Comparison of Temporal Methods for Sensory Analysis

Rinkiny Ghatak
Madhumitha M
Anjali Elizabeth Paul

BMath First Year

Indian Statistical Institute, Bangalore

Abstract

Our aim in this project is to compare temporal methods for sensory perception using various tools of statistical analysis.
In this report we will show some of the statistical methods and techniques we applied on the data in the paper given to us: "Data set of sensory perception of chocolates, guacamole, ice teas and crisps collected with consumers using six different temporal methods" (Visalli et al, 2022). Here the temporal methods used were :

1. Temporal Dominance of Sensations (TDS),
2. Temporal Check-All-That-Apply (TCATA),
3. Attack-Evolution-Finish dominance (AEF-D),
4. Attack-Evolution-Finish applicability (AEF-A),
5. Free-Comment Attack-Evolution-Finish Dominance(FC-AEF-D) and
6. Free-Comment Attack-Evolution-Finish Applicability (FC-AEF-A).

These vary in the parameters: dominance vs. applicability, periods vs. continuous time, simultaneous vs. retrospective measures and list of terms vs. Free-Comment. Our aim is to compare the six methods based on the above parameters and try to find which method is better for showing the product properties and distinguishing between separate products.

Contents

1 Introduction

Sensory analysis of food is a scientific approach that is used to measure, analyse, and interpret human responses to different food products. It uses principles of experimental design and statistical analysis.

The traditional sensory descriptive analysis methods generally focus on attribute intensities at the time of evaluation. For example, panelists would evaluate the flavor intensity of a beverage after only a few sips. Temporal methods, on the other hand, study the change of attributes over time, whether it is intensity or dominance. For example, panelists would evaluate the flavor intensity while sipping the beverage.

These methods varied in whether
1. Attributes could be selected from a predefined list or the consumer could give his/her own comments(free-comment)
2. The reported attributes were those that caught the consumers attention at that given time (dominant) or all applicable attributes were reported.
3. Responses were collected throughout perception of the product(continuous) or in periods (Attack-Evolution-Finish) of the tasting.

Method	**Choice of attributes**	**Reported attributes**	**Temporal resolution**
TDS	Predefined list	Dominant ones, one at a time	Continuous
TCATA	Predefined list	Applicable ones, zero,one or several at a time	Continuous
AEF-D	Predefined list	Dominant ones, one at a time	Periods
AEF-A	Predefined list	Applicable ones, zero,one or several at a time	Periods
FC-AEF-D	Free-Comment	Dominant ones, one at a time	Periods
FC-AEF-A	Free Comment	Dominant ones, one at a time	Periods

2 Instructions and Data collection for each method

2.1 Consumers

The consumers were selected from those registered at the ChemoSens Platform's PanelSens database. They were randomly assigned to one of the six panels with a constraint of balance in gender and age between panels. Each panel used a different temporal method to describe the temporal evolution of the samples from each product category over three sessions, one at lab and two at home, on different days.

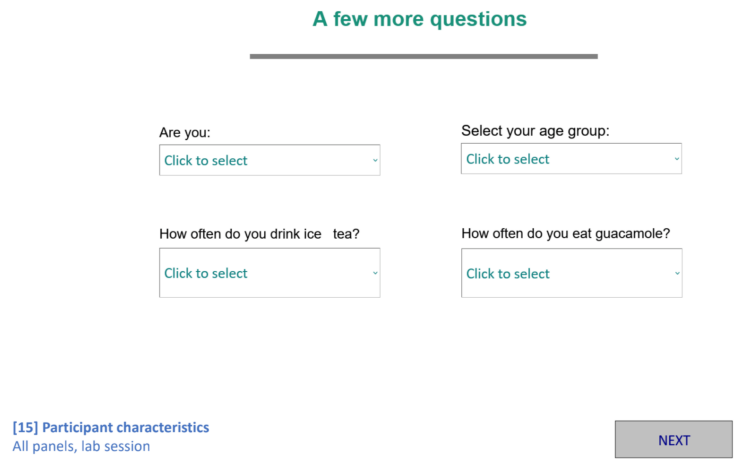


Figure 1: Consumer questions

The sheet "Consumer" provides information about the recruited consumers. "Panel" is the panel to which the consumer has been randomly assigned (TDS, TCATA, AEF_D, AEF_A, FC_AEF_D, FC_AEF_A).

"Consumer" is the 3-character code of the consumer. "Gender" is the gender reported by the consumer (M for male or F for female). "Age" is the age range reported by the consumer (18_30: from 18 to 30 years old, 31_45: from 31 to 45 years old, 46_64: from 46 to 64 years old).

"Consumption_IceTea", "Consumption_Guacamole", "Consumption_Chocolate", "Consumption_Crisp" are the frequencies of consumptions of each product category (ice teas, guacamoles, dark chocolates, crisps) reported by the consumers (never, less than once a month, at least once a month, at least once a week). "Panel", "Consumer" and "ProductCategory" columns are reported in each sheet following this one.

2.2 TDS

TDS instructions: “For each crisp, the consumers proceeded as follows. They took a bite, while simultaneously pressing the “Mouthing” button. A list of buttons were displayed on the screen. Throughout the tasting of the crisp, as soon as they perceived a dominant sensation, they had to press the button corresponding to that sensation. Some sensations might have never been selected, while some might have been selected multiple times during the tasting. They continued to indicate the sensations perceived after swallowing. When the consumers no longer perceived anything, they clicked on “I don’t perceive anything anymore” button. The consumers could only taste one crisp of each sample of crisps. They had to familiarize themselves with the sensations available and their location on the screen before putting the product in their mouth.”

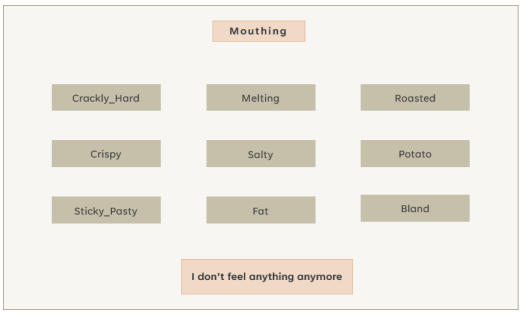


Figure 2: TDS measurement screen

The sheet “TDS” contains the temporal descriptions reported by the consumers of the panel TDS. “Product” is the identifier of the product (character). “Time” is the time of each click on the attribute in seconds (numeric). “Attribute” is the code of the attribute (character). “Score” is 1 if “Attribute” has been considered dominant (TDS) by “Consumer” for “Product” during “Period” (numeric).

Panel	Consumer	ProductCategory	Product	Time	Attribute	Score
TDS	A01	Crisp	C1	0	START	1
TDS	A01	Crisp	C1	4.011	Crackly_Hard	1
TDS	A01	Crisp	C1	7.671	Crispy	1
TDS	A01	Crisp	C1	14.512	Potato	1
TDS	A01	Crisp	C1	22.11	Roasted	1
TDS	A01	Crisp	C1	25.358	STOP	1
TDS	A01	Crisp	C2	0	START	1
TDS	A01	Crisp	C2	2.422	Crackly_Hard	1
TDS	A01	Crisp	C2	8.189	Potato	1
TDS	A01	Crisp	C2	9.797	Crispy	1
TDS	A01	Crisp	C2	20.908	STOP	1
TDS	A01	Crisp	C3	0	START	1
TDS	A01	Crisp	C3	0.857	Crackly_Hard	1
TDS	A01	Crisp	C3	3.881	Salty	1
TDS	A01	Crisp	C3	9.657	Potato	1
TDS	A01	Crisp	C3	11.489	Roasted	1
TDS	A01	Crisp	C3	14.132	STOP	1
TDS	A01	Crisp	C4	0	START	1
TDS	A01	Crisp	C4	3.189	Bland	1
TDS	A01	Crisp	C4	7.18	Potato	1
TDS	A01	Crisp	C4	13.477	Roasted	1
TDS	A01	Crisp	C4	15.959	STOP	1

Figure 3: TDS data extract

2.3 TCATA

TCATA instructions (for crisps): “For each crisp, the consumers proceeded as follows. They took a bite, while simultaneously pressing the “Mouthing” button. A list of checkboxes were displayed on the screen. Throughout the tasting of the crisp, as soon as they perceived a sensation, they had to check the checkbox corresponding to that sensation. They needed to uncheck the checkbox as soon as a particular sensation was not perceived any longer. Some sensations might have never been selected, others might have been selected multiple times during the tasting of the crisp. They had to continue to check the attributes perceived and uncheck the attributes no longer perceived after swallowing. When the consumers no longer perceived anything, they click on the “I don’t perceive anything anymore” button. The consumers could taste only one bite of each sample of crisp. They were asked to familiarize themselves with the sensations available and their location on the screen before putting the product in your mouth.”

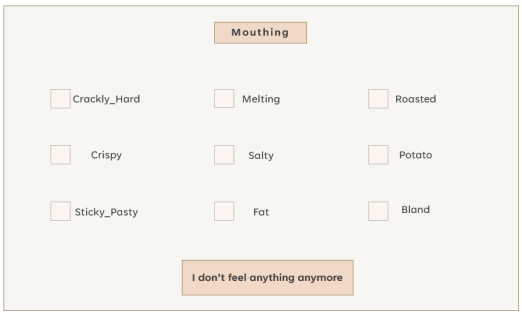


Figure 4: TCATA measurement screen

The sheet “TCATA“ contains the temporal descriptions reported by the consumers of the panel TCATA. “Product” is the identifier of the product (character). “Time” is the time of each click on the attribute in seconds (numeric). “Attribute” is the code of the attribute (character). “Score” is 1 if “Attribute” has been considered applicable (TCATA) by “Consumer” for “Product” during “Period” (numeric). For TCATA, an attribute remains applicable until the end or until deselected, in this case a new entry with score=0 is recorded.

Panel	Consumer	ProductCategory	Product	Time	Attribute	Score
TCATA	B04	Crisp	C1	0	START	1
TCATA	B04	Crisp	C1	7.25	Crackly_Hard	1
TCATA	B04	Crisp	C1	8.329	Salty	1
TCATA	B04	Crisp	C1	10.599	Crispy	1
TCATA	B04	Crisp	C1	15.758	Bland	1
TCATA	B04	Crisp	C1	19.233	Potato	1
TCATA	B04	Crisp	C1	34.055	Salty	0
TCATA	B04	Crisp	C1	38.412	STOP	1
TCATA	B04	Crisp	C2	0	START	1
TCATA	B04	Crisp	C2	9.524	Bland	1
TCATA	B04	Crisp	C2	12.974	Crispy	1
TCATA	B04	Crisp	C2	14.878	Potato	1
TCATA	B04	Crisp	C2	26.635	STOP	1
TCATA	B04	Crisp	C3	0	START	1
TCATA	B04	Crisp	C3	0.711	Crackly_Hard	1
TCATA	B04	Crisp	C3	1.956	Crispy	1
TCATA	B04	Crisp	C3	4.799	Fat	1
TCATA	B04	Crisp	C3	9.371	Potato	1
TCATA	B04	Crisp	C3	10.634	Salty	1
TCATA	B04	Crisp	C3	14.987	Roasted	1
TCATA	B04	Crisp	C3	34.197	Salty	0
TCATA	B04	Crisp	C3	35.155	Salty	1
TCATA	B04	Crisp	C3	35.883	STOP	1
TCATA	B04	Crisp	C4	0	START	1
TCATA	B04	Crisp	C4	4.506	Bland	1
TCATA	B04	Crisp	C4	17.622	Potato	1
TCATA	B04	Crisp	C4	18.904	Crispy	1
TCATA	B04	Crisp	C4	35.374	STOP	1

Figure 5: TCATA data extract

2.4 AEF-D

AEF-D instructions (for crisps): “For each crisp, the consumers proceeded as follows. They took a bite, while simultaneously pressing the “Mouthing” button. When they no longer perceived anything, they clicked the “Next” button. At that moment, they were asked to describe their perception by choosing, from a list of terms, the dominant sensation for each period of their perception: beginning(attack), middle(evolution) and end(finish). Some sensations may never be selected, others may be selected in several periods. An example is given to you on the following page. The consumers could taste only one bite of each sample of crisp.

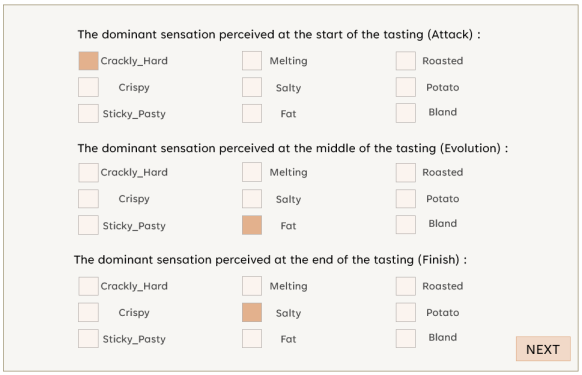


Figure 6: AEF-D measurement screen

The sheet “AEF_D” contains the temporal descriptions reported by the consumers of the panel AEF-D. “Product” is the identifier of the product (character). “Period” is the identifier of the period (A: attack, E: evolution, F: Finish). “Attribute” is the code of the attribute (character). “Score” is 1 if “Attribute” has been considered dominant by “Consumer” for “Product” during “Period”, 0 otherwise (numeric).

Panel	Consumer	ProductCategory	Product	Period	Attribute	Score
AEF_D	C08	Crisp	C1	A	Crackly_Hard	1
AEF_D	C08	Crisp	C1	A	Crispy	0
AEF_D	C08	Crisp	C1	A	Sticky_Pasty	0
AEF_D	C08	Crisp	C1	A	Melting	0
AEF_D	C08	Crisp	C1	A	Salty	0
AEF_D	C08	Crisp	C1	A	Fat	0
AEF_D	C08	Crisp	C1	A	Potato	0
AEF_D	C08	Crisp	C1	A	Roasted	0
AEF_D	C08	Crisp	C1	A	Bland	0
AEF_D	C08	Crisp	C1	E	Crackly_Hard	0
AEF_D	C08	Crisp	C1	E	Crispy	0
AEF_D	C08	Crisp	C1	E	Sticky_Pasty	0
AEF_D	C08	Crisp	C1	E	Melting	0
AEF_D	C08	Crisp	C1	E	Salty	0
AEF_D	C08	Crisp	C1	E	Fat	1
AEF_D	C08	Crisp	C1	E	Potato	0
AEF_D	C08	Crisp	C1	E	Roasted	0
AEF_D	C08	Crisp	C1	E	Bland	0
AEF_D	C08	Crisp	C1	F	Crackly_Hard	0
AEF_D	C08	Crisp	C1	F	Crispy	0
AEF_D	C08	Crisp	C1	F	Sticky_Pasty	0
AEF_D	C08	Crisp	C1	F	Melting	0
AEF_D	C08	Crisp	C1	F	Salty	1
AEF_D	C08	Crisp	C1	F	Fat	0
AEF_D	C08	Crisp	C1	F	Potato	0
AEF_D	C08	Crisp	C1	F	Roasted	0
AEF_D	C08	Crisp	C1	F	Bland	0

Figure 7: AEF-D data extract

2.5 AEF-A

AEF-A instructions (for crisps): “For each crisp, the consumers proceeded as follows. They took a bite, while simultaneously pressing the “Mouthing” button. When they no longer perceived anything, they pressed the “Next” button. At that moment, the consumers were asked to describe their perception by choosing, from a list of terms, one or several sensations for each period of their perception: beginning, middle and end. Some sensations may never be selected, others may be selected in several periods. An example is given to you on the following page. The consumers could taste only one bite of each sample of crisp.

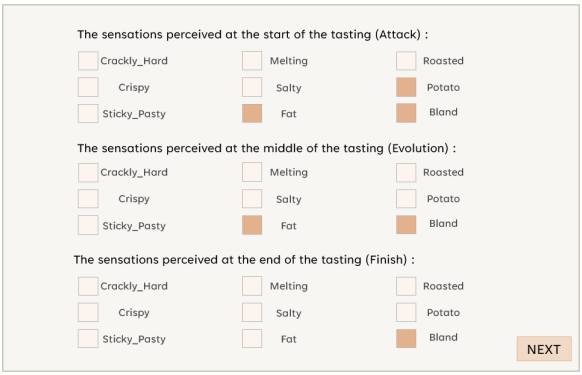


Figure 8: AEF-A measurement screen

The sheet “AEF_A“ contains the temporal descriptions reported by the consumers of the panel AEF-A. “Product” is the identifier of the product (character). “Period” is the identifier of the period (A: attack, E: evolution, F: Finish). “Attribute” is the code of the attribute (character). “Score” is 1 if “Attribute” has been considered applicable by “Consumer” for “Product” during “Period”, 0 otherwise (numeric).

Panel	Consumer	ProductCategory	Product	Period	Attribute	Score
AEF_A	D01	Crisp	C1	A	Crackly_Hard	0
AEF_A	D01	Crisp	C1	A	Crispy	0
AEF_A	D01	Crisp	C1	A	Sticky_Pasty	0
AEF_A	D01	Crisp	C1	A	Melting	0
AEF_A	D01	Crisp	C1	A	Salty	0
AEF_A	D01	Crisp	C1	A	Fat	1
AEF_A	D01	Crisp	C1	A	Potato	1
AEF_A	D01	Crisp	C1	A	Roasted	0
AEF_A	D01	Crisp	C1	A	Bland	1
AEF_A	D01	Crisp	C1	E	Crackly_Hard	0
AEF_A	D01	Crisp	C1	E	Crispy	0
AEF_A	D01	Crisp	C1	E	Sticky_Pasty	0
AEF_A	D01	Crisp	C1	E	Melting	0
AEF_A	D01	Crisp	C1	E	Salty	0
AEF_A	D01	Crisp	C1	E	Fat	1
AEF_A	D01	Crisp	C1	E	Potato	0
AEF_A	D01	Crisp	C1	E	Roasted	0
AEF_A	D01	Crisp	C1	E	Bland	1
AEF_A	D01	Crisp	C1	F	Crackly_Hard	0
AEF_A	D01	Crisp	C1	F	Crispy	0
AEF_A	D01	Crisp	C1	F	Sticky_Pasty	0
AEF_A	D01	Crisp	C1	F	Melting	0
AEF_A	D01	Crisp	C1	F	Salty	0
AEF_A	D01	Crisp	C1	F	Fat	0
AEF_A	D01	Crisp	C1	F	Potato	0
AEF_A	D01	Crisp	C1	F	Roasted	0
AEF_A	D01	Crisp	C1	F	Bland	1

Figure 9: AEF-A data extract

2.6 FC-AEF-D

FC-AEF-D instructions (for crisps): “For each crisp, the consumers proceeded as follows. They took a bite, while simultaneously pressing the “Mouthing” button. When they no longer perceived anything, they pressed the “Next” button. At that moment, they were asked to describe, in their own words, the dominant sensation they experienced for each period of perception: beginning, middle and end. An example is given to you on the following page. They were asked to only use words, and not make sentences. Compound words and expressions are allowed. Example: "long in the mouth". The consumers could only taste one crisp from each sample of crisps”

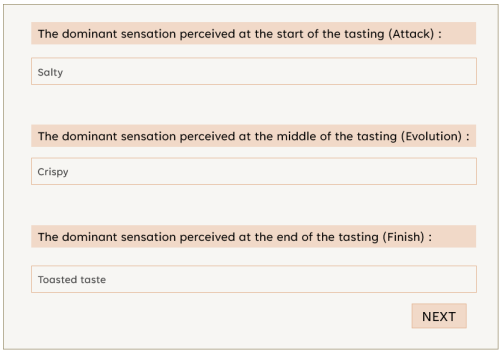


Figure 10: FC-AEF-D measurement screen

The sheet “FC_AEF_D” contains the temporal descriptions reported by the consumers of the panel FC-AEF-D. “Product” is the identifier of the product (character). “Period” is the identifier of the period (A: attack, E: evolution, F: Finish). “FrenchRawDescription” is the Free-Comment reported by the consumer (free text, in French). “EnglishRawDescription” is the English translation of “FrenchRawDescription” made using deepL translator and checked by the authors of the data paper.
The sheet “Duration“ contains the durations of tasting of each “Product” by each “Consumer” from each “Panel”.
“Duration” is the duration from the click on the start button to the click on the stop button, in seconds (numeric).

Panel	Consumer	ProductCategory	Product	Period	EnglishRawDescription
FC_AEF_D	E01	Crisp	C1	A	crispy
FC_AEF_D	E01	Crisp	C1	E	salty
FC_AEF_D	E01	Crisp	C1	F	good
FC_AEF_D	E01	Crisp	C2	A	salty
FC_AEF_D	E01	Crisp	C2	E	crispy
FC_AEF_D	E01	Crisp	C2	F	toasted taste
FC_AEF_D	E01	Crisp	C3	A	bright
FC_AEF_D	E01	Crisp	C3	E	balanced
FC_AEF_D	E01	Crisp	C3	F	toasted taste
FC_AEF_D	E01	Crisp	C4	A	bland
FC_AEF_D	E01	Crisp	C4	E	bold
FC_AEF_D	E01	Crisp	C4	F	aftertaste

Figure 11: FC-AEF-D data extract

2.7 FC-AEF-A

FC-AEF-A instructions (for ice tea): “For each crisp, they proceeded as follows. They took a bite, while simultaneously pressing the “Mouthing” button. When they no longer perceived anything, they pressed the “Next” button. At that moment, the consumers were asked to describe, using their own words, the sensations they perceived during each period of perception: beginning, middle and end. An example is given to you on the following page.They were asked to only use words, and not make sentences. Compound words and expressions are allowed. Example: "long in the mouth". The consumers could only taste one crisp from each sample of crisps”

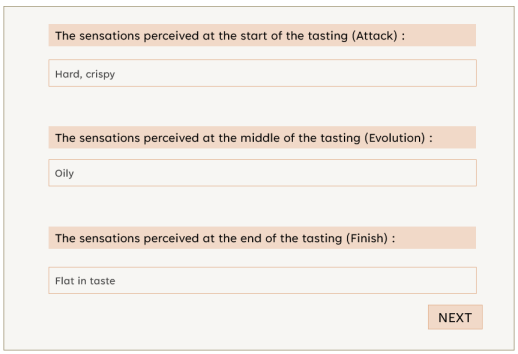


Figure 12: FC-AEF-A measurement screen

The sheets “FC_AEF_A“ contain the temporal descriptions reported by the consumers of the FC-AEF-A panel. “Product” is the identifier of the product (character).
“Period” is the identifier of the period (A: attack, E: evolution, F: Finish).
“FrenchRawDescription” is the Free-Comment reported by the consumer (free text, in French). “EnglishRawDescription” is the English translation of “FrenchRawDescription” made using deepL translator and checked by the authors of the data paper.

Panel	Consumer	ProductCategory	Product	Period	EnglishRawDescription
FC_AEF_A	F01	Crisp	C1	A	salty
FC_AEF_A	F01	Crisp	C1	E	crispy
FC_AEF_A	F01	Crisp	C1	F	flat in taste
FC_AEF_A	F01	Crisp	C2	A	salty
FC_AEF_A	F01	Crisp	C2	E	crispy
FC_AEF_A	F01	Crisp	C2	F	oily
FC_AEF_A	F01	Crisp	C3	A	hard, crispy
FC_AEF_A	F01	Crisp	C3	E	nothing
FC_AEF_A	F01	Crisp	C3	F	salty
FC_AEF_A	F01	Crisp	C4	A	thin
FC_AEF_A	F01	Crisp	C4	E	fat
FC_AEF_A	F01	Crisp	C4	F	bland

Figure 13: FC-AEF-A data extract

2.8 Liking

The sheet “Liking” contains the liking scores reported for each “Product” by each “Consumer” from each “Panel”. “Liking” is the value rated on a discrete scale (numeric, between 1 and 9).

Panel	Consumer	ProductCategory	Product	Liking
FC_AEF_D	E01	Crisp	C1	7
FC_AEF_D	E01	Crisp	C2	8
FC_AEF_D	E01	Crisp	C3	9
FC_AEF_D	E01	Crisp	C4	2
FC_AEF_D	E01	Crisp	C1_rep	5
FC_AEF_D	E02	Crisp	C1	3
FC_AEF_D	E02	Crisp	C2	3
FC_AEF_D	E02	Crisp	C3	6
FC_AEF_D	E02	Crisp	C4	2
FC_AEF_D	E02	Crisp	C1_rep	7
FC_AEF_D	E03	Crisp	C1	9
FC_AEF_D	E03	Crisp	C2	8
FC_AEF_D	E03	Crisp	C3	8
FC_AEF_D	E03	Crisp	C4	1
FC_AEF_D	E03	Crisp	C1_rep	8
FC_AEF_D	E06	Crisp	C1	6
FC_AEF_D	E06	Crisp	C2	7
FC_AEF_D	E06	Crisp	C3	8
FC_AEF_D	E06	Crisp	C4	4
FC_AEF_D	E06	Crisp	C1_rep	2

Figure 14: Liking data extract

2.9 Difficulty

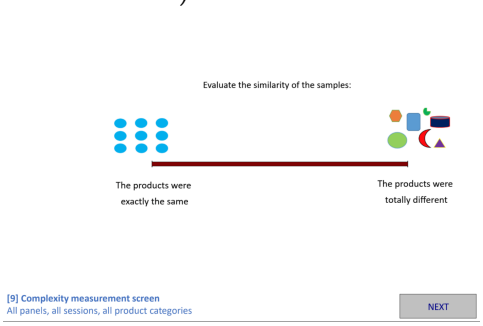
The sheet “Difficulty“ contains the scores of difficulty of the evaluation task reported for each context by each “Consumer” from each “Panel”. “Context” is the location of the measure (lab or home). “Score” is the score on the structured scale (numeric, between 0 and 10, precision of 0.01).

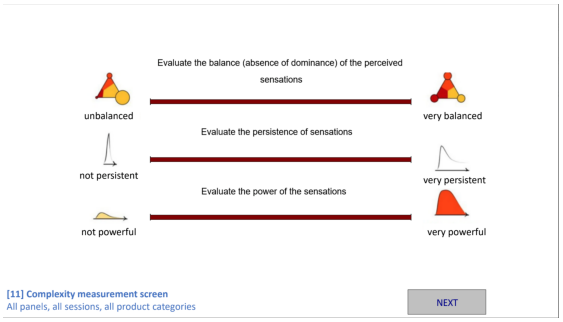
Panel	Consumer	ProductCategory	Difficulty
AEF_A	D01	Lab	7.61
AEF_A	D03	Lab	1
AEF_A	D05	Lab	5.87
AEF_A	D08	Lab	0.2
AEF_A	D09	Lab	3.03
AEF_A	D10	Lab	6.33
AEF_A	D11	Lab	8.01
AEF_A	D12	Lab	2.7
AEF_A	D13	Lab	6.47
AEF_A	D14	Lab	0.53
AEF_A	D16	Lab	3.54
AEF_A	D73	Lab	4.28
AEF_A	D74	Lab	5.85
AEF_A	D21	Lab	2.73

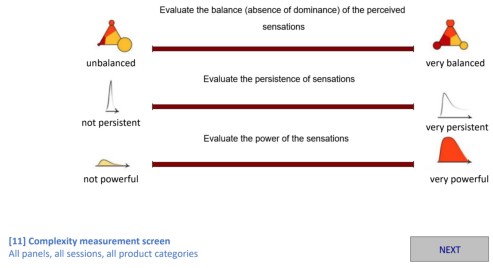
Figure 15: Difficulty data extract

2.10 Complexity

The sheet “Complexity“ contains the scores of the different items of the complexity questionnaire reported for each “ProductCategory” by each “Consumer” of each “Panel”. “Attribute” is the code of the item (IntensityOfDifferences, Familiarity, NumberOfSensations, EaseOfIdentification, Harmony, Balance, Persistence, Power, Complexity). “Score” is the score on the structured scale (numeric, between 0 and 10, precision of 0.01).







Panel	Consumer	ProductCategory	Attribute	Score
FC_AEF_D	E01	Guacamole	IntensityOfDifferences	2.54
FC_AEF_D	E01	Guacamole	Familiarity	5.08
FC_AEF_D	E01	Guacamole	NumberOfSensations	7.34
FC_AEF_D	E01	Guacamole	EaseOfIdentification	6.61
FC_AEF_D	E01	Guacamole	Harmony	5.1
FC_AEF_D	E01	Guacamole	Balance	4.81
FC_AEF_D	E01	Guacamole	Persistence	6.01
FC_AEF_D	E01	Guacamole	Power	6.28
FC_AEF_D	E01	Guacamole	Complexity	7.69

3 Principle Component Analysis(PCA) on Complexity data

3.1 Quick Overview of PCA

3.1.1 What is PCA?

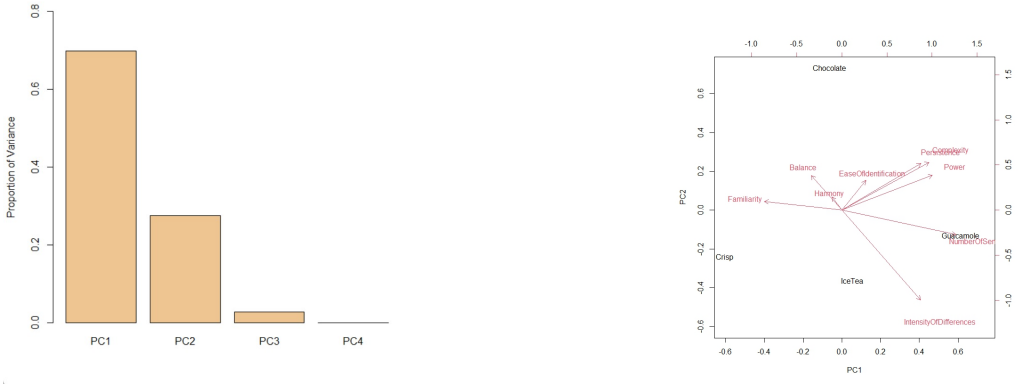
Principal component analysis (PCA) is a popular statistical technique for analyzing large datasets containing a high number of dimensions per observation, increasing the interpretability of data while preserving the maximum amount of information, and enabling the visualization of multidimensional data. In short, it is a statistical technique for reducing the dimensionality of a dataset.
This is accomplished by linearly transforming the data into a new coordinate system where most of the variation in the data can be described with fewer dimensions than the initial data.
Many studies use the first two principal components in order to plot the data in two dimensions and to visually identify clusters of closely related data points.

3.1.2 How to interpret it?

- In the PCA biplot, the variables are represented as arrows and the data points (or observations) are represented as dots.
- Clusters of dots imply that those data points are very closely related with respect to those variables.
- Before making the biplot, we generally make a scree plot. A scree plot is a line/bar plot of the eigenvalues of factors or principal components in an analysis. It shows the proportion of variance for each principal component, which shows how much information is preserved in that component. If the scree plot shows that we can compress the multiple dimensions to 2 dimensions without loss of too much information, then we go ahead with PCA plot in a two-dimensional space.
- Angles between the arrows show the correlation between those variables. For example, close to 0 degrees angle between two variables show very high positive correlation, 180 degrees show very high negative correlation and close to 90 degrees angle imply almost no correlation between those two variables.
- The points which are cluttered together are more similar/closely related to each other with respect to the variables. That is why PCA is generally used to identify which data points are similar.

3.2 The PCA on complexity done in the given paper

We want to plot a PCA biplot where the variables are IntensityOfDifferences, Familiarity, NumberOfSensations, EaseOfIdentification, Harmony, Balance, Persistence, Power, Complexity from the complexity data and the data points are chocolate, guacamole, crisp and iced tea.
From the scree plot we can see that most of the information is kept in the first two principal components. So we can plot a two dimensional biplot without loss of too much information.



(a) Scree plot

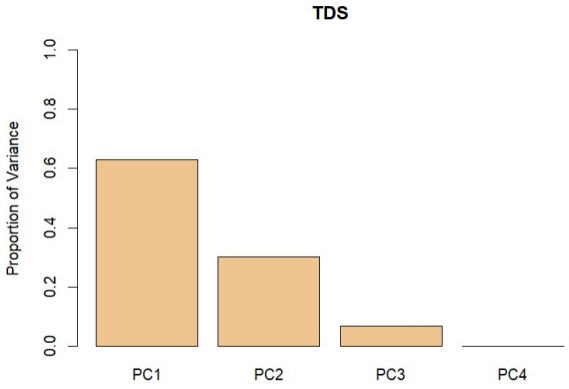
(b) PCA

Figure 16: Scree plot and PCA on complexity combining all methods

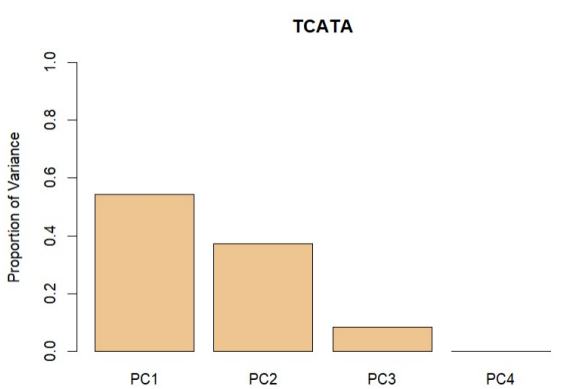
But from here we don't get any new inference. So, instead we shall do seperate PCA for different methods and check if they are consistent or not.

3.3 PCA biplot for comparison between different methods

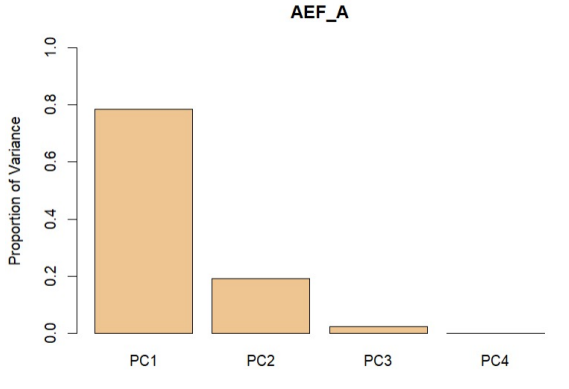
We plot PCA biplots seperately for different methods where the variables are IntensityOfDifferences, Familiarity, NumberOfSensations, EaseOfIdentification, Harmony, Balance, Persistence, Power, Complexity from the complexity data and the data points are chocolate, guacamole, crisp and iced tea.
First we look at the corresponding scree plots.



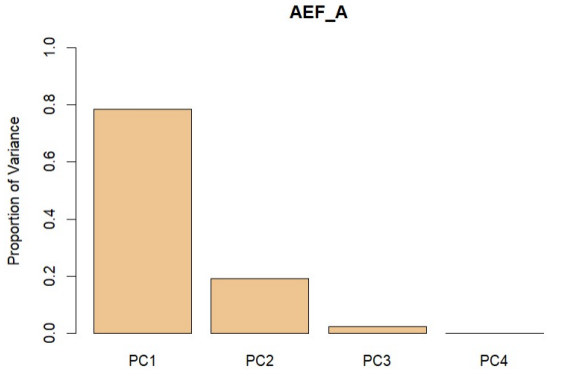
(a) TDS scree plot



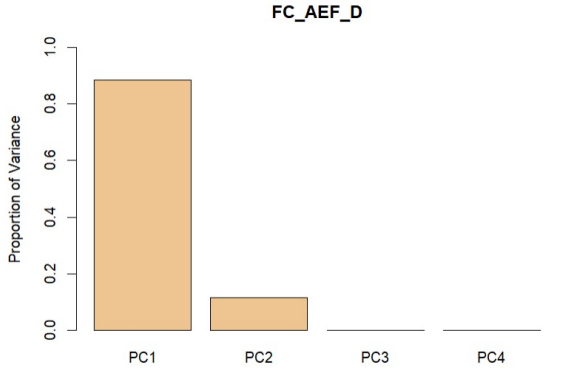
(b) TCATA scree plot



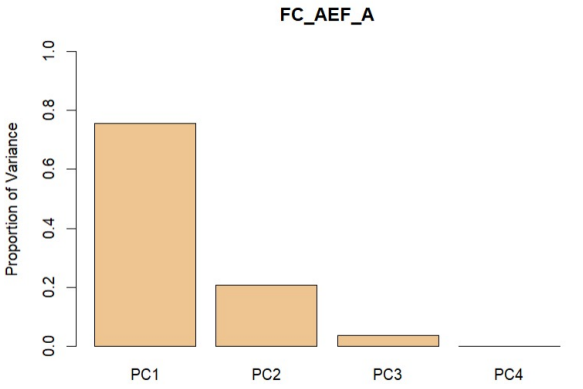
(c) AEF-D scree plot



(d) AEF-A scree plot



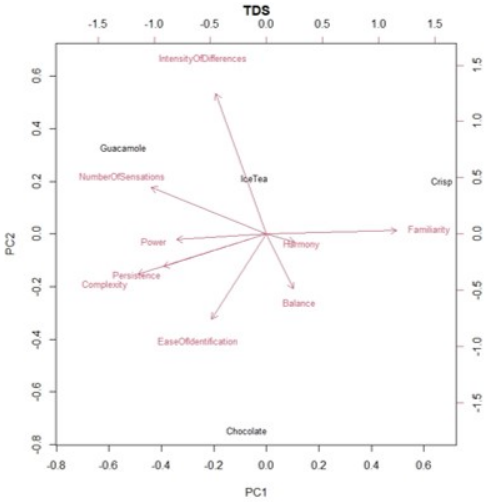
(e) FC-AEF-D scree plot



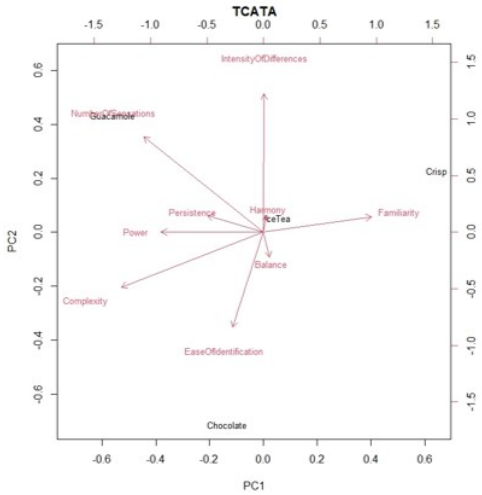
(f) FC-AEF-A scree plot

Figure 17: Scree plots for the six methods

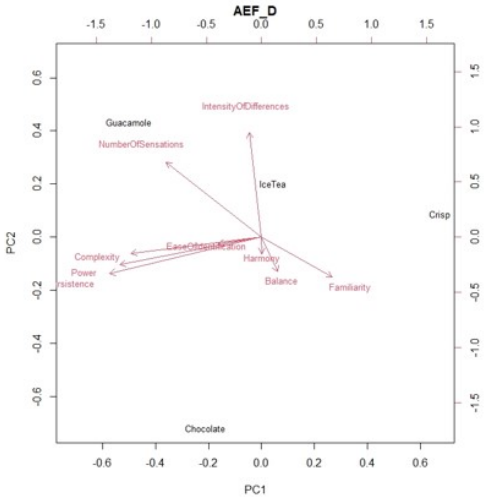
In each cases, most of the information is kept in the first two principal components. So we can plot two dimensional biplots without loss of too much information.



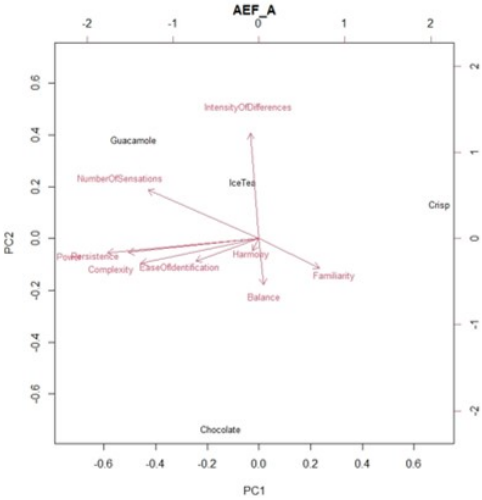
(a) TDS PCA biplot



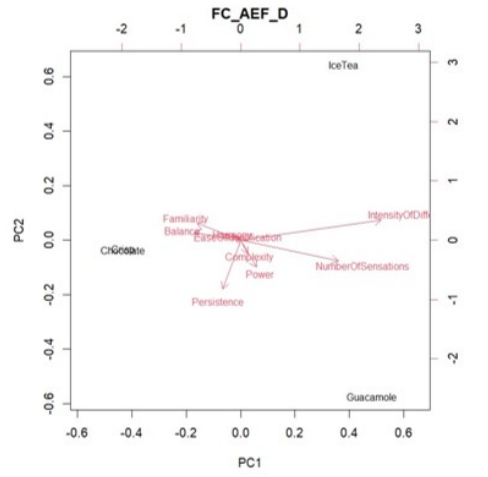
(b) TCATA PCA biplot



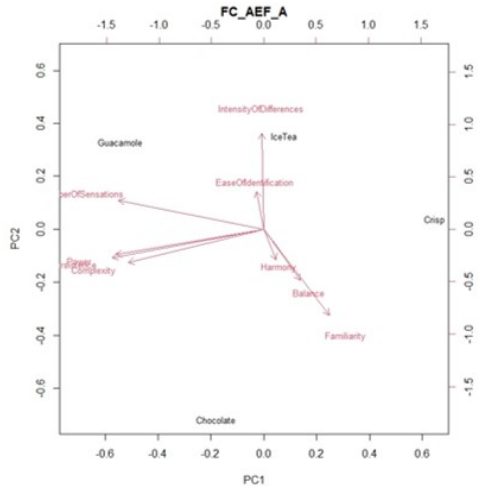
(c) AEF-D PCA biplot



(d) AEF-A PCA biplot



(e) FC-AEF-D PCA biplot



(f) FC-AEF-A PCA biplot

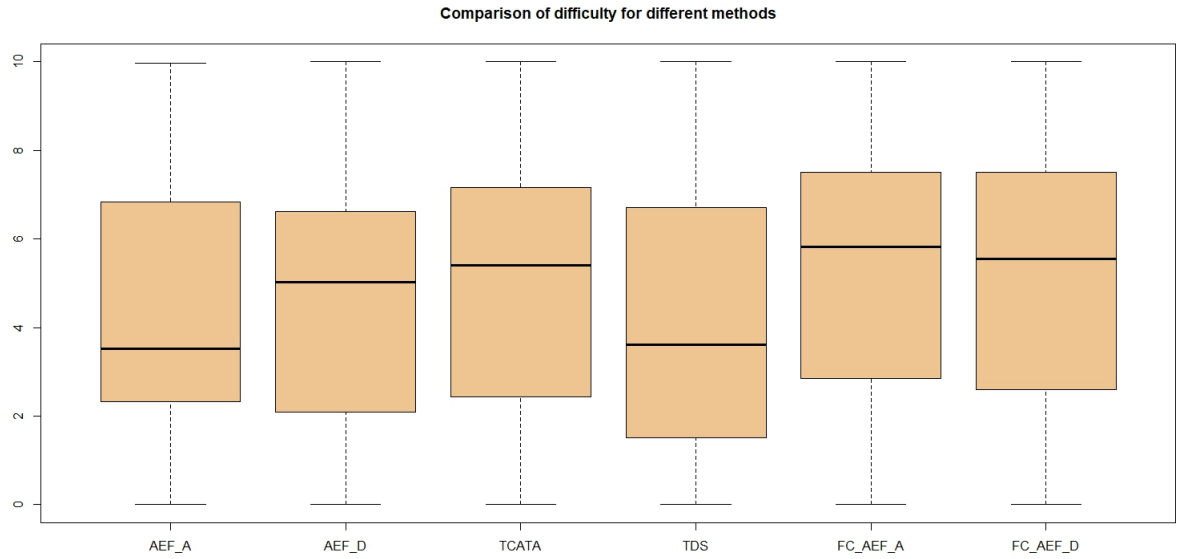
Figure 18: PCA Biplots for the six methods

All the PCA biplots look similar.From this, we can say that each panel has consumers with similar tastes, which allows us to compare these methods with the given data.

4 Comparison of difficulty for different methods

4.1 Boxplots

According to the difficulty data collected from the consumers, we want to compare the difficulty of the different methods. First we make boxplots of the difficulty scores for each method.



4.2 ANOVA

Now we want to see if all the methods are similarly difficult or not. To statistically test that, we shall do ANOVA with the null hypothesis saying that the difficulty mean is the same for all the methods. We check that the data is approximately normal so we can apply ANOVA.

4.2.1 Hypothesis 1

Null Hypothesis (H_0): $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6$, where μ_i is the mean of difficulty for the ith method.
(Method 1: AEF-A, Method 2: AEF-D, Method 3: TCATA, Method 4: TDS, Method 5: FC-AEF-A, Method 6: FC-AEF-A)

Alternate Hypothesis (H_a): At least one of the means are different.

The sum of squares for treatments (SST) $= \sum_{i=1}^{6} n_i(\bar{x}_i - \bar{x})^2 = 144.4829$

The sum of squares for errors (SSE) $= \sum_{i=1}^{6} (n_i - 1)s_i^2 = 6922$

$$\text{MST} = \frac{\text{SST}}{k-1} = \frac{144.4829}{6-1} = 72.24146$$

$$\text{MSE} = \frac{\text{SSE}}{n-k} = \frac{6922}{847-6} = 8.201422$$

$$F = \frac{\text{MST}}{\text{MSE}} = 8.808407$$

The p-value can be calculated by $p = 1 - \texttt{pf}(F, 5, 844) = 0.0001636571$. Clearly, we can see that the p-value is very close to zero, so it is statistically significant, and we can reject the null hypothesis. This means that not all the methods have a similar difficulty.

From the boxplots, we can see that the boxplots look similar for AEF-A, AEF-D and TDS. On the other hand, the boxplots are similar for TCATA, FC-AEF-D and FC-AEF-A.
So we formulate two new hypotheses:

1. The difficulty mean is the same for TCATA, FC-AEF-D and FC-AEF-A.
2. The difficulty mean is the same for AEF-A, AEF-D and TDS.

4.2.2 Hypothesis 2

Null Hypothesis (H_0): $\mu_1 = \mu_2 = \mu_3$, where μ_i is the mean of difficulty for the i th method.
(Method 1:TCATA, Method 2: FC-AEF-D, Method 3:FC-AEF-A)

Alternate Hypothesis (H_a): At least one of the means are different.

The sum of squares for treatments (SST) $= \sum_{i=1}^{3} n_i(\bar{x}_i - \bar{x})^2 = 6.776736$

The sum of squares for errors(SSE)$= \sum_{i=1}^{3} (n_i - 1)s_i^2 = 3577.122$

$$\text{MST} = \frac{\text{SST}}{k-1} = \frac{6.776736}{3-1} = 3.388368$$
$$\text{MSE} = \frac{\text{SSE}}{n-k} = \frac{3577.122}{426-3} = 8.456554$$
$$F = \frac{\text{MST}}{\text{MSE}} = 0.4006795$$

The p-value can be calculated by $p = 1 - \texttt{pf}(F, 2, 423) = 0.6701187$. We can see that the p-value is MORE THAN 0.5, so we cannot reject the null hypothesis even at a confidence level of 95%.

4.2.3 Hypothesis 3

Null Hypothesis (H_0): $\mu_1 = \mu_2 = \mu_3$, where μ_i is the mean of difficulty for the ith method.
(Method 1:AEF-A, Method 2: AEF-D, Method 3:TDS)

Alternate Hypothesis (H_a): At least one of the means are different.

The sum of squares for treatments (SST)$=\sum_{i=1}^{3} n_i(\bar{x}_i - \bar{x})^2 = 9.641525$

The sum of squares for errors (SSE)$= \sum_{i=1}^{3} (n_i - 1)s_i^2 = 3344.877$

$$\text{MST} = \frac{\text{SST}}{k-1} = \frac{9.641525}{3-1} = 4.820763$$
$$\text{MSE} = \frac{\text{SSE}}{n-k} = \frac{3344.877}{421-3} = 8.002099$$
$$F = \frac{\text{MST}}{\text{MSE}} = 0.6024373$$

The p-value can be calculated by $p = 1 - \texttt{pf}(F, 2, 418) = 0.5479503$. We can see that the p value is MORE THAN 0.5, so we cannot reject the null hypothesis even at a confidence level of 95%.

4.3 Inference

From the ANOVA test we can infer that AEF-A, AEF-D and TDS have almost similar difficulties. On the other hand, TCATA, FC-AEF-D and FC-AEF-A have almost similar difficulties.
AEF-A, AEF-D and TDS have a lower difficulty than TCATA, FC-AEF-D and FC-AEF-A, making them a better choice of method in terms of difficulty.

5 TDS vs TCATA (Dominance vs Applicability)

TDS and TCATA curves and difference curves are plotted using R for different products to compare the products. In this subsection, we explain how these curves were constructed and we compared the two methods using their difference plots for the same pair of products.

5.1 Curve Construction

5.1.1 TDS Curve Construction

Dominance rate is the proportion of consumers that cite a given attribute as dominant at a given time. We plot dominance rate for each attribute (from the list : Crackly Hard, Crispy, Sticky Pasty, Melting, Salty, Fat, Potato, Roasted and Bland), for each crisp product C1, C2, C3, C4 as follows:

- Since different consumers have different chewing speeds which clearly affects the tasting duration in an undesirable manner, we standardized the time intervals to range between 0 and 100 for each consumer to make them comparable.
- We divided 0 to 100 into 100 sub-intervals and then computed proportion of consumers that perceived the given attribute as dominant in the given interval (approximation of dominance rate). We could do this because the interval is very small.
- Then we plotted the dominance rate for each attribute and superimposed the nine plots to make comparing different products easier.

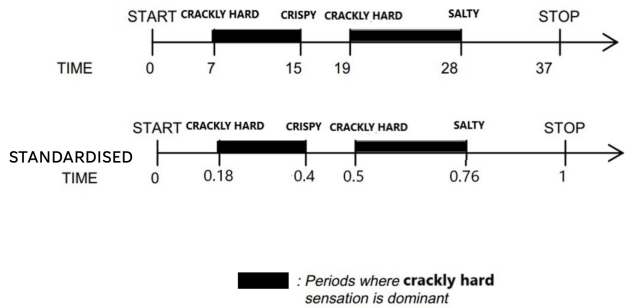


Figure 19: Standardizing tasting time of a consumer

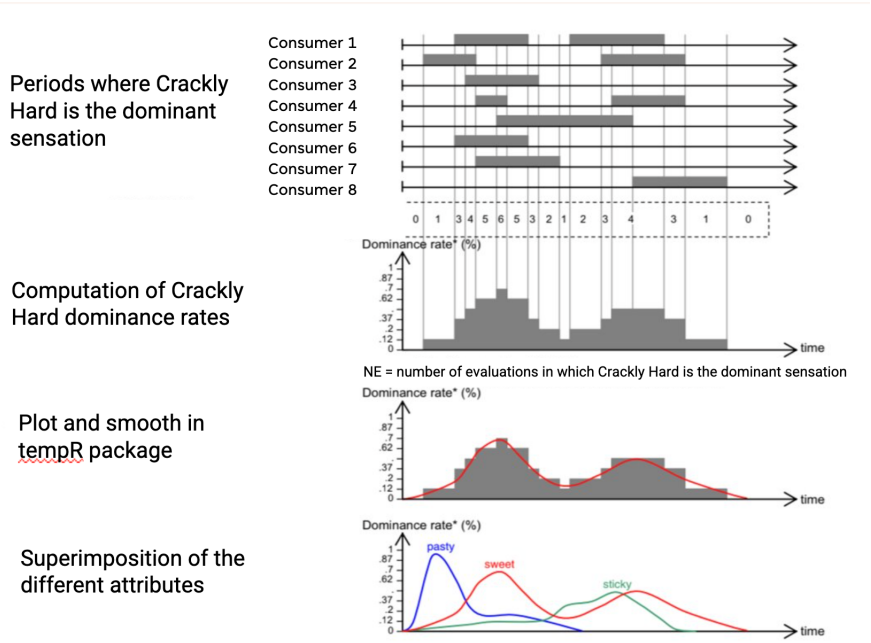
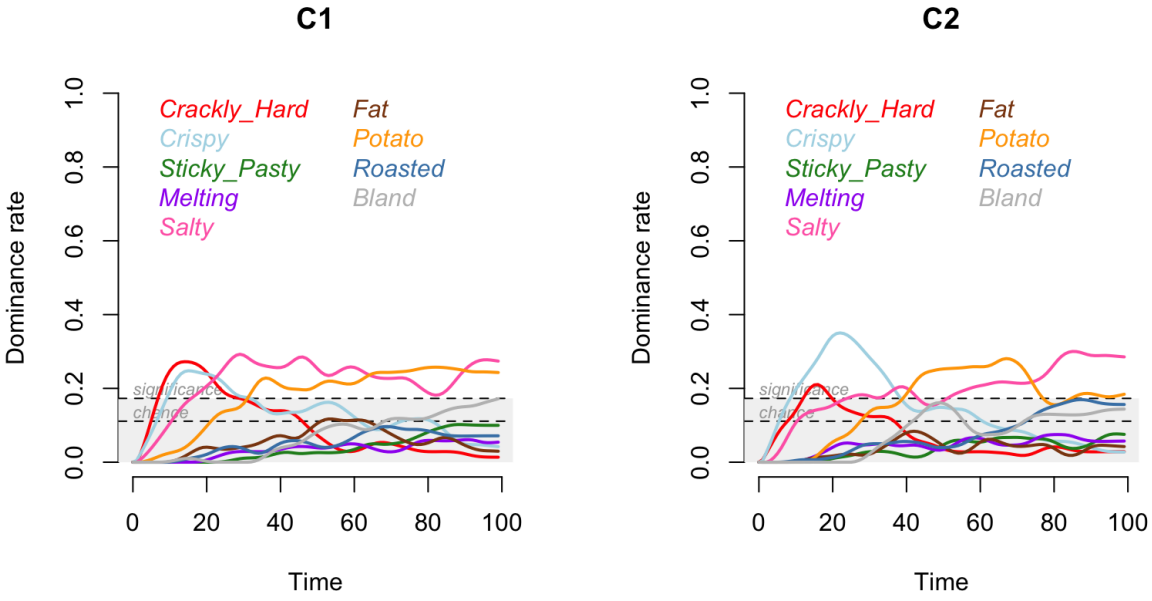


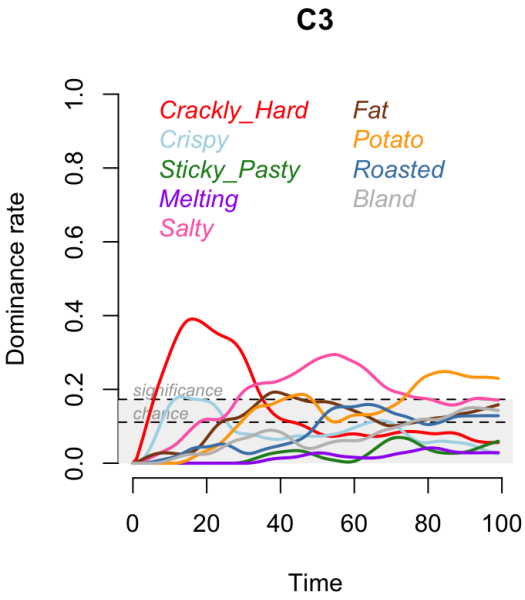
Figure 20: Constructing a TDS curve

- We took the chance level, $P_0 = \frac{1}{p}$, where p is number of attributes since exactly one attribute is dominant at a given time and each attribute has equal chance of being randomly chosen.
- We then constructed a 95% confidence interval around P_0 . Wherever the dominance rate is above the upper bound (this is called the significance level), the dominance rate is said to be significant.
- Two lines for significance and chance level were plotted with the curves to make interpretation easier.
- One can plot the difference between dominance rates of two products with time to compare two products. These plots are called TDS difference plots. We have plotted TDS curves for the four crisps and the six pairwise TDS difference plots:

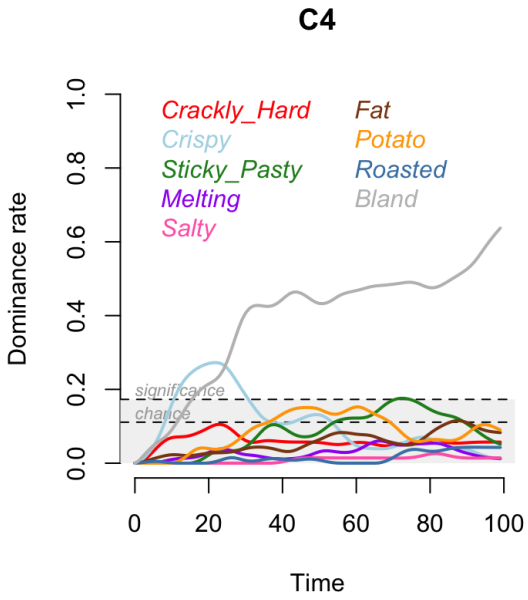


(a) C1 TDS curve

(b) C2 TDS curve



(c) C3 TDS curve



(d) C4 TDS curve

Figure 21: Dominance vs Applicability

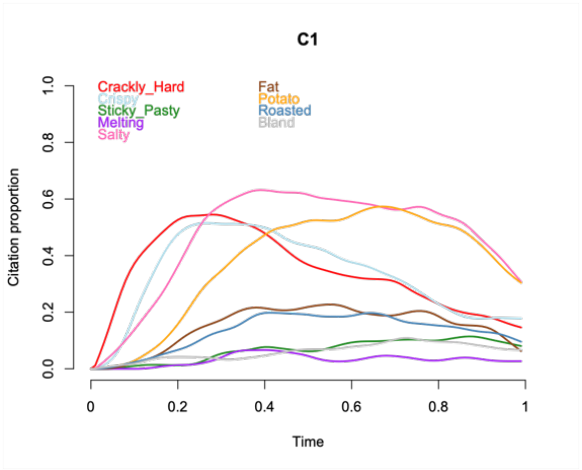
5.1.2 TCATA curve construction

Citation proportion is the proportion of consumers that have cited a given attribute at a given time. This is similar in concept to dominance rate, but it is different since more than one attribute may be cited by the same consumer at a given time.

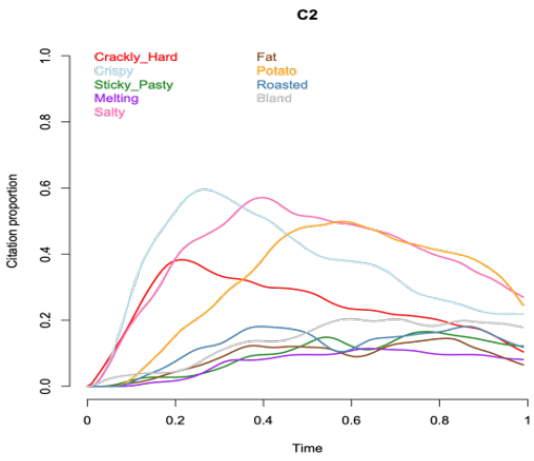
- As done in the case of TDS curves we plot citation proportion for each attribute from the same list (Crackly Hard, Crispy, Sticky Pasty, Melting, Salty, Fat, Potato, Roasted and Bland), for each

crisp product (C1, C2, C3, C4) and superimpose these nine curves for each product.

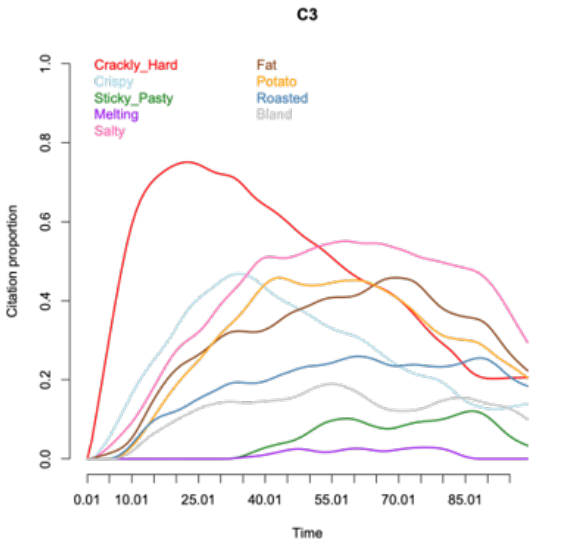
- We also plot the difference between citation proportions of two products for each pair of the four crisps. These plots are called TCATA difference plots.



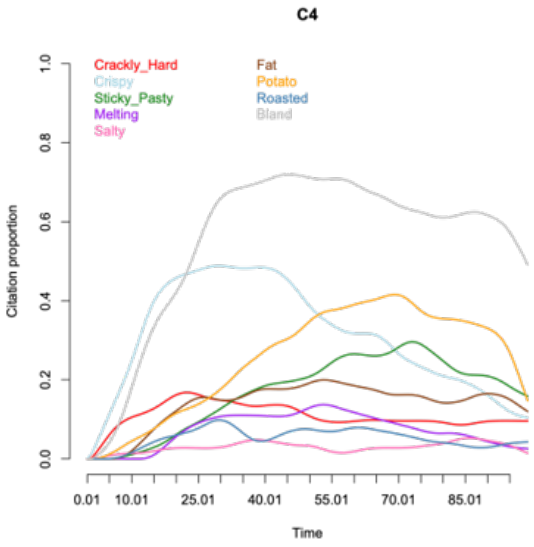
(a) C1 TCATA curve



(b) C2 TCATA curve



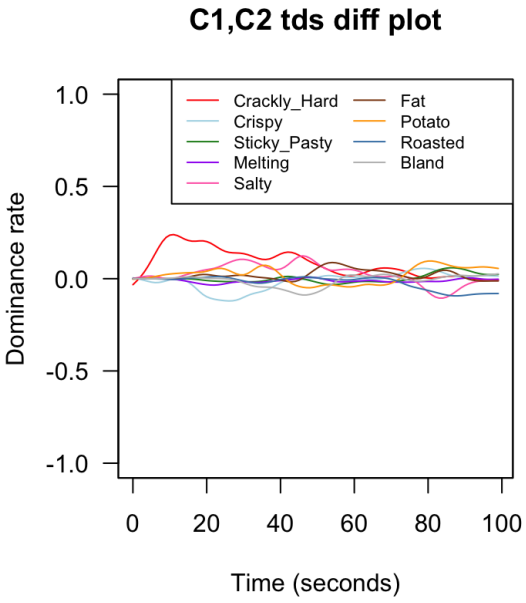
(c) C3 TCATA curve



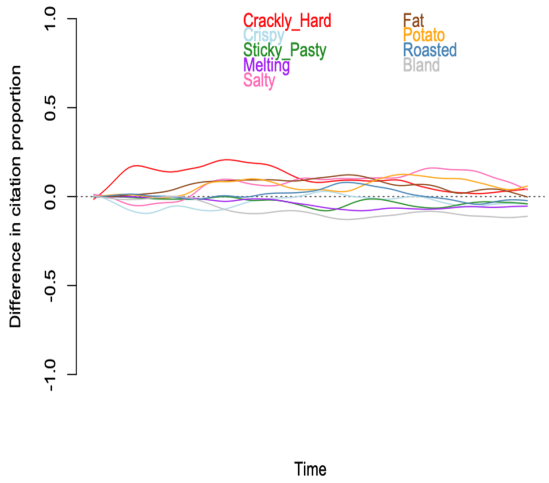
(d) C4 TCATA curve

Figure 22: Dominance vs Applicability

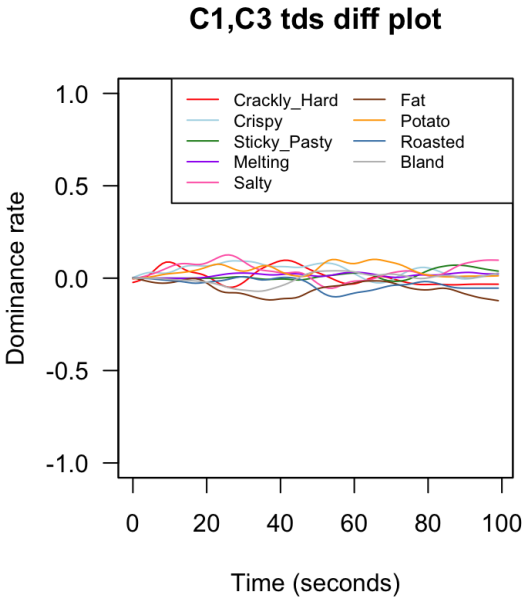
5.2 Comparison between the difference curves made using TDS and TCATA



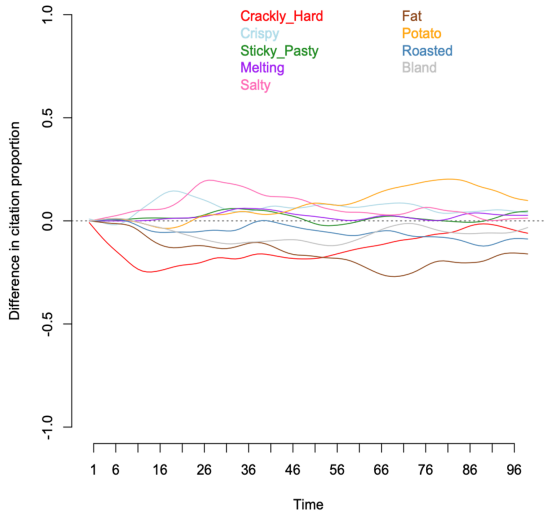
(a) C1-C2 TDS difference plot



(b) C1-C2 TCATA difference plot

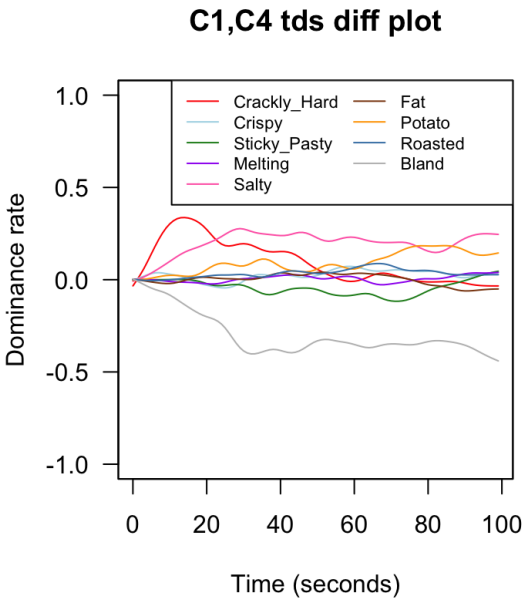


(c) C1-C3 TDS difference plot

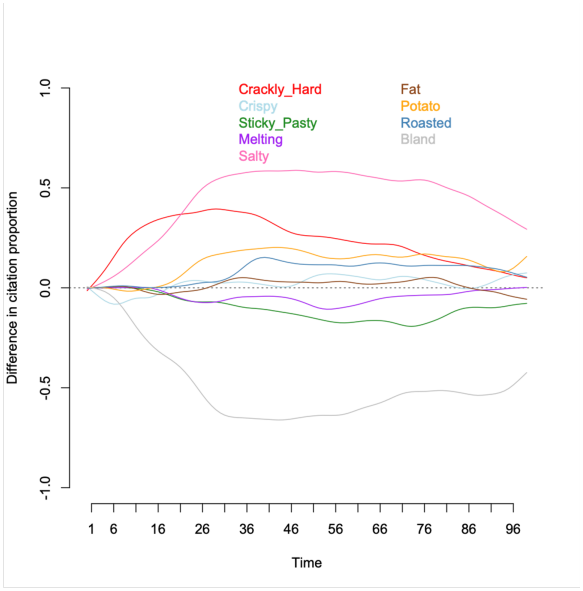


(d) C1-C3 TCATA difference plot

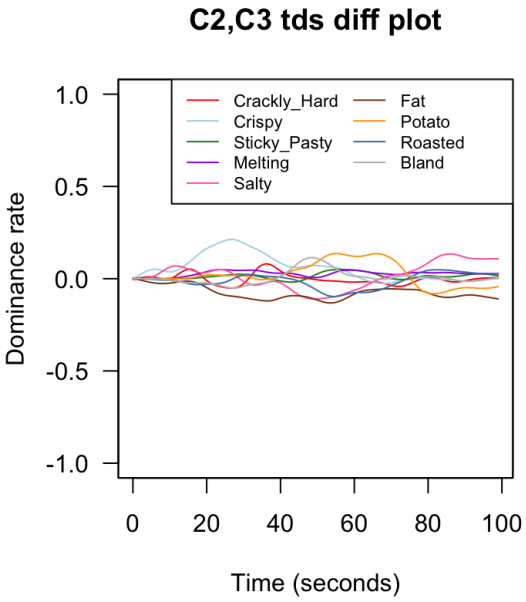
Figure 23: Dominance vs Applicability(Continuous)



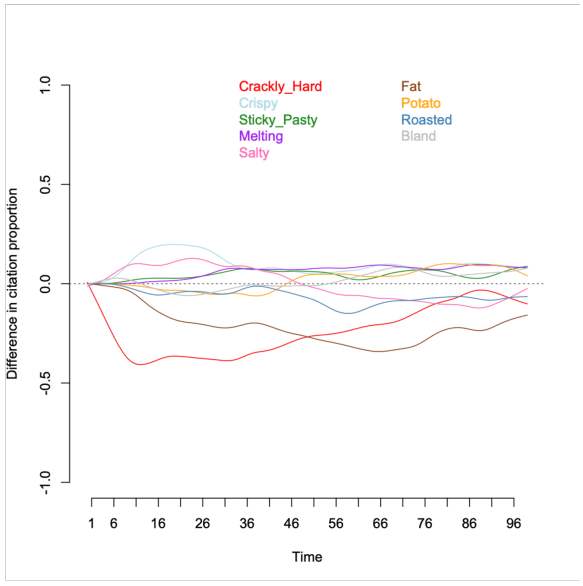
(a) C1-C4 TDS difference plot



(b) C1-C4 TCATA difference plot

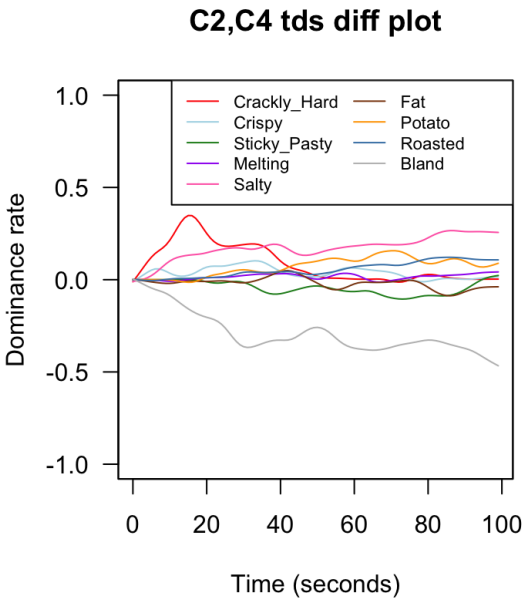


(c) C2-C3 TDS difference plot

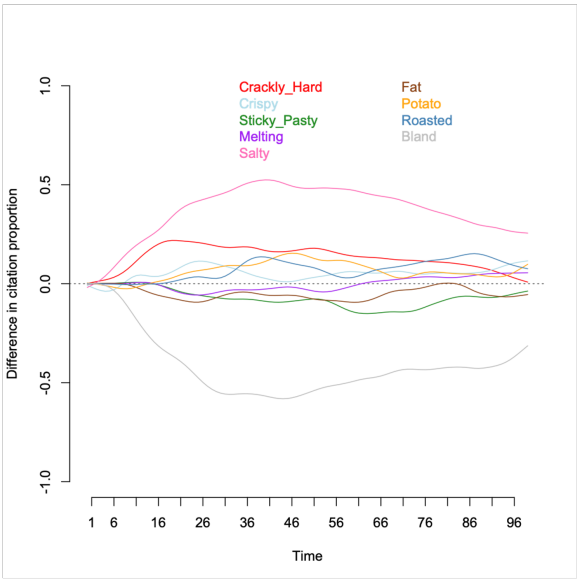


(d) C2-C3 TCATA difference plot

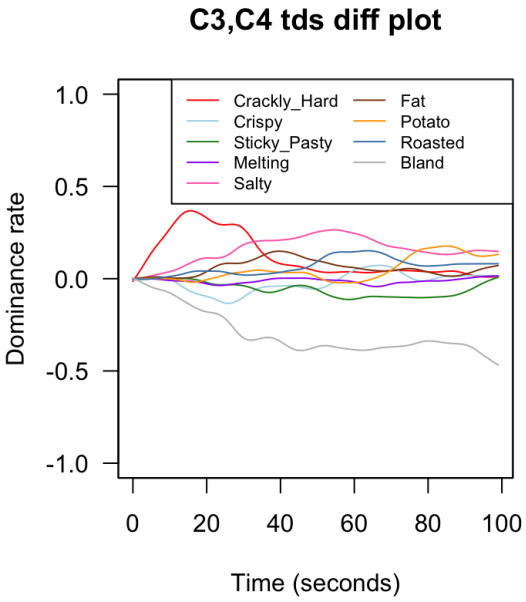
Figure 24: Dominance vs Applicability(Continuous)



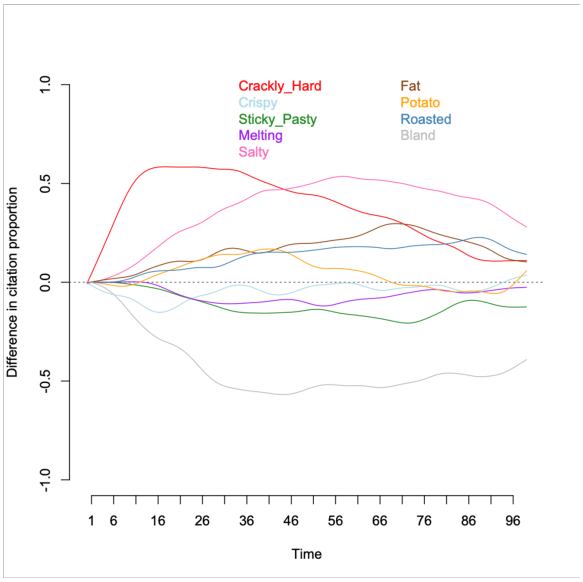
(a) C2-C4 TDS difference plot



(b) C2-C4 TCATA difference plot



(c) C3-C4 TDS difference plot



(d) C3-C4 TCATA difference plot

Figure 25: Dominance vs Applicability(Continuous)

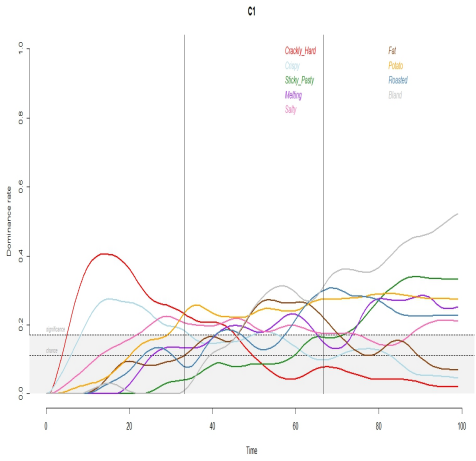
5.3 Inference

For each product, the TDS curves and the TCATA curves are quite similar. For each pair of crisp products as well, the TDS and TCATA difference plots seem very similar. This implies that both methods distinguish products in a similar manner. These similarities indicate the consistency across methods differing in the parameter Dominance vs Appicability.

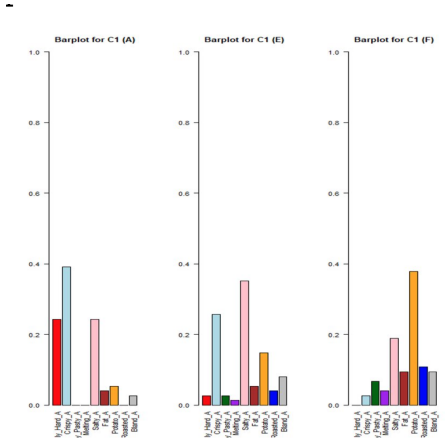
6 TDS vs AEF (Continuous vs Periodic)

6.1 Comparison plots

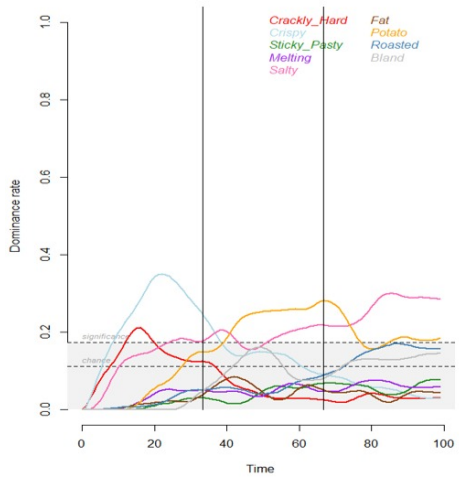
To compare the methods TDS and AEF, we plotted the AEF citation proportion barplots for each attribute in each period for each product and compared with the corresponding TDS plot of dominance rates for the same product.



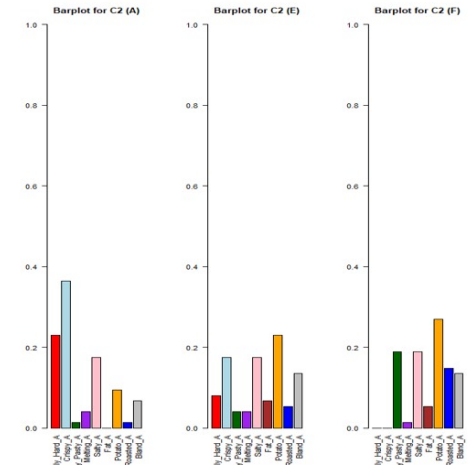
(a) C1 TDS curve



(b) C1 AEF-D Barplot

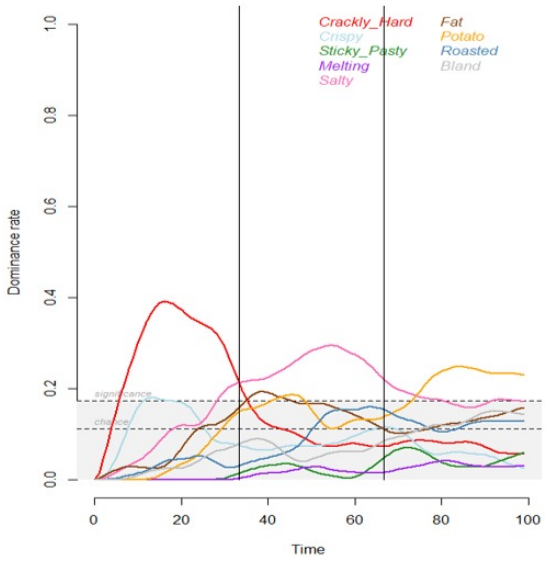


(c) C2 TDS curve

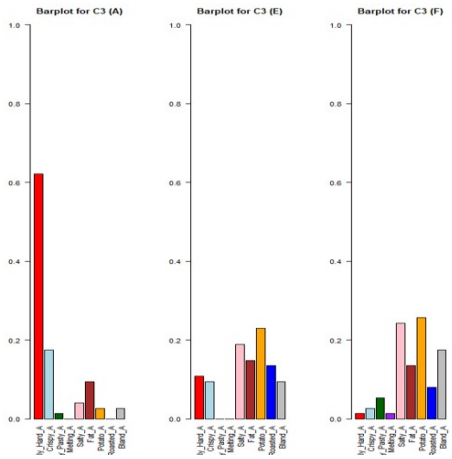


(d) C2 AEF-D Barplot

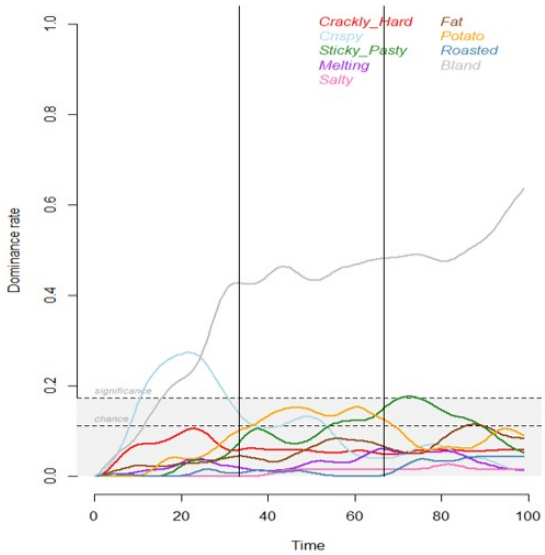
Figure 26: Continuous vs Periodic



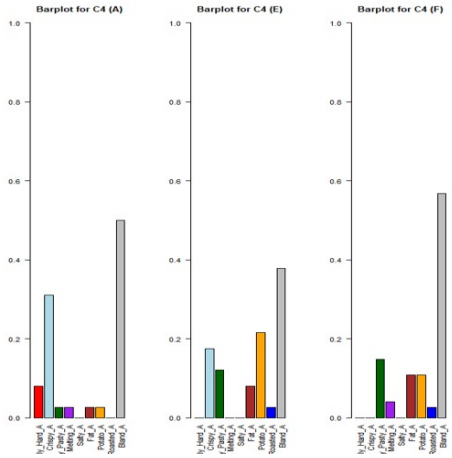
(a) C3 TDS curve



(b) C3 AEF-D Barplot



(c) C4 TDS curve



(d) C4 AEF-D Barplot

Figure 27: Continuous vs Periodic

6.2 Inference from the plots

The plots for the two methods look very similar and they both shows all the important attributes of a product. The similarity between the two indicates the consistency between the two methods differing in the parameter Continuous vs Periodic .

Even though AEF is periodic and gives data for 3 seperate intervals only, there is not too much loss of information about the products as compared to TDS.

7 Comparison between methods using correspondence analysis

So far from the plots, it is evident that the methods are distinguishing products in a very similar way. Now we want to check if that is true using Correspondence Analysis.

7.1 Quick Overview of CA

7.1.1 What Is CA ?

Correspondence analysis (CA) is a multivariate statistical technique that reveals the relationship between and within two groups of variables. It is conceptually similar to Principal Component Analysis but applies to categorical rather than continuous data. PCA works with the data values while CA works with relative values, so CA is more applicable for our analysis. In a similar manner to PCA, it provides a means of displaying or summarizing a set of data in two-dimensional graphical form. Its aim is to display in a biplot any structure hidden in the multivariate setting of the data table.

7.1.2 How does CA work?

- *Contingency Table*: Contingency table is a table that displays frequency distribution of the variables. Of the two groups of variables that is being compared one group is put as the row labels and another as the column labels. Each cell in the table shows how many data points corresponds to that row and column label.
- *Expected Values*: The table of the expected values holds the expected number of data points in the cells if we consider that there is no correlation within and between the row and the column labels.
- *Residuals*: Residuals of each cell the difference between the observed value and the expected value.
- *Observed Proportions*: Observed proportions is equal to the value in a cell divided by the total sum of all of the values in the contingency table.
- *Row and Column Masses*: Row masses are the sums of the observed proportions for the rows. Similarly, column masses are the sums of the observed proportions for the columns.
- *Expected Proportion* Observed proportions is equal to the value in a cell divided by the total sum of all of the values in the expected value table.
- *Indexed Residuals*: Indexed residuals are residuals divided by expected proportion.
- *Standardised Residuals*: Standardised residuals are indexed residuals multiplied by square root of expected proportions.

Then, singular value decomposition is done on the matrix of standardised residuals, say $S = UDV$ where D is the diagonal matrix and U and V are invertible matrices. The eigenvalues extracted from the diagonal matrix D give the dimensions. Eigenvalues as proportions gives the amount of variance captured in the corresponding dimension of the CA, which shows the amount of information kept in that dimension. The coordinates of the row and column labels are found from the invertible matrices.
In the CA biplot, the row labels are represented by dots and the columns labels are represented by triangles.

7.1.3 How To Interpret CA?

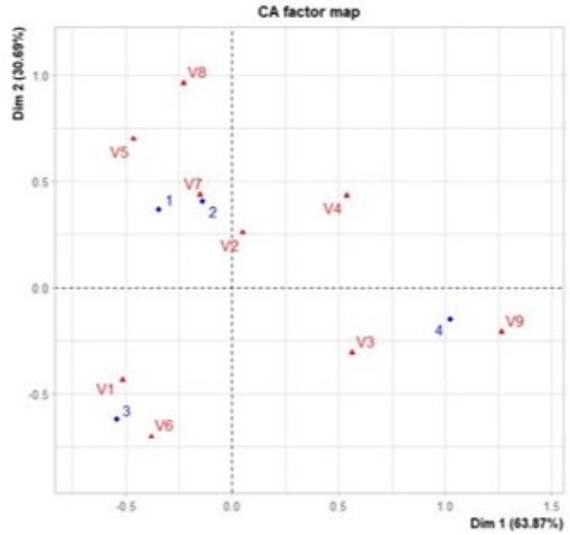
- In the CA plot, the further things are from the origin, the more informative the CA is about them. It is not that reliable for things that are too much near the origin.
- The more is the sum of the proportion of variance of the two dimensions, the lesser is the loss of information and hence the better the CA is in understanding the correlation between the variables.
- Proximity between the row labels indicates similarity between them.
- Proximity between the column labels indicates similarity between them.
- The angle between the row and column labels indicates the correlation between them (angle between them means angle between the lines joining them to the origin). For example, close to 0 degrees angle between two variables show very high positive correlation, 180 degrees show very high negative correlation and close to 90 degrees angle imply almost no correlation between those two variables.

7.2 Comparison between AEF-D and AEF-A (Dominance vs Applicablility)

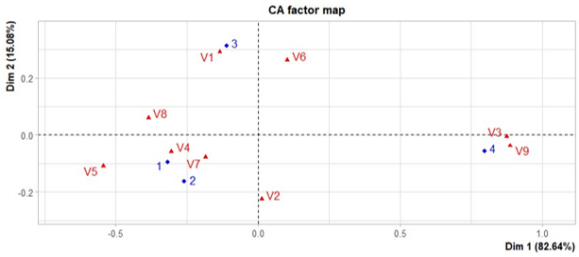
7.2.1 How to extract the AEF-D and AEF-A data?

For both the methods AEF-D and AEF-A, the list of attributes is the predefined list Crackly Hard, Crispy, Sticky Pasty, Melting, Salty, Fat, Potato, Roasted and Bland. We count the number of consumers who chose a specific attribute at a given period for both the methods for each product.
We make contingency table from that data where the row labels are the four different products C1, C2, C3, C4 and the column labels are the nine different attributes. We do CA using those contingency tables.

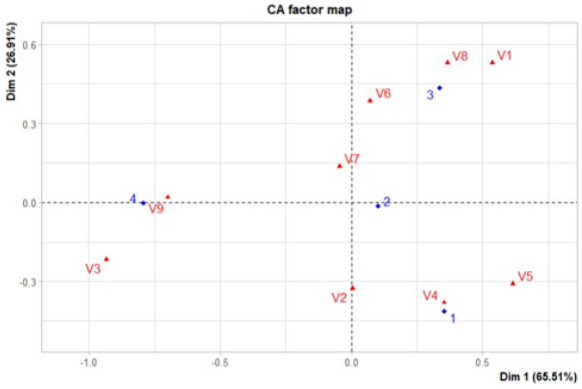
The variables for AEF-D and AEF-A are:
V1 Crackly Hard
V2 Crispy
V3 Sticky Pasty
V4 Melting
V5 Salty
V6 Fat
V7 Potato
V8 Roasted
V9 Bland



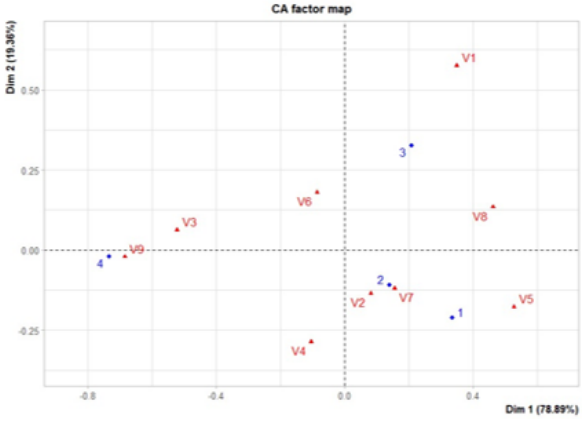
(a) AEF-D Attack



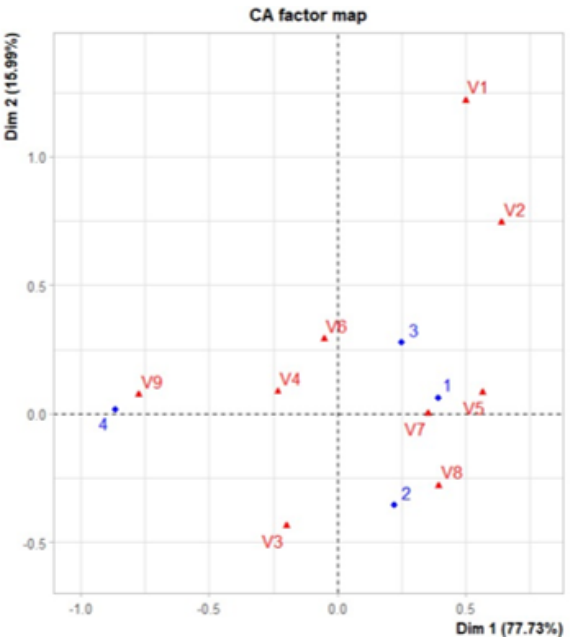
(b) AEF-A Attack



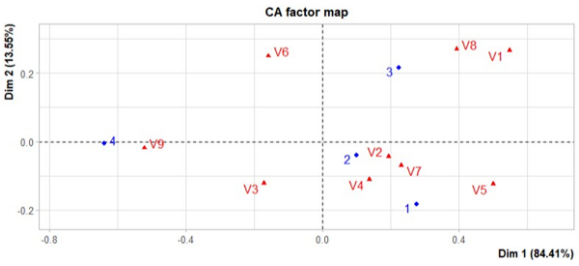
(c) AEF-D Evolution



(d) AEF-A Evolution



(e) AEF-D Finish



(f) AEF-A Finish

Figure 28: Dominance vs Applicability (Periodic)

7.2.2 Inference from the AEF-D and AEF-A Plots

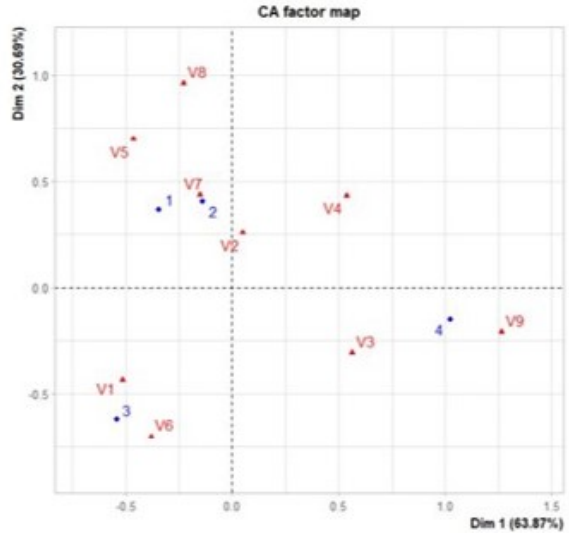
We can see that the AEF-A and AEF-D CA plots are similar. For example, using both methods we can see that in the attack stage the products C1 and C2 are very similar while C4 is very different to the other products. Both methods show bland as a very important property of C4 in this period. The similarity in the CA plots means that both the methods differentiate between the products in a similar manner and also both methods are similarly good at showing the significant properties of the different products.

7.3 Comparison between AEF-D and TDS (Periodic vs Continuous)

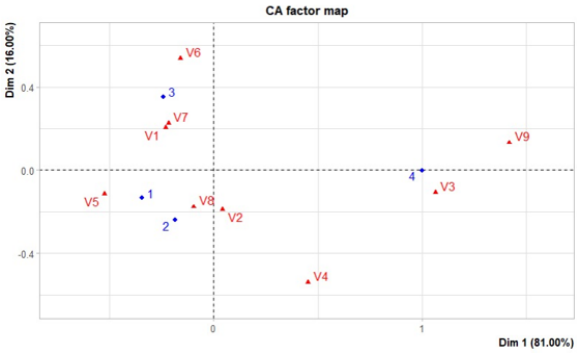
7.3.1 How to extract the AEF-D and TDS Data

For AEF-D, we have already made the CA biplot. For TDS, we divide the entire duration for each consumer into 3 equal parts. The three parts correspond to the Attack, Evolution and Finish stages respectively. Now similar to AEF-D, we count how many consumers chose a specific attribute at a given period for each product.
We make contingency table from that data where the row labels are the four different products C1, C2, C3, C4 and the column labels are the nine different attributes. We do CA using that contingency table.

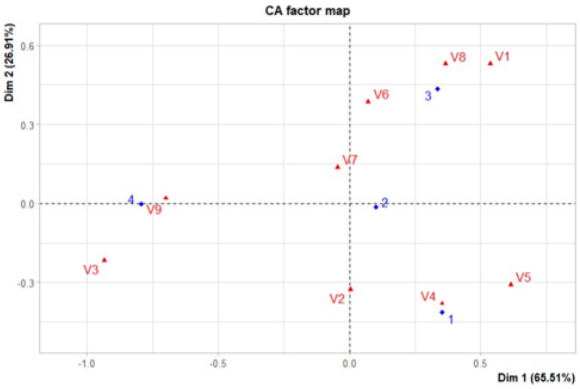
The variables for AEF-D and TDS are:
V1 Crackly Hard
V2 Crispy
V3 Sticky Pasty
V4 Melting
V5 Salty
V6 Fat
V7 Potato
V8 Roasted
V9 Bland



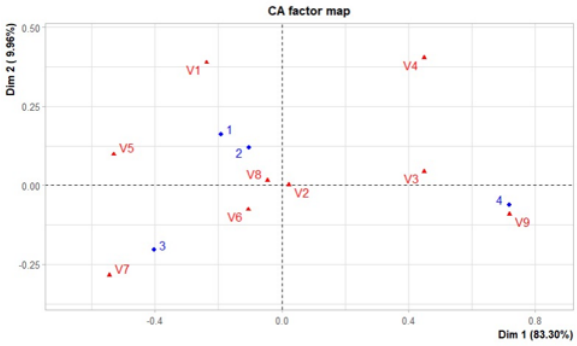
(a) AEF-D Attack



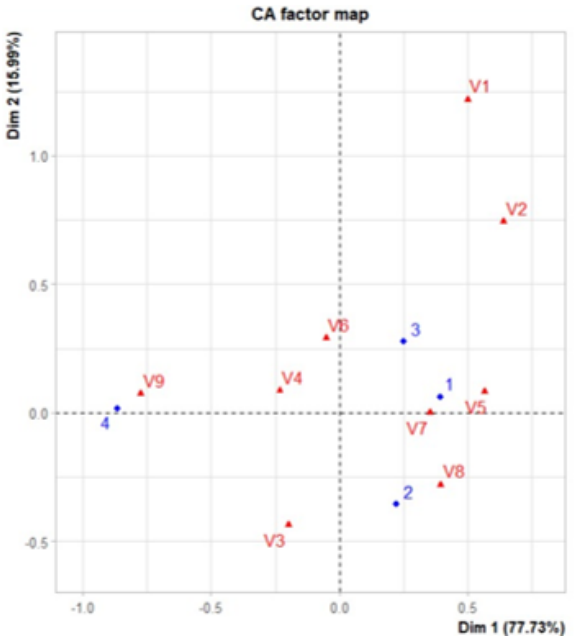
(b) TDS Attack



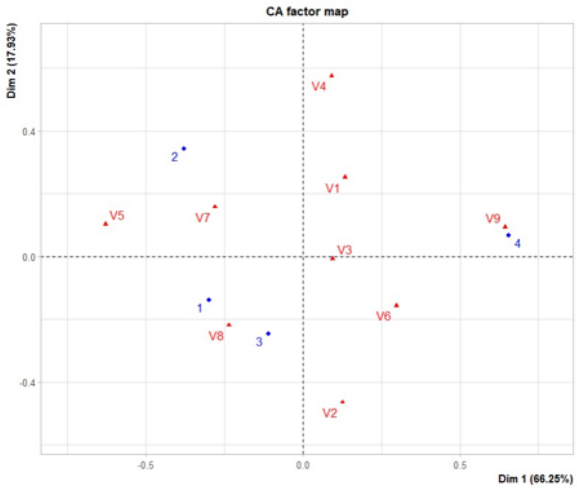
(c) AEF-D Evolution



(d) TDS Evolution



(e) AEF-D Finish



(f) TDS Finish

Figure 29: Periodic vs Continuous

7.3.2 Inference from the AEF-D and TDS Plots

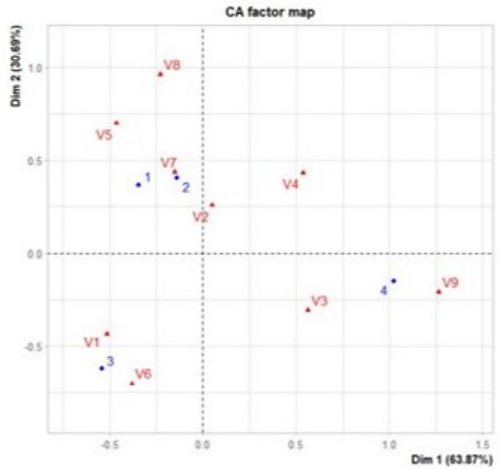
We can see that the TDS and AEF-D CA plots are similar. For example, using both methods we can see that in the attack stage the products C1 and C2 are very similar while C4 is very different to the other products. Both methods show bland as a very important property of C4 in this period. This means that both the methods differentiate between the products in a similar manner and also both methods are similarly good at showing the significant properties of the different products.

7.4 Comparison between AEF-D and FC-AEF-D (Free Comment vs Predefined List)

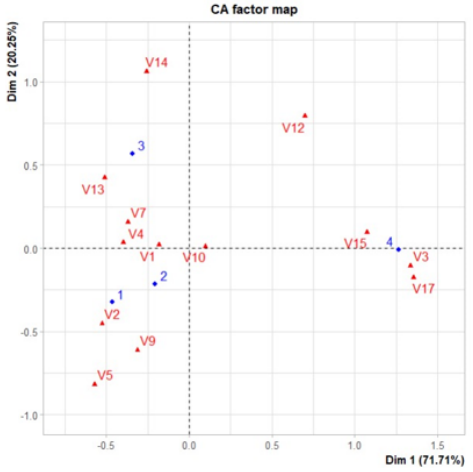
7.4.1 How to extract the FC-AEF-D data?

First, we extract the attributes which have been mentioned in the free comments at least 4 times by the consumers, using an R code. Now we manually rectify the list of this attributes, for example:
1. Removing useless remarks such as “nothing”, “0”,“pleasant”, “unpleasant”
2. Clubbing “little salty”,“very salty” and “salty” together as “salty”
This way we get: "crispy", "salty", "bland", "crunchy", "potato", "melting", "crackly", "pasty", "light", "fat", "rancid", "oily", "thick", "hard", "soft", "floury", "thin", which we use as our attribute list.
Note that this list contains all the attributes that were in the predefined list of attributes and more. Now similar to AEF-D, we count how many consumers chose a specific attribute at a given period for each product.
We make contingency table from that data where the row labels are the four different products C1, C2, C3, C4 and the column labels are the different attributes. We do CA using that contingency table.

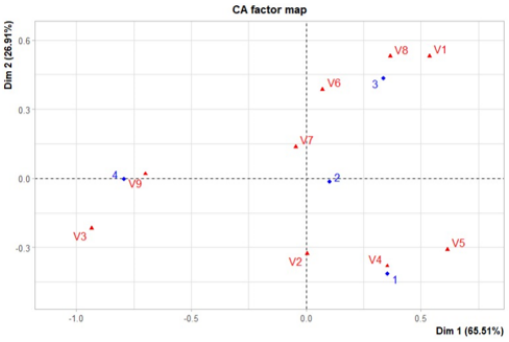
The variables for AEF-D are:	The variables for FC-AEF-D are:
V1 Crackly Hard	V1 Crispy
V2 Crispy	V2 Salty
V3 Sticky Pasty	V3 Bland
V4 Melting	V4 Crunchy
V5 Salty	V5 Potato
V6 Fat	V6 Melting
V7 Potato	V7 Crackly
V8 Roasted	V8 Pasty
V9 Bland	V9 Light
	V10 Fat
	V11 Rancid
	V12 Oily
	V13 Thick
	V14 Hard
	V15 Soft
	V16 Floury
	V17 Thin



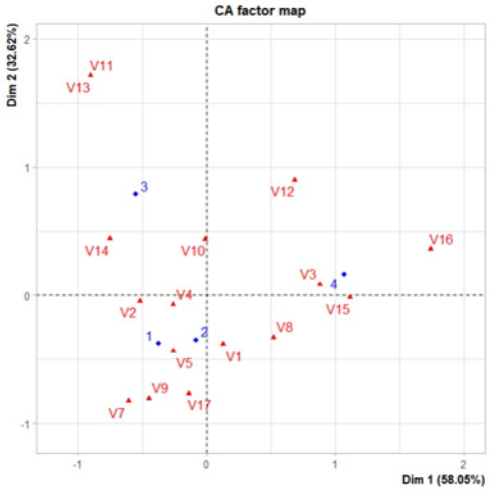
(a) AEF-D Attack



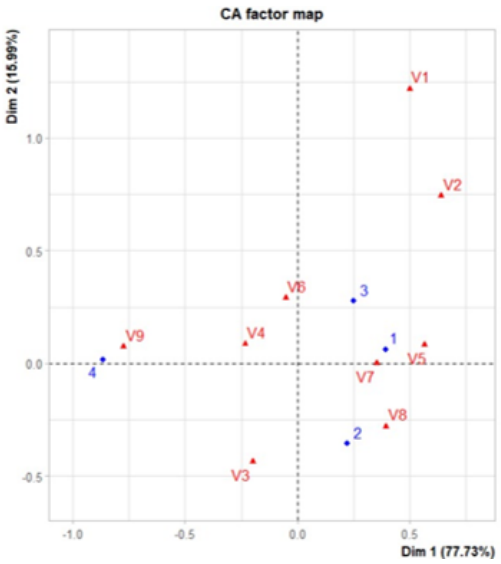
(b) FC-AEF-D Attack



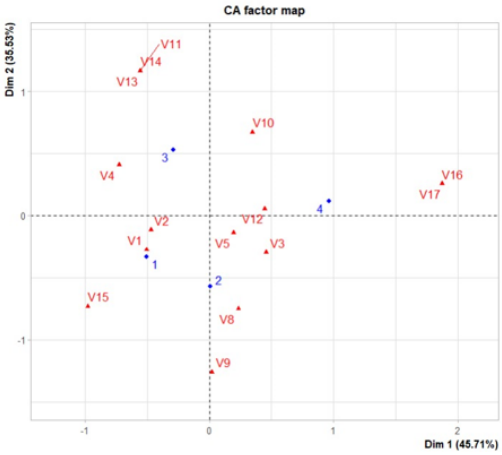
(c) AEF-D Evolution



(d) FC-AEF-D Evolution



(e) AEF-D Finish



(f) FC-AEF-D Finish

Figure 30: Predefined list vs Free Comment

7.4.2 Inference from the FC-AEF-D and AEF-D Plots

We can see that even with a different set of attributes,the FC-AEF-D and AEF-D CA plots are similar. For example, using both methods we can see that in the attack stage the products C1 and C2 are very similar while C4 is very different to the other products. Both methods show bland as a very important property of C4 in this period. This means that both the methods differentiate between the products in a similar manner. But because FC has a bigger list of attributes it is better at showing the significant properties of the different products.
Note that FC new attribute list contains all the attributes present in the predefined list and many more. So, FC-AEF-D gives more information than AEF-D because of a bigger list of attributes. For example, we can see that rancid is a very important attribute for the product C3, which also contributes in distinguishing it from the other products. But it was absent in the predefined list.
Using a pre-established list of sensory descriptors induces several biases, thus not using such a list is the most important benefit of FC. Lists of sensory descriptors are likely to steer consumers in some directions and suggest to them sensory descriptors they would not have thought without the list.
On the contrary, FC enables the gathering of spontaneous unbiased descriptions that are not influenced by the practitioners and their preselection of possibly applicable sensory descriptors.

8 Conclusion

We can conclude that whether the method is periodic or continuous, dominant or applicable, has a pre-defined attribute list or free comment, the products are differentiated in a similar manner.
From the ANOVA we did on the difficulty means of the six methods, it is evident that TCATA, FC-AEF-D and FC-AEF-A have a higher difficulty than AEF-A, AEF-D and TDS.
The free comment data gave us more attributes than the pre-defined list, which is a lot more informative than the 9 attributes from the pre-defined list of attributes. Hence, in spite of being more difficult, Free comment is better than having a pre-defined list of attributes.

9 Extensions

Here is the list of extensions we have done which were not there in the original paper.

- PCA biplots for comparison between different methods in subsection 3.3
- Comparison of difficulty for different methods using boxplots and ANOVA in Section 4
- Plotting and comparing the TDS and TCATA curves in Section 5
- Comparison between TDS and AEF in Section 6
- Comparison between different methods using correspondence analysis in Section 7

10 References

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