A MULTI-OBJECTIVE OPTIMIZATION APPROACH USING THE RFM MODEL IN DIRECT MARKETING

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ABSTRACT

Given the vast amount of data generated by customers' online and offline purchases, many organizations today are turning to data analytics to help design their direct marketing campaigns and introduce personalized promotions for customers. Data analytics allows companies to implement more effective market segmentation strategies, customize promotional offers, allocate marketing resources efficiently, and improve customer relationship management. The implementation of such strategies is often hampered by limited budgets and the ever-changing priorities and goals of marketing campaigns. This paper suggests and demonstrates the use of a goal programming approach to determine which customer segments should be targeted to achieve profit maximization given various priorities and budget constraints for a hypothetical direct marketing campaign. Using historical data, the proposed model identifies customer segments based on the classic RFM model—i.e., recency, frequency, and monetary value profiles. Then, considering different marketing priorities, the goal programming model helps identify the profile segments most worthy of pursuit. Real marketing data are used to illustrate the proposed approach.

Keywords: Multi-Objective Programming, RFM, Direct Marketing, Data Analytics

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INTRODUCTION

Direct marketing is all about customer data: their characteristics, their buying habits, and their buying potential. Data is obtained from many sources, including internally generated data, public databases, and third party list vendors. The widespread use of data analytics by many direct marketing firms allows them to use this customer data to fine-tune their marketing strategies with precision and accuracy. Data analytics involves the strategic and extensive use of data and quantitative analysis to improve business decision making (Davenport and Harris, 2007, 2010). Customer data and data analytics are especially important in direct marketing because they are used to help firms improve response rates, conversion rates, and campaign profitability (Davenport and Harris, 2007; Dyer, 2003; Hambleton, 2013).

One particular analytical tool used frequently in direct marketing is the RFM model. The recency-frequency-monetary value (RFM) framework leads to highly effective direct marketing campaigns by enabling companies to categorize customers into homogenous segments based on their previous purchasing behavior and then design highly customized promotional campaigns to reach those customers. According to this approach, customer data on the recency of purchase (R), frequency of purchase (F), and monetary value of purchase (M) are captured and stored for each customer. Then, customers with similar values are grouped together, and targeted promotional offers are created to reach them. For example, if a given customer segment shows a low value for recency and relatively high values for frequency and monetary value, these customers are typically approached with a "we want you back" marketing strategy. If a given customer segment shows a low monetary value and high values for frequency and recency, a more relevant "up-selling" marketing strategy could be designed to generate additional sales revenue.

The RFM model typically assumes unlimited marketing resources, however, and suggests that a company can reach all its customers, even customers with less than optimal RFM scores. Clearly, most organizations operate under yearly budget constraints, and therefore such assumptions are impractical. Adding optimization to the well-known RFM approach to help allocate resources most effectively was recommended by Fader et al. (2005b) as an important next step for future research.

In addition, the importance of the R, F, and M components in the RFM approach for a given marketing campaign might not be the same. For example, a company trying to improve its customer retention rate might be interested primarily in recency, i.e., prioritizing the return of lost customers who may have defected to the competition. For the same campaign, frequency and monetary values might be second and third priorities, respectively. When confronted with both spending limits and differing goals, marketing managers should allocate marketing resources toward those customers with the greatest long-term profit potential.

This research proposes a multi-objective optimization methodology based on a goal programming (GP) approach to profit maximization for direct marketers using RFM data. One unique characteristic of this (GP) model is the inclusion of varying direct marketing objectives as well as corresponding budget constraints.

In addition to balancing marketing priorities with marketing budgets, companies must also strive to achieve a balance between two types of errors for any given campaign: Type I and Type II. A Type I error would occur when organizations ignore customers (mistakenly) who could have returned and repurchased, thereby providing the firm with additional revenue and profit. Type II errors occur when companies (unknowingly) target customers with their marketing campaigns who are not ready to purchase (Venkatesan & Kumar, 2004). The model proposed in this research creates a balance between a Type I and a Type II error by identifying the proper RFM segments to target. It also identifies the RFM segments which should not be pursued because they are: a) not profitable; b) do not align with marketing priorities; or c) strain the marketing budget. That is, the model can help direct marketing firms maximize profitability by determining whether they should continue spending on (or curtail their relationships with) given RFM customer segments. A unique contribution of this research is that RFM data are incorporated into a GP approach that includes both marketing goals and budgets to determine the most profitable customer segments to target.

The research paper is organized in the following manner. First, a brief overview of data analytics in direct marketing is provided, along with the RFM framework. The next section discusses the GP formulation to customer profitability utilizing RFM data and provides the GP mathematical formulation of the model. Variations of the model are shown through the use of purchasing data from a CDNOW dataset[1] containing almost 7,000 records. Research conclusions are then presented, and implications of the goal programming approach to profit maximization are discussed

DIRECT MARKETING AND DATA ANALYTICS

Overview of Data Analytics

Using data to make decisions is critical to superior business performance. Yet, another 2.5 quintillion bytes are added to the data universe every day (Edala, 2012). This includes over 350 billion corporate emails, 400 million tweets, and one billion Facebook posts (Hambelton, 2013). The era of big data is here.

Despite vast quantities of data, however, a survey of 254 U.S. business managers found that 40 percent of major business decisions are made according to managers' gut or intuition, not on the basis of fact (Accenture, 2008). Data analytics refers to the strategic and extensive use of data, quantitative analysis, and explanatory and predictive models to make better decisions and take right actions (Davenport and Harris, 2007, 2010). Stated another way, data analytics refers to the use of analysis, data, and systematic reasoning to make decisions (Davenport et al., 2010). It is considered a subset of business intelligence which is the set of "technologies and processes that use data to understand and analyze business performance" (Davenport and Harris, 2007, p. 7). Business intelligence includes data access and reporting as well as data analytics.

The critical point is that data alone is insufficient. The true value of data analytics is the analysis of that data to improve business decisions and the subsequent actions an organization takes as a result of that analysis. Used properly, data analytics can help firms anticipate and respond quickly to changes in the marketplace, improve their competitive standing, and achieve important goals such as profit maximization (Franks, 2012). More specifically, it can help firms optimize prices (Advertising Age, 2013), reduce costs, improve efficiency, manage risk, and in the long run, dramatically improve a company's decision-making process and outcomes (Davenport et al., 2010).

Data Analytics and Direct Marketing

Direct marketing firms collect huge quantities of customer data such as contact information, demographics, geographic data, lifestyle data, financial data, purchase history,

[1] Source: http://www.brucehardie.com/datasets/

preferences, media usage, and more. Today's digital world has opened up new marketing channels to direct marketers (e.g., social, mobile, email, and location-based marketing), but that also means more data coming from more sources—internal and external, online and off-line. Yet integrating customer data from across marketing channels is the number one challenge for customer intelligence professionals (Sridharan, Frankland and Smith, 2011). Even with enterprise resource planning (ERP) systems to help integrate data across business functions, companies still need to access and analyze data from a variety of systems to make better decisions (Davenport et al., 2010,).

Thus, successful direct marketing requires a substantial investment in big data and data analytics. In fact, marketers' external costs of data intelligence and software in the U.S. were around $60 billion in 2011 (Brinker, 2012). Notably, this does not include in-house expenses of marketing intelligence such as IT departments, data analysts, or CIOs. Big customer data and data analytics are especially important to direct marketers because they help increase response rates, conversion rates, total sales, and the ROI of marketing campaigns (Davenport and Harris, 2007; Dyer, 2003; Hambleton, 2013). And when data from loyalty programs is mined, analytics can be used to increase customer loyalty and retention (Hambleton, 2013; Sridharan et al., 2012).

To do so, however, direct marketers need flexibility when designing promotional campaigns. Flexibility in campaign management allows for more targeted, specific, customized, and personalized marketing offers, all of which lead to higher response rates (Franks, 2012). The ability to customize offers and messages depends on having customer data that is accurate, accessible, timely, relevant, and fully integrated with other marketing and operational data. Data analytics can then help the creation of many different marketing campaigns, utilizing variables such as customers' demographic characteristics, credit scores, or previous purchases (Martinez, 2011). Campaign results are collected and stored, then used to fuel the next analysis and the next customized marketing campaign.

To enable such customization, direct marketing managers need customer data to create sets of potential buyers, i.e., to generate a list for its promotions. One way to generate a customer list is to use a scoring model. Scoring models rank customers according to a set of predetermined criteria, assign a score to each customer, and then group customers with the same or similar scores so as to send them a specific type of promotion. Some scoring models are quite simple; others involve complex statistical analysis. A well-known and popular scoring model used in direct marketing is the RFM model.

Direct Marketing and the RFM Model

As noted earlier, using RFM involves choosing customers based on when they last purchased (recency), how often they purchased (frequency), and how much they spent (monetary value) on past purchases (Blattberg et al., 2009; Fader et al., 2005a; Rhee & McIntyre, 2009). The RFM criteria are used frequently because, as measures of customers' prior behavior, they are key predictors of their future purchase behavior (Berry and Linoff, 2004; Bolton, 1998; Fader et al., 2005b; Malthouse and Blattberg, 2005; Sridharan et al., 2012).

Many firms consider recency especially important because a long period of purchase inactivity can be a signal that a customer has permanently ended his/her relationship with the firm (Dwyer, 1989). Accordingly, many companies will assign maximum value to recency, with lesser importance attached to monetary value and frequency (Reinartz & Kumar, 2000; Venkatesan et al., 2007). Regarding the monetary value of customer purchases, sometimes the average purchase amount per customer transaction is used rather than a total (e.g., Fader et al., 2005b). Customers are then categorized by their RFM probabilities to indicate their profitability potential. They are subsequently selected (or not selected) for the next direct marketing campaign based on this profit profile. Thus, RFM analysis helps guide marketing resource allocation in a way that maximizes profitability (Venkatesan et al., 2007).

The RFM model has been used for many years as an analytical technique, even though more sophisticated methods have been developed recently. It has the advantage of simplicity (McCarty & Hastak, 2007), and many data mining algorithms are based on the RFM framework. The research described here combines RFM data with marketing budget constraints, and then uses a goal programming approach to evaluate a direct marketing campaign. The analytic model can be used to guide marketing spending vis-à-vis various customer segments, i.e., either continue investing in or scaling back investments in any given RFM segment. A novel characteristic of this approach is the combination of marketing priorities and preferences for given customer segments while recognizing the reality of annual spending limits on direct marketing programs. In addition, in the complex area of data analytics, the RFM framework offers even small firms with limited resources the opportunity to use data analytics fairly easily and capably.

Another contribution of this research is that RFM data is incorporated into a GP approach into a single model for all customers who are potential targets of a direct marketing campaign. A previous approach (e.g., Bhaskar et al., 2009) utilized mathematical programming (MP) and RFM analysis in a study of personalized promotions for multiplex customers in a customer loyalty program, incorporating business constraints. However, the algorithm in the Bhaskar et al. research separated RFM analysis from mathematical programming. RFM was used for non-recent customers, and MP was used for current customers. This research incorporates everything into a single model.

GOAL PROGRAMMING FORMULATION

The GP Approach

Goal programming is a multi-objective mathematical programming approach in which there are a number of objectives, and some of them are treated as constraints instead of objectives. When developing a specific direct marketing campaign, managers must determine their cutoff points for recency (R), frequency (F), and monetary values (M) with the goal of maximizing customer profitability within a limited budget. If a manager is not concerned about F and M, then a simple linear program to determine the cutoff point for R can be generated. This solution will generate a maximum profitability of, let's say V_R.

Similar calculations show that the maximum profit for the cutoff value of F is V_F, and the maximum profit for the M cutoff point is V_M. The modeler could take each of the values V_R, V_F, and V_M as marketing "goals" and try to find a solution that comes closest to all of the goals. Since it may not be possible to reach all goals simultaneously, the modeler should create a set of penalties for not reaching each goal. This penalty would depend on the importance of reaching a particular segment. If the modeler values R more than F, and then F more than M, the penalties could be P1, P2, and P3 respectively, where P1>P2>P3>0. The modeler then creates a new set of variables s_1, s_2, and s_3. The problem can then be formulated as:

Minimize $Z = P1s_1 + P2s_2 + P3s_3$

subject to:

$\{\textit{objective function of the R model}\} + s_1 = V_R$
$\{\textit{objective function of the F model}\} + s_2 = V_F$
$\{\textit{objective function of the M model}\} + s_3 = V_M$
+ all constraints in the original LPs (including budget constraints)

In order to illustrate the GP model, a sample of a CDNOW dataset, as used in Fader et al. (2005a), is utilized. The sample consists of historical buying data for 2,357 customers. It contains 6,696 records. Each individual record contains a customer ID, a transaction date, and a dollar value for each transaction. This data set was previously used to show how Excel could be employed to automate calculation processes when grouping customers into various RFM segments (Fader et al., 2005a).

Notations Used for the Optimization Models

i = *1... 5* index used to identify the group of customers in a given recency category;
j = *1…5* index used to identify the group of customers in a given frequency category;
k = *1…5* index used to identify the group of customers in a given monetary category;
V = expected revenue from a returned customer;
p_i = probability that a customer of recency i makes a purchase;
p_j = probability that a customer of frequency j makes a purchase;
p_k = probability that a customer of monetary group k makes a purchase;
N_i = number of customers who are presently in recency i;
N_j = number of customers who are presently in frequency j;
N_k = number of customers who are presently in monetary group k;
C = average cost to reach a customer during the direct marketing campaign;
B = budget available for the direct marketing campaign.

Model Formulation for the Recency Case

Let the decision variable for this case be a 0-1 unknown variable as follows:

x_i = 1 if customers in recency i are reached through the direct marketing campaign;
0, otherwise.

Using the above notations, a 0-1 mixed integer GP formulation is presented:

Maximize:

$$Z_r = \sum_{i=1}^{R} N_i (p_i V - C) x_i \tag{1}$$

subject to:

$$\sum_{i=1}^{R} N_i C x_i \le B \tag{2}$$

$$x_i = \{0,1\} \qquad i = 1 \ldots R \tag{3}$$

Equation (1) is the objective function. It maximizes the expected profit (Z_r) of the direct marketing campaign. As noted earlier, a customer in a state of recency i has a p_i chance of purchasing and a $(1- p_i)$ chance of not purchasing. The profit from a customer who purchases is calculated as $(V - C)$. When a customer does not purchase, the expected profit is simply $(-C)$. Therefore, the expected value of the profit from a single customer in state i is:

$$p_i (V - C) + (1 - p_i)(-C) \tag{4}$$

This can be simplified to:

$$p_i V - C \tag{5}$$

Since there are N_i customers in the recency i, the expected profit from this group of customers is:

$$N_i (p_i V - C) \tag{6}$$

Thus, (1) indicates the sum of profits for all groups of customers for which a marketing decision to advertise to them ($x_i=1$) is made. Equation (2) assures that the available budget for the campaign (B) is not exceeded. The actual cost of the marketing campaign is represented on the left side of the equation, which is calculated as the sum of campaign costs for each group *i* of customers. Equation (3) represents the binary constraints for the decision variables x_i.

Solving the Model for the Recency Case

The model is applied as follows. Customers are first placed into five groups in which group one represents those customers with the *least* recent purchases, and group five consists of those customers who have purchased *most* recently. Then, the total number of customers belonging to each group can be determined using a pivot table. Pivot tables can also be used to calculate the probability (p_i) that a customer in group *i* will make a purchase.

Appendix A shows that, given a campaign budget of B= $12,500, a cost to reach a customer of C= $7.50, and the average revenue from the purchasing customer of V= $35, the company should only select customers of recency 3, 4, and 5 for future promotional efforts. This solution will generate a total profit of $24,851 (see Appendix A).

Model Formulation for the Frequency Case

In this section, *frequency* is considered as a dimension in our 0-1 GP model. Again, the goal is to stay within the marketing budget constraints while maximizing the profits from potential customer purchases.

Let the decision variable for this case be a 0-1 unknown variable as follows:

x_j = 1 if customers in frequency *j* are reached in the promotional campaign;
0 otherwise.

The 0-1 mixed integer GP formulation is presented for the Frequency Case:

Maximize:

$$Z_f = \sum_{j=1}^{F} N_j (p_j jV - C) x_j \qquad (7)$$

subject to:

$$\sum_{j=1}^{F} N_j C x_j \leq B \qquad (8)$$

$$x_j = \{0,1\} \qquad j=1 \ldots F \qquad (9)$$

The objective function which maximizes the expected profit (Z_f) of the marketing campaign is shown in Equation (7). Equation (8) assures that the available marketing budget *B* for this campaign is not exceeded. The left side of the equation represents the actual cost of the campaign, which is calculated as the sum of campaign costs for each group *i* of customers. Equation (9) represents the binary constraints for the decision variables x_j.

Solving the Model for the Frequency Case

This case is, of course, applicable to firms where frequency and recency are the only significant values in their marketing campaigns. In these cases, customers are organized first into five groups. Each group G_j contains customers who belong to frequency value *j* (1, 2…, 5). Like the previous example, pivot tables can be used to calculate the probability of purchase (p_j) by a customer in group *j*. The results indicate that customers in the frequency 3, 4, and 5 must be reached. This solution will generate a total profit of $41,876 (see Appendix B).

Model Formulation for the Monetary Value Case

In this section, the model considers *monetary value*. As in the previous cases, the objective remains the same: maximize profits from potential customer purchases while staying with the annual budget constraint.

Let the decision variable for this case be a 0-1 unknown variable as follows:

x_k = 1 if customers in monetary group *k* are reached;

0, otherwise.

Maximize:

$$Z_m = \sum_{k=1}^{M} N_k (p_k kV - C) x_k \qquad (10)$$

subject to:

$$\sum_{k=1}^{M} N_k C x_k \le B \qquad (11)$$

$$x_k = \{0,1\} \qquad k=1 \ldots M \qquad (12)$$

Equation (10) is the objective function for the model which maximizes the expected profit (Z_m) of the marketing campaign. As stated earlier, a customer in a state monetary *k* has a p_k chance of purchasing and a $(1- p_k)$ chance of not purchasing. Equation (11) assures that the available budget for the campaign *(B)* is not exceeded. The left side of Equation (11) represents the campaign's actual cost, which is calculated as the sum of campaign costs for each group *i* of customers. Equation (12) represents the binary constraints for the decision variables x_k.

Solving the Model for the Monetary Value Case

Appendix C provides a summary of the optimal solution for the monetary model. This figure shows the profitable segments for the firm. The results indicate that any future direct marketing campaign must exclude the customer segments with monetary values of M=1, M=2, and M=3 as they are clearly unprofitable. This solution will generate a total profit of $51,858 (see Appendix C).

Incorporating Priorities into the Model

The above three models indicate that M is the most important variable of the RFM framework as the total profit generated is the highest at $51,858. However, the marketing department is interested in investigating the impact of setting the following priorities:

- Priority 1 (P1 = 200): Recency
- Priority 2 (P2 = 100): Frequency
- Priority 3 (P3 = 50): Monetary Value

The following is the GP formulation which minimizes the penalties of not reaching the marketing goals.

Minimize $Z = 200s_1 + 100s_2 + 50s_3$ (13)

subject to:

$$\sum_{i=1}^{R} N_i (p_i V - C) x_i + s_1 = V_R \qquad (14)$$

$$\sum_{j=1}^{F} N_j (p_j jV - C) x_j + s_2 = V_F \qquad (15)$$

$$\sum_{k=1}^{M} N_k (p_k kV - C) x_k + s_3 = V_M \qquad (16)$$

$$\sum_{i=1}^{R} N_i C x_i + \sum_{f=1}^{F} N_f C x_f + \sum_{k=1}^{M} N_k C x_k \le B \qquad (17)$$

$x_i = \{0,1\}$ $\quad$ *i = 1 … R* $\quad$ (18)

$x_f = \{0,1\}$ $\quad$ *f = 1 … F* $\quad$ (19)

$x_k = \{0,1\}$ $\quad$ *k = 1…M* $\quad$ (20)

In the above formulation, (13) represents the objective function. Minimization of *s1* has priority over minimization of *s2* since *s1* has a larger contribution coefficent (200>100). Similarly, minimizing *s3* has the lowest priority. (14), (15), and (16) represent the new set of constraints added to the model to ensure that previous achievement of profit goals from each respective model (VR= $24,851, VF= $41,876, and VM= $51,858) still need to be achieved. (17) assures that the overall budget (B=$12,500) is not exceeded. Finally, (18), (19), and (20) ensure binary solution values for the decision variables.

Solving the Overall Model

Appendix D shows the optimal solution to the goal programming approach. As seen, the total profit for the solution is $42,274, and the solution suggests that the direct marketing campaign must reach customers with a recency value of 5 and frequency values of 4 and 5. Because priority was given primarily to recency, then to frequency, with the lowest priority given to monetary value, the solution suggests no promotional offers should be based on monetary value.

SUMMARY OF RESULTS

The optimal solutions for four variations of the RFM model proposed here are provided in the data analysis and iullustrated in Appendices A-D: a recency model, a frequency model, a monetary value model, and a full RFM model. The Excel templates for each model are available upon request by contacting the first author.

The optimal solution for the recency model suggests that only customers with recency values of 3, 4, and 5 should be targeted for future promotional efforts. This solution will generate a total profit of $24,851. In the frequency model, the results indicate that any future marketing campaign should be focused on those customers with frequency values of 3, 4, and 5. This solution generates a profit of $41,876. The results for the monetary value model show that additional marketing resources should *not be allocated* toward the customer segments with monetary values of M=1, M=2, and M=3 as they are clearly unprofitable. That is, these segments should not be targeted in a future direct marketing campaign. The monetary value solution will generate a total profit of $51,858.

The optimal solution to the goal programming approach indicates that only customers with a recency value of 5 and frequency values of 4 and 5 should be selected by the firm for future promotional efforts, i.e., additional marketing investment should be made. Customers with recency values of 1, 2, 3, and 4, as well as customers with frequency values of 1, 2, and 3, would be excluded as targets of future campaigns. The total profit for the goal programming solution is $42,274. No priority should be placed on the monetary value data; therefore no differential marketing action should be based on monetary value. Excluding certain customer segments from direct marketing efforts should provide managers with greater ROI for a given marketing investment as greater resources will be available to spend on the most lucrative segments.

CONCLUSIONS AND DISCUSSION

Pressure to maximize marketing return on investment is increasing, and chief marketing officers (CMOs) everywhere have been forced to reduce budgets in recent years (e.g., Wong, 2009). At the same time, the direct marketing industry is currently outpacing the overall economy (DMA, 2013), representing almost 53 percent of all U.S. advertising expenditures in 2012, spending over $168 billion (accounting for 8.7 percent of GDP) and generating a ROI of over $12 for every dollar spent (Direct Marketing Association, 2012). The top five direct marketing agencies earned over $3.5 billion in 2011, and that represented only their U.S. revenue. Thus, direct marketing continues to play an effective and growing role in the overall marketing arsenal of many organizations.

As CMOs are increasingly forced to achieve superior results with inferior budgets, analyzing marketing data and prioritizing marketing spending become even more crucial. Low response rates in direct marketing make budget constraints an even greater challenge for the direct response firm (e.g., 1-4 percent average response for direct mail to outbound telemarketing). Investing scarce resources on customers who are not yet willing to buy (a Type II error) is not only inefficient, but could represent a possible threat to a firm's long-term financial viability (Ferrante, 2009; Venkatesan & Kumar, 2004). The multi-objective optimization approach used in this research achieves a balance between Type I (missing profitable customers) and Type II errors. It helps identify both appropriate and inappropriate RFM segments based on three core characteristics: profitability, marketing objectives, and budget constraints. By finding the most profitable customer segments (given various marketing objectives and spending limits), a GP approach applied to RFM data can provide a firm with optimal solutions to and flexibility in marketing spending decisions—in a single model. Depending upon a given RFM segment's profit potential, a marketing firm can determine whether to continue targeting that segment in efforts to generate even more sales, or whether it should spend its scarce resources on alternative (i.e., more profitable) groups.

This research can therefore be used as a type of scoring model for practitioners to enable the transformation of purchasing history data, i.e., RFM data, into a useful decision model which can be applied to many marketing situations and to any imposed budget limitation. Because this research factors in budget constraints and different marketing priorities, the decision model demonstrated here has considerable long-term utility for maximizing the profitability of customer segments.

This study has limitations, but these can provide avenues for future research in the area. For example, because RFM frameworks represent historical behavior, their ability to accurately capture and predict future behavior and profit potential has been questioned (Blattberg et al., 2009; Rhee & McIntyre, 2009). While predicting any consumer behavior, using any type of model, is inherently uncertain (and this GP model is no exception), accuracy is always a potential limitation when forecasting is based on historical data. As the current model addresses only a six month time period, and Venkatesan et al. (2007) argue that up to three years is considered an acceptable horizon for estimates in customer selection models, this may perhaps mitigate forecasting accuracy concerns. In other words, the shorter the time horizon considered, the less variation there is likely to be between past and future purchasing behavior (i.e., there is less time and opportunity for intervening exogenous variables to disrupt behavioral patterns). As noted by Davenport et al. (2010, p. 159), however, a company must still constantly review and manage its analytical models, be alert to "model decay," monitor relevant external events, and keep track of all competing models.

Ideally, firms will eventually integrate additional customer data with RFM data as RFM focuses on customer purchasing behavior, not necessarily customer *search* behavior. That is, it doesn't consider the value of customer information when no purchase is made. With respect to future data collection, direct marketing managers should consider capturing web browsing data as well as transactional data, e.g., "X percent of customers clicking on Link Y ultimately visited Site Z and purchased Brand A." This helps identify customers' search behaviors, choice criteria, and decision-making paths, all of which help us understand customer behavior better, and therefore predict it more accurately. One European retailer identified products that customers browsed on the company website but did not purchase. Follow up emails were then sent to customers with personalized messages that encouraged purchase and included promotional offers for products viewed but not bought (Franks, 2012, p. 17).

In addition to website browsing, other customer contact points can be valuable as well. For example, customer emails, social networking messages (e.g., Facebook "likes"), and customer phone calls can all indicate customer interest and propensity to buy in the future, thus generating sales and profits for the firm. At the very least, these data could provide a greater understanding of customer behavior which can lead to more effective marketing offers and messages.

Data analytics is a future goal that does not represent present reality for many U.S. firms (Accenture, 2008). Yet sound managerial decision-making relies on effective data analytics. The value of any customer data is in how it's analyzed and then used to inform managers and help them make better business decisions (Franks, 2012). The GP approach used in this RFM analysis offers several advantages to direct marketers. It's simple, easy to use, and can account for a large number of variables, constraints, and objectives.

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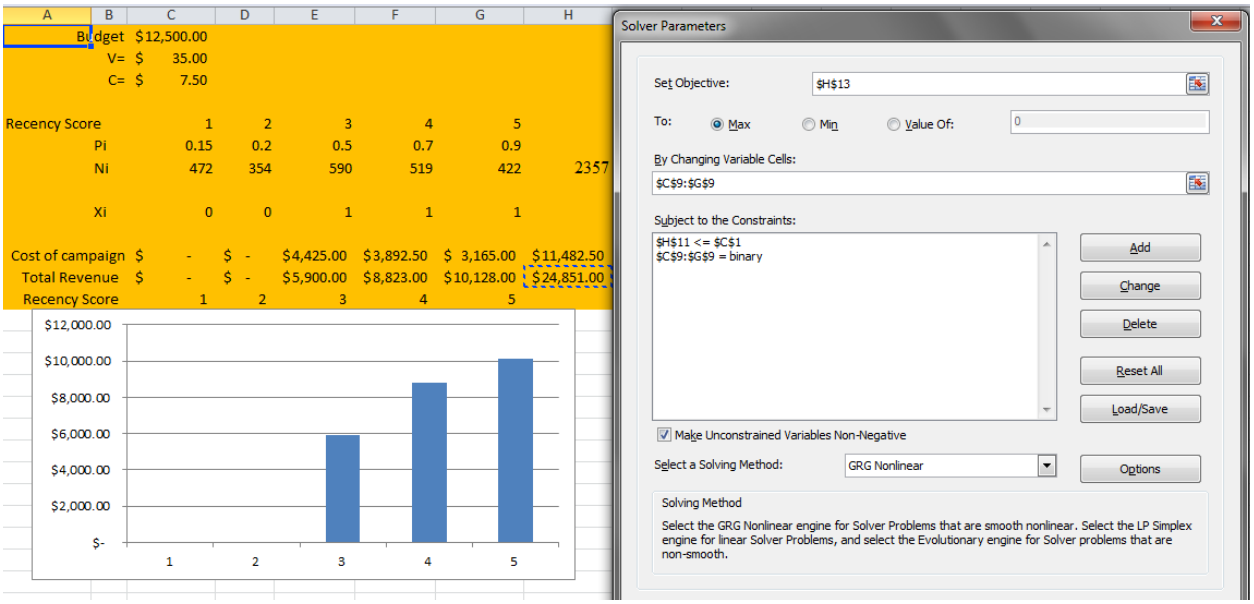
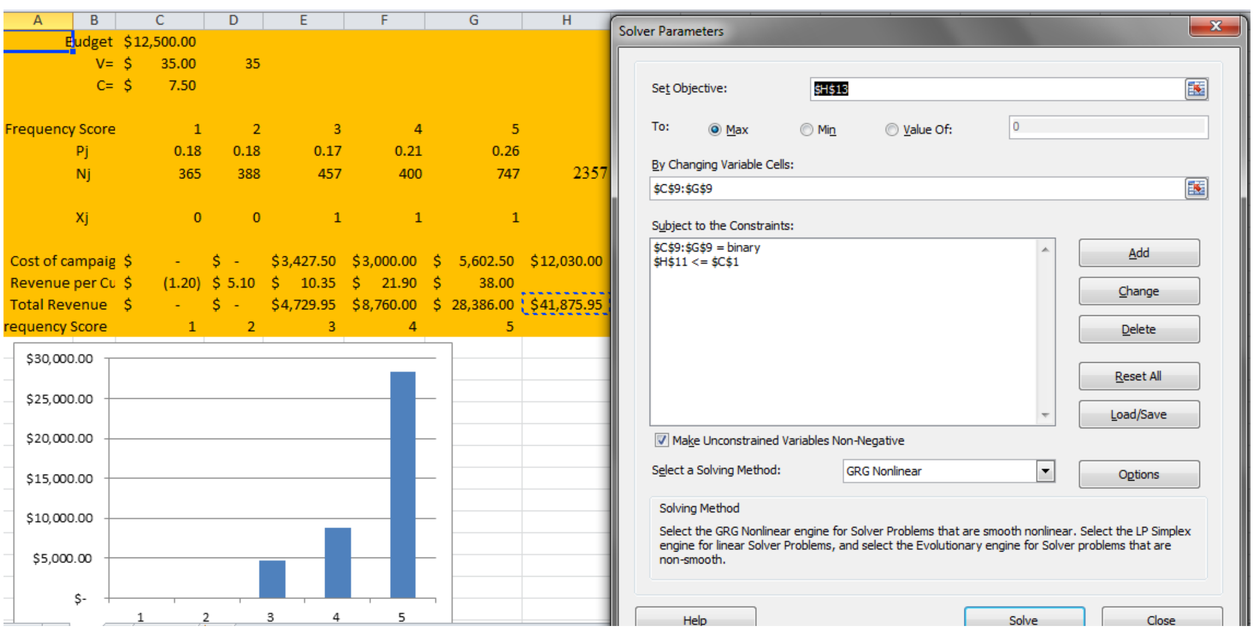
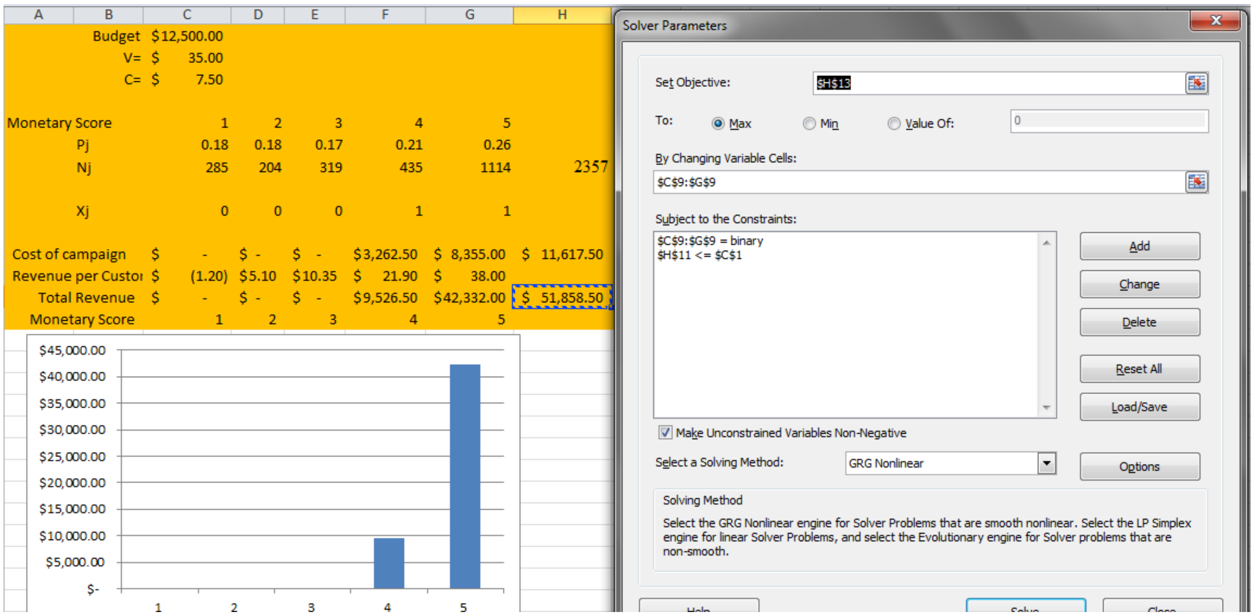
Appendix A: Optimal Solution for the Recency Model



Appendix B: Optimal Solution for the Frequency Model



Appendix C: Optimal Solution for the Monetary Model



Appendix D: Optimal Goal Programming Solution