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Portfolio Optimization Based on First Choice

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Background: First choice, sometimes called discrete choice, involves the selection of an item from a number of mutually exclusive items. This means that when a consumer chooses an item, this choice necessarily implies that all other items are rejected. There are numerous models to account for first choice[1,2] and often these models predict the probability of choice based on a continuous function of driver variables. In this report we instead focus on a discrete approach to optimization, meaning that we use tools from discrete mathematics to account for the choices made by consumers.

One application in which a need for discrete optimization arises is when liking data have been collected in a category appraisal and the data are unfolded to create a map containing product and ideal point locations based on product-ideal similarity[3,4,5]. On such a map, liking scores can be predicted as a function of the distance between the ideal points corresponding to consumers and the product locations on the map. In general subjects tend to prefer products whose locations are close to their ideal points. Using such a map it is possible to determine optimal locations for new products subject to a variety of different meanings of the word *optimal*[6]. In particular it is often the case that some of the products are competitor products and the goal is to deploy a portfolio of our own products that best competes with the collection of competitor products. This is the setting for what is known as competitive optimization and in this setting we optimize the number of first choice counts obtained by products in our portfolio instead of by competitor products. In other words we maximize the number of consumers that would be predicted to choose one of our products as their favorite product instead of choosing one of the competitor products. This problem is a discrete optimization problem, making it potentially very complex but also approachable using recently developed mathematical tools. Once the optimal arrangement for the portfolio of our products has been determined it is then possible to create target profiles to guide product development.

Scenario: You work for a major beverage company that plans to launch a line of three green tea-based beverages in order to compete in the emerging green tea beverage category. Given your company's large manufacturing base and distribution network your company expects to be a major player in this category immediately upon entry and you have identified three rival companies, hereafter labeled C_1, C_2 and C_3, as your main competition. You conduct a large scale category appraisal involving three products from each of companies C_1 and C_2, two products from company C_3 and four of your own prototypes. From the resulting liking data you construct the map shown in Figure 1. In this map the competitor products and prototypes are displayed against a contour background of consumer ideal point densities. Lighter regions correspond to greater density. Your goal in launching your new product line is to create a portfolio of three products that competes with the products from companies C_1, C_2 and C_3 as effectively as possible.

First Choice Optimization: In order to determine the optimal competitive portfolio you seek to optimize the number of first choice counts obtained by your portfolio instead of by products manufactured by your rivals. In other words you seek to maximize the number of consumers that are closer to one of your products than they are to any of the rival products. Note that you seek for the products in your portfolio to occupy different locations as they will need both to work together to capture first choice counts from the consumers and to avoid cannibalizing each other. In addition, notice that for the purposes of this optimization you will at first not consider the locations of your prototypes. This is because you first wish to determine what the hypothetical optimal solution would be for your portfolio. Once you determine the optimal hypothetical solution you will then evaluate the usefulness of your prototypes in helping you to realize this optimal solution. You will consider which of your prototypes are sufficiently close to products in the optimal portfolio to be implemented and which prototypes will require additional product development work.

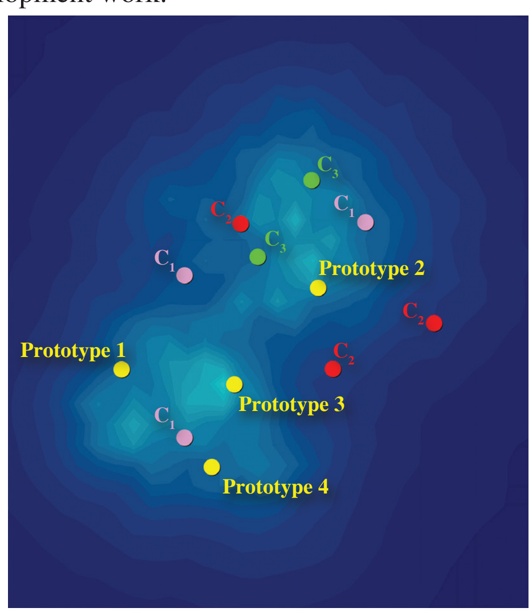

Figure 1. Landscape Segmentation Analysis® map with original products.

A Discrete Problem: For the optimization to proceed we first posit a large number of possible locations for the products in the optimal portfolio. We then seek the combination of three products from this set of possible locations that best competes as a team against the rival products. For each hypothesized arrangement of products we compute the number of first choice counts that arrangement would receive relative to the competing products. Since first choice counts can only assume integer values it is not appropriate to use standard optimization techniques based on calculus. Fortunately, advances in discrete mathematics and in computing power allow us to solve this optimization problem using a modification of a technique known as backtracking[7,8]. Backtracking is a search technique that allows one to intelligently search through a vast number of combinations, eliminating without consideration combinations whose failure to produce an optimal solution could be predicted from information discovered earlier in the search. Using a backtracking technique, all combinations of product locations that maximize the first choice count against the competition can be discovered. From the set of all portfolios that maximize the first choice count we then select the single portfolio that is on average the most pleasing to the consumers.

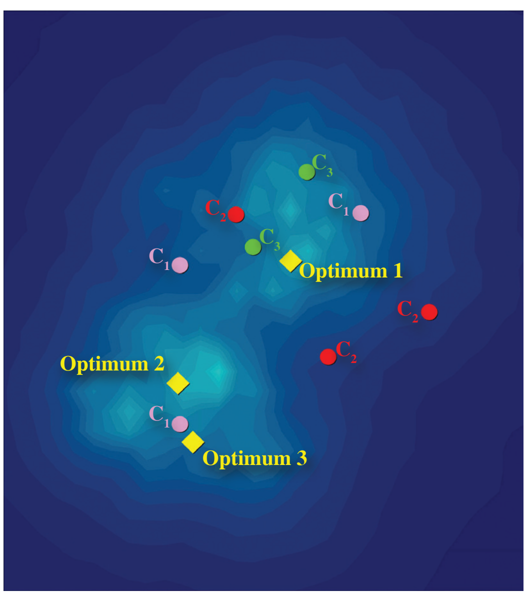

Figure 2. Landscape Segmentation Analysis® map with optimal portfolio.

Creating a Portfolio: The optimal competitive portfolio for your scenario is shown in Figure 2. Comparison with Figure 1 shows that Prototypes 2 and 4 are very close to products in this optimal portfolio and as such are reasonable choices for inclusion in your future portfolio. Protoypes 1 and 3 appear on opposite sides of the remaining member of the optimal portfolio and after regressing sensory and analytic information onto your map you determine that the dimension on which these prototypes differ most is bitterness. You also determine that Prototype 1 is at the more bitter end of the scale while Prototype 3 is less bitter. Thus you conclude that by either making Prototype 1 slightly less bitter or by making Prototype 3 slightly more you can obtain a third beverage suitable for inclusion in your final portfolio. Product development informs you that Prototype 1 can easily be made slightly less bitter and you tentatively plan for the inclusion of a slightly less bitter version of Prototype 1 in your future portfolio.

Conclusion: First choice optimization is a difficult but important problem in market research as it allows for the creation of maximally competitive portfolios of products. In combination with a map containing product and individual ideal point locations a technique known as backtracking can be used to determine optimal portfolios. Once a single target portfolio has been identified it is then possible to regress sensory and analytic information onto the map to create target profiles and to guide the development of products for inclusion in an optimal portfolio. When prototypes have been included in the original test one can also determine whether the prototypes can be used either as is or with slight modification as part of an optimally competitive portfolio.

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