(i) < \mathbf{s}(j) \Rightarrow x_i \prec x_j\big) \right\}. \tag{1}$$

Note that the set $\theta_{\mathbf{s}}$ is always non-empty.

Incorporating the rankings provided by the untrained panellists into the vectors of scores provided by the trained panellists requires defining a cost function. Thus, we define a convex combination of the 'distances' associated with the vectors of scores provided by the trained panellists and the rankings provided by the untrained panellists, as follows:

$$C_\alpha(\mathbf{s}) = \frac{\alpha}{B_T} \sum_{i=1}^{n_T} d_1(\mathbf{s}, \mathbf{s}_i) + \frac{(1-\alpha)}{B_U} \min_{\precsim \in \theta_{\mathbf{s}}} \sum_{i=1}^{n_U} K(\precsim, \precsim_i). \tag{2}$$

where $B_T = n_T \cdot n \cdot (k-1)$ and $B_U = n_U \cdot n \cdot (n-1)$ are normalizing constants, and $\alpha \in [0, 1]$ is a parameter that controls the influence of the scoring and ranking information. In particular, larger values of α give more importance to the trained panellists, whereas smaller values of α give more importance to the untrained panellists.

Finally, we consider the consensus vector(s) of scores to be the minimizer(s) of Eqs. (2) for a fixed α, as follows:

$$\mathbf{s}^*_\alpha = \underset{\mathbf{s} \in \{1,\ldots,k\}^n}{\arg\min}\; C_\alpha(\mathbf{s}). \tag{3}$$

Note that there can be multiple minimizers $\mathbf{s}^*_\alpha$ for the same α.

[5] Note that we write the word 'distance' between quotation marks since we are comparing objects of a different nature, and, thus, we are lacking the semantics associated with the mathematical formalization of a distance (metric).

Example 3. We continue with the data from Examples 1 and 2. To determine the consensus score that should be assigned to each of these samples, we consider the problem defined by Eq. (3) by computing $C_\alpha(\mathbf{s})$ for each of the 625 vectors of scores. For simplicity, we show one computation for the vector of scores $\mathbf{s} = (4,3,2,2)$, which was determined as the consensus vector of scores in Example 1, with $\sum_{i=1}^{10} d_1(\mathbf{s},\mathbf{s}_i) = 34$. The distances associated with the vectors of scores are bounded by the upper bound $B_T = 10 \cdot 4 \cdot 4 = 160$, whereas the distances associated with the rankings are bounded by the upper bound $B_U = 28 \cdot 4 \cdot 3 = 336$. Now, we consider the set $\theta_\mathbf{s}$ of all possible rankings that do not contradict $\mathbf{s}$. Since the score of x_1 is the largest, x_1 is ranked above the other samples. Similarly, x_2 is ranked above x_3 and x_4. Since the scores of x_3 and x_4 are equal, any of the following cases applies: x_3 is ranked above x_4, x_3 and x_4 are tied, and x_4 is ranked above x_3, as follows:

$$\theta_{(4,3,2,2)} = \left\{ \begin{array}{c} x_4 \prec x_3 \prec x_2 \prec x_1 \,, \\ x_3 \sim x_4 \prec x_2 \prec x_1 \,, \\ x_3 \prec x_4 \prec x_2 \prec x_1 \end{array} \right\} .$$

We compute the sum of the Kemeny distances between each $\precsim \in \theta_\mathbf{s}$ and the rankings provided by the untrained panellists. The results are summarized in Table 3.

$\precsim$	$\sum_{i=1}^{28} K(\precsim, \precsim_i)$
$x_4 \prec x_3 \prec x_2 \prec x_1$	109
$x_3 \sim x_4 \prec x_2 \prec x_1$	129
$x_3 \prec x_4 \prec x_2 \prec x_1$	153

Table 3. Sum of Kemeny distances between each ranking $\precsim$ that does not contradict $\mathbf{s} = (4,3,2,2)$ and the rankings provided by the untrained panellists.

Finally, we select the ranking that minimizes the sum of Kemeny distances among those in $\theta_\mathbf{s}$ and compute $C_\alpha(\mathbf{s})$ as follows:

$$\begin{aligned} C_\alpha(\mathbf{s}) &= \frac{\alpha}{160} \sum_{i=1}^{10} d_1(\mathbf{s},\mathbf{s}_i) + \frac{(1-\alpha)}{336} \, \min \begin{pmatrix} \sum_{i=1}^{28} K(x_4 \prec x_3 \prec x_2 \prec x_1, \precsim_i) \,, \\ \sum_{i=1}^{28} K(x_3 \sim x_4 \prec x_2 \prec x_1, \precsim_i) \,, \\ \sum_{i=1}^{28} K(x_3 \prec x_4 \prec x_2 \prec x_1, \precsim_i) \end{pmatrix} \\ &= \frac{109}{336} - \frac{6016}{53760} \, \alpha \,. \end{aligned}$$

After computing $C_\alpha(\mathbf{s})$ for each of the 625 possible vectors of scores $\mathbf{s}$, we illustrate in Figure 2 all the $\mathbf{s}_\alpha^*$ that minimize $C_\alpha(\mathbf{s})$ for at least one value of $\alpha \in [0,1]$. One should note that, for $\alpha = 0$, there will always be multiple minimizers $\mathbf{s}_0^*$ associated with all vectors of scores that are not contradicted by the Kemeny median. Since we know from Example 2 that $\precsim^* = x_4 \prec x_3 \sim x_2 \prec x_1$ is the Kemeny median, we illustrate (in black) all the vectors of scores $\mathbf{s}_0^*$ that are not contradicted by this $\precsim^*$. These vectors of scores form a fan-shaped pattern starting at $\alpha = 0$ since, at the left end, they all result in the same value $C_0(\mathbf{s})$, and, at the right end, they result in (mostly) different values $C_1(\mathbf{s})$.

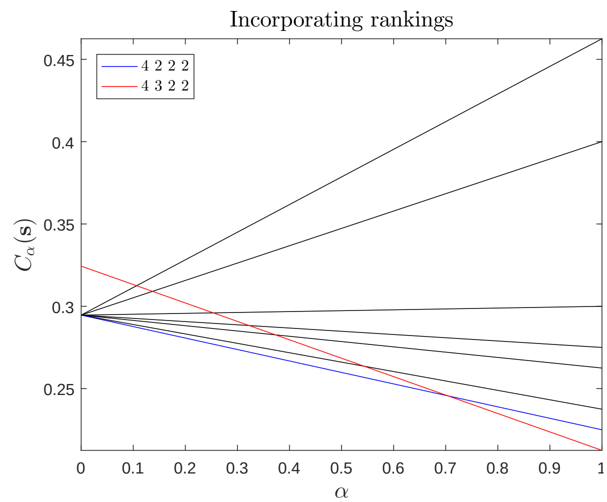

Fig. 2. Illustration of the vectors of scores $\mathbf{s}^*_\alpha$ that minimize $C_\alpha(\mathbf{s})$ for $\alpha \in [0, 1]$.

Since we do not intend to rely only on the rankings provided by the untrained panellists, we ignore the minimizers for $\alpha = 0$. The obtained minimizers $\mathbf{s}^*_\alpha$ are summarized as follows:

$$\mathbf{s}^*_\alpha = \begin{cases} \{(4,2,2,2)\} & \text{, if } 0 < \alpha < \frac{50}{71}\,, \\ \{(4,2,2,2)\,,(4,3,2,2)\} & \text{, if } \alpha = \frac{50}{71}\,, \\ \{(4,3,2,2)\} & \text{, if } \alpha > \frac{50}{71}\,. \end{cases} \tag{4}$$

We deduce based on the vectors of scores provided by the trained panellists that x_2 is ranked at a better position than x_3 and x_4, since the former is assigned a higher score than the former in the consensus vector of scores for large values of α. However, incorporating the rankings provided by the untrained panellists hints that these samples are similar. $\triangleleft$

3.2 Improving the quality of the assessment of a consensus ranking

To compute the 'distance' between each possible ranking $\precsim$ and the vectors of scores provided by the trained panellists, we define the set $\varphi_\precsim$ of all possible vectors of scores that do not contradict $\precsim$, as follows:

$$\varphi_\precsim = \big\{\mathbf{s} \in \{1,\ldots,k\}^n \,\big|\, (\forall i,j \in \{1,\ldots,n\})\big(x_i \precsim x_j \Rightarrow \mathbf{s}(i) \le \mathbf{s}(j)\big)\big\}\,. \tag{5}$$

Note that the set $\varphi_{\precsim}$ is always non-empty.

The convex combination of the 'distances' associated with the vectors of scores provided by the trained panellists and the rankings provided by the untrained panellists is now defined as follows:

$$D_\alpha(\precsim) = \frac{\alpha}{B_T} \min_{\mathbf{s} \in \varphi_{\precsim}} \sum_{i=1}^{n_T} d_1(\mathbf{s}, \mathbf{s}_i) + \frac{(1-\alpha)}{B_U} \sum_{i=1}^{n_U} K(\precsim, \precsim_i) \,. \tag{6}$$

Finally, we consider the consensus ranking(s) to be the minimizer(s) of Eqs. (6) for a fixed α, as follows:

$$\precsim_\alpha^* = \arg\min_{\precsim \in \mathcal{W}} D_\alpha(\precsim) \,. \tag{7}$$

Note that there can be multiple minimizers $\precsim_\alpha^*$ for the same α.

Since $\alpha \in [0,1]$ can take infinite values, it will be impossible to compute $\mathbf{s}_\alpha^*$ (resp. $\precsim_\alpha^*$) for each α. Therefore, bearing in mind that, for any fixed vector of scores $\mathbf{s}$ (resp. ranking $\precsim$), the corresponding $f(\alpha) := C_\alpha(\mathbf{s})$ (resp. $g(\alpha) := D_\alpha(\precsim)$) can be visualized as a line, we can compare the lines of each possible pair of vectors of scores (resp. rankings). When comparing two lines, we distinguish three cases: there are no points of intersection, there is exactly one point of intersection, or both lines coincide. These facts can then be used to analytically compute $\mathbf{s}_\alpha^*$ and $\precsim_\alpha^*$ as a function of α.

Example 4. We continue with the data from Example 3. To determine the consensus ranking of the samples, we consider the problem defined by Eq. (7) by computing $D_\alpha(\precsim)$ for each of the 75 rankings. For simplicity, we show one computation for the ranking $\precsim = x_4 \prec x_3 \sim x_2 \prec x_1$, which was determined as the consensus ranking in Example 2, with $\sum_{i=1}^{28} K(\precsim, \precsim_i) = 99$. Now, we consider the set $\varphi_{\precsim}$ of all possible vectors of scores that do not contradict $\precsim$.

$$\varphi_{x_4 \prec x_3 \sim x_2 \prec x_1} = \left\{ \mathbf{s} \in \{1, \ldots, 5\}^4 \mid \mathbf{s}(4) \leq \mathbf{s}(3) = \mathbf{s}(2) \leq \mathbf{s}(1) \right\} \,.$$

We compute the sum of the ℓ_1-distances between each $\mathbf{s} \in \varphi_{\precsim}$ and the vectors of scores provided by the untrained panellists. We note that the vector of scores among those in $\varphi_{\precsim}$ that minimizes the sum of the ℓ_1-distances is $(4,2,2,2)$ with $\sum_{i=1}^{10} d_1(\mathbf{s}, \mathbf{s}_i) = 36$. Finally, we obtain:

$$D_\alpha(\precsim) = \frac{113}{336} - \frac{5984}{53760} \alpha \,.$$

After computing $D_\alpha(\precsim)$ for each of the 75 possible rankings $\precsim$, we illustrate in Figure 3 all the $\precsim_\alpha^*$ that minimize $D_\alpha(\precsim)$ for at least one value of $\alpha \in [0,1]$. One should note that, for $\alpha = 1$, there will always be multiple minimizers $\mathbf{s}_1^*$ associated with all rankings that are not contradicted by the median. Since we know from Example 1 that $\mathbf{s}^* = (4,3,2,2)$ is the median, we illustrate all the rankings $\precsim_1^*$ that are not contradicted by this $\mathbf{s}^*$. These rankings form a fan-shaped pattern starting at $\alpha = 1$ since, at the right end, they all result in the same value $D_1(\precsim)$, and, at the left end, they result in (mostly) different values $D_0(\precsim)$.

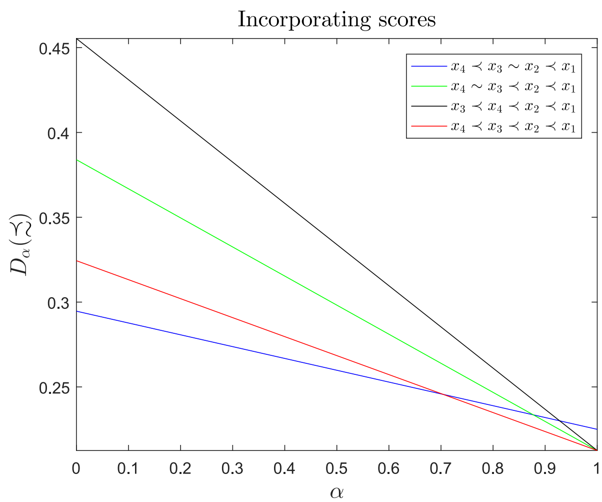

Fig. 3. Illustration of the rankings $\precsim_\alpha^*$ that minimize $D_\alpha(\precsim)$ for $\alpha \in [0, 1]$.

Since we do not intend to rely only on the scores provided by the trained panellists, we ignore the minimizers for $\alpha = 1$. The obtained minimizers $\precsim_\alpha^*$ are summarized as follows:

$$\mathbf{s}_\alpha^* = \begin{cases} \{x_4 \prec x_3 \sim x_2 \prec x_1\} & , \text{ if } \quad \alpha < \frac{50}{71}\,, \\ \left\{\begin{matrix} x_4 \prec x_3 \sim x_2 \prec x_1 \\ x_4 \prec x_3 \prec x_2 \prec x_1 \end{matrix}\right\} & , \text{ if } \quad \alpha = \frac{50}{71}\,, \\ \{x_4 \prec x_3 \prec x_2 \prec x_1\} & , \text{ if } \frac{50}{71} < \alpha < 1\,. \end{cases} \tag{8}$$

We deduce based on the rankings provided by the untrained panellists that x_2 and x_3 are similar. However, incorporating the vectors of scores provided by the trained panellists hints that sample x_2 might be ranked above sample x_3. $\triangleleft$

3.3 Discussion

A deeper analysis of the results of the preceding subsections shows that both trained and untrained panellists agree that samples x_1 and x_4 are, respectively, the best and worst samples in $X = \{x_1, x_2, x_3, x_4\}$. However, there is a disagreement with regard to samples x_2 and x_3. While trained panellists considered sample x_2 to be better than sample x_3, untrained panellists did not see significant differences between both samples. Thus, as can be concluded from both Eqs. (4) and (8), samples x_2 and x_3 result to be similar ($\mathbf{s}^*(3) = \mathbf{s}^*(2)$ and $x_3 \sim^* x_2$) for smaller values of α (i.e., in case more importance is given to the untrained panellists), whereas sample x_2 results to be better than sample x_3 ($\mathbf{s}^*(3) < \mathbf{s}^*(2)$ and $x_3 \prec^* x_2$) for larger values of α (i.e., in case more importance is given to the trained panellists).

4 Conclusions

In this paper, we have discussed how to combine absolute and relative information in order to improve the quality of the assessment of food samples. In particular, we have proposed a method based on a convex combination of the distances associated with the median and the Kemeny median. We have illustrated the use of this method using real-life examples, where the freshness of Atlantic salmon was studied, and showed the influence of combining scores and rankings on obtaining the consensus vector of scores and consensus ranking.

Acknowledgments

We gratefully acknowledge Innovation by Science and Technology (IWT) (now known as Flanders Innovation and Entrepreneurship (VLAIO)) for their support of the project CheckPack (IWT-SBO-130036) - Integrated optical sensors in food packaging to simultaneously detect early-spoilage and check package integrity. Raúl Pérez-Fernández is supported as a postdoc by the Research Foundation of Flanders (FWO17/PDO/160).

References

1. Argyri, A.A., Doulgeraki, A.I., Blana, V.A., Panagou, E.Z., Nychas, G.J.E.: Potential of a simple HPLC-based approach for the identification of the spoilage status of minced beef stored at various temperatures and packaging systems. International Journal of Food Microbiology **150**(1) (2011) 25–33
2. Argyri, A.A., Panagou, E.Z., Tarantilis, P.A., Polysiou, M., Nychas, G.J.E.: Rapid qualitative and quantitative detection of beef fillets spoilage based on Fourier transform infrared spectroscopy data and artificial neural networks. Sensors and Actuators B: Chemical **145**(1) (2010) 146–154
3. Rogers, H.B., Brooks, J.C., Martin, J.N., Tittor, A., Miller, M.F., Brashears, M.M.: The impact of packaging system and temperature abuse on the shelf life characteristics of ground beef. Meat Science **97**(1) (2014) 1–10
4. Smolander, M., Hurme, E., Latva-Kala, K., Luoma, T., Alakomi, H.L., Ahvenainen, R.: Myoglobin-based indicators for the evaluation of freshness of unmarinated broiler cuts. Innovative Food Science and Emerging Technologies **3**(3) (2002) 279–288

5. Amerine, M.A., Pangborn, R.N., Poessler, E.B.: Principles of Sensory Evaluation of Food. Academic Press, New York (1965)
6. Sader, M., Pérez-fernández, R., Kuuliala, L., Devlieghere, F., De Baets, B.: A combined scoring and ranking approach for determining overall food quality. submitted (2018)
7. Franceschini, F., Galetto, M., Varetto, M.: Qualitative ordinal scales: The concept of ordinal range. Quality Engineering **16**(4) (2004) 515–524
8. Kemeny, J.G.: Mathematics without numbers. Daedalus **88**(4) (1959) 577–591
9. Kendall, M.G.: A new measure of correlation. Biometrika **30**(1-2) (1938) 81–93