Optimizing Customer Mail Streams at Fingerhut

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Fingerhut mails up to 120 catalogs per year to each of its 7 million customers. With this dense mail plan and mailing decisions made independently for each catalog, many customers were receiving redundant and unproductive catalogs. To identify and eliminate this excessive operational expense, IBM and Fingerhut together developed an optimization system that selects the most profitable sequence of catalogs, called a mail stream, for each customer. With mail streams, Fingerhut makes better mailing decisions at the customer level, resulting in increased profits. Today, Fingerhut runs this application weekly to find the most profitable mail stream for each customer.

Fingerhut Companies, Inc. is one of the largest direct-marketing and online retailers in the United States. It has been a wholly owned subsidiary of Federated Department Stores, Inc. since March 1999. Federated acquired Fingerhut because of its core competencies: a proprietary customer database, its direct-marketing expertise, and a state-of-the-art information infrastructure. Fingerhut sells a broad range of products and services through direct-marketing channels—catalogs, telemarketing, and the Internet. Within its catalog operations, Fingerhut mails more than 340,000,000 catalogs annually to its 7,000,000 active customers. In 1998, Fingerhut had net revenue (gross revenue less returns, exchanges, and allowances) of approximately \$1.9 billion with a pretax income of \$55 million. Based in Minnetonka, Minnesota, Fingerhut and its subsidiaries employ approximately 10,000 people.

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MARKETING—SEGMENTATION
STATISTICS—CLUSTER ANALYSIS

The Problem

Traditionally, Fingerhut followed the standard marketing approach to managing customer contacts, choosing the best customers for each catalog. It calls this approach vertical marketing. Using a refined selection process, its systems considered thousands of customer attributes to make those decisions. But the result was that Fingerhut still wound up with separate decisions on each customer for each catalog, a classic case of data silos.

During the 1990s, Fingerhut dramatically increased the number of catalogs it produced and the number of catalogs it mailed. Between 1990 and 1995, Fingerhut added almost a catalog a week. Theoretically, a customer could receive 120 catalogs each year, and in fact, some of Fingerhut's best customers did.

As a result, Fingerhut started to see cannibalization or saturation between catalogs. Fingerhut considers a mailing *saturative* if it does not generate unique revenue. For example, if 80 percent of a catalog's revenue would have occurred had it not been mailed, that catalog is 80 percent saturative. Put another way, catalogs began siphoning off one another's revenue, decreasing the productivity of all catalogs. The data silos inherent in vertical marketing prevented Fingerhut from seeing how catalogs were affecting each other. The business problem was to identify and eliminate unproductive or saturative contacts without harming catalog revenues.

The Solution

Fingerhut turned to IBM's business intelligence consultants because of their expertise in horizontal marketing, an innovative approach to optimizing customer contacts. Together, Fingerhut and IBM formed a partnership to meet Fingerhut's business need. Fingerhut supplied the statisticians, direct-marketing expertise, and programming resources, while IBM brought the horizontal-marketing concepts and mathematical-optimization expertise. The seven authors led the team, all seven working for Fingerhut or IBM at the time of this project. The authors pulled in other technical experts from both Fingerhut and IBM, as needed.

The team developed a customer-selection system called mail-stream optimization (MSO) which focuses on the customer, not the catalog. MSO selects the most profitable mail stream for each customer while considering saturation, advertising limits, and catalog preferences. A *mail stream* is a set of mailings planned for the immediate future, typically over the next 12 weeks.

MSO chooses the best catalogs for each customer—not merely the best customers for each catalog. Mailing decisions are customer-centric and precisely coordinated between catalogs, and they explicitly address the saturation issue.

The MSO System

The MSO system consists of a number of steps (Figure 1).

The MSO scoring cycle begins with data. Fingerhut has a nine-terabyte warehouse that contains data on customers and catalogs, both of which are critical to MSO. Fingerhut has 3,000 customer attributes computed from purchase, mail, and payment histories, along with demographic information. In addition to the customer attributes are 100 catalog attributes, including numerous content and for-

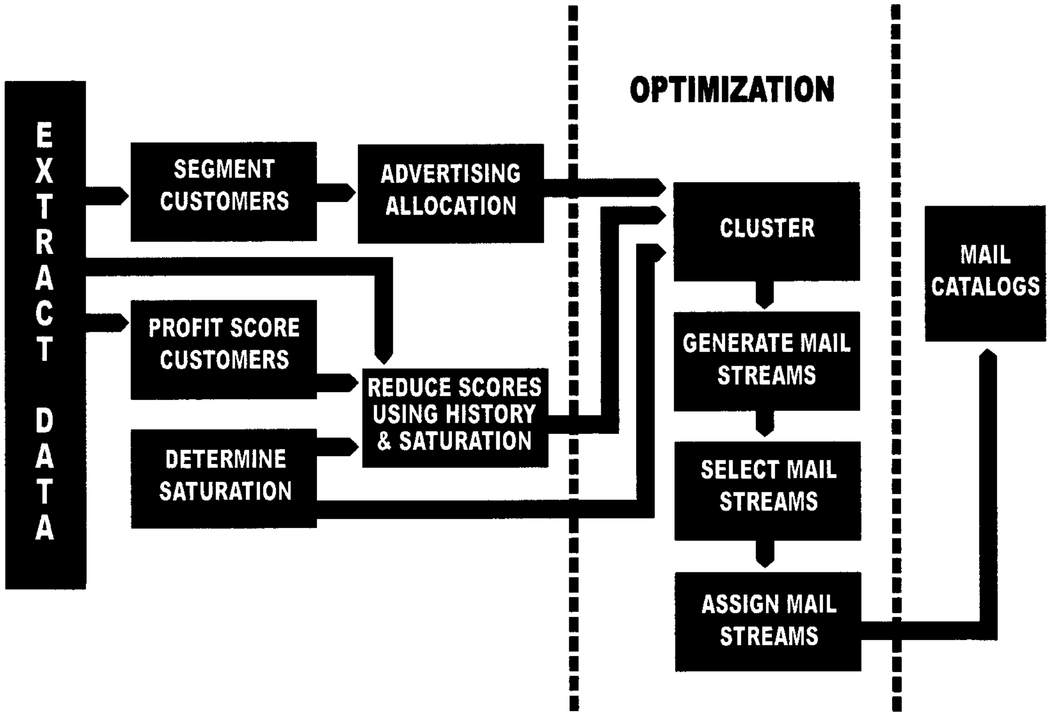

Figure 1: Fingerhut executes the MSO cycle weekly, extracting data, then building the components needed for the optimization process, and finally carrying out the optimization steps.

mat features to reflect exactly what each catalog contains.

Each week, Fingerhut extracts about 200 gigabytes of customer and catalog data from the warehouse and loads that information into MSO, which kicks off the MSO process.

The MSO System: Customer Segmentation

To assign appropriate advertising levels to each customer, Fingerhut uses homogeneous customer groups. Each group is similar in terms of projected customer value and advertising productivity. We explored data-mining techniques and other modeling techniques, to produce a combination of macro or high-level classes, and micro or low-level classes. Fingerhut uses two measures in defining macro classes: long-term customer value and length of time as a customer. For the micro classes, we use statistical prediction models to estimate customer value and advertising productivity over the next 12 months. In the customer segmentation step, Fingerhut partitions the 7 million customers into 100 micro classes.

The MSO System: Advertising Allocation

The team adapted asset-allocation techniques from financial applications to determine the amount to spend on advertising for each micro class. We applied the technique to Fingerhut's customer base in an effort to produce a portfolio of activities that would maximize return (net revenue) for the fewest advertising dollars, while constraining the portfolio to meet certain corporate and mailing objectives.

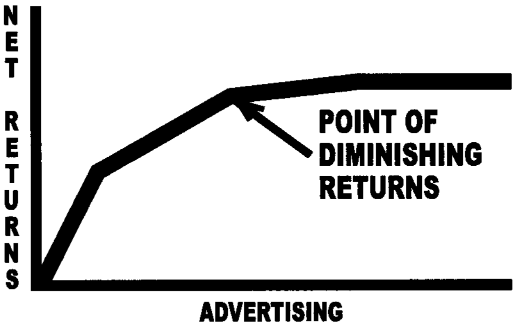

Figure 2: The risk/return curve is a piecewise linear concave function. After the point of diminishing returns, additional advertising expenditures yield little to no gain.

In the first step of advertising allocation, we create curves that describe diminishing returns for each micro class. These curves can be described as risk/return curves because they describe the relationship between the advertising spending (risk) and the revenue (net returns) attained through that spending. The challenge is to invest in advertising up to the point of diminishing returns (Figure 2). Past the point of diminishing returns, any level of continued spending yields little to no financial gain.

The risk/return-curve model fits a piecewise linear curve for each micro class to determine a best-fit line (Figure 2). We solve a linear program to find the lines that form the piecewise curve. We made the slopes of the piecewise linear curves nonincreasing to ensure concavity of the continuous function. To reduce the noise of the data, we first group data according to advertising dollars and then plot mean advertising cost and mean revenue per group (or *bin*). The properties of a piecewise linear curve make the advertising-allocation-optimization model quite tractable.

Once we complete the curves for all micro classes, we execute the second step in advertising allocation. We spread overall annual advertising budget across all micro classes using a linear-programming model. When building the optimal diversified portfolio of customer segments, the advertising-allocation model uses the risk/return curves and looks for slope changes to make investment decisions (that is, advertising budgets for each micro class). The result of advertising allocation is a set of lower and upper advertising constraints for each micro class.

The MSO System: Customer-Profit Scoring

Customer-profit scoring is vital to MSO. At this stage, Fingerhut uses a predictive model to score each customer for each catalog in the upcoming three months. We compute expected profitability as if the customer were to receive each individual catalog on its planned mail date.

The regression-based models behind customer-profit scoring were in place before we developed MSO, but we made two crucial enhancements. In the past, Fingerhut used segmentation solely to rank customers from best to worst. Now it predicts expected profit for each customer and catalog. Also, it now keeps scores at the individual customer level rather than rolling them up into broader segments. That means it can now use customer scores to compare customer performance, both within a single catalog and across multiple catalogs.

Fingerhut uses a combination of predictive models and marketing costs to compute each profit score. We use precise regression models to predict the customer's propensity to buy—and if they do, to calculate the purchase amount, probability of product return, and likelihood of payment. The profit score accurately predicts the dollars-and-cents income that can be expected if the customer receives a particular catalog. Fingerhut adjusts scores when a particular catalog's forecasted performance differs substantially from the performance for a prior mailing of that same catalog to ensure continued accuracy. The precision and comparability of those scores are what enable us to carry out the balance of MSO.

Fingerhut executes profit scoring every week, using updated customer and catalog data. Changes in a customer's behavior (making a purchase, making a payment, buying from a new product category, and so forth) are reflected in the weekly scores. Changes in a catalog's forecasted profit components are also reflected in the weekly scores.

The MSO System: Saturation

One of the keys to mail-stream optimization is the concept of saturation, that each catalog can affect all other catalogs in the mail stream. For the MSO application, the team modeled saturation by considering the pair-wise interactions of catalogs as they affect each other's revenue when they are mailed to the same customers. We combine these pair-wise interactions into a *saturation matrix*, labeling the matrix rows and columns with catalogs in mail-date order (Table 1). Each row of the saturation matrix represents a mailed catalog and each column represents an affected catalog. For example in Table 1, when catalog A is mailed, the revenue of catalog C is expected to decrease by five percent.

By working closely with Fingerhut's marketing department and conducting outside research with other firms, the team found that three major factors contribute to saturation:
—merchandising content,
—promotion and presentation features, and
—time between mailings.

Fingerhut has conducted mail tests that clearly indicate that the revenue lost to

		History			Current		Future Weeks			
		A	B	C	1	2	3	4	. . .	40
History	A	1.00	0.04	0.05	0.01	0.02	0.03	0.00		0.04
	B	0.02	1.00	0.01	0.03	0.04	0.01	0.00		0.02
	C	0.04	0.03	1.00	0.05	0.02	0.03	0.00		0.03
Current Week	1	0.05	0.03	0.02	1.00	0.01	0.04	0.00		0.04
	2	0.03	0.04	0.05	0.03	1.00	0.04	0.00		0.05
Future Weeks	3	0.02	0.01	0.03	0.02	0.02	1.00	0.00		0.01
	4	0.00	0.00	0.00	0.00	0.00	0.00	1.00		0.00
	. . .									
	40	0.02	0.04	0.01	0.03	0.05	0.02	0.00		1.00

Table 1: Each saturation matrix entry represents the percent of revenue taken away from each affected catalog (across the top) when one catalog (down the left-hand column) is mailed. For example, when catalog A is mailed, the revenue of catalog C is expected to decrease by five percent.

saturation increases when it mails catalogs with similar merchandise or similar features fairly close together in time; the more time between the catalogs, the less the saturative impact.

To model saturation, the team developed *similarity matrices* to represent catalog's similarity to each other with respect to merchandise content and promotional or presentation features. We developed a series of regression models to combine merchandise-similarity measures and promotional- and presentation-similarity measures to produce an overall similarity measure. The dependent variable came from Fingerhut's data warehouse. For each pair of catalogs, we calculate the total revenue of products that are common to both. This common revenue represents the maximum revenue that one catalog would gain should the other not be mailed. The resulting regression models produce a predicted similarity matrix, which represents the maximum saturation that could occur should the catalogs be mailed on the same day. We then use the timing matrix as a discount factor against the predicted similarity matrix to calculate the final saturation matrix. In equation form, the saturation matrix is

$$\text{Saturative effect (A,B)} = [\text{time effect (A,B)}] * [\text{similarity (A,B)}].$$

Time effect (A,B) is the discounting factor due to time, as a function of the days between mail dates and the respective shelf lives. Similarity (A,B) is a weighted combination of the merchandise- and promotion-similarity matrices.

If either of the two factors equals 0, then the saturative effect equals 0, matching business expectations and requirements. If both factors are 1, the saturative effect equals 1, the outcome of mailing the exact same catalogs to the customer on the same day.

We validated the final matrix by calling on the domain expertise of the Fingerhut marketing department and using data from previous saturation mail tests. We gave Marketing access to the saturation matrix through a *saturation lever*, a coefficient to the saturation matrix that Marketing can use to increase or decrease the saturative impact in choosing mail streams.

In addition to helping Fingerhut to identify the most profitable mail streams, the saturation matrix provides it with information for constructing the overall mail plan. Row sums represent the percentage of revenue that a catalog took away from all other catalogs in the mail plan. Column sums represent the percentage of revenue that a catalog lost to all other catalogs in the mail plan.

The MSO System: Reducing Scores Using History and Saturation

Next, we saturate or discount customer profit scores based on the catalogs a customer has received in the past three months. We use the saturation matrix to discount the profit scores, based on each catalog received in the past three months paired with each catalog in the upcoming three months. For example, if a customer received a jewelry catalog last week, that customer's score for the jewelry-catalog mailing next week would be discounted heavily. The result of this step is a stream of historically saturated profit scores for each customer and each catalog in the upcoming mail plan.

The MSO System: Optimization

In the optimization phase, we assign the most profitable set of mail streams to customers while enforcing a variety of budget, management, and technical constraints. Using the building blocks from the previous steps, we solve the optimization problem in four steps.

(1) We cluster customers to produce a tractable optimization problem.

(2) We solve an optimization problem for each cluster, generating potential mail streams, given advertising constraints.

(3) We solve a global optimization problem to find the best allocation of mail streams across all customer clusters.

(4) We translate the cluster-level solution to the customer level.

The MSO System: Clustering

It became evident during prototype testing that optimizing over the entire problem (7 million customers and 30 to 50 catalogs) was infeasible given the computational restraints of even state-of-the-art computers. The problem has 2^n binary (mail/no mail) variables, where n is equal to 280 million (7 million customers times 40 catalogs). To address this obstacle, we execute a clustering step to bring the problem down to a manageable size.

We form clusters within micro classes, which are already homogeneous with respect to customer value and advertising productivity. We use each customer's stream of historically saturated profit scores, corresponding to the stream of future mailings, in the clustering step. The goal is to group like customers together in clusters, since Fingerhut will treat all customers within the same cluster in an identical manner. With clustering, we reduce the problem size to 2^n binary (mail/no mail) variables, where n is equal to $40z$ (40 catalogs times z clusters). The number of clusters within each micro class has been set at 20 since MSO implementation, yielding about 2,000 clusters or 80,000 binary variables to solve simultaneously.

Fingerhut aimed to reduce advertising expense by eight percent.

The clustering technique employed had to run both efficiently and with no intervention. IBM consultants developed a customized clustering algorithm meeting both criteria. The algorithm uses the fundamental MSO equation, Equation (1) in the appendix, based on the optimal mail stream for each cluster.

We outline the clustering steps:

Assume there are N catalog scores for each customer.

Assume M is the desired number of clusters.

(1) Randomly select M customers to be the initial cluster centers.

(2) For each cluster center, determine the optimal mail stream based on the advertising budget for that micro class.

(3) Assign to the cluster the remaining customers whose optimal streams are most profitable according to their N catalog scores.

(4) Determine the new cluster center by computing the average catalog score across all customers assigned to that cluster for each of the N catalogs.

(5) Check the stopping criteria: number of iterations, overall profit changed by less

than x percent, cluster-center optimal streams unchanged.

(6) If we meet none of the stopping criteria, go back to step (3); otherwise stop.

At the end of the clustering step, customers have been grouped into clusters, with each cluster having an associated stream of historically saturated profit scores.

The MSO System: Generating the Mail Streams

In the optimization process, we employ a column-generation mathematical-programming-based approach, consisting of two steps: In mail-stream generation (MSG), we create good candidate mail stems for each cluster independently. Next, in mail-stream selection (MSS), we perform a constraint-based global optimization across all mail streams generated in MSG.

In the MSG optimization step, we generate a set of candidate mail streams for each cluster, using customer profit scores, the saturation matrix, and catalog advertising costs. The MSG optimization is designed to solve the following problem:

Given

(1) advertising costs for each catalog,

(2) the saturation matrix,

(3) expected profit for each catalog within each cluster, and

(4) the total advertising budget for each cluster,

select the most profitable mail stream without exceeding the budget (Appendix).

By selecting a range of advertising budget values and solving the MSG optimization problem for each budget value, we can generate a good set of candidate mail streams for each cluster. Each candidate mail stream is optimal with respect to the corresponding advertising budget. The user controls the number of candidates generated; since the MSO implementation at Fingerhut, the number of candidates has been set to 10.

The MSO System: Selecting Mail Streams

In generating mail streams, we make the best decision for each cluster, and in mail-stream selection (MSS) we make the best global decision by considering all clusters and cross-cluster constraints. In the MSS

It is directly responsible for a \$3.5 million annual profit gain.

optimization step, we incorporate the candidate mail streams for each cluster generated during MSG, add a variety of budget, management, and technical constraints, and produce a promotional plan that maximizes profit across the enterprise.

To understand how the MSS model works, it helps to recall the customer segmentation and clustering hierarchy. We first form micro classes by segmenting customers based on value and advertising productivity and then form homogeneous clusters within each micro class based on the customer-profit scores of various mail streams. For each cluster, the MSG optimization step produces a set of advertising-based candidate mail streams. MSS finds the optimal mail stream for each cluster. MSS does not specify the mail stream for each individual customer in a cluster but rather how to cover the cluster using the candidate mail streams. Since clusters are considered homogeneous (that is, cluster members are indistinguishable), the actual assignment of mail streams to customers in a cluster is an operational detail we did not model in MSS. Instead, we handle assignment in the next step, mail-stream assignment (MSA).

The MSS optimization formulation includes the following constraints on the selection of candidate mail streams:

—Catalog advertising constraints, which insure that the aggregate advertising cost over all customers does not exceed the budget for each catalog;

—Micro-class advertising constraints, which insure that advertising expenditures for each micro class fall within the bounds determined during the advertising-allocation step;

—A cluster-covering constraint, which ensures that every customer in a cluster receives a mail stream; and

—The total advertising constraint that can be imposed by management, particularly for what-if analyses to determine the effect of overall cuts or increases.

The MSS objective function is to maximize the total profit across the enterprise; MSS optimizes across all customer clusters and all catalogs. To ensure a feasible solution, we used variable upper bounding with penalties in the objective function, with the highest penalty assigned to the cluster-covering constraint. We did this because the MSO system runs in a production environment, and it must produce a final solution. Infeasibility is not an option, and every customer cluster must get a mail stream (Appendix).

The MSO System: Assigning Mail Streams

In mail-stream assignment (MSA), we translate the cluster-level results from MSS back to the customer level. We assign each customer in a particular cluster the optimal mail stream for that cluster. This creates an actionable file, including mail flags for each customer and each catalog in the upcoming mail plan. Fingerhut uses this information in its selection process for each catalog.

The Mail Test

Fingerhut consistently tests new mailing approaches, and with a system of this size and importance, we definitely needed to test before implementation. For the mail test, we randomly chose test and control groups from our entire list. Each group consisted of 10 percent or 700,000 individuals. The control group received mailings according to the traditional vertical-marketing methods. The test group received fewer, more appropriate mailings as a result of MSO. The goal was to remove 70- to 80-percent-saturative mailings with an acceptable reduction in revenue. In particular, Fingerhut aimed to reduce advertising expense by eight percent with a revenue decrease of at most 1.6 percent. We monitored mailing results throughout the test, then totaled each group's actual advertising expense and revenue performance.

Overall, advertising costs for the test group fell six percent with just a 1.5 percent loss in revenue. More important, the test group actually generated a two-percent profit gain, which meant we had boosted profitability on slightly lower revenue—precisely what we'd sought to achieve. MSO had eliminated mailings that were over 82-percent saturative.

MSO proved to be effective for all cus-

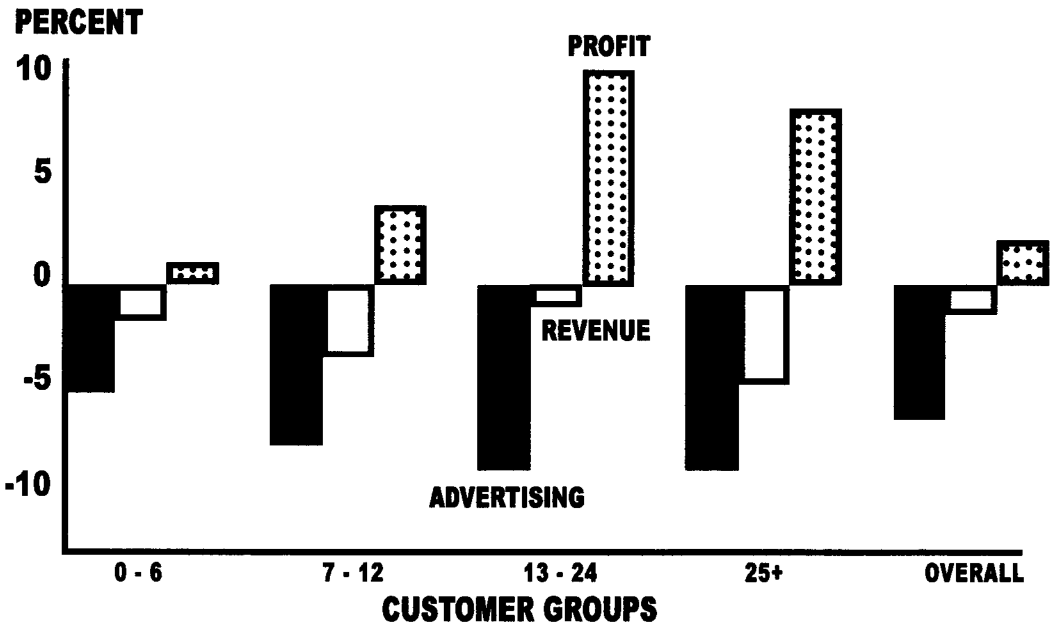

Figure 3: Mail test results are plotted for four customer groups (defined by months since the customer's last purchase) and overall. MSO is most effective for customers who made their last purchases 13 to 24 months earlier.

tomer groups, particularly for those who made their last purchase 13 to 24 months earlier (Figure 3). Based on these results, Fingerhut fully launched its MSO system in September of 1998, applying the MSO process weekly to all existing customers.

Implementation

MSO now runs weekly, considers six months of catalogs, and completes in fewer than 12 hours. The system solves 10,000 integer-programming problems and one 20,000-variable linear-programming problem. It runs on an IBM SP2 with four CPUs, using IBM's OSL software to solve the optimization problems. Customer-profit scores and the saturation matrix are computed with SAS; parallelization is managed by Torrent System's Orchestrate software; and any code gaps are filled in with C.

Impacts

Mail-stream optimization replaced a product-centric marketing process with a customer-centric process, with significant payback quantitatively and qualitatively. MSO unquestionably is generating quantifiable benefits for the Fingerhut catalog and, by extension, for Fingerhut Companies overall. It is directly responsible for a \$3.5 million annual profit gain, a very significant figure for Fingerhut. Given its return on investment, the project paid for itself within the first year.

Meanwhile, a second MSO system, which also runs weekly, generates mail streams for another one million newly acquired customers. This consists of customers who have made one purchase but have not yet paid for their orders. The goal is to control advertising and risk while choosing appropriate catalogs to boost response. Based on the first project's success, we put the second system directly into production rather than spending time on another test. In the first 15 months the system has been in operation, new-customer response rates are up more than 20 percent.

MSO's qualitative benefits for Fingerhut are just as significant as its impact on the bottom line. We expect customer satisfaction and retention rates to rise as customers receive fewer, more appropriate catalogs. As a result, Fingerhut will be far more able to nurture the customer relationships that are crucial in its industry. MSO introduced Fingerhut to fresh operations research tools and techniques that its analysts are using to create other successful, optimization-based applications. MSO is also promoting a cultural shift within Fingerhut, moving it into a customer-centric management philosophy that promises to be self-reinforcing as MSO produces greater and greater results.

The project paid for itself within the first year.

Favorable press coverage of MSO has reinforced Fingerhut's direct-mail leadership. MSO won the NCDM (National Center for Database Marketing) Award for Excellence in 1999. Fingerhut and IBM speakers have discussed MSO and related topics at numerous conferences. People are very interested in a real, live, tried-and-true method of building customer relationships.

Fingerhut is currently working to apply MSO concepts to prospective customers and inactive customers. Fingerhut plans to expand the concepts of MSO to all outbound marketing channels, including e-commerce, telemarketing, and third-party marketing contacts. The current MSO optimizes 840 million customer contacts every year; Fingerhut corporate MSO will broaden the scope and optimize 1.4 billion contact decisions each year. Federated's vision is to leverage MSO across its businesses, beginning with Fingerhut and expanding to all Federated companies, channels, and brands.

Conclusion

With MSO and its successors, Fingerhut is leading database marketing into the new millennium. The MSO concept is evolving from optimizing mail streams to eventually optimizing all marketing channels simultaneously.

To outline how MSO fits into its vision of the future, Fingerhut has characterized five revolutions of contact optimization:
(1) RFM (recency, frequency, monetary value) segmentation in which Fingerhut used a few basic customer-data elements to choose customers to contact for a given single marketing event;
(2) Customer Profit Scoring in which it used all available customer data to choose customers to contact for a single marketing event;
(3) MSO in which Fingerhut uses all available customer and catalog data to choose the optimal marketing events for each customer;
(4) Corporate MSO in which it will use all available customer and catalog data to choose the optimal marketing events among all channels and all businesses for each customer; and
(5) Infomediary through which Fingerhut

will use all available customer, catalog, and product data to optimize the personalization of business- and customer-initiated touch points.

Fingerhut is currently building MSO systems for several of its internal businesses and subsidiaries. It plans to bring the individual MSO processes into a central, corporate MSO and finally to fulfill the infomediary vision.

APPENDIX

Advertising Allocation Problem: Risk/Return Curves

The linear-programming model described below is for one micro class; the model is solved once for each micro class.

Sets

$I = \{i\}$ number of bins (determined by a previous step).

$J = \{j\}$ linear pieces that make up the risk/return curve.

Parameters

R_i mean net revenue received in bin i.

l_j left end point of the jth linear piece.

Variables

a_j slope of the jth linear piece.

b_j y-intercept of the jth linear piece.

$d_{i,j}^{+}$ represents the positive deviation of ith "observed" bin point from the jth linear piece.

$d_{i,j}^{-}$ represents the negative deviation of ith "observed" bin point from the jth linear piece.

Constraints

The deviation between the observed bin points and the best-fit piecewise linear curve,

$$d_{ij}^{+} + d_{ij}^{-} = R_i - l_j a_j - b_j.$$

Enforce the slopes of consecutive linear pieces (from left to right) to have nonincreasing slopes,

$$a_i \geq a_{i+1} \quad \forall i.$$

Enforce consecutive linear pieces (from left to right) to be continuous or joined, that is, there are no breaks in the piecewise linear curve,

$$l_j a_{j-1} + b_{j-1} = l_j a_j + b_j \quad \forall j.$$

Objective

Minimize the sum of the positive and negative deviations from the observed bin points,

$$z = \sum_{ij} (d_{ij}^{+} + d_{ij}^{-}).$$

This math program provides the best-fit piecewise linear curve for each micro class individually. When the curves from all micro classes are complete, we have the means to globally determine the optimal allocation of advertising spending.

Problem: Advertising Allocation

We solve a linear program, where constraints are the risk/return curves and the objective function is to maximize net revenue. The result of this step is the optimal advertising bounds for each micro class.

Sets

$I = \{i\}$ micro classes from above.

$K^i = \{k\}$ linear pieces that make up the risk/return curve for micro class i.

Parameters

$r_{i,k}$ right end point of the kth linear piece of the risk/return curve for micro class i.

$r_{i,o}$ right end point of the first linear piece of the risk/return curve for micro class i.

$a_{i,k}$ slope of the kth linear piece of the risk/return curve for micro class i.

b_i y-intercept of the first linear piece of the risk/return curve for micro class i.

P_i population of micro class i.

$\underline{B_i}$ lower bound on the advertising to be allocated to micro class i.

$\overline{B_i}$ upper bound on the advertising to be allocated to micro class i.

B overall advertising to be allocated across all the micro classes.

Variables

$X_{i,k}$ per-micro class i advertising spent in the kth linear piece.

S_i per-person net revenue from micro

class i.

Constraints

This constraint calculates the per-person net revenue generated by the optimal solution for each micro class i,

$$S_i = \sum_k a_{i,k} X_{i,k} + b_i \quad \forall i.$$

Enforce the per-person advertising variables to be bounded above by the incremental spending available in the kth linear piece,

$$X_{i,k} \le r_{i,k} - r_{i,k-1} \quad \forall i, \text{ and } k \in K^i.$$

Enforce consecutive linear pieces (from left to right) to be continuous or joined, that is, to insure there are no breaks in the piecewise linear curve,

$$\sum_{i \in J} \sum_{k \in K^i} x_{i,k} * P_i + r_{i,0} \le B.$$

Enforce the lower bound on the advertising spent in micro class i,

$$\sum_{k \in K^i} x_{i,k} + r_{i,0} \ge \underline{B_i} / P_i \quad \forall i.$$

Enforce the lower bound on the advertising spent in micro class i,

$$\sum_{k \in K^i} x_{i,k} + r_{i,0} \le \overline{B}_i / P_i \quad \forall i.$$

Objective

Maximize the sum of the net revenue generated by all of the micro classes,

$$z = \sum_i P_i s_i.$$

At the end of the optimization model, the results are displayed in a Microsoft Access database. The user can review results and insights provided by the model. The micro-class bounds can be updated (the initial bounds are set at the observed historical minimums and maximums), the model rerun, and the results compared with user knowledge and corporate advertising spending plans.

Mail-Stream Generation (MSG)

Formally, the mail-stream-generation (MSG) optimization problem is

$$\text{Max } z = \sum_p (R_p - E_p) y_p - \sum_{p,p'} R_p S_{p,p'} \, y_p y_{p'} \qquad (1)$$

such that, $\Sigma_p E_p y_p \le B$

where

R_p expected profit for catalog p from customers in micro class,

E_p expense (advertising cost) of catalog p,

$S_{p,p'}$ saturative effect of catalog p on catalog p',

B advertising budget limit for cluster,

y_p to be computed: 1 if catalog p is included in the mail stream, 0 otherwise, and

z to be computed: the expected profit from the resulting mail stream.

Mail-Stream Selection (MSS)

Given the candidate mail streams for clusters generated by MSG and various budget information, MSS performs a profit-maximization optimization over all customer clusters and catalogs.

Indices

$P = \{p\}$ set of catalogs.

$K = \{k\}$ set of customer micro classes.

$J^k = \{j\}$ set of clusters in micro class k.

$M^{k,j} = \{m\}$ set of candidate mail streams for cluster j in micro class k.

Decision Variable

$x_m^{k,j}$ number of customers in micro class k, cluster j to receive mail stream $m \in M^{k,j}$.

Data

$\overline{Q}_p$ upper limit on the number of catalogs p to be mailed.

$\underline{Q}_p$ lower limit on the number of catalogs p to be mailed.

$C_{p,m}^{k,j}$ 1 if catalog p is in candidate mail stream m for micro class k, cluster j; 0 otherwise.

$\overline{A}^k$ upper limit on the advertising budget for micro class k.

$\underline{A}^k$ lower limit on the advertising budget for micro class k.

$F_m^{k,j}$ cost of sending mail stream m to a customer in micro class k, cluster j.

$V^{k,j}$ number of customers in micro class k, cluster j.
$\overline{T}$ upper limit on overall advertising budget.
$\underline{T}$ lower limit on overall advertising budget.
$G_m^{k,j}$ expected profit for sending mail stream m to a customer in micro class k, cluster j.

Constraints

Catalog size (budget) constraint:

$$\underline{Q}_p \leq \sum_{k,j,m \in M^{k,j}} C_{p,m}^{k,j} \, x_m^{k,j} \leq \overline{Q}_p \quad \forall p \in P.$$

Micro-class advertising-budget constraint:

$$\underline{A}^k \leq \sum_{j,m \in M^{k,j}} F_m^{k,j} \, x_m^{k,j} \leq \overline{A}^k \quad \forall k \in K.$$

Cluster mailing requirement (cover) constraint:

$$\sum_{m \in M^{k,j}} x_m^{k,j} = V^{k,j} \quad \forall k \in K,\ j \in J^k.$$

Total advertising-budget constraint:

$$T \leq \sum_{k,j,m \in M^{k,j}} F_m^{k,j} \, x_m^{k,j} \leq \overline{T}.$$

Objective of the optimization is to maximize total profit:

$$\text{Max} \sum_{k,j,m \in M^{k,j}} G_m^{k,j} \, x_m^{k,j}.$$

The following is an excerpt from the presentation given on May 6, 2000 at the Franz Edelman competition, by Richard Tate, President, Fingerhut Catalog, 4400 Baker Road, Minnetonka, Minnesota 55343: "In collaboration with IBM, Fingerhut has created a contact management system that is extremely successful and truly revolutionary. Instead of focusing on individual marketing efforts, MSO's innovative design allows Fingerhut to manage customer contact strategies over multiple advertisements. Mail Stream Optimization is leading the company to more efficient and effective customer relationship marketing, an essential element of success in the new millennium."