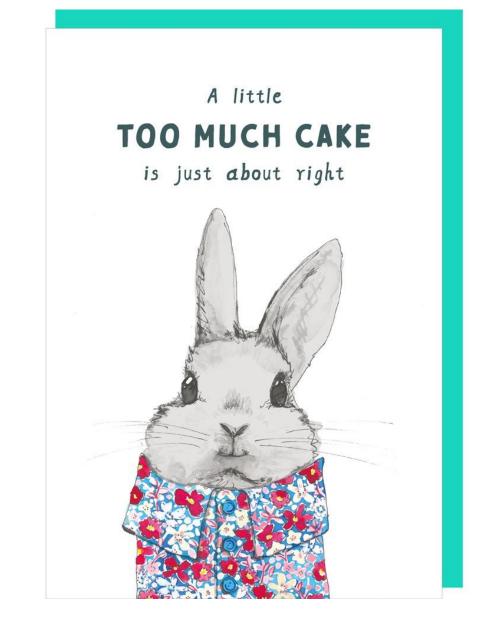
Free Just – About – Right Methodology

Lê Tuấn Phúc - HUST



Let's start with what a JAR is

- ☐ (JAR) scaling is widely applied in the food industry for product development
- The JAR scale is a bipolar measurement. In JAR scaling, two semantically opposite anchors and the midpoint is labeled "Just About Right"
- ☐ JAR scales are very to be an easy way to determine if an attribute's intensity is at an optimal level

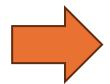


	JUST A	ABOUT RIGHT SCALES	
Category:			
		Very much too sweet	
		Too sweet	
		Slightly too sweet	
		Just about right	
		Slightly not sweet enough	ı
		Not sweet enough	
		Very much not sweet end	ough
Line Scale:			
Not Nearly Sweet enough I		Just about Right I	Much too Sweet
Directional Scal	le:		
		Increase it a lot	
		Increase it moderately	
		Increase it slightly	
		Don't change, leave it the	same
		Decrease it slightly	
		Decrease it moderately	
		Decrease it a lot	

Limitation

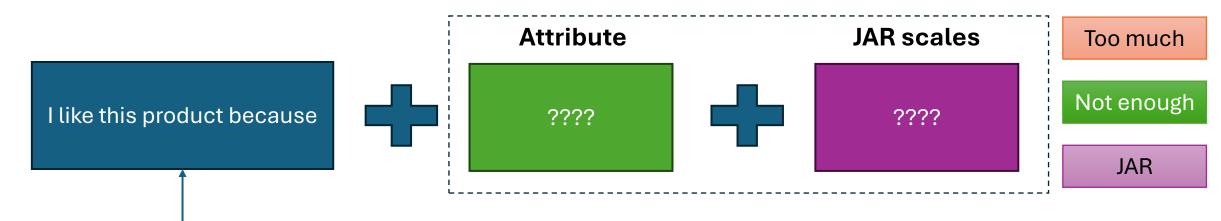


- Predefined, uniform attribute lists are a limitation in sensory evaluation.
- Key attributes may be overlooked if they are not included in the list.
- Consumers may interpret attributes differently, leading to inconsistency.
- Presenting attributes to consumers can bias their evaluations.
- ☐ Attributes on the list may be given more importance than warranted, skewing focus.



A flexible method to capture authentic consumer insights without relying on predefined attribute lists

Free JAR Methodoly



Make a nudge for focus on strengths and weaknesses of product

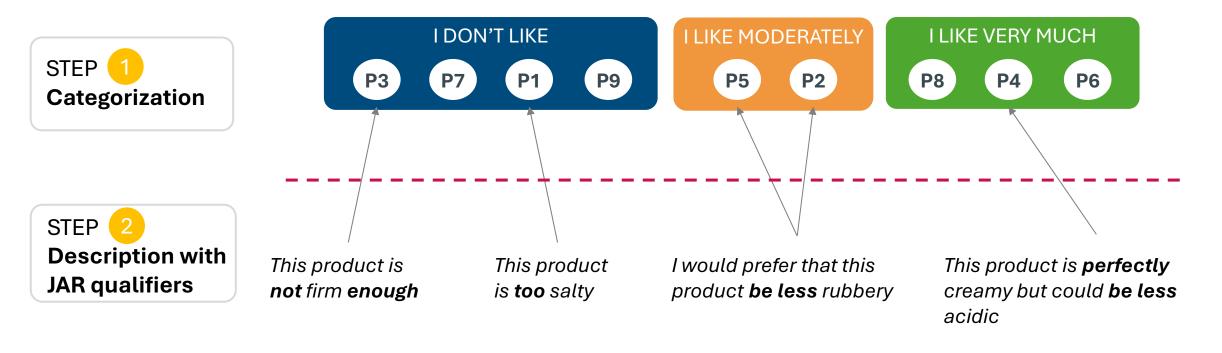
The **Free JAR** process uses **structured** text to capture consumer insights **without predefined attributes**, leveraging the JAR scale to **highlight** product **strengths and weaknesses**.

Freely express



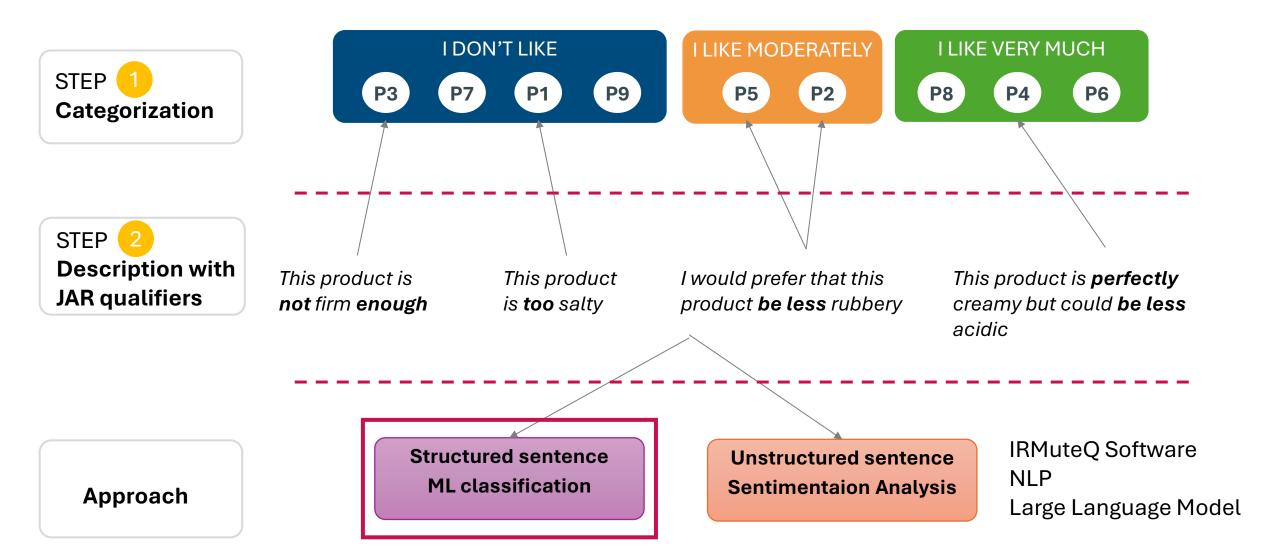
Free JAR Protocol

The **Free JAR** is a two-step methodology:



(Luc et al., 2022)

Free JAR Protocol



Free JAR Procedure

DATA STRUCTURE

Judge	Product	Hedonic category	Free JAR comment			
1	709	В	ngọt_không_đủ,mùi_thơm_vừa_đủ,màu_quá_đậm			
1	495	С	ngọt_không_đủ,mùi_thơm_không_đủ,màu_không_đủ			
1	913	С	đắng_quá_nhiều,chát_quá_nhiều,màu_vừa_đủ			
1	582	В	mùi_thơm_vừa_đủ,chát_vừa_đủ,đắng_không_đủ,màu_không_đủ			
1	136	С	mùi_thơm_vừa_đủ,chát_vừa_đủ,đắng_quá_nhiều,màu_vừa_đủ			

- n be the number of judge
- p the number of products
- → The data resulting from a Free JAR procedure can be stored as a table with 4 columns and p*n rows

Association between a text and a hedonic category

- A I like very much
- **B** I like moderately
- C I don't like

Free JAR Analysis

Y

X

Hedonic	Free JAR comment	chua_vừa_đủ	chát_không_đ ủ	chát_quá_nhiề u	chát_vừa_đủ
1	chát_vừa_đủ,đắng_không_đủ,mùi_thơm_vừa_đủ	0	0	0	1
2	chát_vừa_đủ,mùi_thơm_vừa_đủ	0	0	0	1
1	chát_quá_nhiều,mùi_thơm_vừa_đủ	0	0	1	0
3	chát_không_đủ,mùi_thơm_vừa_đủ	0	1	0	0
1	chát_quá_nhiều,đắng_quá_nhiều,mùi_thơm_vừa_đủ	0	0	1	0
2	ngọt_vừa_đủ,chát_quá_nhiều,mùi_thơm_vừa_đủ,màu_vừa_đủ	0	0	1	0

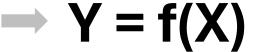


3 I like very much

2 I like moderately

1 I don't like

Supervised classification



Free JAR Analysis

Implementation of a **Random Forest** classifier:

- Modeling of the **link** between the **attributed** presence and the **hedonic** category
- Define the valency score of a given comment:

Valency score = p (« I like very much ») - p (« I don't like »)

-1 ≤ Valency score ≤ 1

→ Quantitative analyses

Luc et al., 2022b

Valency score high

→ The comment is Positive

(I like this product very much)



Valency score low

→ The comment is Negative (I don't like this product)

best_params_

```
'criterion': 'entropy',
```

'max_depth': 15,

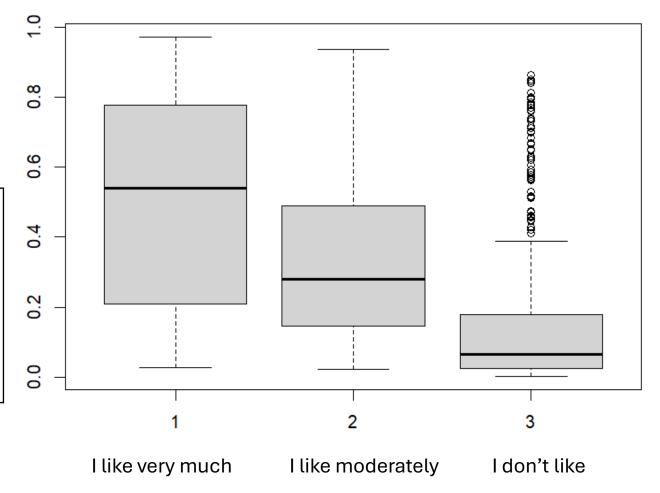
'max_features': 'log2',

'n_estimators': 100

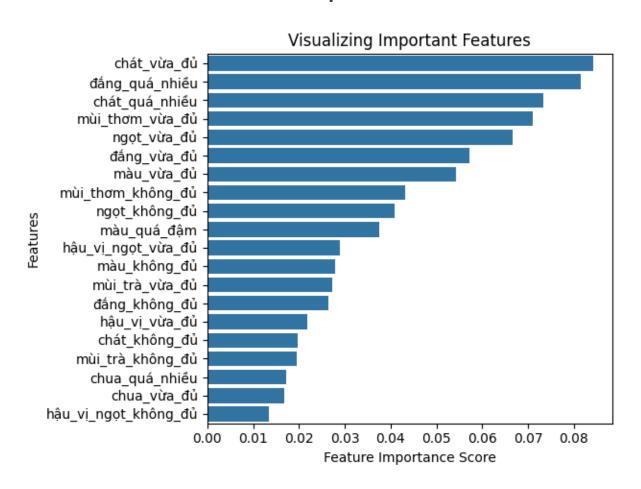
	precision	recall	f1-score	support
1	0.85	0.95	0.9	304
2	0.86	0.79	0.82	213
3	0.94	0.76	0.84	99
accuracy	0.87			616
macro avg	0.88	0.83	0.85	616
weighted avg	0.87	0.87	0.86	616



With selected optimal parameters. The model has an accuracy of 87%



20 feature importance variable



Feature importance refers to techniques for determining the degree to which different features, or variables, impact a machine learning model's predictions



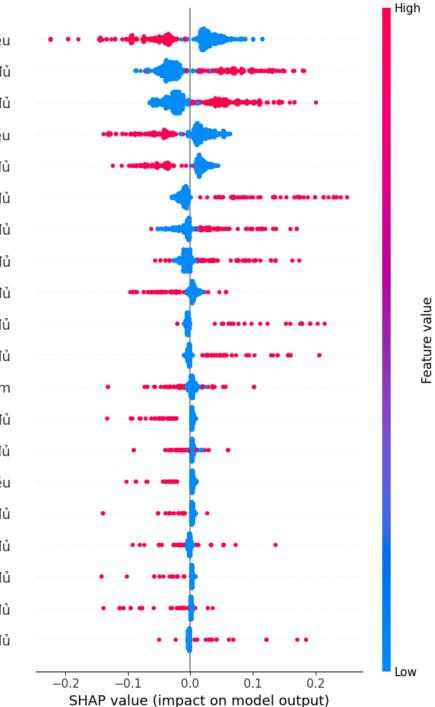
Astringency just right, Astringency too much,
Bitter too much, Aroma just right is the main
attribute for classify hedonic categories

SHAP (SHapley Additive exPlanations) is theoretic approach to explain the output of any machine learning model

Apply SHAP to interpret model

- Astringency too much, Bitter too much, Aroma not enough is the main attribute that negatively affects the occurrence of "I like product".
- Astringent just right and Aroma just right have a positive influence on the occurrence of higher "I like product".

chát quá nhiều chát vừa đủ mùi thơm vừa đủ đáng quá nhiều mùi thơm không đủ ngọt vừa đủ màu_vừa_đủ đáng vừa đủ ngọt không đủ hậu_vị_ngọt_vừa_đủ mùi trà vừa đủ màu_quá_đậm mùi trà không đủ màu không đủ chua_quá_nhiều chua vừa đủ chát không đủ hậu_vị_ngọt_không_đủ đáng không đủ hậu_vị_vừa_đủ

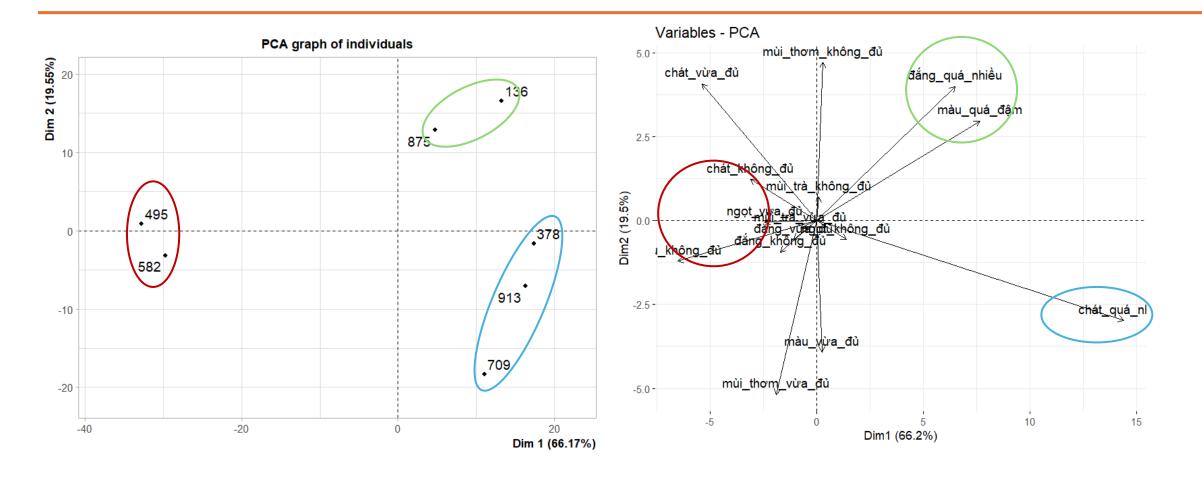


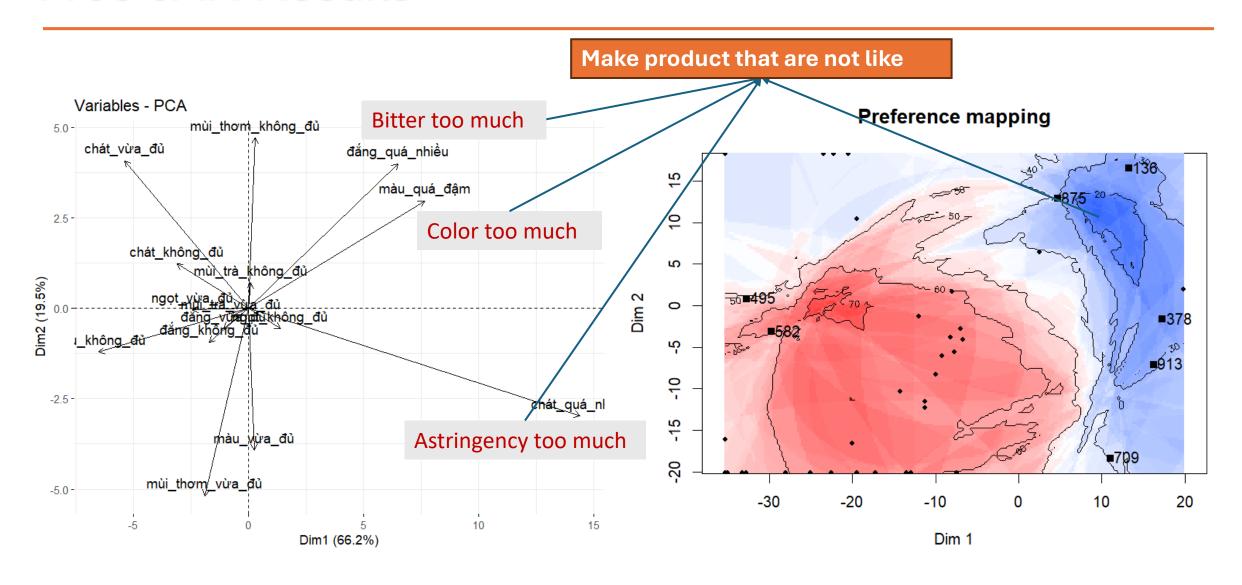
88 Jugde and 7 Product. In the maximum case, that 1 attribute can receive 88x7 = 616

Each attribute was count and calculated its % with maximum case.

Terms that are too few (<5%) can be considered as not contributing much to the product description

	709 🗦	495 🗘	913 🗘	582 🗦	136 🗘	378	875	total_count [‡]	percentage
thanh_vừa_đủ	0	1	1	1	0	2	1	6	0.9740260
thơm_vừa_đủ	2	0	0	0	0	0	0	2	0.3246753
vị_hoa_quả_không_đủ	0	1	0	0	0	0	0	1	0.162337
v <u>i_</u> không_đủ	0	1	0	0	0	0	0	1	0.162337
vi_kim_loại_quá_nhiều	0	0	0	0	0	0	1	1	0.162337
vị_nhạt_không_đủ	1	1	1	1	1	1	0	6	0.974026
vị_thanh_vừa_đủ	0	0	0	1	1	1	0	3	0.487013
vị_trà_không_đủ	1	1	0	0	0	0	0	2	0.324675
vi_trà_quá_nhiều	2	0	0	0	0	0	0	2	0.324675
vị_trà_vừa_đủ	0	1	0	0	0	0	0	1	0.162337
đắng_không_đủ	4	6	5	10	2	5	3	35	5.681818
đẳng_quá_nhiều	18	12	23	13	37	31	21	155	25.162337
đắng_vừa_đủ	11	13	13	15	7	13	15	87	14.123376
đặc_quá_nhiều	0	0	0	0	1	0	0	1	0.162337





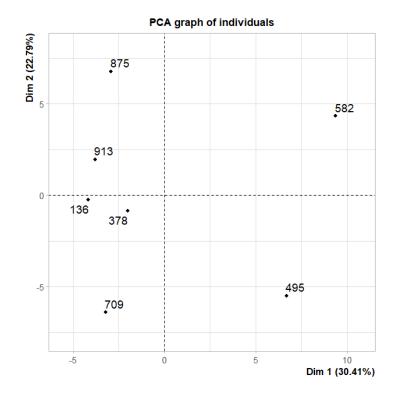
Each entry of this table is the valency score associated with the description of a given respondent and product.

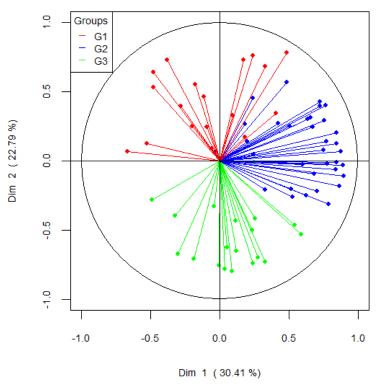
→ Make an internal preference mapping by PCA to identifying which products correspond to groups of consumers.

•	54 ‡	55 ‡	56 [‡]	57 [‡]	58 ‡	59 ‡	60 [‡]
136	-0.66609015	-0.73301933	-0.72880867	-0.5861055056	0.2356101	-0.4405406	-0.1568030
378	-0.08197511	-0.51613823	-0.90255604	-0.7714961745	-0.7531895	-0.6098790	-0.7679865
495	0.38372698	-0.09356122	-0.87081891	-0.0004591183	0.4615966	-0.4125666	-0.9226852
582	-0.68007309	0.80580570	-0.07598381	0.5850284798	0.3295531	-0.6098790	-0.6580867
709	-0.32190269	0.34016227	-0.81504989	-0.6594971668	-0.3682083	-0.4125666	0.6722394
875	-0.92960400	0.80580570	-0.90608316	0.0152609364	-0.7419421	-0.6098790	-0.8504142
913	-0.66361385	-0.49371008	-0.87081891	-0.6651309553	-0.4228199	-0.6098790	0.5820871

The two first components explained 53% of the variability in the data

- Group1 is the group of consumer prefer 875 or 913
- Group2 is the group of consumer like 582
- Group3 is the group of consumer
 who like 709 or 495





Conclustion

Free JAR methodology:

- Through a nudge approach, bring the consumer to provide product improvement keys
- Rich data

The Machine Learning and SHAP approach for FreeJAR is an easy approach and the explanation is good:

- → Get the most out of the data
- → From structured textual data to quantitative data

Interpretability for sensory data: highlight drivers of liking and disliking.