Cross-Selling: Offering the Right Product to the Right Customer at the Right Time

Wagner A. Kamakura

Duke University

SUMMARY. Cross-selling is an old and valuable technique used by salespeople to increase order size and to transform single-product buyers into multi-product ones. More recently, cross-selling has evolved into a strategy for customer relationship management. This article starts with a discussion of the benefits and pitfalls of cross-selling as a strategy for customer development within the context of CRM, oriented towards increasing the firm's share of the customer wallet, broadening the scope of the relationship with the customer, and increasing customer retention. This discussion is followed by a review of some of the analytical tools for identifying prospects for cross-selling, and by a discussion of technological and organizational requirements for the successful implementation of cross-selling. doi:10.1300/J366v06n03_03 *[Article copies available for a fee from The Haworth Document Delivery Service: 1-800-HAWORTH. E-mail address: <docdelivery@haworthpress.com> Website: <http://www.HaworthPress.com> © 2007 by The Haworth Press, Inc. All rights reserved.]*

Wagner A. Kamakura is Ford Motor Co. Professor of Global Marketing at the Fuqua School of Business, Duke University, One Towerview Road, Durham, NC 27708 (E-mail: kamakura@duke.edu).

[Haworth co-indexing entry note]: "Cross-Selling: Offering the Right Product to the Right Customer at the Right Time." Kamakura, Wagner A. Co-published simultaneously in *Journal of Relationship Marketing* (Best Business Books, an imprint of The Haworth Press, Inc.) Vol. 6, No. 3/4, 2007, pp. 41-58; and: *Profit Maximization Through Customer Relationship Marketing: Measurement, Prediction and Implementation* (ed: Lerzan Aksoy, Timothy L. Keiningham, and David Bejou) Best Business Books, an imprint of The Haworth Press, Inc., 2007, pp. 41-58. Single or multiple copies of this article are available for a fee from The Haworth Document Delivery Service [1-800-HAWORTH, 9:00 a.m. - 5:00 p.m. (EST). E-mail address: docdelivery@haworthpress.com].

Available online at http://jrm.haworthpress.com
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doi:10.1300/J366v06n03_03

KEYWORDS. Cross-selling, up-selling, acquisition pattern analysis, collaborative filtering, recommendation systems

INTRODUCTION

Cross-selling is one of the most useful tools in a salesperson's toolbox when it comes to increasing sales volume per customer. It is hard to avoid being cross-sold into an extra order of fries when buying a sandwich at any fast food restaurant. Some even argue that the obesity epidemic plaguing America is partly because we are often up-sold into "super-sizing" our meal orders.

Cross-selling and up-selling are relatively old and established sales tools. Cross-selling involves the sales of additional items related (or sometimes unrelated) to a previously purchased item, while up-selling involves the increase of order volume either by the sales of more units of the same purchased item, or the upgrading into a more expensive version of the purchased item. Even though these sales techniques are relatively old and established, their practice has changed substantially with the modern advent of customer relationship management. As tools for personal selling, cross/up-selling required perception and intervention by the salesperson to suggest the handbag that matched the dress chosen by the customer, or the lamp that complemented the sofa. In traditional retailing, the bank clerk would look at the customer's record while finishing a transaction and immediately suggest another service that suited her needs. Similarly, a gas-station attendant would offer to check the tires, oil and windshield wipers, and create opportunities to cross-sell services that met the driver's needs at that moment. Unfortunately, many services transaction are now mediated by information technology, eliminating direct human communication, thereby reducing the opportunities of cross-selling as practiced in the past. For this reason, cross-selling had to evolve by complementing human intuition and reasoning with information technology. Rather than relying on a sales or services representative to decide whether to cross-sell and which item to offer, modern cross-selling utilizes analytical tools to study the customer's past behavior, correlate this information with similar customers, and then identify potential cross-selling opportunities at each contact with the customer. Because modern cross-selling is not necessarily done in a context with frequent person-to-person interactions, it has to be more event and value-driven than the more persuasive cross-selling of the past.

Within the context of customer relationship management, cross-selling has become a valuable strategy for customer development, for several reasons. First, there is a belief that it costs five times less to serve an existing customer than to acquire a new one (Rothfeder 2003). Second, reported response rates from cross-selling efforts are 2 to 5 times greater than cold sales (Andrews 1999). Third, cross-selling leads to a broader scope for the customer relationship, increasing not only share of wallet but also the firm's "share of mind" with the customer. Fourth, by broadening the scope of the relationship, cross-selling increases the actual and psychological costs of switching, improving retention (Kamakura et al. 2003). Fifth, as the customer buys more products and services from the firm and broadens the scope of the relationship, the firm learns more about the customer's needs and preferences, improving its ability to target marketing efforts and to cross-sell. This information advantage, added with the higher costs of switching, produces a virtual local monopoly for the firm, which is then better able to compete for its customers than other firms that do not have an established relationship or access to the same information about their needs and preferences. For the reasons above, many customer-focused enterprises are taking advantage of cross-selling as a tool for customer development. The California State Automobile Association (CSAA), through an analysis of its customer database, found that a member who used roadside assistance in the first year is likely to continue using the service, and is a candidate for insurance cross-sell. On the other hand, an auto insurance customer who also enrolled in roadside assistance but never used it in the first year is likely to allow the service to lapse. Through similar product acquisition sequence analyses, CSAA identifies threats and opportunities for the cross-sales of services to its customers. At Citicorp, call center operators ask credit card customers if they are interested in auto insurance; those who answer positively are transferred to a Travelers auto insurance call center. Corporate clients on the other hand, are introduced to a Salomon Smith Barney (another unit of Citicorp) representative. Restoration Hardware, Inc., a home furnishing retailer, matched web, retail and catalog purchases to each mailing to find that catalog sales result into cross-sales at other channels. More than 40% of online purchases were linked to the catalog and these customers purchased 30% more than web-only shoppers, and customers who received the catalog spent 25% more in its stores than those who didn't. Based on these results, Restoration doubled its catalog run, targeting them to customers with highest predicted potential as repeat buyers.

While implementing these cross-selling strategies, firms realized that cross-selling is more effective in inbound than outbound customer contacts. In other words, it is better to cross-sell when the customer calls the firm than to call the customer for the purpose of cross-selling. Some of the reasons for this important finding are intuitive. First, costs are lower, as the contact is initiated by the customer, and there is no waste in reaching the customer. Second, since the customer initiated the contact, the mindset is already centered on the firm and its services, simplifying the sales task. Third, if the customer called with a problem and it is solved to her satisfaction, the customer is more receptive to the cross-selling suggestion, particularly when this suggestion meets her needs. For example, if the customer called because of an overdraft on her account, and the overdraft is explained and resolved, she will be more open to consider enrollment into an overdraft-protection plan. If cross-selling is properly done, it will be viewed as a service, rather than a sales pitch.

For the reasons above, many firms in the financial services, telecommunications, and other services industries are transforming their service call centers from cost centers to profit centers. The focus in these profit centers is to first resolve the customers' problem and then make a cross-selling suggestion.

Given these benefits, there is a risk for the firm to overdo its cross-selling strategy, thereby alienating its customers. However, in general, customers' reaction to cross-selling is surprisingly positive. A study conducted in 2005 by Forum Corp., a Boston global leader in workplace learning, with a sample of 1624 consumers around the world (focused on older, more affluent consumers) showed that 88% value service reps who suggest alternative products and services that better meet their needs. More importantly, 42% said they buy additional services/products "sometimes" or "frequently." The top factors affecting their willingness to consider purchasing additional products/services were satisfaction with current purchase and how well additional services meet their needs. Among service rep behaviors that induce purchases, the top ones were:

- focusing on customers' needs, rather than pushing a product
- solving the customer problem before talking about additional products
- describing how the additional product will benefit the customer

Customers were most annoyed when service reps continue to sell after the customer says he's not interested, when they are obviously reading from a script, and they try to push products that are not useful to the customer.

The main drawback of exaggerating the cross-selling efforts is "over-touching" the customer. Bombarding the customer with cross-selling offers will train the customer to ignore these efforts, thereby de-sensitizing the customer to future cross-selling efforts. At the extreme, the customer becomes annoyed, and the cross-selling strategy produces the opposite of its ultimate goals, leading to customer attrition. This is why cross-selling must be implemented through carefully targeted customer contacts, to offer *the right product to the right customer at the right time*. Next, we discuss the tools developed in the literature to attain this goal.

ANALYTICAL TOOLS FOR CROSS-SELLING

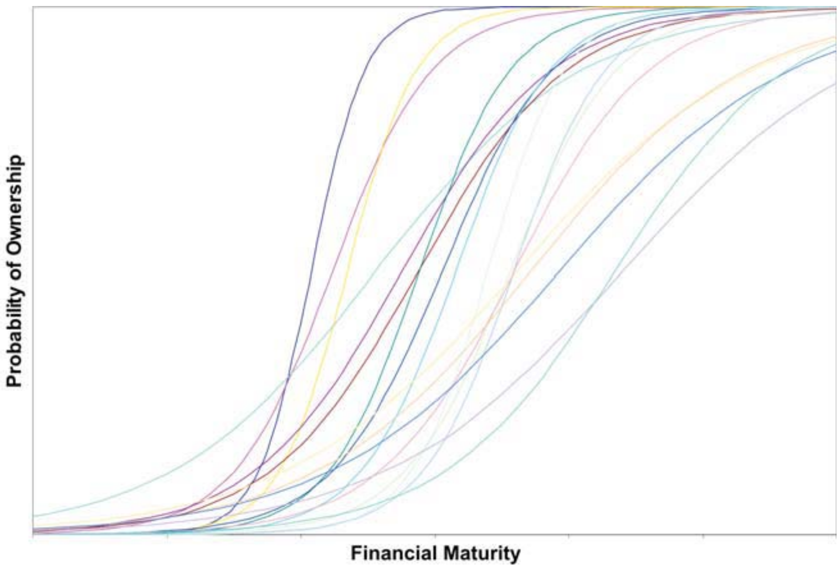
The analytical tools that make cross-selling possible in a CRM context can be classified into two main groups: *Acquisition Pattern Analysis* and *Collaborative Filtering*. The main purpose in *acquisition pattern analysis* is to identify the next logical step for the customer, in terms of product/service acquisition, based on the pattern of previous acquisitions and on the pattern of other customers. For example, a business person who acquires a PDA may next acquire a carrying case, followed by additional memory, software, etc. A cable subscriber may subscribe to on-demand programming, followed by broadband Internet access, followed by VoIP phone service, etc. While the first category of cross-selling tools focuses on the sequence of acquisitions, *collaborative filtering* looks at the patterns of associations among purchases across customers, to identify suggestions of other items that would go along with the purchased one. For example, as soon as a book is added to the shopping cart, Amazon.com suggests other titles purchased by customers who bought that same book. Similarly, Netflix, would look at a customer's rentals and ratings to suggest movies that were rented and liked by customers with similar rentals and preferences.

Acquisition Pattern Analysis

Even though acquisition pattern analysis has been subject of study in the past (Paroush 1965, Stafford, Kasulis and Lusch 1982, Dickson, Lusch and Wilkie 1983, Feick 1987), the first study using acquisition pattern analysis for cross-selling purposes was published by Kamakura, Ramaswami and Srivastava (1991). The basic argument in their study is that consumers must balance multiple financial objectives while they evolve through their life cycles. At the early stages, consumers finance current consumption with future income through credit. As they mature, their income surpasses their consumption and therefore they finance past and future consumption with current income through loan payments and savings/investments, respectively. Later in life, they finance current consumption with past income from retirement savings/investments. Because of these changes, these authors argue that there should be a natural sequence of acquisition for financial services, which they investigate using a methodology called latent trait analysis. The basic idea behind latent trait analysis (also known as item-response theory) is that items (services) and people (customers) can be measured in a common unidimensional scale that measures the probability that a customer uses a service through a logistic function. The location of a customer in this unidimensional scale measures the customers "financial maturity" so that a mature customer will have a high probability of using most of the services, while a less mature customer will only use the most common services such as a checking account. The position of a service in this same scale measures its "difficulty," or the financial maturity required for a customer to have an even chance of using the service. Kamakura et al. (1991) apply this latent trait model to data indicating usage of 18 services by 3,034 members of a financial services panel, obtaining the results shown in Figure 1. This figure plots *item characteristic curves* for each of the 18 financial services, with the probability of ownership in the vertical axis as a function of the customers' financial maturity, showing that some services are relatively "easy," requiring only a moderate level of financial maturity for ownership, while others are more difficult and therefore owned only by customers with high maturity. Kamakura et al. (1991) show that the order of "difficulty" for these services was quite consistent with their hypothesized order from basic services (checking, savings, credit card) up to more advanced current-income post-retirement services (timed deposits, annuities). As a test of their proposed cross-selling framework, Kamakura et al. (1991) demonstrate how it can be used for the qualification of cross-selling leads.

Given the characteristic curves displayed in Figure 1, and data on the services already used (or not) by each customer, it is fairly straightforward to identify the next service in the acquisition sequence for each customer. Based on the current usage of services from one particular customer and the characteristic curves for all services, one obtains a

FIGURE 1. Item characteristic curves for 18 financial services.



measure of the customer's current financial maturity. For example, Figure 2a illustrates the current usage by one hypothetical customer, shown in the dark curves, which produces an estimate of the customer's financial maturity (vertical line). Given the customer's measurement of financial maturity and the characteristic curves for the non-used services, one can see that the next likely acquisition would be the service indicated by an arrow in Figure 2a. Figure 2b illustrates another hypothetical case, where there is a gap in the services currently used by the customer. In this case, the model suggests the service representing the gap (marked by a circle in the figure) would be the cross-selling suggestion.

The latent trait model illustrated above allows the services to differ not only in their "difficulty" but also on how usage probability changes with customer financial maturity. In other words, the characteristic curves are allowed to have different slopes, as shown in Figure 1. A more restricted version, constraining the slopes to be the same for all services (also known as the Rasch model), was later proposed by Soutar and Cornish-Ward (1997). A more flexible approach than Kamakura et al. (1991), using non-parametric characteristic (Mokken) curves was

FIGURE 2a. Cross-selling opportunity for one customer (next likely acquisition).

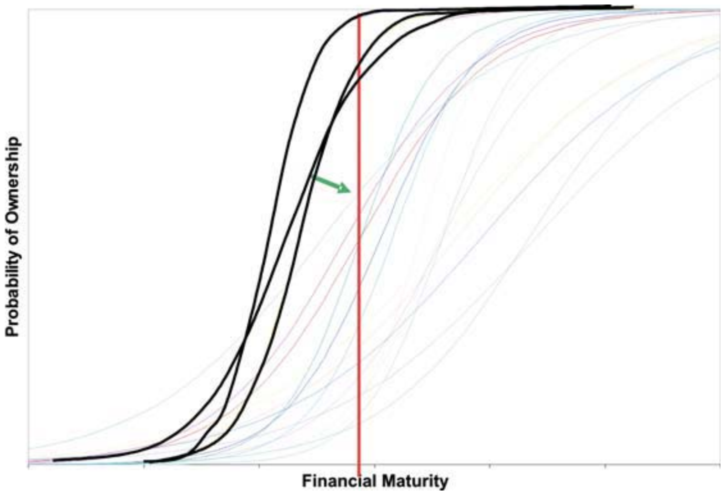
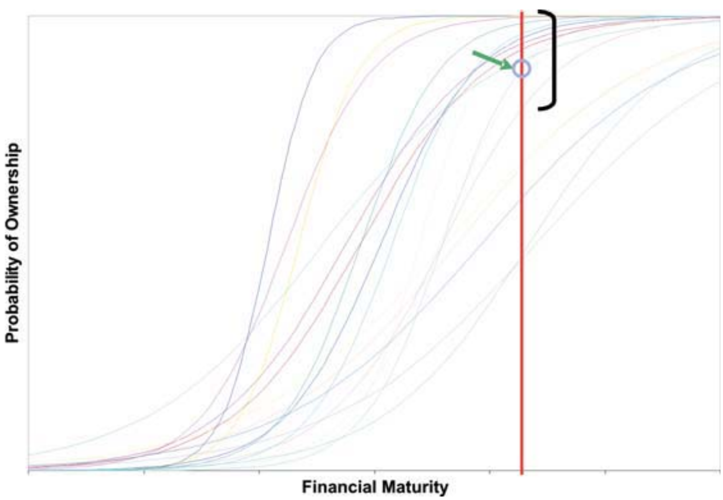


FIGURE 2b. Cross-selling opportunity for one customer (ownership gap).

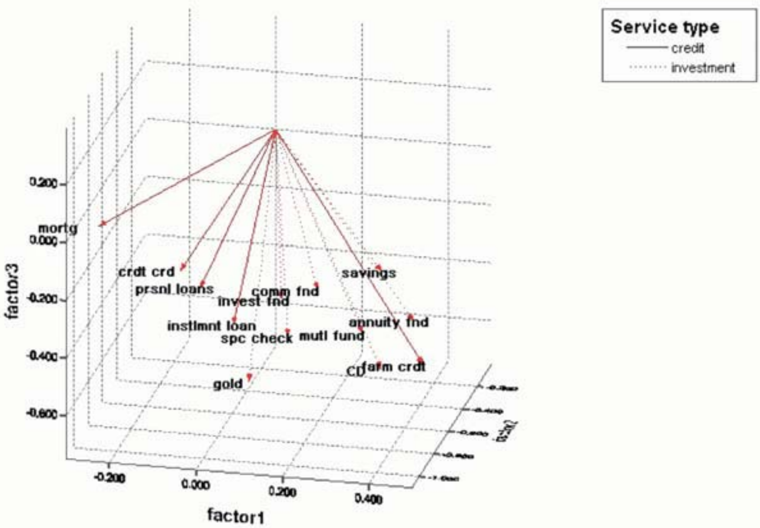


proposed by Paas (2003). Like the Rasch model and other latent-trait extensions, Mokken curves attempt to position customers and products along a unidimensional scale. However, instead of prescribing a logistic function relating the probability of ownership and the latent scale, Mokken scales produce a non-parametric probability function that is monotonically increasing with the scale value, resulting in more flexible characteristic curves. Paas and Molenaar (2005) compare the predictive performance of Mokken scales and Latent Class Analysis, a technique previously used by Feick (1982) for acquisition pattern analysis. The two models were fitted on the ownership data observed in one year for nine financial products, and used to make predictions about future acquisitions for each customer and product, in a subsequent period of 6 years. They found that Mokken scales produced 3.3% of false negatives (customer is predicted not to acquire, but actually acquires), compared to 4.2% for the latent class model. On the other hand, Mokken scales produced more (93.5%) false positives (customer is predicted to acquire but doesn't) compared to 88.5% for the latent class model. Firms concerned about missing opportunities would prefer Mokken scales, while firms interested in minimizing direct costs would prefer the latent class model.

The latent trait models and Mokken scales discussed above assume that customers and services can be positioned along a single continuum, making the strong assumption that acquisition patterns are unidimensional. This assumption is relaxed by Kamakura, Wedel, de Rosa and Mazzon (2003) who allow for multi-dimensional acquisition patterns and demonstrate that usage of financial services is multidimensional. Figure 3, adapted from Kamakura et al. (2003) shows the directions of higher likelihood of usage for multiple financial services. Each vector points to the direction of higher usage probability for a particular service; customers with scores located further in this direction will be the most likely to use the service. Based on the vectors for credit (solid lines) and investment (traced lines) services, one can see that customers with high potential for acquisition of these two types of services have different combination of scores on the three dimensions or factors, although there is a strong correlation between the usage probabilities for these two types of services.

Another important aspect of cross-selling addressed by Kamakura et al. (2003) was the fact that in many industries (such as banking, retailing, insurance, etc.) most customers maintain multiple relationships, and therefore, the fact that a customer does not use a service with the firm does not necessarily imply that the customer is not a user some-

FIGURE 3. Three-dimensional mapping of service usage.



where else. For this purpose, these authors propose a data-augmentation tool to augment the firm's customer database with data imputed from external sources, such as sample surveys, syndicated services, etc. Once the customer database is augmented with data imputed from external sources, the manager can implement more focused and effective cross-selling strategies. If a customer shows a high usage probability for a particular service, and doesn't yet use it with the firm, the firm must educate the customer about the benefits of the service and how well it meets the customer's needs. On the other hand, if he is likely to already use the service elsewhere, the focus must be in persuading the customer to switch usage towards the firm.

Another multidimensional acquisition pattern analysis was proposed by Kamakura, Kossar and Wedel (2004). However, the main focus in their application was in the identification of customers who are not only likely to acquire a new product, but also likely to do it sooner than others. The identification of innovators is important in the diffusion of new products, as these innovators are likely to disseminate information about the new product and therefore help its diffusion. This model is applied to identify physicians who are likely to be early adopters for a new drug, based on the pattern of adoption of multiple drugs introduced in the past. Because individual data on drug prescription is widely available for the population of physicians in the US, pharmaceutical companies can use these databases to study the pattern of previous adoptions and identify the likely early adopters of a new drug. Kamakura et al. (2004) test their approach on five new drugs, with predictive performance that can be characterized as between good to excellent, depending on the drug.

Longitudinal Acquisition Pattern Analysis

The approaches reviewed above attempt to infer the acquisition sequence for services or products from cross-sectional data, something that cannot be verified empirically, but is usually the only feasible alternative given available data. More recently, authors have focused on the situation where longitudinal data is readily available. For example, rather than identifying concurrent patterns of product acquisitions, Knott, Hayes and Neslin (2002) apply logistic regressions to usage data from two periods to predict whether customers will (or will not) purchase a product in the next period, given usage data from the previous period on all products, along with other customer characteristics. The estimated regression coefficients showing the impact of ownership of each product in the previous period unto the probability of acquiring another product in the subsequent period predict how usage of one product in one period increases/lowers the chances that another product is acquired in the next period. Among all predictors they have considered, including customer demographics and monetary value, they conclude that current product usage was the most critical in predicting usage in the subsequent period.

Li, Sun and Wilcox (2004) extend the cross-sectional approach of Kamakura et al (1991) to the situation when longitudinal data is available. They consider the decision to acquire each service as a binary choice by the customer, which depends on the latent utility of the product. Like the latent-trait model, they assume that the utility for a product to a customer depends on the relative location of the product and the customer on a unidimensional scale. However, their model is applied to longitudinal data, and the location of the customer at any given time is assumed to change as a function of the relationship the customer has with the firm. They formulate their problem as a multivariate (multiple products) binary Probit model. By allowing the customer "maturity" to change over time as a function of his/her past relationship with the firm, their model accounts for the fact that demand for services will change over time, and takes into account the long-term impact of past product acquisitions over future ones.

Paas, Bijmolt and Vermunt (2005) propose a latent Markov model that uses panel data on the financial services used by each panelist over a period of 7 years, rather than inferring the sequence of acquisition from cross-sectional data. The latent Markov model is an extension of the latent class model (Feick 1982) where latent classes are defined on the bases of the services used in a given year, and the probabilities of belonging to each of these latent segments are assumed to change from period to period according to a first-order Markov process. The first-order Markov process, which reflects how customer needs change over time, is used to project the probability that the customer will belong to each of the latent segments in the future. Combining these projected membership probabilities with the usage probabilities for each of the services by each latent segment it is then possible to compute the probability that the customer will be using any service in the future, thereby providing leads for cross-selling purposes.

Empirical results reported by Paas et al. (2005) show that, at the aggregate, the financial services follow a common order of acquisitions. However, for individual customers this general order of acquisitions does not necessarily apply, making the latent-class Markov model superior to the unidimensional scaling models based on cross-sectional data. Because they have longitudinal data from each customer spanning 7 years, Paas et al. (2005) are able to verify and compare the predictive performance of the proposed model.

Collaborative Filtering

The analytical tools for cross-selling reviewed so far focused on identifying the "next-to-buy" or "next-to-offer" service, based on "natural" acquisition sequences observed across customers and over time. The analytical tools we discuss next focus on making recommendations based on the associations between the product recently purchased and others offered by the firm. Even though the term "collaborative filtering" is usually applied to the earlier algorithms for item recommendations (Hey 1991, Goldberg, Nichols, Oki and Terry 1992, Robinson 1998, Herlocker, Konstan and Riedl 1999) we use it to categorize other tools proposed for the same purpose, and focus our review on their application to cross-selling. Collaborative filtering was first introduced by Goldberg et al. (1992) to help users filter their e-mails. The basic idea in collaborative filtering is to predict a customer's preferences as a weighted average of other customers' preferences, using weights that are proportional to the correlations between the preferences by the focal customer and all "collaborators" over a common set of products. In its original formulation (Goldberg et al. 1992), collaborative filtering used explicit ratings of each e-mail piece by the "collaborators" in the system. In most implementations for cross-selling, preferences are "revealed" implicitly through the customers' decision (not) to purchase certain products and services. The customer database consists of "votes" v_{ij} by each customer i on product j. The mean vote by customer i is then $\bar{v}_i = \sum_{j \varepsilon I_i} v_{ij} \Big/ |I_i|$, where I_i is the set of all votes by customer i (Breese, Heckerman and Kadie 1998), and the predicted vote by a focal customer a for product j is a weighted average of the votes by all other users,

$$P_{aj} = \bar{v}_a + \sum_{i \neq a}^{n} w(a,i)(v_{ij} - \bar{v}_i),$$

where n is the number of customers, $\sum_{i \neq a}^{n} w(a,i) = 1$ and the weights $w(a,i)$ are proportional to the preference similarity between focal customer a and collaborator i. Collaborative filtering algorithms differ on how the similarity among collaborators is measured (Breese et al. 1998). Recommendation systems based on this basic collaborative filtering idea are commonly found on the Internet (see Ansari, Essegaier and Kohli 2000 for a review of these Internet recommendation systems).

The basic collaborative filtering algorithm described above operates over the entire customer database to make predictions for one focal customer, as it requires the computation of weights and the weighted average across all customers. Another approach is to first use the database to estimate or "train" a model, which is then used to make predictions. A wide range of models and algorithms has been developed for this purpose using machine learning or statistical modeling.

Among the most popular machine learning techniques used for this purpose is the extraction of association rules from customer databases (Agrawal, Imielinski and Swami 1993; Anand, Hughes, Bell and Patrick 1997), which produce a set of rules describing the most common associations among products and services, such as PDA => Memory

Card [support = 0.30; confidence = 0.80]. This association implies that 30% of PDA buyers also buy a Memory Card, and that this association rule has a reliability of 80%. This type of association rule, particularly those involving a higher association order, are obviously useful to identify recommendations for cross-selling. An entirely different perspective to cross-selling is taken by Netessine, Savin and Xiao (2006), who argue that online cross-selling recommendations are more effective when bundled at a discount to make the package more attractive, which in fact is commonly found in Internet retailing. However, in these situations, it might be more profitable to sell the items individually at regular prices, depending on the risk of future stock-outs. Considering this situation, Netessine et al. (2006) propose a cross-selling model that blends combinatorial optimization (package selection) with stochastic dynamic programming (package pricing) to define the most profitable cross-selling bundles for each customer. Their model implements revenue management, so that cross-selling packages are formed taking into account the risk of stock-outs and costs of inventory replenishment.

On the statistical side, a wide range of models has been proposed for collaborative filtering, such as latent class models (Breese et al. 1998) and Bayesian networks (Heckerman 1996, Chickering, Heckerman and Meek 1997). The main idea in these approaches is to identify a structure underlying the associations among products and between customers and products, and then use this structure to draw cross-selling recommendations. Yancy and Allenby (2003) propose a multivariate binomial probit model to uncover the association among products across all customers. The multivariate distribution of latent utilities or values for the products is then used to compute conditional probabilities for the usage of a focal product, given information on the usage of all other products. When the number of products is large (say $N = 80$), this multivariate approach may lack parsimony, as it will require the estimation of $N^*(N-1)/2 = 3{,}160$ parameters only for the covariance matrix. For these larger cases with more than a dozen of products/services, Wedel and Kamakura (2001) propose a more parsimonious approach in which the covariance of the multivariate distribution is decomposed into its principal components, considerably reducing the number of parameters that need to be estimated, and therefore potentially enhancing the predictive performance for large problems.

Moon and Russell (2005) propose a two-stage statistical approach that is conceptually similar to the earlier collaborative filtering algorithms. First, they use data on product usage by all customers to obtain a joint mapping of products and customers, so that customers with similar patterns of product usage are located closer to each other in the map. This map defines the similarity in tastes for every pair of customers, as in the original collaborative filtering algorithms. Then, to compute the probability that a focal customer would use a focal product, Moon and Russell (2005) utilize a binary auto-logistic model where this probability is a function of whether other customers use the same focal product, weighted by a measure of similarity between these customers and the focal customer. Comparing the predictive comparison of their proposed approach with neural networks, a traditional collaborative filtering algorithm and logistic regression, Moon and Russell (2005) find that their approach is clearly better, particularly at low selection rates (top 6 deciles or lower), where this type of model is often most useful.

MAKING CROSS-SELLING WORK

The analytical tools for cross-selling reviewed in the previous section are only instruments that facilitate the implementation of a cross-selling strategy. Three major technological components of the enterprise must be in place before such strategy can be effectively implemented. First, managers must have already accumulated a comprehensive customer database detailing activities of each customer, so that the tools we discussed earlier can be calibrated and applied for across-selling purposes. Second, an enterprise-wide data warehouse must be in operation to provide managers and service representatives with a 360 degree view of each customer across all contact points, with the proper filters so that employees have access to all the relevant information for their interactions with customers. Third, a contact-management application is needed to manage and register customer contacts. This contact-management application, when integrated with the data warehouse and the analytical tools discussed earlier, will allow the customer services representative to identify cross-selling opportunities while fielding (inbound) service or (outbound) sales calls.

However, information technology is necessary, but not sufficient for the effective implementation of a cross-selling strategy. There are several organizational barriers that might prevent the successful implementation of cross-selling. One of them is the traditional organizational structure along product lines, which creates a “silo” mentality where employees associated with one product line do not feel responsible for other lines, regardless of the fact that they might all be serving the same customer. This product-centric structure also results into segregated databases so that managers on one side of the firm don't know about the relationship their customers maintain with other units within the same firm, preventing the use of acquisition pattern analysis or collaborative filtering, thereby hampering an effective implementation of cross-selling. Effective cross-selling through inbound contacts also requires that service representatives become salespeople. Rather than problem solvers or mere order takers, these service representatives must be trained to develop selling skills. Moreover, they must be provided with adequate incentives to perform this new and important selling function. The incentive structure must be enough to motivate but also properly calibrated not to distract the workforce from its main responsibilities. The "serve, then sell" philosophy must be maintained for the cross-selling strategy to work. In summary, aside from the technological investments, senior management must encourage company-wide dedication to cross-selling, demonstrated by incentives to encourage employees to share data and to add the selling function to their normal functions, and by the discipline to measure results in real time and reward employees based on them.

Finally, it is important to consider cross-selling within the context of the firm's overall CRM strategy. Quite often, managers follow a product-centric approach to cross-selling, where the decision is made to cross-sell a particular product, and then the customer database is "mined" to identify the best prospects for that product. This product-centric cross-selling is myopic and runs the risk of over-touching the firm's best customers, as they are more likely to fall in the "best prospects" list for each new product-centric cross-selling campaign. A much more effective approach is customer-centric, where cross-selling is only one of the possible treatments for each customer. This customer-centric approach starts with a thorough analysis of the customer's needs, and value to the firm, which then leads to the choice of treatment for the customer. If the customer relationship needs development, increasing the share of wallet or broadening the scope of the relationship, then cross-selling would be appropriate, as long as the firm is able to offer additional product/services that fit the customer's current needs. On the other hand, if the customer is already a highly valuable one who devotes a large share of wallet to the firm, cross-selling might be counter-productive, even if the customer scores as a high prospect in analytical models. In this case, the firm is better of making sure that it serves well and retains the customer.

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doi:10.1300/J366v06n03_03

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