Pangborn Sensory Science Symposium
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Workshop 4 - Combinatorial Tools in Sensory Science and Consumer Research

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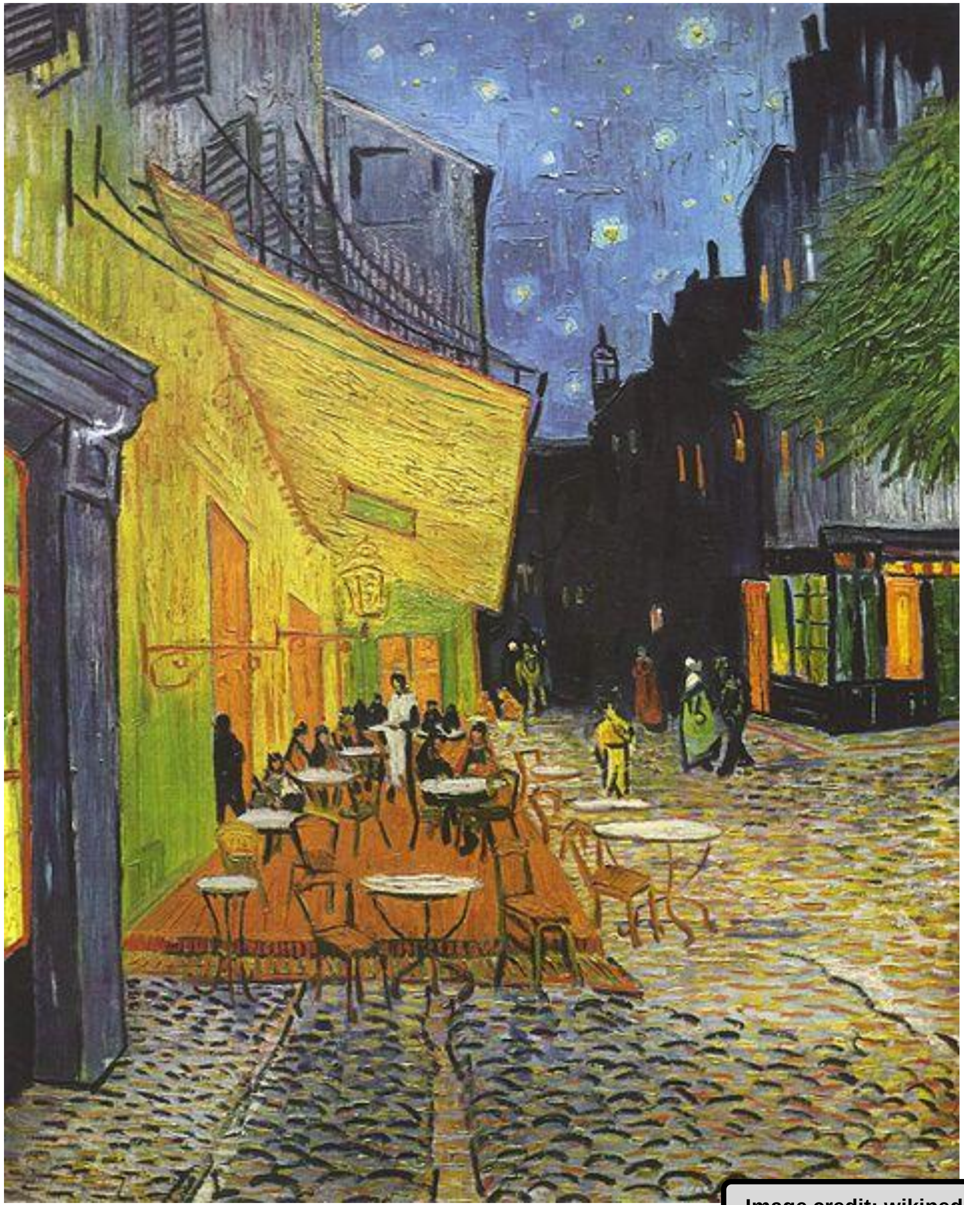

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"By this simple combination [of orange, chrome, yellow and blue] I obtain a mysterious effect, like a star in the depths of an azure sky."

- Vincent Van Gogh

Optimal Combinations

- Many practical problems involve optimizing combinations

  - Ingredient combinations
    - Pizzas 
    - Juices 
    - Salads 

  - Flavor combinations
    - Potato chips 
    - Sauces 
    - Candy bars 

  - Component or feature combinations
    - Boxed lunches 
    - Meals ready to eat 
    - Automobiles 
    - Political candidates 
    - …

Combinatorial Tools

- A **combinatorial tool** is any tool that studies combinations
- Many combinatorial tools exist:
  - Conjoint analysis (Luce & Tukey, 1964; Green & Rao, 1971)
  - Total Unduplicated Reach and Frequency (Miaoulis et al., 1990)
  - Graph Theoretic Analysis (Ennis et al., 2009, Nestrud et al., 2011)
- Workshop goals:
  - Overview combinatorial tools
  - Demonstrate use of tools through examples
  - Guide choice of tools for specific challenges

Talks 1 & 2

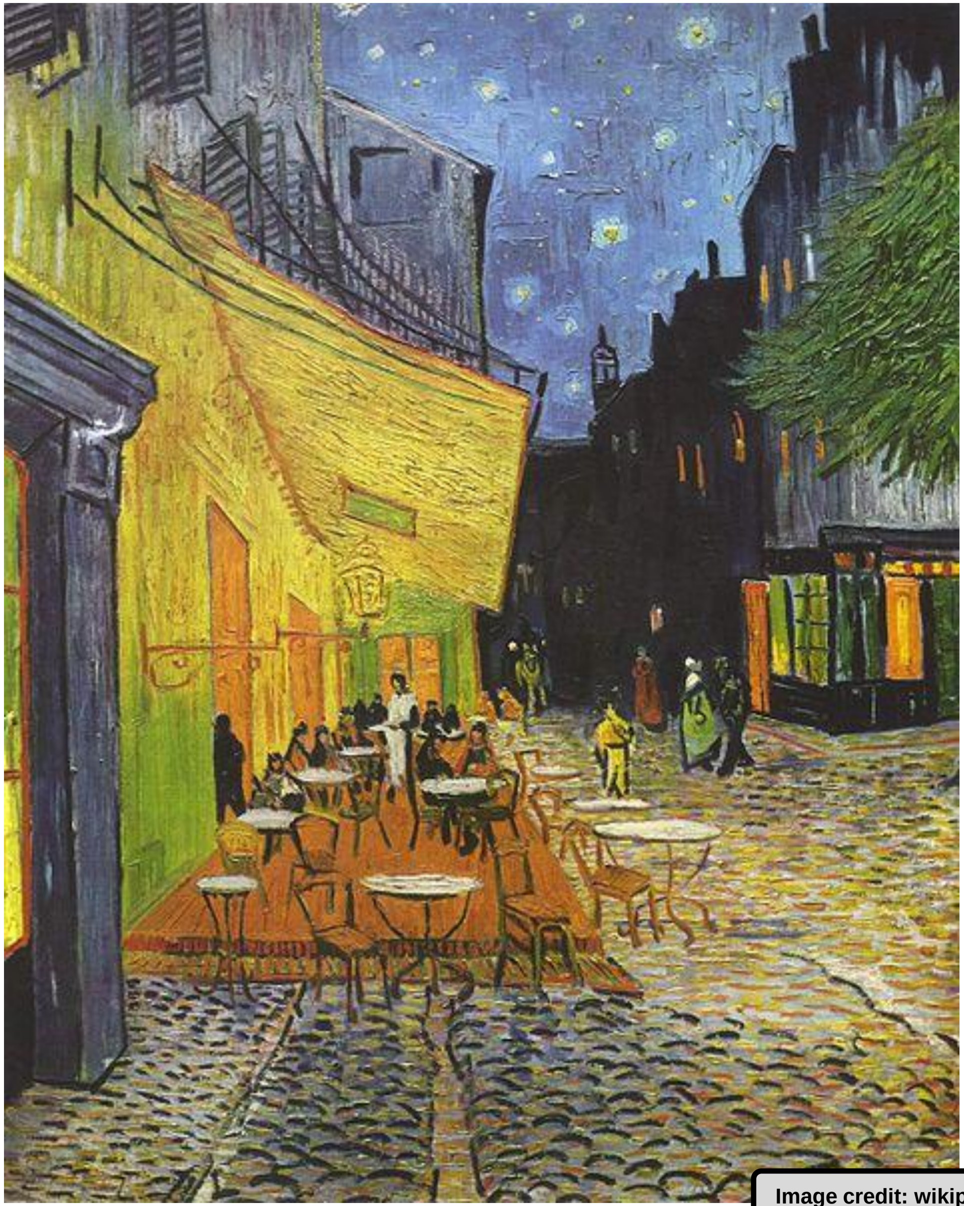
- **Talk 1: Using Conjoint Analysis to Understand the Senior Dining Experience**
  - *Chris R. Loss, The Culinary Institute of America, New York, NY, USA*
  - *Howard R. Moskowitz, Moskowitz Jacobs Incorporated, New York, NY, USA*

- **Talk 2: Total Unduplicated Reach and Frequency (TURF): History, Strengths, Weaknesses and Improvements**
  - *Frank Rossi, Kraft Foods, Glenview, IL, USA*

Talks 3 & 4

- **Talk 3: Validating a Graph Theoretic Approach at the Individual and Group Levels**
  - *Michael A. Nestrud, U.S. Army R., D. & E. Laboratories, Natick, MA, USA*
  - *John M. Ennis, The Institute for Perception, Richmond, VA, USA*
  - *Charles M. Fayle, The Institute for Perception, Richmond, VA, USA*
  - *Daniel M. Ennis, The Institute for Perception, Richmond, VA, USA*
  - *Harry T. Lawless, Cornell University, Ithaca, NY, USA*

- **Talk 4: Selecting the Best Combinatorial Tools for your Specific Challenges**
  - *John M. Ennis, The Institute for Perception, Richmond, VA, USA*
  - *Daniel M. Ennis, The Institute for Perception, Richmond, VA, USA*
  - *Charles M. Fayle, The Institute for Perception, Richmond, VA, USA*



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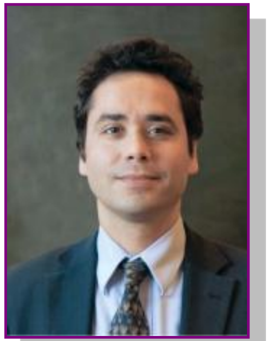
Chris R. Loss



Director of the Department of Menu Research & Development at The Culinary Institute of America

- Ph.D. in Food Science from Cornell University
- Culinary Arts degree from The Culinary Institute of America
- Responsible for fostering research amongst culinary faculty, and developing new curricula in the culinary arts and sciences
- Research focuses:
  - Consumer behavior in the food service environment
  - Evaluation of seasoning strategies to achieve lower sodium levels
- Serves on the Board of Directors for the Research Chefs Association
- 2008 winner of Research Chefs Association “Pioneer Award”

Using a conjoint study to understand senior dining: identifying consumer segmentation and factors that drive interest

Workshop 4: Combinatorial Tools in Sensory Science

and Consumer Research

9th Pangborn Sensory Science Symposium

Toronto Canada

September 7, 2011

THE CULINARY INSTITUTE OF AMERICA

Chris Loss, Ph.D., Dept. Menu Research and Development
The Culinary Institute of America
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Outline

- Growth and ageing of the senior consumer

- Approach and design of conjoint studies

- Senior dining conjoint study

  > Objective

  > Design and analysis

  > Results

  - impact factors and segmentation
  - consumer typing tool

  > Conclusions

Growth and ageing of the senior consumer segment

- Demography: Consumers of 65 years or older will increase by 40% within 5 years and triple by 2050 (US Census, 2009)

Besse Cooper, 115 years, Georgia USA

http://www.huffingtonpost.com/2011/08/26/worlds-oldest-person-mark_n_938490.html

- Biology: As … Frongillo, 1992); dec … paired ability to identify … bility.

- Psycholog … on overall quality of li … 99; Costa, 2010); eati …

- Paucity of science-based studies and, in turn, need for systematized development of product offerings for seniors

What Conjoint Analysis Offers

- Range of stimuli: Computer generates systematically varied combinations of elements (independent variables) describing features, benefits, pictures, etc.

- Mixtures: Combinations presented to consumers and ratings (dependent variable) obtained

- Rigorous deconstruction: Data analyzed by regression to estimate part worth contribution of each element and create a utility score showing how each element drives ‘interest’ (yes in a yes/no decision)

- Further analysis using persuasion model (clustering) allows for segmentation based on population with differing utility scores

Approach and Design of Conjoint Study

- Ratings: Collected on 1-9 scale but converted to binary (no/yes)
  - 1-6 → 0; 7-9 →100
- Ordinary least squares regression (OLS): Reveals 'driving power' of element to 'yes' (rating of 7-9)… ***easy for management to use***
- Interest model: Shows percent of respondents who find a particular element interesting/important – the impact value, i.e., would change rating to 7-9 if element present
- Individual-level model: Data at individual level, allows building from bottom up

Segmentation by Clustering

- Granular: Revisit individual data, use 1-9 rating as dependent variable, run OLS regression
- Individual Profile: Each person generates vector of coefficients
- Cluster: Divide respondents based upon similar patterns of coefficients (from their individual-level models)
- Rationale – More granularity about information allowing consumer segmentation

Senior Dining Conjoint Study Objective

- Use conjoint analysis to provide more granular information about the senior dinning experience

  - Learn: what drives their interests

  - Discover: senior consumer segments

  - Apply: Create mind-typing tools to better understand individual-level needs of specific customers

Raw Material: Categories and Elements

- Focus groups at senior living facilities across the U.S. presented common themes/categories pertaining to the senior dining experience (Schutz and Loss, in progress)

<u>Categories</u>

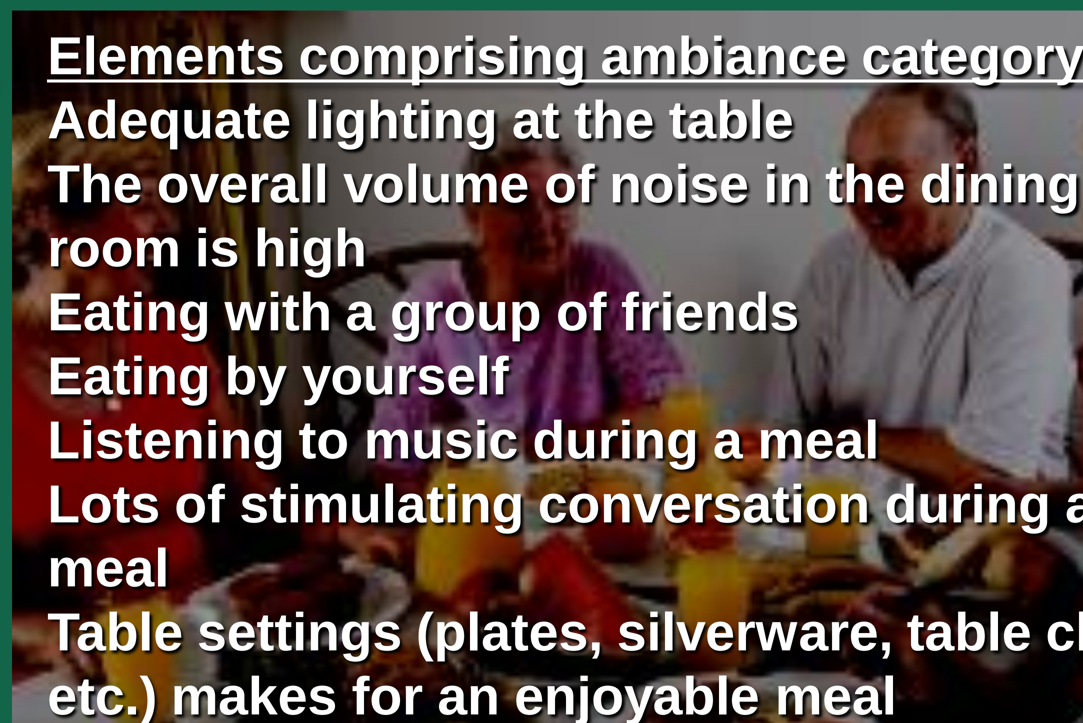
Ambiance

Service

Nutritional information

Specific food items

Sensory rewards



<u>Elements comprising ambiance category</u>

Adequate lighting at the table

The overall volume of noise in the dining room is high

Eating with a group of friends

Eating by yourself

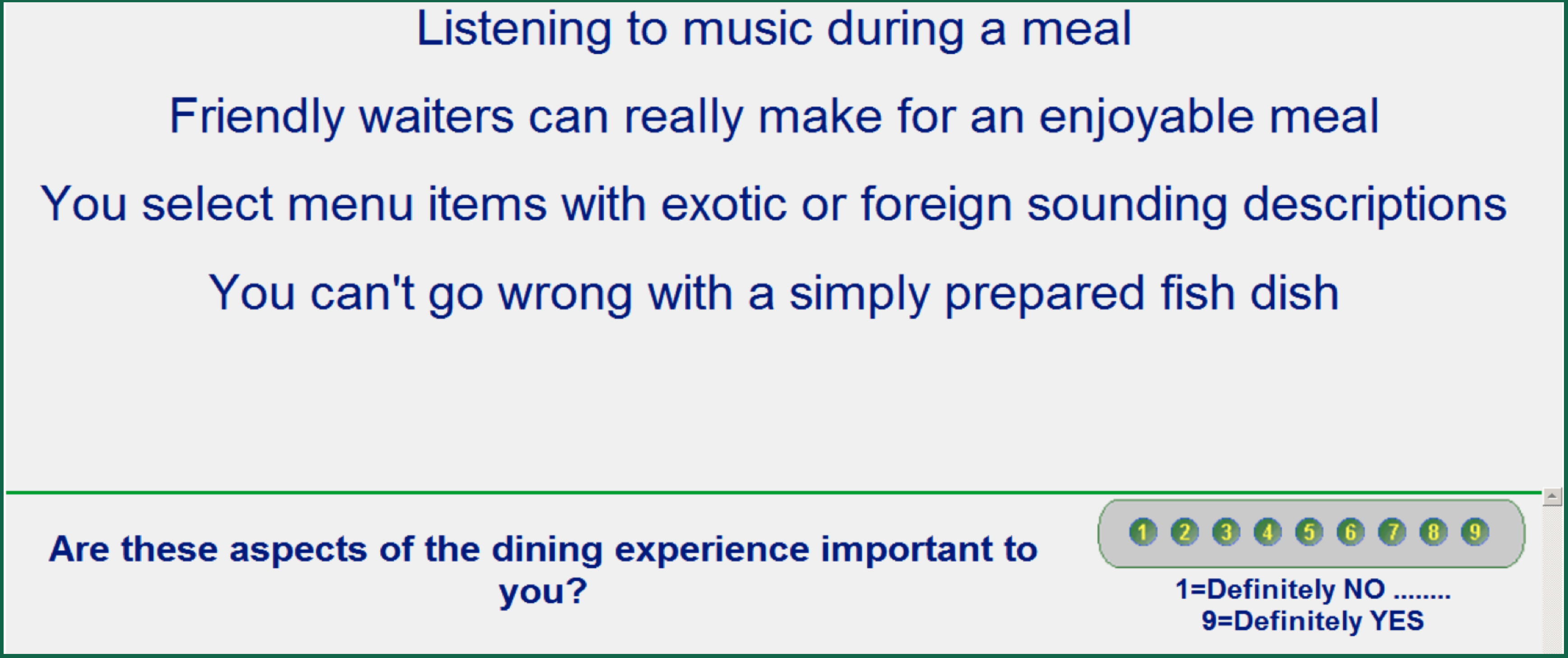
Listening to music during a meal

Lots of stimulating conversation during a meal

Table settings (plates, silverware, table cloth etc.) makes for an enjoyable meal

Online Survey for Data Collection

- 108 seniors >65yrs; 56 male/52 Female
- Email invitation included brief description of project and link to survey
- Respondent read and rated vignettes, comprising different elements.
- Vignette rated as a single ‘ad’



OLS Regression → Interest (Binary) Model

- Deconstructs the power of the 35 elements to drive the binary response, not important or important

- This transformation enables us to talk about the percent of respondents who find a particular element important…defined as '***would change rating of vignette from a low of 1-6 to a high of 7-9***'

- Minimizes concern regarding 'what does a 3 or a 5 or an 8 *MEAN*?'

- The experimental design makes all the elements statistically independent, therefore OLS generates impact values without regard to the category from which the element came.

Interest Model deconstructs mind – can't game the data
Not many positives
But many negatives …with different themes

Element	Impact value
Food is served hot out of the oven every time	7
Waiters let you substitute items	4
Clear and simple wording on the menu makes it easy to decide what you will order	4
You can't go wrong with a simply prepared fish dish	-10
Foods with soft textures are your preference	-11
You enjoy vegetables that are thoroughly cooked	-12
If it contains chicken you will like it	-12
You select menu items with exotic or foreign sounding descriptions	-12
Red meat is your choice every time	-13
You enjoy hot and spicy flavors	-14
Eating by yourself	-15
The overall volume of noise in the dining room is high	-21

Results From the Interest Model

- The additive constant is 64
    - > respondents are interested in description of the dining situation
    - > 64% would rate it 7-9 in the absence of elements

- Strongest elements reassure problems will not occur (e.g.: food is served hot out of the oven every time)

- Elements that describe food or refer to negative dining experiences generate a negative impact

Segmenting the Respondents

- Data already in place: Matrix for each person's vignette ratings (9-point rating)
- Rework the data: Recreate a model for each respondent relating the 9-point rating to the presence/absence of elements
- Estimate coefficients and additive constant: This is the Persuasion Model which is more granular because it uses the 9-point rating
- Cluster respondents: Using pattern of their coefficients … off-the-shelf-software
- Seg 1 – Meal as a social occasion, Seg 2 – Meal as a task

Segment 1: Meal as a Social Occasion

	Seg1	Seg 2
Base size	**45**	**63**
Additive constant (likelihood to rate 7-9 in absence of elements)	**54**	**72**
Segment 1 – Meal as an occasion		
Lots of stimulating conversation during a meal	**8**	**-2**
Waiters remember the type of food or drink you like	**7**	**-1**
Food is served hot out of the oven every time	**6**	**7**
Red meat is your choice every time	**6**	**-27**
The overall volume of noise in the dining room is high	***-11***	***-28***
You prefer food that is under salted	***-11***	***-3***
If it contains chicken you will like it	***-11***	***-13***
You love fresh uncooked vegetables (salads for example) at every meal	***-13***	***-3***
Listing the amount of fat in menu items helps you decide what to order	***-13***	***-3***
Total calories for each item listed on the menu to help you make your selections	***-14***	***-1***
You enjoy hot and spicy flavors	***-15***	***-14***
Eating by yourself	***-21***	***-11***

Segment 2: Meal as a Task

Segment 2 – Meal as a task	**Seg 1**	**Seg 2**
Clear and simple wording on the menu makes it easy to decide what you will order	**0**	**8**
Food is served hot out of the oven every time	**6**	**7**
You prefer food that is served warm	***0***	***-9***
You can't go wrong with a simply prepared fish dish	***-9***	***-10***
Eating by yourself	***-21***	***-11***
Foods with soft textures are your preference	***-9***	***-12***
If it contains chicken you will like it	***-11***	***-13***
Family style service with bowls of food to pass around the table	***1***	***-13***
You enjoy hot and spicy flavors	***-15***	***-14***
You select menu items with exotic or foreign sounding descriptions	***-9***	***-15***
You like large portions of food	***4***	***-18***
You enjoy vegetables that are thoroughly cooked	***-2***	***-19***
Red meat is your choice every time	***6***	***-27***
The overall volume of noise in the dining room is high	***-11***	***-28***

The Two Segments

- Segment 1:

  - 45 of the 108, find messages important when topic is *meal as an occasion* (convivial companions).

  - We can reach these people by talking about senior dining just as one might talk about a meal with friends.

- Segment 2:

  - 63 of 108, look at *meal as a task*
    (drudgery diners)

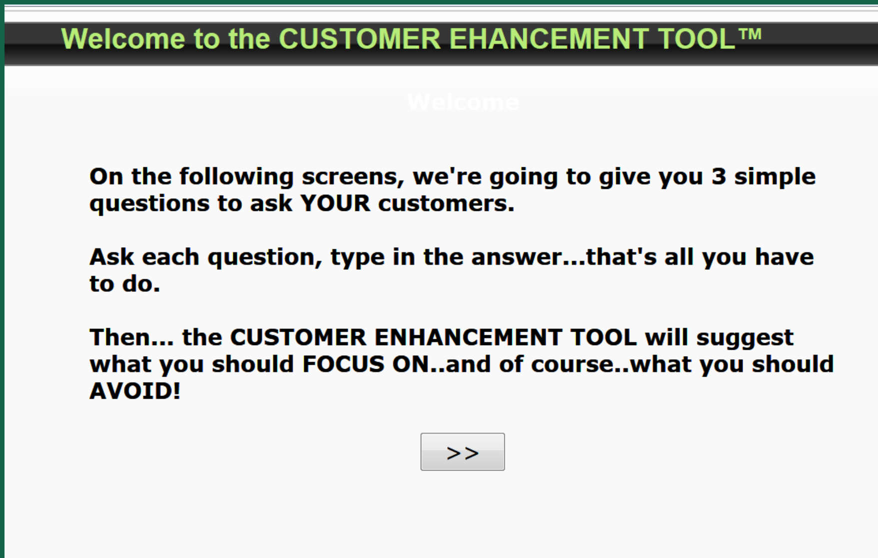
  - Just want hot food and an easier time.

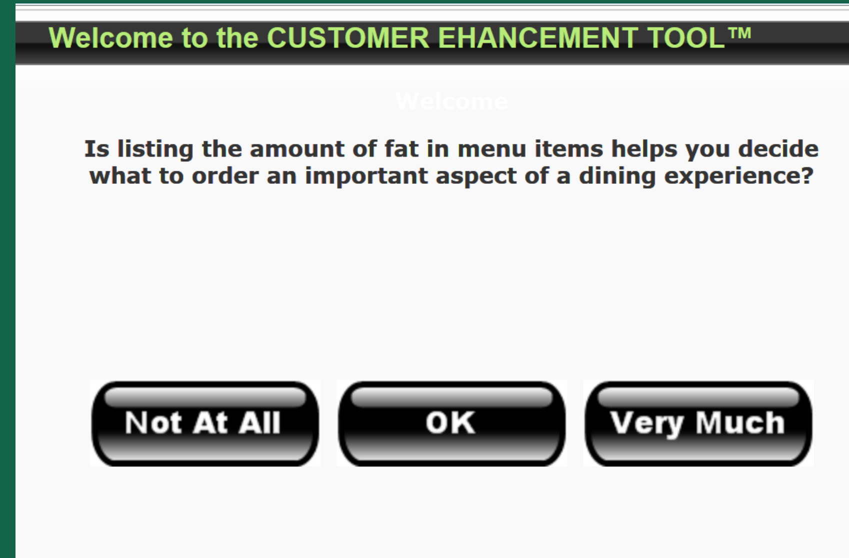
  - Nothing more elaborate than that

NEW: From Knowledge to Application

- How do we ensure a better dining experience?
- Identify the segment to which a senior belongs using discriminant function analysis
- And then craft the correct experience
- Create short, 3-4 question survey, easy to do, 3-rating points

Typing Tool





	Classification Functions		How five hypothetical people might				
	Segment 1 Meal as an occasion	Segment 2 Meal as a task	Per1	Per2	Per3	Per4	Per5
Additive constant	-5.855	-5.963					
Waiters remember the type of food or drink you like	1.556	0.572	1	3	1	2	1
Food is served hot out of the oven every time	1.283	2.083	2	2	2	3	1
Clear and simple wording on the menu	1.562	0.849	3	2	3	1	1
Value of the classification function for each segment, and segment assignment based on the classification function showing the higher positive value		**Seg1: Meal as an occasion**	**5.5**	**8.4**	**4.2**	4	1.1
		Seg2: Meal as a task	**5.5**	7.8	3.4	**4.3**	**1.7**

Conclusions

- Dining is an important part of a senior's daily life (additive constant = 64)
- Use clear and simple wording in menu item descriptions; allow substitutions for menu items; serve food fresh and hot
- Food attributes are not as important to seniors as the context -focus on experiential aspects of dining
- Clustering revealed 2 senior mind-sets:
  - convivial companions
  - drudgery diner
- "Typing Tool" can be used to help guide chefs/product developers and senior living facility managers who want to provide an optimal dining experience for their resident segments

Acknowledgments

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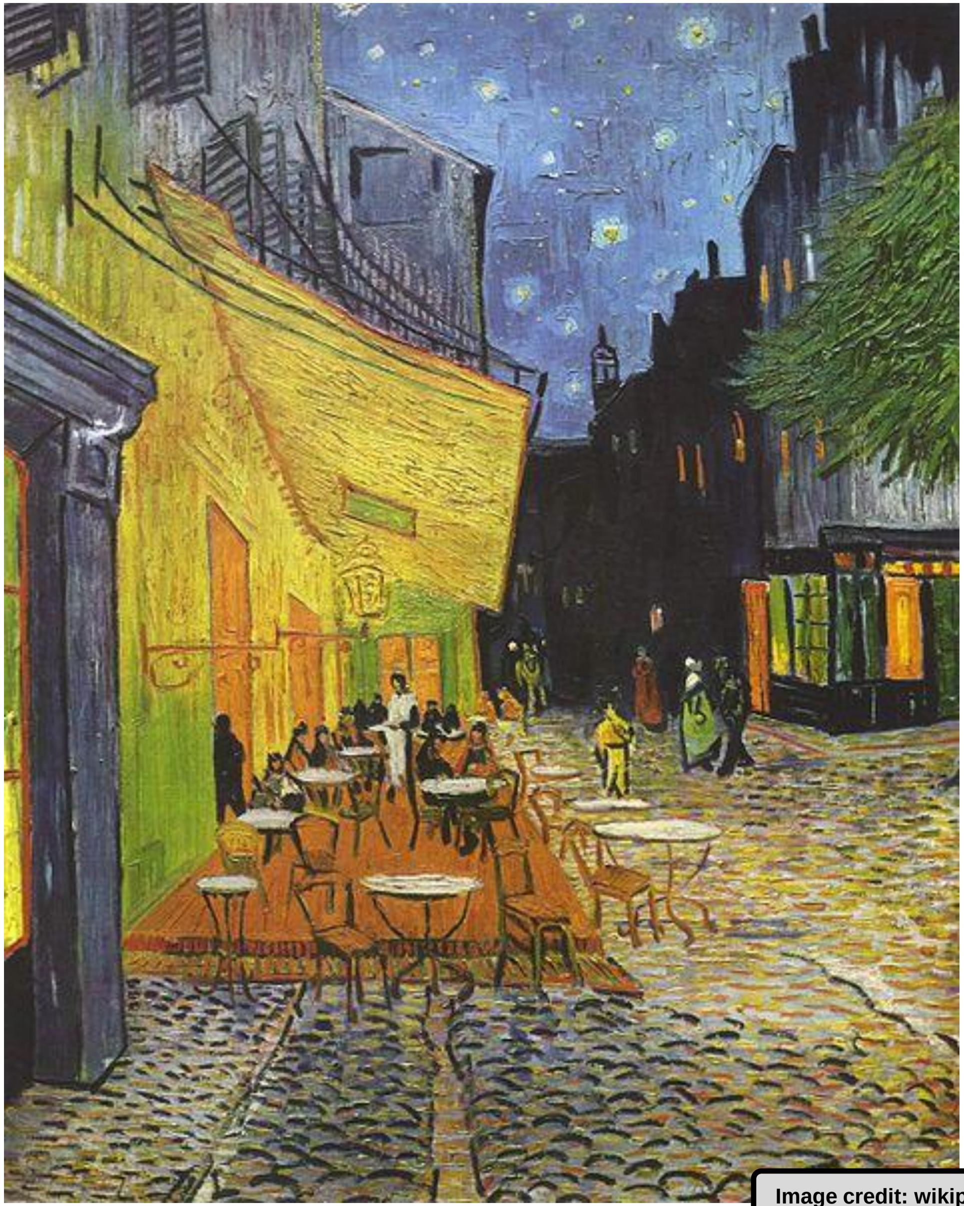
  For more information on MRFDI:

  http://menuscience.ciachef.edu/research

- Dr. Howard Schutz, UC. Davis

- Danny Moskowitz, Moskowitz Jacob Inc.

- Vi Living



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Frank Rossi

Associate Director, Global Statistics, for Kraft Foods in Glenview, Illinois

- Supports product development efforts within Kraft Foods
- Consults internally with the Operations, Quality and Marketing Research
- Published expert on the statistical aspects of product testing
- Held statistical consulting positions with General Foods Corporation and Campbell Soup Company
- B.S. in Mathematics and M.A. in Statistics from The Pennsylvania State University

Total Unduplicated Reach and Frequency (TURF): History, Strengths, Weaknesses and Improvements

Frank Rossi

Kraft Foods

What is TURF analysis?

- TURF is Total Unduplicated Reach and Frequency
- Based on the media concepts of "reach" and "frequency"
  - Media schedulers want to maximize the number of people reached and/or the frequency of exposure to a media campaign
  - Used to select the optimum set of media elements
- Finds combinations of a fixed number that reach as many respondents as possible
- Used in marketing to build or extend product lines
  - Reach refers to the proportion of consumers that would be interested in *at least one* offering
  - Frequency refers to how often consumers purchase each offering

Maximizing Reach

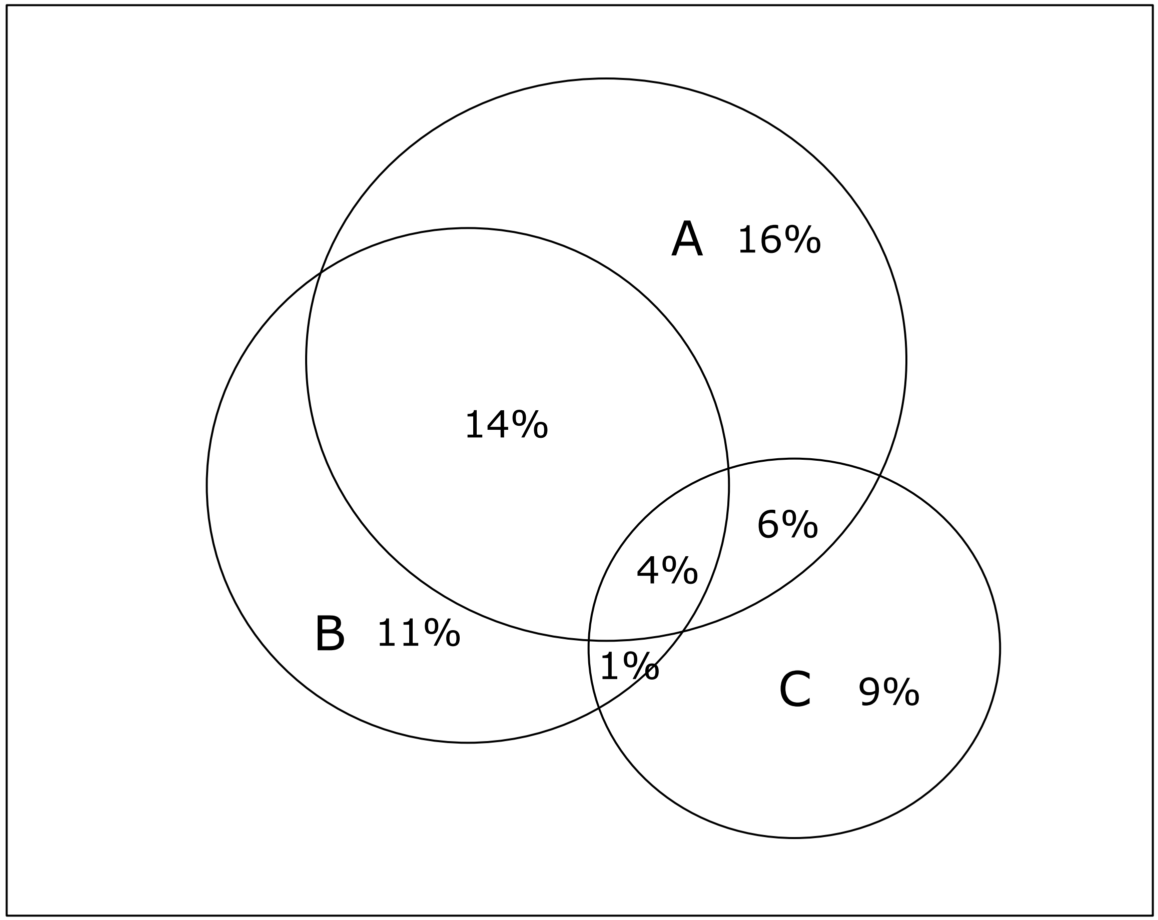
- Objective is to maximize penetration (proportion of consumers interested in at least one offering)
- Different measures can be used to achieve this
  - Purchase Intent
  - Overall Liking
  - Any measure of interest can be used
- Measures are converted to a binary response
  - Top box or top two box proportions for purchase intent
  - Proportion of respondents responding “like extremely” or “like very much” on the nine point hedonic scale
  - Any binary conversion of interest can be used

Understanding Reach

- Consider a simple case of three potential products, A, B and C with % top box rating percentages:
    - A = 40%, B = 30%, C = 20%
- Most important in quantifying reach is the intersection of these sets
    - What proportion of consumers have top box ratings for:
        - both A and B but not C (AB = 18%)
        - both A and C but not B (AC = 10%)
        - both B and C but not A (BC = 1%)
        - A, B and C (ABC = 4%)

Visualizing the Purchase Intent Space

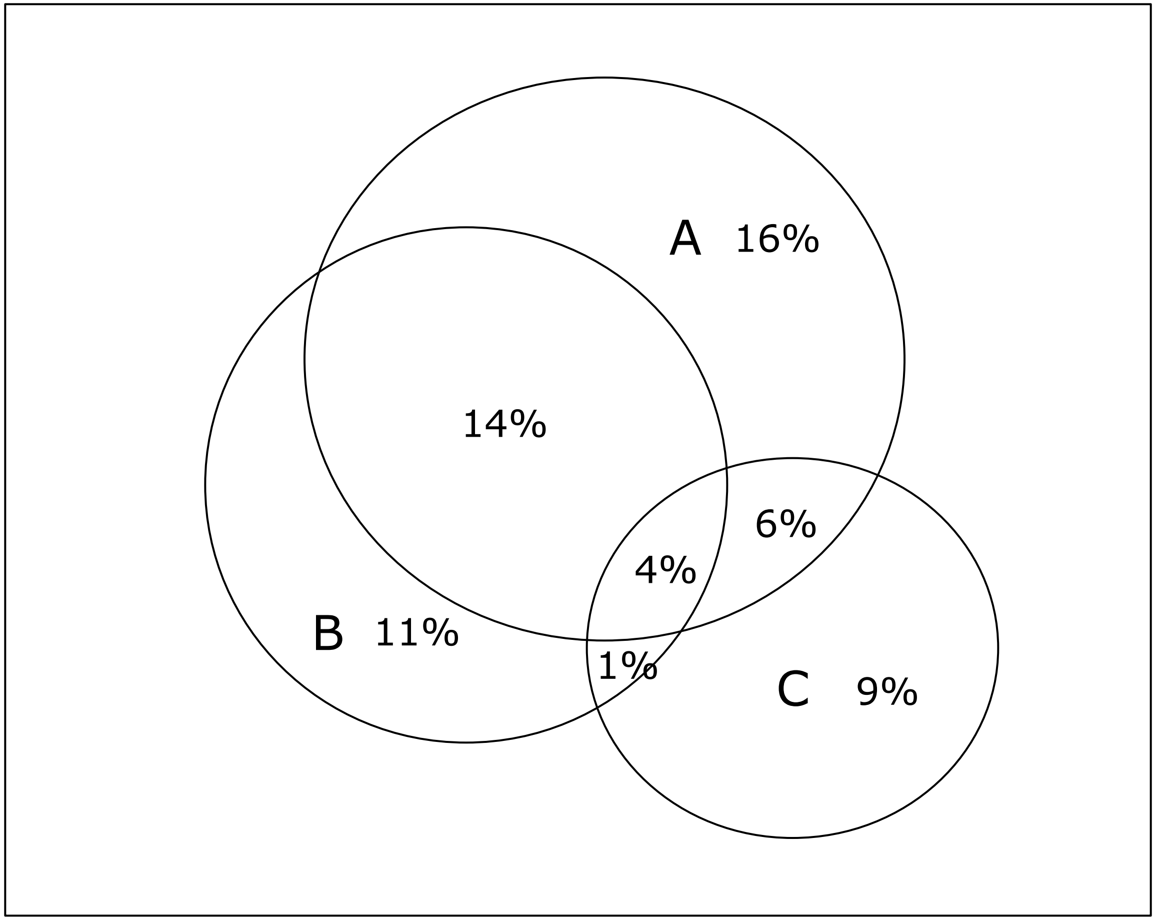
A = 40%
B = 30%
C = 20%
AB = 18%
AC = 10%
BC = 5%
ABC = 5%



A Reach = 16% + 14% + 6% + 4% = 40%

Calculating Unduplicated Reach

A = 40%
B = 30%
C = 20%
AB = 18%
AC = 10%
BC = 1%
ABC = 5%



AB Reach = + + + + + = 52%

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Understanding Frequency

- Can be estimated in a number of ways
  - Simple - calculate the total number of times products are desired in a given combination (no additional measure used)
  - More complex – use the average stated purchase frequency (additional measure) of purchase intenders for any given flavor as a multiplier

Flavor	Reach	Sample Size	Average Purchase Frequency	Purchase Occasions
A	40%	300	2.0	240
B	30%	300	4.0	360
C	20%	300	1.8	108

  - Frequency estimates for any portfolio combinations are calculated similarly as with reach

History of TURF as a Marketing Tool

- Proposed by Miaoulis, Free and Parsons in 1990 as an approach for identifying product portfolios
- Ennis added comparative statistical tests of resulting optimum product/concept sets and alternative sets (TURFSTAT, 1995)
- Applications expand to other areas – concepts, product features…
  - The number of elements can be much larger in these studies
- Krieger and Green expanded the methodology by proposing potential enhancements
  - Respondents assigned weights reflecting purchase frequency
  - Requirement that a minimum number of elements in a bundle be present for a respondent to be reached
  - Approximation algorithm for large problems
  - Consideration of constraints on bundles

TURF Example – Nutrition Bars

- A company wishes to introduce a line of nutrition bars
- What is the optimum number of bars in the portfolio?
- What specific flavors should be offered in the portfolio?
- 15 potential flavors are identified:

Caramel Nut	Chocolate Mint	Mocha Chip
Chocolate Peanut Butter	Almond Brownie	Peanut Butter
Lemon Crunch	Cookie Dough	Honey Yoghurt
S'mores	Double Chocolate Brownie	Chocolate Almond
Triple Chocolate	Honey Peanut	Chocolate Carmel

TURF Example – Nutrition Bars

- 197 Consumers rate each of the potential offerings on a 9 point hedonic liking scale
- Data is converted to a binary response based on if their response is an 8 ("like very much") or 9 ("like extremely")
- Results for the individual offerings

Product	Frequency	Frequency (%)
Almond Brownie	73	37
S'mores	65	33
Lemon Crunch	63	32
Honey Yoghurt	63	32
Chocolate Almond	59	30
Double Chocolate Brownie	54	27
Mocha Chip	52	26
Chocolate Mint	50	25
Cookie Dough	42	21
Honey Peanut	37	19
Triple Chocolate	36	18
Peanut Butter	32	16
Caramel Nut	27	14
Chocolate Peanut Butter	9	5
Chocolate Carmel	9	5

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TURF Example – Nutrition Bars

- TURF analysis identifies the best offerings for product portfolios of size 3 to 7 based on *reach*
  - The best 3 product portfolio contains S'mores, Almond Brownie and Honey Yoghurt, reaching 64% of respondents

	3 product line	4 product line	5 product line	6 product line	7 product line
Total Reach (%)	64	71	75	79	82
Caramel Nut					
Chocolate Peanut Butter					
Lemon Crunch		X	X	X	X
S'mores	X				
Triple Chocolate				X	X
Chocolate Mint					
Almond Brownie	X	X	X	X	X
Cookie Dough					
Double Chocolate Brownie				X	X
Honey Peanut					
Mocha Chip			X	X	X
Peanut Butter					X
Honey Yoghurt	X	X	X		
Chocolate Almond		X	X	X	X
Chocolate Carmel					

  - An optimal portfolio of a larger size may not contain products in the optimal portfolios of smaller sizes

TURF Example – Nutrition Bars

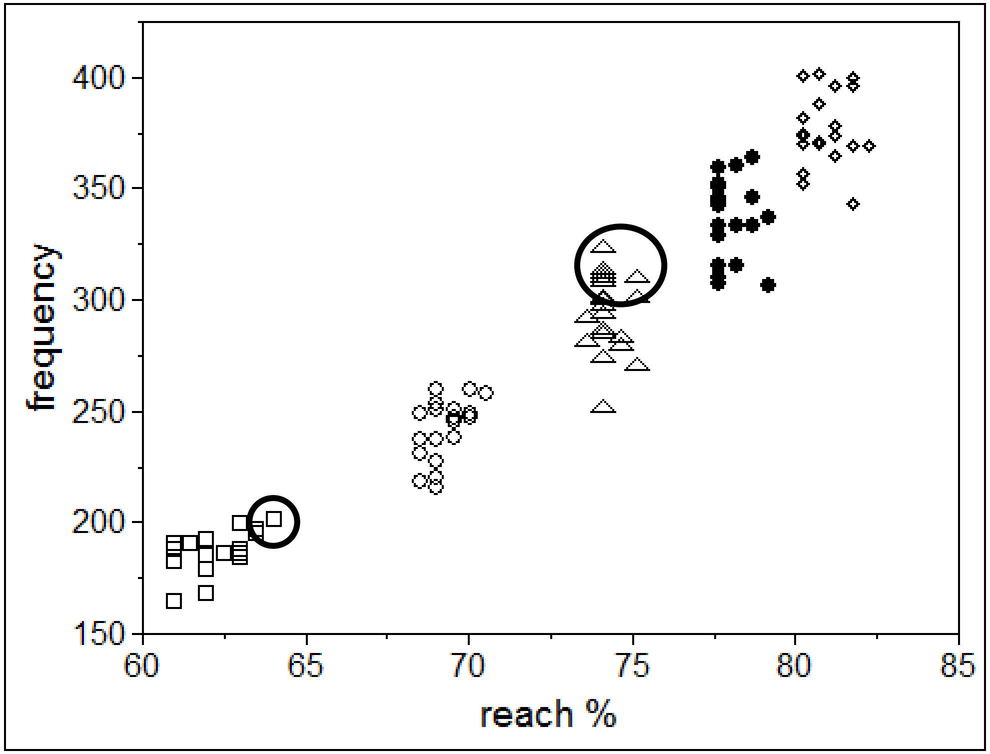
- TURF analysis identifies the best offerings for product portfolios of size 3 to 7 based on *frequency*
  - The best 3 product portfolio contains S'mores, Almond Brownie and Honey Yoghurt with a total frequency of 201

	3 product line	4 product line	5 product line	6 product line	7 product line
Total Frequency	201	264	323	377	429
Caramel Nut					
Chocolate Peanut Butter					
Lemon Crunch		63	63	63	63
S'mores	65	65	65	65	65
Triple Chocolate					
Chocolate Mint					
Almond Brownie	73	73	73	73	73
Cookie Dough					
Double Chocolate Brownie				54	54
Honey Peanut					
Mocha Chip					52
Peanut Butter					
Honey Yoghurt	63	63	63	63	63
Chocolate Almond			59	59	59
Chocolate Carmel					

  - Maximizing frequency for lines with increasing numbers of products means adding the product with the largest individual reach

TURF Example – Nutrition Bars

- Trading off reach and frequency will identify the potential portfolio options



  - The best 3 product portfolio maximizes both reach and frequency
  - Different solutions maximize reach and frequency for a 5 product portfolio

Strengths of TURF

- Clearly identifies actionable portfolio opportunities
- Simple mathematical calculations
- Can be used with any measure of interest
- Can be used in conjunction with other methodologies
  - Discrete choice conjoint studies, where individual respondent utilities are estimated for element combinations using hierarchical Bayes, mixed logit or finite mixture models (Adler, Smith and Dumont, 2010)
  - Benefit segmentation, where segments are identified on characteristics such as brand perception, product usage and user characteristics, with TURF used in portfolio optimization for the segments

Weaknesses of TURF

- Though the computations are simple, there can be many, many, many of them
  - The total number of calculations for subsets of k products from a total of n is: $$\sum_{k=1}^{n} \binom{n}{k}$$
  - The total number expands astronomically with the size of the problem
    - For a study with **10** potential product offerings there are **1,023** reach calculations
    - For a study with **50** potential product offerings there are **1,125,899,906,842,623** reach calculations
- Even though computing power continues to increase substantially, total enumeration may then not be possible for some large problems

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Improvements to TURF

- Approximation algorithms
  - Do not guarantee to find the true optimum solution
  - Krieger and Green (2000)
  - Adler, Smith and Dumont (2010)
- eTURF developed by Ennis and Fayle (2011)
  - Identifies only the true optimal solutions
  - Close to optimal solutions that may be more commercially feasible not identified
- A combination of the eTURF with approximate solutions may be most powerful and useful
  - eTURF finds optimal solutions
  - More commercially feasible solutions identified by approximate methods can be judged versus optimal

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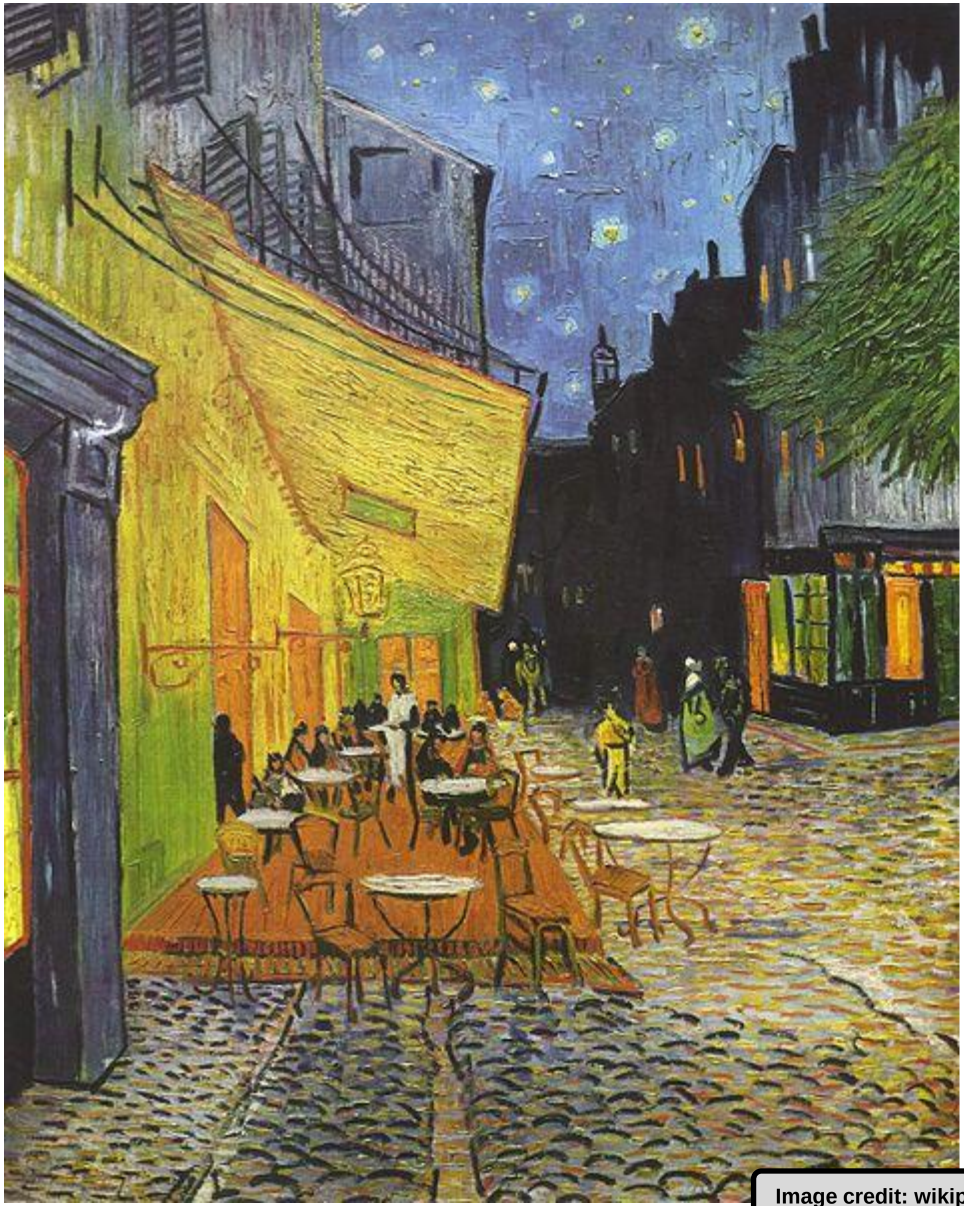
make today delicious



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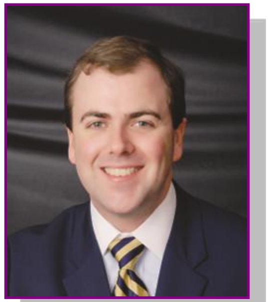
Michael A. Nestrud



ORISE Postdoctoral Associate at the U.S. Army Natick Research Development and Engineering Laboratories

- Ph.D. in Sensory Evaluation and B.S. in Food Science from Cornell University
- Culinary Arts degree from the Culinary Institute of America
- Research concentrations include multivariate perception, novel flavor compounds, chef vs. consumer perception, emotions and graph theoretic analysis
- Invited speaker for the Research Chefs Association
- Featured on National Public Radio's "Science out of the Box" in 2009
- Winner of 2009 Pangborn Student Award and 2008 Institute for Perception Award

Validating a graph theoretic approach at the individual and group levels

Nestrud, M.; Ennis, J.; Fayle, C.; Ennis, D. Lawless, H.

Pangborn 2011, September 7th, 2011

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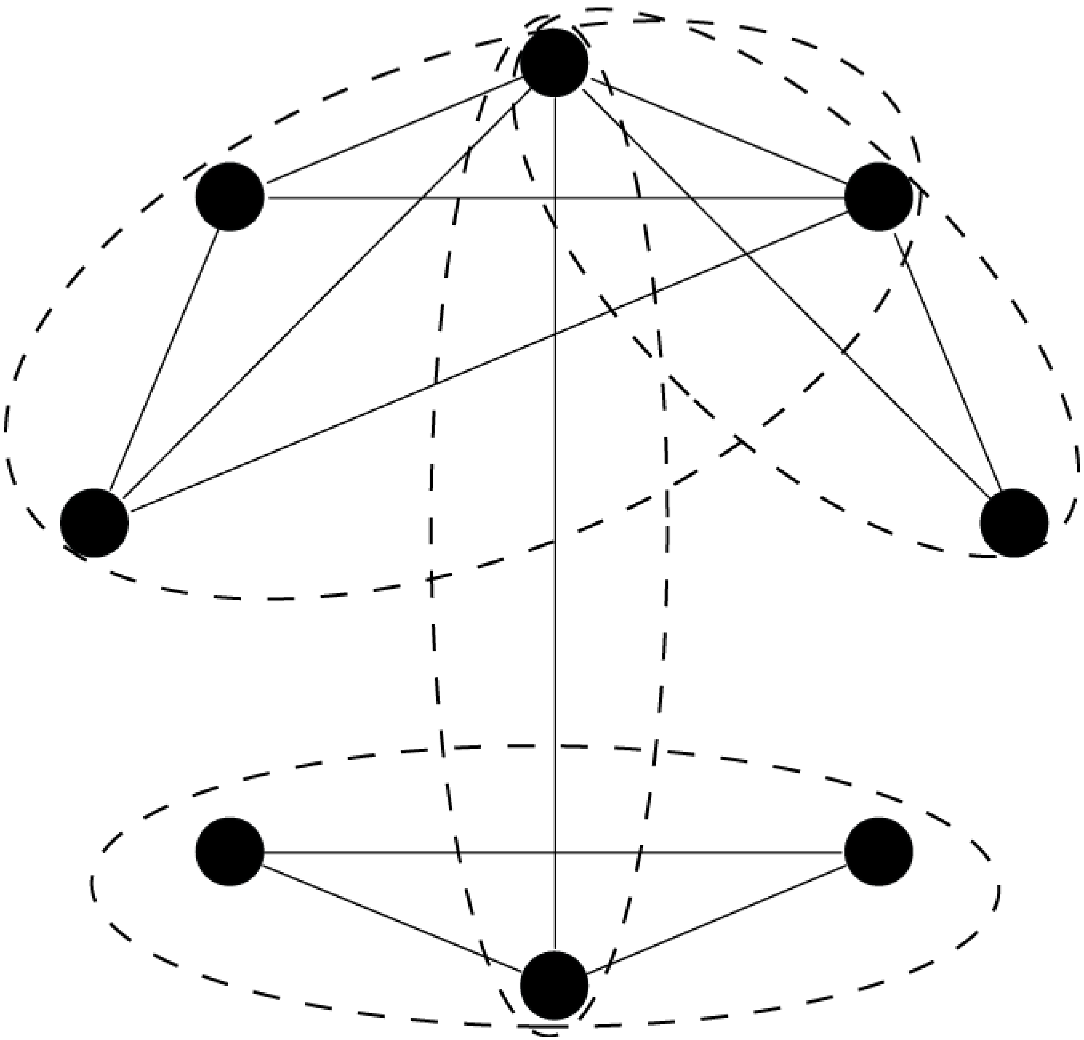
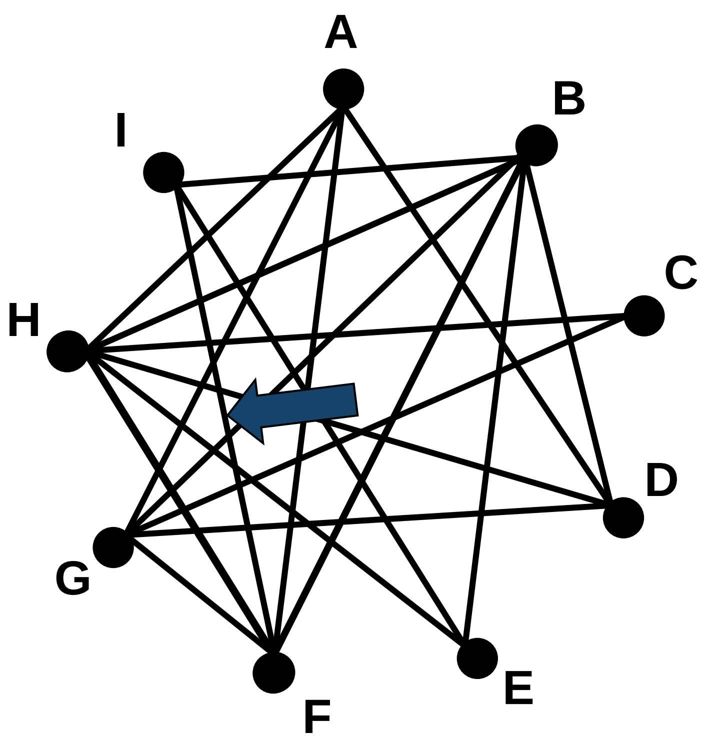


Compatibility and Graph Theory

	Item A	Item B	Item C	Item D	Item E	Item F	Item G	Item H	Item I
Item A									
Item B	0								
Item C	0	0							
Item D	1	1	1						
Item E	0	1	0	0					
Item F	1	1	0	0	0				
Item G	1	1	1	1	0	1			
Item H	1	1	1	1	1	1	0		
Item I	0	1	0	1	1	1	0	0	



Rationale

- Prediction of peoples' preferences for combinations is more complex than linear additivity for individual items. (Eindhoven & Peryam '69, Lawless '94)
- Overall liking is not exactly a combination of individual components (Moskowitz & Krieger, '95)

Defining the Technique

1) Validate supercombinatorality at individual level.
2) Validate supercombinatorality at group level.
3) Extend graph technique to find optimal combinations of menu items (e.g. entrée, starch, dessert).

Supercombinatorality of Group Responses

Gino's East Chicago, IL

Pizza Methodology

- Determine top 25 pizza ingredients
- Ask subjects compatibility information for 300 pairs of the 25 ingredients
- Combine responses into group compatibility matrix
- Determine threshold for responses
- Determine set of non-max cliques, max-cliques and non-cliques based on group triangular matrix
- Compare difference between distributions of responses for each of the three groups

Top 25 Pizza Ingredients

Ingredients			
Anchovy	Artichoke	Bacon	Basil
Black Olive	Broccoli	Chicken	Eggplant
Feta	Green Bell Pepper	Ground Sausage	Ham
Italian Sausage	Jalapeno	Mushroom	Onion
Pepperoni	Pineapple	Prosciutto	Red Bell Pepper
Red Onion	Ricotta Cheese	Roasted Garlic	Spinach
Tomato			

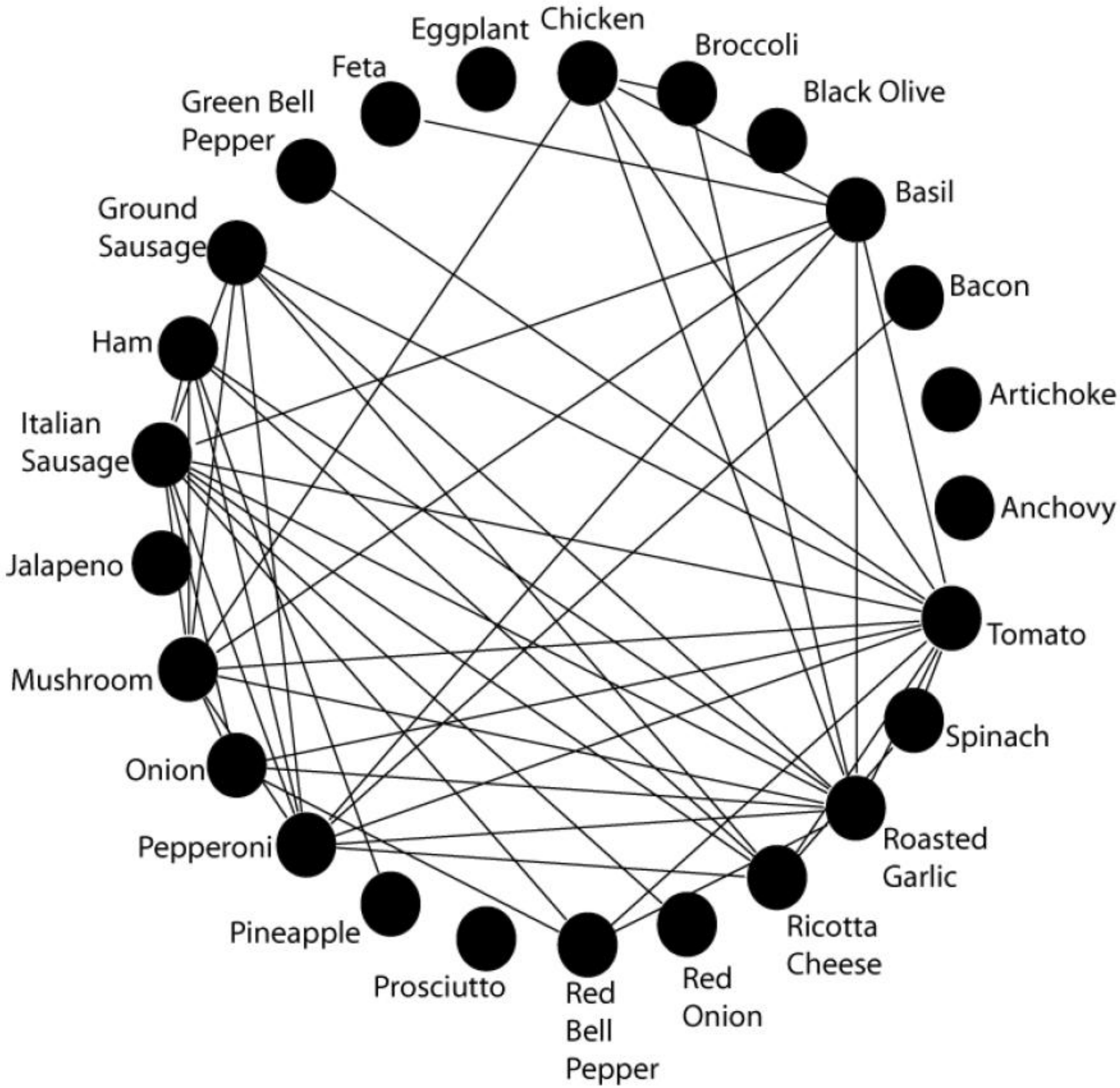
Compatibility matrix for pizza ingredients.

	Anchovy	Artichoke	Bacon	Basil	Black Olive	Broccoli	Chicken	Eggplant	Feta	Green Bell	Sausage	Ham	Italian Sausage	Jalapeno	Mushroom	Onion	Pepperoni	Pineapple	Prosciutto	Red Bell	Red Onion	Ricotta	Roasted Garlic
Artichoke	20																						
Bacon	17	56																					
Basil	22	58	68																				
Black Olive	21	48	50	52																			
Broccoli	18	52	63	65	54																		
Chicken	17	60	76	86	49	80																	
Eggplant	17	50	46	61	46	61	59																
Feta	16	58	69	80	58	70	76	63															
Green Bell Pepper	14	50	56	65	46	66	68	52	61														
Ground Sausage	21	56	77	78	54	66	70	59	75	75													
Ham	18	51	78	74	57	70	67	51	69	68	78												
Italian Sausage	18	59	78	83	54	63	74	59	77	77	82	79											
Jalapeno	14	27	35	35	31	30	39	30	30	35	38	39	42										
Mushroom	25	64	76	79	63	78	82	61	71	69	82	85	81	38									
Onion	22	56	77	65	51	64	75	61	62	72	78	73	85	34	84								
Pepperoni	17	45	81	80	57	65	71	53	69	73	81	79	89	36	88	76							
Pineapple	11	38	66	47	36	47	64	32	54	50	64	79	57	29	53	46	53						
Prosciutto Ham	16	47	69	69	52	57	63	47	72	61	69	66	72	39	75	64	67	66					
Red Bell Pepper	23	53	72	73	55	67	76	61	67	71	77	73	79	40	77	79	74	49	63				
Red Onion	20	54	73	60	53	61	65	57	64	66	77	70	79	33	76	49	72	42	61	72			
Ricotta Cheese	18	59	69	76	50	71	76	60	63	63	81	80	83	32	71	71	82	55	73	70	66		
Roasted Garlic	22	58	76	85	59	80	86	68	76	71	87	80	90	33	87	82	87	50	75	84	73	78	
Spinach	22	58	72	75	57	66	77	60	77	66	77	69	74	29	77	75	64	45	61	76	63	79	78

Thresholds

	Artichoke	Bacon	Broccoli	Chicken	Feta	Sausage	Ricotta	Spinach	Tomato
Artichoke									
Bacon	0.59								
Broccoli	0.49	0.51							
Chicken	1	1	1						
Feta	0.45	1	0.38	0.52					
Sausage	1	1	0.21	0.54	0.54				
Ricotta	1	1	1	1	0.23	1			
Spinach	1	1	1	1	1	1	0.58		
Tomato	0.48	1	0.52	1	1	1	0.57	0.48	

*Based on combined data from many surveys


Eggplant
Chicken
Broccoli
Feta
Black Olive
Green Bell Pepper
Basil
Ground Sausage
Bacon
Ham
Artichoke
Italian Sausage
Anchovy
Jalapeno
Tomato
Mushroom
Spinach
Onion
Roasted Garlic
Pepperoni
Ricotta Cheese
Pineapple
Prosciutto
Red Onion
Red Bell Pepper

Maximal cliques

Clique	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6
1	Anchovy					
2	Artichoke					
3	Black Olive					
4	Eggplant					
5	Jalapeno					
6	Prosciutto Ham					
7	Bacon	Pepperoni				
8	Basil	Feta				
9	Ham	Pineapple				
10	Green Bell Pepper	Tomato				
11	Italian Sausage	Red Onion				
12	Broccoli	Chicken	Roasted Garlic			
13	Ricotta Cheese	Spinach	Tomato			
14	Ham	Italian Sausage	Pepperoni	Ricotta Cheese		
15	Ham	Italian Sausage	Mushroom	Pepperoni	Roasted Garlic	
16	Basil	Chicken	Mushroom	Roasted Garlic	Tomato	
17	Ground Sausage	Italian Sausage	Pepperoni	Ricotta Cheese	Tomato	
18	Italian Sausage	Mushroom	Onion	Roasted Garlic	Tomato	
19	Italian Sausage	Onion	Red Bell Pepper	Roasted Garlic	Tomato	
20	Basil	Italian Sausage	Mushroom	Pepperoni	Roasted Garlic	Tomato
21	Ground Sausage	Italian Sausage	Mushroom	Pepperoni	Roasted Garlic	Tomato

Proportion of Panelists whom chose pizzas of combination sizes 1-6 and overall to be compatible. There is a trend of decreasing compatibility as size increases.

Combination Size	Max Cliques	Non-max Cliques	Non-Cliques
1	0.41	0.68	0.48
2	0.64	0.69	0.42
3	0.66	0.62	0.36
4	0.56	0.62	0.29
5	0.57	0.58	0.26
6	0.55	0.68	0.37
Overall	0.55	0.65	0.37

Supercombinatorality of Individual responses

Salad Subjects & Questionnaire

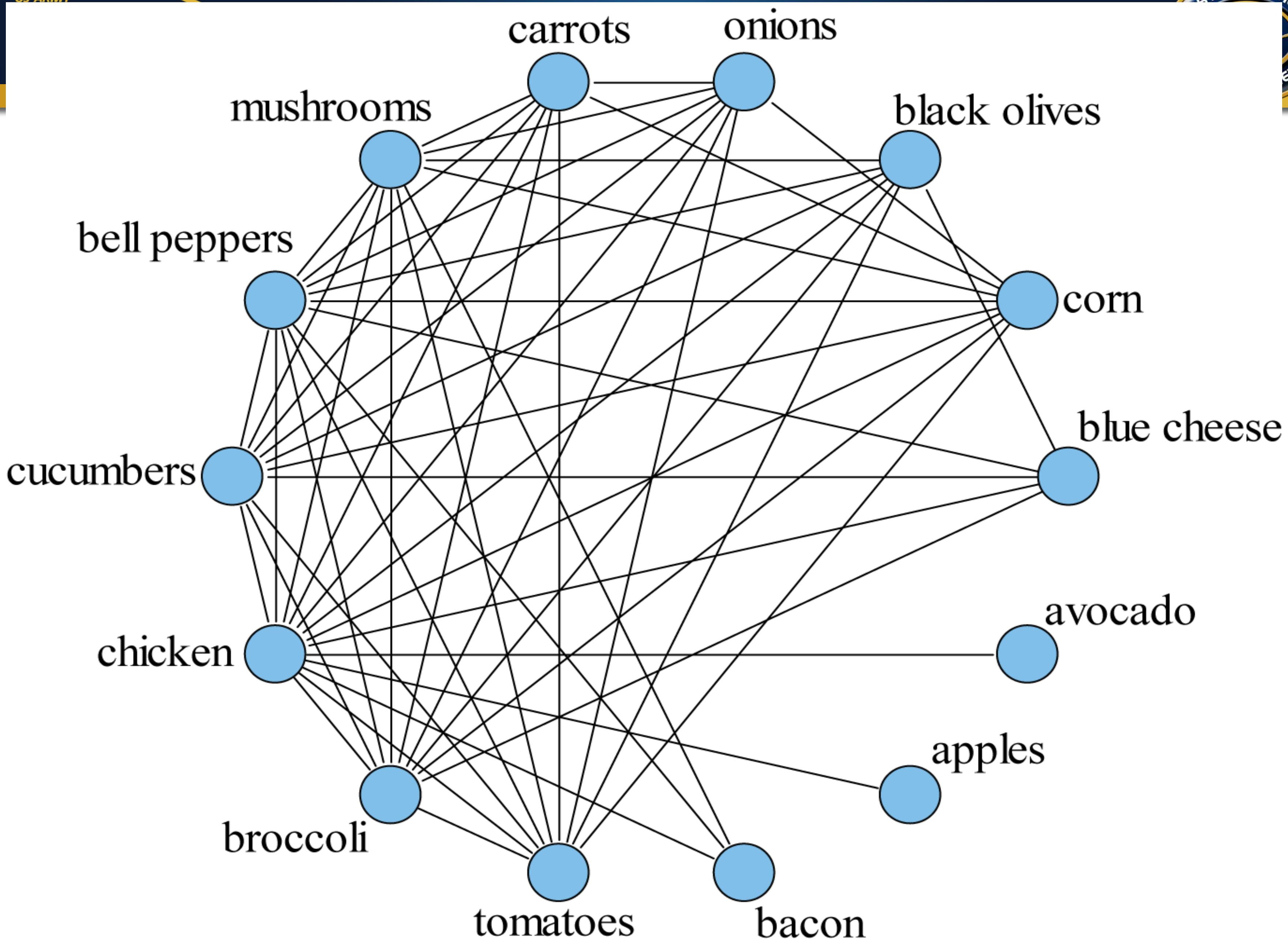
- 1) Gather list of top 25 salad ingredients from consumers
- 2) Ask subjects whether they would like each ingredient from the top 25 list on a salad.
- 3) Using results from (2), ask subjects about all possible pairs.
- 4) Predict combinations of 3-8 ingredients (cliques), and ask subjects whether they would like these salads.
- 5) Compare (4) to random non-cliques of equivalent sizes.

$$H_o : P(clique) = P(non - clique)$$

$$H_a : P(clique) \neq P(non - clique)$$

25 Salad Ingredients

Ingredients			
Tomatoes	Cucumbers	Carrots	Croutons
Bacon	Blue Cheese	Spinach	Almonds
Chicken	Chickpeas	Feta Cheese	Onions
Sunflower Seeds	Black Olives	Broccoli	Dried Cranberries
Hard-Boiled Egg	Cheddar	Mushroom	Avocado
Corn	Apples	Walnuts	Beets
Bell Peppers			


carrots
onions
mushrooms
black olives
bell peppers
corn
blue cheese
cucumbers
avocado
chicken
apples
broccoli
tomatoes
bacon

Predicted and random salad combinations with subject responses

CLIQUE	ITEMS	RESPONSE
TRUE	Corn, tomato, broccoli, chicken, bell peppers, mushrooms, carrots, onions	TRUE
FALSE	Blue cheese, bacon, tomatoes, carrots, apples, mushrooms, broccoli, sunflower seeds	FALSE
TRUE	Chicken, bacon, mushrooms, bell peppers	TRUE
FALSE	Cucumbers, onions, corn, black olives	FALSE

Analysis

- Wilcoxon Matched Pairs Signed Rank Test on counts of compatible cliques vs. non cliques per clique size and total.
- Non-parametric equivalent of a paired t-test

$$Ho: \sum(\textit{positive differences}) = \sum(\textit{negative differences})$$

$$Ha: \sum(\textit{positive differences}) \neq \sum(\textit{negative differences})$$

Individual Supercombinatorality is a Real Effect

Combination Size	P(clique)	P(non-clique)	Wilcox p-value
3	0.52	0.26	0.025
4	0.54	0.28	0.023
5	0.79	0.52	0.016
6	0.90	0.46	<0.001
7	0.79	0.55	0.006
8	0.93	0.53	<0.001

Thank you

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Armand Cardello
Jeannette Kennedy
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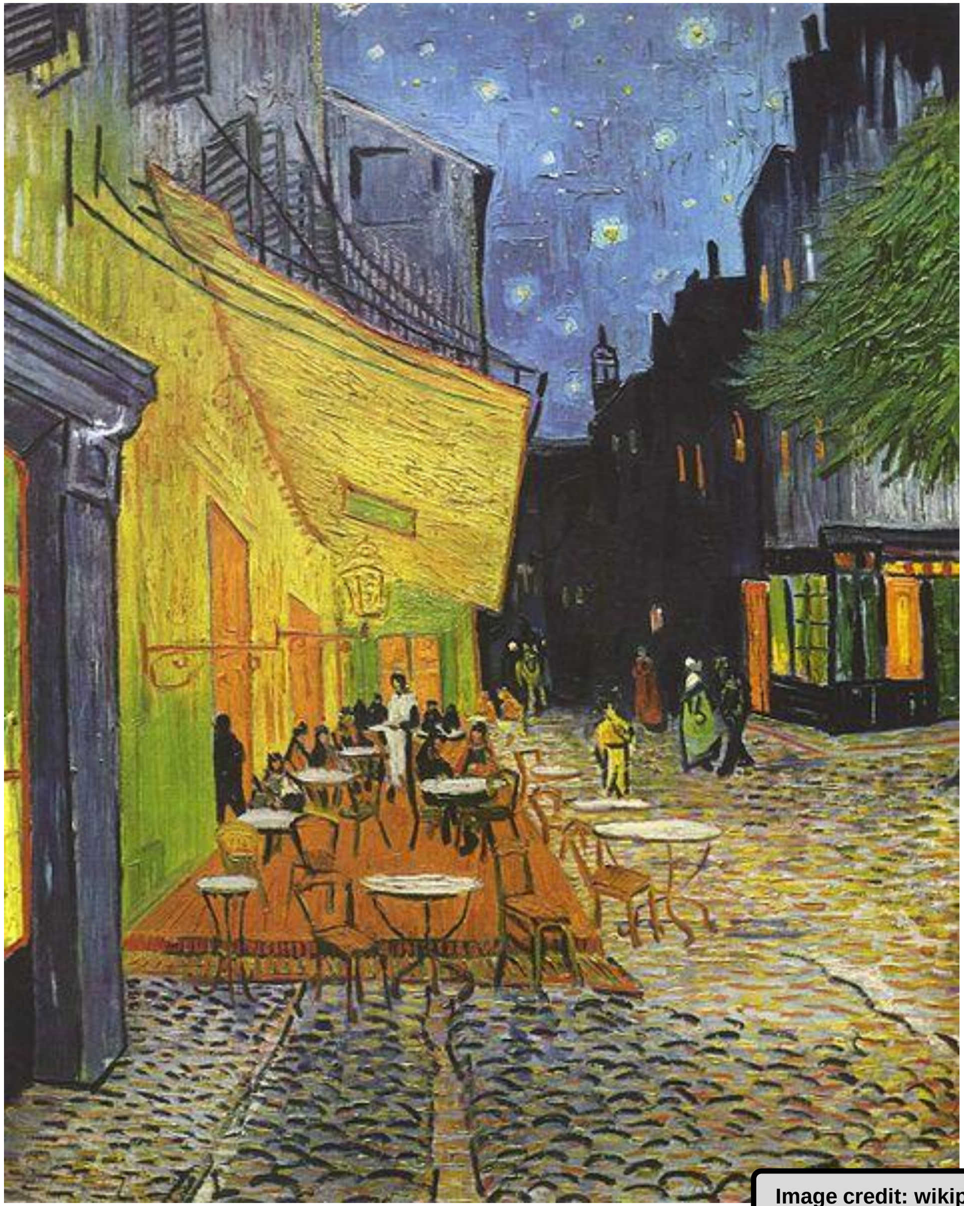

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Selecting the Best Combinatorial Tool for Your Specific Challenges

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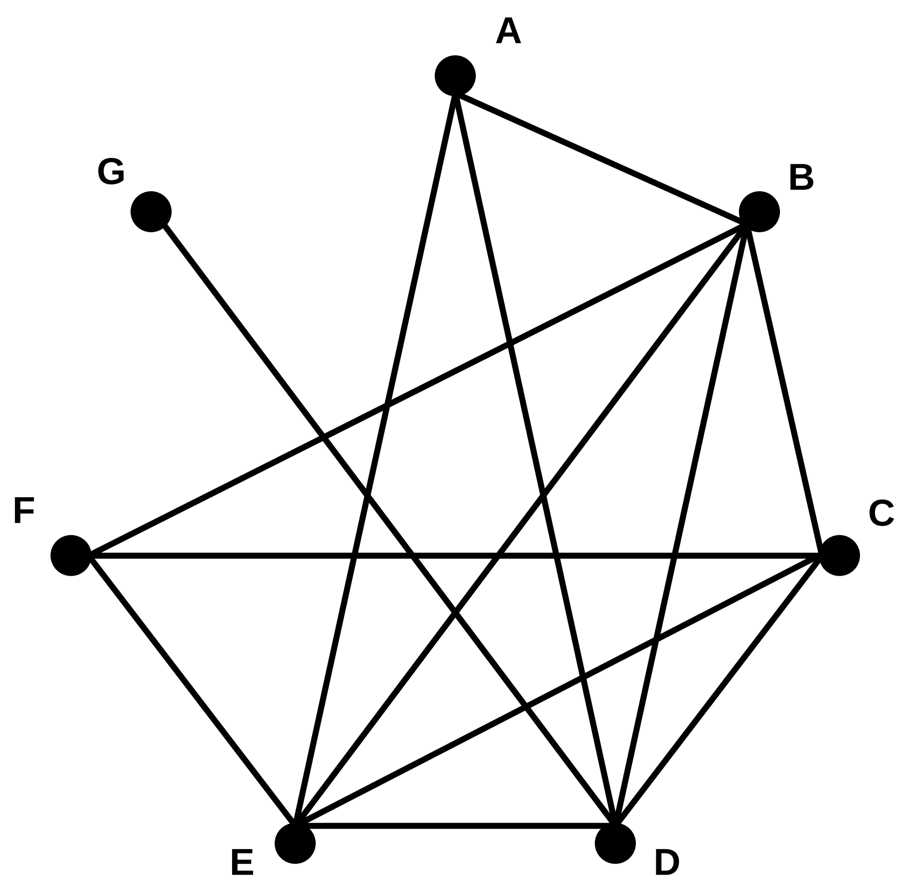
Combinatorial Tools

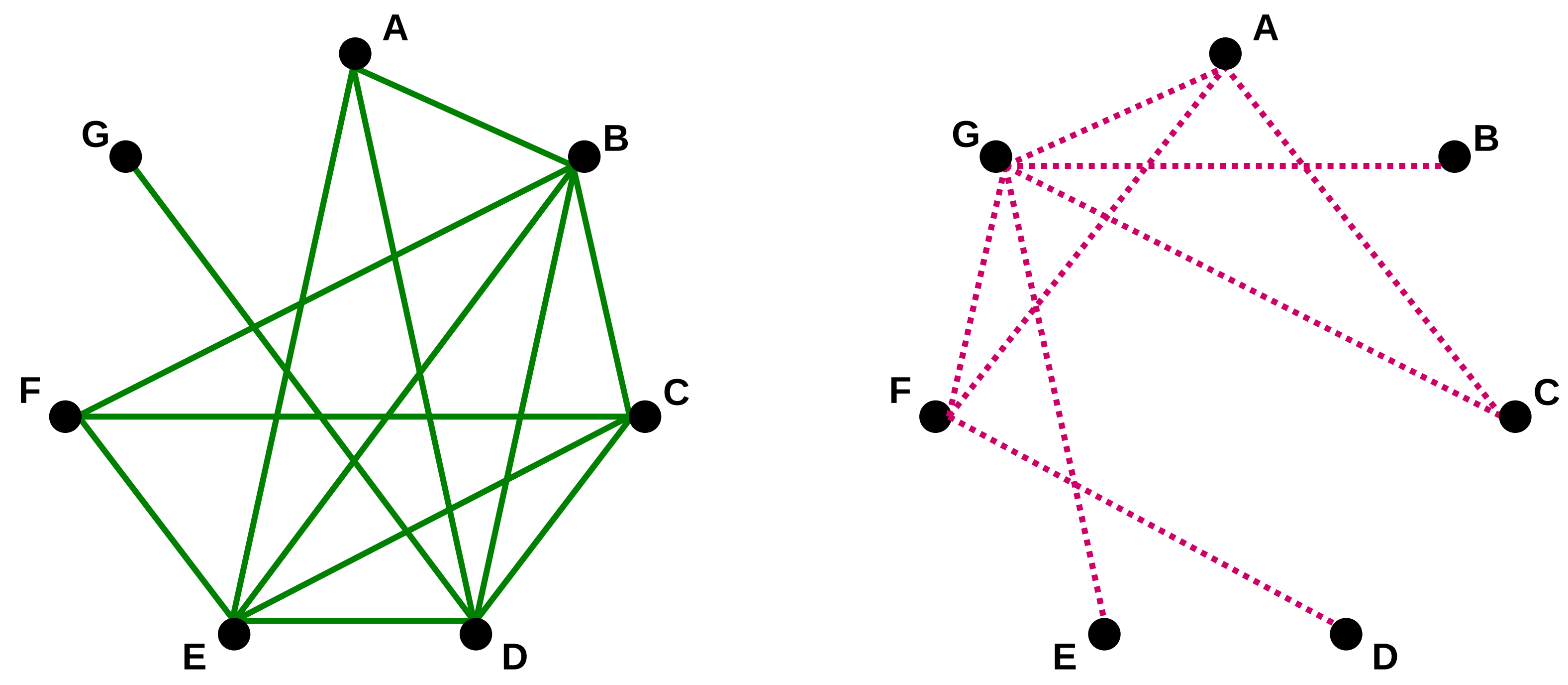
- Combinatorial tools find best combinations
- Three types of combinatorial tools in this workshop
  - Conjoint Analysis
  - Total Unduplicated Reach and Frequency (TURF)
  - Graph Theoretic Analysis (GTA) using cliques
- Each tool has a unique approach
  - Conjoint Analysis finds utilities for each component
  - TURF finds best coverage for combinations
  - GTA finds compatible combinations
- Observation: GTA can also find incompatible combinations
  - Choose products to include in a category appraisal
  - Select factories for monitoring
  - Determine levels of attributes for conjoint analysis study

An Additional Tool - Independent Sets



Independent Sets and Cliques

➢ **Independent sets** are **cliques** in the complement graph



➢ Clique finding techniques also find independent sets

Cookie Selection

- Want 9 cookies out of 19 for category appraisal
- 4 competitor cookies must be included
- Need to select 5 remaining cookies

Happy Elf 1	Chocolate Island 1	Sunny Lemon	Oatmeal Bliss	Prototype 3
Happy Elf 2	Chocolate Island 2	Peanut Heaven	Orange Crisp	Prototype 4
Sugar Farms 1	Oatmeal Raisin 1	Butter Bar	Prototype 1	Prototype 5
Sugar Farms 2	Oatmeal Raisin 2	Cravin' Raisin	Prototype 2	

Sensory Profiles

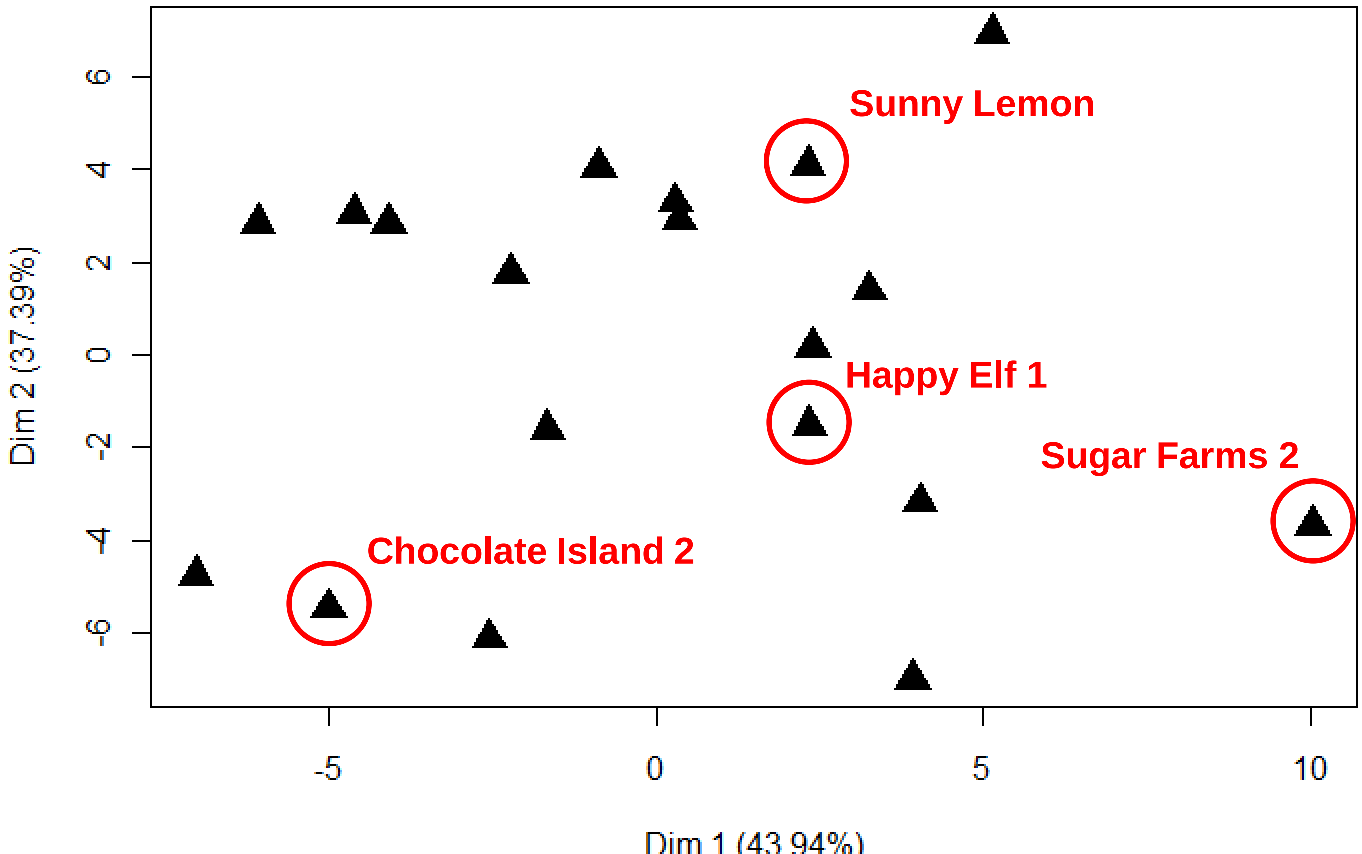
- Have sensory profiles for each of the 19 cookies on 42 attributes:

Cookie	Hardness	Vanilla	Chocolate Flavor	Sweetness	•••
Happy Elf 1	3.719	4.532	2.454	5.324	•••
Happy Elf 2	3.872	5.431	3.967	5.505	•••
Sugar Farms 1	3.582	4.264	3.358	5.024	•••
Sugar Farms 2	3.602	4.355	3.099	4.448	•••
Chocolate Island 1	4.622	5.759	4.447	6.248	•••
Chocolate Island 2	4.483	5.495	4.235	6.178	•••
Oatmeal Raisin 1	4.058	5.087	2.944	4.839	•••
Oatmeal Raisin 2	3.946	4.970	3.918	5.957	•••
Sunny Lemon	3.306	4.711	2.749	5.097	•••
Peanut Heaven	4.580	5.575	4.165	6.586	•••
•••	•••	•••	•••	•••	•••

- Goal: Select 5 more cookies to find 9 cookies that maximally spread sensory space
- Step 1: Use PCA to quantify sensory differences
- Step 2: Use independent sets to find most different set of 9 cookies containing the 4 specified cookies

Principle Components Analysis

- 81% of variance in cookies explained by first two principle components
- Four cookies must be included



(PCA run using FactoMineR)

Distance Matrix

- For each pair of cookies we compute distance

	Happy Elf 1	Happy Elf 2	Sugar Farms 1	Sugar Farms 2	Chocolate Island 1	•••
Happy Elf 1	0.000	2.536	4.693	9.615	6.530	•••
Happy Elf 2	2.536	0.000	2.161	8.364	9.054	•••
Sugar Farms 1	4.693	2.161	0.000	7.628	11.190	•••
Sugar Farms 2	9.615	8.364	7.628	0.000	14.040	•••
Chocolate Island 1	6.530	9.054	11.190	14.040	0.000	•••
•••	•••	•••	•••	•••	•••	•••

- Use distance to define “connected”
  - Cookies that are close together are connected
  - Cookies that are far apart are not connected
- Find independent set with 9 cookies that contains the 4 competitor cookies

Cookie Selection

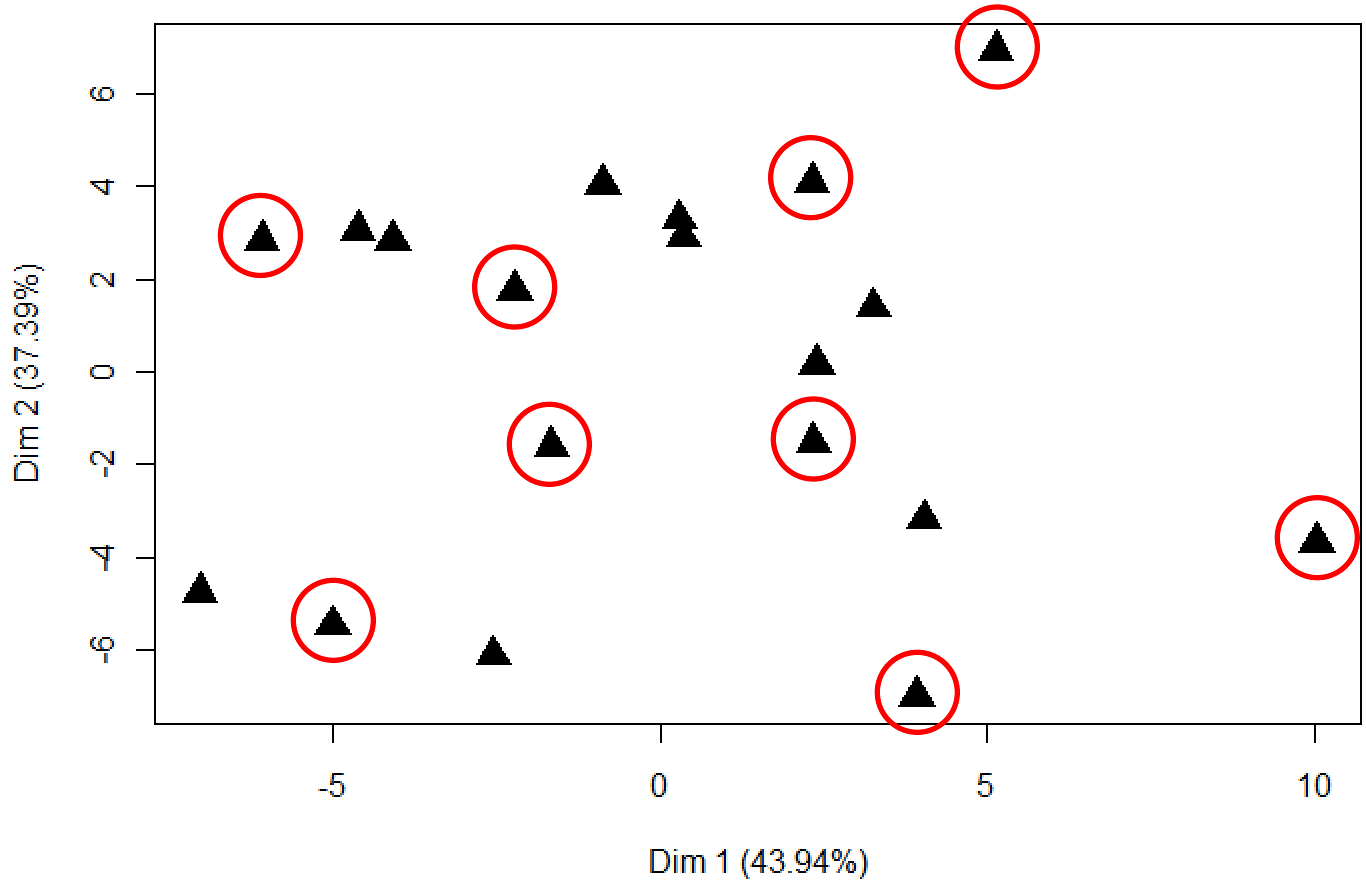
- The following cookies were selected

Happy Elf 1	Sunny Lemon
Happy Elf 2	Peanut Heaven
Sugar Farms 2	Prototype 2
Chocolate Island 2	Prototype 5
Oatmeal Raisin 2	

- These cookies are maximally spread among all groups of 9 cookies containing the 4 competitor products

Principle Components Analysis

- The nine selected cookies cover the sensory space well



Selecting the Best Tools

Conjoint Analysis

- Strengths:
  - Detailed information including statistics
  - Returns information for individual users
  - Enables market simulations
- Weaknesses:
  - Some rigidity to experimental designs
  - Assumes single best product per respondent
  - Difficulties with large numbers of combinations
- Ideal Applications:
  - Pricing research
  - Brand strength investigations
  - Fine tuning of existing products

TURF

- Strengths:
  - Mathematics simple with statistics developed
  - Wide variety of applications
  - Clear guidance
- Weaknesses:
  - Definition of “reached” can be arbitrary
  - Assumptions simplistic
  - Trouble with large number of combinations
- Ideal Applications:
  - Portfolio optimization
  - Choosing benefits to emphasize in marketing
  - Selecting combinations of media for advertising

Graph Theoretic Analysis

- Strengths:
  - Well suited to large problems
  - Highly customizable
  - Combines well with existing tools
- Weaknesses:
  - Less quantitative than conjoint
  - Weaker market predictions
  - Statistics still undeveloped
- Ideal Applications:
  - Screening large number of combinations
  - Selecting products for inclusion in category appraisal
  - Reducing number of attribute levels
  - Finding multiple ideal combinations

Selecting the Best Tools

Problem Type	Combinatorial Tool
Pricing research	Conjoint Analysis
Brand strength investigation	Conjoint Analysis
Fine tuning of existing products	Conjoint Analysis
Market share prediction	Conjoint Analysis/TURF
Portfolio optimization	TURF
Advertising strategy	TURF
Maximizing portfolio diversity	TURF
Screening combinations	Graph Theoretic Analysis
Product selection	Graph Theoretic Analysis
Reducing attribute levels	Graph Theoretic Analysis
Finding multiple ideal combinations	Graph Theoretic Analysis

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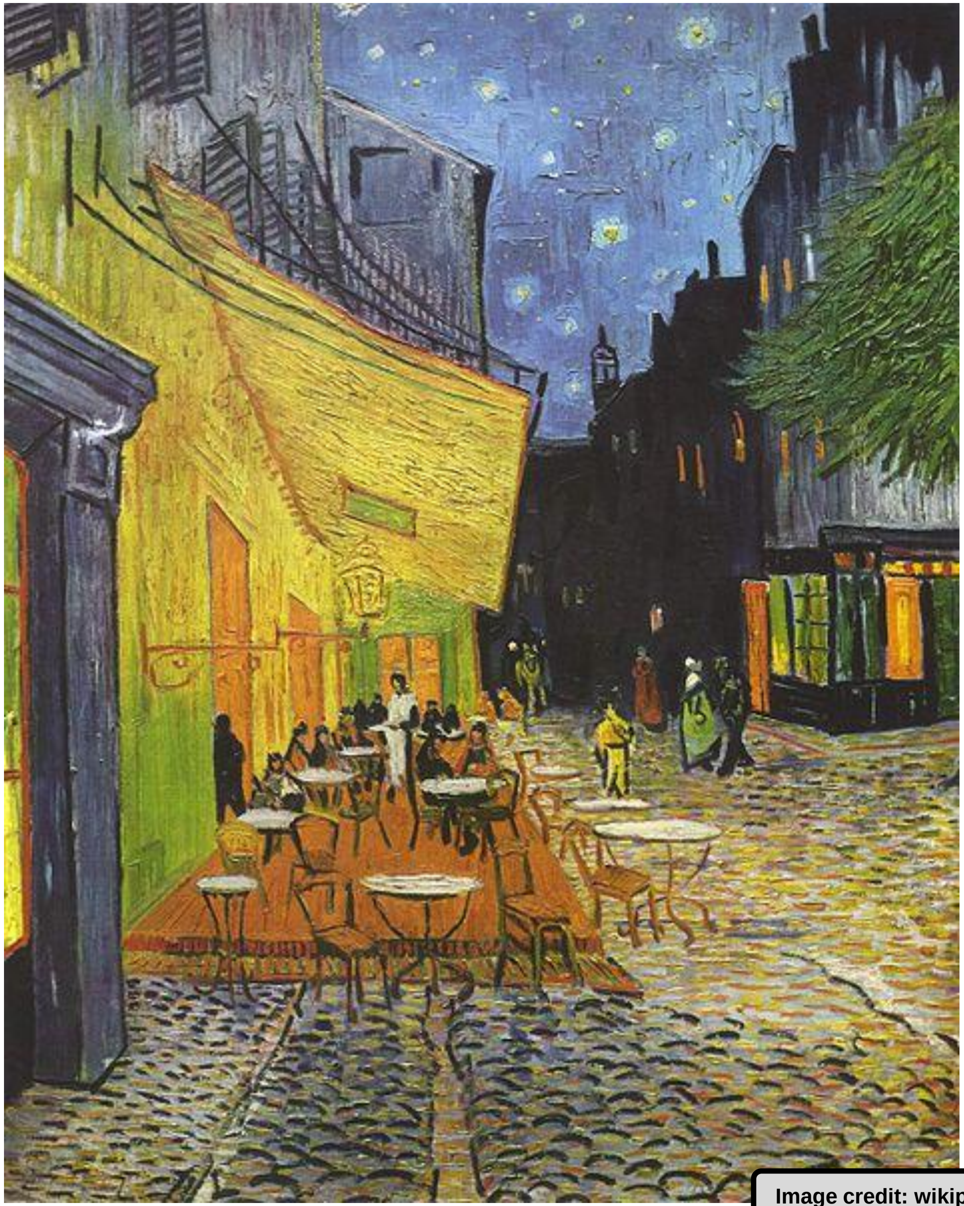

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