Reprinted from IFPress (2017) 20(3) 3,4

Large TURF Problems: Finding Custom Solutions

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Background: In previous technical reports, we have separately considered the topic of efficient searches for compatible combinations from large numbers of possibilities[1] and the topic of modern techniques for approaching large TURF problems using the *e*TURF 2.0 technique[2]. These two topics share a common structure that allows them to be combined to facilitate custom TURF analyses that incorporate unique aspects of project goals directly into the search for best solutions. Such customizations of TURF analysis have long been a source of interest within market research[3] and, in this report, we look at one such custom analysis using a technique called *linear programming*.

Scenario: You work for a large manufacturer of consumer packaged goods that produces a line of sparkling fruit juice beverages[4]. Because of stagnant brand growth despite the relative health of the product category overall, management has decided that the brand line must undergo a "refresh" in which the flavors as well as the brand concepts and marketed benefits are to be reevaluated. As part of this refresh, combinations of juice flavors are to be considered as well as single flavors, and series of concepts and benefits have also been developed for consideration from both focus group and social media sourced research. In total, there are 9 flavors, 8 concepts, and 8 benefits to be considered, comprising 25 total items for consideration for the brand line refresh. These items are shown in Table 1.

Flavors		
Apple	Lime	Peach
Blueberry	Orange	Pineapple
Cherry	Mango	Pomegranate

Concepts	
Abundance	Healthy
Authentic	Let loose
Breezy	Smooth
Classic	Social

Benefits	
All-natural	Low-carb
Crisp	Relaxing
Fizzy	Reviving
Goes down easy	Satisfying

Table 1. Flavors, concepts, and benefits for consideration for "Brand Line Refresh."

You are aware that items that combine well in pairs also combine well in larger combinations[5,6]. Hence, you begin your work into the brand line refresh by conducting a nationwide internet-based survey in which 1,000 regular fruit juice and/or soft drink consumers who are non-rejectors of sparkling fruit juice beverages provide their opinions as to whether or not the items listed above are compatible in the context of sparkling fruit juice beverages. Figure 1 shows an example screenshot from the survey. Once programming is completed, the survey requires only a few days for data collection, and has a median time to survey completion of just under 10 minutes per respondent.

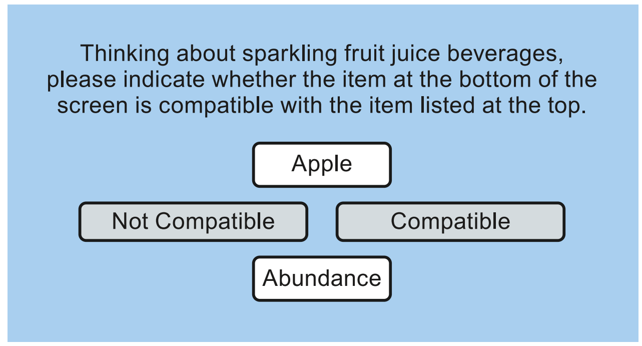

Figure 1. Example screenshot from the main body of the compatibility survey.

Challenge with Problem Size: With your compatibility data in hand, you work on the problem of finding promising combinations of flavors, concepts, and benefits to seed ideas for the brand line refresh. The problem is larger than you expected, however – if you define a product bundle to be a combination of items containing at least 1 but no more than 3 items from each of the three categories (flavors, concepts, benefits), then there are more than a million[7] possible product bundles. Moreover, even if you employ clique finding techniques from graph theory, as described in previous technical reports[8], these techniques do not provide a simple way to specify additional requirements, such as your desire to specify minimum and maximum numbers of items from each category. You need an efficient method with which to incorporate these constraints into your analysis.

Linear Programming: To handle additional complexity in large search problems, and especially to handle complex conditions on desired solutions, a useful approach is *linear programming*[9]. Originally developed during the 1800s, but rising in popularity following World War II, linear programming is a set of optimization techniques designed to solve a particular family of optimization problems. Specifically, whenever one seeks to maximize a function that is a linear combination[10] of variables that are bounded by constraints that are themselves linear combinations, it is possible to solve large problems quickly. This is because the set of points at which possible solutions may occur is surprisingly small, and increasingly clever algorithms have been developed to allow for rapid search through this set. In addition, we are often only concerned with whether or not certain items—such as the flavors, concepts, and benefits in our example—should be included in the solution set. When this is the case, we can use a specialized set of tools called *binary linear programming* in which variables explicitly capture the information as to whether or not an item should be included; these tools allow for rapid solutions to a wide variety of problems in consumer science[11].

Bundle 1	Bundle 2	Bundle 3	Bundle 4	Bundle 5
Apple	Mango	Orange	Cherry	Blueberry
Authentic	Peach	Pineapple	Lime	Cherry
Classic	Abundance	Breezy	Social	Pomegranate
Healthy	Smooth	Social	Fizzy	Healthy
All-natural	Goes down easy	Let loose	Reviving	All-natural
Satisfying	Relaxing	Reviving	Crisp	Low-carb

Table 2. Bundles in an optimal portfolio.

Finding Best Bundles: In order to find a best portfolio of product bundles for your brand line refresh, you plan a two-stage process. First, you plan to employ linear programming to determine, for each respondent, the full set of all bundles containing at least one item and no more than three items from each category, with a total bundle size of no more than six items. These specifications, which are straightforward to implement as linear constraints of the variables involved, reflect practical considerations associated with implementing your brand line refresh. Similarly, it is possible to formulate linear conditions specifying that all chosen items must be considered pairwise compatible by the respondent under consideration. Second, once you know which bundles each respondent finds fully compatible, you plan to run a TURF analysis on the bundles you discover in stage one of your search. Through this two-stage analysis, you will combine ideas from graph theory and TURF, all facilitated by linear programming.

As you start your analyses in stage one, you notice there are 15 respondents who reported all items compatible with each other. These respondents are highlighted on the histogram shown in Figure 2. Considering these data as non-informative, you discard these respondents and analyze the data from the remaining 985 respondents.

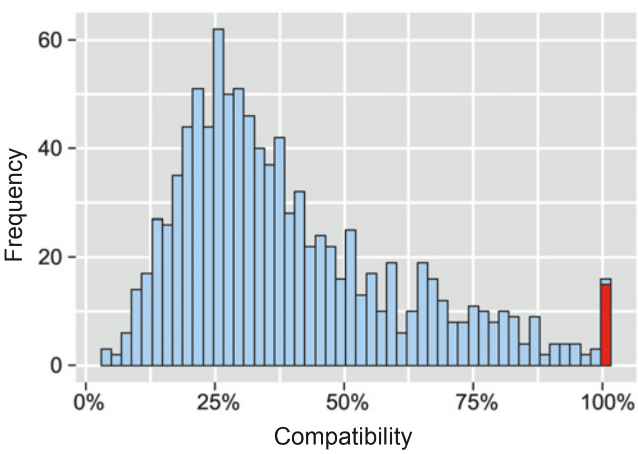

Figure 2. Respondent compatibility proportions.

You then employ linear programming to find 36,484 unique bundles that at least one respondent finds compatible. Given the sheer number of bundles, you decide to focus on the top 1,000 bundles within this set that contain exactly six items[12]. Considering a respondent to be "reached" by a bundle if they find that bundle compatible, you find that 850 respondents are reached by at least one such bundle.

Focusing on these bundles of size six, you move forward to stage two. Using *e*TURF 2.0, you select an optimal portfolio of size five, which contains the bundles shown in Table 2. These bundles will now be used to provide direction to the brand line refresh.

Conclusion: By using linear programming, it is now possible to solve a wide variety problems that were either too large or too complex to consider previously. In addition, the techniques discussed in this report combine well with internet-based research, which can quickly collect large amounts of data at relatively low cost. Using the combination of linear programming and internet-based research, consumer scientists can now quickly and inexpensively to find new insights to guide their work.

References and Notes

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2. Ennis, J. M. and Russ, W. J. (2017). *e*TURF 2.0: From astronomical numbers of portfolios to a single optimum. In D. M. Ennis, J. M. Ennis, and B. Rousseau (Eds.), *Tools and Applications of Sensory and Consumer Science* (pp. 122-123). Richmond, VA : The Institute for Perception. (Original work published 2016)
3. Krieger, A. M. and Green, P. E. (2000). TURF revisited: Enhancements to total unduplicated reach and frequency analysis. *Marketing Research,* **12**(4), 30-36.
4. Data analyzed in this technical report adapted from data collected in collaboration with Carolyn Corbett of CRG Global.
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6. 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.
7. 1,091,856 possible product bundles, in fact.
8. E.g. Ennis, J. M., Fayle, C.M., and Ennis, D. M. (2017). From many to few: A graph theoretic screening tool for product developers. In D. M. Ennis, J. M. Ennis, and B. Rousseau (Eds.), *Tools and Applications of Sensory and Consumer Science* (pp. 114-115). Richmond, VA : The Institute for Perception. (Original work published 2011)
9. Sultan, A. (2014). *Linear Programming: An Introduction with Applications.* Lexington, KY: Elsevier.
10. A linear combination is a sum of multiplies of the variables involved, such as $5x_1 + 6x_2 - 9x_3$.
11. E.g. Serra, D. (2013). Implementing TURF analysis through binary linear programming. *Food Quality and Preference,* **28**(1), 382-388.
12. This is an arbitrary choice made for illustrative purposes within this technical report. The specifics of your project goals could lead to different choices in practice.