#### 13TH PANGBORN SENSORY SCIENCE SYMPOSIUM

#### **PANGBORN 2019**



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# A Three-Step Approach to Characterizing Consumer Segmentation via Machine Learning



William J. Russ
The Institute for Perception



John M. Ennis\*



<sup>\*</sup>Research conducted at The Institute for Perception

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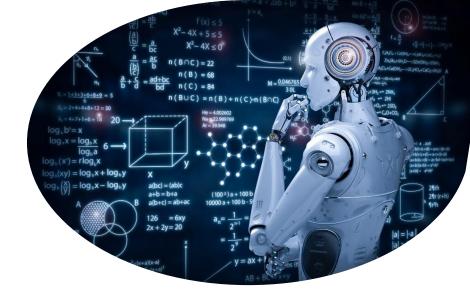


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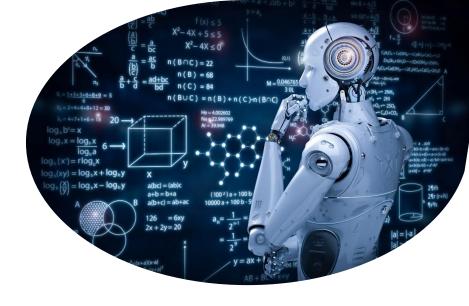
- Background
- Scenario
- Three Step Approach
  - •Step 1: Unfolding
  - Step 2: Segmentation
  - Step 3: Segment Characterization
    - Standard Approaches
    - Machine Learning Approach
- Conclusions







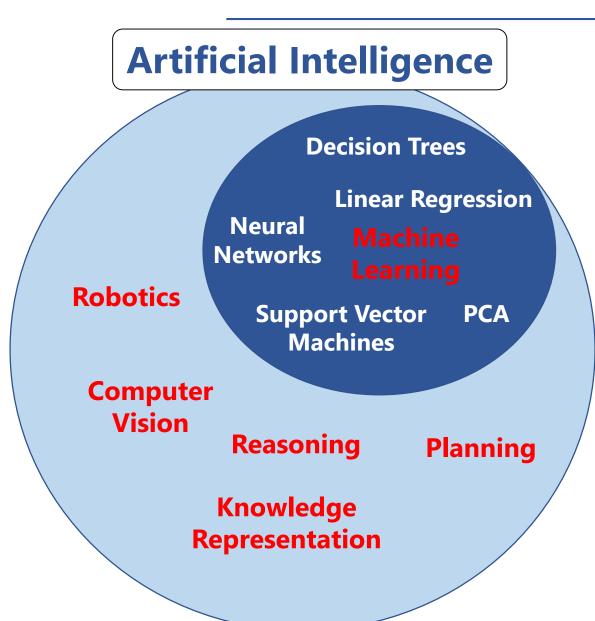
## A Three-Step Approach to Characterizing Consumer Segmentation via Machine Learning



## Background



## **Artificial Intelligence (AI) and Machine Learning?**



 Goal of AI is to either model human intelligence or create rational agents

 Machine Learning focuses on improving task performance with additional data

Machine Learning is a subfield of Al

## **Applications of Al**

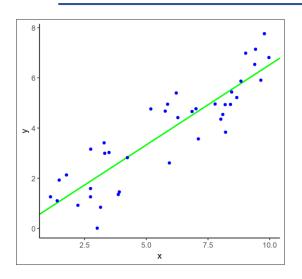


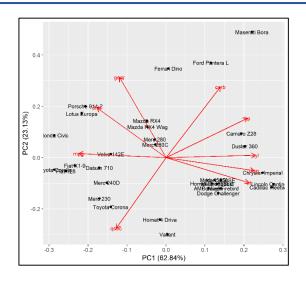
 Similar to introduction of applications of electricity

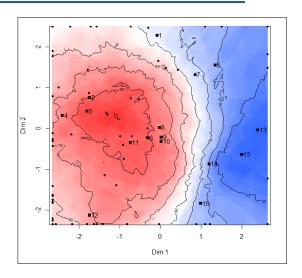
Current techniques and approaches will evolve

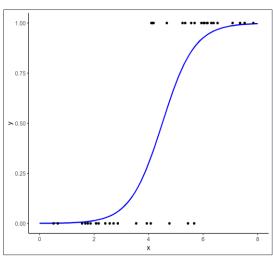
New techniques and opportunities will arise

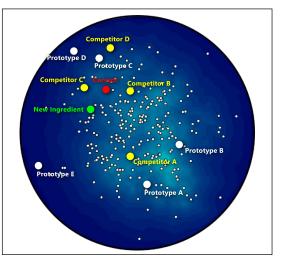
## **Standard Machine Learning Techniques**











Linear and Logistic Regression

**Dimensionality Reduction** 

Mapping and Unfolding

## **Machine Learning Advances**



Computational Power



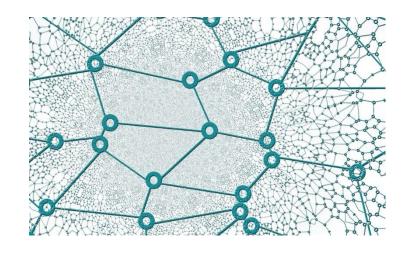
Algorithmic Improvements



**Crossover from Other Fields** 

## **Applications of Machine Learning**







Large Quantities of Data

**Combinations** (Combinatorial Explosion)

Regression and Classification

**But data quality is still paramount!** 





## A Three-Step Approach to Characterizing Consumer Segmentation via Machine Learning



## Scenario





# Scenario (Inspired from a Client Project)



- Brand of boutique barbecue sauces
  - Need well-positioned portfolio of sauces for the US national market

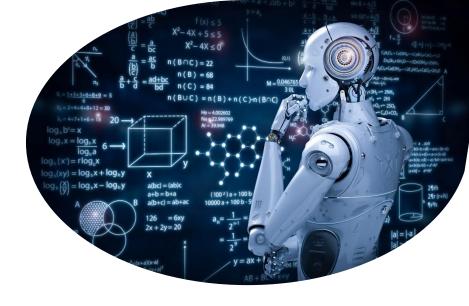


- Nationwide category appraisal
  - 8 test products evaluated over two days
    - 5 own (current brand, 4 prototypes) B<sub>1</sub> B<sub>2</sub> B<sub>3</sub> B<sub>4</sub> B<sub>5</sub>
    - 3 competitors C<sub>1</sub> C<sub>2</sub> C<sub>3</sub>
  - N=423 category users
- Question:
  - To whom should we market which product?





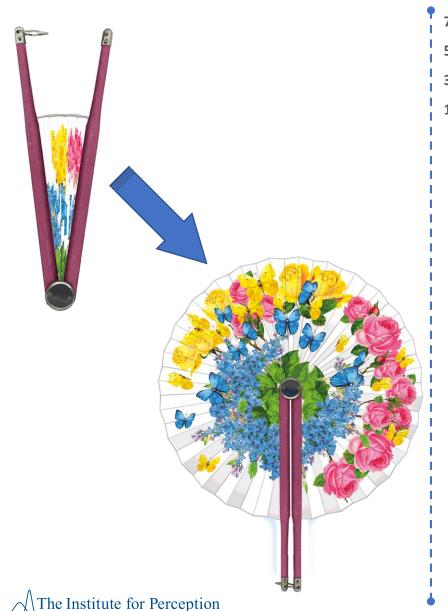
## A Three-Step Approach to Characterizing Consumer Segmentation via Machine Learning

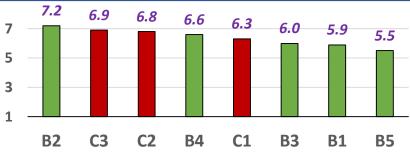


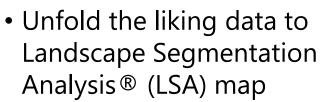
## **Three Step Approach**



## **Step 1: Unfolding**



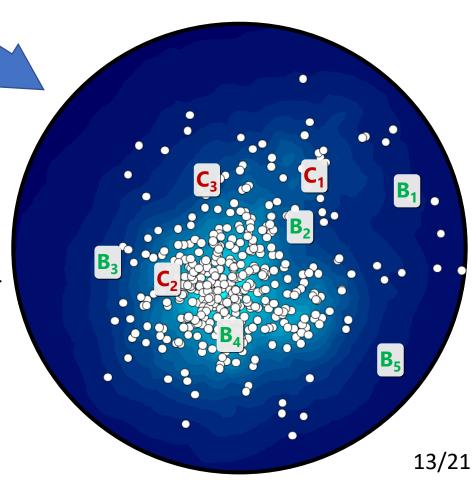




 Respondents with similar liking patterns have similar ideal locations

• Use ideals to conduct consumer segmentation

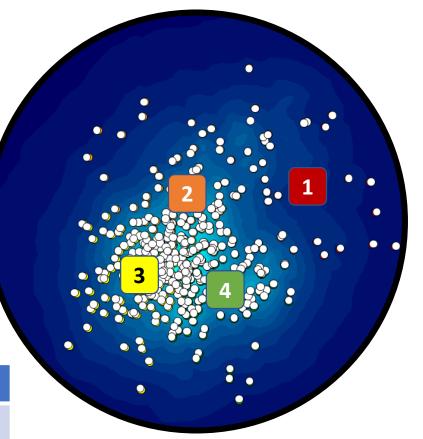


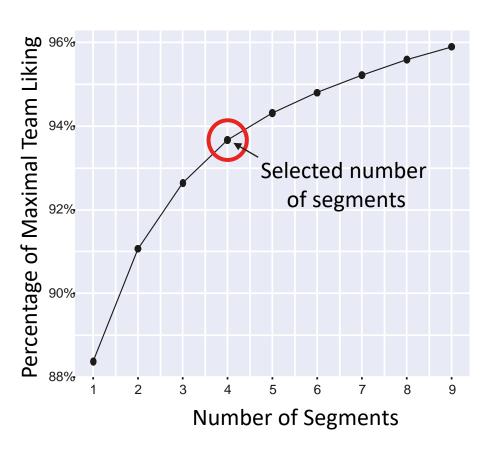


## **Step 2: Identify Consumer Segments**

- Cluster individuals into segments with similar liking patterns using portfolio optimization
- To decide how many segments, use a scree plot
- Diminishing returns appear at four segments

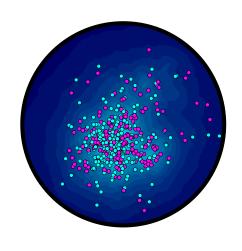
Segment		Counts	Percentages		
	1		75	18%	
	2		94	22%	
	3		162	38%	
	4		92	22%	





Note: Machine learning tools generally perform best when there are roughly equal numbers of subjects in each cluster

## **Step 3: Characterizing the Segments**



**Standard Approaches?** 

or

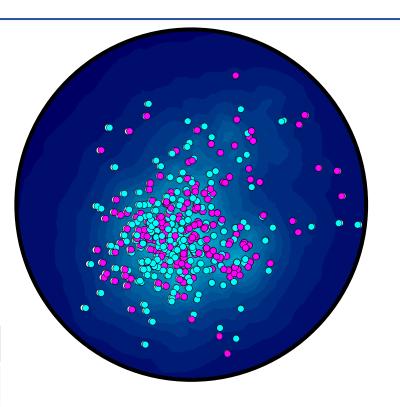
START HERE (ROOT)

**Machine Learning Approach?** 

## **Standard Approaches**

- Consider various pre-defined consumer groups
- E.g. color-coded by gender
- Means not significantly different

Segment	Men	Women	
1	57%	43%	
2	38%	62%	
3	63%	37%	
4	63%	37%	

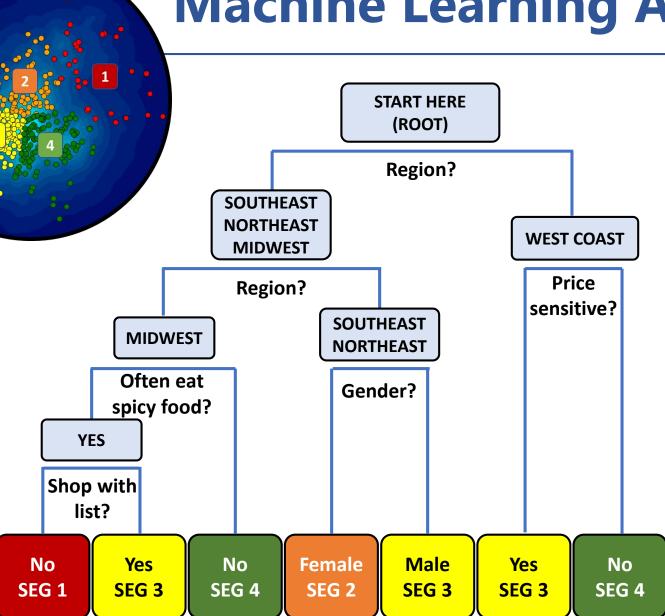


Examine hedonic clusters one consumer variable at a time



Segment	Southeast	Midwest	Northeast	West Coast
1	28%	44%	20%	8%
2	34.%	13%	37%	16%
3	21%	24%	23%	33%
4	23%	30%	24%	23%

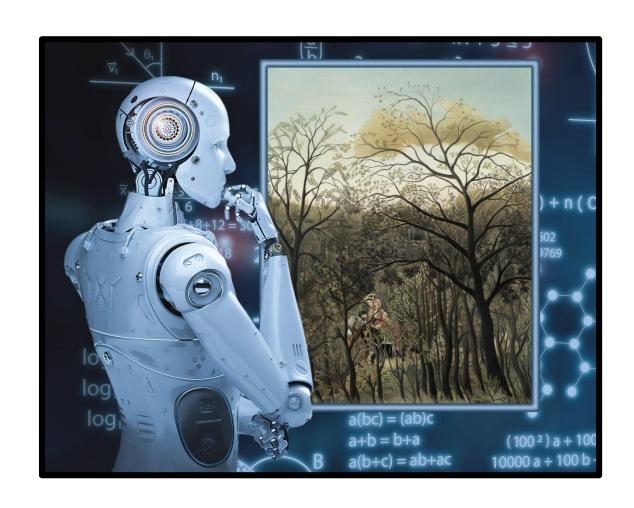
# Machine Learning Approach



- Using demographic, behavioral, and psychographic variables, we classify the segments via decision trees
- Can compare hundreds of variables and their interactions automatically
- Obtain combinations to describe segments
- May have multiple descriptions for one segment

#### **Conclusions**

- Machine learning provides new tools and improves existing techniques for consumer insights
- It is now possible to find multiple characterizations for consumer segments in terms of psychographic, demographic, and behavioral data
- These characterizations can be used to guide marketing, product development, and future research



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## Thank you very much for your attention

## References (1/2)

- 1. D.M. Ennis, J.M.Ennis, and B. Rousseau (2018). Tools and Applications of Sensory and Consumer Science. Richmond, VA: The Institute for Perception.
- 2. Ennis, D. M. and Ennis, J. M. Mapping hedonic data: A process perspective. *Journal of Sensory Studies*, **28**, 324-334.
- 3. Ennis, J. M., Ennis, D. M., and Fayle, C. M. (2010). Optimum Product Selection for a Drivers of Liking<sup>®</sup> Project. *IFPress*, **13**(1) 2-3.
- 4. Ennis, J. M., & Fayle, C. M. (2010). Portfolio optimization based on first choice. IFPress, 13(2), 2–3.
- 5. Ennis, J. M., Fayle, C. M., and Ennis, D. M. (2012). eTURF: A competitive TURF algorithm for large datasets. *Food Quality and Preference*, **23**(1), 44-48.
- 6. Ennis, J. M. and Russ, W. J. (2016). eTURF 2.0: From Astronomical Numbers of Portfolios to a Single Optimum. IFPress, **19**(2) 3-4.
- 7. James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112). New York: springer.

## References (2/2)

- 8. Friedman, J., Hastie, T., & Tibshirani, R. (2001). *The elements of statistical learning* (Vol. 1, pp. 337-387). New York: Springer series in statistics.
- 9. Géron, A. (2017). Hands-on machine learning with Scikit-Learn and TensorFlow: concepts, tools, and techniques to build intelligent systems. "O'Reilly Media, Inc.".
- 10. Nestrud, M. A., Ennis, J. M., Fayle, C. M., Ennis, D. M., and Lawless, H. T. (2011). Validating a graph theoretic screening approach to food item combinations. *Journal of Sensory Studies*, **26**(5), 331-338.
- 11. Nestrud, M. A., Ennis, J. M., and Lawless, H. T. (2012). A group level validation of the supercombinatorality property: Finding high-quality ingredient combinations using pairwise information. *Food Quality and Preference*, **25**(1), 23-28.
- 12. Patterson, J., & Gibson, A. (2017). Deep learning: A practitioner's approach. "O'Reilly Media, Inc.".
- 13. Rousseau, B., Ennis, D. M., and Rossi, F. (2012). Internal preference mapping and the issue of satiety. *Food Quality and Preference*, **24**(1), 67-74.
- 14. Worch, T. and Ennis, J. M. (2013). Investigating the single ideal assumption using Ideal Profile Method. *Food Quality and Preference*, **29**(1), 40-47.