International Journal of Innovation, Management and Technology, Vol. 1, No. 1, April 2010
ISSN: 2010-0248

Fuzzy Mathematical Model for Up-Sell Solution

Manoj Kumar Jain, A. K. Dalela and Sandeep Kumar Tiwari

***Abstract*—These instructions give you guidelines for preparing papers for the International Journal of Computer Theory and Engineering (IJCTE). Use this document as a template if you are using Microsoft Word 6.0 or later. Otherwise, use this document as an instruction set. The electronic file of your paper will be formatted further at International Journal of Computer Theory and Engineering. Define all symbols used in the abstract. Do not cite references in the abstract. Do not delete the blank line immediately above the abstract; it sets the footnote at the bottom of this column.**

***Index Terms*—About four key words or phrases in alphabetical order, separated by commas.**

I. Introduction

Up-sell: Up-sell is a term to describe the practice that you can sell the most profitable products or services to a customer. You may provide multiple options or multiple versions of a product or a group of similar products. For a customer, based on their requirement, you can choose a best fit product with most profit margins.

Up-sell is important for your business due to increasing competitions and market volatility. You need to maximize your customer value by selling more to your existing customers. Up-sell is keys drivers of deploying a business intelligence analytical application, which can help you to identify new source of revenues [7].

Customer database provide the information to financial industry is "the right product to the right customer at the right time". However, a practical and effective implementation of above is not easy task to do.

What makes this particularly difficult is that companies have more than one product and operate under a complex set of business constraints. Choosing which products to offer to which customers in order to maximize the marketing return on investment and meet the business rules is enormously complex. This paper outlines a framework for solving up-sell problem. In this paper we have taken an example as applied to data from Xyzbank [5, 6 and 7].

Xyzbank is one of the India's premier financial institutions. It is comprised of Domestic Banking, Wealth Management, and International Banking and Xyz Capital groups. The Domestic Bank employs more than 25,000 people and has over 8 million customers. The Wealth Management Group incorporates key personal investment and advisory activities within the Xyzbank Group. Xyzbank is the most International of all the Indian banks, its International Banking Group has more than 22,000 employees and provides retail banking services in more than 50 countries. The Xyz Capital Group provides corporate and investment banking on a global basis. As such, Xyzbank is able to offer a full suite of financial products to its clients [12].

Xyzbank has made a deliberate effort to become a customer focused institution, as opposed to a vertical product driven company. The bank's formally stated goal is "to be the best at helping customers become financially better of by providing relevant solutions to their unique needs". A direct consequence of this goal is that marketing campaigns are multiple product campaigns as opposed to single product campaigns. This transforms the fuzzy modeling and campaign targeting process from a fairly simple application of individual response models into a significantly more complex problem of choosing which product, if any, to offer to which customer and through which channel. The benefit is that campaigns are more customers focused then in the past [10, 12 and 14].

I often get asked, "Well where should you do this? Where's the best place to try to do an up-sell?" It really is going to require testing; and that's really kind of the bottom line message – that if you're not doing up-sells, you need to start experimenting with those. If you don't have that capability in your shopping cart, you need to get it – both to do an up- sell and a cross sell. And you need to have the flexibility within your shopping cart to do that in a way that allows some trying out of different methods [3, 6].

As far as the best place to do it, you can do it as a part of the pre-shopping cart process in your content management system – within your category pages or your product pages. The places where we've seen it to be most potent is definitely on the product pages because they're going to be looking at a very specific product; so you can give them a very specific up-sell. But it can also work quite well within the shopping cart or both on the product page and within the shopping cart [12, 13].

Now setting up-sell in the shopping cart or on the product page may be relatively easy or may be fairly complex, depending on how your shopping cart is set up. A lot of shopping carts will allow you to do the user generated up sell; and also do a hand picked up-sell, which can also be really good, because you as the business owner or product manager have a really in-depth understanding of product, which probably goes well beyond what your typical customer has. So there's also suggestions that you'll want to test out or that

Manoj Kumar Jain is with School of Studies in Mathematics, Vikram University, Ujjain. M.P, INDIA, Email: Manoj.kumarjain@gmail.com
A. K. Dalela is with Department of Mathematics, Govt Science College, Jabalpur, M. P., INDIA, Email : dalela@ymail.com
Sandeep Kumar Tiwari is with School of Studies in Mathematics, Vikram University, Ujjain. M.P, Email: skt_tiwari75@yahoo.co.in

you know items that really fit well together [2, 11].

So the idea is, if you can test out both formats – both the user generated and the business owner generated – and also be able to – as we spoke about earlier – be able to test those at various points throughout the process, both in the content management and the shopping cart.

II. Business Problem

Strategy marketing community has changed significantly over the last several years for up-sell. In the past, marketing strategy applied business rules to target customers directly and targeting customers solely on their product gaps or on marketers' business intuition. Marketers have also applied FRM type analysis (*frequency*, r*egency*, and *monetary* measurements) as well as product gaps are used to target customers for specific offers. The current approach, which has extensive use, relies on predictive response models to target customers for selling most profitable products or services to a customer. These models accurately estimate the probability that a customer will respond to a *specific* offer and can significantly increase the response rate to a product offering.

However, simply knowing a customer's probability of responding to a particular offer is not enough when a company has several products to promote and other business constraints to consider in its market planning. Marketing departments also face the problem of knowing which *product* to offer to which *customer*, not just which customer to offer a product. In practice, many short-term rules are used. Prioritization rules based on response rates or estimated expected profitability measures have been used; business rules to prioritize based on products that can be marketed are sometimes used; and product response models to select customers for a particular campaign are also used. One approach that is easily implemented but, for reasons outlined later, may not produce optimal customer contact plans relies on a measure of expected offer profitability to choose which products to offer which customers. This implies that the estimated probability of response multiplied by the profit given customer response less direct costs. However, a shortcoming of this approach is its inability to effectively handle complex constraints on the customer contact plan.

A. Business Constraints

Marketing departments have set of business constraints. Typically, there are restrictions on the minimum and maximum number of product offers that can be sent in a campaign, there are limits on channel capacity, limits on funding available for the campaign, and campaign return-on-investment hurdle rates that must be met. These are a sample of the constraints that marketing departments must meet when executing a campaign. Some time they used ad-hoc approaches for same to meet these constraints. The opportunity costs of the business constraints are generally not known. Constraints are usually negotiated among marketing, product lines and delivery channel management. If the cost of a constraint was known prior, then the company could choose to relax the constraint by adding more resources. For example, channel capacity could be increased if it were known that there was a significant return on the investment by doing so. Knowledge of the opportunity costs could help evaluate these management decisions. The approach we take is to transform the up-sell marketing problem into an optimization problem that is designed to generate the maximum incremental profit from a limited amount of resources, subject to the necessary business constraints. This paper will describe an actionable framework that will satisfy up-sell business problem.

III. Solution Framework

The approach to solving above problem is to model it as a capacitated assignment problem. This type of problem is an integer program. It can be unambiguously expressed with a mathematical formulation.

Let $x_{ij} = 1$ if customer *i* is offered product *j*, and 0 if not;
Let $y_{ik} = 1$ if customer i offer k product along with j and 0 if not
Let r_{ij} the expected profit of offering customer *i* product *j*
Let c_{ij} the cost of offering customer *i* product *j*; let *R* be the corporate hurdle rate. Then, a very simplified version of the problem can be expressed as finding the x_{ij} and y_{ik} *fuzzy variable* that satisfies

$$\text{Max} \sum_{ij} x_{ij} r_{ij} + \sum_{ik} y_{ik} r_{ik}$$

Subject to

$$\left(\sum_{ij} x_{ij}\, c_{ij} + \sum_{ik} y_{ik} c_{ik}\right) \leq \text{Campaign budget}$$

$$\sum_{i} x_{ij} \geq \min \textit{of product j offer}$$

$$\sum_{i} y_{ik} \geq \min \textit{of product k offer}$$

$$\sum_{ij} x_{ij} r_{ij} + \sum_{ik} y_{jk}\, r_{ik} \geq \left(\sum_{ij} x_{ij} c_{ij} + \sum_{ik} y_{ik} c_{ik}\right)(1+R)$$

$$\mathbf{x_{ij}} \in \{0,1\} \qquad \mathbf{y_{ik}} \in \{0,1\}$$

This formulation captures only the bare elements of the problem. It will useful to account for multiple campaigns composed of different products, multiple channels, and channel capacity constraints just to name a few possibilities. However, the model can easily be extended to cover virtually any business constraint, but the basic formulation remains the same. It is important to note that this ideal formulation is difficult to solve because of its scale. For 1 million customers and 20 products there are 20 million integer fuzzy variables x_{ij} and y_{ik}, this yields $2^{20,000,000} * 2^{20,000,000}$ possible customer-offer combinations.

It is not practical to solve problems formulated in this ideal way because size to high. , it is possible to approximate the ideal formulation and arrive at a formulation that is practical to solve. There are numerous ways to approach this approximation; one approach is to sample from the customer base and use that sample as representative for the optimization. This approach, it is to aggregate customers based on the coefficients c_{ij} and r_{ij} in the ideal formulation. Aggregation can be considered natural in this setting particularly when we understand that much of the data is consistent and estimated. For example, the cost data c_{ij} are most likely to be consistent across customers for a given product. Similarly, the estimated expected profit r_{ij} is most likely the result of fuzzy modeling techniques such as predictive response models. The implementation of this framework is loosely coupled to the chosen form of the predictive response models. As long as the customer/offer specific response rate is represented as a probability, the proposed framework can handle it.

A. Response Model

The expected incremental profit of a specific offer to a customer is an estimate based on response models and detailed product profitability calculations. Xyzbank has an active group of predictive modelers that is constantly building response models for individual offers. These response models are used to estimate *the probability that a customer will accept a specific offer*. Xyzbank's data warehouse has detailed account level profitability calculations for all of its products. This profitability information is used to estimate the near term incremental profit *given that the customer accepts the specific offer*. Once a specific offer is made to a customer there are two possible outcomes: the customer can accept or reject the offer. Using the offer specific response models the probability of both states is known for each customer. The incremental profit for both states is also know; it is zero if the customer rejects the offer and the mean near-term profitability for new accounts of the specific type if the offer is accepted. With this information, the expected incremental profit of the offer can be calculated for each customer/offer combination. The cost of making each offer is also known and is largely dependent on the channel through which the offer is made.

B. Channels

Xyzbank has several distribution channels through which campaigns can be executed. The main channels for direct marketing are direct mail, retail branch centers and call centers. For this example we assume that leads sent to the branch officers and call centers are follow-ups from a direct mail piece and that offers designated as direct mail are direct mail only. The use of the branch and call centers for follow-ups has been shown to have a positive effect on the probability of response to the offer when compared to direct mail alone. Of course, the lead delivery costs vary with the channel used. In this example we have used costs per lead of \$3.00, \$1.50 and \$1.00 for the branch, call centre and direct mail only channels respectively.

C. Business Constraints

Several practical issues surround the campaign execution process that affects the customer/offer selection process, for this application to be acceptable for implementation these business constraints must be maintained. The following business rules have been translated into constraints that can be applied to the optimization model:

- Campaign costs cannot exceed \$1 million.
- The campaign must have a return on investment of at least the corporate hurdle rate. In this example we have used 20%, which is not necessarily the bank's actual corporate hurdle rate.
- The branch and call centre channels have a certain capacity constraint for timely processing of campaign generated leads. In the example, the call centre can accept up to 500,000 leads, the branch can handle up to 250,000 leads and direct mail is unlimited.
- Product offer minimums are also required to satisfy internal bank objectives. For the purposes of this example we set all offer minimums to 20,000 with two exceptions. The RESP offer, which has an extremely limited eligible universe, had a lower bound of 2,500 and one of the Xyz online offers had a lower bound of 5,000.
- Cannot offer products to customers who already have that product at Xyzbank.
- The standard marketing exclusions, such as credit risk or do not solicit, must also be strictly adhered to.

D. Optimization

The estimates for customer/offer expected incremental profit, costs and business constraints serve as inputs to the profit optimization phase of the campaign design. The profit optimization phase is independent of the construction of these inputs. This means that as response models, profit estimates or costs are refined as long as the results are represented in the same manner, the optimization phase will be able to accept them as inputs. This property is important as the bank is constantly testing and refining these inputs as the market place is ever changing.

IV. Results

The result of this algorithm is an allocation, of a specific offer, or no offer, to each customer. Also output is the associated expected incremental profit by customer making that offer. This solution is a Xyzbank data set that has a customer identifier, the expected return, offer and channel designation. The full data set is 2.5 million records; the table below shows the first 25 records.

Customer Id	Offer	Expected Return
182723		.
200688		.
32937		.
722119		.
2137391		.
992639		.
60721		.
483601	profitoffer2dm	0.0005
1164964		.
25469		.
1008244		.
179891		.
410488	profitoffer10dm	3.1852
1484008		.
184804		.
335018		.
983111		.
387834	profitoffer5cc	13.0782
1100914		.
1507075		.
1559899		.
309931		.
657640		.
2075404		.
1095694		.

Figure 1: Sample of the solution dataset.

To better understand the solution, it is useful to look at several charts that summarize the solution and a report that is produced by the algorithm. Offer frequency chat given into figure 2.

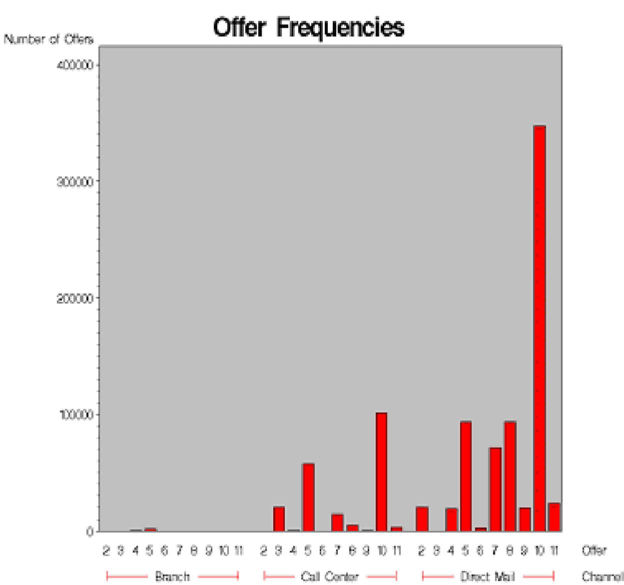

Figure: 2. Offer Frequencies.

V. Conclusion

This offer optimization approach provides three significant improvements over other, more standard, approaches to the problem of campaign design.

- First and foremost, the developed solution produces significantly more incremental profit than competing solutions for up-sell. The campaign incremental profit is almost twice as high as that of the standard approach.
- Secondly, this technique is designed to implement multiple constraints and therefore affords the business more control over the direct marketing process. Attempting to satisfy several business constraints simultaneously using ad hoc techniques is a very labor-intensive task and generally produces poor results.
- Finally, the additional information that can be presented as a part of this solution can provide the business with more insight into the customer base, product offerings and the effects of the constraints.

This insight can be used to guide the company to craft better investment decisions in order to make future campaigns even more successful.

References

[1] Haily Liu Lau, Kin-nam Chow and Connie (2004). A database approach to cross selling in the banking industry: Practices, strategies and challenges. The Journal of Database Marketing, 11(3), 2004.

[2] F Dwyer and James R Evans (1981). A branch and bound algorithm for the list selection problem in direct mailing advertising. Management Science, 27(6), 1981.

[3] Fusun Gonul , Meng Ze Shi (1998), Optimal Mailing of Catalogs: a New Methodology Using Estimable Structural Dynamic Programming Models, Management Science, v.44 n.9, p.1249-1262, September 1998

[4] Michael Lewis (2005), Research Note: A Dynamic Programming Approach to Customer Relationship Pricing, Management Science, v.51 n.6, p.986-994, June 2005

[5] M. Tolga Akçura , Kannan Srinivasan (2005), Research Note: Customer Intimacy and Cross-Selling Strategy, Management Science, v.51 n.6, p.1007-1012, June 2005

[6] Deb Campbell , Randy Erdahl , Doug Johnson , Eric Bibelnieks , Michael Haydock , Mark Bullock , Harlan Crowder(2001), Optimizing Customer Mail Streams at Fingerhut, Interfaces, v.31 n.1, p.77-90, January 2001

[7] Andrew Storey , Marc-david Cohen(2002), Exploiting response models: optimizing cross-sell and up-sell opportunities in banking, Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining, July 23-26, 2002, Edmonton, Alberta, Canada

[8] J. J. Buckley(1988), Possibilistic linear programming with triangular fuzzy numbers, Fuzzy Sets and Systems, v.26 n.1, p.135-138, April, 1988.

[9] Young-Jou Lai , Ching-Lai Hwang (1992), A new approach to some possibilistic linear programming problems, Fuzzy Sets and Systems, v.49 n.2, p.121-133, July 27, 1992

[10] H Tanaka, H Ichihashi, and K Asai (1984). A formulation of fuzzy linear programming problem based on comparison of fuzzy numbers. Control and Cybernetics, 13:185-194, 1984.

[11] Hwang Ching-Lai Lai Young-Jou (1994). Multiple objective decision making - methods and applications. In Lecture Notes in Economics and Mathematical Systems. Springer Verlag, 1994.

[12] Cohen, M. (2000), "Offer Optimization, Optimizing customer value," SAS *Internal Technical Paper*. May 2001.

[13] Cohen, M., and Parks, J. (2000), "Optimizing the Allocation of Cross-Selling Effort," *Proceedings of the DiamondSug 2000 Conference*, San Francisco.

[14] Cohen, M. (2000), "Targeted Marketing, Optimizing the customer/event/channel assignment," SAS *Internal Technical Paper.* December 2000.