Another way to treat JAR scales: application to the sensory characterization of products

BERTHELO Sébastien, BROSSIER Morgan, GOURRET Damien, PAGÈS Jérôme

AGROCAMPUS OUEST – Laboratoire de Mathématiques Appliquées

65 rue de Saint Brieuc , CS 84215, 35042 Rennes cedex , France

Introduction

Sensory tests are often conducted in blind conditions but don't refer to the real conditions of consumption. Also, the aim of this study is to observe how some information like the packaging can affect the sensorial perception of a food product, the orange juice. For that, a sensory analysis was performed in two situations: in blind and with information. The same questionnaire, using a 5-points "Just About Right" scales and a hedonic scale, was filled by 105 assessors for each session.

Nowadays, the penalty analysis tests the significance of the mean drop (difference in mean hedonic score between those who feel a flavor has too much or not enough of an attribute and those who feel that attribute is just right). However, this method doesn't consider the relation between descriptors causing a bad estimation of penalties. This poster presents a new methodology to treat penalty analysis to better determine drivers of liking.

Consumers' data

The questionnaire is structured as follows:

› 6 sensorial descriptors using a 5-points «Just About Right » (JAR) scale:

- Color Nuance (Nc)
- Odor Intensity (Io)
- Sugar Taste (Su)
- Acidity (Ac)
- Bitterness (Am)
- Pulpy Character (Pu)

Not enough at all	Not enough	JAR	Too much	Far too much
☐	☐	☐	☐	☐

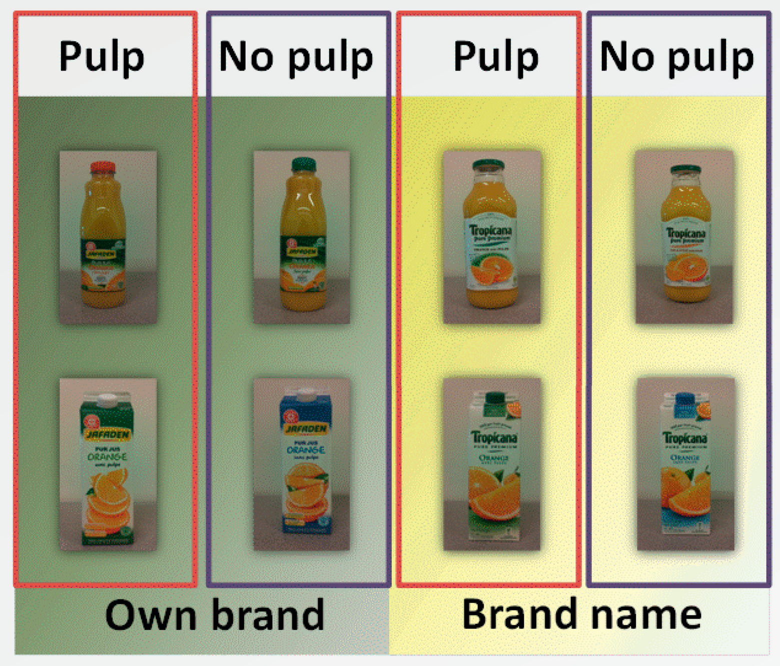
› 1 hedonic score (0-10 scale)

105 assessors evaluated 8 orange juices in two situations:

Situation 1
Blind sensory analysis

Situation 2
Sensory analysis with information (packaging, price, shelf…)

Product category



Method

Penalty Analysis

In sensory analysis, descriptors are often correlated between them. Also, it seems important to consider them together in a model in order to not admit that a single descriptor impacts the overall score. A product is evaluated with the set of variables. The proposed models will avoid an overestimation of the coefficients for all the descriptors which are considered together in the model. The new methodology is performed in 4 steps:

1- JAR scale are aggregated in 3 levels (« Not enough » , « JAR », « Too much»).

2- For each descriptor, levels are recoded in complete disjunctive table.

3- Anova model is performed with all the descriptors. Nevertheless, modality "JAR" is not included in the model to get $\alpha_{JAR} = 0$ and so will be considered in the constant. Recoded variables are analysed as quantitative variables.

4- Other factors (Product and assessor) can be added in the model: the constraint $\Sigma\alpha i = 0$ is applied in the model and these variables are qualitative.

✓ Also, the quality of the model is improved.

✓ The penalty analysis is performed with the following analysis of variance:

Assessor	Product	Nc Not_enough	Nc JAR	Nc Too_much	…	Pu Not_enough	Pu JAR	Pu Too_much	Hedonic score
1	JApA	0	~~1~~	0		0	~~1~~	0	6
1	JSpR	0	~~0~~	1		0	~~0~~	1	5
1	TApR	1	~~0~~	0		1	~~0~~	0	2
…	…	…	~~…~~	…	…	…	~~…~~	…	…
105	TApA	0	~~0~~	1		0	~~0~~	1	8

› Modalities of descriptors are treated in quantitative

› « JAR » modality is not included in the model to be present in the constant (as the reference): regression coefficients represent penalties and are directly interpretable.

All products together Analysis: Model 1

Hedonic score ~ $Descriptor_1$_Not enough + $Descriptor_1$_Too much + … + $Descriptor_p$_Not enough + $Descriptor_p$_Too much + Product + Assessor

Modalities of descriptors (in blue) are quantitative and their coefficient estimated correspond to the penalty.

Considering all the descriptors and all the products, the penalty estimation is improved. Moreover, a significant is associated for each penalty.

Results for the situation 1 using this model are presented below:

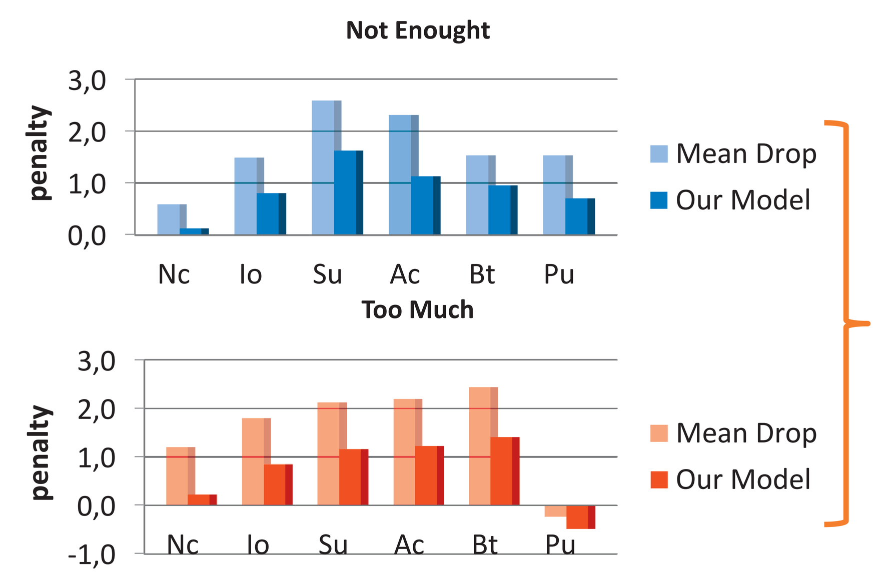
	Penalty	P_value
Nc -	0,59	5,3E-06
Nc +	0,3	0,02
Io -	0,53	2,6E-06
Io +	0,52	0,01
Su -	1,52	4,5E-28
Su +	1,2	1,4E-23
Ac -	1,11	2,0E-16
Ac +	0,96	2,6E-16
Bt -	1,05	2,6E-11
Bt +	1,2	7,2E-25
Pu -	0,8	6,0E-08
Pu +	0,82	7,0E-08

The most penalizing defects on the hedonic score are those related to the balance of flavours whatever orange juices.

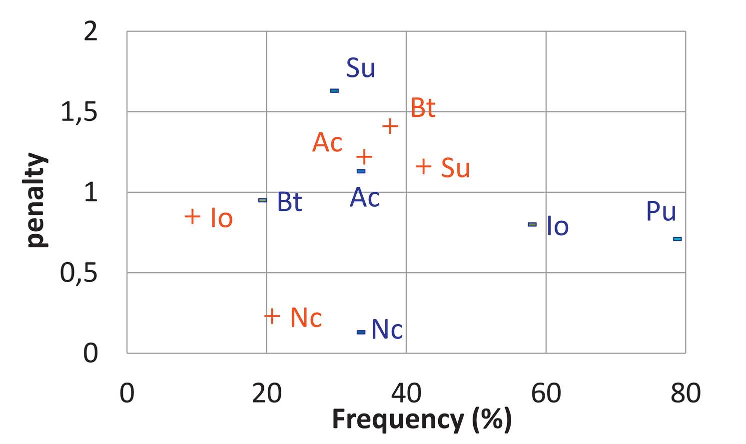
Analysis by product: Model 2

Hedonic score ~ $Descriptor_1$_Not enough + $Descriptor_1$_Too much + … + $Descriptor_p$_Not enough + $Descriptor_p$_Too much

This model is advocated to estimate penalties of one product. Graphics below compare estimations of penalties performed with our model and done with classic method (mean drop). We observed that the mean drop overestimates penalties of each descriptor.



Example of useful graph to observe penalties with the new model (for the orange juice JSpR in situation 1):



Results

Penalty analysis

To answer the issue, the first model is used on each dataset obtained from both situations.

The method directly returns penalties (driven by the modalities "Not enough" and "Too much" of descriptors) on the hedonic score.

For example, in situation 1, when the character "Not enough sweet" is chosen by a assessor, the estimated hedonic score is reduced by more than 1.5 points whatever the orange juice.

A significant Brand effect appears in situation 2: Brand name products are over-evaluated by about 0.3 points. Instead, Own brands are underestimated by 0.3 points (difference of 0.6 points between both) on a 0-10 scale.

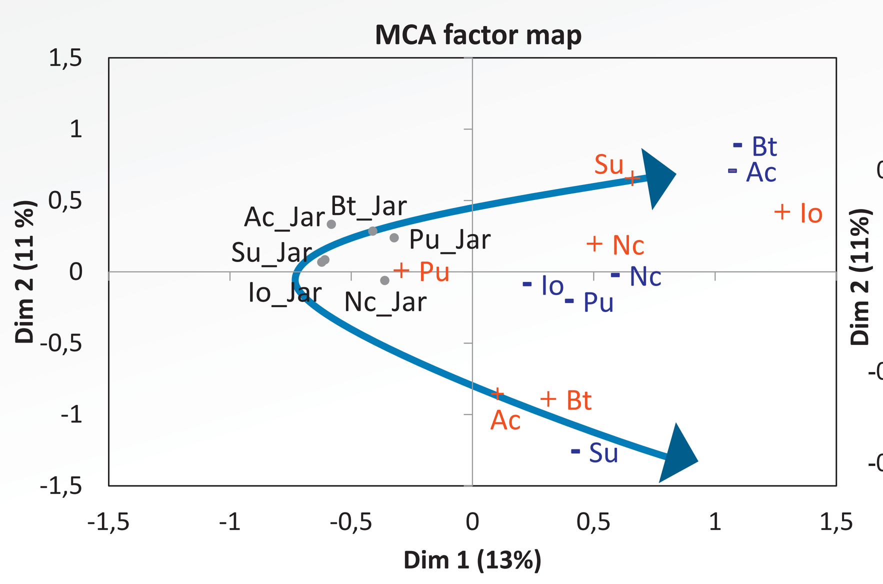
	Penalties Situation 1	Penalties Situation 2
Constant	8,39	8,34
Nc -	-0,59	-0,33
Nc +	-0,30	-0,38
Io -	-0,52	-0,35
Io +	-0,51	-0,24
Su -	-1,51	-1,30
Su +	-1,20	-0,81
Ac -	-1,11	-1,09
Ac +	-0,95	-1,11
Bt -	-1,05	-1,15
Bt +	-1,19	-1,21
Pu -	-0,80	-0,84
Pu +	-0,81	-0,95
Pulp -Pulp	0,006	0,01
Pulp -No_Pulp	-0,06	-0,01
Preservation-Ref	0,04	0,10
Preservation-Non_Ref	-0,04	-0,10
Brand-Own Brand	-0,01	-0,30
Brand-Brand_Name	0,01	0,30

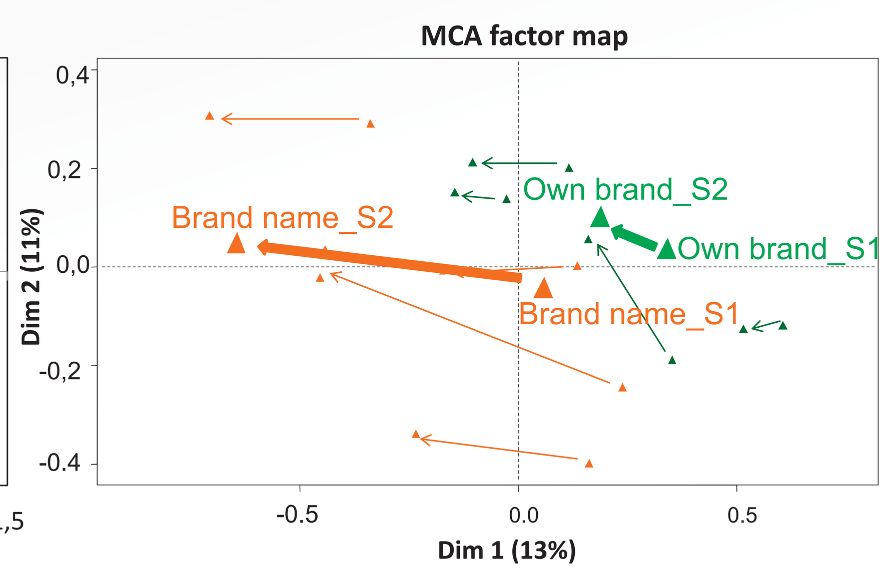
An optimal design allows to decompose the product effect

Multiple Correspondence Analysis (MCA)

In parallel with the method (model 1), a multivariate analysis (MCA) was performed on the dataset to quickly view the presence or absence of defects for each product.

A relationship between descriptors is highlighted on the factor map, which justifies taking them all together in the model. For example, a product perceived as "Not enough acid" will also be seen as "Too bitter" and "Too sweet".





Brand name products are considered to have fewer defects than Own brand orange juices, whatever the situation. In situation 2, Brand name products benefit of their brand image and are less penalized.

Conclusion

A part of results shows that the brand name is less penalized than the own brand by assessors and every products were perceived as better quality when information was available. The model proposed allows a better estimation of penalties and to easily identify important descriptors by considering all of them into an Anova model. The method can be adjusted according to the issue: study a product category or only one product

This methodology is available with an Add-in Excel : https://sites.google.com/site/anotherwaytotreatjarscales