CONSUMER DIVERSITY IN SENSORY EVALUATION DATA

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VP Innovation & Research

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Compusense

Decisions related to experimental design and statistical analysis in sensory evaluation are often guided by standard practices.

Does a study that is designed and analyzed in a manner that is consistent with these practices always make sense?

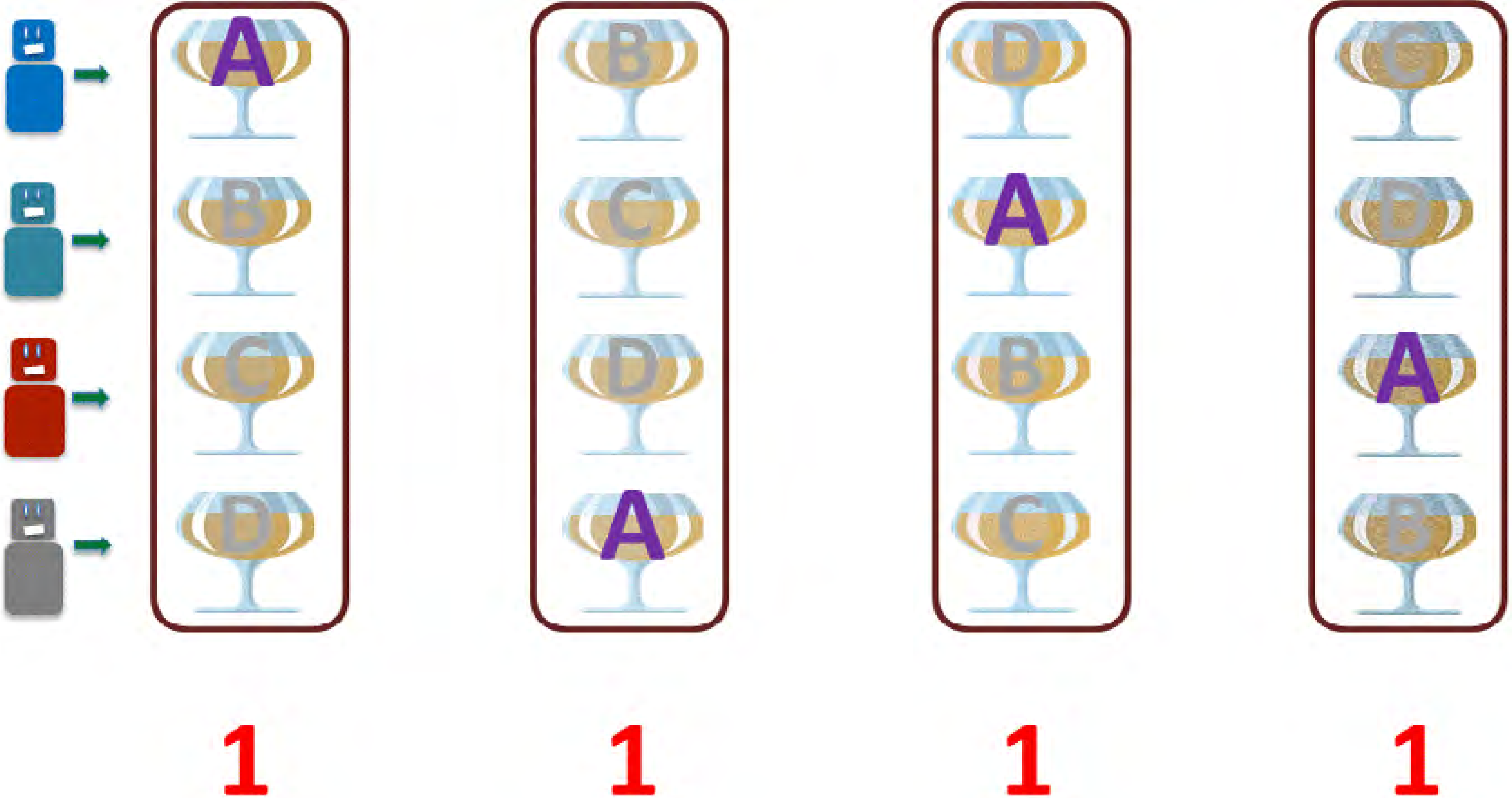

"A foolish consistency is the hobgoblin of little minds..."
Ralph Waldo Emerson
1841

Who is an "average consumer"?

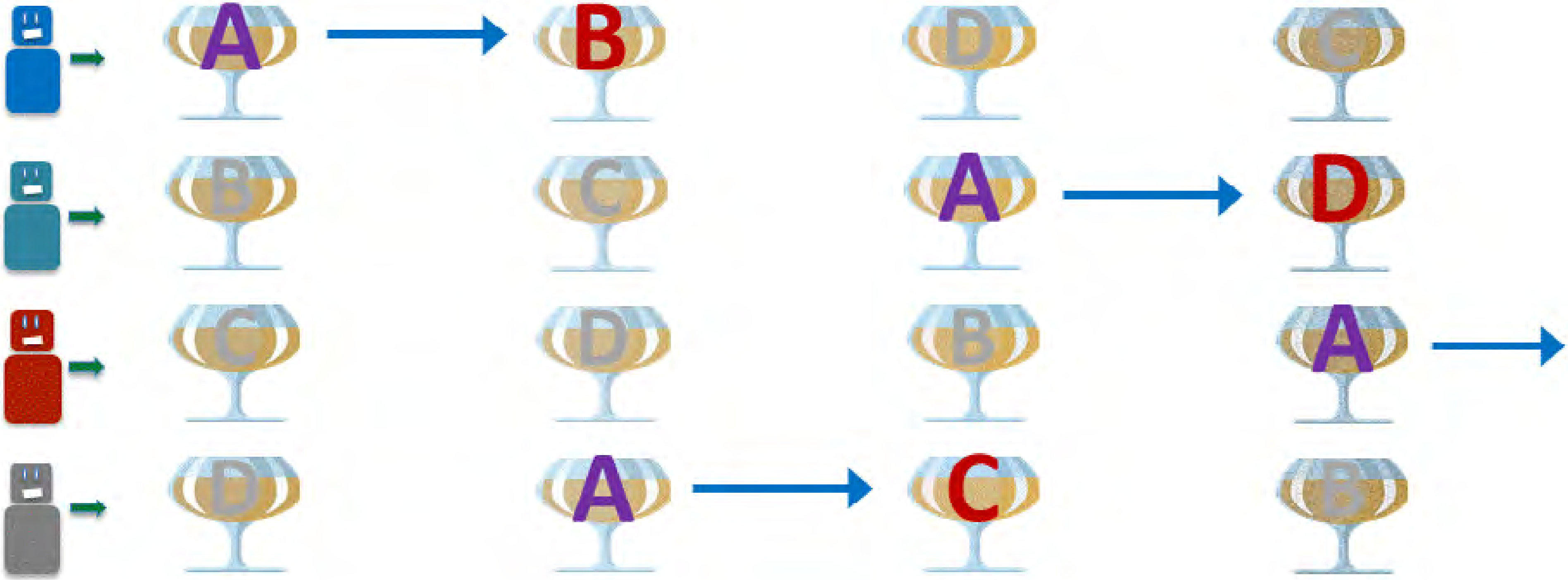
Part I:
Hedonic data

Part I: Consumer acceptance

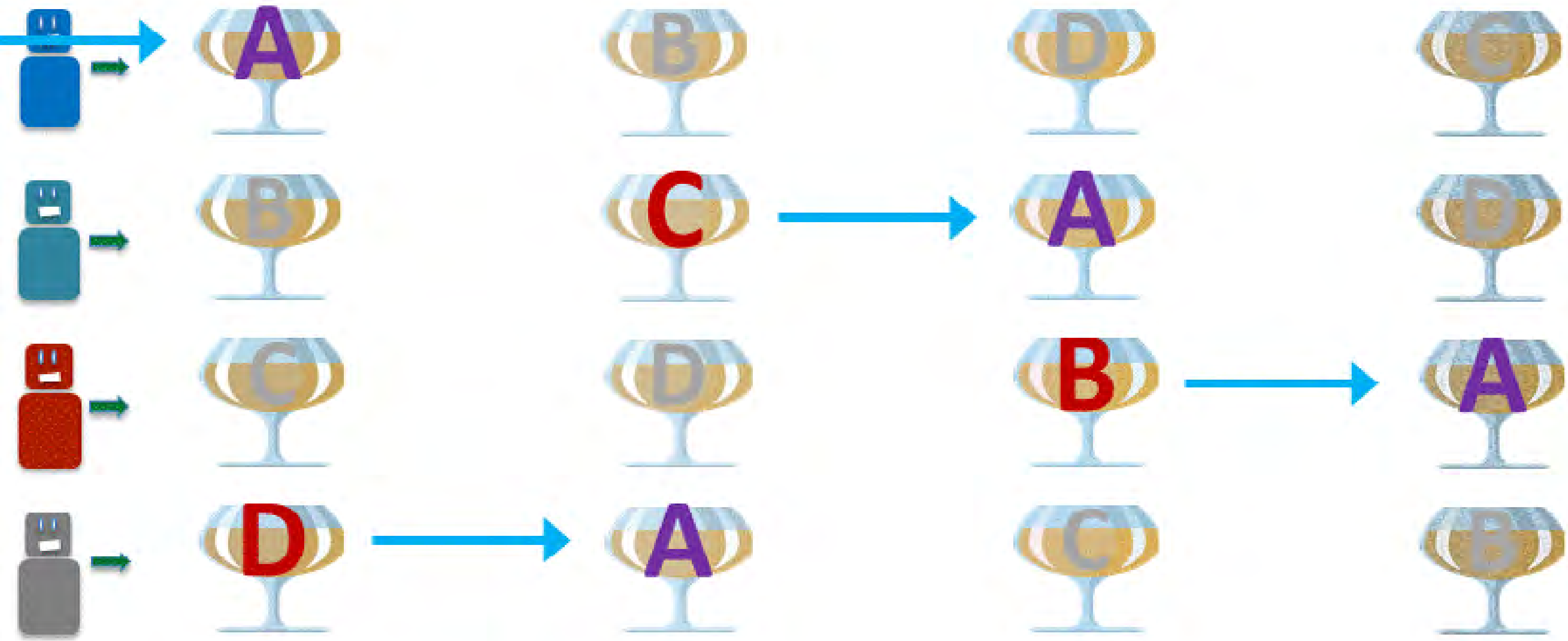

A
B
C
D



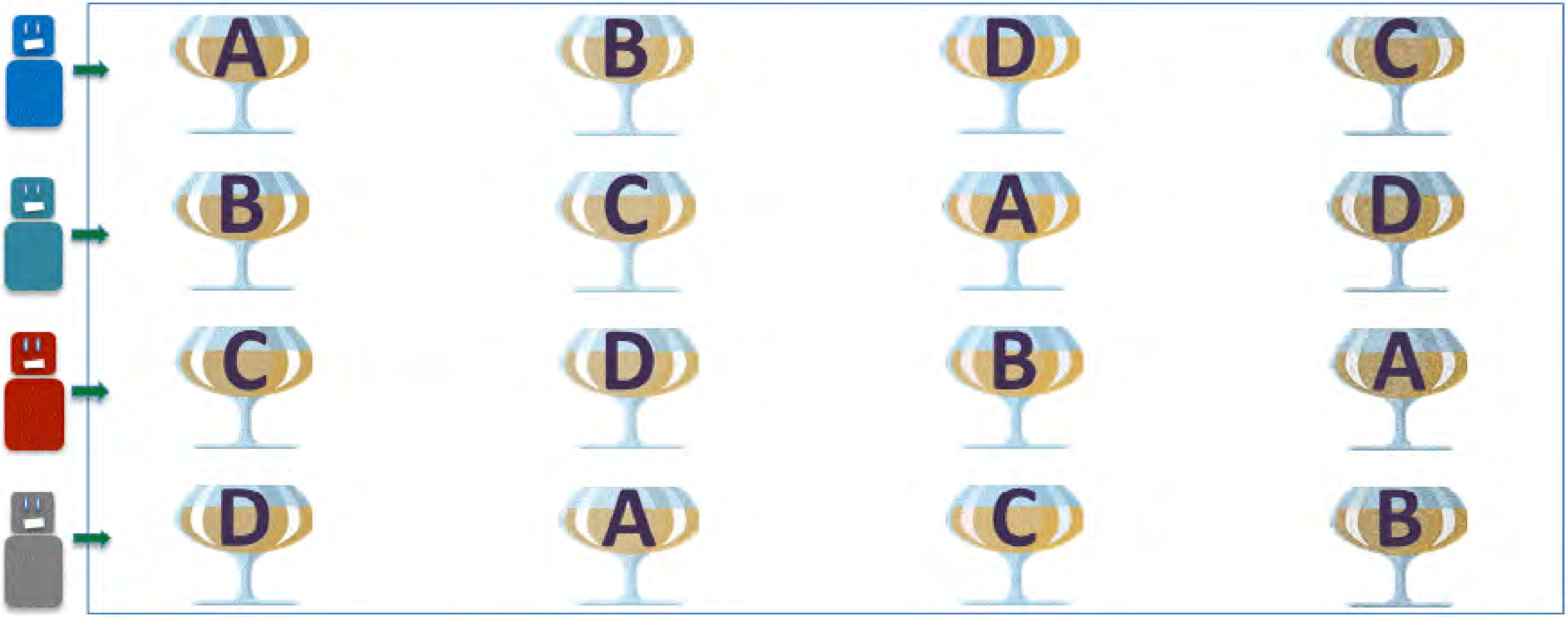
Williams (1949)



Williams (1949)

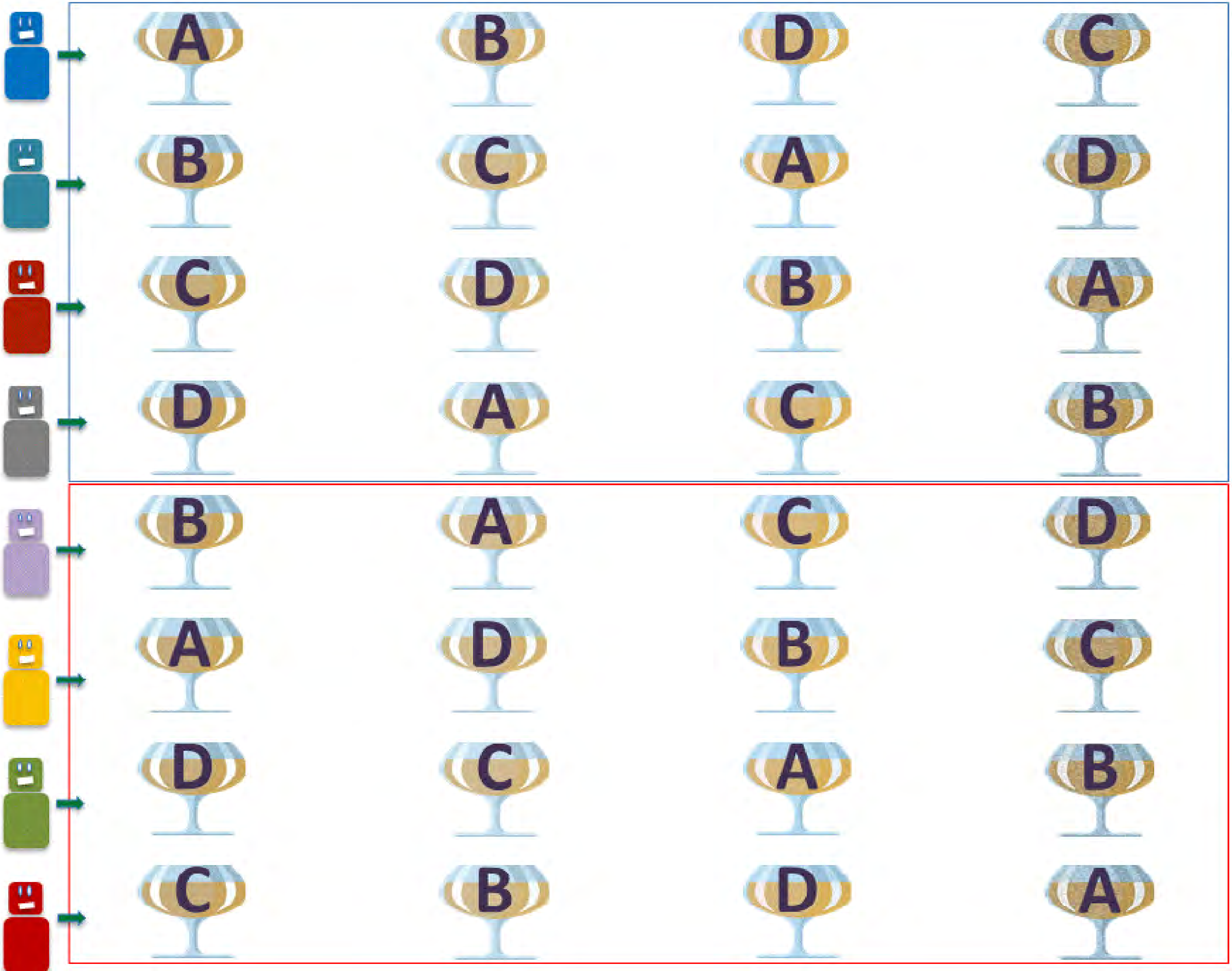


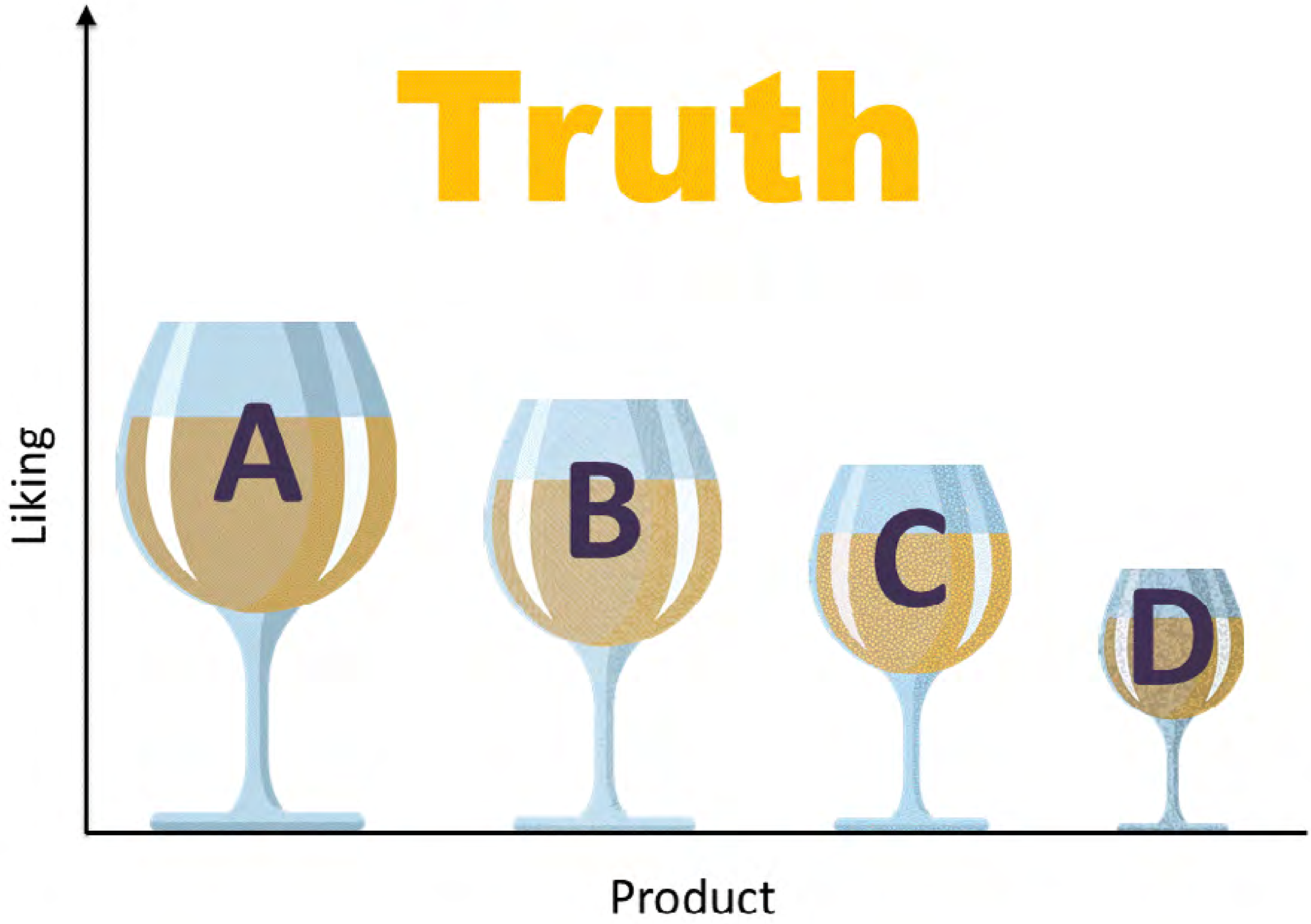
Williams (1949)

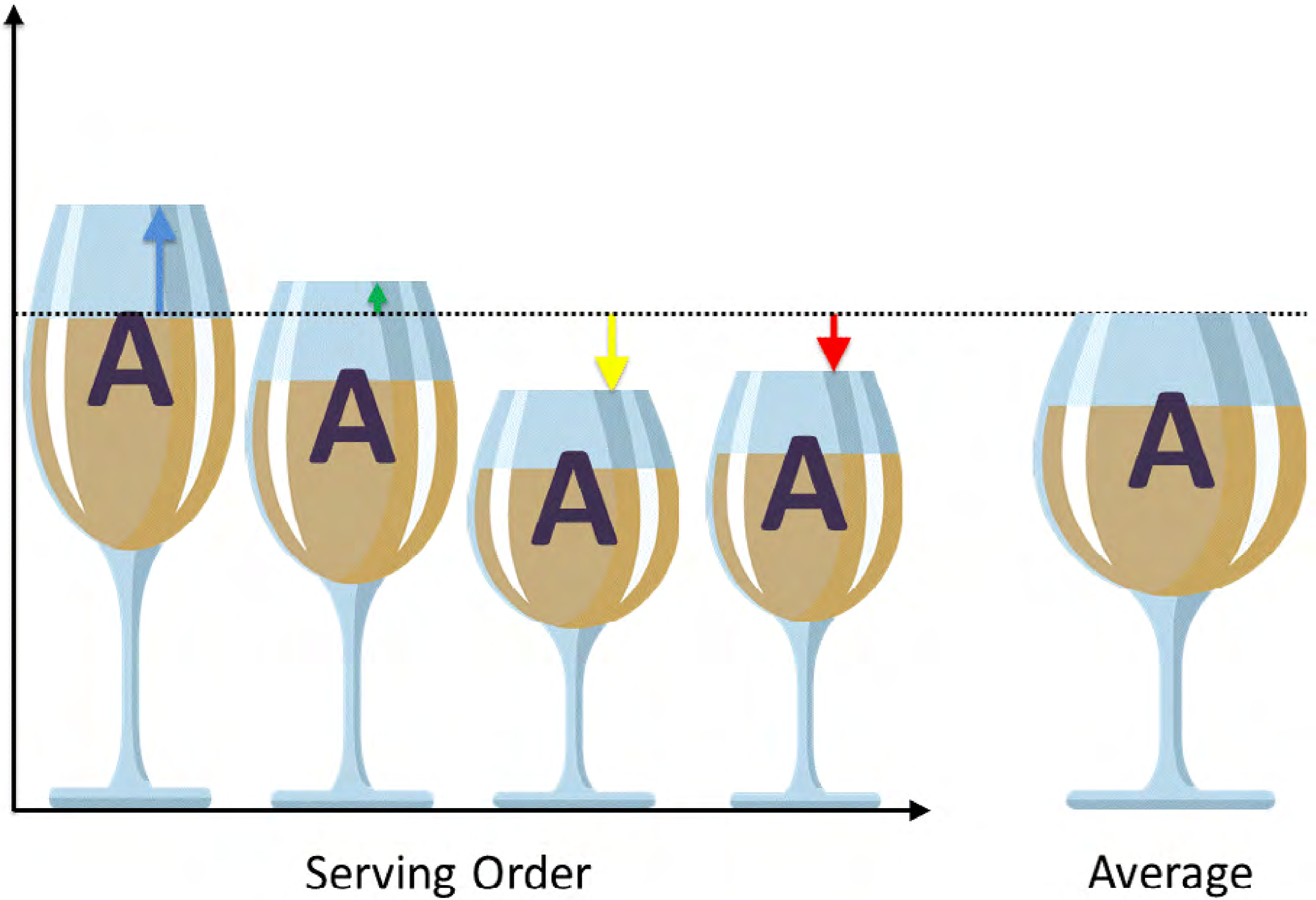


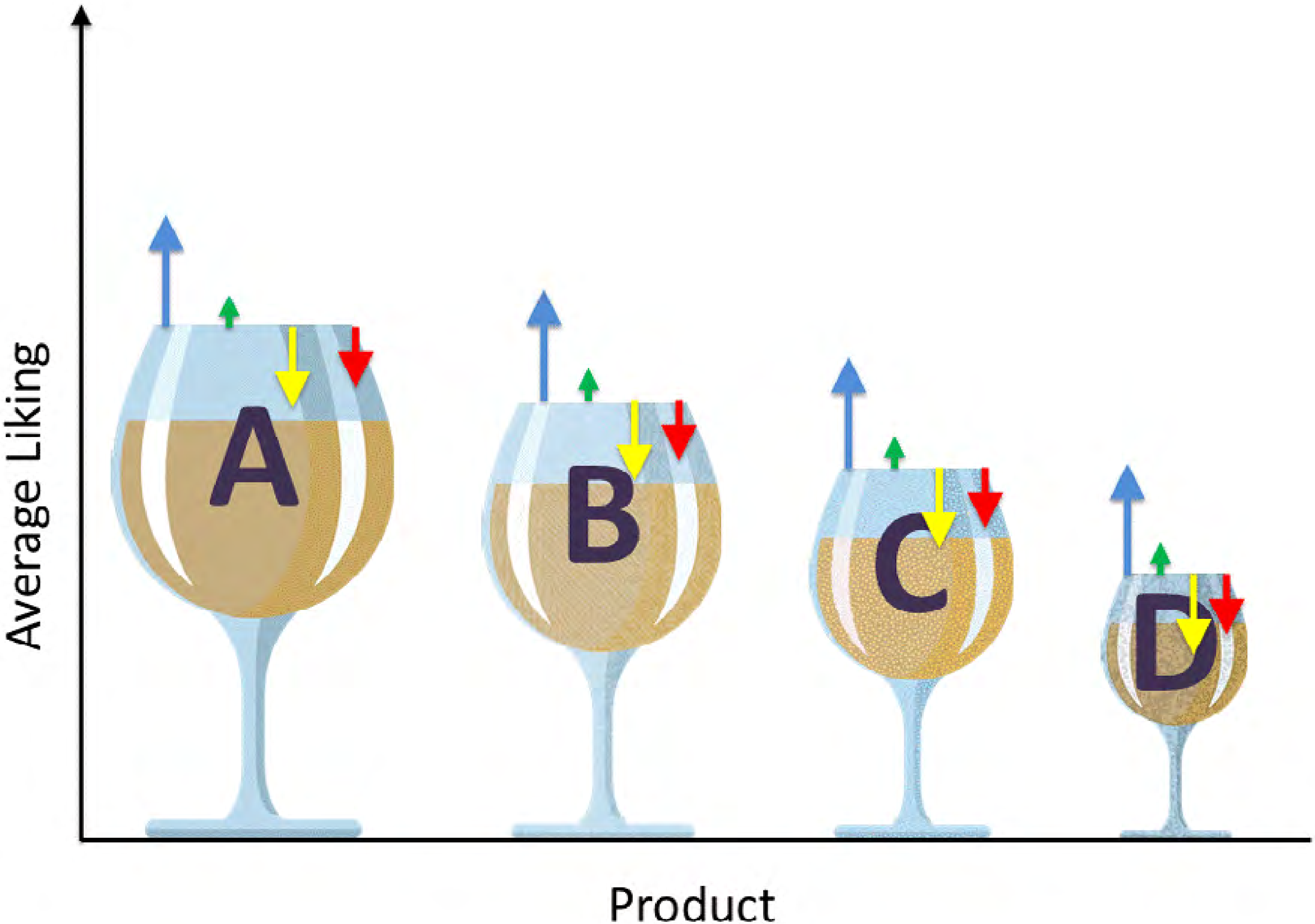
Williams design (4 treatments)

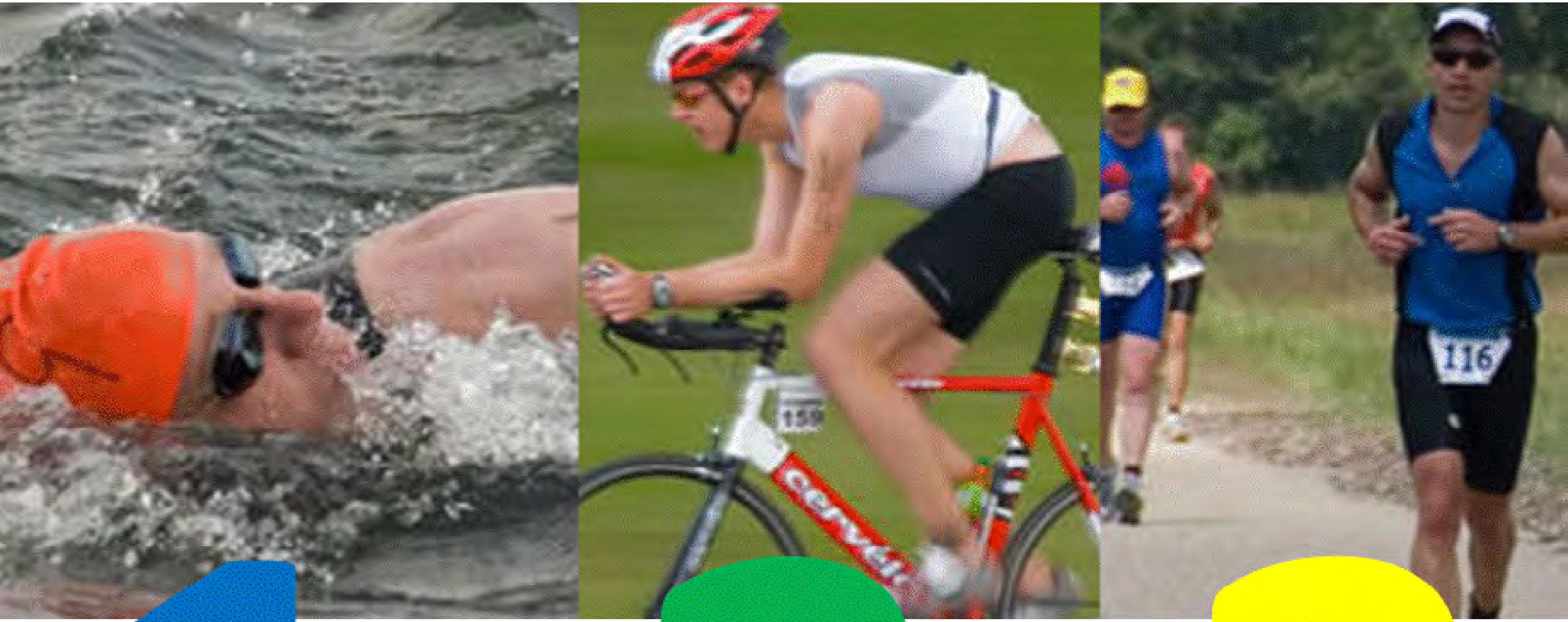
Williams (1949)


A B D C
B C A D
C D B A
D A C B
B A C D
A D B C
D C A B
C B D A

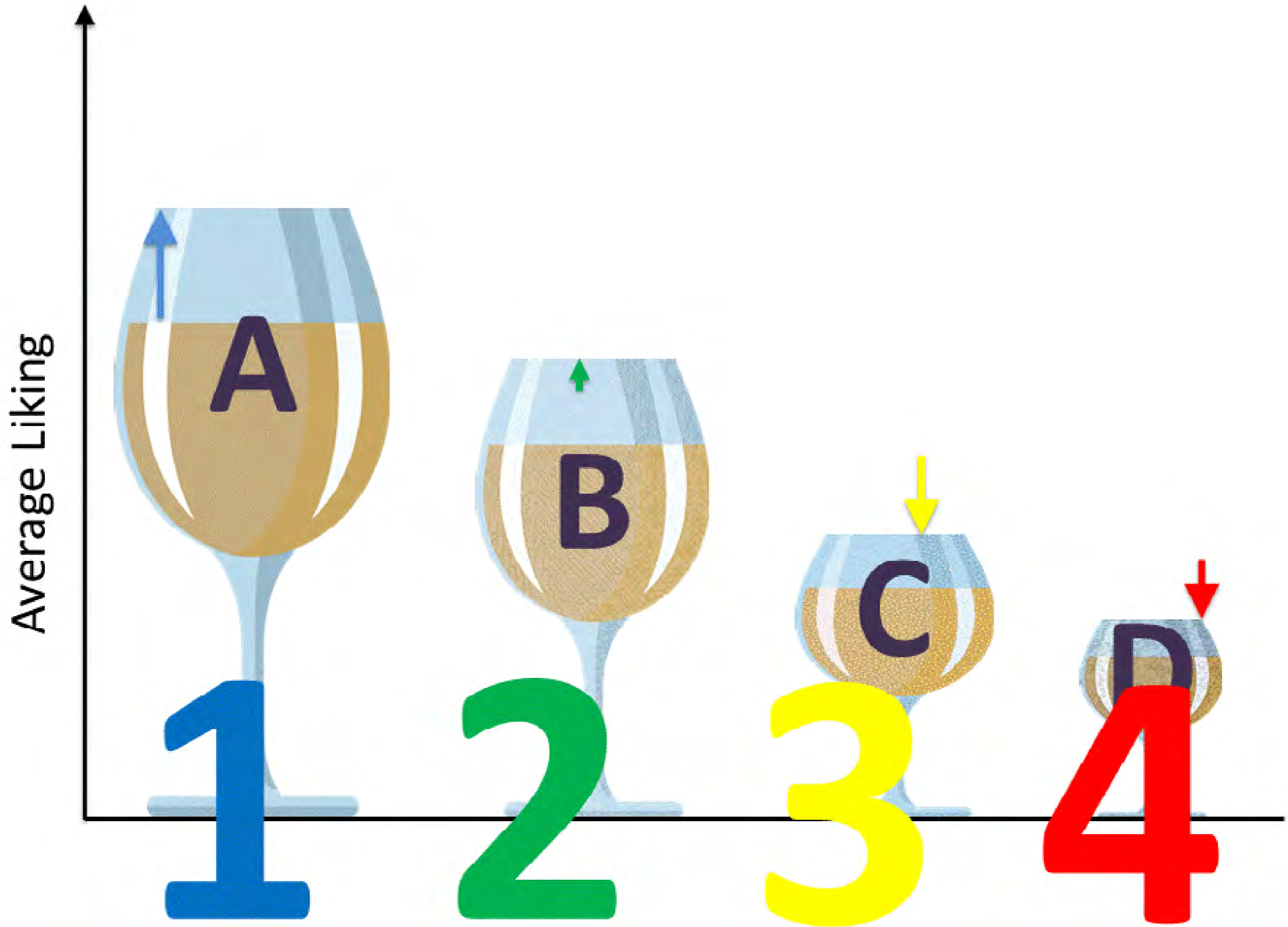

Truth
Liking
A
B
C
D
Product


A
A
A
A
A
Serving Order
Average


Average Liking
A
B
C
D
Product



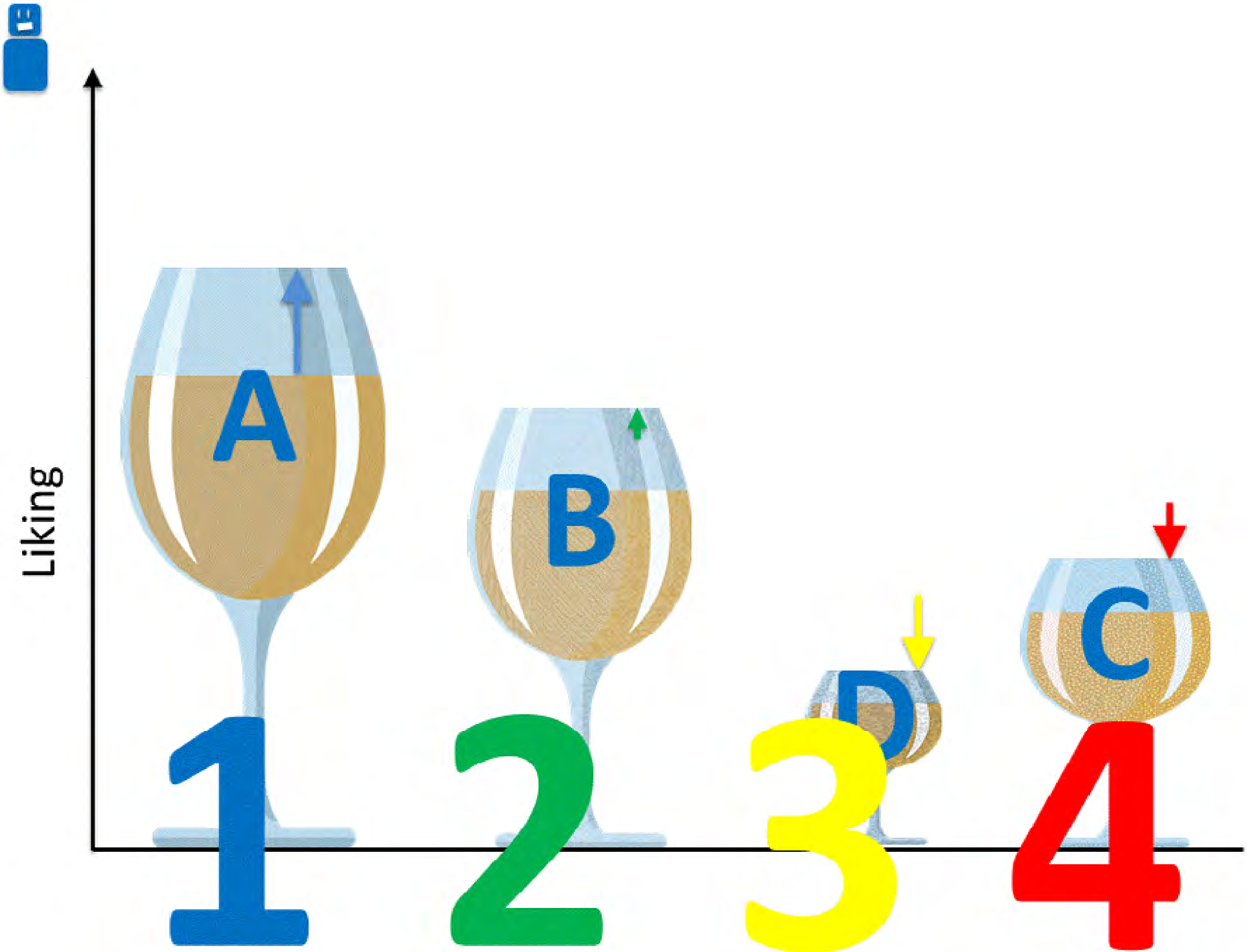
1 2 3



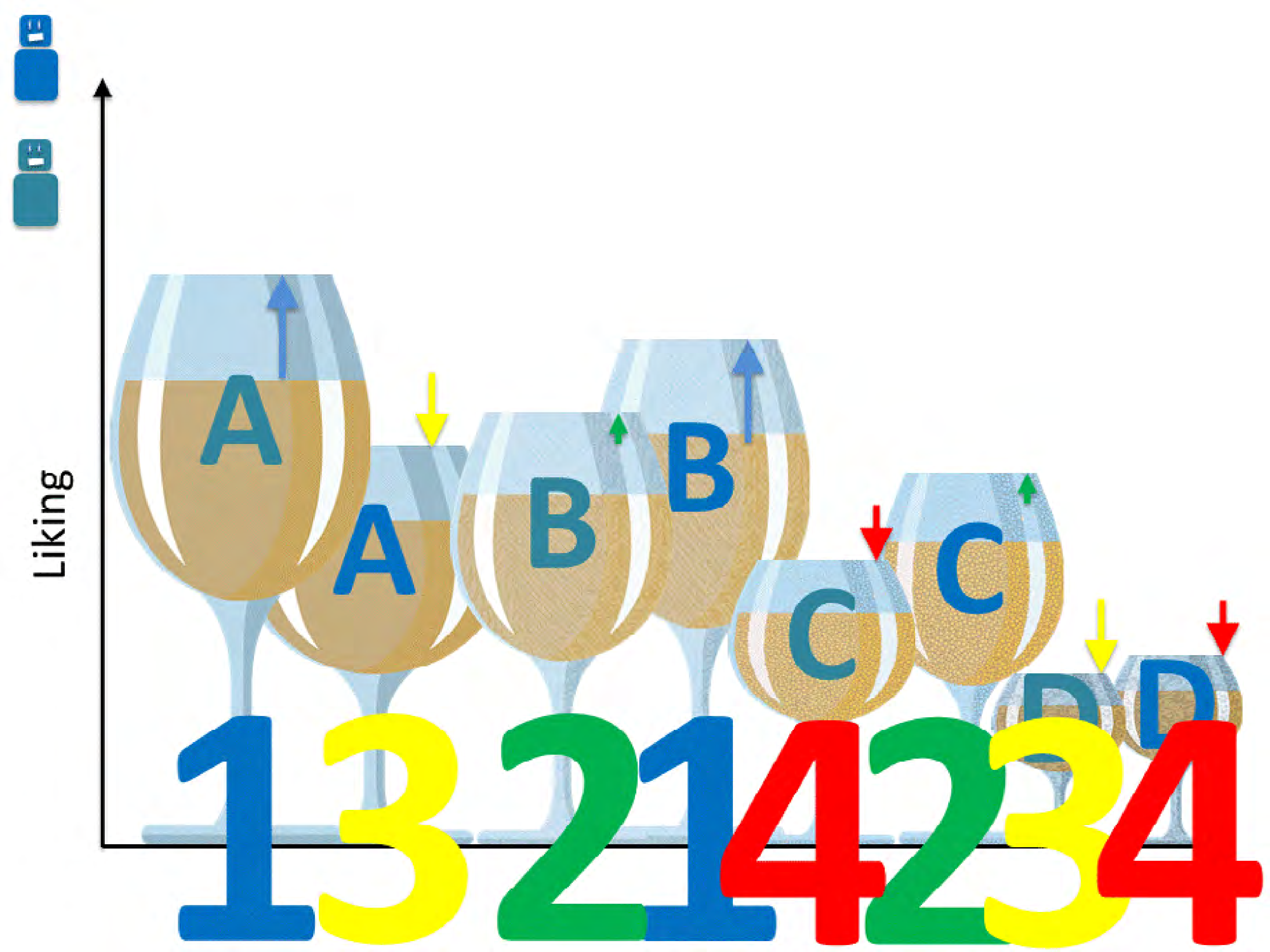
Average Liking
A
B
C
D
1
2
3
4


Average Liking
A
B
C
D
1
2
3
4

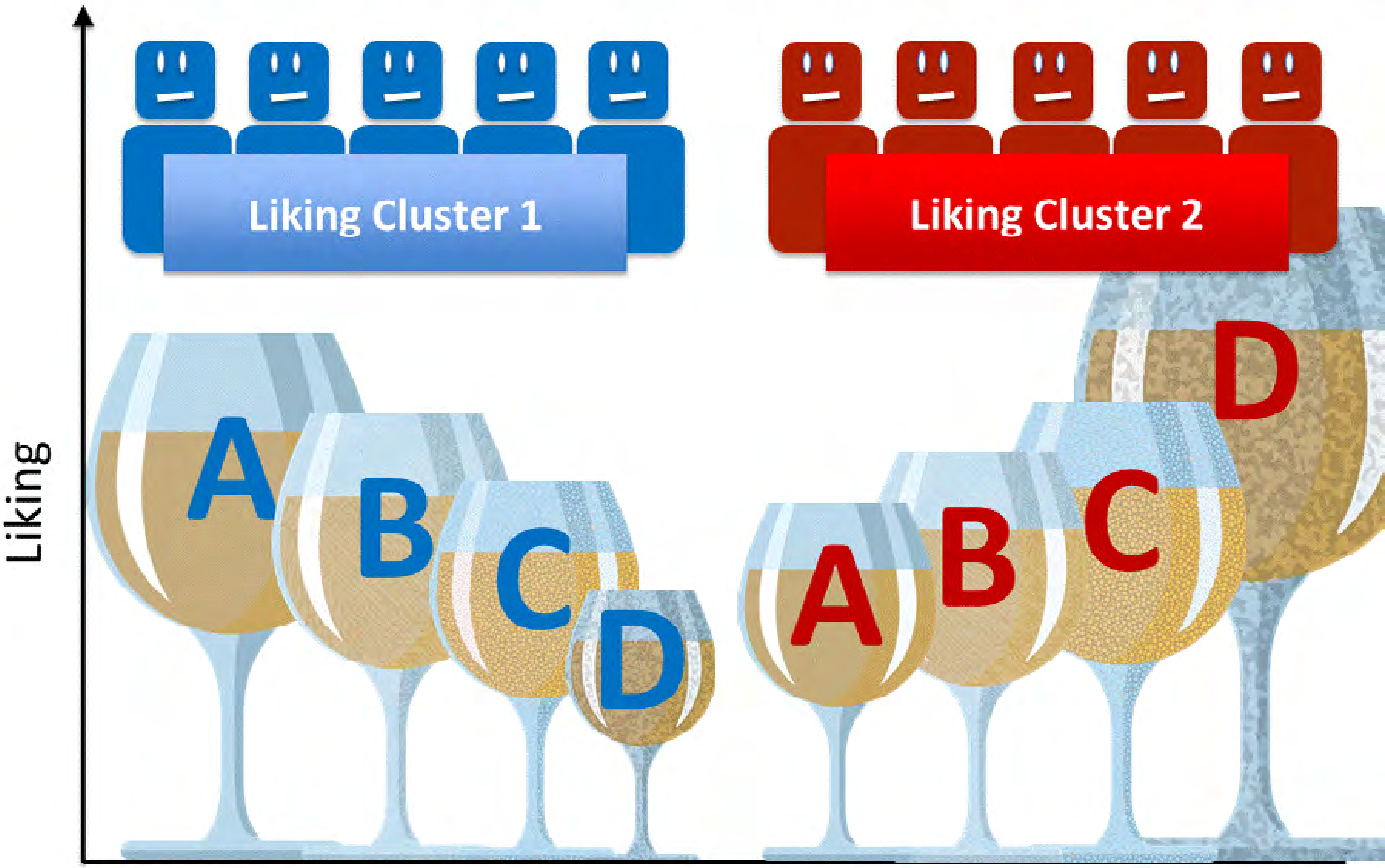

A
B
D
C
Liking
1
2
3
4



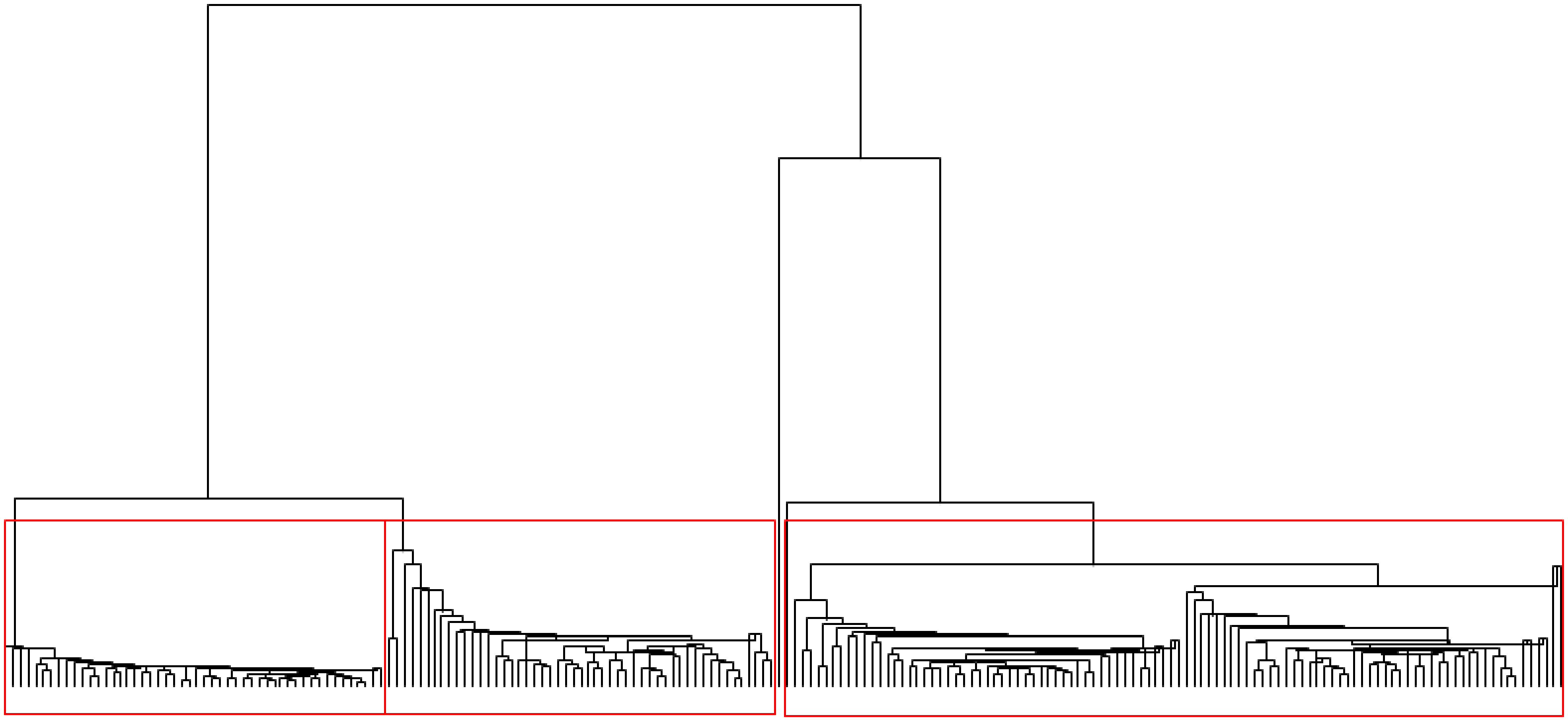
Liking
A
B
D
C
1
2
3
4



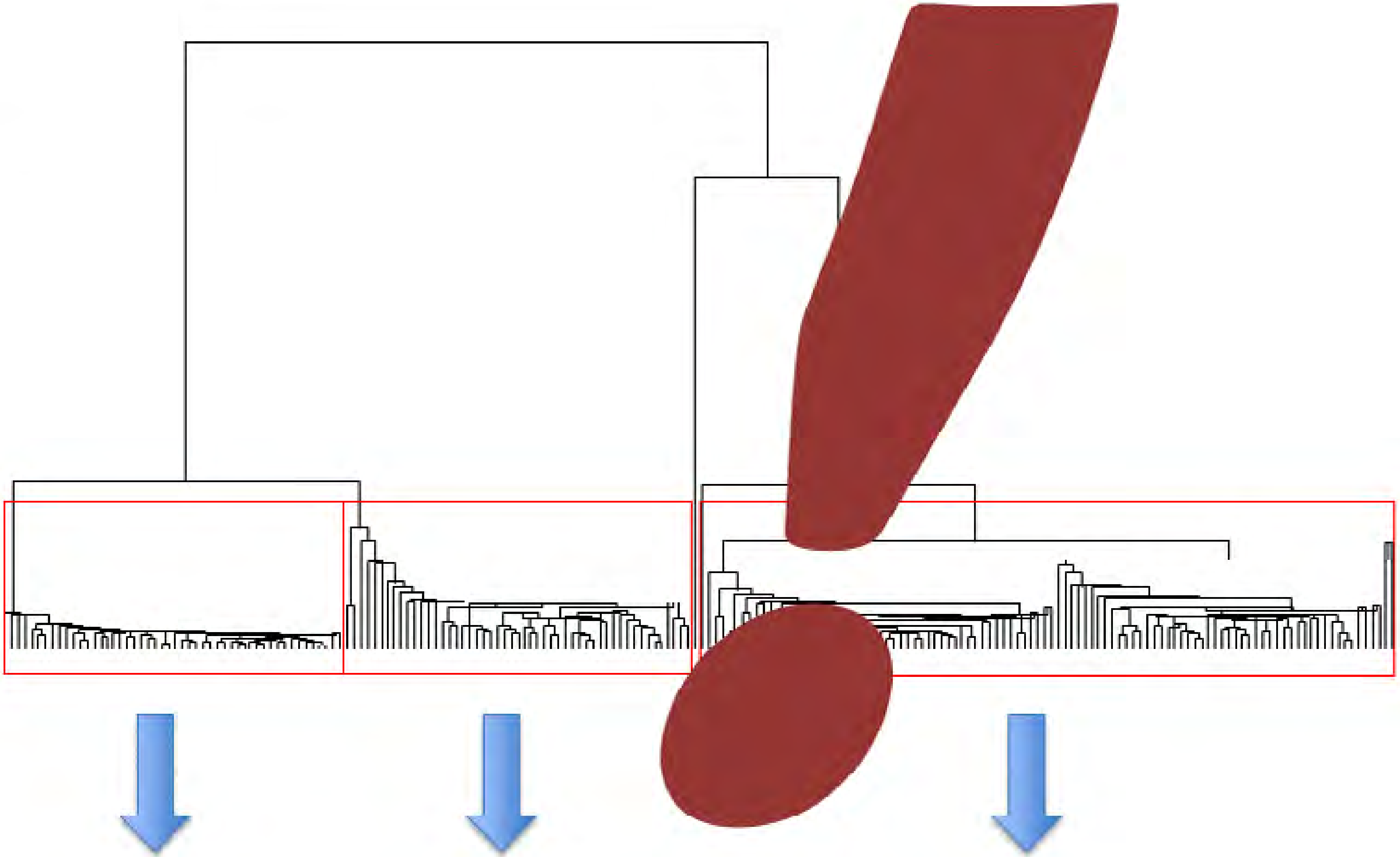
Liking
A
A
B
B
C
C
D
D
1
3
2
1
4
2
3
4


Liking Cluster 1
Liking Cluster 2
Liking
A
B
C
D
A
B
C
D

HCA



HCA



First sample was...

A D B or C

Various authors have reported situations in which consumers are clustered according to the randomly allocated serving orders.

Think about that when using this data in preference mapping!

Liking responses will be influenced by context effects and various biases. Thus we should think of liking responses as ***momentary*** and not as a fixed property of the consumer.

Also **replication** of consumer panel results seems more important than **repeatability** of individual consumers.

Liking data

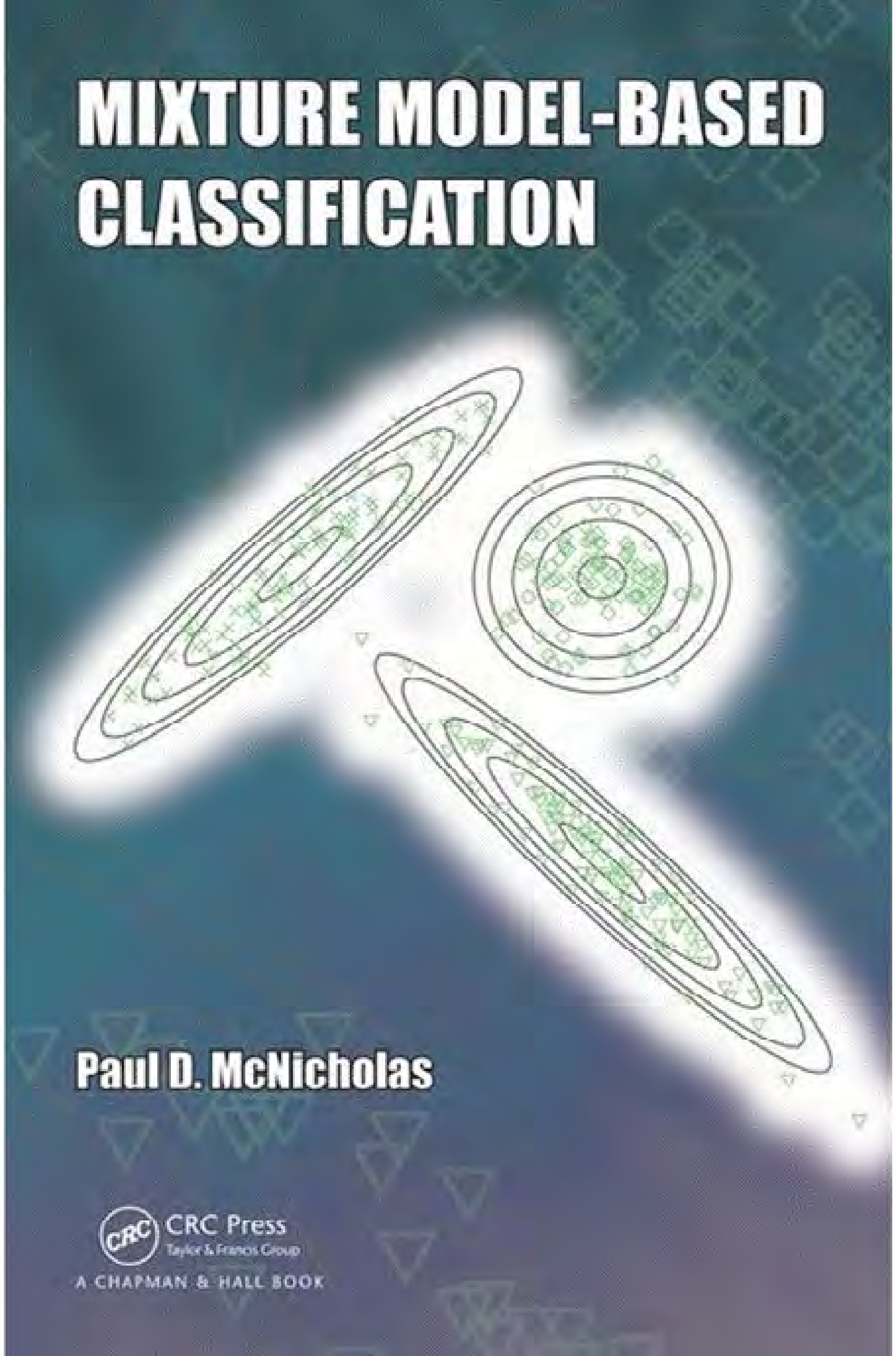
organize (scaled?) liking data into a 2D array

	A	B	C	D
	5	4	5	5
	8	[illegible]	[illegible]	6
	7	6	6	7

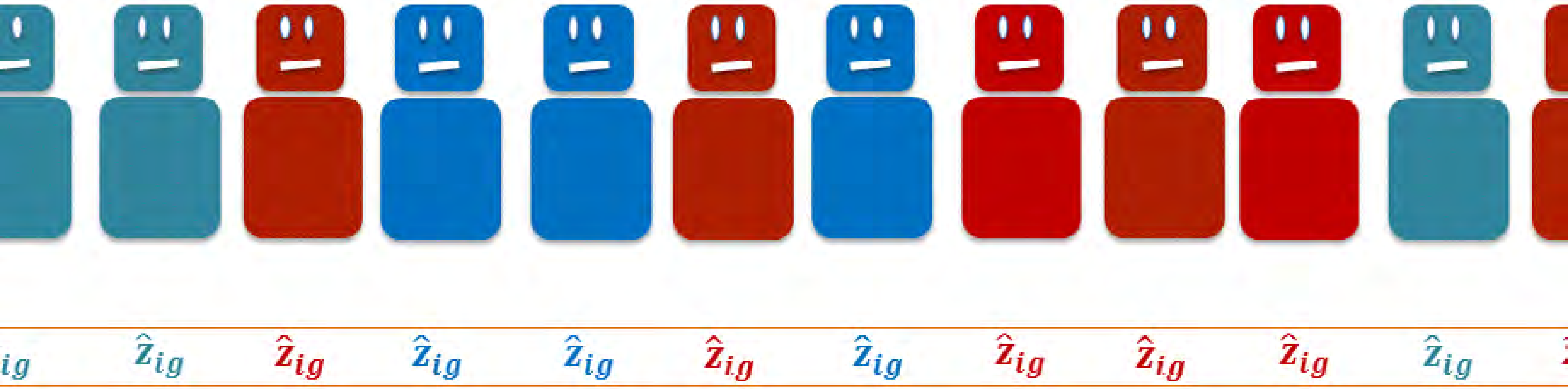
Rows: Consumers

×

Columns: Products


MIXTURE MODEL-BASED
CLASSIFICATION
Paul D. McNicholas
CRC Press
Taylor & Francis Group
A CHAPMAN & HALL BOOK

Gaussian Mixture Model



Initialize $\hat{z}_{ig}$.

M step – update $\hat{\pi}_g$, $\hat{\mu}_g$, $\hat{\Sigma}_g$.

E step – update $\hat{z}_{ig}$ classification predictions.

(Stop when converged.)

see McNicholas (2017, Ch. 2)

Higher dimensional data

Attempt to relate

observed variables (p)

to

latent variables (q)

where **q** $<$ **p** ...and perhaps **q** $\ll$ **p**.

see McNicholas (2017, Ch. 3)

Mixture of Factor Analyzers

$$\mu_g, \Sigma_g = \mathbf{\Lambda}_g \mathbf{\Lambda}'_g + \mathbf{\Psi}_g$$

Group 1: $\mu, \Sigma = \mathbf{\Lambda}\mathbf{\Lambda}' + \mathbf{\Psi}$

Group 2: $\mu, \Sigma = \mathbf{\Lambda}\mathbf{\Lambda}' + \mathbf{\Psi}$

Group 3: $\mu, \Sigma = \mathbf{\Lambda}\mathbf{\Lambda}' + \mathbf{\Psi}$

see McNicholas (2017, Ch. 3)

Parsimonious Gaussian Mixture Model

$$\mu_g, \Sigma_g = \boldsymbol{\Lambda}_g \boldsymbol{\Lambda}'_g + \omega_g \Delta_g$$

with CUU constraints

$$\begin{aligned} \boldsymbol{\Lambda}_g &= \boldsymbol{\Lambda} \\ \Delta_g &= \Delta \\ \Delta_g &= I \\ \omega_g &= \omega \end{aligned}$$

see McNicholas (2017, Ch. 3)

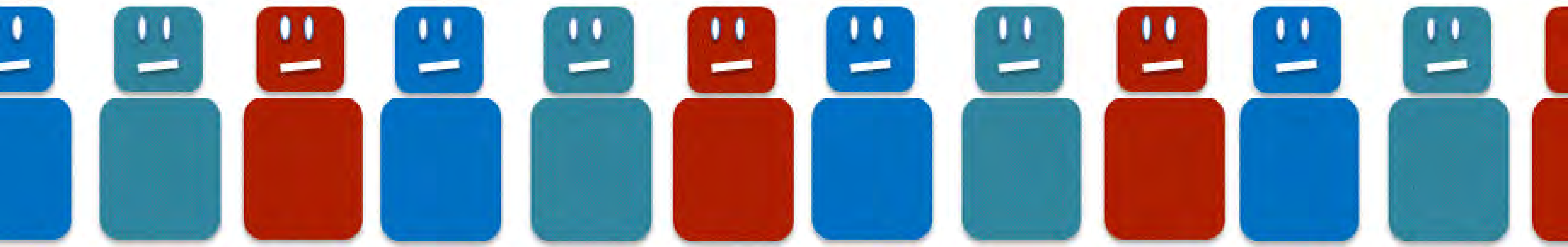
Model selection via the
Bayesian Information Criterion (BIC),
which imposes a penalty for each
additional parameter.

see McNicholas (2017, Ch. 7)

Clusters: heterogeneous

Products: variables

Order: nil



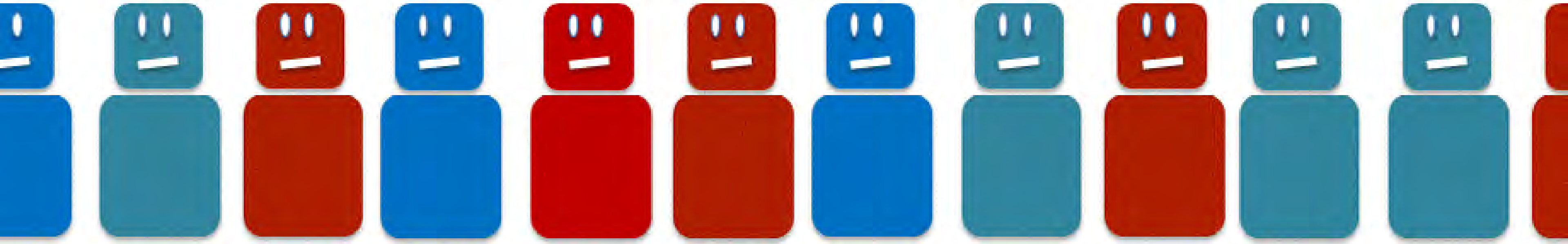
Obtain the best model*

* e.g. Franczak et al. (2015) used a mixture of factor analyzers with data imputation that was updated iteratively based on predicted cluster memberships

Clusters: heterogeneous

Products: variables

Order: homogeneous



Estimate and remove *common* order effects

Penalize BIC accordingly.

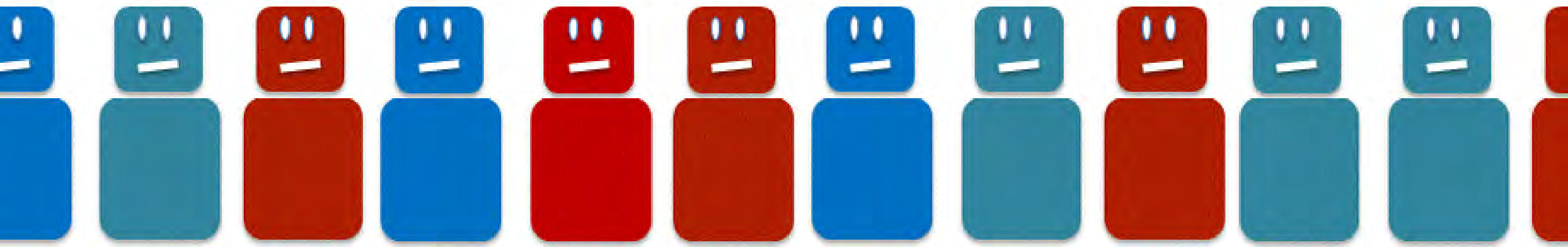
Obtain best mixture model.

Research in Progress…

Clusters: heterogeneous

Products: variables

Order: heterogeneous



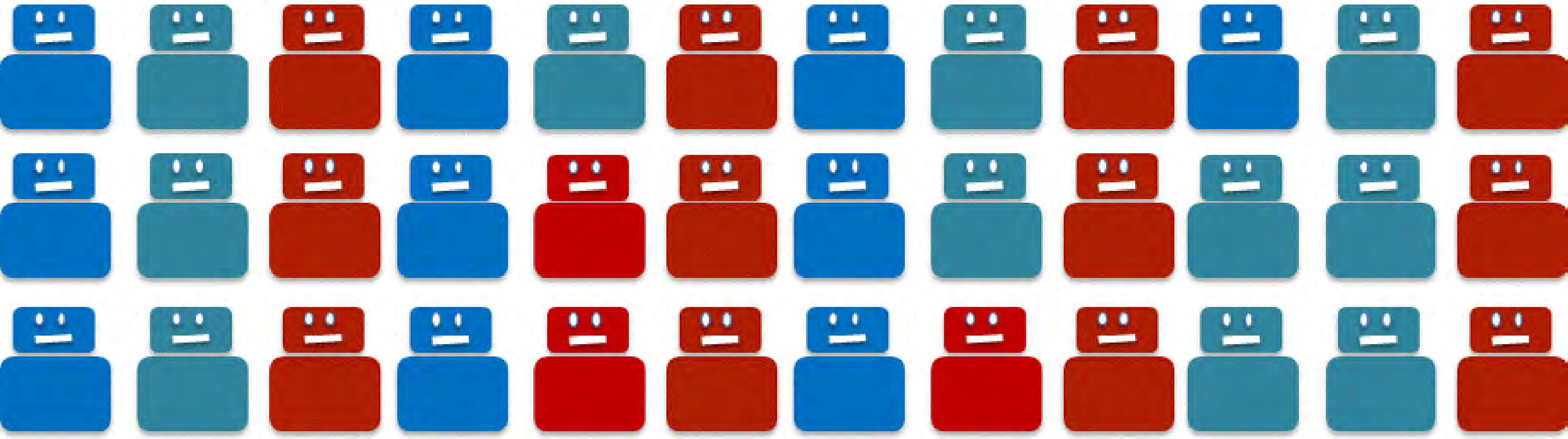
Estimate & remove order effects *per group.*

Penalize BIC accordingly.

Obtain best mixture model.

Research in Progress...

Comparison



Model selection via BIC.

Review plots (original scale and latent space).

Research in Progress...


Consumer acceptance
(repeated measures)

Some Potential Strategies

Conventional clustering

use summary data (e.g. sample means)

unfold data

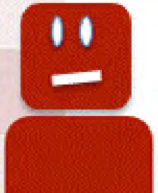
Clustering matrices

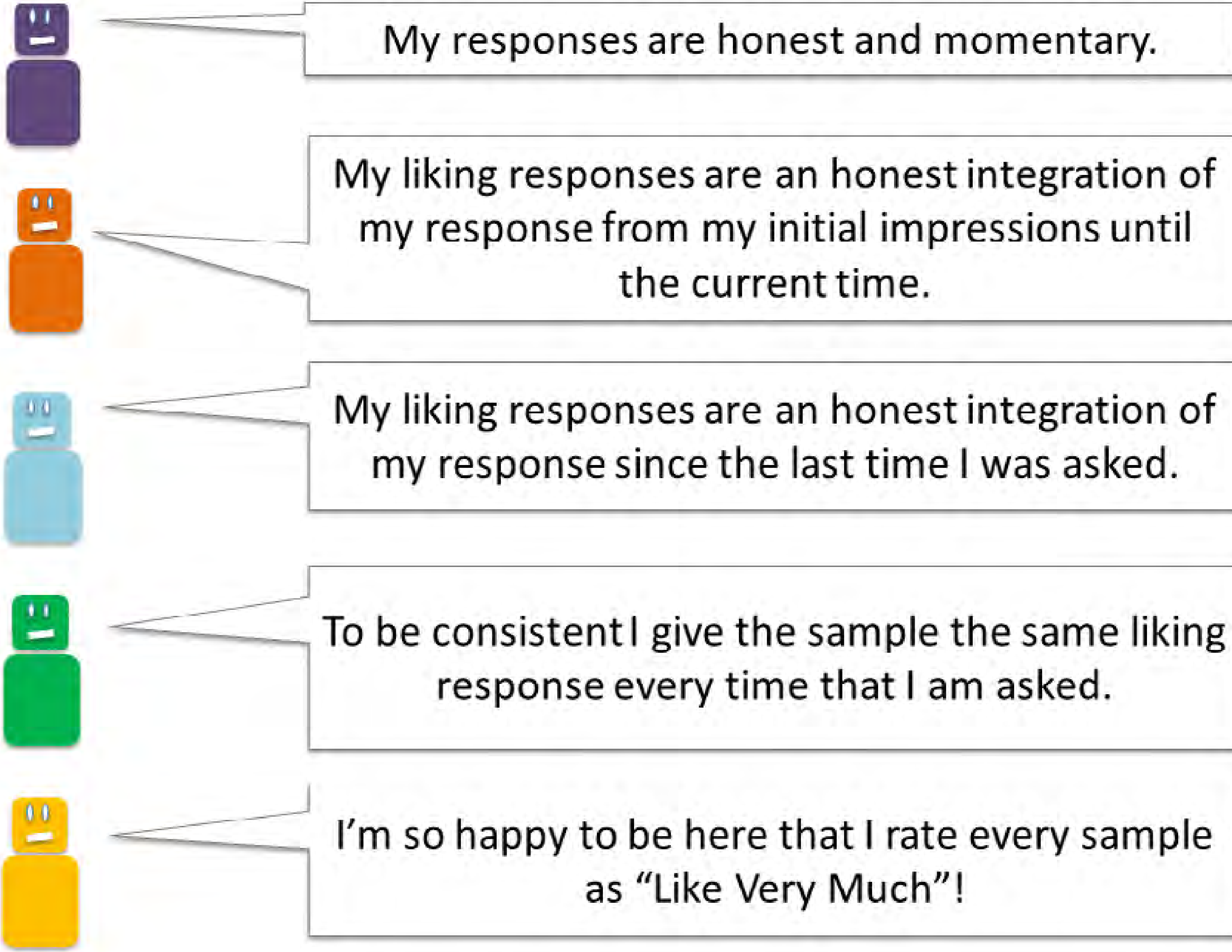
E.g., cluster consumers assuming a mixture of matrix normal distributions

		1 min	2 min	5 min	10 min
A	4th	7	6	6	5
B	3rd	5	7	6	4
C	1st	8	7	6	5
D	2nd	7	8	6	5

	2 min	5 min	10 min
A	8	8	8
B	5	5	5
C	8	7	6
	8	6	6

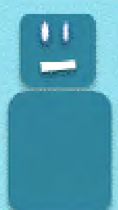
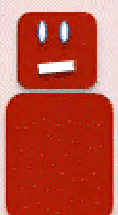
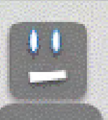
		1 min	2 min	5 min	10 min
A	2nd	7	7	8	7
B	1st	9	8	8	6
C	4th	5	6	7	6
D	3rd	8	8	7	7




My responses are honest and momentary.
My liking responses are an honest integration of my response from my initial impressions until the current time.
My liking responses are an honest integration of my response since the last time I was asked.
To be consistent I give the sample the same liking response every time that I am asked.
I'm so happy to be here that I rate every sample as "Like Very Much"!

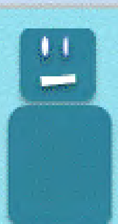
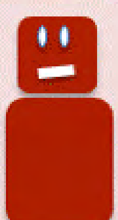
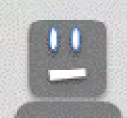
Point in time data

e.g. at 10 min.

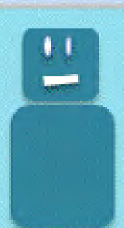
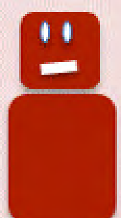
	A	B	C	D
	5	4	5	5
	8	5	6	6
	7	6	6	7
	5	5	[illegible]	5

Summarize data

e.g. area under curve

	A	B	C	D
	24	22	26	26
	32	21	28	28
	29	31	24	30
	25	[illegible]	[illegible]	[illegible]

Unfold data

	A1	A2	A5	A10	B1	B2	B5	B10	C1	C2	C5	C10	D1	D2	D5	D10
	7	6	6	5	5	7	6	4	8	7	6	5	7	8	6	5
	8	8	8	8	6	5	5	5	7	8	7	6	8	8	6	6
	7	7	8	7	9	8	8	6	5	6	7	6	8	8	7	7
	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

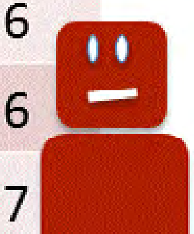
Matrix clustering

This is a potential application for matrix normal mixture model-based clustering*.

		1 min	2 min	5 min	10 min
A	4th	7	6	6	5
B	3rd	5	7	6	4
C	1st	8	7	6	5
D	2nd	7	8	6	5

		1 min	2 min	5 min	10 min
A	1st	8	8	8	8
B	4th	6	5	5	5
C	3rd	7	8	7	6
D	2nd	8	8	6	6

		1 min	2 min	5 min	10 min
A	2nd	7	7	8	7
B	1st	9	8	8	6
C	4th	5	6	7	6
D	3rd	8	8	7	7



* See Li (2014, Ch. 3) for applications of matrix clustering to selected sensory evaluation data.


Incomplete block
designs

Balanced Incomplete Block Design

Each consumer evaluates k of t samples ($k < t$)

t-present-k design

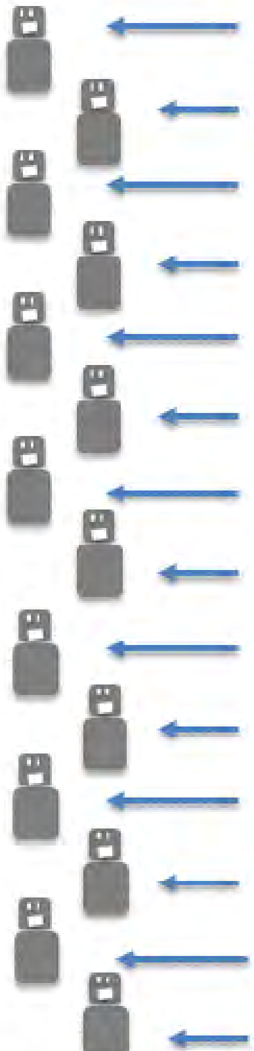
Goal:

Order and carryover balanced

Unbiased product estimates

Wakeling & Macfie (1995)

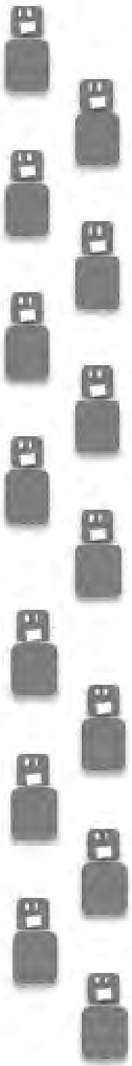
Balanced Incomplete Block Design



F	A	I	D
B	C	E	I
H	E	J	B
I	F	C	A
E	B	H	C
G	J	D	H
A	D	F	G
C	I	B	F
D	G	A	J
J	H	G	E
D	C	G	B
I	H	F	J
B	G	C	D
A	B	D	E
…	…	…	…

Wakeling & Macfie (1995)

Balanced Incomplete Block Design



F	A	I	D
B	C	E	I
H	E	J	B
I	F	C	A
E	B	H	C
G	J	D	H
A	D	F	G
C	I	B	F
D	G	A	J
J	H	G	E
D	C	G	B
I	H	F	J
B	G	C	D
A	B	D	E
...	...	...	...

Wakeling & Macfie (1995)

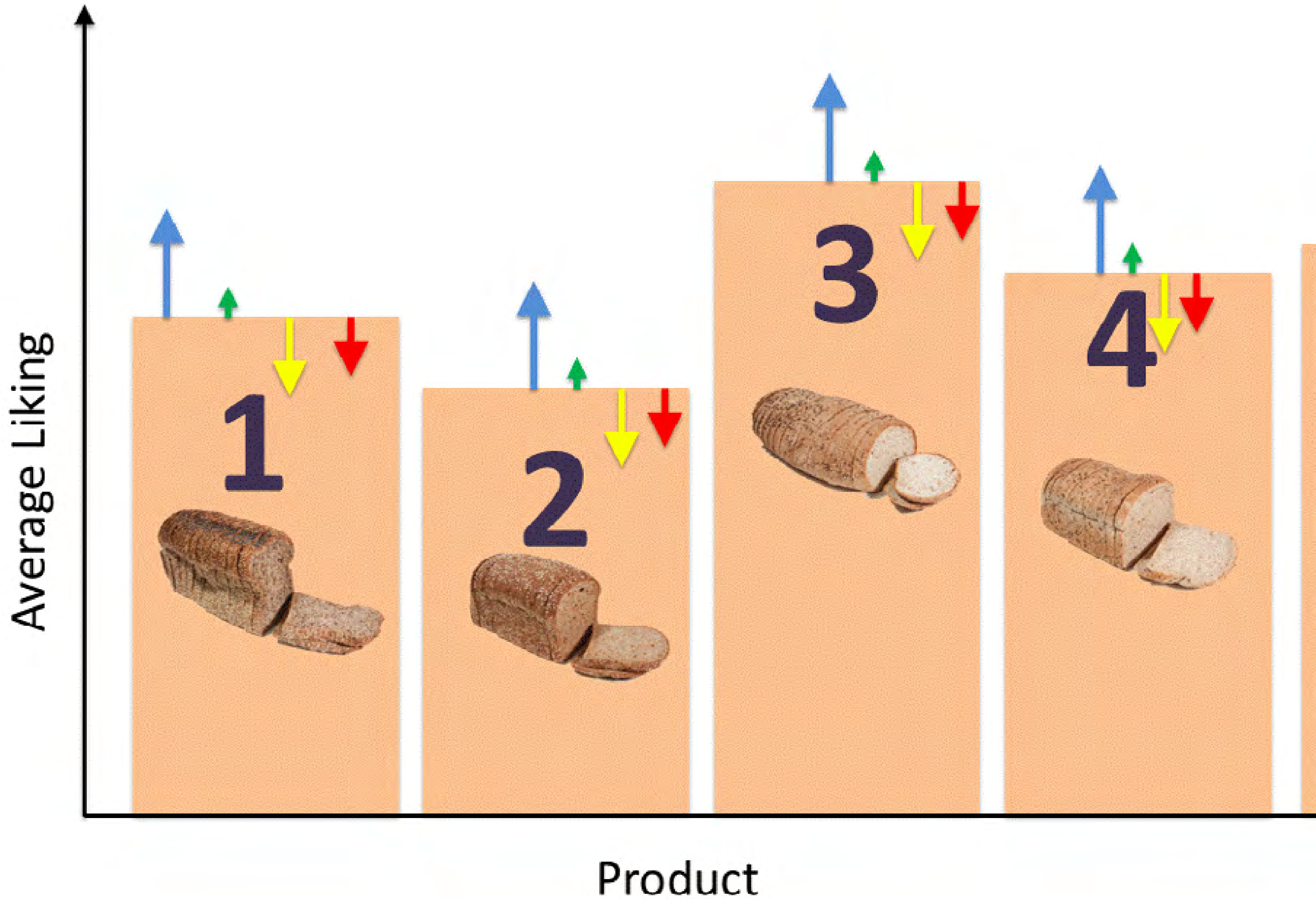
Balanced Incomplete Block Design

F	A	I	D
B	C	E	I
H	E	J	B
I	F	C	A
E	B	H	C
G	J	D	H
A	D	F	G
C	I	B	F
D	G	A	J
J	H	G	E
D	C	G	B
I	H	F	J
B	G	C	D
A	B	D	E
...	...	...	...

Wakeling & Macfie (1995)

Consumer data

	1	2	3	4	5	6	7	8	9	10
			6	5		7			5	
	8	8			4			5		
			8	7			8			6
		6				5	5			9



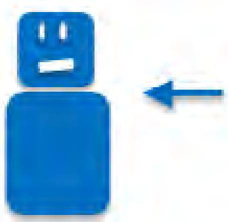
Average Liking
1
2
3
4
Product

There is additional information!

A trained sensory descriptive analysis panel evaluated 16 whole grain breads...

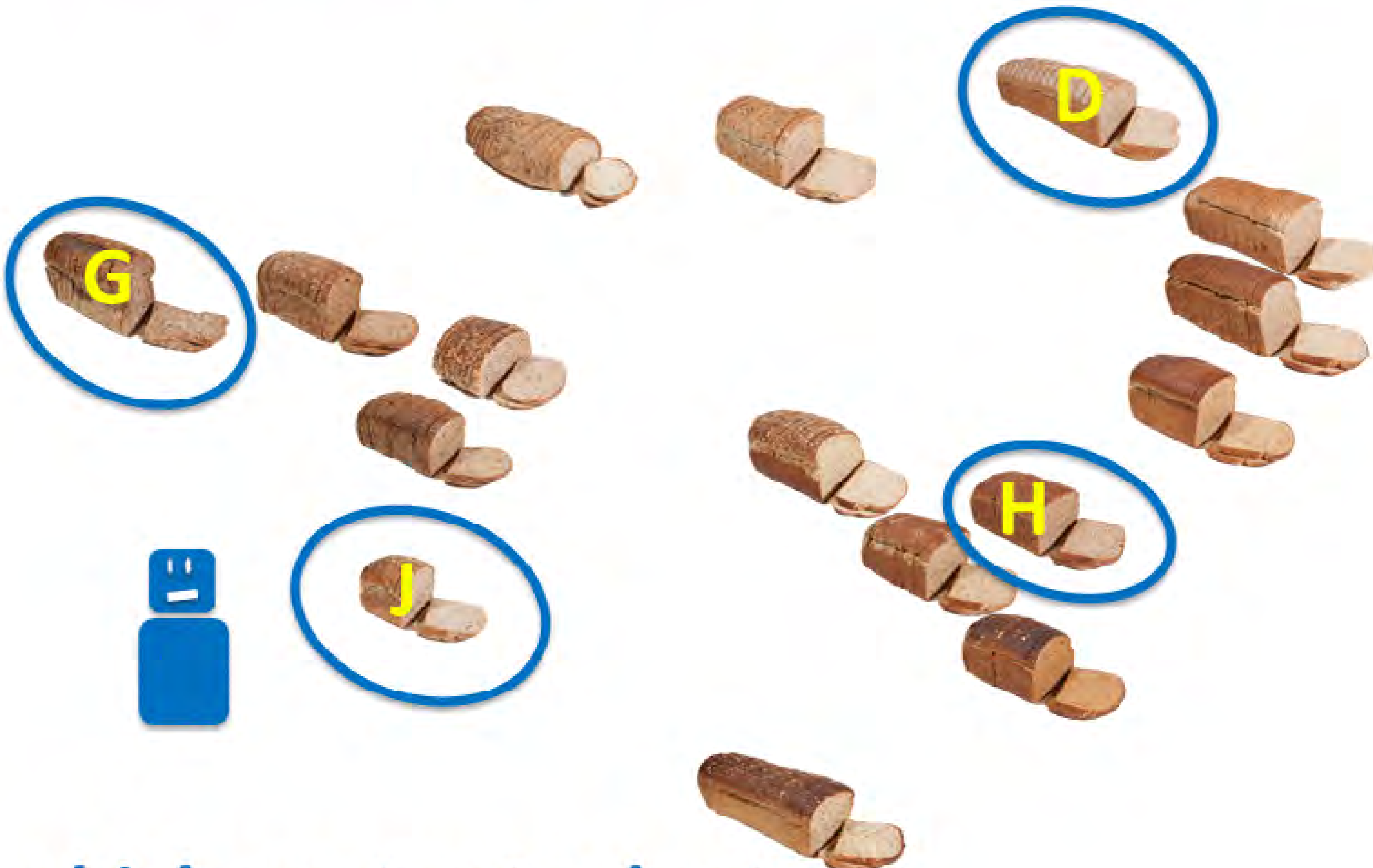
Sensory space

Balanced Incomplete Block Design



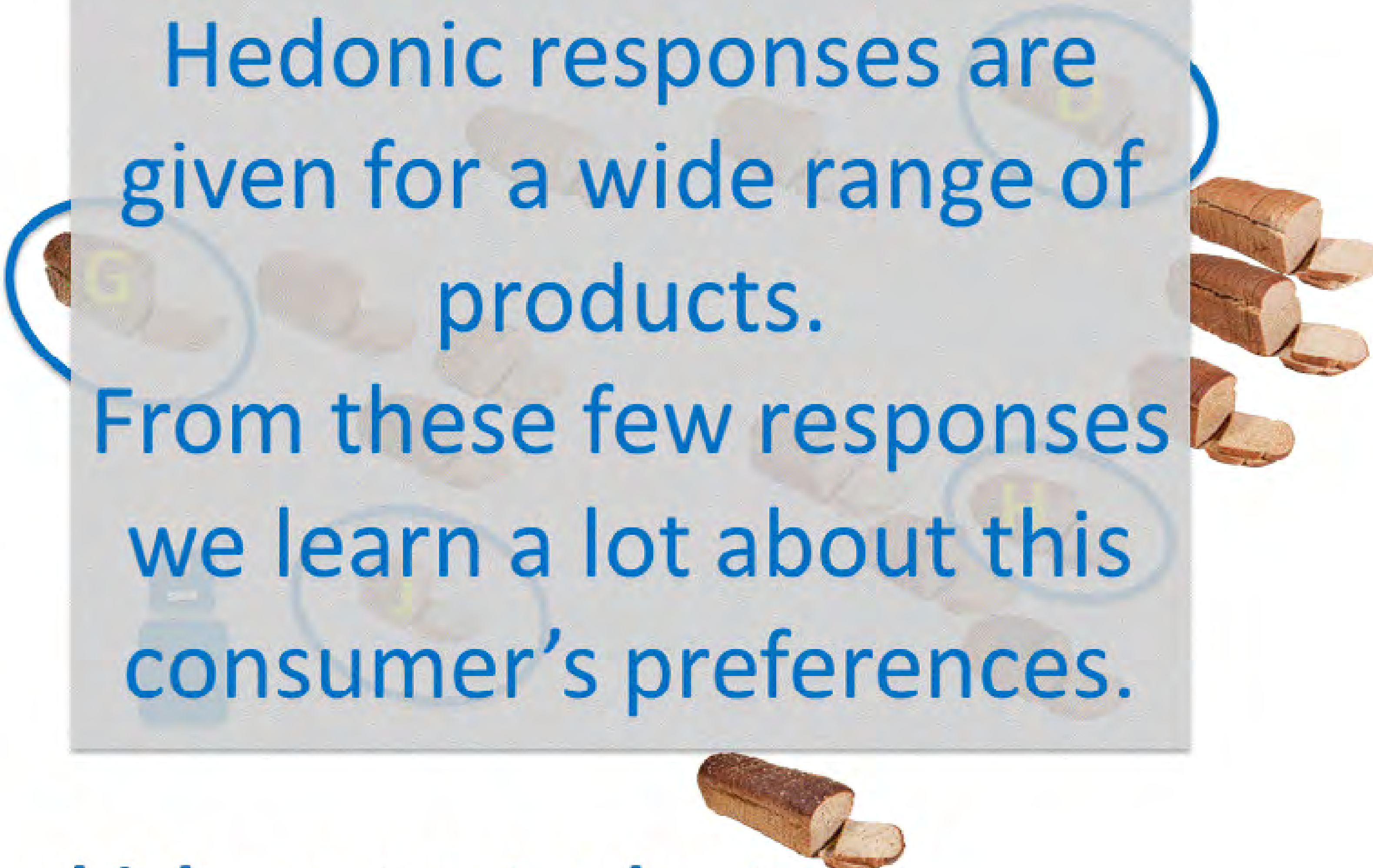
F	A	I	D
B	C	E	I
H	E	J	B
I	F	C	A
E	B	H	C
G	**J**	**D**	**H**
A	D	F	G
C	I	B	F
D	G	A	J
J	H	G	E
D	C	G	B
I	H	F	J
B	G	C	D
A	B	D	E
...	...	...	...

Sample set order #6



a high-contrast subset

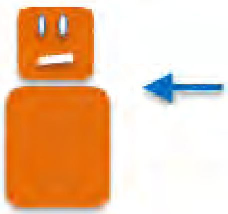
Sample set order #6



Hedonic responses are given for a wide range of products.
From these few responses we learn a lot about this consumer's preferences.

a high-contrast subset

Balanced Incomplete Block Design



F	A	I	D
B	C	E	I
H	E	J	B
I	F	C	A
E	**B**	**H**	**C**
G	J	D	H
A	D	F	G
C	I	B	F
D	G	A	J
J	H	G	E
D	C	G	B
I	H	F	J
B	G	C	D
A	B	D	E
…	…	…	…

Sample set order #5

a low-contrast subset

Sample set order #5

Hedonic responses are given for a narrow range of products.
So we learn little about this consumer's preferences.

a low-contrast subset

Would this product have been liked or disliked

a low-contrast subset

Sensory Informed Design

t-present-*k* design

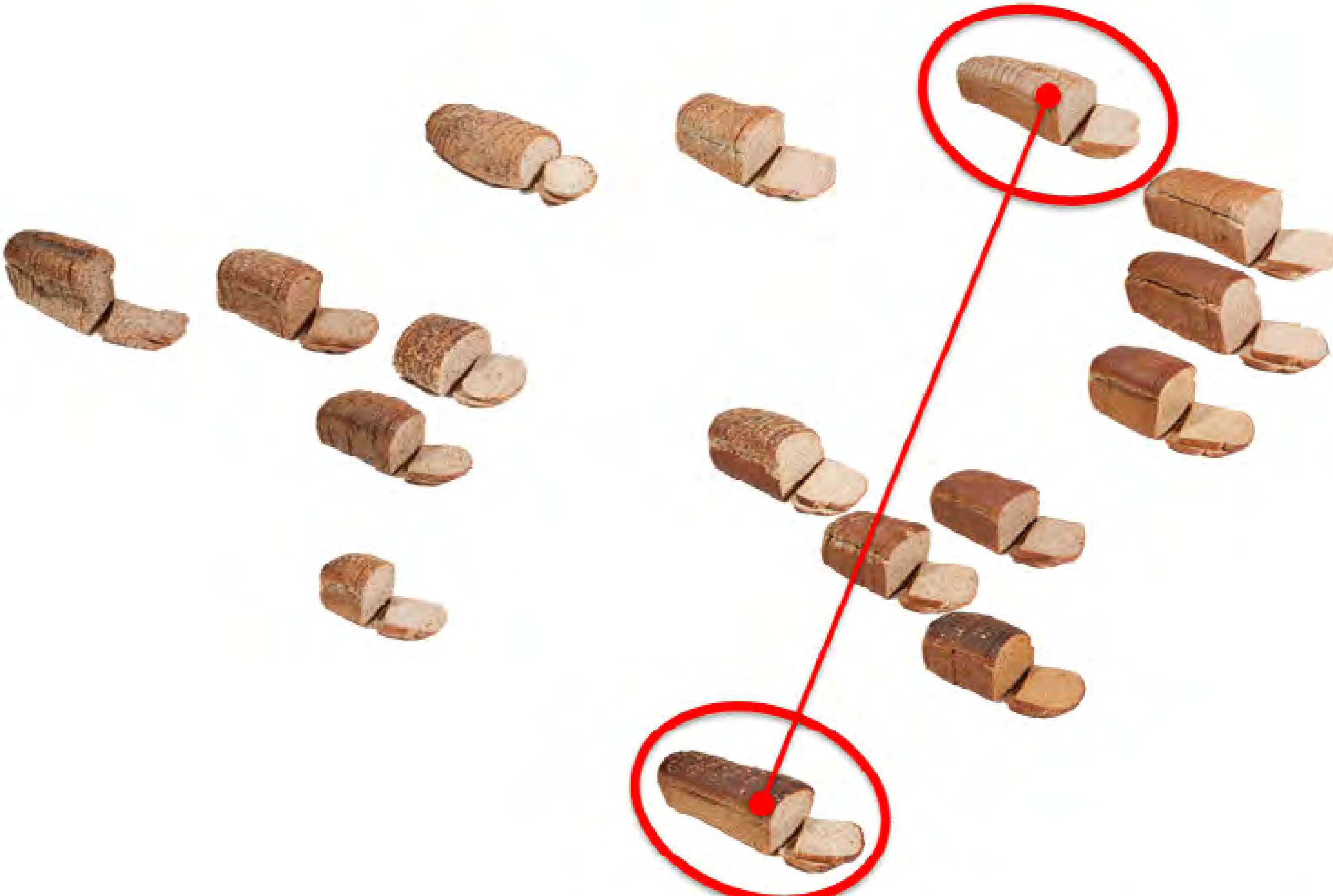
Goal:

Favour sample sets with sensory contrast

Order balanced

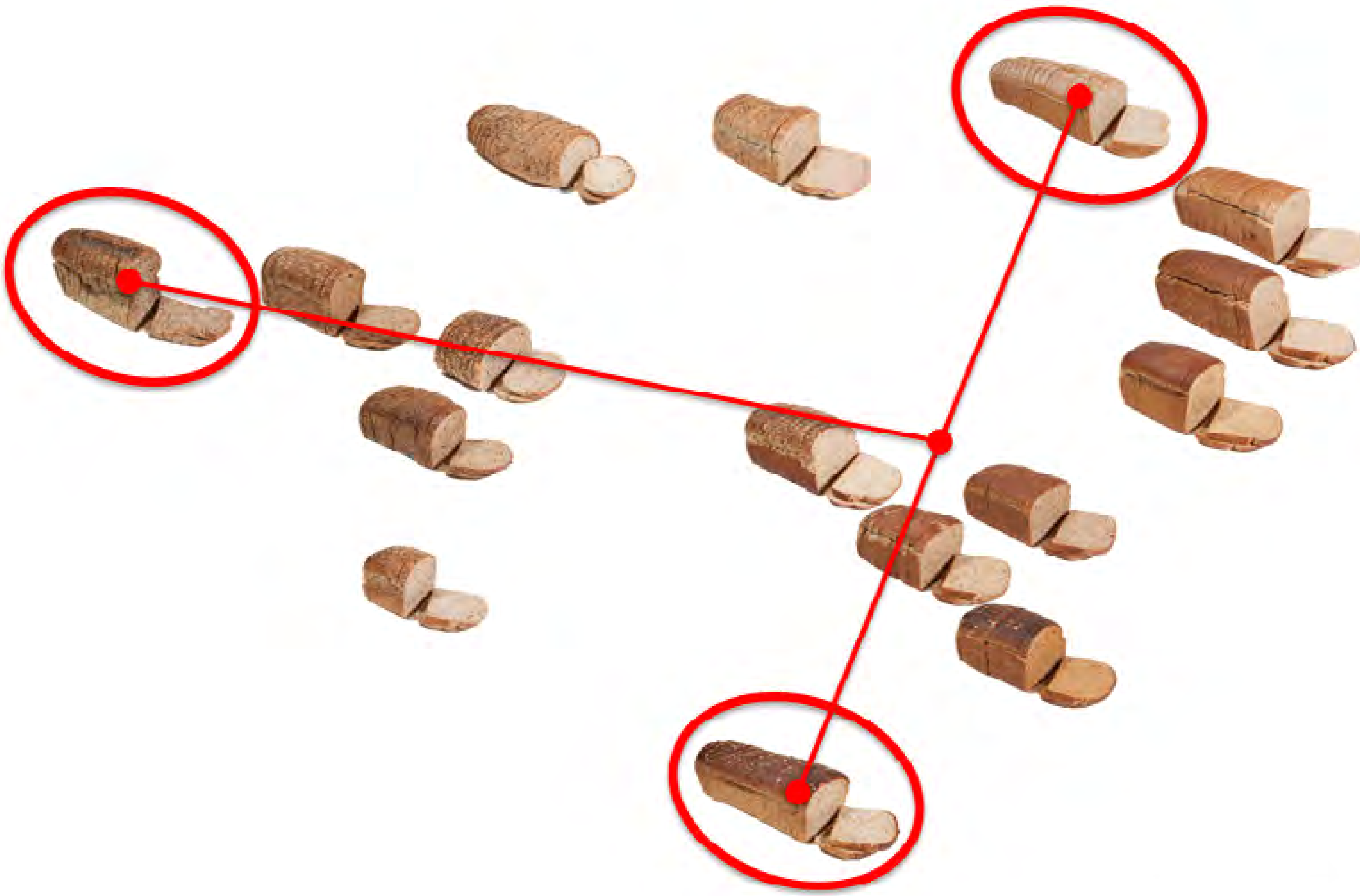
Compromise: carryover unbalanced

Sensory Informed Design



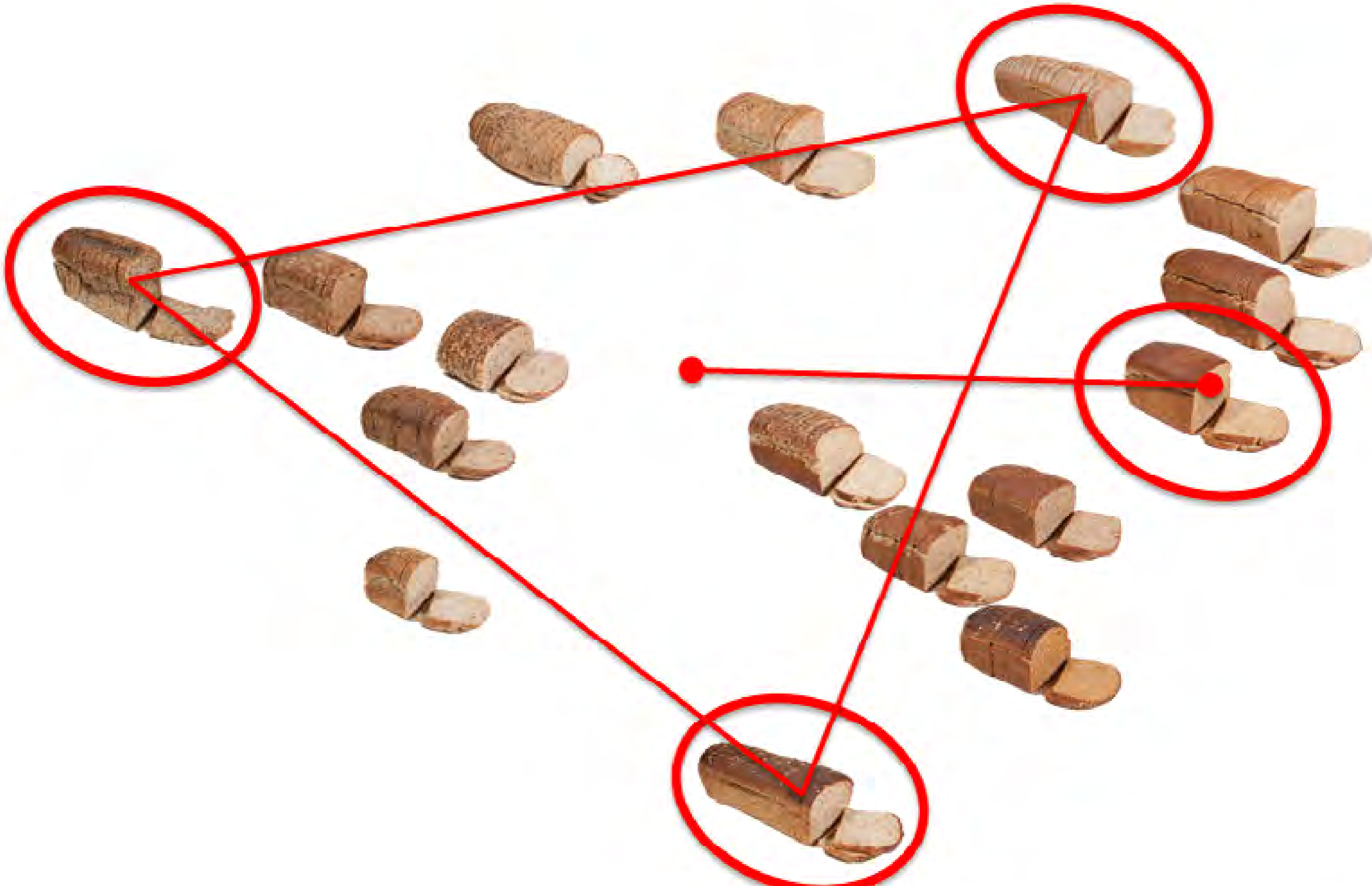
Franczak, Browne, McNicholas, & Findlay (2015)

Sensory Informed Design



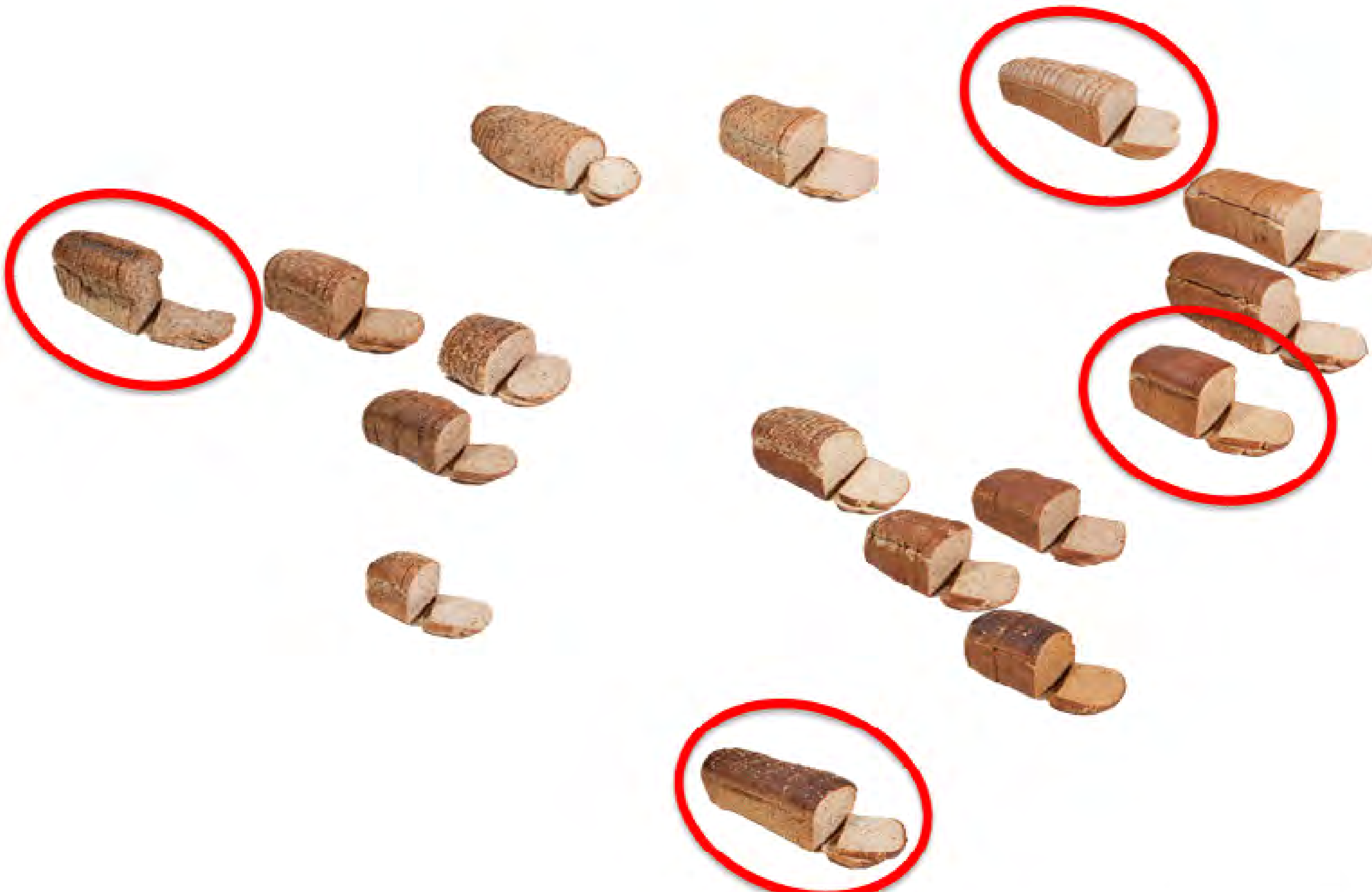
Franczak, Browne, McNicholas, & Findlay (2015)

Sensory Informed Design



Franczak, Browne, McNicholas, & Findlay (2015)

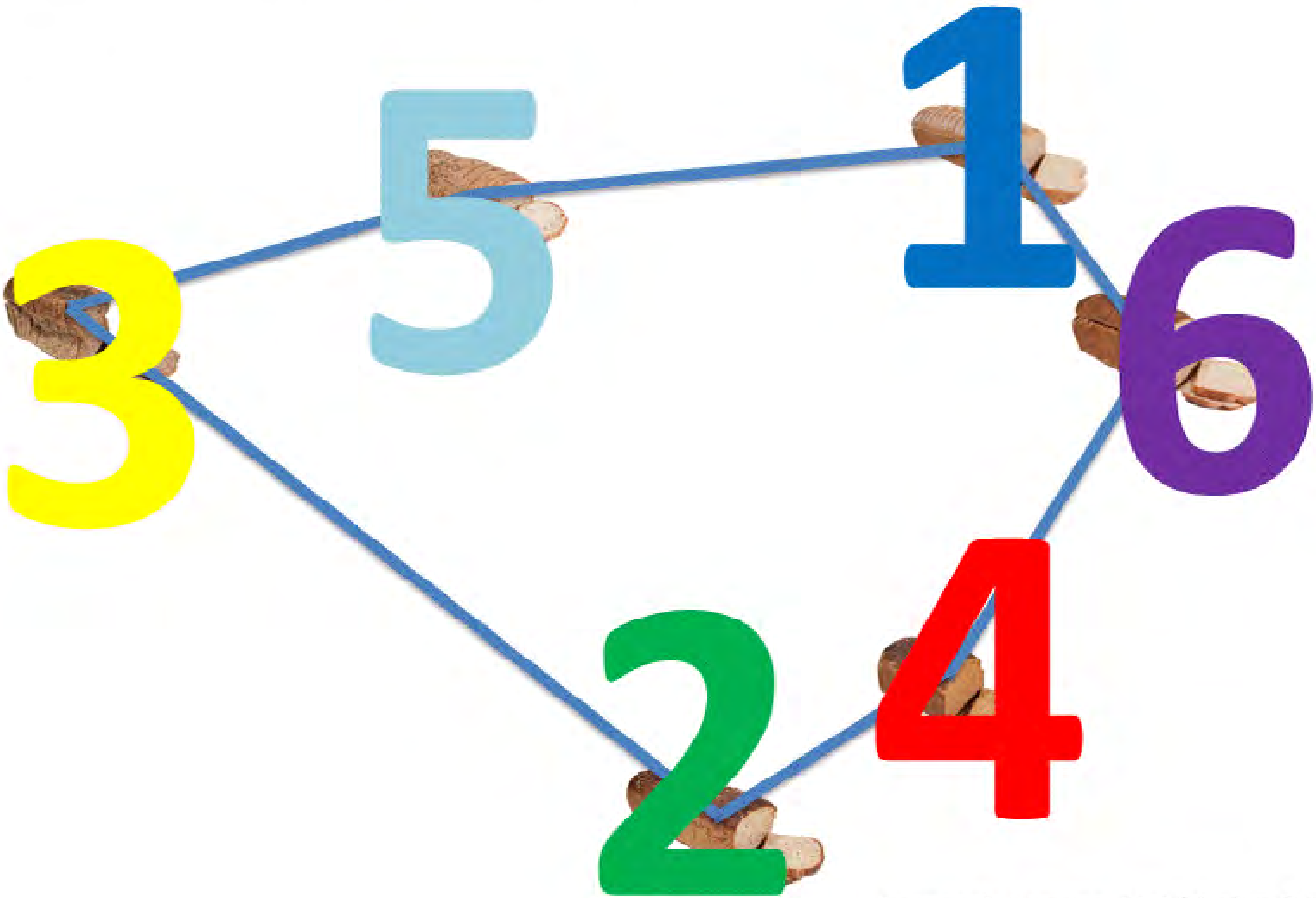
Sensory Informed Design



Franczak, Browne, McNicholas, & Findlay (2015)

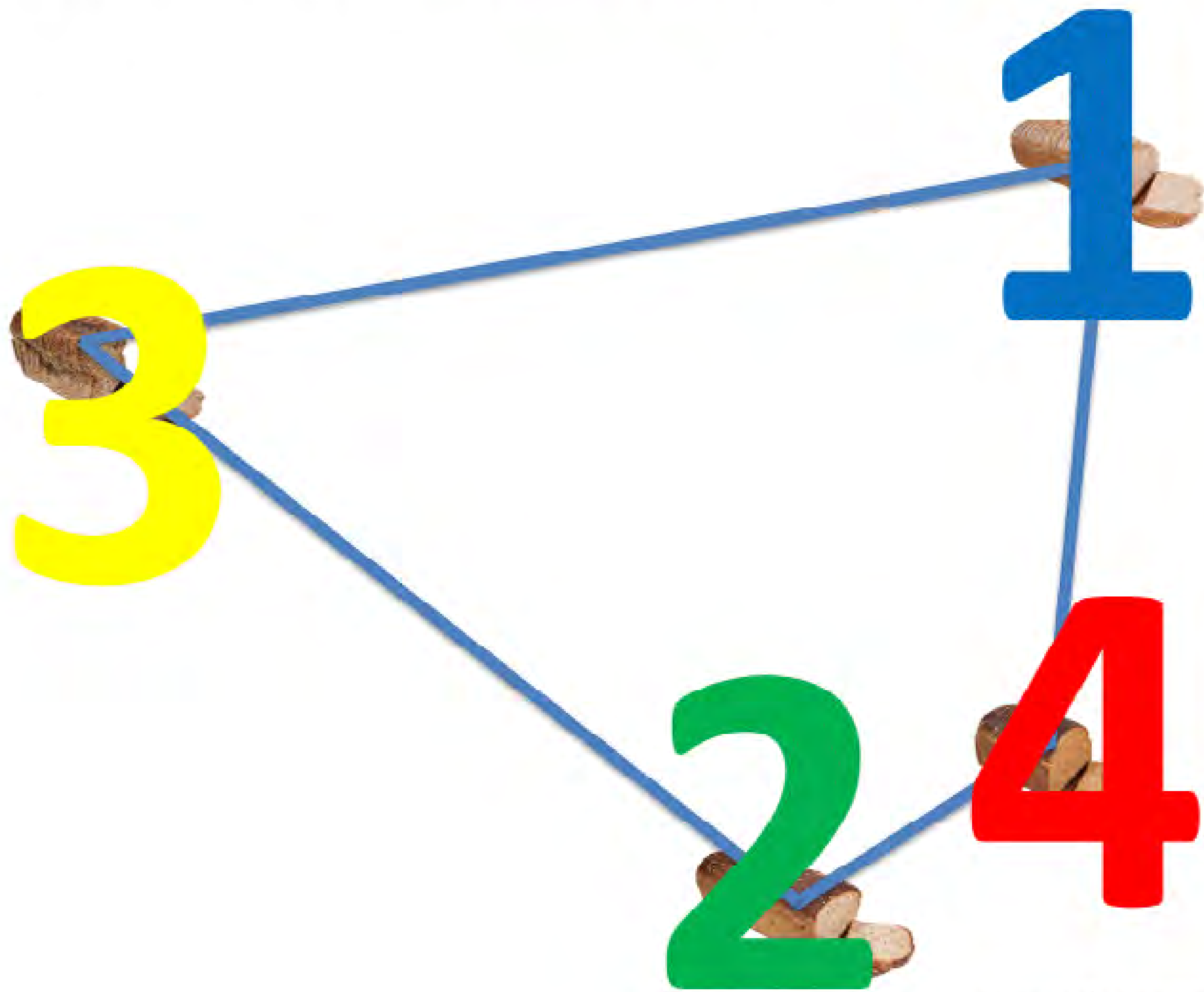
Franczak et al. (2015) describe a
16-present-6 sensory informed design.

Sensory Informed design (16-present-6 design)



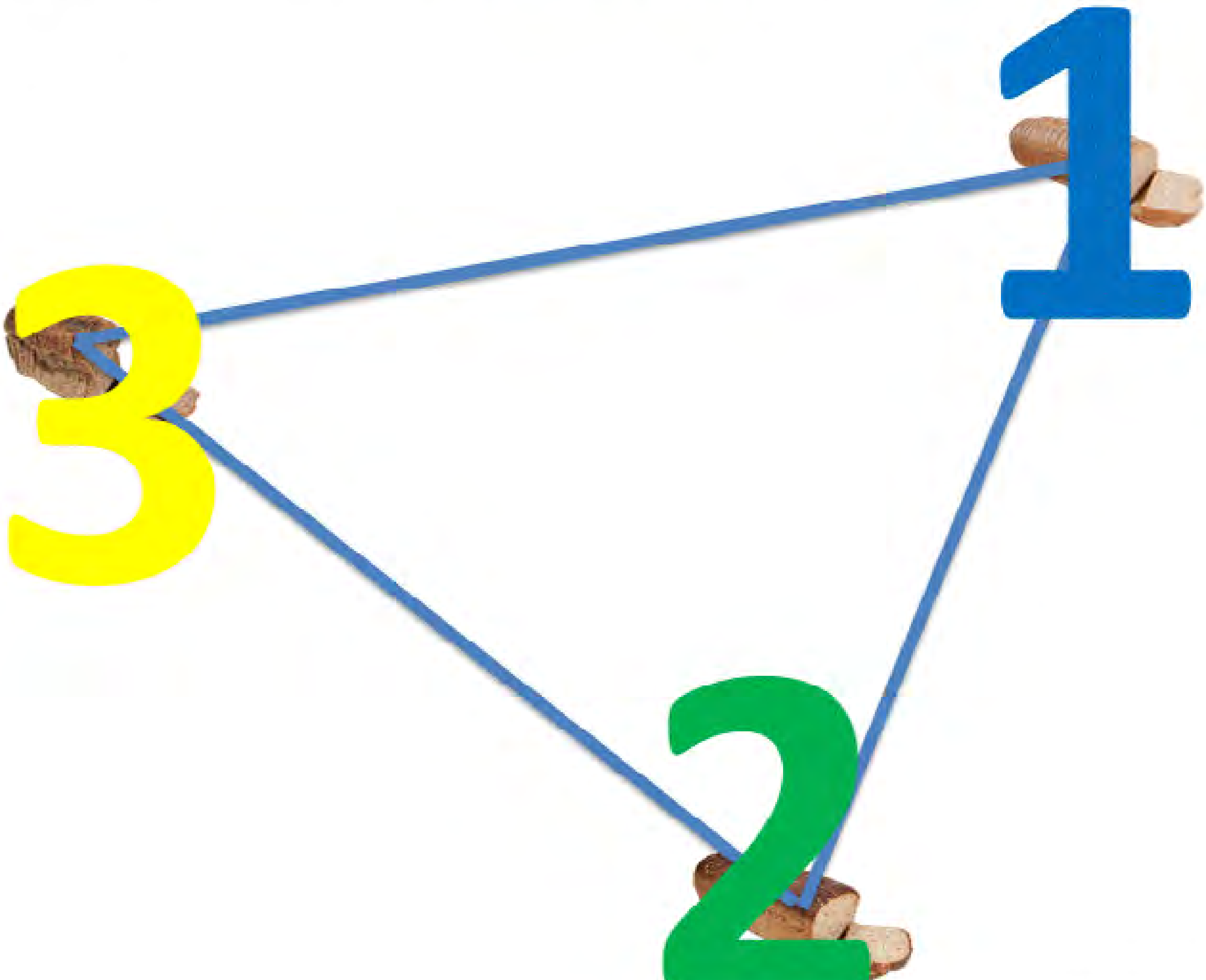
Franczak, Browne, McNicholas, & Findlay (2015)

Sensory Informed design
(16-present-4 *nested* design)



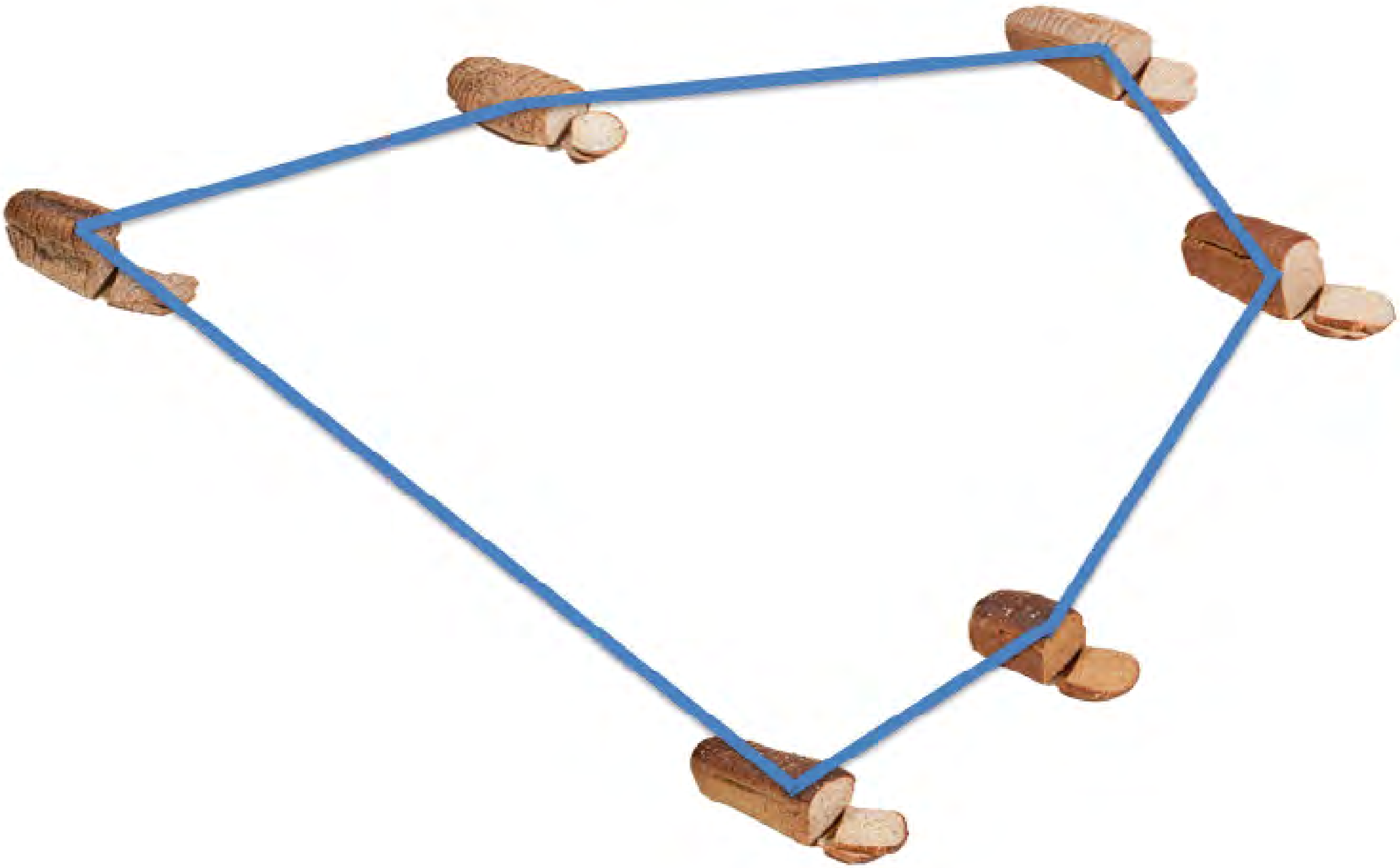
Franczak, Browne, McNicholas, & Findlay (2015)

Sensory Informed design
(16-present-3 *nested* design)



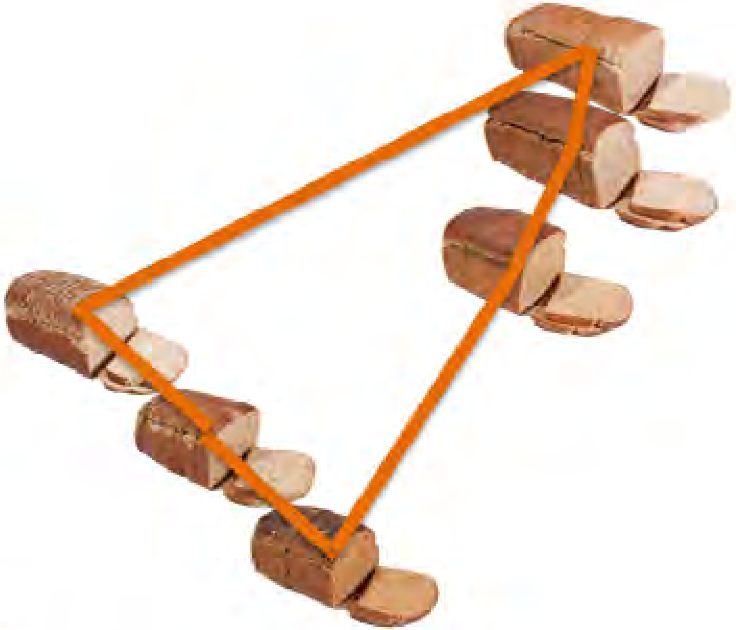
Franczak, Browne, McNicholas, & Findlay (2015)

Scaling data?



Franczak, Browne, McNicholas, & Findlay (2015)

Scaling data?

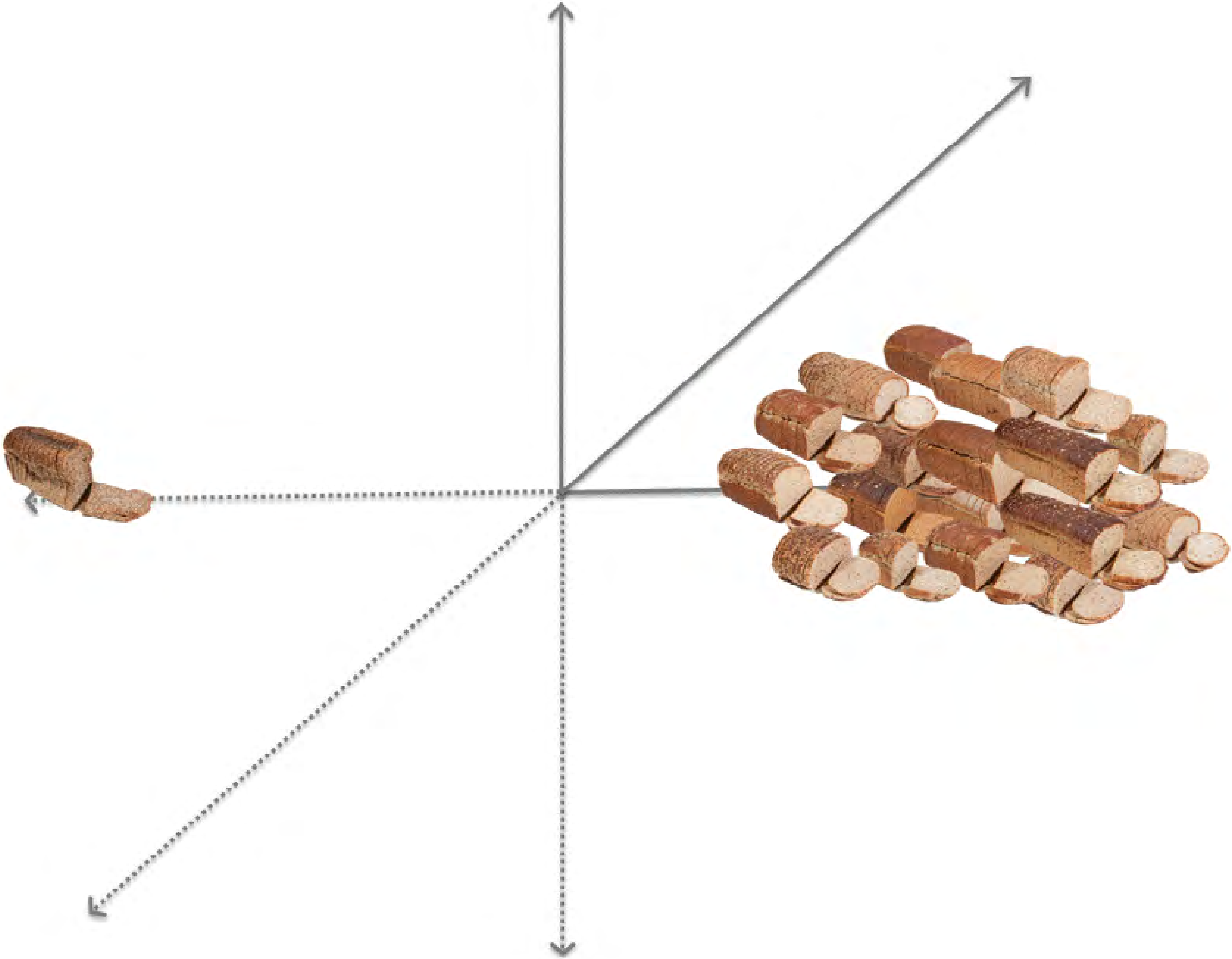


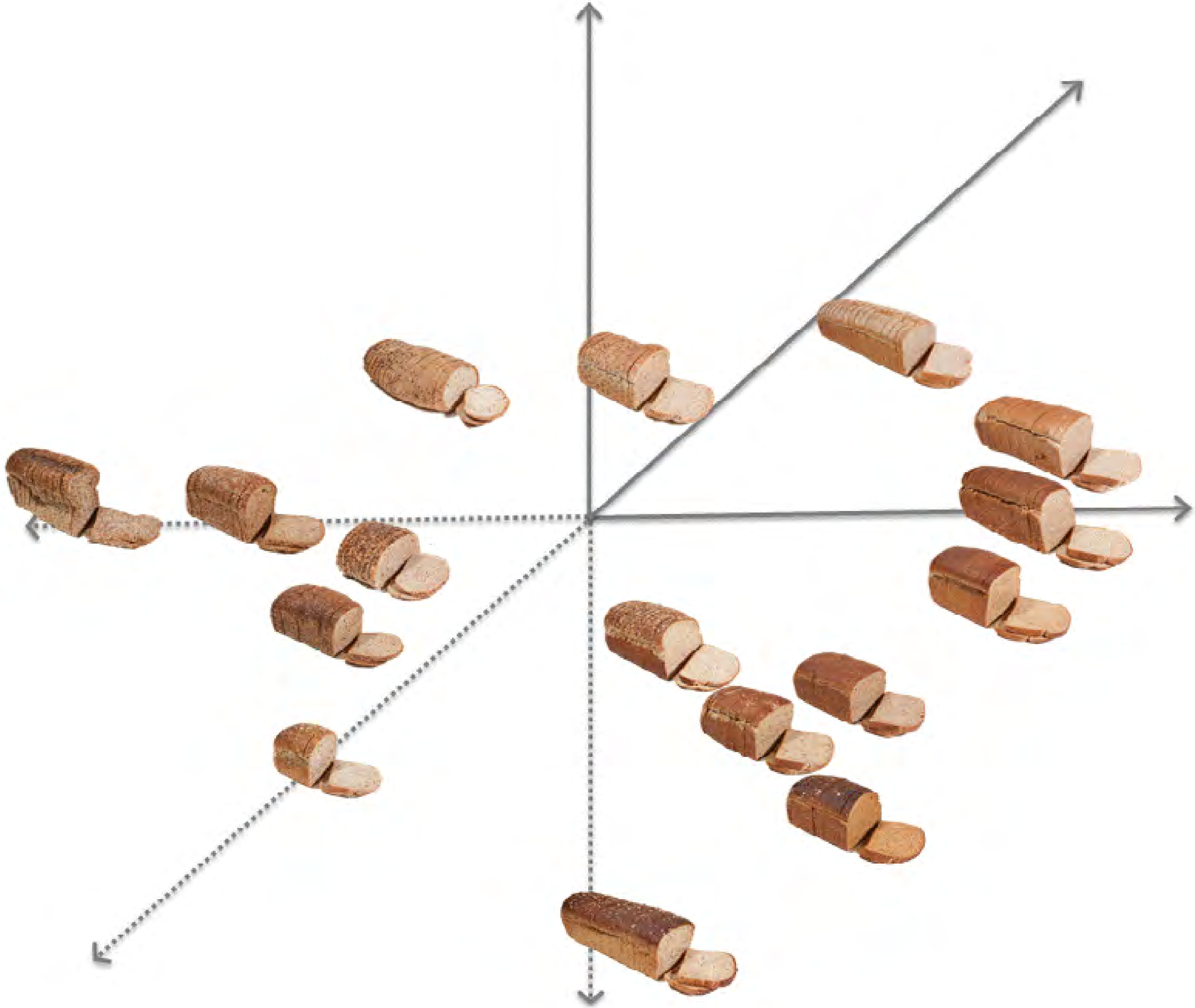
Is it *really* wise to
center or rescale this
consumer's liking data?

Sensory Informed Designs

t	number of products
	product variability
	sensory space
k	number of samples presented
N	number of consumers
	consumer diversity
& c.	context effects & biases (e.g. order)
	scale used for data collection
	sensory-liking relationship

Further research required!

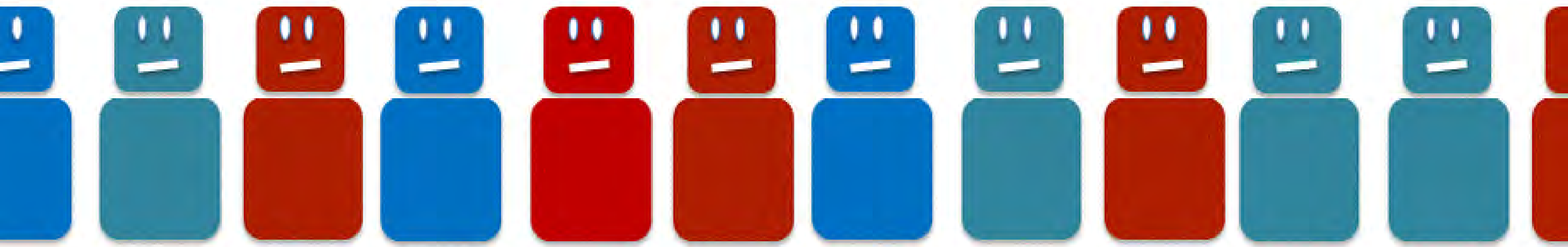




Clusters: heterogeneous

Products: variables

Order: heterogeneous



Estimate & remove order effects *per group.*

Estimate and impute missing data *per group* via conditional E-steps.

Obtain best mixture mo…

Penalize BIC according…

Research in Progress…

Part II: Consumer perception

Please check all that apply.

- ☐ Artificial Flavor
- ☐ Bitter Taste
- ☐ Cheap Taste
- ☐ Earthy Flavor
- ☐ Expensive Flavor
- ☐ Fresh Orange Flavor
- ☐ Fresh Squeezed Flavor
- ☐ From Concentrate Flavor
- ☐ Green/Unripe Orange Flavor
- ☐ High Acidic/Sour/Tart Taste
- ☐ High Sweet Taste
- ☐ Lemon Flavor
- ☐ Low Sweet Taste
- ☐ Low Acidic/Sour/Tart Taste
- ☐ Natural Flavor
- ☐ Not From Concentrate Flavor
- ☐ Organic Flavor
- ☐ Other Citrus Flavor
- ☐ Oxidized Flavor
- ☐ Papery/Cardboard Flavor
- ☐ Plastic Flavor
- ☐ Processed Flavor
- ☐ Refreshing Flavor
- ☐ Rotten/Overripe Orange Flavor
- ☐ Shelf Stable Flavor
- ☐ Strong Flavor
- ☐ Weak/Watery Flavor
- ☐ None of these apply

Check-all-that-apply (CATA) questions

Question order

Liking → CATA

Meyners & Castura (2014)

Investigate

perception responses within **liking clusters**

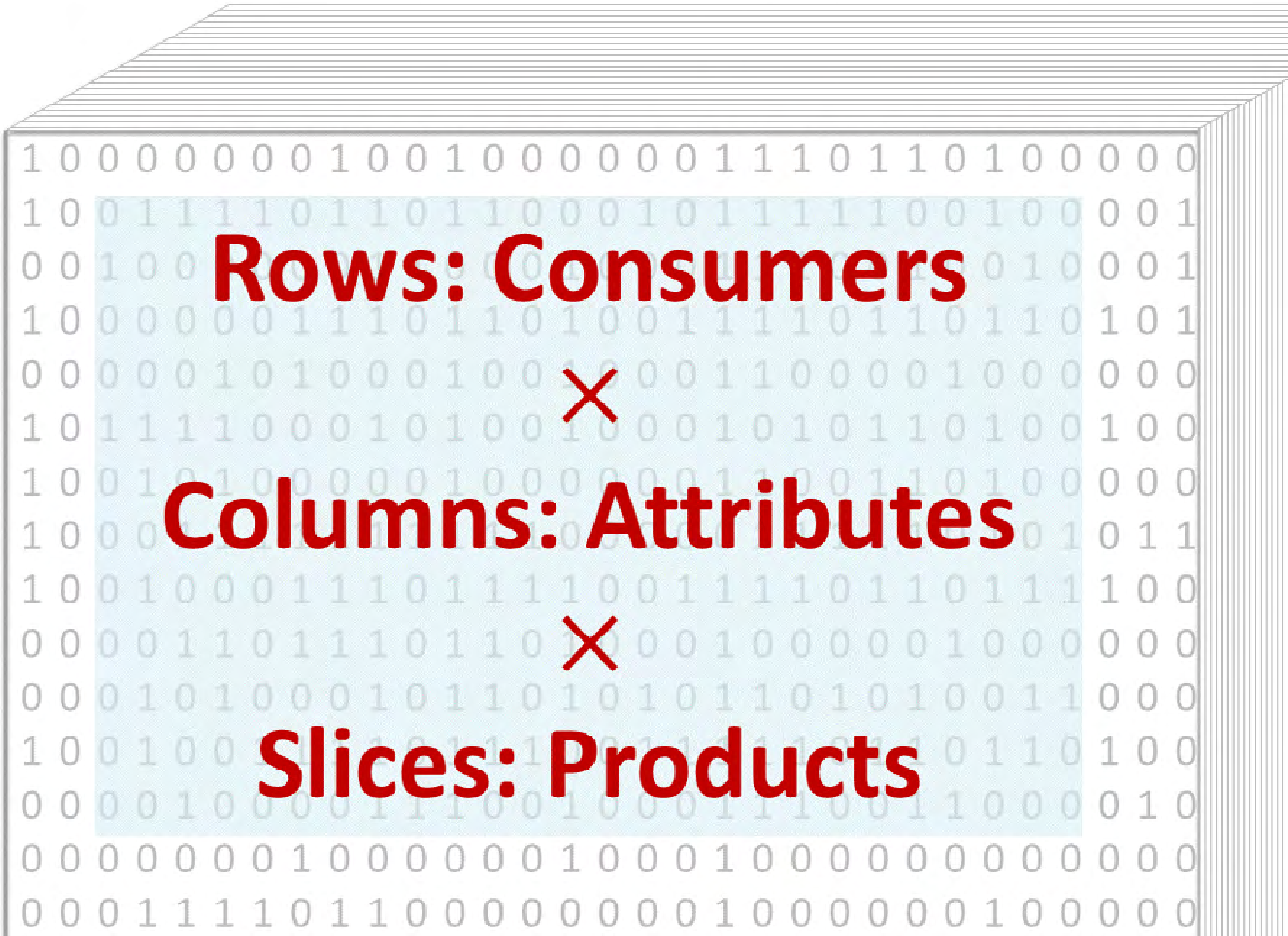
and / or

liking responses within **perception clusters**

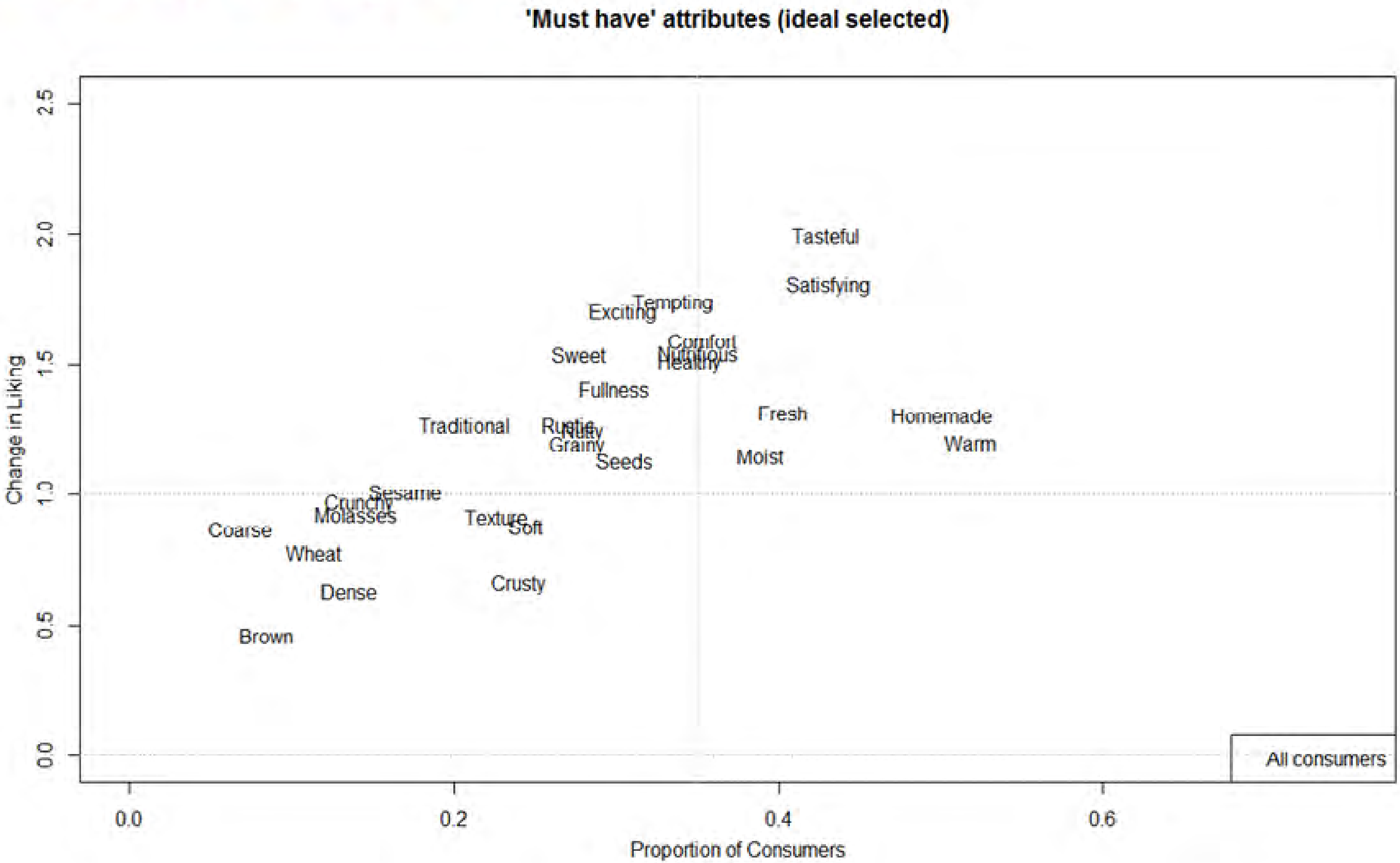
Balance sample serving orders & **Balance attribute positions**

A	B	D	C
B	C	A	D
C	D	B	A
D	A	C	B
B	A	C	D
A	D	B	C
D	C	A	B
C	B	D	A
C	B	A	D

a	b	h	c	g	d	f	e
b	c	a	d	h	e	g	f
c	d	b	e	a	f	h	g
d	e	c	f	b	e	a	h
e	f	d	g	c	f	b	a
f	g	e	h	d	g	c	b
g	h	f	a	e	a	d	c
h	a	g	b	f	b	e	d
g	e	c	d	a	b	h	d

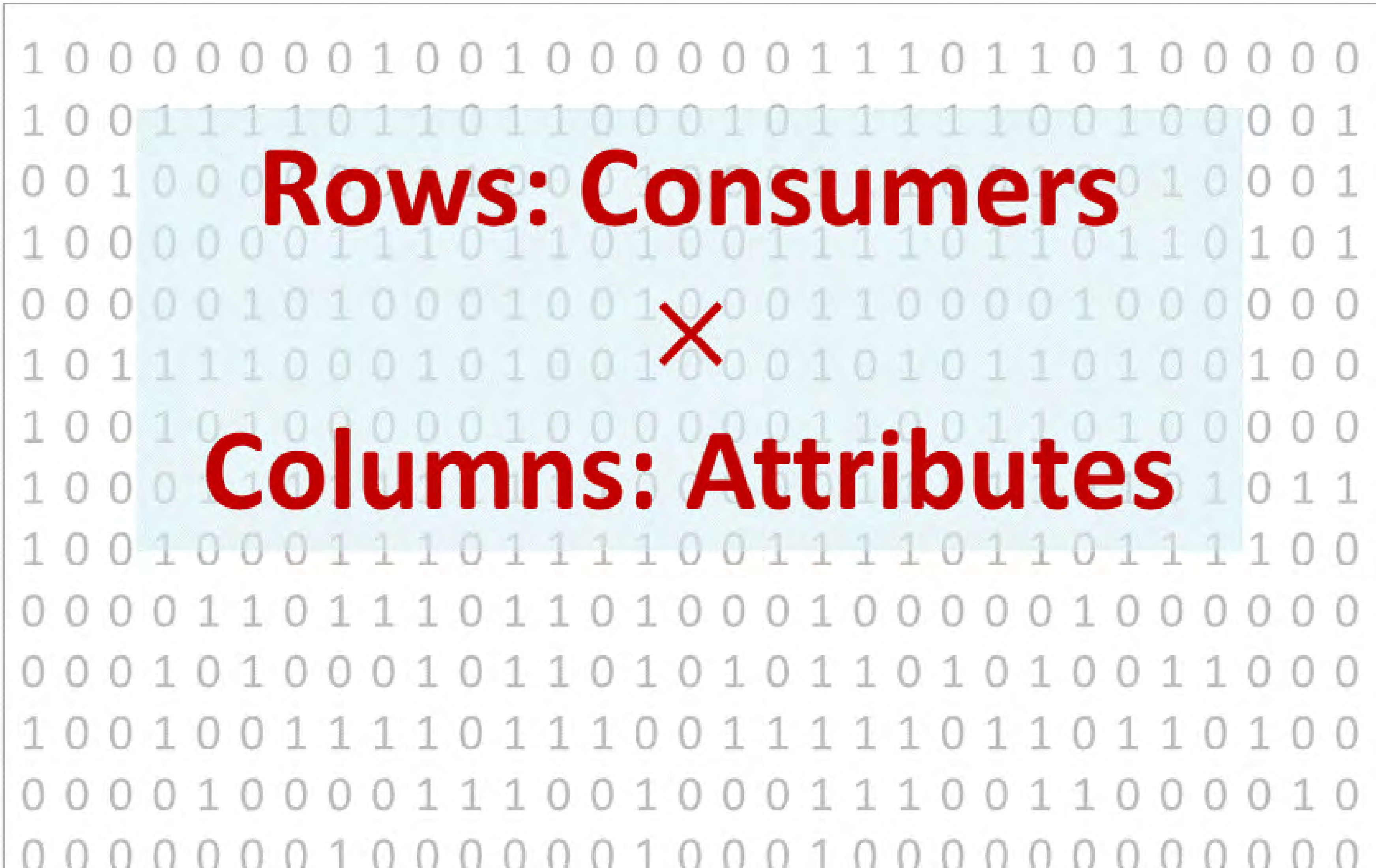

Rows: Consumers
×
Columns: Attributes
×
Slices: Products

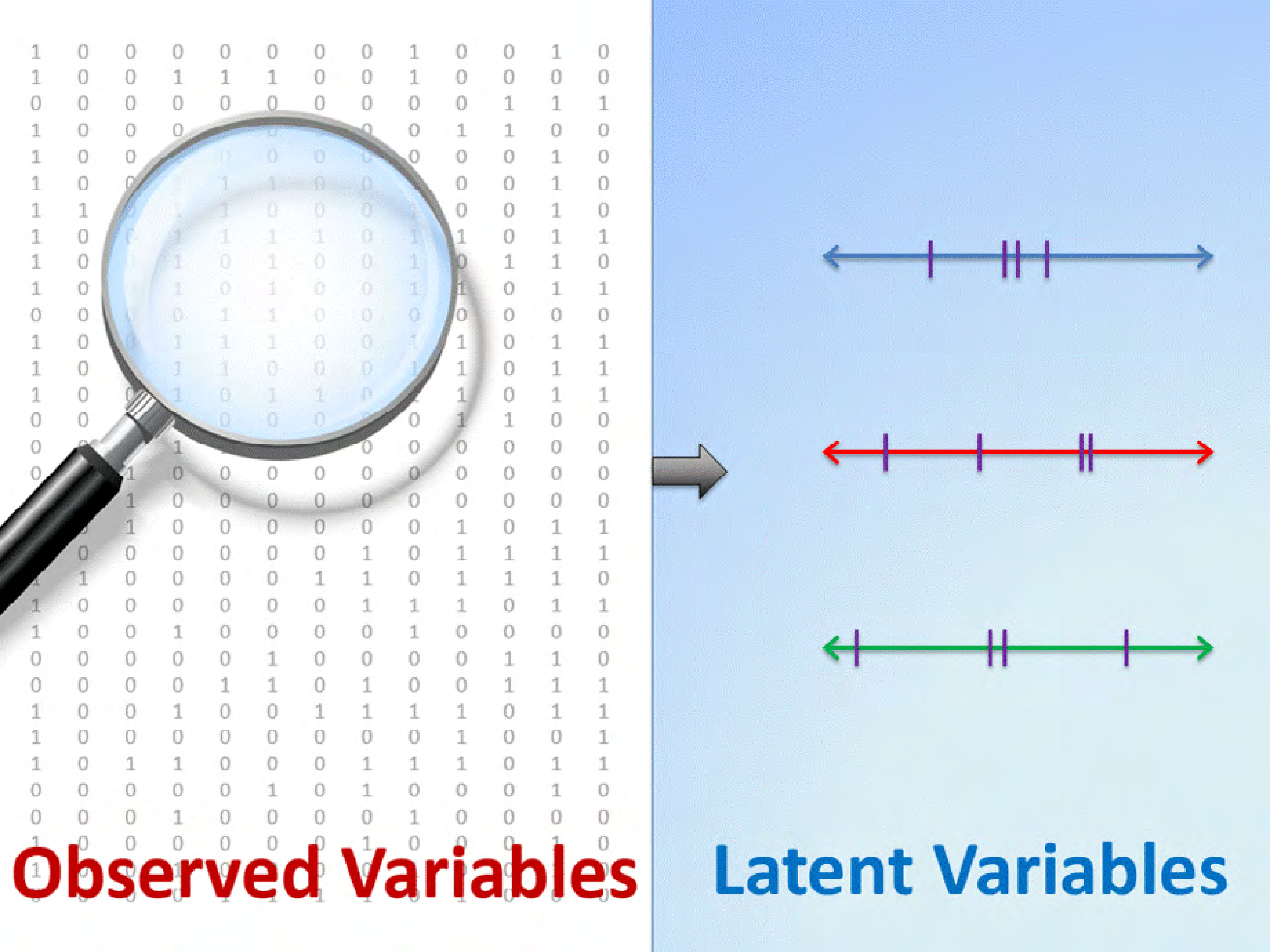
Penalty analysis



Meyners, Castura, & Carr (2013)

“Ideal Product”





Observed Variables
Latent Variables

Mixture of Latent Trait Models with Common Slope Parameters

Attribute ***k***, Consumer ***i***, Group ***g***

$$\boldsymbol{p\left(x_{ik} = 1 \mid y_{ig}, z_{ig} = 1\right) = \frac{1}{1 + exp(-w'_k y_{ig})}}$$

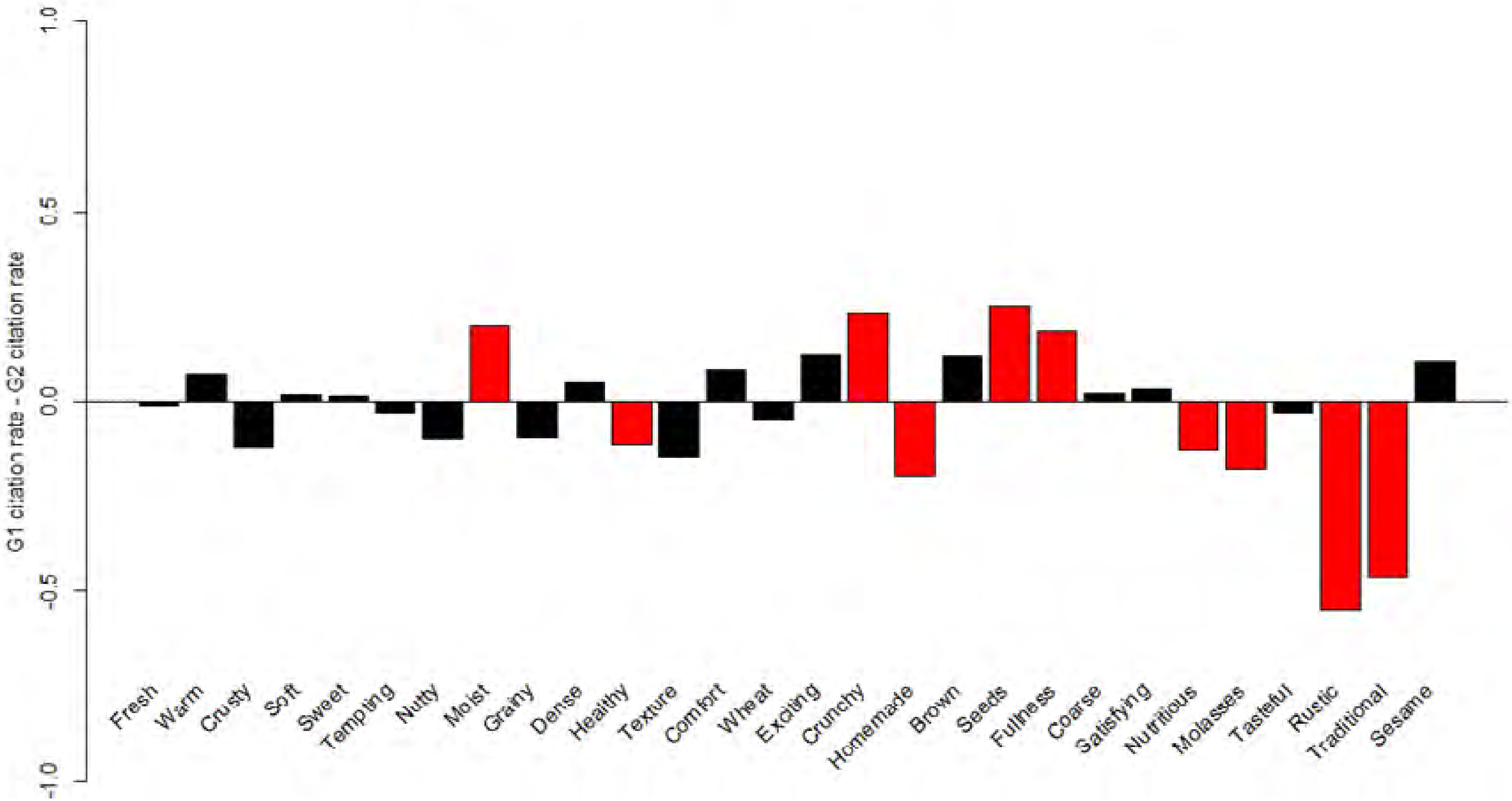
$$Y_{ig} \sim \mathbf{MVN}(\mu_g, \Sigma_g)$$

$$\Sigma_g = \lambda_g \mathbf{Q}_g \mathbf{A}_g \mathbf{Q}_g'$$

Volume **Orientation** **Shape**

Tang, Browne & McNicholas (2014)

Difference in Attribute Selection Rates for the Ideal Product



Consumers clustered by CATA profiles of an ideal bread into G1 (n=56) and G2 (n=105) via mixture of latent trait models with common slope parameters (MCLT)

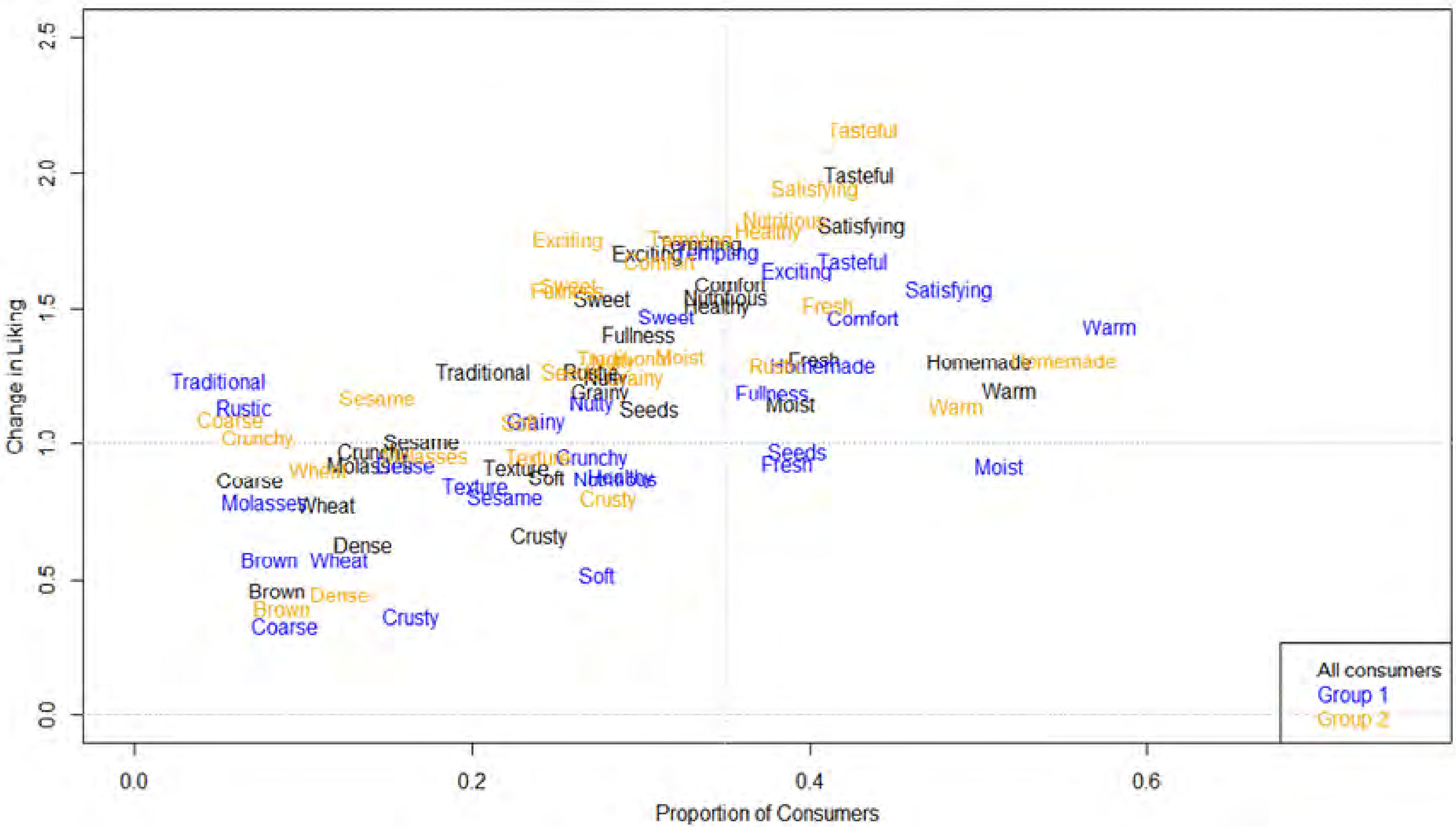
Citation proportions differ significantly

Citation proportions do not differ significantly

BIC selects the following solution:
2 groups, 2 latent variables

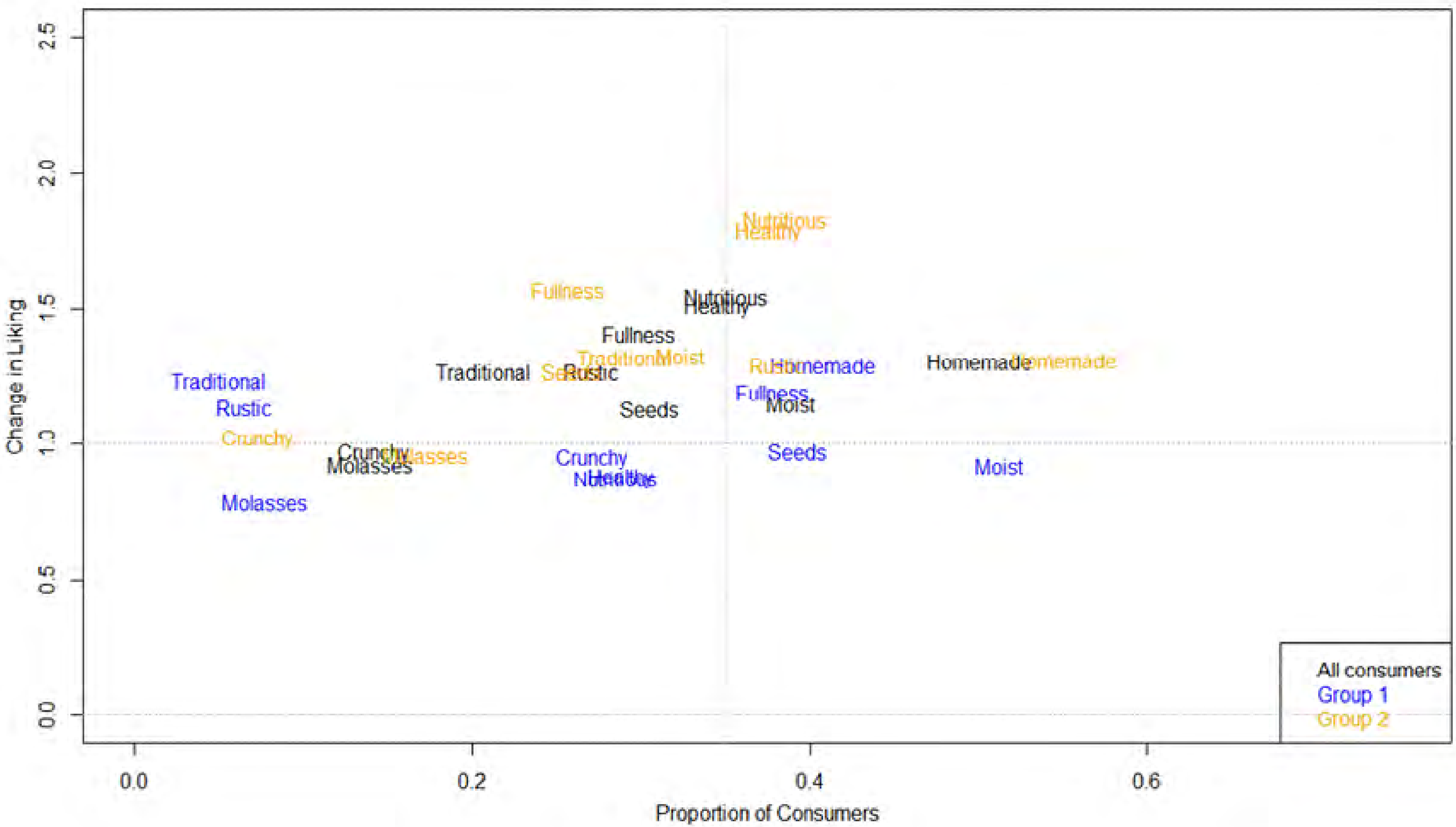
Early results from research (in progress)

'Must have' attributes (ideal selected)



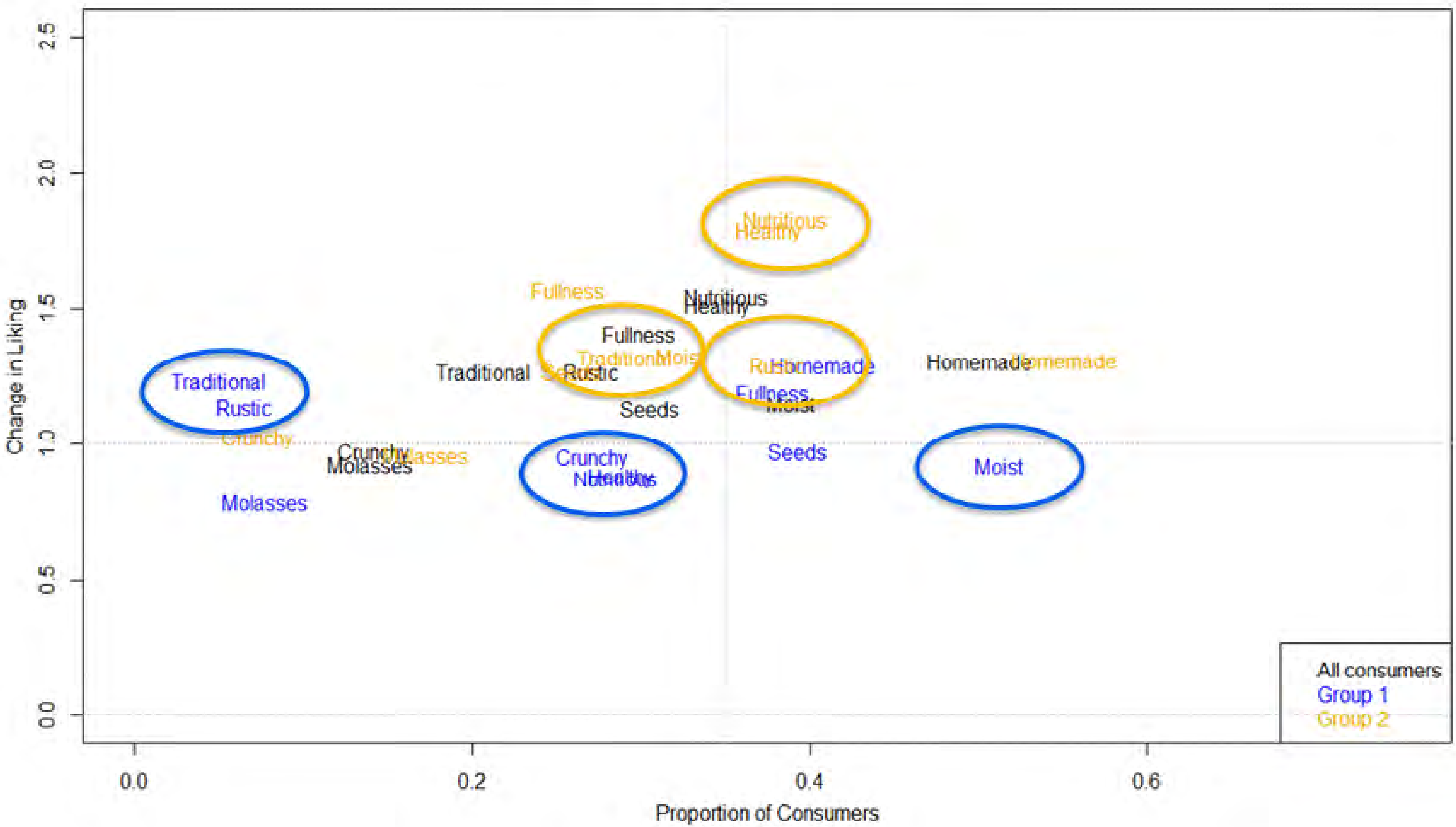
Early results from research (in progress)

'Must have' attributes (ideal selected)

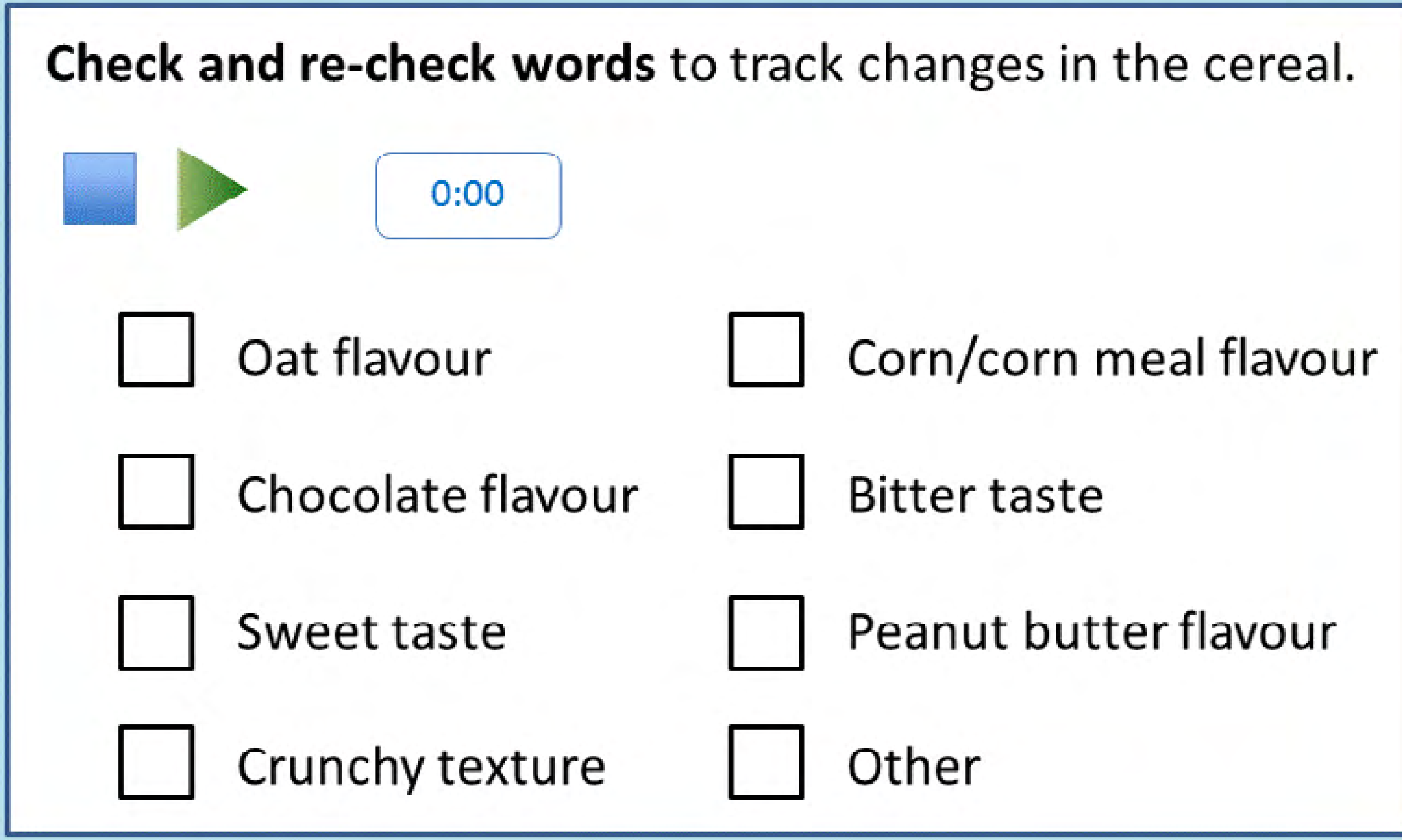


Early results from research (in progress)

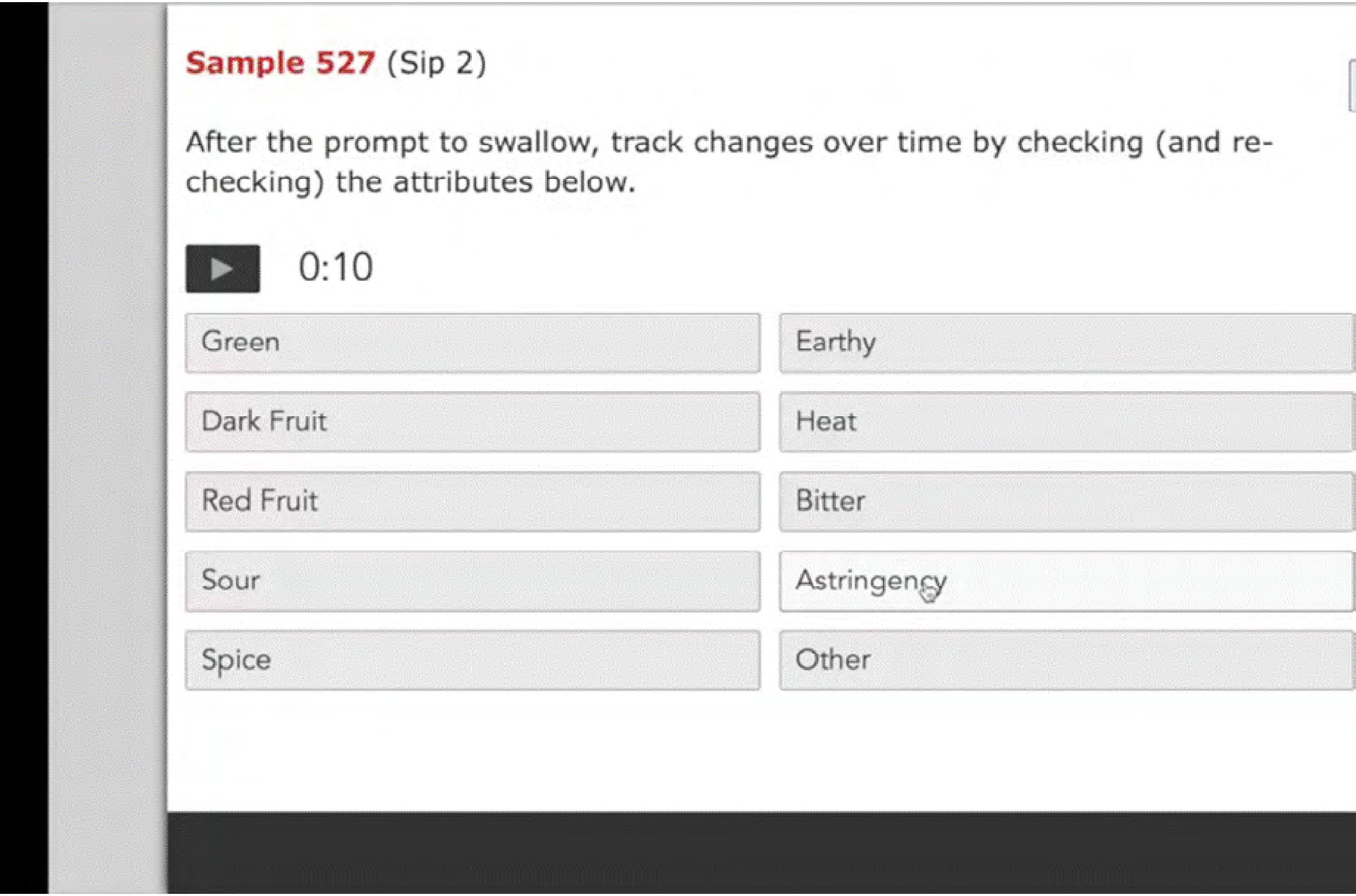
'Must have' attributes (ideal selected)



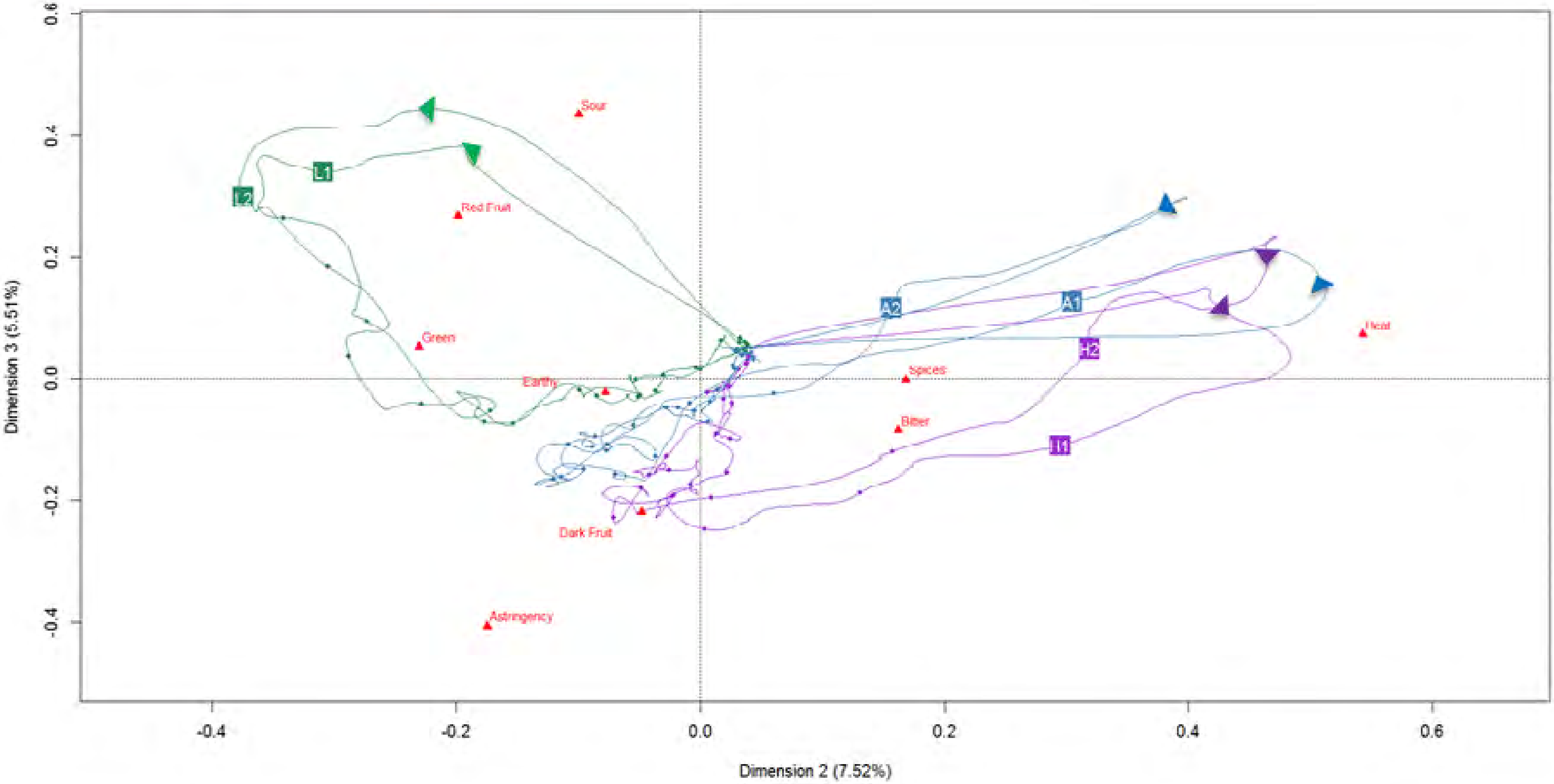
Early results from research (in progress)



Temporal Check-all-that-apply (TCATA)

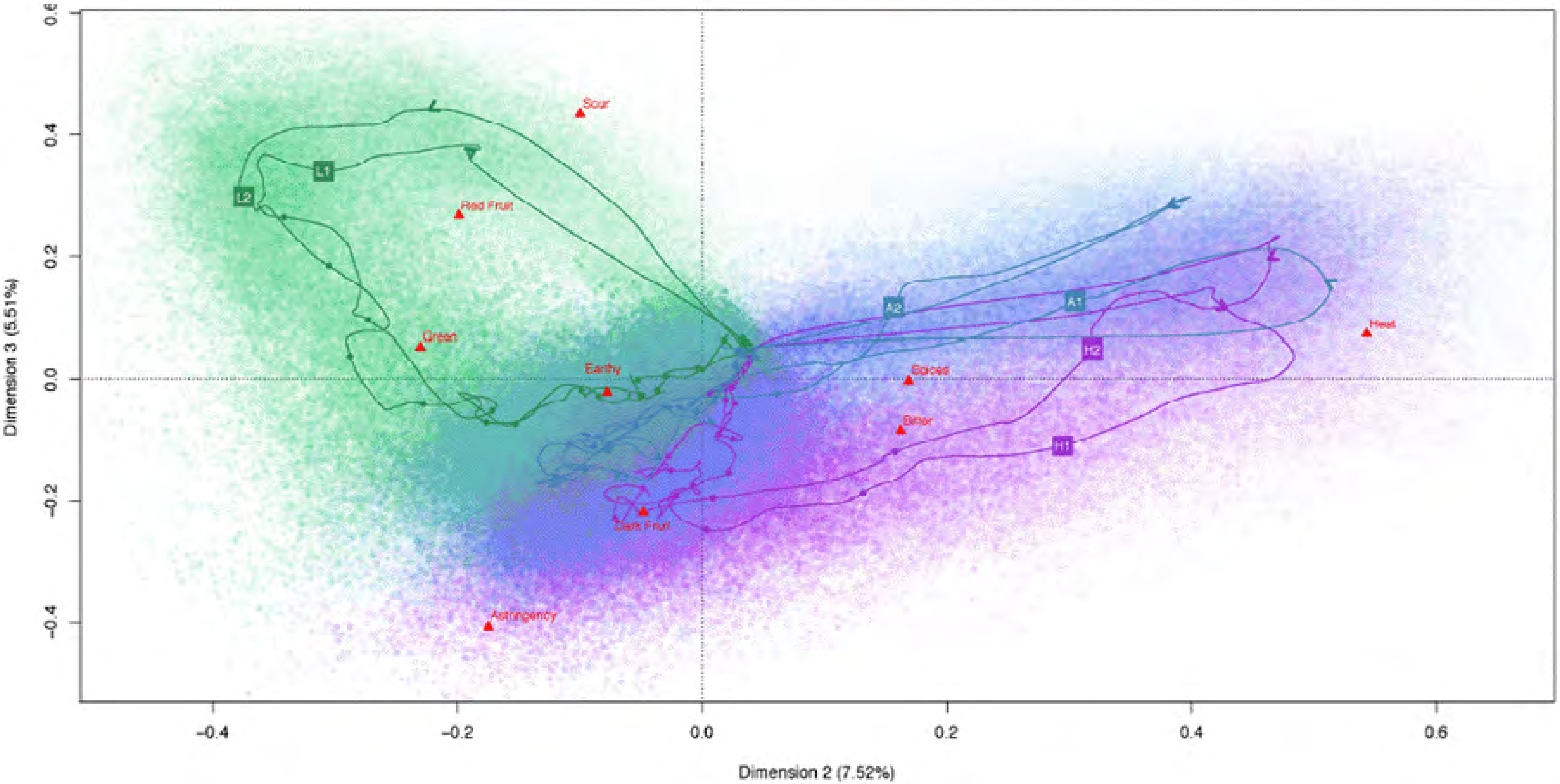

Sample 527 (Sip 2)
After the prompt to swallow, track changes over time by checking (and re-checking) the attributes below.
0:10
Green
Earthy
Dark Fruit
Heat
Red Fruit
Bitter
Sour
Astringency
Spice
Other

Trajectories



Castura, Baker & Ross (2017)

Trajectories & contrails



Castura, Baker, & Ross (2017)

TCATA studies: Question order

TCATA → Liking

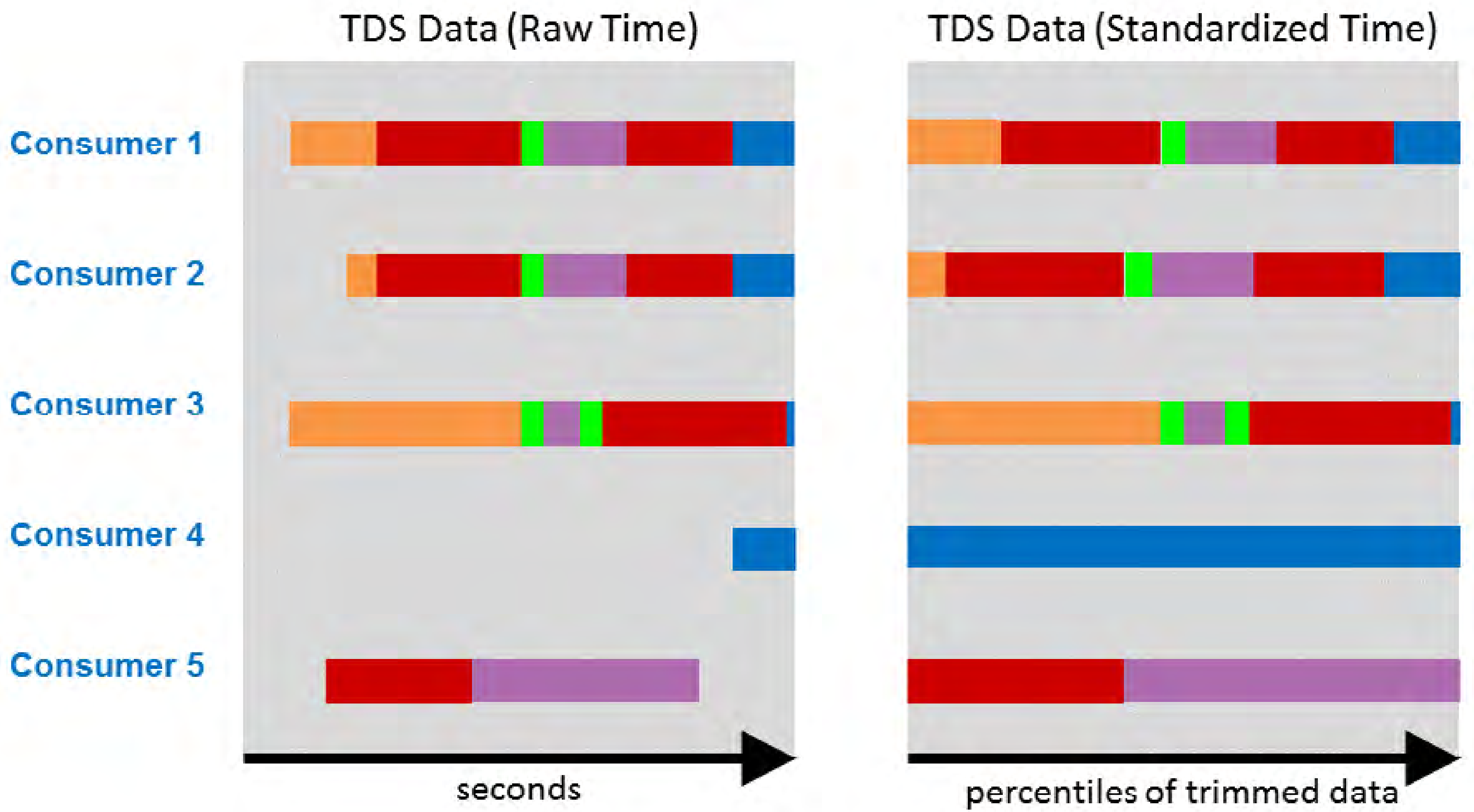
Investigate

perception responses within **liking clusters**

and / or

liking responses within **perception clusters**

Time standardization



Meyners & Castura (2017, SAAFoST 2017 Post-Meeting Workshop)

Time standardization

This can have a dramatic effect on results!

Are we **aligning** or **distorting** the data?

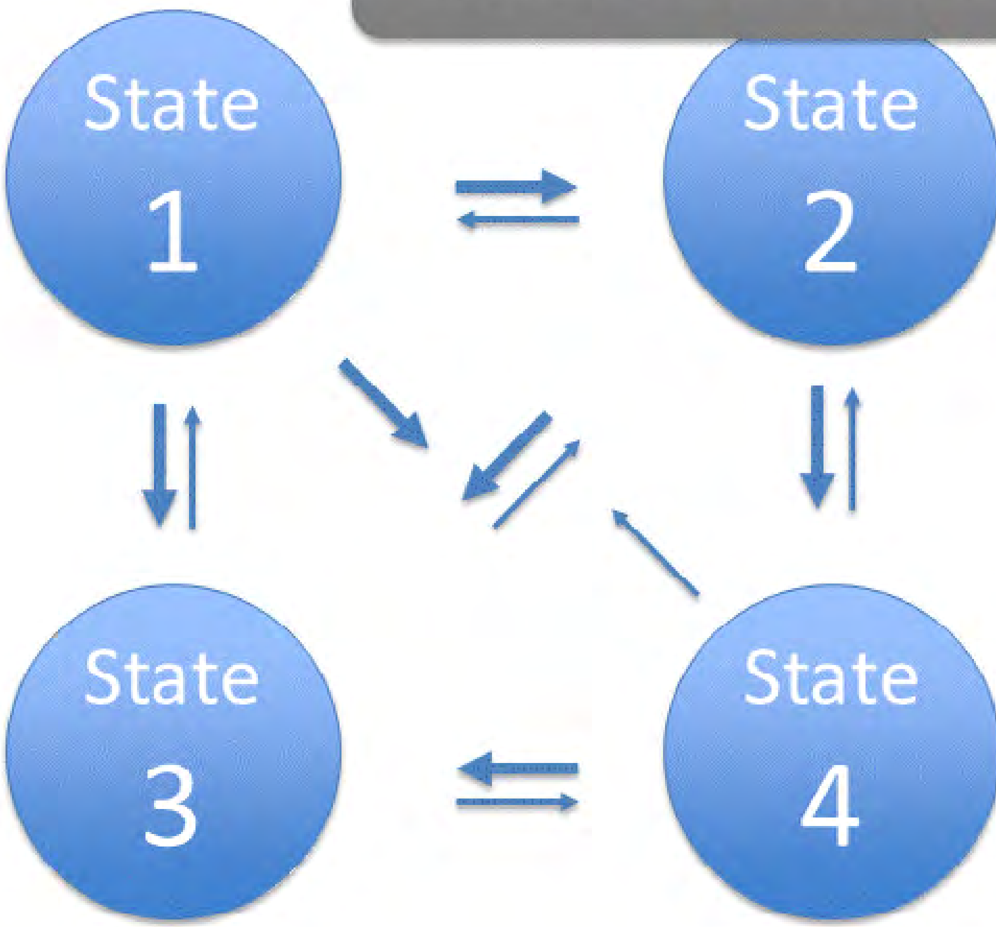
In TCATA evaluations of sparkling wines, **duration of perception** was found to increase with carbonation level… thus **time standardizing removes real product effects**!

Apply with caution!

McMahon, Culver, Castura, & Ross (2017)

Hidden Markov Models for clustering consumers based on dynamic (TCATA) perception data.

Research in Progress…



Part III:

Conclusion


"A foolish consistency is the hobgoblin of little minds…"
Ralph Waldo Emerson
1841

Does a study that is designed and analyzed in a manner that is consistent with standard practices always make sense?

Of course not.

It's important to follow the design and analysis rules that need to be followed and break the rules that need to be broken.

Which rules are which?

"Experience is knowing when to put your hand in the wood chipper."

Chris Findlay, as quoted by **John Hayes**

at the Society of Sensory Professionals 2014 Conference

in Tucson, Arizona

Selected References

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THANK YOU MERCI

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