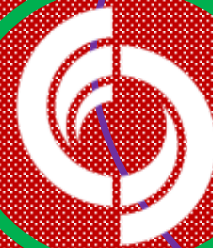


Consumer hedonic studies with incomplete block designs

J. C. Castura
Compusense Inc.



Compusense®

Acknowledgements

A black and white kitten is the central focus, standing on a dark, textured rock. It is reaching out with its right front paw towards a small, delicate pink flower with green leaves. The kitten has dark fur on its back and head, with white fur on its chest and paws. Its eyes are blue and focused on the flower. The background is a soft-focus view of a body of water and a distant shoreline under a pale sky.

Thanks to **Brian Franczak** (MacEwan University, Edmonton, Alberta, Canada) and **Chris Findlay** (Compusense Inc., Guelph, Ontario, Canada) for helpful discussions.

Thanks to **Josef Zach** (Ipsos Marketing, Munich, Germany) for the invitation to join this workshop and for providing the workshop data set.

Some Takeaways

Data is not Good just because it is Complete

- It is “the devil we know”
- Consumer responses change as the test progresses
- Sometimes less is more...

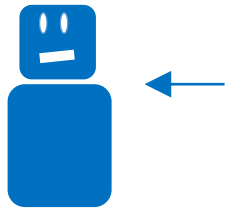
Data is not Good just because it is Incomplete

- Impact of first-position effect is more pronounced
- Sometimes less is less...

Sensory space

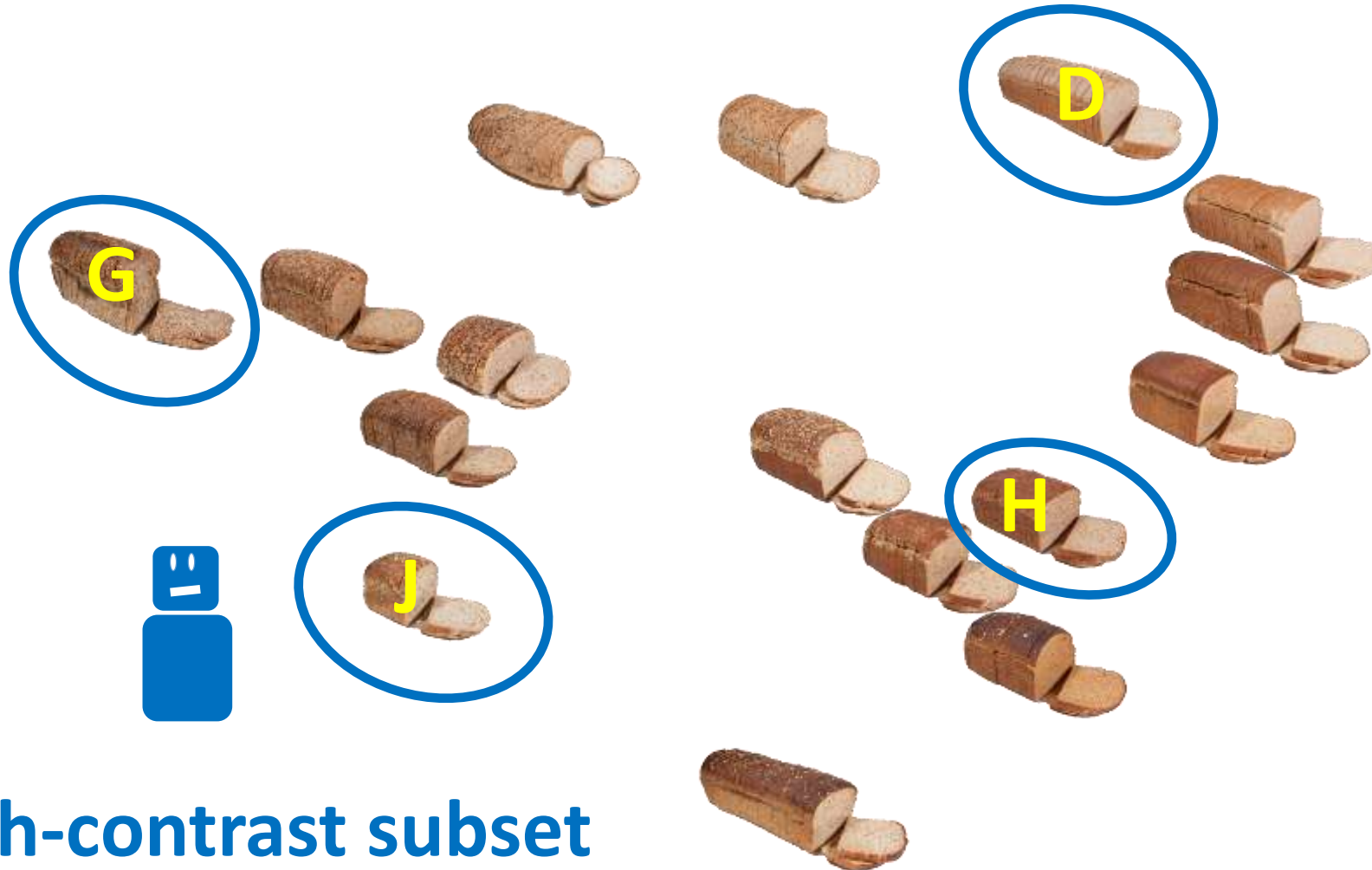


Balanced incomplete block design



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
...

Balanced incomplete block design



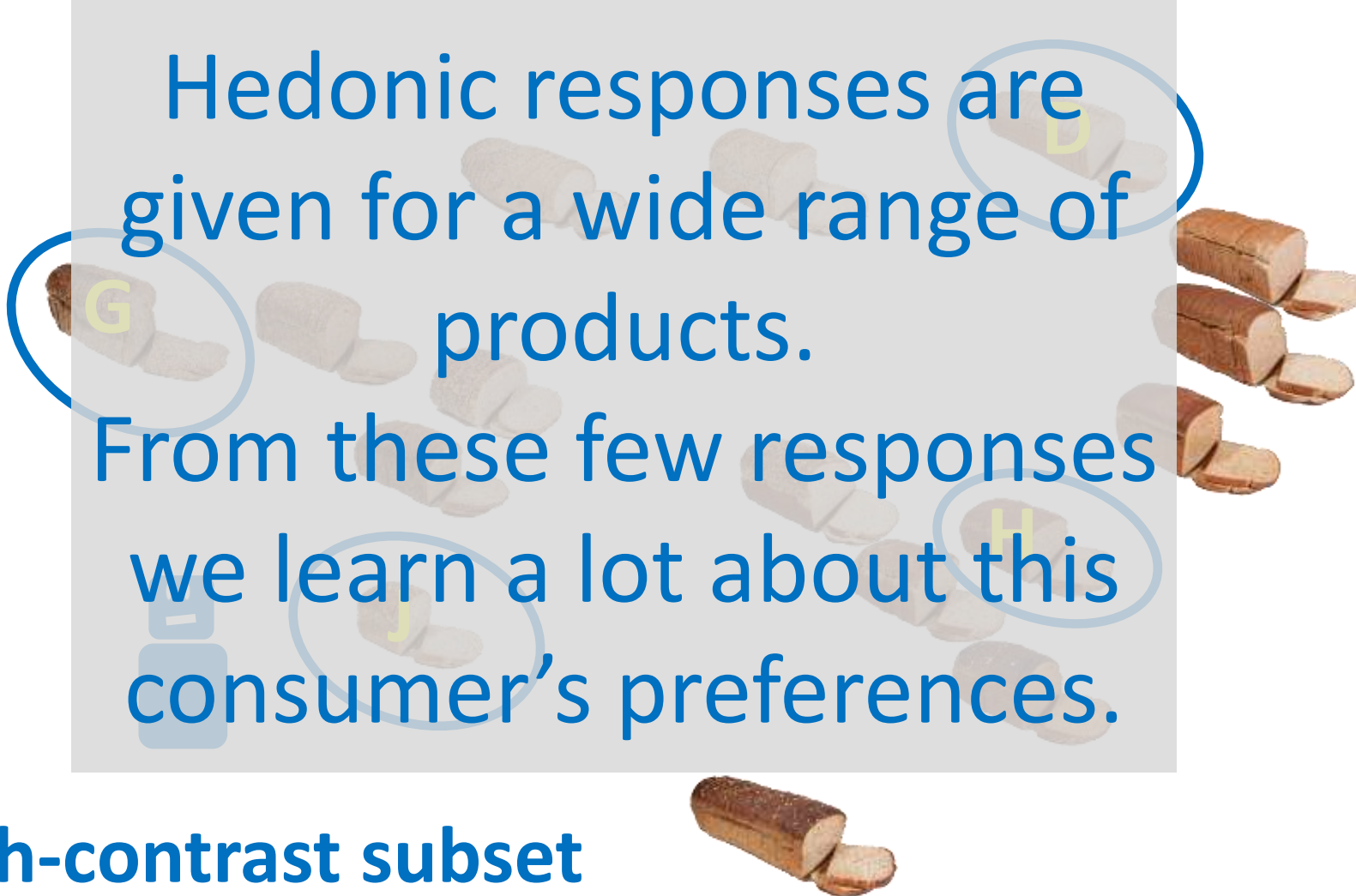
A high-contrast subset

Balanced incomplete block design

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



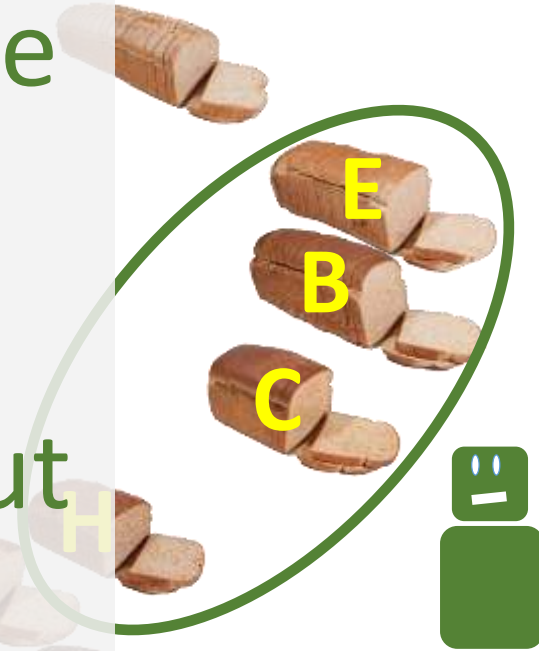
F	A	I	D
B	C	E	I
H	E	J	B
I	F	C	A
E	B	H	C
G	J	D	H
A	D	F	G
C	I	B	F
D	G	A	J
J	H	G	E
D	C	G	B
I	H	F	J
B	G	C	D
A	B	D	E
...

Balanced incomplete block design



Balanced incomplete block design

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

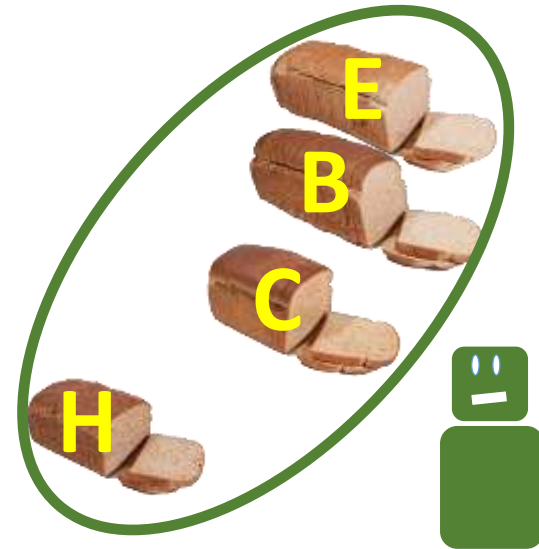


A low-contrast subset

Balanced incomplete block design



Would this
product have
been liked or
disliked

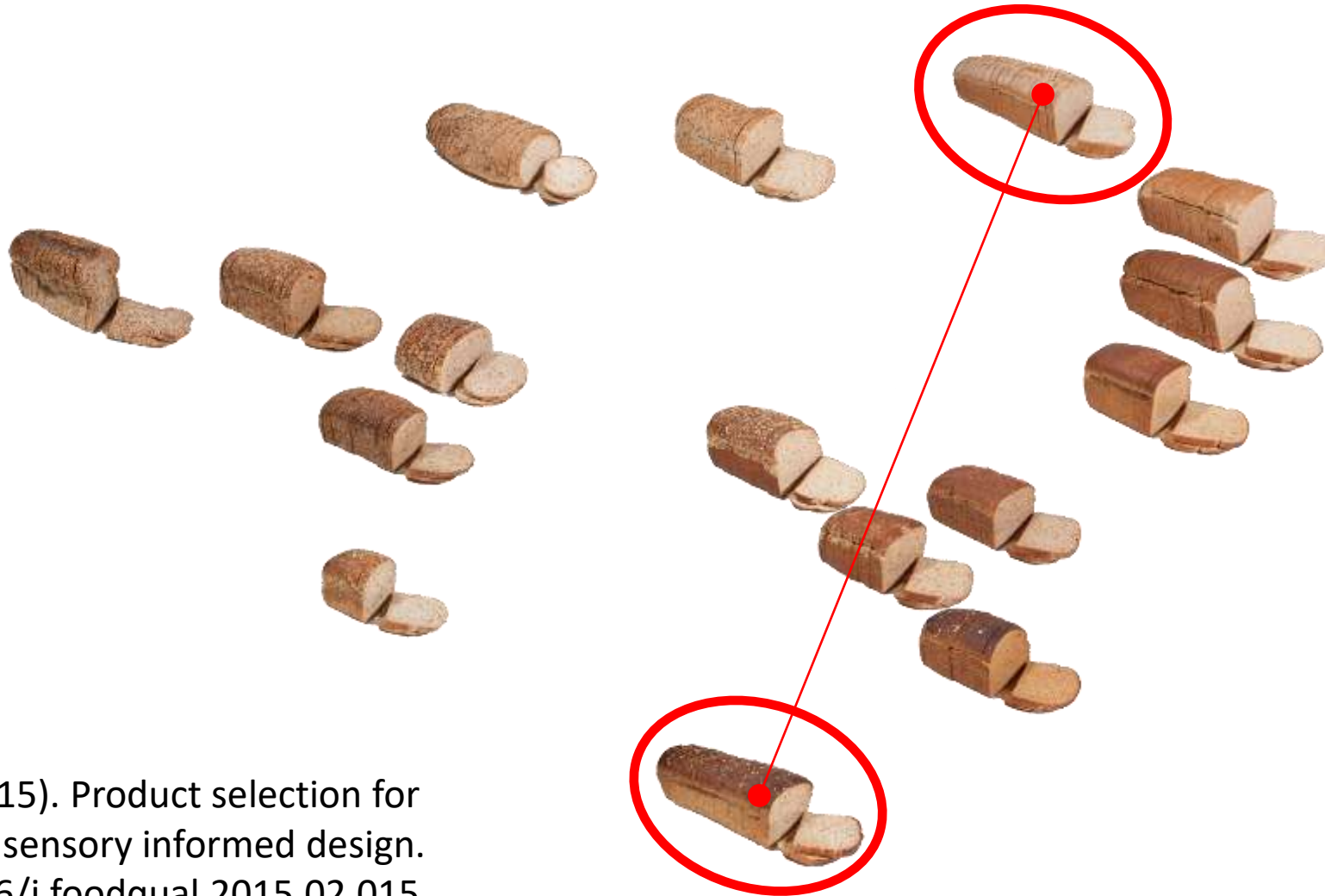


A low-contrast subset

The image features three loaves of bread against a white background. The top loaf is a simple, golden-brown round loaf. The middle loaf is a darker, crustier round loaf with a cracked surface. The bottom loaf is a long, oval-shaped loaf, also with a cracked crust. Several slices have been cut from the bottom two loaves, revealing a light-colored, porous interior. Overlaid on the center of the bread is the text "Sensory-informed design" in a bold, light blue, sans-serif font.

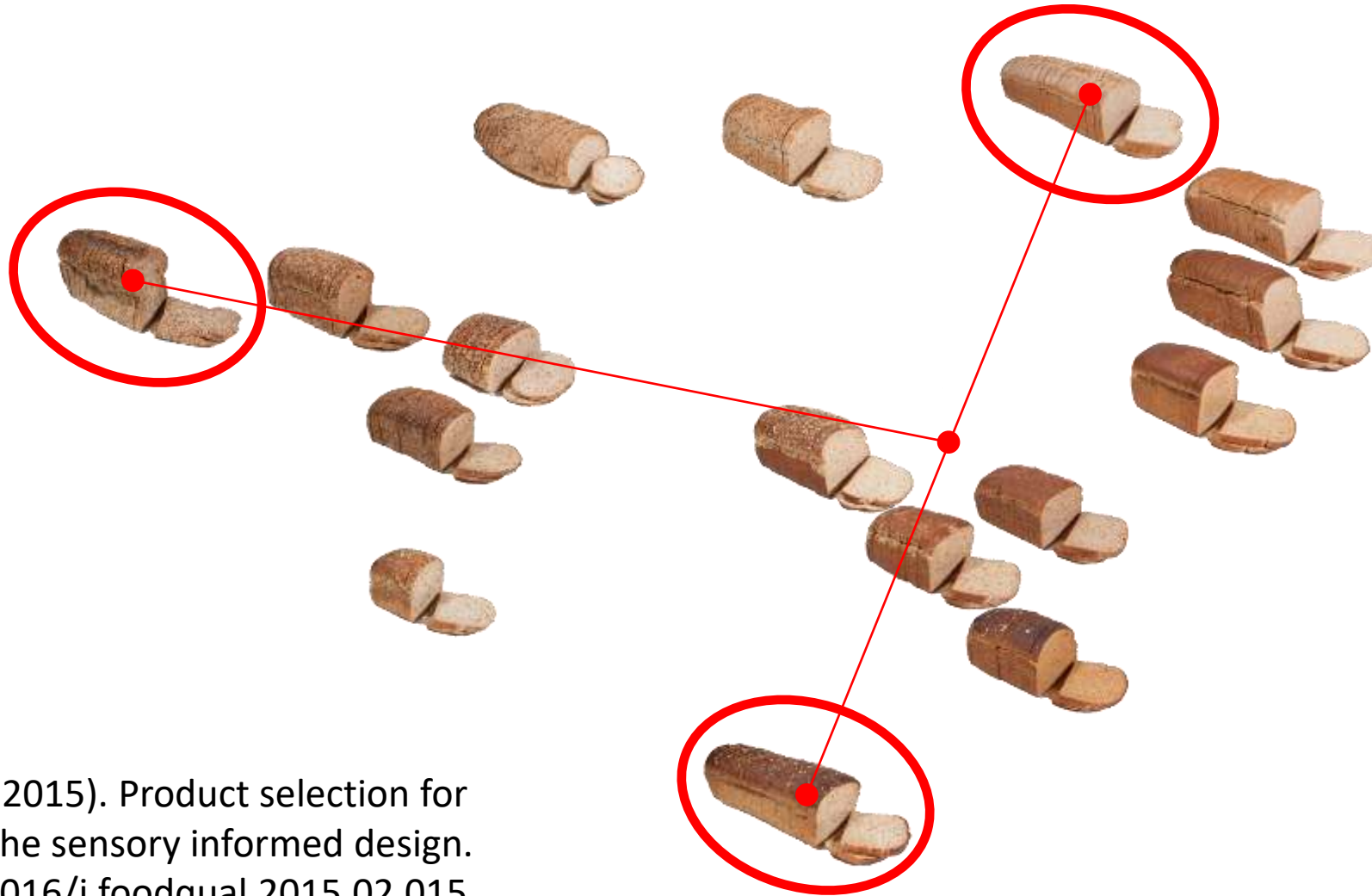
Sensory-informed design

Sensory-informed design



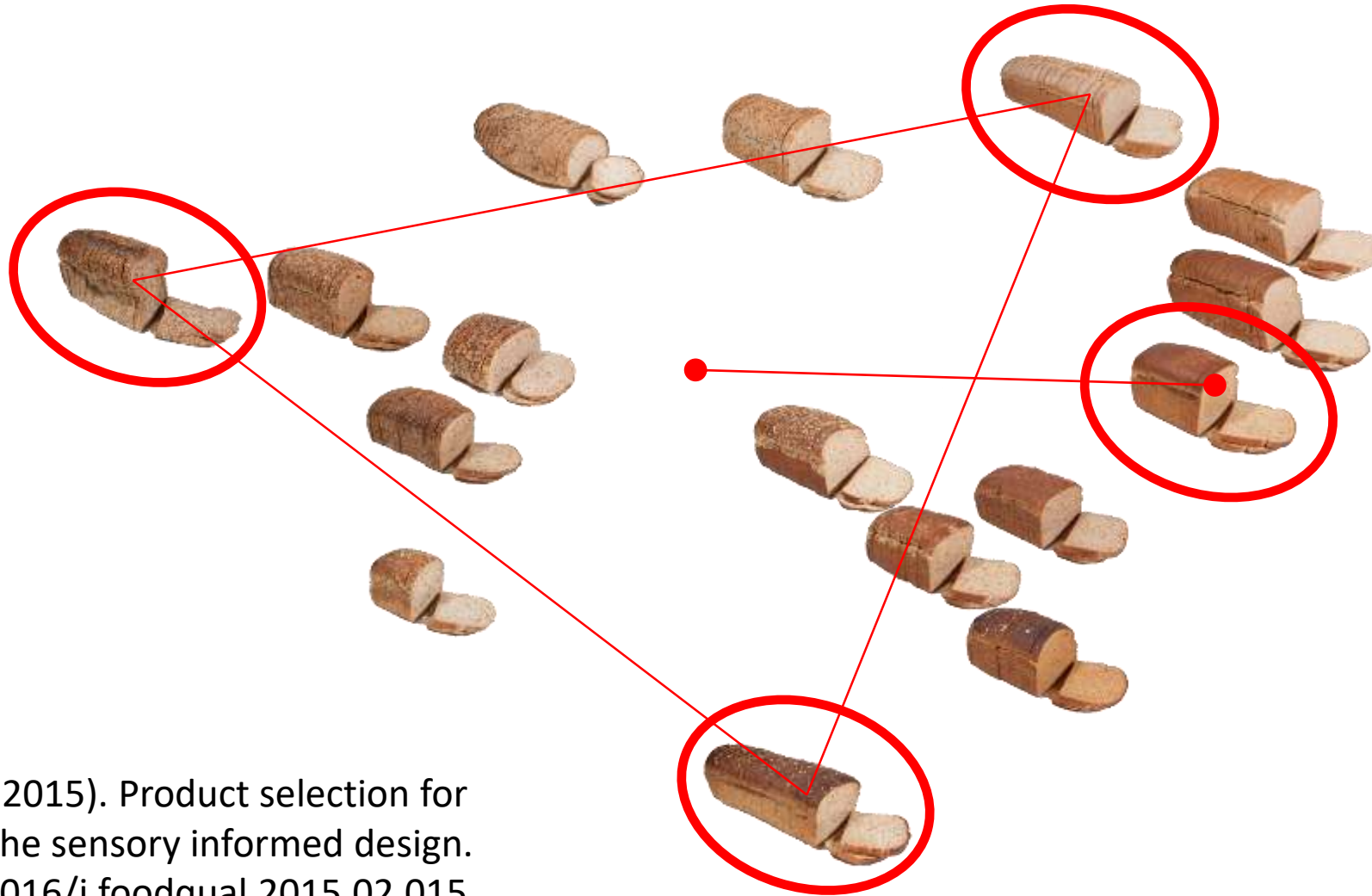
Franczak et al. (2015). Product selection for liking studies: The sensory informed design. *FQAP*, doi: 10.1016/j.foodqual.2015.02.015.

Sensory-informed design



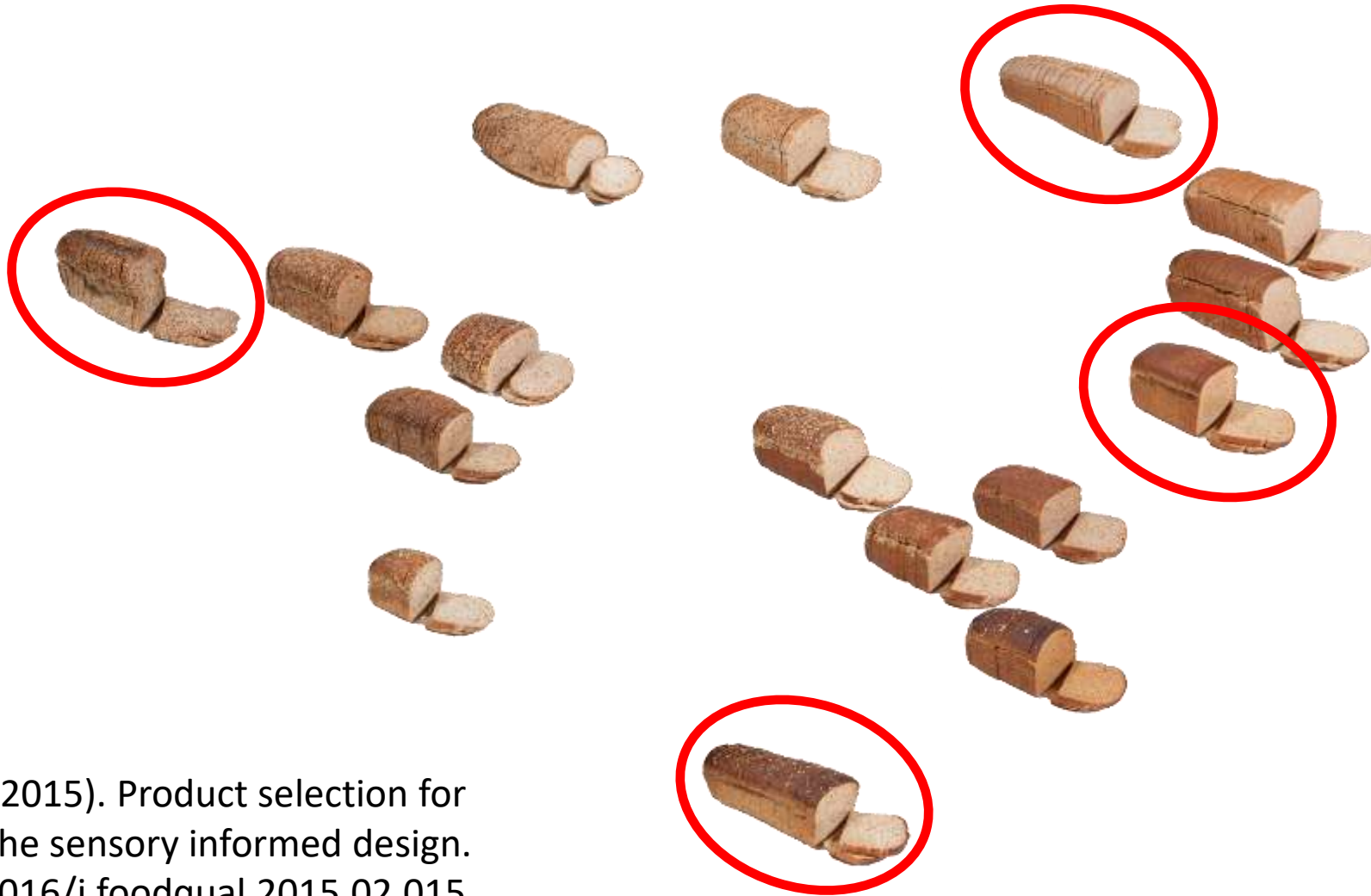
Franczak et al. (2015). Product selection for liking studies: The sensory informed design. *FQAP*, doi: 10.1016/j.foodqual.2015.02.015.

Sensory-informed design



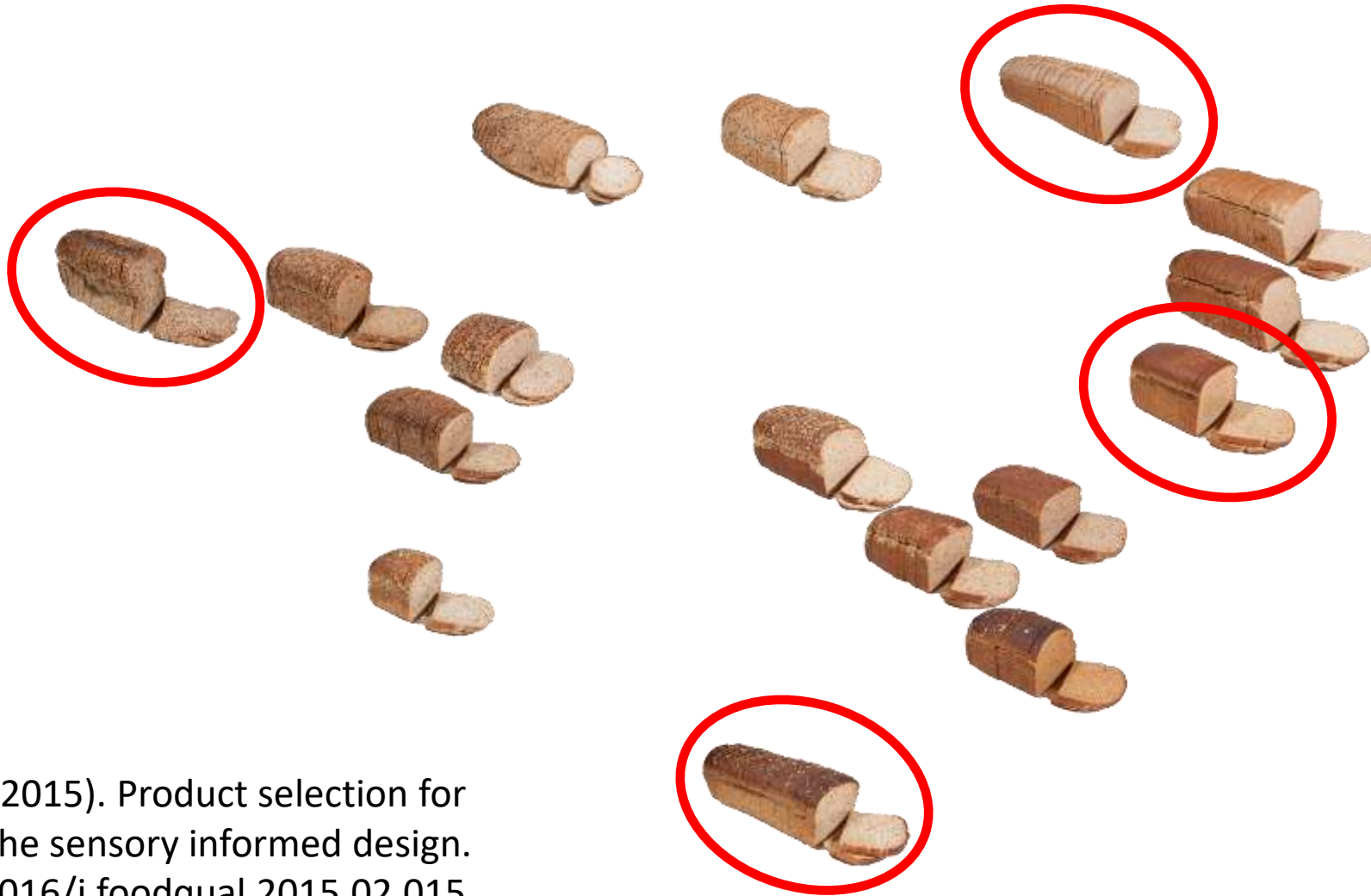
Franczak et al. (2015). Product selection for liking studies: The sensory informed design. *FQAP*, doi: 10.1016/j.foodqual.2015.02.015.

Sensory-informed design



Franczak et al. (2015). Product selection for liking studies: The sensory informed design. *FQAP*, doi: 10.1016/j.foodqual.2015.02.015.

Sensory-informed design



**Order
balanced**

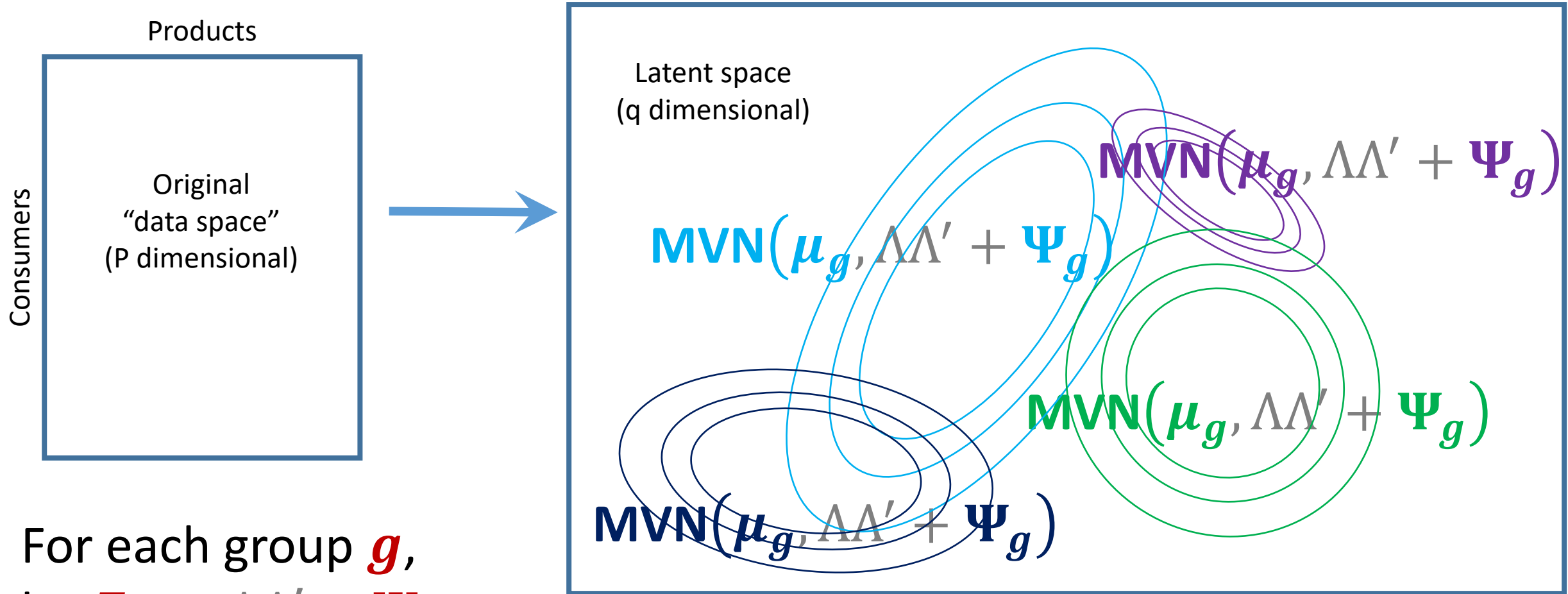
**Every
subset has
reasonably
high
contrast**

(...in as many
dimensions as is
relevant..)

Franczak et al. (2015). Product selection for
liking studies: The sensory informed design.
FQAP, doi: 10.1016/j.foodqual.2015.02.015.

Mixture of factor analyzers

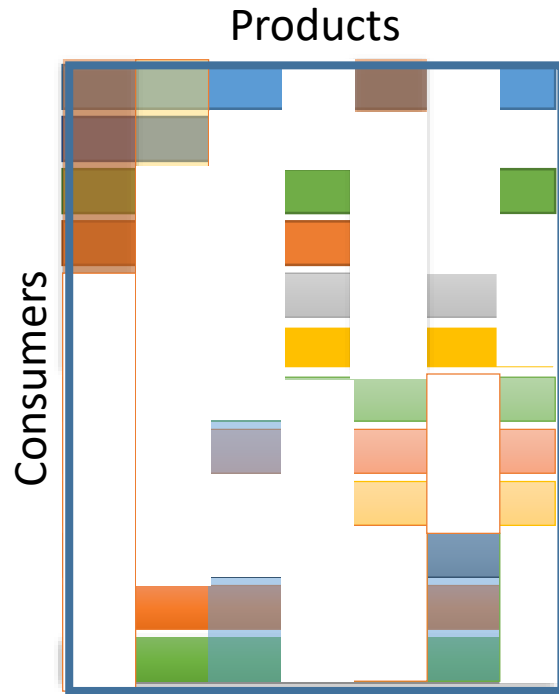
“MBC” model based clustering



For each group g ,
let $\Sigma_g = \Lambda\Lambda' + \Psi_g$,

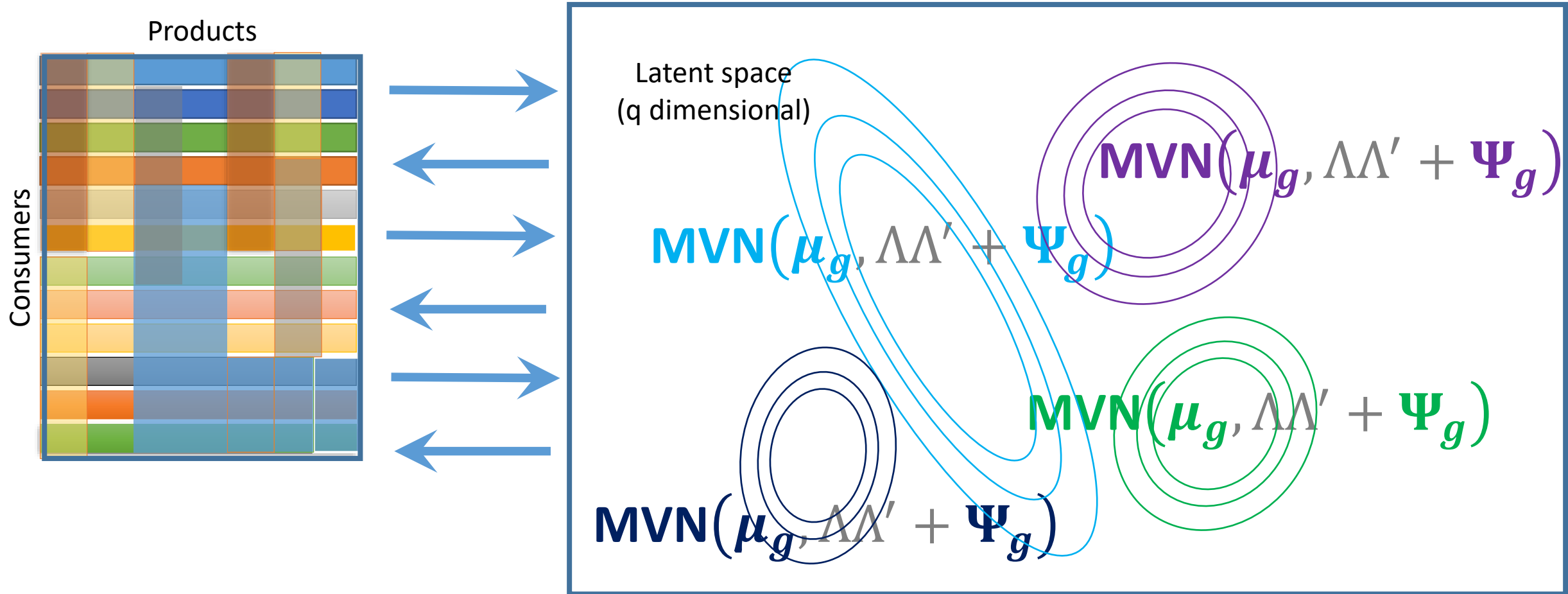
where Λ is a common loading matrix (shared by all groups).

Model-based clustering + clusterwise imputation



Browne, R.P., McNicholas, P.D., & Findlay, C.J. (2013).
A partial EM algorithm for clustering white breads.
arXiv preprint arXiv:1302.6625.

Model-based clustering + clusterwise imputation



“MBC + Imputation”
model based clustering and imputation

Browne, R.P., McNicholas, P.D., & Findlay, C.J. (2013).
A partial EM algorithm for clustering white breads.
arXiv preprint arXiv:1302.6625.

Sensory-informed design

What are the benefits?

Faster! ... Cheaper! ... Better?

Will it work for every product category?

Will it work for ***my*** product category?

It depends...

Risk comes from not knowing what you are doing.*

Samples need to span the relevant sensory space

- Relevant sensory space cannot be too complex
- Samples must span attributes that drive the hedonic response
- Needs to be enough samples presented (not too many... not too few...)

Must be a high enough signal-noise ratio

- Tricky if products are too variable
- ...or if order effects are too strong

Need good design and analysis

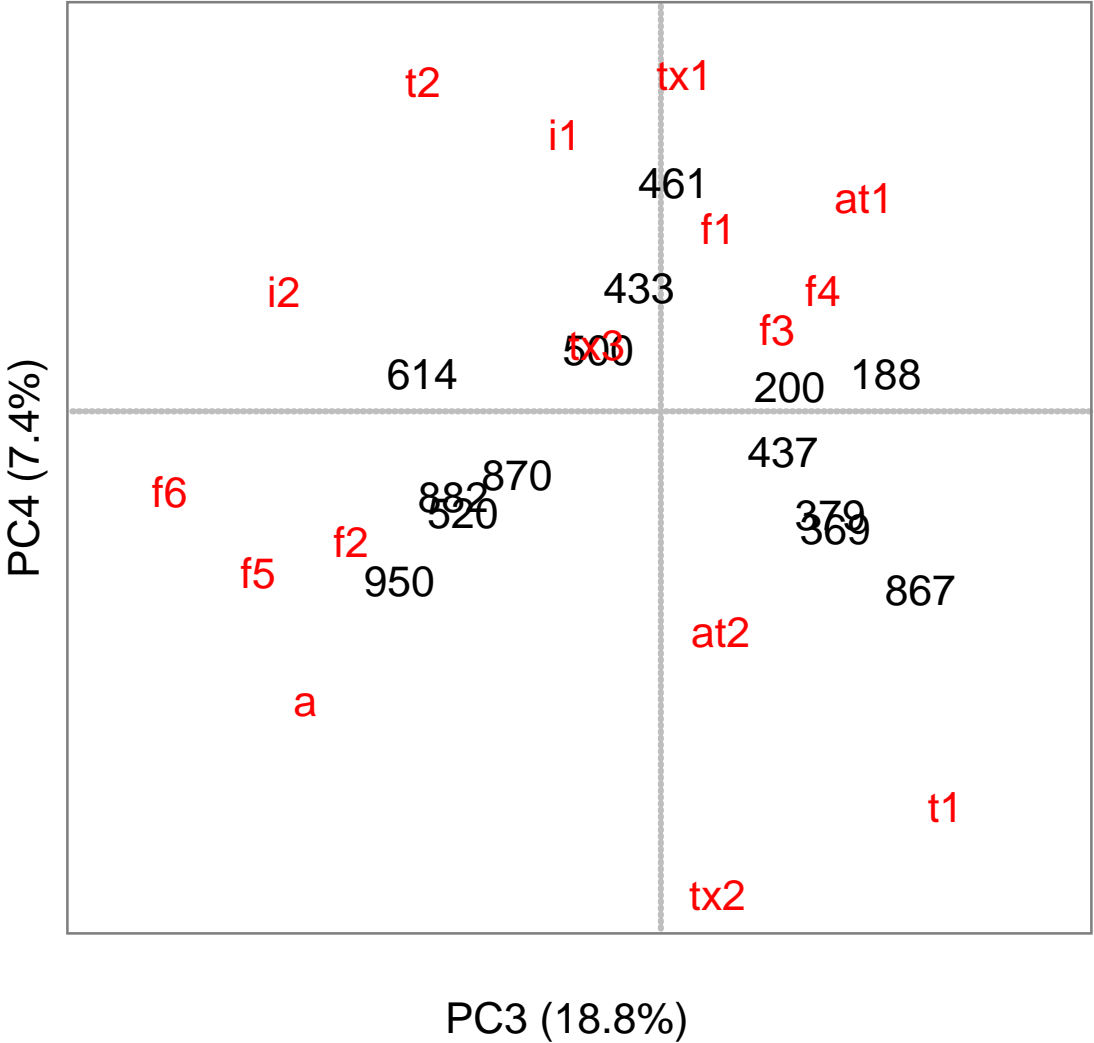
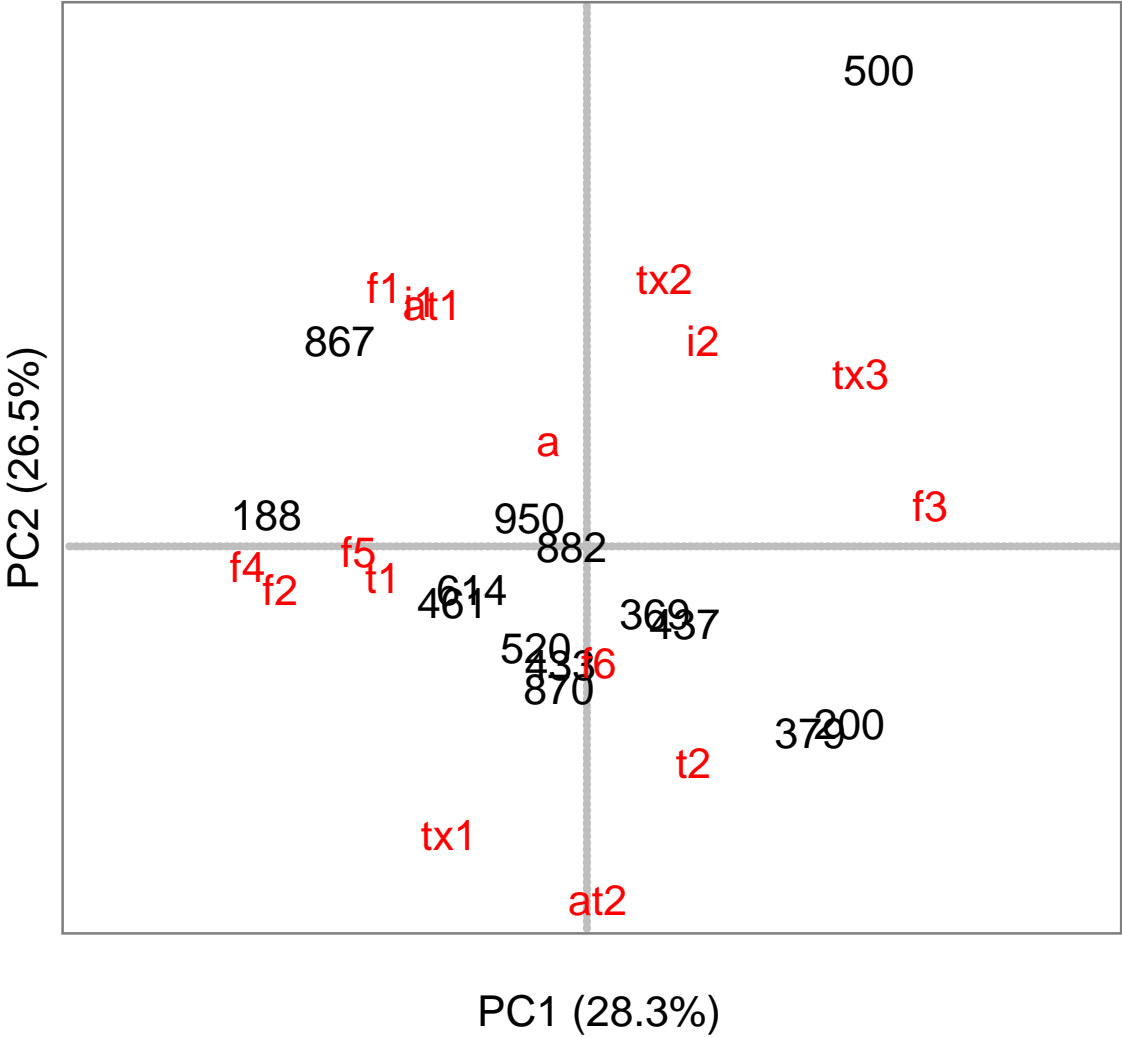
- Select consumers from the target user population
- Get good descriptive sensory data and analyze it well
- Get the experimental design from a good algorithm
- Do clustering and imputation properly
- Beware the R defaults, run many times with random starts

** quote from Warren Buffet*

The Workshop Data Set

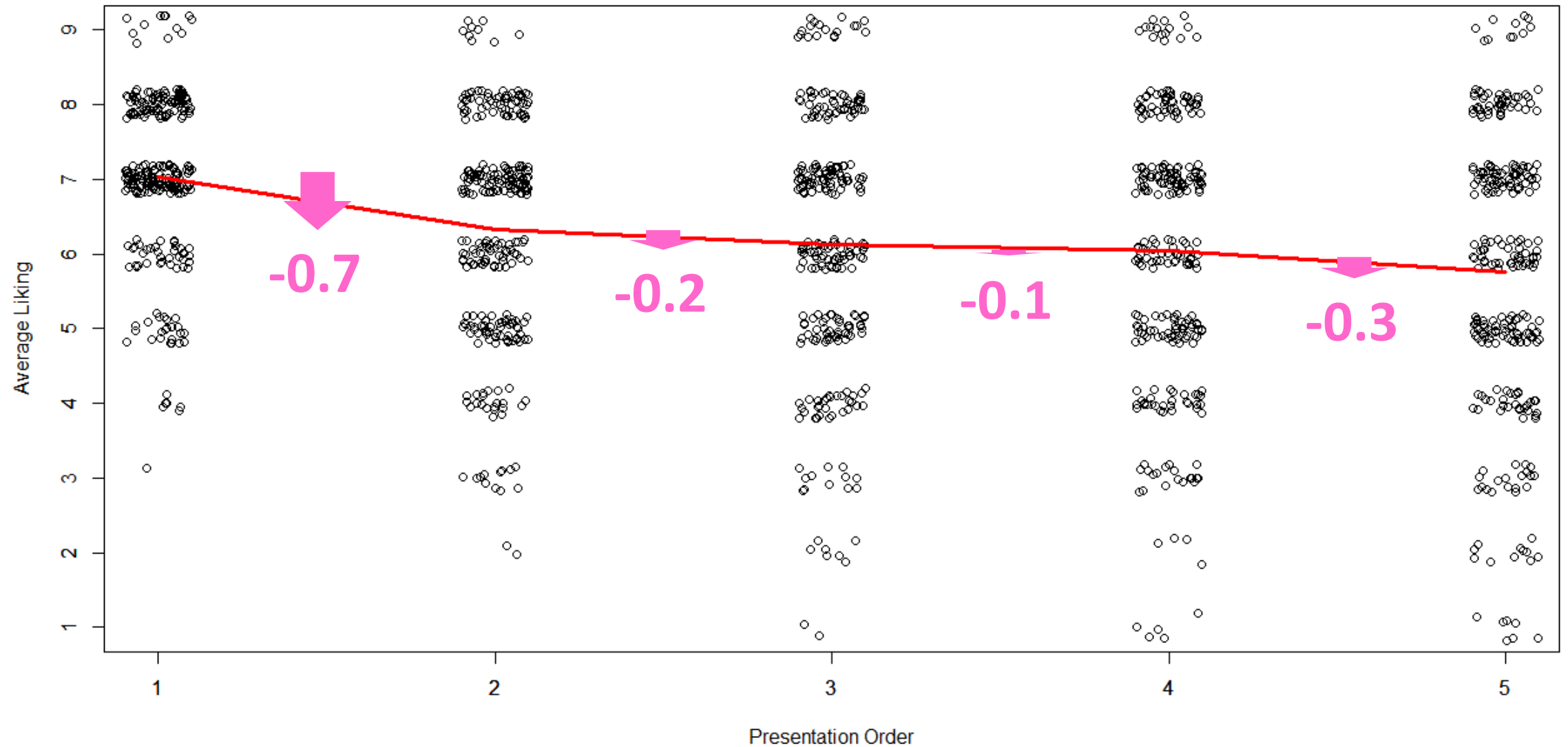
Spatial Sensory Segmentation

Sensory space



Order effects

Day 1 Results



Some ideas

Preference vs. Liking clusters

Compensation for order effects

High-contrast subsets vs. All subsets

Complete results vs. Day 1 (<1/3 of data)

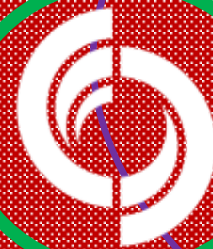


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