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ABSTRACT

The analytical marketing literature reflects a growing number of algorithms which seek the best position for a single new product entrant in an existing product-market. Each solution algorithm has proposed a somewhat different conceptualization of product-market structure and of market decision making. This paper presents a critical comparison of these algorithms to assess the consequence of the simplifications made by each of the algorithms.

INTRODUCTION

A model of any managerially relevant system is by definition an approximation to some more complex "reality." That "reality" is not an absolute but rather is limited by the analyst's insight, understanding, and motivation. The decision regarding how much realism to build into a model is therefore a highly pragmatic one. While simple models are to be preferred over more complex ones, one must ensure that such simplification is not merely the result of inadequate analysis or a desire to make resulting solution approaches tractable. Especially when the management scientist contributes a solution algorithm s/he must be careful that problem definition is not constrained by the requirements of the algorithm, but rather the converse. When different analysts propose algorithms to solve what is ostensibly the same problem, they should conceptualize that problem environment similarly. This facilitates comparison of their solution algorithms. On those occasions where this does not occur, comparative testing of the proposed solutions is still possible in the context of a problem definition which is at least as complex as that assumed by any one. This offers one way of ascertaining whether simplifications introduced by any analyst are consequential or not.

The purpose of this paper is to conduct such a comparative test in an area of growing importance for managerial planning and strategy--optimal new product positioning. The analytical marketing literature reflects a growing number of algorithms

which see the best position for a single new product entrant in an existing product-market. Each solution algorithm has proposed a somewhat different conceptualization of product-market structure and of market decision-making. We wanted to represent a common market reality in terms of the union of assumptions associated with (most of) these authors' efforts. Each of the algorithms to be compared was operationalized in the more simplified setting permitted by its own assumptions. The (nearly) "optimal" solution (new product position) each algorithm reached could then be evaluated in the more complex, common model of market "reality." By so doing, the consequence of "simplifications" necessitated by the use of each model could be investigated.

The models compared in this study make use of the market structure and choice modelling approach proposed by Shocker and Srinivasan (1974) and elaborated by the authors' (1979) article. GRID SEARCH and PRODSRCH (a type of gradient procedure) are operationalizations of suggestions made in 1974 by Shocker and Srinivasan. Also compared are Albers and Brockhoff's (1977) PROPOSAS; Zufryden's (1977) ZIPMAP; and the method IV of Gavish, Horsky, and Srikanth (GHS) (1981). These algorithms have not been compared previously (a lone exception being Albers and Brockhoff's (1979) comparison of PROPOSAS with ZIPMAP). Each author has simply defended his approach as being logical and computationally efficient (although computational times may vary significantly with the different computer systems used).

Other algorithms for new product positioning have appeared

in the literature, indicating that the area remains one of active research interest. Pessemier's (1974) STRATOP; Urban's (1975) PERCEPTOR; Hauser and Simmie's (1981) operationalization and extension of Kelvin Lancaster's (1971) economic theory; Green, Carroll, and Goldberg's (1981), POSSE; and Bachem and Simon's (1981) non-acronym formulation exemplify these other approaches. Aside from reasons of budget and time, they are excluded here because they either suppose a conceptual framework for market structure and decision-making substantially different from the others (Hauser and Simmie), or involve added measurement stages which would bias comparison in the type of simulation carried out here (Urban, Green-Carroll-Goldberg), or make use of algorithms which are insufficiently different from the approaches compared in the present study to warrant separate treatment (Pessemier, Bachem and Simon). Hauser and Simmie, Pessemier, and Bachem and Simon incorporate costs and prices explicitly in their framework. They argue the inclusion of such effects affords a major advantage for their models. While the incorporation of costs permits the formulation of profit objectives (rather than the sales or share of preference objectives that will be assumed here), neither of these procedures operationalizes cost functions in a defensible manner. (Bachem and Simon ignore measurement issues entirely.) Urban's approach involves multi-stage data collection, resulting in successive refinement of the measures of market structure. The other models are all single stage. Green, Carroll, and Goldberg's POSSE is a proprietary program whose detail has not been completely published. In addition, it

introduces an extra modelling step (a fitted quadratic response surface) not present in the other approaches. There appeared no way to simulate this step without knowledge of an appropriate error function. An arbitrary assumption here could have introduced a major source of bias.

THE MARKET SIMULATION

The Market Model

Following Shocker and Srinivasan (1974, 1979), products or services are conceptualized as bundles of benefits and (consumer-relevant) costs. A product-market is presumed to consist of those products judged by relevant (potential) customers to be appropriate for some generic purpose. The competing alternatives are representable as (point) locations in a perceptual space spanned by attribute dimensions determinant of brand preference/choice in that market. Preference behavior on the part of different customer segments is presumed to be modelable as a linear combination of the different product attribute discrepancies (from some desired or ideal product). The ideal point (attribute discrepancy) model is used as this is the only one posited by several of the analytical frameworks examined (see Shocker and Srinivasan (1979) for a review of the logical and empirical justification for multi-attribute models generally). This customer model represents relative preference as an inverse function of an idiosyncratic weighted distance from the customer's "ideal" or most desired attribute combination to that

represented by each available product. Following Pessemier, et al. (1971), choice is modelled probabilistically as a function of this measure of preference where the individual or segment is presumed to choose from among the k-closest competitors, where k is an integer-valued parameter which can vary between 1 and the number of available brands. We operationalize this framework in terms of the following notation. Let:

B = the set of n_B existing brands which constitutes the product-market of interest, $j = 1, 2, \ldots, n_B$.

M = the set of n_M individuals and/or market segments which represent demand for the products in B, $i = 1, 2, \ldots, n_M$.

$A(n_A)$ = the n_A-dimensional space spanned by determinant product attributes, i.e., $p = 1, 2, \ldots, n_A$.

$R(n_A)$ = a major subspace of A in which existing and new products may feasibly be located. R is determined by technological, economic, and managerial constraints. $R \neq A$, in general.

$Y_j = \{y_{jp}\}$ = the modal perception (over all segments in M) of the j^{th} product on the p^{th} dimension in A.

$W_i = \{w_{ip}\}$ = the set of attribute weights for the i^{th} segment, reflecting the relative effect of the p^{th} attribute in the i^{th} segments' preference decision-making.

$I_i = \{I_{ip}\}$ = the most desired attribute levels ("ideal point") of the attributes for the i^{th} market segment. This ideal point will be assumed finite, but it need not lie in R.

d_{ij} = the evaluation of the j^{th} product alternative by the i^{th} market segment. This evaluation may be in the form of a preference rating, intention to buy, etc. Several alternative definitions of d_{ij} (also interpretable as a measure of proximity of the j^{th} product to the i^{th} segments' ideal point) have been proposed in the literature. The alternative mdoels are generally special cases of the weighted Euclidean model (1) and are examples of what Green and Srinivasan (1978) have termed conjoint anlaysis models.

$$d_{ij} = \left[\sum_{p=1}^{n_A} (I_{ip} - y_{jp})^2 w_{ip} \right]^{1/2}$$

S_i = the i^{th} segements' demand (in $ or units) for

all products in B over the period. S_i will be presumed constant.

Π_{ij} = the share if the i^{th} segments' demand allocated to the j^{th} product alternative. $\Pi_{ij} = f(d_{ij}^{-1})$ and

$$\sum_{j=1}^{n_B} \Pi_{ij} = 1 \quad \text{for all } i = 1, 2, \ldots, n_m$$

Following Bachem and Simon (1981) and Shocker and Srinivasan (1974), several forms for Π_{ij} (decision rules) can be considered:

Case 1. Every available alternative could have some non-zero likelihood of purchase e.g., $\Pi_{ij} = a_i/d_{ij}^b$ where $a_i = 1/\sum_{j=1}^{n_B} (1/d_{ij}^b)$ and b is a parameter which varies with the product class (Pessemier, et al 1971). Since producers would tend to locate their products at or near concentrations of demand; if ideal points are distributed throughout the space and/or attribute weights vary substantially across segments, this decision rule should lead to relatively high likelihoods of selection for some products and low ones for others (with some arbitrary assignment of segment demand to any product located precisely at the segment's ideal point (if this occurred)). This rule says that whether or not a segment purchases a brand, there is always the potential to do so, particularly if the time period over which predictions are expected to hold is long. As a model

of segment behavior, it is more credible than as a model of individual behavior, where individuals often are observed to restrict their purchases to many fewer than all available brands (Silk and Urban 1978).

Case 2. Those who argue individuals would rarely purchase brands they did not like (or judged unsuitable for their intended usage or with which they were unfamiliar), might prefer a rule which limited positive probabilities of purchase to a subset of alternatives. Individuals are also more likely to become familiar with products which better meet their objectives, due to self-interest (Aaker and Myers 1974), therefore a parameter k, (possibly k_i which varies with each individual) which restricts choice to the k "closest" alternatives, whould lead to a definition of $\Pi_{ij} = a_i/d_{ij}^b$ for $d_{ij} \leq d_i^{(k)}$, where $d_i^{(k)}$ is the distance from the i^{th} segment's ideal point to its k^{th} closest product, and $\Pi_{ij} = 0$ otherwise.

Case 3. A third rule assumes that individuals purchase only their most preferred brand, i.e., k = 1, so that $\Pi_{ij} = 1$ for that j for which $d_{ij} = d_i^{(1)}$ and $\Pi_{ij} = 0$ otherwise. The logic for this would be compelling if choice was deterministic, and all product alternatives were equally available and familiar (that is, why should individuals purchase other than their first choice under such circumstances?). However, since likelihood of choice will typically depend upon other factors besides product characteristics (such as convenience, availability, salesperson recomendations, brand last purchased, and special situations) one would expect some variance in actual behaviors. Surprisingly,

then, Pessemier, et al (1971) found that this first choice model gave good predictions in the aggregate even though it was inferior to Case 1 (above) in predicting individual-level choice. Whether analysis at the level of market segments, rather than individuals, would affect this result is not known, and should depend upon the basis for segmentation used. Additional support for a first choice model was found by Parker and Srinivasan (1976). The conditional logit model has also been used to model frequency of first choice among groups of customers (Hauser and Koppelman 1979, Punj and Staelin 1978) with good predictive results, and represents yet another alternative to those already discussed.

The form of the objective function for optimal location of a single new product concept changes with the different forms for Π_{ij}. Assume that the firm's single objective is to maximize total incremental demand, or preference share, from the new product introduction. This means that we must account for any demand for the new product which is cannibalized from the firm's existing brands. Let

Ψ_i = the set of k out of the n_B existing products closest to the i^{th} segments ideal point,

Ψ_i^* = the set of k out of the $n_B + 1$ products, existing and new, closest to that point,

χ_i = a subset of Ψ_i consisting of existing

products marketed by the introducing firm, i.e., self-products,

χ_i^* = a subset of Ψ_i^* consisting of all brands (existing and new) marketed by the introducing firm,

Π_{ij} = the set of product likelihoods of purchase before new product introduction,

Π^*_{ij} = the set of product likelihoods of purchase after new product introduction,

$x = \{x_p\}$ = the new product location,

and

L = an arbitrarily large number.

Then we wish to

$$\text{Maximize} \quad \sum_{i=1}^{M} u_i \left(\frac{\sum_{j \in \chi_i^*} \Pi^*_{ij}}{\sum_{j \in \Psi_i^*} \Pi^*_{ij}} - \frac{\sum_{j \in \chi_i} \Pi_{ij}}{\sum_{j \in \Psi_i} \Pi_{ij}} \right) S_i$$

subject to:

$$d_i^{(k)} (1 - u_i) < \left[\sum_{p=1}^{n} {}^{A} (I_{ij} - x_p)^2 w_{ij} \right]^{1/2} < d_i^{(k)} + L(1 - u_i)$$

for all $x \in R$, and $i \in M$ where u_i is zero or one depending on whether (1) or not (0) the new product is among the k closest for the i-th segment.

This formulation results in a nonlinear, mixed integer programming problem, involving the location of the new product and indicators as to whether it lies within the k-closest set of products for a market segment.

If we assume that every brand alternative has non-zero probability of purchase, then the quadratic constraints never become binding (i.e., we have $u_i = 1$ for all $i \in M$), and the problem reduces to an unconstrainted maximization of the objective function over R. If $1 < k < n_B + 1$, then we must consider the quadratic constraints, but the Π_{ij}'s will be continuous, except when χ_i changes for a segment. This means that the derivatives of the objective function will be well-behaved almost everywhere, so that gradient-based techniques may be of value. Finally, when $k = 1$, Π_{ij} will be non-zero for only one product, so that the objective function simplifies considerably.

The major complication in this formulation is the nonlinear constraints which serve as a linkage between the location variables and the χ_i^* sets. With a weighted Euclidean distance measure, even for $k = 1$, the problem reduces to an integer programming problem with quadratic constraints, which is a difficult problem to solve in a reasonable amount of time. (Technically it is NP-complete. See Garey and Johnson (1979) for

a thorough discussion of this topic.)

To understand how several authors have tried to avoid this intractability, it is helpful to consider the geometry of the situation (as represented by Exhibit 1 for the case of k = 1), using a weighted Euclidean distance measure for the d_{ij}. What we have is a hyperellipsoidic region around each ideal point, where any product placed within this region is guaranteed to capture some of theat segment's demand, and any one outside that region will capture none of it. Each hyperellipsoid is centered at an

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(Insert Exhibit 1 about here)

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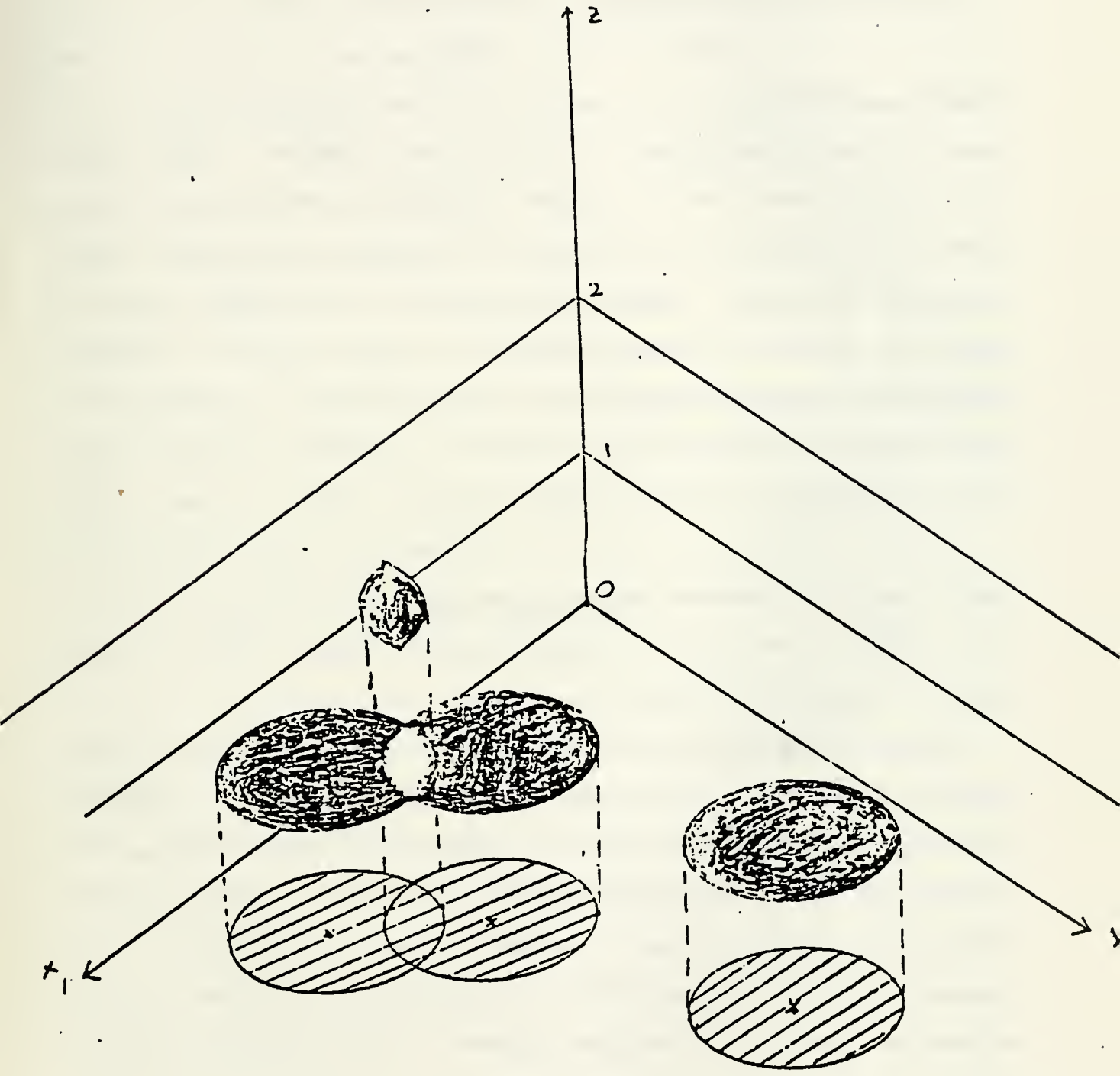
ideal point, has its axes parallel to the attribute (coordinate) axes; its boundary just touches the existing k-closest product to the ideal point, and its eccentricity is determined by the relative attribute weightings--if the weights are equal, it is a hypersphere, and the more unequal the weights are, the "flatter" and more oval it is. The optimization problem is then to examine the feasible (i.e., within R) places where these hyperellipsoids intersect, and to locate the new product in that feasible intersection region which will capture the greatest quantity of new sales. The difficulty in going from that conceptual ideal to implementable mathematics is that each intersection region is an area determined by a set of simultaneous nonlinear equations--the

Exhibit 1

Objective Function for a k=1 Problem

and Equal Sales Potentials



identification of which is on the order of difficulty of the solution to an entire nonlinear programming problem.

There are both desirable and undesirable implications from setting up the problem in this form. By allowing x to be situated anywhere in R, we have a problem for which sensitivity analysis can be performed. We also have to assume, though, that the attribute axes are continuous, and that a market segment may alter its probabilities of purchase with even a miniscule change in product location. Nominal attributes, or those which could be fixed at only a finite number of levels, would introduce additional integer variables into the formulation, substantially increasing its computational complexity. Zufryden (1979) allowed for such attributes with a linear objective function determined by conjoint anlaysis and linear constraints, thus proposing the use of integer programming as a solution procedure. Green, et al. (1981), also using a conjoint framework, allows for a quadratic objective function.

The complexity of this model also depends on how we define R--that part of A in which a new product may be feasibly placed. While it is reasonable to assume that there are at least linear attribute constraints on the location of feasible product alternatives (e.g., so as to preserve the assumption of similar cost), only the GRID SEARCH and PRODSRCH algorithms and the method of Gavish, Horsky and Srikanth are able to accomodate them.

Positioning Algorithms

The several positioning algorithms which are compared in the current simulation are very briefly discussed below. A more complete description of each is contained in Sudharshan (1982) and, of course, in the original.

1. Grid Search is a modification of explicit enumeration which tries to locate an optimum by imposing successively finer grids on smaller and smaller regions of R in n_A-dimensional space. The search strategy is a simple one. A relatively coarse grid is imposed on the feasible region, and the objective function is evaluated at the centroid of each resulting parallelotope. The region with the highest value is retained, a second grid with the same number of divisions as the original is imposed over it, and the process repeats until the grid structure is too fine to be consequential.

2. General Nonlinear Optimizers (PRODSRCH). PRODSRCH, based on the general purpose nonlinear optimizer QRMNEW (May 1979), is representative of "gradient search" methods. It is a modified Newton algorithm; that is, it uses both first and second derivative information in generating search directions, although it does not require the user to supply analytical derivatives. The notion of local variations embedded in it yields a guarantee of at least first order convergence and, at each iteration, information on the sensitivity of the correct solution to changes in the attibute levels. The step-size used for derivative approximation is upper- and lower-bounded by the user so that the method will examine perturbations from its current "solution"

(i.e., new locations) at least as large as the "perceptual threshold" (the minimum change in attribute level presumed detectable by the average individual), as well as avoid the numerical problem brought on by the flat surfaces depicted in Exhibit 1. QRMNEW has been shown to perform competitively with comparable programs (May 1979), and to converge dependably for a wide range of settings of its parameters.

Finally, it should be noted that the complexity of the next two algorithms discussed, PROPOSAS and ZIPMAP, is dependent upon the number of market segments, since each segment generates, respectively, another hyperellipsoid or parallelotope. The complexity of PRODSRCH is chiefly dependent on the number of attributes, since it treats that space directly.

3. The PROPOSAS method of Albers and Brockhoff deals with the case of k=1, and, in its most recent version (Albers 19789), the computer code for which was provided us by Sonke Albers, allows for differentially weighted attributes and segments. They assume that there are no constraints on search, i.e., R = A.

The general approach is that of Branch-and-Bound (implicit enumeration). PROPOSAS selects sets of segments to investigate, in decreasing order of weighted potential incremental revenue, and stops when the incumbent best new location found is superior to that which could be obtained form any of the remaining sets. PROPOSAS consists of two parts - ENUSOS and INTSEA. ENUSOS generates a list of segments whose hyperellipsoids intersect pairwise and INTSEA tries to find a point of intersection for any given set of segments. The largest weighted (by sales potential)

set of hyperellipsoids, all of which intersect pairwise, is then selected and a point in that intersection is found heuristically.

4. Zufryden (1977) approximates the k=1 problem instead of trying to deal with it heuristically as Albers and Brockhoff do. The major difficulty in the general formulation is the hyperellipsoids, so Zufryden's algorithm, termed ZIPMAP, approximates them by linear constraints. Geometrically, this means replacing each hyperellipsoid in Exhibit 1 with a parallelotope whose sides are parallel to the coordinate axes. If a new product, then, falls within the parallelotope, it will be considered as capturing a given segment's demand. Zufryden also assumes that all segments have equal sales potential, and that there are no constraints on the search area, although unequal salience weights are allowed. Given these points, the linearization idea has two real advantages--it makes the formulation a linear integer program, which is comparatively easy to solve, and it allows realization of a key geometric benefit from rectangular shapes. That is, if n parallelotopes, all aligned with parallel sides, are pairwise intersecting, then they intersect n-wise; a result not true for hyperellipsoids.

Two related difficulties exist. First, a hyperellipsoid is not a parallelotope, and thus the linearization is arbitrary; it can be an interior one, an exterior one, or something of both. Second, sovling the linearized problem yields, as a solution, an area (the intersection of the largest set of parallelotopes) rather than a point . If all the linearizations were strictly interior ones, any point in that region is feasible and may be

optimal. If not, then one is left with having to determine where in that region, if anywhere, do all the underlying hyperellipsoids intersect? To find a point-location we use an interior approximation (see the appendix of Sudharshan (1982) for details of its construction) and use a grid search of the resulting intersection area to find the better point location.

5. Gavish, Horsky, and Srikanth (GHS) (1981) propose a basic approach which incorporates certain ideas similar to those of PROPOSAS and ZIPMAP. They assume a k=1 model, with equal sales potentials and finite ideal points, although attribute weights are allowed to be idiosyncratic and explicit constraints on search can be incorporated. A key notion is the restriction of search to points on the surfaces of hyperellipsoids. While the set of optimal locations is in reality an area, and a conservative estimation approach might seek an interior point, there is no loss in generality, and a substantial gain in efficiency by this assumption.

To overcome the computational complexity of their basic approach, GHS propose a number of heuristics which result in relatively short computation times. Four methods using line generation are described. The basic idea is that since one is able to verify if a line passes through a hyperellipsoid, and where its entry and exit points are, it is possible to find good intersection regions if one generates good lines. Note that the probability of a random line intersecting the optimal region will be affected by the region's size and that, as the number of existing products grows, one would expect that region to have an

increasingly smaller n_A-dimensional volume. On the recommendation of K. Srikanth (1981), we implemented their Method IV. It selects a starting "solution" by generating a "large number" of random points, and choosing the best one. A line is then drawn from the incumbent solution z to the point nearest it on the surface of the hyperellipsoid of each segment not captured by z. Each of these lines are searched, and, if a segment of any one of them yields an improvement, an end point of such a segment replaces the incumbent and the process repeats. The method starts by considering, for each pair of hyperellipsoids i and j, the point on the surface of i closest to the center of j and the point on the surface of j closest to the center of i.

The Simulation

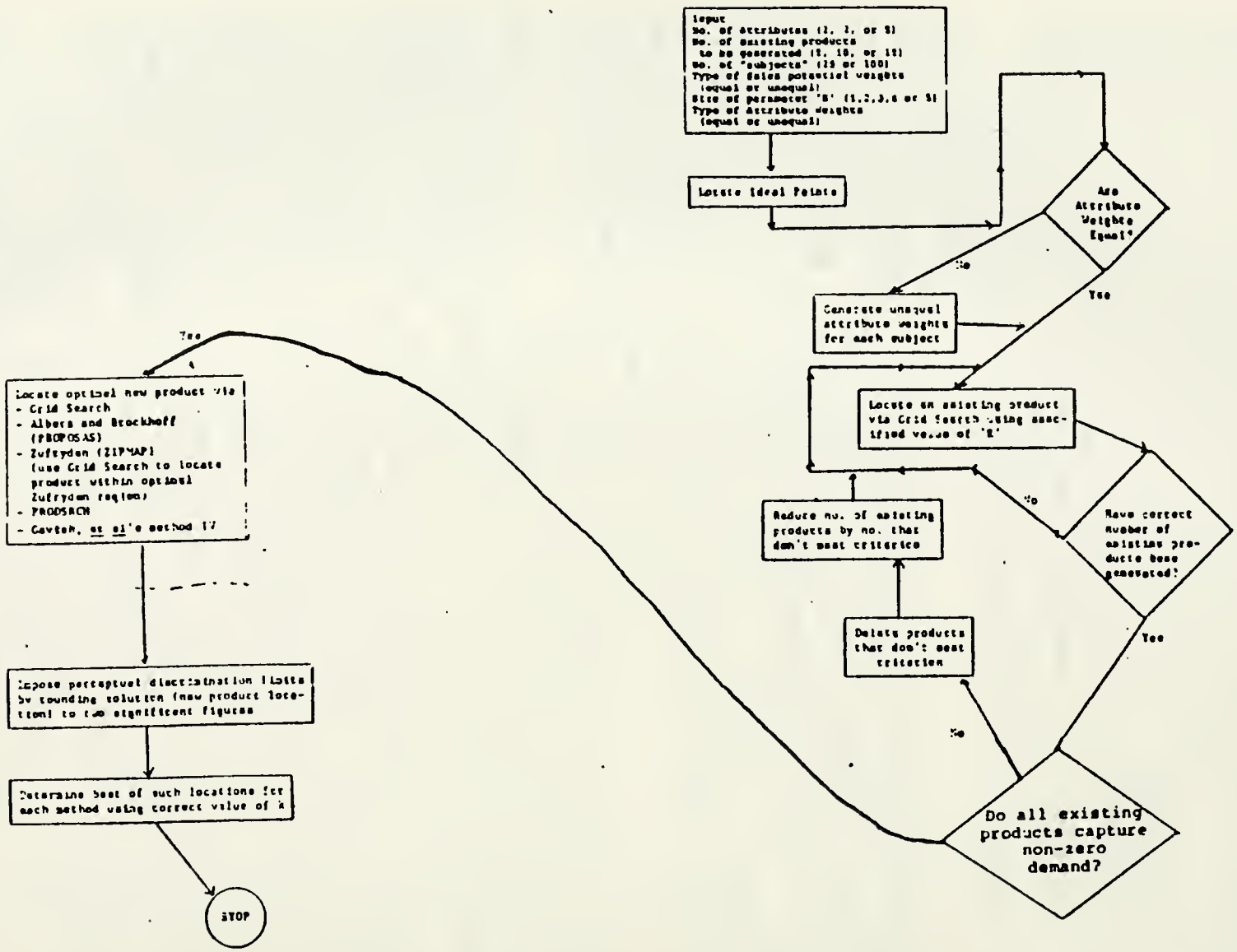
The problems of meaningfully comparing the several frameworks above (in terms of estimates of market behavior toward the new concepts generated) are not trivial given the paucity of published work reporting relevant empirical findings regarding market structure and behavior. Most applications of similar frameworks have been proprietary (Wind 1973; Green, Carroll, and Goldberg 1981) and, at best, report summarized results. We made reasonable assumptions to construct a market environment which comprised, approximately, the union of features suggested in the market models assumed by the other authors. A purpose of our simulation, which was also limited by our computer budget, was to investigate whether or not simplifications made to speed computation substantially affect the objective function value of

the ultimate new product location. For example, assuming equal attribute weights in decision models when in reality they are highly unequal is questionable, but it might be that in a market involving few products and many customers, the intersection regions for the two cases might not differ substantially. A flow diagram for this simulation is presented as Exhibit 2.

Insert Exhibit 2 about here

We presume a perceptual space of relatively low dimensionality, an assumption supported by cognitive limitations on human information processing capacity (Bettman 1979). Individuals are presumed to have simplified their decision-making by previously eliminating choice alternatives which lack important characteristics. Consequently, the alternatives which remain in the choice set may be similar in terms of their possession of significant characteristics. Those products which define the product class differ in terms of a relatively small number of attributes which can be traded off in the manner prescribed by the multi-attribute customer decision-models assumed above (Shocker and Srinivasan 1979). Two dimensions is the minimum assumed. A two dimensional solution is readily visualized and is consistent with several reported empirical studies (Johnson, 1971, Pessemier 1982). Since the search routines could behave differently in spaces of higher

Flowchart of Simulation



dimensionality, we also investigated spaces of three and five dimensions, the latter being consistent with generally accepted limits on human cognitive capabilities (Miller 1953).

Search occurs over an intervally-scaled region, with arbitrary limits of 1 to 10 on each attribute dimension - presumed to encompass the range of possible values for existing and ideal products. Interactions between attributes in this simulation had to be ignored since such constrained search could not be undertaken readily in conjunction with PROPOSAS or ZIPMAP.

Ideal points for individuals were located by generating the appropriate number of two digit numbers drawn from a high variance normal distribution ($\mu = 5.5$, $\sigma = 3$) defined over the region 1 - 10. While other distributions are plausible, the normal is consistent with the limited empirical evidence available (Kuehn and Day 1962, Day 1968).

We considered equal attribute weights as well as the unequal ones created by drawing from a normal distribution ($\mu = 5$, $\sigma = 2$) . The weights were normalized to sum to unity for any individual, since they can be only relative weights in empirical calibration using multiattribute modes (Shocker and Srinivasan 1974).

Since the various algorithms, including GRID SEARCH, treat perceptual spaces as continuous (although GRID SEARCH can be adapted to discrete spaces through choice of an appropriate grid structure), new product locations may be established to an arbitrary (and unimplementable) degree of precision. Kuehn and Day (1962), among others, developed models which acknowledged

limited human discriminal ability and accepted the notion that consumers cannot distinguish very small scale differences. Consequently, existing products were located by rounding any solution from grid search to two significant digits. Note that, alternatively, a grid could have been defined at "one-tenth of a unit" lattice points throughout the feasible region. Rounding was preferred since it was more generalizeable to other search algorithms, even though rounding could possibly change the optimal solution. Two significant digits were chosen to create a non-trivial search task (91^{n_A} possible product locations in n_A-dimensions). Problems were run to create small ($n_B = 5$), medium ($n_B = 10$) and large ($n_B = 15$) numbers of existing product alternatives, provided that each new product had to be closest to (capture the demand of) at least one customer.

The numbers of simulated customers was either small ($n_M = 25$) or large ($n_M = 100$). Under the "small" condition, it was assumed that each "customer" represented a different market segment. The segmented markets were represented in terms of unequal sales potentials according to an 80-20 rule (20% of the segments accounted for eighty percent of sales volume). Two normal distributions were created with equal variances but different means ($\mu_1 = 32$, $\mu_2 = 2$, $\sigma = 1$) and each segment was arbitarily assigned to one or another distribution according to a sampling rule (without replacement) which assured that 20% of the segment would have sales potentials drawn from the distribution with mean μ_1. Since all simulated markets were to be of the same aggregate size and since only relative size of each segment

mattered, the resulting draws were summed and the relative shares of market potential assigned to each segment were used in the simulation. Under the "larger" condition it was assumed that individual customers were being modelled, each of whom represented equivalent sales potential. This condition was similar to the conditions under which PROPOSAS, and Gavish, Horsky and Shirkanth has been tested (although some runs with as large as 500 simulated customers were reported by these authors, a limited computer budget precluded such here). The effect of different-sized markets and differing numbers of customers was not investigated in the present study. Rather, the focus was on the effect of equal and unequal weighting under circumstances that might have existed had the study been based upon market research results (although such studies often will have sample sizes larger than 100).

It appears reasonable to assume that existing products will be located at or near concentrations of demand rather than scattered randomly throughout the feasible region. Each simulated market is, consequently, constructed sequentially by locating an intial product at the centroid of ideal points and then adding new products one at a time until the desired number is obtained. A single Grid Search routine is used to construct the market. Each simulated market is constructed using the value for k (1 to 5) that will be used in the subsequent new product search. In this way a potential source of contamination is avoided (by having a different value of k used in searching for new product concepts than was used in constructing the market).

The simulation involves some 90 possible design combinations: three levels of existing products (5, 10, or 15); five values for k (1 to 5); three attribute space dimensinalities (2, 3, or 5 attributes); and equal or unequal attribute weights. Each search algoirthm was implemented insofar as fesible within each design configuration. Five replications of each design combination were undertaken. As noted above, each model can only be implemented in the design configuration appropriate to its capabilities (i.e., algorithms other than GRID SEARCH and PRODSRCH cannot deal with $k > 1$ and consequently k must equal unity in all such implementations). The solution reached by each algorithm was evaluated, however, in terms of the full design conditions (i.e., $k > 1$).

RESULTS

Results are reported separately for the "segmented" (small number ($n_M = 25$) of unequally weighted, simulated customers) and "non-segmented" (larger number ($n_M = 100$) of equally weighted customers) simulated markets. To explore the effects of the different search algorithms, we regressed the design characteristics of each simulated market (encoded as dummy variables) as well as the search algorithm used (also encoded as dummy variables) on a dependent variable termed relative preference share (RPS). Although the total demand available for capture by <u>all</u> competing brands (existing and new) was identical in each simulated market, the fraction of that demand available

for capture by a new product differed across these markets. This was so because such demand potential depends upon the specific "positions" of the existing brands relative to market desires (ideal points). Specific values for existing product and ideal point locations, specific attribute effects, and different segment sales potentials could not easily be incorporated into the analysis and thus it was deemed desirable to express the results of each simulation run in relative terms. None of the algorithms compared here can guarantee a globally optimal solution, so that the solution (share of demand) obtained by any algorithm (for the new product it located), was expressed relative to the highest value obtained by any algorithm. This dependent variable (relative perference share or RPS), consequently, is positive valued at unity or less.

Ordinary Least Squares (OLS) dummy variables regression (with intercept), was used as the principal means of analysis. Strictly speaking, OLS is inappropriate when the dependent variable is constrained. Given the large number of degrees of freedom involved in each analysis (which permits reference to the asymptotic properties of the estimates) and the well-known robustness of the OLS procedure, the conclusions drawn from such analysis appear reasonable. This assertion is further supported by results from the pooled regressions (discussed below) where fewer than 8 percent (segmented markets) and 0.3% (non-segmented markets) of predicted values lay "out of range."

Exhibit 3 indicates statistically significant regression coefficients for both the "segmented" (part a) and "non-

segmented" (part b) market conditions. The data from the simulation runs have been analyzed too ways, one in which the effects of all the explanatory variables are accounted for statistically (the so-called pooled regression model) and one in which the effects of each independent predictor (other than the search algorithm used) are mechanically held constant while the statistical relation between the remaining variables is examined (subset regression models). By holding constant the effects of each explanatory variable we can see more clearly how the performance of the different search algorithms varys with changes in each market specification parameter. Plots of t-statistic variation across the regressions associated with different levels of each parameter are shown in Exhibit 4. All regression equations are statistically significant ($\alpha < .01$).

Insert exhibit 3 about here

Referring to Exhibit 3, we see that significantly more variance is accounted for by the set of variables in the segmented market regression(s) (R^2 = 0.60 vs. 0.16). Moreover, differences in RPS (the dependent variable) between the search algorithms are more pronounced for the segmented markets. This can also be seen from the average RPS values (shown in Exhibit 5b). Since most search algorithms were specifically designed for

Exhibit 3
Overall and Subset Regressions

(A)
Segmented Markets
Regression Coefficients
(by Type of Simulated Market)

Regression Corresponding to Market Type	SAMPLE SIZE	Coefficients Corresponding to Dummy Variables P10	P15	K2	K3	K4	K5	DZIP (ZIPMAP)	DPROD (PRODSRCH)	DPROP (GHS)	DGHS (GHS)
Overall	2250	-0.124	-0.201	-0.094	-0.117	-0.131	-0.129	0.145	0.493	0.168	-0.137
		(-11.35)	(-18.39)	(-6.66)	(-831)	(-9.29)	(-9.18)	(-10.31)	(35.01)	(11.94)	(-9.74)
k = 1	450		-0.17	-	-	-	-	*	0.39	0.514	*
			(-6.6)						(11.72)	(15.44)	
k = 2	450	-0.172	-0.259	-	-	-	-	-0.176	0.515	0.193	-0.153
		(-7.58)	(-11.41)					(-6.01)	(17.56)	(6.61)	(-5.23)
k = 3	450	-0.141	-0.217	-	-	-	-	-0.192	0.499	0.076	-0.193
		(-6.42)	(-9.42)					(-6.81)	(17.65)	(2.7)	(-6.81)
k = 4	450	-0.127	-0.172	-	-	-	-	-0.184	0.524	*	-0.165
		(-6.16)	(-8.32)					(-6.89)	(19.66)		(-6.17)
k = 5	450	-0.125	-0.185	-	-	-	-	-0.162	0.536	*	-0.132
		(-5.79)	(-8.55)	-	-	-	-	(-5.82)	(19.25)		(-4.74)
Equal Att. Wt	1125	-0.103	-0.226	-0.097	-0.126	-0.15	-0.147	-0.144	0.495	0.14	-0.139
		(-6.89)	(-15.06)	(-5.02)	(-6.53)	(-7.76)	(-7.62)	(-7.43)	(25.62)	(7.26)	(-7.18)
Unequal Att. Wt.	1125	-0.145	-0.176	-0.091	-0.108	-0.112	-0.111	-0.147	-0.491	0.196	-0.136
		(-9.16)	(-11.15)	(-4.46)	(-5.3)	(-5.49)	(-5.46)	(-7.21)	(24.12)	(9.63)	(-6.66)
No. of Prod. = 5	750	-	-	*	-0.725	-0.016	0.101	-0.208	0.279	*	-0.208
					(-3.35)	(-.489)	(-4.66)	(-9.61)	(12.89)		(-9.59)
No. of Prod. = 10	750	-	-	-0.143	-0.159	-0.179	-0.172	-0.13	0.523	0.19	-0.106
				(-5.95)	(-6.62)	(-7.46)	(-7.15)	(-5.42)	(21.73)	(7.9)	(-4.42)
No. of Prod. = 15	750	-	-	-0.114	-0.12	-0.108	-0.115	-0.098	0.768	0.284	-0.098
				(4.71)	(-4.95)	(-4.46)	(4.77)	(-4.04)	(28.08)	(11.75)	(-4.06)
No. of Att. = 2	750	-0.087	-0.169	-0.121	-0.12	-0.148	-0.143	*	0.541	0.259	-0.087
		(-4.31)	(-8.41)	(-4.67)	(-4.64)	(-5.72)	(-5.51)		(20.86)	(10.01)	(-3.37)
No. of Att. = 3	750	-0.123	-0.176	-0.092	-0.119	-0.143	-0.151	-0.143	0.512	0.156	-0.106
		(-6.49)	(-9.28)	(-3.77)	(-4.86)	(-5.83)	(-6.18)	(-5.81)	(20.89)	(6.38)	(-4.31)
No. of Att. = 5	750	-0.162	-0.257	-0.068	-0.112	-0.102	-0.094	-0.248	0.427	0.089	-0.219
		(-9.58)	-0.37)	(-3.12)	(-5.13)	(-4.66)	(-4.29)	(-11.35)	(19.56)	(4.08)	(-10.04)

(8)

Non-Segmented Markets
Regression Coefficients
(by Type of Simulated Market)

Regression Corresponding to Market Type	SAMPLE SIZE	Coefficients Corresponding to Dummy Variables								
		P10	P15	K2	K3	K4	K5	DZIP (ZIPMAP)	DPROD (PRODSRCH)	DPROP (GHS)
Overall	1800	0.046 (7.131)	0.039 (5.988)	0.035 (4.259)	0.031 (3.7)	*	*	-0.02 (-2.719)	0.081 (10.865)	0.029 (3.847)
k = 1	360	*	*	-	-	-	-	0.068 (4.141)	*	0.179 (10.862)
k = 2	360	*	*	-	-	-	-	*	0.05 (3.817)	0.056 (4.24)
k = 3	360	*	-	-	-	-	-	*	0.087 (6.668)	*
k = 4	360	0.14 (10.623)	0.119 (9.017)	-	-	-	-	-0.046 (-3.005)	0.134 (8.8)	*
k = 5	360	*	*	-	-	-	-	-0.081 (-6.136)	0.109 (8.32)	-0.076 (-5.818)
Equal Att. Wt.	900	0.05 (5.408)	0.033 (3.596)	0.039 (3.272)	*	*	*	*	0.089 (8.351)	0.028 (2.63)
Unequal Att. Wt.	900	0.042 (4.659)	0.044 (4.892)	0.032 (2.739)	-0.031 (2.676)	*	*	*	0.0719 (6.982)	0.029 (2.811)
No. of Prod = 5	600	-	-	*	*	0.102 (-6.823)	-0.082 (-5.478)	-0.05 (-3.708)	0.113 8.411)	*
No. of Prod = 10	600	-	-	0.034 (2.791)	*	0.037 (3.027)	*	*	0.073 (6.741)	0.036 (3.33)
No. of Prod = 15	600	-	-	0.036 (2.614)	0.052 (3.8)	*	0.04 (2.914)	*	0.057 (4.603)	0.056 (4.555)
No. of Att. = 2	600	0.053 (4.803)	*	*	*	-0.042 (-2.899)	*	*	0.095 (7.435)	0.038 (2.959)
No. of Att. = 3	600	0.035) (3.112)	0.04 (3.586)	*	*	*	-0.04 (-2.725)	*	0.092 (7.132)	0.329 (2.562)
No. of Att. = 5	600	0.05 (4.657)	0.054 (5.009)	0.061 (4.405)	0.075 (5.431)	0.037 (2.694)	*	-0.078 (6.457)	0.055 (4.474)	*

Coefficients for Equal and Unequal Attribute Weights and for Number of Attributes were included inthe regressions, but were generally not significant ($\alpha < .01$)

*Coefficient insignificant for $\alpha < 0.01$

-not defined

t-atstiatic are in parentheses.

All regression equations were significant at the 0.01 level.

non-segmented markets, their similarity of performance in such cases is not surprising. Also the results for the Zufryden algorithm (a poor performer in the segmented cases) were not available for the non-segmented cases, thereby possibly further reducing variance in the dependent variable.

The magnitudes of the regression coefficients are more or less directly comparable since the factorial design used to generate "market conditions" is balanced. They are interpretable much as beta weights, since all predictors are dummy variables. The search algorithm used has the greatest effect on RPS followed by the number of products and size of consideration set (value of k). Equal or unequal attribute weights and the dimensionality of the attribute space do not appear to have significant effects upon the quality of solution obtained. Ex post, the first result seems plausible since the effect of different attribute weights is differentially to emphasize discrepancies on specific attribute dimensions. Random determination of such attribute weights for respondents whose ideal points are randomly distributed through the space should not tend to produce a systematic effect. One would expect all algorithms to perform less well in spaces of higher dimensionality, especially PRODSRCH, GRID SEARCH and the methods of Gavish, Horsky, and Srikanth (GHS IV), where difficulty in optimization is directly related to the dimensionality of the space.

Overall, PRODSRCH is the better performing algorithm. This result is undoubtedly due in large measure to its flexibility (it and GRID SEARCH are the only techniques which can accomodate all

parameter specifications). PROPOSAS is the second better performing in the case of segmented markets, again probably because it was able explicitly to consider unequal segment potentials. The method of GHS IV was second best for the case of non-segmented markets. Surprisingly, PROPOSAS drops to fourth behind GRID SEARCH in this less restrictive setting. ZIPMAP performed very poorly in the case of segmented markets and could not be included in the non-segmented market cases because it failed to converge in sufficiently few (e.g., 20) iterations to be implementable within our computer budget.

While these overall orderings of methods are informative, there are specific conditions where different results obtained. Exhibit 4 plots t-statistics associated with dummy variables representing each algorithm versus the parameter value held constant in the subset regressions of Exhibit 3. (The effect of plotting t-statistics rather than dummy variable coefficients is to emphasize differences in statistical significance.)

Insert Exhibit 4 About Here

Number of attributes. PRODSRCH remains the superior algorithm (relative to GRID SEARCH) as the dimensionality of the market increases (Exhibits 4a, b). PROPOSAS is second in the case of segmented markets whereas GHSIV is second in the case of

SEGMENTED MARKETS

NON-SEGMENTED MARKETS

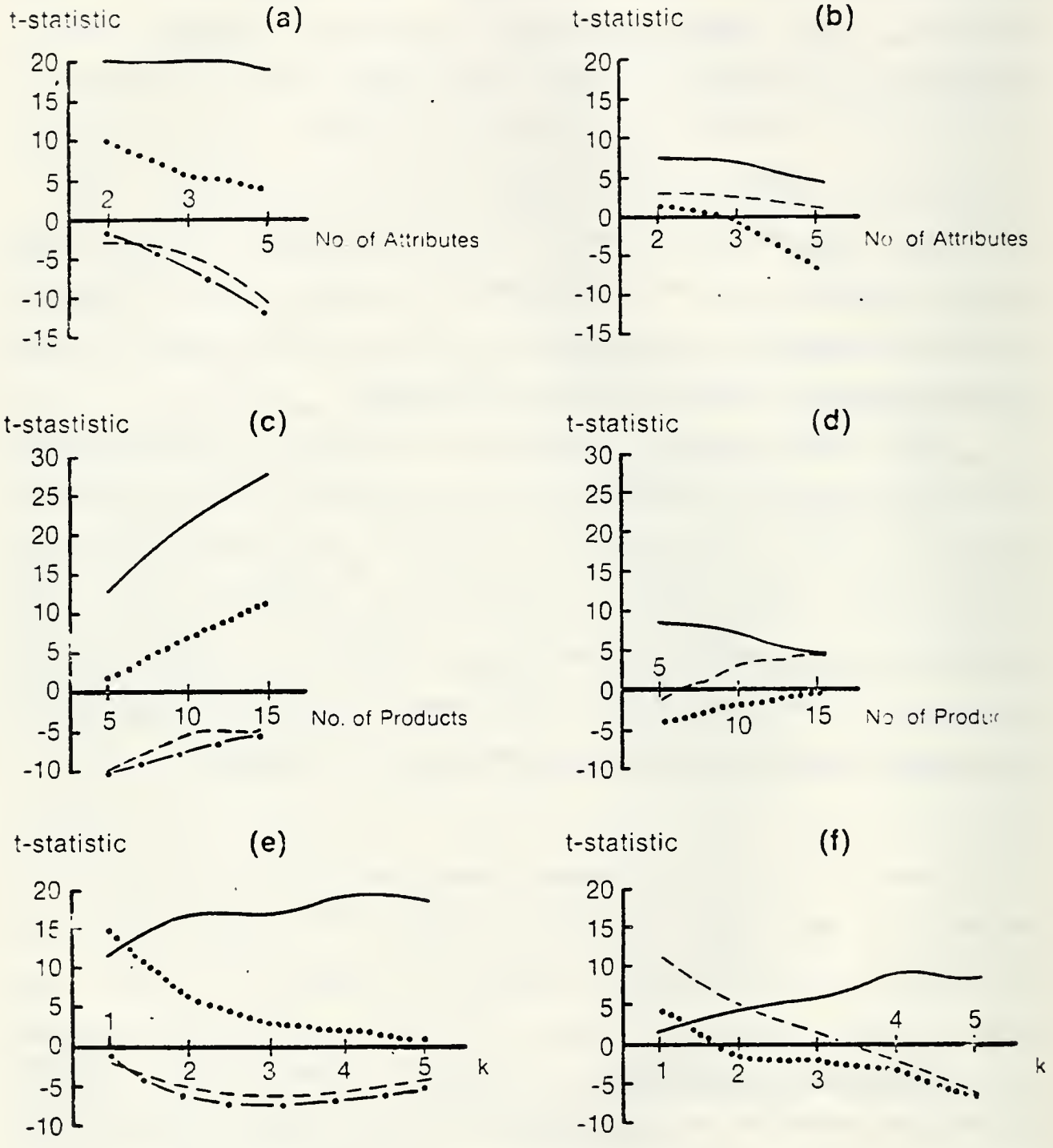


Exhibit 4
Plot t-statistic (relative to Grid Search) versus attribute level
(based upon subset regressions)

KEY:
——— PRODSRCH
– – – – – GHS IV
····· PROPOSAS
·—·—· ZIPMAP

non-segmented markets. All differences are statistically significant from GRID SEARCH (and each other). In the case of segmented markets, both GHS IV and ZIPMAP are inferior to and worsen relative to GRID SEARCH as the dimensionality of the space increases. In the case of non-segmented markets, PROPOSAS is statistically indistinguishable from GRID SEARCH in attribute spaces of low dimensionality ($n_A < 2$), but becomes significantly inferior as the dimensionality increases ($n_A > 3$).

Number of Products. All algorithms appear to improve relative to GRID SEARCH as the number of existing products increases (PRODSRCH diminishes in relative importance only in the case of non-segmented markets). Exhibits 4c, d show that PRODSRCH is again the better performing algorithm in both segmented and non-segmented markets. In the case of non-segmented markets, PRODSRCH becomes indistinguishable from GHS IV as the number of existing products increases ($n_B = 15$). As before, PROPOSAS is second best performing in the segmented market cases whereas GHS is second best in non-segmented markets. GRID SEARCH and PROPOSAS (segmented markets) and GRID SEARCH and GHS IV (non-segmented markets) are virtually indistinguishable in markets with small numbers of products ($n_B = 5$).

Size of Consideration Set. Perhaps the more interesting distinctions occur in relation to differences in size of consideration set (Exhibits 4e, f). When k = 1, PROPOSAS, which can incorporate unequal segment weights, is significantly the

better performing algorithm in the segmented market cases and GHS IV is in the non-segmented market cases. These are both special purpose algorithms designed specifically for the k = 1 condition and it is not surprising that they outperform PRODSRCH there. In the case of non-segmented markets, PROPOSAS also outperforms PRODSRCH under this condition. But all algorithms appear to worsen (relative to PRODSRCH) with increasing k.

A more detailed way of examining the simulation output is to note the micro-market configurations in which a given algorithm dominated (see Exhibit 5).

Insert Exhibit 5 About Here

Unlike the preceding analyses, "purified" algorithm effects are not isolated statistically (since average RPS alone is used as the basis for this Exhibit). The average RPS of the dominant algorithm in each cell ranged from 0.89 to 1.00. We note that PRODSRCH was the dominant algorithm in 131/180 = 73% of all simulated market types. Its lowest average RPS was 0.72 over all cases. GHSIV was next more dominant overall (26/180 = 14% of all market configuration types), but was never the dominant algorithm in segmented markets. For the non-segmented markets, it was

Exhibit 5

A. The Specific Algorithms Dominating Each Market Configuration

	Segmented Markets						Non-Segmented Markets					
No. of Products =	5						5					
No. of Attributes =	2		3		5		2		3		5	
Attribute Weight =	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.
k = 1 (PS)	PROP	(PROP)	(PROP)	(PROP)	(GHS)	GHS	(GHS)	(GHS)	(GHS)	(GHS)		
k = 2 (PS)	PS	PS	PS	PS	(PS)	(PS)	(GHS)	(GHS)	(PS)	(GHS)	(GHS)	
k = 3 (PS)	PS	PS	(PS)	(PS)	(PS)	PS	PS	PS PS	(PS)	PS		
k = 4 PS	(PS)	PS	PS	PS	PS	PS	(PS)	PS (PS)	PS	PS		
k = 5 PS	PS	PS	PS	PS	PS	PS	PS	PS PS	PS	PS		

No. of Products =	10						10					
No. of Attributes =	2		3		5		2		3		5	
Attribute weight =	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.
k = 1 PROP	PROP	PROP	PROP	PROP	PROP	(GHS)	GHS	PROP	(GHS)	GHS	(GHS)	
k = 2 (PS)	(PS)	(PS)	PS	PS	PS	PS	(PROP)	GHS (PS)	(PS)	(GHS)		
k = 3 PS	(PS)	(PS)	(PS)	PS	PS	PS	PS	(PS)	(PS)	PS	PS	
k = 4 (PS)	(PS)	PS	(PS)	PS	PS	PS	PS	(PS)	(PS)	PS	(PS)	
k = 5 PS	(PS)	PS	PS	(PS)	PS	PS	PS	PS PS	PS	PS		

No. of Products =	15						15					
No. of Attributes =	2		3		5		2		3		5	
Attribute Weight =	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.	Eq.	Uneq.
k = 1 (PROP)	PROP	(PS)	PROP	PROP	PROP	GHS	(GHS)	(PROP)	(PROP)	GHS	GHS	
k = 2 PS	PS	PS	(PS)	PS	PS	(PS)	GHS	(PS)	(GHS)	(GHS)	(GHS)	
k = 3 PS	PS	PS	PS	PS	PS	PS	(PROP)	(PS)	(PROP)	(GHS)	6S	
k = 4 PS	(PS)	PS	PS	PS	PS	(PS)	PS	PS (PS)	(PS)	PS		
k = 5 PS	(PS)	PS	PS	PS	PS	PS	(PS)	(PS)	(PS)	(PS)	PS	

Legend
- GS = GRID SEARCH
- PS = PROOSRCH
- PROP = PROPOSAS
- GHS = Method IV, Gavish Horsky Srikanth
- ( ) = The method produced highest average (n = 5) RPS (< .99)

Average RPS > .99

Exhibit 5
B. Mean and Range of Average RPS by Algorithm

Segmented Markets (algorithms listed in order of average RPS)

	PRODSRCH	PROPOSAS	GRID SEARCH	GHS IV	ZIPMAP
Mean	.959	.635	.469	.329	.324
Std. Dev.	(.102)	(.282)	(.269)	(.219)	(.239)
Range	(.72-1.0)	(.29-1.0)	(.07-.89)	(.09-.72)	(.06-.70)

Non-Segmented Markets (algorithms listed in order of average RPS)

	PRODSRCH	GHS IV	GRID SEARCH	PROPOSAS
Mean	.946	.894	.865	.845
Std. Dev.	(.095)	(.130)	(.106)	(.130)
Range	(.73-1.0)	(.61-1.0)	(.66-.99)	(.58-1.0)

(16/18 = 89% when k = 1). When k = 1, the range of average RPS for PROPOSAS is 0.87 - 1.00, mean = 0.98 (segmented markets) and 0.61 - 1.00, mean = 0.88 (non-segmented markets).

generally the dominant algorithm in cases where k = 1 (15/18 = 83%) and k = 2 (10/18 = 56%). The fact that it was the dominant algorithm for cases where k = 2 is significant in light of the fact that this algorithm does not incorporate probabilistic choice. Its lowest average RPS in the k = 1 or k = 2, non-segmented markets was 0.89. PROPOSAS was the third more dominant overall (22/180 = 12%), but was rarely dominant in non-segmented markets and never dominant in other than the k = 1 case for segmented markets (16/18 = 89% when k = 1). When k = 1, the range of average RPS for PROPOSAS is 0.87 - 1.00, mean = 0.98 (segmented markets) and 0.61 - 1.00, mean = 0.88 (non-segmented markets).

GRID SEARCH is generally the middle performer in both types of markets and was only once the dominant algorithm. It was a substantially better performer in non-segmented markets (although recall that differential segment weights were incorporated in this algorithm). ZIPMAP was only tested in segmented markets, where it consistently provided poor results.

DISCUSSION

The market manipulations which seemed to have the greater effect on relative results were the use of unequally weighted segments and the size of consideration set. Both these changes are related to statistically significant differences in the performances of GHS IV and PROPOSAS, particularly. The unequally

weighted segmentation is, of course, confounded with the number of customers (25 and 100) and thus a correct attribution should await further research where number of customers is varied under controlled conditions. Yet, it is plausible to expect that since the larger-sized problems are more complex, the apparent superiority of the GHS IV algorithm to PROPOSAS may generalize. PROPOSAS's superiority in the case of the smaller-sized problems may be traceable solely to its ability to incorporate unequal segment weightings.

Correct specification of the size of consideration set (and the related concept of probabilistic choice) seems important. Algorithms which assume $k = 1$ in a $k > 1$ world perform significantly less well in the study. Surprisingly, GRID SEARCH (which could explicitly consider the correct value of k) was markedly inferior to PRODSRCH in solution quality, resulting in an average RPS approximately 50% of that obtained by PRODSRCH (in segmented markets). GRID SEARCH was also outperformed by PROPOSAS, an algorithm which could not incorporate values of k different from unity. These observations may, of course, say more about our operationalization of GRID SEARCH, since by a suitable choice of fineness of grid one should be able to obtain a global optimum, albeit at a substantial cost in computational efficiency. Exhibit 4, in addition to providing plots of t-statistics versus parameter level, mirrors the direct effect of changes in RPS due to parameter changes. (This is so because the regression coefficient is interpretable as change in RPS in the

presence of each algorithm and the specific algorithm accounts for most of the explained variance). Exhibits 4e, f show declines for all algorithms (other than PRODSRCH) with increasing k. (A fact also confirmed by examination of average RPS directly, although these data are not reported here. GRID SEARCH remains approximately constant in average RPS for all values of k.). Sudharshan (1982) discusses several empirical methods for estimating the "correct" value of k and, using small samples, demonstrates the superior performance of PRODSRCH over GHS IV empirically.

PRODSRCH performs well in virtually all simulations. It is most often the better performer and rarely worse than second. It is statistically inferior to GHS IV and PROPOSAS only under the conditions for which those algorithms were specifically designed. Even when it is the second performer, its RPS is not substantially below the leader (Exhibits 4, 5b) a fact which was not always true for the other algorithms. Additionally, PRODSRCH offers considerable flexibility to the modelling process. We have already noted that only it and GRID SEARCH are able to consider probabilistic choice and employ linear constraints on search. But it is also easily able to be used with multiattribute decision models different from the ideal point model (e.g., vector, conjoint, mixed models), whereas the other algorithms (but again with the exception of GRID SEARCH) cannot. Nominally-scaled attributes can also be incorporated into the PRODSRCH framework.

ZIPMAP performed rather poorly in the segmented markets in which it was able to be tested. The algorithm was not, of course, specifically designed for such cases and perhaps this represents an unfair test. Further, we made use of a specific interior approximation (albeit one which was designed to maximize the volume of each hyperellipsoid contained therein, see Sudharshan (1982)). It is possible that different interior or exterior approximations would have resulted in superior outcomes. Yet one does not have the luxury of knowing whether the same such approximation will be suitable for all implementations of the methodology. The slow convergence of this algorithm, which we experienced, also may serve to discourage further experimentation with ZIPMAP.

FINAL REMARKS

The study has, despite some limitations, provided useful and needed comparisons of several of the more prominent algorithms for identifying promising new product possibilities. We have varied certain parameter specifications in an attempt to discover which elements of our market model are more critical to the performance of these different search algorithms. The more fundamental question which we hsve not answered is with respect to the realism and usefulness of the market model itself. Further research, particularly empirical research, is necessary to determine the adequacy of such models.

Products are represented as points in a common space spanned by determinant attributes. This assertion of a common space is one of operational simplicity since otherwise a single new product possibility would have to be identified simultaneously in some potentially large number of idiosyncratic market structures. These structures can be expected to vary across individuals because marketing actions by competing firms will be differentially perceived. Customers can have different familiarities or experiences with the existing product alternatives which can lead to variability in their perception. Perceptual measurement can introduce another source of error. Each of the product point locations in some hypothesized common perceptual space might better be considered as the centroid of some underlying perceptual distribution. High variance in such distributions may limit the usefulness of models of the sort we have been considering. A further complication is introduced by the fact that any new product discovered this way is also identified by a single point location. Actualizing such a location into a tangible product and marketing program remains the major problem for all approaches to new product development. Algorithms efficient enough to permit sensitivity analyses of their "optimal" solutions may offer a practical advantage.

The ideal point model can be criticized as too limiting a multiattribute model. Ideal points imply that some finite level of an attribute is optimal and greater or lesser quantities than this are less preferred, ceteris paribus. Some attributes may be

better regarded as features which are either present or absent and hence nominally-scaled (e.g., conjoint analysis, see Green, Carroll and Goldberg (1981)). Such complexities pose problems for several of the search algorithms considered here. Decision-modelling flexibility would appear to be a very desirable characteristic since the nature of relevant attributes and models of the preference/choice decision process should rightfully be an empirical question. The choices should vary with the product category and, perhaps, the skill and insight of the analyst.

Searches for "optimal" new product concepts may result in trival or obvious possibilities if such search is unconstrained. A high quality, low price alternative may be everyone's dream, but may also be impractical. Models which must ignore differential costs of development, manufacturing, and marketing may lead to less profitable real world solutions. If vector models of decision-making are incorporated into the objective function, an unconstrained model may also produce results which are not useful. Technical or economic logic may or may not be enough to enable managerial judgment to provide reasonable constraints. There are admittedly pragmatic problems in eliciting realistic constraints which do not preclude desirable solutions. There will also be limitations on the types of contraints (e.g., linear versus non-linear, continuous versus discontinuous) which can be considered by a given search algorithm. But the superior algorithm may well be the one with the greater flexibility in this regard.

Flexible algorithms such as the PRODSRCH or GRID SEARCH tested here and the POSSE package of programs (Green, Carroll, and Goldberg (1981)) would seem to afford the better opportunity for moving closer to solutions that prove desirable in that more complex reality we call real world markets. Such algorithms can better accomodate such reality while retaining their all important tractability. Further empirical testing of these frameworks and comparison with more conventional/traditional methods for generating new product ideas can only help to provide better understanding of the limits of their usefulness and of the possibilities they afford for better implementation of the marketing concept.

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